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An Application of Model Seeding to Search-based Unit Test Generation for Gson


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Abstract. Model seeding is a strategy for injecting additional information in a search-based test generation process in the form of models, representing usages of the classes of the software under test. These models are used during the search-process to generate logical sequences of calls whenever an instance of a specific class is required. Model seeding was originally proposed for search-based crash reproduction. We adapted it to unit test generation using EVO SUITE and applied it to Gson, a Java library to convert Java objects from and to JSON. Although our study shows mixed results, it identifies potential future research directions.

Keywords: Model seeding · Search-based software testing · Case study

1 Introduction

Over the years, several techniques have been developed to generate unit tests by applying search-based algorithms to source code. Among the existing tools, EVO SUITE is one of the references in the state-of-the-art for Java unit test generation [5]. It has been developed and maintained over the years and received several contributions to improve code coverage and mutation score of the generated tests or to generate tests for specific purposes. Despite the numerous improvements, one of the challenges still faced by EVO SUITE is the generation of complex objects with logical (i.e., not random) sequences of method calls. There exist several strategies to address this challenge partially. Among those, seeding [7] consists of the injection of additional information that will be used during the search. For instance, constant values collected from the source code, and the usage (as-is) of objects collected from an existing test suite.

In their recent study, Derakhshanfar et al. [3] propose to abstract the behavior of the different classes of the system under test (SUT) using a transition system model. For each class, one transition system describes the sequences of method calls previously observed on the instances of that class. They seeded those models to a search-based crash reproduction algorithm to generate complex objects and found that it improved the overall crash reproduction rate. Crash reproduction does not seek to cover all the elements of a class under test (CUT) but rather to generate a test exercising a specific behavior causing the software to crash.
For unit test generation, the coverage of different elements of a CUT also requires specific objects that might be difficult to generate randomly. In this paper, we applied model seeding for unit test generation using EvoSuite on a set of eight classes from the Gson library. We compare model seeding to the default configuration of EvoSuite w.r.t. the branch coverage and mutation scores achieved by the generated tests.

2 Evaluation setup

Classes under test. Gson is a Java serialization and deserialization library to convert Java Objects into JSON and back.\(^1\) It is used as a dependency by more than 222,000 projects on GitHub. We used Gson v.2.8.7 (5924 LOC) and selected 8 classes with at least one method (with the exception of the toString and equals method) with a cyclomatic complexity above 3: Gson, JsonReader, JsonTreeReader, JsonTreeWriter, JsonWriter, LinkedHashMapTreeMap, LinkedListMap, and TypeAdapters. The overall branch coverage of the existing manually written tests is 79%, and the overall mutation score is 75%.

Learning the models. We followed Derakhshanfar et al.'s [3] approach and generated our models using the existing source code and tests of the Gson library. For each class used in the project, each time an object is created, we collected the sequence of methods called on this object. For that, we statically analyzed the source code of Gson and dynamically executed (a heavily instrumented version of the) existing test cases. The models are then learned from the collected call sequences using a 2-gram inference. Learning the models is a one-time operation. Models are then seeded to the different executions of EvoSuite. In total, we collected 328 models for 328 different classes. The average number of states is 7 and the average number of transitions is 15. We rely on the implementation of Derakhshanfar et al. [3] to collect call sequences and learn the different models, and on EvoSuite-RAMP,\(^2\) a customized version of EvoSuite [5] for unit test generation.

Configurations. Model seeding works either online or offline. In the offline mode, during the initialization of the search, for each model, EvoSuite-RAMP creates a fixed number of objects by selecting abstract behaviors from the model. For each selected abstract behavior, it instantiates the object, calls the corresponding methods, and adds the result to an object pool. Whenever an object is required, the search process copies (with a defined probability \(p_{\text{object\_pool}}\) one object and its method calls from this object pool. Additionally, during the initialization of the population, EvoSuite-RAMP can also copy (with a defined probability \(seed\_clone\)) an instance of the CUT (as-is) from the object pool and use it as a plain (initial) test. In the online mode, objects are created during the search process using the same procedure. The main difference with the offline mode is that the objects are created on demand, slightly overloading the search process. For our evaluation, we used the online mode as it does

\(^1\) https://github.com/google/gson

\(^2\) https://github.com/STAMP-project/evosuite-ramp
not overload the initialization and generates only objects required by the search
(and therefore leaves more budget for the search itself). We used probabilities
\( p_{\text{object pool}} = 0.3 \), and \( \text{seed clone} = 0.3 \), following Derakhshanfar et al. [3].

To select abstract behaviors, EVO\textsc{suite-RAMP} supports \textit{random selection},
(corresponding to random walks in the models, and \textit{dissimilarity selection}, trying
to increase diversity in the selected behaviors. For our evaluation, we used \textit{random selection} as it gave slightly better results in our initial trial.

In our evaluation, we compare unit test generation with model seeding activated (\textit{model s.}) to the default EVO\textsc{suite} configuration (\textit{default}). For both configurations, we used \texttt{DynaMOSA} [6] with the default set of objectives (\textit{i.e.}, branch,
line, weak mutation, input, output, method, and exception coverage) and a
search budget of 180 seconds. Additionally, we deactivated model seeding after
90 seconds to increase exploration. We ran our evaluation (1600 runs) on a server
with 12 CPU cores @ 3.50 GHz. The total execution time for unit test generation
took around 40 minutes. Our replication package is available on Zenodo [4].

\textbf{Data analysis.} For each class under test, we compare the generated test
suites \textit{w.r.t.} their branch coverage (reported by EVO\textsc{suite-RAMP}) and their
mutation score, computed using \texttt{PIT v1.4.3} [1] with \textsc{All} mutation operators
activated. The total execution time for the mutation analysis of the 1600 generated
test suites took around 2 days. We used the the non-parametric Wilcoxon Rank
Sum test (\( \alpha = 0.05 \)) for Type I error, and the Vargha-Delaney statistic \( \hat{A}_{12} \) to
evaluate the effect size between \textit{model s. and default}.

\section{Results}

Figure 1 presents the branch coverage and mutation score of the test suites
generated using the \textit{default} and \textit{model s.} configurations. On average, the highest
branch coverage is achieved by the \textit{default} configuration for the class \texttt{JsonTreeReader}
with 92.04\%. The lowest branch coverage is, on average, also achieved
by the \textit{default} configuration for the class \texttt{TypeAdapters} with 50.04\%. For the
mutation score, the highest average mutation score is achieved by the \textit{model s.}
configuration for the \texttt{TypeAdapters} class with a score of 93.75\%, and the
lowest average mutation score is also achieved by \textit{model s.} configuration on the
\texttt{LinkedHashSetTreeMap} class with an average of 35.91\%.

For each class, we compared the coverage and mutation score of the generated
test suites. The configuration \textit{model s.} achieved significant better results (\( \alpha \leq 0.05 \))
for three classes (with two small and one large \( \hat{A}_{12} \) magnitudes). It performs
worse compared to the \textit{default} configuration for two classes (with one small and
one medium \( \hat{A}_{12} \) magnitudes). For the mutation score, the \textit{model s.} configuration
performed significantly better (\( \alpha \leq 0.05 \)) on three classes (with two small and
one large \( \hat{A}_{12} \) magnitudes). The \textit{default} configuration performed better for two
classes (with one small and one medium \( \hat{A}_{12} \) magnitudes).

In general, our results are mixed. The \textit{model s.} configuration can lead to
an improvement of the mutation score with, in general, a lower variability than
the \textit{default} configuration. The most interesting class of our evaluation is the
JsonReader class for which model s. achieves a significantly worse branch coverage (p-value = 4.98 × 10^{-15}) with a large magnitude (\bar{A}_{12} = 0.180) than default, but, in the same time, also achieves a significantly better (p-value = 9.26 × 10^{-25}) mutation score, also with a large magnitude (\bar{A}_{12} = 0.92). We focus our discussion on the JsonReader class.

4 Discussion and future work

**Code complexity and model generation.** From analyzing the project using CODEMR\(^3\), we see that the JsonReader class is the most complex class of the project with a very-high complexity rate and a Weighted Method Count (WMC) of 359 for 891 lines of code (LOC). Complex code is a well-known challenge for search-based testing algorithms.

At the same time, the model generated from the collected call sequences for JsonReader is highly connected with an average degree (i.e., the average number of incoming and outgoing transitions per state) of 9.0, 252 transitions for only 28 states, and a BFS height of 6 (i.e., number of levels when navigating the model using a breadth-first search algorithm). This permissiveness of the model tends to indicate that the usages are not well captured and that the model can provide only limited guidance. Future research will investigate the usages of other learning approaches (including higher-values of n for the n-gram inference).

\(^3\) [https://www.codemr.co.uk](https://www.codemr.co.uk)
to better reflect the usages of the classes. Additionally, the models are created from the source code and the existing tests. We followed the procedure defined by Derakhshanfar et al. [3] with the same assumption that the existing tests are representative of valid usages of the classes (for crash reproduction). However, this assumption might not be right for unit testing. Therefore, future research will investigate other sources of call sequences, like projects using Gson, as well as including information about object and parameter values for those calls.

**Mutation analysis.** To further investigate the mutants killed by the generated tests, we performed a combined mutation analysis on the JsonReader class. For that, we used all the tests generated out of the 10 rounds of execution and the manually written tests from the JsonReaderTest and JsonReaderPathTest test suites. Figure 2 presents the number of mutants killed, grouped by the source of the test suite. Mutants killed by more than one test suite coming from different sources are placed at intersections in the diagram.

We see that between 7.8% and 8% of the mutants are killed only by a generated test suite. Additionally, we see that between 62% and 64.7% of the mutants are killed by both manually written and automatically generated tests, which tends to confirm that effort on testing can be reduced using automated approaches. Figure 2 also shows that the largest amount of mutants only killed by EvoSuite (7.4%) are killed both by the default and the model s. configurations. This tends to indicate that the randomness of the evolution process helps to explore new areas of the search space, compared to manually written tests. We also see that 25 mutants are killed only by the model s. configuration, and 37 mutants are killed only by the default configuration. Finally, from figs. 1 and 2, we see that the default configuration achieves a significantly lower mutation score, compared to model s., but kills a larger diversity of mutants (at least once) when the 10 test suites are merged together.

**Test case understandability.** In this case study, we only consider the functional properties (i.e., branch coverage and mutation score) of the gener-
ated tests. Recent studies have investigated other aspects of generated tests, like the readability and understandability by a developer [2]. We believe that, by generating objects with common usages, model seeding can contribute to improving test case readability and understandability. From the manual analysis of the test cases killing 25 mutants only killed by the model s. configuration, we could retrace the usages of the JsonReader class observed in the test case in the usage model of the class. The confirmation that having such usages in the test cases helps in reading and understanding them is left for future work.

5 Conclusion

In this case study, we applied model seeding for unit test generation using EvoSuite-RAMP on eight classes from the Gson library. We compared model seeding to the default configuration of EvoSuite. Overall, results are mixed. Using model seeding can lead to an improvement of branch coverage and mutation score in some cases. We also discussed several aspects of model seeding for unit test generation and identified potential future research directions regarding the collection of call sequences and generation of the models, and the usage of model seeding to improve the understandability of automatically generated tests.

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