Natural language processing meets software testing

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March 15, 2016

• A sequence of instructions that perform some task

An engineered object amenable to formal analysis

• A sequence of instructions that perform some task

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- A sequence of instructions that perform some task
- Test cases
- Version control history
- Issue tracker
- Documentation

• .

How should it be analyzed?

Analysis of a natural object

- Machine learning over executions
- Version control history analysis
- Bug prediction
- Upgrade safety
- Prioritizing warnings
- Program repair

Natural language in programs

This talk:

- Variable names: find undesired variable interactions
- 2. Error messages and user manuals: find inadequate diagnostic messages
- 3. Procedure documentation: generate test oracles

Undesired variable interactions

```
int totalPrice;
int itemPrice;
int shippingDistance;
totalPrice = itemPrice + shippingDistance;
```

Undesired variable interactions

```
int totalPrice;
int itemPrice;
int shippingDistance;
totalPrice = itemPrice + shippingDistance;
```

- The compiler issues no warning
- A human can tell the abstract types are different

Idea:

- Cluster variables based on usage in program operations
- Cluster variables based on words in variable names
 Differences indicate bugs or poor variable names

Clustering based on operations

Abstract type inference [ISSTA 2006]

```
int totalCost(int miles, int price, int tax) {
  int year = 2016;
  if ((miles > 1000) && (year > 2000)) {
    int shippingFee = 10;
    return price + tax + shippingFee;
  } else {
    return price + tax;
```

Clustering based on operations

Abstract type inference [ISSTA 2006]

```
int totalCost(int miles, int price, int tax) {
  int year = 2016;
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```

Clustering based on variable names

Compute variable name similarity

- 1. Tokenize each variable into dictionary words
 - in_authskey15 ⇒ {"in", "authentications", "key"}
 - Expand abbreviations, best-effort tokenization
- 2. Compute word similarity
 - For all $w1 \in var1$ and $w2 \in var2$, use WordNet or edit distance
- 3. Combine word similarity into variable name similarity
 - maxwordsim(w1) = maximum wordsim(w1, w2) for w2 ∈ var2
 - varsim(var1) = average maxwordsim(w1) for w1 ∈ var1

Results

- Found an undesired variable interaction in grep if (depth < delta[tree->label]) delta[tree->label] = depth;
- Loses top 3 bytes of depth
- Not exploitable because of guards elsewhere in program, but not obvious here

Inadequate diagnostic messages

Scenario: user supplies a wrong configuration option
 --port_num=100.0

Problem: software issues an unhelpful error message

- "... unexpected system failure ..."
- "... unable to establish connection ..."
- Better: "--port_num should be an integer"

Goal: detect such problems before shipping the code

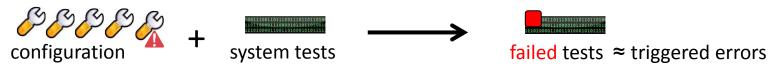
Challenges for proactive detection of inadequate diagnostic messages

• How to trigger a configuration error?

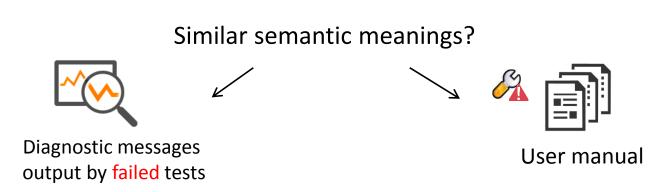
• How to *determine the inadequacy* of a diagnostic message?

ConfDiagDetector's solutions

- How to trigger a configuration error?
 - Configuration mutation + run system tests



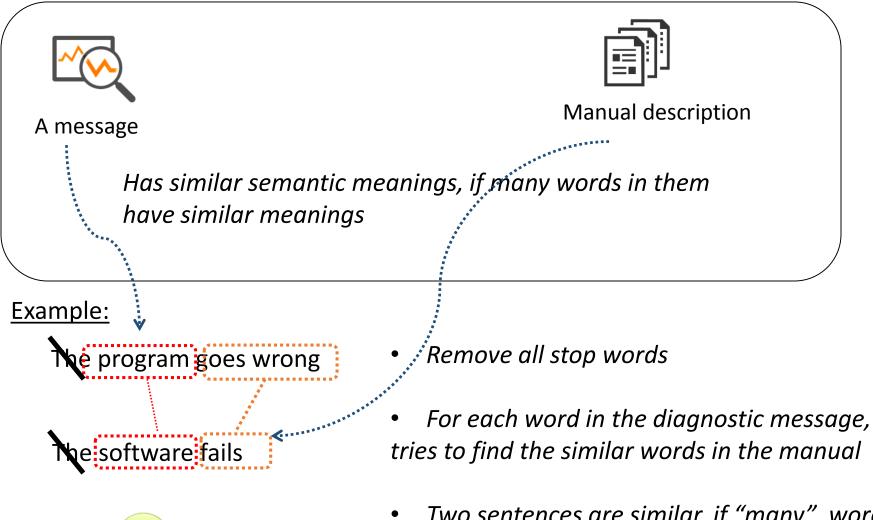
How to determine the inadequacy of a diagnostic message?
 Use a NLP technique to check its semantic meaning



Message analysis

- A message is adequate, if it
 - contains the mutated option name or value OR
 - has a similar semantic meaning with the manual description

Text similarity technique [Mihalcea'06]



• Two sentences are similar, if "many" words are similar between them.

Results

- Reported 25 missing and 18 inadequate messages in Weka, JMeter, Jetty, Derby
- Validation by 3 programmers:
 - 0% false negative rate
 - 2% false positive rate

Test oracles for exceptional behavior

Exceptional behavior is a significant source of failures, but is under-tested (significantly less coverage)

Goal: create test oracles (= **assert** statements)

Although programmers may not write tests, the programmer does provide other indications: procedure documentation (e.g., Javadoc)

```
/**
 * Checks whether the comparator is now locked
 * against further changes.
 *
 * @throws UnsupportedOperationException if the
 * comparator is locked
 */
```

protected void checkLocked() {...}

Text to code

- 1. Parse the @throws expression using the Stanford Parser
 - Parse tree, grammatical relations, cross-references
 - Challenges:
 - Often not a well-formed sentence; code snippets as nouns/verbs
 - Referents are implicit, assumes coding knowledge
- 2. Match each subject to a Java element
 - Pattern matching
 - Semantic similarity
 - Lexical similarity to identifiers, types, documentation
- 3. Match each predicate to a Java element
- 4. Create assert statement from expressions and methods

Automatically generated tests

- A test generation tool outputs:
 - Passing tests useful for regression testing
 - Failing tests indicates a program bug
- Without a formal specification, tool guesses whether a given behavior is correct
 - False positives: report a failing test that was due to illegal inputs
 - False negatives: fail to report a failing test because it might have been due to illegal inputs
- Results: Reduced false positive test failures in EvoSuite by 1/3 or more

Machine learning + software engineering

- Software is more than source code
- Formal program analysis is useful, but insufficient
- Analyze and generate all software artifacts

A rich space for further exploration