Applying Classification Techniques to Remotely-Collected Program Execution Data

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Testing & Analysis after Deployment

Program P

SE Tasks
- Test adequacy
- Usability testing
- Failure classification
- Coverage analysis
- Impact analysis
- Fault localization

Field Data
- Residual coverage data
- GUI interactions
- Caller/callee profiles
- Partial coverage data
- Dynamic slices
- Various profiles (returns, ...)

[Pavlopoulou99] Test adequacy
[Hilbert00] Usability testing
[Dickinson01] Failure classification
[Bowring02] Coverage analysis
[Orso03] Impact analysis
[Liblit05] Fault localization

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Tradeoffs of T&A after Deployment

• In-house
  (+) Complete control (measurements, reruns, …)
  (-) Small fraction of behaviors

• In the field
  (+) All (exercised) behaviors
  (-) Little control
  • Only partial measures, no reruns, …
  • In particular, no oracles
  • Currently, mostly crashes
Our Goal

Provide a technique for automatically identifying failures

- Mainly, in the field
- Useful in-house too
  - Automatically generated test cases
Overview

• Motivation and Goal
• General Approach
• Empirical Studies
• Conclusion and Future Work
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Background: Classification Techniques

Classification -> Supervised learning -> Machine learning

Many existing techniques (logistic regression, neural networks, tree-based classifiers, SVM, ...)

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Background: Random Forests Classifiers

- **Tree-based classifiers**
  - Partition predictor space in hyper-rectangular regions
  - Regions are assigned a label
  (+) Easy to interpret
  (-) Unstable

- **Random forests [Breiman01]**
  - Integrate many (500) tree classifiers
  - Classification via a voting scheme
  (+) Easy to interpret
  (+) Stable
Our Approach

Some critical open issues

- What data should we collect?
- What tradeoffs exist between different types of data?
- How reliable/generalizable are the statistical analyses?
Specific Research Questions

RQ1: Can we reliably classify program outcomes using execution data?

RQ2: If so, what type of execution data should we collect?

RQ3: How can we reduce runtime data collection overhead while still producing accurate and reliable classifications?

⇒ Set of exploratory studies
Overview

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Experimental Setup (I)

Subject program

- JABA bytecode analysis library
- 60 KLOC, 400 classes, 3000 methods
- 19 single-fault versions ("golden version" + 1 real fault)

Training set

- 707 test cases (7 drivers applied to 101 input programs)
- Collected various kinds of execution data (e.g., counts for throws, catch blocks, basic blocks, branches, methods, call edges, ...)
- "Golden version" to label passing/failing runs
**Experimental Setup (II)**

<table>
<thead>
<tr>
<th>In-House</th>
<th>Training Set 2/3</th>
<th>Learning Algorithm</th>
<th>Model (random forest)</th>
</tr>
</thead>
<tbody>
<tr>
<td>In the Field</td>
<td>Training Set 1/3</td>
<td>Classifier Model</td>
<td>Predicted Outcome (pass/fail)</td>
</tr>
</tbody>
</table>

**Ideal setting, but**

- Expensive
- Difficult to get enough data points
- Oracle problem

=> Simulate users’ runs

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RQ1 & RQ2: Can We Classify at All? How?

- **RQ1**: Can we reliably classify program outcomes using execution data?
- **RQ2**: Assuming we can classify program outcomes, what type of execution data should we collect?

  - We first considered a specific kind of execution data: basic-block counts (~20K) (simple measure, intuitively related to faults)
  - Results: classification error estimates always almost 0!
  - But, time overheard ~15% and data volume not negligible

=> Other kinds of execution data
RQ1 & RQ2: Can We Classify at All? How?

- We considered other kinds of execution data:
  - Basic-block counts yielded almost perfect predictors
    => richer data not considered
  - Counts for: throws, catch-blocks, methods, and call-edges

- Results
  - Throw and catch-block counts are poor predictors
  - Method counts produced nearly perfect models
    - As accurate as block counts, but much cheaper to collect
    - 3000 methods vs. 20000 blocks (overhead < 5%)
  - Branch and call-edge counts equally accurate, but more costly than method counts

Preliminary conclusion (1): Possible to classify program runs; method counts provided high accuracy at low cost
RQ3: Can We Collect Less Information?

- Method-count models used between 2 and 7 method counts. Great for instrumentation, but...
- Two alternative hypotheses
  - Few methods are relevant -> must choose specific methods well
  - Many, redundant methods -> method selection less important
- To investigate, performed 100 random samplings
  - Took 10% random samples of method counts and rebuilt models
  - Models were excellent 90% of the times
  - Evidence that many method counts are good predictors

Preliminary conclusion (2): “failure signal” spread, rather than localized to single entities => estimates can be based on a few data, collected with negligible overhead
Validity of the Analysis

Two main issues to consider

• Multiplicity
• Generality
Statistical Issues -- Multiplicity

When # of predictors far exceeds # of data points, the likelihood of finding spurious relationship increases

• i.e., random relationships confused for real ones

We took two steps to address the problem

• Consider method counts
  (least number of predictors)
• Conducted study in which we
  • Randomly permuted method counts
  • Took a 10% random sample of method counts and rebuilt models (100 times)

=> Never found good models based on this data

Preliminary conclusion (3): Results are unlikely to be due to random chance
Statistical Issues -- Generality

Classifiers for 1 specific bug are useful, but...

- We would like to have models that encode “correct behavior” for the application in general
- Looked for predictors that worked in general
  ⇒ Found 11 excellent predictors for all versions

Programs typically contain more than 1 bug

- Applied our approach to 6 multi-bug versions
- Models had error rates less than 2% in most cases

Preliminary conclusion (4): Results promising w.r.t. generality (but need to investigate further)
Overview

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• General Approach
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Summary

• Possible to classify program outcomes using execution data

• Method counts gave high accuracy at low cost

• Estimates can be computed based on very few data, collected with negligible overhead

• Our results are unlikely to depend on random chance and are promising in terms of generality

• But, these are still preliminary results, and we need to investigate further
Future Work

- Multiple faults
- Investigate relationship between predictors and failures
- Investigate relationship between predictors and faults
- Conduct further experiments with system(s) in actual use