Automated Test Case Generation

Literature Review

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ABSTRACT

This report reviews the motivation of automated test case generation and discusses some of the challenges involved. It then outlines the main approaches that have been attempted and describes some notable examples of each. Last, it discusses possibilities for future research in the field.

Keywords

automated testing; search algorithms; genetic algorithms; constraint satisfaction

1. INTRODUCTION

Testing is an important part of software development which can increase confidence that software is free of defects and will work as intended. In particular, unit tests are often able to isolate defects to a small part of the codebase, which saves a lot of developer time compared to observing a bug as the software is being used and having to determine which code is causing the bug. Tests are also useful well after the relevant feature has been added, as in addition to ensuring that the feature works properly initially, they can be used to detect features which were broken with the addition of related code.

The main drawback to software testing is the time and effort taken to write the test cases. It has been estimated that the typical project spends around half of its time on testing [4]. This is typically done manually by someone with direct knowledge of the codebase, so the writing of test cases requires a lot of programmer time which could alternatively be used on something more productive.

Automated test case generation is the task of automatically generating high-quality test cases, where "high-quality" is typically defined as having high code coverage (roughly, the amount of the code explored through choosing the right inputs to cover all branches) or some similar metric [10].

This is, in general, a very challenging task. The space of all inputs to a function is too large to simply iterate over and perform an exhaustive search, especially when the input is of a structured type such as a list or tree. The fact that branching instructions are discrete (control flow cannot partially follow one path) makes maximizing code coverage a discrete optimization problem, which are usually much more difficult than continuous ones.

In addition, the constraints describing whether control flow reaches a given location are sometimes very specific (that is, they are satisfied for a small fraction of the input space) and not readily apparent from a quick pass through the source code. For example, a relatively simple constraint would be that in a function which takes a list as an argument, a given line of code might be reached only when the list is sorted except for the last element, and a different parameter has a certain value. It would be very difficult for a search algorithm to find a value that satisfies this constraint "on accident," and to extract this constraint from the code it is necessary to use inefficient techniques such as symbolic execution.

2. SEARCH-BASED METHODS

One possible approach to test case generation is to use a search algorithm (usually local search) to find in the space of possible inputs the ones that maximize code coverage [1]. The search operators depend on the type of the inputs to a function; they could be as simple as randomly changing one parameter when they are integer-valued, but are more complicated for functions that, for example, take as input a complex data structure.

Search methods are complicated by the fact that, because test case generation is usually formulated as a discrete optimization problem, the objective function does not improve smoothly as the search approaches an opti-

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mum. Instead, the problem is characterized by sudden jumps when a constraint goes from not being satisfied to being satisfied.

2.1 Harmen Sthamer: The Automatic Generation of Software Test Data Using Genetic Algorithms

One early attempt at using a search algorithm for test case generation was by Harmen Sthamer in his PhD thesis [17], which used a genetic algorithm to find test cases for several different types of simple example functions, and found that the genetic algorithm outperformed a random search in terms of both runtime and the number of test cases required for a certain amount of code coverage.

He had four stated hypotheses before he begun his work. The first was that a genetic algorithm would outperform random search, which was the entire motivation for the project. The second was that out of all of the parameters for the genetic algorithm (population size, mutation rate, etc.) there would be a setting for the parameters which would work well for a variety of functions with different input types. This is highly desirable as the goal of automated test case generation is to reduce manual effort, and requiring hand-tuning of parameters for different functions would partially negate this. The third hypothesis was that test generation would be successful for loops with varying numbers of iterations: specifically no iterations, one, two and more than two. The last hypothesis was that test cases generated would be adequate, as to be confirmed by mutation analysis [5]. After some experimentation he confirmed all of these hypotheses to be true.

The first type of function tested was functions with arithmetic and branch instructions but no loops. Results on these functions were very good; random testing did not do as well, mainly due to the noncontinuity and small size of some subdomains (becuase of the arithmetic operations, sometimes a very precise value had to be chosen for one input in order to reach a given branch).

Next, he tested on functions with loops that took complex data structures such as lists as input. Several cases were identified where the genetic algorithm was unable to find a satisfying test case due to complex constraints on the input, but it again drastically outperformed random testing, achieving the same code coverage with as few as one thirteenth of the tests.

Sthamer's evolutionary approach outperformed random testing, but was not benchmarked against any more sophisticated methods.

2.2 Gordon Fraser and Andrea Arcuri: Evolutionary Generation of Whole Test Suites

Most automated test case generation methods work by targeting a given part of a codebase and running the generator many times, each run targeting a different part so that together the cases cover as much of the code as possible. Fraser and Arcuri [7] develop an alternate method in which they evolve the entire test suite at the same time.

This has many advantages over the traditional approach. If there is a part of the code which is not reached for any input, a traditional search-based method will typically be run until a maximum iteration count is reached, wasting a significant amount of time. When evolving the entire test suite, however, no time is spent directly on individual parts of the code, so none of the generated suites will cover that part of the code but no time will be wasted in order to determine that it could not be reached.

The same applies to code which is sometimes reached, but very rarely (and therefore difficult to generate a test case for). If a reduction of the runtime of the test generator is desired, the suite-based method can simply be run for fewer iterations to find a set of easy to find test cases with as high coverage as possible. With the traditional method, however, it is not known ahead of time which cases will be hard to find.

In addition, when an input is chosen to cover one part of the code, it will also naturally cover other parts. When generating individual test cases using the traditional approach, this leads to wasted effort if a test case covering the additional code has already been generated.

They benchmarked their approach on six large Java projects. Five were open source projects, and to increase the variety of the test code they additionally tested on an industrial case study project which Arcuri had previously researched [2]. Using these six codebases, they compared the approach to a modified version of their own method that generated individual test cases rather than test suites. They kept as many details as possible the same between the two methods; they were interested in comparing case-based generators to suite-based generators and not in comparing actual search algorithms, so their goal in keeping the two methods similar was to isolate the effect of changing the approach from case-based to suite-based. However, this could impact the results, as it is not obvious that methods that would work the best for suite-based generation would also work well for case-based generation, so it is possible that the method they chose favored the suite-based approach.

As both methods tested were randomized algorithms, the results can and will vary between runs and it is necessary to ensure statistical significance of the results. This was achieved using the Mann-Whitney U test with a significance level of 0.05. They found that the test suite size required to achieve a certain coverage was low averaged across all tests, with a statistically significant improvement on most individual tests.

To visualize the results they calculated, for each test case and each run, the statistical significance and plotted a box plot. An example is shown in Figure 1, where

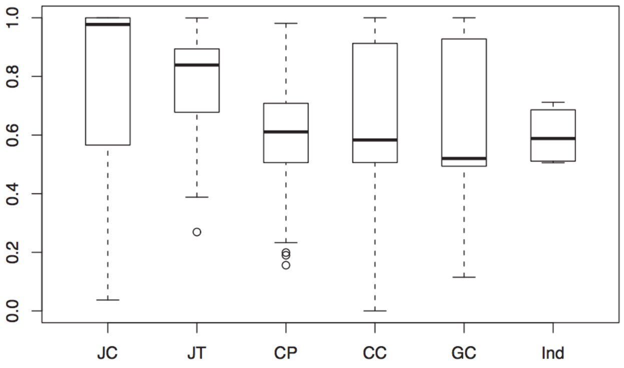


Figure 1: Box plot of code coverage for each run on each test case

a value of 1 means that their method had better coverage and 0 means that the baseline was better. The middle quartiles of the box plot can be viewed as a 50% confidence interval.

2.3 Nirmal Kumar Gupta and Mukesh Kumar Rohil: Improving GA Based Automated Test Data Generation Technique for Object Oriented Software

Gupta and Rohil [9] present a method which is also based on evolving an entire test suite using a genetic algorithm. Their contribution is that they explicitly construct the control flow graph (CFG) of the program and assign weights to each node which depend on how many times that node was reached across the test suite. Mutations are then chosen with increased probability of reaching nodes with low weights (nodes that were not visited as often) to increase code coverage.

The authors claim that their method outperforms random testing, but do not give any concrete results of random testing to compare their results to. In addition, random testing is not a very ambitious benchmark to beat, as many sophisticated methods which also beat random testing have been developed, and it would be useful to compare their result to these. Despite the lack of analysis, the method seems interesting and is probably worth looking into further.

2.4 Gordon Fraser and Andreas Zeller: Mutation-Driven Generation of Unit Tests and Oracles

Fraser and Zeller [8] again use a genetic algorithm to generate test cases, but use a fitness evaluation function other than code coverage. They introduce mutations (randomly created defects) in the code, and search for test cases that give a different output from the original code and the mutated code. This ensures that the chosen inputs are sensitive to small changes in the code, which means that they will hopefully be able to detect other defects as well.

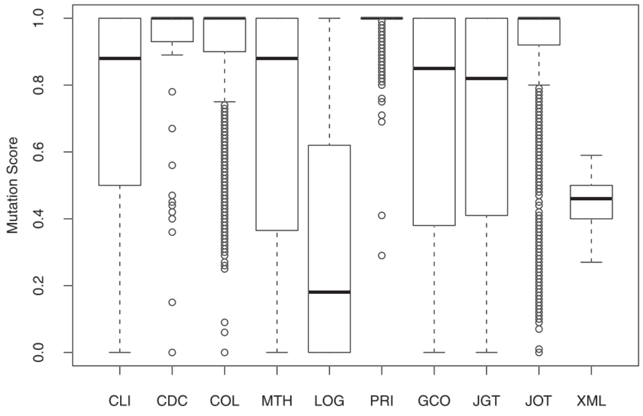


Figure 2: Box plot of mutation score for each run on each test case

One motivation of mutation analysis is that it is closer to the actual goal of software testing, and therefore hopefully more likely to generate test cases that are actually useful. The goal of maximimum code coverage is somewhat arbitrary, as the goal of reaching every point in the code is just a means to an end; the actual focus of testing is to find defects, which is what mutation analysis is designed to do.

The authors found that when compared to hand-written tests, their framework was able to generate test cases that were both smaller and better at detecting defects. Tests were performed on 10 open source Java libraries including several Apache Commons projects, Google Collections and others. They displayed their results using similar plots to those of Fraser and Arcuri, which show the distribution over results for each test case. An example is shown in Figure 2.

3. OTHER METHODS

3.1 Matt Staats and Corina Păsăreanu: Parallel Symbolic Execution for Structural Test Generation

One alternative method is parallel symbolic execution, in which a function run is simulated without assigning concrete values to each variable. Instead, variables are associated with symbolic values which, for each point in the code, record which assignments to the variable lead to that code path. Test cases can be generated by executing a function symbolicly and choosing a set of inputs with sufficient combined coverage, which can be determined by checking whether each input satisfies the conditions of various symbolic values. Figure 3 shows the symbolic execution tree associated with the code in Figure 4.

This approach is very accurate and efficient for small, simple functions, but does not scale well to larger and more complicated ones. The number of paths in a func-

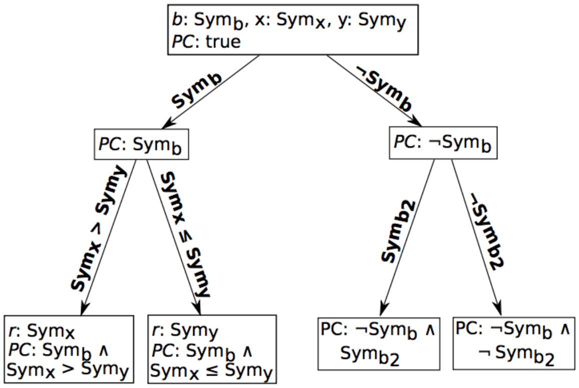
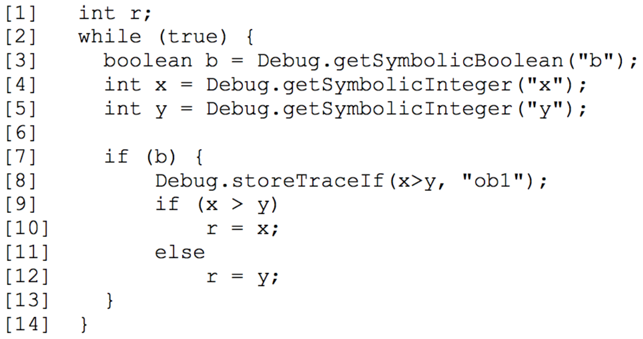


Figure 3: Symbolic execution tree showing the constraints at each node



```
int r;
while (true) {
  boolean b = Debug.getSymbolicBoolean("b");
  int x = Debug.getSymbolicInteger("x");
  int y = Debug.getSymbolicInteger("y");

  if (b) {
      Debug.storeTraceIf(x>y, "ob1");
      if (x > y)
          r = x;
      else
          r = y;
  }
}
```

Figure 4: Code resulting in the symbolic execution tree in Figure 3

tion grow exponentially with its length assuming a constant density of branching instructions, and complicated functions can lead to complicated constraints which are intractable to satisfy.

Staats and Păsăreanu [16] use a method called "selective concretization" to improve the running time of symbolic execution. Selective concretization involves using some heuristics to concretize variables (convert from a symbolic variable to a concrete value) at dynamically chosen locations in the execution tree. This reduces both the branching factor of the tree (and hence the number of nodes) and the number of variables in the resulting constraint satisfaction problems. Both of these asymptotically improve the runtime of symbolic execution and allow it to handle larger problems.

They benchmark this method by comparing it to a random depth-first search of the execution tree, and conclude that at the same depth and with the same runtime, it obtains better code coverage. They used a parallel implementation based on a custom client-server framework, and obtained a speedup that was almost linear in the number of parallel threads.

3.2 Richard DeMillo and A. Offutt: Constraint-Based Automatic Test Data Generation

DeMillo and Offutt [6] use mutation analysis as described in Section 2.4, but use a constraint satisfaction algorithm instead of an evolutionary one. They use symbolic execution as described above with an extra condition associated with each variable which represents whether the current state differs between the original and mutated code.

One limitation is that due to the exponential runtime of constraint satisfaction, this method is unable to be applied to large systems. The authors mention decomposing the system into individual components and testing each individually; however, this is sometimes impossible due to the system architecture. In addition, the smaller the pieces into which the system must be broken, the more redundant and overlapping test cases must be generated as discussed in Section 2.2.

Their method demonstrated promising results on the standard benchmark problem TRITYP (triangle type) but this is a particularly small example, but this took a non-negligible amount of time and (again due to the exponential runtime of constraint satisfaction algorithms) it is likely that the largest problems the approach is capable of solving are not much larger than TRITYP.

3.3 Jan Malburg and Gordon Fraser: Combining Search-Based and Constraint-Based Testing

Malburg and Fraser [14] combine search-based and constraint-based methods by using a genetic algorithm with a constraint solver during the mutation step which ensures that mutation changes the input in a way that explores some other code path. They report that this approach obtains many of the advantages of each method with few of the disadvantages. The fact that these methods complement each other and excel in areas where the other performs poorly was noted by [13].

One of the main limitations of pure constraint-based test case generation is the intractability of constraint satisfaction with a large number of constraints, which means that these methods must be either very simplified or applied to only a small segment of code, which is unable to take into account global dependencies. The hybrid method of Malburg and Fraser, however, is able to explore large regions of the input space (and therefore find a solution which is hopefully closer to globally optimal) using the search algorithm while only making local changes for which constraint satisfaction is tractable.

This addresses the problem with many other local search algorithms for test case generation, which is that it is difficult to find improved solutions in the local neighborhood due to discontinuities in the objective function. Instead of addressing this through a more informative objective function, their method modifies the mutation step to move in directions which are likely to improve the solutions.

They compare their method to random testing, a simple genetic algorithm and a constraint satisfaction approach, and obtain performance that is better than all the others on most test cases, and tied for best on the others. Statistical significance is ensured using the Mann-Whitney U test for the reasons given in Section 2.2.

3.4 Arthur Baars et. al.: Symbolic Search-Based Testing

Baars et. al. [3], like Malburg and Fraser, use a hybrid method that combines a search algorithm with symbolic techniques. They run partial symbolic execution on the source code, which tracks some properties of the code path previously taken but does not store the actual constraints representing that path, which allows it to avoid the exponential blowup of number of paths encountered when using full symbolic execution.

Given these metrics about the different code paths, they define a measure of how close an input came to reaching a target part of the code, and use this measure to define an alternative fitness function. This fitness function is more informative as it indicates how close a test case came to meeting certain coverage goals, as opposed to standard code coverage metrics which just take into account whether a given line was executed or not.

The authors tested their fitness function using two different search algorithms: a hill climbing algorithm named the Alternating Variable Method [12] and an evolutionary approach by Wegener et. al. [18].

The authors use the Wilcoxon signed rank test to ensure statistical significance. This differs from the Mann-Whitney U test used in other papers in that instead of considering the results of each method to be an independent sample, it uses matched pairs and directly compares the data points from each method. This difference is justified because as opposed to the other papers which are comparing multiple different methods, this paper compares a method to itself with and without the modification of changing the fitness function, so the pairs can be viewed as before and after data. Using this test they determined that the modified fitness function improved code coverage for a given test case size with a p-value of 2.2×10^{-16}, which means that the results are extremely statistically significant.

One notable result was that the hill climbing method improved more from the change than the genetic algorithm did. This is probably mainly due to the fact that the hill climbing method had the lower performance initially, and therefore the most room for improvement.

Because most other work on search-based test case generation has concerned the search algorithm itself and for the most part has all used the same fitness function (code coverage), this work is orthogonal to the approach of many other methods. Therefore it does not directly address the limitations of other methods, but rather gives a complementary technique which can be used in conjunction with various search algorithms.

To conclude, the authors suggest that the fitness function they developed be used in future research in search-based test case generation, as it significantly outperformed traditional code coverage metrics.

3.5 Casper S. Jensen, Mukul R. Prasad and Anders Møller: Automated Testing with Targeted Event Sequence Generation

This paper [11] addresses test case generation for mobile applications, where rather than scalar values or complex data structures, an input consists of a sequence of UI events such as tapping an on-screen button. Their approach is based on concolic execution, a hybrid of symbolic execution and concrete (or “regular”) execution, similar to the approach of Staats and Păsăreanu.

Next, given the output of concolic executive along with a target location in the code, they locate the UI state corresponding to that code and perform a backwards search in a state transition model of the UI in order to find a sequence of actions that leads to that UI state, and consequently leads to that code being executed. An example of a UI state transition model is shown in Figure 5.

They concluded that this approach was successful, as it was able to find paths to several hard to reach locations which were not found by random testing. An advantage of their implementation was that it only required the bytecode of the application that is being tested, and not the source code itself (black-box testing).

This approach tests at the interface level in contrast with the previous approaches, which unit tested indi-

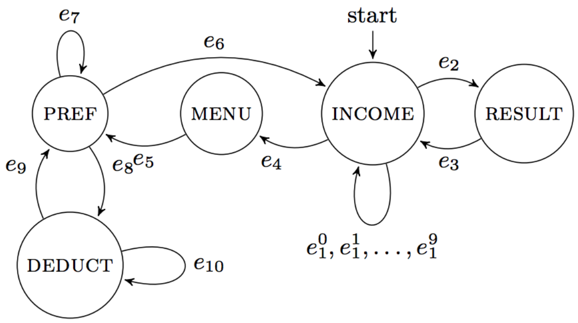


Figure 5: State transition diagram of one of the applications tested by Jensen et. al.

vidual parts of the code. Depending on the type of application and the organization of the development team, this may be either an advantage or a disadvantage.

3.6 Rohan Sharma et. al.: A Comparison of Constraint-Based and Sequence-Based Generation of Complex Input Data Structures

This paper [15], rather than directly address the task of test case generation, addresses the subproblem of generating complex data structures such as trees. It does not attempt to maximize code coverage or any other test quality metric; instead it simply compares methods for enumerating data structures of a given type for use in test case generators.

The paper mentions test case generation as one of the primary motivations for input structure generation, but the methods used have several limitations that hinder their applicability to test generation. Primarily, they perform an exhaustive enumeration of structures for a given size, which as previously mentioned is typically much too large to search over. Possible future work to move towards the goal of using this approach for automated testing would be to define some fitness function and incorporate some sort of search algorithm to find not all inputs, but the ones that maximize the objective function.

4. CONCLUSIONS

Based on the papers reviewed it seems to be the case that genetic algorithms outperform constraint-based methods on all but the most trivial problems due to the lack of scalability of constraint satisfaction algorithms. However, hybrid methods seem to outperform both (or at least might have the potential to) and represent a promising direction for future research. Malburg and Fraser claim that their hybrid method achieves the advantages of both approaches with few of the downsides, and the combining of multiple methods leads to a vast number of possibilities, most of which have yet to be explored.

Another area which seems ideal for future work is the development of new fitness functions. The lack of improvement in the immediate neighborhood of most points due to the discrete nature of the code coverage objective causes problems for local search algorithms, and Baars et. al. show promising results using a modified fitness function based on a more meaningful metric of distance from an optimum. There are still many possibilities for improved fitness functions, which based on results so far should have a dramatic effect on performance of search algorithms.

5. REFERENCES

[1] S. Anand, E. K. Burke, T. Y. Chen, J. Clark, M. B. Cohen, W. Grieskamp, M. Harman, M. J. Harrold, and P. Mcminn. An orchestrated survey of methodologies for automated software test case generation. *J. Syst. Softw.*, 86(8):1978–2001, Aug. 2013.

[2] A. Arcuri, M. Z. Iqbal, and L. Briand. Black-box system testing of real-time embedded systems using random and search-based testing. In *Proceedings of the 22Nd IFIP WG 6.1 International Conference on Testing Software and Systems*, ICTSS'10, pages 95–110, Berlin, Heidelberg, 2010. Springer-Verlag.

[3] A. Baars, M. Harman, Y. Hassoun, K. Lakhotia, P. McMinn, P. Tonella, and T. Vos. Symbolic search-based testing. In *Automated Software Engineering (ASE), 2011 26th IEEE/ACM International Conference on*, pages 53–62, Nov 2011.

[4] B. Beizer. *Software Testing Techniques (2nd Ed.)*. Van Nostrand Reinhold Co., New York, NY, USA, 1990.

[5] R. A. DeMillo. Completely validated software: Test adequacy and program mutation (panel session). In *Proceedings of the 11th International Conference on Software Engineering*, ICSE '89, pages 355–356, New York, NY, USA, 1989. ACM.

[6] R. A. DeMillo and A. J. Offutt. Constraint-based automatic test data generation. *IEEE Trans. Softw. Eng.*, 17(9):900–910, Sept. 1991.

[7] G. Fraser and A. Arcuri. Evolutionary generation of whole test suites. In *Quality Software (QSIC), 2011 11th International Conference on*, pages 31–40, July 2011.

[8] G. Fraser and A. Zeller. Mutation-driven generation of unit tests and oracles. In *Proceedings of the 19th International Symposium on Software Testing and Analysis*, ISSTA '10, pages 147–158, New York, NY, USA, 2010. ACM.

[9] N. Gupta and M. Rohil. Improving GA based automated test data generation technique for object oriented software. In *Advance Computing Conference (IACC), 2013 IEEE 3rd*

International, pages 249–253, Feb 2013.

[10] M. Harman and P. McMinn. A theoretical and empirical study of search-based testing: Local, global, and hybrid search. *Software Engineering, IEEE Transactions on*, 36(2):226–247, March 2010.

[11] C. S. Jensen, M. R. Prasad, and A. Møller. Automated testing with targeted event sequence generation. In *Proceedings of the 2013 International Symposium on Software Testing and Analysis*, ISSTA 2013, pages 67–77, New York, NY, USA, 2013. ACM.

[12] B. Korel. Automated software test data generation. *IEEE Trans. Softw. Eng.*, 16(8):870–879, Aug. 1990.

[13] K. Lakhotia, N. Tillmann, M. Harman, and J. De Halleux. Flopsy: Search-based floating point constraint solving for symbolic execution. In *Proceedings of the 22Nd IFIP WG 6.1 International Conference on Testing Software and Systems*, ICTSS'10, pages 142–157, Berlin, Heidelberg, 2010. Springer-Verlag.

[14] J. Malburg and G. Fraser. Combining search-based and constraint-based testing. In *Proceedings of the 2011 26th IEEE/ACM International Conference on Automated Software Engineering*, ASE '11, pages 436–439, Washington, DC, USA, 2011. IEEE Computer Society.

[15] R. Sharma, M. Gligoric, V. Jagannath, and D. Marinov. A comparison of constraint-based and sequence-based generation of complex input data structures. In *ICST Workshops*, pages 337–342. IEEE Computer Society, 2010.

[16] M. Staats and C. Păsăreanu. Parallel symbolic execution for structural test generation. In *Proceedings of the 19th International Symposium on Software Testing and Analysis*, ISSTA '10, pages 183–194, New York, NY, USA, 2010. ACM.

[17] H. H. Sthamer. *The Automatic Generation of Software Test Data Using Genetic Algorithms*. PhD thesis, University of Glamorgan, 11 1995.

[18] J. Wegener, A. Baresel, and H. Sthamer. Evolutionary test environment for automatic structural testing. *Information & Software Technology*, 43(14):841–854, 2001.