# Finding Latent Code Errors via Machine Learning over Program Executions

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# Bubble Sort

```
// Return a sorted copy of the argument
double[] bubble_sort(double[] in) {
  double[] out = array_copy(in);
  for (int x = out.length - 1; x >= 1; x--)
    for (int y = x - 1; y >= 1; y--)
      if (out[y] > out[y+1])
        swap (out[y], out[y+1]);
  return out;
}
```

# Bubble Sort

Faulty (?) Code:

```
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Fault-revealing properties

out[0] = in[0]

out[1] ≤ in[1]

# Bubble Sort

Faulty Code:

```
// Return a sorted copy of the argument
double[] bubble_sort(double[] in) {
  double[] out = array_copy(in);
  for (int x = out.length - 1; x >= 1; x--)
    // lower bound should be 0, not 1
    for (int y = x - 1; y >= 1; y--)
      if (out[y] > out[y+1])
        swap (out[y], out[y+1]);
  return out;
}
```

Fault-revealing properties

out[0] = in[0]

out[1] ≤ in[1]

# Outline

- Intuition for Fault Detection
- Latent Error Finding Technique
- Fault Invariant Classifier Implementation
- Accuracy Experiment
- Usability Experiment
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# Targeted Errors

- Latent Errors
  - unknown errors
    - may be discovered later
    - no manifestation
  - not discovered by test suite

# Targeted Programs

- Programs that contain latent errors
- Test inputs are easy to generate, but test outputs can be hard to compute, e.g.:
  - Complex computation programs
  - GUI programs
  - Programs without formal specification

# Learning from Fixes

Program A:

```
...
print (a[a.size] + “elements”);
...
```

Fixed Program A:

```
...
print (a[a.size - 1] + “elements”);
...
```

Program B:

```
...
if (store[store.length] > 0);
...
```

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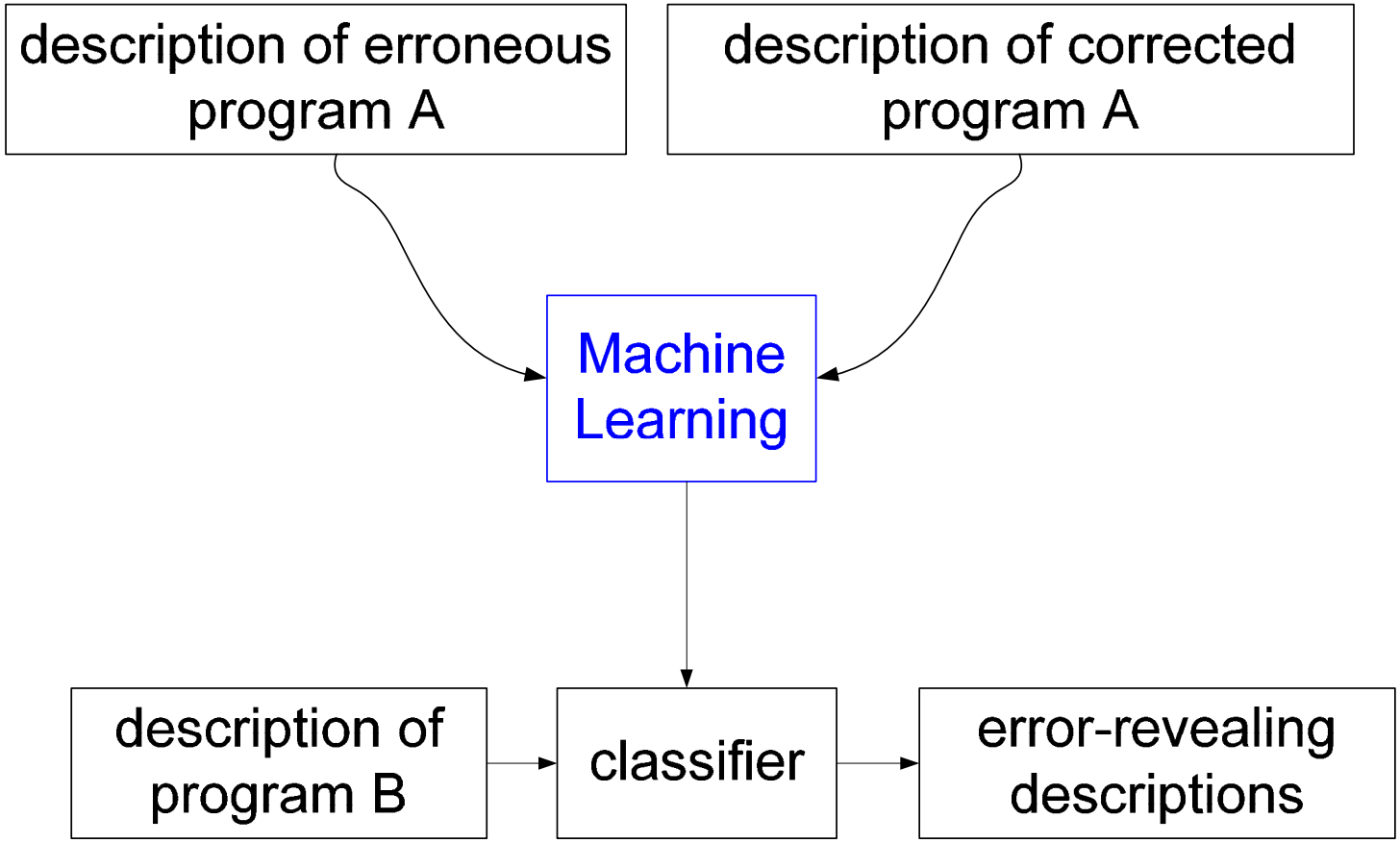
# Program Description Mapping

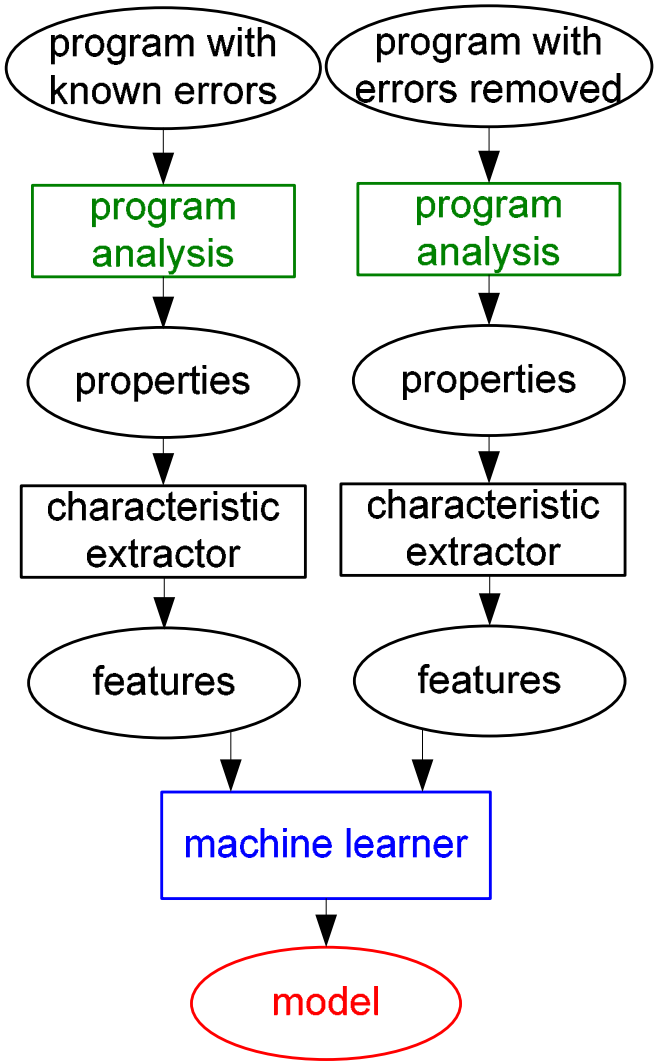


# Machine Learning Approach

- Extracts knowledge from a training set
- Creates a model that classifies new objects

- Requires a numerical description of the samples

# Training a Model

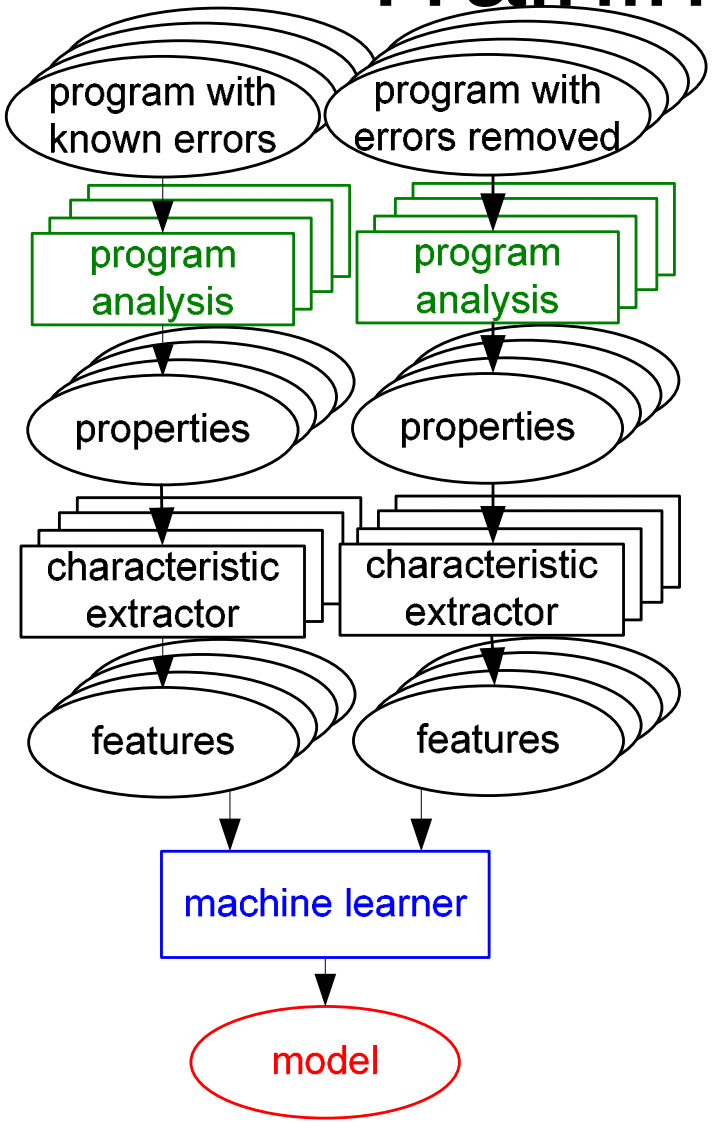



Examples:

out[1] ≤ in[1]

⟨1,0,0,2⟩

# Training a Model

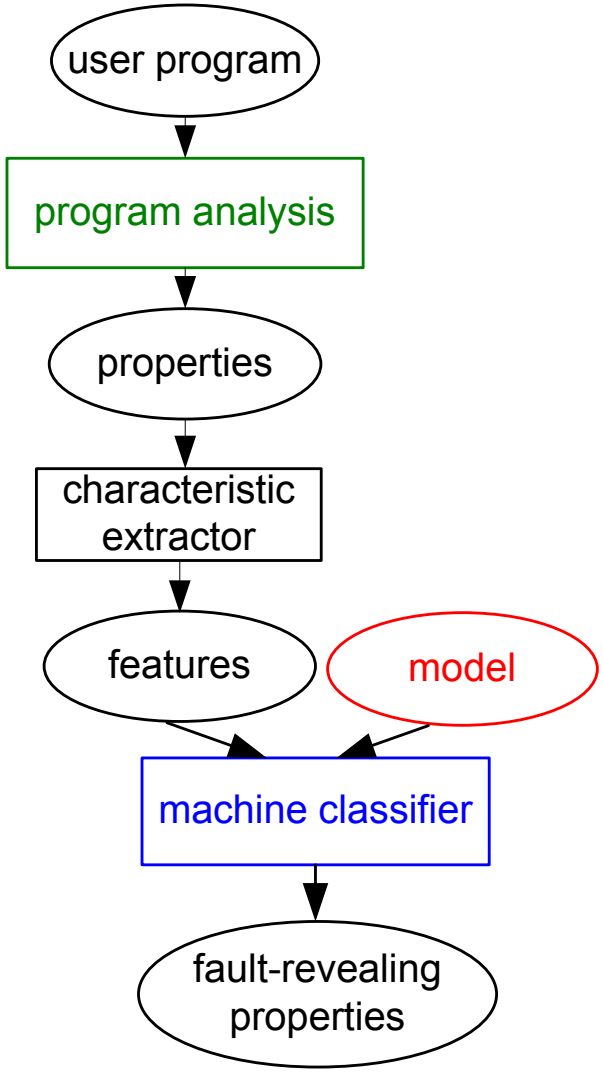



Examples:

out[1] ≤ in[1]

⟨1,0,0,2⟩

# Classifying Properties



# Related Work

- Redundancy in source code [Xie et al. 2002]
  - find an error
  - 1.5-2 times improvement over random sampling
- Relevance:
- same goal
- we have 50 times improvement over random sampling (for C programs)

# Related Work

- [Xie et al. 2002]
- Partial invariant violation [Hangal et al. 2002]
  - is there an error?

- Relevance:
- similar program analysis
- similar goal

# Related Work

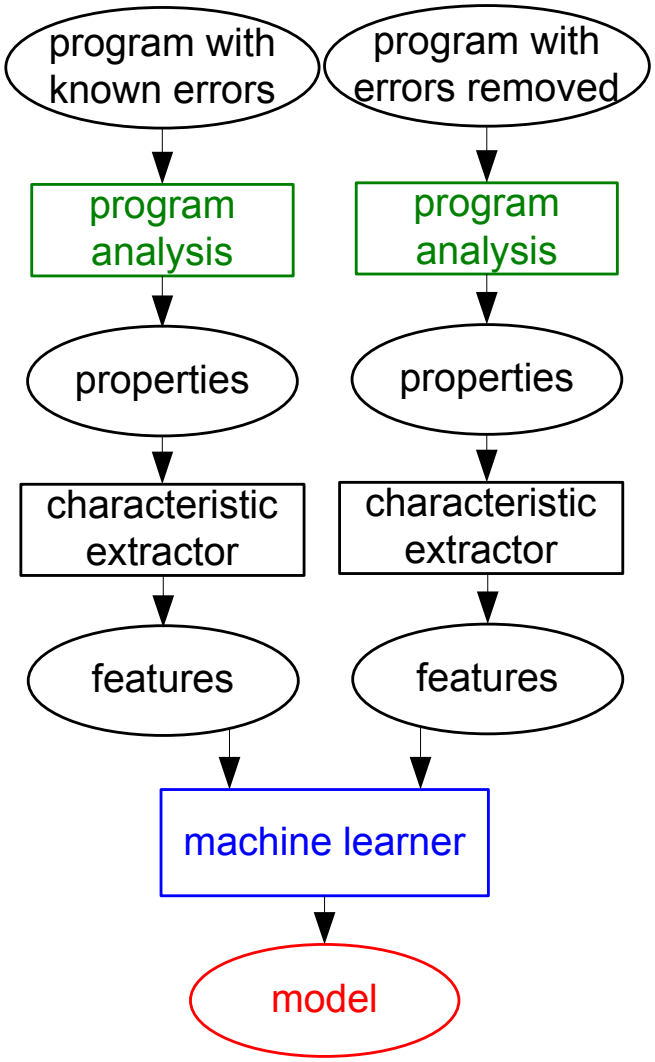
- [Xie et al. 2002]
- [Hangal et al. 2002]
- Clustering of function call profiles [Dickinson et al. 2001, Podgurski et al. 2003]
  - find relevant tests
  - select faulty executions

- Relevance:

- uses machine learning

# Latent Error-Finding Technique

- Abstract properties
- Abstract features
- Generalizes to new properties and programs



# Model

- A function:
  - {set of features} → {fault-revealing, non-fault-revealing}
- Examples:
  - Linear combination functions
  - If-Then rules

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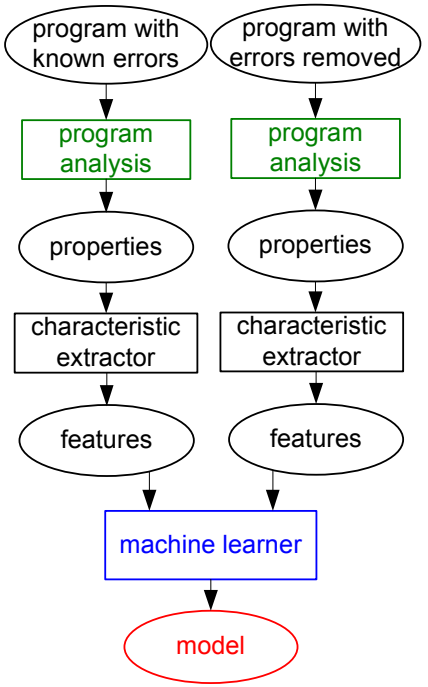
# Tools Required for Fault Invariant Classifier

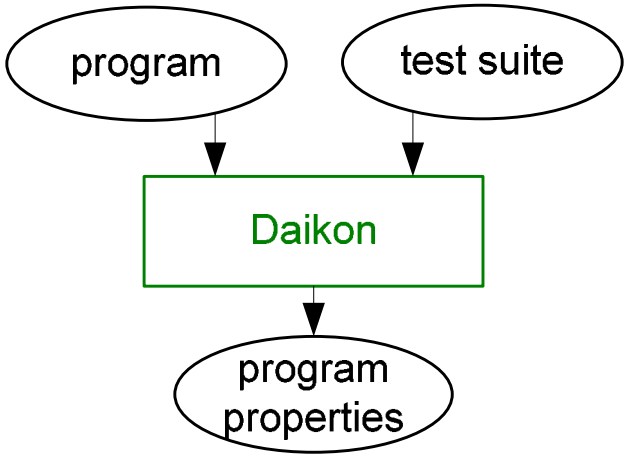
- Program Property Extractor
  - Daikon: Dynamic analysis tool
- Property to Characteristic Vector Converter
- Machine Learning
  - Support Vector Machines (SVMfu)

- technique is equally applicable to static and dynamic analysis



# Daikon: Program Property Extractor

- Daikon
  - Dynamic analysis tool
  - Reports properties that are true over program executions




  - Examples:
    - myPositiveInt > 0
    - length = data.size

# Characteristic Vector Extractor

- Daikon uses Java objects to represent properties
- Converter extracts all possible numeric information from those objects
  - # of variables e.g. $x>5 \rightarrow 1$ $x \in \text{array} \rightarrow 2$
  - is inequality? e.g. $x>5 \rightarrow 1$ $x \in \text{array} \rightarrow 0$
  - involves an array? e.g. $x>5 \rightarrow 0$ $x \in \text{array} \rightarrow 1$
- Total: 388 features

# Support Vector Machine Model

- Predictive power
- But not explicative power
- Consists of thousands of support vectors that define a separating area of the search space

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# Subject Programs

- 12 Programs
  - C and Java programs
  - Largest: 9500 lines
  - 373 errors (132 seeded, 241 real)
    - with corrected versions
  - Authors (at least 132):
    - Students
    - Industry
    - Researchers

# Accuracy Experiment

- Goal:
  - Test if machine learning can extrapolate knowledge from some programs to others

- Train on errors from all but one program
- Classify properties for each version of that one program
- Compare to expected results

# Measurements and Definitions

- Fault-revealing property:
  - property of an erroneous program but not of that program with the error corrected
  - indicative of an error
- Brevity:
  - average number of properties one must examine to find a fault-revealing property
  - best possible brevity is 1

# Accuracy Experiment Results

- C programs (single-error)
  - brevity = 2.2
  - improvement = 49.6 times
- Java programs (mostly multiple-error)
  - brevity = 1.7
  - improvement = 4.8 times

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# Fault Invariant Classifier Usability Study

- Would properties identified by the fault invariant classifier lead a programmer to errors in code?

- Preliminary experimentation:
  - 1 programmer's evaluation
  - 2 programs (41 errors, 410 properties)

# Usability Study Results

- Replace (32 errors)
  - 68% of properties reported fault-revealing would lead a programmer to the error
- Schedule (9 errors)
  - 58% of properties reported fault-revealing would lead a programmer to the error

The majority of the reported properties were effective in indicating errors

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# Conclusion

- Designed a technique for finding latent errors
- Implemented a fully automated Fault Invariant Classifier
- Fault Invariant Classifier revealed fault-revealing properties with brevity around 2
- Most of the fault-revealing properties are expected to lead a programmer to the error
- Overall, examining 3 properties is expected to lead a programmer to the error in our tests

# Backup Slides

- Works Cited
- Explicative Machine Learning Model

# Works Cited

[Dickinson et al. 2001] W. Dickinson, D. Leon, and A. Podgurski. Finding failures by clus
execution profiles. In ICSE, pages 339–348, May 2001.

[Hangal at al. 2002] S. Hangal and M. S. Lam. Tracking down software bugs using autor
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[Podgurski at al. 2003] A. Podgurski, D. Leon, P. Francis, W. Masri, M. Minch, J. Sun, ar
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[Xie et al. 2002] Y. Xie and D. Engler. Using redundancies to find errors. In FSE, pages
Nov. 2002.

# Explicative Machine Learning Model

- C5.0 decision tree machine learner
- Examples:
- Based on large number of samples and neither an equality nor a linear relationship of three variables ➔ likely fault-revealing
- Sequences contains no duplicates or always contains an element ➔ likely fault-revealing
  - No field accesses ➔ even more likely fault-revealing