A COMPREHENSIVE FRAMEWORK FOR TESTING DATABASE-CENTRIC SOFTWARE APPLICATIONS

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The database is a critical component of many modern software applications. Recent reports indicate that the vast majority of database use occurs from within an application program. Indeed, database-centric applications have been implemented to create digital libraries, scientific data repositories, and electronic commerce applications. However, a database-centric application is very different from a traditional software system because it interacts with a database that has a complex state and structure. This dissertation formulates a comprehensive framework to address the challenges that are associated with the efficient and effective testing of database-centric applications. The database-aware approach to testing includes: (i) a fault model, (ii) several unified representations of a program's database interactions, (iii) a family of test adequacy criteria, (iv) a test coverage monitoring component, and (v) tools for reducing and re-ordering a test suite during regression testing.

This dissertation analyzes the worst-case time complexity of every important testing algorithm. This analysis is complemented by experiments that measure the efficiency and effectiveness of the database-aware testing techniques. Each tool is evaluated by using it to test six database-centric applications. The experiments show that the database-aware representations can be constructed with moderate time and space overhead. The adequacy criteria call for test suites to cover 20% more requirements than traditional criteria and this ensures the accurate assessment of test suite quality. It is possible to enumerate data flow-based test requirements in less than one minute and coverage tree path requirements are normally identified in no more than ten seconds. The experimental results also indicate that the coverage monitor can insert instrumentation probes into all six of the applications in fewer than ten seconds. Although instrumentation may moderately increase the static space overhead of an application, the coverage monitoring techniques only increase testing time by 55% on average. A coverage tree often can be stored in less than five seconds even though the coverage report may consume up to twenty-five megabytes of storage. The regression tester usually reduces or prioritizes a test suite in under five seconds. The experiments also demonstrate that the modified test suite is frequently more streamlined than the initial tests.

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PREFACE

So now, come back to your God! Act on the principles of love and justice, and always live in confident dependence on your God.
Hosea 12:6 (New Living Translation)

1.0 INTRODUCTION

1.1 THE RISE OF THE DATABASE

Modern day academic institutions, corporations, and individuals are producing information at an amazing rate. Recent studies estimate that approximately five exabytes (10^{18} bytes) of new information were stored in print, film, magnetic, and optical storage media during the year 2002 [Lyman and Varian, 2003]. Additional results from the same study demonstrate that ninety-two percent of new information was stored on magnetic media such as the traditional hard drive. In an attempt to ensure that it is convenient and efficient to insert, retrieve, and remove information, data managers frequently place data into a structured collection called a *database*. In 1997, Knight Ridder's DIALOG was the world's largest database because it used seven terabytes of storage. In 2002, the Stanford Linear Accelerator Center maintained the world's largest database that contained approximately 500 terabytes of valuable experiment data [Lyman and Varian, 2003]. Since the year 2005, it is common for many academic and industrial organizations to store hundreds of megabytes, terabytes, and even petabytes of critical data in databases [Becla and Wang, 2005, Hicks, 2003].

A database is only useful for storing information if people can correctly and efficiently (i) query, update, and remove existing data and (ii) insert new data. To this end, software developers frequently implement a *database-centric application* – a program that interacts with the complex state and structure of database(s). [1] Database-centric applications have been implemented to create electronic journals [Marchionini and Maurer, 1995], scientific data repositories [Moore et al., 1998, Stolte et al., 2003], warehouses of aerial, satellite, and topographic images [Barclay et al., 2000], electronic commerce applications [Halfond and Orso, 2005], and national science digital libraries [Janee and Frew, 2002, Lagoze et al., 2002]. Since a database-centric application uses a program to query and modify the database, there is a direct relationship between the quality of the data in the database and the correctness of the program that interacts with the database. If the program in a database-centric application contains defects, corruption of the important data within the database could occur. *Software testing* is a valuable technique that can be used to establish confidence in the correctness of, and isolate defects within, database-centric applications. In recent years, traditional approaches to program and database testing focused on independently testing the program and the databases that constitute a database-centric application. There is a relative dearth of techniques that address the testing of a database-centric application by testing the program's interaction with the databases.

[1] This dissertation uses the term "database-centric application." Other terms that have been used in the literature include "database-driven application," "database application," and "database system."

Jeppesen GPS navigation database corruption

"About 350 airspace boundaries contained in Jeppesen NavData are incorrect, the FAA has warned. The error occurred at Jeppesen after a software upgrade when information was pulled from a database containing 20,000 airspace boundaries worldwide for the March NavData update, which takes effect March 20. Only a dozen are in the United States, including Chicago; Louisville, Kentucky; Fayetteville, North Carolina; Santa Ana, California; Las Vegas; Honolulu; Des Moines; and Oklahoma City. The error could cause pilot alerts to be given by GPS units too early or too late. Pilots are advised to use multiple sources of information, such as carrying paper charts (Jeppesen paper charts are unaffected by the problem), and contacting controlling agencies by radio to avoid airspace violations" [Neumann, 2003].

Figure 1.1: A Defect in a Real World Database-Centric Application.

Figure 1.1 provides an example of a defect that impacted the proper operation of a real world database-centric application [Neumann, 2003]. This example clearly demonstrates the importance of, and the need for, a comprehensive framework that can support the testing of database-centric applications. While the details associated with the defects in the NavData system are not available, it is illustrative to make some assumptions about how the airspace boundaries were corrupted by the NavData database-centric application. For example, suppose that NavData is designed to interact with two databases: D_{rnd}, a remote NavData database that contains all of the desired updates to the world's airspace boundaries and D_{lnd}, the local NavData database that is installed on a pilot's aircraft guidance computer. Next, assume that each airplane's local installation of NavData is configured to periodically connect to and query D_{rnd} in order to update the local D_{lnd}. Using the description in Figure 1.1 and the speculations about the implementation of NavData, it is clear that the NavData update routine contains a severe defect that violates the integrity of database D_{lnd}. We specifically designed the testing framework to guide the isolation and prevention of a class of database interaction defects that includes this hypothesized defect.

1.2 OVERVIEW OF THE RESEARCH CONTRIBUTIONS

1.2.1 Technical Contributions

Conventional approaches to software testing exclusively focus on the program under test and ignore the program's interaction with its execution environment. Section 1.1 shows that the relational database is a noteworthy software component in the execution environment of a modern program. Yet, traditional software testing techniques do not consider how a program *interacts* with the complex *state* and *structure* of a database. This research addresses the challenge of efficiently and effectively incorporating database state and structure during the testing and analysis of a program's database interactions. The main contribution of this research is the description, design, implementation, and evaluation of a collection of testing techniques called DIATOMS, for *D*atabase-centr*I*c *A*pplication *T*esting t*O*ol *M*odule*S*. This research specifically focuses on the testing of a program's interaction with one or more *relational* databases. We provide tools to fully support each technique within the comprehensive framework for testing database-centric applications.

The foundation of each testing technique is a model of the faults that could occur when a program interacts with a relational database. The framework includes a database-aware *test adequacy* component that identifies the test requirements that must be covered in order to adequately test an application. A test coverage monitoring technique instruments the application under test and records how the program interacts with the databases during test suite execution. DIATOMS also provides database-aware test suite *reduction* and *prioritization* components that support regression testing. The approach to test suite reduction discovers and removes the redundant test cases within a test suite. The prioritization scheme re-orders the tests in an attempt to improve test suite effectiveness. We provide a worst-case analysis of the performance of every key algorithm within DIATOMS. We also empirically evaluate each of the techniques by testing several real world case study applications. In summary, the technical contributions of this research include:

1. **Fault Model**: Conventional fault models only consider how defects in the input and structure of a program might lead to a failure. We provide a fault model that explains how a program's interactions can violate the integrity of a relational database. The model describes four types of program defects that could compromise data quality.
2. **Database-Aware Representations**: Traditional program representations focus on control and data flow within the program and do not show how a program interacts with a database. We develop database-aware finite state machines, control flow graphs, and call trees in order to statically and dynamically represent the structure and behavior of a database-centric application.
3. **Test Adequacy Criteria**: Current program-based adequacy criteria do not evaluate how well a test suite exercises the database interactions. DIATOMS enumerates test requirements by using data flow analysis algorithms that operate on a database-aware control flow graph. We also furnish a subsumption hierarchy that organizes the database-aware adequacy criteria according to their strength.
4. **Test Coverage Monitoring**: Existing test coverage monitoring schemes do not record how a program interacts with its databases during test suite execution. The coverage monitor instruments the program under test with statements that capture the database interactions. The component stores coverage results in a manner that minimizes storage overhead while preserving all of the necessary coverage information.
5. **Test Suite Reduction**: The execution of a test for a database-centric application involves costly manipulations of the state of the database. Therefore, the removal of the redundant tests can significantly decrease the overall testing time. However, traditional test suite reduction schemes remove a test if it redundantly covers program-based test requirements. Our approach to test suite reduction deletes a test case from the test suite if it performs unnecessary database interactions.
6. **Test Suite Prioritization**: Conventional approaches to test suite prioritization re-order a test suite according to its ability to cover program-based test requirements. Our database-aware prioritizer creates test case orderings that cover the database interactions at the fastest rate possible. This type of prioritization is more likely to reveal database interaction faults earlier in the testing process.

1.2.2 A New Perspective on Software Testing

A program executes in an environment that might contain components such as an operating system, database, file system, graphical user interface, wireless sensor network, distributed system middleware, and/or virtual machine. Since a modern software application often interacts with a diverse execution environment in a complicated and unpredictable manner, there is a clear need for techniques that test an application, an application's execution environment, and the interaction between the software application and its environment. This research shows how to perform environment-aware testing for a specific environmental factor – the relational database. However, the concepts, terminology, tool implementations, and experiment designs provided by this research can serve as the foundation for testing techniques that focus on other software components in the execution environment.

1.3 OVERVIEW OF THE DATABASE-AWARE TESTING FRAMEWORK

We designed, implemented, and tested each of the database-aware techniques with great attention to detail. We used hundreds of unit and integration tests to demonstrate the correctness of each testing tool. For example, the coverage monitoring component contains over one hundred test cases. The four test suites for this component comprise 2282 non-commented source statements (NCSS) while the eighteen classes in the tool itself only contain 1326 NCSS. Furthermore, all of the source code contains extensive documentation. We successfully applied the techniques to the testing and analysis of small and moderate size case study applications. The following goals guided the implementation of the presented testing techniques:

1. **Comprehensive and Customized**: DIATOMS establishes a conceptual foundation that supports the design and implementation of testing techniques for each of the important stages in the software testing life cycle for database-centric applications. We customized the comprehensive suite of techniques provided by DIATOMS in order to handle the inherent challenges associated with the testing and analysis of database-centric applications.
2. **Practical and Applicable**: DIATOMS is useful for practicing software engineers. Unlike some existing program testing techniques (e.g., [Addy and Sitaraman, 1999, Doong and Frankl, 1994, Sitaraman et al., 1993]), DIATOMS does not require knowledge of formal specification or architectural description languages. DIATOMS does not force testers to write descriptions of the state and/or structure of the databases and the program, as required in [Willmor and Embury, 2006]. DIATOMS also utilizes software testing tools (e.g., [Hightower, 2001, Jeffries, 1999]) that are already accepted by practicing software developers.
3. **Highly Automated**: The tools within DIATOMS automate the testing process whenever possible. Unlike prior approaches to testing (e.g., [Barbey et al., 1996, Chays et al., 2000, MacColl et al., 1998, Richardson et al., 1992]), DIATOMS does not require the tester to manually specify the test requirements. DIATOMS can monitor test coverage and report test results in an automated fashion. The

presented approach can automatically calculate the adequacy of the test suites. Finally, DIATOMS provides automated regression test suite reduction and prioritization techniques.

4. **Tester Involvement**: The automated characteristic of DIATOMS must be balanced by the close involvement of the software tester [Marick, 1998, Pettichord, 1999]. Each of the techniques provided by DIATOMS enables the tester to offer recommendations and advice. For example, the tester can review the list of test requirements that was automatically specified by DIATOMS and then augment this listing. A tester can add tests back to the reduced test suite and/or modify the re-ordering produced by the test prioritizer.

5. **Platform Independent and Portable**: Whenever possible, the tools within DIATOMS are implemented in the platform-independent Java programming language. Other tools within DIATOMS are implemented in common scripting languages that are provided by all workstations that use the Unix and GNU/Linux operating systems. The testing techniques avoid the modification of common infrastructure software such as operating systems kernels, substantial programming language libraries, relational database management systems (RDBMS), and the Java virtual machine (JVM). Furthermore, the test requirements, test execution results, and output from the testing and analysis of the application under test are always stored in a platform-independent representation.

6. **Relevant to Popular Technologies**: DIATOMS focuses on the testing and analysis of database-centric applications that consist of general purpose programming language constructs and embedded structured query language (SQL) statements. Specifically, DIATOMS handles applications that are written in the Java programming language and use Java database connectivity (JDBC) drivers to communicate with a relational database management system. The DIATOMS prototype focuses on the testing and analysis of database-centric applications that interact with MySQL, PostgreSQL, or HSQLDB relational databases [Monjian, 2000, Stinson, 2001, Yarger et al., 1999]. The experimentation with the testing techniques always configured the case study applications to use the HSQLDB RDBMS because it provides an efficient and fully functional in-memory database.

7. **General Approach**: We balanced the relevancy of DIATOMS to currently popular technologies with the general nature of the framework. Even though DIATOMS initially targets applications that use the object-oriented Java language, the framework is also relevant for applications written with procedural programming languages. Despite the fact that DIATOMS focuses on relational database management systems, many parts of the framework should also be useful for database-centric applications that use object-oriented [Zand et al., 1995], object-relational [Seshadri, 1998], and eXtensible Markup Language (XML) databases [Jagadish et al., 2002, Meier, 2003]. DIATOMS can also be extended to test distributed applications that use external storage systems such as a distributed hash table (DHT) [Rhea et al., 2005] or a tuple space [Arnold et al., 2002].

8. **Efficient and Scalable**: DIATOMS uses database-aware testing and analysis algorithms that are both efficient and scalable. For example, the test adequacy component can efficiently enumerate test require-

ments and the test coverage monitoring technique records coverage information with low time and space overheads. Furthermore, the regression testing component was able to efficiently identify a modified test suite that was more effective than the original tests. The experimental results show that the techniques provided by DIATOMS are applicable to both small and medium-scale programs that interact with databases. Although additional experimentation is certainly required, the results suggest that the majority of DIATOMS can also be used to test large-scale database-centric applications.

1.4 ORGANIZATION OF THE DISSERTATION

Chapter 2 presents a model of execution-based software testing and reviews the related work. Chapter 3 provides an overview of the testing framework, discusses the experimental design used in the evaluation of the testing techniques, and examines each case study application. Chapter 4 introduces a family of database-aware test adequacy criteria. In this chapter, we explore the subsumption hierarchy that formalizes the relationship between each criterion in the test adequacy family. The fourth chapter also shows that traditional data flow-based test adequacy criteria are not sufficient because they only focus on program variables and they disregard the entities within the relational database. Chapter 5 describes and empirically evaluates a database-aware test adequacy component that determines how well a test suite exercises the program's interactions with the relational databases. Chapter 6 discusses the database-aware test coverage monitoring (TCM) technique. This chapter explains how we instrument an application in order to support the creation of coverage reports that contain details about all of the program's database interactions.

Chapter 7 introduces the database-aware TCM component and shows how we insert the monitoring instrumentation. In this chapter we empirically evaluate the costs that are associated with program instrumentation and the process of test coverage monitoring. Chapter 8 presents a database-aware approach to test suite reduction that identifies and removes the tests that redundantly cover the program's database interactions. This chapter also describes test suite prioritization techniques that use test coverage information to re-order the tests in an attempt to maximize the potential for finding defects earlier in the testing process. Chapter 9 reviews the contributions of this research and identifies promising areas for future work. Appendix A summarizes the notation conventions that we use throughout this dissertation. Appendix B describes each case study application that we employ during experimentation. This appendix contains information about the size and structure of the programs and their test suites. Finally, Appendix C furnishes additional tables of data and examples that support our discussion of the experiment results.

2.0 BACKGROUND

2.1 INTRODUCTION

Since this research describes and evaluates a comprehensive framework for testing database-centric software applications, this chapter reviews the relevant database and software testing concepts. We also examine the related research and the shortcomings of existing techniques. In particular, this chapter provides:

1. A description of the relational database model, the relational database management system, and the structured query language (SQL) (Section 2.2).
2. The intuitive definition of a database-centric software application that supports the formal characterization that is developed in Chapter 4 (Section 2.3).
3. The definition of a graph and tree-based representation of a traditional program that can be enhanced to represent database-centric applications (Section 2.4).
4. A discussion of the relevant software testing concepts and terminology and the description of an execution-based software testing model (Section 2.5).
5. A review of the research that is related to the testing and analysis of database-centric software applications (Section 2.6).

2.2 RELATIONAL DATABASES

This research focuses on the testing and analysis of database-centric applications that interact with relational databases. Our concentration on relational databases is due to the frequent use of relational databases in database-centric applications [Barclay et al., 2000, Stolte et al., 2003]. Furthermore, there are techniques that transform semi-structured data into structured data that then can be stored in a relational database [Laender et al., 2002, Ribeiro-Neto et al., 1999]. Finally, the relational database is also capable of storing data that uses a non-relational representation [Khan and Rao, 2001, Kleoptissner, 1995], A *relational database management system* (RDBMS) is a set of procedures that are used to access, update, and modify a collection of structured data called a database [Codd, 1970, 1979, Silberschatz et al., 2006]. The fundamental concept in the relational data model is a *relation*. A relational database is a set of relations where a relation of attributes $A_1, \ldots, A_z$, with domains $M_1, \ldots, M_z$, is a subset of $M_1 \times \ldots \times M_z$. That is, a relation is simply

select $A_1, A_2, \ldots, A_z$
from $rel_1, rel_2, \ldots, rel_w$
where $\mathcal{P}$

(a)

delete from rel_j
where $\mathcal{P}$

(b)

insert into $rel_j(A_1, A_2, \ldots, A_z)$
values$(v_1, v_2, \ldots, v_z)$

(c)

update rel_j
set $A_l = F(A'_l)$
where $\mathcal{P}$

(d)

$$\mathcal{P} \text{ contains sub-predicates } V_\phi \; \Re \; V_\psi$$

$$\Re \in \{<, \leq, >, \geq, \neq, \textbf{in}, \textbf{between}, \textbf{like}\}$$

$$V_\phi \in \{A_1, A_2, \ldots, A_z\}$$

Figure 2.1: General Form of the SQL DML Operations.

a set of *records*. Each record in a relation is an ordered set of attribute values. Finally, a *relational database schema* describes the logical design of the relations in the database and a *relational database instance* is a populated example of the schema [Chamberlin, 1976, Codd, 1970, 1979, Silberschatz et al., 2006].

This research directly focuses on the SQL data manipulation language (DML) operations of **select**, **update**, **insert**, and **delete** and also considers SQL statements that combine these commands in an appropriate fashion. Since Chapter 4's family of test adequacy criteria uses data flow information, the chosen model of the structured query language contains the features of the SQL 1999 standard that are most relevant to the flow of data in a database-centric application (c.f. Section 3.4 for a clarification of this assertion and a review of the testing framework's main limitations). This research relies upon the description of the SQL operations provided by Figure 2.1. Parts (a), (b), and (d) of Figure 2.1 contain a reference to logical predicate $\mathcal{P}$ that includes sub-predicates of the form $V_\phi \; \Re \; V_\psi$ with $\Re \in \{<, \leq, >, \geq, \neq, \textbf{in}, \textbf{between}, \textbf{like}\}$ and V_ϕ is any attribute from the set $\{A_1, A_2, \ldots, A_z\}$. The sub-predicates in $\mathcal{P}$ are connected by a logical operator such as **and** or **or**. The variable V_ψ is defined in a fashion similar to V_ϕ; however, V_ψ can also be an arbitrary string, a pattern description, or the result of the execution of a nested **select** query. Also, the $v_1, \ldots, v_z$ in Figure 2.1(c) represent the specific attribute values that are inserted into relation rel_j. Table A1 in Appendix A summarizes the notation conventions that we use to describe relational databases.

2.3 OVERVIEW OF DATABASE-CENTRIC APPLICATIONS

A program is an organized collection of algorithms that manipulates data structures in an attempt to solve a problem [Wirth, 1976]. Intuitively, a database-centric application consists of a relational database management system, one or more relational databases, and a program that interacts with the databases through the management system. Figure 2.2 shows an example of a database-centric application and some

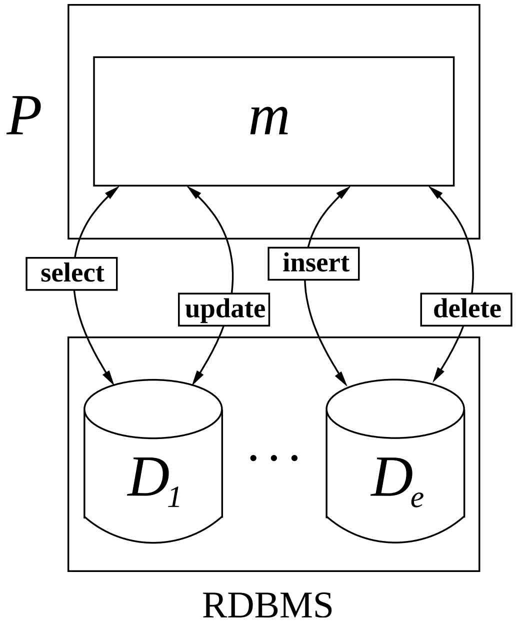


Figure 2.2: High Level View of a Database-Centric Application.

of the canonical operations that the program can use to interact with the databases $D_1, \ldots, D_e$. In this example, program P uses method m to submit structured query language statements to the RDBMS that processes the SQL, performs the requested query and/or database manipulation, and returns any results back to the program. The program in Figure 2.2 uses the SQL data manipulation language statements in order to view and modify the state of the database.

This research uses a transaction manager database-centric application to make the discussion in subsequent chapters more concrete. The transaction manager is also one of the case study applications that we use in the empirical studies and describe in more detail in Chapter 3 (for brevity, we will refer to this application as `TM` throughout the remainder of this dissertation).[1] `TM` performs an unlimited number of banking transactions with an account once an appropriate personal identification number (PIN) has been provided. Supported operations include the capability to deposit or withdraw money, transfer money from one account to another, and check the balance of an existing account. The `TM` application interacts with a *Bank* database that consists of the *UserInfo* and *Account* relations. The *UserInfo* relation contains the *card_number*, *pin_number*, *user_name*, and *acct_lock* attributes while the *Account* relation includes the *id*, *acct_name*, *user_name*, *balance*, and *card_number* attributes. Figure 2.3 provides the data definition language (DDL) statements used to create the *UserInfo* and *Account* relations. This discussion assumes that `TM` is implemented in Java and it interacts with a Java-based relational database. The Web site `http://www.hsqldb.org/` describes the RDBMS and specifies the subset of SQL that it supports.

[1] This research adheres to the following typographic conventions: relational database entities are in italics (e.g., *UserInfo* and *card_number*), structured query language keywords are in bold (e.g., **select** and **foreign key**), and program variables are in typewriter font (e.g., `transfer` and `id`).

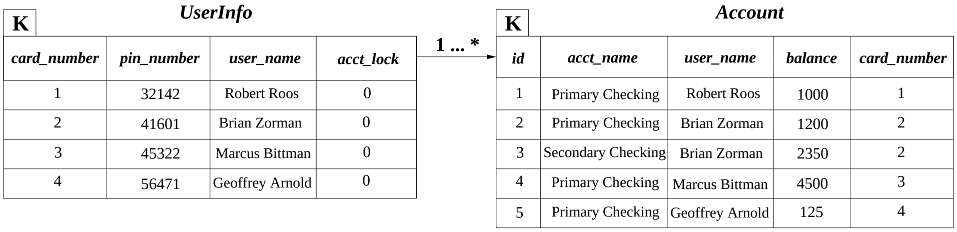
create table *UserInfo (card_number int* **not null identity**, *pin_number int* **not null**, *user_name varchar(50)* **not null**, *acct_lock int)*

(a)

create table *Account (id int* **not null identity**, *account_name varchar(50)* **not null**, *user_name varchar(50)* **not null**, *balance int* **default** *'0', card_number int* **not null**, **foreign key**(card_number) **references** *UserInfo(card_number));*

(b)

Figure 2.3: SQL DDL Statements Used to Create the (a) *UserInfo* and (b) *Account* Relations.



UserInfo

card_number	pin_number	user_name	acct_lock
1	32142	Robert Roos	0
2	41601	Brian Zorman	0
3	45322	Marcus Bittman	0
4	56471	Geoffrey Arnold	0

Account

id	acct_name	user_name	balance	card_number
1	Primary Checking	Robert Roos	1000	1
2	Primary Checking	Brian Zorman	1200	2
3	Secondary Checking	Brian Zorman	2350	2
4	Primary Checking	Marcus Bittman	4500	3
5	Primary Checking	Geoffrey Arnold	125	4

Figure 2.4: An Instance of the Relational Database Schema in the `TM` Application.

Figure 2.4 shows an example instance of the relational schema for the *Bank* database. The *UserInfo* relation uses the *card_number* attribute as a key that uniquely identifies each of the users while the *id* attribute is the key in the *Account* relation. In Figure 2.3, the SQL **identity** keyword declares that an attribute is a key. In Figure 2.4, the "K" above an attribute denotes a key. The *UserInfo* relation contains four records and the *Account* relation contains five records.[2] A foreign key constraint requires that every *card_number* in *Account* is associated with a *card_number* in the *UserInfo* relation. Figure 2.3(b) shows that this constraint is specified in DDL by using the **foreign key** and **references** key words. Furthermore, there is a one-to-many relationship between the *card_number* attribute in *UserInfo* and the *Account* relation's *card_number* attribute. A single user of `TM` can access one or more accounts (e.g., user "Brian Zorman" maintains primary and a secondary checking accounts).

Figure 2.5 provides a specific example of the general SQL DML statements that were described by Figure 2.1. Intuitively, a **select** operation allows the program to issue a query that requests certain data items from the database. The **insert** operation places new data in the database while the **update** and **delete** operations respectively change and remove existing data. If the program submits incorrect **select**, **update**, **insert**, and **delete** operations it will communicate incorrect data to P's method m and/or corrupt the data within one of the databases $D_1, \ldots, D_e$. For example, suppose that an account accumulates interest at a higher rate if the balance is above $\$10,000$. The SQL **select** statement in Figure 2.5(a) incorrectly identifies all accounts that have a balance greater than $\$1,000$. If a program submits this defective **select**

[2] In the literature, the terms "relation" and "table" are used interchangeably. The words "record" and "tuple" also have the same intuitive meaning. This research always use the terms relation and record.

```
select account_name, user_name
from Account
where balance > 1000
```

(a)

```
delete from Account
where card_number = 2
```

(b)

```
insert into Account
values(-10, “Primary Checking”,
          “Robert S. Roos”, 1800, 1)
```

(c)

```
update UserInfo
set acct_lock = 1
where card_number = 5
```

(d)

Figure 2.5: Specific Examples of the SQL DML Operations.

to the database, all of the accounts with a balance greater than \$1,000 will accrue interest even though this violates the banking policy. If the program provides the wrong *card_number* during the execution of the **delete** and **update** statements of Figure 2.5(b) and Figure 2.5(d) this would also corrupt the state of the database. When a program executes the SQL **insert** statement in Figure 2.5(c), this would incorrectly modify the database to include an *Account* record with an *id* of -10. Ultimately, faults in the program's interaction with the database can lead to the defective behavior of the entire application.

2.4 TRADITIONAL PROGRAM REPRESENTATIONS FOR TESTING

Software testing and analysis tools use a program representation to statically and dynamically model the structure and behavior of an application. The chosen program representation has an impact upon all software testing activities. For the purposes of analysis and testing, a specific operation within a program or an entire program can be represented as a control flow graph (CFG). A *control flow graph* provides a static representation of all of the possible ways that a program could execute. Intuitively, a control flow graph for a single program method is a set of nodes and edges, where a node is an executable program entity (e.g., a source code statement or a method) and an edge is a transfer of control from one program entity to another. An *intraprocedural* CFG is a graph representation for a single program operation while an *interprocedural* CFG statically represents the flow of control between the program's methods [Harrold and Soffa, 1994, Sinha et al., 2001]. A *call tree* offers a dynamic view of the program under test since it shows which source code elements were actually executed during testing and it can store data about input parameters and program variable state [Ammons et al., 1997]. Yet, the traditional control flow graph and call tree do not contain nodes or edges that explicitly represent how a program interacts with a relational database.

$G = \langle \mathcal{N}, \mathcal{E} \rangle$ denotes a control flow graph G for program P's method m. $\mathcal{N}$ represents the set of CFG nodes and $\mathcal{E}$ denotes the set of CFG edges. Each control flow graph G contains the nodes $\mathit{entry}, \mathit{exit} \in \mathcal{N}$ that demarcate the entry and exit points of the graph. We define the *dynamic call tree* (DCT) in a fashion analogous to the CFG, except for the restrictions that it (i) has a single distinguished node, the *root*, that marks the initial testing operation and (ii) does not contain any cycles. The *path* $\langle N_\rho, \ldots, N_\phi \rangle$ represents

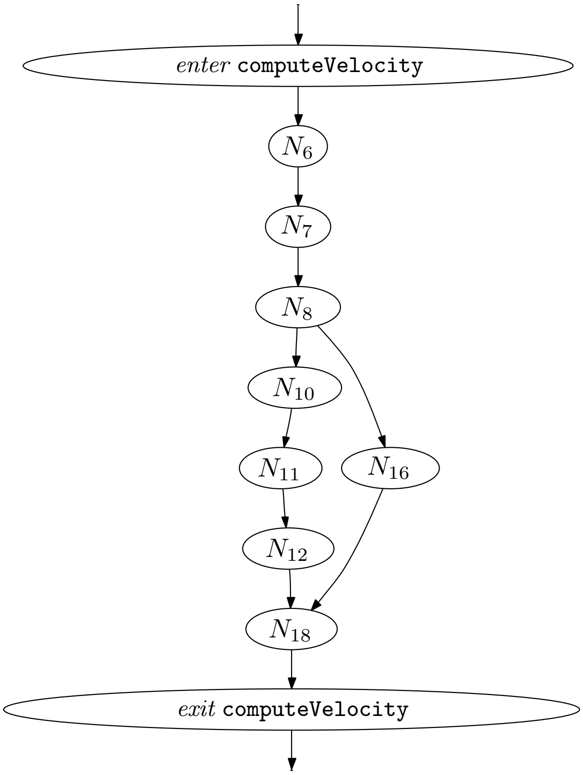
```
import java.lang.Math;
public class Kinetic
{
  public static String computeVelocity(int kinetic, int mass)
  {
    int velocity_squared, velocity;
    StringBuffer final_velocity = new StringBuffer();
    if( mass != 0 )
    {
      velocity_squared = 2 * (kinetic / mass);
      velocity = (int)Math.sqrt(velocity_squared);
      final_velocity.append(velocity);
    }
    else
    {
      final_velocity.append(”Undefined”);
    }
    return final_velocity.toString();
  }
}
```

Figure 2.6: Code Segment of a Traditional Program.

one way to traverse the CFG from arbitrary node N_ρ to node N_ϕ. Finally, a *complete path* is a sequence of nodes in a CFG that starts at the entry node and ends at the exit node. A path in a CFG represents one way that a method could be executed. A DCT path records a sequence of method calls that were actually executed during testing. For a CFG edge (N_ρ, N_ϕ), the notation *succ*(N_ρ) denotes the successor(s) of N_ρ, or in this example N_ϕ. For the same CFG edge, the notation *pred*(N_ϕ) is the predecessor(s) of N_ϕ and for this example edge it corresponds to N_ρ. Table A2 in Appendix A summarizes the notation that describes these traditional program representations.

There are many different graph-based and tree-based representations for programs. Harrold and Rothermel survey a number of static graph-based representations and the algorithms and tool support used to construct these representations [Harrold and Rothermel, 1995, 1996]. For example, the *class control flow graph* (CCFG) represents the static control flow among the methods within a specific class and therefore provides a limited interprocedural representation of a program [Harrold and Rothermel, 1994, 1996]. Ammons et al. describe the *calling context tree* (CCT) that depicts the execution of a method in the historical context of the methods that were executed before and after this method [Ammons et al., 1997]. The chosen representation for the program under test influences the test adequacy criteria that are subsequently used to measure the quality of existing test suites and support the implementation of new tests. Furthermore, the program representation also impacts regression testing activities such as test suite reduction and prioritization. Program analysis framework such as Aristotle [Harrold and Rothermel, 1995], Soot [Vallée-Rai et al., 1999], or AspectJ [Elrad et al., 2001, Kiczales et al., 2001a] create conventional graph and tree-based representations. This research demonstrates that we can also use these frameworks to produce database-aware models of an application's static structure and dynamic behavior.

In order to make the discussion of the traditional graph-based program representations more concrete, Figure 2.6 provides a Java class called `Kinetic` that contains a `static` method called `computeVelocity`



$$\boxed{succ(N_8) = \{N_{10}, N_{16}\} \text{ and } pred(N_{18}) = \{N_{12}, N_{16}\}}$$

Figure 2.7: A Traditional Control Flow Graph.

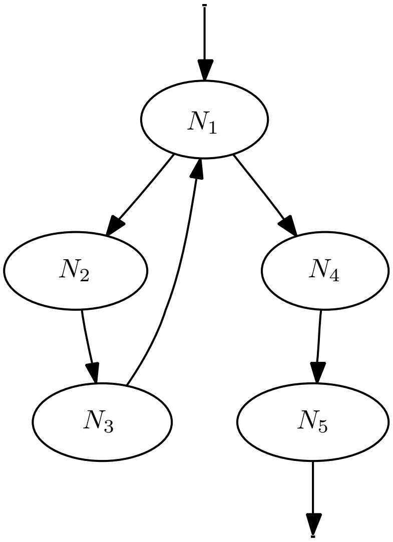


Figure 2.8: A Control Flow Graph of an Iteration Construct.

[Paul, 1996]. Since Kinetic does not interact with a relational database, we classify it as a traditional program and not as a database-centric application. The computeVelocity operation calculates the velocity of an object based upon its kinetic energy and its mass. This method uses the knowledge that the kinetic energy of an object, K, is defined as $K = \frac{1}{2}mv^2$. Figure 2.7 shows the control flow graph for the computeVelocity method. The path $\langle entry_{cv}, N_6, N_7, N_8, N_{16}, N_{18}, exit_{cv}\rangle$ represents a complete path in this example CFG and $\langle N_6, N_7, N_8\rangle$ is a path from node N_6 to node N_8. Inspection of the CFG in Figure 2.7 reveals that $succ(N_8) = \{N_{10}, N_{16}\}$ and $pred(N_{18}) = \{N_{12}, N_{16}\}$. A dynamic call tree for computeVelocity includes all of the nodes that were actually executed during the testing of the method. Even though computeVelocity does not contain any iteration constructs like a for, while, or do while loop, Figure 2.8 shows that it is also possible to represent iteration in a CFG. In this while loop node N_2 and N_3 are executed until the condition that is tested in node N_1 is false and then nodes N_4 and N_5 are executed. Our testing techniques use tree and graph-based representations that fully model iteration, recursion, method calls, and database interactions.

2.5 TRADITIONAL EXECUTION-BASED SOFTWARE TESTING

2.5.1 Preliminaries

Conventional software testing techniques focus on the source code and specification of a program and ignore the important database component of the database-centric application depicted in Figure 2.2. Even though most program-based software testing techniques are not directly applicable to the testing of a database-centric application, these approaches offer a conceptual foundation for this research. Any approach to testing database-centric applications must address many of the same fundamental testing challenges that traditional testing techniques already consider. It is important to observe that the testing of traditional programs is challenging because the domain of program inputs is so large that it is not possible to test with every input and there are too many possible program execution paths to test [Kaner et al., 1993]. Indeed, Young and Taylor have noted that every software testing technique must involve some trade-off between accuracy and computational cost because the presence (or lack thereof) of defects within a program is an undecidable property [Young and Taylor, 1989]. The theoretical limitations of testing clearly indicate that it is impossible to propose and implement a software testing framework that is completely accurate and applicable to arbitrary database-centric applications.

The IEEE standard defines a *failure* as the external, incorrect behavior of a program [IEEE, 1996]. Traditionally, the anomalous behavior of a program is observed when incorrect output is produced or a runtime failure occurs. Furthermore, the IEEE standard defines a *fault* (alternatively known as a *defect*) as a collection of program source code statements that causes a failure. Finally, an error is a mistake made by a programmer during the implementation of a software system [IEEE, 1996].[3] One purpose of software

[3] While these definitions are standard in the software engineering and software testing research community, they are different than those that are normally used in the fault-tolerant computing community. For example, this community defines a fault as the underlying phenomenon that causes an error. Furthermore, an error is recognized as a deviation in the system state from the correct state. For more details, please refer to [Jalote, 1998].

testing is to reveal software faults in order to ensure that they do not manifest themselves as runtime failures. Another goal of software testing is to establish an overall confidence in the quality of the program under test. Even though database-centric applications are tested for the same reasons, the terminology used to describe traditional testing techniques must be revised and extended in order to correctly explain the testing of this new class of applications. In the context of database-centric applications, faults could exist within the program, the data within the relational databases, or the interactions between the program and the databases. Moreover, a fault might only manifest itself as a failure when both the program and the database are in a certain anomalous state.

This research focuses on execution-based software testing techniques. It is also possible to perform non-execution-based software testing through the usage of software inspections [Fagan, 1976]. All execution-based testing techniques are either program-based, specification-based, or combined [Zhu et al., 1997]. This research uses program-based (alternatively known as structural or white-box) testing approaches that rely upon the program's source code in order to create and evaluate a test suite [Zhu et al., 1997]. It is important for the described testing techniques to have source code access because it is the program's source code that reveals how the application interacts with the databases.[4] Unlike traditional program-based testing methodologies, the presented testing approach considers one or more of the following: (i) the source code of the program, (ii) the relational schema, (iii) the current instance of the relational schema, and (iv) the manner in which the program interacts with the relational databases. Several of the testing techniques presented in this research, including test coverage monitoring and test suite reduction and prioritization, can be configured to operate without source code access.

2.5.2 Model of Execution-Based Software Testing

Figure 2.9 provides a model of execution-based software testing. In the subsequent sections of this chapter, we describe each of these stages in light of traditional software testing techniques. This model is only one valid and useful view of software testing. Our model of software testing takes as input a program under test P, a test suite T, and a test adequacy criterion C. Even though we assume that P is tested with a provided test suite, Chapter 9 explains that there are no inherent limitations within the framework that would prevent the inclusion of an automated test generation technique. The formulation of a test adequacy criterion C is a function of the chosen representation for P and a specific understanding of the "good" qualities that a test suite should possess. The test adequacy component analyzes P in light of the chosen C and constructs a listing of the test requirements that must be covered before the entire test suite can be judged as completely adequate.

Even though manual testing is possible, this research focuses on the automated execution of test suites. During test suite execution, the test coverage monitoring technique records information about the behavior

[4] Throughout this research, the definition of the term source code includes any description of a software application that is fully executable. In the context of database-centric applications written in the Java programming language, Java bytecodes are an example of a type of source code.

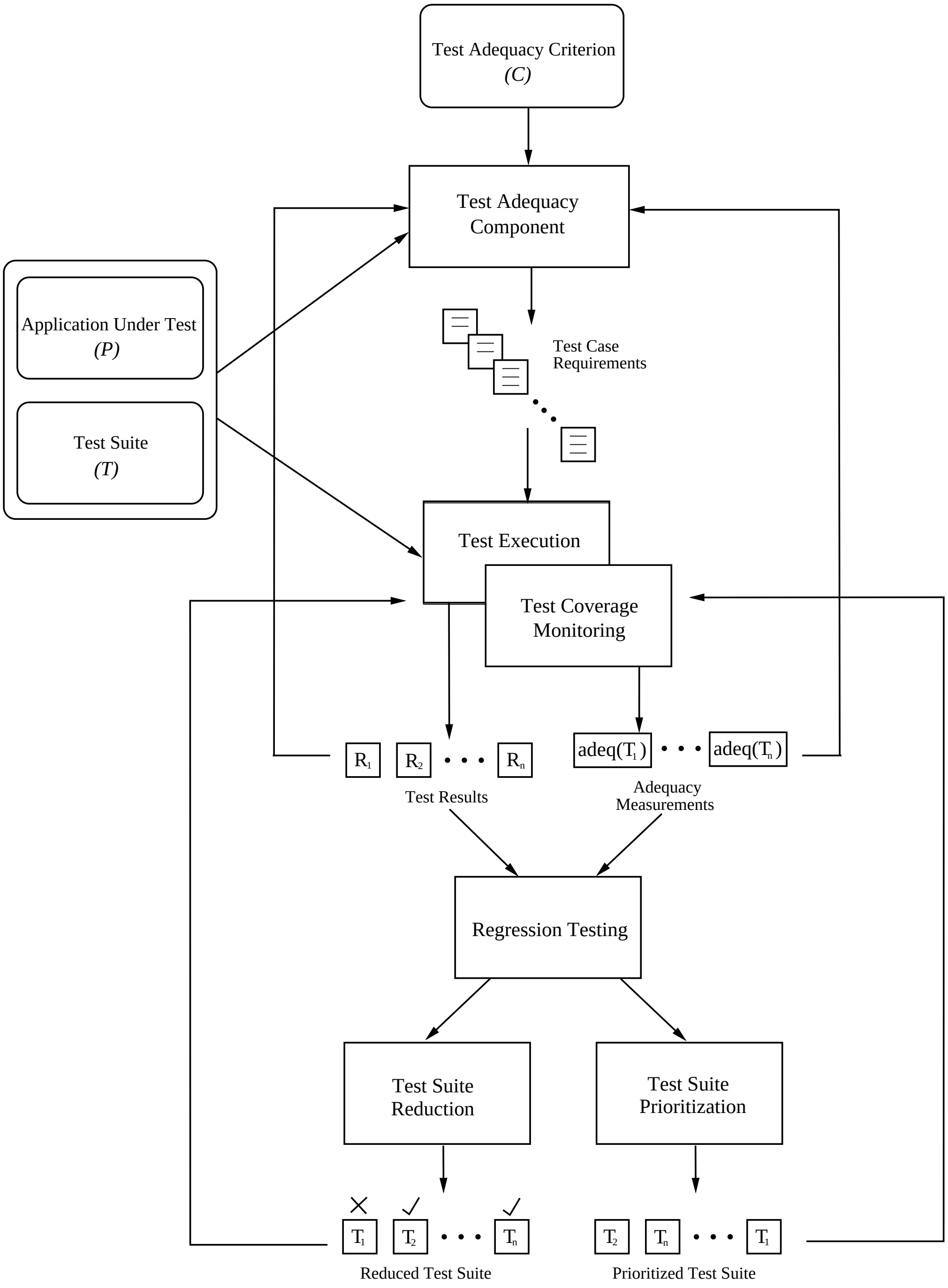


Figure 2.9: Execution-Based Software Testing Model for Traditional Programs.

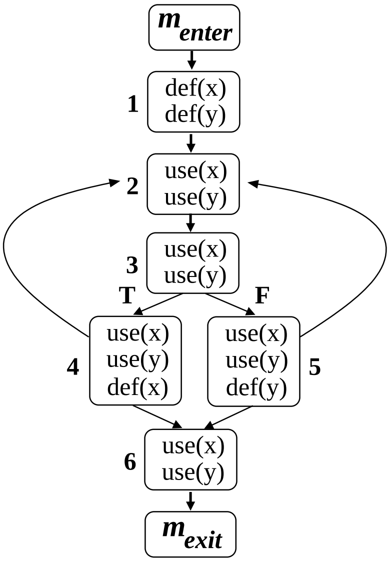


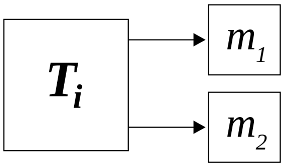
Figure 2.10: Intuitive Example of a Control Flow Graph.

of the test suite and the program under test. The test coverage monitor identifies which test requirements were covered during testing and then calculates an adequacy measurement for each test case, as depicted in Figure 2.9. Finally, regression testing is an important software maintenance activity that attempts to ensure that the addition of new functionality and/or the removal of program faults does not negatively impact the correctness of P. Approaches to test suite reduction identify a subset of the entire test suite that can still adequately test the program. Traditional test suite prioritization techniques normally re-order the execution of the test suite so that the rate of test requirement coverage or the potential for fault detection is maximized.

2.5.3 Test Adequacy Criteria

Test adequacy criteria embody certain characteristics of test case "quality" or "goodness." Test adequacy criteria can be viewed in light of a program's control flow graph, and the program paths and variable values that must be exercised. Intuitively, if a test adequacy criterion C_α requires the exercising of more path and variable value combinations than criterion C_β, it is "stronger" than C_β. More formally, a test adequacy criterion C_α *subsumes* a test adequacy criterion C_β if every test suite that satisfies C_α also satisfies C_β [Clarke et al., 1985, Rapps and Weyuker, 1985]. Two adequacy criteria C_α and C_β are *equivalent* if C_α subsumes C_β and vice versa. Finally, a test adequacy criterion C_α *strictly subsumes* criterion C_β if and only if C_α subsumes C_β and C_β does not subsume C_α [Clarke et al., 1985, Rapps and Weyuker, 1985].

Some software test adequacy criteria are based upon the control flow graph of a program under test. *Control flow-based* criteria solely attempt to ensure that a test suite covers certain source code locations with the rationale that a fault will not manifest itself in a failure unless it is executed [Morell, 1990, Voas, 1992]. While several control flow-based adequacy criterion are relatively easy to satisfy (e.g., *all-nodes* or statement coverage), others are so strong that it is generally not possible for a test suite to test P and satisfy



Test Requirements m_1

Requirement	COV?
R1	✓
R2	
R3	
R4	✓

Test Requirements m_2

Requirement	COV?
R1	✓
R2	
R3	✓
R4	✓
R5	
R6	✓

Figure 2.11: Calculating Test Case Adequacy.

the criterion (i.e., *all-paths* coverage). For example, the *all-nodes* criterion requires a test suite to cover all of the nodes in the control flow graph of the method under test and the *all-edges* criterion forces the coverage of the CFG edges. Some control flow-based adequacy criteria focus on the control structure of a program and the value of the variables that are used in conditional logic predicates. Since this research does not specifically develop control flow-based test criteria, we omit a discussion of criteria such as condition-decision coverage (CDC) and multiple-condition decision coverage (MCDC) [Jones and Harrold, 2003].

If the tests cause the definition of a program variable and then never use this variable, it is not possible for the test suite to reveal the program's defective variable definitions. *Data flow-based* test adequacy criteria require coverage of the control flow graph by forcing the execution of program paths that involve the definition and subsequent use of program variables. For a standard program, the occurrence of a variable on the left hand side of an assignment statement is a *definition* of this variable (e.g., `int a = 0;` defines the variable `a`). The occurrence of a variable on the right hand side of an assignment statement is a *computation-use* (or *c-use*) of this variable (e.g., `int a = b++;` includes a c-use of the variable `b`). Finally, when a variable appears in the predicate of a conditional logic statement or an iteration construct is a *predicate-use* (or *p-use*) of the variable [Frankl and Weyuker, 1988, Rapps and Weyuker, 1982] (e.g., `if(flag){...}` has a p-use of the boolean variable `flag`).

A *def-c-use* association includes a node that defines a program variable and a node that subsequently c-uses the same variable. Furthermore, a *def-p-use* association corresponds to a node that causes the definition of a variable and the later p-use of the variable at another CFG node [Frankl and Weyuker, 1988, Rapps and Weyuker, 1982]. A *def-use* association contains the node that defines a program variable and the node that subsequently defines or uses the same variable (i.e., the def-use association does not distinguish between a p-use or a c-use) [Hutchins et al., 1994]. A def-use association for variable *var* is a triple $\langle N_{def}, N_{use}, var\rangle$ where N_{def} defines variable *var* and N_{use} uses this variable. Figure 2.10 provides an example of a control flow graph that includes a total of sixteen def-use associations such as $\langle N_1, N_4, x\rangle$.

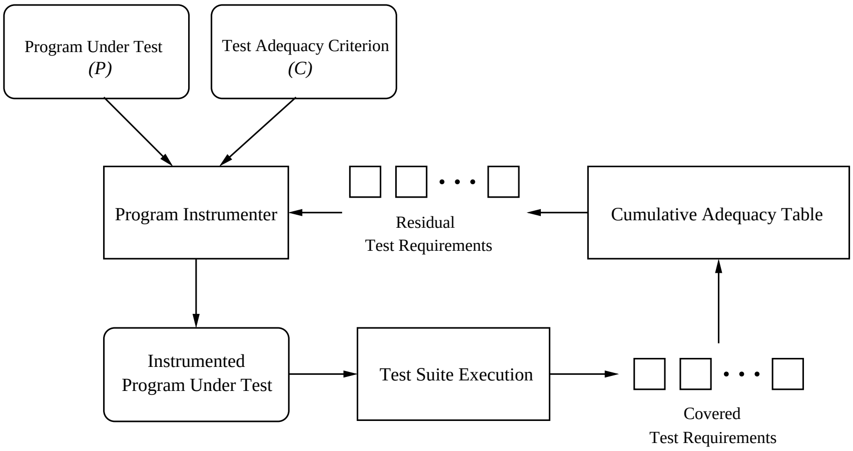


Figure 2.12: The Iterative Process of Test Coverage Monitoring.

In [Rapps and Weyuker, 1982], the authors propose a family of test adequacy criteria based upon the data flow information in a program. Among their test adequacy measures, the *all-uses* data flow adequacy criterion requires a test suite to cover all of the def-c-use and def-p-use associations in a program. The *all-uses* criterion is commonly used as the basis for data flow testing. Alternatively, the *all-DUs* test adequacy criterion requires the coverage of def-use associations [Hutchins et al., 1994]. Due to the fact that data flow-based test adequacy criteria track the flow of data within a program, they are particularly well-suited to serve as a foundation for the adequacy criteria that support the testing of database-centric applications [Kapfhammer and Soffa, 2003] (this assertion is further explored and justified in Chapter 4).

2.5.4 Test Coverage Monitoring

If test suites are provided with the program under test, it is important to measure the adequacy of these tests in order to decide if the program under test is being tested "thoroughly." If the *all-nodes* criterion is selected to measure the adequacy of a T used to test the `computeVelocity` method in Figure 2.6, then the test coverage monitor (TCM) must determine whether the nodes $enter_{cv}, n_6, n_7, n_8, n_{10}, n_{11}, n_{12}, n_{16}, n_{18}, exit_{cv}$ were executed during testing. Alternatively, if C is the *all-uses* test adequacy criterion, then the test coverage monitor would record whether or not the test suite causes the execution of the def-c-use and def-p-use associations within `computeVelocity`. Line 11 of `computeVelocity` contains a definition of the variable `velocity` and lines 12 contains a computation-use of `velocity`. The TCM component would include this def-use association in the listing of test requirements subject to monitoring. Once the coverage of test requirements is known, we can calculate the adequacy of a test case as the ratio between the test's covered test requirements and the total number of requirements. Figure 2.11 shows a test case T_i that tests two methods m_1 and m_2. This test yields an adequacy of 50% for its testing of m_1, an adequacy of 67% for m_2, and a cumulative adequacy of 60% for both of the methods. These adequacy scores are calculated under the assumption that there are a total of ten unique requirements for T_i to cover and the test is able to cover six of them overall.

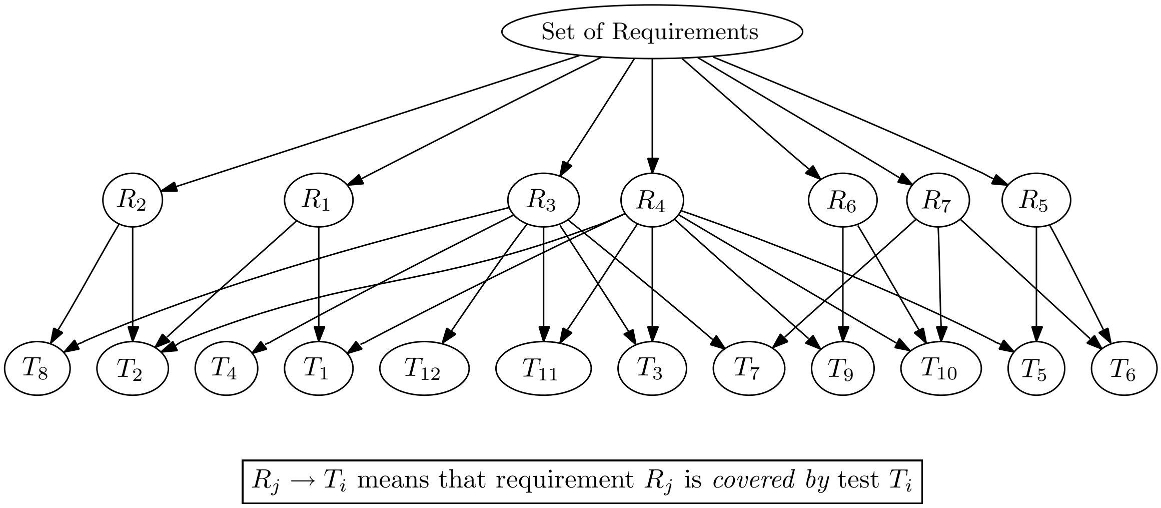


Figure 2.13: A Test Suite that is a Candidate for Reduction.

Test coverage monitoring techniques frequently require instrumentation of the test suite and/or the program under test in order to report which test requirements are covered during the execution of T. Among other goals, the instrumentation must efficiently monitor test coverage without changing the semantics of the program and the test suite. Pavlopoulou and Young have proposed, designed, and implemented a *residual test adequacy evaluator* that instruments the program under test and calculates the adequacy of the test suites used during development [Pavlopoulou and Young, 1999]. Figure 2.12 provides a high level depiction of this test adequacy evaluation tool for Java programs (many other test coverage monitoring techniques would adhere to a similar architecture). The residual coverage tool described by these authors can also measure the coverage of test requirements after a software system is deployed and it is being used in the field. This test coverage monitoring tool provides the ability to incrementally remove the test coverage probes placed in the program under test after the associated test requirements have been exercised [Pavlopoulou and Young, 1999]. More recently, Misurda et al. presented the Jazz test coverage monitoring technique that records information about the execution of edges, nodes, and def-use associations [Misurda et al., 2005]. The Jazz structural testing tool uses a modified Jikes Research Virtual Machine (RVM) to introduce and remove instrumentation in a demand-driven fashion.

2.5.5 Test Suite Reduction

A test suite can consist of test cases that overlap in their coverage of test requirements. Figure 2.13 shows how seven separate test requirements are covered by twelve unique test cases. In this tree, a directed edge from a requirement R_j to a test case T_i indicates that R_j is *covered by* T_i (or, that T_i *covers* R_j). For example, an edge between a requirement R_2 and a test case T_8 indicates that R_2 is covered by T_8 or T_8 covers R_2. The test coverage monitor establishes the *covered by* relationship, as described in Section 2.5.4. Since the test suite in Figure 2.13 contains a significant amount of overlap in test requirement coverage, it

Test Case	Faults				
	f_1	f_2	f_3	f_4	f_5
T_1			✓		
T_2	✓				
T_3	✓	✓			
T_4				✓	✓
T_5		✓			

Table 2.1: The Faults Detected by a Test Suite.

is a candidate for reduction. Test suite reduction techniques identify a potentially smaller set of tests that cover the same requirements as the initial test suite. We can use reduction during regression testing if it is too expensive to execute the complete test suite. Inspection of Figure 2.13 reveals that we could execute a reduced test suite consisting of $T_2, T_3, T_6,$ and T_9 instead of the original twelve test cases and still cover all of the seven requirements. Recently developed reduction algorithms attempt to maximize both coverage and defect detection rates while still decreasing the size of the test suite [Black et al., 2004].

Harrold et al. present a test suite reduction technique that is formulated in terms of a heuristic solution to the hitting set problem [Harrold et al., 1993]. Their approach creates a mapping from each test case to the test requirement(s) that it covers and it uses a custom heuristic for finding a reduced test suite. McMaster and Memon apply the algorithm of [Harrold et al., 1993] to a mapping from test cases to test requirements that are extracted from an earlier execution of the test suite [McMaster and Memon, 2005]. These authors argue that reduction should be performed whenever test cases produce the same call stacks during test execution. The standard technique of Harrold et al. is often applied after performing a static analysis of the program under test in order to locate the test requirements. In contrast, the approach of McMaster and Memon uses low overhead instrumentation to identify the call stacks that arise during testing [McMaster and Memon, 2005].

2.5.6 Test Suite Prioritization

Test prioritization schemes typically create a single re-ordering of the test suite that can be executed after many subsequent changes to the program under test [Do et al., 2004, Rothermel et al., 2001]. Test case prioritization techniques re-order the execution of a test suite in an attempt to ensure that (i) defects are revealed earlier in the test execution phase and/or (ii) the tests cover the requirements as rapidly as possible. If testing must be terminated early, a re-ordered test suite can also be more effective at finding faults than one that was not prioritized [Rothermel et al., 2001]. Normally, a software tester is not aware of the defect locations within the program under test. However, to make this discussion more concrete, suppose that program P is tested with test suite T and a priori knowledge of the faults within P is available. Table 2.1 shows an example of a simple test suite and the faults that each test can reveal. In this example, there are five faults that are revealed by certain test cases. In this test suite, some tests isolate more faults than other test cases. In particular, tests T_3 and T_4 are able to reveal more of the faults within the program under test than the other test cases. Intuitively, it would be better if these two test cases were executed before the other tests within the suite. Over the entire execution of the test suite, the test suite ordering $\sigma_1 = \langle T_1, T_2, T_3, T_4, T_5 \rangle$ yields a smaller weighted average percentage of isolated defects than the ordering $\sigma_2 = \langle T_3, T_4, T_1, T_2, T_5 \rangle$ (i.e., σ_2 detects faults faster than σ_1).

Since the existence of a priori knowledge about the location of faults within the program under test is unlikely, regression test suite prioritization algorithms must use a proxy for this complete knowledge. Current regression test suite prioritization algorithms are motivated by the empirical investigations of the effectiveness of test adequacy criteria which indicate that tests that are not highly adequate are often less likely to reveal program defects [Harder et al., 2003, Hutchins et al., 1994]. In light of the correlation between low adequacy test suites and the decreased potential to reveal a defect [Hutchins et al., 1994], a prioritization algorithm might chose to execute highly adequate tests before those with lower adequacy. Of course, since highly adequate tests are not guaranteed to always reveal the most defects, prioritization schemes can still fail to produce an optimal ordering of the tests [Hutchins et al., 1994, Rummel et al., 2005]. Yet, reports of industrial experience suggest that prioritization is both a cost-effective and valuable testing technique [Srivastava and Thiagarajan, 2002]. Recently developed prioritization techniques are time-aware because they generate test suite orderings that rapidly cover code while always terminating after a specified period of time [Walcott et al., 2006].

2.5.7 Discussion of the Testing Model

In the execution-based testing model of Figure 2.9, one testing technique produces output that is then used as the input to another technique. For example, the test suite executor and the test coverage monitor generate test results and adequacy measurements that are used by the approaches to regression testing. The output of a reduction or prioritization algorithm is a new test suite that can be used during future executions of the suite. Figure 2.9 also presents a model of execution-based software testing that contains cycles. Execution-based testing terminates when the adequacy of the test suite exceeds a pre-defined level, the testers determine that they have established sufficient confidence in the correctness of the program, or the testing budget has been exhausted [Zhu et al., 1997]. This research provides an execution-based testing framework where (i) interoperable modules produce input and output that is meaningful to all of the other components and (ii) testing can be repeated until an established termination condition has been met.

2.6 TESTING DATABASE-CENTRIC APPLICATIONS

While a significant amount of research has focused on the testing and analysis of programs, there is a relative dearth of work that specifically examines the testing of database-centric applications. We distinguish the presented research from the following related work because it provides a *comprehensive* testing framework and a suite of automated tools that can be applied to a wide range of database-centric applications. Our research also represents the most complete evaluation of the efficiency and effectiveness of approaches to database-aware testing. When we compare our empirical evaluations to those in prior work, it is also clear that we used the largest number of case study applications during experimentation. This research was initially motivated by the observation that even simple software applications have complicated and ever-changing operating environments that increase the number of interfaces and the interface interactions that must be tested [Whittaker and Voas, 2000]. These authors point out that device drivers, operating systems, and databases are all aspects of a software system's environment that are often ignored during testing. However, they do not propose and evaluate specific techniques that support the software testing process.

Even though Jin and Offutt highlight test adequacy criteria that incorporate a program's interaction with its environment [Jin and Offutt, 1998], these authors do not specifically address the challenges associated with test adequacy criteria for database-centric applications. Dauo et al. use data flow information to support the regression testing of database-centric applications. However, their exploration of data flow issues does not include either a representation for a database-centric application or a complete description of a database interaction association [Daou et al., 2001]. Another coverage criterion measures the adequacy of SQL **select** queries in light of a database that has already been populated with data [Suarez-Cabal and Tuya, 2004]. This approach can automatically calculate the coverage of a single query, identify a subset of the database that will yield the same level of coverage as the initial database, and provide guidance that might increase database coverage. However, this scheme focuses on the **select** statement and it does not consider the program that submits the queries to the relational database. Finally, Halfond and Orso present an adequacy criterion that is complementary to our family of data flow-based criteria [Halfond and Orso, 2006]. Their command-form coverage criterion ensures that a test suite causes the program under test to submit as many of the viable SQL commands as is possible. That is, they use static analysis to identify all of the SQL commands that the program could submit and then determine how many of these statements are actually generated during testing.

Chan and Cheung propose a technique that tests database-centric applications that are written in a general purpose programming languages, such as Java, C, or C++, and include embedded structured query language statements that are designed to interact with a relational database [Chan and Cheung, 1999a,b]. This approach transforms the embedded SQL statements within a database-centric application into general purpose programming language constructs. In [Chan and Cheung, 1999a], the authors provide C code segments that describe the selection, projection, union, difference, and cartesian product operators that form the relational algebra and thus heavily influence the structured query language. Once the embedded SQL statements within the program under test have been transformed into general purpose programming language constructs, it is possible to apply traditional control flow-based criteria to the problem of testing programs that interact with one or more relational databases. However, their focus on the control flow of a program ignores important information about the flow of data between the program and the databases.

Chays et al. and Chays and Deng describe several challenges associated with testing database-centric applications and propose the AGENDA tool suite as a solution to some of these challenges [Chays et al., 2000, Chays and Deng, 2003, Chays et al., 2002]. In [Chays et al., 2000], the authors propose a partially automatable software testing technique, inspired by the category-partition method [Ostrand and Balcer, 1988], that attempts to determine if a program behaves according to specification. When provided with the relational schema of the databases used by the application under test and a description of the categories and choices for the attributes required by the relational tables, the AGENDA tool can generate meaningful test databases [Chays and Deng, 2003, Chays et al., 2002]. AGENDA also provides a number of database testing heuristics, such as "determine the impact of using attribute boundary values" or "determine the impact of null attribute values" that can enable the tester to gain insights into the behavior of a program when it interacts with a database that contains "interesting" states [Chays et al., 2000, Chays and Deng, 2003, Chays et al., 2002]. Deng et al. have also extended AGENDA to support the testing of database transaction concurrency by using a data flow analysis to determine database transaction schedules that may reveal program faults [Deng et al., 2003]. It is important to observe that the current prototype of the AGENDA framework is designed to support the testing of database-centric applications that contain a single query [Chays et al., 2004]. This testing scheme is limited since the majority of database-centric applications contain many database interactions (in fact, Chapter 3 reveals that each of our case study applications has between 5 and 45 database interactions).

Neufeld et al. and Zhang et al. describe approaches that are similar to [Chays et al., 2000, Chays and Deng, 2003, Chays et al., 2002] because they generate database states using knowledge of the constraints in the relational schema [Neufeld et al., 1993, Zhang et al., 2001]. Yet, neither of these approaches explicitly provides a framework to support common testing activities like those depicted in Figure 2.9. While Gray et al. generate test databases that satisfy the constraints in the relational schema, their approach focuses on the rapid generation of large random data sets that support performance testing [Gray et al., 1994]. Instead of handling the generation of test databases, Slutz addresses the issues associated with automatically creating the statements that support the querying and manipulation of relational databases [Slutz, 1998]. This approach generates database query and manipulation statements outside of the context of a program that interacts with a database. Willmor and Embury also describe an automated test data generation scheme that can produce test data when given a predicate logic condition that describes the desired database state [Willmor and Embury, 2006].

Haftmann et al. present a regression test prioritization scheme that re-orders a test suite in an attempt to avoid RDBMS restarts [Haftmann et al., 2005a]. Their approach executes the test suite without database restarts and observes whether or not each test case passes. A test ordering conflict is recorded in a database if the exclusion of a restart between the two tests causes the otherwise passing tests to fail [Haftmann et al., 2005a]. These authors also describe prioritization heuristics that re-order a test suite in an attempt to avoid the test conflicts that were stored within the conflict database. Haftmann et al. have extended their basic technique to support the parallel execution of the test suite on a cluster of testing computers [Haftmann et al., 2005b]. None of their prioritization approaches use either static or dynamic analysis to observe how the test cases interact with specific relational database entities. As such, these prioritizers must coarsely identify the test conflicts through an examination of the test results. Furthermore, Haftmann et al. focus on improving the efficiency of regression testing and do not propose techniques to create more effective prioritizations. Finally, Willmor and Embury propose a regression test selection technique that can identify a subset of a test suite to use during subsequent rounds of testing [Willmor and Embury, 2005]. Their approach is similar to the presented reduction technique but it could exhibit limited reductions and performance concerns because it performs a conservative static analysis of the entire database-centric application.

2.7 CONCLUSION

This chapter reviews the data management and software testing concepts underlying our comprehensive testing framework. This chapter intuitively defines a database-centric application that we subsequently refine in Chapter 4. This chapter also provides a model for execution-based software testing that Chapter 3 extends to support the testing of a database-centric application. This testing model include components that measure test adequacy, monitor test coverage, and perform regression testing. Chapters 4 and 5 introduce a family of data flow-based test adequacy criteria that focuses on a program's database interactions. We present database-aware approaches for test coverage monitoring and regression testing in Chapter 6 through Chapter 8. Finally, this chapter examines the strengths and weaknesses of existing approaches to testing programs that interact with databases. The review of the related research clearly demonstrates that there is a need for a comprehensive framework that tests database-centric applications.

3.0 IMPLEMENTATION AND EVALUATION OF THE TESTING FRAMEWORK

3.1 INTRODUCTION

This chapter provides an overview of our framework for testing database-centric applications. We also describe the (i) case study applications that were tested with the database-aware framework, (ii) design of the experiments to evaluate the efficiency and effectiveness of the testing techniques, and (iii) high level threats to experiment validity. In summary, this chapter includes:

1. An overview of a framework for testing database-centric applications (Sections 3.2, 3.3, and 3.4).
2. A detailed examination of the case study applications that were used during experimentation and an overview of the design of the experiments used in subsequent chapters (Sections 3.5 and 3.6).
3. An analysis of the threats to the validity of the experiments and a presentation of the steps that were taken to control these threats (Section 3.7).

3.2 OVERVIEW

This chapter serves as the central location for the (i) survey of the database-aware testing framework, (ii) detailed characterization of the case study applications that we use during the empirical evaluation of the testing techniques, and (iii) overview of the experiment design that we employ throughout the entire process of experimentation. In particular, Section 3.3 explains the inputs and outputs of every testing tool and it shows the connection points between each of the components. This type of discussion contextualizes the testing techniques and demonstrates how each component contributes to the complete framework. We also clarify how database-aware testing is similar to and different from traditional testing schemes.

There are no well-established metrics that we can use to characterize a database-centric application according to its static and dynamic complexity. Therefore, Section 3.5 reports the value of traditional complexity metrics such as the (i) number of non-commented source statements (NCSS) and (ii) method level cyclomatic complexity number (CCN). Calculating NCSS and CCN allows us to compare our case study applications to those that were used in prior empirical studies. We also complement the discussion of these traditional complexity metrics with a review of the structure of the each application's relational database. Furthermore, we examine the (i) size and structure of each test suite and (ii) testing strategies that each application uses to verify the correctness of the program's database interactions. Since many of the following chapters contain the results from experiments with the testing components, Sections 3.6 and 3.7 review the general design that governs all of our experimentation. Structuring the dissertation in this manner avoids the need to repeatedly explain how we configured the execution environment and controlled the factors that could compromise the validity of our experimental results.

3.3 HIGHLIGHTS OF THE DATABASE-AWARE TESTING FRAMEWORK

Figure 3.1 describes our model for the execution-based testing of a database-centric application. This framework differs from the one that was presented in Chapter 2 because it accepts the following additional inputs: (i) a relational database management system, (ii) the state of one or more databases, and (iii) the relational schema that describes the organization of the databases. Each of the provided testing techniques is database-aware because it considers the state and structure of the relational databases. For example, the test adequacy component produces test case requirements called database interaction associations. These associations require the test suites to define and use the *entities* within the databases (e.g., the relations, records, attributes, and attribute values that are a part of the database's state and structure). Each test case populates the database with some initial state, executes one or more of the methods under test, and then invokes an oracle that compares an expected database state to the actual state that the method produced. The test executor also manipulates the state of the databases and could restart the RDBMS in order to ensure that the tests execute correctly.

The test execution phase outputs test results that contain (i) the outcome of executing each test case and (ii) portions of database state that support the debugging process. The database-aware test coverage monitor can construct multiple types of test coverage monitoring trees that record how the program and the test suite define and use the databases. The coverage monitoring trees contain nodes and edges that represent the program's interaction with the databases. The test coverage monitor (TCM) efficiently inspects the state of the relational database in order to create these database-aware trees. We use the TCM trees to produce adequacy measurements that reflect how well the test suite actually defines and uses the database at multiple levels of interaction granularity. Finally, the regression test prioritization and reduction techniques use the database-aware test coverage monitoring tree and the test adequacy measurements to re-order and reduce the test suite. The test reduction algorithm identifies a potentially smaller test suite that still covers the same set of database-aware test requirements. The prioritizer can re-order the test suite so that the tests maximize their potential for finding database interaction defects as early as is possible.

3.4 LIMITATIONS OF THE APPROACH

Figure 3.2 depicts a classification scheme for database-centric applications that extends the classification proposed in [Chan and Cheung, 1999a,b]. Every database-centric application must interact with its databases using either an "Embedded" or an "Interface" approach. In the "Embedded" approach that is normally asso-

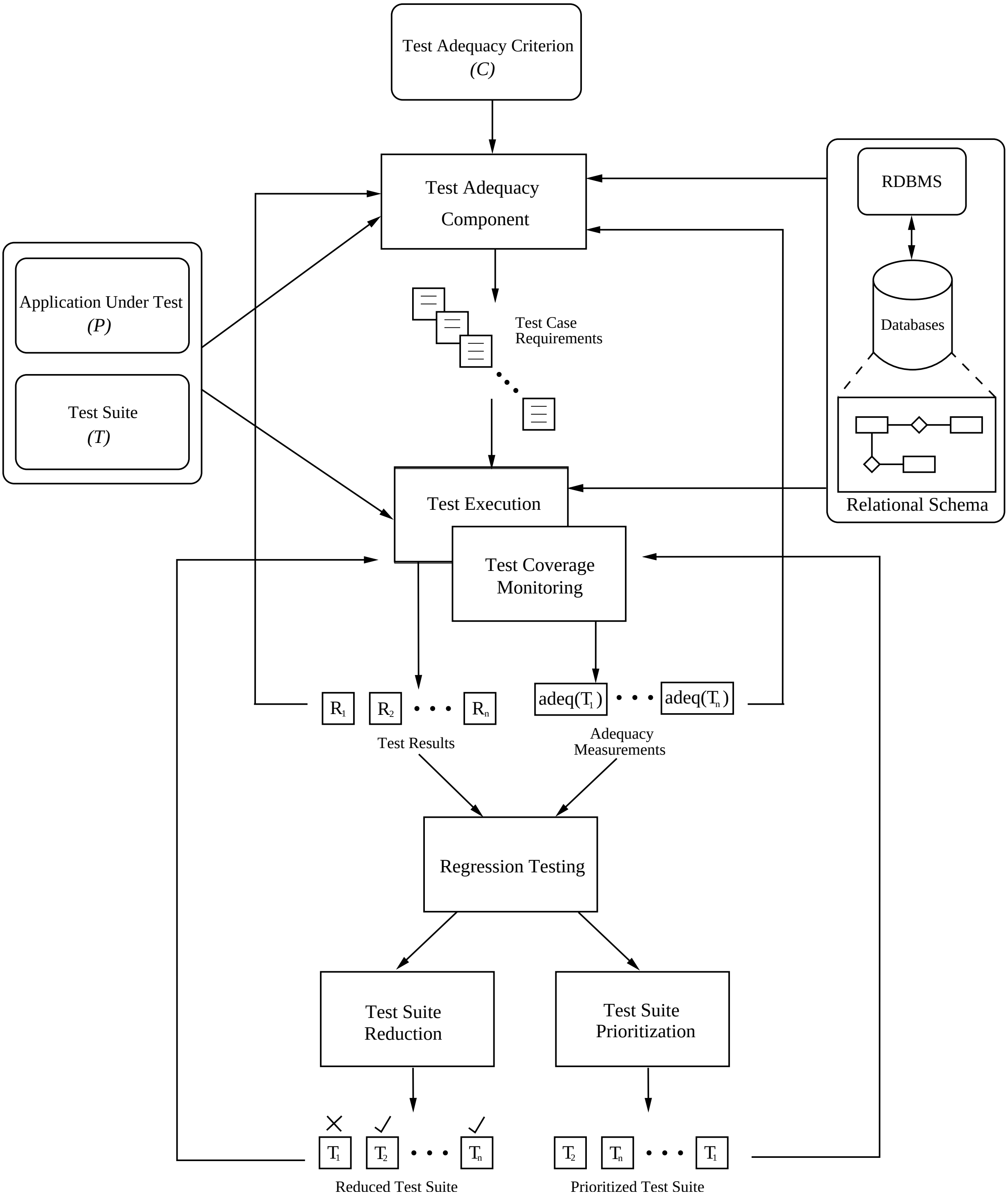


Figure 3.1: Execution-Based Software Testing Model for Database-Centric Applications.

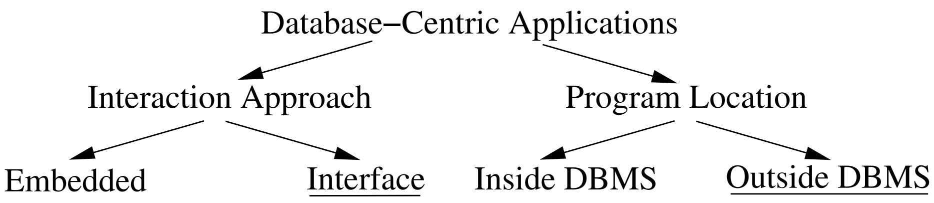


Figure 3.2: Classification Scheme for Database-Centric Applications.

ciated with the use of languages such as SQLJ, the program component contains embedded SQL statements that are transformed during a pre-compilation phase [Silberschatz et al., 2006]. Alternatively, a database-centric application that adheres to the "Interface" approach uses a database connectivity driver that can submit SQL statements to and return results from the database. Finally, the program component of a database-centric application can either exist inside or outside of the database management system. If a database-centric application consists of stored procedures that the RDBMS executes, then this program exists inside of the database management system. A program is located outside of the RDBMS if it interacts with the database through a standard interface like JDBC.

In Figure 3.2, a leaf from the "Interaction Approach" subtree can be paired with a leaf from the "Program Location" subtree, yielding four different possible configurations of a database-centric application: Embedded-Inside, Embedded-Outside, Interface-Inside, and Interface-Outside. The framework focuses on the testing and analysis of database-centric applications that adhere to the Interface-Outside architecture and it does not contain support for the analysis of applications that use stored procedures or triggers. Even though this research focuses on the Interface-Outside configuration of a database-centric application, Chapter 9 explains how we could extend the framework to test other types of applications. These current restrictions are not inherent limitations of the individual testing components. Instead, we view this as evidence of the need for new program analysis frameworks that support the (i) control and data flow analysis and (ii) instrumentation of programs written in languages such as SQLJ or PL/SQL. If program analysis techniques existed for these languages, then it would be possible to enumerate test requirements, monitor coverage, and perform regression testing.

Since many current relational database management systems restrict or do not support the definition of virtual relations with **create view** [Silberschatz et al., 2006], the framework does not analyze database-centric applications that use the **create view** statement. The database-aware testing framework does not support the testing of concurrent applications that use transactions. As such, the test adequacy component does not consider database transactions during the creation of the representation and the enumeration of test requirements. We further assume that each application executes a database interaction under an auto-commit directive that treats each SQL command as an indivisible unit of work. However, each of the aforementioned limitations does not impact the empirical results that we present because none of the case study application use these features of SQL. Chapter 9 describes the steps that must be taken to improve the framework so that it supports these facets of the structured query language.

Since all of the testing techniques are based on the state and structure of a database-centric application, they are not properly suited for detecting omission faults (c.f. Sections 4.2 and 4.3 for a justification of this assertion). The testing framework does not focus on finding the defects within P that incorrectly manipulate or display a program variable whose value is the result of a correct database interaction. For example, the testing tools will not highlight a fault where P correctly submits a **select** statement to retrieve the value of attribute A_l and then incorrectly updates the graphical user interface (GUI) by producing a label that indicates it is the value of attribute $A_{l'}$. The combination of adequacy criteria that consider program variables, database entities, and GUI elements will support the identification of this type of defect.

3.5 CHARACTERIZING THE CASE STUDY APPLICATIONS

3.5.1 High Level Description

We empirically evaluated each testing technique in Figure 3.1 by using it to test and analyze one or more of the six case study applications.[1] Each command line-based application is organized into a single Java package with a varying number of classes and methods. All of the database-centric applications include a build system written with the Apache Ant framework. The test suite for each case study application uses the DBUnit 2.1 extension of the popular JUnit 3.8.1 testing framework. Every application interacts with either a 1.7.3 or a 1.8.0 HSQLDB in-memory relational database that executes within the same Java virtual machine as the application itself. Since the case study applications use the standard Java database connectivity (JDBC) interface, it is possible to configure the programs to use other databases such as MySQL [Yarger et al., 1999] or PostreSQL [Monjian, 2000]. This section also characterizes each case study application according to the number of classes, methods, and *non-commented source code statements* (NCSS) it contains. Tables 3.1 and 3.2 provide a high level description of each case study application by reporting the average number of classes, methods, and NCSS per program, class, and method. In these two tables the term "method" refers to any executable code body within the program and thus includes the test cases.

For each method m_k with $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$ we also calculated its *cyclomatic complexity number* (CCN) $v(G_k) = |\mathcal{E}_k| - |\mathcal{N}_k| + |\mathcal{B}_k|$ [McCabe and Butler, 1989]. We use $\mathcal{B}_k \subset \mathcal{N}_k$ to denote the set of non-executable nodes within a method's CFG. Since the nodes $entry_k, exit_k \in \mathcal{N}_k$ (i.e., the nodes that demarcate a CFG's entry and exit points) are the only non-executable nodes in our CFG, we always have $|\mathcal{B}_k| = 2$ in the equation for $v(G_k)$. The CCN is the maximum number of linearly independent paths through the CFG of a method m_k [McCabe and Butler, 1989]. Figure 3.3 shows that $v(G_k) = 1$ for a method m_k that contains a single straight-line code segment. Figure 3.4 reveals that $v(G_k) = 2$ when G_k contains a single conditional logic statement. Adding the edge (N_4, N_1) to the CFG of Figure 3.4 increases the CCN by one, as demonstrated in Figure 3.5. Finally, Figure 3.6 shows the calculation of $v(G_k)$ for a CFG that uses iteration and conditional logic constructs to form a G_k with five linearly independent paths. Table A3 in Appendix A summarizes this chapter's use of notation.

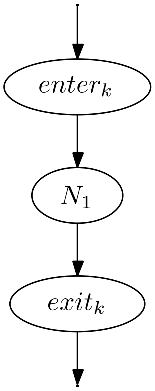
[1] Unless specified otherwise, Gregory M. Kapfhammer implemented each case study application. The author also implemented the test suite for each case study application.

Name	**Classes**	**Methods**	**NCSS**	**Per**
`Reminder` (`RM`)	9	55.0	548.0	*Program*
		6.11	60.89	*Class*
			9.96	*Method*
`FindFile` (`FF`)	5	49.0	558.0	*Program*
		9.8	111.6	*Class*
			11.39	*Method*
`Pithy` (`PI`)	11	73.0	579.0	*Program*
		6.64	52.64	*Class*
			7.93	*Method*

Table 3.1: High Level Description of the `RM`, `FF`, and `PI` Case Study Applications.

Name	**Classes**	**Methods**	**NCSS**	**Per**
`StudentTracker` (`ST`)	9	72.0	620.0	*Program*
		8.0	68.89	*Class*
			8.61	*Method*
`TransactionManager` (`TM`)	6	87.0	748.0	*Program*
		14.5	124.67	*Class*
			8.6	*Method*
`GradeBook` (`GB`)	10	147.0	1455.0	*Program*
		14.7	145.5	*Class*
			9.9	*Method*

Table 3.2: High Level Description of the `TM`, `ST`, and `GB` Case Study Applications.



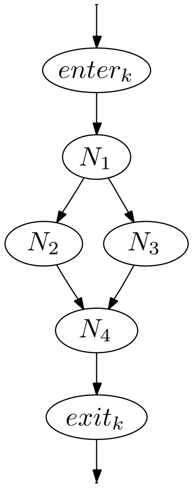
$$\begin{aligned} v(G_k) &= |\mathcal{E}_k| - |\mathcal{N}_k| + |\mathcal{B}_k| \\ &= 2 - 3 + 2 \\ &= 1 \end{aligned}$$

Figure 3.3: Cyclomatic Complexity of a Simple Method.

Higher values for $v(G_k)$ reveal that there are more paths that must be tested and this could suggest that the method m_k is more "complex" than a method $m_{k'}$ with a lower $v(G_{k'})$ [Shepperd, 1988]. Table 3.3 reports the average cyclomatic complexity across all methods within P. It is crucial to observe that calculating the CCN for a traditional CFG does not take into account the method's interaction with a relational database. Therefore, the reported CCN values represent a lower bound on the "complexity" of the methods within the program under test and they should only be used as a rough characterization of application complexity. Chapter 9 identifies the development of a complexity metric for database-centric applications as an area for future research.

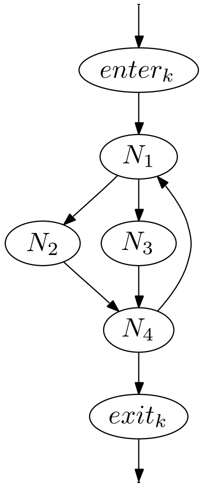
Table 3.1 shows that `Reminder` (`RM`) is the smallest case study application with a total of 548 NCSS. This application provides methods such as `addEvent` and `getCurrentCriticalEvents` that store events including birthdays and appointments and then generate reminders for these events. The methods in `RM` have an average CCN of 2.09 and Table B1 in Appendix B provides additional details about the `RM` application. Table 3.1 indicates that `FindFile` (`FF`) is the second smallest case study application with 558 NCSS. `FF` is an enhanced version of the file system searching application called `FindFile` that is available for download at `http://www.hsqldb.org/`. `FF` contains methods such as `listFiles`, `removeFiles`, and `fillFileNames` that have an average CCN of 2.02. Table B2 in Appendix B offers additional information about the `FF` application. The cyclomatic complexity numbers for `RM` and `FF` suggest that these programs have "simple" methods if their database interactions are not taken into account.

The `Pithy` (`PI`) case study application contains 579 NCSS, as noted in Table 3.1. `Pithy` is an extended implementation of an example program available from `http://uk.builder.com/`. This application stores and generates quotations with methods such as `addQuote` and `getQuote`. Similar to `RM` and `FF`, the `PI` case study application has an average CCN of 2.05. Table B3 in Appendix B includes additional details about the



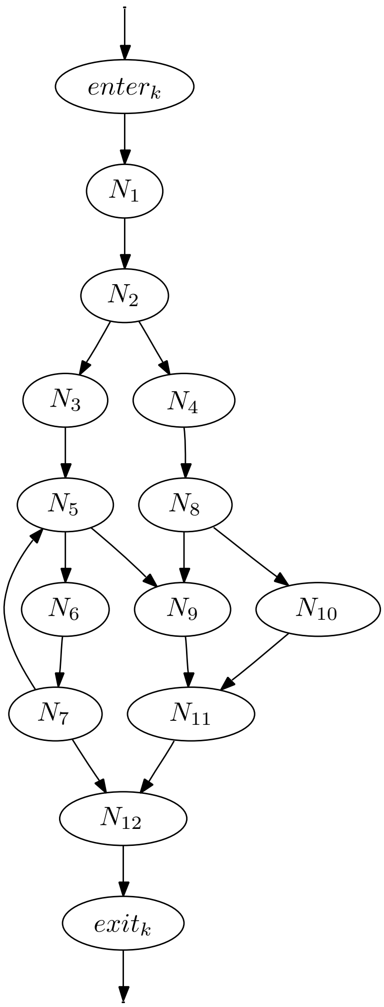
$$
\begin{aligned}
v(G_k) &= |\mathcal{E}_k| - |\mathcal{N}_k| + |\mathcal{B}_k| \\
&= 6 - 6 + 2 \\
&= 2
\end{aligned}
$$

Figure 3.4: Cyclomatic Complexity of a Method with Conditional Logic.



$$
\begin{aligned}
v(G_k) &= |\mathcal{E}_k| - |\mathcal{N}_k| + |\mathcal{B}_k| \\
&= 7 - 6 + 2 \\
&= 3
\end{aligned}
$$

Figure 3.5: Cyclomatic Complexity of a Method with Conditional Logic and Iteration.



$$\begin{aligned} v(G_k) &= |\mathcal{E}_k| - |\mathcal{N}_k| + |\mathcal{B}_k| \\ &= 17 - 14 + 2 \\ &= 5 \end{aligned}$$

$$\begin{aligned} \pi_1 &= \langle enter_k, N_1, N_2, N_3, N_5, N_6, N_7, N_{12}, exit_k \rangle \\ \pi_2 &= \langle enter_k, N_1, N_2, N_3, N_5, N_6, N_7, N_5, N_6, N_7, N_{12}, exit_k \rangle \\ \pi_3 &= \langle enter_k, N_1, N_2, N_3, N_5, N_9, N_{11}, N_{12}, exit_k \rangle \\ \pi_4 &= \langle enter_k, N_1, N_2, N_4, N_8, N_9, N_{11}, N_{12}, exit_k \rangle \\ \pi_5 &= \langle enter_k, N_1, N_2, N_4, N_8, N_{10}, N_{11}, N_{12}, exit_k \rangle \end{aligned}$$

Figure 3.6: Cyclomatic Complexity of a Method.

Application	Average Method CCN
RM	2.09
FF	2.02
PI	2.05
ST	1.65
TM	2.21
GB	2.60

Table 3.3: Average Method Cyclomatic Complexity Measurements.

classes and methods in PI. Table 3.2 reveals that the StudentTracker (ST) case study application contains 620 NCSS and is the third largest application. This application uses methods such as insertStudent and getAllStudents to track administrative information about college students. The average method CCN for ST is 1.65 even though the application contains more executable source statements than RM, FF, or PI. This is due to the fact that several methods within ST consist of straight-line code segments that reduce the average method CCN. Table B4 in Appendix B provides more information about the StudentTracker application.

As described in Chapter 2, the TransactionManager (TM) application interacts with the *Bank* database. At 748 NCSS, TransactionManager is the second largest case study application. It furnishes methods such as removeAccount, removeUser, transfer, withdraw, and deposit. The average method cyclomatic complexity number of TM is 2.21 and thus it is slightly more complex than the smaller applications. Table B5 in Appendix B offers additional information about TM. Table 3.2 shows that GradeBook (GB) is the largest case study application with 1455 NCSS. This application provides 147 methods that include getExams, addLab, and getFinalProjectScore. GB exhibits the largest average method CCN with a value of 2.60. Even though GB's average CCN is not significantly larger than the average CCNs of the other case study applications, it does have many methods with cyclomatic complexities of 5 through 14. In contrast, the CCNs for the other applications normally range from 1 to 5. Table B6 in Appendix B provides more details concerning GB.

The data in Table 3.1, Table 3.2, and Table B1 through Table B6 in Appendix B indicate that all of the applications have relatively small method code bodies that range in average size from 7.93 to 11.39 NCSS. The largest applications, GB and TM, also have the most methods per class (14.5 and 14.7 methods per class, respectively). In contrast, the smaller applications such as RM and PI only have an average of 6.11 and 6.64 methods per class. While descriptive statistics do not reveal anything about the quality of the source code documentation, the tables in Appendix B demonstrate that most of the methods contain JavaDoc comments. The "Classes" column in the tables from Appendix B denotes the number of inner classes that are declared within the specified class. The chosen case study applications do not use inner classes and thus this column always contains zeros. However, the presented framework supports the testing and analysis of database-centric applications that use any of the major features of Java (e.g., static methods and variables, inner classes, iteration, and recursion).

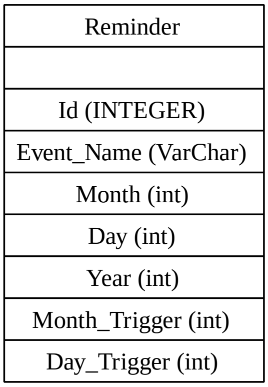


Figure 3.7: Relational Schema for `Reminder`.

3.5.2 Relational Schemas

The test coverage monitoring component described in Chapter 6 includes a technique that records the SQL data definition language statements that construct the relations within an application's database. The component also contains a tool that can automatically visualize each relational schema. This section provides a graphical depiction of the relational schema that is used by each case study application. Figure 3.7 describes the relational schema for the `Reminder` case study application. The *Reminder* relation contains seven attributes that are either of type `Integer`, `int`, or `Varchar`. `Integer` and `int` correspond to the same variable type and the Java language-based HSQLDB uses the `java.lang.Integer` data type to store these attributes. Attributes of type `Varchar` store variable length character data and HSQLDB internally represents them as `java.lang.String` variables. Figure 3.8 shows the relational schema for `FindFile`'s database. The *Files* relation contains two `Varchar` attributes called *Path* and *Name*. Even though this database has a simple schema, `FF` was incorporated into the experiments because it provides functionality that scans a file system to extract and store path and file name information. Therefore, `FindFile` can automatically create very large databases that support the evaluation of a testing technique's scalability.

Figure 3.9 provides the relational schema for `Pithy`'s database. The *id* attribute is a unique identification number for each quotation and the *pith* attribute stores a `Varchar`-based textual representation of a quotation. The *category* attribute is also of type `Varchar` and it classifies the quotation into one or more user-defined categories. The experiments include the `Pithy` application because it comes with a large pre-defined database of quotations. Figure 3.10 reveals that `StudentTracker` also interacts with a simple database that contains the *Student* relation with the *Id* and *Name* attributes of type `Varchar`. The `TransactionManager` application uses two tables called *Account* and *UserInfo*, as depicted in Figure 3.11 and previously described in Chapter 2. The experiments use the `ST` and `TM` applications because they contain methods that have sequences of database interactions. For example, the `transfer` method within `TM` follows the execution of a **select** statement with two **update** statements. Therefore, the correct operation of the **update**s depends upon the correctness of the **select**.

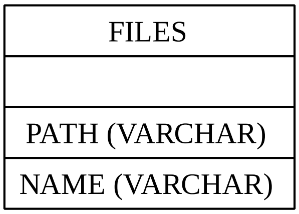


Figure 3.8: Relational Schema for `FindFile`.

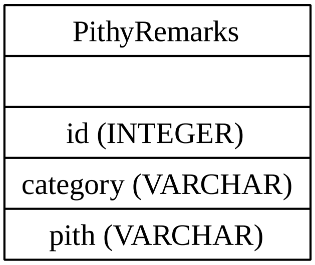


Figure 3.9: Relational Schema for `Pithy`.

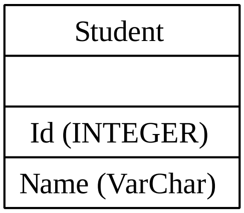


Figure 3.10: Relational Schema for `StudentTracker`.

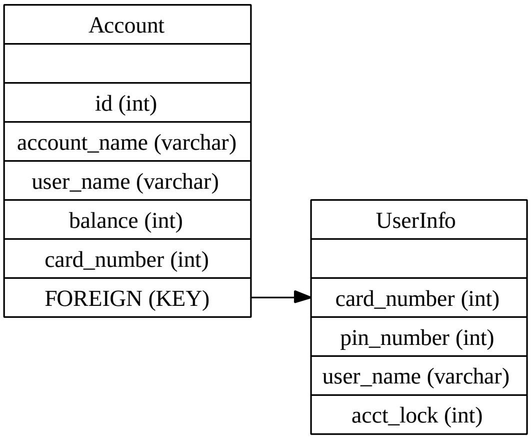


Figure 3.11: Relational Schema for `TransactionManager`.

Application	Test NCSS / Total NCSS
RM	227/548 = 50.5%
FF	330/558 = 59.1%
PI	203/579 = 35.1%
ST	365/620 = 58.9%
TM	355/748 = 47.5%
GB	769/1455 = 52.8%

Table 3.4: Characterization of the Test Suites.

Figure 3.12 explains the structure of the nine relations that are subject to interaction by the `GradeBook` application. We used `GB` to empirically evaluate the testing techniques because it interacts with a moderate size database that contains thirty-three attributes of varying type. The *Master* table uses the `Integer` and `Decimal` attribute types to describe how different class scores contribute to the final grade in a college-level science course. The HSQLDB database stores a `Decimal` attribute with the Java type `java.math.BigDecimal` that provides immutable and arbitrary-precision signed decimal numbers. For example, if `GradeBook` stores .2 within the *FinalProject* attribute this indicates that 20% of the course grade is associated with the grade on the final project. The source code of `GradeBook` also contains checks to ensure that the values of *Master*'s attributes sum to 1.0.

The *Student* relation uses `Integer` and `Varchar` attributes to store identification and contact information about each student in the class. Finally, the *ExamMaster* relation stores the description of each examination that was given during the course and the *ExamScores* relation persists the examination scores for each student. The `GradeBook` application does not create a foreign key constraint from the *ExamId* attribute in the *ExamScores* relation to *ExamMaster*'s *ExamId*. Instead, `GradeBook` uses Java methods to enforce the constraint that each score in *ExamScores* corresponds with a unique examination in *ExamMaster*. The remaining tables such as *LabMaster* and *LabScores* are defined analogously to *ExamMaster* and *ExamScores*. These characteristics of `GradeBook`'s implementation demonstrate the importance of testing the interactions between the program and the relational database. As noted in Chapter 9, we intend to investigate the reverse engineering of program-enforced integrity constraints as part of future research.

3.5.3 Detailed Characterization

3.5.3.1 Test Suites The test suite for each application is organized into one or more Java classes. The test executor recognizes the methods with names beginning with the word "`test`" as individual test cases. A single test class (e.g., `TestReminder` for `RM`) also contains many methods that support the testing process. Support methods such as `getDataSet`, `getConnection`, `setUp`, and `tearDown` are required by the JUnit and DBUnit testing frameworks. Table 3.4 shows that the test code (e.g., both the support and "`test`" methods) is often a significant portion of the application's entire code base. Across all of the case study applications, the test suite code comprises 50.65% of the total NCSS. Table 3.5 characterizes the size of each test suite according to the number of test cases and oracle execution locations. These results indicate that the largest

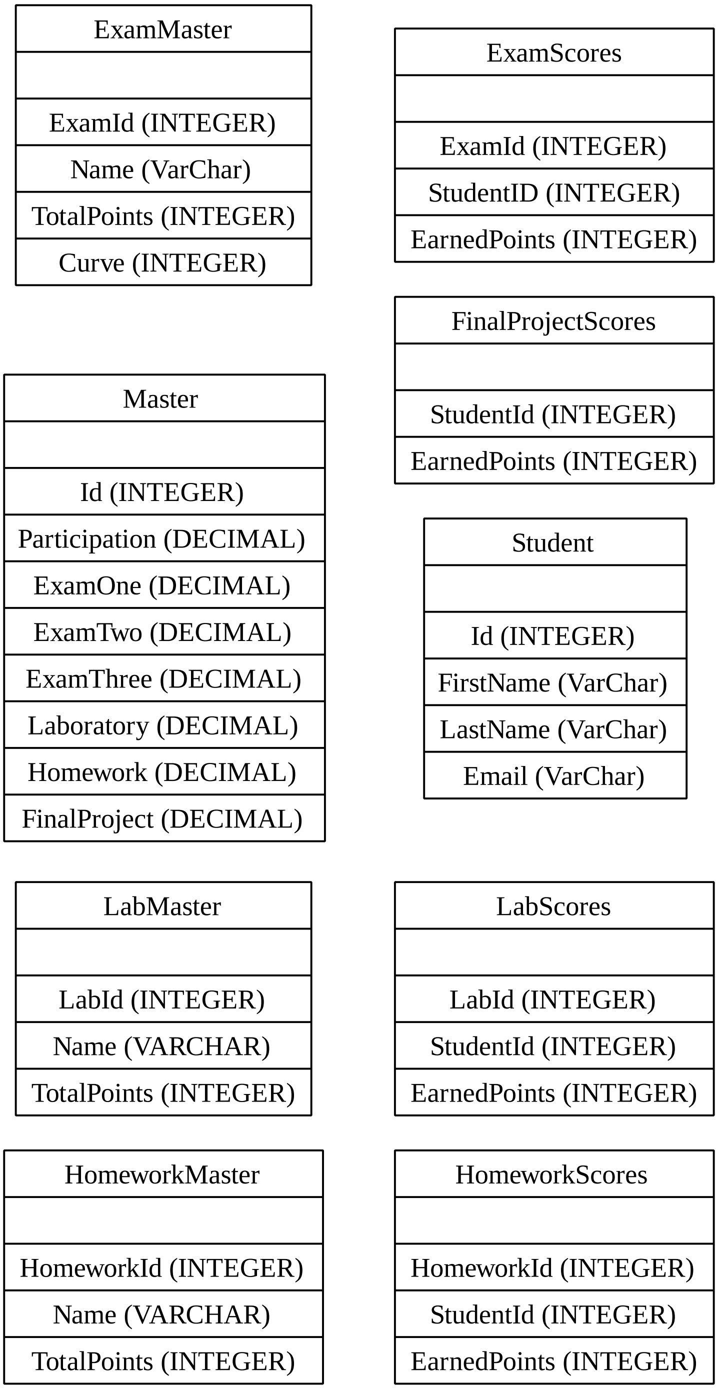


Figure 3.12: Relational Schema for `GradeBook`.

Application	Num of Test Cases	Num of Oracle Exec	Avg Oracle Exec Per Test
RM	13	25	1.9
FF	16	80	5.0
PI	15	34	2.3
ST	25	59	2.4
TM	27	91	3.4
GB	51	91	1.8

Table 3.5: Number of Test Cases and Oracle Executions.

Application	Num of executeUpdate Calls	Num of executeQuery Calls	Total
RM	3	4	7
FF	3	4	7
PI	3	2	5
ST	4	3	7
TM	36	9	45
GB	11	23	34

Table 3.6: Database Interactions in the Case Study Applications.

number of test cases is 91 (TM and GB) and the smallest number of tests is 25 (RM). Across all case study applications, the average size of a test suite is approximately 63 tests.

Table 3.5 also reveals that the average number of oracles per test case ranges between 1.8 (GB) and 5 (FF). The test suite for FindFile exhibits a high number of oracle executions per test because the tests often check the correctness of the file names that are stored within the database on a per file name basis. GradeBook shows the smallest number of oracle executions per test because it has the most test cases. Moreover, each GB test case contains only one or two oracle executions that compare the expected and actual states of entire database relations. Table B7 through Table B12 in Appendix B provide the name of each test case and the Java class in which it is located. These tables show that many test suites contain test cases such as testDatabaseServerIsRunning and testMakeDatabaseConnection. This is due to the fact that the correctness of the methods that start and connect to the RDBMS is crucial to the proper operation of the entire application.

Some case study applications have a dedicated Java class that is responsible for creating the relations in the database (e.g., the GradeBookCreator class in the GB application creates all of the tables described in Section 3.5.2) and this class is often tested with its own test cases. Analysis of the case study applications also reveals that many of their test suites contain tests that perform a single operation repeatedly. For example, the testDoesNotStartServerAgain method in TestFindFile starts the database server and then checks to ensure that the server does not start again after multiple invocations of the RDBMS startup methods. Furthermore, the testInsertAndRemoveStudentIterativeSmall test case for ST uses program methods to iteratively **insert** information about a student and then **delete** all records of information pertaining to the same student. This test determines if the ST application always assigns unique identification numbers

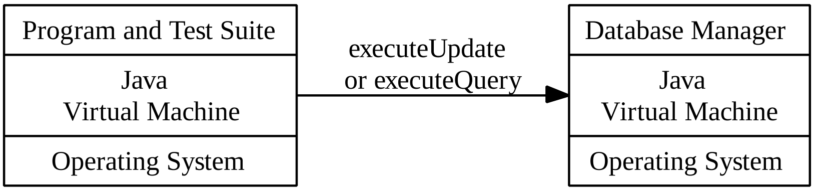


Figure 3.13: Using the Java Database Connectivity Interface to Perform a Database Interaction.

to all of the students. Further examination indicates that some tests use program methods to add data to the database and then execute a database-aware oracle (e.g., `testAddOnePithyRemark` in `PI`). Other tests use program methods to **insert** data, **delete** data records, and then finally execute an oracle (e.g., `testInsertAndRemoveStudent` in `ST`). Finally, some test cases directly modify the state of the database using DBUnit primitives, execute methods within the program under test, and then execute an oracle to inspect the database state (e.g., `testGetAccountBalance` in `TM`). When considered cumulatively, the tests for the case study applications represent a wide range of different testing strategies.

3.5.3.2 Database Interactions As depicted in Figure 3.13, the case study applications interact with their relational database through the use of the `executeUpdate` and `executeQuery` methods that are provided by HSQLDB's implementation of the `java.sql.Statement` interface. The `executeUpdate` method submits SQL data manipulation statements such as **update**, **insert**, and **delete**. The same method can also submit SQL data definition statements such as **create table** and **drop table**. For example, `FF` uses `executeUpdate` to submit the statement **drop table** *files*. The `executeQuery` method always submits a SQL **select** command. The `java.sql.Statement` interface also provides other interaction methods, such as `execute`, that can send an arbitrary SQL command to the database. However, the selected case study applications do not use these alternative database interaction methods. Table 3.6 categorizes all of the database interactions within the applications. This table shows that the smaller case study applications have the least interactions while the largest applications, `TM` and `GB`, also have the most interactions. It is critical to note that the case study applications express their database interactions as `java.lang.String`s that can only be partially characterized through static analysis (e.g., the database interaction might be dependent upon user input or data values stored in external files). When examined as a whole, the case study applications contain a wide range of database interactions that vary according to their static structure and use of the Java database connectivity interface.

3.6 DESIGN OF THE EXPERIMENTS

The overarching goal of the experiments is to measure the efficiency and effectiveness of the testing techniques presented by this research. Chapter 4 through Chapter 8 describe the specific experiment design that supports the evaluation of each phase of the software testing life cycle. We implemented the entire testing framework in the Java, Mathematica, and `tcsh` programming languages. The implementation also includes a substantial test suite for each of the approaches to testing. Chapter 4 describes the initial experiments that were conducted on a GNU/Linux workstation with kernel 2.4.18-14smp, LinuxThreads 0.10, dual 1 GHz Pentium III Xeon processors, 512 MB of main memory, and a SCSI disk subsystem. The subsequent experiments described in Chapter 6 through Chapter 8 were performed on a GNU/Linux workstation with kernel 2.6.11-1.1369, Native POSIX Thread Library (NPTL) version 2.3.5, a dual core 3.0 GHz Pentium IV processor, 2 GB of main memory, and 1 MB of L1 processor cache. This workstation used a Serial ATA connection to the hard drive and we enabled CPU hyper-threading in order to support thread-level parallelism on the processor. All of the experiments use a JVM version 1.5.0 that was configured to operate in Java HotSpot$^{\text{TM}}$client mode. The maximum size of the JVM heap varied depending upon the memory demands of the experiment. Subsequent chapters explain the remaining details about the experiment design and the evaluation metrics.

3.7 THREATS TO VALIDITY

The experiments described in this research are subject to *validity threats*. *Internal* threats to validity are those factors that have the potential to impact the measured variables defined in Chapter 4 through Chapter 8. One internal validity threat is associated with defects in the prototype of the database-aware testing tools. Defects within any of the testing techniques would impact the experiment results. This threat is controlled by the implementation and frequent execution of a regression test suite for the entire testing framework. Furthermore, we applied the prototype to smaller known examples, and we manually checked the correctness of these results. We also controlled this threat by incorporating tools and Java class libraries that are frequently used by software testing researchers and practitioners (e.g., JUnit [Do et al., 2004], DBUnit [Dallaway, 2002], and Soot [Vallée-Rai et al., 2000]). Since we have repeatedly used these tools without experiencing errors or anomalous results, we have a confidence in their correctness and we judge that they did not negatively impact the validity of our empirical studies. The efficiency of each testing technique was measured by Java programming language instrumentation that inserted profiling statements into the source code of the testing techniques. To ensure that the profilers yielded accurate timings, we measured the wall clock time for the execution of a testing tool and compared this to the time that was calculated by the profiler. In order to prevent inappropriate variations in the time overhead, we used the same workstation for all experiments within a chapter and we prevented external user logins to this workstation during the empirical analysis.

External threats to validity are factors that limit the ability to generalize the experimental results. Since the empirical studies described by this research use a limited number of case study applications, we cannot claim that these results are guaranteed to generalize to other database-centric applications. However, Section 3.5 shows that the experiments use six small to moderate size applications that vary in terms of their

NCSS, cyclomatic complexity, test suite structure, and type of database interaction. We also configured each case study application to interact with the real world HSQLDB RDBMS that is used in current applications such as OpenOffice and Mathematica. Another threat to external validity is related to the size of the selected case study applications and their test suites. If we compare our case study applications to those that were used in other studies by [Tonella, 2004] (mean size of 607.5), [McMinn and Holcombe, 2005] (mean size of 119.2), [Harrold et al., 1993] (mean size of 33.6), and the Siemens application suite [Rothermel et al., 2001] (mean size 354.4), the average size of our programs and test suites (mean size 571) is comparable to the size of the other applications. Since both Tonella, McMinn and Holcombe, and Harrold et al. report a lines of code (LOC) size metric instead of an NCSS metric, it is possible that our case study applications have a larger static size than those programs used in prior experimentation. Finally, the case study applications in these previous studies do not interact with a relational database. The last threat to external validity is that the author of this dissertation implemented and tested each case study application. We implemented our own applications because the software testing research community has not established a repository of database-centric applications.

3.8 CONCLUSION

This chapter offers a brief overview of our comprehensive framework for testing database-centric applications. Subsequent chapters will provide more details about the test adequacy component and our approaches to test coverage monitoring, and test suite reduction and prioritization. This chapter examines the case study applications that we used to empirically evaluate the testing techniques described in Chapter 4 through Chapter 8. We report the number of classes, methods, and non-commented source statements in each of the case study applications. This chapter includes a definition of cyclomatic complexity and a summary of the average cyclomatic complexity across all of the methods within an application. We also examine the test suite and the relational schema for each database-centric application. For each test suite we report the number of tests and we characterize the tests according to their static structure and dynamic behavior. We graphically depict each relational schema and explain how the programs use the JDBC interface to submit SQL statements to the database. This chapter concludes with a high level review of the experiment design and a discussion of the steps we took to address the threats to the validity of our experiments.

4.0 FAMILY OF TEST ADEQUACY CRITERIA

4.1 INTRODUCTION

This chapter describes a fault model for database-centric applications and a family of database-aware test adequacy criteria. The fault model describes how a program can violate the integrity of a relational database. We also explain why our data flow-based adequacy criteria support the isolation of faults that violate database integrity. Finally, we compare our database-aware criteria to traditional adequacy criteria that solely focus on program variables. In particular, this chapter offers:

1. A fault model that describes the interaction patterns that frequently lead to the violation of relational database integrity (Section 4.2).
2. The definition of a family of test adequacy criteria for database-centric applications that extends the traditional data flow-based *all-DUs* criterion (Sections 4.3.1 and 4.3.2).
3. The presentation of a subsumption hierarchy that characterizes the relative strength of each database-aware test adequacy criterion (Section 4.3.3).
4. The discussion of the suitability of the test adequacy criteria and a comparison to traditional structural adequacy metrics (Section 4.3.4 and 4.3.5).

4.2 DATABASE INTERACTION FAULT MODEL

We define a database-centric application $A = \langle P, \langle D_1, \ldots, D_e \rangle, \langle S_1, \ldots, S_e \rangle \rangle$ to consist of a program P and databases $D_1, \ldots, D_e$ that are specified by relational schemas $S_1, \ldots, S_e$. Our testing framework ensures that the tests for A can isolate the type of interaction faults that are commonly found in a database-centric application. Accuracy, relevancy, completeness, and consistency are commonly associated with the quality of the data that is stored in a database [Motro, 1989, Strong et al., 1997, Wand and Wang, 1996]. The testing framework's fault model uses the conception of database integrity initially proposed in [Motro, 1989]. This research views the *integrity* of A's databases as a function of the *validity* and *completeness* of the data that is stored in each database. We specify the correct behavior of method m_k's interaction with database D_f from the perspective of the expected database state, denoted D_x. The fault model assumes that the relational database is in a valid state before the execution of method m_k. If $D_f = D_x$ after executing m_k, then we know that method m_k performed as anticipated. If the expected and actual database states are not equal, then this demonstrates that there is a defect within m_k that violates the integrity of the database.

Type (1-v): Method m_k submits a SQL **update** or **insert** statement that incorrectly modifies the attribute values in D_f so that $D_f \neq D_x$.

(a)

Type (1-c): Method m_k submits a SQL **delete** statement that incorrectly removes attribute values from D_f so that $D_f \subset D_x$.

(b)

Type (2-v): Method m_k does not submit a SQL **delete** statement to remove attribute values from D_f so that $D_f \supset D_x$.

(c)

Type (2-c): Method m_k does not submit a SQL **update** or **insert** statement and fails to place attribute values into D_f so that $D_f \neq D_x$.

(d)

Figure 4.1: Summary of the Program Defects that Violate Database Integrity.

Figure 4.1 summarizes the four types of database interaction defects that could exist in a database-centric application. Figure 4.1(a) and (c) describe violations of database validity and Figure 4.1(b) and (d) explain completeness violations. Method m_k contains a type (1-v) integrity violation if it executes either a SQL **update** or an **insert** statement that produces $D_f \neq D_x$. If $D_f \subset D_x$ after the execution of method m_k, then this indicates that m_k contains a type (1-c) defect that submits a **delete** that removes more records than anticipated. A method m_k contains a type (2-v) violation of database integrity if it fails to submit a **delete** statement and $D_f \supset D_x$. If method m_k contains a type (2-c) integrity violation that does not submit either an **update** or an **insert** statement, then this will also yield $D_f \neq D_x$.

We further classify the faults within a database-centric application as either faults of commission or omission [Basili and Perricone, 1984]. A fault of *commission* corresponds to an incorrect executable statement within the program under test. Faults of *omission* are those faults that are the result of the programmer forgetting to include executable code within the program under test. Type (1-c) and (1-v) violations of database integrity are faults of commission because they involve the incorrect use of the SQL **update**, **insert**, and **delete** statements. We also classify type (2-c) and (2-v) integrity violations as either commission faults or omission faults. A type (2-c) or (2-v) commission fault exists within m_k when the control flow of the method prevents the execution of the correct SQL statement. We categorize a type (2-c) or (2-v) integrity violation as an omission fault when m_k does not contain the appropriate SQL **update**, **insert**, or **delete** command. The testing framework supports the identification of all type (1-c) and (1-v) defects and type (2-c) and (2-v) commission faults.

4.2.1 Type (1-c) and (2-v) Defects

This chapter uses the `TM` application to provide specific examples of the four ways that a program can violate the integrity of a relational database.[1] The type (1-c) and (2-v) defects both involve the incorrect use of the SQL **delete** statement. Among other functionality, the `TM` application provides the ability to remove a

[1] For simplicity, this research assumes that the methods within the `TM` application will not concurrently access the relational database. Thus, the source code of the `TM` does not use transactions to avoid concurrency control problems.

The `removeAccount(int id)` operation should completely remove the user account that is specified by the provided `id`. If the removal of the account from the *Account* relation results in an `TM` user that no longer maintains any accounts in the `TM` application, any additional user information should also be removed from the *UserInfo* relation.

(a)

The `transfer(int source_id, int dest_id, double balance)` operation should withdraw `balance` dollars from the account specified by `source_id`, deposit this amount into the account specified by `dest_id`, and return `true` to signal success. If the account associated with the `source_id` has a balance that is less than the specified `balance`, then the transfer must not occur and the operation should return `false`.

(b)

Figure 4.2: The Natural Language Specifications for the (a) `removeAccount` and (b) `transfer` Methods.

specified account. Since it uses a SQL **delete** statement, the `removeAccount` method could contain either a (1-c) or a (2-v) defect. The natural language specification for the `removeAccount` method is provided in Figure 4.2(a). Figure 4.3 shows a defective implementation of the `removeAccount` operation in the Java programming language.[2] In this method, line 4 constructs a structured query language statement that is supposed to remove the specified account from the *Account* relation. Since this line erroneously builds a **where** clause that compares the *card_number* attribute to the provided `id` parameter instead of using the *id* attribute, the database interaction on line 6 is faulty. If we call `removeAccount(2)` with the input state shown in Figure 2.4, then the method from Figure 4.3 incorrectly removes both of the accounts that are owned by user "Brian Zorman" instead of deleting the account with an *id* of 2. This operation contains a type (1-c) defect that violates the completeness of the relational database.

Figure 4.4 provides another implementation of `removeAccount` that resolves the defect that exists in the operation from Figure 4.3. However, this method still does not correctly implement Figure 4.2(a)'s specification for the `removeAccount` method. Lines 4 and 6 of this method correctly build the `String removeAcct` and interact with the database. However, the method lacks an additional interaction to **delete** the information from the *UserInfo* relation when the user removes his or her last account from the *Account* relation (for the purposes of discussion, we assume that the RDBMS either could not be or was not configured to automatically handle the referential integrity constraint between the two relations). Therefore, the `removeAccount` method in Figure 4.4 contains a type (2-v) defect that violates the validity of `TM`'s database. We classify this defect as a fault of omission because the program source code does not contain a database interaction to remove attribute values from the *UserInfo* relation.

[2] In the method listing in Figure 4.3 and all subsequent source code listing, the variable `connect` corresponds to the already initialized connection to the *Bank* database.

```java
public boolean removeAccount(int id) throws SQLException
{
  boolean completed = false;
  String removeAcct = “delete from Account where card_number = ” + id;
  Statement removeStmt = connect.createStatement();
  int removeAccountResult = removeStmt.executeUpdate(removeAcct);
  if( removeAccountResult == 1 )
  {
    completed = true;
  }
  return completed;
}
```

Figure 4.3: A Type (1-c) Defect in the `removeAccount` Method.

```java
public boolean removeAccount(int id) throws SQLException
{
  boolean completed = false;
  String removeAcct = “delete from Account where id = ” + id;
  Statement removeStmt = connect.createStatement();
  int removeAccountResult = removeStmt.executeUpdate(removeAcct);
  if( removeAccountResult == 1 )
  {
    completed = true;
  }
  return completed;
}
```

Figure 4.4: A Type (2-v) Defect in the `removeAccount` Method.

```java
public boolean transfer(int source_uid, int dest_uid,
                        double amount) throws SQLException
{
  boolean completed = false;
  String qs = “select id, balance from Account;”;
  Statement stmt = connect.createStatement();
  ResultSet rs = stmt.executeQuery(qs);
  while( rs.next() )
  {
    int id = rs.getInt(“id”);
    double balance = rs.getDouble(“balance”);
    if( id == source_uid && amount <= balance )
    {
      String qu_withdraw = “update Account set balance = balance−” +
         amount + “ where id = “ + source_uid + “;”;
      Statement update_withdraw = connect.createStatement();
      int result_withdraw = update_withdraw.executeUpdate(qu_withdraw);

      String qu_deposit = “update Account set balance = balance+” +
         amount + “ where id = “ + dest_uid + “;”;
      Statement update_deposit = connect.createStatement();
      int result_deposit = update_deposit.executeUpdate(qu_deposit);

      if( result_withdraw == 1 && result_deposit == 1 )
        completed = true;
    }
  }
  return completed;
}
```

Figure 4.5: A Correct Implementation of the `transfer` Method.

4.2.2 Type (1-v) and (2-c) Defects

The type (1-v) and (2-c) defects both involve the incorrect use of either the SQL **update** or **insert** statements. We use the `transfer` method to provide an example of the improper modification or deletion of data that already exists in a relational database. Figure 4.5 shows a correct implementation of the `transfer` method that is specified by the natural language description provided in Figure 4.2(b). Suppose that the SQL **update** statement constructed on lines 14 and 15 made reference to `dest_id` instead of `source_id`. Furthermore, suppose that the SQL **update** statement created on lines 19 and 20 referenced `source_id` instead of `dest_id`. If this hypothesized defect exists within the `transfer` method, the `transfer` operation will withdraw money from the account associated with `dest_id` and deposit `amount` dollars into the account associated with `source_id`. This hypothesized modification to `transfer` creates a type (1-v) violation of database validity because it places incorrect balances into `TM`'s *Bank* database.

Suppose we replace the second condition of the `if` statement on line 12 in Figure 4.5 with the condition `amount >= balance`. If the `transfer` operation contained this hypothesized defect, the transfer will not occur even if account `source_id` contained sufficient funds. In this circumstance, the *balance* attribute values for the two accounts will not be properly modified. This potential modification to `transfer` introduces a type (2-c) violation of database completeness. This is due to the fact that `transfer` fails to place appropriate values for *balance* inside of the *Account* relation. This type (2-c) violation is also a fault of commission because incorrect conditional logic prevents the method under test from executing a correct database interaction.

4.3 DATABASE-AWARE TEST ADEQUACY CRITERIA

4.3.1 Traditional Definition-Use Associations

Throughout the discussion of our family of data flow-based test adequacy criteria for database-centric applications, we adhere to the notation initially proposed in [Rapps and Weyuker, 1985]. We focus on the definition of intraprocedural definition-use associations for CFG $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$. A *definition clear path* $\pi_{var} = \langle N_\rho, \ldots, N_\phi \rangle$ for variable *var* is a path in G_k such that (i) N_ρ contains a definition of *var*, (ii) N_ϕ contains a use of *var*, and (iii) none of the nodes $N_{\rho+1}, \ldots, N_\phi$ contain a subsequent definition of *var*. We say that node N_ρ contains a *reaching definition* for the use of *var* at N_ϕ if there exists a definition clear path $\pi_{var} = \langle N_\rho, \ldots, N_\phi \rangle$. We define $RD(G_k, N_\phi, var)$ as the set of nodes that contain reaching definitions for the use of the variable *var* at N_ϕ. We define the *def-use association* as a triple $\langle N_{def}, N_{use}, var \rangle$ such that $N_{def} \in RD(G_k, N_{use}, var)$. As initially defined in Chapter 2, a *complete path* is a sequence of nodes in a method's control flow graph that starts at the CFG's entry node and ends at its exit node. A test case T_i *covers* a def-use association if it executes a complete path π_{var} that has a definition clear sub-path from node N_{def} to N_{use}. For more details about traditional data flow-based test adequacy criteria, refer to [Rapps and Weyuker, 1985, Zhu et al., 1997]. Table A5 in Appendix A reviews the notation that we use to define the def-use association.

select *account_name*, *user_name*
from *Account*
where *balance* $>$ 1000

Type: *using*

(a)

delete from *Account*
where *card_number* $= 2$

Type: *defining-using*

(b)

insert into *Account*
values(10, “Primary Checking”,
“Robert S. Roos”, 1800, 1)

Type: *defining*

(c)

update *UserInfo*
set *acct_lock* $= 1$
where *card_number* $= 5$

Type: *defining-using*

(d)

Figure 4.6: Database Interaction Types for the SQL DML Operations.

4.3.2 Test Adequacy for Database-Centric Applications

A *database interaction point* (DIP) is a source code location in a method m_k that submits a SQL statement to a relational database. For example, the `removeAccount` method in Figure 4.3 contains a database interaction point on line 6. A DIP in method m_k is of *type* defining, using, or defining-using. Method m_k performs a *using* interaction when it submits a SQL **select** to a database. For example, Figure 4.6(a) describes a **select** statement that uses the attributes in the *Account* relation. We classify m_k's submission of a SQL **insert** command as a *defining* interaction since it adds a record to a relation. Figure 4.6(c) shows an **insert** statement that defines the attributes of *Account*. The SQL **update** and **delete** commands are both of type *defining-using*. Figure 4.6(b) includes a **delete** statement that defines all of the attributes in *Account* while also using the *card_number* in the same relation. The **update** command in Figure 4.6(d) defines the *acct_lock* attribute and uses the *card_number* in *UserInfo*.

Database-centric application A interacts with the relational databases $D_1, \ldots, D_e$ at different levels of granularity. P's interaction with a relational database management system can be viewed at the level of databases, relations, records, attributes, or attribute values [Daou et al., 2001]. In the example depicted in Figure 4.7, program P's interaction with relational database D_f can also be viewed as an interaction with the relations rel_1 and rel_2 that are contained within the database. Figure 4.7 shows that m_k interacts with a single record inside of D_f's relation rel_1. Method m_k also interacts with attribute G inside of relation rel_2. Furthermore, P's method m_k interacts with a specific value of the attribute E. Figure 4.7 illustrates how the granularity of a database interaction varies. Viewing a program's interaction with a database at the record level is finer than the relation level. Considering P's database interactions at the attribute level is coarser than at the attribute value level.

While traditional def-use associations are related to the variables in the program under test, this research presents the intraprocedural database interaction association (DIA) that defines and uses an entity in a relational database. We represent the method m_k as a database interaction control flow graph (DI-CFG)

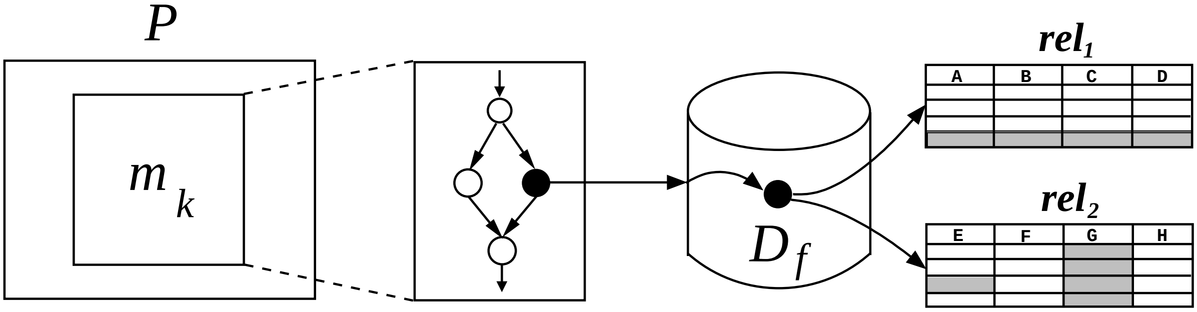


Figure 4.7: Database Interactions at Multiple Levels of Granularity.

$G_{DI(k)} = \langle \mathcal{N}_{DI(k)}, \mathcal{E}_{DI(k)} \rangle$. We define $\mathcal{N}_{DI(k)}$ as a set of nodes that contains definitions and uses of both database entities and program variables. The set $\mathcal{E}_{DI(k)}$ contains the set of edges that transfer control between the nodes in $\mathcal{N}_{DI(k)}$. Chapter 5 explains the structure of $G_{DI(k)}$ and the steps that the adequacy component takes to automatically generate a method's DI-CFG. We define $\mathcal{D}(G_{DI(k)})$ as the set of database names that are subject to interaction in the method m_k. We respectively define $\mathcal{R}(G_{DI(k)})$, $\mathcal{A}(G_{DI(k)})$, $\mathcal{R}_c(G_{DI(k)})$, and $\mathcal{A}_v(G_{DI(k)})$ as the sets of relation, attribute, record, and attribute value names. Chapter 5 discusses the techniques that we use to analyze A and enumerate these sets of relational database entities. A database interaction association is a triple $\langle N_{def}, N_{use}, var_{DB} \rangle$ where the definition of relational database entity var_{DB} happens in node N_{def} and a use occurs in node N_{use}. However, each database interaction association is defined for a relational database entity var_{DB} that is a member of one of the sets $\mathcal{D}(G_{DI(k)})$, $\mathcal{R}(G_{DI(k)})$, $\mathcal{A}(G_{DI(k)})$, $\mathcal{R}_c(G_{DI(k)})$, $\mathcal{A}_v(G_{DI(k)})$. The data flow analyzer described in Chapter 5 performs reaching definitions analysis in order to identify the DIAs within the DI-CFG $G_{DI(k)}$.

While the database interaction association is similar to a traditional def-use association, it does have additional semantics that are different from a def-use association for a program variable. When N_{def} corresponds to the execution of a SQL **delete** statement, the semantics of a DIA differ from the traditional understanding of a def-use association. For example, the database interaction association $\langle N_{def}, N_{use}, var_{DB} \rangle$ with $var_{DB} \in \mathcal{R}_c(G_{DI(k)})$ requires the definition and use of a record that is stored within a specific relation of a database. If N_{def} corresponds to the execution of the SQL **delete** statement, then m_k removes the record var_{DB} from the database and it is no longer available for use. Therefore, the *all-record-DUs* and *all-attribute-value-DUs* test adequacy criteria allow the use of var_{DB} on node N_{use} to correspond to the use of a *phantom record*, or a record that once existed in a previous state of the database but was removed during testing. The existence of phantom records (and analogously, *phantom attribute values*) forces the test coverage monitoring component to observe the program's manipulation of the relational database and retain information about the deleted records. However, the use of phantom records requires a test suite to execute operations that remove records from a database and then verify that the records are no longer available.

As discussed in Section 2.5.3, we can measure the adequacy, or "goodness," of a test suite in many different fashions. The standard *all-DUs* test adequacy criterion that drives def-use testing [Hutchins et al., 1994] is not sufficient for the testing of database-centric applications because it does not capture a program's interaction with a relational database. The test adequacy component uses the DI-CFG to produce DIAs instead of (or, in addition to) the def-use associations for the variables in the program. This research presents a family of test adequacy criteria that includes the *all-database-DUs*, *all-relation-DUs*, *all-attribute-DUs*, *all-record-DUs*, and *all-attribute-value-DUs*. Definition 1 defines the *all-database-DUs* test adequacy criterion which requires a test suite T to cover all of the DIAs in the method under test. We define the *all-relation-DUs*, *all-attribute-DUs*, *all-record-DUs*, and *all-attribute-value-DUs* test adequacy criteria in an analogous manner by substituting one of the sets $\mathcal{R}(G_{DI(k)})$, $\mathcal{A}(G_{DI(k)})$, $\mathcal{R}_c(G_{DI(k)})$, or $\mathcal{A}_v(G_{DI(k)})$ for the $\mathcal{D}(G_{DI(k)})$ in Definition 1.

Definition 1. A test suite T for method m_k's DI-CFG $G_{DI(k)} = \langle \mathcal{N}_{DI(k)}, \mathcal{E}_{DI(k)} \rangle$ satisfies the *all-database-DUs* test adequacy criterion if and only if there exists a test T_i to cover each association $\langle N_{def}, N_{use}, var_{DB} \rangle$ where $var_{DB} \in \mathcal{D}(G_{DI(k)})$ and $N_{def}, N_{use} \in \mathcal{N}_{DI(k)}$.

4.3.3 Subsumption of the Test Adequacy Criteria

This research presents a subsumption hierarchy for database-centric applications that assumes a test suite T is independent and thus each test case begins execution with the same database state. In adherence to Section 4.2's definition of a database-centric application A, the subsumption hierarchy holds when program P interacts with at least one database and a maximum of e total databases. The subsumption hierarchy also requires that each database D_f contains at least one relation and it allows a database to contain a maximum of w relations. We also assume that schema S_f specifies that rel_j has attributes $A_1, \ldots, A_{\mathcal{Z}_j}$. The hierarchy makes no restrictions on the maximum number of records that a relation contains. For the purpose of discussing the subsumption hierarchy, we suppose that relation $rel_j = \{t_1, \ldots, t_u\}$ is in database D_f. Figure 4.8 summarizes the subsumption relationships between the database-aware test adequacy criteria.

A test adequacy criterion C_α *subsumes* a test adequacy criterion C_β if every test suite that satisfies C_α also satisfies C_β [Rapps and Weyuker, 1985]. In Figure 4.8, the nodes C_α and C_β represent adequacy criteria and a directed edge $C_\alpha \rightarrow C_\beta$ indicates that C_α subsumes C_β. For example, a test suite that covers all of the DIAs for the u records within rel_j will also cover the DIAs for the relation itself and thus *all-record-DUs* subsumes *all-relation-DUs*. The other subsumption edges $C_\alpha \rightarrow C_\beta$ hold under similar reasoning. If there is a path in the subsumption hierarchy from C_α to C_β, then we know that C_α subsumes C_β by transitivity. For example, Figure 4.8 reveals that *all-attribute-value-DUs* subsumes *all-relation-DUs*. There is no subsumption relationship between *all-record-DUs* and *all-attribute-DUs*. This is due to the fact that T could cover all of the attribute-based DIAs by only exercising one of the u records within the relation rel_j. Moreover, a test suite T could satisfy *all-record-DUs* by interacting with a single attribute $A_{\mathcal{Z}_j}$ in each record of rel_j. The hierarchy in Figure 4.8 also reveals that *all-attribute-value-DUs* is the "strongest" test adequacy criteria and *all-database-DUs* is the "weakest" metric.

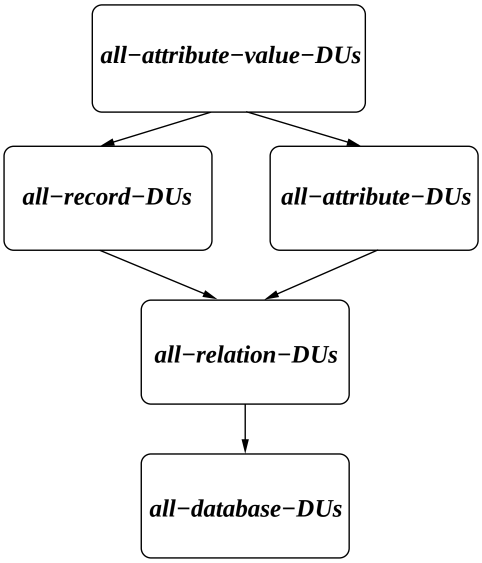


Figure 4.8: The Subsumption Hierarchy for the Database-Aware Test Criteria.

4.3.4 Suitability of the Test Adequacy Criteria

A test is more likely to reveal database interaction points that cause type (1-c) and (1-v) violations if it first executes a program operation that incorrectly modifies the database and then it subsequently uses the database. For example, a test case for the defective `removeAccount` operation listed in Figure 4.3 would expose the program defect on line 4 if it first executed `removeAccount(2)`. Next, the test could call a `listAccounts` operation to verify that the account with $id = 2$ was not in the database and all other accounts (in particular, the one where $id = 3$ and $card\_number = 2$) were still inside of the *Account* relation. The test could also use an oracle to directly access the state of the database and reveal the defect in `removeAccount`. By requiring the coverage of database interaction associations, the presented family of test adequacy criteria can determine whether or not the provided tests are well suited to revealing type (1-c) and (1-v) defects.

The test adequacy criteria also evaluate the capability of a test suite to isolate type (2-c) and (2-v) commission faults. This is due to the fact that the component assigns low adequacy scores to the test cases that do not execute the program's database interactions. Methods that are only tested by low adequacy tests are more likely to contain latent type (2-c) and (2-v) commission defects. We do not focus on the creation of adequacy criteria to support the isolation of type (2-c) and (2-v) omission defects that fail to **update**, **insert**, and **delete** data values. This is due to the fact that structural adequacy criteria, like the family proposed by this research, are not well suited to revealing omission faults [Marick, 1999, 2000]. The data flow-based test adequacy criteria will not yield any test requirements for methods that contain type (2-c) and (2-v) omission faults because the database interactions do not exist within the source code. Chapter 9 observes that database-aware versions of existing approaches to (i) code inspection (e.g., [Shull et al., 2001]), (ii) black-box testing (e.g., [Ostrand and Balcer, 1988]), and/or (iii) automatic defect isolation (e.g, [Hovemeyer and Pugh, 2004]) could be more appropriate for identifying omission faults [Marick, 2000].

```
1   public boolean removeAccount(int id) throws SQLException
2   {
3      boolean completed = false;
4      String removeAcct = “delete from Account where id = ” + id;
5      Statement removeStmt = connect.createStatement();
6      int removeAccountResult = removeStmt.executeUpdate(removeAcct);
7      String selectAcct = “select * from Account where ” +
8             “balance =” + id;
9      Statement selectStmt = connect.createStatement();
10     ResultSet selectAccountResult = selectStmt.
11            executeQuery(selectAcct);
12     if( removeAccountResult == 1 && !selectAccountResult.next() )
13       {
14          completed = true;
15       }
16     return completed;
17  }
```

Figure 4.9: A `removeAccount` Method with Incorrect Error Checking.

4.3.5 Comparison to Traditional Adequacy Criteria

Figure 4.9 contains a faulty implementation of the `removeAccount` method that incorrectly determines if the desired rows were removed from the *Account* relation (i.e., lines 7 and 8 should contain `‘‘select * from Account where id = ’’ + id;` instead of `‘‘select * from Account where balance = ’’ + id;`). Yet, test adequacy criteria based upon control flow and data flow information, such as *all-nodes*, *all-edges*, and *all-DUs*, will indicate that a test for this method is highly adequate and they will not focus a tester's attention on this incorrect implementation of `removeAccount`. This is due to the fact that these criteria exclusively focus on the control flow within the program's source code and the data flow between program variables. For example, the *all-nodes* (or, statement coverage) criterion requires a test case to execute all of the source code statements within the `removeAccount` method in Figure 4.9. Furthermore, the *all-edges* (or, branch coverage) criterion stipulates that a test execute all of the transfers of control between `removeAccount`'s statements [Zhu et al., 1997]. The *all-DUs* adequacy criterion requires the tests to cover the definition-use associations for all of the program variables in `removeAccount`.

If a test case calls `removeAccount(2)`, then it will cover all of the nodes in the method. Table 4.1 shows that the same test case will also cover 87.5% of the edges within the method under test. This table represents an edge in the method under test as (N_ρ, N_ϕ) when there is a transfer of control from node N_ρ to N_ϕ (for source code statements that span lines ρ and ϕ we represent this as node $N_{\rho:\phi}$). Table 4.1 reveals that the test does not cover the edge (N_{12}, N_{16}) because `removeAccount(2)` executes the `if` statement's body. However, the execution of an additional test that calls `removeAccount(-4)` will cover the edge (N_{12}, N_{16}) and yield 100% coverage for the test suite. Finally, Table 4.2 demonstrates that a test's invocation of `removeAccount(2)` will afford 100% coverage of the def-use associations within this method. Thus, traditional adequacy criteria will classify a test suite for this method as highly adequate even though it does not reveal the defect.

When a test invokes `removeAccount(2)` this will cause the execution of line 6 and line 11 without guaranteeing that the **delete** on line 6 removes the record with $id = 2$ and the **select** on line 11 contains

Edge	Covered?
(N_3, N_4)	✓
(N_4, N_5)	✓
$(N_6, N_{7:8})$	✓
$(N_{7:8}, N_9)$	✓
$(N_9, N_{10:11})$	✓
$(N_{10:11}, N_{12})$	✓
(N_{12}, N_{14})	✓
(N_{12}, N_{16})	×

T_i calls `removeAccount(2)` for 87.5% *all-edges* coverage.

Table 4.1: The Edges Covered by a Test Case.

the appropriate **where** clause. Even though both *all-nodes* and *all-edges* require a test case to execute the database interactions on line 6 and line 11, these criteria do not ensure that `removeAccount` interacts with the correct entities in the relational database. The definition of the `String` variable `selectAcct` on line 9 and the use on line 11 forms a definition-use association for the variable `selectAcct`. The *all-DUs* criterion judges a test as adequate if it creates paths from the entrance to the exit of `removeAccount` that cover all of the def-use associations for all of the program variables like `selectAcct`. Since *all-DUs* ignores the state of the database, most tests for `removeAccount` will be highly adequate with respect to *all-DUs* and exhibit low adequacy when evaluated by the database-aware test adequacy criteria.

Suppose that we use the database-aware test adequacy criteria to measure the quality of `TM`'s test suite with the *all-record-DUs* adequacy criterion. The component will evaluate `removeAccount`'s tests with respect to their ability to define and then subsequently use the records in the *Account* relation. Since lines 4 and 8 of Figure 4.9 use the method parameter `id` to define `removeAcct` and `selectAcct`, a static analysis will not reveal the records that the method uses. Therefore, the *all-record-DUs* test adequacy criterion conservatively requires the definition and use of all of the records in the *Account* relation. A test that causes `removeAccount` to define the record where $id = 2$ will not be able to use this record. This is because the **select** statement executed on line 11 incorrectly references the *balance* attribute instead of *id*.[3] A **select** statement that is executed with the clause **where** $balance = 2$ will not use any records of the *Account* relation depicted in Figure 2.4 because all accounts currently have balances greater than \$125.00. The inability to define and use the records in the *Account* relation will yield low adequacy scores for `removeAccount`'s tests. These low scores will focus attention on this method during testing and increase the potential for revealing the defective database interaction on line 11.

[3] Since the database interaction on line 6 of `removeAccount` does remove the record from the *Account* relation where $id = 2$, the *all-record-DUs* criterion actually requires the use of a phantom record, as discussed in Section 4.3.2.

Def-Use Association	**Covered?**
$\langle N_3, N_{16}, \texttt{completed}\rangle$	✓
$\langle N_3, N_{14}, \texttt{completed}\rangle$	✓
$\langle N_4, N_6, \texttt{removeAcct}\rangle$	✓
$\langle N_5, N_6, \texttt{removeStmt}\rangle$	✓
$\langle N_6, N_{16}, \texttt{removeAccountResult}\rangle$	✓
$\langle N_{7:8}, N_{10:11}, \texttt{selectAccount}\rangle$	✓
$\langle N_9, N_{10:11}, \texttt{selectStmt}\rangle$	✓
$\langle N_{10:11}, N_{12}, \texttt{selectStmt}\rangle$	✓

T_i calls `removeAccount(2)` for 100% *all-DUs* coverage.

Table 4.2: The Def-Use Associations Covered by a Test Case.

4.4 CONCLUSION

This chapter defines a database-centric application A that consists of a program P, relational databases $D_1, \ldots, D_e$, and relational schemas $S_1, \ldots, S_e$. We discuss a database interaction fault model and the type (1-c), (1-v), (2-c), (2-v) defects that could violate the completeness and validity of A's databases. We also classify database interaction faults as faults of commission or omission. This chapter presents a family of database-aware test adequacy criteria that are uniquely suited for the isolation of all type (1-c) and (1-v) defects and type (2-c) and (2-v) commission faults. We furnish a subsumption hierarchy that organizes the test adequacy criteria according to their strength. This hierarchy reveals that *all-attribute-value-DUs* is the strongest adequacy criterion and *all-database-DUs* is the weakest. This chapter concludes by comparing our database-aware test adequacy criteria to traditional structural test adequacy metrics. For example, we use a defective `removeAccount` method to demonstrate that the traditional *all-nodes*, *all-edges*, and *all-DUs* will assign a high adequacy score to a simple test suite. We also show that a database-aware criterion such as *all-record-DUs* increases the potential for revealing faulty database interactions by assigning low adequacy values to the same tests. Chapter 5 shows how the test adequacy component automatically creates the DI-CFGs and performs the data flow analysis to identify the DIAs. Finally, Chapters 6 through 8 explain an alternative type of test requirement that focuses on the behavior of the program during testing.

5.0 TEST ADEQUACY COMPONENT

5.1 INTRODUCTION

This chapter describes a test adequacy component that analyzes a database-centric application and generates a set of database interaction associations (DIAs). As discussed in Chapter 4, these DIAs are the requirements that state how an application must be tested in order to achieve a confidence in the correctness of the database interactions. The testing techniques in Chapters 6 through 8 can use these requirements to guide the effective testing of a database-centric application. In summary, this chapter provides:

1. A high level overview of the techniques within the test adequacy component (Section 5.2).
2. An interprocedural program representation that supports the identification of test requirements (Section 5.3).
3. A model for a database interaction and the algorithms that enumerate database entities (Section 5.4).
4. A representation for a database-centric application that describes a program's interaction with relational database entities at multiple levels of granularity (Section 5.5).
5. An empirical examination of the time and space overhead incurred during the generation of intraprocedural database interaction associations for two case study applications (Section 5.7 through Section 5.10).
6. A review of the test adequacy component's implementation and a concluding discussion (Section 5.6 and Section 5.11).

5.2 OVERVIEW OF THE TEST ADEQUACY COMPONENT

Figure 5.1 depicts the high level architecture of the test adequacy component. This component analyzes program P in light of database-aware test adequacy criterion C and produces a set of database interaction associations. The test adequacy criterion C is one of the database-aware criterion that we presented in Chapter 4. The first stage produces an interprocedural control flow graph (ICFG) for program P. Next, the database interaction analyzer uses the ICFG in order to identify the database interaction points (DIPs) within the program under test. These DIPs send a SQL **select**, **update**, **insert**, or **delete** statement to the database. However, the SQL command might not be fully specified in the source code of the method under test. Many database-centric applications contain database interactions that send a SQL command whose elements are specified during program execution. Furthermore, a method often contains one or more control flow paths that lead to a single database interaction point.

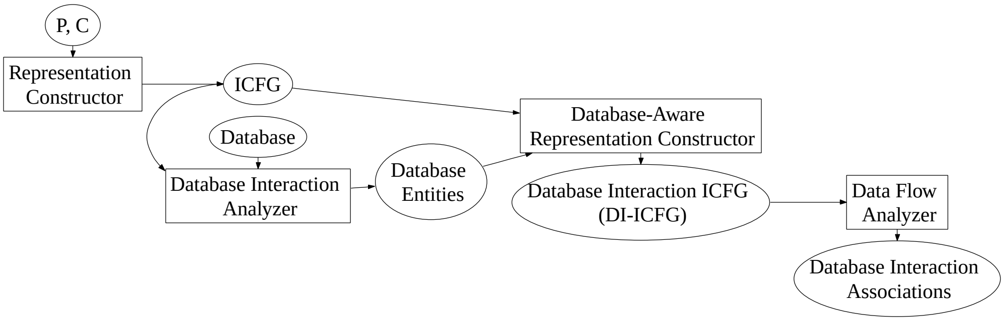

P, C
Representation Constructor
ICFG
Database
Database Interaction Analyzer
Database Entities
Database-Aware Representation Constructor
Database Interaction ICFG (DI-ICFG)
Data Flow Analyzer
Database Interaction Associations

Figure 5.1: High Level Architecture of the Test Adequacy Component.

The adequacy component includes a database interaction analyzer that models each DIP as a database interaction finite state machine (DI-FSM). The DI-FSM models all of the possible SQL statements that program P could submit to a database at a particular DIP. The database interaction analyzer correctly handles (i) SQL commands that are not statically specified and (ii) interaction points that exist on multiple paths of the ICFG. We consult a DI-FSM during the enumeration of the set of database entities that are subject to interaction at a DIP. Next, we use the set of database entities and the ICFG to construct a database interaction interprocedural control flow graph (DI-ICFG). The DI-ICFG includes nodes and edges that represent a program's interaction with a relational database. The data flow analyzer uses the DI-ICFG to generate the database interaction associations. The test adequacy component can leverage traditional data flow analysis algorithms that were designed for program variables (e.g., [Duesterwald et al., 1996]) since we designed the DI-ICFG to fully model the program's definition and use of the database.

5.3 REPRESENTING THE PROGRAM UNDER TEST

In order to support the enumeration of test requirements, the test adequacy component represents a database-centric application $A = \langle P, \langle D_1, \ldots, D_e \rangle, \langle S_1, \ldots, S_e \rangle \rangle$ as an interprocedural control flow graph. The following Definition 2 defines the interprocedural control flow graph G_P that traditionally represents program P. Figure 5.1 shows that the component initially constructs an ICFG for P with the goal of subsequently creating a DI-ICFG that fully describes the interactions between P and the $D_1, \ldots, D_e$ within A. The traditional ICFG contains all of the CFGs for each of P's methods and the edges that connect these graphs. Each CFG G_j can have *call* m_k and *return* m_k nodes that respectively demarcate the call to and the return from another method m_k. Figure 5.2 demonstrates how the CFGs for methods m_j and m_k are connected when the CFG for m_j contains an invocation of the method m_k. In an attempt to preserve the simplicity of the CFGs, Figures 5.2 and 5.3 use nodes with the label "…" to represent other nodes within G_j and G_k. Definition 2 and Figure 5.2 reveal that G_P provides an edge that connects the *call* node in G_j to the *enter* node in G_k. The ICFG also includes an edge from the *exit* node in G_k to the *return* node in G_j. Table A6 in Appendix A more fully describes the notation for the ICFG representation of program P.

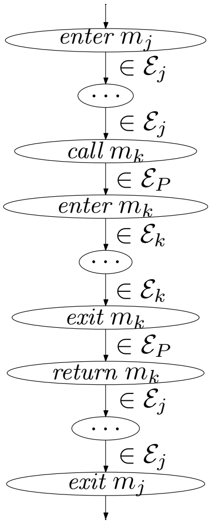


Figure 5.2: Connecting the Intraprocedural CFGs.

Definition 2. An *program interprocedural control flow graph* $G_P = \langle \Gamma_P, \mathcal{E}_P \rangle$ consists of the set of intraprocedural control flow graphs Γ_P and the set of edges $\mathcal{E}_P$. For each method m_k in P, there exists a $G_k \in \Gamma_P$. For any method m_j that invokes method m_k there exists (i) CFGs $G_j, G_k \in \Gamma_P$ with $\mathit{call}\, m_k, \mathit{return}\, m_k \in \mathcal{N}_j$ and $\mathit{enter}\, m_k, \mathit{exit}\, m_k \in \mathcal{N}_k$ and (ii) edges $(\mathit{call}\, m_k, \mathit{enter}\, m_k), (\mathit{exit}\, m_k, \mathit{return}\, m_k) \in \mathcal{E}_P$.

Figure 5.3 provides part of the ICFG for the `TM` case study application and the `getAccountBalance` method in Figure 5.9. We simplified this ICFG by including nodes of the form *call* m_k to represent method invocations that were not expanded. For example, we did not add the full CFG for the `inputPin` method after the node *call* inputPin. However, Figure 5.3 does contain the CFG for the `getAccountBalance` method. We use the line numbers in `getAccountBalance`'s source code listing to number the nodes within this CFG. For example, the node N_6 corresponds to line 6 of Figure 5.9 where `getAccountBalance` submits a SQL **select** statement to the *Bank* database. It is important to observe that the traditional ICFG in Figure 5.3 does not contain nodes that capture the program's interaction with the database entities.

5.4 ANALYZING A DATABASE INTERACTION

5.4.1 Overview of the Analysis

Figure 5.4 offers a high level overview of the database interaction analysis that we perform and Section 5.4.2 reviews the common terms and notation that we use throughout our discussion of the process depicted in this figure. First, the test adequacy component models a database interaction using the interprocedural control flow graph and any statically available information from the database interaction point. The database interaction modeling component creates a database interaction finite state machine, as further discussed in Section 5.4.3. Figure 5.4 reveals that the generation functions described in Section 5.4.4 use this DI-FSM to enumerate the sets of database entities. Section 5.5 explains how we use these sets of database entities

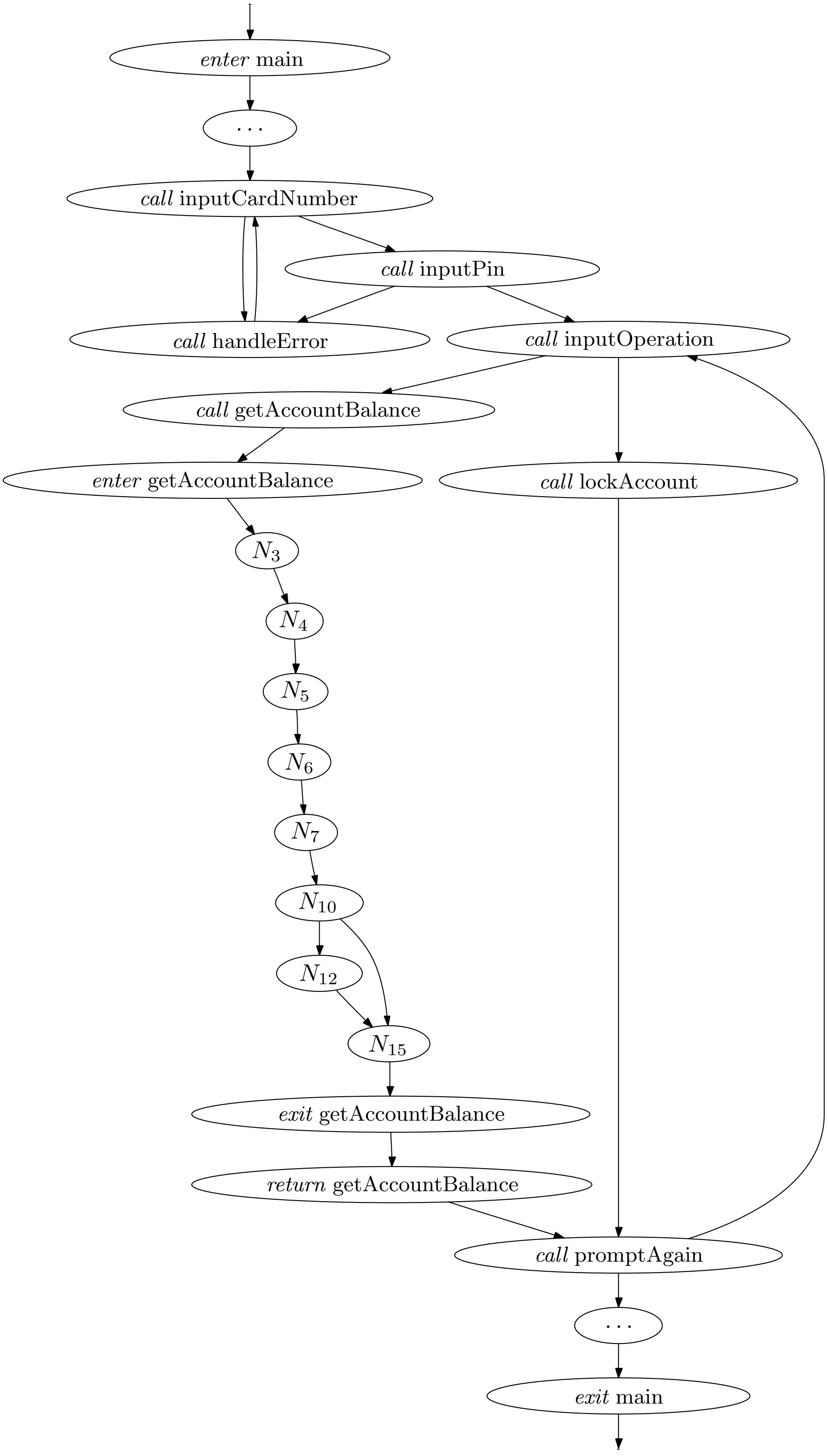


Figure 5.3: A Partial Interprocedural CFG for the `TM` Database-Centric Application.

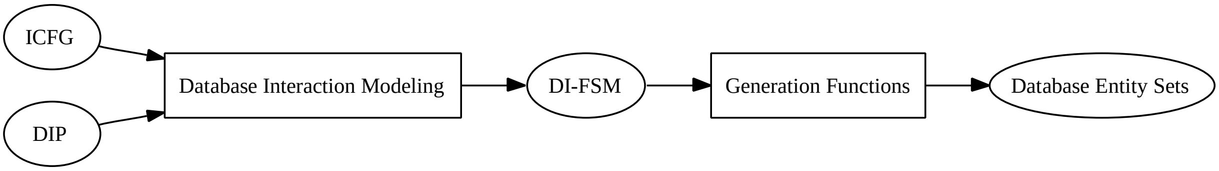


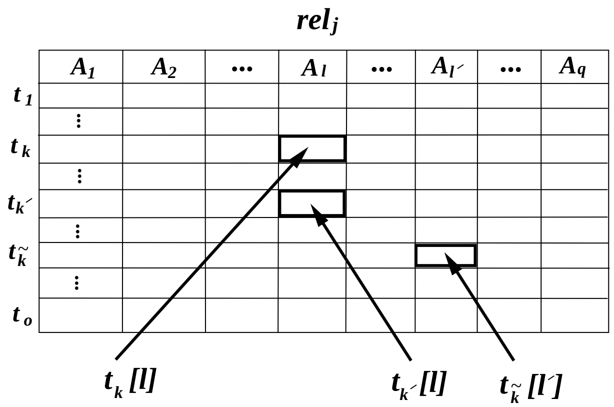
Figure 5.4: The Process of Database Interaction Analysis.

to (i) automatically generate a database-aware control flow graph and (ii) perform a data flow analysis that enumerates the test requirements. Tables A7 and A8 in Appendix A summarize the notation that we develop in the remainder of this chapter.

5.4.2 Representing a Database's State and Structure

Method m_k's control flow graph $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$ can contain one or more database interaction points, each of which corresponds to a database interaction node $N_r \in \mathcal{N}_k$. The source code in Figure 5.9 has a DIP on line 6 (i.e., "`ResultSet rs = stmt.executeQuery(qs)`") and the method listing in Figure 5.11 contains a DIP on line 7 (i.e., "`int result_lock = update_lock.executeUpdate(qu_lck)`"). The test adequacy component analyzes the state and structure of the relational databases in order to enumerate unique names for the database entities that are subject to interaction at node N_r. Suppose that program P interacts with database D_f at node N_r. We view database D_f as a set of relations so that $D_f = \{rel_1, \ldots, rel_w\}$ and we define a relation $rel_j = \{t_1, \ldots, t_u\}$ as a set of records. Each record is an ordered set of attribute values such that $t_k = \langle t_k[1], \ldots, t_k[q] \rangle$. We use the notation $t_k[l]$ to denote the value of the lth attribute of the kth record in a specified relation. In order to differentiate between the name of a database entity and its contents, we use the functions $name(D_f)$, $name(\mathcal{C}, rel_j)$, and $name(\mathcal{C}, t_k)$ to respectively return the unique names of the database D_f, the relation rel_j in database D_f, and rel_j's record t_k. For example, rel_j is a set of records while $name(\mathcal{C}, rel_j)$ is the unique name of the relation. The *name* function uses a context stack $\mathcal{C}$ to record the complete context for a database entity.

A relational database D_f can contain duplicate values in different database records. The adequacy component uses the context stack $\mathcal{C}$ to ensure that *name* returns a unique identifier for duplicate attribute values. At the attribute value level, two cases of entity value duplication are relevant: (i) the same attribute contains the same value in one or more records or (ii) two different attributes contain the same value in one or more records. Figure 5.5 shows a relation rel_j where certain attributes have the same value as the attribute value $t_k[l]$ (the same attribute values are represented by cells that have a darkened border). In circumstance (i), the record $t_{k'}$ has the same value for attribute A_l as record t_k (i.e., $t_k[l] = t_{k'}[l]$). However, Figures 5.6(a) and 5.6(b) show that $t_k[l]$ and $t_{k'}[l]$ have different context stacks and thus *name* can return unique identifiers for each attribute value (i.e., $name(\mathcal{C}, t_k[l]) \neq name(\mathcal{C}, t_{k'}[l])$ even though $t_k[l] = t_{k'}[l]$). In case (ii), the attribute $A_{l'}$ contains the same value as the attribute A_l in the record $t_{\tilde{k}}$ (i.e., $t_k[l] = t_{\tilde{k}}[l']$). Since Figures 5.6(a) and 5.6(c) reveal that $t_k[l]$ and $t_{\tilde{k}}[l']$ have different context stacks, *name*



Value Duplication: $t_k[l] = t_{k'}[l]$ and $t_k[l] = t_{\tilde{l}}[l']$

Figure 5.5: Value Duplication in a Relational Database.

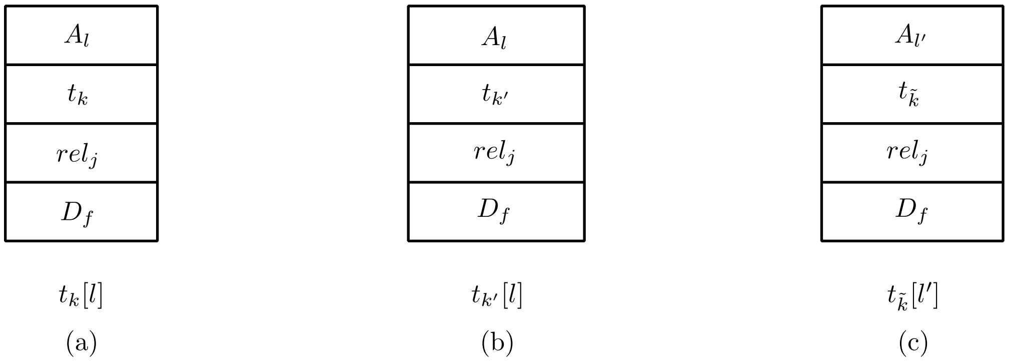
can return unique identifiers for these duplicate attribute values (i.e., $name(\mathcal{C}, t_k[l]) \neq name(\mathcal{C}, t_{\tilde{k}}[l'])$ even though $t_k[l] = t_{\tilde{k}}[l']$). The test adequacy component also uses the context stack $\mathcal{C}$ and the *name* function to accommodate value duplication at the relation, attribute, and record levels.

5.4.3 Representing a Database Interaction

The adequacy component produces a *database interaction finite state machine* to model the interaction at a single CFG node N_r. According to the following Definition 3, F_r contains the set of internal states Q and the set of final states $Q_f \subseteq Q$. The DI-FSM begins the processing of input string s at the initial state $q_0 \in Q$. The transition function $\delta : Q \times \Sigma \rightarrow Q$ allows F_r to move from state $q \in Q$ to state $q' \in Q$ whenever γ is the current symbol in s and $\delta(q, \gamma) = q'$ is a transition. We know that CFG node N_r can submit a SQL string s to the database if and only if F_r terminates in a final state $q \in Q_f$ when it processes input s.

Definition 3. A database interaction node N_r is represented by a *database interaction finite state machine* $F_r = \langle Q, Q_f, q_0, \delta, \Sigma \rangle$ where Q is a non-empty set of internal states, $Q_f \subseteq Q$ is the set of final states, $q_0 \in Q$ is the start state, $\delta : Q \times \Sigma \rightarrow Q$ is the transition function, and Σ is the input alphabet.

F_r's input alphabet Σ consists of all the terminals in the SQL grammar (e.g., **select**, **where**, attribute A_z, relation rel_j, etc.) and additional symbols $\mu, R, A,$ and O. The symbol μ denotes an unknown input and a transition uses μ to indicate that this aspect of the database interaction is not statically detectable. F_r uses the additional symbols $R, A,$ and O to respectively denote the relation, attribute, and operation inputs and to provide semantic meaning to the other transitions. The transitions $\delta(q, q') = rel_j$ and $\delta(q, q') = R$ show that rel_j is a recognized relation in the databases. The transitions $\delta(q, q') = A_l$ and $\delta(q, q') = A$ indicate that A_l is a valid database attribute. If $\mathbf{op} \in \{\mathbf{select}, \mathbf{update}, \mathbf{insert}, \mathbf{delete}\}$ and F_r has the transitions $\delta(q, q') = \mathbf{op}$ and $\delta(q, q') = O$, then this reveals that **op** is a correct SQL operation. For brevity, we call the transition $\delta(q, q') = R$ an $R-$transition and define the μ, A and O-transitions analogously. The component adds the $R, A, O-$transitions to F_r using a context-free language (CFL) reachability algorithm that "parses"



$t_k[l]$ (a) $t_{k'}[l]$ (b) $t_{\tilde{k}}[l']$ (c)

Figure 5.6: Context Stacks for Duplicate Attribute Values.

the finite state machine with a parser for the SQL grammar [Melski and Reps, 1997, Reps et al., 1995]. In this chapter, all figures that depict DI-FSMs use a bold node to indicate a final state and a dashed edge to represent the $R, A, O-$transitions that the CFL reachability algorithm adds.

The following Definition 4 classifies F_r's database interaction as static, partially dynamic, or dynamic. If P's source code fully specifies the interaction, then N_r performs a *static* interaction and the component creates an F_r that does not contain any $\mu-$transitions. If P does not statically specify a portion of the database interaction, then the component produces a *partially dynamic* F_r that contains at least one $\mu-$transition. The component generates a *dynamic* DI-FSM if the database interaction at N_r is specified at run-time. Definition 4 classifies F_r as dynamic when it only contains two states $q_o, q' \in Q$, $q' \in Q_f$, and the single transition $\delta(q_0, \mu) = q'$. Since the dynamic DI-FSM in Figure 5.7 accepts any SQL string, the test adequacy component must conservatively assume that N_r interacts with all of the attribute values in all of the databases.

Definition 4. A database interaction represented by $F_r = \langle Q, Q_f, q_0, \delta, \Sigma \rangle$ is (i) *static* if $(\forall q, q' \in Q)$ $(\delta(q, \mu) \neq q')$, (ii) *partially dynamic* if $(\forall q, q' \in Q)$ $(\exists \delta(q, \mu) = q')$, or (iii) *dynamic* if $|Q| = 2$, $|Q_f| = 1$, $q_0, q' \in Q$, $q' \in Q_f$, and $\delta(q_0, \mu) = q'$.

Figure 5.8 provides the DI-FSM for line 4 of the `getAccountBalance` method in Figure 5.9. This DI-FSM consists of five states with $q_0 \in Q$ as the initial state and $q_5 \in Q$ as the final state. The O-transition in this DI-FSM identifies **select** as a valid SQL operation. The DI-FSM uses two A-transitions to reveal that *id* and *balance* are attributes. Figure 5.8 also contains an R-transition to show that *Account* is a correct relation. Since the declaration of `String qs` completely defines the database interaction on line 6 of Figure 5.9, the static F_r in Figure 5.8 does not have any μ-transitions. The test adequacy component can precisely enumerate the database entities used by `getAccountBalance` because the DI-FSM is static.

The partially dynamic DI-FSM in Figure 5.10 models the database interaction on lines 5 and 6 of Figure 5.11. The $O-$transition in the DI-FSM indicates that **update** is a correct SQL operation. The $A-$transitions reveal that *acct_lock* and *card_number* are attributes in the *Bank* database. The $R-$transition

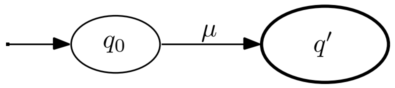


Figure 5.7: The DI-FSM for a Dynamic Interaction Point.

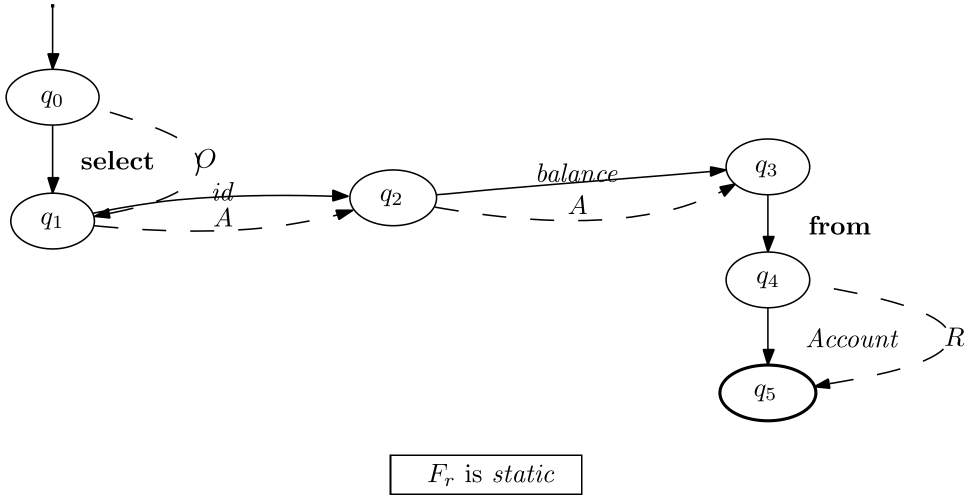


Figure 5.8: The DI-FSM for the `getAccountBalance` Method.

```
public double getAccountBalance(int uid) throws SQLException
{
   double balance = -1.0;
   String qs = “select id, balance from Account;”;
   Statement stmt = connect.createStatement();
   ResultSet rs = stmt.executeQuery(qs);
   while( rs.next() )
   {
      if( rs.getInt(“id”) == uid )
      {
         balance = rs.getDouble(“balance”);
      }
   }
   return balance;
}
```

Figure 5.9: The Implementation of the `getAccountBalance` Method.

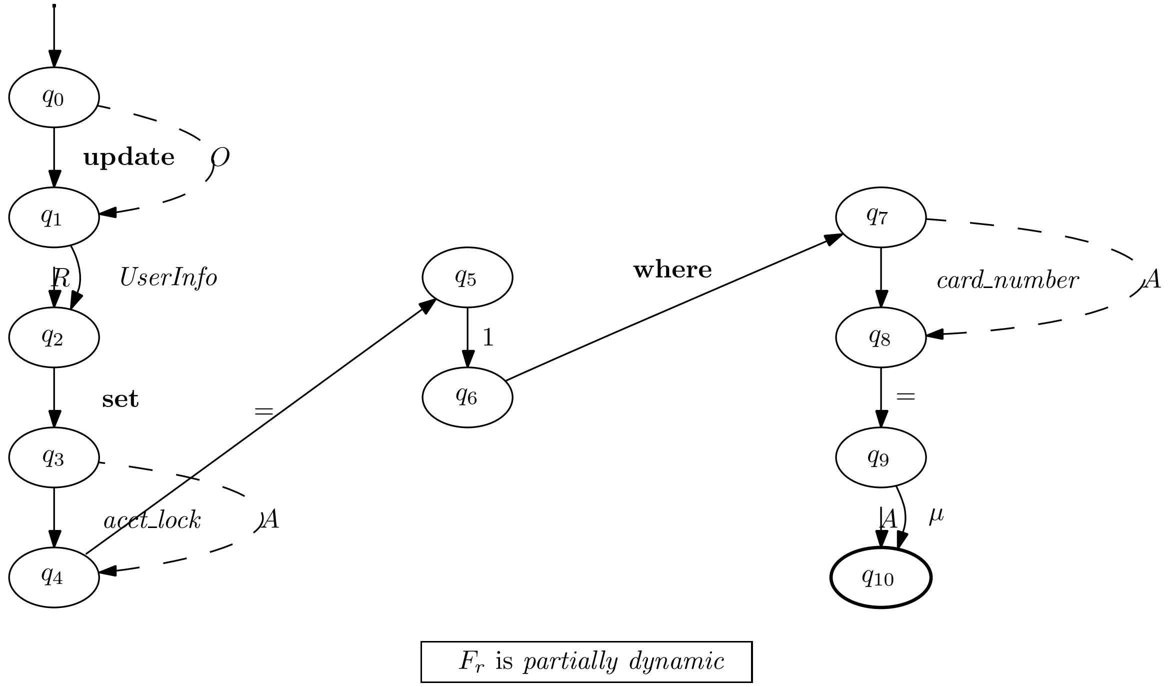


Figure 5.10: The DI-FSM for the `lockAccount` Method.

```
public boolean lockAccount(int c_n) throws SQLException
{
  boolean completed = false;
  String qu_lck = “update UserInfo set acct_lock=1” +
     “ where card_number=” + c_n + “;”;
  Statement update_lock = m_connect.createStatement();
  int result_lock = update_lock.executeUpdate(qu_lck);
  if( result_lock == 1 )
  {
    completed = true;
  }
  return completed;
}
```

Figure 5.11: The Implementation of the `lockAccount` Method.

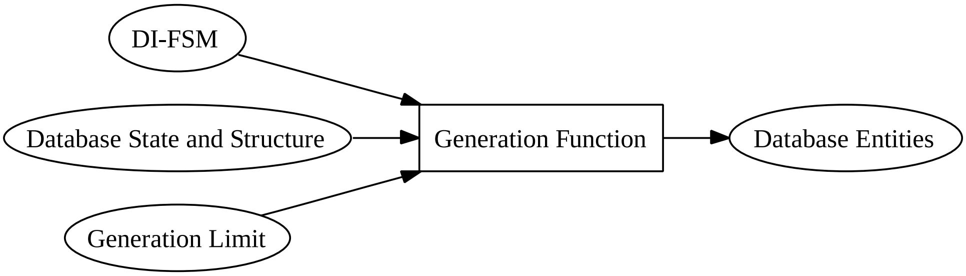


Figure 5.12: Inputs and Output of a Generation Function.

in the DI-FSM also shows that `lockAccount` interacts with the *UserInfo* relation. We classify the DI-FSM in Figure 5.10 as partially dynamic because it contains a μ-transition. The component creates the transition $\delta(q_9, \mu) = q_{10}$ because the `lockAccount` method uses the `c_n` parameter to define the **where** clause. During the analysis of the `lockAccount` method, the adequacy component conservatively enumerates all of the database entities in the *UserInfo* relation.

The test adequacy component constructs a DI-FSM like the ones provided in Figure 5.13 through Figure 5.15 whenever P uses an iteration or recursion construct to assemble the SQL string that it submits to the database. We create the DI-FSM in Figure 5.13 because P iteratively constructs a listing of attributes to **select** from relation rel_j. The component produces the DI-FSM in Figure 5.14 since P uses iteration to create the list of relations. We make Figure 5.15's DI-FSM when P uses iteration to designate both the attributes and the relations. We classify the DI-FSMs in Figure 5.13 through Figure 5.15 as partially dynamic because they contain one or more μ-transitions. Even though we focus the discussion on the **select** statement, the adequacy component uses similarly defined techniques to create DI-FSMs for the **update**, **insert**, and **delete** commands.

5.4.4 Generating Relational Database Entities

The adequacy component uses *generation functions* to conservatively identify the database entities that are subject to interaction at node N_r. Figure 5.12 shows that a generation function analyzes both the DI-FSM associated with a database interaction point and the current state of the relational database. The output of a generation function is a set of entities that are (i) part of either the databases' state or structure and (ii) subject to interaction at the specified DIP. We present generation functions for the five levels of database interaction granularity (e.g., the database, relation, attribute, record, and attribute value levels). For real world database-centric applications, the generation functions can return a prohibitively large number of database entities. This is due to the fact that the state of a database is practically infinite [Chays et al., 2000].

We use the parameter λ in order to limit the number of generated database entities and thus ensure that it is practical to enumerate database-aware test requirements. Suppose that a generation function GEN returns

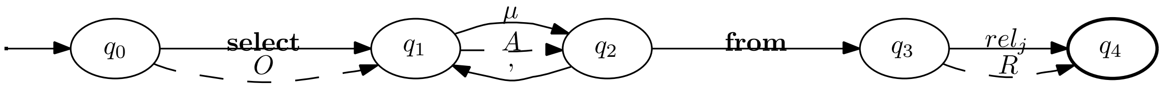


Figure 5.13: A DI-FSM with Unknown Attributes.

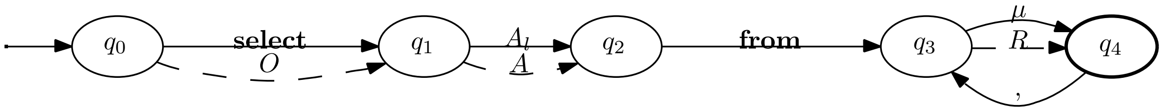


Figure 5.14: A DI-FSM with Unknown Relations.

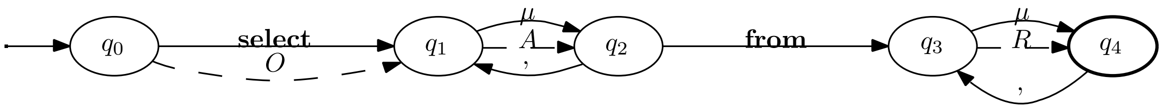


Figure 5.15: A DI-FSM with Unknown Attributes and Relations.

w database entities and we have $GEN =_\lambda \{d_1, \ldots, d_w\}$. We use the $=_\lambda$ operator to indicate that GEN returns all w database entities when $\lambda \geq w$ and one of the $\binom{w}{\lambda}$ sets of λ entities when $\lambda < w$. For example, suppose that the *UserInfo* relation contains five records of data when the adequacy component invokes the GEN function. Since *UserInfo* has four attributes, this mean that GEN could return up to twenty attribute values. However, if we set $\lambda = 10$, then GEN may return any ten of the twenty attribute values that are in the *UserInfo* relation. Throughout our discussion of the generation functions, we also assume that any statically specified fragment of a SQL statement adheres to the format described in Figure 2.1.

5.4.4.1 Databases The test adequacy component uses the GEN_D function to discover the databases that are subject to interaction at node N_r. All Java programs that connect to relational databases must use one of the `getConnection` methods that the `java.sql.DriverManager` class provides. Since the connection variable var can be defined at one or more nodes within P's ICFG G_P, we use reaching definitions analysis to identify all of var's definition nodes that reach the use at N_r. If node N_r uses the database connection variable var, then Equation (5.1) provides the generation function $GEN_D(G_P, N_r, var, \lambda)$ that returns the databases with which node N_r interacts. This equation uses $\mathcal{D}_\rho$ to denote the set of databases to which reaching definition node N_ρ could bind connection variable var. If the database D_f is statically specified at N_ρ, then $\mathcal{D}_\rho = \{D_f\}$. We conservatively assume that N_r connects to any of the databases if N_ρ specifies the database at run-time and thus $\mathcal{D}_\rho = \{D_1, \ldots, D_e\}$.

$$GEN_D(G_P, N_r, var, \lambda) =_\lambda \bigcup_{N_\rho \in RD(G_P, N_r, var)} \mathcal{D}_\rho \tag{5.1}$$

Since GEN_D must identify the set $RD(G_P, N_r, var)$ for connection variable var, we know that the worst-case time complexity of GEN_D is $O(\Upsilon \times \Psi \times \Omega + \lambda)$ where Equation (5.2) through Equation (5.4) respectively define Υ, Ψ, and Ω. In the time complexity for GEN_D the term $\Upsilon \times \Psi \times \Omega$ corresponds to the worst-case time complexity for the computation of $RD(G_P, N_r, var)$ in a demand-driven fashion [Duesterwald et al., 1996]. Equation (5.2) uses $caller(m_j, m_k)$ to denote the set of nodes $call\ m_j \in \mathcal{N}_k$ for the CFGs $G_j, G_k \in \Gamma_P$. Therefore, Υ is the maximum number of calls to the same method within one of P's methods. Equation (5.3) uses $define(N_k)$ to denote the set of nodes that contain definitions of program variables and thus Ψ is the maximum number of variable definitions within one of P's methods. Equation (5.4) defines Ω as the total number of nodes in all of the control flow graphs. Finally, the λ term in GEN_D's time complexity corresponds to the use of Equation (5.1) to iteratively create the set $\mathcal{D}_\rho$ and return at most λ databases.

$$\Upsilon = max\{\ |caller(m_j, m_k)|\ :\ G_j, G_k \in \Gamma_P\} \tag{5.2}$$

$$\Psi = max\{\ |define(N_k)|\ :\ G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle \in \Gamma_P\} \tag{5.3}$$

$$\Omega = \sum_{G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle \in \Gamma_P} |\mathcal{N}_k| \tag{5.4}$$

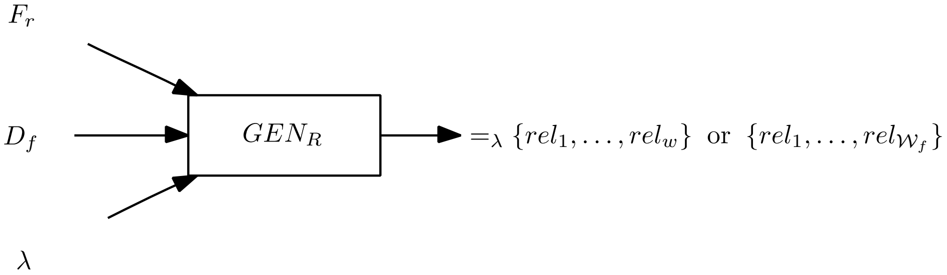

F_r
D_f
λ
GEN_R
$=_\lambda \{rel_1, \ldots, rel_w\}$ or $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$

Figure 5.16: The $GEN_R(F_r, D_f, \lambda)$ Function for the **select** Statement.

5.4.4.2 Relations Figure 5.16 shows the input and output when the $GEN_R(F_r, D_f, \lambda)$ function enumerates up to λ relations that are used in a **select** statement. This figure reveals that $GEN_R(F_r, D_f, \lambda) =_\lambda \{rel_1, \ldots, rel_w\}$ or $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$. GEN_R returns $\{rel_1, \ldots, rel_w\}$ when F_r does not contain the transitions $\delta(q, R) = q'$ and $\delta(q, \mu) = q'$ for $q, q' \in Q$ (i.e., the **select** statement fully specifies its relations) and these w relations are inside of the database D_f. In this circumstance, GEN_R outputs each relation $rel_j \in \{rel_1, \ldots, rel_w\}$ when $\delta(q, rel_j) = q'$ and $\delta(q, R) = q'$. Figure 5.16 uses $\mathcal{W}_f$ to denote the total number of relations in database D_f. If there exists states $q, q' \in Q$ with $\delta(q, R) = q'$ and $\delta(q, \mu) = q'$ (i.e., the **select** command has one or more unspecified relations), then GEN_R outputs $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$. GEN_R also returns $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$ when the DI-FSM F_r specifies the relations $rel_1, \ldots, rel_w$ but these relations are not inside of D_f.

GEN_R conservatively produces this output when GEN_D returns D_f and F_r does not reveal anything about N_r's interaction with the relations in this database. If we take the output of a relation rel_j as the basic operation, then we know that GEN_R has a worst-case time complexity of $O(\lambda)$. The other generation functions GEN_A, GEN_{R_c}, and GEN_{A_v} also have the same time complexity. Figure 5.17 shows the input and output for the GEN_R function that handles the **update**, **insert**, and **delete** statements. Since these SQL commands only interact with a single relation, GEN_R returns rel_j when the relation is statically specified in F_r. Like the GEN_R for the SQL **select**, this generation function also returns $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$ whenever (i) F_r contains one or more μ-transitions for the relation or (ii) the specified relation is not in D_f.

5.4.4.3 Attributes, Records, and Attribute Values Figure 5.18 reveals that the GEN_A function returns two different outputs depending upon the structure of F_r and the relation rel_j. If F_r does not contain $\delta(q, A) = q'$ and $\delta(q, \mu) = q'$ for $q, q' \in Q$ (i.e., the **select** statement fully specifies its attributes) and these z attributes are inside of the relation rel_j, then GEN_A returns $\{A_1, \ldots, A_z\}$. If F_r has one or more μ-transitions that have an A-transition decoration, then we assume that N_r interacts with all of the $\mathcal{Z}_j$ attributes in rel_j and GEN_A returns $\{A_1, \ldots, A_{\mathcal{Z}_j}\}$. GEN_A also returns this set when F_r specifies an interaction with $A_1, \ldots, A_z$ and these attributes are not inside of the input relation rel_j.

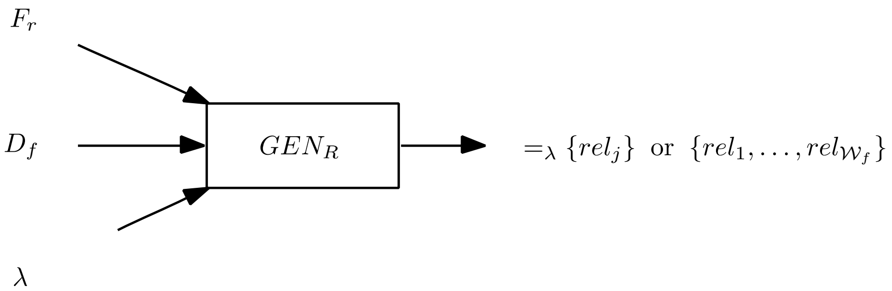

F_r
D_f
λ
GEN_R
$=_\lambda \{rel_j\}$ or $\{rel_1, \ldots, rel_{\mathcal{W}_f}\}$

Figure 5.17: The $GEN_R(F_r, D_f, \lambda)$ Function for the **update**, **insert**, and **delete** Statements.

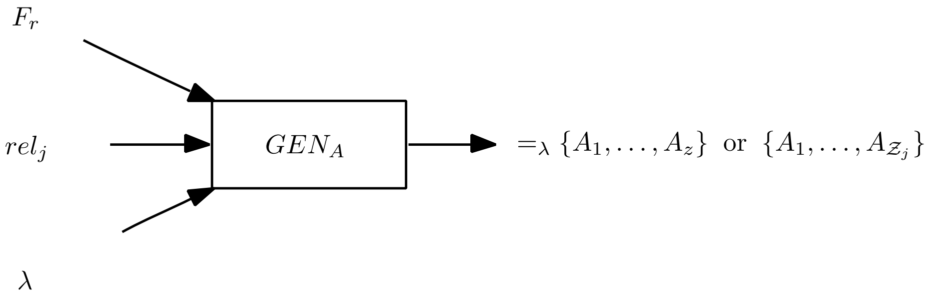

F_r
rel_j
λ
GEN_A
$=_\lambda \{A_1, \ldots, A_z\}$ or $\{A_1, \ldots, A_{\mathcal{Z}_j}\}$

Figure 5.18: The $GEN_A(F_r, rel_j, \lambda)$ Function for the **select** Statement.

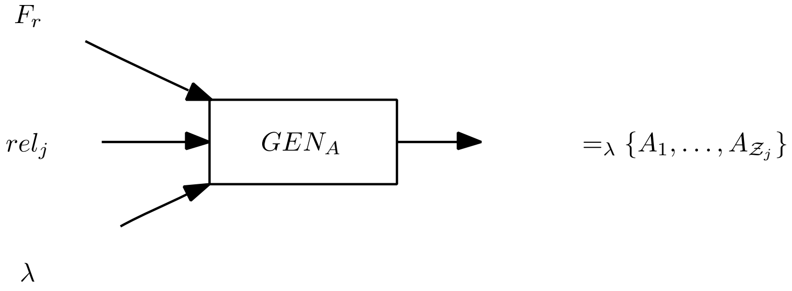


Figure 5.19: The $GEN_A(F_r, rel_j, \lambda)$ Function for the **insert** and **delete** Statements.

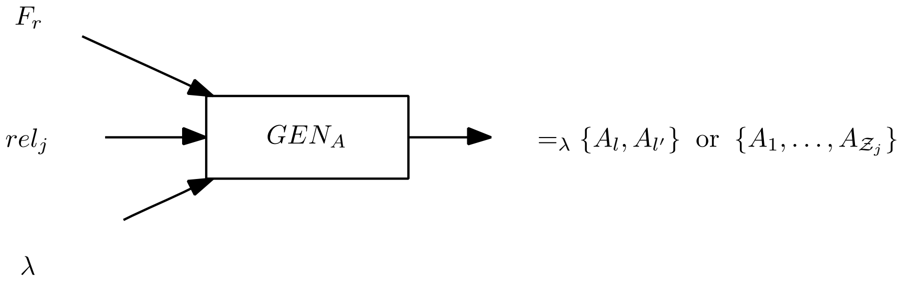

F_r
rel_j
λ
GEN_A
$=_\lambda \{A_l, A_{l'}\}$ or $\{A_1, \ldots, A_{\mathcal{Z}_j}\}$

Figure 5.20: The $GEN_A(F_r, rel_j, \lambda)$ Function for the **update** Statement.

Figure 5.19 reveals that the GEN_A function for the SQL **insert** and **delete** statements always returns $\{A_1, \ldots, A_{\mathcal{Z}_j}\}$. This is due to the fact that the **insert** and **delete** statements always interact with all of the attributes in the relation rel_j, regardless of whether or not there exists states $q, q' \in Q$ with $\delta(q, A) = q'$ and $\delta(q, \mu) = q'$. Figure 5.20 shows the output of the GEN_A function for the SQL **update** statement. GEN_A returns $\{A_l, A_{l'}\}$ when these attributes are statically specified in F_r and rel_j contains these attributes. We conservatively return $\{A_1, \ldots, A_{\mathcal{Z}_j}\}$ when F_r has one or more dynamic attribute transitions or the specified A_l and $A_{l'}$ are not contained in relation rel_j. We also provide GEN_{R_c} and GEN_{A_v} generation functions that analyze the state of the input relation and record, respectively. Since these two functions focus on the state of the database, they do not need to examine the F_r that models the SQL statement. The function $GEN_{R_c}(rel_j, \lambda)$ inspects the state of relation $rel_j = \{t_1, \ldots, t_u\}$ and returns (i) one of the $\binom{u}{\lambda}$ sets of records when $\lambda < u$ or (ii) all u records when $\lambda \geq u$. Finally, $GEN_{A_v}(t_k, \lambda)$ examines the state of record $t_k = \langle t_k[1], \ldots, t_k[z] \rangle$ and outputs (i) one of the $\binom{z}{\lambda}$ sets of attribute values when $\lambda < z$ or (ii) all z attribute values when $\lambda \geq z$.

5.4.5 Enumerating Unique Names for Database Entities

The test adequacy component invokes *enumeration algorithms* like *EnumerateDatabases* and *EnumerateRelations*. These algorithms use the (i) *name* function, (iii) context stack, and (i) generation functions in order to enumerate a set of unique database entity names that are involved in the interaction at node N_r. Figure 5.21 contains the *EnumerateDatabases* algorithm that returns the set of database names denoted $\mathcal{D}$. Line 1 initializes $\mathcal{D}$ to the empty set. After GEN_D performs a reaching definitions analysis on G_P, the algorithm adds the name of each D_f into the set $\mathcal{D}$. Our characterization of the worst-case time complexity of *EnumerateDatabases* and the other enumeration algorithms assumes the prior invocation of the *GEN* functions and the caching of their output.[1] If we take line 3 as the basic operation, then we know that *EnumerateDatabases* has a worst-case time complexity of $O(|GEN_D|)$. We use the notation $|GEN_D|$ to stand

[1] Our implementation of the adequacy component caches the output of a *GEN* function for specific inputs. This technique reduces time overhead at the cost of increasing space overhead. The worst-case time complexity of every enumeration algorithm would increase by one or more factors of λ if we assumed that the algorithms *do not* use caching. These additional factor(s) corresponds to the repeated invocation of *GEN* during the use of the *CreateRepresentation* algorithm in Figure 5.28.

```
Algorithm $EnumerateDatabases(G_P, F_r, N_r, var, \lambda)$
Input: ICFG $G_P$;
       DI-FSM $F_r$;
       Database Interaction Node $N_r$;
       Database Connection Variable $var$;
       Generation Function Limit $\lambda$
Output: Set of Database Names $\mathcal{D}$
1.  $\mathcal{D} \leftarrow \emptyset$
2.  for $D_f \in GEN_D(G_P, N_r, var, \lambda)$
3.      do $\mathcal{D} \leftarrow \mathcal{D} \cup \{name(D_f)\}$
4.  return $\mathcal{D}$
```

Figure 5.21: The *EnumerateDatabases* Algorithm.

for the number of unique database entity names that GEN_D returns. We can also classify this algorithm as $O(\lambda)$ since GEN_D can return at most λ databases. In certain applications, such as `TM`, the program only interacts with one database. We know that $\mathcal{D} = \{$*"Bank"*$\}$ at all of `TM`'s database interaction points because the application only interacts with the *Bank* database.

Figure 5.22 provides the *EnumerateRelations* algorithm that uses the generation functions GEN_D and GEN_R to enumerate the set of relation names $\mathcal{R}$ that are subject to interaction at node N_r. Line 1 initializes the context stack $\mathcal{C}$ to $\perp$, the symbol that we use to denote the empty stack. Line 2 of *EnumerateRelations* initializes $\mathcal{R}$ to the empty set and the remaining lines of the algorithm populate this set. Line 3 uses the database generation function GEN_D and line 4 pushes the database D_f onto the context stack. Next, line 5 uses GEN_R to generate relation rel_j and line 6 adds the current relation name to $\mathcal{R}$. Since *EnumerateRelations* contains two nested **for** loops, we know that the algorithm is $O(|GEN_D| \times |GEN_R|)$. We can also characterize the worst-case time complexity of *EnumerateRelations* as $O(\lambda^2)$ because the generation functions can respectively return at most λ databases and relations. The `getAccountBalance` method in Figure 5.9 has a database interaction point on line 6 so that $\mathcal{R} = \{$*"Bank.Account"*$\}$. Furthermore, the `lockAccount` method described in Figure 5.11 has a database interaction point on line 7 where $\mathcal{R} = \{$*"UserInfo"*$\}$.

Figure 5.23 includes the *EnumerateAttributes* algorithm that returns the set of attribute names $\mathcal{A}$. This algorithm operates in a similar fashion to the *EnumerateRelations* algorithm in Figure 5.22. Line 1 and line 2 initialize the context stack and the set of unique attributes names. The outer **for** loop generates the database name with GEN_D while the inner **for** loops use GEN_R and GEN_A to respectively generate the relations and attributes that are subject to interaction at CFG node N_r. If we regard line 8 as the basic operation, then we can classify *EnumerateAttributes* as $O(|GEN_D| \times |GEN_R| \times |GEN_A|)$ or $O(\lambda^3)$. When the adequacy component analyzes the DIP in the `getAccountBalance` method, it produces $\mathcal{A} = \{$*"Bank.Account.ID"*, *"Bank.Account.Balance"*$\}$. The database interaction point in the `lockAccount` method yields the attribute names $\mathcal{A} = \{$*"Bank.UserInfo.acct_lock"*, *"Bank.UserInfo.card_number"*$\}$.

Figure 5.24 describes the *EnumerateRecords* algorithm that returns the set of unique record names $\mathcal{R}_c$. After initializing $\mathcal{C}$ and $\mathcal{R}_c$, this algorithm uses the GEN_D and GEN_R generation functions and places the resulting D_f and rel_j onto the context stack. Line 7 calls the function GEN_{R_c} and then line 8 adds

```
**Algorithm** *EnumerateRelations*$(G_P, F_r, N_r, var, \lambda)$
**Input:** ICFG $G_P$;
    DI-FSM $F_r$;
    Database Interaction Node $N_r$;
    Database Connection Variable $var$;
    Generation Function Limit $\lambda$
**Output:** Set of Relation Names $\mathcal{R}$
    $\mathcal{C} \leftarrow \perp$
    $\mathcal{R} \leftarrow \emptyset$
    **for** $D_f \in GEN_D(G_P, N_r, var, \lambda)$
        **do** $\mathcal{C}.push(D_f)$
            **for** $rel_j \in GEN_R(F_r, \lambda)$
                **do** $\mathcal{R} \leftarrow \mathcal{R} \cup \{name(\mathcal{C}, rel_j)\}$
            $\mathcal{C}.pop()$
    **return** $\mathcal{R}$
```

Figure 5.22: The *EnumerateRelations* Algorithm.

```
**Algorithm** *EnumerateAttributes*$(G_P, F_r, N_r, var, \lambda)$
**Input:** ICFG $G_P$;
    DI-FSM $F_r$;
    Database Interaction Node $N_r$;
    Database Connection Variable $var$;
    Generation Function Limit $\lambda$
**Output:** Set of Attribute Names $\mathcal{A}$
    $\mathcal{C} \leftarrow \perp$
    $\mathcal{A} \leftarrow \emptyset$
    **for** $D_f \in GEN_D(G_P, N_r, var, \lambda)$
        **do** $\mathcal{C}.push(D_f)$
            **for** $rel_j \in GEN_R(F_r, \lambda)$
                **do** $\mathcal{C}.push(rel_j)$
                    **for** $A_l \in GEN_A(F_r, \lambda)$
                        **do** $\mathcal{A} \leftarrow \mathcal{A} \cup \{name(\mathcal{C}, A_l)\}$
                    $\mathcal{C}.pop()$
            $\mathcal{C}.pop()$
    **return** $\mathcal{A}$
```

Figure 5.23: The *EnumerateAttributes* Algorithm.

```
Algorithm $EnumerateRecords(G_P, F_r, N_r, var, \lambda)$
Input: ICFG $G_P$;
    DI-FSM $F_r$;
    Database Interaction Node $N_r$;
    Database Connection Variable $var$;
    Generation Function Limit $\lambda$
Output: Set of Record Names $\mathcal{R}_c$
$\mathcal{C} \leftarrow \perp$
$\mathcal{R}_c \leftarrow \emptyset$
for $D_f \in GEN_D(G_P, N_r, var, \lambda)$
    do $\mathcal{C}.push(D_f)$
       for $rel_j \in GEN_R(F_r, \lambda)$
           do $\mathcal{C}.push(rel_j)$
              for $t_k \in GEN_{R_c}(rel_j, \lambda)$
                  do $\mathcal{R}_c \leftarrow \mathcal{R}_c \cup \{name(\mathcal{C}, t_k)\}$
              $\mathcal{C}.pop()$
       $\mathcal{C}.pop()$
return $\mathcal{R}_c$
```

Figure 5.24: The *EnumerateRecords* Algorithm.

```
Algorithm $EnumerateAttributeValues(G_P, F_r, N_r, var, \lambda)$
Input: ICFG $G_P$;
    DI-FSM $F_r$;
    Database Interaction Node $N_r$;
    Database Connection Variable $var$;
    Generation Function Limit $\lambda$
Output: Set of Attribute Value Names $\mathcal{A}_v$
$\mathcal{C} \leftarrow \perp$
$\mathcal{A}_v \leftarrow \emptyset$
for $D_f \in GEN_D(G_P, N_r, var, \lambda)$
    do $\mathcal{C}.push(D_f)$
       for $rel_j \in GEN_R(F_r, \lambda)$
           do $\mathcal{C}.push(rel_j)$
              for $t_k \in GEN_{R_c}(rel_j, \lambda)$
                  do $\mathcal{C}.push(t_k)$
                     for $A_l \in GEN_A(F_r, \lambda)$
                         do $\mathcal{C}.push(A_l)$
                            for $t_k[l] \in GEN_{A_v}(t_k, \lambda)$
                                do $\mathcal{A}_v \leftarrow \mathcal{A}_v \cup \{name(\mathcal{C}, t_k[l])\}$
                            $\mathcal{C}.pop()$
                     $\mathcal{C}.pop()$
              $\mathcal{C}.pop()$
       $\mathcal{C}.pop()$
return $\mathcal{A}_v$
```

Figure 5.25: The *EnumerateAttributeValues* Algorithm.

each t_k into the set $\mathcal{R}_c$. If line 8 is the basic operation, then we classify *EnumerateRecords* as $O(|GEN_D| \times |GEN_R| \times |GEN_{R_c}|)$ or $O(\lambda^3)$. If we use the instance of the relational schema provided in Figure 2.4, then the DIP in `getAccountBalance` method produces $\mathcal{R}_c = \{name(\mathcal{C}, \langle 1, \ldots, 1000, 1\rangle), \ldots, name(\mathcal{C}, \langle 5, \ldots, 125, 4\rangle)\}$. Since the DIP in the `lockAccount` method depends upon the input to the operation, *EnumerateRecords* conservatively outputs all of the records inside of the *UserInfo* relation. If we knew that $card\_number = 1$ during the execution of this method (i.e., because `lockAccount` was invoked so that the formal parameter `c_n` $= 1$), *EnumerateRecords* would return $\mathcal{R}_c = \{name(\mathcal{C}, \langle 1, 32142, \ldots, 0\rangle)\}$.

Figure 5.25 provides the *EnumerateAttributeValues* algorithm that returns $\mathcal{A}_v$, the set of unique names for attribute values. Line 3 through line 9 iteratively invoke the GEN_D, GEN_R, GEN_{R_c}, and GEN_A generation functions and respectively push D_f, rel_j, t_k, and A_l onto the context stack $\mathcal{C}$. The function GEN_{A_v} inspects the state of record t_k and returns an attribute value $t_k[l]$. Line 12 of *EnumerateAttributeValues* adds $t_k[l]$ to $\mathcal{A}_v$. If line 12 is the basic operation, then we know that this algorithm is $O(|GEN_D| \times |GEN_R| \times |GEN_{R_c}| \times |GEN_A| \times |GEN_{A_v}|)$ or $O(\lambda^5)$. When the adequacy component analyzes the instance of the relational schema provided in Figure 2.4 and the DIP in the `getAccountBalance` method, this yields $\mathcal{A}_v = \{name(\mathcal{C}, 1), name(\mathcal{C}, 1000), \ldots, name(\mathcal{C}, 5), name(\mathcal{C}, 125)\}$. The input-dependent database interaction point in `lockAccount` forces *EnumerateAttributeValues* to return all of the attribute values within the records of the *UserInfo* relation.

The enumeration algorithms in Figure 5.21 through Figure 5.25 return a set of database entity names for a single interaction point. For example, the output of the *EnumerateRecords* algorithm returns $\mathcal{R}_c$, the set of record names for a single interaction point N_r. Yet, Section 4.3.2 explains that the database-aware test adequacy criteria focus on the database interaction association $\langle N_{def}, N_{use}, var_{DB}\rangle$ where relational database entity var_{DB} is an element of one of the sets $\mathcal{D}(G_k)$, $\mathcal{R}(G_k)$, $\mathcal{A}(G_k)$, $\mathcal{R}_c(G_k)$, or $\mathcal{A}_v(G_k)$. To this end, Equation (5.5) defines $\mathcal{D}(G_k)$, the set of database names that are subject to interaction in the method m_k. This equation uses $\mathcal{D}(N_r)$ to denote the set of databases with which node $N_r \in \mathcal{N}_k$ interacts. Equation (5.5) shows that we enumerate the set $\mathcal{D}(G_k)$ through the iterative invocation of *EnumerateDatabases* algorithm for each database interaction point in the method. We define the sets $\mathcal{R}(G_k)$, $\mathcal{A}(G_k)$, $\mathcal{R}_c(G_k)$, and $\mathcal{A}_v(G_k)$ in an analogous fashion.

$$\mathcal{D}(G_k) = \bigcup_{N_r \in N_k} \mathcal{D}(N_r) \tag{5.5}$$

5.5 CONSTRUCTING A DATABASE-AWARE REPRESENTATION

The database interaction control flow graph is an extended CFG that contains transfers of control to the nodes from one or more database interaction graphs (DIGs). A DIG represents a database interaction point at a single level of interaction granularity and multiple DIGs can exist within a DI-CFG. While the code examples in Figures 5.9 and 5.11 indicate that DIPs occur in assignment statements, the predicate of a conditional logic statement can also perform a database interaction. In order to preserve the semantics of a

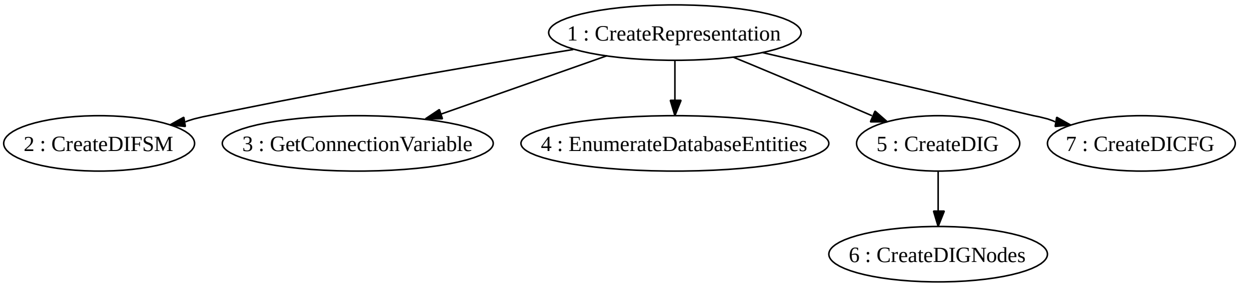


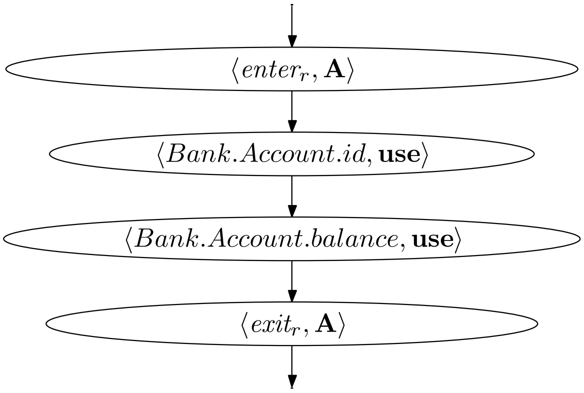
Figure 5.26: The Order of Algorithm Invocation when Constructing the Database-Aware Representation.

method m_k that is represented by $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$, we integrate a DIG before the node $N_r \in \mathcal{N}_k$ where the interaction takes place. Figure 5.26 shows the order in which the adequacy component invokes the algorithms that construct the DI-ICFG.

First, *CreateRepresentation* uses the *CreateDIFSM* algorithm to construct a DI-FSM F_r that models the submitted SQL statement, as described in Section 5.4.3. The *GetConnectionVariable* operation identifies the program variable that N_r uses to communicate with the database, as discussed in Section 5.4.4. Figure 5.26 reveals that *CreateRepresentation* executes the *EnumerateDatabaseEntities* algorithm. Once the names of the database entities are available, *CreateRepresentation* invokes the *CreateDIG* algorithm to construct a database interaction graph. As depicted in Figure 5.27, the DIG models an interaction point at a single level of interaction granularity. *CreateDIG* uses the *CreateDIGNodes* algorithm to construct a definition and/or use node for each one of the database entities involved in the interaction. Finally, *CreateRepresentation* calls *CreateDICFG* in order to produce a DI-CFG for each traditional CFG. A single DI-CFG $G_{DI(k)}$ statically represents all of the definitions and uses of relational database entities that could occur during the execution of m_k. Since the DI-CFG is an extension of a traditional CFG, $G_{DI(k)}$ also represents all of the definitions and uses of the program variables in method m_k.

While Figure 5.26 presents a high level ordering of the algorithm invocations, the *CreateRepresentation* algorithm in Figure 5.28 explicitly shows the iterative construction of the program's database aware representation on a per method basis. Since this algorithm does not modify the connections between CFGs, line 1 of *CreateRepresentation* initializes the set of DI-ICFG edges to the set of edges within the traditional ICFG. Line 2 initializes the set of DI-CFGs for program P, denoted $\Gamma_{DI(P)}$, to the empty set and lines 3 through 15 create a DI-CFG and then add it to this set. For each CFG $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle \in \Gamma_P$, lines 4 and 5 initialize the set of database interaction graphs, $\Gamma_{DI(k)}$, and the set of database entity names, $\mathcal{M}_k$, to the empty set. For every database interaction node $N_r \in \mathcal{N}_k$, line 7 calls the *CreateDIFSM* algorithm that produces a DI-FSM to model the database interaction and line 8 determines that *var* is the database connection variable used at this node.

Lines 9 through 15 of Figure 5.28 indicate that the algorithm constructs a DIG for each level $L_k \in \mathcal{L}(k)$. The function $\mathcal{L}(k)$ returns the levels of database interaction granularity at which we represent the interactions


$\langle enter_r, \mathbf{A} \rangle$
$\langle Bank.Account.id, \mathbf{use} \rangle$
$\langle Bank.Account.balance, \mathbf{use} \rangle$
$\langle exit_r, \mathbf{A} \rangle$

$$\boxed{\mathcal{M}_r = \{Bank.Account.id, Bank.Account.balance\} \text{ and } L_k = \mathbf{A}}$$

Figure 5.27: A Database Interaction Graph.

in method m_k. To this end, we require that $\mathcal{L}(k) \subseteq \{\mathbf{D}, \mathbf{R}, \mathbf{A}, \mathbf{R_c}, \mathbf{A_v}\}$ and we assume that the tester specifies $\mathcal{L}(k)$. If $\mathbf{D} \in \mathcal{L}(k)$, then *CreateRepresentation* must construct a DIG to model a method m_k's interaction with a relational database at the database level. Line 10 calls the *EnumerateDatabaseEntities* algorithm that subsequently invokes the appropriate enumeration algorithm as specified by the value of L_k. For example, if $L_k = \mathbf{A}$, then the *EnumerateDatabaseEntities* operation invokes the *EnumerateAttributes* algorithm. Line 11 stores this set of database entity names, $\mathcal{M}_r$, in the set of names for the entire method m_k, denoted $\mathcal{M}_k$. A call to the *CreateDIG* algorithm yields the DIG $G_r^{L_k}$ that the *CreateRepresentation* algorithm places into $\Gamma_{DI(k)}$, m_k's set of DIGs.

After the DIGs have been constructed for all interaction points and interaction levels, the *CreateDICFG* algorithm integrates the DIGs into the CFG G_k in order to produce the DI-CFG $G_{DI(k)}$. Line 14 of Figure 5.28 shows that the *CreateDICFG* algorithm uses the traditional CFG, the set of DIGs, and the set of database entity names in order to produce the DI-CFG called $G_{DI(k)}$. The worst-case time complexity of *CreateRepresentation* is $O(|\Gamma_P| \times N_{max} \times L_{max})$ where Γ_P is the set of P's CFGs and Equations (5.6) and (5.7) define N_{max} and L_{max}, respectively. We use N_{max} to denote the maximum number of database interaction points within the CFG of a single method. Equation (5.7) uses L_{max} to stand for the maximum number of interaction levels that were chosen to represent the DIGs for an individual method.

$$N_{max} = max\{ \left| \bigcup_{N_r \in \mathcal{N}_k} N_r \right| \;:\; G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle \in \Gamma_P \; \} \tag{5.6}$$

$$L_{max} = max\{ \; |\mathcal{L}(k)| \;:\; G_k \in \Gamma_P \; \} \tag{5.7}$$

Figure 5.29 provides the *CreateDIG* algorithm that constructs a DIG $G_r = \langle \mathcal{N}_r, \mathcal{E}_r, N_r \rangle$ for a database interaction node N_r. A DIG contains a set of nodes $\mathcal{N}_r$, a set of edges $\mathcal{E}_r$, and the database interaction node whose interaction it represents. Lines 1 and 2 of *CreateDIG* initialize these sets of nodes and edges

```
Algorithm $CreateRepresentation(G_P, \mathcal{L}, \lambda)$
Input: ICFG $G_P = \langle \Gamma_P, \mathcal{E}_P \rangle$;
      Levels of DIP Representation $\mathcal{L}$;
      Generation Function Limit $\lambda$
Output: DI-ICFG $G_{DI(P)} = \langle \Gamma_{DI(P)}, \mathcal{E}_{DI(P)} \rangle$
1.  $\mathcal{E}_{DI(P)} \leftarrow \mathcal{E}_P$
2.  $\Gamma_{DI(P)} \leftarrow \emptyset$
3.  for $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle \in \Gamma_P$
4.      do $\Gamma_{DI(k)} \leftarrow \emptyset$
5.         $\mathcal{M}_k \leftarrow \emptyset$
6.         for $N_r \in \mathcal{N}_k$
7.             do $F_r \leftarrow CreateDIFSM(G_P, N_r)$
8.                $var \leftarrow GetConnectionVariable(N_r)$
9.                for $L_k \in \mathcal{L}(k)$
10.                   do $\mathcal{M}_r \leftarrow EnumerateDatabaseEntities(F_r, var, \lambda, L_k)$
11.                      $\mathcal{M}_k \leftarrow \mathcal{M}_k \cup \mathcal{M}_r$
12.                      $G_r^{L_k} \leftarrow CreateDIG(\mathcal{M}_r, N_r, F_r, L_k)$
13.                      $\Gamma_{DI(k)} \leftarrow \Gamma_{DI(k)} \cup \{G_r^{L_k}\}$
14.        $G_{DI(k)} \leftarrow CreateDICFG(G_k, \Gamma_{DI(k)}, \mathcal{M}_k)$
15.        $\Gamma_{DI(P)} \leftarrow \Gamma_{DI(P)} \cup \{G_{DI(k)}\}$
16. return $\langle \Gamma_{DI(P)}, \mathcal{E}_{DI(P)} \rangle$
```

Figure 5.28: The *CreateRepresentation* Algorithm.

to the empty set. The entry and exit points of a DIG G_r are demarcated by the nodes $\langle entry_r, L_k \rangle$ and $\langle exit_r, L_k \rangle$. These nodes contain the annotation L_k to indicate that G_r represents the database interaction at the granularity level L_k. The nested **for** loops in *CreateDIG* iteratively construct a straight-line code segment that connects all of the database entities $d \in \mathcal{M}_r$. Line 4 shows that we initialize the current node N_p to the entry node and line 6 calls the *CreateDIGNodes* algorithm that returns a tuple of DIG nodes, denoted $\mathcal{N}_d$. Line 8 of Figure 5.29 adds DIG node N_d into the set $\mathcal{N}_r$ and line 9 places the edge (N_p, N_d) into the set $\mathcal{E}_r$. After handling every database entity $d \in \mathcal{M}_r$, the algorithm connects the last node N_p to the exit node of G_r and returns the DIG to the *CreateRepresentation* algorithm. Figure 5.27 shows the DIG that we create for the DI-FSM from Figure 5.8, the set of database entity names $\mathcal{M}_r = \{Bank.Account.id, Bank.Account.balance\}$ and the granularity marker $L_k = \mathbf{A}$. We know that $|\mathcal{N}_d| \in \{1, 2\}$ because *CreateDIGNodes* can return either (i) one definition node, (ii) one use node, or (iii) one definition and one use node. Since $|\mathcal{N}_d|$ is a always a small constant, we have that *CreateDIG* is $O(|\mathcal{M}_r|)$.

Figure 5.30 describes the *CreateDIGNodes* algorithm that returns a tuple of DIG nodes, $\mathcal{N}_d$, when provided with a DI-FSM F_r and a single database entity d. This algorithm uses $\uplus$ as the union operator for tuples. If F_r models a DIP that is defining or using, then this algorithm returns a tuple with a single node of the form $\langle d, op \rangle$ where $op \in \{\mathbf{def}, \mathbf{use}\}$. If F_r models a database interaction that is defining-using, then *CreateDIGNodes* returns a tuple $\mathcal{N}_d = \langle \langle d, \mathbf{use} \rangle, \langle d, \mathbf{def} \rangle \rangle$. We place d's use node before the definition node in order to ensure that the database interaction associations span the DIGs of a DI-CFG. The *Used* operation on line 2 inspects the DI-FSM F_r in order to determine whether the DIP defines or uses d. If we have $\delta(q, \mathbf{select}) = q'$ and $\delta(q, O) = q'$ for $q, q' \in Q$, then *Used* returns **true**. The *Used* operation also returns true when $\delta(q, A) = q'$ and $\delta(q, d) = q'$ and d exists in the **where** clause of either a SQL **delete**

```
**Algorithm** *CreateDIG*$(\mathcal{M}_r, N_r, F_r, L_k)$
**Input:** Set of Database Entity Names $\mathcal{M}_r$;
      Database Interaction Node $N_r$;
      Database Interaction FSM $F_r$;
      Database Interaction Granularity $L_k$;
**Output:** Database Interaction Graph $G_r = \langle \mathcal{N}_r, \mathcal{E}_r, N_r \rangle$
1.  $\mathcal{N}_r \leftarrow \emptyset$
2.  $\mathcal{E}_r \leftarrow \emptyset$
3.  $\mathcal{N}_r \leftarrow \mathcal{N}_r \cup \{\langle entry_r, L_k \rangle, \langle exit_r, L_k \rangle\}$
4.  $N_p \leftarrow \langle entry_r, L_k \rangle$
5.  **for** $d \in \mathcal{M}_r$
6.      **do** $\mathcal{N}_d \leftarrow CreateDIGNodes(F_r, d)$
7.         **for** $N_d \in \mathcal{N}_d$
8.             **do** $\mathcal{N}_r \leftarrow \mathcal{N}_r \cup \{N_d\}$
9.                $\mathcal{E}_r \leftarrow \mathcal{E}_r \cup \{(N_p, N_d)\}$
10.               $N_p \leftarrow N_d$
11. $\mathcal{E}_r \leftarrow \mathcal{E}_r \cup \{(N_p, \langle exit_r, L_k \rangle)\}$
12. **return** $\langle \mathcal{N}_r, \mathcal{E}_r, N_r \rangle$
```

Figure 5.29: The *CreateDIG* Algorithm.

or an **update** statement. The *Defined* method also examines F_r and it operates in an analogous fashion to *Used*. If we assume that the execution time of *Defined* and *Used* is bounded by a small constant, then *CreateDIGNodes* is a $O(1)$ algorithm.

Figure 5.31 gives the *CreateDICFG* algorithm that produces a DI-CFG $G_{DI(k)} = \langle \mathcal{N}_{DI(k)}, \mathcal{E}_{DI(k)} \rangle$ from a traditional CFG G_k, the set of DIGs $\Gamma_{DI(k)}$, and the set of database entity names $\mathcal{M}_k$. Lines 1 and 2 initialize the set of nodes and edges in the DI-CFG to the nodes and edges within the CFG. The *CreateDICFG* algorithm iteratively removes and adds edges to $\mathcal{E}_{DI(k)}$, while only adding nodes to $\mathcal{N}_{DI(k)}$. Lines 3 and 4 initialize the nodes N_l and N_{cr} to **null**. We use N_l to denote the last node in a DIG and N_{cr} points to the current database interaction node N_r. Line 5 calls the *DefineTemporaries* operation that adds nodes to $\mathcal{N}_{DI(k)}$. These nodes define temporary variables that we initialize to the value of method m_k's formal parameters [Duesterwald et al., 1996]. *DefineTemporaries* also treats the entities within the relational database as global variables and inserts temporary variables to represent these data elements.

The *CreateRepresentation* algorithm orders the DIGs within $\Gamma_{DI(k)}$ so that G_r and $G_{r'}$ are adjacent when they represent the same N_r at different levels of granularity. When we encounter the node N_r for the first time, lines 12 through 14 remove the edge (N_p, N_r) from $\mathcal{E}_{DI(k)}$ for each node $N_p \in pred(N_r)$. After we disconnect the predecessor node N_p from N_r, we create a new edge $(N_p, entry_r)$ for the node $entry_r \in \mathcal{N}_r$. Next, line 15 sets node N_l to the exit node of the current G_r so that the algorithm can integrate subsequent DIGs (for the same N_r) after this DIG. Line 16 sets N_{cr} to N_r in order to indicate that N_r is the current database interaction node under analysis. If $N_{cr} \neq N_r$ and $N_l \neq$ **null** (i.e., we have encountered DIGs for a new N_r and there is a residual N_l from the previous execution of the **for** loop on line 6), then line 11 connects the last node N_l to N_{cr}. If G_r is not the first DIG under analysis for a given N_r, then *CreateDICFG* executes lines 18 though 19 so that it can connect the exit node of the previous DIG to the entry node of the current DIG. Finally, line 20 connects the exit node of the last DIG to the last interaction node.

```
**Algorithm** *CreateDIGNodes*$(F_r, d)$
**Input:** Database Interaction FSM $F_r$;
    Database Entity $d$;
**Output:** Tuple of Database Interaction Graph Nodes $\mathcal{N}_d$
$\mathcal{N}_d \leftarrow \emptyset$
**if** $\mathit{Used}(F_r, d) = $ **true**
    **then** $\mathit{op} \leftarrow$ **use**
        $N_d \leftarrow \langle d, \mathit{op} \rangle$
        $\mathcal{N}_d \leftarrow \mathcal{N}_d \uplus \langle N_d \rangle$
**if** $\mathit{Defined}(F_r, d) = $ **true**
    **then** $\mathit{op} \leftarrow$ **define**
        $N_d \leftarrow \langle d, \mathit{op} \rangle$
        $\mathcal{N}_d \leftarrow \mathcal{N}_d \uplus \langle N_d \rangle$
**return** $\mathcal{N}_{DB}$
```

Figure 5.30: The *CreateDIGNodes* Algorithm.

Figure 5.32 shows the DIGs G_r and $G_{r'}$ and the CFG G_k before we integrate them into a single DI-CFG $G_{DI(k)}$. For this example, we assume that $\mathit{pred}(N_r) = \{N_1, \ldots, N_\phi\}$ and $\Gamma_{DI(k)} = \{G_r, G_{r'}\}$. In an attempt to preserve simplicity, suppose that G_r and $G_{r'}$ represent the same N_r at two different levels of interaction granularity. Figure 5.33 depicts the structure of the DI-CFG after the execution of the *CreateDICFG* algorithm. This figure reveals that all nodes $N_p \in \mathit{pred}(N_r)$ are now connected to the entry node of the first DIG, G_r. We also see that *CreateDICFG* connected the exit node of G_r to the entry node of $G_{r'}$. The connection of the last DIG's exit node to node N_r completes the transfer of control back to the nodes within $\mathcal{N}_k$. Figure 5.34 shows the complete DI-CFG for the `lockAccount` operation that represents the method's interaction with the database at the level of database (label **D**) and attribute (label **A**).

The worst-case time complexity of *CreateDICFG* is $O(|\Gamma_{DI(k)}| + N_{tot} \times PRED_{max})$ where $|\Gamma_{DI(k)}|$ is the total number of database interaction graphs for method m_k and Equations (5.8) and (5.9) respectively define N_{tot} and $PRED_{max}$. The variable N_{tot} defines the total number of database interaction nodes within a single CFG $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$. We use $PRED_{max}$ to denote the maximum number of predecessor nodes for an interaction point N_r. The $|\Gamma_{DI(k)}|$ term in the time complexity corresponds to the execution of *CreateDICFG*'s outer **for** loop. The $N_{tot} \times PRED_{max}$ term stands for the execution of the inner **for** loop on lines 12 through 14. Even though these lines execute within a doubly nested **for** loop, they only execute when *CreateDICFG* encounters a new node N_r (i.e., $N_{cr} \neq N_r$). Since no database interaction node $N_r \in \mathcal{N}_k$ can contain more than $PRED_{max}$ predecessors, the body of the inner **for** loop executes with at most $PRED_{max}$ iterations.

$$N_{tot} = \left| \bigcup_{N_r \in \mathcal{N}_k} N_r \right| \tag{5.8}$$

$$PRED_{max} = max\{ \left| \bigcup_{N_p \in pred(N_r)} N_p \right| \; : \; G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle, N_r \in \mathcal{N}_k \} \tag{5.9}$$

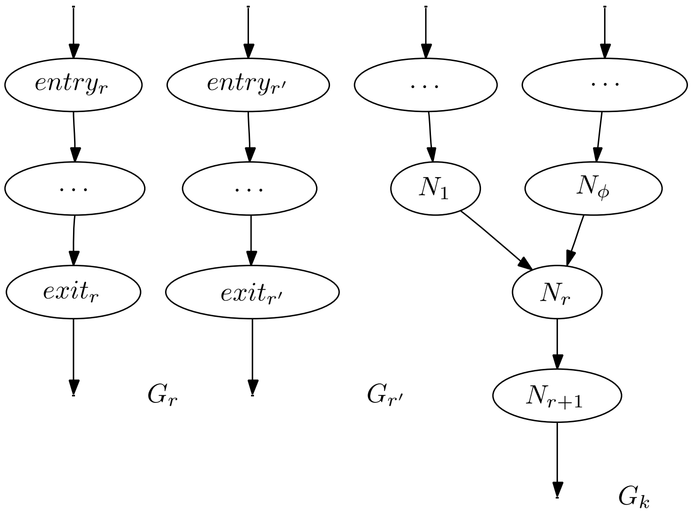
```
**Algorithm** $\mathit{CreateDICFG}(G_k, \Gamma_{DI(k)}, \mathcal{M})$
**Input:** Traditional CFG $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$;
      Set of Database Interaction Graphs $\Gamma_{DI(k)}$;
      Set of Database Entities $\mathcal{M}_k$
**Output:** DI-CFG $G_{DI(k)} = \langle \mathcal{N}_{DI(k)}, \mathcal{E}_{DI(k)} \rangle$
$\mathcal{N}_{DI(k)} \leftarrow \mathcal{N}_k$
$\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_k$
$N_l \leftarrow$ **null**
$N_{cr} \leftarrow$ **null**
$\mathit{DefineTemporaries}(G_k, \mathcal{M}_k)$
**for** $G_r = \langle \mathcal{N}_r, \mathcal{E}_r, N_r, L_r \rangle \in \Gamma_{DI(k)}$
    **do** $\mathcal{N}_{DI(k)} \leftarrow \mathcal{N}_{DI(k)} \cup \mathcal{N}_r$
       $\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} \cup \mathcal{E}_r$
       **if** $N_{cr} \neq N_r$
         **then if** $N_l \neq$ **null**
                 **then** $\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} \cup \{(N_l, N_{cr})\}$
               **for** $N_p \in \mathit{pred}(N_r)$
                   **do** $\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} - \{(N_p, N_r)\}$
                      $\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} \cup \{(N_p, \mathit{entry}_r)\}$
               $N_l \leftarrow \mathit{exit}_r$
               $N_{cr} \leftarrow N_r$
         **else**
               $\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} \cup \{(N_l, \mathit{entry}_r)\}$
               $N_l \leftarrow \mathit{exit}_r$
$\mathcal{E}_{DI(k)} \leftarrow \mathcal{E}_{DI(k)} \cup \{(N_l, N_{cr})\}$
**return** $\langle \mathcal{N}_{DI(k)}, \mathcal{E}_{DI(k)} \rangle$
```

Figure 5.31: The *CreateDICFG* Algorithm.

5.6 IMPLEMENTATION OF THE TEST ADEQUACY COMPONENT

The implementation of the adequacy component uses the Soot 1.2.5 program analysis framework. During the analysis of the methods in a database-centric application, we use the three address code intermediate representation called Jimple [Vallée-Rai et al., 1999, 2000]. Since a database-centric application frequently uses the exception handling constructs of the Java programming language, we use a Soot CFG that conservatively models the flow of exceptions across method boundaries. We also use Soot's points-to analysis techniques in order to (i) identify the heap objects to which a reference variable can point, (ii) resolve the potential destination(s) of all polymorphic method dispatches, and (iii) create the interprocedural control flow graph [Berndl et al., 2003, Lhoták and Hendren, 2003]. It is possible to extend the test adequacy component by incorporating recent demand-driven points-to analysis techniques [Sridharan et al., 2005, Sridharan and Bodik, 2006].

We employ the Java String Analyzer (JSA) to generate a DI-FSM for each DIP in a database-centric application [Christensen et al., 2003]. The adequacy component uses the HSQLDB parser to perform CFL reachability and to annotate a DI-FSM with the $R, A, O-$transitions. The current implementation supports the integration of parsers that handle different SQL dialects. The adequacy component also uses Soot to implement the DI-ICFG creation algorithms described in Section 5.5. Using Soot, the test adequacy component performs an exhaustive intraprocedural data flow analysis in order to enumerate the def-use and database



$\boxed{pred(N_r) = \{N_1, \ldots, N_\phi\} \text{ and } \Gamma_{DI(k)} = \{G_r, G_{r'}\}}$

Figure 5.32: Before the Execution of *CreateDICFG*.

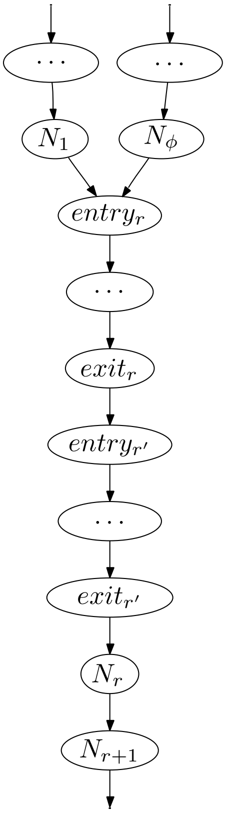


Figure 5.33: After the Execution of *CreateDICFG*.

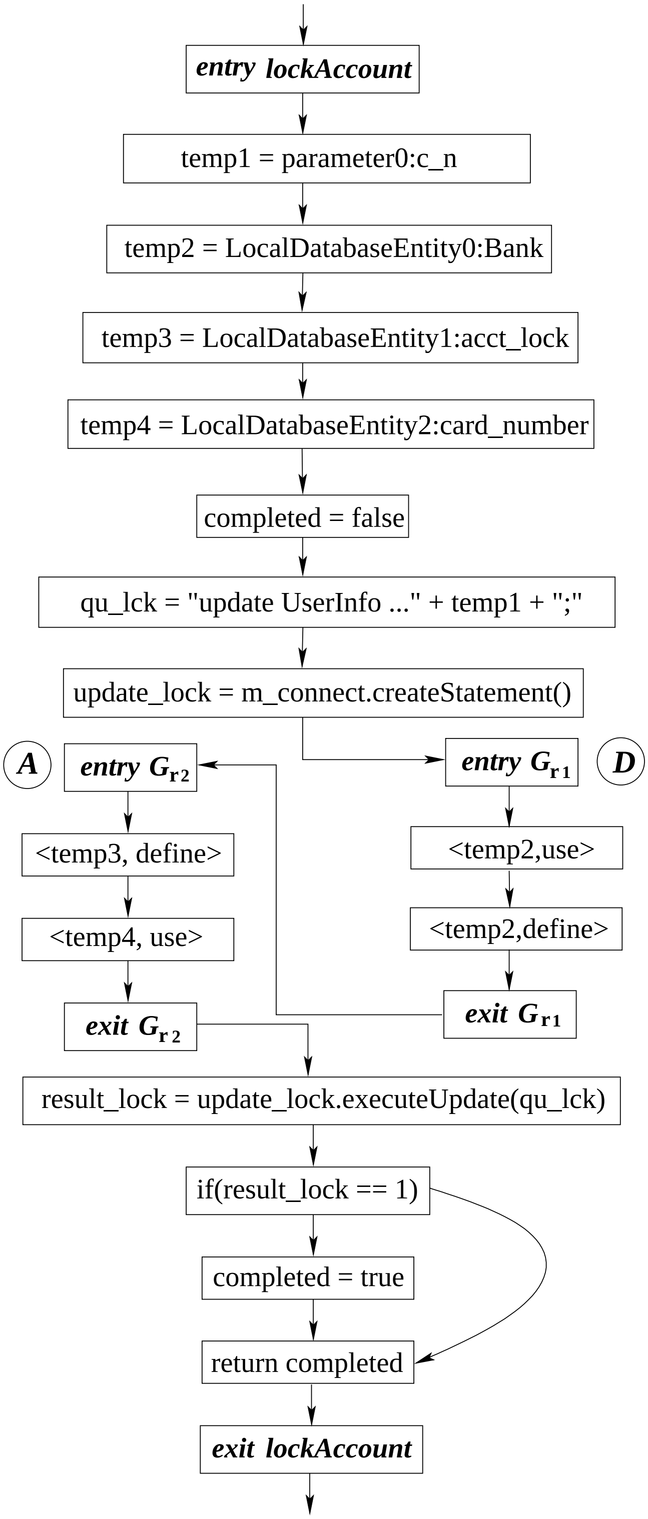

entry lockAccount
temp1 = parameter0:c_n
temp2 = LocalDatabaseEntity0:Bank
temp3 = LocalDatabaseEntity1:acct_lock
temp4 = LocalDatabaseEntity2:card_number
completed = false
qu_lck = "update UserInfo ..." + temp1 + ";"
update_lock = m_connect.createStatement()
A
entry G r2
<temp3, define>
<temp4, use>
exit G r2
entry G r1
D
<temp2,use>
<temp2,define>
exit G r1
result_lock = update_lock.executeUpdate(qu_lck)
if(result_lock == 1)
completed = true
return completed
exit lockAccount

Figure 5.34: A DI-CFG for the `lockAccount` Operation.

Adequacy Criteria Pairing	(A_v, R_c)	(A_v, A)	(A_v, D)	(R_c, R)	(A, R)	(R, D)

Table 5.1: Test Adequacy Pairings for the Measurement of $\mathcal{TR}$.

Adequacy Criteria Pairing	$(P + A_v, P + R_c)$	$(P + A_v, P + A)$	$(P + A_v, P + D)$	
	$(P + R_c, P + R)$	$(P + A, P + R)$	$(P + R, P + D)$	$(P + A_v, P)$

Table 5.2: Test Adequacy Pairings for the Measurement of $\mathcal{T}$ and $\mathcal{S}$.

interaction associations for the individual methods of a database-centric application [Vallée-Rai et al., 1999, 2000]. The adequacy component supports the inclusion of other data flow analyzers as long as they operate on the Jimple intermediate representation.

5.7 EXPERIMENT GOALS AND DESIGN

The primary goal of the experiments is to measure the number of database interaction associations that each test adequacy criterion requires. The secondary experiment goal is the measurement of the time and space overheads of the test requirement enumeration process. We measure the increase and subsequently calculate the percent increase in the number of test requirements when a stronger test adequacy criterion C_α is selected instead of a weaker criterion C_β (i.e., C_α subsumes C_β). The experiments also calculate the additional time and space overheads that are incurred during the enumeration of test requirements with the criterion C_α in place of C_β. We evaluate the number of test requirements ($\mathcal{TR}$), the time overhead ($\mathcal{T}$), and the space overhead ($\mathcal{S}$). We determine space overhead according to the number of nodes ($\mathcal{SN}$) and edges ($\mathcal{SE}$) in the traditional and database-aware control flow graphs. Equation (5.10) defines $\mathcal{TR}_\mathcal{I}(C_\alpha, C_\beta)$, the increase in $\mathcal{TR}$ when the adequacy criterion C_α is used instead of the criterion C_β. Equation (5.11) defines the percent increase in the evaluation metric $\mathcal{TR}$, denoted $\mathcal{TR}_\mathcal{I}^\%(C_\alpha, C_\beta)$. We define the increase and percent increase of $\mathcal{T}$, $\mathcal{SE}$, and $\mathcal{SN}$ in an analogous fashion.

$$\mathcal{TR}_\mathcal{I}(C_\alpha, C_\beta) = \mathcal{TR}(C_\alpha) - \mathcal{TR}(C_\beta) \tag{5.10}$$

$$\mathcal{TR}_\mathcal{I}^\%(C_\alpha, C_\beta) = \frac{\mathcal{TR}_\mathcal{I}(C_\alpha, C_\beta)}{\mathcal{TR}(C_\alpha)} \times 100 \tag{5.11}$$

The experiments compare the following test adequacy criteria: *all-database-DUs* (D), *all-relation-DUs* (R), *all-record-DUs* (R_c), *all-attribute-DUs* (A), *all-attribute-value-DUs* (A_v), and *all-DUs* (P). In order to limit the number of empirical comparisons, we examine $\mathcal{TR}_\mathcal{I}^\%(C_\alpha, C_\beta)$ with the six different adequacy pairs that include (C_α, C_β) for every pair of adjacent adequacy criteria and the additional pairing of the strongest (A_v) and weakest (D) criterion. Table 5.1 summarizes the pairings that we use to evaluate the percent increase in the number of test requirements. For example, the pairing (A_v, R_c) means that we calculate $\mathcal{TR}_\mathcal{I}^\%$ when we use *all-attribute-value-DUs* in place of *all-record-DUs* and (R, D) indicates that we measure the percent increase in $\mathcal{TR}$ when we replace *all-database-DUs* with *all-record-DUs*.

	NCSS	# Methods	# Rels	Total # Attrs	# Attrs Per Rel
mp3cd	2913	452	7	25	3.6

Table 5.3: Characteristics of the mp3cd Case Study Application.

A single execution of the test adequacy component can list test requirements for one or more adequacy criteria. For example, a tester can use the adequacy component to enumerate the test requirements necessitated by the *all-DUs*, *all-database-DUs*, and *all-record-DUs* criteria. We record the time and space overhead required to analyze application A in light of *all-DUs* criterion and one of the database-aware test adequacy criterion. During the evaluation of time and space overhead, we analyze the percent increase in $\mathcal{T}$ and $\mathcal{S}$ for seven different adequacy pairings, as described in Table 5.2. This table uses the notation $P + A_v$ to indicate that we measure the time overhead incurred during the enumeration of traditional def-use associations and attribute value DIAs. For example, $\mathcal{T}_{\mathcal{I}}^{\%}(P + A_v, P + D)$ denotes the percent increase in time overhead when we enumerate test requirements for the *all-attribute-value-DUs* and *all-DUs* criteria instead of the *all-database-DUs* and *all-DUs* criteria.

We use the test adequacy component to identify the test requirements and to calculate $\mathcal{TR}$. We compute the time overhead metric $\mathcal{T}$ with a profiling tool and we measure the space overhead metrics $\mathcal{SN}$ and $\mathcal{SE}$ by counting the number of nodes and edges in the CFGs and the DI-CFGs, respectively. We conducted all of these experiments on the GNU/Linux workstation with kernel 2.4.18-14smp, dual 1 GHz Pentium III Xeon processors, 512 MB of main memory, and a SCSI disk subsystem. We executed the test adequacy component in five separate trials for each case study application and each test adequacy criterion. Since the time overhead metric varied across each trial, we calculate arithmetic means and standard deviations for $\mathcal{T}$ (the $\mathcal{TR}$, $\mathcal{SN}$, and $\mathcal{SE}$ metrics did not vary across the separate trials). We design the bar charts in Figure 5.36 to use an error bar to represent one standard deviation from the arithmetic mean of the time overheads. Since the standard deviation for $\mathcal{T}$ was insignificant, the diamonds at the top of the bars in Figure 5.36 indicate that no visible error bar could be produced.

The experiments applied the adequacy component to two subjects: TransactionManager and mp3cd. The mp3cd subject manages a local collection of MP3 files and it is available for download at http://mp3cdbrowser.sourceforge.net/mp3cd/. We do not use mp3cd in subsequent experiments and we did not discuss it in Chapter 3 because this application does not have a test suite. However, Chapter 3 provides more details about the TM case study application. mp3cd contains 2913 non-commented source statements, not including its JDBC driver. This application also uses the Java bytecode of an MP3 manipulation utility. The MP3 manipulation bytecodes and the complete mp3cd application required the analysis of 453 methods. mp3cd interacts with a relational database that contains seven relations named *Album*, *Altr*, *Aral*, *Artist*, *Cd*, *Track*, and *Version*. Table 5.3 summarizes the characteristics of the mp3cd case study application. In future work we will use the test adequacy component to analyze other database-centric applications.

$\mathcal{TR}_{\mathcal{I}}^{\%}$	(R, D)	(R_c, R)	(A, R)	(A_v, R_c)	(A_v, A)	(A_v, D)
`TM`	4.9	49.3	61.6	60.0	47.2	80.7
`mp3cd`	49.0	49.2	72.4	71.1	46.8	92.5

Table 5.4: Percent Increase in the Number of Test Requirements.

5.8 KEY INSIGHTS FROM THE EXPERIMENTS

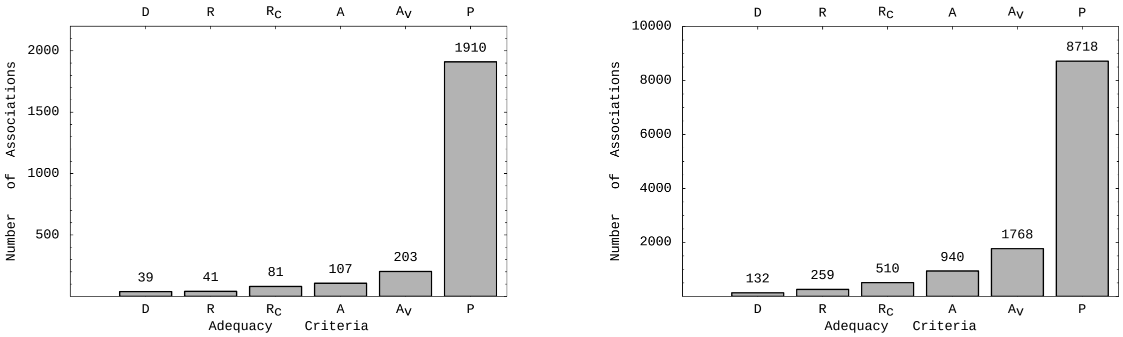
Section 5.9 furnishes a detailed review of the experimental results. This section summarizes the key insights from the experiments that we introduced in Section 5.7. We identify the following high level trends in the empirical results.

1. **Number of Test Requirements**
    a. The database-aware test requirements constitute between 10 and 20% of the total number of data flow-based test requirements.
    b. The number of DIAs increases by almost 50% when we use the state-based *all-record-DUs* adequacy criterion instead of the structure-based *all-relation-DUs*.
2. **Time Overhead**
    a. We can enumerate the test requirements for small and moderate size applications in less than forty seconds. Across multiple executions, this analysis exhibits little variation in time overhead.
    b. Enumerating test requirements at the finest level of database interaction granularity never increases analysis time by more than 15% over the base line configuration.
3. **Space Overhead**
    a. Moderate size applications exhibit a 25% increase in the number of CFG nodes and edges when we include the database interactions at the attribute value level instead of the database level.
    b. For small database states, the use of the state-based *all-record-DUs* instead of the structure-based *all-relation-DUs* only increases the number of CFG nodes and edges by 5%.

5.9 ANALYSIS OF THE EXPERIMENTAL RESULTS

5.9.1 Number of Test Requirements

Table 5.4 shows the percent increase in the number of test requirements for different test adequacy criteria pairs and Figure 5.35 depicts the number of def-use and database interaction associations for both case study applications. Since *all-DUs* does not have a subsumption relationship with any of the database-aware criteria, Table 5.4 does not display any percent increases for a criteria pair involving *all-DUs*. Figure 5.35 shows that *all-DUs* produces a significantly greater number of test requirements than any of the database aware criteria. This is due to the fact that `TM` and `mp3cd` both interact with databases that have relatively few relations and



(a)

(b)

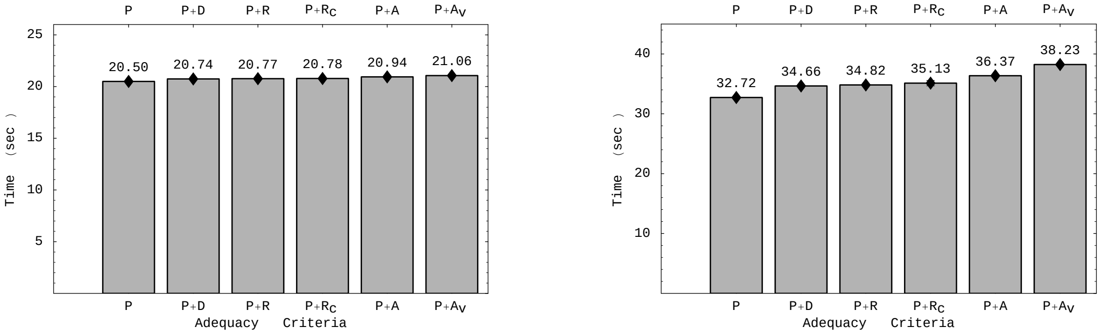
Figure 5.35: Number of Def-Use and Database Interaction Associations for (a) `TM` and (b) `mp3cd`.

records. Since Figure 5.35 reveals that `mp3cd` always produces a greater number of test requirements than `TM`, it is clear that `mp3cd` is a larger application that could be more difficult to test adequately. $\mathcal{TR}^{\%}_{\mathcal{I}}(R, D)$ is 49% for `mp3cd` and only 4.9% for `TM` because `mp3cd` has seven relations and `TM` only has two. When we use the state-based *all-record-DUs* instead of *all-relation-DUs*, this yields an almost 50% increase in $\mathcal{TR}$. These results quantitatively demonstrate that it is more difficult for a test suite to satisfy the adequacy criteria that consider the definition and use of the databases' state.

Even though both case study applications yield larger $\mathcal{TR}^{\%}_{\mathcal{I}}$ values for (A_v, R_c) than (A_v, A), the relationship between these percent increases could change as the number of records within the database increases (the DI-CFGs in this study represented interactions with a small number of records). `TM`'s 80.7% and `mp3cd`'s 92.5% values for $\mathcal{TR}^{\%}_{\mathcal{I}}(A_v, D)$ demonstrate that the strongest criterion requires test suites to cover a considerably greater number of database interaction associations than the weakest criterion. The results in Figure 5.35 also show that `TM`'s 203 attribute value DIAs represent 9.6% of the total number of def-use and database interaction associations. `mp3cd`'s 1768 attribute value DIAs correspond to 16.8% of the total number of variable and database entity associations. These results provide quantitative evidence that the database-aware test adequacy criteria require test suites to exercise additional associations that traditional def-use testing would neglect.

5.9.2 Time Overhead

Table 5.5 shows the percent increase in the time overhead for different test adequacy criteria pairs. Figure 5.36 depicts the time that was required to enumerate the traditional def-use associations (e.g., label P) and all of the associations for the program variables and the database entities at a single level of interaction granularity (e.g., label $P+D$). These graphs show that no execution of the data flow analyzer took more than thirty-nine seconds. Since the the standard deviation for $\mathcal{T}$ was always less than .08 seconds for `TM` and .46 seconds for `mp3cd`, it is clear that the time overhead measurement demonstrated little variation across experiment trials. The time overhead results in Figure 5.36 indicate that the complete data flow analysis of `mp3cd` always takes longer than the same analysis of `TM`. For example, the *all-DUs* criterion requires 37.72 seconds of time



(a)

(b)

Figure 5.36: Time Required to Enumerate Test Requirements for (a) `TM` and (b) `mp3cd`.

overhead for `mp3cd` and 20.5 seconds of time for `TM`. This is due to the fact that `mp3cd` is a larger application that has more data flow-based test requirements than `TM`.

Table 5.5 reveals that the percent increase in analysis time for `TM` is small since $\mathcal{T}_{\mathcal{I}}^{\%}$ is 1.5% for $(P + A_v, P + D)$ and 2.7% with $(P + A_v, P)$. This demonstrates that for small database-centric applications like `TM`, testing can factor in database interaction associations while only incurring a minimal time overhead during test requirement enumeration. For moderate sized applications like `mp3cd`, the time overhead is still satisfactory since Table 5.5 shows that $\mathcal{T}_{\mathcal{I}}^{\%}$ is 9.3% for $(P + A_v, P + D)$ and 14.4% for $(P + A_v, P)$. The database interaction association is at the heart of the family of data flow-based test adequacy criteria. The empirical results suggest that the adequacy component can enumerate DIAs with acceptable time overhead and minimal variability.

5.9.3 Space Overhead

Tables 5.6 and 5.7 respectively provide the percent increases when the space overhead metrics corresponds to the nodes ($\mathcal{SN}$) and edges ($\mathcal{SE}$) within a CFG or DI-CFG. Figure 5.37 displays the space that was needed for both a traditional CFG (e.g., label P) and a DI-CFG that contains the CFG's nodes and edges and the extra DIG nodes and edges that represent the database interaction (e.g., label $P + D$). The space overhead results in Figure 5.37 indicate that both the CFGs and DI-CFGs have on average more edges than nodes. This is due to the fact that Soot 1.2.5's `CompleteUnitGraph` data structure includes an edge from a node to an exception handler CFG whenever that node exists along a sub-path that can throw an exception [Vallée-Rai et al., 1999, 2000]. Tables 5.6 and 5.7 also demonstrate the percent increase in the number of nodes and edges is always less than 5% when we use *all-record-DUs* instead of *all-relation-DUs*. This implies that testing can focus on database records instead of relations without significantly raising the space overhead.

The space overhead metrics always yield higher percent increases for $(P{+}A_v, P{+}R_c)$ than $(P{+}A_v, P{+}A)$. As noted in Section 5.9.1, the relationship between these percent increases could change if the relations within the database contain a greater number of records. Tables 5.6 and 5.7 also reveal that the percent increase

$\mathcal{T}_{\mathcal{I}}^{\%}$	$(P+R, P+D)$	$(P+R_c, P+R)$	$(P+A, P+R)$
`TM`	.1	.04	.8
`mp3cd`	.5	.8	4.3

$\mathcal{T}_{\mathcal{I}}^{\%}$	$(P+A_v, P+R_c)$	$(P+A_v, P+A)$	$(P+A_v, P+D)$	$(P+A_v, P)$
`TM`	1.3	.6	1.5	2.7
`mp3cd`	8.1	4.9	9.3	14.4

Table 5.5: Percent Increase in the Time Overhead.

$\mathcal{SN}_{\mathcal{I}}^{\%}$	$(P+R, P+D)$	$(P+R_c, P+R)$	$(P+A, P+R)$
`TM`	.6	2.5	4.3
`mp3cd`	2.0	3.8	9.5

$\mathcal{SN}_{\mathcal{I}}^{\%}$	$(P+A_v, P+R_c)$	$(P+A_v, P+A)$	$(P+A_v, P+D)$	$(P+A_v, P)$
`TM`	7.5	5.8	10.4	12.2
`mp3cd`	15.5	10.2	20.4	21.6

Table 5.6: Percent Increase in the Space Overhead for Nodes.

in the number of nodes and edges is less than 23% for `mp3` and 11% for `TM` when the weakest database aware criterion (D) is replaced with the strongest criterion (A_v). For smaller applications like `TM` the experimental results suggest that the DI-CFGs will create less than a 13% increase in the number of nodes and edges when we use *all-attribute-value-DUs* and *all-DUs* instead of just *all-DUs*. The results also indicate that moderate size applications such as `mp3cd` will incur no more than a 24% increase in the number of nodes and edges when we evaluate the adequacy of a test suite at the $P + A_v$ level rather than the P level. In summary, the experiments quantitatively confirm that the control flow graph can represent a program's interaction with a relational database in an acceptable amount of space.

5.10 THREATS TO VALIDITY

The experiments described in this chapter are subject to validity threats and Chapter 3 explains the steps that we took to control these threats during experimentation. We also took additional steps to handle the threats that are specific to experimentation with the test adequacy component. Internal threats to validity are those factors that have the potential to impact the measured variables defined in Section 5.7. One internal validity threat is related to defects in the test adequacy component. These defects could compromise the correctness of the (i) control flow graphs, (ii) sets of database entities, or (iii) database interaction associations. We controlled this threat by visualizing all of the DI-CFGs and checking them to ensure correctness. For example, we verified that each database interaction graph was a straight line code

$\mathcal{SE}_{\mathcal{I}}^{\%}$	$(P+R, P+D)$	$(P+R_c, P+R)$	$(P+A, P+R)$
TM	0.0	2.4	4.2
mp3cd	2.1	4.4	10.5

$\mathcal{SE}_{\mathcal{I}}^{\%}$	$(P+A_v, P+R_c)$	$(P+A_v, P+A)$	$(P+A_v, P+D)$	$(P+A_v, P)$
TM	7.4	5.7	9.7	11.4
mp3cd	16.7	11.0	22.1	23.8

Table 5.7: Percent Increase in the Space Overhead for Edges.

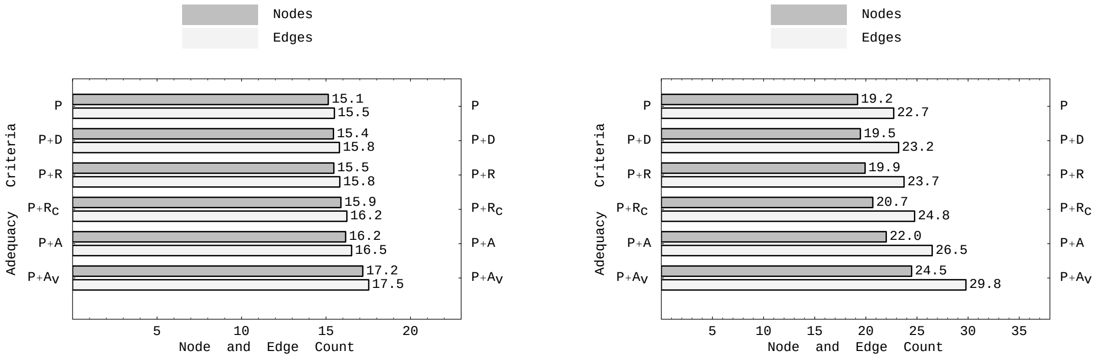
segment that was placed at the correct database interaction location within the DI-CFG. We also selected database interaction points and checked that the interaction analyzer produced a correct set of database entities. Finally, we inspected the sets of database interaction associations for methods in order to guarantee that the data flow analyzer worked properly.

Construct validity is related to the appropriateness of the evaluation metrics described in Section 5.7. Even though $\mathcal{TR}$ does not directly measure the effectiveness of a test adequacy criterion with respect to its ability to isolate defects, it is still useful in an evaluation of the test adequacy component because it reveals the relative difficulty of satisfying an adequacy criterion. The measurement of space overhead by calculating the number of nodes and edges in a control flow graph is not directly tied to the consumption of bytes of memory and thus not as useful to software testing practitioners. Yet, if $\mathcal{S}$ was the number of bytes used by the in-memory or on-disk representation of a database-centric application, then these values could be dependent upon the choice of the file system, operating system, and Java virtual machine. The number of CFG nodes and edges are also established metrics for measuring the size of graphs [Tip and Palsberg, 2000].

The experiments did not measure the costs associated with all aspects of the test adequacy component. Since our research is not directly related to the construction of interprocedural CFGs, we did not focus on the time consumed by the points-to analysis and the CFG construction technique. Moreover, these static analysis techniques have been studied extensively by previous research efforts [Lhoták and Hendren, 2003, 2006]. Our experiments did not concentrate on measuring the cost of DI-FSM creation since other researchers have provided preliminary insights into the performance of this process [Christensen et al., 2003]. Yet, this chapter provides a detailed analytical evaluation of the worst-case time complexity of each key algorithm within the test adequacy component. We judge that the time complexity analysis serves as the foundation for future empirical evaluations of these techniques.

5.11 CONCLUSION

This chapter explains the test adequacy component that (i) constructs a database-aware program representation, (ii) analyzes database interaction points, and (iii) lists the test requirements. We describe the



(a)

(b)

Figure 5.37: Average Space Overhead for (a) `TM` and (b) `mp3cd`.

database interaction finite state machine (DI-FSM) that models a single database interaction point and we explain how to use a DI-FSM to enumerate database entities. We also show how to transform a traditional interprocedural control flow graph (ICFG) into a database interaction interprocedural control flow graph (DI-ICFG). This chapter examines the implementation of the test adequacy component and it provides empirical evidence that it is possible to enumerate database-aware test requirements with acceptable time and space overhead. Further experimentation with larger case study applications will serve to confirm the scalability of enumerating database interaction associations (DIAs). The experiments suggest that our database-aware adequacy criteria obligate test suites to cover test requirements that traditional def-use testing would overlook. In summary, this chapter shows that the test adequacy component is promising and thus warrants further empirical investigation.

6.0 FOUNDATIONS OF TEST COVERAGE MONITORING

6.1 INTRODUCTION

This chapter presents a database-aware test coverage monitoring technique. We identify and address the major challenges associated with monitoring a test suite's coverage of a database-centric application. We encounter these challenges during the (i) instrumentation of a database-centric application, (ii) creation and storage of the coverage results, and (iii) calculation of test suite adequacy. This chapter describes the database-aware test coverage monitoring (TCM) trees that represent a test suite's coverage. We also discuss the algorithms that construct the TCM trees and show how to use these trees to calculate the adequacy of a test suite. In particular, this chapter furnishes:

1. A high level overview of the test coverage monitoring process (Section 6.2).
2. A discussion of the challenges associated with test coverage monitoring (Section 6.3).
3. The description of the TCM trees and the monitoring instrumentation that records coverage information in a database-aware fashion (Section 6.4).
4. An interprocedural representation for a test suite that supports the calculation of test adequacy (Section 6.5.1).
5. A technique for calculating test suite adequacy according to the family of data flow-based adequacy criteria described in Chapter 4 (Section 6.5.2).

6.2 OVERVIEW OF THE COVERAGE MONITORING PROCESS

The overarching goal of test coverage monitoring is to record the requirements that the test suite covers during testing. Since we focus on database-aware test requirements, our test coverage monitor stores information about the definition and use of relational database entities. Figure 6.1 depicts the process of test coverage monitoring. This diagram shows that the instrumentation phase accepts adequacy criteria (e.g., *all-record-DUs* and *all-database-DUs*), a test suite, and the program under test. We instrument the program under test by placing *probes* at key locations within the control flow graph. These probes execute *payloads* that record information about the coverage of the test requirements [Misurda et al., 2005]. For example, suppose that method m_k contains a database interaction that submits a SQL **select** statement to the database. A database-aware test coverage monitor inserts a probe after the execution of the **select** statement in order to inspect the records that match the database query. Since the tests for a database-centric application

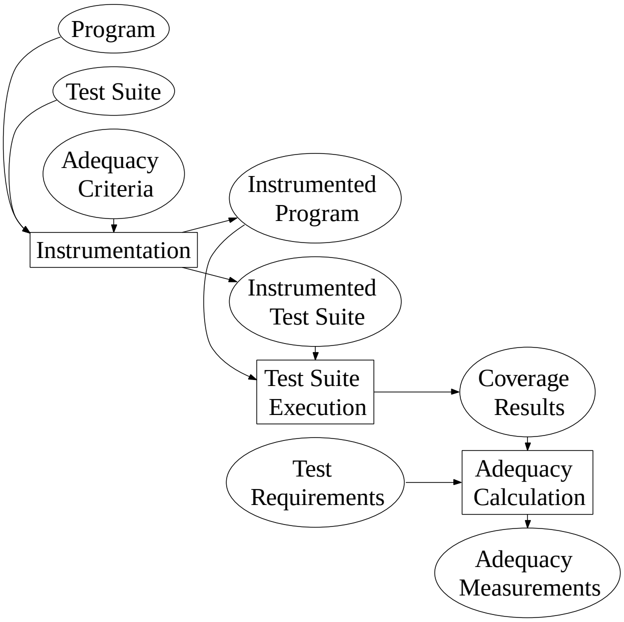


Figure 6.1: Overview of the Test Coverage Monitoring Process.

often modify and inspect the databases [Haftmann et al., 2005a], we also instrument the tests with coverage monitoring probes. For example, assume that a test case uses the SQL **delete** statement to remove records from the database before it executes the method under test. Our database-aware instrumentor inserts probes to identify the attribute values that the test case deleted from the database.

This chapter describes an instrumentation technique that supports the introduction of probes before or during test suite execution. If we instrument the program and test suite before testing, then we adhere to a *static* instrumentation scheme. We perform *dynamic* instrumentation when the test coverage monitoring engine introduces the instrumentation during testing. Even though our coverage monitoring component supports both types of instrumentation, it only requires the use of either static or dynamic instrumentation in order to produce the coverage report. A test coverage monitor must place static instrumentation into the database-centric application each time the source code of the program under test or the test suite changes. The dynamic approach to instrumentation obviates the repeated instrumentation of the database-centric application since it always introduces the payloads during testing. However, the flexibility that dynamic instrumentation affords is offset by the fact that dynamically instrumenting a database-centric application often increases the time overhead of testing more than the use of static instrumentation.

The execution of either a statically or dynamically instrumented program and test suite yields the database-aware coverage results. The coverage report shows how the methods under test define and use the relational database entities. We use the *database interaction test coverage monitoring tree* (DI-TCM) to maintain coverage information on a per-test basis. A DI-TCM contains nodes that correspond to the definition and use of relational database entities in the context of both the method and the test that performed the database interaction. Since the size of a DI-TCM can be prohibitively large, we also leverage compression algorithms in order to reduce the size of the coverage report. When we have the coverage results and the test requirements for a test case, we can calculate the adequacy of this test. The adequacy of a test case is simply the number of covered test requirements divided by the total number of requirements.

6.3 TEST COVERAGE MONITORING CHALLENGES

6.3.1 Location of the Instrumentation

The majority of traditional test coverage monitoring frameworks place instrumentation probes into the program under test through the use of either static instrumentation or Java virtual machine (JVM)-based techniques [Misurda et al., 2005, Pavlopoulou and Young, 1999, Tikir and Hollingsworth, 2002]. It is challenging to develop a database-aware instrumentation approach because the coverage monitor must place the probes in the appropriate locations within the program, the test suite, and/or the execution environment. We use the different execution environments for a Java database-centric application, as depicted in Figure 6.2, to illustrate these challenges with a concrete example. In the context of applications written in Java, we must accommodate the wide variety of Java virtual machines, JDBC drivers, database managers, and operating systems that exist in an application's execution environment. As noted in Chapter 3, we assume that the program and the test suite interact with the database manager through a Java database connectivity driver. Prior monitoring techniques place the instrumentation probes in the (i) program and the test suite (e.g., [Misurda et al., 2005]), (ii) JDBC driver (e.g., [Bloom, 2006]), (iii) relational database management system (e.g., [Chays et al., 2004]), or (iv) operating system (OS) (e.g., [Engel and Freisleben, 2005, Tamches and Miller, 1999]). Figure 6.2(a) shows a program and a test suite that execute on a Java virtual machine and interact with a Java-based RDBMS. We configured the case study applications to execute in this manner, as discussed in Chapter 3. Finally, Figure 6.2(b) describes an application that interacts with a native database manager that directly executes on the operating system instead of using a JVM.

The coverage monitor cannot place instrumentation into the relational database management system because we want the monitoring technique to function properly for all of the database management systems that provide a JDBC interface. Since the testing framework does not require a database-centric application to execute on specific operating system(s), it is not practical to monitor coverage by instrumenting the OS. Moreover, OS-based instrumentation is unlikely to reveal how the JVM executes the test suite. For example, instrumentation in the operating system can capture system calls but it will not normally be able to monitor method invocations within the program and the test suite. The JDBC Web site at `http://developers.sun.com/product/jdbc/drivers/` reveals that there are currently over two hundred different JDBC driver implementations. A JDBC driver could be written in Java or in a combination of the Java, C, and C++ programming languages. If the JDBC driver is partially written in C and/or C++, then it must use the Java Native Interface (JNI) to make its functionality accessible to the database-centric application that uses Java. The testing framework does not stipulate that the database-centric application

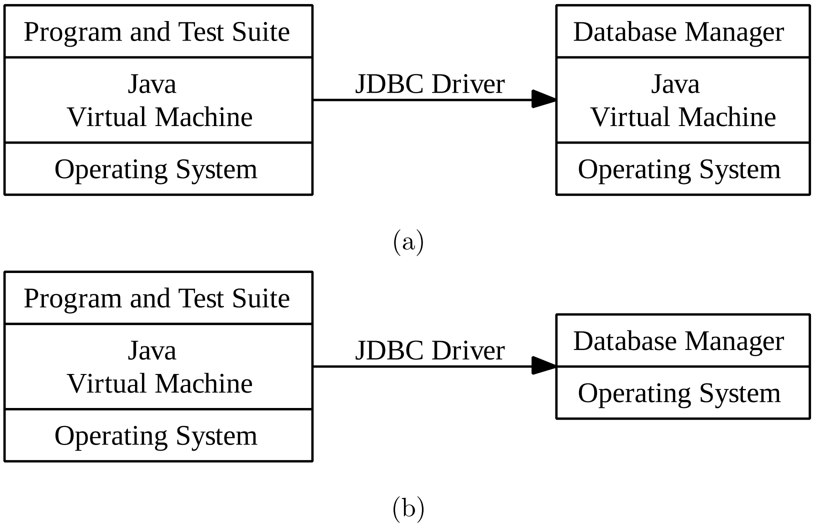


Figure 6.2: The Execution Environment for a Database-Centric Application.

use a particular JDBC driver. Without a general and automated technique for instrumenting an arbitrary JDBC driver, it is unrealistic for the coverage monitor to record database interactions by placing probes into all of the currently available JDBC drivers.

Our database-aware testing framework does not assume that the program and the test suite execute on a certain Java virtual machine. For example, the program and the tests might use the Sun HotSpot$^{\text{TM}}$JVM or the Jikes Research Virtual Machine (RVM) [Alpern et al., 2005]. The wide variety of JVMs indicates that it is challenging to dynamically introduce the test coverage monitoring instrumentation with the JVM that runs the test suite. In light of our analysis of the potential instrumentation locations, we implemented static and dynamic instrumentation techniques that only modify the program and the test suite. Since a tester does not always have access to an application's source code, it is also preferable if the test coverage monitor can statically instrument Java bytecode. To this end, we designed the TCM component so that it can operate on Java source code, bytecode, or a combination of both types of program representations. Finally, our dynamic instrumentation technique operates on well-established interfaces that exist in all Java virtual machines (the current implementation performs *load-time* instrumentation using the JVM class loader).

6.3.2 Types of Instrumentation

Instrumenting a traditional program requires the placement of probes at control flow graph locations that (i) execute CFG nodes and edges, (ii) define and use program variables, and/or (iii) invoke program methods [Misurda et al., 2005, Pavlopoulou and Young, 1999, Tikir and Hollingsworth, 2002]. The payload of a traditional probe simply marks an entity within a control flow graph as covered if a test causes the execution of this entity. For example, a probe that monitors the coverage of CFG nodes executes a payload to record the fact that a node was executed during testing. In contrast, database-aware instrumentation must intercept database interactions and efficiently analyze the state and structure of the databases that are subject to

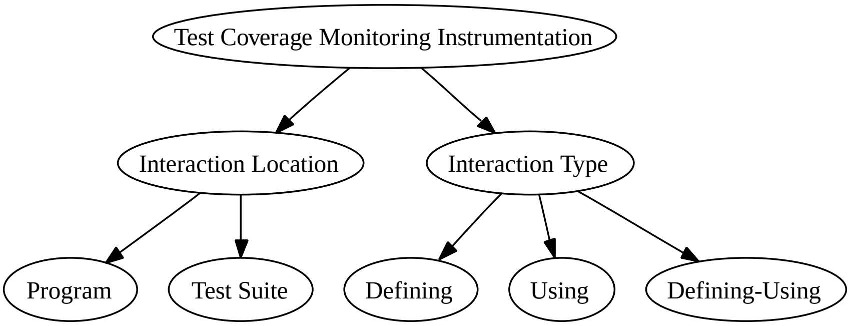


Figure 6.3: Instrumentation for Database-Aware Test Coverage Monitoring.

interaction. For example, the coverage instrumentation for the SQL **delete** statement examines the state of the relational database in order to determine which records were removed.

Figure 6.3 categorizes the types of instrumentation that we use to monitor the coverage of the test suites for a database-centric application. This diagram shows that the *location* of a database interaction is either in the program or the test suite. A database-centric application maintains a significant amount of external state and the tests for a database-centric application frequently change the state of the database [Haftmann et al., 2005a]. For example, a test for the `removeAccount` method in the `TransactionManager` application might need to add accounts into the database before executing the method under test. Since the test suite for a database-centric application directly modifies the state of the database, the test coverage monitor places additional instrumentation into the tests. The coverage monitoring instrumentation must also handle database interactions that are either of *type* defining, using, or defining-using (c.f. Section 4.3.2 for a discussion of these types of interactions).

Similar to [Christensen et al., 2003, Halfond and Orso, 2005], we focus on the testing and analysis of database-centric applications that interact with a database by submitting SQL strings. Since our testing framework does not restrict which relational database management system controls the program's access to the databases, the program of a database-centric application might interact with the databases that are managed by a MySQL, PostreSQL, HSQLDB, or Oracle RDBMS. It is challenging to instrument a database-centric application for coverage monitoring because different RDBMS support different dialects of the structured query language. Figure 6.4 provides four SQL **select** statements that extract records t_{begin} through t_{end} from the relation $rel_j = \{t_1, \ldots, t_u\}$. We use the notation rec_{begin} and rec_{end} to respectively denote the numerical index to records t_{begin} and t_{end}, as depicted in Figure 6.5. The SQL **select** for the Oracle RDBMS uses the **rownum** variable to bound the records in the **select**'s result set while the MySQL, PostreSQL, and HSQLDB statements use the **limit** and/or **offset** keywords. Our test coverage monitor supports the testing of programs that use different RDBMS because the instrumentation limits the parsing of the SQL strings to the syntactical elements that all SQL dialects have in common.

It is also challenging to perform database-aware coverage monitoring because the probes must examine the state and structure of the database without inadvertently introducing defects into the program. Since

select $A_1, A_2, \ldots, A_z$
from rel_j **limit** rec_{begin}, rec_{end}

(a)

select $A_1, A_2, \ldots, A_z$
from rel_j **limit** rec_{end} **offset** rec_{begin}

(b)

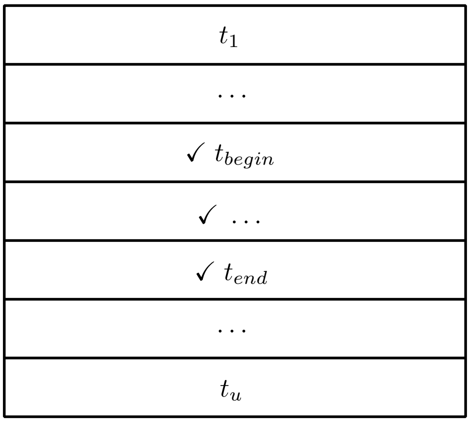
select $A_1, A_2, \ldots, A_z$
from rel_j **limit** rec_{begin} rec_{end}

(c)

select $A_1, A_2, \ldots, A_z$ **from** rel_j
where rownum $\geq rec_{begin}$ **and rownum** $\leq rec_{end}$

(d)

Figure 6.4: Syntax for the SQL **select** in (a) MySQL, (b) PostreSQL, (c) HSQLDB, and (d) Oracle.



t_1
$\ldots$
✓ t_{begin}
✓ $\ldots$
✓ t_{end}
$\ldots$
t_u

Figure 6.5: The Matching Records from the SQL **select** Statement.

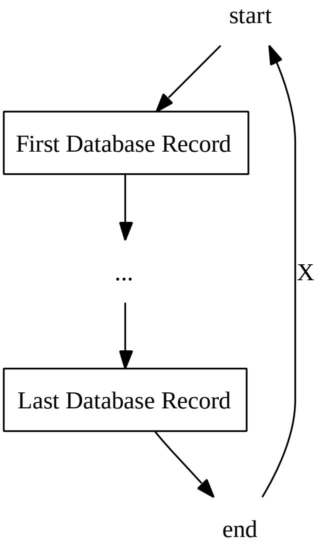


Figure 6.6: Support for a Single Iteration of the Result Set.

this research focuses on the testing and analysis of database-centric applications written in Java, we illustrate this challenge with a concrete example that assumes the use of this language. A using database interaction occurs when the method under test submits a SQL **select** statement to the database. A database-centric application written in Java uses the `executeQuery(String sql)` method to submit a **select** statement. The `executeQuery` operation returns a result set that the calling method inspects in order to determine which database records matched the query. Our database-aware test coverage monitoring probes intercept this result set and save the records that the **select** used.

After the instrumentation analyzes the set of matching records, the probes must return the records to the program under test so that testing can continue. Figure 6.6 demonstrates the default behavior of the program under test when it iterates through the result set that the `executeQuery` method returns. The "X" that labels the directed edge from the end node to the start node indicates that the program can only examine the results of the **select** statement once. If the test coverage monitoring probe iterates through the result set, then the instrumentation will incorrectly change the behavior of the program under test. The method under test will inappropriately terminate if it attempts to analyze a result set that has already been exhausted by the test coverage monitoring instrumentation. This example suggests that the instrumentation must take special steps to preserve the correctness of the application that it is monitoring. Our TCM component uses instrumentation payloads that can either (i) examine a copy of the result set that a **select** statement returns or (ii) transparently modify the result set so that it supports multiple iterations.

The **update**, **insert**, and **delete** statements define and/or use the state of the database. The coverage monitoring instrumentation should identify which database records were modified without relying upon RDBMS-specific facilities, such as triggers, to isolate the altered records. Even though we provide a specific

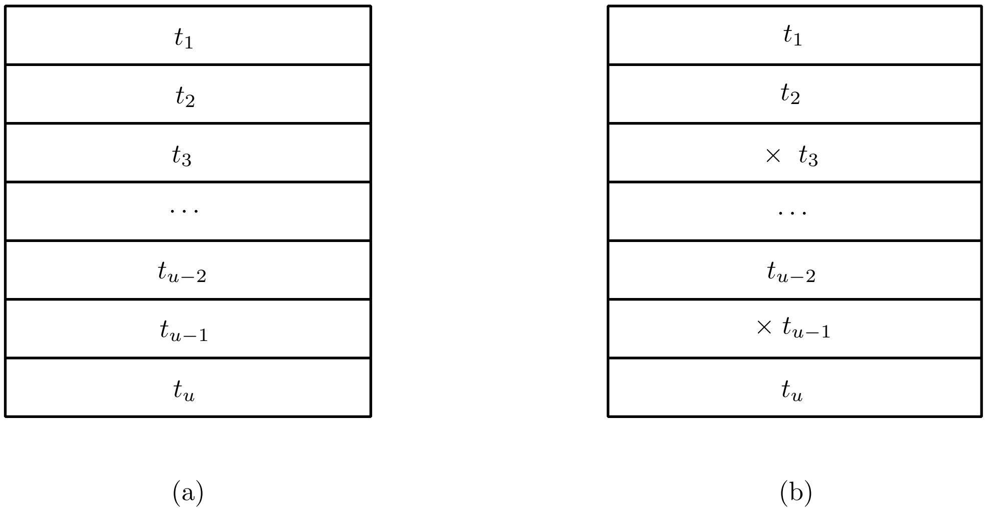


Figure 6.7: A Database Relation (a) Before and (b) After a **delete** Statement.

example of this challenge in the context of the SQL **delete** statement, we also confront similar instrumentation challenges when we handle the **update** and **insert** statements. Since different RDBMS vary the syntax of the SQL **delete** statement, we use instrumentation that minimizes the parsing of the **delete** when it determines which record(s) will be removed. To this end, the coverage monitoring probes preserve a snapshot of the relevant database state *before* and *after* the database interaction occurs. These probes execute a payload that first determines which relation is being defined and then use a SQL **select** statement to record the current state of this relation. Figure 6.7 shows the state of a relation $rel_j = \{t_1, \ldots, t_u\}$ before and after the execution of a SQL **delete** statement. This diagram reveals that the **delete** removed records t_3 and t_{u-1} from relation rel_j. For this example, the probe will add an entry to the coverage report to indicate that the **delete** defined the records t_3 and t_{u-1}. In order to minimize space overhead, we designed the coverage monitoring probe to only maintain the state of the relation that the program is currently defining. Once the RDBMS finishes executing the **delete** statement and the instrumentation records the final state of the database, the probe uses efficient relational difference operators to determine which records were deleted.

We must take into account several additional considerations when we develop the database-aware instrumentation technique. Our primary concern is to ensure that the payloads always preserve the correctness of the database-centric application. Our secondary goal is to control the time and space overhead of the instrumentation payloads. The previous discussion reveals that the coverage monitoring instrumentation for a database-centric application often requires the parsing of SQL strings. Whenever possible, the instrumentation payloads use efficient context-insensitive parsing techniques. Since the monitoring of a single database interaction requires the execution of two probes (i.e., *Before* and *After* instrumentation, as discussed in Section 6.4), we designed the payload at each probe to execute with minimal time overhead. The tester can also decrease the cost of the instrumentation by configuring the probes to store less execution context or record the database interactions at a coarser level of granularity.

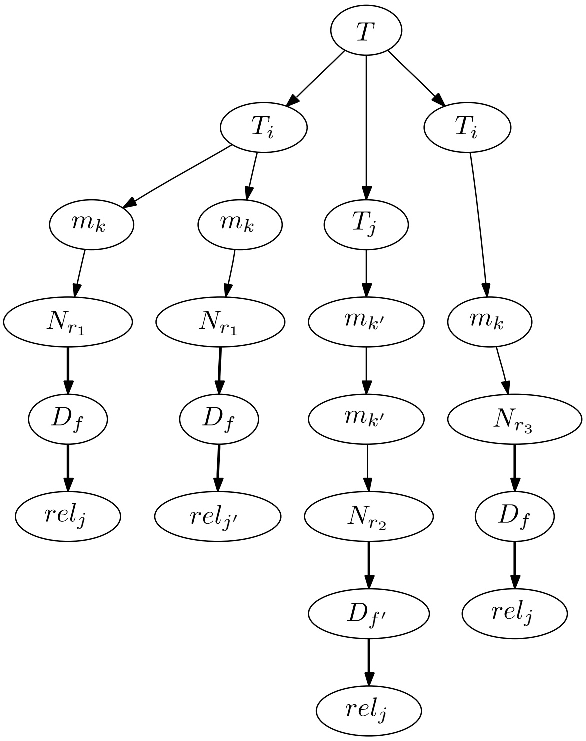


Figure 6.8: A Coverage Monitoring Tree that Offers Full Context for the Test Coverage Results.

In order to reduce the space overhead, the test coverage monitor must release any database state that it does not need to store in the coverage report. For example, the payload for a SQL **delete** statement should relinquish the storage that it uses to maintain the temporary before and after database snapshots. However, the allocation and de-allocation of memory could impact the performance and behavior of the program under test. For example, increasing the use of a JVM's garbage collector (GC) can impact the performance of the program under test [Blackburn et al., 2004, Brecht et al., 2006, Xian et al., 2006]. In the context of a Java database-centric application (and any others that use automatic memory management), the allocation and de-allocation of memory by the coverage monitoring instrumentation should not noticeably impact the behavior of the GC subsystem. To this end, we designed the coverage report so that the tester can trade-off the pressure that a tree places on the memory subsystem with the level of detail that the tree provides.

6.3.3 Format of the Test Coverage Results

The test coverage monitor must record coverage information in the appropriate context in order to permit the calculation of test adequacy. For example, the instrumentation payload should store the definition of a relational database entity in the context of the method that performed the database interaction. When test case T_i tests method m_k, the coverage report needs to reflect the fact that this test causes m_k to define and/or use certain database entities. Yet, the majority of test coverage monitoring tools, such as Clover [Kessis et al., 2005], Jazz [Misurda et al., 2005], and Emma [Roubtsov, 2005], keep coverage results

Tree	Database Aware?	Testing Context	Probe Time Overhead	Tree Space Overhead
CCT	×	Partial	Low - Moderate	Low
DCT	×	Full	Low	Moderate - High
DI-CCT	✓	Partial	Moderate	Moderate
DI-DCT	✓	Full	Moderate	High

Database Aware? $\in \{\times, \checkmark\}$
Context $\in$ {Partial, Full}
Probe Time Overhead $\in$ {Low, Moderate, High}
Tree Space Overhead $\in$ {Low, Moderate, High}

Table 6.1: High Level Comparison of the Different Types of Coverage Monitoring Trees.

on a per-test suite basis. This approach only supports the calculation of adequacy for an entire test suite and it hampers the efficiency of many prioritization techniques [Walcott et al., 2006]. The preservation of testing context also enables debuggers and automatic fault localization tools to more efficiently and effectively isolate defective program and/or database locations [Jones and Harrold, 2005]. Our database-aware coverage monitor always preserves enough testing context to ensure the correct calculation of adequacy in a per-test and per-test suite fashion. It is challenging to devise different types of coverage reports that balance the benefits of full context with the time and space overheads that come with storing additional coverage context. Our coverage monitor achieves this balance by allowing the tester to select different types of TCM trees.

Figure 6.8 provides an example of a coverage report that could be produced by the TCM component described in Chapter 7. For simplicity, we assume that a test suite T contains two tests T_i and T_j. We use edges of the form $T \rightarrow T_i$ and $T_i \rightarrow m_k$ to respectively indicate that test suite T calls test T_i and T_i invokes method m_k. The bold edges $N_{r_1} \rightarrow D_f$ and $D_f \rightarrow rel_j$ demonstrate that database interaction point N_{r_1} interacts with database D_f and relation rel_j. This coverage report fully contextualizes T's testing of methods m_k and $m_{k'}$. In order to preserve the simplicity of the example, this tree does not distinguish between the definition and use of an entity in the database (the database-aware TCM trees that Section 6.4.3 describes make a distinction between nodes that define and use the relational database entities). This tree-based report reveals that the first execution of test T_i calls method m_k two times and both invocations of this method execute database interaction point N_{r_1}.

The tree also shows that T_i's initial call to m_k interacts with relation rel_j and the subsequent call manipulates a different relation $rel_{j'}$. The coverage report indicates that test case T_j tests method $m_{k'}$ and causes the execution of the database interaction at node N_{r_2}. The coverage results demonstrate that (i) the first call to method $m_{k'}$ does not yield any database interactions and (ii) the subsequent recursive call interacts with relation rel_j in the database $D_{f'}$. Since the coverage monitoring tree preserves execution and database interaction context, it is clear that methods m_k and $m_{k'}$ interact with different relations during testing. Figure 6.8 shows that this execution of test suite T calls the test case T_i two times. The tree reveals that the third invocation of method m_k during the second run of T_i causes an interaction with rel_j at the point N_{r_3}.

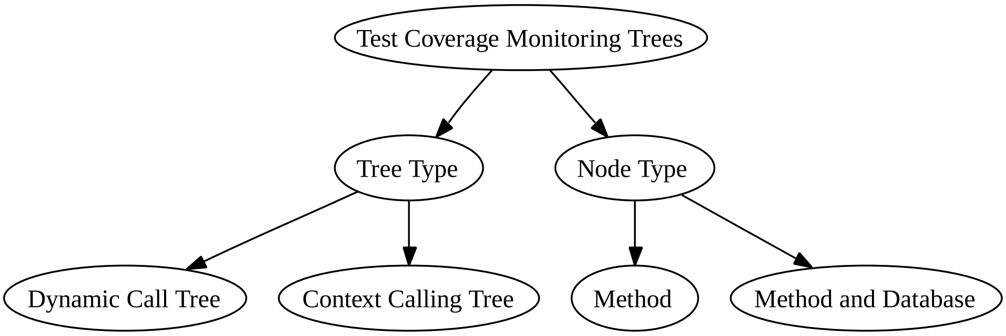


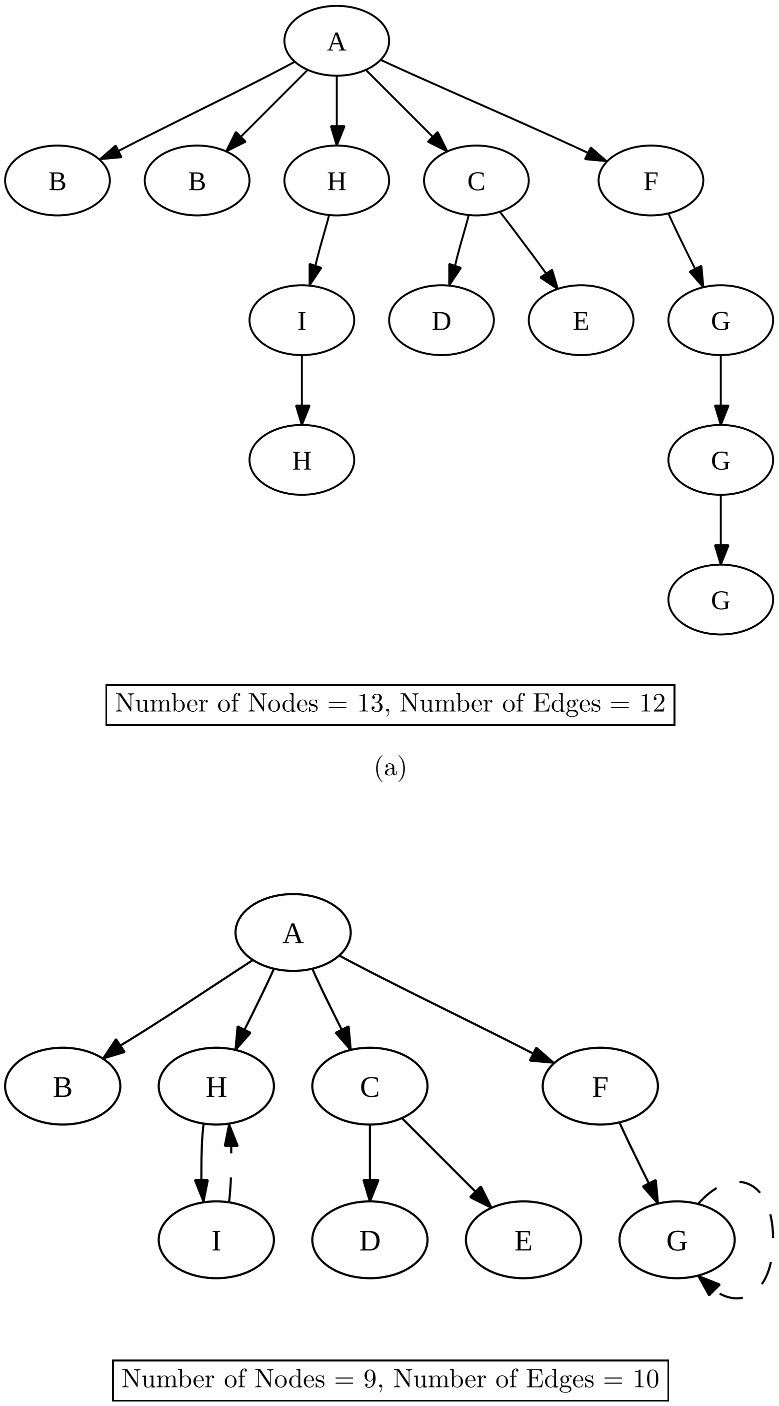
Figure 6.9: Categorization of the Test Coverage Monitoring Trees.

We must consider several additional constraints when we implement the database-aware coverage monitoring component. Debugging and fault localization techniques should be able to analyze the coverage results in order to determine what happened during testing. For example, it might be useful to enumerate all of the failing tests that cause a method to interact with a specific record in a certain database. We can improve the process of debugging a database-centric application if it is possible to use the coverage report to automatically determine which methods do not interact with a database. Since it might be expensive to identify the data flow-based test requirements for some database-centric applications, the coverage results must support the efficient calculation of alternative forms of test adequacy. For example, McMaster and Memon propose a call stack-based coverage metric that avoids data flow analysis by efficiently creating test requirements from the observed behavior of the test suite [McMaster and Memon, 2005]. We have designed the coverage trees so that they can support the calculation of data flow-based adequacy (c.f. Section 6.5) or database-aware call stack coverage (c.f. Chapter 8). Since our coverage monitor stores details about the state and structure of a relational database, the coverage report can become very large. Therefore, we maintain the coverage results in a highly compressible format.

6.4 DATABASE-AWARE TEST COVERAGE MONITORING TREES

6.4.1 Overview

A database interaction at node N_r always occurs through the invocation of a method such as `executeQuery` or `executeUpdate`. Therefore, we construct a coverage report by using instrumentation that operates *before* and *after* the execution of a method. Table 6.1 compares the types of trees that we use to store the coverage information. The test coverage monitor can construct either a *dynamic call tree* (DCT) or a *calling context tree* (CCT). The DCT records the complete execution context while incurring low TCM probe overhead and moderate to high tree space overhead. Alternatively, the CCT provides less execution context and low tree space overheads at the expense of slightly increasing the execution time of the probes. Since both the CCT and the DCT do not record a program's interaction with a relational database, they are not directly suited


A
B
B
H
C
F
I
D
E
G
H
G
G
Number of Nodes = 13, Number of Edges = 12
A
B
H
C
F
I
D
E
G
Number of Nodes = 9, Number of Edges = 10

(a)

(b)

Figure 6.10: Examples of the Traditional (a) Dynamic and (b) Calling Context Trees.

to maintaining the coverage of the tests for a database-centric application. To this end, Table 6.1 shows that the TCM component can also produce a database interaction DCT and CCT (i.e., the DI-DCT and DI-CCT) that could incur additional time and space overhead because they are database-aware.

Figure 6.9 shows that the nodes in a traditional TCM trees always represent method calls (i.e., the "Node Type" subtree contains the leaf node "Method"). The database-aware trees contain nodes that correspond to either a method call or the interaction with a relational database entity (i.e., "Method and Database" is a child of the "Node Type"). Since the DCT includes a node to represent each method and test case that is invoked during the testing process, it preserves the full testing context in a manner that can be used during debugging and fault localization. Even though the CCT coalesces certain nodes in order to minimize space overhead, it still preserves all unique method call and database interaction contexts. Figure 6.10 provides an example of a DCT with thirteen nodes and twelve edges. In this tree a node with the label "A" corresponds to the invocation of the method A and the edge A → B indicates that method A invokes method B. The existence of the two DCT edges A → B reveals that method A repeatedly invokes method B.

In the example from Figure 6.10, the dynamic call tree represents the recursive invocation of method G by chaining together edges of the form G → G. The CCT in Figure 6.10(b) coalesces the DCT nodes and yields a 30.7% reduction in the number of nodes and a 16.6% decrease in the number of edges. For example, the CCT combines the two B nodes in the DCT into a single node. The CCT also coalesces nodes and introduces back edges when a method calls itself recursively (e.g., the DCT path G → G → G) or a method is repeatedly executed (e.g., the DCT path H → I → H). Figure 6.10(b) shows that we depict a CCT back edge with a dashed line.[1] Section 6.4.2 provides a formal definition of the traditional DCT and CCT and Section 6.4.3 explains how we enhance these trees so that they can store the details about a program's database interactions. Section 6.4.4 reveals how the TCM component modifies the control flow graph of a database-centric application in order to introduce the instrumentation that generates the trees. Finally, Section 6.5 describes how we traverse the coverage trees in order to identify the covered test requirements and calculate test suite adequacy.

6.4.2 Traditional Trees

6.4.2.1 Dynamic Call Trees Throughout the remainder of this research, we use τ to denote any type of TCM tree and we use τ_{dct} and τ_{cct} to respectively stand for a dynamic call tree and a calling context tree. Table A9 summarizes the notation that we use to describe the test coverage monitoring trees. Definition 5 defines the dynamic call tree $\tau_{dct} = \langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$. We use $\mathcal{N}_\tau$ as the set of tree nodes and $\mathcal{E}_\tau$ as the set of edges. The node $N_a \in \mathcal{N}_\tau$ is the *active* node that the instrumentation payload references when it makes modifications to τ_{dct}. We use the notation $in(N_\rho)$ and $out(N_\rho)$ to respectively refer to the in-degree and out-degree of a node N_ρ. For example, if the edges (N_{ϕ_1}, N_ρ), (N_{ϕ_2}, N_ρ), and (N_ρ, N_{ϕ_3}) exist in τ_{dct}, then we know that $in(N_\rho) = 2$ and $out(N_\rho) = 1$. The following Definition 5 requires τ_{dct} to have a distinguished

[1] The introduction of one or more back edges into a CCT forms cycle(s). Even though a CCT is not strictly a tree, the tree edges are distinguishable from the back edges [Ammons et al., 1997]. Section 6.4.2 examines this issue in more detail.

node N_0, the root, such that τ_{dct} does not contain any edges of the form (N_ϕ, N_0) (i.e., $in(N_0) = 0$). For all nodes $N_\phi \in \mathcal{N}_\tau - \{N_0\}$, Definition 5 requires $in(N_\phi) = 1$ (i.e., every node except the root must have a unique parent). The dynamic call tree preserves full testing context at the expense of having unbounded depth and breadth [Ammons et al., 1997]. The DCT has unbounded depth because it fully represents recursion and it has unbounded breadth since it completely represents iterative method invocation.

Definition 5. A dynamic call tree τ_{dct} is a four tuple $\langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$ where $\mathcal{N}_\tau$ is a set of nodes, $\mathcal{E}_\tau$ is a set of edges, $N_a \in \mathcal{N}_\tau$ is the active node, and $N_0 \in \mathcal{N}_\tau$ is the root with $in(N_0) = 0$. For all nodes $N_\phi \in \mathcal{N}_\tau - \{N_0\}$, we require $in(N_\phi) = 1$.

Figure 6.11 describes the *InitializeTCMTree* algorithm that creates a tree τ with the root N_0. We invoke this algorithm at the start of test suite execution. *InitializeTCMTree* operates on any of the TCM trees that we describe in Section 6.4.2 and Section 6.4.3. Line 1 stores the root in the set $\mathcal{N}_\tau$ and line 2 initializes $\mathcal{E}_\tau$ to the empty set. Finally, *InitializeTCMTree* makes N_0 the active node and returns τ so that the instrumentation payloads can use it during the remainder of test coverage monitoring. We construct a test coverage monitoring tree by executing instrumentation payloads before and after a method invocation or a database interaction. We use the *Before* and *After* instrumentation payloads to respectively modify τ_{dct} before and after the execution of the structural entity σ. In a conventional control flow graph $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$, σ corresponds to the method invocation node *call* $m_j \in \mathcal{N}_k$ or the database interaction node $N_r \in \mathcal{N}_k$.

Figure 6.12 provides the *Before* instrumentation payload for the traditional dynamic call tree. Intuitively, the *Before* instrumentation adds a new node to the tree as a child of the active node and then returns the updated TCM tree. Line 1 adds the node σ to the set of tree nodes and line 2 adds the edge (N_a, σ) to the set of tree edges. After line 3 updates the active node N_a to refer to the recently added node σ, the *Before* payload returns the modified DCT. Figure 6.13 provides the *After* algorithm that modifies τ_{dct} by updating the tree to show that the program is returning from the current method. This algorithm uses the operation $parent(N_a)$ to retrieve the node N_p when we have $(N_p, N_a) \in \mathcal{E}_\tau$. The *Before* and *After* algorithms for the DCT have a $O(1)$ worst-case time complexity. However, these instrumentation payloads yield large test coverage monitoring trees because they frequently store duplicate nodes within the tree.

6.4.2.2 Calling Context Trees The following Definition 6 defines the CCT $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$. Since the CCT contains a DCT, it still incorporates the sets of nodes and edges, a root, and an active node. In addition to the standard components of a DCT, the calling context tree contains $\mathcal{E}_F$, the set of forward edges, $\mathcal{E}_B$, the set of back edges, and $\mathcal{N}_B$, the set of nodes that receive a back edge. We say that N_ρ *receives* a back edge when $(N_\phi, N_\rho) \in \mathcal{E}_B$. Even though τ_{cct} is not strictly a tree, we can distinguish the back edges in $\mathcal{E}_B$ from the other edges in $\mathcal{E}_\tau$. Any node $N_\rho \in \mathcal{N}_B$ that receives a back edge also maintains an active back edge stack $\mathcal{B}_\rho$. The active back edge stack enables the *After* instrumentation to properly update N_a if a single node receives multiple back edges. When the CCT's *Before* instrumentation adds the back edge (N_ϕ, N_ρ) to τ_{cct}, it also executes $\mathcal{B}_\rho.push(N_\phi)$. If N_ϕ is at the top of $\mathcal{B}_\rho$, then τ_{cct}'s active node should point

```
Algorithm $InitializeTCMTree(N_0)$
Input: Root of the Tree $N_0$
Output: Test Coverage Monitoring Tree $\tau$
    $\mathcal{N}_\tau \leftarrow \{N_0\}$
    $\mathcal{E}_\tau \leftarrow \emptyset$
    $N_a \leftarrow N_0$
    return $\langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
```

Figure 6.11: The *InitializeTCMTree* Algorithm.

```
Algorithm $Before(\tau_{dct}, \sigma)$
Input: Dynamic Call Tree $\tau_{dct} = \langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$;
    Structural Entity $\sigma$
Output: Updated Dynamic Call Tree $\tau_{dct} = \langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
    $\mathcal{N}_\tau \leftarrow \mathcal{N}_\tau \cup \{\sigma\}$
    $\mathcal{E}_\tau \leftarrow \mathcal{E}_\tau \cup \{(N_a, \sigma)\}$
    $N_a \leftarrow \sigma$
    return $\langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
```

Figure 6.12: The *Before* Algorithm for the Dynamic Call Tree.

```
Algorithm $After(\tau_{dct})$
Input: Dynamic Call Tree $\tau_{dct} = \langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
Output: Updated Dynamic Call Tree $\tau_{dct} = \langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
    $N_a \leftarrow parent(N_a)$
    return $\langle \mathcal{N}_\tau, \mathcal{E}_\tau, N_a, N_0 \rangle$
```

Figure 6.13: The *After* Algorithm for the Dynamic Call Tree.

to N_ϕ upon termination of the *After* payload. Definition 6 also states that $in(N_\phi) = 1$ for all CCT nodes $N_\phi \in \mathcal{N}_\tau - \{N_0\} - \mathcal{N}_B$ (i.e., all nodes, except for the root and those nodes that receive back edges, must have a unique parent).

Definition 6. A calling context tree τ_{cct} is a four tuple $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$, where τ_{dct} is a dynamic call tree, $\mathcal{E}_F$ is the set of forward edges, $\mathcal{E}_B$ is the set of back edges, $\mathcal{E}_\tau = \mathcal{E}_B \cup \mathcal{E}_F$ is the full set of edges, and $\mathcal{N}_B = \{N_\rho \ : \ (N_\phi, N_\rho) \in \mathcal{E}_B\}$ is the set of nodes that receive a back edge. For all nodes $N_\phi \in \mathcal{N}_\tau - \{N_0\} - \mathcal{N}_B$, we require $in(N_\phi) = 1$.

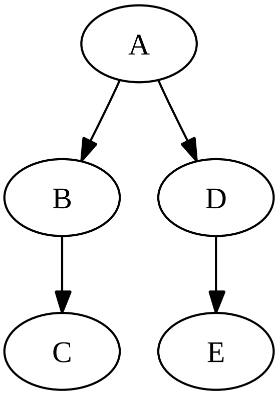
When a new method is called during testing, the CCT instrumentation controls the depth of the TCM tree by examining the previously executed methods in order to find one that is the same as the newly invoked method. If the new method call (or, database interaction) represented by the tree node N_ϕ is *equivalent* to a node N_ρ that already exists in the tree, then the instrumentation designates N_ρ as the new active node. Figure 6.14 provides a recursive implementation of the *EquivalentAncestor* algorithm that determines whether N_ρ is an equivalent ancestor of N_ϕ. Lines 1 and 2 return N_ρ when the input nodes N_ϕ and N_ρ are equivalent. Lines 3 and 4 show that *EquivalentAncestor* returns **null** to signal that the algorithm has reached the root without finding an equivalent ancestor for the node N_ϕ. Line 5 reveals that the search for an equivalent ancestor continues with the recursive call $EquivalentAncestor(\tau_{cct}, N_\phi, parent(N_\rho))$ whenever (i) the equivalent ancestor has not yet been found and (ii) the algorithm is not currently at the root of the tree. For the example CCT in Figure 6.15, *EquivalentAncestor(*τ_{cct}, A, C) returns the node A because this equivalent node exists at a higher point in the tree. However, Figure 6.15 shows that $EquivalentAncestor(\tau_{cct}, D, C)$ returns **null** since the node that corresponds to the invocation of method D is not in the test coverage monitoring tree.

Figure 6.16 gives the *Before* instrumentation payload for the traditional calling context tree. This algorithm examines the children of the active node, denoted $children(N_a)$, in order to determine if structural entity σ has already been invoked by the active node N_a. We say that $N_\phi \in children(N_a)$ if $(N_a, N_\phi) \in \mathcal{E}_\tau$. The assignment statement on line 1 shows that the *Before* algorithm initially assumes that an equivalent child has not yet been found. Line 2 through line 5 iteratively examine each node $N_\phi \in children(N_a)$ in order to determine if N_ϕ is equivalent to σ. If $call\ m_j \in children(N_a)$ and $\sigma = call\ m_j$, then line 4 makes N_ϕ the active node and line 5 assigns the value of **true** to *found*. The CCT's *Before* instrumentation operates in the same manner when $N_r \in children(N_a)$ and $\sigma = N_r$. The *Before* instrumentation in Figure 6.16 terminates and returns the updated test coverage monitoring tree when $\sigma \in children(N_a)$.

The *Before* algorithm executes line 7 through line 16 when σ is not a child of the active node (e.g., $found =$ **false**). Line 7 calls the *EquivalentAncestor* algorithm in order to determine if an ancestor of N_a is equivalent to the node σ. When the call to *EquivalentAncestor* on line 7 of Figure 6.16 returns **null**, the algorithm executes line 9 through line 11 in order to add the node σ to $\mathcal{N}_\tau$ and the edge (N_a, σ) to $\mathcal{E}_\tau$. These lines add node σ to τ_{cct} so that it is a child of the active node and then they make σ the new active node. Line 13 through line 16 of *Before* create a back edge from the active node N_a to σ's equivalent ancestor N_ϕ.

```
**Algorithm** $\mathit{EquivalentAncestor}(\tau_{cct}, N_\phi, N_\rho)$
**Input:** Calling Context Tree $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$;
    Calling Context Tree Nodes $N_\phi$ and $N_\rho$
**Output:** Equivalent Ancestor Node $N_\rho$
    **if** $N_\phi = N_\rho$
      **then return** $N_\rho$
    **if** $N_\rho = N_0$
      **then return null**
    **return** $\mathit{EquivalentAncestor}(\tau_{cct}, N_\phi, \mathit{parent}(N_\rho))$
```

Figure 6.14: The *EquivalentAncestor* Algorithm for the Calling Context Tree.



$$\boxed{\mathit{EquivalentAncestor}(\tau_{cct}, \mathrm{A}, \mathrm{C}) = \mathrm{A}}$$

$$\boxed{\mathit{EquivalentAncestor}(\tau_{cct}, \mathrm{D}, \mathrm{C}) = \textbf{null}}$$

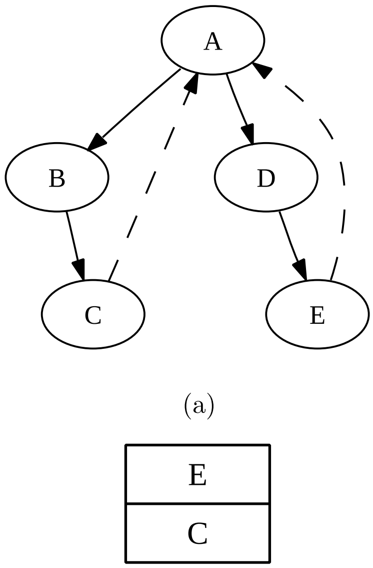
Figure 6.15: Using the *EquivalentAncestor* Algorithm.

```
Algorithm $Before(\tau_{cct}, \sigma)$
Input: Calling Context Tree $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$;
    Structural Entity $\sigma$
Output: Updated Calling Context Tree $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$
found $\leftarrow$ false
for $N_\phi \in children(N_a)$
    do if $N_\phi = \sigma$
        then $N_a \leftarrow N_\phi$
            $found \leftarrow$ true
if found $=$ false
    then $N_\phi \leftarrow EquivalentAncestor(\tau, \sigma, parent(\sigma))$
        if $N_\phi =$ null
            then $\mathcal{N}_\tau \leftarrow \mathcal{N}_\tau \cup \{\sigma\}$
                $\mathcal{E}_\tau \leftarrow \mathcal{E}_\tau \cup \{(N_a, \sigma)\}$
                $N_a \leftarrow \sigma$
            else
                $\mathcal{E}_\tau \leftarrow \mathcal{E}_\tau \cup \{(N_a, N_\phi)\}$
                $\mathcal{E}_B \leftarrow \mathcal{E}_B \cup \{(N_a, N_\phi)\}$
                $\mathcal{B}_\phi.push(N_a)$
                $N_a \leftarrow N_\phi$
return $\langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$
```

Figure 6.16: The *Before* Algorithm for the Calling Context Tree.

```
Algorithm $After(\tau_{cct})$
Input: Calling Context Tree $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$
Output: Updated Calling Context Tree $\tau_{cct} = \langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$
if $\mathcal{B}_a.size() > 0$
    then $N_a \leftarrow \mathcal{B}_a.pop()$
    else
        $N_a \leftarrow parent(N_a)$
return $\langle \tau_{dct}, \mathcal{E}_F, \mathcal{E}_B, \mathcal{N}_B \rangle$
```

Figure 6.17: The *After* Algorithm for the Calling Context Tree.



(a)

(b)

Dynamic Call Chain: A → B → C → A → D → E → A

Figure 6.18: The (a) CCT with Back Edges and (b) Corresponding Active Back Edge Stack.

We also push the node N_a onto N_ϕ's active back edge stack $\mathcal{B}_\phi$ and establish N_ϕ as the new active node. Figure 6.18 illustrates how the the *Before* instrumentation manipulates the active back edge stack and adds in the back edges. This figure shows a simple CCT and the active back edge stack after the execution of the method call chain A → B → C → A → D → E → A during testing. Since E is at the top of $\mathcal{B}_A$, the *After* instrumentation in Figure 6.17 will make node E the active node when it re-traces the back edge (E,A) (i.e., $\mathcal{B}_A$ ensures that *After* follows the back edge (E,A) before it re-traces the edge (C,A)).

If we assume that line 8 through line 16 of *Before* execute in constant time, then the *Before* instrumentation payload in Figure 6.16 has a worst-case time complexity of $O(|children(N_a)| + depth(N_a))$. We recursively define the *depth* function so that $depth(N_0) = 0$ and $depth(N_\phi) = 1 + depth(parent(N_\phi))$. The term $|children(N_a)|$ corresponds to the execution of line 2 through line 5. This worst-case time complexity holds when line 1 through line 4 of Figure 6.14 execute in constant time and the *EquivalentAncestor* algorithm is recursively invoked $depth(N_a) + 1$ times. The worst-case behavior of *EquivalentAncestor* occurs when the root is equivalent to σ, or τ_{cct} does not contain an equivalent ancestor for σ. Even though the time overhead associated with executing *Before* is greater for the CCT than for the DCT, the CCT's *Before* instrumentation yields smaller TCM trees that have bounded breadth and depth [Ammons et al., 1997]. The CCT has bounded depth because it coalesces nodes and uses back edges when methods are recursively invoked during testing (e.g., line 13 through line 16 in Figure 6.16). The CCT has bounded breadth since it coalesces nodes when testing causes the iterative invocation of methods (e.g., line 2 through line 5 of Figure 6.16). Like the DCT's instrumentation, the *After* payload for a CCT is also $O(1)$.

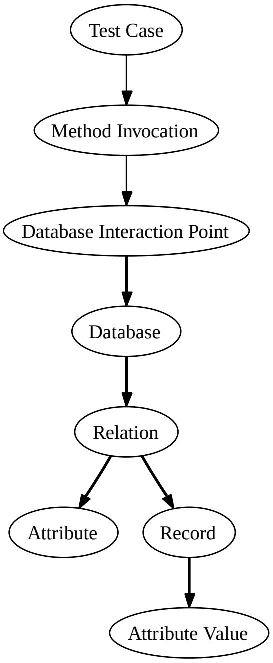


Figure 6.19: The Structure of a Database-Aware TCM Tree.

6.4.3 Database-Aware Trees

The traditional *Before* and *After* instrumentation from Section 6.4.2 does not include functionality to observe a database interaction and update the TCM tree. The test coverage monitor also creates a *database interaction dynamic call tree* (DI-DCT) or a *database interaction calling context tree* (DI-CCT). These database-aware trees still respectively adhere to Definitions 5 and 6. However, the nodes within a DI-DCT or DI-CCT correspond to a (i) method invocation, (ii) definition of a database entity, or (iii) use of a database entity. The instrumentation can insert database entity nodes into the tree at all levels of interaction granularity, as described in Figure 6.19.

Following the convention that we established in Figure 6.8, we use bold edges to connect two database entity nodes. If a node $N_\phi \in \mathcal{N}_\tau$ has the database interaction node $N_r \in \mathcal{N}_\tau$ as its ancestor, then N_ϕ must correspond to the definition or use of a database entity. Figure 6.19 reveals that a database node must have an interaction node as its parent and a relation node is always a child of a database node. Figure 6.19 also shows that we place attribute value nodes below the record that contains the attribute value and the attribute nodes are children of the containing relation. We structure a TCM tree in this manner because it ensures the correct calculation of database-aware adequacy for each test and the entire test suite. Table A10 summarizes the notation that we use to describe the database-aware instrumentation.

6.4.3.1 Instrumentation to Monitor a Database Use

Figure 6.23 provides the *BeforeDatabaseUse* instrumentation payload. The test coverage monitor executes this payload before the use of a database by either a program or a test suite. The program uses the database when it executes a SQL **select** statement.

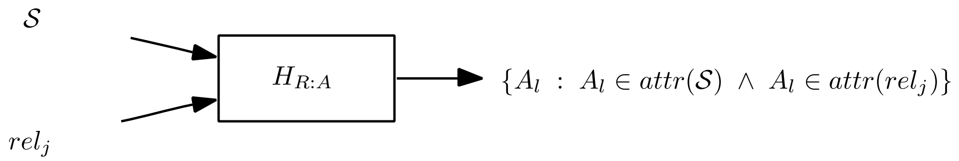

$\mathcal{S}$
rel_j
$H_{R:A}$
$\{A_l \;:\; A_l \in attr(\mathcal{S}) \;\wedge\; A_l \in attr(rel_j)\}$

Figure 6.20: The Function that Maps Relations to Attributes.

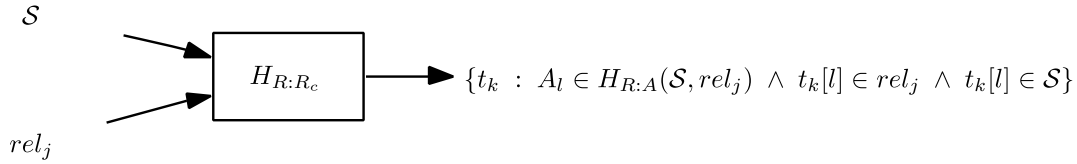

$\mathcal{S}$
rel_j
$H_{R:R_c}$
$\{t_k \;:\; A_l \in H_{R:A}(\mathcal{S}, rel_j) \;\wedge\; t_k[l] \in rel_j \;\wedge\; t_k[l] \in \mathcal{S}\}$

Figure 6.21: The Function that Maps Relations to Records.

A test suite uses the database when it executes an oracle to compare the actual and expected database states. Figure B3 of Appendix B provides a test case that uses a database-aware test oracle to compare the expected and actual state of the *HomeworkMaster* relation in the `GradeBook` database. Figure 6.23 shows that *BeforeDatabaseUse* returns the test coverage monitoring tree that *Before*(τ, N_r) outputs. The call to *Before*(τ, N_r) places node N_r into the TCM tree and establishes this node as the parent for all of the database entity nodes that the instrumentation subsequently adds. The database-aware payloads invoke the appropriate *Before* and *After* instrumentation algorithms based upon the type of the TCM tree τ. If τ is a DCT, then *BeforeDatabaseUse* runs the *Before* instrumentation given in Figure 6.12. Alternatively, if τ is a CCT, then line 1 of Figure 6.23 executes the *Before* algorithm from Figure 6.16.

Figure 6.24 furnishes the *AfterDatabaseUse* instrumentation that determines how a SQL **select** statement uses the database. Since a **select** can specify attributes from multiple relations, its result set $\mathcal{S}$ can contain records whose attribute values are derived from one or more relations in the database. For example, the SQL statement "**select** $A_l, \widehat{A_l}$ **from** $rel_j, \widehat{rel_j}$ where $\mathcal{P}$" will yield a result set $\mathcal{S}$ that mixes attribute values from relations rel_j and $\widehat{rel_j}$ (for the purpose of illustration, we assume that A_l is an attribute of rel_j, relation $\widehat{rel_j}$ contains $\widehat{A_l}$, and $\mathcal{P}$ is an arbitrary predicate whose form we defined in Figure 2.1 of Chapter 2). In order to support the correct calculation of database-aware test adequacy, the instrumentation must determine the containing record and relation for each attribute value in the result set. For example, if relation rel_j contains attribute A_l and $\mathcal{S}$ includes an attribute value from A_l, then the TCM tree must have the edge $(\langle rel_j, \textbf{use}\rangle, \langle A_l, \textbf{use}\rangle)$ in order to indicate that this relation and attribute were used during testing.

AfterDatabaseUse uses the functions $H_{R:A}$ and $H_{R:R_c}$, as respectively defined by Figure 6.20 and Figure 6.21, to identify the attributes and records that $\mathcal{S}$ contains. Figure 6.20 shows that $H_{R:A}$ returns the set of all attributes A_l that exist in both the result set $\mathcal{S}$ and the specified relation rel_j. We use the notation *attr*$(\mathcal{S})$ and *attr*(rel_j) to denote the set of attributes that are associated with $\mathcal{S}$ and rel_j, respectively. Figure 6.21 reveals that $H_{R:R_c}$ outputs the set of records t_k that have an attribute value $t_k[l]$ inside of both the result set $\mathcal{S}$ and the relation rel_j. Figure 6.22 provides an example of the input and output of the functions $H_{R:A}$ and $H_{R:R_c}$. The execution of the SQL **select** statement in Figure 6.22 yields the result set $\mathcal{S}$ that contains two records. In this example, $H_{R:A}(\mathcal{S}, rel_j)$ outputs A_l because this is the only attribute that is in both the input result set and the relation. $H_{R:A}(\mathcal{S}, rel_j)$ does not return the attribute $\widehat{A_l}$ because this attribute exists in the relation $\widehat{rel_j}$. The function $H_{R:R_c}(\mathcal{S}, rel_j)$ returns $\{t_1, t_3\}$ since the attribute values from these records in rel_j are also in $\mathcal{S}$. $H_{R:R_c}(\mathcal{S}, rel_j)$ does not output the record t_2 since it is not in $\mathcal{S}$. Figure 6.22 confirms that the functions $H_{R:A}$ and $H_{R:R_c}$ operate in an analogous fashion when they analyze the result set $\mathcal{S}$ and the relation $\widehat{rel_j}$.

The $AfterDatabaseUse(\tau, N_r, \mathcal{S}, \mathcal{L})$ payload in Figure 6.24 analyzes result set $\mathcal{S}$ in order to updates tree τ after the execution of the database interaction at node N_r. The input function $\mathcal{L}(\tau)$ returns the levels of database interaction granularity at which we represent node N_r's interaction. Following the convention established in Chapter 5, we require that $\mathcal{L}(\tau) \subseteq \{\mathbf{D}, \mathbf{R}, \mathbf{A}, \mathbf{R_c}, \mathbf{A_v}\}$. If $\mathbf{D} \in \mathcal{L}(\tau)$, then the database-aware payloads must include nodes to represent the definition and/or use of the database. When $\mathbf{A_v} \in \mathcal{L}(\tau)$ these payloads create TCM trees with nodes that represent an interaction at the attribute value level. *AfterDatabaseUse* uses *GetDatabase* to determine which database is subject to interaction at N_r.

Since $H_{R:A}$ and $H_{R:R_c}$ accept a relation as one of the two inputs, the *AfterDatabaseUse* payload also uses the *relations*$(\mathcal{S})$ operation to determine which relations have records in the specified result set. Figure 6.22 shows that *relations*$(\mathcal{S}) = \{rel_j, \widehat{rel_j}\}$ for the example SQL **select** statement. The test coverage monitor uses the Java class `java.sql.ResultSetMetaData` to implement $H_{R:A}$, $H_{R:R_c}$, *attr*$(\mathcal{S})$, and *relations*$(\mathcal{S})$. For example, this Java class provides methods such as `getTableName` and `getColumnName`. The `getTableName(int l)` method returns the relation rel_j that contains the attribute A_l and `getColumnName(int l)` returns the fully qualified name for attribute A_l. The test coverage monitor determines the output of *attr*(rel_j) by consulting the relational schema for the current database.

Line 1 of Figure 6.24 initializes the variable *op* to **use** since the *AfterDatabaseUse* payload analyzes a database interaction point that submits a **select** statement. If $\mathbf{D} \in \mathcal{L}(\tau)$, then line 4 creates node $N_D = \langle D_f, op \rangle$ and line 5 executes *Before*(τ, N_D). If a tester specifies that τ should contain relation nodes (i.e., $\mathbf{R} \in \mathcal{L}(\tau)$), then line 7 through line 9 iteratively create node $N_R = \langle rel_j, op \rangle$ and add it to the TCM tree for each relation $rel_j \in relations(\mathcal{S})$. Figure 6.19 shows that the test coverage monitor places attribute nodes below the relation node N_R. Thus, *AfterDatabaseUse* executes line 10 through 14 in order to iteratively place node $N_A = \langle A_l, op \rangle$ into τ for each attribute $A_l \in H_{R:A}(\mathcal{S}, rel_j)$. The use of $H_{R:A}$ ensures that the parent of N_A is the node for the relation rel_j that specifies attribute A_l (i.e., node N_R).

When $\mathbf{R_c} \in \mathcal{L}(\tau)$, line 16 through line 18 call *Before*(τ, N_{R_c}) in order to place a node $N_{R_c} = \langle t_k, op \rangle$ into τ for each record t_k in the current relation rel_j. We use the function $H_{R:R_c}$ in order to guarantee

rel_j

	$\dots$	A_l	$\dots$
t_1		1	
t_2		2	
t_3		3	

$\widehat{rel_j}$

	$\dots$	$\widehat{A_l}$	$\dots$
t_1		A	
t_2		B	
t_3		C	
t_4		D	

$\mathcal{S}$

A_l	$\widehat{A_l}$
1	A
3	D

select $A_l, \widehat{A_l}$
from $rel_j, \widehat{rel_j}$
where $\mathcal{P}$

$$relations(\mathcal{S}) \quad = \quad \{rel_j, \widehat{rel_j}\}$$

$$\begin{array}{rclcrcl} H_{R:A}(\mathcal{S}, rel_j) & = & \{A_l\} & \qquad & H_{R:A}(\mathcal{S}, \widehat{rel_j}) & = & \{\widehat{A_l}\} \\ H_{R:R_c}(\mathcal{S}, rel_j) & = & \{t_1, t_3\} & \qquad & H_{R:R_c}(\mathcal{S}, \widehat{rel_j}) & = & \{t_1, t_4\} \end{array}$$

Figure 6.22: Example of the Functions that Analyze a Result Set.

```
Algorithm $BeforeDatabaseUse(\tau, N_r)$
Input: Test Coverage Monitoring Tree $\tau$;
    Database Interaction Point $N_r$
Output: Updated Test Coverage Monitoring Tree $\tau$
return $Before(\tau, N_r)$
```

Figure 6.23: The *BeforeDatabaseUse* Algorithm.

```
Algorithm $AfterDatabaseUse(\tau, N_r, \mathcal{S}, \mathcal{L})$
Input: Test Coverage Monitoring Tree $\tau$;
    Database Interaction Point $N_r$;
    Database Interaction Result Set $\mathcal{S}$;
    Levels for Representing a Database Interaction $\mathcal{L}$
Output: Updated Test Coverage Monitoring Tree $\tau$
$op \leftarrow$ use
$D_f \leftarrow GetDatabase(N_r)$
if $\mathbf{D} \in \mathcal{L}(\tau)$
  then $N_D \leftarrow \langle D_f, op \rangle$
       $Before(\tau, N_D)$
       if $\mathbf{R} \in \mathcal{L}(\tau)$
         then for $rel_j \in relations(\mathcal{S})$
                do $N_R \leftarrow \langle rel_j, op \rangle$
                   $Before(\tau, N_R)$
                   if $\mathbf{A} \in \mathcal{L}(\tau)$
                     then for $A_l \in H_{R:A}(\mathcal{S}, rel_j)$
                            do $N_A \leftarrow \langle A_l, op \rangle$
                               $Before(\tau, N_A)$
                               $After(\tau)$
                   if $\mathbf{R_c} \in \mathcal{L}(\tau)$
                     then for $t_k \in H_{R:R_c}(\mathcal{S}, rel_j)$
                            do $N_{R_c} \leftarrow \langle t_k, op \rangle$
                               $Before(\tau, N_{R_c})$
                               if $\mathbf{A_v} \in \mathcal{L}(\tau)$
                                 then for $A_l \in H_{R:A}(\mathcal{S}, rel_j)$
                                        do $N_{A_v} \leftarrow \langle t_k[l], op \rangle$
                                           $Before(\tau, N_{A_v})$
                                           $After(\tau)$
                               $After(\tau)$
                   $After(\tau)$
       $After(\tau)$
$After(\tau)$
return $\tau$
```

Figure 6.24: The *AfterDatabaseUse* Algorithm.

that an edge $(N_R, R_{R_c}) \in \mathcal{E}_\tau$ corresponds to the use of a record t_k that (i) exists in the relation rel_j and (ii) has one or more attribute values $t_k[l]$ in the result set $\mathcal{S}$. Line 20 through line 23 of *AfterDatabaseUse* invoke $Before(\tau, N_{A_v})$ and $After(\tau)$ to insert node N_{A_v} into the TCM tree for each attribute value $t_k[l]$ in the current record. The instrumentation always follows a call to $Before(\tau, N_{A_v})$ with an immediate call to $After(\tau)$ because the attribute value nodes are leaves of the test coverage monitoring tree (i.e., $out(N_{A_v}) = 0$ for all attribute value nodes N_{A_v}). The *AfterDatabaseUse* instrumentation orders all of the calls to the *Before* and *After* probes so that the coverage monitoring tree adheres to the structure prescribed by Figure 6.19.

6.4.3.2 Instrumentation to Monitor a Database Definition

Figure 6.29's *BeforeDatabaseDefine* algorithm uses the $GetRelation(N_r)$ operation to parse the SQL command that N_r submits to the RDBMS. The *GetDatabase* and *GetRelation* operations use a regular expression-based parser to identify these syntactical elements in the intercepted SQL statement. After *GetRelation* parses the intercepted SQL statement and identifies rel_j as the relation subject to definition, it executes a **select** to extract rel_j's state. Once this payload has stored rel_j, it returns the output of $Before(\tau, N_r)$ and passes control back to the program under test. The *AfterDatabaseDefine* algorithm in Figure 6.30 extracts the state of the same relation after the program under test executes a SQL **update**, **insert**, or **delete** command.

We use the *symmetric relational difference* (SRD) operator $\bigotimes_{R_c}$ to determine the difference between relation rel_j (i.e., the relation before the execution of the interaction at N_r) and $rel_{j'}$ (i.e., the relation after the execution of the defining interaction). If there is a need to discern the difference between the database record t_k in the relations rel_j and $rel_{j'}$, then we use the *symmetric attribute value difference* (SAVD) operator $\bigotimes_{A_v}$. The TCM component uses the difference operators because they enable the instrumentation to accurately identify changes in a relation without relying upon RDBMS-specific functions such as triggers. Previously developed data change detection techniques (e.g., [Chawathe et al., 1996, Chawathe and Garcia-Molina, 1997, Labio and Garcia-Molina, 1996]) do not support test coverage monitoring because of their (i) focus on non-relational data or (ii) use of lossy compression algorithms. Since the change detectors described in [Chawathe et al., 1996, Chawathe and Garcia-Molina, 1997] operate on rooted trees with node labels, they do not fit our use of the relational data model. We could not use the relational differencing system developed in [Labio and Garcia-Molina, 1996] because this approach uses lossy compression to handle database snapshots that do not fit into memory. Since this scheme can overlook a database modification, it might yield an incorrect coverage report and thus lead to improper test adequacy measurements. To this end, the test coverage monitoring framework uses a database-aware extension of the Myers difference algorithm in the implementation of the SRD and SAVD operators [Myers, 1986].

The following Equation (6.1) defines the $\bigotimes_{R_c}$ operator that considers the contents of the records in two database relations rel_j and $rel_{j'}$ and returns those records whose contents differ. We use $\backslash_{R_c}$ to denote the set difference operator that outputs the records that vary in the two input relations. Equation (6.2) defines the $\bigotimes_{A_v}$ operator that examines two database records t_k and $t_{k'}$ in order to return the attribute values that differ. The symbol $\backslash_{A_v}$ stands for the set difference operator that isolates the attribute values that are not the same in the two input records. The SRD and SAVD operators allow the *AfterDatabaseDefine* instrumentation payload to precisely determine how the database interaction changes the state of the database. Table A11 in Appendix A reviews the meaning and purpose of the relational difference operators.

$$rel_j \bigotimes_{R_c} rel_{j'} = (rel_j \ \backslash_{R_c} \ rel_{j'}) \cup (rel_{j'} \ \backslash_{R_c} \ rel_j) \tag{6.1}$$

$$t_k \in rel_j \bigotimes_{A_v} t_{k'} \in rel_{j'} = (t_k \ \backslash_{A_v} \ t_{k'}) \cup (t_{k'} \ \backslash_{A_v} \ t_k) \tag{6.2}$$

Figure 6.25 shows the output of the SRD and SAVD operators when an **update** statement defines the database. In this example, the **update** changes the value of $t_2[2]$ from 3 to 4. The SRD operator differs from the traditional symmetric difference operator because it uses $\backslash_{R_c}$ instead of the set theoretic difference operator $\backslash$ (i.e., $\backslash_{R_c}$ outputs a record t_k instead of the contents of the record $\langle t_k[1], \ldots, t_k[q] \rangle$). Figure 6.25 reveals that $rel_j \backslash_{R_c} rel_{j'}$ returns t_2 instead of $\langle t_2[1], t_2[2] \rangle$, as returned by the set difference operator. After the SRD operator isolates t_2 as the modified record, we use $\bigotimes_{A_v}$ to find $t_2[2]$, the specific attribute value that was modified by the **update** statement. Unlike the traditional symmetric difference operator, the SAVD operator identifies the modified attribute value instead of the different values of $t_k[l]$ in the two relations. For this example, the symmetric difference of $t_k \in rel_j$ and $t_k \in rel_{j'}$ would return $\{(t_2[2], 3), (t_2[2], 4)\}$ instead of determining that $t_2[2]$ was the only modified attribute value.

Figure 6.26 explains how the database-aware difference operators determine which record a SQL **insert** statement adds to the database. In this example, the SRD operator returns $t_4 \in rel_{j'}$ because this record does not exist in relation rel_j. Since the **insert** statement places t_k into the database, the SAVD operator must return all of the attribute values within this record. The example in Figure 6.27 demonstrates that the database-aware difference operators can also identify the record and attribute values that are removed from relation rel_j by a SQL **delete** statement. Finally, Figure 6.28 shows that we can use the SRD and SAVD operators determine how a SQL statement defines multiple locations within a relation. In this example, a SQL **update** changes $t_1[2]$ to 22 and $t_2[1]$ to 3. The **update** also modifies both of the attribute values in record t_3. Figure 6.28 reveals that the use of the $\bigotimes_{A_v}$ operator for each record $t_k \in rel_j \bigotimes_{R_c} rel_{j'}$ finds each attribute value that the SQL statement defined.

Line 1 of Figure 6.30 initializes the variable *op* to **define** since the *AfterDatabaseDefine* analyzes an interaction that submits a SQL **update**, **insert**, or **delete** statement. Line 2 determines that N_r interacts with database D_f and line 3 stores the state of the defined relation in relation $rel_{j'}$. If $\mathbf{D} \in \mathcal{L}(\tau)$, then line 5 creates the node $N_D = \langle D_f, op \rangle$ and line 6 calls $Before(\tau, N_D)$. If a tester specifies that τ should contain nodes concerning the definition of relations (i.e., $\mathbf{R} \in \mathcal{L}(\tau)$), then line 8 through line 9 iteratively construct node $N_r = \langle rel_j, op \rangle$ and place it in the TCM tree (the coverage monitoring framework ensures that *AfterDatabaseDefine* has access to the rel_j that *BeforeDatabaseDefine* stored). Line 10 initializes the set $\mathcal{A}_{def}$ to the empty set. We use this set to store all of the attributes that are subject to definition at node N_r. *AfterDatabaseDefine* identifies each $A_l \in \mathcal{A}_{def}$ through the iterative application of $\bigotimes_{R_c}$ and $\bigotimes_{A_v}$ on line 12 through line 21.

If $\mathbf{R_c} \in \mathcal{L}(\tau)$, then line 12 applies the SRD operator to the relations rel_j and $rel_{j'}$. Lines 13 and 14 of Figure 6.30 create node $N_{R_c} = \langle t_k, op \rangle$ and place it into the tree by calling $Before(\tau, N_{R_c})$. If $\mathbf{A_v} \in \mathcal{L}(\tau)$, then *AfterDatabaseDefine* uses the SAVD operator to determine which attribute values $t_k[l]$ were defined by the SQL statement. Line 17 through line 20 construct the defining node $N_{A_v} = \langle t_k[l], op \rangle$ and use calls to *Before* and *After* to put this node into τ. These lines of the payload also add A_l to $\mathcal{A}_{def}$ for each attribute value $t_k[l]$. The repeated execution of line 18 for the same attribute A_l does not change the contents of $\mathcal{A}_{def}$ since it is a set. Finally, line 22 through line 26 insert each the attribute definition node $N_A = \langle A_l, op \rangle$ so that $parent(N_A) = N_R$. The *AfterDatabaseDefine* payload must also execute line 12 through line 21 when $\mathbf{A} \in \mathcal{L}(\tau)$ because the instrumentation can only identify $\mathcal{A}_{def}$ by applying the SRD and SAVD operators. This is due to the fact that the defined attributes can vary for each record $t_k \in rel_j \bigotimes_{R_c} rel_{j'}$ (e.g., Figure 6.28 reveals that attribute A_1 is defined in t_1 and both attribute A_1 and A_2 are defined in t_2).

6.4.3.3 Worst-Case Time Complexity

We characterize the worst-case time complexity of *BeforeDatabaseUse*, *AfterDatabaseUse*, *BeforeDatabaseDefine*, and *AfterDatabaseDefine* in this chapter and we empirically evaluate the performance of the coverage monitor in Chapter 7. Table A12 summarizes the notation that we develop in this section. Since a database-aware instrumentation probe always requires the execution of *Before* and *After*, we consider a call to one of these traditional probes as the basic operation (we do not incorporate the time complexity of the DCT and CCT creation probes in the complexities that we develop here). For simplicity, these worst-case time complexities assume a fixed database D_f (relaxing this assumption simply requires that we redefine each time complexity variable as the maximum across all databases). Our worst-case analysis of each database-aware algorithm also assumes that the TCM tree τ will represent each database interaction at all levels of granularity (i.e., $\mathcal{L}(\tau) = \{\mathbf{D}, \mathbf{R}, \mathbf{A}, \mathbf{R_c}, \mathbf{A_v}\}$). We classify the *BeforeDatabaseUse* algorithm in Figure 6.23 as $O(1)$ because it simply invokes the *Before* instrumentation probe that also has a constant worst-case time complexity.

Figure 6.24 shows that the execution time of *AfterDatabaseUse* depends upon the time overhead of the *relations* operation and the $H_{R:A}$ and $H_{R:R_c}$ functions. Since we implement each of these operations using a hash table, we assume that their worst-case time complexity is $O(1)$. The *AfterDatabaseUse* instrumentation probe is $O(\mathcal{W}_f \times \mathcal{M}_{R:A} + \mathcal{W}_f \times \mathcal{M}_{R:A} \times \mathcal{M}_{R:R_c})$ where $\mathcal{W}_f$ stands for the total number of relations in database D_f, as previously defined in Chapter 5.[2] The following Equation (6.3) defines $\mathcal{M}_{R:A}$, the maximum number of attributes in both the relation rel_j and the result set $\mathcal{S}$. The maximal value of $\mathcal{M}_{R:A}$ occurs when the SQL **select** statement requests all of the attributes from a relation in database D_f. The time complexity term $\mathcal{W}_f \times \mathcal{M}_{R:A}$ corresponds to the iterative execution of line 7 through line 14 in Figure 6.24. The following

[2] Simplification of this time complexity yields $O((\mathcal{W}_f \times \mathcal{M}_{R:A}) + (1 + \mathcal{M}_{R:R_c}))$. We do not use this time complexity in our discussion of *AfterDatabaseUse* because it does not closely adhere to the probe's structure.

rel_j

	A_1	A_2
t_1	1	2
t_2	2	3
t_3	3	4

$rel_{j'}$

	A_1	A_2
t_1	1	2
t_2	2	4
t_3	3	4

$$\begin{aligned} rel_j \bigotimes_{R_c} rel_{j'} &= (rel_j \setminus_{R_c} rel_{j'}) \cup (rel_{j'} \setminus_{R_c} rel_j) \\ &= \{t_2\} \cup \{t_2\} \\ &= \{t_2\} \end{aligned}$$

$$t_2 \in rel_j \bigotimes_{A_v} t_2 \in rel_{j'} \quad = \quad \{t_2[2]\}$$

Figure 6.25: Example of the Database-Aware Difference Operators for the **update** Statement.

rel_j

	A_1	A_2
t_1	1	2
t_2	2	3
t_3	3	4

$rel_{j'}$

	A_1	A_2
t_1	1	2
t_2	2	3
t_3	3	4
t_4	4	5

$$\begin{aligned} rel_j \bigotimes_{R_c} rel_{j'} &= (rel_j \setminus_{R_c} rel_{j'}) \cup (rel_{j'} \setminus_{R_c} rel_j) \\ &= \emptyset \cup \{t_4\} \\ &= \{t_4\} \end{aligned}$$

$$t_4 \in rel_j \bigotimes_{A_v} t_4 \in rel_{j'} \quad = \quad \{t_4[1], t_4[2]\}$$

Figure 6.26: Example of the Database-Aware Difference Operators for the **insert** Statement.

rel_j

	A_1	A_2
t_1	1	2
t_2	2	3
t_3	3	4

$rel_{j'}$

	A_1	A_2
t_1	1	2
t_3	3	4

$$\begin{aligned} rel_j \underset{R_c}{\bigotimes} rel_{j'} &= (rel_j \setminus_{R_c} rel_{j'}) \cup (rel_{j'} \setminus_{R_c} rel_j) \\ &= \{t_2\} \cup \emptyset \\ &= \{t_2\} \end{aligned}$$

$$t_2 \in rel_j \underset{A_v}{\bigotimes} t_2 \in rel_{j'} = \{t_2[1], t_2[2]\}$$

Figure 6.27: Example of the Database-Aware Difference Operators for the **delete** Statement.

rel_j

	A_1	A_2
t_1	1	2
t_2	2	3
t_3	3	4

$rel_{j'}$

	A_1	A_2
t_1	1	22
t_2	3	3
t_3	4	44

$$\begin{aligned} rel_j \underset{R_c}{\bigotimes} rel_{j'} &= (rel_j \setminus_{R_c} rel_{j'}) \cup (rel_{j'} \setminus_{R_c} rel_j) \\ &= \{t_1, t_2, t_3\} \cup \{t_1, t_2, t_3\} \\ &= \{t_1, t_2, t_3\} \end{aligned}$$

$$t_1 \in rel_j \underset{A_v}{\bigotimes} t_1 \in rel_{j'} = \{t_1[2]\}$$

$$t_2 \in rel_j \underset{A_v}{\bigotimes} t_2 \in rel_{j'} = \{t_2[1]\}$$

$$t_3 \in rel_j \underset{A_v}{\bigotimes} t_3 \in rel_{j'} = \{t_3[1], t_3[2]\}$$

Figure 6.28: An Additional Example of the Database-Aware Difference Operators.

```
Algorithm $BeforeDatabaseDefine(\tau, N_r)$
Input: Test Coverage Monitoring Tree $\tau$;
    Database Interaction Point $N_r$
Output: Updated Test Coverage Monitoring Tree $\tau$
$rel_j \leftarrow GetRelation(N_r)$
return $Before(\tau, N_r)$
```

Figure 6.29: The *BeforeDatabaseDefine* Algorithm.

```
Algorithm $AfterDatabaseDefine(\tau, N_r, \mathcal{L})$
Input: Test Coverage Monitoring Tree $\tau$;
    Database Interaction Point $N_r$;
    Levels for Representing a Database Interaction $\mathcal{L}$
Output: Updated Test Coverage Monitoring Tree $\tau$
$op \leftarrow$ define
$D_f \leftarrow GetDatabase(N_r)$
$rel_{j'} \leftarrow GetRelation(N_r)$
if $\mathbf{D} \in \mathcal{L}(\tau)$
   then $N_D \leftarrow \langle D_f, op \rangle$
        $Before(\tau, N_D)$
        if $\mathbf{R} \in \mathcal{L}(\tau)$
           then $N_R \leftarrow \langle rel_j, op \rangle$
                $Before(\tau, N_R)$
                $\mathcal{A}_{def} \leftarrow \emptyset$
                if $\mathbf{R_c} \in \mathcal{L}(\tau) \vee \mathbf{A} \in \mathcal{L}(\tau)$
                   then for $t_k \in (rel_j \bigotimes_{R_c} rel_{j'})$
                        do $N_{R_c} \leftarrow \langle t_k, op \rangle$
                           $Before(\tau, N_{R_c})$
                           if $\mathbf{A_v} \in \mathcal{L}(\tau) \vee \mathbf{A} \in \mathcal{L}(\tau)$
                              then for $t_k[l] \in (t_k \in rel_j \bigotimes_{A_v} t_k \in rel_{j'})$
                                   do $N_{A_v} \leftarrow \langle t_k[l], op \rangle$
                                      $\mathcal{A}_{def} \leftarrow \mathcal{A}_{def} \cup \{A_l\}$
                                      $Before(\tau, N_{A_v})$
                                      $After(\tau)$
                           $After(\tau)$
                if $\mathbf{A} \in \mathcal{L}(\tau)$
                   then for $A_l \in \mathcal{A}_{def}$
                        do $N_A \leftarrow \langle A_l, op \rangle$
                           $Before(\tau, N_A)$
                           $After(\tau)$
                $After(\tau)$
        $After(\tau)$
$After(\tau)$
return $\tau$
```

Figure 6.30: The *AfterDatabaseDefine* Algorithm.

Equation (6.4) defines $\mathcal{M}_{R:R_c}$, the maximum number of records that have an attribute value in both rel_j and $\mathcal{S}$. The variable $\mathcal{M}_{R:R_c}$ takes on its greatest value when the **select**'s **where** clause predicate matches every record in the specified relation. The time complexity term $\mathcal{W}_f \times \mathcal{M}_{R:A} \times \mathcal{M}_{R:R_c}$ refers to the iterative execution of line 16 through line 23 for each $rel_j \in relation(\mathcal{S})$.

$$\mathcal{M}_{R:A} \quad = \quad max\{\ |H_{R:A}(\mathcal{S}, rel_j)|\ :\ rel_j \in relations(\mathcal{S})\ \} \tag{6.3}$$

$$\mathcal{M}_{R:R_c} \quad = \quad max\{\ |H_{R:R_c}(\mathcal{S}, rel_j)|\ :\ rel_j \in relations(\mathcal{S})\ \} \tag{6.4}$$

The *BeforeDatabaseDefine* instrumentation probe in Figure 6.29 has a worst-case time complexity of $O(t_{max})$ where $t_{max} = max\{\ |rel_j|\ :\ rel_j \in D_f\ \}$ is the maximum number of records in the database D_f. For the derivation of this time complexity, we take the return of an individual database record as the basic operation. We characterize *BeforeDatabaseDefine* in this manner because the instrumentation calls $GetRelation(N_r)$ in order to extract the state of the relation that is subject to interaction at node N_r. Figure 6.30 shows that the execution time of *AfterDatabaseDefine* depends on the time overhead of the SRD and SAVD operators. Our derivation of the time complexity for $\bigotimes_{R_c}$ and $\bigotimes_{A_v}$ leverages the prior analytical evaluation of the Myers difference algorithm upon which we base our operators [Myers, 1986]. Using the notation that we established in Chapter 5, our analysis assumes that $rel_j = \{t_1, \ldots, t_u\}$, $rel_{j'} = \{t_1, \ldots, t_{u'}\}$, and each $t_k = \langle t_k[1], \ldots, t_k[q]\rangle$ (i.e., rel_j and $rel_{j'}$ are respectively of length u and u' and all of the records in rel_j and $rel_{j'}$ are of length q). The $SRD(j, j')$ term defined in Equation (6.5) is the worst-case time complexity for the execution of $rel_j \bigotimes_{R_c} rel_{j'}$ on line 12 of *AfterDatabaseDefine*. We use the notation $\Lambda(j, j')$ to denote the length of the longest common subsequence (LCS) between relations rel_j and $rel_{j'}$. For more details about the computation of $\Lambda(j, j')$, please refer to [Hirschberg, 1977, Ullman et al., 1976]. Equation (6.5) reveals that the worst-case time complexity of the SRD operator is a function of the sum of the lengths of rel_j and $rel_{j'}$ (i.e., $u + u'$) and the length of the LCS for the relations (i.e., $\Lambda(j, j')$).[3]

$$SRD(j, j') = 2 \times (u + u') \times (u + u' - \Lambda(j, j')) \tag{6.5}$$

The $SAVD(k, j, j')$ term defined in Equation (6.6) is the worst-case time complexity of the SAVD operator that *AfterDatabaseDefine* executes on line 16 of Figure 6.30. The notation $\Lambda(k, j, j')$ stands for the length of the LCS between records $t_k \in rel_j$ and $t_k \in rel_{j'}$. The following Equation (6.6) is not the same as Equation (6.5) because we (i) apply the SRD operator to relations of different lengths and (ii) always use the SAVD operator to difference two records of the same length (the records have identical lengths because they come from the before and after snapshots of the same relation). The worst-case analysis of $\bigotimes_{R_c}$ and $\bigotimes_{A_v}$ reveals that these operators will perform well when the (i) input relations and records are small and (ii) size of the longest common subsequence is large (these performance trends have also been confirmed in prior empirical studies [Miller and Myers, 1985, Myers, 1986]). We judge that condition (i) will frequently hold for $\bigotimes_{R_c}$ because testers often use small relations during the testing of a database-centric application. Condition

[3] Since differencing algorithms are not the focus of this chapter, we do not present the derivation of Equation (6.5) and Equation (6.6). A more thorough treatment of the worst-case time complexity for the Myers difference algorithm is available in [Myers, 1986].

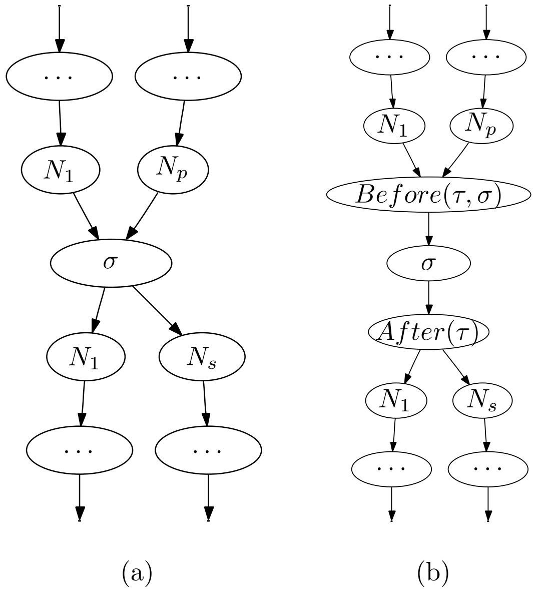
Instrumentation Algorithm	**Worst-Case Time Complexity**
Before (DCT)	$O(1)$
After (DCT)	$O(1)$
Before (CCT)	$O(\lvert children(N_a)\rvert + depth(N_a))$
After (CCT)	$O(1)$
BeforeDatabaseUse	$O(1)$
AfterDatabaseUse	$O(\mathcal{W}_f \times \mathcal{M}_{R:A} + \mathcal{W}_f \times \mathcal{M}_{R:A} \times \mathcal{M}_{R:R_c})$
BeforeDatabaseDefine	$O(t_{max})$
AfterDatabaseDefine	$O(SRD(j, j') + \lvert\mathcal{A}_{max}\rvert + \lvert\bigotimes_{R_c}\rvert \times SAVD(k, j, j') \times \lvert\bigotimes_{A_v}\rvert)$

Table 6.2: Summary of the Time Complexities for the Instrumentation Probes.

(i) will also hold for $\bigotimes_{A_v}$ because many databases have a small to moderate number of attributes per relation. Since the SQL **insert** statement only modifies a single record in a relation, this suggests that condition (ii) is true for both the SRD and SAVD operators. It is possible that an **update** or **delete** statement could remove many of the records from relation rel_j and yield large values for $\Lambda(j, j')$ and $\Lambda(k, j, j')$. However, an examination of the behavior of our case study applications suggests that most tests cause the program to **update** or **delete** a small number of records.

$$SAVD(k, j, j') = 4q \times (2q - \Lambda(k, j, j')) \tag{6.6}$$

We categorize the *AfterDatabaseDefine* instrumentation as $O(SRD(j, j') + |\mathcal{A}_{max}| + |\bigotimes_{R_c}| \times SAVD(k, j, j') \times |\bigotimes_{A_v}|)$ where Equation (6.5) and Equation (6.6) respectively define $SRD(j, j')$ and $SAVD(k, j, j')$. We use $|\bigotimes_{R_c}|$ to denote the cardinality of the set that results from executing $rel_j \bigotimes_{R_c} rel_{j'}$ and we define $|\bigotimes_{A_v}|$ in a similar manner. This time complexity corresponds to the circumstance when *AfterDatabaseDefine* (i) applies the SRD operator to relations rel_j and $rel_{j'}$ (line 12), (ii) uses the SAVD operator for each $t_k \in (rel_j \bigotimes_{R_c} rel_{j'})$ (line 16 through line 20), and (iii) iteratively invokes *Before* and *After* for each $A_l \in \mathcal{A}_{def}$ (line 23 through line 26). The $|\mathcal{A}_{max}|$ term in the time complexity for *AfterDatabaseDefine* refers to the iterative execution of line 24 through line 26 for each attribute $A_l \in \mathcal{A}_{def}$. We define $\mathcal{A}_{max}$ as the maximum number of attributes that differ in the relations rel_j and $rel_{j'}$. $\mathcal{A}_{max}$ takes on its greatest value when the SQL statement defines all of the attributes in relation rel_j. Therefore, the value of $\mathcal{A}_{max}$ depends upon the structure of the SQL **update**, **insert**, or **define** that N_r submits to the database. Table 6.2 reviews the worst-case time complexity for each of the instrumentation probes that this chapter describes. This table suggests that (i) it is more costly to create a CCT than it is to produce a DCT and (ii) the construction of a DI-CCT will incur a greater time overhead than the creation of a DI-DCT. These worst-case time complexities also indicate that it is less time consuming to create a traditional TCM than it is to make a database-aware tree.



(a) (b)

$pred(\sigma) = \{N_1, \ldots, N_p\}$ and $succ(\sigma) = \{N_1, \ldots, N_s\}$

Figure 6.31: (a) Before and (b) After the Introduction of the Database-Aware Instrumentation.

6.4.4 Inserting the Database-Aware Instrumentation

As discussed in Section 6.3.2, our test coverage monitoring component introduces the instrumentation payloads in either a static or a dynamic fashion. Figure 6.31(a) shows a partial control flow graph before we introduce the instrumentation. In this example, the σ node corresponds to either a method invocation (e.g., *call* m_k) or a database interaction (e.g., N_r). If σ is a method call, then we insert a call to the *Before*(τ, σ) payload for either the DCT or the CCT. We introduce a call to *BeforeDatabaseUse*(τ, N_r) or *BeforeDatabaseDefine*(τ, N_r) when σ corresponds to a database interaction point. If N_r submits a SQL statement that contains a statically detectable operation (e.g., the **select** operation is specified in the SQL string), then we add a call to the appropriate database-aware instrumentation. However, if static analysis does not reveal whether N_r submits a defining or a using SQL statement, then we insert a call to a *BeforeDatabase* instrumentation probe that (i) dynamically determines the type of the database interaction point (DIP) and (ii) uses this DIP type information to invoke either the *BeforeDatabaseUse* or *BeforeDatabaseDefine* payload. For example, if the *BeforeDatabase* probe determines that N_r submits a SQL **delete** statement during testing, then the coverage monitor invokes *BeforeDatabaseDefine*. The use of the intermediate *BeforeDatabase* probe ensures that we invoke the correct payload at the expense of increasing the testing time.

For each CFG $G_k = \langle \mathcal{N}_k, \mathcal{E}_k \rangle$, we insert a call to one of the *Before* payloads by first removing each edge $(N_\phi, \sigma) \in \mathcal{E}_k$ for all nodes $N_\phi \in pred(\sigma)$. The instrumentor also adds the edge $(N_\phi, Before(\tau, \sigma))$ to $\mathcal{E}_k$ for each predecessor node N_ϕ. The insertion of the edge $(Before(\tau, \sigma), \sigma)$ completes the introduction of the *Before* payload. If σ corresponds to a method invocation, then the instrumentation component

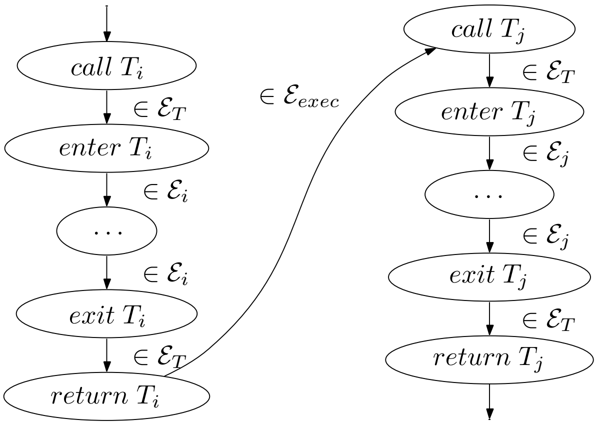


Figure 6.32: Connecting the CFGs for Adjacent Test Cases.

places a call to *After*(τ) in the control flow graph. We introduce the traditional *After* payload by first removing the edge $(\sigma, N_\phi) \in \mathcal{E}_k$ for each node $N_\phi \in succ(\sigma)$. Next, we add the edge $(\sigma, After(\tau))$ and introduce $(After(\tau), N_\phi)$ for all nodes $N_\phi \in succ(\sigma)$. The instrumentor adds one of the *AfterDatabaseUse*, *AfterDatabaseDefine*, or *AfterDatabase* instrumentation payloads into the control flow graph when σ is a database interaction. We place a call to the appropriate *After* payload when the type of the database interaction is statically detectable and we use the *AfterDatabase* instrumentation to dynamically dispatch to the correct instrumentation otherwise. Figure 6.31(b) shows a control flow graph after the introduction of the test coverage monitoring instrumentation. Even though this instrumented CFG contains probes to construct a traditional TCM tree, the replacement of *Before*(τ, σ) and *After*(τ) with the equivalent database-aware probes will support the creation of either a DI-DCT or a DI-CCT.

6.5 CALCULATING TEST ADEQUACY

6.5.1 Representing Database-Aware Test Suites

The test coverage monitor records coverage information so that we can calculate adequacy on either a per-test or per-test suite basis. A test suite is a collection of test cases that invoke program operations and inspect the results in order to determine if the methods performed correctly. Definition 7 defines a test suite T that tests a database-centric application and Table A13 in Appendix A summarizes the notation developed in this section. The notation $\Delta_i = T_i(\Delta_{i-1})$ means that test case T_i was executed with input test state Δ_{i-1} and subsequently produced test state Δ_i. Intuitively, the state of a database-centric application includes the values of all of the program's variables and the state of the databases with which the program interacts during testing.

Definition 7. A *test suite* T is a triple $\langle \Delta_0, \langle T_1, \ldots, T_n \rangle, \langle \Delta_1, \ldots, \Delta_n \rangle \rangle$, consisting of an initial test state, Δ_0, a test case sequence $\langle T_1, \ldots, T_n \rangle$ for state Δ_0, and expected test states $\langle \Delta_1, \ldots, \Delta_n \rangle$ where $\Delta_i = T_i(\Delta_{i-1})$ for $i = 1, \ldots, n$.

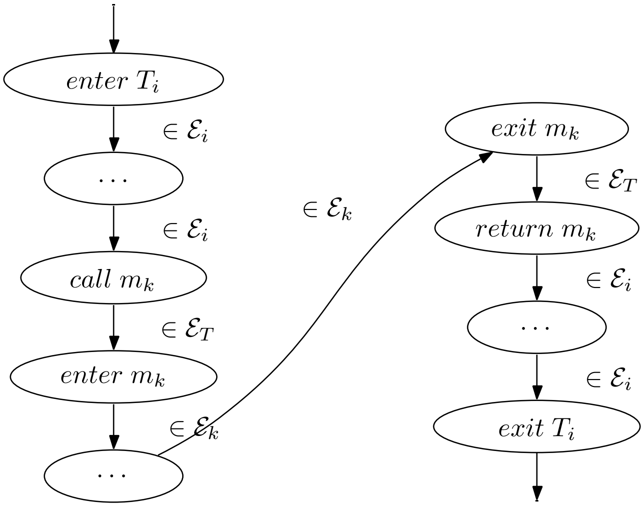


Figure 6.33: Connecting a Test Case to a Method Under Test.

In order to calculate adequacy in a per-test and per-test suite manner, we must determine which methods are tested by each test case. To this end, we describe an interprocedural representation that models the (i) flow of control within an individual test and (ii) connection between each test case in the test suite. Definition 8 states the condition under which we classify the two test cases T_i and T_j as adjacent. T_i and T_j are *adjacent* if the test case sequence $\langle T_1, \ldots, T_n \rangle$ contains the subsequence $\langle T_i, T_j \rangle$ (i.e., $T_i = T_{j-1}$). Definition 9 defines the interprocedural control flow graph representation for a test suite $T = \langle T_1, \ldots, T_n \rangle$ that tests a program P. A control flow graph $G_i = \langle \mathcal{N}_i, \mathcal{E}_i \rangle$ for test T_i contains nodes *enter* T_i, *exit* $T_i \in \mathcal{N}_i$ that respectively demarcate the unique entry and exit points of the test case. We construct the test suite ICFG G_T so that the method *execute* T controls the execution of the test suite. The *execute* T method runs each test in turn and handles the failure of an individual test case. Figure 6.32 shows that we connect the control flow graphs $G_i \in \Gamma_T$ and $G_j \in \Gamma_T$ when the test cases T_i and T_j are adjacent. We also connect the CFGs $G_i \in \Gamma_T$ and $G_k \in \Gamma_P$ when a test case T_i executes method m_k, as depicted in Figure 6.33.

Definition 8. Test cases T_i and T_j are *adjacent* if and only if $T_i, T_j \in \langle T_1, \ldots, T_n \rangle$ and $T_i = T_{j-1}$.

Definition 9. An *interprocedural test control flow graph* $G_T = \langle \Gamma_T, \mathcal{E}_T \rangle$ consists of the set of intraprocedural control flow graphs Γ_T and the set of edges $\mathcal{E}_T$. For each test case $T_i \in \langle T_1, \ldots, T_n \rangle$, there exists a $G_i \in \Gamma_T$. The CFG $G_{exec} = \langle \mathcal{N}_{exec}, \mathcal{E}_{exec} \rangle \in \Gamma_T$ represents the test execution method *execute* T. For any adjacent test cases T_i and T_j there exists (i) CFGs $G_i, G_j \in \Gamma_T$, (ii) *call* T_i, *return* $T_i \in \mathcal{N}_{exec}$, (iii) *call* T_j, *return* $T_j \in \mathcal{N}_{exec}$, (iv) *enter* T_i, *exit* $T_i \in \mathcal{N}_i$, (v) *enter* T_j, *exit* $T_j \in \mathcal{N}_j$, and (vi) edges that connect these nodes according to Figure 6.32. For a test case T_i that tests method m_k there exists (i) $G_i \in \Gamma_T$ and $G_k \in \Gamma_P$, (ii) *enter* T_i, *exit* T_i, *call* m_k, *return* $m_k \in \mathcal{N}_i$, (iii) *enter* m_k, *exit* $m_k \in \mathcal{N}_k$, and (iv) edges that connect these nodes according to Figure 6.33.

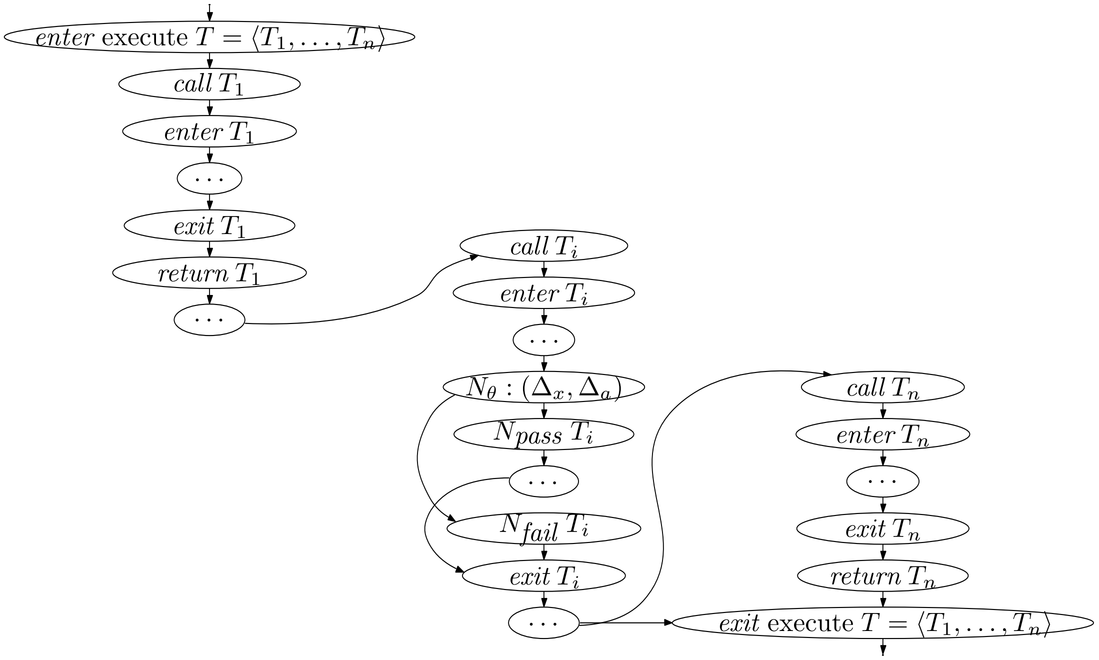


Figure 6.34: A Partial Interprocedural Control Flow Graph for a Test Suite.

Figure 6.34 depicts a partial ICFG for a test suite $T = \langle T_1, \ldots, T_n \rangle$. In an attempt to preserve simplicity, this schematic uses nodes with the label "…" to denote arbitrary ICFG nodes and edges. Figure 6.34 shows that the CFG G_{exec} contains nodes that transfer control to each of the test cases. For example, the edge ($\textit{enter}$ execute $T = \langle T_1, \ldots, T_n \rangle, \textit{call } T_1$) represents a transfer of control to test T_1 and the edge ($\textit{return } T_n, \textit{enter}$ execute $T = \langle T_1, \ldots, T_n \rangle$) indicates the completion of both T_n and the termination of the test execution method. Test case T_i's CFG $G_i = \langle \mathcal{N}_i, \mathcal{E}_i \rangle$ contains zero or more *test oracle execution* nodes $N_\theta \in \mathcal{N}_i$. The node N_θ corresponds to the execution of an oracle θ that compares the actual test state Δ_a to the expected test state Δ_x. If $\Delta_x = \Delta_a$, then the test oracle returns *true* and the successor node $N_{pass}\ T_i$ records the passing outcome of this test. If $\Delta_x \neq \Delta_a$, then the test oracle returns *false* and the successor node $N_{fail}\ T_i$ registers the failure of T_i. Figure 6.34 shows that the failure of the oracle at N_θ triggers the termination of test case T_i and then the halt of the entire test suite T. Whenever N_θ returns *true*, test suite execution continues until either all of the tests have correctly executed or an oracle failure is encountered.

6.5.2 Calculating Data Flow-Based Adequacy

Since a failing test case suggests that there is a defect in the program under test, we focus on calculating the adequacy of a passing test case T_i and test suite T. Focusing on the calculation of adequacy for a passing test suite is prudent because the failure of the program under test might prevent our instrumentation from capturing all of the covered test requirements. We classify a test case T_i as *passing* if all oracle nodes $N_\theta \in \mathcal{N}_i$ return *true* for a test CFG $G_i = \langle \mathcal{N}_i, \mathcal{E}_i \rangle$. A test suite $T = \langle T_1, \ldots, T_n \rangle$ is passing if all of T's test cases are also passing. The following Equation (6.7) provides the means for calculating $\textit{adeq}(T_i)$, the adequacy of a test case T_i. This equation shows that the adequacy of a test case T_i is the number of covered requirements divided by the total number of test requirements. This equation uses $\mathcal{U}(i)$ to denote the set of methods that are tested by test case T_i. During the static analysis that enumerates $\mathcal{U}(i)$, the test adequacy component follows the edges between adjacent test cases until it finds the CFG for T_i. For an interprocedural test CFG $G_T = \langle \Gamma_T, \mathcal{E}_T \rangle$, we know that $G_k \in \mathcal{U}(i)$ when *call* $m_k \in \mathcal{N}_i$ for a test case CFG $G_i \in \Gamma_T$. For example, Figure 6.33 reveals that test case T_i tests method m_k. Equation (6.7) uses $\upsilon(i,k)$ to denote the set of test requirements that T_i covered during the testing of method m_k and $\chi(k)$ to stand for the complete set of requirements for m_k.

$$adeq(T_i) = \frac{\sum_{G_k \in \mathcal{U}(i)} |\upsilon(i,k)|}{\sum_{G_k \in \mathcal{U}(i)} |\chi(k)|} \tag{6.7}$$

We traverse a test coverage monitoring tree in order to identify $\upsilon(i,k)$. For example, suppose that we test a database-centric application at the relation level (i.e., $\mathbf{R} \in \mathcal{L}(\tau)$) and method m_k contains a database interaction association involving relation rel_j (i.e., $\langle N_{def}, N_{use}, rel_j \rangle \in \chi(k)$). If T_i tests method m_k (i.e., $G_k \in \mathcal{U}(i)$) and it causes m_k to define and use rel_j, then we mark the database interaction association $\langle N_{def}, N_{use}, rel_j \rangle$ as covered. We know that the test covers this DIA if testing yields a TCM tree τ that contains the nodes $N_{R_1} = \langle rel_j, \mathbf{def} \rangle$ and $N_{R_2} = \langle rel_j, \mathbf{use} \rangle$ such that (i) *call* T_i is an ancestor of *call* m_k and (ii) *call* m_k is an ancestor of nodes N_{R_1} and N_{R_2}. In the context of data flow testing, we use the database-aware test adequacy component described in Chapter 5 to enumerate $\chi(k)$. For an interprocedural CFG $G_P = \langle \Gamma_P, \mathcal{E}_P \rangle$, Equation (6.8) defines the adequacy of an entire test suite T as the number of covered requirements divided by the total number of requirements over all methods $G_k \in \Gamma_P$.

$$adeq(T) = \frac{\sum_{G_k \in \Gamma_P} |\upsilon(k)|}{\sum_{G_k \in \Gamma_P} |\chi(k)|} \tag{6.8}$$

6.6 CONCLUSION

This chapter presents a database-aware coverage monitoring technique. We explain why it is challenging to (i) instrument a database-centric application and (ii) accurately and efficiently store the test coverage monitoring results. This chapter also introduces the database interaction dynamic call tree (DI-DCT) and the database interaction calling context tree (DI-CCT) and reveals how we use these trees to calculate the adequacy of a test suite. In particular, we provide a formal definition of each test coverage monitoring tree and we describe the instrumentation probes that construct a tree. We show how to insert database-aware instrumentation probes before and after the execution of both a program method and a database interaction. Finally, we explain how to use (i) an interprocedural representation of a program's test suite and (ii) the TCM tree in order to calculate adequacy on a per-test and per-test suite basis. Chapter 7 describes the implementation of the database-aware test coverage monitoring component and presents empirical performance results for this key element of our testing framework. Chapter 8 presents a regression testing technique that leverages the output of the test coverage monitor.

7.0 TEST COVERAGE MONITORING COMPONENT

7.1 INTRODUCTION

This chapter describes the test coverage monitoring component that (i) instruments a database-centric application and (ii) creates and stores a test coverage monitoring tree. We explain how the coverage monitor uses aspect-oriented programming (AOP) techniques to statically and dynamically instrument the program and the test suite. This chapter also shows how the monitoring component leverages existing compression algorithms to reduce the size of the coverage report. The chapter describes the goals and design for an experiment to measure the performance of our approach to database-aware test coverage monitoring. We conducted experiments to measure the time required to statically instrument the case study applications. We also performed experiments to identify the impact that the coverage monitoring instrumentation has on the static size of each application. Finally, we empirically evaluated how different configurations of the coverage monitor increase test suite execution time and we characterize the size and structure of the test coverage monitoring trees. In summary, this chapter includes:

1. A high level overview of the different configurations of the database-aware test coverage monitor (Section 7.2).
2. Details about the implementation of the instrumentation technique and the test coverage monitoring trees (Section 7.3)
3. The design of an experiment to measure the performance of the coverage monitor, an overview of the experimental results, and a discussion of the steps that we took to control the threats to experiment validity (Sections 7.4, 7.5, and 7.7).
4. An empirical evaluation of the costs that are associated with instrumenting the program and the test suite (Section 7.6.1) and monitoring coverage during test suite execution (Section 7.6.2).
5. An identification of the relationship between the size, structure, and compressibility of a TCM tree and the configuration of the coverage monitoring component (Sections 7.6.3 and 7.6.4)

7.2 OVERVIEW OF THE COVERAGE MONITORING COMPONENT

Figure 7.1 depicts the different ways that we can configure the test coverage monitoring component. This tree shows that we can introduce the instrumentation probes in either a dynamic or a static fashion, as

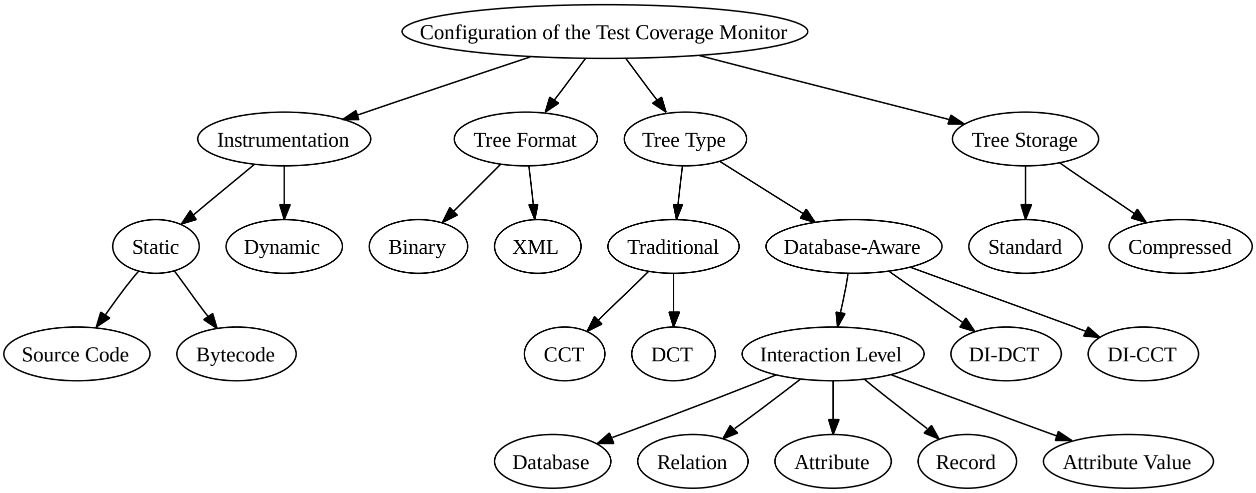


Figure 7.1: Different Configurations of the Test Coverage Monitoring Component.

discussed in Chapter 6. We use aspect-oriented programming (AOP) techniques and the AspectJ programming language in order to place the TCM probes before and after method calls and database interaction points [Elrad et al., 2001, Kiczales et al., 2001a]. Figure 7.1 shows that the use of AspectJ enables us to statically insert the instrumentation into either the source code or the Java bytecode of the case study applications. The dynamic instrumentation technique always places the coverage monitoring probes into the bytecode of a Java application. Our monitoring framework records coverage information in a TCM tree and the component can store this tree in either a binary or an eXtensible Markup Language (XML) format. Since we implemented the TCM component in the Java programming language, we use Java's serialization mechanism to store the trees in a binary format. The coverage monitor supports a binary format because this representation may result in reduced storage requirements [Geer, 2005].

Our testing framework also maintains the TCM trees in XML because this text-based encoding enables independence from execution environment factors such as the computer architecture, operating system, and programming language [Ferragina et al., 2006, Lin et al., 2005]. Since XML uses markup tags to express the structure of the TCM tree and the markup is repeated for each node, the trees often consume a significant amount of storage. However, several recently developed compression algorithms can substantially reduce the size of the trees that we encode in XML [Ferragina et al., 2006, Liefke and Suciu, 2000, Lin et al., 2005, Ng et al., 2006]. It is also possible to store the XML-based trees in an XML database (e.g., TIMBER [Jagadish et al., 2002]) and this would enable a tester to issue queries about the state and structure of the tree during the debugging process [Lin et al., 2005, Shasha et al., 2002]. For example, the tester might wish to determine which failing test case(s) interact with a certain relation or attribute in a database. Figure 7.1 shows that the coverage monitor can either produce a traditional tree (e.g., DCT or CCT) or a database-aware tree (e.g., DI-DCT or DI-CCT). If the tree is database-aware, then we must also configure the monitoring component to record coverage at a certain level of interaction granularity (e.g., relation or attribute value).

```
pointcut executeMethod():  chosenClass() && execution(* *(..));
```

(a)

```
pointcut chosenClass():  (within(gradebook.*) ||
within(org.hsqldb.sample.*) || within(reminder.*) ||
within(com.runstate.pithy.*) || within(student.*) ||
within(TransactionAgent.*));
```

(b)

```
before():  executeMethod() && if(monitorEnabled){ <...> }
```

(c)

Figure 7.2: AspectJ Pointcuts and Advice for the *Before* Instrumentation Probe.

7.3 IMPLEMENTATION OF THE COVERAGE MONITOR

7.3.1 Instrumentation

The AspectJ language supports the introduction of arbitrary code segments at certain join points within a Java application. A *join point* is a well-defined location in the control flow graph of a program. For example, AspectJ can identify join points related to the execution of (i) a method or a constructor, (ii) an exception handler, or (iii) a reference to a field of an object. We use AspectJ to define *pointcuts* that identify specific join points and the values that are available at these points. For example, Figure 7.2(a) describes the `executeMethod` pointcut that is part of the coverage monitoring framework. The `execution(* *(..))` portion of this pointcut indicates that we want AspectJ to monitor the execution of all the methods and constructors that occur within `chosenClass()`. Figure 7.2(b) shows that we currently define `chosenClass()` to include all of the case study applications that we described in Chapter 3. Figure 7.2(c) provides an example of *advice* that will be executed when the `executeMethod` pointcut occurs during test suite execution. The body of the advice for `executeMethod` can invoke the *Before* instrumentation probe that we defined in Chapter 6. The test coverage monitor contains additional pointcuts and `before` and `after` advice that we use to construct the DCT, CCT, DI-DCT, and DI-CCT. For more details about aspect-oriented programming and the AspectJ language, please refer to [Elrad et al., 2001, Kiczales et al., 2001a].

A single execution of the static instrumentor can introduce the monitoring probes into one or more case study applications. We say that the instrumentor operates in *batch mode* when it inserts TCM probes into multiple applications during a single run. Since static instrumentation normally increases the size of an application's bytecode, the coverage monitoring framework incorporates *compression algorithms* such as Pack [Pugh, 1999]. This compression technique is specifically designed to reduce the size of Java bytecodes and it is now fully integrated into the Java 1.5 libraries and virtual machine. Bytecode compression techniques reduce the cost of transmitting the statically instrumented application across a network or storing it on a file system. Figure 7.3 provides an overview of the dynamic instrumentation process. Our goal is to correctly instrument the program and the test suite with minimal time overhead. The static instrumentation technique places

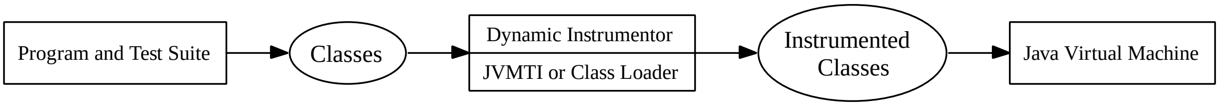


Figure 7.3: Overview of the Dynamic Instrumentation Process.

probes into the all of the classes of the program and the test suite. Currently, we use a load-time technique to dynamically instrument the program and the tests on a per-class basis. Identifying the appropriate unit of instrumentation is a trade-off between (i) instrumenting only those program units that are actually executed during testing and (ii) minimizing the number of calls to the dynamic instrumentation module.

Relying on per-class instrumentation could inefficiently force the insertion of TCM probes into methods that will never be used during test suite execution. However, our per-class instrumentation scheme is simple and it greatly minimizes the number of separate invocations of the instrumentor. Per-class instrumentation is also an efficient approach when the test suite invokes the majority of the methods within the case study application. We judge that it is likely that the tests will execute most of the program's methods since method coverage is often used to measure the adequacy of a test suite [Zhu et al., 1997]. Figure 7.3 shows that the current prototype uses either the Java Virtual Machine Tool Interface (JVMTI) or a custom Java class loader to introduce the probes. Prior testing and analysis techniques frequently use one or both of these interfaces (or, the JVMTI's precursor, the JVM Profiler Interface) during the instrumentation or observation of a Java program (e.g., [Binder, 2005, Dufour et al., 2003, Zhuang et al., 2006]). We will investigate the different granularities at which we can introduce instrumentation in future work, as further discussed in Chapter 9. We designed the dynamic instrumentor so that it only places probes in the classes that are a part of the program and the test suite.

7.3.2 Tree Format and Storage

Since the test coverage monitoring trees record the behavior of the program during testing, they must be stored in order to support debugging and/or automatic fault localization. We performed experiments to determine how the encoding of a test coverage monitoring tree would impact the size of the trees. Our preliminary experimental results suggested that the binary encoding was more compact than the text-based XML representation for the same TCM tree. For example, a dynamic call tree that represents ten method invocations was 1497 bytes when stored in a binary format and 9762 bytes in XML. For this simple TCM tree, the XML encoding yields a file size that is 552% greater than the binary representation. The experimental results in Section 7.6 suggest that the difference between the two representations is even more marked for larger coverage monitoring trees. However, recent empirical results reveal that XML files often exhibit better compressibility than binary files [Liefke and Suciu, 2000]. In fact, several of our experiments also demonstrate that the XML-aware compression techniques yield an XML-based tree that is smaller than the compressed version of the binary tree. Finally, recent XML compression algorithms create a compressed format that enables a tester to query the compressed XML file without completely decompressing the tree

[Lin et al., 2005, Ferragina et al., 2006]. In an attempt to (i) reduce storage requirements and (ii) speed up the network transmission of the coverage reports, we leverage traditional compression algorithms such Gzip and Zip [Lelewer and Hirschberg, 1987, Morse, 2005] to compress the binary trees and we use XMill [Liefke and Suciu, 2000] and XMLPPM [Cheney, 2001] to shrink the XML trees.[1]

7.4 EXPERIMENT GOALS AND DESIGN

The primary goal of the experiments is to measure the performance of the test coverage monitoring component. Section 7.6 formally defines each evaluation metric and then describes the results from applying the TCM component to each of the case study applications. We implemented the current version of the test coverage monitor with the Java 1.5 and AspectJ 1.5 programming languages. Even though our implementation of the TCM component supports dynamic instrumentation with either the JVM tools interface or a custom class loader, the experiments focus on measuring the performance of the class loading approach. Since most Java virtual machines (e.g., the Sun JVM and the Jikes RVM) use the same type of class loader interface, this choice ensures that our experimental results are more likely to generalize to other execution environments. We also designed the experiment in this manner because our preliminary results revealed that the "heavy weight" JVMTI introduced significant time overheads, in confirmation of prior results [Popovici et al., 2002]. In future work we will also evaluate the performance of dynamic instrumentation with the JVMTI and recent JVM-based techniques that dynamically introduce the instrumentation (e.g., [Bockisch et al., 2006, Golbeck and Kiczales, 2007]). We configured the static instrumentation technique to operate on the bytecode of a case study application. In future research, we will evaluate the performance of statically instrumenting the (i) Java source code and (ii) different combinations of source code and bytecode.

Since the time overhead metrics varied across each trial, we calculate arithmetic means and standard deviations for all of these timings (the space overhead and tree characterization metrics did not vary across trials). The standard deviation measures the amount of dispersion in the recorded data sets and higher values for this descriptive statistic suggest that the data values are more dispersed. When we plot a bar chart, we place a standard deviation error bar at the top of the bar and we use a diamond when the standard deviation is small. We also use a box and whisker plot to visually compare the experiment results from different configurations of the coverage monitor. Unless specified otherwise, the box spans the distance between the 25% and 75% *quantile* and the whiskers extend to cover the non-outlying data points. The qth quantile is the point at which q% of the recorded data points fall below and $1 - q$% fall above a specific data value. Our box and whisker plots represent data outliers with small square shaped points. We plot an *empirical cumulative distribution function* (ECDF) to support further examination of a data set. An ECDF gives the cumulative percentage of the recorded data set whose values fall below a specific value. For more details about these statistical analysis and visualization techniques, please refer to [Dowdy et al., 2004].

[1] XMill and XMLPPM do not directly support the querying of a compressed XML file. We were not able to use the compression techniques that provide this functionality (e.g., [Lin et al., 2005, Ferragina et al., 2006]) because they were not freely distributed at the time of writing.

We performed all of the experiments on a GNU/Linux workstation with kernel 2.6.11-1.1369, a dual core 3.0 GHz Pentium IV processor, 2 GB of main memory, and 1 MB of L1 processor cache. In order to improve performance, we implemented portions of the TCM component in a multi-threaded fashion and we configured the workstation to use the Native POSIX Thread Library (NPTL) version 2.3.5. We always executed the static instrumentor in ten separate trials for each case study application. For each possible configuration of the coverage monitor (c.f. Figure 7.1), we ran the test suite ten times. Section 7.6 provides a definition of each evaluation metric and explains how we measured it during experimentation. Table C2 summarizes each of these metrics and Table A14 explains the additional notation that we use during the discussion of the experimental results.

7.5 KEY INSIGHTS FROM THE EXPERIMENTS

The experimental results in Section 7.6 complement Chapter 6's analytical evaluation of the TCM instrumentation probes. Due to the comprehensive nature of our empirical evaluation, we offer the following insights from the experiments:

1. **Static Instrumentation**
   a. *Time Overhead*: The static instrumentation technique requires less than six seconds to insert coverage probes into a database-centric application. A batch approach to instrumentation can attach the probes to six applications in less than nine seconds. Across all applications, the instrumentation of a program and its test suite requires no more than five seconds.
   b. *Space Overhead*: For all of the studied applications, static instrumentation increases the space overhead by 420% on average. We judge that this increase is acceptable because it successfully controls the time overhead of coverage monitoring.
2. **Test Suite Execution**
   a. *Type of Instrumentation*: The use of statically introduced probes lengthens testing time by 12.5% while dynamic instrumentation causes a 52% increase in test execution time.
   b. *Type of Coverage Tree*: Calling context trees are less expensive to produce than the dynamic call tree. Using static instrumentation to create a TCM tree respectively increases testing time by 12.5% and 26.1% for the CCT and DCT.
   c. *Interaction Level*: Using a CCT to record coverage at the finest level of database interaction granularity (e.g., attribute value) only increases testing time by 54%.
   d. *Storing the Coverage Tree*: The time required for tree storage ranges from less than 200 milliseconds for the binary CCT to three seconds for the XML-based DCT.
3. **Test Coverage Trees**
   a. *Number of Nodes and Edges*: The CCT has node and edge counts that range from 144 at the program level to 22992 at the level of attribute values. The number of DCT nodes ranges from a minimum of 433 to a maximum of 87538.

b. *Memory Size*: The in-memory size of the TCM trees ranges from 423 KB to almost 24 MB. Small TCM trees place little, if any, pressure on the memory subsystem of the JVM while the largest trees require an increase in heap storage space.

c. *File System Size*: The XML encoding yields TCM trees that are larger than the binary encoding of the same tree. Yet, XML-aware compression algorithms can considerably reduce the size of the coverage report.

d. *Tree Characterization*: The coverage trees are normally "short" and "bushy," in confirmation of previous empirical studies [Ammons et al., 1997]. A DI-CCT at the finest level of database interaction granularity often consumes less space overhead than a traditional DCT.

7.6 ANALYSIS OF THE EXPERIMENTAL RESULTS

7.6.1 Instrumentation

The static instrumentor can insert the coverage monitoring probes into one or more applications. We measure $\mathcal{T}_{instr}(\mathcal{A})$, the time required to statically instrument the applications in the set $\mathcal{A}$. For example, if $\mathcal{A} = \{\texttt{FF}\}$, then the TCM component will introduce the probes into the `FindFile` case study application. Alternatively, if $\mathcal{A}' = \{\texttt{FF}, \texttt{GB}, \texttt{TM}\}$, then the instrumentation module operates in batch mode and places probes into the `FindFile`, `GradeBook`, and `TransactionManager` applications. We report the increase and percent increase in $\mathcal{T}_{instr}$ when we perform static instrumentation with the application set $\mathcal{A}'$ instead of $\mathcal{A}$ and $\mathcal{A} \subset \mathcal{A}'$. Equation (7.1) defines the increase in $\mathcal{T}_{instr}$ when we replace the application set $\mathcal{A}$ with $\mathcal{A}'$. Equation (7.2) defines the percent increase in evaluation metric $\mathcal{T}_{instr}$, denoted $\mathcal{T}^{\%I}_{instr}(\mathcal{A}', \mathcal{A})$. We compute the time overhead metrics $\mathcal{T}_{instr}$ with the operating system-based timer `/usr/bin/time`.

$$\mathcal{T}^{I}_{instr}(\mathcal{A}', \mathcal{A}) = \mathcal{T}_{instr}(\mathcal{A}') - \mathcal{T}_{instr}(\mathcal{A}) \tag{7.1}$$

$$\mathcal{T}^{\%I}_{instr}(\mathcal{A}', \mathcal{A}) = \frac{\mathcal{T}^{I}_{instr}(\mathcal{A}', \mathcal{A})}{\mathcal{T}_{instr}(\mathcal{A})} \times 100 \tag{7.2}$$

We use T_s and A_s to denote a test suite and an application that were statically instrumented and we say that T_d and A_d are tests and an application that we dynamically instrument. We evaluate $\mathcal{S}(A)$ and $\mathcal{S}(A_s)$, the respective size of an application A before and after static instrumentation. Finally, we report $\mathcal{S}(A, c)$ and $\mathcal{S}(A_s, c)$ the size of applications A and A_s when compressed with compression technique c. Currently, our framework can compress Java bytecodes using Zip [Lelewer and Hirschberg, 1987], Gzip [Morse, 2005], and Pack [Pugh, 1999]. We also compute the increase and percent increase in space overhead associated with the static instrumentation, respectively denoted $\mathcal{S}^{I}(A_s, A)$ and $\mathcal{S}^{\%I}(A_s, A)$ (we use equations similar to Equations (7.1) and (7.2) in order to calculate these values). Since dynamic instrumentation occurs during test suite execution, we do not explicitly measure the increase in space overhead that results from inserting the instrumentation probes.[2]

[2] The Sun JVM that we used during experimentation does not include facilities to report the in-memory size of Java bytecode or the native code that results from just-in-time (JIT) compilation. As discussed in Chapter 9, we will explore the use of the Jikes RVM and the experiment design developed in [Zhang and Krintz, 2005] in order to measure $\mathcal{S}(A_d)$.

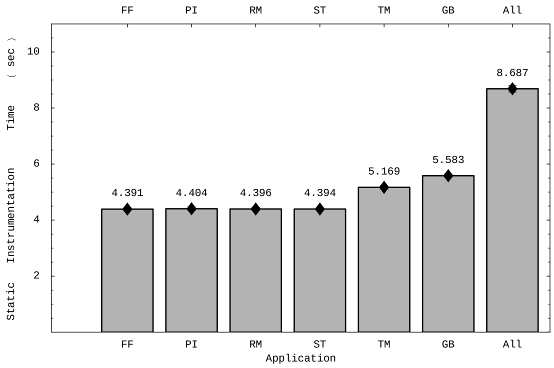


Figure 7.4: Static Instrumentation Time.

7.6.1.1 Instrumentation Time Overhead Figure 7.4 presents the time overhead associated with the static instrumentation of the case study applications. The results show that $\mathcal{T}_{instr}$ is never more than approximately 4.5 seconds and the instrumentation process exhibits little variability. For example, ten executions of the instrumentor on the `ST` application yielded a mean instrumentation time of 4.4 seconds with a standard deviation of .04 seconds. Figure 7.4 also provides the static instrumentation time results for the larger case study applications (i.e., `TM` and `GB`) and a batch execution of the instrumentor. For the box labeled "All," we configured the static instrumentation technique to introduce probes into all of the case study applications. Our experiments reveal that the instrumentation of a larger application (e.g., `GB`) incurs one additional second of time overhead when compared to instrumenting a smaller application (e.g., `FF`). Since we can instrument all of the case study applications is 9 seconds or less, the results in Figure 7.4 also suggest that we can efficiently instrument more than one application with a single run of the instrumentor. If we take $\mathcal{A} = \{\texttt{ST}\}$ and $\mathcal{A}'$ as the set of all applications, then we know that $\mathcal{T}_{instr}^{\%I}(\mathcal{A}', \mathcal{A}) = 97\%$ for the instrumentation of six applications instead of one. Across all of the case study applications, static instrumentation takes 4.72 seconds on average. In summary, we judge that our approach to static instrumentation introduces the instrumentation probes with minimal time overhead.

7.6.1.2 Instrumentation Space Overhead We use A_s to denote the statically instrumented version of an application A. A_s includes additional bytecode instructions at the boundaries of all method invocations and database interactions. The static instrumentor also outputs an archive that contains the bytecode of the coverage monitoring probes. In preparation for a call to the *Before* probe, the instrumentation must (i) store the contents of the program stack in local variables, (ii) check to ensure that coverage monitoring is enabled, (iii) load the probe, and (iv) invoke the probe. The instrumentor also adds additional bytecode instructions to handle any exceptions that might be thrown by a coverage monitoring probe (e.g., we use exception handlers to manage the problems that occur when the storage of the TCM trees exceeds the space available for file storage). We disassembled each of the case study applications in order to discern how many additional instructions were needed to use the test coverage monitoring probes. For example, the

Compression Technique	Before Instr (bytes)	After Instr (bytes)
None	29275	887609
Zip	15623	41351
Gzip	10624	35594
Pack	5699	34497

Table 7.1: Average Static Size Across All Instrumented Case Study Applications.

Compression Technique	Probe Size (bytes)
None	119205
Zip	40017
Gzip	34982
Pack	35277

Table 7.2: Size of the Test Coverage Monitoring Probes.

constructor for the `org.hsqldb.sample.FindFile` class contains three bytecode instructions in the initial version of `FindFile` and twenty-seven after static instrumentation (Figures B1 and B2 in Appendix B provide the bytecode for this constructor). A noteworthy design choice of the AspectJ compiler is that it accepts an increase in static application size for a reduction in execution time by always using additional bytecode operations instead of Java's reflection mechanism [Hilsdale and Hugunin, 2004, Kiczales et al., 2001b]. We attribute the marked increase in the number of bytecode instructions, and thus the $S(A_s)$ metric, to this design choice. Section 7.6.2 offers further investigation of this trade-off between time and space overhead.

Figure 7.5 presents the size of each case study application before and after the introduction of the calls to the instrumentation probes. In these graphs, the bar grouping with the label "ZIP" corresponds to the size of a traditional Java archive (JAR) file that contains the application's bytecodes. The "GZIP" and "PACK" labels refer to the size of A or A_s after we applied the Gzip and Pack compression algorithms. Since Java applications are normally distributed in archives, we only report the size of the uncompressed bytecodes in the summary results of Tables 7.1 and 7.2. The graphs in Figure 7.5 reveal that statically inserting the instrumentation probes increases the space overhead of the case study applications. For example, Figure 7.5(f) shows that $\mathcal{S}(\mathtt{GB}_s) = 75782$ bytes and $\mathcal{S}(\mathtt{GB}) = 25084$ bytes such that $\mathcal{S}^{\%I}(\mathtt{GB}_s, \mathtt{GB}) = 202\%$ when we use the Zip compression algorithm. Figure 7.5(b) indicates that the `FindFile` case study application has the smallest bytecodes since $\mathcal{S}(\mathtt{FF}) = 10748$. This graph also shows that the size of `FindFile`'s bytecode increases to 33304 bytes after we insert the calls to the TCM probes so that $\mathcal{S}^{\%I}(\mathtt{FF}_s, \mathtt{FF}) = 209\%$.

Table 7.1 shows the average size, across all case study applications, of the bytecodes before and after the execution of the static instrumentor. These results reveal that the Pack compression algorithm is the most effective at controlling the increase in the space overhead of an instrumented application. Using Pack

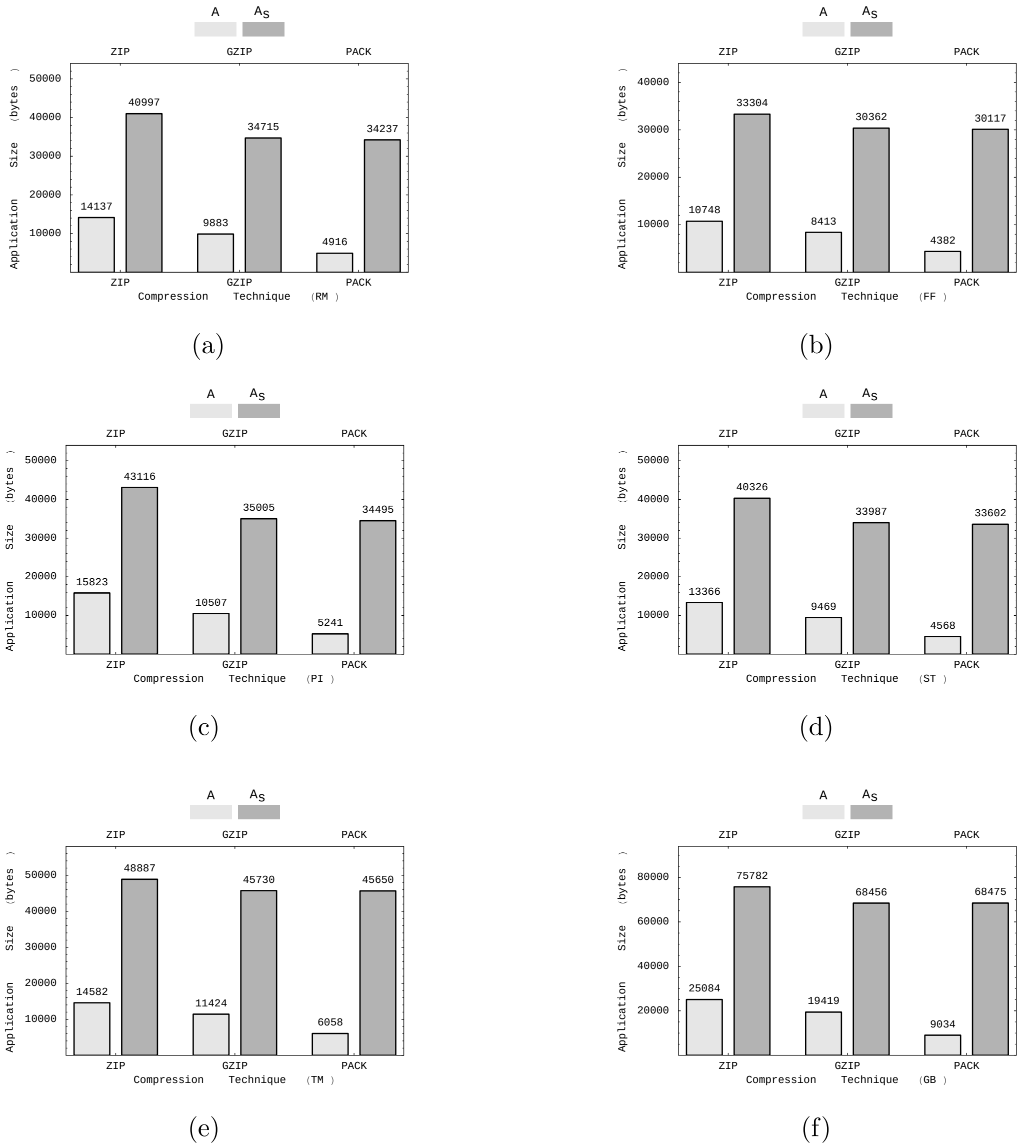


Figure 7.5: Size of the Statically Instrumented Applications.

Application	$\mathcal{T}^{\%I}_{exec}(\langle T_s, A_s, \tau_{cct}\rangle, \langle T, A\rangle)$
PI	18.45
ST	14.75
TM	15.67
GB	9.9

Table 7.3: Percent Increase in Testing Time when Static Instrumentation Generates a CCT.

compression instead of no compression yields a 96% reduction in the size of the instrumented applications. We also observe that the Pack compressor reduces the bytecode size of the non-instrumented applications by 80.5%. This result suggest that statically instrumented applications are more compressible than those that were not instrumented. The difference in these reduction percentages is due to the fact that A_s repetitively uses the same bytecode instructions when it invokes the TCM probes.

Table 7.2 gives the size of the compressed archive that contains the test coverage monitoring probes. Since we do not have to customize the probes for a specific database-centric application, the Java virtual machine always consults these probes when an application invokes any instrumentation. Our experiment results demonstrate that the Gzip and Pack algorithms are best suited for reducing the size of the coverage monitoring probes. Employing either Gzip or Pack instead of no compression leads to a 70% reduction in the static size of the instrumentation probes. If we consider the use of Zip compression and the overall size of an instrumented application (i.e., the compressed size of A_s plus the compressed size of the probes), then the use of static TCM instrumentation increases space overhead by 420% on average across all applications. However, the results in Section 7.6.2 suggest that the noticeable increase in space overhead is acceptable because it supports efficient test coverage monitoring.

7.6.2 Test Suite Execution Time

We conducted experiments to measure $\mathcal{T}_{exec}(T, A)$, the time required to test application A with test suite T. Since $\mathcal{T}_{exec}(T, A)$ corresponds to the execution of T and A without any test coverage monitoring instrumentation, we use this metric to establish a base line for testing time. Following the notation established in Chapter 6, we define $L \in \mathcal{L}(\tau)$ as the level of database interaction granularity at which the TCM component will record coverage information. We use $\mathcal{L}(\tau) = \{\mathbf{P}, \mathbf{D}, \mathbf{R}, \mathbf{A}, \mathbf{R_c}, \mathbf{A_v}\}$ and we take $\mathbf{P}$ as the coverage marker that causes the creation of a traditional coverage tree (e.g., a DCT or a CCT). The use of any marker $L \in \mathcal{L}(\tau) \setminus \{\mathbf{P}\}$ leads to the construction of a database-aware TCM tree (e.g., a DI-DCT or a DI-CCT). We measure $\mathcal{T}_{exec}(T_s, A_s, \tau)$, the time required to perform testing and generate the TCM tree τ during the execution of the statically instrumented program and test suite (we define $\mathcal{T}_{exec}(T_d, A_d, \tau)$ in an analogous fashion). As in Chapter 6, we use τ_{cct} and τ_{dct} to differentiate between the calling context and dynamic TCM trees that the coverage monitor generates. We compute $\mathcal{T}_{exec}$ with the operating system-based timer `/usr/bin/time`.

Instrumentation Technique	**Tree Type**	**TCM Time (sec)**	**Percent Increase** (%)
Static	CCT	7.44	12.5
Static	DCT	8.35	26.1
Dynamic	CCT	10.17	53.0
Dynamic	DCT	11.0	66.0

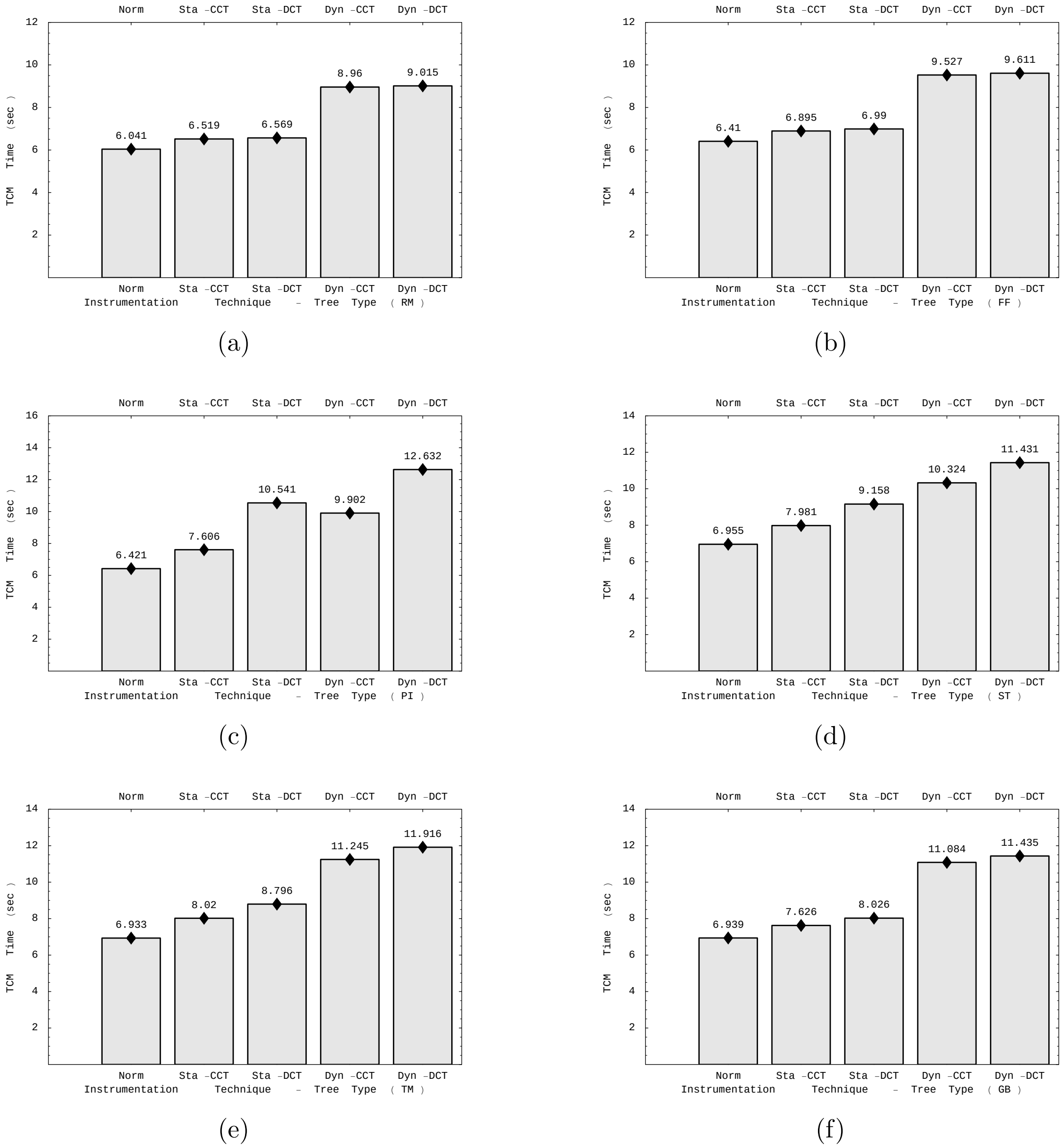
Normal Average Testing Time: 6.62 sec

Table 7.4: Average Test Coverage Monitoring Time Across All Case Study Applications.

In order to compare the performance of the TCM component when we vary the type of instrumentation and the TCM tree, we calculate the increase and percent increase when we perform testing with statically introduced probes instead of no instrumentation. We also report the increase and percent increase in testing time when we use dynamically inserted probes rather than using no instrumentation. For a fixed instrumentation technique, we use equations similar to Equations (7.1) and (7.2) to calculate the increase and percent increase in test suite execution time when a finer interaction granularity L' is used instead of L (e.g., $L' = \mathbf{A_v}$ and $L = \mathbf{D}$). Since the test coverage monitor stores the TCM tree after executing the tests, we measure $\mathcal{T}_{store}(T, A, \tau)$, the time required to maintain application A's coverage tree τ.

7.6.2.1 Static and Dynamic Instrumentation Costs For the experiments that measured $\mathcal{T}_{exec}$, we initially configured the TCM component to generate a traditional TCM tree (e.g., $L = \mathbf{P}$) and we stored all of the trees in the binary representation. During these experiments we systematically varied the type of tree (e.g., DCT or CCT) and the type of instrumentation (e.g., static or dynamic). The "Norm" label in Figure 7.6 refers to the testing time for a case study application when we did not monitor coverage. The labels "Sta" or "Dyn" respectively refer to the use of static or dynamic instrumentation. Figure 7.6(a) and Figure 7.6(b) reveal that static test coverage monitoring does not introduce a noticeable time overhead for the small case study applications like `RM` and `FF`. For example, we observe that $\mathcal{T}_{exec}(T, \texttt{FF}) = 6.41$ seconds and $\mathcal{T}_{exec}(T_s, \texttt{FF}_s, \tau_{cct}) = 6.90$ seconds and this represents a percent increase in testing time of only 7.57%. The results in Figure 7.6(a) and Figure 7.6(b) also suggest that there is little difference in the time overhead required to create a CCT or a DCT. However, the experiments indicate that even the small applications do demonstrate an increase in testing time when we use dynamic instrumentation instead of statically introducing the probes. For example, Figure 7.6(a) shows that $\mathcal{T}_{exec}(T_s, \texttt{RM}_s, \tau_{cct}) = 6.52$ seconds and $\mathcal{T}_{exec}(T_d, \texttt{RM}_d, \tau_{cct}) = 8.96$ seconds and this corresponds to a 37.44% increase in test suite execution time.

The experimental results in Figure 7.6 suggest that the larger case study applications (e.g., `PI`, `ST`, `TM`, and `GB`) do exhibit a difference in testing time when the statically introduced instrumentation creates a CCT. However, Table 7.3 shows that the value for $\mathcal{T}^{\%I}_{exec}(\langle T_s, A_s, \tau_{cct}\rangle, \langle T, A\rangle)$ ranges between 9% and 19% for these applications. Figure 7.6 also reveals that the flexibility afforded by dynamic instrumentation increases testing time of the larger applications from 6 seconds to approximately 12 seconds. For applications such as `GB`,



(a) (b) (c) (d) (e) (f)

Figure 7.6: Test Coverage Monitoring Time with Static and Dynamic Instrumentation.

CCT Interaction Level	**TCM Time (sec)**	**Percent Increase (%)**
Program	7.44	12.39
Database	7.51	13.44
Relation	7.56	14.20
Attribute	8.91	34.59
Record	8.90	34.44
Attribute Value	10.14	53.17

Normal Average Testing Time: 6.62 sec

Table 7.5: Average TCM Time Across All Applications when Granularity is Varied.

we observe an acceptable percent increase in testing time since $\mathcal{T}^{\%I}_{exec}(\langle T_d, \texttt{GB}_d, \tau_{cct}\rangle, \langle T, \texttt{GB}\rangle) = 59.28\%$ and $\mathcal{T}^{\%I}_{exec}(\langle T_d, \texttt{GB}_d, \tau_{cct}\rangle, \langle T_s, \texttt{GB}_s, \tau_{cct}\rangle) = 45.34\%$. We also note that the graphs in Figure 7.6(d) - (f) demonstrate a "stair step" trend in testing time as the horizontal axis transitions from normal testing to dynamic testing with the DCT. These results indicate that, for many database-centric applications, normal testing will incur the least time overhead and dynamic testing that produces a DI-DCT will require the most test execution time.

Interestingly, Figure 7.6(c) shows that the `PI` application exhibits higher time overheads for the static DCT configuration than the dynamic CCT approach to coverage monitoring. We attribute this to the fact that the `PI` test suite has tests that repeatedly executed a method (e.g., `testMultipleAddIterativeLarge`).[3] This type of testing behavior causes the TCM component to perform many more updates to τ_{dct} than to τ_{cct} and this increases the time that it must devote to node creation and tree maintenance. For the `PI` case study application, the time for coverage tree manipulation dominates the time needed to dynamically introduce the instrumentation probes. This experimental outcome reveals that the use of the CCT to record coverage information can result in better performance for applications that frequently use iteration during testing. Even though the majority of our programs do not heavily rely upon recursive methods, we anticipate similar performance results for this type of database-centric application. Finally, Table 7.4 shows that normal testing time, across all case study applications, is 6.62 seconds. This table points out that our coverage monitoring techniques increase testing time by approximately 12% to 66%, depending upon the technique and tree type used by the TCM component. When $L = \mathbf{P}$, we judge that our approach to test coverage monitoring demonstrates time overheads that are comparable to other TCM schemes (e.g., [Misurda et al., 2005, Pavlopoulou and Young, 1999, Tikir and Hollingsworth, 2002]).

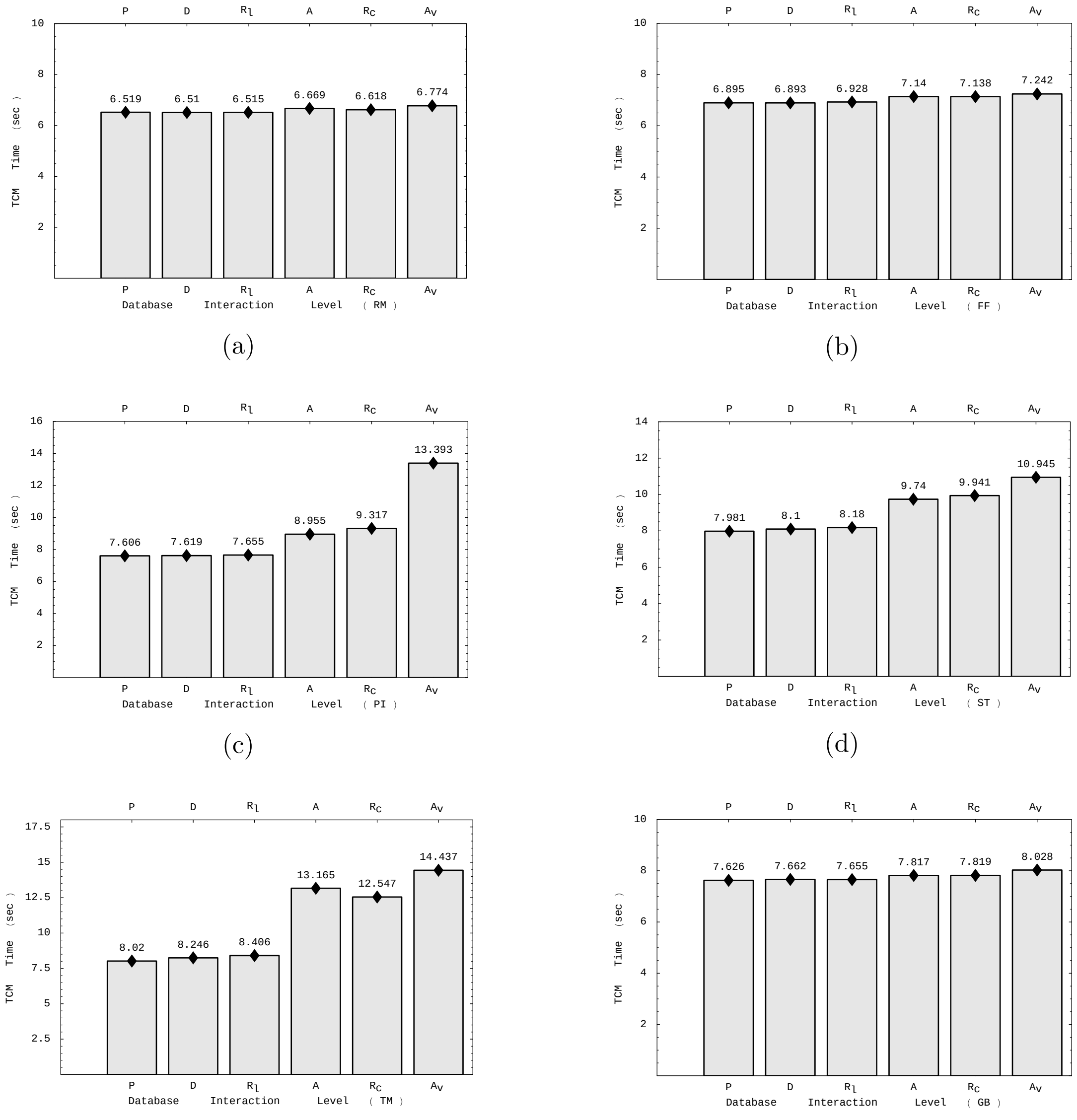
7.6.2.2 Varying Database Interaction Granularity We conducted experiments in order to ascertain how the variation of database interaction granularity would impact the time overhead of testing. For these

[3] The tests for other case study applications such as `ST` and `TM` also use iteration constructs. However, none of these applications exhibit such a pronounced use of iteration during testing.

experiments, we always used static instrumentation and we stored all of the trees in the binary representation. These experiments also focused on the use of the CCT to record coverage information. As shown on the horizontal axis of the graphs in Figure 7.7, we executed the test coverage monitor for all applications and all levels of database interaction granularity (e.g., $L = \mathbf{P}$ through $L = \mathbf{A_v}$). For several applications such as RM, FF, and GB, we observe that there is only a small increase in test coverage monitoring time when we vary the database interaction level. For example, the value of $\mathcal{T}_{exec}^{\%I}(\langle T_s, A_s, \tau_{cct}, \mathbf{A_v}\rangle, \langle T_s, A_s, \tau_{cct}, \mathbf{P}\rangle)$ is less than 6% for RM, FF, and GB. This is due to the fact that a test case for these applications normally interacts with a minimal number of entities in the relational database. In light of the fact that GB is the largest application in terms of non-commented source statements (NCSS), it is clear that we cannot predict test coverage monitoring time by solely focusing on the static size of the source code.

Figure 7.7(c) and (d) demonstrate that the PI and ST applications exhibit a marked increase in testing time as the database interaction granularity transitions from the program to the attribute value level. Testing time increases because both PI and ST iteratively interact with a large portion of the relational database and this type of testing behavior necessitates the insertion of more nodes into the TCM tree. PI shows a more noticeable increase at the attribute value level than ST because it interacts with a relation that has three attributes while ST's relation only contains two attributes (see Figures 3.9 and 3.10 in Section 3.5.2 for a description of the relational schema for the databases that PI and ST respectively use). Even though $\mathcal{T}_{exec}(T_s, A_s, \tau_{cct}, \mathbf{A_v})$ is 13.40 for PI and 10.95 for ST, the coarser levels of database interaction (e.g., database and relation) only introduce minimal testing time overhead. Figure 7.7(e) reveals that $\mathcal{T}_{exec}(T_s, \mathtt{TM}_s, \tau_{cct}, \mathbf{A}) > \mathcal{T}_{exec}(T_s, \mathtt{TM}_s, \tau_{cct}, \mathbf{R_c})$ because TM interacts with a relation that normally contains more attributes that records during test suite execution. Table 7.5 provides the average value of $\mathcal{T}_{exec}$ across all case study applications when we varied the database interaction granularity. These results indicate that we can efficiently monitor coverage at all levels of interaction if we use static instrumentation to construct a database-aware calling context tree. For example, coverage monitoring at the relation level only incurs a 14.20% increase in testing time and the TCM component can record coverage at the attribute value level with a 53.17% increase in time overhead.

7.6.2.3 Storage Time for the TCM Tree Since the TCM component must store the test coverage tree after the completion of testing, we also performed experiments to measure $\mathcal{T}_{store}(T, A, \tau)$. During these experiments we always used static instrumentation. Employing either static or dynamic instrumentation yielded similar results because the TCM component that stores the coverage trees is not subject to instrumentation. In an attempt to establish a performance baseline, we configured the TCM component to produce τ when $L = \mathbf{P}$. We also investigated the variation in tree storage time when the test coverage monitor generated either a CCT or a DCT in the binary or XML representation. Table 7.6 provides the average TCM tree storage time across all of the case study applications. The results in this table suggest that the coverage monitor can store the binary tree in less time than the XML tree. For example, $\mathcal{T}_{store}^{bin}(T, A, \tau_{cct}) = 144.9$ milliseconds and $\mathcal{T}_{store}^{xml}(T, A, \tau_{cct}) = 408.17$ milliseconds. Figure 7.8 records the



(a) (b) (c) (d) (e) (f)

Figure 7.7: Test Coverage Monitoring Time at Different Database Interaction Levels.

Tree Type	Tree Representation	Tree Storage Time (msec)
CCT	Binary	144.9
DCT	Binary	1011.72
CCT	XML	408.17
DCT	XML	2569.22

Table 7.6: Average TCM Tree Storage Time Across All Case Study Applications.

number of milliseconds that were required to store the TCM tree in the four different configurations (i.e., CCT-Bin, DCT-Bin, CCT-XML, and DCT-XML). Figure 7.8(a), (b), and (f) exhibit an increase in $\mathcal{T}_{store}$ as we transition from CCT-Bin to DCT-XML on the horizontal axis. This is due to the fact that the test suites for RM, FF, and GB do not make heavy use of either iteration or recursion and thus the CCT probes do not enable a significant reduction in either the tree size or $\mathcal{T}_{store}$. For this type of case study application, the chosen representation has a greater impact upon tree storage time than the type of the TCM tree. We also observe that $\mathcal{T}_{store}$ is less than one second for RM and FF and below two seconds for GB.

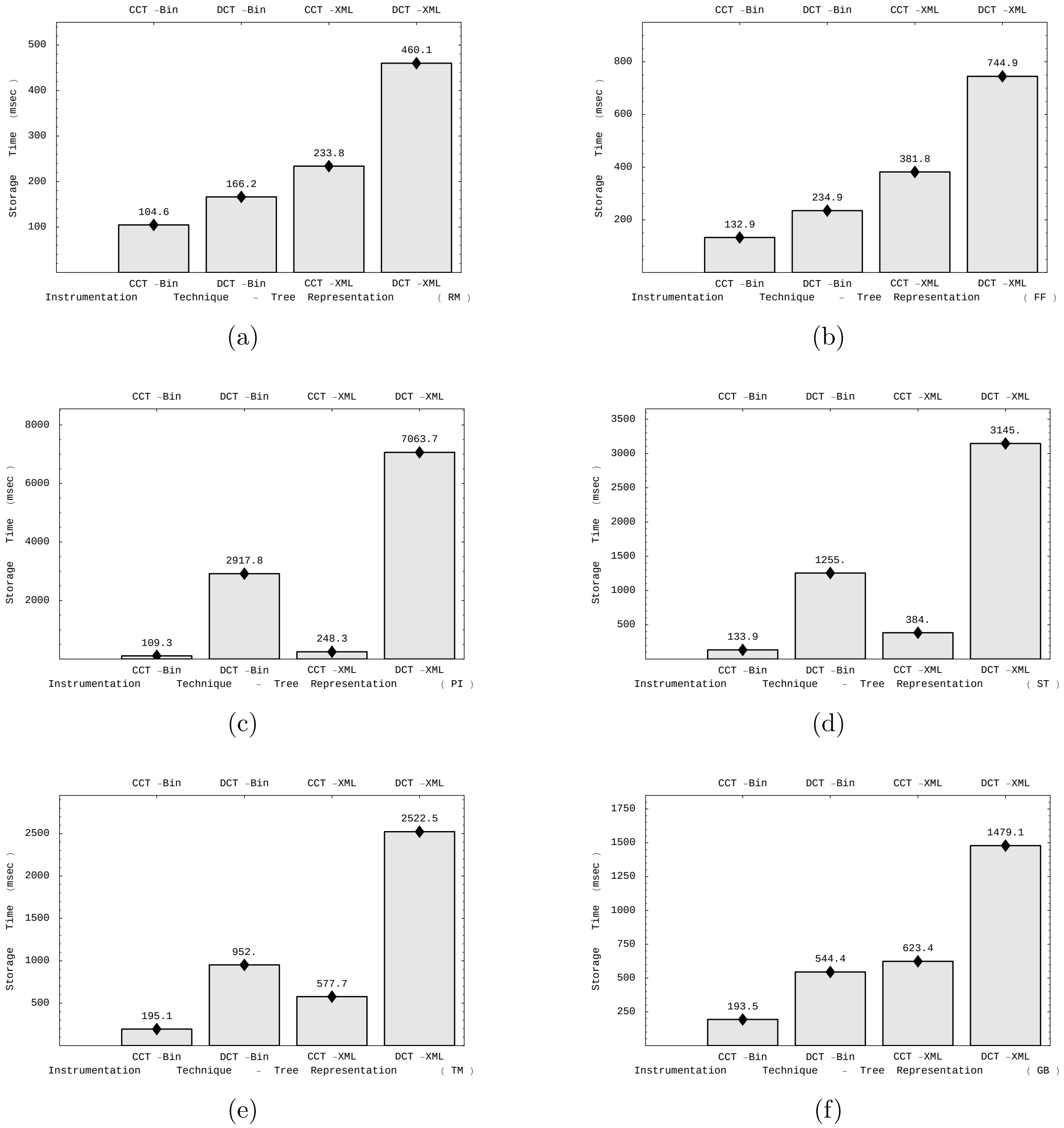
The PI, ST, and TM case study applications use iteration constructs during testing (as discussed in Section 7.6.2.1, the tests for PI use more iteration than the tests for any other application). When the TCM component records the coverage with τ_{cct} instead of τ_{dct}, it coalesces nodes and reduces the overall size of the tree. This characteristic of the CCT yields binary and XML TCM trees that are significantly smaller than their DCT counterparts. For example, Figure 7.8(e) demonstrates that $\mathcal{T}^{xml}_{store}(T, \texttt{TM}, \tau_{cct}) = 577.7$ milliseconds while $\mathcal{T}^{bin}_{store}(T, \texttt{TM}, \tau_{cct}) = 952$ milliseconds. As anticipated, this trend is more pronounced for the PI application such that $\mathcal{T}^{bin}_{store}(T, \texttt{PI}, \tau_{cct}) = 248.3$ milliseconds and $\mathcal{T}^{xml}_{store}(T, \texttt{PI}, \tau_{dct}) = 2917.8$ milliseconds. If an application or its tests makes frequent use of iteration and/or recursion, the experiments reveal that the type of the tree will have a more pronounced influence on storage time than the tree encoding.

7.6.3 Tree Space Overhead

We used the test coverage monitor to create a TCM tree for each case study application and then we calculated platform-independent and platform-dependent measures of tree space overhead. In support of measurements that are independent of both the programming language and the execution environment, we calculate $\mathcal{S}_{\mathcal{N}}(A, \tau, L)$ and $\mathcal{S}_{\mathcal{E}}(A, \tau, L)$, the respective number of nodes and edges in a TCM tree τ when it represents the database interactions at level L. Since the dynamic call tree does not contain back edges, we know that $\mathcal{S}_{\mathcal{E}}(A, \tau_{dct}, L) = |\mathcal{N}_\tau| - 1$. Equations (7.3) and (7.4) show that we calculate $\mathcal{S}_{\mathcal{E}}(A, \tau_{cct}, L)$ by counting the number of nodes and the number of back edges in the CCT. We determine the impact that the database interaction granularity has on space overhead by reporting the increase and percent increase in the number of nodes and edges when a marker L is replaced with one of finer granularity, L' (e.g., $L = \mathbf{R}_l$ and $L' = \mathbf{R}_c$).

$$\mathcal{S}_{\mathcal{E}}(A, \tau_{cct}, L) = |\mathcal{E}_F| + |\mathcal{E}_B| \qquad (7.3)$$

$$= |\mathcal{N}_\tau| - 1 + |\mathcal{E}_B| \qquad (7.4)$$



(a)

(b)

(c)

(d)

(e)

(f)

Figure 7.8: Time Required to Store the Test Coverage Monitoring Trees.

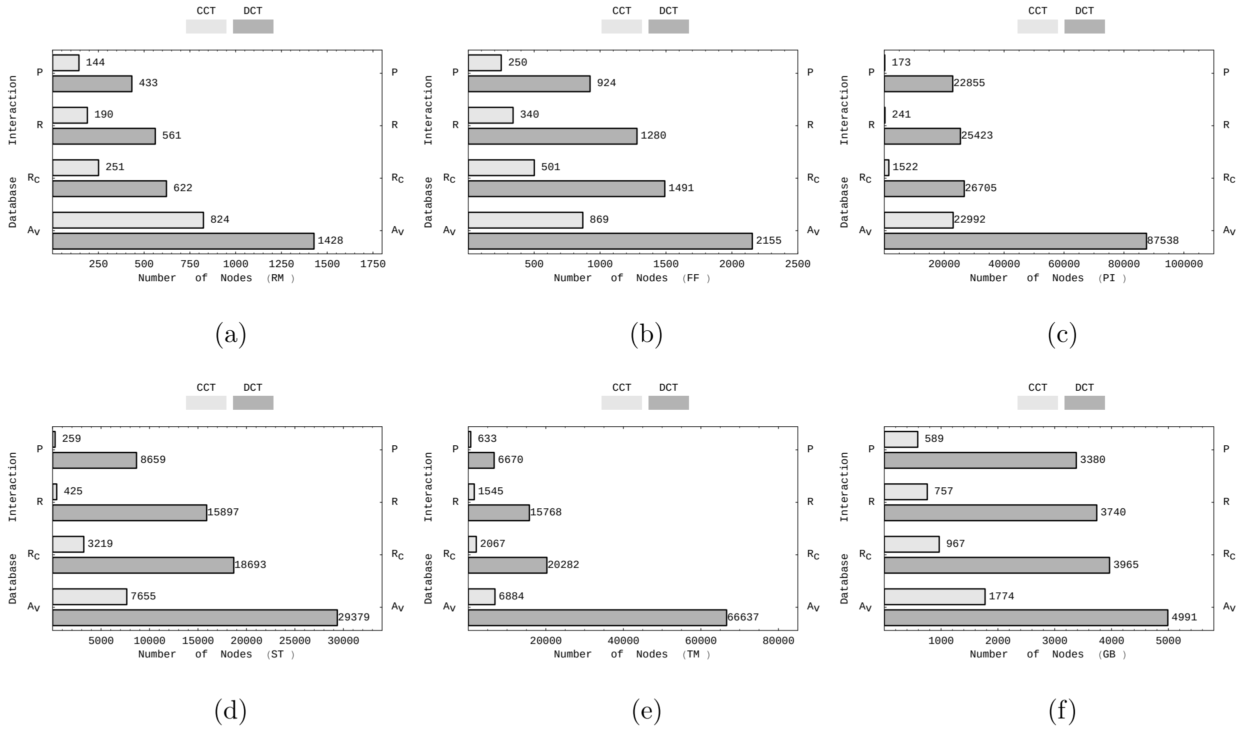
Since the size of the TCM tree can impact the performance of test suite execution (e.g., by increasing pressure on the memory subsystem [Xian et al., 2006]), we determine the in-memory size of the test coverage monitoring tree, denoted $\mathcal{S}_{mem}(A, \tau, L)$. We traverse the tree and use Roubtsov's sizing technique in order to calculate $\mathcal{S}_{mem}$ [Roubtsov, 2003]. Our tools calculate the in-memory size of a TCM tree under the assumption that the size of a tree node is the sum of the size of all of its data fields. Furthermore, we also assume that the overall size of a TCM tree is the sum of the sizes of every individual tree node. Our approach to in-memory sizing also requires the definition of the size of an instance of `java.lang.Object` and each of the primitive data types supported by a Java virtual machine. We assume the use of a standard 32-bit JVM and we specify the size of the data types according to Table C1 in Appendix C. For example, we adopt the convention that an `int` and a `long` respectively consume 4 and 8 bytes of memory. Following the guidelines established in [Roubtsov, 2003], we ignore any memory alignment issues that only arise in specific Java virtual machines and computer architectures. We judge that this assumption is reasonable because these variations in the execution environment normally yield minor changes in the actual data type size. Recent Java profilers also make the same simplifying assumptions and report the calculation of accurate object sizes [Pearce et al., 2006].

We measure the size of the trees that the coverage monitor stores because we anticipate that testers will preserve these trees in order to support debugging. To this end, we calculate $\mathcal{S}_{bin}(A, \tau, L)$ and $\mathcal{S}_{xml}(A, \tau, L)$, the respective size of application A's TCM tree τ when it is encoded in either the binary or the XML format. We examine how a compression algorithm c can reduce the size of tree τ and we calculate $\mathcal{S}_{bin}(A, \tau, L, c)$ and $\mathcal{S}_{xml}(A, \tau, L, c)$. Using Equations (7.5) and (7.6), we compute the reduction and percent reduction in the evaluation metrics $\mathcal{S}_{bin}$ and $\mathcal{S}_{xml}$ when we apply compression technique c to τ. The TCM component uses the standard Java serialization primitive to produce the binary tree and it uses the XStream serialization tool to create the XML-based encoding [Schaible, 2006]. We evaluate the use of Zip [Lelewer and Hirschberg, 1987], Gzip [Morse, 2005], XMill [Liefke and Suciu, 2000] and XMLPPM [Cheney, 2001] to compress the test coverage monitoring trees. We use the size reported by the file system in order to determine $\mathcal{S}_{bin}$ and $\mathcal{S}_{xml}$.

$$\mathcal{S}^{R}(A, \tau, L, c) = \mathcal{S}(A, \tau, L) - \mathcal{S}(A, \tau, L, c) \tag{7.5}$$

$$\mathcal{S}^{\%R}(A, \tau, L, c) = \frac{\mathcal{S}^{R}(A, \tau, L, c)}{\mathcal{S}(A, \tau, L)} \times 100 \tag{7.6}$$

7.6.3.1 Nodes and Edges in the TCM Tree During the experiments to characterize the structure of the TCM tree, we always used the static instrumentation technique and we encoded the trees in the binary format. Instead of calculating $\mathcal{S}_{\mathcal{N}}$ and $\mathcal{S}_{\mathcal{E}}$ for all levels of database interaction, we focused the experiments on the program, relation, record, and attribute value levels. We selected these levels because (i) **P** provides an appropriate base line for comparison, (ii) **R** represents a database interaction in a structural fashion, and (iii) $\mathbf{R_c}$ and $\mathbf{A_v}$ both record an interaction in a manner that incorporates database state. The graphs in Figure 7.9 confirm the results that we found in the previous experiments. We see that the static size of a case



(a) (b) (c)

(d) (e) (f)

Figure 7.9: Number of Nodes in the Test Coverage Monitoring Trees.

study application is not an appropriate predictor for the number of nodes in the TCM tree. For example, Figure 7.9(c) and Figure 7.9(f) show that $\mathcal{S}_{\mathcal{N}}(\texttt{PI}, \tau_{dct}, \mathbf{A_v}) = 87538$ while $\mathcal{S}_{\mathcal{N}}(\texttt{GB}, \tau_{dct}, \mathbf{A_v}) = 4991$. Once again, this trend is due to the fact that PI's tests iteratively invoke many more methods than the GB's tests.

Across all of the applications, the number of nodes in τ_{cct} ranges from a minimum of 144 at the program level (e.g., RM) to a maximum of 22922 at the attribute value level (e.g., PI). The graphs in Figure 7.9 show that the $\mathcal{S}_{\mathcal{N}}$ metric for τ_{dct} ranges from 433 nodes (e.g., RM) to 87538 nodes (e.g., PI). For the applications that exhibit moderate to heavy use of either iteration (e.g., PI, ST, and TM) or recursion (e.g., FF), the experiments reveal that there is a marked increase in the number of nodes when the TCM component generates a DCT instead of a CCT. Table 7.7 reports the average number of TCM tree nodes across all of the case study applications. We see that the DI-CCT can represent the database interactions at the finest level of granularity (e.g., $\mathbf{A_v}$) and still use less nodes that a conventional DCT (e.g., $\mathbf{P}$). We also observe that the attribute value level DI-DCT is one order of magnitude larger than the comparable DI-CCT. When space overhead must be controlled, these results suggest that a tester should only record coverage with a dynamic call tree when the additional context is absolutely needed to support debugging.

FindFile is the only case study application that uses recursion during testing. Therefore, Figure 7.10 tracks $\mathcal{S}_{\mathcal{N}}(\texttt{PI}, \tau_{cct}, L)$ for the four chosen database interaction levels. A label on the vertical axis of this graph designates the type of tree (e.g., "C" or "D") and the level (e.g., "P" or "A_v") and thus the label "C-P" stands for a CCT at the program level. This figure shows that there is a constant number of back

Tree Type	**P**	**R**	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	341	583	1421	6833
DCT	7154	10445	11960	32021

Table 7.7: Average Number of Nodes in the TCM Tree Across All Applications.

edges when we vary the level of database interaction. This is due to the fact that FF's tests do not cause the program under test to recursively perform a database interaction. As part of future empirical research, we will study the number of back edges in the CCT of applications that recursively interact with a database.

7.6.3.2 Memory and Filesystem Size of the TCM Tree Table 7.8 reports the value of $\mathcal{S}_{mem}$ for all of the case study applications and each of the four chosen levels of database interaction. Our measurement of the actual in-heap size of the TCM trees confirms the results in Section 7.6.3.1. This indicates that the platform-independent measures of TCM tree size (e.g., $\mathcal{S}_{\mathcal{N}}$ and $\mathcal{S}_{\mathcal{E}}$) are reliable measures of tree space overhead. Table 7.8 shows that (i) the CCT is normally much smaller than the DCT and (ii) a fixed tree type is smaller at the **P** level than at the $\mathbf{A_v}$ level. Interestingly, FF's TCM tree only consumes 679385 bytes of heap space when the coverage monitor uses a DCT to record database interactions at the attribute value level. This result suggests that it is possible to completely monitor the coverage of small scale database-centric applications with a reasonable increase in JVM heap consumption.

The RM application yields the smallest DCT at the $\mathbf{A_v}$ level (e.g., 433593 bytes), while PI creates the largest attribute value DCT (e.g., 25313633 bytes). We found that TCM trees like the ones produced for RM and FF placed little pressure on the JVM's garbage collector and did not noticeably increase testing time. In contrast, PI's 24 MB coverage tree did introduce additional memory pressure and require both extra invocations of the GC subsystem and a larger maximum heap. Chapter 9 explains that our future research will assess the impact of the test coverage monitoring instrumentation upon the behavior of the garbage collector. Finally, Table 7.8 shows that the TCM tree consumes an acceptable amount of space overhead when we use the CCT to record coverage at the program, relation, and record levels. Excluding the Pithy application, we observe that the record level CCT can represent all database interactions with no more than 697643 bytes.

Figure 7.11 provides the compressed and un-compressed file system sizes of the CCT and the DCT that record coverage at the program level. We focus our analysis on the RM, ST, and PI case study applications because Figure 7.9 and Table 7.8 reveal that their TCM trees can be roughly classified as small, medium, and large in comparison to the other trees (note that this trend only holds for the CCT at the **P** level). In future research, we will analyze the value of the $\mathcal{S}_{bin}$ and $\mathcal{S}_{xml}$ metrics for the relation, record, and attribute value levels. Across these three applications and for both the binary and XML representation, RM exhibits the smallest tree sizes and ST has the largest. For example, Figure 7.11(a) - (c) demonstrate that $\mathcal{S}_{bin}(\texttt{RM}, \tau_{cct}, \mathbf{P}) = 22.5$ KB, $\mathcal{S}_{bin}(\texttt{ST}, \tau_{cct}, \mathbf{P}) = 39.1$ KB, and $\mathcal{S}_{bin}(\texttt{PI}, \tau_{cct}, \mathbf{P}) = 25.8$ KB (the XML

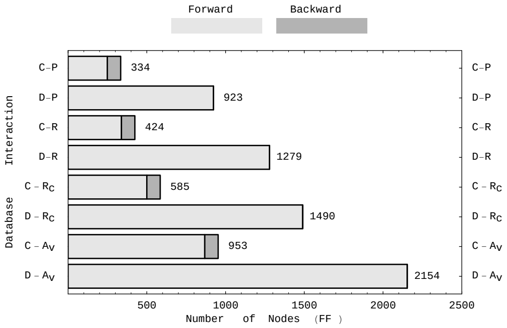


Figure 7.10: Number of Edges in the Test Coverage Monitoring Trees.

representation yields an analogous trend). We attribute this result to the fact that PI invokes a small number of methods during testing and thus its CCT can coalesce more nodes than the CCT for the ST application. Since Figure 7.9 and Table 7.8 also evidence this same trend, we conclude that all of our space overhead metrics (i.e., number of nodes, in-memory size, and file system size) produce corresponding results.

For the binary representation, Figure 7.11 indicates that the Gzip and Zip compression techniques offer a significant size reduction for the TCM trees of every application. For example, $\mathcal{S}_{bin}^{\%R}(\texttt{PI}, \tau_{cct}, \text{Gzip}) = 89.5\%$ and $\mathcal{S}_{bin}^{\%R}(\texttt{PI}, \tau_{dct}, \text{Gzip}) = 95.2\%$. The results reveal that $\mathcal{S}_{bin}^{\%R}(A, \tau_{cct}, c)$ is normally less than $\mathcal{S}_{bin}^{\%R}(A, \tau_{dct}, c)$ since the DCT frequently contains more duplicate node information than the CCT. During experimentation, we also noted that the compression of τ_{cct} and τ_{dct} incurred no more than one or two seconds of time overhead. Figure 7.11(d) - (f) show that the XML encoded TCM trees can be very large without the use of compression. For example, Figure 7.11(f) illustrates that PI's τ_{dct} consumes 25430 KB of storage when we encode it in XML. In contrast, the same tree is 1264 KB when the TCM component stored it in a binary format. We omit a more detailed discussion of the space overhead metrics for FF, TM, and GB because the investigation of the TCM tree sizes for these case study applications yielded similar trends.

Figure 7.11 shows that the XMill compression technique is the most effective at reducing the size of the XML-based TCM tree. We observe that XMill reduces the size of ST's DCT from 9650 KB to 2.36 KB while Gzip, Zip, and XMLPPM create a compressed tree of approximately 7.0 KB. Even though both types of TCM trees and tree encodings demonstrate substantial compression ratios, our experiments also identified an interesting trend concerning the compressibility of the binary and the XML representation. For example, we note that $\mathcal{S}_{xml}(\texttt{PI}, \tau_{dct}, \text{XMill}) = 2.36$ KB while Gzip reduces the same XML-based tree to 4.89 KB. More importantly, Figure 7.11 highlights the fact that Gzip only decreases the binary version of this tree to 3.59 KB. We see that the XML-aware technique yields a smaller TCM tree than the Gzip or Zip compression of the same binary tree. This is due to the fact that the eXtensible Markup Language reveals information about the structure of a TCM tree and XMill takes advantage of this meta-data to group similar nodes and improve compressibility. Even though XMill's reduction in absolute space overhead comes with a compression time of four seconds and a decompression time of two seconds, we judge that the compressed XML encoding should be considered if a tester will store a TCM tree on the file system or transmit it across a network.

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	52311	62899	92851	248375
DCT	158635	187881	217825	433593

`Reminder`

(a)

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	96115	116425	170119	272517
DCT	348645	428789	498967	679385

`FindFile`

(b)

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	60047	75489	2747971	8522835
DCT	4910199	5487383	8159165	25315633

`Pithy`

(c)

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	92913	130659	979027	2169569
DCT	3055397	4697137	5543397	8314685

`StudentTracker`

(d)

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	241067	449417	697643	2007231
DCT	2522271	4598789	6765835	19427555

`TransactionManager`

(e)

	$\mathbf{P}$	$\mathbf{R}$	$\mathbf{R_c}$	$\mathbf{A_v}$
CCT	227611	266267	338743	557871
DCT	1350335	1432771	1509417	1785923

`GradeBook`

(f)

Table 7.8: Memory Sizes of the Test Coverage Monitoring Trees (bytes).

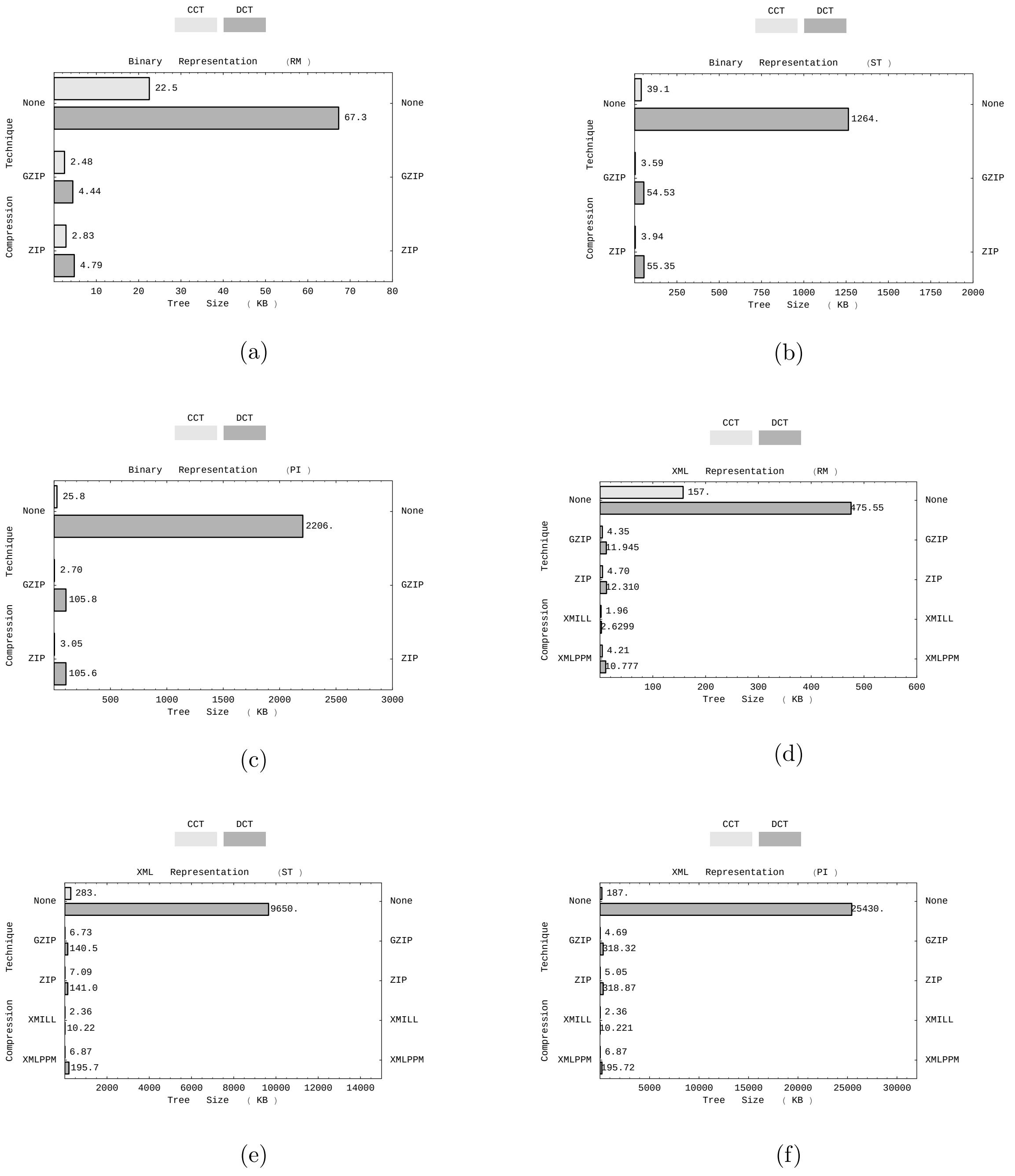
7.6.4 Detailed Tree Characterization

In order to better explain the results in Section 7.6.3, we took additional steps to characterize the test coverage monitoring trees. Following [Ammons et al., 1997], we also calculated several metrics that characterize the structure of the coverage monitoring trees in terms of tree height, node out degree, and node replication. Equation (7.7) defines $out_{avg}(A, \tau, L)$, the average out degree of a tree τ with the set of nodes $\mathcal{N}_\tau$. Since the external nodes in τ can artificially reduce the measurement of the average node out degree, we define $\mathcal{X}_\tau = \{N_\phi \,:\, out(N_\phi) = 0\}$ as the set of external nodes in τ. We use Equation (7.8) to calculate the average out degree of the internal nodes in the coverage monitoring tree τ. Equations (7.7) and (7.8) both use L to denote the level at which the TCM tree represents all of the database interactions. We also report out_{max}, the maximum out degree of a TCM tree.

$$out_{avg}(A, \tau, L) = \frac{\sum_{N_\phi \in \mathcal{N}_\tau} out(N_\phi)}{\mathcal{S}_{\mathcal{N}}(A, \tau, L)} \tag{7.7}$$

$$out_{avg}(A, \tau, \mathcal{X}_\tau, L) = \frac{\sum_{N_\phi \in \mathcal{N}_\tau \setminus \mathcal{X}_\tau} out(N_\phi)}{\mathcal{S}_{\mathcal{N}}(A, \tau, L) - |\mathcal{X}_\tau|} \tag{7.8}$$

Our tree characterization discussion always uses the *depth* function that we defined in Chapter 6 (i.e., $depth(N_0) = 0$ and $depth(N_\phi) = 1 + depth(parent(N_\phi))$). Finally, we report the $height(A, \tau, L)$ of a tree τ as the maximum depth for all of the external nodes $N_\phi \in \mathcal{X}_\tau$. Figure 7.12 provides the $Height(\tau, N_\phi)$ algorithm that returns the height of tree τ when we call $Height(\tau, N_0)$. *Height* correctly handles the back



(a)

(b)

(c)

(d)

(e)

(f)

Figure 7.11: Compressed and Uncompressed Size of the TCM Trees.

edges that can exist in the calling context tree by using the *ContainsBackEdgeFrom* operation to determine if edge $(N_\phi, N_\rho) \in \mathcal{E}_B$. Since the dynamic call tree does not contain back edges, the *ContainsBackEdgeFrom* operation always returns **false** when τ is a DCT.

A node N_ϕ in the TCM tree τ always corresponds to a method invocation, database interaction point, or a relational database entity. The instrumentation probes that build the coverage monitoring trees can introduce replicated nodes into τ and this increases the space consumption of a tree. For example, if tests T_i and T_j both test method m_k, then the tree node *call* m_k will exist at two different locations within the tree. Figure 7.13 provides the *Replication* algorithm that we use to determine the amount of node level replication within a TCM tree. We call *Replication*$(\mathcal{H}, \tau, N_0)$ with an empty hash table $\mathcal{H}$ in order to determine the replication count for each unique node in τ. This algorithm uses the hash table $\mathcal{H}$ to store key value pairs of the form (N_ϕ, r) where N_ϕ is a unique tree node and r is the replication count for this node. We use the *Replication* algorithm to populate $\mathcal{H}$ with a replication count for each unique node in τ and then we calculate the average node replication, r_{avg}, with Equation (7.9). In the analysis of the experimental results, we use the notation $r_{avg}(A, \tau, L)$ to stand for the average level of replication for a specific application A and an interaction level L. Higher average replication counts offer one explanation for a coverage monitoring tree that exhibits high values for the evaluation metrics $\mathcal{T}_{store}$, $\mathcal{S}_{mem}$, $\mathcal{S}_{bin}$, and $\mathcal{S}_{xml}$. Finally, we report r_{max}, the maximum node replication count for a TCM tree.

$$r_{avg}(\mathcal{H}) = \frac{\displaystyle\sum_{(N_\phi, r) \in \mathcal{H}} r}{|\mathcal{H}|} \tag{7.9}$$

7.6.4.1 Height of the TCM Tree Table 7.9 provides the height of the TCM tree for each of the case study applications. We determined the height of a CCT and a DCT that maintains coverage information at either the program, relation, record, or attribute value level (as such, each entry in Table 7.9 gives the tree heights in the level order of $\mathbf{P}, \mathbf{R_l}, \mathbf{R_c}, \mathbf{A_v}$). Even though Section 7.6.3 indicates that the testing of the `PI` and `GB` applications yields very different TCM trees, this table shows that the trees have very similar heights. We also see that the height of the DCT is often the same as the CCT (e.g., `RM`) or just slightly greater (e.g., `FF`). When the coverage monitor created a TCM tree at the $\mathbf{A_v}$ level instead of $\mathbf{P}$, this increased the tree height by three or four additional nodes. For the calling context tree, we see that *height*$(\texttt{FF}, \tau_{cct}, \mathbf{P}) = 5$ and *height*$(\texttt{FF}, \tau_{cct}, \mathbf{A_v}) = 9$. If we consider the dynamic call tree, Table 7.9 shows that *height*$(\texttt{FF}, \tau_{dct}, \mathbf{P}) = 6$ and *height*$(\texttt{FF}, \tau_{dct}, \mathbf{A_v}) = 10$. Since the TCM trees are so "bushy," it is clear that the overall size of a TCM tree is not heavily influenced by its height. Interestingly, this result corroborates the empirical characterization of the procedural CCT that is reported in [Ammons et al., 1997].

7.6.4.2 Node Out Degree We focused the analysis of a TCM tree's node out degree by excluding the external nodes from our analysis. As part of future research, we will include the leaf nodes and identify how this impacts the measured value of $out_{avg}(A, \tau, L)$. Figure 7.14 through Figure 7.16 offer different views of

```
**Algorithm** $Height(\tau, N_\phi)$
**Input:** Test Coverage Monitoring Tree $\tau$;
    Current Tree Node $N_\phi$
**Output:** Height of the Tree $h$
if $out(N_\phi) = 0$
    then return $0$
$h \leftarrow 0$
for $N_\rho \in children(N_\phi)$
    do if $ContainsBackEdgeFrom(\tau, N_\rho, N_\phi) = \textbf{false}$
        then $h \leftarrow max(h, Height(\tau, N_\rho))$
return $1 + h$
```

Figure 7.12: The *Height* Algorithm for a Test Coverage Monitoring Tree.

```
**Algorithm** $Replication(\mathcal{H}, \tau, N_\phi)$
**Input:** Hash Table of Node Replication Counts $\mathcal{H}$;
    Test Coverage Monitoring Tree $\tau$;
    Current Tree Node $N_\phi$
if $\mathcal{H}.get(N_\phi) = \emptyset$
    then $\mathcal{H}.put(N_\phi, 1)$
    else
        $r \leftarrow \mathcal{H}.get(N_\phi)$
        $r \leftarrow r + 1$
        $\mathcal{H}.put(N_\phi, r)$
for $N_\rho \in children(N_\phi)$
    do if $ContainsBackEdgeFrom(\tau, N_\rho, N_\phi) = \textbf{false}$
        then $Replication(\mathcal{H}, \tau, N_\rho)$
```

Figure 7.13: The *Replication* Algorithm for a Test Coverage Monitoring Tree.

Application	CCT Height	DCT Height
`RM`	$(6, 7, 8, 9)$	$(6, 7, 8, 9)$
`FF`	$(5, 7, 8, 9)$	$(6, 8, 9, 10)$
`PI`	$(6, 6, 7, 8)$	$(6, 6, 7, 8)$
`ST`	$(6, 7, 8, 9)$	$(6, 7, 8, 9)$
`TM`	$(5, 7, 8, 9)$	$(5, 7, 8, 9)$
`GB`	$(6, 7, 8, 9)$	$(6, 7, 8, 9)$

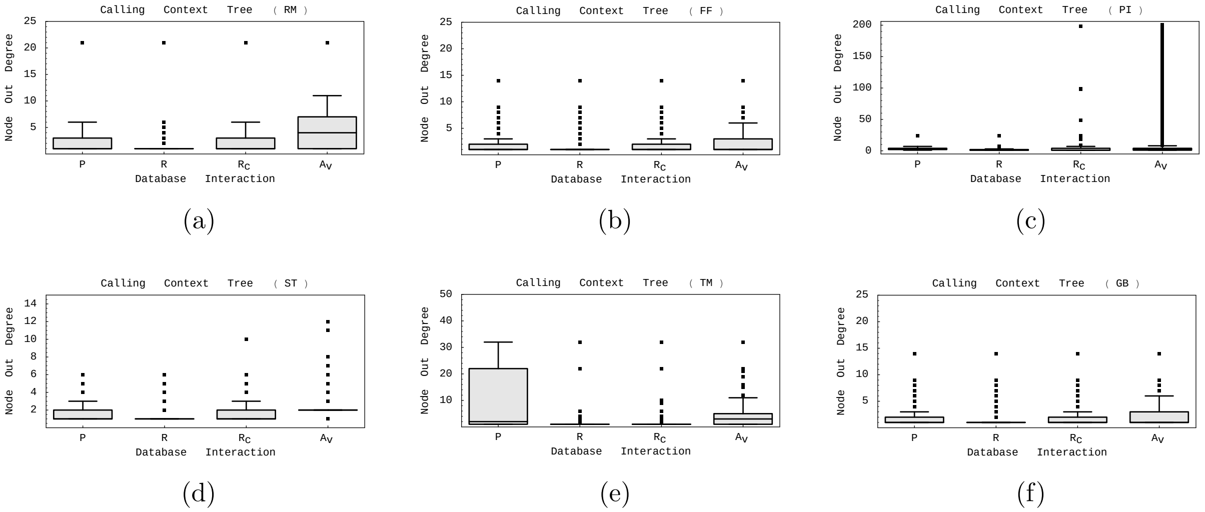
Data Format: $(\mathbf{P}, \mathbf{R_l}, \mathbf{R_c}, \mathbf{A_v})$

Table 7.9: Height of the Test Coverage Monitoring Trees.

the $out(A, \tau, L)$ metric for all of the database-centric applications. In particular, Figure 7.14 provides a box and whisker plot of the node out degree for the six case study applications. The graphs demonstrate that the out degree for a single node can be as low as one to five children and as great as 700 children. Across the majority of the case study applications, many nodes have a substantial number of children and this result suggests that the $out_{avg}(A, \tau, L)$ does impact the size of the TCM tree. For example, the experiments reveal that $out_{avg}(\texttt{PI}, \tau_{cct}, \mathbf{P}) = 3.25$ with a standard deviation of 3.19 while $out_{avg}(\texttt{PI}, \tau_{cct}, \mathbf{A_v}) = 16.01$ and a standard deviation of 34.8. This explains the result in Table 7.8 where `PI`'s CCT at the attribute value level consumes 8522835 bytes of heap storage space

Figures 7.14 and 7.15 show that the DCT has a higher average node out degree than the CCT, for the majority of the applications. Of course, we attribute this result to the fact that the CCT instrumentation payloads can coalesce more nodes than the DCT probes. For example, we see that $out_{max}(\texttt{ST}, \tau_{cct}, \mathbf{P}) = 6$ and $out_{max}(\texttt{ST}, \tau_{dct}, \mathbf{P}) = 25$. However, for some applications (e.g., `RM`) there is little difference in the node out degree when we compare τ_{cct} and τ_{dct}. Figure 7.14 also suggests that the CCT does an acceptable job at controlling node out degree when we monitor coverage at finer levels of database interaction. The empirical cumulative distribution function (ECDF) in Figure 7.16(a) reveals that almost 90% of the nodes in `PI`'s $\mathbf{A_v}$ level CCT have a node out degree of less than 50. However, the ECDFs in Figure 7.16 demonstrate that the node out degree of a database-aware TCM tree can be as high as 700 children. Our empirical characterization of the $out(A, \tau, L)$ further explains why testers should use the CCT to record the coverage of most types of tests for database-centric applications.

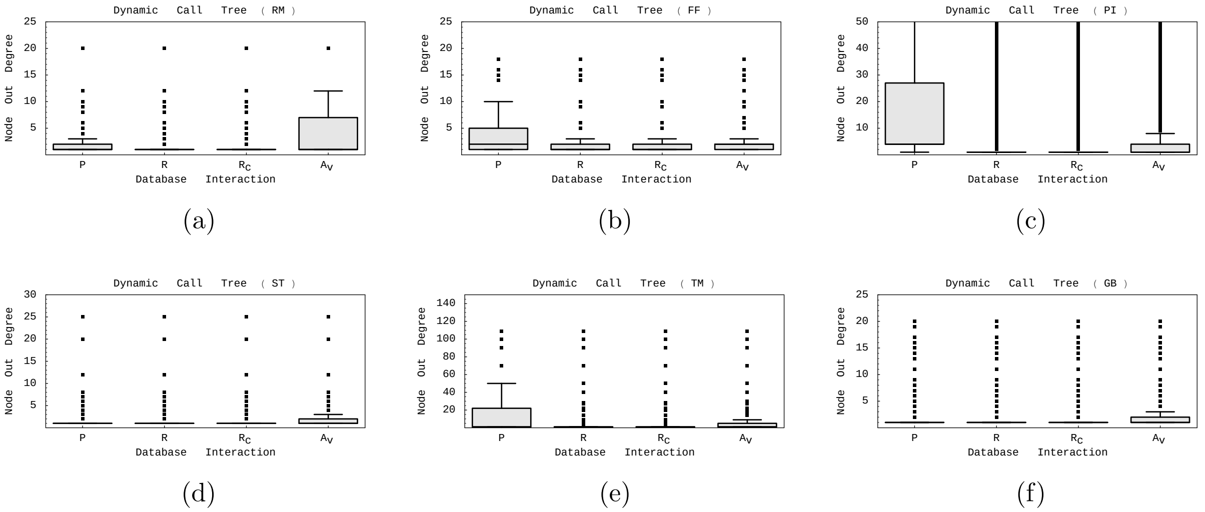
7.6.4.3 Node Replication Counts It is desirable to produce a TCM tree that avoids replication in all circumstances where the coalescing of a node does not destroy testing context. Figure 7.17 through Figure 7.19 furnish different views of node level replication within the coverage trees for all six case study applications. Specifically, Figures 7.17 and 7.18 demonstrate that the DCT has much high replication than the CCT. For example, we see that $r_{max}(\texttt{FF}, \tau_{cct}, \mathbf{P}) = 25$ while $r_{max}(\texttt{FF}, \tau_{dct}, \mathbf{P}) = 100$ and `FF`'s τ_{dct} has several outlying nodes with replication counts in the range of 50 to 100 nodes. Figures 7.17 and



(a) (b) (c)

(d) (e) (f)

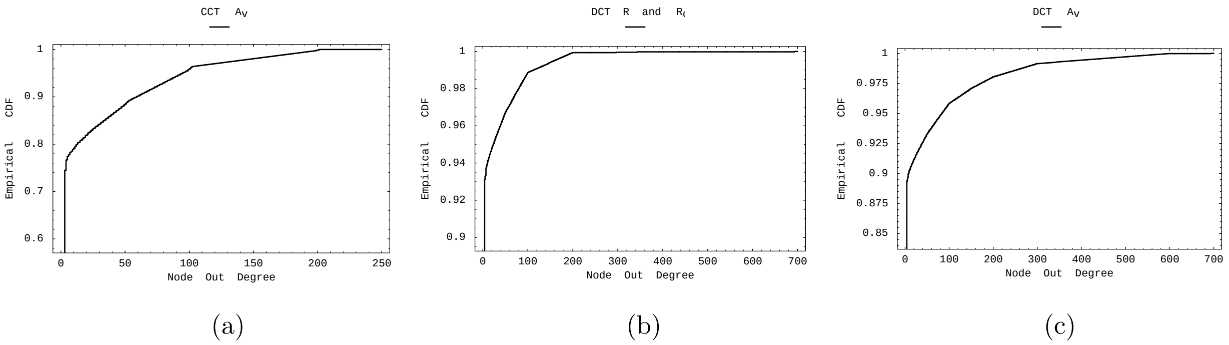
Figure 7.14: Node Out Degree of the CCT Test Coverage Monitoring Trees.



(a) (b) (c)

(d) (e) (f)

Figure 7.15: Node Out Degree of the DCT Test Coverage Monitoring Trees.



(a) (b) (c)

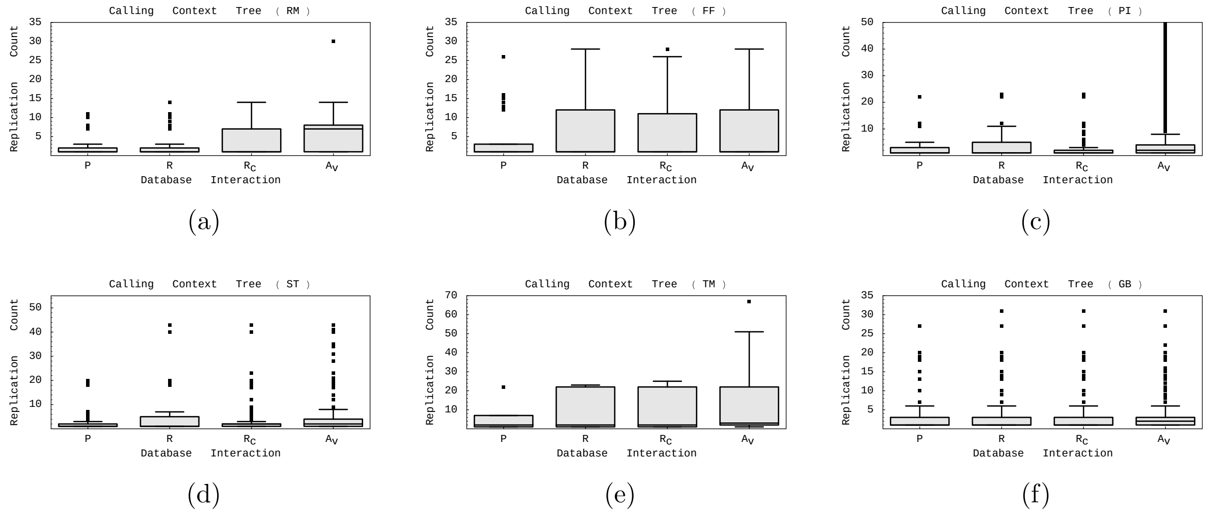
Figure 7.16: ECDFs of the Node Out Degree for the Pithy TCM Trees.

7.18 also demonstrate that $r_{max}(\texttt{TM}, \tau_{cct}, \mathbf{P}) = 25$ and $r_{max}(\texttt{FF}, \tau_{dct}, \mathbf{P}) > 200$. Our analysis reveals that $r_{avg}(\texttt{FF}, \tau_{cct}, \mathbf{R}) = 5.31$ with a standard deviation of 7.37. However, we also found that the use of the DCT at the same record level yielded $r_{avg}(\texttt{FF}, \tau_{cct}, \mathbf{R}) = 20.0$ with with a standard deviation of 30.51. In comparison to the DCT, these results clearly indicate that the CCT does a very good job at controlling the maximum and average node replication counts.

For most applications, Figures 7.17 and 7.18 demonstrate that the CCT controls node replication well when we transition from $\mathbf{P}$ to $\mathbf{A_v}$. Figure 7.17(e) shows that TM's CCT has a maximum node out degree of 70 while Figure 7.18(e) reveals that the corresponding DCT has node(s) with a replication count of over 400. Figure 7.19 offers ECDFs that further characterize the node replication count for PI's coverage monitoring trees. The graph in Figure 7.19(a) indicates that 90% of the nodes in the $\mathbf{A_v}$-level CCT still have a replication count less than 50. Yet, this same CCT has a small number of nodes that are replicated in the tree 350 times. In comparison, the program level CCT for PI never has a replication count higher than 50. Figure 7.19(b) shows that this trend is more pronounced for the DI-DCT. While the majority of PI's nodes have a count less than 1000, a small percentage of nodes are replicated in the tree more than 5000 times. Our analysis suggests that it is difficult for either the CCT or the DCT to control replication at the $\mathbf{A_v}$ level. If it is desirable to control node replication, then we judge that the tester should rarely monitor coverage at the level of attribute values. Since Section 7.6.2 indicates that coverage monitoring at $\mathbf{A_v}$ never increases testing time by more than six seconds, we judge that the high values for r are acceptable if this type of information is needed for debugging.

7.7 THREATS TO VALIDITY

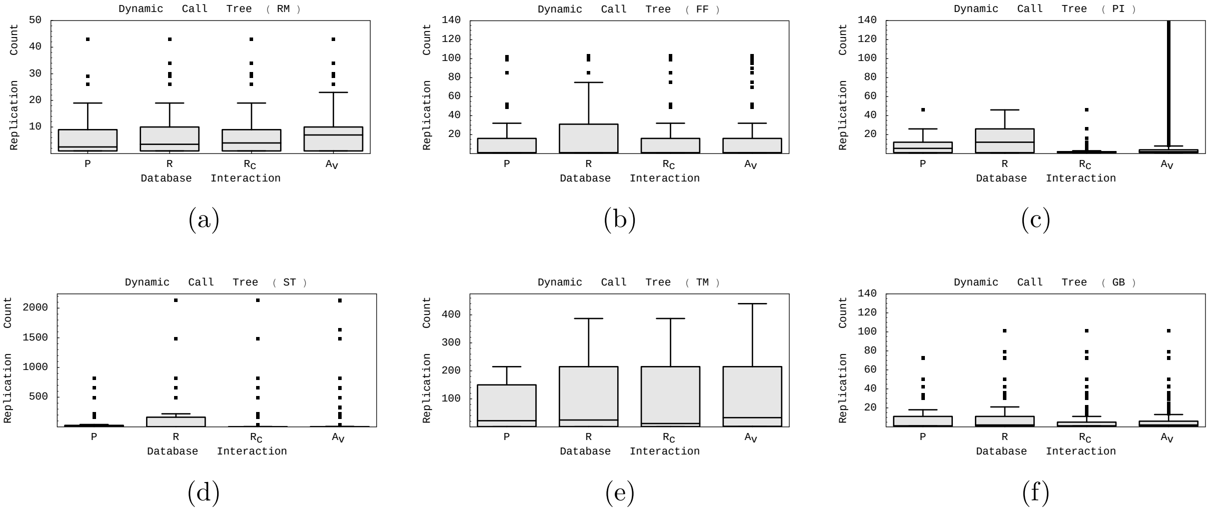
The experiments described in this chapter are subject to validity threats and Chapter 3 reveals the steps that we took to control these threats during all of the experimentation for this dissertation. We also took additional steps to handle the threats that are specific to experimentation with the coverage monitoring component. Internal threats to validity are those factors that have the potential to impact the measured variables defined in Sections 7.4 and 7.6. One internal validity threat is related to defects in the TCM component. These defects could could compromise the correctness of the test coverage monitoring trees and the final measurement of test suite adequacy. We controlled this threat by visualizing small TCM trees and checking them to ensure correctness. We implemented an automated check to guarantee that the tree's active node points to the root (e.g., $N_a = N_0$) when the TCM component terminates. We automatically ensure that the tree adheres to the structure described in Figure 6.19 of Chapter 6. We verify that the leaves of a tree always correspond to either a method invocation or the correct level for the database interactions. For example, if $L = \mathbf{D}$, then there should be no attribute values in the tree and an external node must always be either a method call or a database entity. The coverage monitor also ensures that a DCT does not have any back edges. We judge that threats to construct validity were controlled since Sections 7.4 and 7.6 describe a wide range of evaluation metrics that are useful to both researchers and practitioners.



(a) (b) (c)

(d) (e) (f)

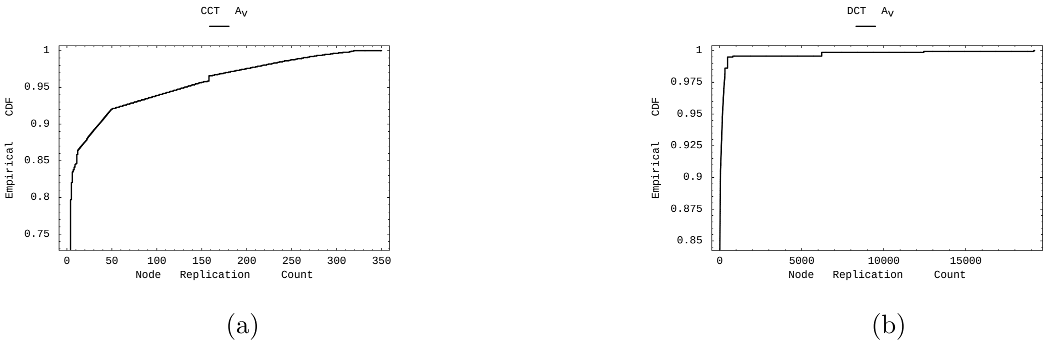
Figure 7.17: Node Replication of the CCT Test Coverage Monitoring Trees.



(a) (b) (c)

(d) (e) (f)

Figure 7.18: Node Replication of the DCT Test Coverage Monitoring Trees.



(a) (b)

Figure 7.19: ECDFs of the Node Replication Count for the `Pithy` TCM Trees.

7.8 CONCLUSION

This chapter describes the design, implementation, and empirical evaluation of a component that performs database-aware test coverage monitoring. We explain how to use aspect-oriented programming techniques to introduce the TCM probes in either a static or a dynamic fashion. After discussing the goals and design for an experiment to measure the performance of our approach to monitoring, we systematically state each evaluation metric and analyze the experimental results. Since our technique does not use a customized JVM to produce the reports, we judge that the experimental results establish an upper bound on the costs associated with database-aware monitoring. We anticipate further reductions in test coverage monitoring time if we use recently developed JVM-based techniques to introduce the instrumentation (e.g., [Bockisch et al., 2006, Golbeck and Kiczales, 2007]). The experiments furnish several key insights into the fundamental performance trade-offs for the different configurations of the TCM component. For example, we found that efficient coverage monitoring often requires the use of a static instrumentation technique that increases the static space overhead of a database-centric application.

The experiment data suggests that a DI-CCT at the finest level of database interaction granularity often consumes less space overhead than a traditional DCT. The empirical results also indicate that monitoring coverage at the attribute value level has the potential to increase average node out degree and replication counts in the TCM trees. We also discovered that the XML-based tree encoding has exceptional compressibility and it often yields very small coverage reports. In general, we find that most configurations of the TCM component yield acceptable time and space overheads for the chosen applications. Since our coverage monitoring component builds traditional and database-aware TCM trees, it can also be used to support regression test suite reduction techniques for normal programs [McMaster and Memon, 2005]. The TCM trees can also serve as a vehicle for efficient time-aware test suite prioritization because they record coverage information on a per-test basis [Walcott et al., 2006]. Chapter 8 explains how we use the DI-DCT and DI-CCT to perform database-aware regression test suite reduction and prioritization.

8.0 REGRESSION TESTING

8.1 INTRODUCTION

This chapter introduces database-aware techniques for regression testing. It describes an approach to regression test suite reduction that efficiently identifies a smaller test suite that covers the same test requirements as the original tests. We also present a method for regression test prioritization that re-orders a test suite so that it rapidly covers the test requirements. These regression testing algorithms can improve the efficiency and effectiveness of testing whenever it is possible to precisely determine which requirements are covered by a test case. This chapter also demonstrates how to use a path in a database-aware coverage tree as a test requirement that supports reduction and prioritization. We performed experiments to measure the efficiency of the regression testing techniques and to identify how reduction and prioritization impact both testing time and effectiveness. In summary, this chapter provides:

1. A high level overview of the regression testing process (Section 8.2).
2. A demonstration of the practical benefits of regression test suite reduction and prioritization (Section 8.3).
3. The algorithms that we use to identify test paths within a database-aware coverage tree and a discussion of how these paths can be used as test requirements (Section 8.4).
4. The description of database-aware reduction and prioritization techniques that consider both the tests' overlap in requirement coverage and the time overhead of an individual test (Section 8.5)
5. Metrics for evaluating the effectiveness of reduced and prioritized test suites (Section 8.6).
6. Details about the implementation of the database-aware regression testing component (Section 8.7).
7. The design of an experiment to measure the performance of the regression tester, a summary of the experimental results, and an examination of the steps that we took to control experiment validity (Sections 8.8, 8.9, and 8.11).
8. An empirical evaluation of the costs associated with analyzing the coverage report and identifying a reduced or prioritized test suite (Sections 8.10.2 and 8.10.3).
9. An experimental examination of the impact that the database-aware regression testing techniques have on test suite execution time and effectiveness (Sections 8.10.2 and 8.10.3).

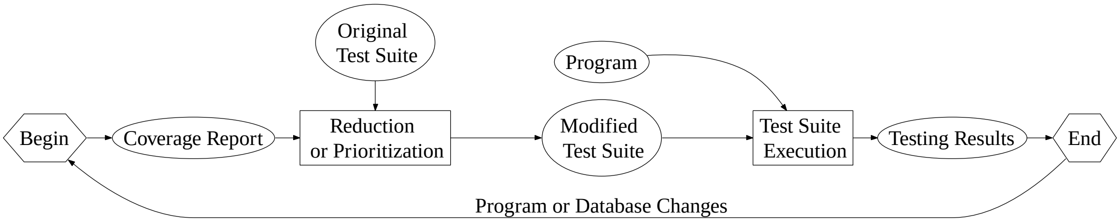
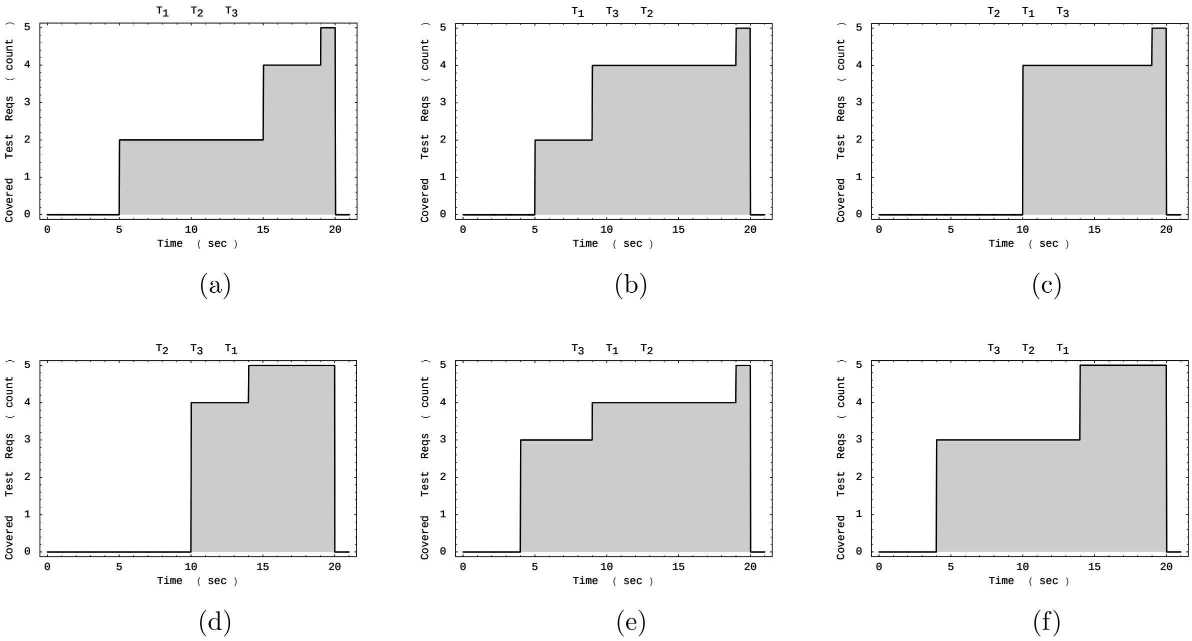


Figure 8.1: Overview of the Database-Aware Regression Testing Process.

8.2 OVERVIEW OF REGRESSION TESTING

Figure 8.1 provides an overview of database-aware regression testing. *Database-aware regression testing* is the process of executing a test suite whenever changes are made to the (i) program, (ii) state of the database, or (iii) relational schema of the database. Regression testing ensures that the introduction of either a bug fix or a new feature does not impact the correctness of the application. In the *general* regression testing (GRT) model, we re-order or reduce the test suite and then use the modified test suite during many subsequent rounds of regression testing [Rothermel et al., 2001]. The *version specific* regression testing (VSRT) model suggests that the test suite should be re-ordered or reduced after each modification to the database-centric application. Version specific approaches to regression testing are valuable because they always consider the current state and structure of both the program and the database. However, version specific regression testing requires efficient implementations of the (i) test requirement enumerator, (ii) test coverage monitor, (iii) test adequacy calculator, and (iv) reduction and/or prioritization technique. Any regression testing approach that can efficiently operate in a version specific fashion should also support general regression testing. Therefore, we focus on version specific regression testing schemes.

Before reducing or prioritizing the test suite, we analyze the coverage report in order to determine how the tests covered the requirements. Currently, the regression tester examines the database-aware test coverage trees and uses a path in the tree as a test requirement. Our approach to reduction and prioritization can properly operate as long as we can determine which requirements are covered by a test case. Therefore, the regression tester can also reduce and/or prioritize tests with the database interaction associations (DIAs) that are described in Chapter 4. Yet, the coverage tree paths still reveal how the test cases cause the program to interact with both the methods under test and the entities in the relational database. This type of requirement is particularly useful when a database-centric application contains many partially dynamic and dynamic database interaction points. We judge that the tree-based requirement is ideal for our case study applications since Chapter 3 reveals that they have few static database interactions and Chapter 7 demonstrates that the coverage monitor can efficiently create these trees during test execution. Using a coverage tree path as a test requirement also avoids the need to repeatedly execute the data flow analyzer in order to enumerate the DIAs after a change occurs in any part of the database-centric application. We judge that the tree-based requirements are well suited for either version specific or general regression testing and the DIAs are most useful in the GRT model.



(a) (b) (c)

(d) (e) (f)

Figure 8.2: Coverage Effectiveness of Regression Test Prioritizations.

The reduction and prioritization techniques analyze the original test suite and the per-test coverage information in order to create a modified test suite. In the context of reduction, the primary goal is to identify a subset of the original test cases that covers the same test requirements. Controlling the size of the test suite in this manner can improve the efficiency of testing without compromising coverage or unduly decreasing fault detection effectiveness. A prioritization algorithm re-orders a test suite so that it covers test requirements and reveals faults more effectively than the initial ordering. We describe approaches to reduction and prioritization that consider the tests' overlap in coverage and the actual cost associated with executing each test. Since overlap-aware regression testing requires a heuristic solution to the NP-complete minimal set cover (MSC) problem [Garey and Johnson, 1979], we also propose reduction and prioritization algorithms that ignore overlap in an attempt to improve efficiency. However, the overlap-aware reduction and prioritization techniques employ the greedy approximation algorithm that is provably the best for MSC [Feige, 1998, Vazirani, 2001] and the experiments also demonstrate that our approach is very efficient. Our regression testing component differs from the schemes previously developed by [Do et al., 2004, Harrold et al., 1993, Rothermel et al., 2001] because it (i) considers the actual cost of executing a test and (ii) uses test requirements that incorporate details about a database interaction.

8.3 THE BENEFITS OF REGRESSION TESTING

Suppose that a test suite $T = \langle T_1, T_2, T_3 \rangle$ tests program P and covers a total of five test requirements. These requirements might be (i) coverage tree paths, (ii) def-use and database interaction associations, or (iii) nodes and edges in a control flow graph. Table 8.1 shows that test T_2 takes ten seconds to execute while T_1 and T_3 respectively consume five and four seconds during test suite execution. Even though this test suite only

Test Case	**Test Execution Time (sec)**
T_1	5
T_2	10
T_3	4

$\boxed{\text{Total Testing Time} = 19 \text{ seconds}}$

Table 8.1: Test Suite Execution Time.

Test Case	**Requirements**				
	R_1	R_2	R_3	R_4	R_5
T_1	✓	✓			
T_2	✓	✓	✓		✓
T_3	✓			✓	✓

Table 8.2: Test Requirement Coverage for a Test Suite.

Test Ordering	**Coverage Area**	**Coverage Effectiveness**
T_1 T_2 T_3	36	.3798
T_1 T_3 T_2	48	.5053
T_2 T_1 T_3	36	.3798
T_2 T_3 T_1	41	.4316
T_3 T_1 T_2	55	.5789
T_3 T_2 T_1	55	.5789

$\boxed{\text{Ideal Coverage Area} = 95}$

Table 8.3: Test Coverage Effectiveness.

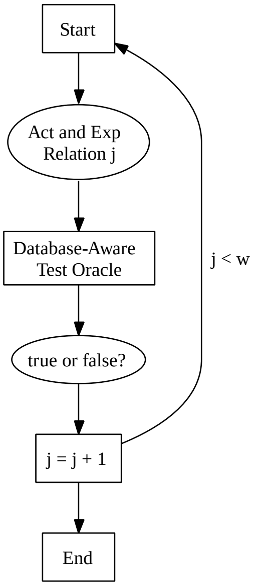
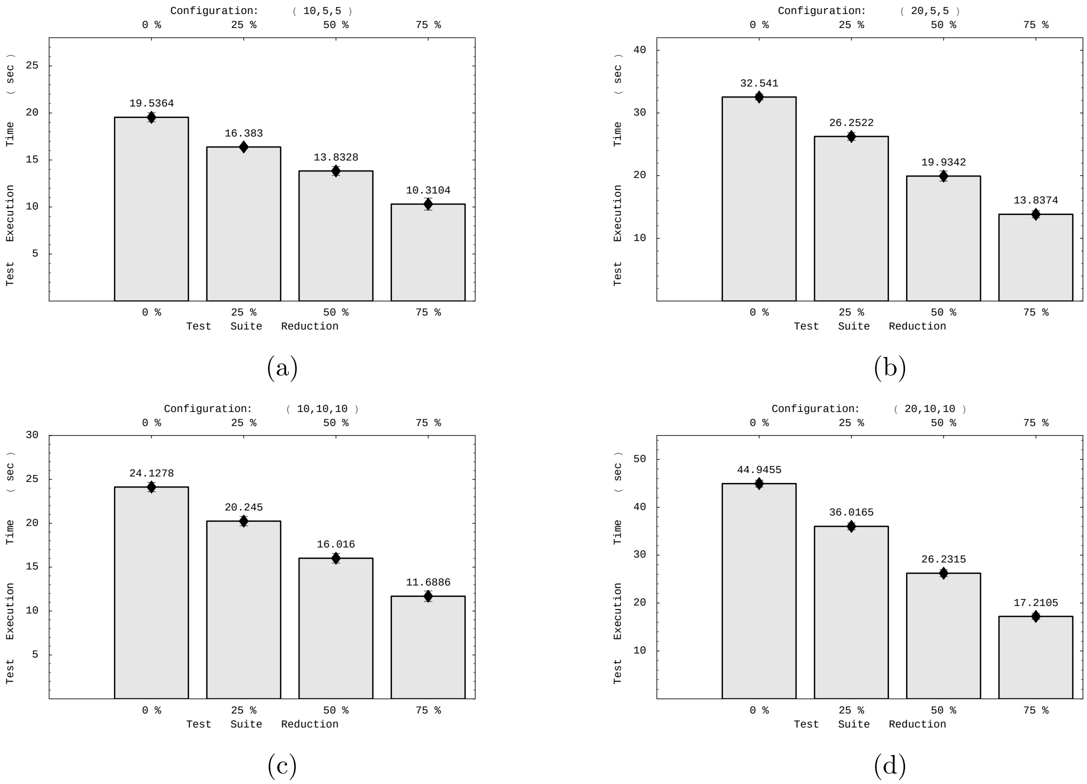


Figure 8.3: Executing the Database-Aware Test Oracle.

executes for nineteen seconds, the tests for a database-centric application might consume more time if they interact with large databases. Table 8.2 reveals that none of the test cases cover all of the test requirements. As is the case for most real world test suites, there is an overlap in how the tests cover the requirements (e.g., all of the tests cover requirement R_1). In this example, we assume that test T_2 covers four requirements and T_3 and T_1 cover three and two requirements, respectively. There are $3! = 3 \times 2 \times 1 = 6$ different orderings in which we could execute this simple test suite. In order to characterize the coverage effectiveness of a test suite prioritization, Figure 8.2 plots the cumulative number of covered test requirements during the execution of T. The shaded area under these coverage curves highlights the effectiveness of a test ordering (i.e., a large shaded area suggests that an ordering is highly effective).

We construct a coverage function with the assumption that a requirement is marked as covered when one of its covering test cases terminates. For example, Figure 8.2(a) shows that the execution of T_1 leads to the coverage of two test requirements (i.e., R_1 and R_2) after five seconds of test suite execution. This figure also reveals that the cumulative coverage of the test suite increases to four when T_2 terminates (i.e., T_2 covers R_3 and R_5 after executing for ten seconds). A high coverage area indicates that the test ordering covers the requirements faster than a test suite order with a low coverage area. Furthermore, an *ideal* test suite would immediately cover all of the test requirements. Intuitively, we define the *coverage effectiveness* of a prioritized test suite as the ratio between its coverage area and the coverage area of the ideal test suite (c.f. Section 8.6 for a formal definition of this metric). According to this definition, a coverage effectiveness value falls inclusively between 0 and 1 with higher values indicating a better test suite. Since high coverage test cases are more likely to reveal program faults than those with low coverage [Frankl and Weiss, 1993, Hutchins et al., 1994], it is sensible to re-order test suites in a manner that maximizes coverage effectiveness.



(a)

(b)

(c)

(d)

Figure 8.4: Test Suite Execution Times for Reduced Test Suites.

Figure 8.2 and Table 8.3 demonstrate that not all of T's prioritizations have the same coverage effectiveness. In fact, the test suite ordering $T = \langle T_1, T_2, T_3 \rangle$ yields a coverage area of 36 and an effectiveness value of only .3798. The results in Figure 8.2 and Table 8.3 also show that different test orderings can lead to the same effectiveness value. For example, Table 8.3 indicates that the orderings $T = \langle T_1, T_2, T_3 \rangle$ and $T = \langle T_2, T_1, T_3 \rangle$ have the same low coverage effectiveness. Visual inspection of the plots in Figures 8.2(e) and (f) suggest that the test orderings $T = \langle T_3, T_1, T_2 \rangle$ and $T = \langle T_3, T_2, T_1 \rangle$ both cover the requirements faster than any of the other orderings. Indeed, Table 8.3 shows that these orderings have a coverage effectiveness of .5789. The high effectiveness of these two orderings is due to the fact that they initially execute test T_3 and thus cover three requirements in only four seconds. Furthermore, Figure 8.2(f) exposes the fact that test case T_1 is redundant if it is executed after T_3 and T_2 (i.e., the coverage curve attains the maximum height of five after executing for only 15 seconds). This example demonstrates that (i) prioritization can improve the effectiveness of testing and (ii) a test suite can contain tests that redundantly cover the test requirements.

We conducted an empirical study with a real database-aware test suite in order to measure the practical benefits of reduction. This test suite contains sixty tests that all perform the same operation. Following the notation established in Chapter 2, we assume that a test interacts with a relational database that contains w relations and each relation rel_j contains q attributes. Each test case is also configured to insert u records into a relation and then repeatedly execute a database-aware test oracle for all w relations. As depicted in Figure 8.3, the database-aware oracle compares the actual and expected state of each relation

Configuration	α	β	R^2
$(10, 5, 5)$	19.55	-12.09	.997
$(20, 5, 5)$	32.51	-24.97	.999
$(10, 10, 10)$	24.25	-16.62	.999
$(20, 10, 10)$	45.05	-37.20	.999

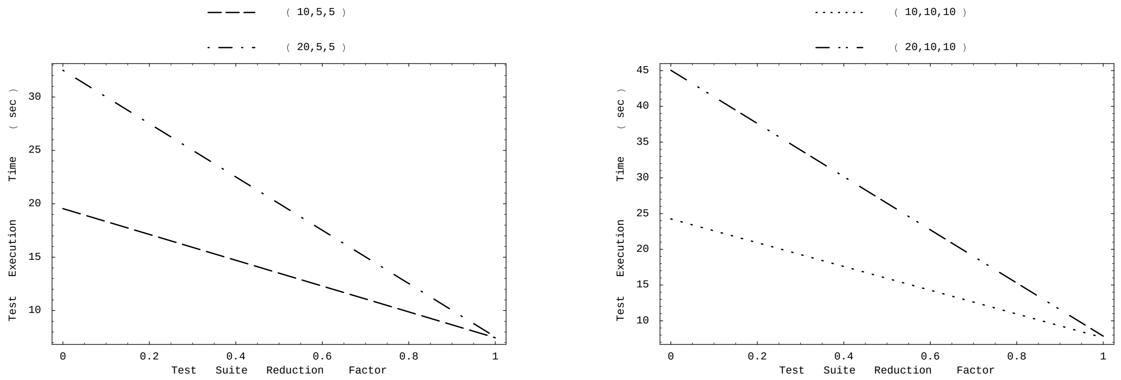
$$\boxed{f(\varrho) = \alpha + \beta \times \varrho}$$

Table 8.4: Summary of the Linear Regression Analysis.

rel_j, returning `true` when the states are the same and returning `false` otherwise. After each test case performs the $w \times q \times u$ attribute value comparisons, it removes the u records from each of the w relations. A database-aware test suite of this nature models a testing process that performs many database interactions. Table C3 in Appendix C provides additional information about this test suite.

We executed the test suite with four different reduction factors $\varrho \in \{0, .25, .5, .75\}$ (i.e., $\varrho = .5$ corresponds to a 50% reduction in the number of tests). In this circumstance, a 0% reduction executes all sixty test cases and a 75% reduction runs fifteen tests. Since we performed this experiment with the sole purpose of determining how reduction can impact the efficiency of testing, we randomly reduced the test suite to the designated size. We also configured the database to execute in four different configurations that we describe with the notation (w, u, q). For this study, we used databases in the configurations $(10, 5, 5)$, $(20, 5, 5)$, $(10, 10, 10)$, and $(20, 10, 10)$. In these experiments, $(10, 5, 5)$ corresponds to a small database containing ten relations, each with five records and five attributes. The smallest database requires 250 attribute value comparisons while the largest database, denoted $(20, 10, 10)$, causes the test oracle to compare 2000 attribute values. We ran each unique test suite and database configuration five times and we calculated arithmetic means and standard deviations for testing time. For the bar charts in Figure 8.4, a diamond at the top of a bar indicates a small standard deviation.

Figure 8.4 reveals that a 75% reduction in the number of test cases reduces testing time by 47 to 62%, depending upon the size of the database. For example, Figure 8.4(a) shows that the execution of 15 test cases requires 10 seconds of test execution time while the full test suite does not terminate until almost twenty seconds have elapsed. Figure 8.4(d) reveals that the 75% reduction decreases testing time by almost 62% when the tests manipulate the $(20, 10, 10)$ database. A test suite that interacts with a large database benefits from reduction more than a suite for a small database since a single large database test is more costly to run than a small database test. Moreover, the percent reduction in test suite size will normally be higher than the percent reduction in testing time because the test suite executor must incur one time costs associated with tasks such as connecting to the database. Even though the $(20, 5, 5)$ and $(10, 10, 10)$ tests respectively perform 500 and 1000 comparisons, Figures 8.4(b) and (c) show that $(20, 5, 5)$ exhibits higher test execution times than $(10, 10, 10)$. This trend is due to the fact it is more costly for the test executor to load rel_j's actual and expected state than it is for the database-aware test oracle to compare additional attribute values.



(a)

(b)

Figure 8.5: Trends in Testing Time for Reduced Test Suites.

We performed a linear regression analysis in order to confirm the aforementioned trends and to support the prediction of testing time for percent reductions that we did not explicitly examine. We found a least squares fit for the function $f(\varrho) = \alpha + \beta \times \varrho$ where $\varrho \in [0, 1]$ is the reduction factor and α and β are the linear coefficients of the model. We evaluated the quality of the linear model by calculating the coefficient of determination, $R^2 \in [0, 1]$ (high R^2 values suggest that the model is a good predictor for the observed values). Table 8.4 summarizes the results from the regression analysis and Figure 8.5 plots the trends lines for the four different database configurations. As anticipated, the trend line for $(20, 10, 10)$ has the sharpest slope while $(10, 5, 5)$ exhibits the most gradual reduction in testing time. Figure 8.5 also indicates that the tests require approximately seven seconds to (i) initialize the Java virtual machine and the in-memory database server and (ii) create a database connection (we anticipate that this value would be lower if the application connected to a previously started database server). Provided that a reduction technique can preserve the test suite's effectiveness, these empirical results suggest that reduction can significantly decrease testing time.

8.4 USING DATABASE-AWARE COVERAGE TREES

A database-aware test coverage monitoring tree τ reveals how the test suite T caused the program to interact with the databases. As discussed in Section 8.2, we can use the paths in the TCM tree as a test requirement. Previous approaches to regression testing used the coverage tree paths to reduce the test suites for procedural C programs and GUI applications [McMaster and Memon, 2005, 2006]. Our techniques are distinguished from prior work because the regression tester (i) handles paths from both the dynamic call tree (DCT) and the calling context tree (CCT), (ii) uses coverage trees that represent database interactions, and (iii) attempts to make reduction or prioritization more efficient by coalescing tree paths. In support of database-aware regression testing, we denote $\Pi(\tau)$ as the multiset of paths in the coverage tree τ. We define $\Pi(\tau)$ as a multiset because coverage trees like the DCT can contain the same path more than once. Table A15 in Appendix A summarizes the notation that we use to describe the path-based test requirements.

Coverage Tree Path
$\pi_1 = \langle \mathit{call}\ m_1, \mathit{call}\ m_2, \mathit{call}\ m_3, \mathit{use}\ D_f \rangle$
$\pi_2 = \langle \mathit{call}\ m_1, \mathit{call}\ m_2, \mathit{call}\ m_3 \rangle$
$\pi_3 = \langle \mathit{call}\ m_1, \mathit{call}\ m_3, \mathit{call}\ m_4 \rangle$
$\pi_4 = \langle \mathit{call}\ m_2, \mathit{call}\ m_3, \mathit{use}\ D_f \rangle$

Table 8.5: Examples of Paths in a Test Coverage Tree.

Following the path notation established in Chapter 4, we define a path $\pi \in \Pi(\tau)$ as a sequence of nodes such that $\pi = \langle N_\rho, \ldots, N_\phi \rangle$. For a path $\pi \in \Pi(\tau)$, we require (i) $N_\rho = N_0$ (i.e., the first node in the path is the root) and (ii) $N_\phi \in \mathcal{X}_\tau$ (i.e., the last node is a member of the external node set $\mathcal{X}_\tau = \{N_\phi : \mathit{out}(N_\phi) = 0\}$). When $\pi = \langle N_\rho, \ldots, N_\phi \rangle$ and $|\pi| = m$, we use the notation $\pi[0]$ and $\pi[m-1]$ to respectively reference nodes N_ρ and N_ϕ. Table 8.5 provides four concrete examples of simple coverage tree paths that we will use to support the discussion in this section. In these paths, a node of the form *call* m_k corresponds to the invocation of method m_k during testing and the node *use* D_f represents an interaction point that executes a SQL **select** command and thus uses the database D_f. For the tree path π_1 in Table 8.5, we see that $\pi_1[0] = \mathit{call}\ m_1$ and $\pi_1[m-1] = \mathit{use}\ D_f$. For any two test paths π and π', we say that $N_\rho \in \pi$ and $N_\phi \in \pi'$ are *corresponding* nodes if $\pi[j] = N_\rho$, $\pi'[j'] = N_\phi$, and $j = j'$. For the coverage tree paths π_1 and π_4 in Table 8.5, we observe that $\pi_1[0] = \mathit{call}\ m_1$ and $\pi_4[0] = \mathit{call}\ m_2$ are corresponding nodes.

Since our focus is on using a coverage tree path as a test requirement, we define $\Pi(\tau, T_i)$ as the multiset of tree paths for the test case T_i. For a path $\pi \in \Pi(\tau, T_i)$, we require π to be a sequence of nodes such that $N_\rho = \mathit{call}\ T_i$ and $N_\phi \in \mathcal{X}_\tau$. We present several mechanisms for reducing the size of $\Pi(\tau, T_i)$ because the worst-case running time of the reduction and prioritization techniques is bound by the number of test cases and test requirements (c.f. Section 8.5 for the details concerning the time complexities of these algorithms). To this end, we define $\Pi_\upsilon(\tau, T_i) \subseteq \Pi(\tau, T_i)$ as the set of unique test paths for test case T_i. In support of enumerating $\Pi_\upsilon(\tau, T_i)$, Figure 8.6 defines an algorithm for determining path equality. The *IsEqual* algorithm always returns **false** if the two test coverage paths are of a different length. If the two paths are of the same length and each node in π is equal to the corresponding node in π', then *IsEqual* returns **true**.[1] For example, we see that $\pi_1 \neq \pi_2$ because the paths are of different lengths and $\pi_2 \neq \pi_3$ since $\pi_2[1] \neq \pi_3[1]$ and $\pi_2[2] \neq \pi_3[2]$.

Even though $\Pi_\upsilon(\tau, T_i)$ does not contain more than one element for each equivalent test path, it can still contain paths that are duplicative from the testing perspective. If path π includes all of the nodes in π' and some additional nodes, then we say that π is a *super path* of π' and π' is a *sub-path* of π. Intuitively, a super path is stronger than all of its sub-paths because it always exercises the same methods and database entities as each sub-path. We use $\sqsupset$ as the super path operator and we write $\pi \sqsupset \pi'$ to indicate that π is a

[1] This chapter presents several brute-force path comparison operators that the regression tester uses to identify the test requirements. Since these path-based operators are clearly related to traditional text processing techniques, it might be beneficial to enhance them by using time saving heuristics (e.g., [Ager et al., 2006, Boyer and Moore, 1977, Knuth et al., 1977, Salmela et al., 2006, Sunday, 1990]). Since text processing is not the focus of this research and the empirical results suggest that our path enumeration techniques are efficient, we intend to pursue these enhancements as part of future work.

```
**Algorithm** *IsEqual*$(\pi, \pi')$
**Input:** Coverage Tree Paths $\pi, \pi'$
**Output:** Boolean Value for Path Equality
if $|\pi| \neq |\pi'|$
    then return false
    else
        for $N_\phi \in \pi$
            do for $N_\rho \in \pi'$
                do if $N_\phi \neq N_\rho$
                    then return false
return true
```

Figure 8.6: The *IsEqual* Algorithm for the Coverage Tree Paths.

super path of π'. Figure 8.7 provides the *IsSuperPath* algorithm that returns **true** when $\pi \sqsupset \pi'$ and **false** when the super path relationship does not hold. Since a super path π always corresponds to a longer call sequence than a sub-path π', *IsSuperPath* returns **false** if π contains fewer nodes than π'. When $|\pi| > |\pi'|$, *IsSuperPath* compares $\pi[0, |\pi'| - 1]$ to π' using the *IsEquals* algorithm defined in Figure 8.6. For the example paths π_1 and π_2 in Table 8.5, we observe that $\pi_1 \sqsupset \pi_2$. However, *IsSuperPath*(π_2, π_1) = **false** because $|\pi_2| < |\pi_1|$. *IsSuperPath*(π_2, π_3) also returns **false** since π_2 and π_3 correspond to different calling contexts.

Since the CCT instrumentation probes that we defined in Chapter 7 already coalesce the test paths according to $\sqsupset$, the super path operator will not reduce the size of $\Pi_{\upsilon}(\tau_{cct}, T_i)$. However, applying $\sqsupset$ to $\Pi_{\upsilon}(\tau_{dct}, T_i)$ can reduce the number of test requirements and thus make regression testing more efficient. If path π' exists within path π, then we say that π is a *containing path* for π' and we write $\pi \succ \pi'$. Figure 8.8 gives the *IsContainingPath* algorithm that returns **true** when $\pi \succ \pi'$ and **false** when $\pi \not\succ \pi'$. *IsContainingPath* examines all of the possible locations where π' could "fit" into π and returns **true** if a matching location is found. The algorithm returns **false** if it does not locate a matching region after comparing each $|\pi'|$ length sub-path in π to π'.

Suppose that we execute *IsContainingPath*(π_1, π_4) with the paths π_1 and π_4 from Table 8.5. For these inputs, we see that j iteratively takes on the value of 0 and 1 since $|\pi_1| = 4$ and $|\pi_4| = 3$. The first iteration of the **for** loop uses *IsEqual* in order to determine that $\pi_1[0, 2] \neq \pi_4$. Since the second iteration reveals that $\pi_1[1, 3] = \pi_4$, the *IsContainingPath* algorithm returns **true** and thus we know that $\pi_1 \succ \pi_4$. Coalescing tree paths according to the path containment operator should reduce the number of test requirements. However, decreasing the number of paths with $\succ$ may compromise the capability of the requirements to capture the behavior of the program during testing. This is due to the fact that a containing path corresponds to a different testing context when it exercises the same methods and database entities as the contained path. For example, both π_1 and π_4 include an interaction with database D_f after the prior execution of m_1 and m_2. However, the containing path π_1 uses D_f in the context of successive calls to m_1, m_2, and m_3 while π_4 does not have the initial invocation of m_1.

We refer to $\sqsupset$ and $\succ$ as *path dominance operators* and we use $\dashv$ to stand for either of these two operators. We define $\Pi_{\mu}(\tau, T_i, \dashv) \subseteq \Pi_{\upsilon}(\tau, T_i)$ as the set of *maximally unique test paths* for the test T_i and the dominance operator $\dashv$. We say that $\pi \in \Pi_{\mu}(\tau, T_i, \dashv)$ is maximally unique because it dominates all of the other unique test paths under the dominance operator $\dashv$. Figure 8.9 describes the *KeepMaximalUnique* algorithm that applies $\dashv$ to $\Pi_\upsilon(\tau, T_i)$ in an attempt to reduce the number of test requirements. Intuitively, *KeepMaximalUnique* compares each test path $\pi \in \Pi_\upsilon(\tau, T_i)$ to all of other test paths π' that could dominate π according to $\dashv$. A test path π is only included in $\Pi_\mu(\tau, T_i)$ if *KeepMaximalUnique* demonstrates that it dominates all of the other test paths. This algorithm uses $\Pi_\eta(\tau, T_i)$ to store each of the test paths that it has previously examined. For each new test path $\pi \in \Pi_\upsilon(\tau, T_i)$, *KeepMaximalUnique* places π into the set of examined paths and then compares it to all of the other paths π' that either have not yet been examined or have already been proven to be maximally unique. The algorithm assumes that the current π is dominant and uses a call to *IsDominant* to prove otherwise. The *IsDominant* algorithm invokes either the *IsSuperPath* or *IsContainingPath* algorithm, depending upon the chosen dominance operator.

Suppose that a test case T_i covered each of the paths in Table 8.5. In this circumstance, we know that $\Pi_\upsilon(\tau, T_i)$ includes all four of these test paths because each one is unique. However, the set $\Pi_\mu(\tau, T_i, \sqsupset) = \{\pi_1, \pi_3, \pi_4\}$ does not contain π_2 because $\pi_1 \sqsupset \pi_2$. The requirement set $\Pi_\mu(\tau, T_i, \succ) = \{\pi_1, \pi_3\}$ does not contain either π_2 or π_4 because $\pi_1 \succ \pi_2$ and $\pi_1 \succ \pi_4$. This example clearly demonstrates that the use of the *KeepMaximalUnique* algorithm can reduce the number of test requirements and thus decrease the time that we must devote to either reduction or prioritization. Yet, there is a trade-off associated with applying $\dashv$ since the execution of *KeepMaximalUnique* incurs an additional time overhead that might not yield a commensurate decrease in the time consumed by the reduction or prioritization algorithm. Section 8.10 empirically investigates this trade-off by measuring the time overhead for enumerating the coverage tree paths and creating the modified test suite.

Once we have identified $\Pi_\mu(\tau, T_i, \dashv)$ for each test case T_i, we must apply Equation (8.1) in order to identify the set of maximally unique test requirements for the entire test suite. If the tester forgoes the use of *KeepMaximalUnique*, we can also identify $\Pi_\upsilon(\tau, T)$ with Equation (8.2). The reduction and prioritization algorithms described in Section 8.5 analyze how the test cases overlap in their coverage of the test paths in either $\Pi_\mu(\tau, T, \dashv)$ or $\Pi_\upsilon(\tau, T)$. However, if there is a $\pi \in \Pi_\mu(\tau, T_i, \dashv)$ and $\pi' \in \Pi_\mu(\tau, T_i', \dashv)$ such that $\pi \dashv \pi'$, the regression tester will not view this as an overlap in requirement coverage. For example, suppose that for $T = \langle T_i, \hat{T}_i \rangle$, T_i covers paths π_1 and π_2 and $\hat{T}_i$ covers π_3 and π_4. Coalescing these test paths according to $\succ$ yields $\Pi_\mu(\tau, T_i, \succ) = \{\pi_1\}$, $\Pi_\mu(\tau, \hat{T}_i, \succ) = \{\pi_3, \pi_4\}$, and $\Pi_\mu(\tau, T, \succ) = \{\pi_1, \pi_3, \pi_4\}$. Since we did not apply $\succ$ to the entire test suite, the regression tester does not recognize that $\pi_1 \succ \pi_4$ and this may increase the time overhead for creating the modified test suite and/or lead to the removal of fewer tests from the initial suite. In principle, we can extend the *KeepMaximalUnique* algorithm to operate on the entire test suite. We reserve the study of this approach for future research.

$$\Pi_\mu(\tau, T, \dashv) = \bigcup_{i=1}^{n} \Pi_\mu(\tau, T_i, \dashv) \tag{8.1}$$

$$\Pi_\upsilon(\tau, T) = \bigcup_{i=1}^{n} \Pi_\upsilon(\tau, T_i) \tag{8.2}$$

```
Algorithm IsSuperPath($\pi, \pi'$)
Input: Coverage Tree Paths $\pi, \pi'$
Output: Boolean Value for the Super Path Operator $\sqsupset$
if $|\pi| \leq |\pi'|$
   then return false
return IsEqual($\pi[0, |\pi'| - 1], \pi'$)
```

Figure 8.7: The *IsSuperPath* Algorithm for the Coverage Tree Paths.

```
Algorithm IsContainingPath($\pi, \pi'$)
Input: Coverage Tree Paths $\pi, \pi'$
Output: Boolean Value for the Containing Path Operator $\succ$
if $|\pi| \leq |\pi'|$
   then return false
for $j \in \{0, \ldots, |\pi| - |\pi'|\}$
     do if IsEquals($\pi[j, j + |\pi'| - 1], \pi'$) = true
          then return true
return false
```

Figure 8.8: The *IsContainingPath* Algorithm for the Coverage Tree Paths.

```
Algorithm KeepMaximalUnique($\Pi_\upsilon(\tau, T_i), \dashv$)
Input: Set of Unique Test Paths $\Pi_\upsilon(\tau, T_i)$;
       Path Dominance Operator $\dashv$
Output: Set of Maximally Unique Test Paths $\Pi_\mu(\tau, T_i)$
$\Pi_\mu(\tau, T_i) \leftarrow \emptyset$
$\Pi_\eta(\tau, T_i) \leftarrow \emptyset$
for $\pi \in \Pi_\upsilon(\tau, T_i)$
     do $\Pi_\eta(\tau, T_i) \leftarrow \Pi_\eta(\tau, T_i) \cup \{\pi\}$
        dominant $\leftarrow$ true
        for $\pi' \in (\Pi_\upsilon(\tau, T_i) \setminus \Pi_\eta(\tau, T_i)) \cup \Pi_\mu(\tau, T_i)$
            do if IsDominant($\pi', \pi, \dashv$) = true
                  then dominant $\leftarrow$ false
        if dominant = true
           then $\Pi_\mu(\tau, T_i) \leftarrow \Pi_\mu(\tau, T_i) \cup \{\pi\}$
return $\Pi_\mu(\tau, T_i)$
```

Figure 8.9: The *KeepMaximalUnique* Algorithm for the Coverage Tree Paths.

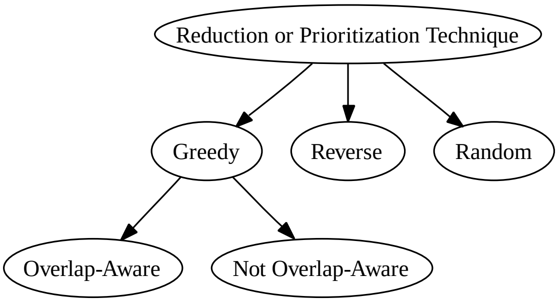


Figure 8.10: Classifying our Approaches to Regression Testing.

8.5 DATABASE-AWARE REGRESSION TESTING

Figure 8.10 shows that the regression testing component supports both test suite reduction and prioritization. In particular, we furnish overlap-aware greedy techniques that are based on the approximation algorithm for the minimal set cover problem [Feige, 1998, Vazirani, 2001]. Greedy reduction with overlap awareness iteratively selects the most cost-effective test case for inclusion in the reduced test suite. During every successive iteration, the overlap-aware greedy algorithm re-calculates the cost-effectiveness for each leftover test according to how well it covers the remaining test requirements. This reduction technique terminates when the reduced test suite covers all of the test requirements that the initial tests cover. Since this approach to reduction leaves the excess tests in the initial test suite, the overlap-aware prioritization scheme identifies a test re-ordering by repeatedly reducing the residual tests. The prioritizer's invocation of the overlap-aware reducer continues until the original suite of tests is empty.

Prioritization that is not overlap-aware re-orders the tests by sorting them according to a cost-effectiveness metric [Rothermel et al., 2001, Rummel et al., 2005]. When provided with a target size for the reduced test suite, the regression tester sorts the tests by cost-effectiveness and then selects test cases until the new test suite reaches the size limit. The overlap-aware reduction and prioritization techniques have the potential to identify a new test suite that is more effective than the suite that was created by ignoring the overlap in requirement coverage. However, the algorithms that are based upon the greedy heuristic for minimal set cover normally require more execution time than the techniques that disregard the overlap. Figure 8.10 also indicates that the regression testing component reverses the initial tests in order to generate a prioritized test suite [Walcott et al., 2006]. This scheme may be useful if a tester always adds new, and possibly more effective, tests to the end of the test suite. Test reduction via reversal selects tests from the reversed test suite until reaching the provided target size. We also employ random reduction and prioritization as a form of experimental control [Do et al., 2004, Rothermel et al., 2001, Walcott et al., 2006].

Figure 8.11 provides the *GreedyReductionWithOverlap* (GRO) algorithm that produces the reduced test suite T_r after repeatedly analyzing how each remaining test covers the requirements in $\Pi(T)$. Following the notation established in Chapter 5, this algorithm uses $\uplus$ as the union operator for tuples. GRO initializes T_r

```
**Algorithm** *GreedyReductionWithOverlap*$(T, \Pi(T))$
**Input:** Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Coverage Set $\Pi(T)$
**Output:** Reduced Test Suite $T_r$
$T_r \leftarrow \emptyset,\ \Pi(T_r) \leftarrow \emptyset,\ \hat{T} \leftarrow T$
**while** $\Pi(T_r) \neq \Pi(T)$
    **do** $\varphi \leftarrow \infty$
        $T_\varphi \leftarrow$ **null**
        **for** $T_i \in \hat{T}$
            **do if** $\Pi(T_i) \setminus \Pi(T_r) \neq \emptyset$
                **then** $\varphi_i \leftarrow \frac{time(\langle T_i \rangle)}{|\Pi(T_i) \setminus \Pi(T_r)|}$
                    **if** $\varphi_i < \varphi$
                      **then** $T_\varphi \leftarrow T_i$
                           $\varphi \leftarrow \varphi_i$
                **else**
                    $\hat{T} \leftarrow \hat{T} \setminus T_i$
        $T_r \leftarrow T_r \uplus T_\varphi$
        $\hat{T} \leftarrow \hat{T} \setminus T_\varphi$
        $\Pi(T_r) \leftarrow \Pi(T_r) \cup \Pi(T_\varphi)$
$T \leftarrow T \setminus T_r$
**return** $T_r$
```

Figure 8.11: The *GreedyReductionWithOverlap* (GRO) Algorithm.

```
**Algorithm** *GreedyPrioritizationWithOverlap*$(T, \Pi(T))$
**Input:** Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Coverage Set $\Pi(T)$
**Output:** Prioritized Test Suite $T_p$
$T_p \leftarrow \emptyset,\ \Pi_\ell(T) \leftarrow \Pi(T)$
**while** $T \neq \emptyset$
    **do** $T_r \leftarrow$ *GreedyReductionWithOverlap*$(T, \Pi_\ell(T))$
        $T_p \leftarrow T_p \uplus T_r$
        $\Pi_l(T) \leftarrow \emptyset$
        **for** $T_i \in T$
            **do** $\Pi_\ell(T) \leftarrow \Pi_\ell(T) \cup \Pi(T_i)$
**return** $T_p$
```

Figure 8.12: The *GreedyPrioritizationWithOverlap* (GPO) Algorithm.

```
**Algorithm** *GreedyReductionWithoutOverlap*$(T, n^*, \varphi)$
**Input:** Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Suite Target Size $n^*$;
    Test Cost-Effectiveness Metric $\varphi$
**Output:** Reduced Test Suite $T_r$
$\hat{T} \leftarrow Sort(T, \varphi)$
$T_r \leftarrow \hat{T}[1, n^*]$
**return** $T_r$
```

Figure 8.13: The *GreedyReductionWithoutOverlap* (GR) Algorithm.

to the empty set and iteratively adds the most cost-effective test into the reduced test suite. Equation (8.4) defines the greedy cost-effectiveness metric φ_i for test case T_i. This equation uses the $time(\langle T_i \rangle)$ function to calculate the execution time of the singleton test tuple $\langle T_i \rangle$. More generally, we require $time(\langle T_1, \ldots, T_n \rangle)$ to return the time overhead associated with executing all of the n tests in the input tuple. According to Equation (8.4), φ_i is the average cost at which test case T_i covers the $|\Pi(T_i) \setminus \Pi(T_r)|$ requirements that are not yet covered by T_r [Vazirani, 2001]. Therefore, each iteration of GRO's outer **while** loop finds the test case with the lowest cost-effectiveness value and places it into T_r.

$$\varphi_i = \frac{time(\langle T_i \rangle)}{|\Pi(T_i) \setminus \Pi(T_r)|} \tag{8.3}$$

GRO initializes the temporary test suite $\hat{T}$ to contain all of T's tests and then selects test cases from $\hat{T}$. Line 2 of Figure 8.11 shows that GRO terminates when $\Pi(T_r) = \Pi(T)$. Line 5 through line 12 are responsible for (i) identifying T_φ, the next test that GRO will add to T_r, and (ii) removing any non-viable test T_i that does not cover at least one of the un-covered requirements (i.e., T_i is *non-viable* when $\Pi(T_i) \setminus \Pi(T_r) = \emptyset$). Lines 13 and 14 respectively place T_φ into T_r and then remove this test from $\hat{T}$ so that it is not considered during later executions of GRO's outer **while** loop. Finally, line 15 augments $\Pi(T_r)$ so that this set contains $\Pi(T_\varphi)$, the set of requirements that T_φ covers. Since we want GRO to support prioritization via successive invocations of the reducer, line 16 updates T so that it no longer contains any of the tests in T_r. We know that *GreedyReductionWithOverlap* is $O(|\Pi(T)| \times |T|)$ or $O(m \times n)$ because the algorithm contains a **for** loop nested within a **while** loop [Rothermel et al., 2001, Vazirani, 2001].

Figure 8.12 contains the *GreedyPrioritizationWithOverlap* (GPO) algorithm that uses the GRO algorithm to re-order test suite T according to its coverage of the requirements in $\Pi(T)$. GPO initializes the prioritized test suite T_p to the empty set and uses $\Pi_\ell(T)$ to store the live test requirements. We say that a requirement is *live* as long as it is covered by a test case that remains in T after one or more calls to *GreedyReductionWithOverlap*. Each invocation of GRO yields both (i) a new reduced T_r that we place in T_p and (ii) a smaller number of residual tests in the original T. After each round of reduction, lines 5 through 7 reinitialize $\Pi_\ell(T)$ to the empty set and insert all of the live requirements into this set. GPO uses the newly populated $\Pi_\ell(T)$ during the next call to GRO. Line 2 shows that the prioritization process continues until $T = \emptyset$. The worst-case time complexity of *GreedyPrioritizationWithOverlap* is $O(n \times (m \times n) + n^2)$ or $O(n^2 \times (1 + m))$. The $n \times (m \times n)$ term in the time complexity stands for GPO's repeated invocation of *GreedyReductionWithOverlap* and the n^2 term corresponds to the cost of iteratively populating $\Pi_\ell(T)$ during each execution of the outer **while** loop. Since overlap-aware greedy prioritization must re-order the entire test suite, it is more expensive than GRO in the worst case.

Figure 8.13 describes the *GreedyReductionWithoutOverlap* (GR) algorithm that reduces a test suite T to the target size $n^* \in \{0, \ldots, n-1\}$. GR uses the cost-effectiveness metric φ when it sorts the tests in T. For a test case T_i, we use one of the three definitions for φ_i: (i) $\frac{time(\langle T_i \rangle)}{|\Pi(T_i)|}$, the ratio between the test's cost and coverage, (ii) $time(\langle T_i \rangle)$, the cost of the test and (iii) $|\Pi(T_i)|$, the number of requirements that

Test Case	**Test Cost**	**Test Coverage**	**Cost to Coverage Ratio**
T_1	1	5	1/5
T_2	2	5	2/5
T_3	2	6	2/6

(a)

Effectiveness Metric	**Test Case Order**
Cost	T_1, T_2, T_3
Coverage	$T_3.T_1, T_2$
Ratio	T_1, T_3, T_2

(b)

Table 8.6: The Cost and Coverage of a Test Suite.

are covered by the test. When φ_i is either the cost to coverage ratio or the cost of each test, the GR algorithm sorts T in *ascending* order. If φ_i is the coverage of a test case, then we sort the test suite in *descending* order. Figure 8.13 shows that GR stores the output of $Sort(T, \varphi)$ in $\hat{T}$ and then creates T_r so that it contains $\hat{T}$'s first n^* tests (i.e., we use the notation $\hat{T}[1, n^*]$ to denote the sub-tuple $\langle T_1, \ldots, T_{n^*} \rangle$). Finally, Figure 8.14 demonstrates that *GreedyPrioritizationWithoutOverlap* (GP) returns the test suite that results from sorting T according to φ. If we assume that the enumeration of $T[1, n^*]$ occurs in linear time, then GR is $O(\log_2 n + n^*)$ and GP is $O(\log_2 n)$. These time complexities both include a $\log_2 n$ term because they sort the input test suite T in order to respectively create T_r and T_p. The n^* term in GR's worst-case time complexity corresponds to the execution of line 2 in Figure 8.13 (i.e., $T_r \leftarrow T[1, n^*]$).

Using GR to perform reduction requires the selection of the target size parameter n^*. When provided with a testing time limit and the average time overhead of a test case, we could pick n^* so that test execution roughly fits into the time budget. In order to ensure a fair experimental comparison between GRO and GR, we set $n^* = |T_r|$ after using GRO to identify T_r. The choice of φ can also change the ordering of the tests in the modified test suite created by either GR or GP. For example, suppose that GP prioritizes test suite $T = \langle T_1, T_2, T_3 \rangle$, as described in Table 8.6(a). Re-ordering T according to cost gives the initial ordering $\langle T_1, T_2, T_3 \rangle$ since T_1 consumes one time unit and T_2 and T_3 both consume two time units (for this example, we resolve ties by creating the order $\langle T_i, T_k \rangle$ when $i < k$ or $\langle T_k, T_i \rangle$ if $i > k$). Prioritization according to test requirement coverage yields the ordering $\langle T_3, T_1, T_2 \rangle$ because T_3 covers six requirements and T_1 and T_2 both cover five. Table 8.6(b) also shows that prioritization by the cost to coverage ratio creates the ordering $\langle T_1, T_3, T_2 \rangle$. In contrast to GRO and GPO, the reduction and prioritization techniques that ignore test coverage overlap may require the tuning of n^* (GR) and φ (GR and GP) in order to ensure that the modified test suite is both efficient and effective.

Figures 8.15 and 8.16 furnish the *ReverseReduction* (RVR) and *ReversePrioritization* (RVP) algorithms. RVR and RVP differ from GR and GP in that they use *Reverse* instead of *Sort*. Since reversal of the test tuple $T[1, n^*]$ is $O(n^*)$, we know that RVR is $O(2n^*)$ and RVP is $O(n)$. Figures 8.17 and 8.18 give the *RandomReduction* (RAR) and *RandomPrioritization* (RAP) algorithms. These algorithms are different than

```
Algorithm $GreedyPrioritizationWithoutOverlap(T, \varphi)$
Input: Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Cost-Effectiveness Metric $\varphi$
Output: Prioritized Test Suite $T_p$
    $T_p \leftarrow Sort(T, \varphi)$
    return $T_p$
```

Figure 8.14: The *GreedyPrioritizationWithoutOverlap* (GP) Algorithm.

```
Algorithm $ReverseReduction(T, n^*)$
Input: Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Suite Target Size $n^*$
Output: Reduced Test Suite $T_r$
    $\hat{T} \leftarrow T[1, n^*]$
    $T_r \leftarrow Reverse(\hat{T})$
    return $T_r$
```

Figure 8.15: The *ReverseReduction* (RVR) Algorithm.

```
Algorithm $ReversePrioritization(T)$
Input: Test Suite $T = \langle T_1, \ldots, T_n \rangle$
Output: Prioritized Test Suite $T_p$
    $T_p \leftarrow Reverse(T)$
    return $T_p$
```

Figure 8.16: The *ReversePrioritization* (RVP) Algorithm.

```
Algorithm $RandomReduction(T, n^*)$
Input: Test Suite $T = \langle T_1, \ldots, T_n \rangle$;
    Test Suite Target Size $n^*$
Output: Reduced Test Suite $T_r$
    $\hat{T} \leftarrow T[1, n^*]$
    $T_r \leftarrow Shuffle(\hat{T})$
    return $T_r$
```

Figure 8.17: The *RandomReduction* (RAR) Algorithm.

```
Algorithm $RandomPrioritization(T)$
Input: Test Suite $T = \langle T_1, \ldots, T_n \rangle$
Output: Prioritized Test Suite $T_p$
    $T_p \leftarrow Shuffle(T)$
    return $T_p$
```

Figure 8.18: The *RandomPrioritization* (RAP) Algorithm.

Regression Testing Algorithm	**Worst-Case Time Complexity**
GreedyReductionWithOverlap (GRO)	$O(m \times n)$
GreedyPrioritizationWithOverlap (GRO)	$O(n^2 \times (1 + m))$
GreedyReductionWithoutOverlap (GR)	$O(\log_2 n + n^*)$
GreedyPrioritizationWithoutOverlap (GP)	$O(\log_2 n)$
ReverseReduction (RVR)	$O(2n^*)$
ReversePrioritization (RVP)	$O(n)$
RandomReduction (RAR)	$O(2n^*)$
RandomPrioritization (RAP)	$O(n)$

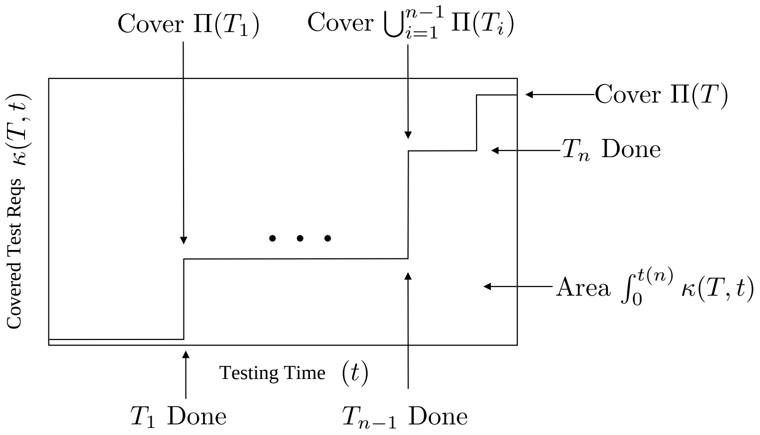
Table 8.7: Summary of the Worst-Case Time Complexities.

reduction and prioritization by reversal because the invoke *Shuffle* instead of *Reverse*. However, RAR and RAP also have worst-case case time complexities of $O(2n^*)$ and $O(n)$, respectively. This result is due to the fact that *Reverse* and *Shuffle* are both linear time algorithms. Table 8.7 summarizes the worst-case time complexities of the reduction and prioritization algorithms provided by the regression testing component. Finally, Table A16 in Appendix A reviews the notation that we develop in this section.

8.6 EVALUATING THE EFFECTIVENESS OF A TEST SUITE

We must evaluate the effectiveness of the modified test suite that was created by the reduction or prioritization technique. Most measures of effectiveness can only be calculated after using a mutation testing tool to seed faults into the program under test. If a mutation tester is not available, then it is possible to manually seed faults into the source code of a case study application. Upon the completion of fault seeding, we can evaluate a prioritized test suite by determining how well it exposes the seeded faults. The *average percentage of faults detected* (APFD) is the metric that best represents this type of approach to empirically evaluating a prioritization technique [Rothermel et al., 2001]. Reliance upon manual fault seeding can be problematic because it is costly, prone to error, and a potential source for experimental bias. Preliminary empirical results suggest that it may be acceptable to measure a test suite's fault detection effectiveness by using a mutation testing tool [Andrews et al., 2005, Do and Rothermel, 2006]. Yet, there are no mutation testing tools that consider a program's database interactions. Furthermore, no experiments have been done to confirm whether or not a mutation tester can guide the evaluation of database-aware test prioritization.

It is important to devise an effectiveness metric for prioritized test suites that does not require fault seeding. If requirement coverage is stored on a per test case basis and the coverage monitor records the execution time for each test, then it is possible to calculate our measure of coverage effectiveness. First, we create a *cumulative coverage* function that describes how test requirement coverage varies over time. We construct this coverage function under the assumption that a requirement is marked as covered upon



Cover $\Pi(T_1)$
Cover $\bigcup_{i=1}^{n-1} \Pi(T_i)$
Cover $\Pi(T)$
T_n Done
Area $\int_0^{t(n)} \kappa(T, t)$
Covered Test Reqs $\kappa(T, t)$
Testing Time (t)
T_1 Done
T_{n-1} Done

Figure 8.19: The Cumulative Coverage of a Test Suite.

the completion of one of its covering tests. Integrating this function yields the *coverage area* of the test suite. Intuitively, a large coverage area suggests that a particular re-ordering of a test suite is highly effective. In support of an approach to comparing different prioritizations of the same test suite, we define *coverage effectiveness* (CE) as the ratio between the re-ordered suite's coverage area and the coverage area of the ideal test suite. As mentioned in Section 8.3, an *ideal* test suite immediately covers all of the test requirements. Since high coverage tests are more likely to reveal program faults than those with low coverage [Hutchins et al., 1994], CE is an appropriate metric for characterizing a re-ordered test suite. Even though CE and APFD are similar because they both calculate an area under a curve, CE obviates the need for fault seeding. Therefore, CE is useful when manual fault seeding is too costly or mutation testing is not feasible. We envisage the use of CE in conjunction with previously developed metrics such as APFD.

Equation (8.4) defines $\xi(T, T_p) \in [0, 1]$, the coverage effectiveness of the prioritized test suite T_p that was derived from T. Suppose that the regression tester creates T_p and $\hat{T_p}$ after applying two different prioritization techniques to T. If $\xi(T, T_p) > \xi(T, \hat{T_p})$, then we know that T_p is more coverage effective than $\hat{T_p}$. For this example, we would prefer the first approach to reduction instead of the second. The numerator of Equation (8.4) is the integral of $\kappa(T_p, t)$, the requirement coverage for test suite T_p at time t during test suite execution. Equation (8.4)'s denominator is the integral of $\bar{\kappa}(T, t)$, the requirement coverage for the ideal version of T. Calculating $\xi(T, T_p)$ requires the integration of both the κ and $\bar{\kappa}$ functions in the closed interval between 0 and $t(n)$. Equation (8.5) defines $t(n')$ as the time required to execute the first n' test cases in T. For example, $t(1)$ would return the time overhead for test T_1 and $t(n)$ calculates the running time for the entire suite of n test cases. Finally, Equation (8.4) uses t to stand for a specific point in time during testing.

$$\xi(T, T_p) = \frac{\int_0^{t(n)} \kappa(T_p, t)}{\int_0^{t(n)} \bar{\kappa}(T, t)} \tag{8.4}$$

$$t(n') = \sum_{i=1}^{n'} time(T_i) \tag{8.5}$$

Since the ideal test suite immediately covers all of the test requirements, Equation (8.6) shows that $\bar{\kappa}(T, t)$ is constant across all time inputs t for a specific test suite T. If T covers the requirements in the set $\Pi(T)$, then $\bar{\kappa}(T, t)$ indicates that an ideal suite would cover all $\pi \in \Pi(T)$ right away. Finally, Equation (8.7) defines the piecewise function $\kappa(T, t)$ that describes the cumulative coverage of T at time t during testing. We define $\kappa(T, t)$ as an $(n+1)$-part piecewise function when $T = \langle T_1, \ldots, T_n \rangle$. Equation (8.7) reveals that $\kappa(T, t) = 0$ until the completion of test case T_1 (i.e., $t < t(1)$). In the time period after the execution of T_1 and during the running of T_2 (i.e., $t \in [t(1), t(2))$), the value of κ shows that T has covered a total of $|\Pi(T_1)|$ test requirements. After running the first $n-1$ tests, κ's output indicates that T has covered $\left|\bigcup_{i=1}^{n-1} \Pi(T_i)\right|$ test requirements until the test executor completes the execution of the final test T_n (i.e., $t \in [t(n-1), t(n))$). We define κ to maintain the maximum height of $|\Pi(T)|$ for all time points $t \geq t(n)$. Figure 8.19 graphically demonstrates how we construct the cumulative coverage function κ. Even though our definition of ξ and κ leverages the notation for coverage tree paths, it is also possible to calculate coverage efficiency according to the test suite's coverage of other types of test requirements such as the database interaction association. Table A17 in Appendix A reviews the notation that we develop during the discussion of the coverage effectiveness for a test prioritization.

$$\bar{\kappa}(T, t) = \left| \bigcup_{i=1}^{n} \Pi(T_i) \right| \tag{8.6}$$

$$\kappa(T, t) = \begin{cases} 0 & t < t(1) \\ |\Pi(T_1)| & t \in [t(1), t(2)) \\ \vdots & \vdots \\ \left|\bigcup_{i=1}^{n-1} \Pi(T_i)\right| & t \in [t(n-1), t(n)) \\ |\Pi(T)| & t \geq t(n) \end{cases} \tag{8.7}$$

We can only use the previous formulation of coverage effectiveness when we evaluate the prioritization of a test suite. This is due to the fact that different reduction techniques frequently create test suites that vary in their reduction of the (i) number of tests, (ii) overall test suite execution time, and (iii) coverage of the test requirements. To this end, we present two metrics for evaluating the efficiency of a reduced test suite. Equation (8.8) defines $\varrho_n(T, T_r) \in [0, 1]$, the *reduction factor for test size* (RFS) of the original test suite T and reduced test suite T_r. Furthermore, Equation (8.9) defines $\varrho_t(T, T_r) \in [0, 1]$, the *reduction factor for testing time* (RFT). High values for RFS and RFT suggest that a reduced test suite is very efficient. Suppose that the regression tester analyzes test suite T and creates two reduced test suites called T_r and $\hat{T}_r$. If $\varrho_n(T, T_r) > \varrho_n(T, \hat{T}_r)$ and $\varrho_t(T, T_r) > \varrho_t(T, \hat{T}_r)$, then we know that T_r is more efficient than $\hat{T}_r$.

$$\varrho_n(T, T_r) = \frac{|T| - |T_r|}{|T|} \tag{8.8}$$

$$\varrho_t(T, T_r) = \frac{time(T) - time(T_r)}{time(T)} \tag{8.9}$$

ν_r	$\hat{\nu}_r$	Comparison
$\langle .4, .5, .8 \rangle$	$\langle .4, .5, .9 \rangle$	$\hat{\nu}_r \gg \nu_r$
$\langle .4, .5, 1 \rangle$	$\langle .4, .55, 1 \rangle$	$\hat{\nu}_r \gg \nu_r$
$\langle .6, .5, 1 \rangle$	$\langle .4, .5, 1 \rangle$	$\nu_r \gg \hat{\nu}_r$
$\langle .4, .5, 1 \rangle$	$\langle .55, .75, .9 \rangle$	$\nu_r \sim \hat{\nu}_r$

Table 8.8: Comparing Test Suite Reductions.

We must also evaluate the effectiveness of a reduced test suite. The majority of prior empirical research calculates the decrease in fault detection effectiveness for a reduced test suite after seeding faults into the program under test (e.g., [Jones and Harrold, 2003, McMaster and Memon, 2005]). We judge that it is important to devise a measure of effectiveness that can be used instead of or in conjunction with a fault-based measurement. To this end, Equation (8.10) defines the *reduction factor for test requirements* (RFR) as $\varrho_\pi(T, T_r) \in [0, 1]$. Unlike the RFS and RFT metrics, we prefer low values for $\varrho_\pi(T, T_r)$ because this indicates that a reduced test suite T_r covers the majority of the requirements that the initial tests cover. To avoid confusion during the empirical comparison of different reduction techniques, we define the *preservation factor for test requirements* (PFR) as $\nu_\pi(T, T_r) = 1 - \varrho_\pi(T, T_r)$ such that $\nu_\pi(T, T_r) \in [0, 1]$. If a reduced test suite has a high PFR factor, then we know that it covers most of the requirements that the original tests cover. The overlap-aware greedy reduction algorithm that we defined in Section 8.5 (i.e., GRO) always creates a T_r that covers all of the test requirements and thus $\nu_\pi(T, T_r) = 1$. However, the other reduction techniques (i.e., GR, RVR, and RAR) are not guaranteed to construct a test suite that covers all $\pi \in \Pi(T)$ and thus they may yield values for ν_π that are less than one. Even though we defined ϱ_π and ν_π in the context of coverage tree paths, we can also use these coverage effectiveness metrics in conjunction with reduction techniques that use other types of test requirements (e.g., the database interaction associations).

$$\varrho_\pi(T, T_r) = \frac{|\Pi(T)| - |\Pi(T_r)|}{|\Pi(T)|} \tag{8.10}$$

In order to facilitate the comparison between different approaches to reduction, we employ $\nu_r = \langle \varrho_n, \varrho_t, \nu_\pi \rangle$ to organize the evaluation metrics for test suite T_r. Table 8.8 summarizes the four different evaluation tuples that we use to explain the process of comparing different reduction algorithms. Suppose that two different reduction techniques create T_r and $\hat{T}_r$ that are respectively characterized by the evaluation tuples $\nu_r = \langle .4, .5, .8 \rangle$ and $\hat{\nu}_r = \langle .4, .5, .9 \rangle$. In this example, we would prefer the $\hat{\nu}_r$ configuration because it (i) has the same values for ϱ_n and ϱ_t (i.e., the reduction factors for the number of tests and the overall testing time) and (ii) preserves the coverage of more test requirements since $\widehat{\nu_\pi} > \nu_\pi$. If $\nu_r = \langle .4, .5, 1 \rangle$ and $\hat{\nu}_r = \langle .4, .55, 1 \rangle$, then we would prefer the reduced suite with $\hat{\nu}_r$ because it fully preserves requirement coverage while yielding a larger value for ϱ_t (i.e., $.55 > .5$). Next, suppose that $\nu_r = \langle .6, .5, 1 \rangle$ and $\hat{\nu}_r = \langle .4, .5, 1 \rangle$. In this situation, we would favor ν_r's reduction algorithm since it yields the smallest test suite (i.e., $\varrho_n > \widehat{\varrho_n}$ since $.6 > .4$). This choice is sensible because it will control test execution time if there is an increase in the startup and shutdown costs associated with running a test.

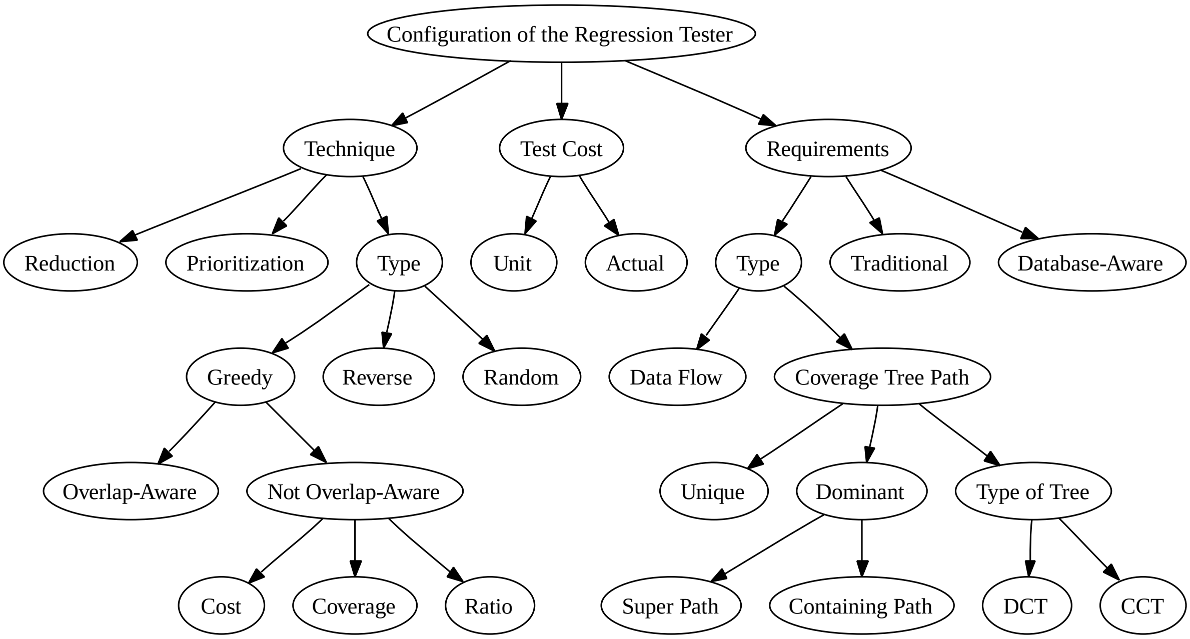


Figure 8.20: Different Configurations of the Regression Testing Component.

During the evaluation of reduction algorithms, it may not always be clear which technique is the most appropriate for a given database-centric application and its test suite. For example, assume that $\nu_r = \langle .4, .5, 1 \rangle$ and $\hat{\nu}_r = \langle .55, .75, .9 \rangle$, as provided by Table 8.8. In this example, $\hat{\nu}_r$ shows that $\hat{T}_r$ is (i) better at reducing testing time and (ii) worse at preserving requirement coverage when we compare it to T_r. In this circumstance, we must choose the reduction technique that best fits the current regression testing process. For example, it may be prudent to select $\hat{\nu}_r$ when the test suite is executed in a time constrained environment (e.g., [Kapfhammer et al., 2005, Walcott et al., 2006]) or the tests are repeatedly run during continuous testing (e.g., [Saff and Ernst, 2004]). If the correctness of the application is the highest priority, then it is advisable to use the reduction technique that leads to T_r and ν_r. For the reduced test suites T_r and $\hat{T}_r$ and their respective evaluation tuples ν_r and $\hat{\nu}_r$, we write $\nu_r \gg \hat{\nu}_r$ when the logical predicate in Equation (8.11) holds (i.e., we *prefer* T_r to $\hat{T}_r$). If $\nu_r \gg \hat{\nu}_r$, then we know that T_r is as good as $\hat{T}_r$ for all three evaluation metrics and better than $\hat{T}_r$ for at least one metric.[2] If Equation (8.11) does not hold for test suites T_r and $\hat{T}_r$ that were produced by two different reduction techniques (i.e., $\nu_r \not\gg \hat{\nu}_r$ and $\hat{\nu}_r \not\gg \nu_r$), then we write $\nu_r \sim \hat{\nu}_r$ (i.e., T_r and $\hat{T}_r$ are *similar*). Since we have no preference between T_r and $\hat{T}_r$ when $\nu_r \sim \hat{\nu}_r$, we must use the constraints inherent in the testing process to inform the selection of the best reduction technique. Table A18 in Appendix A reviews the notation that we use to describe the evaluation of a reduced test suite.

$$\forall \nu \in \nu_r, \hat{\nu} \in \hat{\nu}_r : (\nu \geq \hat{\nu}) \;\wedge\; \exists \nu \in \nu_r, \hat{\nu} \in \hat{\nu}_r : (\nu > \hat{\nu}) \qquad (8.11)$$

[2] Our definition of the $\gg$ operator is based on the concept of pareto efficiency that is employed in the fields of economics and multi-objective optimization (please refer to [Zitzler and Thiele, 1999] for more details about these areas).

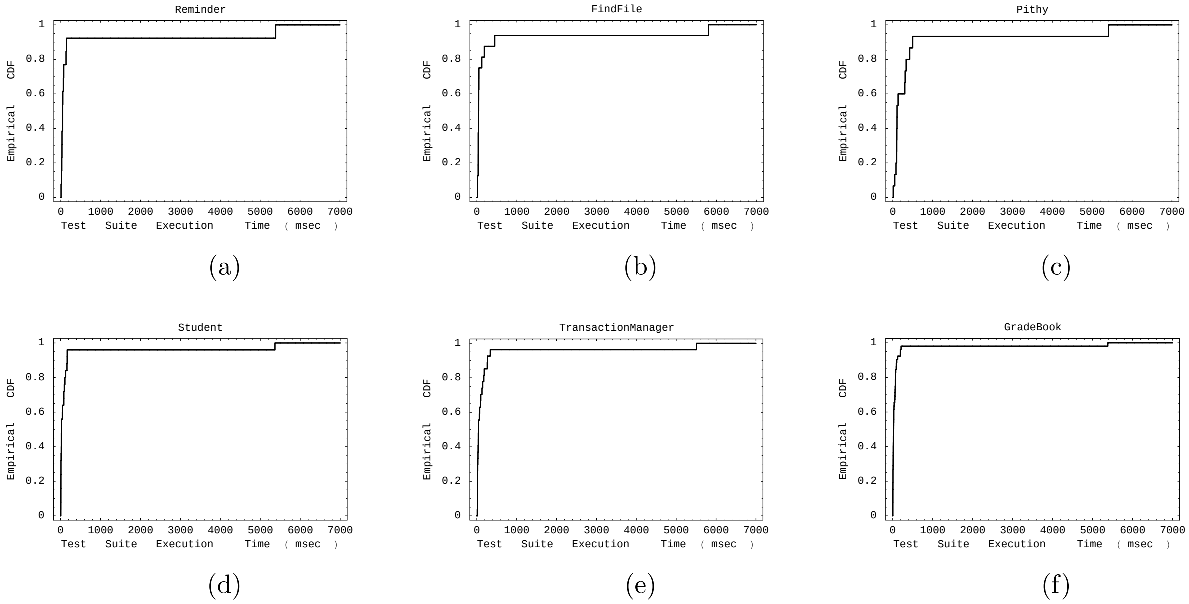
8.7 IMPLEMENTATION OF THE REGRESSION TESTING COMPONENT

Figure 8.20 describes the different configurations of the regression testing component. Section 8.4 provides a detailed discussion of the "Requirements" subtree and Section 8.5 examines the "Technique" subtree. We implemented the regression testing component in the Java 1.5.0 programming language. For simplicity, we convert a coverage tree path into a `java.lang.String` and we use the `startsWith` and `contains` methods in the implementation of the path dominance operators. For example, the regression tester transforms the tree paths π and π' into strings s and s'. If we have $\pi \sqsupset \pi'$ (i.e., π is a super path for π'), then we know that s.`startsWith`(s') returns `true`. Furthermore, if $\pi \succ \pi'$ holds (i.e., π is a containing path for π'), then we know that s.`contains`(s') returns `true`.

Even though the empirical results in Section 8.10 suggest that the use of `java.lang.String` exhibits acceptable performance, we intend to use more efficient string implementations (e.g., [Boldi and Vigna, 2005]) and text processing algorithms (e.g., [Sunday, 1990]) to further reduce the time overhead of test path enumeration. Since the default JUnit and DBUnit test executors do not support reduction or prioritization, we enhanced these tools to read external configurations. When prioritization is enabled, the test executor ignores the default ordering of the tests and re-orders them before testing starts. If reduction is chosen, then the test suite execution engine only runs a test if it is specified in the external configuration file. Even though each configuration file is automatically generated by the regression testing component, the tester may manually modify these configurations when necessary. Since our regression testing tools incorporate a test's actual running time, we enhanced the coverage monitor so that it (i) uses instrumentation probes to time the execution of a test and (ii) stores this data in the coverage report.

8.8 EXPERIMENT GOALS AND DESIGN

We conducted experiments to measure the performance of the algorithms that (i) enumerate the tree-based test requirements and (ii) reduce or prioritize the test suite. We also investigate how reduction and prioritization impact the efficiency and effectiveness of regression testing (c.f. Section 8.6 for a discussion of the primary evaluation metrics). We characterize each case study application in order to explain why the efficiency and effectiveness of the algorithms vary across the different applications. Since the existence of many long running test cases may limit the opportunities for reduction and/or prioritization [Elbaum et al., 2001], we calculate the running time for each test case in a test suite. Furthermore, we measure how many tests cover each individual test requirement because a test suite with a high overlap in requirement coverage is more amenable to reduction. If a test suite is composed of many tests that create numerous tree paths and there is a small number of test requirements, then it is likely that this suite is fit for reduction. Thus, we count the number of tree paths that are created by each test case. Finally, we report how many unique tree paths are covered by the entire test suite because the worst-case time complexity of GRO and GPO is bound by both the number of test cases (i.e., $|T|$ or n) and the number of requirements (i.e., $|\Pi(T)|$ or m).



(a) (b) (c) (d) (e) (f)

Figure 8.21: ECDFs for Test Case Execution Time.

Figure 8.20 shows that the regression tester can reduce or re-order the test suite by incorporating either the unit cost or the actual cost of running a test. Under the *unit cost* assumption, a regression testing algorithm supposes that all of the test cases execute for the same amount of time. With the exception of [Elbaum et al., 2001, Walcott et al., 2006], the majority of regression testing tools operate under the unit cost assumption (e.g., [Jeffrey and Gupta, 2007, Harrold et al., 1993, McMaster and Memon, 2005, Tallam and Gupta, 2005]). However, it is not advisable to make this assumption during the regression testing of a database-centric application. When a test suite mixes database-aware test cases with those that do not perform database interactions, the time overhead of the tests can vary by one or more orders of magnitude. Figure 8.21 presents an empirical cumulative distribution function (ECDF) of test execution time for the test suite of each case study application. As noted in Chapter 7, an ECDF gives the cumulative percentage of the recorded data set whose values fall below a specific value. In these graphs, a sharply rising ECDF indicates that most test cases are very fast. An ECDF curve that rises more gradually would suggest that the test suite has a greater concentration of long running tests.

For brevity, our discussion of test case execution time focuses on the `FF` application (the other case study applications demonstrate similar testing patterns). `FindFile`'s ECDF in Figure 8.21(b) reveals that almost 90% of the test cases have execution times below 500 milliseconds and over 60% of tests run in under 200 milliseconds. We also observe that a small percentage of the tests run for almost six seconds. After investigating the source code of `FindFile`'s test suite, we noted that the fast test cases perform few, if any, database interactions. The more costly test cases execute many database-aware test oracles and often interact with more than one of the database's relations. Generally, the most expensive tests incur a high time overhead because they ensure the correctness of the database server's startup and shutdown routines by starting and stopping the server. We anticipate that these costs would be much higher if `FindFile` restarted a stand-alone RDBMS (e.g., MySQL [Yarger et al., 1999] or PostreSQL [Monjian, 2000]) instead of the in-memory HSQLDB database management system. The graphs in Figure 8.21 demonstrate that all of the test suites contain many tests that execute very quickly (i.e., in less than 100 milliseconds) and a few tests that run for approximately five or six seconds. This evidence clearly suggests that there is a substantial difference in the time overhead for the tests and thus motivates the use of the *actual* test execution time. Since our test coverage monitor records the time overhead for running each test case, all of the experiments use the actual test execution cost. In future work, we will examine how the unit cost assumption impacts database-aware regression testing.

It is important to perform reduction and prioritization for our case study applications even though Table 8.9 shows that all of the test suites execute in less than ten seconds. A testing time of ten seconds may be too costly in certain software development processes, such as extreme programming, that promote a short implementation and testing cycle and the frequent execution of very fast tests [Poole and Huisman, 2001]. If a test suite is executed in a time sensitive environment (e.g., [Walcott et al., 2006]), the tests are run during continuous testing (e.g., [Saff and Ernst, 2004]), or testing occurs in a resource constrained environment (e.g., [Kapfhammer et al., 2005]), then it also may be too expensive to run all of the tests. Furthermore, recent research suggests that the test executor should restart the RDBMS server after the execution of every test case [Haftmann et al., 2005a]. This approach is useful because it is often difficult for a tester to ensure that all of the tests restore the database state that they modified. For example, test execution may have side effects if a test case modifies the state of the database and the RDBMS subsequently changes one or more relations when it enforces integrity constraints or executes triggers.

We judge that it is not absolutely necessary to restart the server upon the completion of a test because each of our test suites executes in an independent fashion. However, in light of the recommendations made by [Haftmann et al., 2005a], we estimated the execution time of each test suite under the assumption that the tests are non-independent and the executor repeatedly performs server restarts in order to purge the database's state. After studying the testing behavior of each case study application, we concluded that a restart of the HSQLDB server takes approximately five seconds. Table 8.9 reveals that the execution of a test suite with server restarts will consume between 32 and 43 seconds of testing time. Therefore, it is important to perform reduction and/or prioritization if the (i) testing process dictates that tests must run in a rapid fashion, (ii) testing occurs in an environment with time or resource constraints, and/or (iii) test executor always restarts the RDBMS because the tests do not properly cleanse the database.

Figure 8.20 shows that the regression testing component can analyze both traditional and database-aware DCTs and CCTs. The experiments use coverage trees that record database interactions at the relation, attribute, record, and attribute value levels (e.g., $\mathbf{R_l}$, $\mathbf{A}$, $\mathbf{R_c}$, and $\mathbf{A_v}$). We selected the $\mathbf{R_l}$ and $\mathbf{A}$ levels since they focus on the structure of the database. Furthermore, we included the $\mathbf{R_c}$ and $\mathbf{A_v}$ levels because they represent a program's interaction with the database's state. We observe that the program and database

Application	Without Restarts (sec)	With Restarts (sec)
`Reminder`	6.164	32.053
`FindFile`	6.966	36.379
`Pithy`	8.243	52.864
`StudentTracker`	6.686	34.767
`TransactionManager`	8.211	42.697
`GradeBook`	7.576	39.395

Table 8.9: Test Suite Execution Time With and Without Database Server Restarts.

levels (e.g., **P** and **D**) yield equivalent coverage trees in our experiments. This is due to the fact that all of the applications interact with one database. Since a database interaction point will only lead to a higher number of test requirements if it interacts with more than one database entity, the **P**-level and **D**-level trees always yield the same number of test requirements. For example, suppose that the database interaction point I_r submits the SQL command **select** $*$ **from** rel_j. If node N_ϕ precedes I_r, then the **P**-level and **D**-level coverage trees will respectively contain the path $N_\phi \rightarrow I_r$ and $N_\phi \rightarrow I_r \rightarrow use(D_f)$.

For all of the applications except `TM` and `GB`, the **D**-level and $\mathbf{R_l}$-level trees will always render the same number of tree paths. This is due to the fact that all of the other case study applications use a database that only contains one relation. In the context of the previous SQL statement, an R_l-level tree would still lead to the single test path $N_\phi \rightarrow I_r \rightarrow use(D_f) \rightarrow use(rel_j)$. However, assume that the database contains relations rel_j and $\widehat{rel_j}$ and I_r executes the command **select** $*$ **from** rel_j **where** $rel_j.A_l = \widehat{rel_j}.\hat{A}_l$. In this circumstance, the $\mathbf{R_l}$-level tree contains the two test paths $N_\phi \rightarrow I_r \rightarrow use(D_f) \rightarrow use(rel_j)$ and $N_\phi \rightarrow I_r \rightarrow use(D_f) \rightarrow use(\widehat{rel_j})$. Since only `TM` and `GB` contain interaction patterns like the second SQL statement, we omit both the **P** and **D** levels from the empirical study (i.e., for the other four applications, the **D** and $\mathbf{R_l}$ levels would lead to the same experimental outcomes). For completeness, Table C4 in Appendix C furnishes the results from enumerating the **P**-level test requirements for `TM` and `GB`.

We configured the test coverage monitor to create an XML-based coverage tree and we traverse this tree during requirement enumeration. Since XML parsing is often the limiting factor in the performance of an application [Nicola and John, 2003], we judge that this choice ensures that we characterize the worst-case performance of our technique for enumerating the test paths. In fact, preliminary experiments suggest that the use of a binary coverage tree may halve test path enumeration time when we analyze the largest coverage trees. The experiments also focused on using the database-aware calling context tree (i.e., the DI-CCT) instead of the DI-DCT because previous empirical studies (e.g., [McMaster and Memon, 2005, 2006]) used the traditional version of the CCT. Since the CCT instrumentation probes already coalesce tree paths according to the super path operator, we time the enumeration of the set $\Pi_\mu(\tau_{cct}, T, \sqsupset)$. We also apply the containing path operator in order to measure the time consumed during the enumeration of $\Pi_\mu(\tau_{cct}, T, \succ)$ (c.f. Section 8.4 for a discussion of the enumeration algorithms and the path dominance operators).

Even though the case study applications are written in a fashion that allows the tests to start their own instance of the HSQLDB server, we assume that every database-centric application connects to a previously started database management system. We set up the reduction and prioritization algorithms so that they analyze the coverage information in the set $\Pi_{\mu}(\tau_{cct}, T_i, \dashv)$ for each test case T_i. In addition to using all of the prioritization techniques that are listed in Table 8.7, we also report the effectiveness of the initial ordering of the test suite. Since the GR, RVR, and RAR reduction techniques require a target size, we executed the GRO algorithm first and then use the size of the resulting test suite as input to the other algorithms. As an experimental control, we generated fifty randomly reduced and prioritized test suites. We calculate the average value of each evaluation metric across all fifty of the test suites. In order to ensure a fair comparison, we employed a uniformly distributed pseudo-random number generator to create fifty seeds. Throughout the entire experimentation process, we used the first seed to initialize the pseudo-random number generator that governs the creation of the first randomly reduced or re-ordered test suite (the second seed is used for the second test suite and so forth). We judge that this design improves the repeatability of the experiments. As part of future research, we intend to employ Walcott et al.'s approach to randomly generating a large number of test suite orderings and reductions [Walcott et al., 2006].

Finally, we executed the (i) test requirement enumerator and (ii) reduction or prioritization algorithm in five separate trials. Since the time overhead metrics varied across each trial, we calculate arithmetic means and standard deviations for all of these timings (the metrics that characterize a case study application did not vary across trials). As in Chapter 7, we use box and whisker plots and bar charts to visualize the empirical results (c.f. Section 7.4 for a discussion of these approaches to data visualization). When we visualize a time overhead, we create a bar chart so that the height of the bar corresponds to the arithmetic mean of the measurements. We do not include error bars in the bar charts in Figure 8.22 because the standard deviations were very small. We performed all of the experiments on a GNU/Linux workstation with kernel 2.6.11-1.1369, Native POSIX Thread Library (NPTL) version 2.3.5, a dual core 3.0 GHz Pentium IV processor, 2 GB of main memory, and 1 MB of L1 processor cache.

8.9 KEYS INSIGHTS FROM THE EXPERIMENTS

The experimental results in Section 8.10 complement the analytical evaluation of the regression testing algorithms in Sections 8.4 and 8.5. Due to the comprehensive nature of the empirical analysis, we furnish the following insights from the experiments:

1. *Test Path Enumeration*: It is often possible to enumerate the tree-based test paths in less than one second. The enumeration process is the most expensive when we identify the paths in a coverage tree that represents a database interaction at the attribute value level. In the majority of circumstances, we can identify the tree paths in the $\mathbf{A_v}$-level DI-CCT in less than six seconds. We conclude that the tree-based test requirement is suitable for both version specific and general regression testing.
2. *Test Suite Reduction*:
   a. <u>Effectiveness</u>: The reduced test suites are between 30 and 80% smaller than the original test suite. Across all of the case study applications, the *GreedyReductionWithOverlap* (GRO) algorithm yields

a test suite that contains 51% fewer test cases. The use of GRO leads to test suites that always cover the same requirements as the original tests while decreasing testing time by between 7 and 78%. Even though the other approaches to reduction (i.e., GR, RVR, and RAR) may lead to a substantial decrease in testing time, these techniques often compromise the coverage preservation of the modified test suite.

b. Efficiency: All configurations of the reduction component can execute in under one second. We find that the execution of the GRO algorithm normally consumes less than 500 milliseconds, while the GR, RVR, and RAR techniques only run for three to five milliseconds. We judge that the reduction tool is suitable for use in either the general or version specific approach to regression testing.

3. *Test Suite Prioritization*:

a. Effectiveness: In comparison to the original ordering of `GB`'s test suite, the *GreedyPrioritizationWithOverlap* (GPO) causes the coverage effectiveness (CE) value to increase from .22 to .94. For the other case study applications, we find that the GPO technique creates test orderings that attain higher CE values than either the randomly prioritized or the original test suite.

b. Efficiency: Extensive study of the performance of the prioritization component suggests that it is also very efficient. Paralleling the results from using the reduction algorithms, we find that GPO always runs in less than 1.5 seconds. Furthermore, the GP, RVP, and RAP techniques can identify a re-ordered test suite in less than 5 milliseconds.

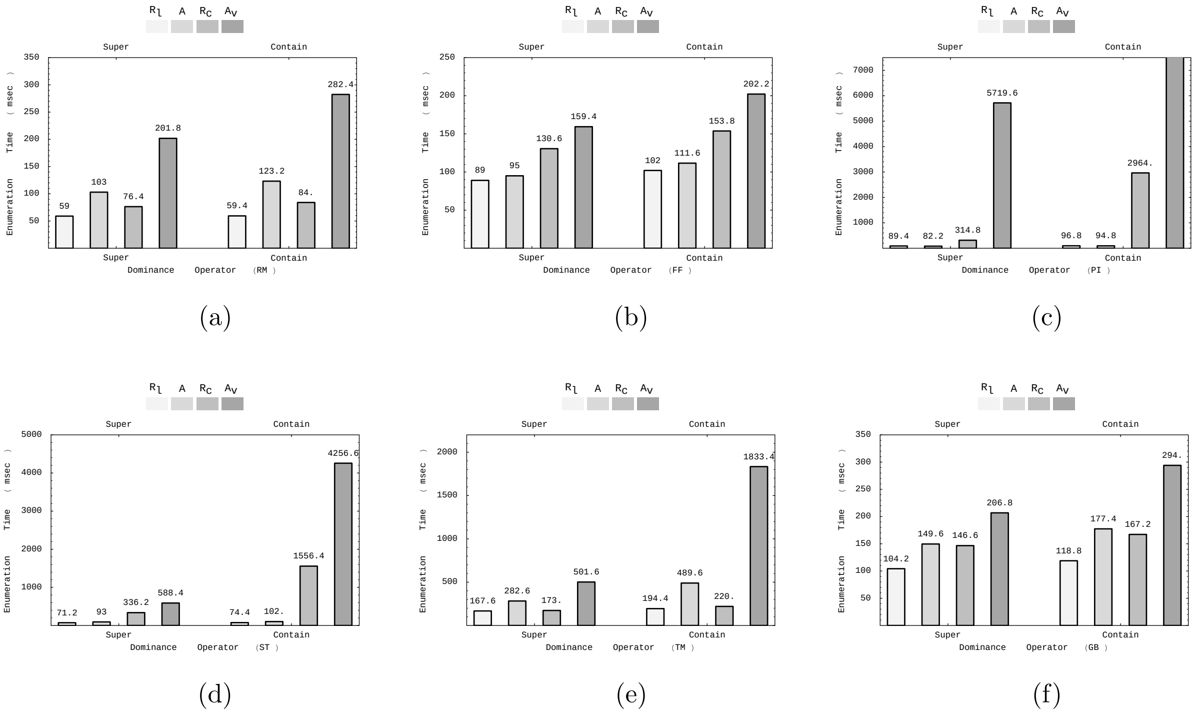
8.10 ANALYSIS OF THE EXPERIMENTAL RESULTS

8.10.1 Coverage Information

We conducted experiments to measure $\mathcal{T}_{\Pi}(A, \tau, L, \dashv)$, the time required to analyze application A's coverage tree τ and enumerate the test paths in $\Pi_{\mu}(\tau, T, \dashv)$. For example, $\mathcal{T}_{\Pi}(\texttt{FF}, \tau_{cct}, \mathbf{R_l}, \succ)$ is the time overhead associated with identifying the test paths in `FindFile`'s relation level CCT when we use the containing path operator. The following Equation (8.12) defines the number of paths that are created by the individual test cases, denoted $\mathcal{C}^{\Sigma}_{\Pi}(A, \tau, L, \dashv)$. As stated in the following Equation (8.13), $\mathcal{S}^{\cup}_{\Pi}(A, \tau, L, \dashv)$ is the number of unique paths that are created by the entire test suite. The $\mathcal{C}^{\Sigma}_{\Pi}$ evaluation metric helps us to understand the time overhead associated with path enumeration because we must traverse τ_{cct} in order to identify every $\pi \in \Pi_{\mu}(\tau_{cct}, T_i, \dashv)$ for each test case T_i. A low value for $\mathcal{S}^{\cup}_{\Pi}$ suggests that reduction or prioritization is likely to be efficient while a high number foreshadows a more time consuming run of the regression tester.

$$\mathcal{C}^{\Sigma}_{\Pi}(A, \tau, L, \dashv) = \sum_{i=1}^{n} |\Pi_{\mu}(\tau, T_i, \dashv)| \tag{8.12}$$

$$\mathcal{S}^{\cup}_{\Pi}(A, \tau, L, \dashv) = \left| \bigcup_{i=1}^{n} \Pi_{\mu}(\tau, T_i, \dashv) \right| = |\Pi_{\mu}(\tau, T, \dashv)| \tag{8.13}$$



(a) (b) (c)

(d) (e) (f)

Figure 8.22: Test Path Enumeration Time.

Figure 8.22 provides the measurements of the time overhead associated with enumerating the test paths. In many circumstances, it is possible to identify all of the paths in less than 100 milliseconds (e.g., when we apply the super path operator to either the record or attribute level CCT for both FF and ST). In the context of RM, FF, and GB, we complete the enumeration of the paths at any level of interaction in less than one second. Across all of the case study applications, it is more costly to apply the containing path operator than it is to just enumerate the super paths. This result is due to the fact that *IsContainingPath* iteratively invokes *IsEquals* while *IsSuperPath* only calls *IsEquals* once. We identify two main trends in the measurements for $\mathcal{T}_{\Pi}$ as we transition from $\mathbf{R_l}$ to $\mathbf{A_v}$: (i) the time overhead increases monotonically (e.g., FF, PI, and ST) or (ii) enumeration time varies in a "zig-zag" fashion (e.g., RM, TM, and GB). We attribute the first trend to test suites that insert many records into the database during test execution. For example, both FF and ST repeatedly add records to relations that only contain two attributes (i.e., FF interacts with the *Files* relation and ST modifies the *Student* table). In contrast, the second empirical trend is due to the fact that the tests place few records into the database and thus the number of paths is greater at the **A** level than the $\mathbf{R_c}$ level. For example, many of RM's test cases only place a few records into a *Reminder* relation that contains seven attributes. Across all of the applications, we note that the values for $\mathcal{T}_{\Pi}$ are very often similar at the levels of $\mathbf{R_l}$, **A**, and $\mathbf{R_c}$.

Some experiments reveal moderately high enumeration times when we applied the path containment operator at the levels of record and attribute value (e.g., ST and TM). The results in Figure 8.22 also demonstrate that the value of $\mathcal{T}_{\Pi}$ is always the highest for the $\mathbf{A_v}$-level coverage tree. Even though PI exhibits

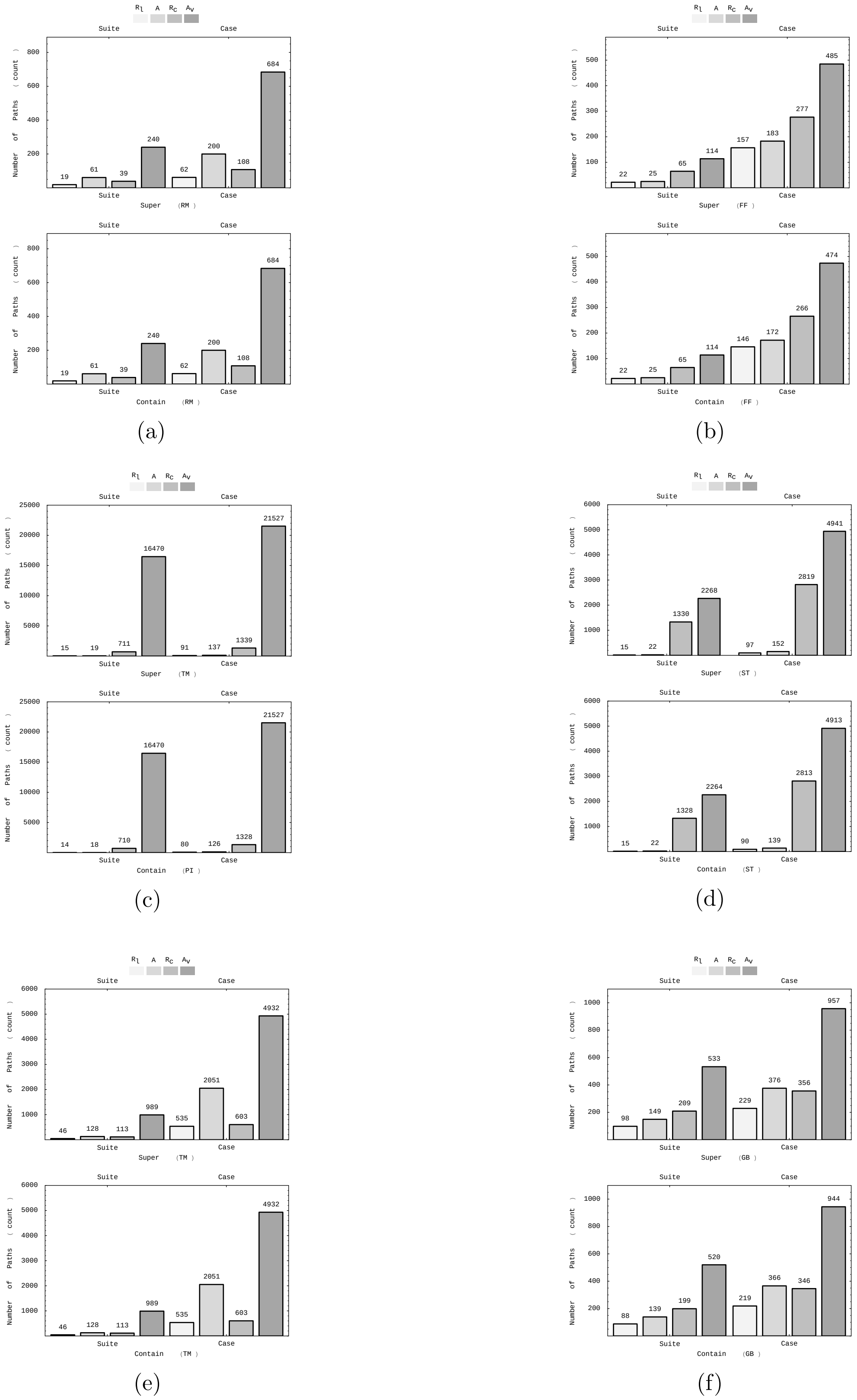


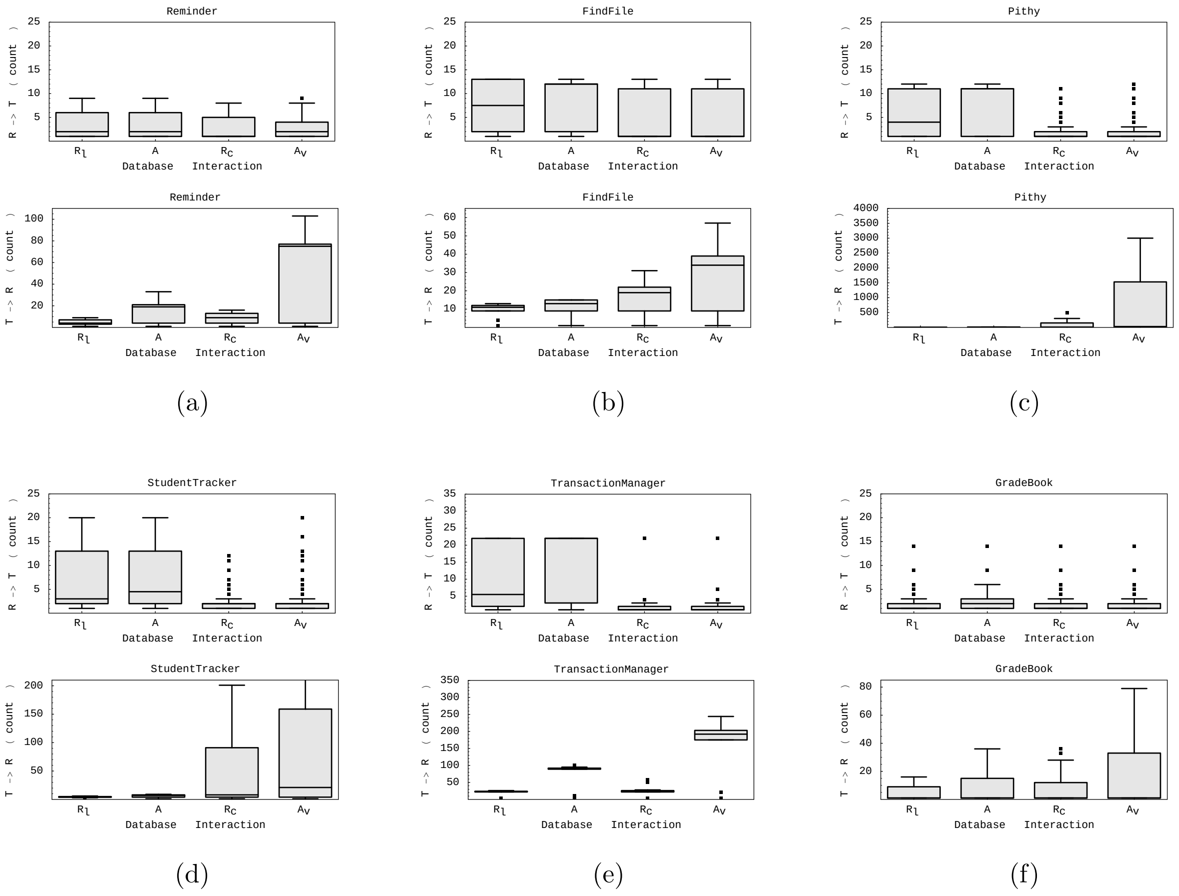
Figure 8.23: Number of Test Requirements.

enumeration times of less than one second at the $\mathbf{A}$ and $\mathbf{R_c}$ levels, $\mathcal{T}_\Pi$ is almost six seconds at the $\mathbf{A_v}$ level when we enumerate $\Pi_\mu(T_{cct}, T, \sqsupset)$. After profiling the path enumeration process, we determined that the majority of this time was spent parsing and validating the 38 megabyte XML file that stored the coverage results. However, applying the containing path operator to `PI`'s $\mathbf{A_v}$-level coverage tree caused $\mathcal{T}_\Pi$ to increase to over one minute. In this configuration, the execution profiles of the path enumerator show that most of its time was spent performing garbage collection and executing the *IsContainingPath* and *IsEquals* algorithms. This result highlights the only circumstance in which the use of a naive text processing algorithm does not support the efficient identification of the test requirements. Yet, the experimental results support the conclusion that we can use the coverage tree path during both the general and version specific regression testing of a database-centric application.

We also counted the number of test requirements that were enumerated for each application, as depicted in Figure 8.23. Each pair of graphs shows the number of test requirements that we identified after applying the super path (i.e., the top graph) and the containing path (i.e., the bottom graph) operators. In a single graph, a bar group with the "Suite" label corresponds to the measurement of $\mathcal{S}_\Pi^\cup$. We use the "Case" label for the evaluation metric $\mathcal{C}_\Pi^\Sigma$. As discussed in Section 8.4, the containing path operator may reduce the total number of test requirements if the test suite often performs the same series of operations in a different context. The results in Figure 8.23 demonstrate that the containing path operator does not reduce the number of test requirements for the `RM` and `TM` applications. The empirical results show that $\succ$ does decrease the value of $\mathcal{S}_\Pi^\cup$ for `PI`, `ST`, and `GB`. In fact, `GB`'s number of suite level test requirements dropped by thirteen after we applied the $\succ$ operator. Section 8.10.2 investigates whether or not decreasing the number of requirements shortens the time needed to reduce or prioritize `GB`'s test suite.

Classifying the case study applications according to the $\mathcal{S}_\Pi$ and $\mathcal{C}_\Pi$ metrics leads to three distinct groups of applications with (i) less than one thousand (e.g., `RM`, `FF`, and `GB`), (ii) less than five thousand (e.g., `ST` and `TM`), and (iii) greater than five thousand (e.g., `PI`) test requirements. This result suggests that reduction and prioritization is likely to be the (i) most time consuming for `PI` and (ii) most efficient for `RM`, `FF`, and `GB`. Across all of the applications, Figure 8.23(d) reveals that `ST` has the fewest requirements (i.e., fifteen at the $\mathbf{R_l}$ level) and Figure 8.23(c) demonstrates that `PI` has the most (i.e., 16470 at the $\mathbf{A_v}$ level). As anticipated, an $\mathbf{A_v}$-level coverage tree yields more test paths than the corresponding $\mathbf{R_l}$-level tree. We also find that the value of $\mathcal{S}_\Pi^\cup$ is normally much smaller than the corresponding value for $\mathcal{C}_\Pi^\Sigma$. For example, $\mathcal{S}_\Pi^\cup(\texttt{FF}, \tau_{cct}, \mathbf{A_v}, \sqsupset) = 240$ while $\mathcal{C}_\Pi^\Sigma(\texttt{FF}, \tau_{cct}, \mathbf{A_v}, \sqsupset) = 684$. The decrease is even more dramatic for the `TM` application: out of the 4932 test paths at the test case level, only 989 of these paths are unique. This experimental trend indicates that there is a substantial overlap in the tests' coverage of the requirements. Thus, we judge that all of these test suites may be amenable to reduction. Section 8.10.2 studies whether this overlap leads to a reduced test suite that exhibits a noticeable decrease in testing time.

As discussed in Section 8.4, $\Pi(\tau, T_i, \dashv)$ is the set of test requirements that test T_i covers. For a test suite T, we calculate the value of $|\Pi(\tau, T_i, \dashv)|$ for all of the tests in order to characterize how they cover



(a)

(b)

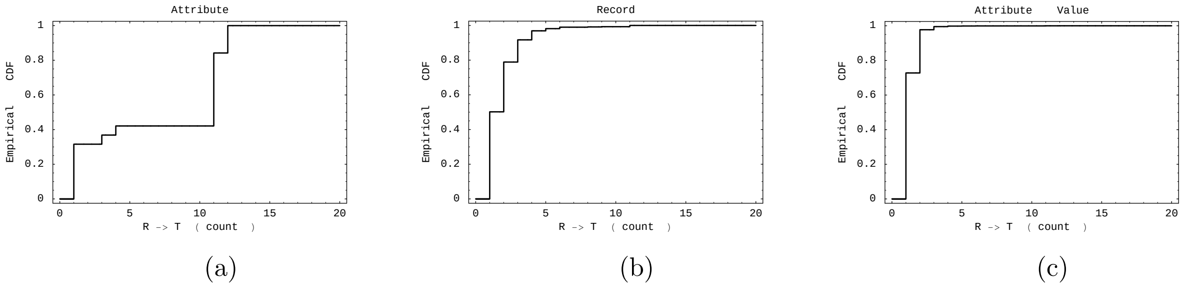
(c)

(d)

(e)

(f)

Figure 8.24: Coverage Relationships.



(a)

(b)

(c)

Figure 8.25: ECDFs for `Pithy`'s Coverage Relationships.

the requirements in $\Pi(\tau, T, \dashv)$. A high average value for $|\Pi(\tau, T_i, \dashv)|$ suggests that most tests cover many requirements and thus there is a greater potential for an overlap in coverage. If there are many requirements and the majority of the test cases cover a small number of requirements, then it is unlikely that the test suite is fit for reduction. Equation (8.14) defines the set of test cases that cover the requirement π, denoted $T(\tau, \pi, \dashv)$. If a test suite has a high average value for $|T(\tau, \pi, \dashv)|$, then this indicates that a requirement is often covered by many test cases. In this circumstance, the test suite may be a good candidate for reduction. However, we observe that $|\Pi(\tau, T_i, \dashv)|$ and $|T(\tau, \pi, \dashv)|$ are only rough indicators for the (i) performance of the reduction and prioritization algorithms and (ii) efficiency and effectiveness of the modified test suite (i.e., these evaluation metrics do not characterize the exact overlap in requirement coverage).

$$T(\tau, \pi, \dashv) = \{T_i : \pi \in \Pi(\tau, T_i, \dashv)\} \tag{8.14}$$

Figure 8.24 depicts the coverage relationships that are evident in the test suite of every case study application. Each pair of graphs shows the number of tests that cover a requirement (i.e., the top graph) and the number of requirements that are covered by a test (i.e., the bottom graph). We organize the horizontal axis of these graphs by an increase in the database interaction granularity. For these box and whisker plots, the label "$R \rightarrow T$" corresponds to the $|T(\tau, \pi, \dashv)|$ metric and "$T \rightarrow R$" labels the measurements for $|\Pi(\tau, T_i, \dashv)|$. Since the bar charts in Figure 8.23 only furnish summary results for the number of test requirements (i.e., $\mathcal{S}_\Pi$ and $\mathcal{C}_\Pi$), we judge that Figure 8.24's "$T \rightarrow R$" plots offer additional insight into a test suite's coverage relationships. In this study, we focus on the use of the super path operator (preliminary results from applying the containing path operator suggest that the trends are similar). The `PI`, `ST`, and `TM` applications all exhibit a sharp decrease in the average value of $|T(\tau, \pi, \dashv)|$ as we transition from the $\mathbf{R_l}$-level to the $\mathbf{A_v}$-level coverage tree. However, the `RM` and `FF` applications display a gradual decrease in the same evaluation metric. We attribute this dichotomy to the fact that the tests for `RM` and `FF` perform a variety of modifications to the same small collection of data records. On the contrary, `PI`, `ST`, and `TM` have a test suite that places a greater variety of records into the relational database.

We studied how these two different testing strategies impact the coverage relationships for a database-centric application. For brevity, we focus our analysis on the `Pithy` case study application. The empirical cumulative distribution function in Figure 8.25(a) reveals that recording coverage at the attribute level leads to 60% of the tests requirements being covered by at least ten tests. Yet, Figures 8.25(b) and (c) demonstrate that the record and attribute value trees result in approximately 75% of the requirements being covered by no more than two tests. This trend clearly suggests that there is a trade-off associated with collecting coverage information at a fine level of database interaction granularity. On one hand, this type of coverage report more accurately captures the behavior of the program under test and may be more useful during testing and debugging. However, the $\mathbf{A_v}$-level coverage tree drives down the value of $|T(\tau, \pi, \dashv)|$ and thus it could limit the potential for reduction. Nevertheless, if the tests for a database-centric application frequently insert records that only differ in a few locations, the $\mathbf{A_v}$-level requirements may lead to a better reduction factor than coverage tree paths at the $\mathbf{R_c}$-level (c.f. Section 8.10.2.2 for a detailed explanation of this phenomenon).

The box and whisker plots in Figure 8.24 also reveal that an increase in database interaction granularity causes the average value of $|\Pi(\tau, T_i, \dashv)|$ to (i) stay the same (e.g., `FF` and `GB`), (ii) moderately increase (e.g., `RM`, `ST`, and `TM`), or (iii) grow sharply (e.g., `PI`). For applications in the first two categories, we anticipate that reduction or prioritization with $\mathbf{A_v}$-level requirements will not consume significantly more time than regression testing with the $\mathbf{R_l}$-level coverage tree. Once again, the bottom plot in Figure 8.24(c) attests to the fact that it may be expensive use the $\mathbf{A_v}$-level requirements to reduce or re-order `Pithy`'s test suite (i.e., many of `PI`'s tests create numerous test paths and this leads to a total of 16470 unique requirements). Finally, the top plot in Figure 8.24(f) reveals that `GB`'s average value for $|T(\tau, \pi, \dashv)|$ is very low at all levels of database interaction. Since this trend is not evident for the other case study applications, it affirms the fact that `GradeBook` is likely to exhibit a smaller value for RFS than the other applications.

8.10.2 Test Reduction

8.10.2.1 Efficiency Extensive experimentation with the reduction tool demonstrates that efficient test suite reduction is possible for all case study applications at all levels of database interaction. We find that every configuration of the reduction component can identify the redundant test cases in less than one second. In most circumstances, the *GreedyReductionWithOverlap* (GRO) technique can reduce the most challenging test suites (i.e., those with the most tests and requirements) in less than 500 milliseconds. We observe that reduction only requires one second of time overhead when we handle the `Pithy` case study application at the attribute value level. This is a noteworthy result because `PI` has over 16000 $\mathbf{A_v}$-based test requirements, as shown in Figure 8.23(c) in Section 8.10.1. The other approaches to test suite reduction (i.e., GR, RVR, and RAR) always reduce the test suite in less than five milliseconds. These empirical trends indicate that it is not necessary to apply the containing path operator in an attempt to (i) reduce the number of test requirements and (ii) make reduction more efficient. We anticipate that the containing path operator may be more useful during the regression testing of larger database-centric applications. Finally, we found that each reduction technique exhibits little performance variability since the standard deviation across trials was normally less than a few milliseconds. In light of these results, we anticipate that the performance of the reduction component will favorably scale when we apply it to larger case study applications. These experimental outcomes also suggest that the reduction algorithms are appropriate for use in the context of both version specific and general regression testing.

8.10.2.2 Test Suite Size Table 8.10 provides the values of ϱ_n, the reduction factor for the size of the test suite. We derived the values in this table by applying the GRO algorithm to the test suite for each application. We use the notation $\varrho_n(A, L)$ to denote the RFS value for the application A at database interaction level L. If all of the test cases execute for a uniform time period, then ϱ_n roughly corresponds to the reduction in testing time, denoted ϱ_t. However, Section 8.10.2.3 demonstrates that the value of ϱ_t may be higher or lower than ϱ_n, depending upon the characteristics of the application and the tests. High

Application	**Relation**	**Attribute**	**Record**	**Attribute Value**	**All**
`RM` (13)	$(7, .462)$	$(7, .462)$	$(10, .300)$	$(9, .308)$	$(8.25, .365)$
`FF` (16)	$(7, .563)$	$(7, .563)$	$(11, .313)$	$(11, .313)$	$(9, .438)$
`PI` (15)	$(6, .600)$	$(6, .600)$	$(8, .700)$	$(7, .533)$	$(6.75, .550)$
`ST` (25)	$(5, .800)$	$(5, .760)$	$(11, .560)$	$(10, .600)$	$(7.75, .690)$
`TM` (27)	$(14, .481)$	$(14, .481)$	$(15, .449)$	$(14, .481)$	$(14.25, .472)$
`GB` (51)	$(33, .352)$	$(33, .352)$	$(33, .352)$	$(32, .373)$	$(32.75, .358)$
All (24.5)	$(12, .510)$	$(12.17, .503)$	$(14.667, .401)$	$(13.83, .435)$	

Data Format: $(|T_r|, \varrho_n)$

Table 8.10: Reduction Factors for the Size of a Test Suite.

values for ϱ_n serve to control testing time when the test executor must regularly restart the database server in order to enforce test case independence. Overall, we observe that `ST` exhibits the best reduction factor and `GB` has the worst, as generally predicted by our analysis in Section 8.10.1. That is, across all of the levels of database interaction, Table 8.10 shows that `ST` has an average reduction factor of .69 and `GB`'s average value for RFS is .3578. Across all of the applications, the average value of ϱ_n was .51 at the relation level and .4354 at the attribute value level. In summary, we see that it is possible to decrease the size of the test suite with the GRO technique.

The results in Table 8.10 reveal that the value of RFS is normally the highest at the relation level and the lowest at the record level. The value of $\varrho_n(A, \mathbf{R_l})$ is greater than ϱ_n at the other database interaction levels because most applications only interact with a small number of relations. For example, `ST` uses the *Student* relation and `TM` only stores data in *UserInfo* and *Account*. If testing occurs at the $\mathbf{R_l}$ level, then there is a high overlap in requirement coverage and this leads to substantial reduction factors. Since `GB` has the most relations, it exhibits the smallest value for $\varrho(A, \mathbf{R_l})$. It may be advisable to perform reduction at the $\mathbf{A}$ level instead of the $\mathbf{R_l}$ level because the (i) reduction algorithms are efficient at both of these levels, (ii) value of ϱ_n is comparable at the $\mathbf{R_l}$ and $\mathbf{A}$ levels, and (iii) attribute level coverage tree is normally better at differentiating the behavior of the test cases.

Further analysis of the data in Table 8.10 also demonstrates a marked decreased in ϱ_n when we transition from the attribute to the record level. Across all of the applications, we see that ϱ_n drops from .503 to .401 when GRO analyzes the $\mathbf{R_c}$-level coverage tree instead of the $\mathbf{A}$-level coverage report. This result suggests the potential for reduction is limited if (i) the test cases often place different records into the database and (ii) reduction is performed at the $\mathbf{R_c}$ level. Interestingly, the reduction factor increases when we perform the analysis at the $\mathbf{A_v}$ level rather than the $\mathbf{R_c}$ level. For example, Table 8.10 shows that the average value of ϱ_n increases to .4354 when the reduction component analyzes the attribute value DI-CCT. We ascribe this

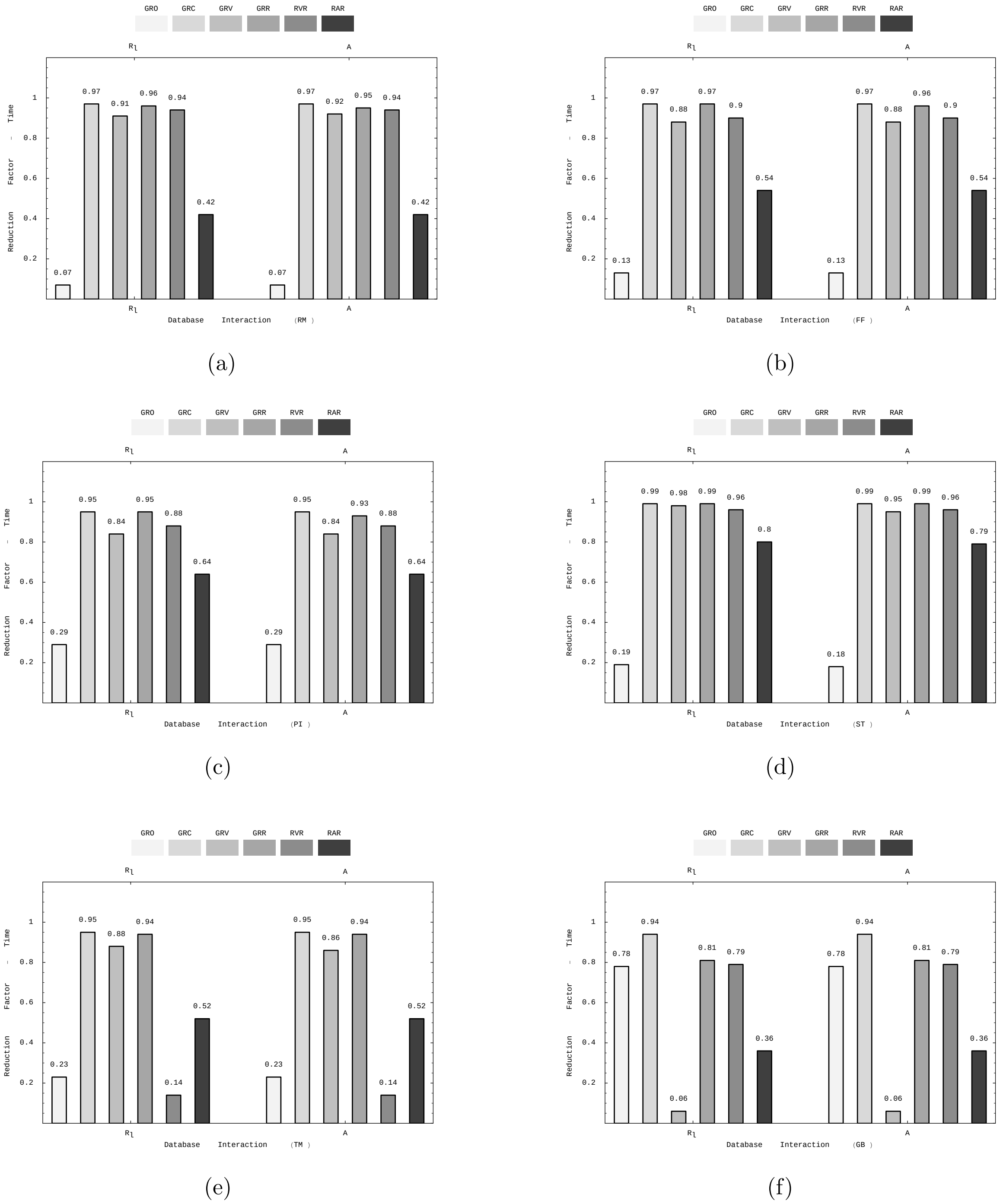
Abbreviation	Meaning
GRC	*GreedyReductionWithoutOverlap* - Cost
GRV	*GreedyReductionWithoutOverlap* - Coverage
GRR	*GreedyReductionWithoutOverlap* - Ratio

Table 8.11: Summary of the Abbreviations Used to Describe the Reduction Techniques.

empirical trend to the fact that the tests often insert records that only differ by a small number of attribute values. The RFS value increases at the $\mathbf{A_v}$ level because it is now possible to identify the commonalities in the behavior of the tests as they interact with the state of the database. Since the reduction process is efficient at both the levels of record and attribute value, it is sensible to perform reduction with the $\mathbf{A_v}$-level requirements instead of the $\mathbf{R_c}$-based tree paths.

8.10.2.3 Reductions in Testing Time Figures 8.26 and 8.27 present the values for the reduction factor in testing time, denoted $\varrho_t(A, L)$. We organized the bar charts so that Figure 8.26 provides the results for the structure-based interaction levels (i.e., $\mathbf{R_l}$ and $\mathbf{A}$) and Figure 8.27 furnishes the outcomes associated with using the state-based levels (i.e., $\mathbf{R_c}$ and $\mathbf{A_v}$). Table 8.11 summarizes the abbreviations that we use in the legends for all of the remaining bar charts in this chapter (c.f. Table 8.7 for a review of the abbreviations that we previously defined). For example, GRC stand for the use of *GreedyReductionWithoutOverlap* in combination with the cost-based ordering criterion. We also use the abbreviation GR to stand for any of the greedy techniques listed in Table 8.11. The most notable trend in these empirical results is that GRO consistently exhibits the worst value for ϱ_t across all of the applications. We see that GRO's value for RFT varies from a low of $\varrho_t(\texttt{RM}, \mathbf{R_l}) = .07$ to a high of $\varrho_t(\texttt{GB}, \mathbf{A_v}) = .78$.

Interestingly, the empirical study demonstrates that GRO can substantially reduce testing time for `GB` even though the ϱ_n values for this application never exceed .38. This result suggests that it is not sufficient to evaluate a test suite reduction technique by only measuring how many tests are removed from the original suite (yet, most empirical studies of reduction algorithms focus on the RFS metric [Jeffrey and Gupta, 2007, Harrold et al., 1993, McMaster and Memon, 2005]). Furthermore, this outcome demonstrates the importance of using the execution time of a test case during regression testing process. We also find that many of the other reduction techniques (e.g., GR and RVR) frequently yield test suites with values for ϱ_t that range from .8 to .98. Furthermore, we see that random reduction often leads to better reduction factors than GRO. These results are due to the fact that GRO must continue to select test cases until all of the requirements have been covered. In the context of applications like `RM`, this frequently compels GRO to select one or more of the slow test cases. Since the other reduction schemes (e.g., GR and RVR) do not guarantee complete coverage of the test requirements, they are not always forced to include slow tests in the modified suite. However, Section 8.10.2.4 shows that GR's higher value for ϱ_t is often accompanied by a poor preservation of test suite coverage and thus these reduction techniques are likely to compromise fault detection effectiveness.



(a) (b)

(c) (d)

(e) (f)

Figure 8.26: Reduction Factor for Test Suite Execution Time (Relation and Attribute).

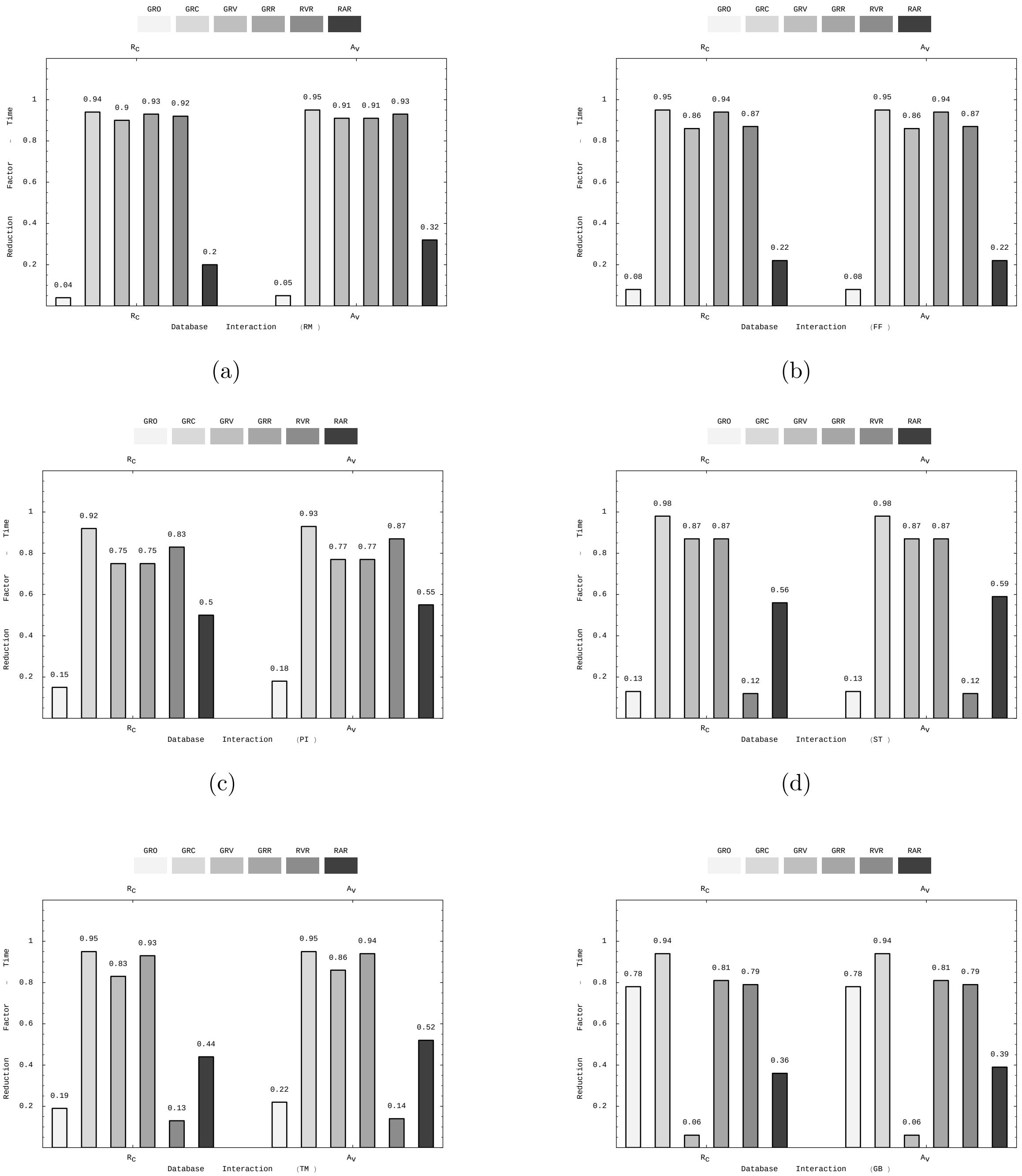


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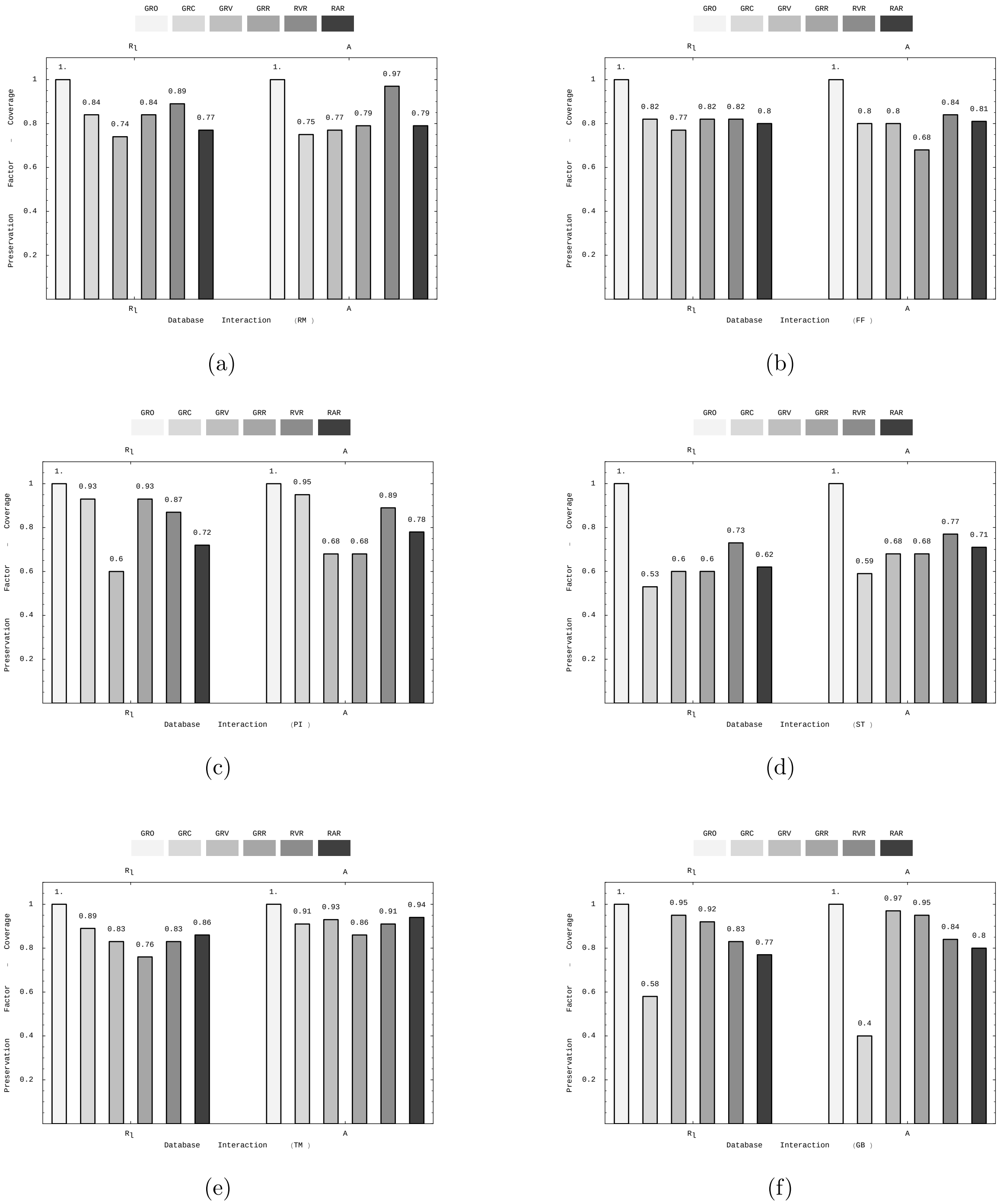
Figure 8.27: Reduction Factor for Test Suite Execution Time (Record and Attribute Value).

The experiments also reveal that the value of ϱ_t (i) decreases when we use GRV instead of GRC and (ii) subsequently increases back to near-GRC levels when we employ GRR. Since the cost-based technique sorts the tests according to their execution times, it makes sense that GRC will lead to high values for ϱ_t. For many applications (e.g., `PI` in Figure 8.26(c) and `TM` in Figure 8.27(e)), we observe that GRV's focus on the highest coverage tests causes a noticeable decrease in ϱ_t when we employ GRV instead of GRC. As an additional example, Figure 8.26(b) shows that `FindFile`'s test suite causes the reduction factor to drop from .95 to .85 when we use GRV rather than GRC. This trend suggests that a myopic focus on the test requirements may cause GRV to select slow tests that attain high coverage. With the exception of the `StudentTracker` application, the GRR scheme normally increases the RFT value and thus leads to test suites that execute almost as efficiently as those that were produced by GRC. For the `GradeBook` application, GRV creates a test suite whose reduction factor is only .06. We attribute this to the fact that the GRV reduction algorithm still selects some of `GB`'s tests even though they have both a high coverage and a high time overhead.

Across all of the applications, the GR algorithms normally exhibit the highest RFT values. In many cases, the RVR technique creates a reversed test suite whose value for ϱ_t is greater than GRO's value and yet still less than the corresponding ϱ_t value for GRC and GRR. For the `TM` application, Figures 8.26(e) and 8.27(e) demonstrate that RVR leads to a value for ϱ_t that is much worse than RAR's value. We find a similar trend for the `ST` application, as evidenced by the results in Figure 8.27(d). Interestingly, RVR only leads to poor RFT values for `ST` when we operate at the $\mathbf{R_c}$ and $\mathbf{A_v}$. This phenomenon occurs because GRO creates test suites for `ST` that respectively contain 15 and 14 tests at the $\mathbf{R_c}$ and $\mathbf{A_v}$ levels. When the target size is high the RVR algorithm selects more tests from the reversal of the original test suite and this leads to a lower value for ϱ_t. In summary, these result shows that the RVR technique should not be used if slow tests have been recently placed at the end of the original test suite (in this circumstance, Section 8.10.2.4 reveals that RVR may also compromise the preservation of requirement coverage). If the time overhead of each test case is unknown and it is likely that the tests exhibit considerable variability in execution time, then we do not recommend the use of RVR during the regression testing of a database-centric application.

8.10.2.4 Coverage Preservation Figures 8.28 and 8.29 present the values of the preservation factor for test requirements, denoted $\nu_\pi(A, L)$. A high PFR value is ideal because it ensures that the reduced test suite is likely to detect faults as well as the original suite. As anticipated, GRO yields a perfect score for ν_π across all applications and every level of database interaction. However, we find that the other reduction schemes preserve coverage with varying levels of success. A noteworthy trend is that the GRC scheme exhibits erratic preservation of test requirements. For the `PI` and `ST` applications, Figures 8.29(c) and (d) demonstrate that GRC's value for ν_π is significantly lower than the value for random reduction. Yet, Figures 8.28(c) and (d) reveal that this pattern is less pronounced when we employ the structure-based test requirements. Overall, these examples demonstrate that GRC's shortsighted focus on the cost of a test case causes it to select fast tests that cover few of the requirements. We attribute these results to the fact that the database-aware tests



(a)

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Figure 8.28: Preservation Factor for Test Suite Coverage (Relation and Attribute).

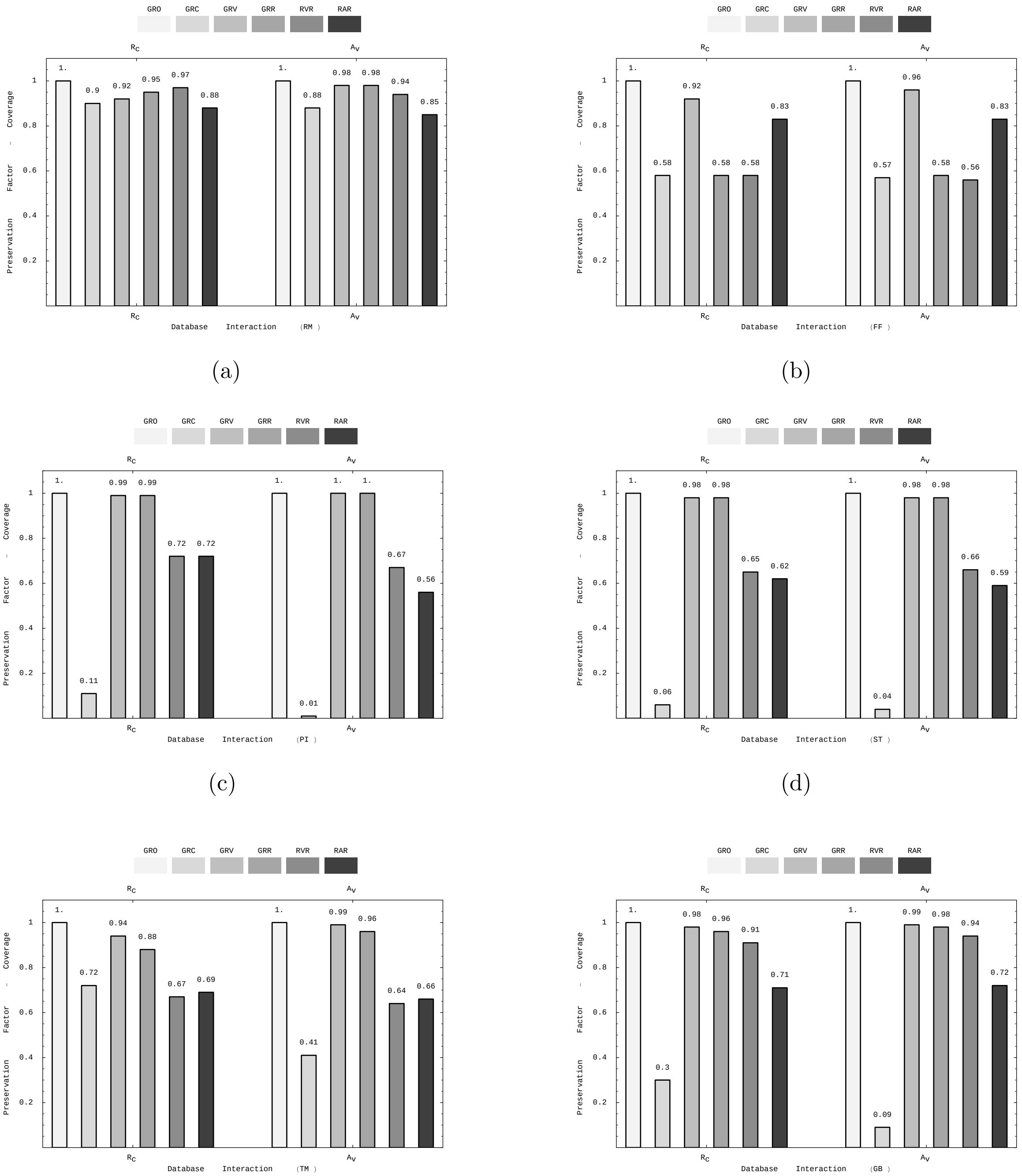

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Figure 8.29: Preservation Factor for Test Suite Coverage (Record and Attribute Value).

Abbreviation	Meaning
GPC	*GreedyPrioritizationWithoutOverlap* - Cost
GPV	*GreedyPrioritizationWithoutOverlap* - Coverage
GPR	*GreedyPrioritizationWithoutOverlap* - Ratio
ORP	*OriginalPrioritization*

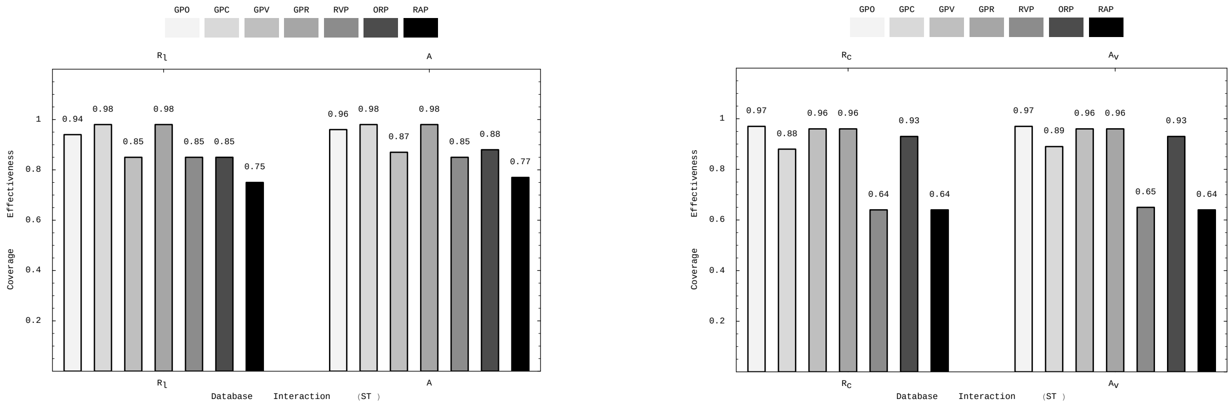
Table 8.12: Summary of the Abbreviations Used to Describe the Prioritization Techniques.

create most of the coverage tree paths when we record coverage at the $\mathbf{R_c}$ or $\mathbf{A_v}$ levels. Therefore, GRC includes the low coverage tests that do not interact with the database when it picks the fast test cases. In general, we observe that GRC is not well suited to reducing database-aware test suites because there is often an inverse relationship between testing time and requirement coverage.

The empirical study also suggests that it may also be misleading to exclusively focus on the coverage of the test requirements. For example, Figure 8.28(c) shows that GRV creates a reduced test suite for `Pithy` that has a lower PFR value than GRC, GRR, and RVR. For example, we see that ν_π drops from .93 to .6 when we use GRV instead of GRC. Further study of the reduced test suite reveals that the highest coverage tests have longer running times. The inclusion of these tests in the reduced test suite eventually prevents GRV from including other tests that cumulatively cover more requirements in less time. For `PI`, we observe that the use of GRR increases the value of ν_π to near-GRO levels. However, Figure 8.28(e) demonstrates that using GRR may still lead to a decrease in PFR that severely compromises coverage. In fact, the use of the $\mathbf{R_l}$-level requirements for `TM` leads to preservation factors that are worse than those that we see for random reduction. Therefore, ratio-based sorting of the test cases is not guaranteed to preserve coverage better than the other greedy techniques that ignore overlap.

In conclusion, we often find that one or more of GRC, GRV, GRR, or RVR exhibit coverage preservation values that are worse than the corresponding values for the randomly reduced test suite. For example, Figure 8.29(b) indicates that three reduction techniques lead to ν_π values that are worse than random. In particular, the use of GRC, GRR, or RVR to reduce `FF`'s test suite leads to $\nu_\pi = .58$ even though random reduction exhibits a ν_π value of .83. If small to moderate reductions are acceptable and coverage preservation is important, then we recommend the use of *GreedyReductionWithOverlap*. We advocate the use of GRO because the empirical results demonstrate that ignoring the overlap in the tests' coverage may cause the GR algorithms to improvidently include tests within the reduced suite. Even though GRO may lead to reduction factors that are smaller than GR and RVR, we judge that it is an appropriate choice if variations in coverage preservation are not desirable.

If we adopt the notion of preference under the $\gg$ operator, as defined in Section 8.6, then it is clear that there are few configurations of the reduction component that regularly identify reduced test suites that are both efficient and effective. For brevity, we focus on a specific example to illustrate the main point. If we consider the reduced test suites for `ST` at the $\mathbf{R_c}$ level, then GRO and GRC are respectively described by the evaluation tuples $\mathsf{v}_r = \langle .56, .13, 1.0 \rangle$ and $\hat{\mathsf{v}}_r = \langle .56, .99, .04 \rangle$. Following the definition of $\gg$ in Equation (8.11),



(a) (b)

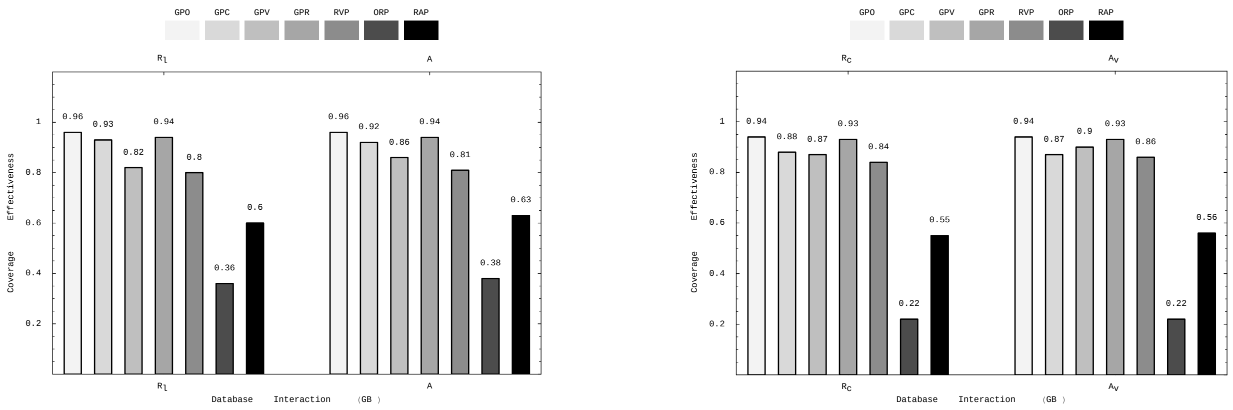
Figure 8.30: Coverage Effectiveness for the `StudentTracker` Application.

we see that $\nu_r \not\gg \hat{\nu}_r$ and $\hat{\nu}_r \not\gg \nu_r$ and thus $\nu_r \sim \hat{\nu}_r$ (i.e., ν_r and $\hat{\nu}_r$ describe approaches to reduction that are similar according to the evaluation metrics stated in Section 8.6). In this circumstance, the correct choice for the regression testing of `ST` is dictated by the testing process. Severe time constraints would suggest the use of GRC, while the overlap-aware GRO technique would be preferred when coverage preservation is more important. As part of future work, we intend to exhaustively compare the different reductions with the $\gg$ operator.

8.10.3 Test Prioritization

We also conducted an empirical study in order to determine how prioritization impacts the coverage effectiveness (CE) of a test suite (c.f. Section 8.6 for a definition of the CE metric). Paralleling the results in Section 8.10.2.1, the experiments reveal that the prioritization component is also efficient for the chosen applications. We selected the `StudentTracker` and `GradeBook` applications for further analysis because these case studies (i) respectively represent the best and the worst values for ϱ_n and (ii) support a discussion of the most relevant experimental trends. Table 8.12 summarizes the abbreviations that we use to describe the different approaches to prioritization (c.f. Table 8.7 for a review of the abbreviations that were previously defined). For example, GPR stands for the use of *GreedyPrioritizationWithoutOverlap* in conjunction with the ratio-based ordering criterion.

Figure 8.30 presents the coverage effectiveness value, denoted ξ, for the `ST` application. Since `ST` exhibits high values for ϱ_n, it is evident that there are many redundant tests in the original test suite. Therefore, we anticipate that many of the prioritization techniques should yield high CE values. Indeed, Figure 8.30 reveals that all of the greedy techniques create test suites with ξ values greater than .85. For this application, we see that GPC and GPR have CE values of .98 and GPO has a CE value of .94. Furthermore, Figure 8.30 demonstrates that most of the prioritization algorithms, with the exception of RVP at the $\mathbf{R_c}$ and $\mathbf{A_v}$ levels, perform much better than random prioritization. Since `ST`'s tests have a substantial amount of overlap,



(a)

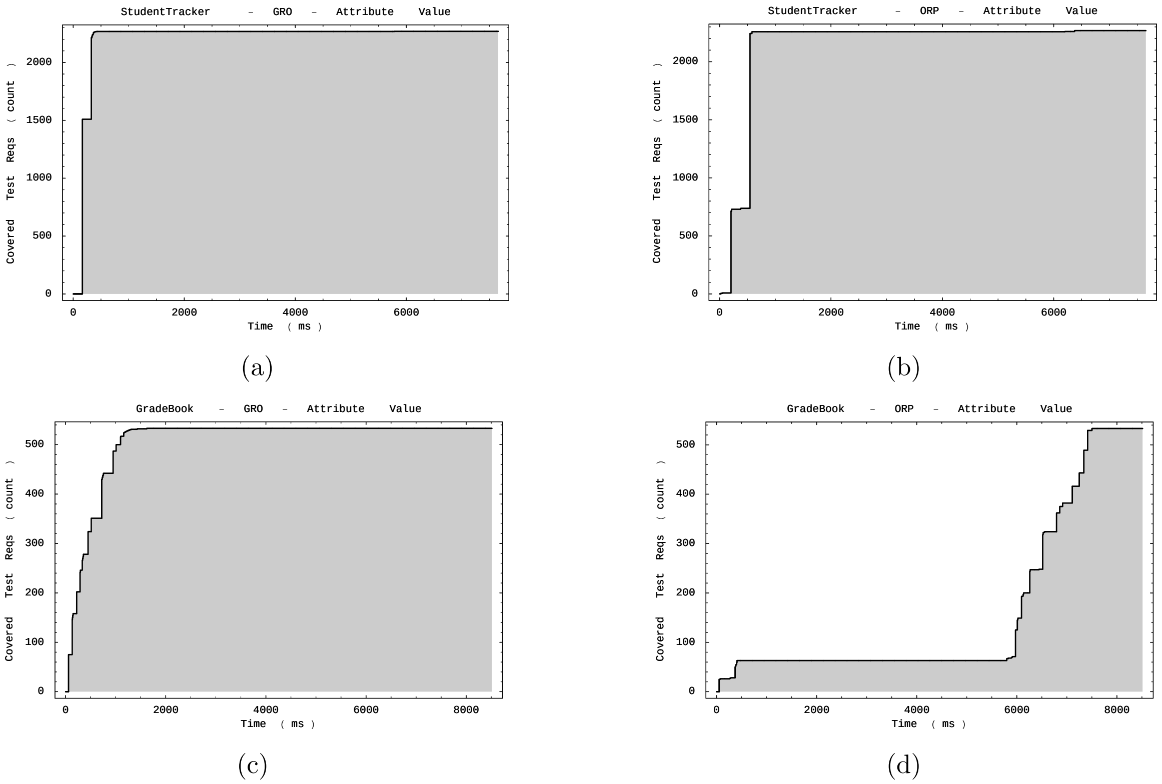
(b)

Figure 8.31: Coverage Effectiveness for the GradeBook Application.

we also notice that the original ordering of the test suite attains high values for ξ (e.g., $\xi = .93$ when we represent the database interactions at the $\mathbf{R_c}$ and $\mathbf{A_v}$ levels).

Figure 8.31 provides the CE values for the GradeBook case study application. GB's low values for ϱ_n attest to the fact that the test suite for this application does not include many tests that redundantly cover the requirements. The bottom box and whisker plot in Figure 8.24(f) also reveals that there is a wide variation in how many requirements are covered by a single test case. Therefore, we judge that it is more difficult to identify a prioritization that will rapidly cover GB's test requirements. In contrast to the empirical outcomes associated with prioritizing ST's test suite, we observe that applying GPO to GB's test suite always leads to the highest value of ξ. At the $\mathbf{R_c}$ and $\mathbf{A_v}$ levels, Figure 8.31(b) shows that GPO creates test suites with $\xi = .94$. In comparison, we notice that the GP generated test orderings have CE values that are less than GPO's corresponding CE value by between .01 and .07 units. Since higher CE values suggest that the tests are more likely to reveal faults earlier in the testing process, we recommend the use of GPO during the prioritization of tests for a database-centric application that exhibits coverage patterns similar to the ones found in GB's test suite.

The results in Figure 8.31 also point out that random prioritization attains CE values that are much better than the original ordering of the test suite. Furthermore, we also find that the CE value for GPO is much higher than the corresponding CE value for ORP. In an attempt to better understand these experimental outcomes, Figure 8.32 furnishes a plot of κ for the GPO and ORP techniques (c.f. Section 8.6 for a detailed discussion of κ). For the ST application, Figures 8.32(a) and (b) show that both GPO and ORP have a κ function that grows very rapidly. For GB, Figures 8.32(c) and (d) reveal that there is a distinct difference between the κ function for GPO and ORP. Interestingly, this result corroborates a recent discovery concerning the ways in which the re-ordering of a traditional test suite may impact the value of the average percentage of faults detected (APFD) metric [Do et al., 2004].



(a)

(b)

(c)

(d)

Figure 8.32: Visualizing the Cumulative Coverage of `Student` and `GradeBook`.

Following the commentary of Do et al., we postulate that this trend is due to the fact that testers regularly place the newest tests at the end of the test suite. Since the new tests often cover (i) many portions of the database that were not covered by the previous tests and (ii) some database regions that were touched by the earlier test cases, it may be advantageous to use random prioritization in an attempt to spread the high coverage tests throughout the entire suite. If the test cases exhibit a relatively minor overlap in coverage and/or there is significant variation in the total number of requirements covered by a test, then it is always advisable to use one of the prioritization algorithms. That is, it would be better to use random prioritization than it would be to simply execute the tests in their original ordering. Yet, since the performance study shows that GPO is efficient for the chosen applications, we advocate the use of the overlap-aware greedy algorithm if it is important to achieve the highest possible value for the coverage effectiveness metric.

8.11 THREATS TO VALIDITY

The experiments that we describe in this chapter are subject to validity threats. Chapter 3 discusses the steps that we took to control these threats throughout the experimentation process. We also took additional steps to handle the threats that are specific to experimentation with the regression testing component. Internal threats to validity are those factors that have the potential to impact the measured variables defined in Sections 8.6 and 8.10. The primary threat to internal validity is the existence of a defect in the regression testing tool. We controlled this threat by performing an extensive series of correctness tests for the techniques that (i) enumerate the test paths and (ii) reduce or prioritize the test suite. During the testing of the path enumerator, we generated the set of test requirements for small DCTs and CCTs that were both traditional and database-aware. After enumeration, we verified that each set contained the proper test paths. We confirmed that the reduction and prioritization algorithms were properly working by applying them to small instances of the minimal set cover problem. During this process, we tracked the number of algorithm iterations and we ensured that this count never exceeded the known worst-case. Finally, we manually added redundant test cases to the test suite for each case study application. After applying the reduction algorithm, we verified that the reduced test suite did not contain the unnecessary tests. We judge that threats to construct validity were controlled since Sections 8.6 and 8.10 present a wide range of evaluation metrics that are useful to both researchers and practitioners.

8.12 CONCLUSION

This chapter describes the design, implementation, and empirical evaluation of our approach to database-aware regression testing. We provide a high level overview of the regression testing process and we develop examples to demonstrate the practical benefits of reducing or re-ordering the test suite. This chapter also introduces the algorithms that (i) enumerate the coverage tree-based test requirements and (ii) perform database-aware reduction and prioritization. We present approaches to regression testing that consider both the tests' overlap in coverage and the time overhead to execute a test case. This chapter also explains how to evaluate a reduced or prioritized test suite without resorting to the use of a fault seeding mechanism. In particular, we introduce the notion of coverage effectiveness and we show how to construct a cumulative coverage function for a test suite. Finally, we discuss the relevant details associated with the implementation of the regression testing component.

After discussing the goals and design for an experiment to measure the performance of our regression testing techniques, we systematically state each evaluation metric and analyze the experimental results. The enumeration of coverage tree paths is efficient enough to support the identification of this type of requirement in a version specific approach to regression testing. In the context of the largest case study application (i.e., `GradeBook`), we can enumerate the test paths at any level of database interaction in less than 300 milliseconds. In general, we find that some case study applications yield less than one thousand path-based requirements while others create more than ten thousand requirements. The empirical results suggest that most test suites exhibit a moderate overlap in requirement coverage. Yet, for several applications (e.g., `Pithy`), we also observe that many $\mathbf{A_v}$-level test requirements are only covered by one or two test cases. Considerable experimentation with the reduction and prioritization components indicates that it is possible to efficiently create a modified test suite for each of the selected case study applications. Across all of the applications, we also discover that *GreedyReductionWithOverlap* (GRO) identifies test suites that are 51% smaller than the original test suite. Finally, the empirical study reveals that *GreedyPrioritizationWithOverlap* (GPO) can re-order the test suite in a manner that improves coverage effectiveness.

9.0 CONCLUSIONS AND FUTURE WORK

This chapter summarizes the contributions of this research. We also review the key insights from the experimental results. It suggests future work that includes enhancing the presented database-aware testing techniques. We propose several new approaches to testing database-centric applications that leverage the current framework. This chapter reveals other ways that we can use the research's conceptual foundation in order to test a program's interaction with additional environmental factors such as an eXtensible markup language (XML) database or a distributed system middleware. We also discuss ways to use the database-aware tools and techniques in order to test and analyze conventional software applications. In summary, this chapter provides:

1. A review of the contributions of this dissertation (Section 9.1).
2. A high level summary of the empirical results (Section 9.2).
3. A detailed discussion of future work that leverages the concepts, techniques, and tools developed by this research (Section 9.3).

9.1 SUMMARY OF THE CONTRIBUTIONS

The database is a ubiquitous technology that many academic institutions, corporations, and individuals use to manage data. However, a database is only useful for storing information if users can correctly and efficiently (i) query, update, and remove existing data and (ii) insert new data. To this end, software developers often implement database-centric applications that interact with one or more relational databases. Indeed, Silberschatz et al. observe that "practically all use of databases occurs from within application programs" [Silberschatz et al., 2006, pg. 311]. A database-centric application is very different from a traditional software system because it interacts with a database that has a complex state and structure. To the best of our knowledge, this dissertation formulates the first comprehensive framework to address the challenges that are associated with the efficient and effective testing of database-centric applications. The main contribution of this research is the description, design, implementation, and evaluation of a collection of testing techniques called DIATOMS, for *D*atabase-centr*I*c *A*pplication *T*esting t*O*ol *M*odule*S*. We developed tools to fully support each technique within the comprehensive framework for testing database-centric applications. The contributions of this research include:

1. **Fault Model**: The database-aware fault model explains how a program's database interactions could violate the *integrity* of a relational database. We focus on program interactions that could negatively impact the *validity* and *completeness* of the database [Motro, 1989]. The type (1-c) and (2-v) defects involve the incorrect use of the SQL **delete** statement. If a program contains a type (1-v) or (2-c) defect, then it submits an incorrect SQL **update** or **insert** statement to the database. We further classify database interaction faults as either commission or omission defects. A fault of *commission* corresponds to an incorrect executable statement in the program. A programmer introduces an *omission* fault when he/she forgets to include important executable code segments in the program. The database-aware testing framework supports the identification of all type (1-c) and (1-v) defects and type (2-c) and (2-v) commission faults.

2. **Database-Aware Representations**:

    a. *Control Flow Graphs*: Many database-centric applications use the Java Database Connectivity (JDBC) interface to submit structured query language (SQL) statements to a relational database. Even though a traditional control flow graph (CFG) contains a node for each database interaction in a program, it does not statically model what takes place during the execution of the SQL command. The database interaction interprocedural control flow graph (DI-ICFG) contain nodes and edges that characterize how the program defines and uses the state and structure of the database.

    b. *Finite State Machines*: The test adequacy component automatically generates a *database interaction finite state machine* (DI-FSM) to model each program location that submits a SQL command to the database. We use the DI-FSMs to model the SQL **select**, **update**, **insert**, and **delete** statements that are constructed by the program during testing. We consult the DI-FSMs in order to (i) determine which database entities are subject to interaction at a given CFG node and (ii) create a DI-CFG from a conventional CFG.

    c. *Call Trees*: The traditional *dynamic call tree* (DCT) and *calling context tree* (CCT) represent the sequence of method invocations that occur during testing. We describe coverage trees that reveal how the program interacts with the database during testing (e.g., the DI-DCT and DI-CCT). A database-aware tree supports both the calculation of coverage and the process of regression testing.

3. **Data Flow-Based Test Adequacy Criteria**:

    a. *Comprehensive Family*: The conventional def-use association is the foundation for data flow-based testing because it models a program's definition and use of variables. This research presents the *database interaction association* (DIA) that reveals how the program defines and uses a relational database entity. We describe a family of database-aware test adequacy criteria that include the structure-based *all-relation-DUs* and the state-based *all-attribute-value-DUs*. For example, the *all-relation-DUs* criterion requires a test suite to cover all of the DIAs in the program that involve the definition and use of the relations in one of the databases.

   b. *Subsumption Hierarchy*: This research furnishes a *subsumption hierarchy* to organize the database-aware test adequacy criteria according to their strength. The hierarchy shows that *all-attribute-value-DUs* is the most difficult adequacy criterion for a test suite to fulfill. We also demonstrate that *all-database-DUs* is the weakest criterion. The hierarchy reveals that there is no subsumption relationship between *all-attribute-DUs* and *all-record-DUs*.

4. **Test Coverage Monitoring**: In order to record a database interaction in the appropriate execution context, we use the DI-DCT and the DI-CCT. We formally describe these database-aware trees and we explain how to automatically insert probes that can produce a tree-based coverage report during test execution. The instrumentation probes intercept the SQL statement that performs a database interaction. After analyzing the SQL command, these probes efficiently inspect the relevant portions of a database's state and structure. Finally, the instrumentation inserts nodes and edges into the DI-DCT and DI-CCT in order to record all of the pertinent information about a database interaction. The coverage monitor uses either *static* or *dynamic* instrumentation to transparently construct these coverage trees during testing.
5. **Regression Testing**: The database-aware regression tester minimizes or re-orders a test suite by using *reduction* and *prioritization* techniques. We describe regression testing algorithms that are applicable whenever it is possible to accurately determine which test requirements are covered by a test case. Our regression tester can consider both the tests' overlap in requirement coverage and the time overhead for an individual test. We also furnish algorithms that improve the efficiency of regression testing by ignoring the overlap in requirement coverage. Even though the regression tester currently uses a path in the database-aware coverage tree as a test requirement, we can also configure it to use the database interaction association. Finally, we describe several new approaches to evaluating the efficiency and effectiveness of either a prioritized or a reduced test suite.
6. **Comprehensive Evaluation**:

   a. *Worst-Case Time Complexity*: We characterize the worst-case complexity of the key algorithms in the comprehensive testing framework. For example, we analyze the algorithms that (i) construct the database-aware representation, (ii) record coverage information, and (iii) prioritize and reduce a test suite. We provide formal statements of each algorithm in order to support the time complexity analysis.

   b. *Case Study Applications*: During the empirical evaluation of the testing techniques, we primarily use six database-centric applications that were written in Java. We offer a detailed characterization of each application by examining the size and structure of both the source code and the relational database. The applications range in size from 548 to 1455 non-commented source statements (NCSS). The database for each application contains between one and nine relations. The applications use various techniques to submit a wide variety of SQL **select**, **update**, **insert**, and **delete** statements. Each case study application has a test suite with test cases that employ many different testing strategies.

c. *Tool Implementation Details*: We implemented and tested each component in the database-aware testing framework. We provide pertinent implementation details about the components that calculate test requirements, monitor coverage, and perform regression testing. For example, we explain how to use aspect-oriented programming (AOP) and the AspectJ language in order to implement a coverage monitor. These details about the tools demonstrate the practicality of our testing techniques and ensure that other researchers can reproduce our experimental results.

d. *Experiment Design*: We fully detail the execution environment and the tool versions that we used during experimentation. We also describe the internal, external, and construct threats that could compromise experiment validity and we explain how we addressed these threats. The chapters employ several visualization techniques in order to explain the empirical results. Finally, we furnish one page summaries that highlight the important insights from each experiment.

9.2 KEY INSIGHTS FROM THE EXPERIMENTS

In order to complement and confirm our analytical evaluation of algorithm performance, we conducted experiments to measure the efficiency and effectiveness of each database-aware testing technique. We calculated different types of *time* and *space* overheads in order to evaluate efficiency. The measurements of effectiveness were different for each of the testing components. Noteworthy insights from the experimental results include:

1. **Data Flow-Based Test Adequacy**:

   a. *Effectiveness*: The data flow-based test requirements for a database-centric application include both the def-use and database interaction associations. The experiments show that the database-aware test requirements constitute between 10 and 20% of the total number of requirements. This result suggests that the database-aware test adequacy criteria call for test suites to cover additional requirements that conventional test criteria ignore.

   b. *Efficiency*: For small and moderate size applications, our data flow analysis algorithm normally enumerates the database-aware test requirements in less than one minute. The experiments also show that the inclusion of database interactions in a program's control flow graph never incurs more than a 25% increase in the number of nodes and edges.

2. **Coverage Monitoring**:

   a. *Effectiveness*: Manual and automated inspections of the coverage reports indicate that the coverage monitor correctly records information concerning program behavior and database interaction. A comparison of the test suite's output before and after the insertion of coverage instrumentation shows that our techniques preserve the syntax and semantics of the program and the tests.

   b. *Efficiency*

      i. <u>Instrumentation</u>: Our static instrumentation technique requires less than six seconds to insert coverage probes into a database-centric application. The batch approach to instrumentation attaches the probes to all six of the applications in less than nine seconds. The dynamic instrumentation scheme incurs moderate overheads (e.g., a 50% increase in testing time) when it introduces the instrumentation during test suite execution. The experiments reveal that the use of static instrumentation increases space overhead by 420% on average. We judge that this is acceptable because it supports efficient coverage monitoring.

   ii. Test Suite Execution: Using static instrumentation to record coverage at coarse levels of database interaction granularity (e.g., the database and relation levels) increases the testing time by less than 15% across all applications. On average, coverage monitoring at the finest level of granularity (e.g., the attribute value level) leads to a 54% increase in testing time overhead.

   iii. Coverage Reports: The size of the in-memory representation of the coverage results range from 400 kilobytes to almost 25 megabytes. The size of this tree-based coverage report ranges from 400 to 88000 nodes, depending upon the static structure and dynamic behavior of the application under test. Even though these reports are large, on average they can be stored in less than three seconds. We found that efficient compression algorithms successfully reduce the size of a coverage report by at least one order of magnitude. The results also show that a DI-CCT at the finest level of database interaction granularity consumes less space overhead than a traditional dynamic call tree.

3. **Regression Testing**:

   a. *Characterizing the Test Suites*: The test suites contain many tests that rapidly execute and a few tests that execute for several seconds. Tests consume a significant amount of execution time if they (i) interact with many portions of the database and/or (ii) restart the database server.

   b. *Test Path Enumeration*: It is often possible to enumerate the tree-based test paths in less than one second. Test path enumeration is the most expensive when we identify the paths in a coverage tree that represents a database interaction at the attribute value level. We conclude that the tree-based test requirement is suitable for both version specific and general regression testing.

   c. *Test Suite Reduction*:

      i. Effectiveness: The reduced test suites are between 30 and 80% smaller than the original test suite. Across all of the case study applications, the *GreedyReductionWithOverlap* (GRO) algorithm yields a test suite that contains 51% fewer test cases. The use of GRO leads to test suites that always cover the same requirements as the original tests while decreasing test execution time by between 7 and 78%. These results indicate that the reduction component can identify a modified test suite that is more streamlined that the original suite.

      ii. Efficiency: All configurations of the regression testing component can execute in under one second. We find that the execution of the GRO algorithm normally consumes less than 500 milliseconds, while the GR, RVR, and RAR techniques only run for three to five milliseconds.

The experimental results suggest that the reduction technique should scale favorably when it is applied to larger case study applications. We conclude that the reduction component is ideal for use in either a version specific or a general regression testing model.

d. *Test Suite Prioritization*:

   i. Effectiveness: In comparison to the original ordering of `GB`'s test suite, the *GreedyPrioritizationWithOverlap* (GPO) causes the coverage effectiveness (CE) value to increase from .22 to .94. For the other case study applications, we find that the GPO technique creates test orderings that attain higher CE values than a randomly prioritized suite.

   ii. Efficiency: Extensive study of the performance of the prioritization component suggests that it is very efficient. Paralleling the results from using the reduction algorithms, we find that GPO always runs in less than 1.5 seconds. Furthermore, the GP, RVP, and RAP techniques can identify a re-ordered test suite in less than 5 milliseconds.

9.3 FUTURE WORK

This section suggests several areas for future research. It is possible to enhance the testing techniques so that they handle other types of database interactions. We can also employ the comprehensive framework during the development of new database-aware testing techniques. For example, we could use the coverage trees during *automatic fault localization* and the *simplification* of a database state that is failure-inducing. A tree-based coverage report supports this type of debugging because it can record the (i) execution context of a faulty interaction and (ii) state of the database that existed before the program's failure. The experiments also suggest several new avenues for research that empirically investigates the trade-offs in the efficiency and effectiveness of testing. The database-aware testing techniques provide a foundation for new tools that test a program's interaction with other environmental factors. Finally, this research reveals several ways to improve traditional testing schemes.

9.3.1 Enhancing the Techniques

1. **Fault Model**: Some database-centric applications use programmer defined transactions so that concurrent database interactions operate correctly. However, our fault model is not tailored for multi-threaded applications that use transactions. Future work should extend the fault model to include the three canonical concurrency control problems known as *lost update*, *inconsistent read*, and *dirty read* [Weikum and Vossen, 2002].
2. **Test Adequacy**: Extending the fault model to incorporate concurrency necessitates the improvement of the test adequacy criteria. Future research should also explore new approaches to enumerating the database interaction associations. Currently, the adequacy component identifies intraprocedural test requirements. Further research could explore the use of interprocedural data flow analysis (e.g., [Harrold and Soffa, 1994]).

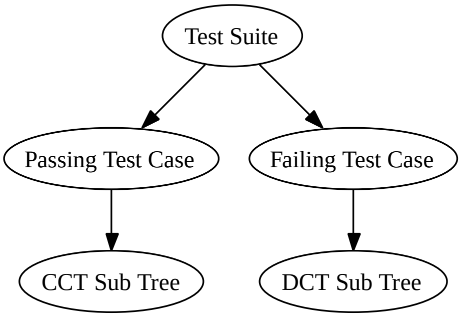
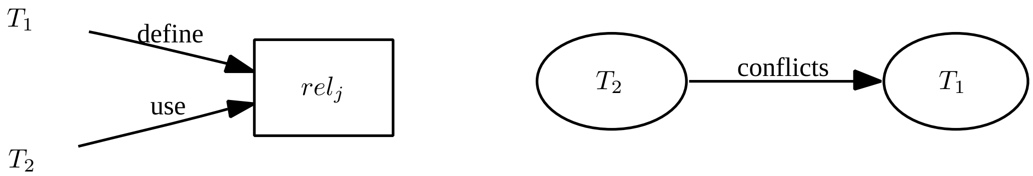


Figure 9.1: The Enhanced Test Coverage Monitoring Tree.

3. **Test Coverage Monitoring**

   a. *Enhanced Coverage Trees*: The dynamic call tree incurs high space overhead because it provides *full* test execution context. The calling context tree decreases space overhead by coalescing tree nodes and thus offering a *partial* context. Future research should investigate a *hybrid call tree* (HCT) that balances the strengths and weaknesses of the DCT and the CCT. This HCT could contain a mixture of CCT and DCT subtrees. If test histories are available, then the HCT could use a DCT to represent the coverage for the tests that execute any of the methods that previously failed. The instrumentation probes for the HCT could create CCT subtrees for all of the tests that execute non-failing methods. As shown in Figure 9.1, the HCT could *selectively* provide additional execution context for those tests that are most likely to reveal faults and thus lead to better support for the debugging process. In principle, the HCT is similar to the incremental call tree described by [Bernat and Miller, 2006]. However, we intend to use the HCT to test and debug database-centric and object-oriented applications and their approach is primarily designed for profiling procedural C programs.

   b. *Alternative Forms of Interaction*: The test coverage monitor (TCM) currently records any database interaction that occurs through the standard JDBC interface. Recent JDBC drivers include new functionality that allows the program to update the database through the result set. Some RDBMS also allow the definition of *views* that combine the pre-defined relations in order to create a *virtual relation*. However, using the SQL **create view** statement to define a virtual relation forces the RDBMS to *maintain* the view when either (i) the underlying relations change or (ii) the state of the view is directly updated. Many RDBMS support the definition of *referential integrity constraints* that create a referencing relationship between two relations. The use of the SQL **references** keyword compels the RDBMS to update the state of the referencing relation when the referenced one changes. Finally, most RDBMS allow the specification of a *trigger* that executes when a certain *event* occurs. Upon the satisfaction of the trigger's *event condition*, the database executes a list of *actions* that may change the state or structure of the relations. Even though our case study applications do



(a) (b)

Figure 9.2: (a) Conflicting Test Cases and (b) a Test Conflict Graph.

not use these features of JDBC and SQL, future research should enhance the coverage monitor to efficiently capture all of these database interactions. Improving the TCM component in this manner will result in more accurate coverage reports and better support for any testing technique that uses coverage information (e.g., regression test suite reduction or prioritization).

c. *New Instrumentation Granularities*: Currently, we perform static instrumentation on all of the loaded classes in the program and the test suite. If static instrumentation occurs frequently and we can preserve information about source code modification, then it would be possible to *selectively* instrument only those methods that were last changed. The coverage monitor dynamically inserts instrumentation on a per-class basis. However, this approach might be inefficient for classes that contain methods that are rarely used during testing. To this end, future work should enhance the dynamic instrumentor so that it inserts probes on a per-method basis. Improving the static and dynamic instrumentation techniques in these ways will reduce the cost of inserting the coverage probes and ensure that coverage monitoring is scalable for larger database-centric applications.

d. *Optimizing the Instrumentation*: We currently rely upon the Java virtual machine (JVM) to dynamically optimize the instrumented programs and we do not perform any static optimization. However, recent research has empirically demonstrated that it can be beneficial to statically and dynamically *optimize* an instrumented program [Luk et al., 2005, Yang et al., 2006]. Future work can use the Soot program analysis framework [Vallée-Rai et al., 1999, 2000] in order to apply static optimizations such as method inlining, constant propagation, and the removal of partially redundant expressions. Further research should also examine whether or not the adaptive optimizations provided by the Jikes RVM [Alpern et al., 2005] can further reduce testing time.

4. **Regression Testing**:

a. *Avoiding RDBMS Restarts*: Sometimes the tests for a database-centric application are not *independent* (i.e., one or more tests do not clear the database state that they created during execution). In this circumstance, test independence must be imposed by clearing out the state of the database and/or restarting the entire database management system. Forcing test independence in this fashion normally leads to a significant increase in testing time. Recent prioritization schemes use heuristics that re-order a test suite in a fashion that avoids some RDBMS restarts [Haftmann et al., 2005a].

We can reduce testing time by using the static and dynamic details about a database interaction as generated by the adequacy and coverage monitoring components. Information about how the tests define and use the database can be leveraged to create a *test conflict graph*. As depicted in Figure 9.2(a), two test cases would conflict if they define and use the same part of the database. Future research could identify new prioritization(s) by applying *topological sorting* algorithms (e.g., [Cormen et al., 2001]) to a test conflict graph like the one in Figure 9.2(b). If we monitor how test conflicts change during regression testing, we can also use more efficient *online* topological sorting algorithms (e.g., [Pearce and Kelly, 2006]) that create test prioritizations without re-analyzing the entire conflict graph. We will investigate how these re-orderings improve the efficiency of testing by avoiding RDBMS restarts.

b. *Time-Aware Testing*: Testing database-centric applications is often time consuming because a database interaction normally involves costly remote method invocations and data transfers. Time-aware regression testing techniques (e.g., [Elbaum et al., 2001, Walcott et al., 2006]) are applicable in this domain since many database-aware test suites should terminate after a pre-defined time interval [Haftmann et al., 2005a]. Future research must leverage database-aware test requirements during the generation of a time sensitive prioritization. Since it is often expensive to produce a time-aware re-ordering or reduction of the tests [Walcott et al., 2006], future work must investigate efficient approaches that heuristically solve the underlying NP-complete problems. For example, we can investigate the use of efficient solvers for the 0/1 knapsack problem (e.g., dynamic programming, branch and bound, and the core algorithm [Kellerer et al., 2004]) when we perform time-aware reduction. In circumstances when regression testing must be timely but a specific time limit is unknown (or, undesirable), we will use multi-objective optimization techniques [Zitzler and Thiele, 1999]. This approach will find the test suite re-ordering(s) and/or reduction(s) that are the most effective at minimizing the test execution time and maximizing the coverage of the test requirements.

c. *Alternative Techniques for Regression Testing*: There are several other approaches to reduction and prioritization that focus on modifying the test suite for a traditional program. For example, the HGS reduction scheme analyzes the test coverage information and initially selects all of the tests that cover a single requirement [Harrold et al., 1993]. In the next iteration, HGS examines all of the requirements that are covered by two tests and it selects the test case with the greatest coverage. The HGS reduction procedure continues to select test cases until it obtains a minimized suite that covers all of the requirements. An alternative approach reduces a test suite by analyzing a concept lattice that represents the coverage information [Tallam and Gupta, 2005]. The lattice-based approach exploits information concerning the (i) requirements that a test case covers and (ii) tests that cover a specific requirement. A recently developed reduction method retains a test case if it is redundant according to a primary adequacy criteria and yet still relevant with regard to secondary and tertiary criteria [Jeffrey and Gupta, 2007]. Finally, [Rothermel et al., 2002] suggest that it may be possible to reduce testing time by joining together test cases that interact with similar regions of the program. We intend to enhance these regression testing algorithms so that they use test requirements such as the (i) paths in the database-aware coverage tree and (ii) database interaction association.

9.3.2 New Database-Aware Testing Techniques

1. **Automated Debugging**: Traditional approaches to *automatic fault localization* identify the source code location that is most likely to contain a program defect [Jones and Harrold, 2005]. Future work should develop fault localizers that use test execution histories (e.g., information about the passing and failing test cases) in order to find defective database interactions. These techniques should also discover which syntactic elements of a SQL command have the highest probability of containing the fault. A comprehensive approach to database-aware automatic debugging must also consider how the state of the database causes a program failure. To this end, future work must devise database-aware *delta debuggers* [Zeller and Hildebrandt, 2002], that can simplify the failure-inducing database state. Our research suggests that it is often valuable to view a database interaction at different levels of granularity (e.g., the structure-based relation level or the state-based record level). Hierarchical delta debuggers (e.g., [Misherghi and Su, 2006]) hold particular promise for efficiently simplifying database state because we can customize them to intelligently view the database at different granularity levels.

2. **Mutation Testing**: A *mutation* adequacy criterion ensures that a test suite can reveal the types of defects that are normally inserted into a program by competent programmers [DeMillo et al., 1988]. This type of testing technique uses *mutation operators* that make small modifications to the source code of the program under test. The majority of approaches to mutation testing exclusively focus on control structures, program variables, and object-oriented features (e.g., [Ma et al., 2002, Offutt et al., 2001]). A recently developed tool mutates a SQL statement that is statically specified outside the context of an executable program [Tuya et al., 2007]. Future research should leverage the static and dynamic analysis techniques provided by the test adequacy and coverage monitoring components. We can use the current framework in order to identify the SQL statements that the program submits during testing. After mutating all of the recorded SQL commands using the technique from [Tuya et al., 2007], we can execute the program with a *mutant* database interaction (we say that the tests *kill* a mutant if they differentiate the faulty interaction from the original SQL statement). Finally, we can calculate mutation coverage as the ratio between the number of *killed* mutants and the *total* number of mutants [Zhu et al., 1997].

3. **Reverse Engineering**: Database designers can define relationships among the attributes in a database by specifying *integrity constraints* in the relational schema. Since software engineers often cannot change the relational schema of a large database, new integrity constraints are frequently encoded in the program's methods. However, a database-centric applications becomes difficult to test, maintain, and understand if the constraints are dispersed throughout the schema and the source code. Future work should develop *reverse engineering* techniques that observe the database state before and after an interaction in

order to detect implicit constraints that are not expressed in the schema. A reverse engineered constraint could be included in a new version of the schema after it was verified by a database administrator. Dynamic invariant detection techniques (e.g., [Ernst et al., 2001, 2006]) can analyze the database state that was extracted from the coverage report in order to identify the program enforced integrity constraints.

4. **Performance Testing and Analysis**: The primary focus of our testing framework is to establish a confidence in the correctness of a program's database interactions. Even though the majority of traditional testing techniques do not consider performance [Vokolos and Weyuker, 1998], future research should investigate the creation of approaches to database-aware performance testing. Performance testing tools will assist software developers in designing high performance queries and selecting the most efficient database configuration in the context of a specific database-centric application. We will extend the test execution component to support the encoding of test oracles about the response time of a database interaction. For example, a *performance oracle* might specify that a test case fails whenever one or more database interactions exceed a specified time threshold. Future work must enhance the test coverage monitoring trees so that they can record information about the performance of each database interaction. A performance-aware regression tester could re-order a test suite so that it is better at finding performance defects earlier in the testing process. A performance-aware prioritization would first execute those test cases that cover the performance sensitive methods (e.g., those methods that contain database interactions, file system calls, or the invocation of remote procedures).

5. **Other Testing and Analysis Techniques**: This research reports the cyclomatic complexity of each case study application. Prior research proposed various complexity metrics that only apply to traditional software applications [Cherniavsky and Smith, 1991, Weyuker, 1988]. Future work should extend these criteria to include details about the relational schema (e.g., the number of relations and the average number of attributes per relation) and the state of the database (e.g., the average number of records per relation). Other previous research scans the source code of a program in an attempt to find locations that match pre-defined bug patterns [Hovemeyer and Pugh, 2004, Reimer et al., 2004]. New fault detectors could verify that a database interaction point never submits a SQL statement that references entities that are not inside of the database. Future research can also use static analyzers to verify that all SQL operators and keywords are spelled correctly. These tools could ensure that the program does not attempt to submit a SQL **select** with the `executeUpdate` method or one of the **update**, **insert**, and **delete** statements with `executeQuery`. Finally, we will develop *automated test data generation* algorithms that create values for both the (i) parameters to the method under test and (ii) entities within the relational database.

9.3.3 Further Empirical Evaluation

Future work must empirically evaluate each of the new testing techniques that were described in Section 9.3.2. Yet, it is also valuable to pursue further empirical studies with the current version of the testing framework.

1. **Additional Case Study Applications**: We intend to evaluate the testing techniques with new case study applications. Future experiments should vary the size of the database in an attempt to more accurately characterize the scalability of each testing tool. We will use applications like `FindFile` to conduct the scalability experiments since it is easy to modify the size of the database for this type of program. None of the current case study applications come with historical details about defects, revisions, or testing outcomes. We plan on creating a publicly accessible repository of database-centric applications that other researchers can use during the evaluation of their database-aware testing techniques. This repository will contain the source code of the tests and the application, details about the relational schema, sample instances of the database, and additional versioning information.

2. **Performance of the Instrumentation**: Many previous empirical studies have measured how instrumentation increases the time overhead of testing and program execution (e.g., [Luk et al., 2005, Misurda et al., 2005]). To the best of our knowledge, no prior research has investigated the impact that the instrumentation has on the (i) behavior of the memory subsystem and (ii) memory footprint of the program and the tests. This type of empirical study is particularly important in the context of instrumentation for database-centric applications because the probes must allocate and de-allocate portions of the database. An experiment of this nature will also clarify whether it is possible to perform database-aware test coverage monitoring in memory constrained environments such as those discussed in [Kapfhammer et al., 2005]. We intend to use recently developed memory profilers (e.g., [Pearce et al., 2006, Rojemo and Runciman, 1996]) in order to characterize the behavior of the JVM's garbage collector and determine how instrumentation impacts space overhead. Using the scheme developed by [Camesi et al., 2006], future work will also examine how the instrumentation changes the CPU consumption of a database-centric application. We plan to conduct similar empirical studies so that we can measure the performance of instrumentation for traditional programs.

3. **Effectiveness of Regression Testing**: The empirical evaluation of the database-aware regression tester primarily focused on measuring the (i) efficiency of the technique itself, (ii) coverage effectiveness of the prioritized test suite, and (iii) reduction in testing time. Even though the value of regression testing has been extensively studied for traditional programs (e.g., [Do et al., 2004, Rothermel et al., 2001, 2002, Rummel et al., 2005]), future research must determine how reduction and prioritization impact the fault detection effectiveness of regression testing for database-centric applications. Since there is preliminary evidence that mutation testing techniques can be used to create seeded faults (e.g., [Andrews et al., 2005, Do and Rothermel, 2006]), we will use our proposed database-aware mutation tester to enumerate faulty database interactions. After seeding these faults into the case study applications, we will determine how reduction and prioritization impact the test suite's ability to detect defects. This empirical study will also attempt to identify the trade-offs that are associated with the efficiency and effectiveness of the database-aware regression testing techniques.

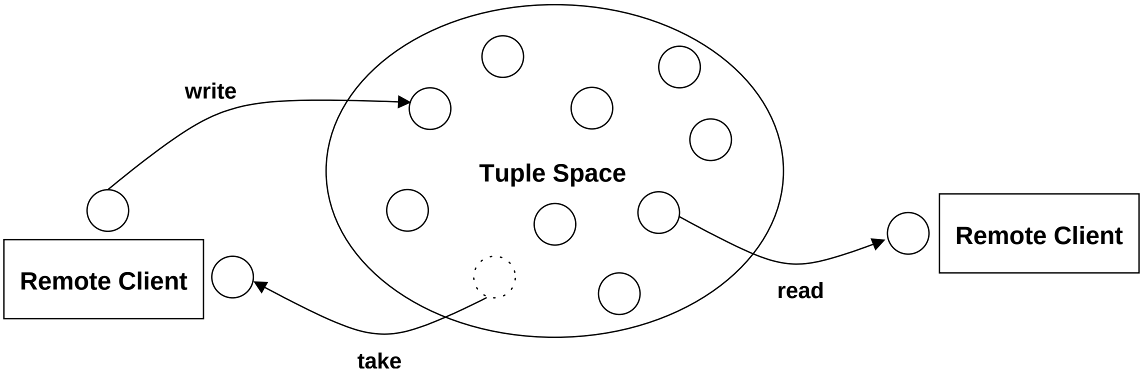


Figure 9.3: Example of a Tuple Space-Based Application.

4. **Assessing Database-Aware Test Oracles**: A test oracle compares the actual and anticipated states of the database in order to determine whether or not the method under test is correct. Some oracles are expensive to execute because they inspect a large portion of the database. Test oracles that examine smaller regions of the database normally incur less execution overhead. Furthermore, a test can execute one or more oracles at arbitrary locations within its control flow graph. Recent research suggests that the type of graphical user interface (GUI) test oracle has a significant impact upon the fault detection effectiveness of a test case [Xie and Memon, 2007]. We intend to conduct experiments to ascertain how the database-aware test oracle impacts the efficiency and effectiveness of testing. We will enhance the test suite execution component to record timings for all of the test oracles and then measure oracle execution time. After using the mutation testing tool to seed database interaction faults, we will also determine how different types of test oracles impact the rate of fault detection. The results from these experiments will yield insight into the characteristics of good test oracles and potentially suggest automated techniques for improving and/or creating database-aware oracles.

9.3.4 Additional Environmental Factors

This research demonstrates the importance of testing a program's interaction with the components in the execution environment. Even though we designed the comprehensive framework to test programs that interact with relational databases, we judge that it can be extended to handle other data management systems such as eXtensible Markup Language (XML) databases (e.g., [Fiebig et al., 2002, Jagadish et al., 2002, Meier, 2003]). It is important to develop testing techniques for XML-based applications since XML is the de-facto language for data interchange and it is now directly integrated into Java [Eisenberg and Melton, 2002, Harren et al., 2005, Li and Agrawal, 2005]. We intend to implement and evaluate XML-aware testing techniques that ensure a program correctly submits XML queries and transformations to the XML data store. If the program under test represents the XML document as a tree (e.g., [Moro et al., 2005, Wang et al., 2003]), then the adequacy criteria will ensure that the tests cause the program to properly define and use the nodes in the tree. We will enhanced event-based test adequacy criteria that were developed for graphical user interfaces (e.g., [Memon et al., 2001]) in order to test XML programs that process XML parsing events (e.g., [Megginson, 2001]).

Future research should also enhance the testing framework to handle distributed applications that interact with data repositories such as *distributed hash tables* (DHTs) (e.g., [Rhea et al., 2005]) and *tuple spaces* (e.g., [Arnold et al., 2002, Murphy et al., 2006]). A DHT furnishes a hash table-like interface with `put` and `get` methods that remotely transfer data in a distributed system. As depicted in Figure 9.3, a tuple space is another type of distributed system middleware that supports data storage and transfer through methods such as `write`, `take`, and `read`. It is important to test programs that interact with DHTs and tuple spaces because these components are widely used to implement peer-to-peer and distributed systems that support scientific and ubiquitous computing (e.g., [Chawathe et al., 2005, Noble and Zlateva, 2001, Rhea et al., 2005, Zorman et al., 2002]). Since the DHT and the tuple space both provide an interface that focuses on the *definition* and *use* of remote data, it is possible to adapt our data flow-based testing techniques to handle this new domain. Future research can extend previous test adequacy criteria for parallel shared memory programs (e.g., [Yang et al., 1998]) in order to support coverage monitoring and regression testing for programs that interact with DHTs and tuple spaces.

9.3.5 Improving Traditional Software Testing and Analysis

Even though our framework focuses on testing database-centric applications, it can also be used to test conventional software systems. This type of future research is feasible because our testing framework correctly operates in both database-aware and traditional configurations. For example, our test coverage monitor constructs traditional CCTs and DCTs and the regression testing techniques reduce and/or re-order any test suite for which coverage results are known. Furthermore, our testing techniques support the full range of features in Java and they interoperate with popular testing tools such as JUnit. Prior work in regression testing focused on using call stacks to reduce the test suite for either a procedural program written in C or a GUI program written in Java [McMaster and Memon, 2005, 2006]. We intend to use the coverage monitoring and regression testing components to perform traditional call stack-based reduction *and* prioritization for object-oriented Java programs. These empirical studies will use the conventional Java programs and JUnit test suites in the software-artifact infrastructure repository (SIR) [Do et al., 2005].

The calling context tree was initially proposed and empirically evaluated in the context of procedural programs [Ammons et al., 1997]. In future research, we will use our framework to characterize the dynamic call tree and the calling context tree for a wide variety of object-oriented programs. We plan to focus our empirical studies on determining how long it takes to create and store the DCT and CCT for object-oriented programs. These studies will calculate the size of the DCT and CCT in order to determine the space overhead associated with storing the trees for testing and fault localization purposes. We can also compare the size and structure of object-oriented control flow graphs and dynamic call trees. A comprehensive empirical study of object-oriented call trees is relevant to traditional software engineering because the CCT and the DCT are a central component of several profilers and debuggers (e.g., [Dmitriev, 2004]). The tool support and the experiment results are also useful for improving dynamic optimization since many JVMs use context-sensitive information about methods calls in order to guide inlining decisions [Hazelwood and Grove, 2003, Zhuang et al., 2006]. To the best of our knowledge, these proposed future research ideas represent the first attempt to investigate call tree-based approaches to the testing and analysis of object-oriented programs.

APPENDIX A

SUMMARY OF THE NOTATION

Variable Name	**Meaning**
$rel_1, \ldots, rel_w$	Relations within the database
rel_j	Arbitrary relation
$A_1, \ldots, A_q$	Attributes within an arbitrary relation
A_l	Arbitrary attribute
$M_1, \ldots, M_q$	Domains of the attributes within an arbitrary relation
$v_1, \ldots, v_q$	Values that are placed within the database by an **insert**
Q	Logical predicate within a **select**, **update**, or **delete** statement
V_ϕ	Any one of the valid attributes within an arbitrary relation
V_ψ	Any valid attribute, string, pattern, or **select** result

Table A1: Relational Databases.

Variable Name	**Meaning**
G	Control flow graph for a method
$\mathcal{N}$	Set of control flow graph nodes
$\mathcal{E}$	Set of control flow graph edges
N_ρ, N_τ	Arbitrary nodes within a control flow graph
$\langle N_\rho, \ldots, N_\tau \rangle$	Arbitrary path within a control flow graph
$succ(N_\rho)$	Successor of node N_ρ
$pred(N_\tau)$	Predecessor of node N_τ

Table A2: Traditional Program Representation.

Variable Name	**Meaning**
G_k	Control flow graph for method m_k
$\mathcal{N}_k$	Set of control flow graph nodes
$\mathcal{E}_k$	Set of control flow graph edges
$\mathcal{B}_k$	Set of non-executable nodes with a method's CFG
$v(G_k)$	Cyclomatic complexity number for a CFG G_k

Table A3: Characterizing a Database-Centric Application.

Set Name	**Meaning**
$G_{DI(k)}$	Database interaction CFG for method m_k
$\mathcal{D}(G_{DI(k)})$	Set of database interactions
$\mathcal{R}(G_{DI(k)})$	Set of relation interactions
$\mathcal{A}(G_{DI(k)})$	Set of attribute interactions
$\mathcal{R}_c(G_{DI(k)})$	Set of record interactions
$\mathcal{A}_v(G_{DI(k)})$	Set of attribute value interactions

Table A4: Database Entity Sets.

Variable Name	**Meaning**
$\langle N_{def}, N_{use}, var \rangle$	Def-use association for program variable *var*
π_{var}	Complete path that covers a def-use association
$G_{DI(k)}$	Database interaction control flow graph for a method
$\mathcal{N}_{DI(k)}$	Set of DI-CFG nodes
$\mathcal{E}_{DI(k)}$	Set of DI-CFG edges
$\langle N_{def}, N_{use}, var_{DB} \rangle$	Database interaction association for database entity var_{DB}
C_α, C_β	Arbitrary test adequacy criteria

Table A5: Database-Aware Test Adequacy Criteria.

Variable Name	**Meaning**
A	A database-centric application
P	Program component of a database-centric application
m	Method within the program component
$D_1, \ldots, D_e$	Relational databases of a database-centric application
D_f	Arbitrary relational database
t_k	Record within a database relation
t_k	Record within a database relation
$t_k[l]$	Attribute value within a specific record
$S_1, \ldots, S_e$	Schemas of the relational databases
S_f	Arbitrary relational schema
G_P	Interprocedural control flow graph for program P
Γ_P	Set of control flow graphs in G_P
$\mathcal{E}_P$	Set of control flow graphs edges in G_P
G_j	Intraprocedural control flow graph for program method m_j

Table A6: Database-Centric Applications.

Variable Name	Meaning
$\mathcal{C}$	Database-aware context stack
$name(D_f)$	Unique database name
$name(\mathcal{C}, rel_j)$	Unique relation name
$name(\mathcal{C}, A_l)$	Unique attribute name
$name(\mathcal{C}, t_k)$	Unique record name
$name(\mathcal{C}, t_k[l])$	Unique attribute value name

Table A7: Enumerating the Sets of Database Entities.

Variable Name	Meaning
N_r	Control flow graph node that interacts with a database
F_r	DI-FSM that models a database interaction at node N_r
Q	Non-empty set of internal states in the DI-FSM F_r
Q_f	Set of final states in the DI-FSM F_r
q_0	Initial state in the DI-FSM F_r
δ	Transition funtion for the DI-FSM F_r
Σ	Input alphabet for the DI-FSM F_r
μ	Unknown input symbol for a transition in the DI-FSM F_r
$GEN_D, \ldots, GEN_{A_v}$	Generation functions for database entities
λ	Generation function limit

Table A8: The Database-Aware Test Adequacy Component.

Variable Name	**Meaning**
N_r	CFG node that performs a databse interaction
$in(N_\rho)$	In degree of a CFG node
$out(N_\rho)$	Out degree of a CFG node
τ	Test coverage monitoring tree
τ_{dct}	Dynamic test coverage monitoring tree
τ_{cct}	Calling context test coverage monitoring tree
$\mathcal{N}_\tau$	Set of TCM tree nodes
$\mathcal{E}_\tau$	Set of TCM tree edges
N_a	Active node in a TCM tree
N_0	Root node in a TCM tree
$\mathcal{E}_F$	Set of forward edges in a CCT
$\mathcal{E}_B$	Set of back edges in a CCT
$\mathcal{N}_B$	Set of nodes that receive a back edge in a CCT
$\mathcal{B}_\phi$	Active back edge stack for a CCT node N_ϕ
σ	Program or database entity to place into a TCM tree

Table A9: Database-Aware Test Coverage Monitoring Trees.

Variable Name	**Meaning**
$H_{R:A}$	Function that maps relations to attributes
$H_{R:R_c}$	Function that maps relations to attributes
A_l and $\widehat{A_l}$	Attributes in a relation
rel_j and $\widehat{rel_j}$	Relations in a database
$\mathcal{S}$	Result set that arises from a SQL **select**
$attr(\mathcal{S})$	The set of attributes associated with result set $\mathcal{S}$
$relations(\mathcal{S})$	The set of relations associated with result set $\mathcal{S}$
$attr(rel_j)$	The set of attributes associated with relation rel_j
$\mathcal{L}(\tau)$	Levels of database interaction for a TCM tree

Table A10: Instrumentation to Create the Database-Aware TCM Trees.

Operator Name	Meaning
$\bigotimes_{R_c}$	Symmetric relational difference operator
$\bigotimes_{A_v}$	Symmetric attribute value difference operator
$\setminus_{R_c}$	Relational difference operator at the record level
$\setminus_{A_v}$	Relational difference operator at the attribute value level

Table A11: Relational Difference Operators.

Variable Name	Meaning
$\mathcal{W}_f$	Total number of relations in database D_f
t_{max}	Maximum number of records in the database D_f
$\mathcal{M}_{R:A}$	Maximum number of attributes in both rel_j and $\mathcal{S}$
$\mathcal{M}_{R:R_c}$	Maximum number of records that have an attribute value in both rel_j and $\mathcal{S}$
$\Lambda(j, j')$	Length of the longest common subsequence (LCS) between rel_j and $rel_{j'}$
$\mathcal{A}_{max}$	Maximum number of attributes that differ in rel_j and $rel_{j'}$

Table A12: Worst-Case Complexity of the Database-Aware Instrumentation.

Variable Name	Meaning
T	Test suite for a database-centric application
T_i	Arbitrary test case within T
Δ_0	Initial test state
Δ_i	Test state produced by test T_i
G_T	Interprocedural control flow graph for test suite T
Γ_T	Set of control flow graphs in G_T
$\mathcal{E}_T$	Set of control flow graphs edges in G_T
N_θ	Node that executes test oracle θ
Δ_x	Expected test state for test oracle θ
Δ_a	Actual test state for test oracle θ

Table A13: Database-Aware Test Suites.

Variable Name	**Meaning**
$\mathcal{A}, \mathcal{A}'$	Sets of applications to statically instrument
T_s, A_s	Statically instrumented test suite and application
T_d, A_d	Dynamically instrumentated test suite and application
L	Database interaction level during test coverage monitoring
c	Arbitrary compression technique for a program or a TCM tree
$\mathcal{X}_\tau$	Set of external nodes in a TCM tree
$\mathcal{H}$	Hash table that stores the replication counts for a TCM tree

Table A14: Describing the Test Coverage Monitor.

Variable Name	**Meaning**
$\Pi(\tau)$	Multiset of paths in the coverage tree τ
π, π'	Arbitrary paths in the coverage tree τ
$\Pi(\tau, T_i)$	Multiset of tree paths for test case T_i
$\Pi_\upsilon(\tau, T_i)$	Set of unique tree paths for test case T_i
$\sqsupset$	Super path operator for coverage tree paths
$\succ$	Containing path operator for coverage tree paths
$\dashv$	Containing path operator for coverage tree paths
$\Pi_\mu(\tau, T_i, \dashv)$	Set of maximally unique tree paths for test case T_i
$\Pi_\eta(\tau, T_i)$	Set of previously examined coverage tree paths for T_i
$\Pi_\upsilon(\tau, T)$	Set of unique tree paths for test suite T
$\Pi_\mu(\tau, T, \dashv)$	Set of maximally unique tree paths for test suite T

Table A15: Paths in the Test Coverage Monitoring Tree.

Variable Name	**Meaning**
$T, \hat{T}$	Original test suites
T_r	Reduced test suite
T_p	Prioritized test suite
φ_i	Cost-effectiveness metric for test case T_i
$time(\langle T_i \rangle)$	Time required to executed test T_i
n^*	Target size for the reduced test suite

Table A16: Database-Aware Regression Testing.

Variable Name	**Meaning**
$\xi(T, T_p)$	Coverage effectiveness of the T_p derived from T
$\kappa(T, t)$	Cummulative coverage of test suite T at time t
$\bar{\kappa}(T, t)$	Cummulative coverage of the ideal test suite T at time t
$t(n')$	The running time for the first n' tests in T

Table A17: Evaluating a Test Suite Prioritization.

Variable Name	**Meaning**
$\varrho_n(T, T_r)$	Reduction factor for the size of a test suite
$\varrho_t(T, T_r)$	Reduction factor for the time to run a test suite
$\varrho_\pi(T, T_r)$	Reduction factor for the number of covered test requirements
$\nu_\pi(T, T_r)$	Preservation factor for the number of covered test requirements
ν_r	Tuple that contains the evaluation metrics for T_r
ν	Specific value for an evaluation metric in ν_r

Table A18: Evaluating a Test Suite Reduction.

APPENDIX B

CASE STUDY APPLICATIONS

Number	NCSS	Methods	Classes	Javadocs	Class
1	91	15	0	15	reminder.ReminderCreator
2	22	0	0	1	reminder.ReminderConstants
3	31	6	0	6	reminder.TestBeforeAllTests
4	5	2	0	1	reminder.ReminderDataException
5	23	4	0	5	reminder.TestReminderCreator
6	62	7	0	8	reminder.Reminder
7	223	15	0	15	reminder.TestReminder
8	18	2	0	0	reminder.AllTests
9	14	4	0	1	reminder.DatabaseDescription

Table B1: `Reminder` (`RM`) Case Study Application.

Number	NCSS	Methods	Classes	Javadocs	Class
1	8	1	0	0	org.hsqldb.sample.FindFileDatabaseCreator
2	10	1	0	1	org.hsqldb.sample.DatabaseExport
3	330	25	0	23	org.hsqldb.sample.TestFindFile
4	14	4	0	1	org.hsqldb.sample.DatabaseDescription
5	161	18	0	16	org.hsqldb.sample.FindFile

Table B2: `FindFile` (`FF`) Case Study Application.

Number	NCSS	Methods	Classes	Javadocs	Class
1	80	12	0	13	com.runstate.pithy.PithyCreator
2	31	6	0	6	com.runstate.pithy.TestBeforeAllTests
3	23	4	0	5	com.runstate.pithy.TestPithyCreator
4	84	10	0	0	com.runstate.pithy.PithyDBHSQLDB
5	20	7	0	0	com.runstate.pithy.Pith
6	95	4	0	1	com.runstate.pithy.PithyCommand
7	6	5	0	0	com.runstate.pithy.PithyDB
8	18	2	0	0	com.runstate.pithy.AllTests
9	14	4	0	1	com.runstate.pithy.DatabaseDescription
10	131	18	0	11	com.runstate.pithy.TestPithy
11	5	1	0	1	com.runstate.pithy.Pithy

Table B3: `Pithy` (`PI`) Case Study Application.

Number	NCSS	Methods	Classes	Javadocs	Class
1	31	6	0	6	student.TestBeforeAllTests
2	37	6	0	7	student.TestStudentCreator
3	5	2	0	1	student.StudentDataException
4	91	15	0	15	student.StudentCreator
5	69	11	0	11	student.Student
6	18	2	0	0	student.AllTests
7	14	4	0	1	student.DatabaseDescription
8	17	0	0	1	student.StudentConstants
9	279	26	0	7	student.TestStudent

Table B4: `StudentTracker` (`ST`) Case Study Application.

Number	NCSS	Methods	Classes	Javadocs	Class
1	337	33	0	10	TransactionAgent.TestMySQLDatabaseAgent
2	263	27	0	22	TransactionAgent.MySQLDatabaseAgent
3	11	10	0	1	TransactionAgent.DatabaseAgent
4	78	11	0	12	TransactionAgent.TransactionAgentCreator
5	18	2	0	0	TransactionAgent.AllTests
6	14	4	0	1	TransactionAgent.DatabaseDescription

Table B5: `TransactionManager` (`TM`) Case Study Application.

Number	NCSS	Methods	Classes	Javadocs	Class
1	197	40	0	41	gradebook.GradeBookCreator
2	34	6	0	6	gradebook.TestBeforeAllTests
3	602	39	0	37	gradebook.TestGradeBook
4	329	29	0	30	gradebook.GradeBook
5	22	4	0	5	gradebook.TestGradeBookCreator
6	19	2	0	0	gradebook.AllTests
7	5	2	0	1	gradebook.GradeBookDataException
8	14	4	0	1	gradebook.DatabaseDescription
9	114	21	0	22	gradebook.TestGradeBookCreatorWithFullDataSet
10	51	0	0	1	gradebook.GradeBookConstants

Table B6: `GradeBook` (`GB`) Case Study Application.

Location	Name
TestBeforeAllTests.java	testDatabaseServerIsRunning()
TestBeforeAllTests.java	testDoesNotStartServerAgain()
TestReminderCreator.java	testMakeDatabaseConnection()
TestReminder.java	testGetEmptyEvents()
TestReminder.java	testAddReminderOneReminder()
TestReminder.java	testAddReminderOneReminderNewNamesAndDate()
TestReminder.java	testAddReminderMultipleReminders()
TestReminder.java	testAddReminderMultipleRemindersCriitcalMonths()
TestReminder.java	testAddReminderMultipleRemindersCriticalDays()
TestReminder.java	testAddReminderMultipleRemindersGetEventInfo()
TestReminder.java	testAddReminderMultipleRemindersDeleteEvent()
TestReminder.java	testAddReminderMultipleRemindersFullEventList()

Table B7: Test Suite for `Reminder`.

Location	Name
TestFindFile.java	testDatabaseServerIsRunning()
TestFindFile.java	testDoesNotStartServerAgain()
TestFindFile.java	testMakeDatabaseConnection()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFilesRemove15()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFilesRemove234()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFilesUpdate1()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFilesUpdate2()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFilesUpdate345()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles1()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles2()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles3()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles4()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryFiveFiles5()
TestFindFile.java	testFindFilePopulateWithLocalDirectoryTenFiles()
TestFindFile.java	testFindFilePopulateWithLocalEmptyDirectory()

Table B8: Test Suite for `FindFile`.

Location	Name
TestBeforeAllTests.java	testDatabaseServerIsRunning()
TestBeforeAllTests.java	testDoesNotStartServerAgain()
TestPithyCreator.java	testMakeDatabaseConnection()
TestPithy.java	testNoInitialPithyRemarks()
TestPithy.java	testAddOnePithyRemark()
TestPithy.java	testAddManyPithyRemarks()
TestPithy.java	testAddManyPithyRemarksCheckCategory()
TestPithy.java	testAdd()
TestPithy.java	testAddIterativeSmallValue()
TestPithy.java	testAddIterativeMediumValue()
TestPithy.java	testAddIterativeLargeValue()
TestPithy.java	testMultipleAdd()
TestPithy.java	testMultipleAddIterativeSmall()
TestPithy.java	testMultipleAddIterativeMedium()
TestPithy.java	testMultipleAddIterativeLarge()

Table B9: Test Suite for `Pithy`.

Location	Name
TestBeforeAllTests.java	testDatabaseServerIsRunning()
TestBeforeAllTests.java	testDoesNotStartServerAgain()
TestStudentCreator.java	testMakeDatabaseConnectionSmall()
TestStudentCreator.java	testMakeDatabaseConnectionMedium()
TestStudentCreator.java	testMakeDatabaseConnectionLarge()
TestStudent.java	testInsertSingleStudent()
TestStudent.java	testInsertSingleStudentIterativeSmall()
TestStudent.java	testInsertAndRemoveStudent()
TestStudent.java	testInsertAndRemoveStudentIterativeSmall()
TestStudent.java	testInsertAndRemoveStudentIterativeMedium()
TestStudent.java	testInsertAndRemoveStudentIterativeLarge()
TestStudent.java	testInsertAndRemoveMultipleStudents()
TestStudent.java	testInsertAndRemoveMultipleStudentsDoNotRemove()
TestStudent.java	testInsertAndUpdateStudentExampleTwoTimes()
TestStudent.java	testInsertAndUpdateStudentExampleSmall()
TestStudent.java	testInsertAndUpdateStudentExampleMedium()
TestStudent.java	testInsertAndUpdateStudentExampleLarge()
TestStudent.java	testRemoveStudentFromEmptyDatabase()
TestStudent.java	testRemoveStudentFromEmptyDatabaseCheckIndividualStudents()
TestStudent.java	testInsertSingleStudentGetSingleStudent()
TestStudent.java	testInsertSingleStudentGetSingleStudentPerformRepeatedly10()
TestStudent.java	testInsertSingleStudentGetSingleStudentPerformRepeatedly50()
TestStudent.java	testInsertSingleStudentGetSingleStudentPerformRepeatedly100()
TestStudent.java	testInsertMultipleStudentGetMultipleStudentsDirectly()
TestStudent.java	testInsertAndUpdateExampleDirectRemove()

Table B10: Test Suite for `StudentTracker`.

Location	Name
TestMySQLDatabaseAgent.java	testDatabaseServerIsRunning()
TestMySQLDatabaseAgent.java	testDoesNotStartServerAgain()
TestMySQLDatabaseAgent.java	testMakeDatabaseConnection()
TestMySQLDatabaseAgent.java	testBasicTestFramework()
TestMySQLDatabaseAgent.java	testMakeDatabaseConnectionRepeatedly10()
TestMySQLDatabaseAgent.java	testCreateDefaultBankState()
TestMySQLDatabaseAgent.java	testRemoveAccountNotPossibleInitialState()
TestMySQLDatabaseAgent.java	testRemoveAccountTwiceDoesNotWorkCorrectly()
TestMySQLDatabaseAgent.java	testRemoveDifferentAccountNumberTwice()
TestMySQLDatabaseAgent.java	testRemoveASingleUser()
TestMySQLDatabaseAgent.java	testVerifySingleUser()
TestMySQLDatabaseAgent.java	testVerifySingleUserRepeatedlyTenTimes()
TestMySQLDatabaseAgent.java	testAccountExistsSingleAccount()
TestMySQLDatabaseAgent.java	testAccountExistsSingleAccountRepeatedly()
TestMySQLDatabaseAgent.java	testGetAccountBalance()
TestMySQLDatabaseAgent.java	testGetAccountBalanceRepeatedly()
TestMySQLDatabaseAgent.java	testGetAccountBalanceAndThenWithdraw()
TestMySQLDatabaseAgent.java	testGetAccountBalanceWithdrawRepeatedly()
TestMySQLDatabaseAgent.java	testDepositForSingleUser()
TestMySQLDatabaseAgent.java	testAccountTransfer()
TestMySQLDatabaseAgent.java	testAccountTransferMultipleTimes()
TestMySQLDatabaseAgent.java	testLockTwoAccounts()
TestMySQLDatabaseAgent.java	testLockUnlockLockTwoAcctsRepeatedlySmall()
TestMySQLDatabaseAgent.java	testDeleteAccounts()
TestMySQLDatabaseAgent.java	testDeleteAccountsRepeatedSmall()
TestMySQLDatabaseAgent.java	testDeleteAccountsRepeatedMedium()
TestMySQLDatabaseAgent.java	testDeleteAccountsRepeatedLarge()

Table B11: Test Suite for `TransactionManager`.

Location	Name
TestBeforeAllTests.java	testDatabaseServerIsRunning()
TestBeforeAllTests.java	testDoesNotStartServerAgain()
TestGradeBookCreator.java	testMakeDatabaseConnection()
TestGradeBookCreatorWithFullDataSet.java	testCreateMasterTable()
TestGradeBookCreatorWithFullDataSet.java	testDropMasterNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateStudentTable()
TestGradeBookCreatorWithFullDataSet.java	testDropStudentNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateExamMasterTable()
TestGradeBookCreatorWithFullDataSet.java	testDropExamMasterNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateExamScoresTable()
TestGradeBookCreatorWithFullDataSet.java	testDropExamScoresNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateLabMasterTable()
TestGradeBookCreatorWithFullDataSet.java	testDropLabMasterNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateLabScoresTable()
TestGradeBookCreatorWithFullDataSet.java	testDropLabScoresNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateHomeworkMasterTable()
TestGradeBookCreatorWithFullDataSet.java	testDropHomeworkMasterNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateHomeworkScoresTable()
TestGradeBookCreatorWithFullDataSet.java	testDropHomeworkScoresNotPossible()
TestGradeBookCreatorWithFullDataSet.java	testCreateFinalProjectScoresTable()
TestGradeBookCreatorWithFullDataSet.java	testDropFinalProjScoresNotPoss()
TestGradeBook.java	testDatabaseServerIsRunning()
TestGradeBook.java	testDoesNotStartServerAgain()
TestGradeBook.java	testPopulateMasterTableWrongPercentages()
TestGradeBook.java	testPopulateMasterTable()
TestGradeBook.java	testAddNullStudentNotPossible()
TestGradeBook.java	testAddEmptyStringStudentNotPossible()
TestGradeBook.java	testAddStudent()
TestGradeBook.java	testAddExamNegativeNotPossible()
TestGradeBook.java	testAddExamNullNotPossible()
TestGradeBook.java	testAddExamsToExamMasterTable()
TestGradeBook.java	testAddExamsToExamMasterTableIncludeCurves()
TestGradeBook.java	testAddExamScoreSecondNegativeNotPossible()
TestGradeBook.java	testAddExamScoreFirstNegativeNotPossible()
TestGradeBook.java	testAddExamScoresToExamScoresTable()
TestGradeBook.java	testCorrectAverageExamScores()
TestGradeBook.java	testAddLabScoreSecondNegativeNotPossible()
TestGradeBook.java	testAddLabScoreFirstNegativeNotPossible()
TestGradeBook.java	testAddLabScoresToLabScoresTable()
TestGradeBook.java	testCorrectAverageLabScores()
TestGradeBook.java	testAddHomeworkScoreSecondNegativeNotPossible()
TestGradeBook.java	testAddHomeworkScoreFirstNegativeNotPossible()
TestGradeBook.java	testAddHomeworkScoresToHomeworkScoresTable()
TestGradeBook.java	testAddFinalProjectScoreSecondNegativeNotPossible()
TestGradeBook.java	testAddFinalProjectScoreFirstNegativeNotPossible()
TestGradeBook.java	testAddFinalProjectScoresToLabScoresTable()
TestGradeBook.java	testCalculateFinalGrade()
TestGradeBook.java	testGetExamIdsAndExamFinalGrade()
TestGradeBook.java	testCalculateLaboratoryFinalGrade()
TestGradeBook.java	testCalculateHomeworkFinalGrade()
TestGradeBook.java	testCalculateFinalProjectFinalGrade()

Table B12: Test Suite for `GradeBook`.

```
public org.hsqldb.sample.FindFile();
  Code:
   0:   aload_0
   1:   invokespecial   #1; //Method java/lang/Object."<init>":()V
   4:   return
```

Figure B1: Bytecode of the `FindFile` Constructor Before Instrumentation.

```
public org.hsqldb.sample.FindFile();
  Code:
   0: aload_0
   1: invokespecial #59; //Method java/lang/Object."<init>":()V
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_0:()Z
   4: invokestatic #385;
   7: ifeq 25
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_1:()Z
   10: invokestatic #382;
   13: ifne 25
   //  Method diatoms/monitor/TraceMonitorTestCoverage.aspectOf:()
   //  Ldiatoms/monitor/TraceMonitorTestCoverage;
   16: invokestatic #373;
   //  Field ajc$tjp_0:Lorg/aspectj/lang/JoinPoint$StaticPart;
   19: getstatic #375;
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$
   //  before$diatoms_monitor_TraceMonitorTestCoverage$1$5a83f1be:
   //  (Lorg/aspectj/lang/JoinPoint$StaticPart;)V
   22: invokevirtual #379;
   25: goto 52
   28: astore_1
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_2:()Z
   29: invokestatic #394;
   32: ifeq 50
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_3:()Z
   35: invokestatic #391;
   38: ifne 50
   //  Method diatoms/monitor/TraceMonitorTestCoverage.aspectOf:()
   //  Ldiatoms/monitor/TraceMonitorTestCoverage;
   41: invokestatic #373;
   //  Field ajc$tjp_0:Lorg/aspectj/lang/JoinPoint$StaticPart;
   44: getstatic #375;
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$after$
   //  diatoms_monitor_TraceMonitorTestCoverage$2$5a83f1be:
   //  (Lorg/aspectj/lang/JoinPoint$StaticPart;)V
   47: invokevirtual #388;
   50: aload_1
   51: athrow
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_2:()Z
   52: invokestatic #394;
   55: ifeq 73
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$if_3:()Z
   58: invokestatic #391;
   61: ifne 73
   //  Method diatoms/monitor/TraceMonitorTestCoverage.aspectOf:()
   //  Ldiatoms/monitor/TraceMonitorTestCoverage;
   64: invokestatic #373;
   //  Field ajc$tjp_0:Lorg/aspectj/lang/JoinPoint$StaticPart;
   67: getstatic #375;
   //  Method diatoms/monitor/TraceMonitorTestCoverage.ajc$after$
   //  diatoms_monitor_TraceMonitorTestCoverage$2$5a83f1be:
   //  (Lorg/aspectj/lang/JoinPoint$StaticPart;)V
   70: invokevirtual #388;
   73: return
```

Figure B2: Bytecode of the `FindFile` Constructor After Instrumentation.

```
public void testAddHomeworkScoresToHomeworkScoresTable()
 {
     try
         {
             // add the three standard exams with their
             // standard point totals
             testGradeBook.addHomework(”HomeworkOne” , 10);
             testGradeBook.addHomework(”HomeworkTwo” , 20);
             testGradeBook.addHomework(”HomeworkThree” , 30);
             // create the expected Exam MASTER from the XML
             IDataSet expectedDatabaseStateFirst = getDataSet();
             ITable expectedHomeworkMasterTable =
                 expectedDatabaseStateFirst.
                 getTable(GradeBookConstants.HOMEWORKMASTER);
             // create the actual Scores Table from the database
             IDataSet actualDatabaseStateFirst =
                 getConnection().createDataSet();
             ITable actualHomeworkMasterTable =
                 actualDatabaseStateFirst.
                 getTable(GradeBookConstants.HOMEWORKMASTER);
             // expected should be equal to actual in terms
             // of both the number of rows and the data
             Assertion.assertEquals(expectedHomeworkMasterTable,
                                    actualHomeworkMasterTable);
         }
         // in order to preserve simplicity, the exception handling
         // code was removed
 }
```

Figure B3: An Example of a Database-Aware Test Case and Oracle.

APPENDIX C

EXPERIMENT DETAILS

Data Type	**Size of the Type (bytes)**
`long`	8
`int`	4
`double`	8
`float`	8
`short`	2
`char`	2
`byte`	1
`boolean`	1
`java.lang.Object` (shell)	8
`java.lang.Object` (reference)	4

Table C1: Estimated Data Type Sizes for a 32-bit Java Virtual Machine.

Variable Name	**Meaning**
$\mathcal{T}_{instr}$	Static instrumentation time
$\mathcal{S}$	Static size of an application
$\mathcal{T}_{exec}$	Test coverage monitoring time
$\mathcal{T}_{store}^{bin}$	Time required for storing a TCM tree in binary
$\mathcal{T}_{store}^{xml}$	Time required for storing a TCM tree in XML
$\mathcal{S}_{\mathcal{N}}$	Number of nodes in a TCM tree
$\mathcal{S}_{mem}$	In memory size of a TCM tree
$\mathcal{S}_{bin}$	File system size of a TCM tree in binary
$\mathcal{S}_{xml}$	File system size of a TCM tree in XML
out_{avg}	Average node out degree of a TCM tree
r_{max}, r_{avg}	Maximum and average node replication count in a TCM tree

Table C2: Metrics Used During the Evaluation of the Test Coverage Monitor.

Number	NCSS	Functions	Classes	Javadocs	Class
1	8	1	0	0	exercise.ExerciseDatabaseCreator
2	187	70	0	10	exercise.TestExercise
3	167	14	0	14	exercise.Exercise
4	10	1	0	1	exercise.DatabaseExport
5	14	4	0	1	exercise.DatabaseDescription

Table C3: `Exercise` (`EX`) Case Study Application.

Dominance Operator ($\dashv$)	**Enumeration Time (ms)**	**Path Count (Suite)**	**Path Count (Case)**
Super Path ($\sqsupset$)	104	90	221
Containing Path ($\succ$)	118	80	211

(a)

Dominance Operator ($\dashv$)	**Enumeration Time (ms)**	**Path Count (Suite)**	**Path Count (Case)**
Super Path ($\sqsupset$)	154	46	535
Containing Path ($\succ$)	195	46	535

(b)

Table C4: Using the Traditional Coverage Tree for (a) `GradeBook` and (b) `TransactionManager`.

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