Neural Unit Test Suggestions

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ABSTRACT

Testing is widely recognized as an important stage of the software development lifecycle. Effective software testing can provide benefits such as documentation, bug finding, and preventing regressions. In particular, unit tests document a unit’s intended functionality. A test oracle, typically expressed as an condition, documents the intended behavior of the unit under a given test prefix. Synthesizing a functional test oracle is a challenging problem, as it has to capture the intended functionality and not the implemented functionality.

In this paper, we propose NUTS (Neural Unit Test Suggestions), a unified transformer-based neural approach to infer both exceptional and assertion test oracles based on the context of the focal method. Our approach can handle units with ambiguous or missing documentation, and even units with a missing implementation. We evaluate our approach on both oracle inference accuracy and implemented functionality. A sufficiently expressive test suite should document functionality under both normal invocations where the precondition is met, and exceptional behaviors where the precondition is violated. Figure 1 shows two examples of unit tests for a Stack class. The tests document a normal invocation (Figure 1a) and an exceptional invocation (Figure 1b). Figure 1a shows a normal invocation of the unit where the test prefix instantiates a Stack and makes sequential calls to push and pop. The test oracle, highlighted in red, asserts that the stack’s isEmpty method should return true at the resultant state. If the unit contains a bug related to the tested behavior (e.g., if pop always fails to remove an item from the stack), this test can help detect the bug. On the other hand, Figure 1b shows the unit’s expected behavior when the precondition of pop is not satisfied. In this case, the intended behavior of calling pop on an empty stack is to raise an exception. As such, the test oracle is the expected exception. The try catch structure ensures that the unit does indeed raise an exception. If the unit contains a bug and does not raise an exception, the test will fail by executing Assert.fail().

Figure 1: Unit tests of a Stack class. The test oracles are highlighted in red. A correct implementation of Stack will be empty after a sequential push and pop and must raise an exception if pop is called on an empty stack.
It is clear that testing has immense benefits. However, authoring high quality unit tests is time consuming. On average, developers spend 15% of their time writing tests [3]. As such, extensive work has been devoted to automated unit test generation [5, 10, 14, 25]. However, test generation tools have no definitive knowledge of the developer’s intended program behavior. This creates a challenge for generating functional test oracles. Instead these tools use program crashes and undesirable exceptions (e.g. null dereference or out of bound array accesses) as the test oracles. Although these tests help find numerous safety bugs in the unit implementation, they do not suffice to find violations of intended functionality and thus do not replace the need for manual unit tests.

Complimentary to automated test generation tools, extensive work has been devoted to test oracle creation from documentation and comments [2, 8, 15, 18, 26]. We refer to these techniques as specification mining methods for test oracle generation. These methods rely on a restricted structure of documentation and a set of handcrafted rules to infer exceptions and assertions for a unit. However, given users do not follow a prescribed format for writing documentations, or omit them altogether, these methods fail to extract interesting oracles on most real-world software components. In our evaluation, we show that these methods cannot infer bug-finding assertions for a benchmark of real world java projects.

Recently, neural generative models have shown promise in generating functional test oracles [21–23]. Neural methods are more flexible than specification mining approaches as they do not rely on fixed patterns. This flexibility makes neural generative models robust to imprecise or even missing documentation. However, we find in our evaluation that these methods struggle to generate accurate oracles due to the large space of possible assertions. Further, these methods do not generate exceptional test oracles crucial for testing real-world software components.

In summary, an effective test generation approach must infer both exception and assertion oracles that accurately reflect developer intent, and find bugs in real world programs. Additionally, such an approach must gracefully handle cases with ambiguous or missing documentation, or even missing implementations.

We propose a neural approach to infer both exceptional and assertion bug finding test oracles: NUTS. To address the limitations of existing neural generative methods, we propose a new approach that reformulates the oracle generation problem as a ranking over a small set of highly likely, possible oracles. We base our approach on the empirical observation that oracles in developer-written unit tests typically follow a small number of common patterns. We describe a taxonomy on these patterns and define a simple grammar that expresses this taxonomy. We use this grammar along with type-based constraints to restrict the space of candidate oracles and produce well-formed test oracles satisfying syntactic and some semantic correctness. To perform ranking, we develop a two-step neural ranking procedure using pretrained transformers trained to score candidate oracles.

We evaluate our approach on both test oracle inference and bug-finding. Our technique improves accuracy by 33% over existing oracle inference approaches, achieving 96% accuracy on a held out test dataset that fits our grammar and constraints, and 69% accuracy on an overall assertion benchmark, a relative improvement of 11% over existing methods. Furthermore, we show that when integrated with a randomized test generation tool (EvoSuite), our approach finds 54 real world bugs in java benchmark, defects4j [9]. Our approach finds 27 bugs that are not found by any other automated testing method in our evaluation. We are working on a public release of our implementation.

Contributions. In summary, this paper:

1. Introduces a transformer (neural network) based approach to generating both exceptional and assertion oracles without relying on the unit’s implementation.
2. Derives adapted datasets for exceptional and assertion oracle training that incorporate method signatures and docstrings.
3. Implements NUTS, an end-to-end test generation technique that integrates neural test oracle generation with the automated test generation tool, EvoSuite.
4. Performs an extensive evaluation on test oracle inference. We demonstrate that our approach improves oracle inference accuracy by 33% and finds 54 real world bugs, including 27 bugs that are not found by any other method in our evaluation.

2 RELATED WORK

We broadly categorize related work on unit test generation into (i) automated test generation methods, (ii) specification mining methods, and (iii) neural methods.

2.1 Automated Test Generation Tools

Automated unit test generation techniques use a combination of black-box or white-box techniques to generate interesting test prefix for a unit. For example, tools such as Randoop [13, 14] use random fuzzing of APIs of a unit to construct non-exceptional test prefixes that drives the unit to interesting states. Fuzzers such as AFL [25] use fuzzing on the data inputs of a method to derive interesting values to drive a method. Korat [12] performs test generation for data structure inputs based on lazy unfolding of the type structure. PeX [20] performs concolic execution [7, 16] to enumerate paths in a program and synthesize inputs using a constraint solver to derive inputs.

However, none of these tools explore the generation of test oracle for the sake of finding functional bugs of a unit. These tools rely on program crashes (from implicit or explicit assertions present in the code), or look for a set of undesirable exceptions such as null dereference or out of bounds exceptions. Regression Oracles, used by tools such as EvoSuite [5, 6], are intended to find future bugs and assume the unit under test is correctly implemented. This assumption allows for generating assertions from observed execution behavior. This assumption prevents the oracle from catching non-exceptional bugs, which results in false negatives. Worse, they result in incorrect test oracles when the behavior is derived from buggy programs. Consider the example in Figure 2a that shows a buggy no-op implementation of stack pop. Figure 2b shows a generated unit test with a regression oracle. The test creates a stack and makes sequential push and pop calls. Since the pop method has a buggy no-op implementation, the stack will have one element after executing pop. This causes the regression oracle to generate an incorrect assertion that the stack should not be empty.
Similarly, qualifying any exceptional output as a bug (Safety Oracle) can fail on correctly implemented methods, causing false positives, (e.g., the intended behavior of calling pop() on an empty method is to throw an exception). Figure 2c shows a generated unit test with a safety oracle. A method that relies on safety oracle will also generate a passing test on the buggy pop implementation. Since pop is implemented as a no-op, an exception will not be raised when calling pop on an empty stack. In this case, the test oracle is implicit and asserts that an exception will not be thrown.

Therefore although automated test generation techniques find numerous non-functional bugs, and are useful for detecting regression bugs for future code changes, they are not a substitute for manually written unit tests documenting intended functionality.

2.2 Specification Mining Methods

Specification mining works [2, 8, 15, 18, 26] aim to generate test oracles that accurately reflect the intended behavior (as in Figure 1). Specification mining methods rely on docstring documentation. Unlike randomized test generation methods, specification mining approaches do not have any knowledge of the unit’s implementation and as such, do not require execution. These methods typically define a set of natural language docstring patterns. These patterns cannot capture all docstrings as program comments can be written flexibly without any necessary syntax or structure. Furthermore, since the patterns are hard coded, they are brittle and fail to generalize.

@Tcomment [18] defines natural language patterns along with heuristics to infer nullness properties. However, it cannot generalize to other property or exception types. An example heuristic @Tcomment employs is: generate an “expected NullPointerException” oracle if the keyword @param has the words null and not within 3 words of each other.

A similar technique, ToraDocu [8] uses a combination of pattern, lexical, and semantic similarity matching. Unlike @TComment, ToraDocu is not limited to nullness properties. However, ToraDocu can only generate oracles for exceptional behavior. JDoctor [2] is an extension of ToraDocu that can also generate assertion oracles. However, both of these methods fail to generalize as they still rely heavily on pattern matching.

Lastly, C2S [26] generates JML specifications from docstrings. C2S does not manually define patterns, but instead performs a search over JML tokens. However, C2S relies on a developer written test prefix to filter candidate assertions. C2S has performance improvements over JDoctor in terms of specification synthesis accuracy, but does not improve performance in bug finding.

On average, real-world java projects lack precisely structured docstring documentation. In our evaluation, we show that specification mining methods cannot infer bug-finding oracles for a benchmark of real world java projects.

2.3 Neural Methods

Recently, neural models have shown promise in generating test oracles and even entire unit tests. In contrast to specification mining methods, neural methods are not tied to hard coded patterns and can generalize to flexibly written docstrings. Furthermore, unlike randomized test generation tools, neural methods need not (necessarily) look at nor execute the unit under test.

We refer the reader to CodeBERT [4] for a discussion on the transformer architectures as applied to code. A transformer, like a recurrent neural network, maps a sequence of text into a high dimensional representation, which can then be decoded to solve downstream tasks. While not originally designed for code, they have found many applications with it because they can effectively map function and method bodies, function and method signatures, documentation, comments, etc. into various software engineering specific tasks.

One work in neural test oracle inference, ATLAS is an approach to generate assertion oracles. Given a test prefix and the unit under test, ATLAS [23] generates assertions using a recurrent neural network. ATLAS relies on the unit’s implementation and does not have any knowledge of the docstring documentation. ATLAS exclusively targets assertion oracle generation and does not attempt to infer any exceptional oracles.

Subsequent methods [11, 22, 24] have improved upon ATLAS by using a transformer-based seq2seq architecture pretrained on natural language and code. A transformer seq2seq model outperforms ATLAS in terms of inference accuracy. However, in section 5, we show that in combination with a test prefix generator, it struggles finding real world bugs in Java projects.

Lastly, AthenaTest [21] is a transformer model approach to generate entire unit tests including both prefixes and oracles. AthenaTest takes as input the unit’s context (e.g., surrounding class, method signatures, etc.), and implementation. Like the previous neural methods, it does not have any knowledge of the docstring documentation and relies on the implementation for inferring intended behavior.
3 STRUCTURE OF AN ORACLE

Our approach addresses the limitations of existing neural methods by employing a ranking architecture rather than a generative model. Our model performs assertion oracle inference by ranking a small set of possible oracles. In this section we develop a grammar for describing this set of test oracles. We first describe a taxonomy of commonly occurring oracle structures based on a qualitative investigation of a unit test dataset, and then use this taxonomy to inform the construction of our oracle grammar.

We develop a taxonomy of common oracle structures based on unit tests from methods2test [1], a dataset of Java unit tests collected from GitHub. We describe methods2test in Section 4.1.1. Unit test oracles typically test either exceptional behavior (i.e., verifying an expected exception is raised) or return behavior (assertion oracles). Additionally, an implicit exception oracle is usually present in tests with assertion oracles. That is, a test with an assertion oracle is not expected to raise an exception.

**Taxonomy:** We develop the following taxonomy of oracle usage, drawn from our observations of almost 200K developer-written tests:

1. Expected Exception Oracles. Expected exception oracles verify that executing the test prefix with some invalid usage raises an exception. They are most frequently expressed with the following structure:
   ```java
   try {
       Unit.methodcall(invalidInput);
   } catch (Exception e) {
       verifyException(e, ExceptionType);
   }
   ```

2. Assertion Oracles. Assertion oracles verify correct return behavior, although they will also fail if any exception is thrown. We observe several common assertion patterns:
   (a) **Boolean Assertions.** Boolean assertions are used to check some property of the unit under test is `true`/`false`. They are typically asserted directly on method return values:
       ```java
       Unit.methodcall(input);
       assertEquals(Unit.getStatus(), true);
       ```
   (b) **Nullness Assertions.** Nullness assertions usually check the return value of a method call that processes some input:
       ```java
       Unit.processInput(invalidInput);
       assertEquals(Unit.getFault(), null);
       ```
   (c) **Equality Assertions.** Developers typically write equality assertions to check the return value of a single method call. The return value is usually checked against a constant or literal representing the expected value. In many cases, especially when the unit under test incorporates some data structures, the expected value was previously passed as an argument to some method in the test prefix:
       ```java
       String msg = "foo";
       Unit.sendUnsuccessMessage(msg);
       assertEquals(Unit.getFaultMessage(), msg);
       ```

As we demonstrate in Section 5.2 this taxonomy captures the vast majority of tests (82% of a large dataset of developer written tests).

**Uncommon oracles.** We note several other patterns that occur more rarely, including equality assertions on arrays or assertions on multiple method calls (as opposed to a method call and a constant). We also note that there are some assertion patterns that we never observed in any unit test, although they are often used to express invariants within programs. These include assertions with logical connectives and assertions with inequality constraints.

**Test oracle grammar.** Based on the taxonomy of common oracle structures, we develop a restricted grammar that expresses commonly used test oracles.

```
Test T := O(P)  
Prefix P := statement | P; P  
Oracle O := E(P) | R(P)  
Return Oracle R := P; A  
Exception Oracle E := try(P; fail()); catch(Exception e){verifyException(e, ExceptionType)}  
Assertion A := assertEquals(const|var,expr) | assertTrue(expr) | assertFalse(expr) | assertNotNull(expr) | assertNotNull(expr)  
```

Intuitively, NUTS is a code-generation model for tests that is explicitly designed to exploit the structure of a unit test. This grammar succinctly describes a set of test oracles that are possible candidates for generation. In particular, given a test prefix `P`, we can synthesize either an exceptional oracle `E(P)` or an assertion oracle on the return value of a method `R(P)`. Further, the assertion oracle can be constructed using one of the five `assert*` constructs when instantiated with the return value and other constants and variables.

In the sections that follow, we demonstrate how to (i) prune this set, using type constraints, and (ii) rank the resulting possible test oracles using neural models.

4 NUTS: NEURAL TEST ORACLE GENERATION

In this section we present our approach for inferring test oracles that reflect developer intent. Unlike previous works, NUTS is capable of inferring both exception and assertion oracles. Furthermore, NUTS can handle units with vaguely written or absent docstrings, or even absent implementation. Our approach infers test oracles from only a given test prefix and unit context. Unit context may refer to method signature(s), or a docstring (if present). Notably, the unit context need not include the unit’s implementation.

4.1 Method Overview

NUTS depicted in Figure 3 contains two key components: the Exceptional Oracle Classifier and the Assertion Oracle Ranker.

The Exceptional Oracle Classifier, described further in Section 4.1.1, is powered by a pretrained transformer model fine-tuned on a binary decision task. The model decides if an exception should be thrown according to the developer intent conveyed through the unit context. If the classifier infers that the given test prefix should raise an exception, NUTS has found an exceptional oracle and can now generate a complete test. The resulting test has the *Expected Exception Oracle* format shown in Section 3. Otherwise, the classifier predicts that the input should not raise an exception and NUTS
The model is fine-tuned on ranking the set of candidate assertions. A label of 1 indicates that the sample should raise an exception while a label of 0 indicates that it should not raise an exception. For a given test prefix and unit context, each assertion in the set is ranked, and the highest ranked candidate is selected as the assertion oracle. Lastly, NUTS generates a test with the given test prefix and the inferred assertion oracle.

4.1 Exceptional Oracle Classifier. As mentioned previously, the Exceptional Oracle Classifier is based on a pretrained BERT transformer model. In particular, we use the CodeBERT [4] model trained on both natural language and code. To train the Exceptional Oracle Classifier we fine-tune the pretrained model on the task of exceptional oracle inference. The fine-tuning is performed using a supervised dataset $D = \{(p, c, a, l)\}$ where $p$ is a test prefix, $c$ is a unit context, and $l$ is a binary label ($l \in \{0, 1\}$). A label of 0 indicates that the sample should raise an exception while a label of 0 indicates that it should not raise an exception.

Methods2Test’ dataset. Our training dataset $D$ is variation of the Methods2Test dataset [21], we call Methods2Test’. As the name suggests, Methods2Test is a corpus of unit methods and corresponding developer written unit tests extracted from over 9K open source Java projects. Originally created to train AthenaTest, Methods2Test is structured for the translation task from methods to tests. We adapt Methods2Test to our setting of exception oracle inference. Our adapted dataset, Methods2Test’, has modifications in both the input methods and developer written tests. The input method’s implementation is removed, and the method docstring (if present) is added. The tests are modified to remove any exception or assertion oracles. These stripped oracles are used to create binary labels for expected exceptions. Lastly, we normalize the test method name to prevent potential information leakage. For example, a test method named testThrowsException would leak label information to the model. To remedy this, we rename all tests to follow the format: testN where N is a positive integer. In summary, Methods2Test’ is a supervised dataset for exception oracle inference. It excludes unit implementation and includes docstrings if present. Our resulting dataset contains a training set of more than 432,000 samples.

4.2 Assertion Oracle Ranker

The Assertion Oracle Classifier is also based on the pretrained CodeBERT [4] model. To train the Assertion Oracle Ranker we fine-tune the pretrained model on the task of assertion oracle inference. The fine-tuning is performed using a supervised dataset $D = \{(p, c, a, l)\}$ where $p$ is a test prefix, $c$ is a unit context, $a$ is a candidate assertion and $l$ is a binary label ($l \in \{0, 1\}$). A label of 1 indicates that the given candidate assertion accurately reflects developer intent. For a given $p$ and $c$ only one $a$ can have a label of 1. The other assertions in the candidate set will have a negative label.

Atlas’ dataset. Our training dataset $D$ is a variant of the Atlas dataset [23]. Atlas is a corpus of test case prefixes, corresponding method units, and assertions. Atlas was collected from 9K open source Java projects on GitHub. We modify Atlas to create our variant dataset Atlas’. Similar to our construction of Methods2Test’, we remove the method implementation, normalize the test method name, and remove the assertion from the test case. Then, we generate a set of assertion candidates for each sample and construct our labels to indicate the correct assertion in the set. Our negative samples are also taken from the candidate set of assertions. In summary, Atlas’ is a supervised dataset for assertion oracle inference. It excludes unit test implementation and includes docstrings and a set of candidate assertions for each $(p, c)$ sample. Our resulting dataset contains a training set of over 170,000 samples.

4.3 Candidate Assertion Set Generation

To generate a candidate set of assertions, we use our grammar along with type-based constraints to restrict the space of candidate oracles and enforce syntactic and semantic correctness. Based on the return value of the unit under test, we iteratively construct a set of candidate assertions. Our assertion candidate generation algorithm is shown in Algorithm 1. If the assertion that is being
added requires an additional value (assertEqual), our approach draws likely candidates from Global and Local Dictionaries.

**Global Constant Dictionary.** The Global Constant Dictionary contains the most frequently occurring constant values in the training data. Our global dictionary contains the top K values of each type. The use of a global dictionary is inspired by our observation that the vast majority of constants in test asserts are a few common values. For example, over 90% of the integer constants in asserts in the ATLAS dataset are one of the top 10 most frequently occurring integer values.

**Local Dictionary.** In addition to the global constant dictionary, we also build a local dictionary based on values that appear in the test prefix. Note that these values are not necessarily constants. Variables that appear in the test prefix are also valid local dictionary entries. The use of a local dictionary is based on the observation that many assertions check against values that were previously passed as arguments to methods called in the test prefix.

At inference time, our method makes calls to the Assertion Oracle Ranker for each assertion in the set of candidates. The model passed as arguments to methods called in the test prefix.

4.4 End-to-End EvoSuite integration
We have described a method, NUTS, to infer functional test oracles given a test prefix and unit context. However, in order to catch bugs, a test prefix that exercises the buggy behavior is necessary. To obtain a high quality test prefix, we use the randomized test generation tool EvoSuite. As mentioned in Section 2.1 EvoSuite generates a set of test prefixes guided by coverage. For each of the generated test prefixes, we invoke NUTS to infer a test oracle. In combination with a large set of prefixes that attempt to cover the entirety of the unit, our approach is able to generate functional test oracles that find real world bugs.

Lastly, we note that because we obtain prefixes from EvoSuite, we can safely assume that prefixes will be written in a standardized format. This allows us to make assumptions in the extractRetVal method (Algorithm 1).

5 EVALUATION

Research Questions. We consider the following research questions in our evaluation:

RQ1 Is our grammar representative of most developer-written assertions?
RQ2 Can we infer assertions and exceptional behavior with high accuracy?
RQ3 Can we catch bugs with low false alarms?

5.1 Evaluation Setup
Datasets. Our evaluation uses the ATLAS* and Methods2Test* datasets described in sections 4.2 and 4.1.1 respectively. For exceptional oracle inference, we evaluate on a Methods2Test* held-out test set of size 53,705. For assertion oracle inference, we evaluate on an Atlas* held-out test set of size 8,024.

Bug Benchmark. We evaluate real-world bug finding on the defects4j [9] benchmark. Defects4j is a benchmark of 835 bugs from 17 real world Java projects. Each sample in the benchmark includes both buggy and fixed code versions. Each fixed program version is based on a minimal patch to fix the bug, and passes all the project tests, while each buggy program version fails at least one test. Each bug is based on an error that was logged in the project’s issue tracker and involves source code changes, and is reproducible (i.e., with a deterministic test). The benchmark also includes utilities for generating and evaluating test suites on the programs to determine if generated tests pass on the fixed versions and catch bugs.

Test environment. The evaluation was conducted on a Linux machine with Intel(R) Xeon(R) E5-2690 v3 CPU (2.60GHz) and 112GB main memory. As in the defects4j environment, we use JDK 8.

5.2 RQ1: Oracle Grammar
We evaluate RQ1 on the original ATLAS dataset, which contains a total of 188,157 assertions mined from Java projects. To answer RQ1, we parse each assertion and check if it can be expressed in the grammar based on the assertion method name and structure of the AST. After excluding 695 samples that fail to parse, we find that 154,524 (82%) can be expressed by our grammar.
Of the 32,938 (18%) of assertions that cannot be expressed in our grammar, the majority (23,913, 13%) use assertion methods that we do not include (e.g., assertThat, assertSame). In many cases, the non-matching assertions appear to be symbolically equivalent to assertions expressible in our grammar (Figure 4).

Other assertions that did not match our grammar (5%) include equality assertions on expressions rather than variables or literals. For example:

```java
assertThat(id1.hashCode(), id2.hashCode())
```

Figure 4: The first assertion highlighted in red cannot be expressed in our grammar. However, the equivalent assertion highlighted in green, does fit our grammar.

Although we deliberately exclude generic assertions like these from our grammar, we note for a test executing in a deterministic environment, an equivalent property could be enforced through a syntactic rewrite.

**Result 1:** 82% of the developer-written assertions in the ATLAS dataset are in our grammar, and many other assertions are semantically equivalent to assertions expressed in our grammar.

### 5.3 RQ2: Oracle Inference Accuracy

To answer RQ2, Tables 1 and 2 report accuracy results on a held-out test set. We include results for both exceptional and return test oracle inference.

For exceptional oracle inference (Table 1), our experimental setup involves the Methods2Test* dataset described in Section 4.2. There are no neural techniques for exceptional oracle inference that we are aware of. Instead, we include a random baseline (weighted coin) to illustrate the complexity of the problem space. The coin performs a random choice weighted on the distribution in our training set. In our training set, we observed that 80% of samples are non exceptional. As such, the coin predicts negative labels frequently (and usually correctly), but rarely predicts a positive. The coin performs similarly to our approach in terms of accuracy, but significantly worse in terms of F1 score, as it rarely predicts a positive label correctly.

For assertion oracle inference (Table 2), our experimental setup involves the Atlas* dataset described in Section 4.1.1. The accuracy metric is syntactic; a suggestion is considered correct if it is an exact syntactic match. As a baseline, we compare to a sequence2sequence return test oracle model [22]. The seq2seq model is a transformer pre-trained on natural language and code. In contrast to our approach which performs ranking over a set of template assertions, the seq2seq model generates a test oracle token by token. As such, the model suffers due to the large space of possible oracles. We report results on two held out test sets: an Overall set and an In-Vocab set. The in-vocab set is the subset of the overall set that can be expressed by our grammar and vocabulary based on the local and global dictionaries. Our model achieves 96% accuracy on the in-vocab set compared to 63% by the seq2seq model, and 69% overall accuracy, an 11% relative improvement over the seq2seq model.

**Result 2:** Our assertion oracle inference model achieves over 69% accuracy compared to 62% accuracy from existing approaches. Our exceptional inference model achieves 86% accuracy with an F1 score of .39 relative to a weighted coin baseline’s .15 F1 score.

**Vocabulary size ablation.** We perform an study on K, the vocabulary size of our global dictionary, to examine the tradeoff between generating a larger number of assertion candidates and ranking the assertion candidates accurately. Figure 5 shows the overall model accuracy, percent of samples supported by the vocabulary, and accuracy on samples supported by the vocabulary evaluated on the ATLAS* test set.

For K=0, the global dictionary is unused and only variables and constants in the local dictionary are considered the assertion generation. Using only the local dictionary can still generate correct assertion candidates for approximately 50% of the samples in the test set. Increasing K causes the model accuracy to decline slightly, but causes overall accuracy to improve because more correct assertion candidates are generated using the global dictionary. Once the vocabulary becomes too large however, the model accuracy starts to drop off, and setting higher Ks reduces overall accuracy.

In evaluation, we set K=8 based on tuning on the ATLAS* validation set. This setting achieves the best tradeoff between high model accuracy on the candidate set, and supporting a large set of likely assertions.

**Figure 5:** Evaluation of global dictionary size K on overall accuracy

| Approach          | Accuracy | Precision | Recall | F1-Score |
|-------------------|----------|-----------|--------|----------|
| NUTS Model        | 86%      | .55       | .30    | .39      |
| Weighted Coin     | 76%      | .15       | .13    | .15      |

Table 1: RQ2: Evaluation of Exceptional Oracle Inference

| Approach          | In-Vocab Accuracy | Overall Accuracy |
|-------------------|-------------------|------------------|
| NUTS Model        | 96%               | 69%              |
| Seq2Seq           | 63%               | 62%              |

Table 2: RQ2: Evaluation of assertion oracle Inference
To answer RQ3, we run our end-to-end test generation system, integrated with EvoSuite. As described in section 4.4, the system uses EvoSuite to generate test prefixes guided by coverage. Our models are invoked to generate the test oracles.

**Baselines.** We consider the following baselines in this evaluation:

1. **Randomized Test Generation.** To represent randomized test generation we run Randoop [14], which is a widely used and actively maintained test generation tool used for bug finding. We also run EvoSuite [5] as a baseline, although EvoSuite’s intended use case for regression testing limits its ability to find bugs present in the program. We run both Randoop and EvoSuite for 3 minutes per tested program, following the procedure used in [17].

2. **Neural Test/Oracle Generation.** To test neural methods, we compare with a seq2seq transformer (Codebert) [4] that is pretrained on 3 programming languages (including Java) and finetune it to generate assertions on the ATLAS assertion dataset. We also evaluate against a whole-test generation model, AthenaTest [21].

3. **Specification Mining.** We use JDoctor’s open source implementation to evaluate specification mining approaches. JDoctor supports both exception and assertion oracle generation by parsing specific patterns in docstrings [2]. We integrate the generated oracles with the same evosuite-generated tests used by NUTS in this evaluation. Note that we do not evaluate on C2S [26] because the implementation is not publicly available.

**Evaluation setting.** We evaluate RQ 3 on the Defects4J [9] benchmark. To evaluate the effectiveness of oracles in detecting bugs present in the program, the generated tests are run on a buggy version of the unit under test. We consider a bug is found if a generated test both fails on the buggy program and passes on the fixed program. Since each fixed program is distinguished from the buggy program by a minimal patch fixing the specific bug, a test must be failing due to the specific bug if it only fails on the buggy version.

It is important to note that our evaluation setting is fundamentally different from the regression evaluation setting in which the Defects4J benchmark has been most often been used. In a regression evaluation, tests are generated on the fixed program version and therefore studies of randomized test generation tools generating regression tests are able to find larger numbers of bugs by using regression assumptions to generate higher quality oracles [17]. In our setting where tests are generated on the buggy program version, regression test generation finds no bugs because it will assume the observed buggy behavior is correct.

In addition to evaluating on bugs found, we use per-test metrics for test oracle generation accuracy defined in [2]. These metrics measure the performance of an oracle generation method from a usage perspective. An oracle generation method that generates thousands of erroneously failing tests for every bug found will not be usable in a realistic application setting where a developer must inspect failing tests and determine if the failures represent real bugs or false alarms.

A failing test is considered a “positive” while a passing test is a “negative”. However, a “positive” does not necessarily indicate that the oracle caught the bug. A failing test can indicate one of two things:

1. **True Positive** - The test has a correct oracle and fails due to the buggy implementation
2. **False Positive** - The test has an incorrect oracle and fails on the correct functionality of the unit in the buggy version.

To distinguish between these cases, we run the same test on the unit’s fixed version. If the test fails on the fixed version, we can safely assume the test has an incorrect oracle, and is a FP. Similarly, a passing test can indicate one of two things:

1. **True Negative** - The test has a correct oracle and is testing correct functionality
2. **False Negative** - The test has an incorrect oracle and is testing buggy functionality

Again, to distinguish between these cases, we run the same test on the unit’s fixed version. If the test fails on the fixed version, we can safely assume the test has an incorrect oracle, and is an FN.

We summarize the meaning of these metrics in Figure 6. In our evaluation, we summarize these metrics in the False Positive (FPR), which represents the rate of incorrectly failing tests on non-buggy code. A high FPR implies that a developer will need to validate many tests that have no utility and thus is a good metric for a bug-finding tool.

Table 3 reports overall bug finding performance. NUTS finds 54 total bugs, including 27 that are not found by any other method in our evaluation. The next best performing method, Randoop, finds 20 bugs but with a much higher false positive rate. EvoSuite does not find any bugs because it generates regression oracles. Of the two tested neural methods, AthenaTest also does not generate any bug-finding tests and the seq2seq model run on evosuite-generated test prefixes finds 6 bugs, but incurs a higher error rate. The specification

| Approach               | Bugs Found (TPs) | FPR |
|------------------------|------------------|-----|
| EvoSuite + Ground Truth| 124              | 0%  |
| EvoSuite + NUTS (Ours) | 54              | 25% |
| Randoop                | 20              | 87% |
| EvoSuite               | 0               | 0%  |
| EvoSuite + seq2seq     | 6               | 46% |
| AthenaTest             | 0               | 15% |
| EvoSuite + JDoctor     | 1               | 4%  |

Table 3: RQ3: Overall Bug Finding. *AthenaTest FPR based on 5 projects

| Approach               | Exception Raised | Exception Not Raised | Assertion Failure |
|------------------------|-------------------|----------------------|-------------------|
| EvoSuite + Ground Truth| 36                | 38                   | 50                |
| EvoSuite + NUTS (Ours) | 35                | 5                    | 14                |
| Randoop                | 20                | 0                    | 0                 |
| EvoSuite               | 0                 | 0                    | 0                 |
| EvoSuite + seq2seq     | 0                 | 0                    | 6                 |
| AthenaTest             | 0                 | 0                    | 0                 |
| EvoSuite + JDoctor     | 1                 | 0                    | 0                 |

Table 4: RQ3: Number of Bugs Found by Bug Type

5.4 RQ3: Bug Detection

To answer RQ3, we run our end-to-end test generation system, integrated with EvoSuite, as described in section 4.4, the system uses EvoSuite to generate test prefixes guided by coverage. Our models are invoked to generate the test oracles.
tool JDoctor only finds bug, but is the most precise oracle generation method in the evaluation that is capable of finding bugs.

Table 4 reports a breakdown of bug finding performance on three different bug types: unexpected exception raised, expected exception not raised, and assertion failures. NUTS’s ability to infer exception oracles correctly is critical to its bug finding performance. Overall 40 of the bugs it finds are exceptional, and 5 involve expected exceptions not being raised. None of the other methods in the evaluation detect any expected exception not raised bugs. Of the other evaluated methods, AthenaTest and JDoctor are both capable of generating expected exception bugs in principle but in practice do not generate any on the programs in the evaluation. For raised (unexpected) exceptions, NUTS exception model correctly identifies 35/36 of them are unexpected exceptions. This demonstrates the value of using a neural model for exception oracle generation, which is more flexible than the fixed rules used by a tool like Randoop.

NUTS also identifies 14 assertion bugs. The only other method in the evaluation to generate assertion oracles that catch bugs is the seq2seq generative model, which catches 6 bugs. This illustrates that while NUTS ranking-based oracle generation procedure is effective for bug finding, its overall performance in bug finding comes from providing a unified method for oracle generation that can detect all three types of bugs. In contrast, none of the methods in the evaluation are successful in generating oracles for more than one type of bug, although some such as JDoctor or AthenaTest can in theory generate oracles for all three classes of bugs.

The failure of both AthenaTest and the seq2seq assertion generation model to effectively find bugs illustrate the challenges in neural oracle generation. In practice we found that both AthenaTests whole test generation and the seq2seq assertion model generated many tests and oracles that were not executable. The AthenaTest authors noted this issue in their evaluation, where they found that only 16% of the generated test cases were executable without errors and actively tested the unit under test [21]. The oracle generation model generated 34% executable oracles, and of these we observed that a further 5% were tautologies, resulting in an overall yield of 29% potentially meaningful oracles. In contrast, the ranked oracle generation used by NUTS always generates oracles that are executable and exercise the unit under test.

Note that due to the large volume of generated test candidates that must be individually compiled and run, we estimate the false positive rate of AthenaTest on five projects and otherwise only generate tests specifically on methods exercising buggy code.

Because JDoctor uses precise pattern matching on docstrings, it generates oracles precisely since there must be a docstring comment indicating the specific behavior that is encoded in the oracle. However, on the projects in the defects4j benchmark, this approach succeeds in generating test oracles to catch a single bug. We observed that in practice, many buggy methods either had vaguely worded docstrings or lacked docstrings entirely, and JDoctor created relative few test oracles as a result. JDoctor’s inability to generate sufficient oracles to effectively find bugs illustrates why robustness to vague or missing docstrings is an important requirement for effective oracle generation. In many cases, the bugs detected by NUTS occurred on methods that lacked docstrings, so JDoctor was unable to find them.

Lastly, we note that we obtained Ground Truth oracles by parsing the execution traces of the evosuite generated tests on both fixed and buggy program versions to check for oracles that could distinguish the two versions. These oracles detect 124 out of the 835 bugs in the Defects4J dataset. In order to catch bugs, a test prefix must exercise the buggy behavior and reach a state that is invalid. Our test prefix generation method (EvoSuite) reaches 124 invalid states. Since our approach focuses on test oracle inference rather than test prefix generation, detecting these 124 bugs is the best possible performance for the methods using Evosuite generated prefixes.

**Result 3:** Our approach finds 54 bugs in real world java projects, 27 of which are not found by any existing methods.

### 5.4.1 Case Studies

We consider two case studies of bugs that are detected by NUTS in our evaluation but not by other methods.

**Assertion bug case study.** The first case study, shown in Figure 7 involves a bug in a key-value store used in the Chart java project. The buggy method, shown in Figure 7a, contains incorrect logic that prevents the data structure from updating its index when the most recently added item is removed. This causes the `itemCount()` method to return an incorrect count, because it bases the item count on the index.

The evosuite-generated test for this method shown in Figure 7b uses a regression oracle and generates an assertion based on the observed execution behavior. Because the method is buggy, this results in an incorrect assertion being generated, which not only fails to catch the bug but also could potentially make future detection of the bug more difficult. Figure 7c shows a simplified version of an unexpected exception oracle, which is the approach used by Randoop in the evaluation.

In contrast to these two approaches, NUTS generates the correct oracle by performing a ranking over a small number of assertions on integers and the return value of `itemCount()`. This identifies that after calling `removeValue(8)`, the most likely assertion is `assertEquals(8, kv.itemCount())`.

**Expected exception case study.** Figure 8 illustrates how NUTS is able to catch an unexpected exception bug detected in our evaluation. The bug in the `NumberUtils.createNumber` method of the Java Lang project prevents the method from correctly detecting invalid inputs and raising an exception. The exception ranking model predicts that the `createNumber("0XT")` call should raise an exception based on the method signature and context, and NUTS generates an oracle based on this prediction to pass the test if an exception is raised on fail otherwise. In contrast, a safety oracle that checks for unexpected exceptions cannot detect this type of bug where a

| TP | Fail | Pass |
|----|------|------|
| FP | Fail | Fail |
| TN | Pass | Pass |
| FN | Pass | Fail |

**Figure 6: Bug Finding Metrics**
This paper presents NUTS, a neural technique to infer both exception and assertion test oracles from a given test prefix and unit context. NUTS is a two step transformer based architecture that is capable of generating oracles for units without implementation or docstrings. It improves upon generative neural assertion oracle inference techniques by ranking a small of likely candidate assertions. When integrated with a random test generation tool (Evosuite) to obtain prefixes, NUTS finds 54 real world bugs, out-performing existing test oracle inference techniques. Additionally, this paper presents two datasets for future work in neural exception and assertion test oracle inference.

REFERENCES
[1] [n.d.]. Methods2Test. https://github.com/microsoft/methods2test.
[2] Arianna Blasi, Alberto Goffi, Konstantin Kuznetsov, Alessandra Gorla, Michael D. Ernst, Mauro Pezze, and Sergio Delgado Castellanos. 2018. Translating Code Comments to Procedure Specifications. In Proceedings of the 27th ACM SIGSOFT International Symposium on Software Testing and Analysis (Amsterdam, Netherlands) (ISSTA 2018). Association for Computing Machinery, New York, NY, USA, 242–253. https://doi.org/10.1145/3213846.3213872
[3] Ermira Daka and Gordon Fraser. 2014. A Survey on Unit Testing Practices and Problems. In 2014 IEEE 25th International Symposium on Software Reliability Engineering, 201–211. https://doi.org/10.1109/ISSRE.2014.11
[4] Zhangyin Feng, Duyu Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Lin, Daxin Jiang, and Ming Zhou. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. arXiv:2002.08155 [cs.CL]
[5] Gordon Fraser and Andrea Arcuri. 2011. Evolutionary Generation of Whole Test Suites. In International Conference On Quality Software (QSIC). IEEE Computer Society, Los Alamitos, CA, USA, 31–40. https://doi.org/10.1109/QSIC.2011.19
[6] Gordon Fraser and Andrea Arcuri. 2014. A large-scale evaluation of automated unit test generation using evosuite. ACM Transactions on Software Engineering and Methodology (TOSEM) 24, 2 (2014), 1–42.
[7] Patrice Godefroid, Nils Klarlund, and Koushik Sen. 2005. DART: directed automated random testing. In Proceedings of the ACM SIGPLAN 2005 Conference on Programming Language Design and Implementation, Chicago, IL, USA, June 12-15, 2005. Vivek Sarkar and Mary W. Hall (Eds.). ACM, 213–223. https://doi.org/10.1145/1065010.1065036
[8] Alberto Goffi, Alessandra Gorla, Michael D. Ernst, and Mauro Pezze. 2016. Automated Generation of Oracles for Exceptional Behaviors. In Proceedings of the 25th International Symposium on Software Testing and Analysis (Saarbrücken, Germany) (ISSTA 2016). Association for Computing Machinery, New York, NY, USA, 213–224. https://doi.org/10.1145/2931037.2931061
[9] Frenet Just, Darioush Jalali, and Michael D. Ernst. 2014. Detect4Spec: A Database of existing faults to enable controlled testing studies for Java programs. In ISSTA 2014, Proceedings of the 2014 International Symposium on Software Testing and Analysis. San Jose, CA, USA, 437–449. Tool demo.
[10] Stephan Lukaszyk, Florian Knoop, and Gordon Fraser. 2020. Automated Unit Test Generation for Python. In Proceedings of the 12th Symposium on Search-Based Software Engineering (SSBSE 2020, Bari, Italy, October 7–8) (Lecture Notes in Computer Science, Vol. 12420) (Saarbrücken, Germany) (Lecture Notes in Computer Science, Vol. 12420). Springer, 9–24. https://doi.org/10.1007/978-3-030-59763-7_2
[11] Antonio Mastropaolo, Simone Scalabrino, Nathan Cooper, David Nader Palacio, Denys Poshyvanyk, Rocco Oliveto, and Gabriele Bavota. 2021. Studying the usage of text-to-test transfer transformer to support code-related tasks. In 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 336–347.
[12] Aleksandar Milicevic, Sasa Misailovic, Darko Marinov, and Sarfraz Khurshid. 2007. Konat: A Tool for Generating Structurally Complex Test Inputs. In 29th International Conference on Software Engineering (ICSE 2007), Minneapolis, MN, USA, May 20-26, 2007. IEEE Computer Society, 771–774. https://doi.org/10.1109/ICSE.2007.48
[13] Carlos Pacheco and Michael D Ernst. 2007. Randomop: feedback-directed random testing for Java. In Companion to the 22nd ACM SIGPLAN conference on Object-oriented programming systems and applications companion. 815–816.
[14] Carlos Pacheco, Shuvendu K. Lahiri, Michael D. Ernst, and Thomas Ball. 2007. Feedback-directed random test generation. In ICSE 2007, Proceedings of the 29th International Conference on Software Engineering, Minneapolis, MN, USA, 75–84.
[15] Rahul Pandita, Xuosheng Xiao, Hao Zhong, Tao Xie, Stephen Oney, and Amit Paradkar. 2012. Inference method specifications from natural language API
descriptions. In *Proceedings of the 5th IEEE International Conference on Software Testing, Verification and Validation (ICST 2012)*, Montreal, Canada, 260–269.

[19] Tassey and Gregory. 2002. The Economic Impacts of Inadequate Infrastructure for Software Testing. (05 2002).

[20] Nikolai Tillmann and Jonathan de Halleux. 2008. Pex-White Box Test Generation for .NET. In *Proceedings - 2nd International Conference, TAP 2008, Prato, Italy, April 9-11, 2008. Proceedings (Lecture Notes in Computer Science, Vol. 4966)*, Bernhard Beckert and Reiner Hahnle (Eds.). Springer, 134–153. https://doi.org/10.1007/978-3-540-79124-9_10

[21] Michele Tufano, Dawn Drain, Alexey Svyatkovskiy, Shao Kun Deng, and Neel Sundaresan. 2021. Unit Test Case Generation with Transformers and Focal Context. arXiv:2009.05617 [cs.SE]

[22] Michele Tufano, Dawn Drain, Alexey Svyatkovskiy, and Neel Sundaresan. 2020. Generating Accurate Assert Statements for Unit Test Cases using Pretrained Transformers. arXiv:2009.05634 [cs.SE]

[23] Cody Watson, Michele Tufano, Kevin Moran, Gabriele Bavota, and Denys Poshyvanyk. 2020. On learning meaningful assert statements for unit test cases. *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering* (Jun 2020). https://doi.org/10.1145/3377811.3380429

[24] Robert White and Jens Krinke. 2020. Reassert: Deep learning for assert generation. arXiv preprint arXiv:2011.09784 (2020).

[25] Michal Zalewski. 2015. American Fuzzy Lop (AFL). http://lcamtuf.coredump.cx/afl/

[26] Juan Zhai, Yu Shi, Minxue Pan, Guian Zhou, Yongxiang Liu, Chunrong Fang, Shiqing Ma, Lin Tan, and Xiangyu Zhang. 2020. C2S: Translating Natural Language Comments to Formal Program Specifications. In *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (Virtual Event, USA) (ESEC/FSE 2020)*. Association for Computing Machinery, New York, NY, USA, 25–37. https://doi.org/10.1145/3368089.3409716