Using Machine Learning to Support Software Debugging

By

Xuetao Liu

A thesis submitted to

The Faculty of Graduate Studies and Research

In partial fulfillment of the requirements for the degree of

Master of Applied Science

Ottawa-Carleton Institute for

Electrical and Computer Engineering

Department of Systems and Computer Engineering

Carleton University

Ottawa, Ontario, Canada

September 2007

Copyright © 2007 by Xuetao Liu

Library and
Archives Canada

Bibliothèque et
Archives Canada

Published Heritage
Branch

Direction du
Patrimoine de l'édition

395 Wellington Street
Ottawa ON K1A 0N4
Canada

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file Votre référence

ISBN: 978-0-494-33659-5

Our file Notre référence

ISBN: 978-0-494-33659-5

NOTICE:

The author has granted a non-exclusive license allowing Library and Archives Canada to reproduce, publish, archive, preserve, conserve, communicate to the public by telecommunication or on the Internet, loan, distribute and sell theses worldwide, for commercial or non-commercial purposes, in microform, paper, electronic and/or any other formats.

The author retains copyright ownership and moral rights in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

AVIS:

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque et Archives Canada de reproduire, publier, archiver, sauvegarder, conserver, transmettre au public par télécommunication ou par l'Internet, prêter, distribuer et vendre des thèses partout dans le monde, à des fins commerciales ou autres, sur support microforme, papier, électronique et/ou autres formats.

L'auteur conserve la propriété du droit d'auteur et des droits moraux qui protègent cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

In compliance with the Canadian Privacy Act some supporting forms may have been removed from this thesis.

Conformément à la loi canadienne sur la protection de la vie privée, quelques formulaires secondaires ont été enlevés de cette thèse.

While these forms may be included in the document page count, their removal does not represent any loss of content from the thesis.

Bien que ces formulaires aient inclus dans la pagination, il n'y aura aucun contenu manquant.

Canada

Abstract

Using a specific machine learning technique, this thesis proposes a method to identify suspicious statements during debugging which applies principles similar to Tarantula, an existing suspicious statement identification technique, but addresses its main flaw: its difficulty of dealing with the presence of multiple faults since it assumes that failing test cases execute the same fault(s). The improvement we present in this thesis is through the use of C4.5 decision trees to identify various failure conditions based on information regarding the test cases' inputs and outputs. Failing test cases executing under similar conditions are then assumed to fail due to the same fault. Statements are then considered suspicious if they are covered by a large proportion of failing test cases that execute under similar conditions. We report on two case studies that demonstrate improvement over the original Tarantula technique in terms of statement ranking. Another contribution of the thesis is to show that failure conditions as modeled by a C4.5 decision tree accurately predict failures and can therefore be used to help debugging.

Acknowledgements

I would like to thank my thesis supervisors Dr. Lionel Briand and Dr. Yvan Labiche for their guidance and financial support. They opened a door to me into the areas of software quality assurance and software quality management and gave me professional support, guidance and advice in the process of this research.

I would like to thank my wife Haizhen Mou, who gave me and continues to give me, such a great, active and meaningful life in Canada. Without her, I could not accomplish this thesis.

I would like to thank my parents, my brother and sister-in-law for their continuous and unconditional support through my life. I would also like to thank my parents-in-law and brother-in-law, who help me to deal with our errands.

I would like to thank everyone at the SQUALL lab for a great, friendly and supportive work environment.

I would like to express my appreciation to Dr. Zhiqiu Huang and his wife Professor Qing Li, Professor Zhangquan Lv, and my friends from EMSoftware lab of Nanjing University of Aeronautics and Astronautics, for their friendship and support in the past eight years.

I would also like to thank all the researchers who worked on and improved the Space program and artifacts over the years.

Xuetao Liu

August 30, 2007

Table of Contents

ABSTRACT.....	I
ACKNOWLEDGEMENTS	II
TABLE OF CONTENTS.....	III
LIST OF FIGURES	VI
LIST OF TABLES.....	VII
CHAPTER 1 INTRODUCTION.....	1
1.1 CONTRIBUTIONS	3
1.2 ORGANIZATION OF THESIS	3
CHAPTER 2 RELATED WORK	4
2.1 AUTOMATED SOFTWARE DEBUGGING TECHNIQUES.....	4
2.1.1 <i>Software debugging process</i>	4
2.1.2 <i>Manual software debugging strategies</i>	6
2.1.3 <i>Automated debugging techniques</i>	7
2.2 FAULT LOCALIZATION TECHNIQUES	8
2.2.1 <i>Fault localization based on anomaly</i>	8
2.2.2 <i>Fault localization based on clusters</i>	13
2.2.3 <i>Diagnosis algorithm evaluation</i>	15
2.3 MACHINE LEARNING AND DEBUGGING	17
2.4 DISCUSSION	19
CHAPTER 3 BACKGROUND INFORMATION.....	20
3.1 CATEGORY-PARTITION.....	20
3.2 RULE INDUCTION ALGORITHMS	22
3.2.1 <i>Introduction</i>	22
3.2.2 <i>Model performance: Ten-fold cross-validation</i>	26
3.2.3 <i>Model performance: cost of error prediction</i>	27
3.2.3.1 True positive rate and false positive rate.....	27
3.2.3.2 ROC area	28

3.2.3.3	Precision and recall.....	29
3.2.3.4	F-measure	29
3.3	STATISTICS BACKGROUND	30
CHAPTER 4	STATEMENT RANKING STRATEGIES.....	31
4.1	DEFINITION	31
4.2	TARANTULA COLORING	32
4.3	RANKING STATEMENTS BASED ON C4.5 RULES.....	34
4.3.1	<i>Generating a C4.5 classification tree</i>	34
4.3.2	<i>Selecting rules</i>	38
4.3.3	<i>Computing a statement ranking</i>	38
4.3.3.1	Heuristics.....	38
4.3.3.2	Ranking statements.....	40
4.3.4	<i>Iterative debugging process</i>	42
4.4	MANUAL EFFORT AND AUTOMATION	44
CHAPTER 5	CASE STUDIES.....	46
5.1	CASE STUDY PROCESS	46
5.2	CASE STUDY 1: THE SPACE PROGRAM	47
5.2.1	<i>Introduction</i>	47
5.2.2	<i>A multi-fault version of Space</i>	49
5.2.3	<i>Rule induction based on category partition</i>	50
5.2.4	<i>Cost-Effectiveness analysis</i>	52
5.2.4.1	Strategy one: fix all faults in the ranked set of statements	53
5.2.4.2	Strategy two: fix faults in the first 20% of ranked statements.....	58
5.2.5	<i>Diagnosis accuracy evaluation</i>	61
5.3	CASE STUDY 2: THE PACKHEXCHAR PROGRAM	62
5.3.1	<i>Introduction</i>	62
5.3.2	<i>A multi-fault version of PackHexChar</i>	63
5.3.3	<i>Rule Induction Based on Category Partition</i>	64
5.3.4	<i>The statistical cost-effectiveness analysis</i>	65
CHAPTER 6	CONCLUSIONS AND FUTURE WORK.....	67
6.1	CONCLUSIONS.....	67
6.2	FUTURE WORK	68

CHAPTER 7	REFERENCE	70
APPENDIX A	TRIANGLE PROGRAM	73
APPENDIX B	CLASS DIAGRAM OF RUBAR ALGORITHM	75
APPENDIX C	SPACE PROGRAM	76
C.1	THE SPACE PROGRAM	76
C.2	CATEGORY PARTITION DEFINITION	76
C.3	DETAILED ANALYSIS RESULT	90
C.3.1	<i>Strategy one: diagnose all statements executed</i>	90
C.3.2	<i>Strategy two: diagnose 20% statements executed</i>	91
APPENDIX D	THE PACKHEXCHAR PROGRAM	92
D.1	SAMPLE C4.5 TREES	92
D.1.1	<i>Ver-71</i>	92
D.1.2	<i>Ver-4872</i>	93
D.1.3	<i>Ver-13849</i>	93

List of Figures

Figure 2-1 TRAFFIC: the seven steps in debugging	5
Figure 2-2 the software debugging process	5
Figure 2-3 Set Union and Set Intersection.....	10
Figure 2-4 Relationship between the size of DBBs and the diagnosis accuracy [3]	17
Figure 3-1 Decision tree generated by Weka	24
Figure 3-2 Decision tree for the weather data.....	25
Figure 3-3 A sample ROC curve.....	29
Figure 4-1 Decision tree generated on raw inputs	35
Figure 4-2 Decision tree of Triangle program generated by Weka.....	36
Figure 4-3 Decision tree generated on complete CP definition.....	36
Figure 4-4 Decision tree generated on non-complete CP definition.....	37
Figure 4-5 Statement divisions by test cases	40
Figure 4-6 Statement Ranking using Weight(s)	41
Figure 4-7 Iterative debugging process.....	43
Figure 5-1 Cross validation confusion matrix	51
Figure 5-2 Fixing all the faults in the statement(s) executed.....	54
Figure 5-3 Execution sequence of faults: Bug16, Bug22 and Bug23.....	56
Figure 5-4 Fixing faults in the first 20% of ranked statements.....	59
Figure 5-5 Statistical statement ranking of 135 faulty versions	66
Figure A-1 Sample faulty Triangle program.....	73

List of Tables

Table 3-1 A sample CP definition of the triangle program	21
Table 3-2 The weather data.....	23
Table 4-1 Matrix of statement weight.....	42
Table 5-1 Example Fail rules with accuracy and test case coverage	51
Table 5-2 Execution result of multi-fault version	54
Table 5-3 Faulty statements and their ranks	56
Table 5-4 Fixing faults in the first 20% of ranked statements	58
Table 5-5 Diagnosis accuracy evaluation	62
Table 5-6 Statistical accuracy of stratified 10-fold cross-validation by class.....	65
Table A-1 A test suite and the test result of the triangle program	74
Table A-2 The test suite described by the CP definition.....	74

CHAPTER 1 INTRODUCTION

In the software life cycle, software testing is a critical element of software quality assurance [25]. In most cases, a software development group spends around 50 percent of total project effort on testing [10, 25]. Software debugging is one of the most time-consuming activities during software testing. When a test case uncovers an error, software debugging is the process that locates and removes the defect. Locating faults that cause failures is a very complex endeavor [37]. Though many techniques exist to support fault localization, this thesis is re-visiting the technique (Tarantula) that has shown to perform best on existing empirical studies [14]. Tarantula ranks statements by the degree of suspicion, which is determined by the proportion of the number of failing test cases that execute that statement over the number of passing test cases that execute that statement. Based on a careful analysis of Tarantula's cost-effectiveness, we identify a significant problem affecting its applicability and propose a solution to improve it based on the application of a machine learning technique (C4.5). At a high level, Tarantula uses the proportion of test cases that fail when executing a specific statement to determine the ranking of statements in terms of their likelihood to contain a fault. One important issue is that this method assumes that test cases fail due to the same fault, a situation that nearly never occurs in the presence of multiple faults. Another issue is that duplicated test cases would dramatically affect the ranking result generated by Tarantula.

We use the C4.5 decision tree algorithm [26] to analyze test executions and identify distinct conditions of failures in terms of properties on inputs and outputs. Note that, as further discussed below, a test specification is required (e.g., category partition [21]) as

raw test case inputs are not helpful for machine learning algorithms to identify meaningful conditions of failures. Following a strategy similar to Tarantula, within each selected rule identified by C4.5, we analyze the statements executed by the test cases matching that rule and obtain a ranking of executed statements indicating the degree of suspicion of those statements. The rankings of all conditions are then combined into a single statement ranking. The most important difference with Tarantula is that because the statement coverage of test cases is analyzed within each distinct failure condition, these test cases are then more likely to fail due to the same faults, an assumption that does not hold when analyzing all test cases at once.

Note that, the failure conditions identified are of interest in their own right, independently of how they help statement ranking. We expect that programmers/testers would be helped a great deal if they are able to retrieve, from test case definitions and executions, precise conditions on inputs that are almost certain to trigger failures.

Through two case studies, we show that our solution has a practically significant, positive impact when compared to Tarantula. We also demonstrate that C4.5, following our procedure, can retrieve accurate rules predicting failures, thus implying that conditions triggering failures can be automatically and precisely characterized in terms of input and output properties.

The above approach can be applied in a number of contexts. For example, this might suit very well the test-driven development processes where large test suites are developed up-front and are available during development. It however requires that equivalence classes or categories/choices be defined to specify the test cases or at least—but this is less efficient—to re-express test cases at a high level of abstraction (test specification) in

order to feed the machine learning algorithm. Our approach is probably more cost-effective when test suites are specified by using a systematic, black-box technique.

1.1 Contributions

This thesis introduces a new strategy (RUBAR) to support software debugging by ranking the statements according to their degree of suspicion and by identifying the input conditions leading to failure. The contributions of this thesis include:

- (1) Providing a fault-localization technique in a multi-fault environment;
- (2) Combining the Category-Partition technique and machine learning technique to aid software debugging;
- (3) Applying the C4.5 machine learning technique to find the conditions of failure, which can benefit software debugging directly or indirectly;
- (4) Improving the Tarantula statement ranking technique by grouping test cases according to (similar) conditions of execution, and therefore according to the possible causes of failure;
- (5) Empirical evaluation of our approach on two case studies.

1.2 Organization of thesis

The structure of this thesis is as follows. Chapter 2 discusses the related work. Chapter 3 presents a brief introduction on machine learning and the testing techniques used in this thesis. Chapter 4 revisits the Tarantula technique and presents the principles and rationale of our approach. Chapter 5 reports on our case studies and Chapter 6 presents conclusions and points out directions for future work.

CHAPTER 2 RELATED WORK

A number of techniques exist to support the systematic debugging of software. The family of techniques directly relevant to our approach is used to detect anomalies, using Zeller's terminology [37], i.e., differences (e.g., in terms of coverage) between passing and failing executions of the program. These anomalies are good candidates for fault sites, hopefully helping to narrow down the amount of source code to investigate, and therefore reducing the time (and cost) required to locate faults.

2.1 Automated software debugging techniques

The objective of software debugging [25, 37] is realized by a combination of systematic evaluation, intuition and luck. As opposed to other activities in software testing that follows a set of precise rules, e.g., making test plans or designing test cases, the software debugging process relies on a programmer's experience, knowledge and intuition, which is hard to control and predict.

2.1.1 Software debugging process

Software debugging refers to the combined process of software diagnosis (fault localization), defect detection, and defect removal [35, 36]. Software diagnosis is to find possible causes of failure; defect detection is to locate the exact statement(s), the root of failure; and defect removal is to fix the faulty statement(s). Zeller [37] decomposed software debugging process into seven steps named TRAFFIC (Figure 2-1).

Track the problem in the database.
Reproduce the failure.
Automate and simplify the test case.
Find possible infection origins.
Focus on the most likely origins.
Isolate the infection chain.
Correct the defect.

Figure 2-1 TRAFFIC: the seven steps in debugging

In general, software debugging begins with a failure of the program, which is detected by the execution of a test case(s) (Figure 2-2). After a set of time-consuming and tedious debugging activities, the debugging process will always end with one of the two outcomes [25]: (1) the cause of fault(s) is found and corrected, or (2) the cause is not found. In the latter case, the test suite is not abundant enough to help solve the problem. Therefore, the programmer (or tester) may suspect a cause, design new test case(s) to validate the suspicion, and work toward defect correction in an iterative process. In this thesis, we assume that the test suite has enough test cases to help detect and correct any fault the program has. Therefore, the problem of test suite improvement (e.g. [3, 5]) is not in the scope of this thesis.

Figure 2-2 the software debugging process

Of the activities of software debugging, diagnosis (fault localization) represents 95% of

the problem solving effort [20] and is the most important and difficult activity. This also makes the debugging process hard to predict and control. In principle, all faults can be solved manually [37]; but in practice, it is unwise to rely on manual debugging alone. There are some techniques (or strategies) [37] and tools (e.g. GDB, xSlice [1]) to aid software diagnosis and facilitate fault localization.

2.1.2 Manual software debugging strategies

Manual software debugging means that debugging tools provide no or little help during the process of software diagnosis. Manual software debugging is efficient only when the programmers are very familiar with the system under test or the program is very small. That is, sometimes programmers are able to guess the cause of a failure from the inputs and/or outputs of failed test cases. In this case, the programmers may like to diagnose the system manually. In general, there are three types of manual debugging strategies [20]:

- *Brute force*: probably the most common and least efficient method of isolating the cause of a software failure [20, 37]. Brute force techniques are mainly used by debugging tools. The typical brute force techniques include memory dumps, run-time traces, break-points, studying execution states, and manually inserted assertions.
- *Backtracking*: a fairly common and efficient approach that can be used in small programs. Beginning at the point where a failure has been uncovered, the source code is traced backward (manually) until the site of the cause is found. It is obvious that, as the number of source lines increases, the number of potential backward paths may become unmanageably large.
- *Cause elimination*: This technique is based on induction and deduction and introduces

the concepts of binary partitions. By cause elimination, a skilled programmer may find the defects without looking into the code. The data (input(s) and output(s) of the test cases) related to the failure occurrence are organized to isolate potential causes.

2.1.3 Automated debugging techniques

Since manual debugging is inefficient and time-consuming, there have been many studies on automated debugging techniques, to simplify debugging activities (especially the software diagnosis activity) or to guide the debugging process. In [37], Zeller classified the existing automated debugging techniques as:

- *Simplified input*: a debugging technique to identify duplicate problem reports and facilitate debugging. The basic idea of this technique is that the circumstances (inputs) not relevant for the problem can be omitted. After the simplification, a simple test case that contains only the relevant inputs can be generated. One of the input simplification techniques is the “*divide-and-conquer*” method introduced in [37], which uses the “*binary tree*” strategy to simplify the inputs. Once a test case fails, the inputs of the test case will be divided into two parts and two new test cases will be generated according to the input divisions. The program will be executed on both the new test cases. The inputs of the failed test case will be selected and divided again, until the smallest set of inputs causing the program to fail is obtained.
- *Program slice*: A program slice [31] is a portion of the program comprising of a set of statements which contribute, either directly or indirectly, to the value of certain variables at a certain point in the program. Program slices can be helpful in

uncovering *code smells*¹, especially in finding the common errors such as use of uninitialized variables, unused variables, or misused variables.

- *Anomalies*: In general, we can assume that a program works well most of the time. If a program fails nonetheless, we can use our knowledge about the passing runs and focus on the differences between the passing runs and the failing run. Such difference points out anomalies. Most of the automated software debugging techniques rely on anomalies to locate the cause of failures.
- *Cause-effect chain*: In [7], Clever and Zeller presented a state-based debugging technique named Cause Transition Technique. Instead of comparing the program state of a failing and a passing run, the technique makes hypotheses about how state changes will affect output. A cause transition is where a cause originates—that is, a cause transition points to program code that causes the transition and hence the failure.

In a realistic environment, these techniques can be combined to locate the defect(s) systematically. In this thesis, we introduce a new automated fault localization technique, which belongs to the anomalies category, which we further discuss next.

2.2 Fault localization techniques

2.2.1 Fault localization based on anomaly

Set Union and Set Intersection [27] are the simplest techniques to detect anomalies, which use the difference(s) among the failing executions and the passing executions to find suspicious statements. In 1982, Weiser [32] originally presented the idea of using

¹ A code smell is a hint that something may be wrong in the code. It usually corresponds to common design errors or implementation problems in the program.

static program slices to locate bugs. The basic idea of this theory is that the cause of a failure is more likely to be in the static program slice(s) of the site or variable(s) where the failure is recovered than other program. Agrawal etc [1] presented a technique to help fault localization by computing the difference of the statements executed by two test cases—one passing test case and one failing test case. A faulty statement is more likely to present in the set of statements that are executed by the failing test case and are not executed by the passing test case. In [22], Pan and Spafford presented a set of heuristics that use set algebra of test cases' dynamic slice to reduce the search scope of fault localization. Each heuristic will suggest a set of suspicious statements whose size is usually smaller than the size of the executed statements.

The basic idea of the set union and set intersection technique is that failing and passing executions (likely) involve different statements. It assumes that the faults reside in the statements executed by a failing test case and do not exist in the statements executed by a passing test case. One can therefore look at the statements executed in a failing execution but not in passing executions to locate fault (Set Union—set of statements executed in a failing execution minus the union of the sets of statements executed in passing executions, represented by the shadow part in Figure 2-3(a)). Alternatively, one can *ignore* the statements common to passing executions but absent from a failing execution (Set Intersection—intersection of the sets of statements executed in passing executions minus the set of statements executed in a failing execution, represented by the shadow part in Figure 2-3(b)).

Figure 2-3 Set Union and Set Intersection

Instead of using all the passing runs to perform the statements separation, Renieris and Reiss [27] selectively choose a single best passing run for the set difference operation. The passing run is selected by a Nearest Neighbor algorithm, which consists in finding a single passing execution that is as similar as possible (e.g., in terms of code covered) to a failing execution (i.e., the nearest neighbor). The difference between the two executions is then worth investigating when looking for faulty statements.

In [9], the authors recognize that some failures are due to specific sequences of method calls, rather than simply the coverage of some statements. Their approach is specific to Object-Oriented systems (they work at the class level), and, in particular, Java. The approach is to collect, for each class of the system, the sequences of calls that the instances of the class execute at runtime. The idea is then to compare, for each class, the sequences triggered by a failing execution and the sequences triggered by the passing executions, and then rank the classes in such a way that the classes whose sequence sets differ the most get the higher priority. (See [9] for the precise ranking mechanism.)

These researchers tend to compare one failing execution (instead of several failing ones) against a number of passing ones, assuming different failing executions may be caused by

different faults, which is something unknown beforehand. On the contrary, Jones *et al.* [15] consider all executions together, recognizing that the more a statement is executed by failing executions, the more likely the statement is a faulty statement. The Tarantula technique associates a “color” (ranking) to each statement, accounting for all executions: the redder the statement, the higher the percentage of failing test cases that execute this statement. The statement color can be used to rank the statements, as suggested in [14], in order to support the search for faults during debugging.

A similar technique is discussed in [17]. It is limited to the observation of certain predicates during program execution (e.g., the value of a predicate in an if-statement) as the authors collect execution data from deployed programs, and instrumentation is therefore limited to ensure a reduced impact on the user. The result is a rank of monitored predicates indicating the (statistical) likelihood of the predicate being a failing condition as well as being the fault location. This is expanded upon in [19] where the authors define a similarity function between predicate rankings to group executions that (likely) fail due to the same fault.

As opposed to Tarantula and other ranking techniques, the Set Union, Set Intersection, and Nearest Neighbor techniques simply identify an initial set of suspicious statements to start the search from, not a ranking of statements. As suggested in [14], they can however be augmented to produce a ranking of statements, as originally suggested in [27] for the Nearest Neighbor technique. The ranking is based on a breadth-first search (backward and forward directions) in the system dependence graph from the initial statements. Nodes at the same distance from initial statements are given the same rank.

A number of experimental results discuss how these techniques compare to one another.

First, since the technique in [9], based on method sequences, ranks classes instead of statements, it cannot be directly compared with the other three techniques. The Nearest Neighbor technique has been shown to outperform the Set Union and Set Intersection techniques [27]. Tarantula has been compared to Set Union, Set Intersection and Nearest Neighbor [14]. For comparison purposes, the authors used the so-called Siemens suite of seven different programs [12]: 122 faulty versions (one fault per version) were used. The ranking of each technique was used to identify the rank of the (known) faulty statement of each faulty version. This rank was used to compute a score for each faulty version, corresponding to the percentage of the program (code) that does not need to be examined to find the faulty statement. They then compare the cumulative number of faulty versions, on the Y-axis, as the score goes from 99% (the technique pinpoints the faulty statement) to 0% (all the code has to be verified to find the faulty statement), on the X-axis. Results show that Tarantula outperforms the other three techniques. In particular, in 55.7% of the faulty versions, the fault was found by examining less than 10% of the code. These results were the main motivation for our research to use Tarantula as a basis of comparison to improve upon.

The effectiveness of Tarantula was originally reported in [15] on 20 faulty versions (one fault per version) of the Space program [30]. No ranking was used though, and the authors only studied the coloring of faulty and non-faulty statements, showing that the former were always colored in red (i.e., suspicious) whereas the latter were most of the time colored in green. (A large number of the non-faulty statements received a reddish or yellowish color though.) There were two notable exceptions: for two faulty versions, the faulty statements received an average color (yellow)—they would therefore not

necessarily appear suspicious to the tester—because they were executed by all or most of the test cases. These statements initialize the global variables used by all test case executions. The authors also studied Tarantula on multiple-faults versions. They observed that the effectiveness of Tarantula declines (fewer faulty statements are colored red) as the number of faults increases, though no precise trend can be established.

From the discussion above, we can see that SET operations are the basis of the anomaly debugging techniques. Except for the Nearest-Neighbor algorithm, none of other methods account for the fact that to compare executions and identify suspicious statements, the selected passing executions must be similar to the failing execution. That is, the selected test cases (failing and passing) need to test the same or similar functions. It is only when the failing run and passing runs are similar that the differences between the statements executed by the failing test case and the passing test cases are meaningful.

There are other debugging techniques that are not discussed here, as they are less relevant to our context. These include deduction techniques (e.g., program slicing, delta debugging), and observation techniques (e.g., states, invariants). The interested reader is referenced to [37] for further details.

2.2.2 Fault localization based on clusters

Cluster-based fault localization methods [13, 38] are related to our method directly. This type of method is usually applied in a multi-fault environment, which is more realistic. In a multi-fault environment, the failure of test cases could be caused by different defects. This makes the fault localization more complex than a single fault version does. The fault-localization methods introduced in section 2.1 can not be simply applied in the

multi-fault environment. Otherwise, the effectiveness of fault localization will degrade, as James *et al.* discovered [15].

Since test cases fail due to different faults in a multi-fault environment, it is reasonable to group the failed test cases by the causes of the failure before a diagnosis algorithm is applied for fault localization. That is, the set of failed test cases are partitioned into clusters that target different faults. Then a fault localization method [1, 7, 15, 27] is employed to locate the faulty statement(s) for each cluster. For example, James *et al.* [13] employ the agglomerative hierarchical clustering method [4] to group failed test cases and use the Tarantula coloring method to refine the clusters generated and perform the fault localization. The clustering algorithm uses behavior models, generated from execution data, to group the failed test cases. The second clustering method James *et al.* [13] presented is based on statement ranking generated by a fault-localization algorithm. The technique is to first compute the fault-localization suspiciousness rankings of statements using all the failed test cases (together with all the passed ones), and to use the *Jaccard similarity* metric to compute the pairwise similarities among these rankings. Then the technique clusters statements by taking a closure of the pairs that are marked as similar.

The effectiveness of cluster-based fault localization is evaluated by James *et al.* [13]. They created 100 8-fault versions of the Space program by choosing from the available faults at random. For the two clustering scenarios [13], the mean numbers of statements to be examined before a real fault is localized are observed to be 31.5 and 26.43 respectively.

2.2.3 Diagnosis algorithm evaluation

Diagnosis algorithms aim at isolating a minimal subset of statements which are highly suspected to cause the failure. The smaller the subset of statements containing the real fault, the more accurate a diagnosis algorithm is. Baudry, *et al.* [3] define two criteria to evaluate the accuracy of a diagnosis algorithm:

Diagnosis accuracy: the average number of statements to be examined before finding the actual faulty statement;

Relative diagnosis accuracy: the corresponding percentage of the source code of the program to examine to find the actual faulty statement.

Baudry, *et al.* [3] also identified the main attribute of a program that reduces the diagnosis analysis effort. This attribute is called *DBB: Dynamic Basic Block*; and depends on both the test traces and the code structure. A *dynamic basic block* [3] is a group of statements that are executed by the same set of test cases. From the definition, we can draw out that the statements in a single DBB are indistinguishable [3] and will obtain the same rank in the ranking generated by a diagnosis algorithm. The authors then define an *optimal diagnosis algorithm* as one that always selects the dynamic basic block containing the actual faulty statement(s) as the most suspicious.

An *ideal accuracy of diagnosis* can be defined under the following assumptions. Assuming that faults are uniformly distributed; each statement has the same probability to be faulty. Assuming the diagnosis algorithm is optimal, and then the ideal accuracy of diagnosis can be defined as:

$$IdealAccuracy(P) = \sum_{b \in DBBs} p(b) \times n(b) = \sum_{b \in DBBs} \frac{|b|^2}{2 \times |S|}$$

where:

DBBs is the set of DBB identified by a diagnosis algorithm;

$p(b)$ is the probability that the fault is located in $b \in \text{DBBs}$ and $p(b) = |b|/|S|$, suppose that faults are uniformly distributed and S is the set of executable statements of the program.

$n(b)$ is the average amount of code to examine in a DBB b and $n(b) = |b|/2$.

Through the *ideal accuracy of diagnosis*, Baudry *et. al.* [3] concluded that the size of dynamic basic block is the main attribute which impacts the diagnosis accuracy. They performed their case study on a BOOK system and validated the relationship between the diagnosis accuracy and dynamic basic blocks. The result [3] of the case study is presented as Figure 2-4. We can see that the smaller the size of dynamic basic blocks, the more accurate a diagnosis algorithm [3].

Figure 2-4 Relationship between the size of DBBs and the diagnosis accuracy [3]

There are, of course, other ways once can approach the comparison of these techniques. For example, in [14], James *et al.* evaluated the efficiency of the techniques by recording the amount of time required to use them.

2.3 Machine learning and debugging

Another, more recent, body of work related to our problem, attempts to use data mining techniques to help identify suspicious code. In [18], the authors record passing and failing program executions, monitoring true and false evaluations of predicates (e.g., if statements). They developed a data mining technique that relies on distributions of true and false evaluations in failing and passing executions to rank (suspicious) functions. They limit their analysis to the statements containing predicates, report good results

(buggy functions are ranked first) on the Siemens program suite (each faulty version contains only one fault, though), but do not present any comparison with other techniques. Similarly, Podgurski *et al.* [24] use passing and failing execution profiles to help debugging. The execution profiles entail recorded information that is not limited to predicates but can contain any data that can be collected about program executions (e.g., a program variable value, a call stack). The program execution features in the profile that can best distinguish passing from failing executions are first identified using logistic regression. Because the level of abstraction of the collected data needs to be increased to help predict failure, failing profiles are then grouped using either a cluster analysis technique or a multivariate visualization technique. Those groups are then analyzed by the tester to understand failing execution conditions. The type of properties that can be uncovered using this approach is limited and remains to be investigated.

A machine learning technique is used in [6] to identify general program properties (e.g., variables not initialized) that likely indicate the presence of faults in programs. As opposed to the above-mentioned approaches, it does not require test case executions as it only relies on program analysis (though, for evaluation purposes, the authors use “likely invariants” [11] as program properties, whose discovery requires program executions). For a scalar variable x , examples of properties are: equality to a constant ($x=a$), and lying in a range (e.g., $a < x \leq b$). In the learning step, properties of correct and incorrect programs are used to build a learning model (e.g., Support Vector Machine [33]) to distinguish faulty and non-faulty programs). In the classification step, a new program’s properties are used as inputs and those properties are ranked according to the strength of their association with faulty programs. It should be noted that the approach above requires that

abstract properties be defined beforehand, which is similar to our use of categories and choices.

2.4 Discussion

What we propose in this research is different from the work presented above in the following ways: (1) We reuse black-box testing specifications (under the form of categories and choices) as inputs to identify failure conditions; (2) Failure conditions are formalized as logical rules, so as to provide interpretable inputs to support debugging; (3) These rules are generated by using a machine learning algorithm to automatically generate interpretable rules from transformed test cases; (4) Those rules are then applied to rank statements according to their likelihood of containing a fault; (5) The test cases are clustered according to the test case definitions (abstract test data), instead of the execution data.

One motivation of our research is to rely on inputs that should anyway be part of any test plan and is therefore of general usefulness to the tester beyond debugging. A second motivation is to provide feedback to testers in a form that can be used to better understand the reasons for failure (by the classification rules). Third, we want our technique to handle the common case where multiple faults are present in the program and different executions fail due to different faults.

CHAPTER 3 BACKGROUND INFORMATION

This chapter presents a background of materials that are needed to fully understand this thesis. Section 3.1 introduces the Category-Partition (CP) black box testing technique. Section 3.2 discusses rule induction algorithms and explains the choice of C4.5 decision trees.

3.1 Category-Partition

The Category Partition technique [21] is one of the most well-known black-box techniques. Compared to equivalence class partitioning (in which only partitions input value domains) and other test methods, it is more general and encompassing. The CP method seeks to generate test cases that cover functions. To apply the CP method, one identifies the parameters of each function, the characteristics (categories) of each parameter and the choices of each category. Categories are properties of parameters that can have an influence on the behavior of the software under test (e.g., size of an array in a sorting algorithm). Choices (e.g., whether an array is empty) are the potential value of a category. Test frames (abstract test case) and test data are generated according to the categories and choices defined.

When applying the CP methodology, one is also supposed to define constraints and interdependencies between choices across categories. Because this is not required in our context, we will not refer to this aspect of the CP methodology.

Let's take a simple but hopefully illustrative example: for the Triangle program [16], the input values characterize the length of triangle sides and the output is the type of the

triangle determined by the three sides (Equilateral, Isosceles, Scalene, or NotATriangle).

When applying the CP method we define categories and choices from the features (not from the boundary of the input values for a parameter) of the triangle program. These categories and choices describe the character of the length of the triangle sides and the relationship among them.

Table 3-1 is the category-partition definition of the Triangle program. For instance, the category $\text{compare}(s_1, s_2)$ defines the relationship between the length of sides s_1 and s_2 , which is further described by choices: $s_1 < s_2$, $s_1 = s_2$, and $s_1 > s_2$. The categories CA04 to CA10 in Table 3-1 define the criteria for three values to determine a triangle. Note that we did not define constraints as we discussed above. For more information about the application of constraints, please refer to [21].

Table 3-1 A sample CP definition of the triangle program

	Categories	Choices		Categories	Choices
CA01	$\text{compare}(s_1, s_2)$		CA06	$s_2 < s_1 + s_3$	
	CH0101	$s_1 < s_2$		CH0601	Yes
	CH0102	$s_1 = s_2$		CH0602	No
	CH0103	$s_1 > s_2$	CA07	$s_3 < s_1 + s_2$	
CA02	$\text{compare}(s_2, s_3)$			CH0701	Yes
	CH0201	$s_2 < s_3$		CH0702	No
	CH0202	$s_2 = s_3$	CA08	$s_1 > s_2 - s_3 $	
	CH0203	$s_2 > s_3$		CH0801	Yes
CA03	$\text{compare}(s_3, s_1)$			CH0802	No
	CH0301	$s_3 < s_1$	CA09	$s_2 > s_1 - s_3 $	
	CH0302	$s_3 = s_1$		CH0901	Yes
	CH0303	$s_3 > s_1$		CH0902	No
CA04	$\text{and}(s_1 > 0, s_2 > 0, s_3 > 0)$		CA10	$s_3 > s_1 - s_2 $	
	CH0401	Yes		CH1001	Yes
	CH0402	No		CH1002	No
CA05	$s_1 < s_2 + s_3$				
	CH0501	Yes			
	CH0502	No			

3.2 Rule Induction Algorithms

3.2.1 Introduction

There is a large number of machine learning and data mining techniques [33]. They differ widely in terms of their basic principles, their working assumptions, and their weaknesses and strengths. None of the techniques is inherently better than the other and which one is most appropriate tends to be context dependent.

A specific category of machine learning techniques focuses on classification, which is the problem at hand in this project as we want to explain and predict when test cases fail. These techniques will generate classification rules [33]. Examples of such techniques include the C4.5 decision tree algorithm [26] or the Ripper rule induction algorithm [8]. In our context, the rules would look like conditions on the test inputs and the outputs being associated with probabilities of failures (Fail/Pass classification). The main advantage of these techniques is the interpretability of their models: certain conditions imply a certain probability of failure.

Some classification techniques, like C4.5, partition the data set (e.g., the set of test cases) in a stepwise manner using complex algorithms and heuristics to avoid over-fitting the data with the goal of generating models that are as simple as possible. Others, like Ripper, are so-called covering algorithms [8] and generate rules in a stepwise manner, removing observations that are “covered” by the rule at each step so that the next step works on a reduced set of observations. With coverage algorithms, rules are interdependent in the sense that they form a “decision list” where rules are supposed to be applicable in the order they were generated. Because this makes their interpretation more difficult, we will

use a classification tree algorithm, namely C4.5, and use the WEKA tool [33] to build and assess the trees.

As an example, consider the weather problem [33], which is a simple dataset used by Witten *et. al.* to illustrate machine learning methods. It concerns the conditions (attributes) that are suitable for playing some unspecified game. There are totally four attributes: *outlook*, *temperature*, *humidity*, and *windy*. The outcome is whether to play or not. A sample with 14 instances is given out in Table 3-2. The weather problem is a typical two-call prediction problem, which has two possible results: *yes* or *no*.

Table 3-2 The weather data

Outlook	Temperature	Humidity	Windy	Play
sunny	hot	high	false	no
sunny	hot	high	true	no
overcast	hot	high	false	yes
rainy	mild	high	false	yes
rainy	cool	normal	false	yes
rainy	cool	normal	true	no
overcast	Cool	normal	true	yes
sunny	Mild	high	false	no
sunny	cool	normal	false	yes
rainy	mild	normal	false	yes
sunny	mild	normal	true	yes
Overcast	mild	high	true	yes
Overcast	hot	normal	false	yes
Rainy	mild	high	true	no

Figure 3-1 is the C4.5 classification tree generated by Weka (the J48 algorithm). To generate this tree, we use the default values for all the parameters of the algorithm. The classification tree in Figure 3-1 has five leaves and eight nodes. Line four to line ten describe the structure of the tree. The content of each line is defined using the following grammar:

$$\langle rule \rangle \rightarrow \langle rootLine \rangle \{ \langle nodeLine \rangle \}^* \langle leafLine \rangle \mid \langle leafLine \rangle$$

$\langle rootLine \rangle \rightarrow \langle category \rangle = \langle choice \rangle$

$\langle nodeLine \rangle \rightarrow \{ | \}^? \langle category \rangle = \langle choice \rangle$

$\langle leafLine \rangle \rightarrow \{ | \}^* \langle category \rangle = \langle choice \rangle [: \langle predicatedResult \rangle (total-
instances[/misclassified-instances])$

where total-instances is the number of instances whose inputs satisfy the conditions of a rule;

misclassified-instances is the number of instances whose inputs satisfy the conditions of a rule, but the output does not fit the predicted output of the rule. It is obvious that the misclassified-instances shall be less than the number of correctly-classified instances.

From Figure 3-1, we can see that the rules generated are accurate because there is no misclassified instance: as per the above grammar, misclassifications would appear in parentheses after the '/' character, which is not the case in Figure 3-1. We can also find that it is very fast to generate such a tree (the time taken to build this tree is zero second).

```
J48 pruned tree
-----
outlook = sunny
|  humidity = high: no (3.0)
|  humidity = normal: yes (2.0)
outlook = overcast: yes (4.0)
outlook = rainy
|  windy = TRUE: no (2.0)
|  windy = FALSE: yes (3.0)

Number of Leaves :      5

Size of the tree :  8

Time taken to build model: 0 seconds
```

Figure 3-1 Decision tree generated by Weka

Figure 3-2 is a graphic view of the C4.5 tree of Figure 3-1. Each node represents a (sub)set of instances and is characterized by a number of conditions on input or output properties. Some nodes are terminal (e.g., node 5) whereas others are further decomposed

(e.g., node 4). A terminal node has a class label instead of an attribute; this is the classification and is followed by the number of instances that reach that leaf. The class label of a terminal node is determined by the class of the majority instances classified by the corresponding path. If there were incorrectly classified instances reaching a leaf node, the number would be expressed as *total-instances/misclassified-instances*. Our goal when building the tree is to obtain leaves that are as consistent as possible, i.e., which contain instances that are either mostly *yes* or *no*. This is one of the objectives of the C4.5 algorithm. Edges represent values for an attribute, and a path from the root node of the tree to any leaf can be considered a rule characterizing play or not, i.e., a conjunction of attribute values.

In Figure 3-2, nodes are the attributes of the weather problem and leaves are labeled as “yes” or “no”, which stand for “play” and “no play”. Node (5), for example, captures all instances with “*sunny*” outlook and “*high*” humidity. It is a terminal node predicting “do not play” (labeled as “no”): in this leaf, the number of classified (resp. misclassified) instances is three (resp. zero). Figure 3-2 highlights a rule for one of the paths where *outlook = sunny* AND *humidity = high* predicts *no* (don’t play).

Figure 3-2 Decision tree for the weather data

3.2.2 Model performance: Ten-fold cross-validation

For classification problems, a classifier is the model, generated by a rule induction algorithm on a set of instances called *training set*, to classify the instances. The classifier predicts the class of each instance: if it is correct, that is counted as a success; if not, it is an error. It is natural to measure a classifier's performance in terms of the *error rate* [33], the proportion of errors made over a whole set of instances. Since the classifier is generated on the *training set*, it is common to apply the classifier on another set of instances named *testing set* and assess its error rate on this set. To make the evaluation objective, it is important that the training data was not used in any way to create the classifier [33].

When there are not enough instances for both training set and testing set, cross validation can be applied for rule induction [33]. The standard way of predicting the error rate of a learning technique is to use stratified ten-fold cross-validation [33]. The instances are divided randomly into 10 equal parts. Each part is held out in turn and the classifier is trained on the remaining nine-tenths; then its error rate is calculated on the holdout set.

Thus the learning procedure is executed a total of 10 times on different training sets. Finally, the 10 error estimates are averaged to yield an overall error estimate.

There are also other ways of measuring the error rate of a learning schema [33]: *leave-one-out cross-validation*, *bootstrap*, etc. Since 10-fold cross-validation has become a standard method [33], in our experiments, we will use the ten-fold cross-validation to perform rule induction and evaluate the classifier's performance.

3.2.3 Model performance: cost of error prediction

Ten-fold cross validation evaluates the performance of a generated classification model. Besides the performance, the cost of making wrong classifications shall also be taken into account. Take the two-class prediction, which has two possible outputs (e.g. *yes* and *no*, *pass* and *fail*), as an example. A single prediction has four different possible outcomes:

true positive: the correct prediction of an instance when it is actually positive;

true negative: the correct prediction of an instance when it is actually negative;

false negative: an instance is incorrectly predicted as negative when it is actually positive;

false positive: an instance is incorrectly predicted as positive when it is actually negative;

To estimate the cost of error prediction, several popular criteria are used: *true positive rate (TPR)* and *false positive rate (FPR)* (section 3.2.3.1), ROC area (section 3.2.3.2), *precision* and *recall* (section 3.2.3.3), and F-measure (section 3.2.3.4). There are also other measures to be used to characterize performance of a model, such as the mean-squared error, relative absolute error, correlation coefficient etc. For more details, please refer to Chapter 5 of [33].

3.2.3.1 True positive rate and false positive rate

TPR and *FPR* are the simplest criteria for evaluating the cost of error-prediction. Let's suppose that *TP*, *TN*, *FP*, *FN* denote the number of true positive prediction, true negative prediction, false positive prediction, false negative prediction respectively. Then the *true positive rate (TPR)* is TP divided by the total number of positives, and *false positive rate (FPR)* is FP divided by the total number of negatives. Please note that the summation of TPR and FPR is not 100%.

$$TPR = TP/(TP+FN)$$

$$FPR = FP/(FP+TN)$$

For cost estimation, each false prediction (*false positive* or *false negative*) will be assigned a cost value. The cost of incorrect predictions can be estimated by multiplying the *FPR* (resp. *FNR*) with the *FP* cost (resp. the *FN* cost).

3.2.3.2 ROC area

ROC (Receiver Operating Characteristic) curves are a graphical technique for evaluating classifiers and depict the performance of a classifier without regard to class distribution or error rate [33]. They are usually used in a situation in which the learner is trying to select samples of instances that have a high proportion of positives (e.g. pass). One method to generate a ROC curve is to sort the instances in descending order of the predicted probability of a given class (e.g. pass). The number of positives (resp. negatives) included in the ordered set is plotted on the Y-axis (resp. X-axis), expressed as a percentage of the total number of positives (resp. negative).

Figure 3-3 is a sample of three ROC curves. A point (x%, y%) in the ROC curve indicates

that covering $y\%$ of the true positives gives a false positive rate of $x\%$. That is, if a learner want a $y\%$ of the true positives, he would possibly obtain $y\%*TP+x\%*FP$ instances. Usually, the accuracy of a test is evaluated by the *area under the curve*, or ROC area. Roughly, the larger the area is, the better the model is [33]. A rough guide for the accuracy of classification according to ROC area is the traditional academic point system²:

- ROC area $\in [0.90, 1]$: excellent (A)
- ROC area $\in [0.80, 0.90)$: good (B)
- ROC area $\in [0.70, 0.80)$: fair (C)
- ROC area $\in [0.60, 0.70)$: poor (D)
- ROC area $\in [0.50, 0.60)$: fail (F)

Figure 3-3 A sample ROC curve

3.2.3.3 Precision and recall

The *precision* and *recall* are applied to evaluate a model from the view of the relative cost of *false positive* and *false negative*. The *precision* is the percentage of true positives in the positive predictions; the *recall* is same as TPR. They are defined as:

$$precision = TP/(TP+FP)$$

² <http://gim.unmc.edu/dxtests/ROC1.htm>

$$recall = TPR = TP/(TP+FN)$$

3.2.3.4 F-measure

As *precision* and *recall*, *F-measure* is another measure used in information retrieval to characterize performance of a model:

$$F\text{-measure} = \frac{2 \times recall \times precision}{recall + precision} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

3.3 Statistics background

Mean value is one of the statistics used to evaluate the variance of a set of samples. Besides the mean values, the confidence intervals of the means are also used, because the estimates of the means vary from sample to sample. The interval estimates give an indication of how much uncertainty there is in our estimates of the true mean. The narrower the interval is, the more precise is our estimate³. A confidence interval generates a lower and upper estimated limit for the mean. Confidence limits are expressed in terms of confidence coefficients. Although the choice of confidence coefficient [29] is somewhat arbitrary, in practice 90%, 95%, and 99% intervals are often used, with 95% being the most commonly used. In this thesis, we used the 95% confidence coefficient. The confidence intervals [29] are defined as:

$$\bar{M} \pm t_{\alpha/2, N-1} \frac{S}{\sqrt{N}} \text{ and } S = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (Y_i - \bar{Y})^2}$$

where $\bar{M}$ is the sample mean, S is the sample standard deviation, N is the sample size, α is the desired significance level (here, α equals to 5%), and $t_{\alpha/2, N-1}$ is the quantile of the t distribution with $N-1$ degrees of freedom and can be obtained from the table of “ t

³ <http://www.itl.nist.gov/div898/handbook/eda/section3/eda352.htm>

*Distribution with n Degrees of Freedom*⁴. Note that the confidence coefficient is $1-\alpha$.

⁴ This table can be found in most of the statistical books.

CHAPTER 4 STATEMENT RANKING STRATEGIES

In this chapter, we introduce several statement ranking strategies. We first provide some basic notation (Section 4.1). We then revisit statement coloring according to Tarantula's approach (Section 4.2). We then describe how we adjust Tarantula's ranking based on a C4.5 decision tree (Section 4.3), which is itself based on the notion of abstract test suite or test specification to account for the diversity of execution conditions under which statements are involved in failing test cases.

4.1 Definition

In order to facilitate the precise and concise definition of our methodology, we need to define and formalize a number of basic concepts.

The set of executable statements of the program P being tested and corrected is referred to as S . T is the test suite devised for testing program P (set of test cases). $T_F \cup T_P = T$ where T_F is the set of failed test cases ($T_F \subseteq T$) and T_P is the set of passed test cases ($T_P \subseteq T$): $T_F \cap T_P = \emptyset$. $S(t)$ denotes the statements executed (covered) by test case t , where $t \in T$: $S(t) \subseteq S$.

R_i denotes a specific rule learned by the C4.5 algorithm. The set of rules is denoted by R , where $R_i \in R$. R_F (resp. R_P) is the subset of rules that classifies test cases as Fail (resp. Pass): $R_F \cap R_P = \emptyset$, $R_F \cup R_P = R$.

The set of test cases classified by rule R_i is referred to as $T(R_i)$: $T(R_i) \subseteq T$. If $i < > j$, $T(R_i) \cap T(R_j) = \emptyset$. The latter constraint is due to the partitioning nature of the C4.5

algorithm. Test cases in $T(R_i)$ can pass or fail. Following the same notation as above, $T(R_i) = T_F(R_i) \cup T_P(R_i)$ where $T_F(R_i)$ and $T_P(R_i)$ are the actual failing and passing test cases classified by rule R_i , respectively. The set of statements covered by a rule R_i , i.e., executed by the test cases classified by R_i , is referred to as $S(R_i)$: $S(R_i) = \bigcup_{t \in T(R_i)} S(t)$.

4.2 Tarantula coloring

Following the above formalism, the Tarantula color of a statement s of program P is $Color(s) = passed(s) / (passed(s) + failed(s))$ where $passed(s)$ and $failed(s)$ are the percentages of passing and failing test cases that execute statement s respectively ($Color(s) \in [0, 1]$):

$$passed(s) = |T_P(s)| / |T_P| = |\{t \in T_P, s \in S(t)\}| / |T_P|$$

$$failed(s) = |T_F(s)| / |T_F| = |\{t \in T_F, s \in S(t)\}| / |T_F|$$

where $T_P(s)$ and $T_F(s)$ are the set of passing and failing test cases that execute statement s respectively.

A small value for $Color(s)$ suggests s is a suspicious statement. When statements are not executed by any test case, the authors [14, 15] states that a value of zero should be assigned to $Color(s)$. (Note that this is what the description of Tarantula suggests in [14, 15], although the running example used by the authors suggests that, on the contrary, uncovered statements are not ranked.) However, this makes no theoretical sense as there is no information to indicate that the unexecuted statement is likely to be fault-prone. In fact, no fault causing the observed failures can be possibly located in uncovered statements. This situation is of practical importance as the presence of multiple faults often prevents certain statements from being executed. In our case study, we will discuss

a stepwise debugging process to address this issue of uncovered statements (Chapter 5).

The original $Color(s)$ formula presented above can be re-expressed to demonstrate that the statement ranking only depends on the ratio $|T_P(s)|/|T_F(s)|$.

$$\frac{1}{Color(s)} = 1 + \frac{|T_F(s)|}{|T_F|} * \frac{|T_P|}{|T_P(s)|} = 1 + \frac{|T_P|}{|T_F|} * \frac{|T_F(s)|}{|T_P(s)|}$$

Since $|T_P|/|T_F|$ is constant for a given test set and program version, the ranking of statements, which is ultimately used to focus debugging, exclusively depends on the proportion of test cases that fail and pass when executing a specific statement s . Though this makes intuitive sense, there are two problems with this formula in a multi-fault environment:

- (1) Test cases may fail due to different faults and therefore a statement s may not be relevant to the failing test cases that execute it.
- (2) Redundant test cases that execute the system in identical or similar conditions may artificially affect the ranking.

Another issue is related to how Tarantula rankings were evaluated (section 2.1). Ideally, we would like to assess the cost-effectiveness of rankings. In other words, we want to be able to compare some measure of cost and fault detection. To do so we use a scatter-plot of percentages of statements verified (a surrogate measure for cost) versus percentages of faults contained in those statements (effectiveness) to compare various statement-ranking methods in terms of cost-effectiveness. Though this was not done in the original studies [14, 15], this will be the basis for our case study analysis.

Also related to evaluation is whether each fault should be considered in isolation or whether all faults should be considered in a single program. Tarantula has originally been

used on faulty program versions with a single fault [14, 15] and found to be effective at pinpointing faulty statements on such faulty programs. When used on multiple-fault programs, Tarantula’s effectiveness has shown to decrease [15], probably for the reasons we mentioned above. As acknowledged in [15], this deserves further analysis and is important as it is probably more realistic to perform such studies with multiple faults. This issue is the main focus of the present thesis.

4.3 Ranking statements based on C4.5 rules

In this section we present the rule-based statement ranking (RUBAR) method. We first explain how we apply the Category-Partition technique to generate C4.5 rules (section 4.3.1) and how we select a subset of rules based on all the rules available in the decision tree (section 4.3.2). We then explain the basic principles of using C4.5 rules for deriving a ranking (section 4.3.3). Finally, we introduce the debugging process to apply the RUBAR fault localization technique (section 4.3.4).

4.3.1 Generating a C4.5 classification tree

In order to obtain meaningful and accurate machine learning rules, we cannot simply use the raw input and output values of a test case. Our experience is that they typically lead to meaningless and inaccurate rules because the machine learning algorithm cannot learn what input or output properties are potentially of interest but only which ones matter once they are defined. In other words, without some additional guidance, the learning algorithm is unlikely to find the precise conditions under which test cases fail. Figure 4-1 is a sample of decision tree generated from the raw test data (original test case) in Table A-1 for the Triangle program (section 3.1, Appendix A). It shows that if side 1 (s_1) is

smaller or equal to 2 and side 3 (s_3) is smaller or equal to 5, which corresponds to four test cases (leaf node of the left rule), then the program fails, i.e., misclassifies the triangle. Similarly (right rule), if side 1 (s_1) is strictly greater than 2, the program fails. It is obvious that the information provided by the classification tree is too close to the raw value. That is, the information is too subjective instead of objective. For example, instead of the second rule discussed earlier (Figure 4-1), we would like to say that when a triangle has one side longer than two (not only side s_1), the triangle program may misjudge the type of the triangle.

Figure 4-1 Decision tree generated on raw inputs

Therefore, if no black box testing technique is used beforehand to obtain a test specification, test suites (raw test data) need to be transformed into abstract test suites before rule-induction machine learning algorithms can be applied. The abstract test suite contains the abstract test cases which define the test specifications of the original test cases (raw test data). In our method, we apply the Category-Partition (CP) method to define the test specifications (by categories and choices) and then use the categories and choices to transfer the original test suite into an abstract one.

The reason to use Category-Partition (CP) here is that CP is more general and

encompassing than equivalence class partitioning (which only partitions input value domains) and it is one of the most well-known black-box techniques. Though applying CP clearly represents an overhead, in many environments one would be expected to use a systematic functional testing approach. Reverse engineering a test specification (i.e., categories and choices) is also in any case a useful investment in the context of legacy systems with existing test suites.

Let's take the triangle problem (Appendix A) as an example. Using the category partition definitions of Table 3-1, the original test cases in Table A-1 can be defined by the abstract data in Table A-2. Using the abstract test cases, we can generate a decision tree as Figure 4-2. Figure 4-3 is the graph view of Figure 4-2. From the rules of this tree, we can clearly draw out that when the sides (s_1, s_2, s_3) of a triangle have relationship $s_1 \leq |s_2 - s_3|$, the triangle program would misclassify the triangle. This is exactly what the fault is.

Figure 4-2 Decision tree of Triangle program generated by Weka

Figure 4-3 Decision tree generated on complete CP definition

When applying the CP methodology, one must provide a complete CP definition for the program. The completeness of the CP definition will affect the accuracy of the rules learned directly. Still taking the Triangle program as the sample, suppose that instead of taking all the CP definitions in Table 3-1, we only take the first three categories (CA01, CA02 and CA03) and related choices as the CP definitions of the triangle program. Based on the new abstract test cases and test results, the learning algorithm will be able to generate a C4.5 tree in Figure 4-4, which determines that a test case with inputs $s_1 < s_2$ and $s_3 > s_1$ has a 66.7% (2/3) probability to detect a failure (node 5). It is obvious that the decision tree of Figure 4-3 is more accurate and meaningful than that of Figure 4-4. That is, the completeness of the CP definition is one of the key features in generating an accurate classifier.

Figure 4-4 Decision tree generated on non-complete CP definition

When applying the J48 classification algorithm of Weka, the parameters of the algorithm should be chosen carefully. Our experience shows that if there is only a small set of instances, it is better to run the J48 algorithm with the default values for the parameters:

the `confidenceFactor` (the confidence threshold for pruning) equals to 0.25, the `minNumObj` (the minimum number of instances permissible at a leaf) equals to 2, the `numFolds` (the size of the pruning set) equals to 3, etc. But when there is a large set of instances (such as the SPACE program introduced in section 5.2), our experiences reveal that when the `minNumObj` equals to 10, and the other parameters equals to their default values, Weka can generate a more accurate classification tree.

4.3.2 Selecting rules

A last practical issue is to determine which rules to consider among all the ones identified in a C4.5 decision tree. In order to only account for accurate rules, it seems logical to select rules that are above a certain probability of correct classification (Fail/Pass). We should also consider rules that are based on a large enough number of instances (abstract test cases) in order to avoid the classifications that are due to chance. Deciding about such selection thresholds is of course subjective, but it can be done so as to obtain a reasonable number of rules to base the ranking on and will be dependent on how accurate the rules are overall for the specific test suite under consideration.

4.3.3 Computing a statement ranking

4.3.3.1 Heuristics

Assuming we have an abstract test suite, we are able to generate a C4.5 decision tree where each leaf corresponds to a rule predicting either Pass or Fail. The data set on which to build the tree would then be a set of instances, each corresponding to an abstract test case that is known to pass or fail. The attributes to be selected for the tree construction are pairs (category, choice) characterizing the specification of each test case. Each path

from the root of the tree to a leaf represents a rule characterized by conditions on (category, choice) pairs. Each leaf in the tree corresponds to a partition of the data set of test case instances as introduced in section 4.3.1. A rule leads to a Fail prediction when the instances in its leaf represent a majority of fail test cases, and Pass otherwise. Therefore, a C4.5 rule classifies a set of test cases with similar input conditions and identical test results.

To understand the heuristic we are going to follow, let us first focus on Fail rules and take the example of a particular rule $R_i \in R_F$. If we assume the probability of failure associated with R_i is very high, then what this means is that (nearly) all the test cases in $T(R_i)$ fail under the same or similar conditions. What this suggests is that (nearly) all of these test cases fail due to similar reasons (faults). This in turn can be used to safely rank statements using a strategy similar to Tarantula as all test cases failing within a rule can be safely assumed, in most cases, to fail due to the same fault(s). We thus obtain a ranking for each Fail rule that must then somehow be combined with the ranking of other rules to obtain a final ranking.

Within a failing rule (e.g. R_i), the higher the number of failing test cases covering a statement, the more suspicious the statement. For instance, assume that $T_F(R_i) = \{t_1, t_2, t_3\}$, and that the statements executed by these three test cases are depicted in Figure 4-5. D_1 is the set of statements executed by all three test cases; D_2 is the set of statements executed by two test cases; D_3 is the set of statements executed by only one test case and D_4 is the set of statements executed by none of the test case of rule R_i . According to the above hypothesis, the statements in D_1 (i.e., covered by all three test cases) should be more suspicious than those in D_2 , D_3 , or D_4 . On the contrary, the statements in D_3 should be the

safest of all statements covered by t_1, t_2, t_3 . Since no failed test case executes the statements in D_4 , it is hard to point out the degree of suspicion of these statements. Similarly, if R_i were a Pass rule, we would obtain the opposite result: the statements in D_1 would be the safest and those in D_3 would be the most suspicious. This example illustrates how for each rule we can obtain a partial ordering of statements.

Figure 4-5 Statement divisions by test cases

4.3.3.2 Ranking statements

To implement the above heuristic, we must define a mechanism to combine the ranking of all rules for a given statement. Proceeding with this goal in mind, a statement will be assigned a negative (resp. positive) weight if it is covered by a Fail (resp. Pass) rule. A high absolute weight value implies that a statement is executed by most of the test cases in the rule. The absolute values of weights are normalized within $[0, 1]$ in order to give equivalent weight to all perfect rules, i.e., rules which contain only test cases that either fail or pass. However, if a rule contains test cases with inconsistent Pass/Fail behavior, the maximum absolute weight a rule can contribute will therefore be below 1 and determined by the percentage of test cases it contains in the Fail/Pass category it predicts. The fact that rules should contribute to the extent of the consistency of their test cases'

behavior should be intuitive: less consistent rules have less influence on the final ranking. We have also considered weighting the rules' contributions according to their number of test cases, but this would make the results sensitive to redundant test cases, as discussed above in the case of Tarantula, and would make rarely executed faults difficult to find. Assuming that $Weight(R_i, s)$ and $Weight(s)$ denote the weight of statement s for rule R_i and the overall weight of statement s , respectively, we obtain:

$$Weight(R_i, s) = -|T(s) \cap T_F(R_i)| / |T(R_i)|, \text{ when } R_i \in R_F$$

$$Weight(R_i, s) = |T(s) \cap T_P(R_i)| / |T(R_i)|, \text{ when } R_i \in R_P$$

$$Weight(s) = \sum_{R_i \in R} Weight(R_i, s)$$

This can be visualized as a matrix (Table 4-1) where columns are statements and rows are rules. The matrix contains all the weights of each statement for each rule, all within $[-1, 1]$ as defined above. The last row represents the sum of all rule weights for a given statement, which can then be used to rank statements as depicted in Figure 4-6: Statements with lower weight are ranked first, to follow Tarantula's convention for $Color(s)$.

Figure 4-6 Statement Ranking using Weight(s)

Table 4-1 Matrix of statement weight

	s_1	s_2	s_3	...	s_o
R_{p1}	1	0.01	1	...	0.5
...	...	...	...	...	...
R_{pm}	1	1	0.8	...	0.1
R_{f1}	-1	-1	-1	...	-1
...	...	...	...	...	...
R_{fn}	-1	-1	-0.8	...	0
Sum	-22.1	-18.7	0.06	...	-3.36

4.3.4 Iterative debugging process

The debugging process of a program with several faults is more complex than that of a program with one fault. The presence of multiple faults often prevents certain statements (possibly faulty themselves) from being executed. As a result, not all faults can be covered in a single run. On the other hand, it is also impossible for a programmer to fix all the faults in the executed statements of a single rule. Therefore, the debugging process of a multi-fault program must follow an iterative process, which can be described by Figure 4-7. Suppose that a set of test cases is defined to meet the test requirement and all faults in the program can be recovered by at least one of those test cases. Diagnosing a multi-fault program using the RUBAR technique entails to:

- (1) Define the category partition definitions of the program and apply the “*test case transformation tool*” to generate an abstract test suite;
- (2) Test cases are executed against the system-under-test, which may contain several faults. The test results (Passing or Failing) and execution traces are collected;
- (3) A rule generation tool, i.e. Weka, is applied to generate rules with the abstract test cases and the related test results;

- (4) The RUBAR statement-ranking algorithm is applied to generate a ranking of the statements based on the coverage data and the classification rules;
- (5) Following a fault removing strategy, one or more faults in the executed statements are removed and a new program version containing the left-over faults becomes available for another debugging process (steps 2 to 5 are repeated).

Figure 4-7 Iterative debugging process

The iterative debugging process (Figure 4-7) can be automated by using specific tools. There are lots of commercial and open-source coverage tools that we can rely on to

record the execution trace of each test case, e.g. Emma⁵ and Clover⁶ for Java, Coverage Validator⁷, Telcordia XSuds⁸ and IBM-Rational PureCoverage (now the Rational purifyPlus) for C/C++. In our experiments, we used Emma and Coverage Validator as the coverage tools for Java language and C language separately. Weka [33] is an open-source Java-based machine learning package for data mining tasks. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. The Tarantula algorithm and RUBAR algorithm were also implemented in Java language (Appendix B is the class diagram of the implementation).

To correct the errors in the executed statements (Step 5) before iterating the process, several strategies can be followed:

- (1) All the ranked statements are analyzed and any fault discovered fixed;
- (2) Only the first 20% of the ranked statements are analyzed and any fault discovered fixed. Investigating the first 20% of the ranked statements has been shown to be a reasonable heuristic with Tarantula [15];
- (3) All the ranked statements are analyzed and only the first fault discovered is fixed;
- (4) Any other procedure deemed suitable by the tester can be followed.

It is up to the tester to decide which one of the above procedures to follow.

4.4 Manual Effort and Automation

From the discussion above, the category partition definitions should be as complete as

⁵ <http://sourceforge.net/projects/emma>

⁶ <http://www.atlassian.com/software/clover/>

⁷ <http://www.softwareverify.com/cpp/coverage/index.html>

⁸ <http://xsuds.argreenhouse.com/>

possible. This requires a thorough understanding of the system domain. This is what a tester would typically do when trying to locate faults.

Once the CP specification is defined, the transformation of raw test cases into abstract test cases is easy to be automated. Usually, it takes only a couple of seconds to perform the transformation. For instance, for a large program such as the Space program (section 5.2), for which we defined 83 categories and 582 choices, it took less than a minute to transform the 13,585 test cases into abstract test cases.

The second debugging step, executing test cases and collecting coverage data, may be the most time-consuming activity of the iterative debugging process described by Figure 4-7. The time to collect the coverage data and test results may range from several hours to several days, which depends on the size of the program and the size of the test suite. In practice, most companies use code coverage as one of the criteria to evaluate test performance. Therefore, coverage information becomes a by-product of the testing process. Therefore, the cost of collecting coverage data is not really part of the cost of our strategy.

Debugging step 3 is another automated step. We used the WEKA tool, which implements the C4.5 classification algorithm. For the Space problem, it took eight seconds to generate a tree based on the 13,585 abstract test cases.

As mentioned in section 4.3.4, we developed the RUBAR ranking algorithm, which takes the test results, the coverage data and the rules generated as the inputs. The ranking process can also proceed very quickly. It is obvious that step 5 is a manual process, as this relies on the knowledge and the experience of the programmer. However, as discussed in this chapter, the statement ranking can provide guidance for defect removal.

CHAPTER 5 CASE STUDIES

Our experiments include two case studies which aim at validating RUBAR (section 4.3) and at comparing its effectiveness with Tarantula. This chapter starts with a presentation of the rule-based diagnosis process we used (section 5.1). Then we represent the two case study programs we used and the corresponding results (section 5.2 and section 5.3).

5.1 Case study process

As mentioned above, we apply the Weka tool to generate the C4.5 classification trees and then generate the rules indicating failing or passing conditions of a test case. To select the rules generated by the C4.5 algorithm, in our case study, we select rules with a probability of correct classification above 0.8 and a number of instances above 10.

The case studies followed the iterative process suggested in section 4.3.4. To better evaluate the effectiveness of RUBAR algorithm, we performed the first case study (the Space program) on two scenarios defined in section 4.3.4:

- (1) Inspecting all the ranked statements and fixing any fault discovered;
- (2) Inspecting the first 20% of the ranked statements and fixing any fault discovered;

Since not all statements can be executed in a multi-fault environment and the purpose of software debugging was to identify the location of faults generating the observed failures, we only ranked the unfixed statements since other statements could not possibly contain the faults causing these failures.

After all the faults are located and removed, we appended the rankings of all debugging

iterations and compared the resulting final rankings of all program statements as determined by Tarantula and RUBAR. Note that for each debugging iteration, we only ranked the statements not fixed in the former iteration(s). We then generated a diagram with the statement ranking against the cumulative percentage of faulty statements in the ranking to evaluate the effectiveness of the ranking. We refer to this diagram as the cost-effectiveness diagram.

As discussed above, Baudry *et al.* [3] presented the idea of using the size of DDB (Dynamic basic block) to evaluate the diagnosis accuracy. They validated the relationship by their case study and defined a criterion to measure the accuracy of diagnosis (section 2.2.3). In our case studies, we applied these criteria together with the cost-effectiveness diagram to evaluate the accuracy of the Tarantula and RUBAR methods.

Another important aspect of the case studies is whether the decision tree and rules we generated are accurate. This is of course a prerequisite for such rules to be used for statement ranking purposes but also to assess whether we can characterize failure conditions (Fail rules) in an accurate manner. This will be further discussed below.

5.2 Case study 1: The Space program

5.2.1 Introduction

The Space program was originally developed by the European Space Agency, and was first used in a software engineering study by Pasquini *et al.* [23]. It has subsequently been used in other experiments, and in particular in the initial evaluation of Tarantula [15]. Space allows users to describe the configuration of an array of antennas using a specific array definition language (ADL). It reads a text file containing ADL statements, checks

its conformance to the ADL grammar as well as specific consistency rules, and performs other computations. It is a 5905-NBNC⁹-LOC C program. (See [34] for further details.) During “testing and operational use” of the program, 33 logical faults were identified and eliminated, and the details of the fault-fixing changes were preserved so that the faults could be selectively re-introduced. Vokolos and Frankl [30] used the program for a study in which they compared the effectiveness of regression test selection strategies. For that study, they generated 10,000 test cases using a randomized input generation tool. Rothermel *et al.* [28] later added enough test cases to ensure that each executable decision was covered by at least 30 test cases in each direction; this procedure added 3,585 test cases to the pool. The resulting test pool covers 90, 85, 85, and 80 percent of all blocks, decisions, c-uses, and p-uses present in the program, respectively. The total number of blocks, decisions, c-uses, and p-uses are 2995, 1191, 3733, and 1707, respectively.

During the course of their research, Rothermel *et al.* [28] identified and eliminated five more faults, bringing the total number of versions of the program to 38; however, they found that three of the original versions did not exhibit faulty behavior, reducing the number of non-equivalent versions to 35. We obtained the program, faulty versions and test pool from the Galileo Research Group Subject Infrastructure Repository at the University of Nebraska - Lincoln. In this case study, we used the Space program [23], the mutants and test cases generated by the authors of [23, 28] directly.

⁹ NBNC: Non-blank line, non-comments statements.

5.2.2 A multi-fault version of Space

Among the 35 non-equivalent versions, there are two special versions that contain faults in the initialization statements. Initialization statements are statements to initialize the global variables or to set up the system environments, which will be executed by almost all the test cases. In [15], Jones point out that Tarantula can not correctly color (i.e., rank) those statements. Baudry *et al.* [3] confirmed this situation in their case study. Our case studies also reveal that RUBAR, similarly to Tarantula, does not work well in locating the defects in the initialization statements. Therefore, in the following case studies, we chose not to introduce faults in the initialization statements as Baudry *et al.* did in their case study.

We randomly selected 15 of the 33 original logical faults for our study, avoiding the versions not exhibiting any faulty behavior and containing the initialization fault. We then built one faulty version of Space by introducing, in the correct version, the 15 logical faults, i.e., 34 faulty statements. The rationale was to simulate a realistic situation where a program contains more than one fault. At the same time, the rationale for not including all the 33 original faults was to obtain a balanced number of failing and passing test cases. The failing rate of test cases on a faulty version including the 33 faults is 95.5%, whereas the rate is 47% on the faulty program containing the 15 selected faults. Future work will investigate ways to deal with high failing rates and initialization faults.

When executing the 13,585 test cases on our multi-fault version of Space, we achieve 69.72% statement coverage (as reported by Coverage Validator). The executed statements contained 15 of the 33 faulty statements. Not reaching 100% statement coverage and not executing the 33 faulty statements is not surprising since we have several faults in the

program. Some faults result in the program exiting prematurely, and therefore in some of the statements (containing other faults) not being executed. This, however, can be considered a realistic situation under which to experiment.

5.2.3 Rule induction based on category partition

In our method, we used the category partition technique to characterize the test cases instead of using this technique to devise test cases. Therefore, it is not necessary to identify constraints on choices as suggested by the category-partition technique [21]. When applying category-partition on the *Space* program, we identified 207 parameters, 83 categories, and 582 choices (Appendix C.2). Since the *Space* program is a language processing program, it is not surprising that we defined such a large number of categories and choices.

By applying the C4.5 algorithm on the test suite (with test results against the initial version of *Space* containing all 15 faults), we obtained 285 rules (decision tree leaves). The maximum depth of the tree is 12. That is, the longest rules generated have 12 decisions (conditions). Overall, when performing the ten-fold-cross-validation procedure [33], we obtain the confusion matrix in Figure 5-1. From the matrix, we learn that the C4.5 algorithm misclassified 335 Fail test cases and 550 Pass test cases as Pass test cases (false positive) and Fail test cases (false negative) respectively. For Fail test cases this corresponds to a 91.7% precision and a 94.7% recall, which is very good. Similar percentages are obtained for Pass test cases. What this means is that the rules learned by the decision tree model in a nearly complete and precise manner the conditions under which the *Space* program fails. This result partly reflects the completeness of our categories and choices.

		Predicted class	
		Fail	Pass
Actual class	Fail	6045	335
	Pass	550	6655

Figure 5-1 Cross validation confusion matrix

The accuracy does of course vary across rules as well as the number of test cases they cover. Table 5-1 shows examples of a few Fail rules with their length (# of conditions), the number of test cases they covered (TC), and the accuracy of prediction. The rules we show in Table 5-1 are 17 of the 34 Fail rules that involve more than 10 test cases and achieve an accuracy of at least 80%. Remember that we need enough instances associated with rules to obtain accurate fail/pass probability estimates. According to the rule selection criteria, we also selected 58 Pass rules from the rules generated by the C4.5 algorithm.

Table 5-1 Example Fail rules with accuracy and test case coverage

Rules	length	TC	Accuracy	Rules	length	TC	Accuracy
F109	1	30	100.00%	F004	11	200	94.50%
F025	5	667	99.55%	F012	11	97	93.81%
F104	2	240	98.75%	F005	11	548	93.80%
F106	1	304	98.36%	F070	10	271	93.73%
F105	2	158	97.47%	F069	9	116	92.24%
F107	1	114	97.37%	F087	9	199	91.96%
F009	12	147	97.28%	F016	7	12	91.67%
F010	12	132	96.97%	F086	8	700	91.57%
F003	12	37	94.59%				

As an example, let us look at the rule F025 (Table 5-1). It has a length of five, i.e., it is made of five conditions. 667 test cases are classified by this rule. The failing probability of a test case satisfying the conditions is 99.55%. Without going into too many details about the specification of the Space program, or a detailed description of our parameters, categories, and choices (i.e., our application of category-partition), rule F025 indicates that if a test case:

- 1) defines a triangular grid of antennas (condition 1),*
- 2) defines a uniform amplitude and phase of the antennas (conditions 2 and 3),*
- 3) defines the triangular grid with angle coordinates or Cartesian coordinates, and a value is missing when providing the coordinates (conditions 4 and 5);*
- then, the test case has a failure probability of 99.55%.*

As shown in Table 5-1, many other rules are highly accurate in predicting failure. Note that such information can potentially be useful to support debugging (i.e. simplified inputs) as it characterizes logically and precisely failure conditions. Since the confusion matrix in Figure 5-1 suggests the rules are very accurate, they can therefore be trusted by a programmer trying to understand when and why the program fails.

From the abstract test suite generated, we identified that:

- (1) There are a number of duplicated test cases. Remember that Rothermel *et al.* [28] generated some test cases to make each executable decision covered by at least 30 test cases in each direction. From the discussion above, these duplicated test cases will dramatically affect the effectiveness of the Tarantula fault localization method. We will use a test suite with less redundancy in the second case study.
- (2) These 13585 test cases do not cover all the functions of the *Space* program, although they meet the coverage requirement [28] of Rothermel *et al.*

5.2.4 Cost-Effectiveness analysis

In the first iteration of the RUBAR procedure only 69%, as discussed above, of the statements were reachable. As mentioned in section 5.1, we correct the statements ranked in two strategies: all the faults in the executed statements were found and corrected or only the faults in the first 20% most fault-prone statements were inspected and corrected.

After that, in the subsequent debugging iterations, we only focus on the remaining statements that were left out in the former iteration(s). Finally, the statement rankings of all iterations are appended together.

5.2.4.1 Strategy one: fix all faults in the ranked set of statements

By this strategy, it took two debugging iterations to cover all statements, following the iterative process described in Section 5.1. The cost-effectiveness of the ranking of statements based on Tarantula's coloring is shown in Figure 5-2 (a) when combining the rankings of the two debugging processes (separated by the reference line of the X-axis). The separated ranking of each iteration is showed in Appendix C.3.1. The first iteration involves all the 15 faults (34 faulty statements) whereas the second iteration includes only eight faults (18 faulty statements) that are not ranked in the first iteration. Table 5-2 contains the detailed data about the debugging iterations. The X-axis is the percentage of statements that need to be covered to detect the percentage of faulty statements on the Y-axis. (Note that the rankings stop before 100% statement coverage as this is also the case for the original test suite.) Each observation represents a statement which is assigned a color value and the statements are ranked according to the color value. For example (Figure 5-2 (a)), by visiting the first 10% (resp. 20%) of the covered statements, a tester will visit 17% (resp. 17%) of the faulty statements. Figure 5-2 (b) shows the same curve when using RUBAR for ranking statements: the pattern is visually very different from Figure 5-2 (a), especially in the first iteration.

Table 5-2 Execution result of multi-fault version

	Round 1	Round 2
# of statements	3627	3640
# of logical faults	15	8
# of faulty statements	34	18
# of Passed / Failed test cases	7160/6425	12130/1455
# of Passing / Failing rules	171 / 115	136/61
# (%) of statements executed	2529 (69.72%)	3624 (99.56%)
# of faulty statements covered	16	18

(a) Tarantula **(b) RUBAR****Figure 5-2 Fixing all the faults in the statement(s) executed**

In the second debugging iteration, Tarantula and RUBAR generated similar curves (the second part of the curves in Figure 5-2). But when looking into the statement rankings (Table 5-3), we find that the two methods ranked the faults in different orders. Table 5-3 has two parts. The left part shows the defects (bugs), the corresponding line number(s) the number of passing and failing test cases that execute them, and the ratio of $|T_P(s)|/|T_F(s)|$. For instance, defect number 23 (Bug23), which is a fault on line number 6761, and is executed by 497 (resp. 125) failing (resp. passing) test cases. The right part of Table 5-3 shows the Tarantula and RUBAR rankings of the faulty statements listed in the left part of the table. For instance, Tarantula ranks statement 2593 before statement 2617, before statement 2627 ...

From the ranking result of Tarantula, we can see that the statement ranking depends on the ratio $|T_P(s)|/|T_F(s)|$ (smaller values of ratio are ranked first), as we discussed in section 4.2: the first 6 statements ranked by Tarantula (Table 5-3) are those with 0 passing test cases; the remaining statements are ranked in increasing order of the ratio value. On the other hand, the ranking result of RUBAR has no direct relationship with $|T_P(s)|/|T_F(s)|$.

When further looking into the program and the location of faults Bug16, Bug22 and Bug23, the execution sequence of those faulty statements can be described as Figure 5-3 (control flow graph). The control flow graph shows that statement 6761 can potentially belong to more faulty behaviors than the other three, and that statement 7626 can potentially belong to more faulty behaviors than the remaining two. As a result, statement 6761 should be considered as the most suspicious and the most dangerous of these four statements. Therefore, it would be meaningful if the four faulty statements were ranked following their execution order, which is the ranking generated by RUBAR: statement 6761 before statement 7626, followed by statement 3796 and statement 7627. On the other hand, Tarantula ranked these four statements in an inverse order: e.g., statement 6761 is the last one.

We conclude that the RUBAR ranking is more acceptable and meaningful for debugging purposes than the Tarantula ranking for the Space program and its test suite.

Table 5-3 Faulty statements and their ranks

Defect	Line number	# of test cases executed			Rank	
		Fail	Pass	$ T_F(s) / T_P(s) $	Tarantula	RUBAR
Bug13	2593	687	0	0	2593	2593
Bug13	2617	39	0	0	2617	6761
Bug13	2627	39	0	0	2627	7626
Bug16	3796	243	0	0	3796	3796
Bug23	6761	497	125	0.252	7626	8416
Bug20	7568	242	84	0.347	7627	7627
Bug22	7626	311	0	0	8416	8004 to 8007
Bug22	7627	69	0	0	6761	2617
Bug07	8004 to 8007	252	157	0.623	7568	2627
Bug08	8269 to 8272	111	166	1.495	8004 to 8007	8535
Bug16	8416	484	84	0.174	8535	8269 to 8272
Bug18	8535	33	21	0.636	8269 to 8272	7568

Figure 5-3 Execution sequence of faults: Bug16, Bug22 and Bug23

In general, it is very clear that when comparing Figure 5-2 (a), Figure 5-2 (b) and Table 5-3, Tarantula does not perform well since many of the faulty statements (or the most suspicious statements) seem to be assigned a higher color value and are not ranked among the first statements to be inspected. We believe, for the reasons discussed previously, that this is due to the incapacity of Tarantula to handle multiple faults in a program.

On the other hand, the technique we propose based on C4.5 rules performs much better

(Figure 5-2 (b)). For each debugging iteration, RUBAR always ranks the suspicious statements first, whereas Tarantula is likely to rank some suspicious statements (the statements between 55% and 65% in Figure 5-2 (a)) late in the list. For RUBAR ranking, we can see a very sharp increase in the number of faulty statements covered in the first 20% ranked statements, which is roughly the range of practical interest in our situation, as discussed by Jones *et al.* [15].

As a side discussion, let's focus on the ranking of the (non-faulty) initialization statements of both RUBAR and Tarantula. There are around 310 initialization statements in Space program, which initialize keyword definitions, error messages etc. Since initialization statements are executed by (almost) all test cases, these initialization statements are ranked in the first debugging iteration and spotted in the first segment of both the curves in Figure 5-2. When looking into the statement ranking, we found that each method assigned a similar ranking to these initialization statements, i.e. the range of ranking values of those statements is small: [0.4998, 0.5] for Tarantula, [24.8547, 24.9316] for RUBAR. It is not surprising to obtain such a result since these statements are executed by (almost) all the test cases. But for Tarantula, the initialization statements are ranked in the middle (from 18% to 27%) as Jones mentioned in their experiments [15]. On the contrary, RUBAR ranked the initialization statements near to the end (from 60% to 69%). Since initialization statements are executed by (almost) all test cases, a fault in those statements would not change these rankings drastically. Note that we have experimented with RUBAR and Tarantula on Space with faulty initialization statements and confirmed this. This confirms that both Tarantula and RUBAR are not adequate enough for finding faulty initialization statements.

5.2.4.2 Strategy two: fix faults in the first 20% of the ranked statements

In this second strategy, instead of fixing all the faults in the executed statements, we only fixed the faults in the first 20% of the ranked statements in the iterative process. Following this scenario, we compare the results for both RUBAR and Tarantula. Each technique leads to one specific debugging process from the original multi-fault version of Space program since not the same 20% statements are reported in the first iteration. Both the methods took three debugging processes to fix all the faults as showed in Table 5-4.

Table 5-4 Fixing faults in the first 20% of the ranked statements

	Tarantula			RUBAR		
	Iteration1	Iteration2	Iteration3	Iteration1	Iteration2	Iteration3
# of Statements	3627	3639	3645	3627	3639	3657
# of Faulty statements	34	28	18	34	19	1
# of Passed / Failed Test cases	7160/6425	9339/4246	12351/1234	7160/6425	11986/1599	13371/214
# of Passing / Failing rules	---	---	---	171 / 115	174/ 69	51/28
# (%) of Statements executed	2529 (69.72%)	2837 (77.96%)	3344 (91.72%)	2529 (69.72%)	3352 (92.11%)	3367 (92.07%)
# of Faulty statements covered	16	19	18	16	19	1
# of Faulty statements covered in the first 20% statements ranked	6	10	18	15	18	1

From Table 5-4, we can see that RUBAR acts much better than Tarantula. Tarantula localized 6, 10, and 18 faulty statements in the three debugging iterations respectively, whereas RUBAR localized 15, 18 and one faulty statement(s) in the three debugging iterations. Recall that the iterations focus on 20% of the ranked statements, so by visiting the same number of statements, RUBAR helps localize faults much faster. We can also draw out the similar result from the separated cost-effectiveness curves for both methods in Appendix C.3.2.

Applying the cost-effectiveness analysis on the statement rankings, we obtained Figure 5-4 for both methods with debugging iterations separated by the separation lines in the X-

axis. Obviously, RUBAR acts much better in fault localization than Tarantula. More than 95% faulty statements are ranked in the first 30% by RUBAR. Only about 45% faulty statements are ranked in the first 30% by Tarantula. Appendix C.3.2 gives the statement ranking of each iteration.

Figure 5-4 Fixing faults in the first 20% of the ranked statements

When looking into the statement ranking of Tarantula, we found that nine of the ten faulty statements ranked low (after the first 20%) in the first debugging iteration (Appendix C.3.2) are still ranked lower (after 20%) in the second iteration, and are finally ranked between 9.5% and 20% in the third iteration. In the Space program, eight of these nine faulty statements (belonging to four faults) are in a method named `fixsgrel()` and distributed in four “switch” branches. This method will be executed by a test case that defines a grid and a *rotation* sequential phase. Such a test case will execute one of these four branches (according to the given grid type), but not all test cases will trigger one fault. There are only several hundred test cases (a very small percentage of the total test suite) fitting the above conditions and only a small ratio of the test cases fail. According to the Tarantula algorithm, the statements of method `fixsgrel()` will

therefore obtain a high color value and be ranked very low, since they are only executed by a small portion of failed test cases: they look suspicious to Tarantula but not very suspicious. When applying the C4.5 classification algorithm, these test cases were grouped into 24 failing rules and 37 passing rules with the same input condition “*Grexc_Grpha_Def = ROTATION*” and 10 (resp. 14) of these failing (resp. passing) rules were chosen to perform RUBAR analysis (they satisfy the rule selection criteria). As a result, these statements obtained weight values varying from -0.01 to 0.3 and ranked in the first 20% of the statements. Thanks to C4.5 rules, RUBAR is able to identify those statements more suspiciously than Tarantula. This partly explains the difference between Figure 5-4 (a) and Figure 5-4 (b): some of the statements ranked in the third part of Figure 5-4 (a) are ranked in the first part of Figure 5-4 (b).

The last faulty statement of the nine is very special. It has a low rank in the first two iterations of both methods. After looking into the code, we learnt that this fault lies in a function to initialize the variables of the port definition when no port is defined in the inputs of a test case. This function is somehow like an initialization function and is executed by most of the test cases (except those with a port definition). This is the reason why this faulty statement is ranked very low by both methods. The program version for the third iteration of RUBAR contains only this fault. In the third iteration Weka generated a C4.5 tree in which all the failing rules identify the failing condition above. This verified, from another perspective, the completeness and correctness of our Category-Partition definitions and the idea of using data mining rules to assist program debugging.

5.2.5 Diagnosis accuracy evaluation

As discussed above (section 2.2.3), DBBs can be applied to evaluate diagnosis accuracy. We select three criteria to evaluate the accuracy of the Tarantula coloring method and our RUBAR algorithm: the number of DBBs, the average size of DBB and the *ideal diagnosis accuracy* ($idealAccuracy(P)$ in section 2.2.3). Figure 5-4 presents the evaluation results of the experiments we performed in section 5.2.4.1 and section 5.2.4.2. (Each time, we used the final ranking in the formulas of section 2.2.3.) From these results, RUBAR appears to be more accurate than Tarantula. With the assistance of RUBAR (resp. Tarantula) diagnosis algorithm, the average number of statements to be visited to isolate an actual fault is 25.56 (resp. 34.48) and 7.49 (resp. 11.95) for Strategy one and Strategy two respectively.

Although they generated fewer dynamic basic blocks on the second fault-fixing strategy (fixing the faults in the first 20% the ranking statements) than on the first one (fixing all the faults in the statements ranked), both diagnosis algorithms reduce the average *DBB* size and the *ideal diagnosis accuracy* on the second strategy. When applying Strategy two, ideally, a programmer only needs to visit one third of the statements (11.95/34.48 with Tarantula algorithm and 7.49/25.26 with RUBAR algorithm) as they would do when using Strategy one. That is, when performing fault localization, the second fault-fixing strategy is more efficient than the first one. Just as Jones [14] concluded, the first 20% ranking statements are more fault-prone.

Table 5-5 Diagnosis accuracy evaluation

	Strategy one		Strategy two	
	Tarantula	RUBAR	Tarantula	RUBAR
# of DBBs	417	557	299	480
Average size of DBBs	8.06	6.03	7.29	4.55
Ideal diagnosis accuracy	34.48	25.26	11.95	7.49

5.3 Cast study 2: the PackHexchar program

5.3.1 Introduction

PackHexChar is a Java adaptation of the Sreadhex procedure, used in the GhostScript program and described in [21], to manipulate hexadecimal characters. PackHexChar [5] has three inputs: a string S , two integers $RLEN$ and ODD_DIGIT . The input S is a string of hexadecimal digits. The main purpose of PackHexChar is to generate a compacted representation of S in binary format, specifically as an array of Bytes: e.g., string “34AB”, corresponding to binary values 0011, 0100, 1010, and 1011, is compacted into an array of two Byte values 00110100 and 10101011. In the input string, characters other than hexadecimal ones are ignored. In addition to the array of Bytes, the program returns an integer value. If the input string contains an even number of hexadecimal characters, pairs of hexadecimal characters are compacted, and the returned integer value equals to -1. If the input string contains an odd number of hexadecimal characters, an even number of characters is compacted, and the program returns the remaining hexadecimal character. A user can decide to look at only a sub-string of the input string S , by using the input parameter $RLEN$: the $RLEN$ first characters of S are analyzed and compacted. If $RLEN$ is not a legal value (negative or greater than S 's length), the program returns value -2. The user can also ask the program to append a hexadecimal character at the beginning of S , by using the input parameter ODD_DIGIT . This is useful when a string is split and analyzed

in pieces with repeated calls to `PackHexChar`: a call can return a trailing hexadecimal character, which has to be appended at the beginning of the string during the next call. An `ODD_DIGIT` value of -1 indicates that no character is to be appended. If `ODD_DIGIT` has an illegal value (below -1 or not a hexadecimal value), the program returns value -3.

In [5], the authors implemented the `PackHexChar` program in Java. They also applied the Category-Partition technique on the program and identified nine categories and 36 choices. To perform their case study, the authors generated a pool with 230 mutants of class `PackHexChar` by using MuJava¹⁰. These 230 mutants can be classified into 10 groups according to the mutation operators used. After applying their test suite refinement technique, they generated a test suite with 221 test cases. As a result, each mutant can be killed by at least one test case of the test suite. In this case study, we used those CP definitions, mutants and test cases to perform the experiment.

5.3.2 A multi-fault version of `PackHexChar`

When performing the cost-effectiveness analysis, instead of comparing Tarantula and RUBAR on one multi-fault program version as we did in the first case study, we made a statistical comparison using more than one multi-fault version. To obtain more comparable rankings, we ensured that each fault version contains the same number of faults. According to the size of the `PackHexChar` program and our intention of a balanced number¹¹ of passing and failing test cases, we used three mutants to create each faulty version. We first randomly select 51 mutants from the mutant pool of 230 `PackHexChar` mutants, making sure that at least one mutant was selected for each mutant operator.

¹⁰ <http://ise.gmu.edu/~ofut/mujava/>

¹¹ In this case study, at least 40% and at most 60% test cases shall pass under a multi-fault version. That is, the number of passing test cases shall be larger than 88 and no more than 132 out of the 221 test cases.

These 51 mutants were divided into 20 groups according to the statement they modified. That is, mutants that modify the same “*correct*” statement form a group. Using the 51 mutants we therefore randomly created 135 different PackHexChar program versions¹², each one containing three faults, and making sure that the three faults belonged to three different mutation groups.

Last, we did not follow the iterative process discussed in section 4.3.4 since this would have been too expensive: we would have obtained 135 different series of rankings.

5.3.3 Rule Induction Based on Category Partition

To evaluate the effectiveness of the rule induction technique, we apply the statistics analysis mentioned in section 3.3. In this case study, we used the 95% confidence coefficient and since the sample size is $N = 135$, $t_{0.025,134} = 1.96$.

By applying the C4.5 classification algorithm on the selected 135 faulty versions of PackHexChar, we obtained a classification tree for each version (Appendix D.1 are three sample C4.5 trees generated). These trees are accurate in test case classification; for example, the Fail class has an average 93.9% precision and 89.8% recall (Table 5-6). The mean ROC area is 0.908, which is excellent according to the accuracy point discussed in section 3.2.3.2.

¹² The original PackHexChar program was instrumented with all 51 mutants to be able to selectively enable them or not (e.g., we added control flow statements to enable them). In the results, we made sure not to rank those instrumentation statements.

Table 5-6 Statistical accuracy of stratified 10-fold cross-validation by class

Class	Items	Min value	Max value	Mean value	95% Confidence Interval	
					Lower limit	Upper limit
Fail	TN Rate	0.789	1.000	0.898	0.891	0.905
	FN Rate	0.000	0.226	0.063	0.058	0.069
	Precision	0.816	1.000	0.939	0.932	0.946
	Recall	0.789	1.000	0.898	0.891	0.905
	F-Measure	0.815	0.995	0.916	0.912	0.919
	ROC Area	0.877	0.995	0.908	0.903	0.912
Pass	TP Rate	0.774	1.000	0.937	0.931	0.942
	FP Rate	0.000	0.211	0.102	0.095	0.109
	Precision	0.780	1.000	0.881	0.872	0.890
	Recall	0.774	1.000	0.937	0.931	0.942
	F-Measure	0.831	0.996	0.906	0.902	0.910
	ROC Area	0.877	0.995	0.908	0.903	0.912

These classification trees are also helpful in understanding the failing condition(s) of the failing test cases. Take the fault version Ver-71 as an example, which contains mutant *AODU4*. A test case will kill this mutant when the test case asks for a transformation of an ODD number of hexadecimal characters. From the C4.5 tree in Appendix D.1.1, we can identify that when the input string *s* contains an EVEN number of hexadecimal characters and the ODD_DIGIT value is not -1 (that is, a character will be appended, which makes it a transformation of an ODD number of hexadecimal characters), the test case has a large probability to fail. This is consistent with the effect of the mutant *AODU4*.

5.3.4 The statistical cost-effectiveness analysis

For this experiment, we ranked the statements on each individual faulty version with the Tarantula method and the RUBAR method respectively. To better understand the cost-effectiveness of both methods, we calculate the statistical values (e.g. mean, 95% confidence interval) of those cost-effectiveness analyses of both methods. Then, we obtained the statistical cost-effectiveness of the ranking of statements based on Tarantula

and RUBAR as reported in Figure 5-5(a) and Figure 5-5(b). The middle curve represents the estimation of the mean cost-effectiveness, the bottom curve shows the estimated lower limit of the mean and the top curve shows the estimated upper limit of the mean.

Figure 5-5 Statistical statement ranking of 135 faulty versions

From the graph, we can see that RUBAR acts better than Tarantula. For example, the statement ranked first (the starting point of the curve) by RUBAR has a probability of 9.74% to be a faulty statement, and that statement ranked by Tarantula has a probability of 3.55% to be a faulty statement. By visiting 10% (resp. 30%) statements, RUBAR pinpoints to 20.31% (resp. 66.48%) faulty statements whereas Tarantula pinpoints only 15.66% (resp. 38.89%) faulty statements.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This thesis describes a new strategy (RUBAR) to support debugging by ranking statements according to their likelihood of containing a fault and by identifying in a precise manner the input conditions/properties leading to failure. The general idea is to analyze test case executions using a decision-tree learning algorithm that tries to model which conditions lead to test case failure. Potentially relevant conditions/properties are predefined using a black-box test technique (Category-Partition). Each path in the tree then represents a rule modeling distinct conditions of failures, possibly originating from different faults, and leads to a distinct failure probability prediction. Then, in a way similar to the well-known Tarantula technique, this is used to perform statement ranking by accounting for the statement coverage of failing/passing test cases within each rule, assuming that test cases are likely to fail due to the same faults when belonging to the same rule. The rankings of all Pass and Fail rules is then aggregated to form a final statement ranking to be used by the tester to prioritize his or her search. To summarize, our main objectives are two-fold: (1) deal with programs containing multiple faults and (2) provide testers with precise information regarding the conditions of failure.

Two case studies were presented to demonstrate the improvements generated by our approach when compared to the original Tarantula technique. Results show that many faulty statements would be inspected much earlier when using our approach. The difference is clearly of practical significance. It also confirms, following a procedure

different from the ones applied in literature, that iteratively looking at (and fixing defects in) the first 20% ranked statements is a reasonable heuristic to apply during fault localization.

In addition, though it is harder to demonstrate its practical value in quantitative terms, the C4.5 decision tree is also very accurate at modeling the various conditions of failures, thus helping testers understand what could be the causes of these failures. Such conditions are modeled as rules characterizing the input and output properties of test cases.

6.2 Future work

First, more research is required to accurately locate faults located in initialization statements. The problem is that those faults are often executed equally by failing and passing test cases, leading to those statements being ranked in the middle of the ranking. Our case studies and other researchers' experiments [3, 15] all show that current diagnosis algorithms cannot accurately locate those faults. Different diagnosis algorithms need to be devised.

Most of the existing fault localization algorithms are based on statement coverage. It is usually time-consuming to generate and analyze code coverage for each test case, especially when the test suite and/or the program-under-test are very large. Some research [9, 18] focuses on the method level fault localization, but require instrumentation and analysis of execution traces, which can be expensive and may alter (though slightly) program behavior. Future work will investigate other techniques, such as method coverage, and compare results obtained with statement coverage.

Another issue is the comparison with existing cluster-based fault localization techniques [13, 38] and the debugging-in-parallel method [13]. These methods have been proved to be efficient in a multi-fault scenario. RUBAR is also a cluster-based fault localization method and it uses C4.5 rules to cluster the failed test cases. Compared with [13, 38], RUBAR does not need the execution models to group the failed test cases and the information of the cluster (rule definitions) generated by RUBAR can also help program diagnosis.

Future work should also include additional case studies, and the application of similar ideas to regression testing and software evolution.

CHAPTER 7 REFERENCE

- [1] Agrawal H., Horgan J. R., London S., et al., "Fault Localization using Execution Slices and Dataflow Tests," *International Symposium on Software Reliability Engineering*, Toulouse, France, 1995.
- [2] Araki K., Furukawa Z., and Cheng J., "A General Framework for Debugging," *IEEE Software*, 1991.
- [3] Baudry B., Fleurey F., and Traon Y. L., "Improving Test Suites for Efficient Fault Localization," *International Conference on Software Engineering*, Shanghai, China, 2006.
- [4] Bowring J. F., Rehg J. M., and Harrold M. J., "Active Learning for Automatic Classification of Software Behavior," *Proceeding of the International Symposium on Software Testing and Analysis*, Boston, Massachusetts, USA, 2004.
- [5] Briand L. C., Labiche Y., and Bawar Z., "Using Machine Learning to Refine Black-box Test Specifications and Test Suites," Software Quality Engineering Laboratory, Carleton University TR SCE-07-05, 2007.
- [6] Brun Y. and Ernst M. D., "Finding latent code errors via machine learning over program executions," *International Conference on Software Engineering*, 2004.
- [7] Cleve H. and Zeller A., "Locating Causes of Program Failures," *Proceeding of International Conference on Software Engineering*, St. Louis, Missouri, USA, 2005.
- [8] Cohen W. W. and Singer Y., "Simple, Fast, and Effective Rule Learner," *AAAI/IAAI*, 1999.
- [9] Dallmeier V., Lindig C., and Zeller A., "Lightweight Defect Localization for Java," *European Conference on Object-Oriented Programming*, Glasgow, Scotland, 2005.
- [10] Demillo R. A., Pan H., and Spafford E. H., "Critical Slicing for Software Fault Localization," *ISSTA*, San Diego, California, U.S.A., 1996.
- [11] Ernst M. D., Cockrell J., Griswold W. G., et al., "Dynamically discovering likely program invariants to support program evolution," *IEEE Transaction on Software Engineering*, vol. 27, pp. 1-25, 2001.
- [12] Hutchins M., Froster H., Goradia T., et al., "Experiments on the Effectiveness of Dataflow- and Controlflow-Based Test Adequacy Criteria," *16th IEEE International Conference on Software Engineering*, Sorrento (Italy), 1994.
- [13] Jones J. A., Bowring J. F., and Harrold M. J., "Debugging in Parallel," *ISSTA*, London, England, 2007.
- [14] Jones J. A. and Harrold M. J., "Empirical Evaluation of the Tarantula Automatic Fault-Localization Technique," *International Conference on Automated Software Engineering*, Long Beach, California, 2005.

- [15] Jones J. A., Harrold M. J., and Stasko J. T., "Visualization of Test Information to Assist Fault Localization," *International Conference on Software Engineering*, Orlando, Florida, 2002.
- [16] Jorgensen P. C., *Software Testing: A Craftsman's Approach*, 2nd ed: CRC Press, 1995.
- [17] Liblit B., Naik M., Zheng A. X., et al., "Scalable Statistical Bug Isolation," *ACM SIGPLAN conference on Programming language design and implementation*, 2005.
- [18] Liu C., "Mining Control Flow Abnormality for Logic Error Isolation," *SIAM International Conference on data Mining*, 2006.
- [19] Liu C. and Han J., "Failure Proximity: A Fault Localization-Based Approach," *ACM SIGSOFT Foundations of Software Engineering*, 2006.
- [20] Myers G. J., *The art of Software Testing*, 2nd ed: Hohn Wiley & Sones, Inc, 1979.
- [21] Ostrand T. J. and Balcer M. J., "The Category-Partition Method for Specifying and Generating Functional Test," *Communications of the ACM*, vol. 31, pp. 676-686, 1988.
- [22] Pan H. and Spafford E. H., "Heuristics for Automatic Localization of Software Faults," Purdue Universtiy Technical Report SERC-TR-116-P, 1992.
- [23] Pasquini A., Crespo A., and Matrelle P., "Sensitivity of reliability-growth models to operational profiles errors vs testing accuracy," *IEEE Transactions on Reliability*, vol. 45, pp. 531-540, 1996.
- [24] Podgurski A., Leon D., Francis P., et al., "Automated Support for Classifying Software Failure Reports," *International Conference on Software Engineering*, 2003.
- [25] Pressman R. S., *Software Engineering: A Practitioner's Approach*, 5th ed: McGraw-Hill Companies, Inc, 2001.
- [26] Quinlan J. R., *C4.5: Programs for Machine Learning*: Morgan Kaufmann, 1993.
- [27] Renieris M. and Reiss S. P., "Fault Localization with Nearest Neighbor Queries," *International Conference on Automated Software Engineering*, Montreal, Quebec, 2003.
- [28] Rothermel G., Untch R. H., Chu C., et al., "Prioritizing test cases for regression testing," *IEEE Transactions on Software Engineering*, vol. 27, pp. 929-948, 2001.
- [29] Snedecor G. W. and Cochran W. G., *Statistical Methods*, Eighth ed: Iowa State University Press, 1989.
- [30] Vokolos F. I. and Frankl P. G., "Empirical evaluation of the textual differencing regression testing technique," *IEEE International Conference on Software Maintenance*, Bethesda, MD, USA, 1998.
- [31] Weiser M., "Program slicing," *IEEE Transactions on Software Engineering*, pp. 10:352--357, 1984.

- [32] Weiser M., "Programmers use slices when debugging," *Communications of the ACM*, vol. 25, pp. 446-452, 1982.
- [33] Witten I. H. and Frank E., *Data Mining: Practical Machine Learning Tools and Techniques*, 2nd ed: Morgan Kaufman, 2005.
- [34] Wong W. E., Horgan J. R., Mathur A. P., et al., "Test Set Size Minimization and Fault Detection Effectiveness: A Case Study in a Space Application," Software Engineering Research Center (SERC), Technical Report TR-173-P, 1997.
- [35] Xu S. and Rajlich V., "Cognitive Process during Program Debugging," *the IEEE International Conference on Cognitive Informatics*, Irvine, California, U.S.A., 2004.
- [36] Yoon B. and Garcia O. N., "Cognitive activities and support in debugging," *Proceedings of Annual Symposia on Human Interaction with Complex System*, 1998.
- [37] Zeller A., *Why Programs Fail: A guide to Systematic Debugging*: Morgan Kaufman, 2005.
- [38] Zheng A. X., Jordan M. I., Liblit B., et al., "Statistical Debugging: Simultaneous Identification of Multiple Bugs," *Proceedings of International Conference on Machine Learning*, Pittsburgh, PA, 2006.

APPENDIX A TRIANGLE PROGRAM

The triangle program accepts three integers as inputs, which are taken as the sides of a triangle. The output of this program is the type of the triangle determined by the three sides: Equilateral, Isosceles, Scalene, or NotATriangle.

Table A-1 describes the inputs of ten test cases and the type of triangle determined by these inputs. Suppose that the triangle program has bugs to detect NotATriangle when the sizes are illegal (Figure A-1). The test suite will generate a test result in Table A-1 (the last column).

As mentioned above, the category-partition method can be used to identify the inputs of a program. Table 3-1 is a simple sample of the CP definition for the triangle program. When applied the CP definition of Table 3-1, the test suite of Table A-1 can be described as Table A-2.

```
1 String triangleType(Float s1, Float s2, Float s3){
2
3     /*should check the inputs first*/
4
5     if (s1==s2 && s2==s3)
6         return "Equilateral";
7
8     if (s1==s2 || s2==s3 || s3==s1)
9         return "Isosceles";
10    return "Scalene"
11 }
```

Figure A-1 Sample faulty Triangle program

Table A-1 A test suite and the test result of the triangle program

TC	S_1	S_2	S_3	Expected Result	Test Result
TC ₁	2	4	5	Scalene	Pass
TC ₂	8	10	6	Scalene	Pass
TC ₃	6	6	6	Equilateral	Pass
TC ₄	6	5	5	Isosceles	Pass
TC ₅	11	11	3	Isosceles	Pass
TC ₆	3	2	3	Isosceles	Pass
TC ₇	1	2	3	NotATriangle	Fail
TC ₈	2	5	2	NotATriangle	Fail
TC ₉	0	2	2	NotATriangle	Fail
TC ₁₀	-1	-1	-1	NotATriangle	Fail

Table A-2 The test suite described by the CP definition

TC	CA01	CA02	CA03	CA04	CA05	CA06	CA07	CA08	CA09	CA10	Test Result
TC ₁	$s1 < s2$	$s2 < s3$	$s3 > s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₂	$s1 < s2$	$s2 > s3$	$s3 < s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₃	$s1 = s2$	$s2 = s3$	$s3 = s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₄	$s1 > s2$	$s2 = s3$	$s3 < s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₅	$s1 = s2$	$s2 > s3$	$s3 < s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₆	$s1 > s2$	$s2 < s3$	$s3 = s1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Pass
TC ₇	$s1 < s2$	$s2 < s3$	$s3 > s1$	Yes	Yes	Yes	No	No	No	Yes	Fail
TC ₈	$s1 < s2$	$s2 > s3$	$s3 = s1$	No	Yes	No	Yes	No	Yes	No	Fail
TC ₉	$s1 < s2$	$s2 = s3$	$s3 > s1$	Yes	Yes	No	No	No	No	No	Fail
TC ₁₀	$s1 = s2$	$s2 = s3$	$s3 = s1$	No	No	No	No	No	No	No	Fail

APPENDIX B CLASS DIAGRAM OF RUBAR ALGORITHM

APPENDIX C SPACE PROGRAM

C.1 The Space program

The following table is a brief classification of the mutations of the SPACE program.

Equivalent mutations	mutant01, mutant02, mutant32
Initialization mutations	mutant29, mutant34
Selected mutations	mutant07, mutant08, mutant11, mutant13, mutant14, mutant15, mutant16, mutant17, mutant18, mutant20, mutant22, mutant23, mutant24, mutant31, mutant37

C.2 Category partition definition

PA00	Input Parameter		
	CA0001	Valid Input	
		CH000101	ValidFile [property valid_File]
		CH000102	EmptyFile [ERROR]
	CA0002	Invalid File	
		CH000201	Nonexist_File [ERROR]
		CH000202	Wrong_Parameter_Num [ERROR]
PA01	Group Name		
	CA0101	Length of name	
		CH010101	length=0 [property no_name]
		CH010102	length[1..29] [property gname]
		CH010103	length>=30 [property too_long_gname]
	CA0102	Context of name	
		CH020101	start_with Alpha [if gname]
		CH020102	start_with Number [if gname]
		CH020103	start_with Other_Char [if gname]
		CH020104	in Keyword_list [if gname]
		CH020105	missingValue [if no_name]
PA02	GRID Def		
	CA0201	definition in { SQUARE, RECTANGULAR, HEXAGONAL, TRIANGULAR}	
		CH020101	SQUARE [property G_Square]
		CH020102	RECTANGULAR [property G_Rectangular]
		CH020103	HEXAGONAL [property G_Hexagonal]
		CH020104	TRIANGULAR [property G_Triangular]
	CA0202	other nominal value	
		CH020201	INVALID_VALUE [ERROR]
		CH020202	missingValue [property G_Missing]
PA03	Grid Elem Def		
	CA0301	definition in { STEP, PSTEP, ANGLE, PX}	
		CH030101	STEP [if G_Square or G_Hexagonal, property step]
		CH030102	PSSTEP [if G_Rectangular or G_Triangular, property pstep]
		CH030103	ANGLE [if G_Triangular, property angle]
		CH030104	PX [if G_Triangular, property lateral]
	CA0301	Other value	
		CH030201	INVALID_VALUE [ERROR]
		CH030202	missingValue [if G_Missing]

PA04	Grid Elem Val1			
	CA0401	valid value		
		CH040101	=0	[if step or pstep or angle]
		CH040102	>0	[if step or pstep or angle]
		CH040103	missingValue	[if G Missing or lateral]
	CA0402	invalid value		
		CH040201	<0	[ERROR][if step or pstep or angle]
		CH040202	non-number	[ERROR][if step or pstep or angle]
		CH040203	ErrorMissing	[ERROR][if step or pstep or angle]
PA05	Grid Elem Val2			
	CA0501	valid value		
		CH050101	=0	[if pstep or angle]
		CH050102	>0	[if pstep or angle]
		CH050103	missingValue	[if step or lateral]
	CA0502	invalid value		
		CH050201	<0	[ERROR][if pstep or angle]
		CH050202	non-number	[ERROR][if pstep or angle]
		CH050203	ErrorMissing	[ERROR][if G Square or lateral]
PA06	Grid Elem Triang Val1			
	CA0601	number		
		CH060101	=0	[if angle or literal]
		CH060102	>0	[if angle or literal]
		CH060103	<0	[if angle or literal]
		CH060104	missingValue	[if not (angle or literal)]
	CA0602	non number		
		CH060201	non-number	[ERROR][if angle or literal]
		CH060202	ErrorMissing	[ERROR][if angle or literal]
PA07	Grid Elem Triang Val2			
	CA0701	number		
		CH070101	=0	[if literal]
		CH070102	>0	[if literal]
		CH070103	<0	[if literal]
		CH070104	missingValue	[if not literal]
	CA0702	non number		
		CH070201	non-number	[ERROR][if literal]
		CH070202	ErrorMissing	[ERROR][if literal]
PA08	Grid Elem Triang Val3			
	CA0801	number		
		CH080101	=0	[if literal]
		CH080102	>0	[if literal]
		CH080103	<0	[if literal]
		CH080104	missingValue	[if not literal]
	CA0802	non number		
		CH080201	non-number	[ERROR][if literal]
		CH080202	ErrorMissing	[ERROR][if literal]
PA09	Grid Elem Triang Val3			
	CA0901	number		
		CH090101	=0	[if literal]
		CH090102	>0	[if literal]
		CH090103	<0	[if literal]
		CH090104	missingValue	[if not literal]
	CA0902	non number		
		CH090201	non-number	[ERROR][if literal]

		CH090202	ErrorMissing	[ERROR][if literal]
PA10	Grid Elem Unit			
	CA1001	Definition in { dm, cm, mm, m }		
		CH100101	dm	[if step or pstep]
		CH100102	cm	[if step or pstep]
		CH100103	mm	[if step or pstep]
		CH100104	m	[if step or pstep]
	CA1002	Other value		
		CH100201	INVALID_VALUE	[if step or pstep]
		CH100202	missingValue	
PA11	Grid Elem Angle Unit			
	CA1101	Definition in {deg, rad}		
		CH110101	deg	[if angle]
		CH110102	rad	[if angle]
	CA1102	Other value		
		CH110201	INVALID_VALUE	[if angle]
		CH110202	missingValue	
PA12	Element Name			
	CA1201	Definition in {GEOMETRY}		
		CH120101	GEOMETRY	[property geometry]
	CA1202	length of string		
		CH120201	length=0	[if not geometry, property missing Name]
		CH120202	length[1..29]	[if not geometry, property E Name]
		CH120203	length>=30	[if not geometry, property long Name]
	CA1203	context of name		
		CH120301	start with Alpha	[if E Name]
		CH120302	start with Number	[if E Name]
		CH120303	start with Other Char	[if E Name]
		CH120304	in Keyword list	[if E Name]
PA13	Elem Geometry Def			
	CA1301	Definition in {CIRCULAR, RECTANGULAR }		
		CH130101	CIRCULAR	[if geometry, property E Circular]
		CH130102	RECTANGULAR	[if geometry, property E Rectangular]
	CA1302	Other value		
		CH130201	INVALID_VALUE	[if geometry, property wrong E_Def]
		CH130202	missingValue	[if missing Name]
PA14	Elem Geometry Val1			
	CA1401	unsigned real number		
		CH140101	=0	[if E Circular or E Rectangular]
		CH140102	> 0	[if E Circular or E Rectangular]
	CA1402	wrong value		
		CH140201	<0	[ERROR][if E Circular or E Rectangular]
		CH140202	non-number	[ERROR][if E Circular or E Rectangular]
		CH140203	missingValue	[if wrong E_Def or not geometry]
PA15	Elem Geometry Val2			
	CA1501	unsigned real number		
		CH150101	=0	[if E Rectangular]
		CH150102	> 0	[if E Rectangular]
	CA1502	wrong value		
		CH150201	<0	[ERROR][if E Rectangular]
		CH150202	non-number	[ERROR][if E Rectangular]
		CH150203	ErrorMissing	[ERROR][if E Rectangular]
		CH150204	missingValue	[if not E Rectangular]

PA16	Elem Geometry Unit		
	CA1601	Definition in {dm,cm,mm,m}	
		CH160101	dm [if E_Circular or E_Rectangular]
		CH160102	cm [if E_Circular or E_Rectangular]
		CH160103	mm [if E_Circular or E_Rectangular]
		CH160104	m [if E_Circular or E_Rectangular]
	CA1602	Other value	
		CH160201	INVALID VALUE [ERROR][if E_Circular or E_Rectangular]
		CH160202	missingValue
PA17	Elem Polarization Spec		
	CA1701	Definition in { LINEAR, CIRCULAR }	
		CH170101	LINEAR [if geometry, property E_P_linear]
		CH170102	CIRCULAR [if geometry, property E_P_circular]
	CA1702	Other value	
		CH170201	INVALID VALUE [ERROR]
		CH170202	missingValue
PA18	Elem Polar Def		
	CA1801	Definition in {ORIENTATION, LH, RH }	
		CH180101	ORIENTATION [if E_P_linear, property E_P_orientation]
		CH180102	LH [if E_P_circular]
		CH180103	RH [if E_P_circular]
	CA1802	Other value	
		CH180201	INVALID VALUE [ERROR][if E_P_linear or E_P_circular]
		CH180202	missingValue
PA19	Elem Polar LinePol Val		
	CA1901	Definition in {X, Y}	
		CH190101	X [if E_P_orientation]
		CH190102	Y [if E_P_orientation]
	CA1902	real number	
		CH190201	=0 [if E_P_orientation]
		CH190202	>0 [if E_P_orientation]
		CH190203	<0 [if E_P_linear]
	CA1903	Other value	
		CH190301	INVALID VALUE [ERROR][if E_P_orientation]
		CH190302	errorMissing [ERROR][if E_P_orientation]
		CH190302	missingValue
PA20	Elem Polar LinePol Unit		
	CA2001	Definition in {deg, rad}	
		CH200101	deg [if E_P_orientation]
		CH200102	rad [if E_P_orientation]
	CA2002	null value	
		CH200201	INVALID VALUE [ERROR][if E_P_orientation]
		CH200202	missingValue
PA21	Elem Port Number		
	CA2101	Natural number	
		CH210101	=0 [if geometry, property no_Port]
		CH210102	[1, 998] [if geometry, property medium_Size_Port]
		CH210103	=999 [if geometry, property large_Size_Port]
	CA2102	other number	
		CH210201	>999 [ERROR][if geometry]
		CH210202	<0 [ERROR][if geometry]
		CH210203	real_number [ERROR][if geometry]
	CA2103	other value	

		CH210301	INVALID VALUE	[ERROR][if geometry]
		CH210302	missingValue	
PA22	Elem Port Set ENum			
	CA2201	number of the element		
		CH220101	=0	[if no Port, property missingPortDef]
		CH220102	=1	[if medium Size Port, property onePortDef]
		CH220103	>1	[if medium Size Port or large Size Port]
PA23	Elem Port Orient Val			
	CA2301	content of the set		
		CH230101	X	[if not missingPortDef]
		CH230102	Y	[if not missingPortDef]
		CH230103	>0	[if not missingPortDef]
		CH230104	=0	[if not missingPortDef]
		CH230105	<0	[if not missingPortDef]
		CH230106	combination	[if not (missingPortDef or onePortDef)]
		CH230107	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH230108	allInvalid	[if not missingPortDef]
		CH230109	missingValue	
PA24	Elem Port Orient UNIT			
	CA2401	content of the set		
		CH240101	deg	[if not missingPortDef]
		CH240102	rad	[if not missingPortDef]
		CH240103	combination	[if not (missingPortDef or onePortDef)]
		CH240104	mixedValue	[if not (missingPortDef or onePortDef)]
		CH240105	allInvalid	[if not missingPortDef]
		CH240106	missingValue	
PA25	Elem Port Amp Val			
	CA2501	content of the set		
		CH250101	>0	[if not missingPortDef]
		CH250102	=0	[if not missingPortDef]
		CH250103	<0	[if not missingPortDef]
		CH250104	combination	[if not (missingPortDef or onePortDef)]
		CH250105	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH250106	allInvalid	[if not missingPortDef]
		CH250107	missingValue	
PA26	Elem Port Amp Unit			
	CA2601	content of the set		
		CH260101	dm	[if not missingPortDef]
		CH260102	mm	[if not missingPortDef]
		CH260103	cm	[if not missingPortDef]
		CH260104	m	[if not missingPortDef]
		CH260105	dB	[if not missingPortDef]
		CH260106	POWER	[if not missingPortDef]
		CH260107	LINEAR	[if not missingPortDef]
		CH260108	combination	[if not (missingPortDef or onePortDef)]
		CH260109	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH260110	allInvalid	[if not missingPortDef]
		CH260111	missingValue	
PA27	Elem Port Shdef Val			
	CA2701	content of the set		
		CH270101	>0	[if not missingPortDef]
		CH270102	=0	[if not missingPortDef]
		CH270103	<0	[if not missingPortDef]

		CH270104	combination	[if not (missingPortDef or onePortDef)]
		CH270105	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH270106	allInvalid	[if not missingPortDef]
		CH270107	missingValue	
PA28	Elem Port Shdef Unit			
	CA2801	content of the set		
		CH280101	deg	[if not missingPortDef]
		CH280102	rad	[if not missingPortDef]
		CH280103	combination	[if not (missingPortDef or onePortDef)]
		CH280104	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH280105	allInvalid	[if not missingPortDef]
		CH280106	missingValue	
PA29	Elem Port Scdef Val			
	CA2901	content of the set		
		CH290101	>0	[if not missingPortDef]
		CH290102	=0	[if not missingPortDef]
		CH290103	<0	[if not missingPortDef]
		CH290104	combination	[if not (missingPortDef or onePortDef)]
		CH290105	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH290106	allInvalid	[if not missingPortDef]
		CH290107	missingValue	
PA30	Elem Port Scdef Unit			
	CA3001	content of the set		
		CH300101	deg	[if not missingPortDef]
		CH300102	rad	[if not missingPortDef]
		CH300103	combination	[if not (missingPortDef or onePortDef)]
		CH300104	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH300105	allInvalid	[if not missingPortDef]
PA31	Elem Port Padef Val			
	CA3101	content of the set		
		CH310101	>0	[if not missingPortDef]
		CH310102	=0	[if not missingPortDef]
		CH310103	<0	[if not missingPortDef]
		CH310104	combination	[if not (missingPortDef or onePortDef)]
		CH310105	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH310106	allInvalid	[if not missingPortDef]
		CH310107	missingValue	
PA32	Elem Port Padef Unit			
	CA3201	content of the set		
		CH320101	deg	[if not missingPortDef]
		CH320102	rad	[if not missingPortDef]
		CH320103	combination	[if not (missingPortDef or onePortDef)]
		CH320104	ContainInvalid	[if not (missingPortDef or onePortDef)]
		CH320105	allInvalid	[if not missingPortDef]
PA33	Grgeo Add Def			
	CA3301	Definition in {HEXAGON, BLOCK, NODE, POLYGON}		
		CH330101	NODE	[property node]
		CH330102	HEXAGON	[property hexagon]
		CH330103	BLOCK	[property block]
		CH330104	POLYGON	[property polygon]
	CA3302	Other value		
		CH330201	INVALID VALUE	[ERROR]
		CH330202	errorMissing	[ERROR]

PA34	Grgeo Add Int Val1			
	CA3401	integer		
		CH340101	<0	[if node or hexagon or block or polygon]
		CH340102	=0	[if node or hexagon or block or polygon]
		CH340103	>0	[if node or hexagon or block or polygon]
	CA3402	Other value		
		CH340201	real number	[ERROR][if node or hexagon or block or polygon]
		CH340202	non-number	[ERROR][if node or hexagon or block or polygon]
		CH340203	errorMissing	[ERROR][if node or hexagon or block or polygon]
PA35	Grgeo Add Int Val2			
	CA3501	integer		
		CH350101	<0	[if node or hexagon or block or polygon]
		CH350102	=0	[if node or hexagon or block or polygon]
		CH350103	>0	[if node or hexagon or block or polygon]
	CA3502	Other value		
		CH350201	real number	[ERROR][if node or hexagon or block or polygon]
		CH350202	non-number	[ERROR][if node or hexagon or block or polygon]
		CH350203	errorMissing	[ERROR][if node or hexagon or block or polygon]
PA36	Grgeo Add Int Val3			
	CA3601	integer		
		CH360101	<0	[if block or polygon]
		CH360102	=0	[if block or polygon]
		CH360103	>0	[if block or polygon]
	CA3602	Other value		
		CH360201	real number	[ERROR][if block or polygon]
		CH360202	non-number	[ERROR][if block or polygon]
		CH360203	errorMissing	[ERROR][if block or polygon]
		CH360204	missingValue	[if not(block or polygon)]
PA37	Grgeo Add Int Val4			
	CA3701	integer		
		CH370101	<0	[if block or polygon]
		CH370102	=0	[if block or polygon]
		CH370103	>0	[if block or polygon]
	CA3702	Other value		
		CH370201	real number	[ERROR][if block or polygon]
		CH370202	non-number	[ERROR][if block or polygon]
		CH370203	errorMissing	[ERROR][if block or polygon]
		CH370204	missingValue	[if not(block or polygon)]
PA38	Grgeo Add Int Val5			
	CA3801	integer		
		CH380101	<0	[if polygon]
		CH380102	=0	[if polygon]
		CH380103	>0	[if polygon]
	CA3802	Other value		
		CH380201	real number	[ERROR][if polygon]
		CH380202	non-number	[ERROR][if polygon]
		CH380203	errorMissing	[ERROR][if polygon]
		CH380204	missingValue	[if not(polygon)]
PA39	Grgeo Add Int Val6			
	CA3901	integer		
		CH390101	<0	[if polygon]
		CH390102	=0	[if polygon]
		CH390103	>0	[if polygon]

	CA3802	Other value		
		CH390201	real number	[ERROR][if polygon]
		CH390202	non-number	[ERROR][if polygon]
		CH390203	errorMissing	[ERROR][if polygon]
		CH390204	missingValue	[if not(polygon)]
PA40	Grgeo Add Real Val1			
	CA4001	real number		
		CH400101	<0	[if node]
		CH400102	=0	[if node]
		CH400103	>0	[if node]
	CA4002	Other value		
		CH400201	non-number	[ERROR][if node]
		CH400202	missingValue	
PA41	Grgeo Add Real Val2			
	CA4101	real number		
		CH410101	<0	[if node]
		CH410102	=0	[if node]
		CH410103	>0	[if node]
	CA4102	Other value		
		CH410201	non-number	[ERROR][if node]
		CH410202	missingValue	
PA42	Grgeo Add Real Val3			
	CA4201	real number		
		CH420101	<0	[if node]
		CH420102	=0	[if node]
		CH420103	>0	[if node]
	CA4202	Other value		
		CH420201	non-number	[ERROR][if node]
		CH420202	missingValue	
PA43	Grgeo Add Unit			
	CA4301	Definition in {deg, rad}		
		CH430101	deg	[if node]
		CH430102	rad	[if node]
	CA4302	other value		
		CH430201	INVALID_VALUE	[ERROR][if node]
		CH430202	missingValue	
PA44	Grgeo Additional_def			
	CA4401	number of set element		
		CH440101	=0	[property missingAddSet]
		CH440102	=1	[property singleAddSet]
		CH440103	>1	[property moreAddElem]
	CA4402	content of the set		
		CH440201	NODE	[if singleAddSet]
		CH440202	BLOCK	[if singleAddSet]
		CH440203	HEXAGON	[if singleAddSet]
		CH440204	combination	[if moreAddElem]
		CH440205	missingValue	[if missingAddSet]
PA45	Grgeo Additional Int Val1			
	CA4501	content of the set		
		CH450101	>0	[if not missingAddSet]
		CH450102	<0	[if not missingAddSet]
		CH450103	=0	[if not missingAddSet]
		CH450104	combination	[if not missingAddSet]

		CH450105	InvalidValue	[if not missingAddSet]
		CH450106	missingValue	
PA46	Grgeo Additional Int Val2			
	CA4601	content of the set		
		CH460101	>0	[if not missingAddSet]
		CH460102	<0	[if not missingAddSet]
		CH460103	=0	[if not missingAddSet]
		CH460104	combination	[if not missingAddSet]
		CH460105	InvalidValue	[if not missingAddSet]
		CH460106	missingValue	
PA47	Grgeo Additional Int Val3			
	CA4701	content of the set		
		CH470101	>0	[if not missingAddSet]
		CH470102	<0	[if not missingAddSet]
		CH470103	=0	[if not missingAddSet]
		CH470104	combination	[if not missingAddSet]
		CH470105	InvalidValue	[if not missingAddSet]
		CH470106	missingValue	
PA48	Grgeo Additional Int Val4			
	CA4801	content of the set		
		CH480101	>0	[if not missingAddSet]
		CH480102	<0	[if not missingAddSet]
		CH480103	=0	[if not missingAddSet]
		CH480104	combination	[if not missingAddSet]
		CH480105	InvalidValue	[if not missingAddSet]
		CH480106	missingValue	
PA49	Grgeo Additional Int Val5			
	CA4901	content of the set		
		CH490101	>0	[if not missingAddSet]
		CH490102	<0	[if not missingAddSet]
		CH490103	=0	[if not missingAddSet]
		CH490104	combination	[if not missingAddSet]
		CH490105	InvalidValue	[if not missingAddSet]
		CH490106	missingValue	
PA50	Grgeo Additional Int Val6			
	CA5001	content of the set		
		CH500101	>0	[if not missingAddSet]
		CH500102	<0	[if not missingAddSet]
		CH500103	=0	[if not missingAddSet]
		CH500104	combination	[if not missingAddSet]
		CH500105	InvalidValue	[if not missingAddSet]
		CH500106	missingValue	
PA51	Grgeo Additional Real Val1			
	CA5101	content of the set		
		CH510101	>0	[if not missingAddSet]
		CH510102	<0	[if not missingAddSet]
		CH510103	=0	[if not missingAddSet]
		CH510104	combination	[if not missingAddSet]
		CH510105	InvalidValue	[if not missingAddSet]
		CH510106	missingValue	
PA52	Grgeo Additional Real Val2			
	CA5201	content of the set		
		CH520101	>0	[if not missingAddSet]

		CH520102	<0	[if not missingAddSet]
		CH520103	=0	[if not missingAddSet]
		CH520104	combination	[if not missingAddSet]
		CH520105	InvalidValue	[if not missingAddSet]
		CH520106	missingValue	
PA53	Grgeo Additional Real Val3			
	CA5301	content of the set		
		CH530101	>0	[if not missingAddSet]
		CH530102	<0	[if not missingAddSet]
		CH530103	=0	[if not missingAddSet]
		CH530104	combination	[if not missingAddSet]
		CH530105	InvalidValue	[if not missingAddSet]
		CH530106	missingValue	
PA54	Grgeo Additional Unit			
	CA5401	content of the set		
		CH540101	deg	[if not missingAddSet]
		CH540102	rad	[if not missingAddSet]
		CH540103	combination	[if not missingAddSet]
		CH540104	InvalidValue	[if not missingAddSet]
		CH540105	missingValue	
PA55	Group Grexc Def			
	CA5501	Definition in {GROUP_EXCITATION}		
		CH550101	GROUP_EXCITATION	[property G_Excitation]
	CA5502	other value		
		CH550201	INVALID_VALUE	[ERROR]
		CH550202	errorMissing	[ERROR]
PA56	Grexc Gramp Exec			
	CA5601	Definition in {AMPLITUDE}		
		CH560101	AMPLITUDE	[property G_Amplitude]
	CA5602	other value		
		CH560201	INVALID_VALUE	[ERROR]
		CH560202	errorMissing	[ERROR]
PA57	Grexc Gramp Exec Def			
	CA5701	Definition in {UNIFORM, SECOND}		
		CH570101	UNIFORM	[if G_Amplitude, property gramp_uniform]
		CH570102	SECOND	[if G_Amplitude, property gramp_second]
	CA5702	other value		
		CH570201	INVALID_VALUE	[ERROR][if G_Amplitude]
		CH570202	errorMissing	[ERROR][if G_Amplitude]
PA58	Grexc Gramp Exec Vall			
	CA5801	real number		
		CH580101	=0	[if gramp_uniform or gramp_second]
		CH580102	>0	[if gramp_uniform or gramp_second]
		CH580103	<0	[if gramp_uniform or gramp_second]
	CA5802	Other value		
		CH580201	non-number	[ERROR][if gramp_uniform or gramp_second]
		CH580202	errorMissing	[ERROR][if gramp_second]
		CH580203	missingValue	[if gramp_uniform]
PA59	Grexc Gramp Exec Def2			
	CA5901	Definition in {P1_VAL}		
		CH590101	P1_VAL	[if gramp_second]
	CA5902	Other value		
		CH590201	INVALID_VALUE	[ERROR][if gramp_second]

		CH590202	errorMissing	[ERROR][if gramp_second]
		CH590203	missingValue	
PA60	Grexc Gramp Exec Val2			
	CA6001	real number		
		CH600101	=0	[if gramp_second]
		CH600102	>0	[if gramp_second]
		CH600103	<0	[if gramp_second]
	CA6002	Other value		
		CH600201	non-number	[ERROR][if gramp_second]
		CH600202	errorMissing	[ERROR][if gramp_second]
		CH600203	missingValue	
PA61	Grexc Gramp Exec Def3			
	CA6101	Definition in { P2_VAL }		
		CH610101	P2_VAL	[if gramp_second]
	CA6102	Other value		
		CH610201	INVALID_VALUE	[ERROR][if gramp_second]
		CH610202	errorMissing	[ERROR][if gramp_second]
		CH610203	missingValue	
PA62	Grexc Gramp Exec Val3			
	CA6201	real number		
		CH620101	=0	[if gramp_second]
		CH620102	>0	[if gramp_second]
		CH620103	<0	[if gramp_second]
	CA6202	Other value		
		CH620201	non-number	[ERROR][if gramp_second]
		CH620202	errorMissing	[ERROR][if gramp_second]
		CH620203	missingValue	
PA63	Grexc Gramp Exec Def4			
	CA6301	Definition in { Q1_VAL }		
		CH630101	Q1_VAL	[if gramp_second]
	CA6302	Other value		
		CH630201	INVALID_VALUE	[ERROR][if gramp_second]
		CH630202	errorMissing	[ERROR][if gramp_second]
		CH630203	missingValue	
PA64	Grexc Gramp Exec Val4			
	CA6401	real number		
		CH640101	=0	[if gramp_second]
		CH640102	>0	[if gramp_second]
		CH640103	<0	[if gramp_second]
	CA6402	Other value		
		CH640201	non-number	[ERROR][if gramp_second]
		CH640202	errorMissing	[ERROR][if gramp_second]
		CH640203	missingValue	
PA65	Grexc Gramp Exec Def5			
	CA6501	Definition in { Q2_VAL }		
		CH650101	Q2_VAL	[if gramp_second]
	CA6502	Other value		
		CH650201	INVALID_VALUE	[if gramp_second]
		CH650202	missingValue	
PA66	Grexc Gramp Exec Val5			
	CA6601	real number		
		CH660101	=0	[if gramp_second]
		CH660102	>0	[if gramp_second]

		CH660103	<0	[if gramp_second]
	CA6602	Other value		
		CH660201	non-number	[ERROR][if gramp_second]
		CH660202	errorMissing	[ERROR][if gramp_second]
		CH660203	missingValue	
PA67	Grexc Gramp Exec Unit			
	CA6701	Definition in { m,mm,dm,cm LINEAR, POWER, dB }		
		CH670101	LINEAR	[if gramp_uniform]
		CH670102	POWER	[if gramp_uniform]
		CH670103	dB	[if gramp_uniform]
		CH670104	mm	[if gramp_second]
		CH670105	dm	[if gramp_second]
		CH670106	cm	[if gramp_second]
		CH670107	m	[if gramp_second]
	CA6702	Other value		
		CH670201	INVALID_VALUE	[ERROR][if gramp_uniform or gramp_second]
		CH670202	missingValue	
PA68	Grexc Grpha Exec			
	CA6801	Definition in { PHASE }		
		CH680101	PHASE	[property phase]
	CA6802	other value		
		CH680201	INVALID_VALUE	[ERROR]
PA69	Grexc Grpha Def			
	CA6901	Definition in { UNIFORM, SECOND, ROTATION, POINTING }		
		CH690101	UNIFORM	[property grpha_uniform]
		CH690102	SECOND	[property grpha_second]
		CH690103	ROTATION	[property grpha_rotation]
		CH690104	POINTING	[property grpha_pointing]
	CA6902	other value		
		CH690201	INVALID_VALUE	
PA70	Grexc Grpha Exec Def			
	CA7001	Definition in { CW, CCW, U, THETA }		
		CH700101	CW	[if grpha_rotation]
		CH700102	CCW	[if grpha_rotation]
		CH700103	U	[if grpha_pointing, property pointing_axis]
		CH700104	THETA	[if grpha_pointing, property pointing_angle]
	CA7002	other value		
		CH700201	INVALID_VALUE	[ERROR]
		CH700202	missingValue	
PA71	Grexc Grpha Exec Val1			
	CA7101	values in[-1.1]		
		CH710101	=0	[if not grpha_uniform]
		CH710102	=-1	[if pointing_axis]
		CH710103	=1	[if pointing_axis]
		CH710104	(-1, 0)	[if pointing_axis]
		CH710105	(0, 1)	[if pointing_axis]
	CA7102	real number		
		CH710201	>0	[if not (grpha_uniform or pointing_axis)]
		CH710202	<0	[if not (grpha_uniform or pointing_axis)]
	CA7103	other value		
		CH710301	<-1	[ERROR][if pointing_axis]
		CH710302	>1	[ERROR][if pointing_axis]
		CH710303	non-number	[ERROR][if not grpha_uniform]

		CH710304	missingValue	
PA72	Grexc Grpha Exec Def1			
	CA7201	Definition in {P1_VAL, STEP, V, PHI}		
		CH720101	P1_VAL	[if grpha_second]
		CH720102	STEP	[if grpha_rotation]
		CH720103	V	[if pointing_axis]
		CH720104	PHI	[if pointing_angle]
	CA7202	other value		
		CH720201	INVALID_VALUE	[ERROR]
		CH720202	missingValue	
PA73	Grexc Grpha Exec Val2			
	CA7301	values in[-1.1]		
		CH730101	=0	[if not (grpha_uniform or pointing_angle)]
		CH730102	=-1	[if pointing_axis]
		CH730103	=1	[if pointing_axis]
		CH730104	(-1, 0)	[if pointing_axis]
		CH730105	(0, 1)	[if pointing_axis]
	CA7302	real number		
		CH730201	>0	[if not (grpha_uniform or grpha_pointing)]
		CH730202	<0	[if not (grpha_uniform or grpha_pointing)]
	CA7303	other value		
		CH730301	<-1	[ERROR][if pointing_axis]
		CH730302	>1	[ERROR][if pointing_axis]
		CH730303	non-number	[ERROR][if not (grpha_uniform or pointing_angle)]
		CH730304	missingValue	
PA74	Grexc Grpha Exec Unit1			
	CA7401	Definition in {deg, rad}		
		CH740101	deg	[if grpha_rotation]
		CH740102	rad	[if grpha_rotation]
	CA7402	other value		
		CH740201	INVALID_VALUE	[ERROR]
		CH740202	missingValue	
PA75	Grexc Grpha Exec Def2			
	CA7501	Definition in {P2_VAL, START}		
		CH750101	P2_VAL	[if grpha_second]
		CH750102	START	[if grpha_rotation]
	CA7502	other value		
		CH750201	INVALID_VALUE	[ERROR]
		CH750202	missingValue	
PA76	Grexc Grpha Exec Val3			
	CA7601	real number		
		CH760101	=0	[if not (grpha_uniform or grpha_pointing)]
		CH760102	>0	[if not (grpha_uniform or grpha_pointing)]
		CH760103	<0	[if not (grpha_uniform or grpha_pointing)]
	CA7602	other value		
		CH760201	non-number	[ERROR][if not (grpha_uniform or grpha_pointing)]
		CH760202	missingValue	
PA77	Grexc Grpha Exec Def3			
	CA7701	Definition in {Q1_VAL, STEP}		
		CH770101	Q1_VAL	[if grpha_second]
		CH770102	STEP	[if grpha_rotation]
	CA7702	other nominal value		
		CH770201	INVALID_VALUE	[ERROR]

		CH770202	missingValue	
PA78	Grexc Grpha Exec Val4			
	CA7801	real number		
		CH780101	=0	[if not (grpha_uniform or grpha_rotation or grpha_pointing)]
		CH780102	>0	[if not (grpha_uniform or grpha_rotation or grpha_pointing)]
		CH780103	<0	[if not (grpha_uniform or grpha_rotation or grpha_pointing)]
	CA7802	other value		
		CH780201	non-number	[ERROR][if not (grpha_uniform or grpha_rotation or grpha_pointing)]
		CH780202	missingValue	
PA79	Grexc Grpha Exec Def4			
	CA7901	Definition in { Q2_VAL }		
		CH790101	Q2_VAL	[if grpha_second]
	CA7902	other value		
		CH790201	INVALID_VALUE	[ERROR]
		CH790202	missingValue	
PA80	Grexc Grpha Exec Val5			
	CA8001	real number		
		CH800101	=0	[if not pointing_axis]
		CH800102	>0	[if not pointing_axis]
		CH800103	<0	[if not pointing_axis]
	CA8002	other value		
		CH800201	non-number	[ERROR][if not pointing_axis]
		CH800202	missingValue	
PA81	Grexc Grpha Exec Unit2			
	CA8101	Definition in { deg, rad }		
		CH810101	deg	[if not pointing_axis]
		CH810102	rad	[if not pointing_axis]
	CA8102	other value		
		CH810201	INVALID_VALUE	[ERROR]
		CH810202	missingValue	
PA82	Recursive Def			
	CA8201	Definition in {NONE, TRIANG, POLAR, POL_ORIENT, PHASE}		
		CH820101	NONE	
		CH820102	TRIANG	
		CH820103	POLAR	
		CH820104	POL_ORIENT	
		CH820105	PHASE	
	CA8202	other value		
		CH820201	INVALID_VALUE	[ERROR]
		CH820202	missingValue	
PA83	Test Result			
	CA8301	Test result of the case		
		CH830101	P	
		CH830102	F	

C.3 Detailed analysis result

C.3.1 Strategy one: diagnose all statements executed

C.3.2 Strategy two: diagnose 20% statements executed

APPENDIX D THE PACKHEXCHAR PROGRAM

D.1 Sample C4.5 Trees

D.1.1 Ver-71

```
NUM HEX CHARS IN [0..RLEN] = Zero: F (13.0/3.0)
NUM HEX CHARS IN [0..RLEN] = Odd
|   ODD_DIGIT = odd_digit=-1: F (28.0)
|   ODD_DIGIT = odd_digit=[0...9]: P (27.0/4.0)
|   ODD_DIGIT = odd_digit=[A...F]: P (28.0/6.0)
|   ODD_DIGIT = odd_digit=[a...f]: P (23.0/5.0)
|   ODD_DIGIT = odd_digit<-1: P (0.0)
|   ODD_DIGIT = odd_digit>15: P (0.0)
NUM HEX CHARS IN [0..RLEN] = Even
|   ODD_DIGIT = odd_digit=-1: P (27.0/4.0)
|   ODD_DIGIT = odd_digit=[0...9]: F (27.0)
|   ODD_DIGIT = odd_digit=[A...F]: F (27.0)
|   ODD_DIGIT = odd_digit=[a...f]: F (19.0)
|   ODD_DIGIT = odd_digit<-1: P (1.0)
|   ODD_DIGIT = odd_digit>15: F (1.0)
```

Number of Leaves : 13
Size of the tree : 16

=== Stratified cross-validation ===

Correctly Classified Instances	198	89.5928 %
Incorrectly Classified Instances	23	10.4072 %
Kappa statistic	0.7899	
Mean absolute error	0.1729	
Root mean squared error	0.3034	
Relative absolute error	35.8075 %	
Root relative squared error	61.751 %	
Total Number of Instances	221	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.956	0.145	0.819	0.956	0.882	0.889	P
0.855	0.044	0.966	0.855	0.907	0.889	F

```

=== Confusion Matrix ===
  a   b   <-- classified as
 86   4 |   a = P
 19 112 |   b = F

```

D.1.2 Ver-4872

```

CHAR CASE = N/A: P (13.0)
CHAR CASE = allNumbers: P (52.0)
CHAR CASE = allLowerCase: F (52.0)
CHAR CASE = allCaps: P (52.0)
CHAR CASE = mixedCase: F (52.0/3.0)

```

```

Number of Leaves   :   5
Size of the tree   :   6

```

=== Stratified cross-validation ===

Correctly Classified Instances	218	98.6425 %
Incorrectly Classified Instances	3	1.3575 %
Kappa statistic	0.9727	
Mean absolute error	0.0259	
Root mean squared error	0.1165	
Relative absolute error	5.227 %	
Root relative squared error	23.3818 %	
Total Number of Instances	221	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.975	0	1	0.975	0.987	0.989	P
1	0.025	0.971	1	0.985	0.989	F

```

=== Confusion Matrix ===
  a   b   <-- classified as
 117   3 |   a = P
   0 101 |   b = F

```

D.1.3 Ver-13849

```

CHAR CASE = N/A: P (13.0)
CHAR CASE = allNumbers
|   ODD_DIGIT = odd_digit=-1: F (12.0)
|   ODD_DIGIT = odd_digit=[0...9]: P (14.0)
|   ODD_DIGIT = odd_digit=[A...F]: P (14.0)
|   ODD_DIGIT = odd_digit=[a...f]: P (12.0)

```

```

|   ODD_DIGIT = odd_digit<-1: P (0.0)
|   ODD_DIGIT = odd_digit>15: P (0.0)
CHAR CASE = allLowerCase: F (52.0)
CHAR CASE = allCaps
|   ODD_DIGIT = odd_digit=-1: F (12.0)
|   ODD_DIGIT = odd_digit=[0...9]: P (14.0)
|   ODD_DIGIT = odd_digit=[A...F]: P (14.0)
|   ODD_DIGIT = odd_digit=[a...f]: P (12.0)
|   ODD_DIGIT = odd_digit<-1: P (0.0)
|   ODD_DIGIT = odd_digit>15: P (0.0)
CHAR CASE = mixedCase: F (52.0/12.0)

```

```

Number of Leaves   : 15
Size of the tree   : 18

```

=== Stratified cross-validation ===

Correctly Classified Instances	209	94.5701 %
Incorrectly Classified Instances	12	5.4299 %
Kappa statistic	0.8905	
Mean absolute error	0.0847	
Root mean squared error	0.2075	
Relative absolute error	16.9764 %	
Root relative squared error	41.5466 %	
Total Number of Instances	221	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.886	0	1	0.886	0.939	0.97	P
1	0.114	0.906	1	0.951	0.97	F

=== Confusion Matrix ===

```

a   b   <-- classified as
93  12 |   a = P
0  116 |   b = F

```