DeepBugs: A Learning Approach to Name-based Bug Detection

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Traditional Approach

How to create a new bug detector?



Time-consuming process

Program analysis

Traditional Approach

How to create a new bug detector?



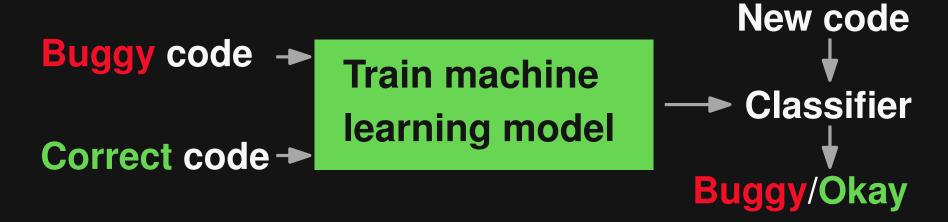
Time-consuming process

Program analysis

- Heuristics, e.g., to avoid spurious warnings
- Carefully tuned algorithms,
 e.g., to ensure scalability

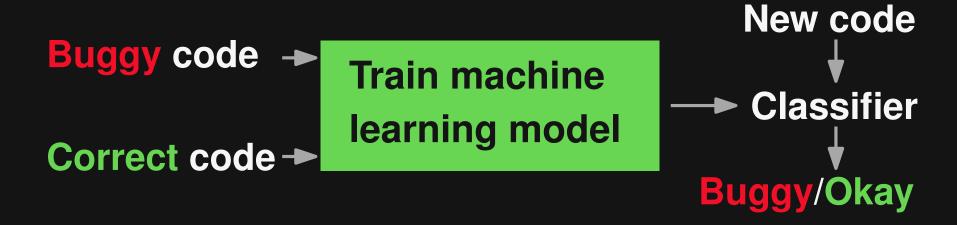
Learning to Find Bugs

Train a model to distinguish correct from buggy code



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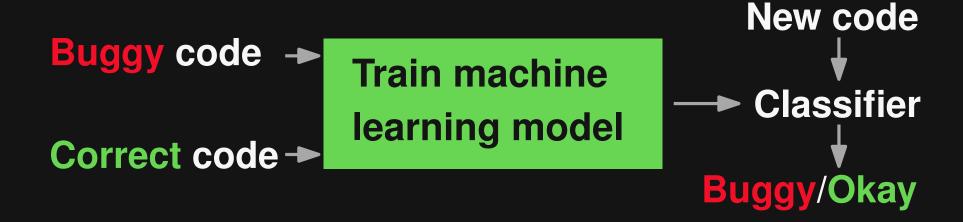


How to get training data?

- Gather past bugs, e.g., from version histories
- Here: Insert artificial bugs via simple program transformations

Learning to Find Bugs

Train a model to distinguish correct from buggy code



How to represent code?

- Token-based, AST-based, graph-based, etc.
- Here: Embeddings of natural language elements in code

Benefits of Learning Bug Detectors

Simplifies the problem

- Before: Writing a program analysis
- Now: Providing examples of buggy and correct code

Catches otherwise missed bugs

- Learns conventions from corpora of existing code
- ML can handle natural language in code, which expresses domain-specific knowledge

Name-related Bugs

What's wrong with this code?

```
function setPoint(x, y) { ... }
var x_dim = 23;
var y_dim = 5;
setPoint(y_dim, x_dim);
```

Name-related Bugs

What's wrong with this code?

```
function setPoint(x, y) { ... }

var x_dim = 23;

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setPoint(y_dim, x_dim);
```

Incorrect order of arguments

Name-related Bugs (2)

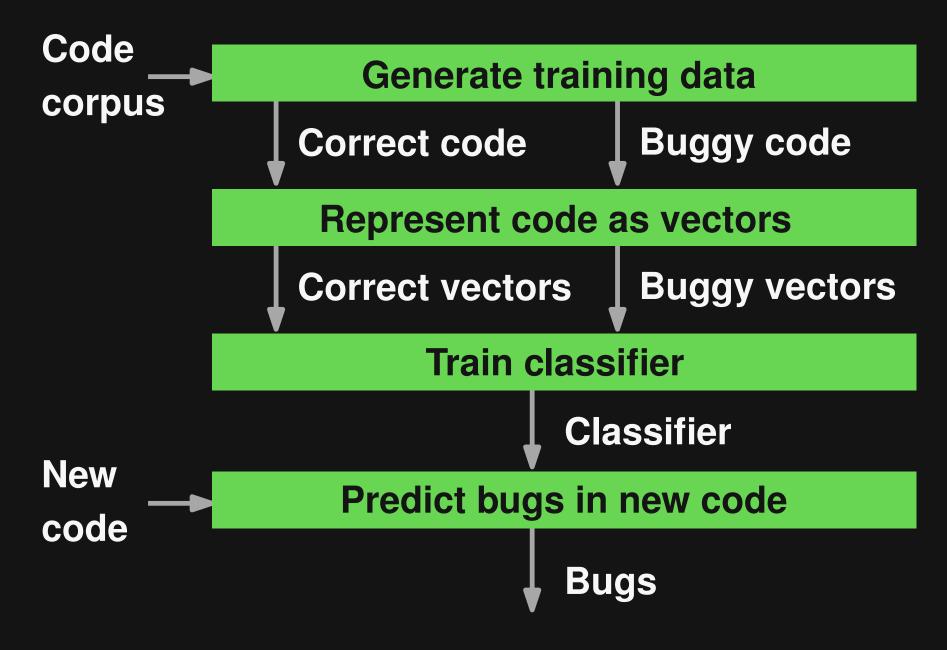
What's wrong with that code?

```
for (j = 0; j < params; j++) {
   if (params[j] == paramVal) {
     ...
   }
}</pre>
```

Name-related Bugs (2)

What's wrong with that code?

Overview of DeepBugs



Simple code transformations to inject artifical bugs into given corpus

Simple code transformations to inject artifical bugs into given corpus

1) Swapped arguments

```
setPoint(x, y) \longrightarrow setPoint(y, x)
```

Simple code transformations to inject artifical bugs into given corpus

2) Wrong binary operator

i <= length

i % length

Randomly selected operator

Simple code transformations to inject artifical bugs into given corpus

3) Wrong binary operand

bits << 2 → bits << next

Randomly selected operand that occurs in same file

Representing Code as Vectors

Goal: Exploit natural language information in identifier names

How to reason about identifier names?

- Prior work: Lexical similarity
 - □ x similar to x_dim
- Want: Semantic similarity
 - □ x similar to width
 - □ list **similar to** seq

Word2Vec

Word embeddings

- Continuous vector representation for each word
- Similar words have similar vectors

Learn embeddings from corpus of text

Context: Surrounding words in sentences

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Word2Vec for Source Code

Natural language

Programming language

- Words
- - ----- Tokens

Word2Vec for Source Code

Natural language

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- Words
 Tokens

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function setPoint(x, y) { ... }
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```
var x_dim = 23;
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Word2Vec for Source Code

```
Natural Programming language language
■ Sentences ► Program
```

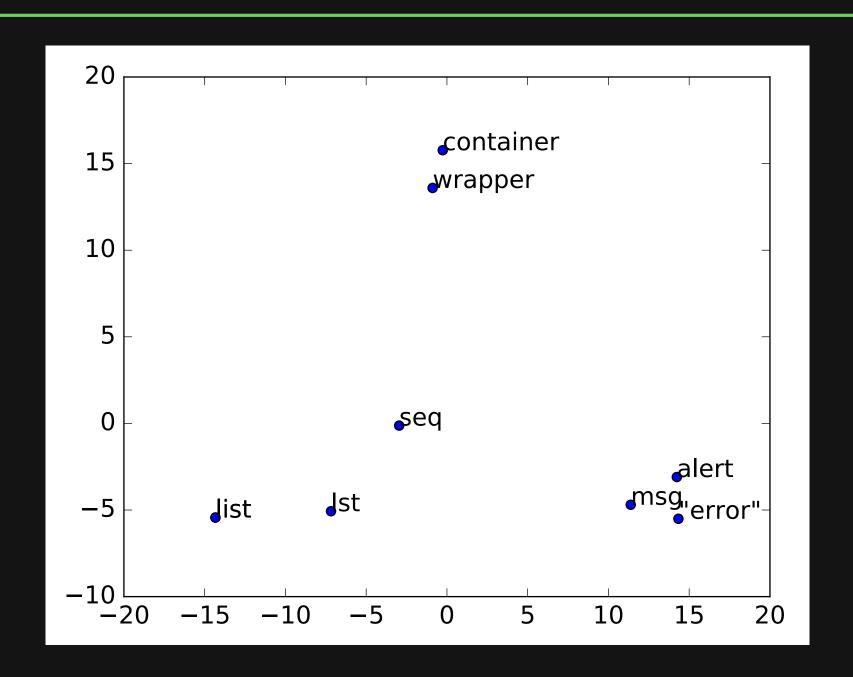
```
function setPoint(x, y) { ... }

var x_dim = Context of x:

var y_dim = function - setPoint - ( - , - y - )

setPoint(y_dim, x_dim);
```

Example: Embeddings



Code Snippets as Vectors

Concatenate embeddings of names in code snippet

1) Swapped arguments

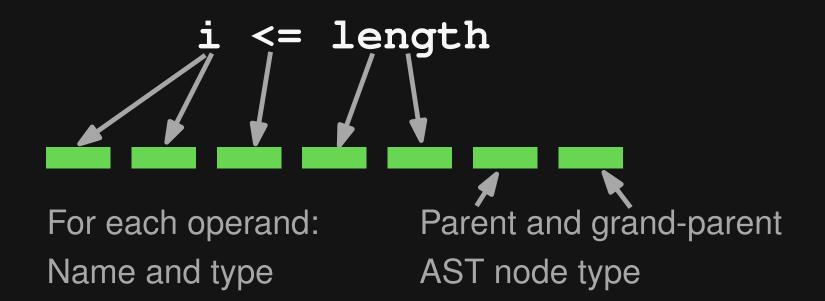


For each argument: Name, type, and formal parameter name

Code Snippets as Vectors

Concatenate embeddings of names in code snippet

2) + 3) Wrong binary operator/operation



Learning the Bug Detector

- Given: Vector representation of code snippet
- Train neural network:
 Predict whether correct or wrong

Vector representation of code snippet Probability that correct Hidden layer

Predicting Bugs in New Code

- Represent code snippet as vector
- Sort warnings by predicted probability that code is incorrect



Evaluation: Setup

68 million lines of JavaScript code

- 150k files [Raychev et al.]
- 100k files for training, 50k files for validation

Bug detector	Examples		
	Training	Validation	
Swapped arguments	1,450,932	739,188	
Wrong binary operator	4,901,356	2,322,190	
Wrong binary operand	4,899,206	2,321,586	

```
// From Angular.js
browserSingleton.startPoller(100,
   function(delay, fn) {
      setTimeout(delay, fn);
   });
```

```
// From Angular.js
browserSingleton.startPoller(100,
    function(delay, fn) {
        setTimeout(delay, fn);
    });
    First argument must be
    callback function
```

```
// From DSP.js
for(var i = 0; i<this.NR_OF_MULTIDELAYS; i++) {</pre>
  // Invert the signal of every even multiDelay
 mixSampleBuffers (outputSamples, ...,
      2%i==0, this.NR OF MULTIDELAYS);
     Should be i%2==0
```

Precision

Bug	Inspected	Bugs	Code	False
detector			quality	pos.
Swapped args.	50	23	0	27
Wrong bin. operator	50	37	7	6
Wrong bin. operand	50	35	0	15
Total	150	95	7	48

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68% true positives. High, even compared to manually created bug detectors

Accuracy of Classifier

Validation accuracy (after training)

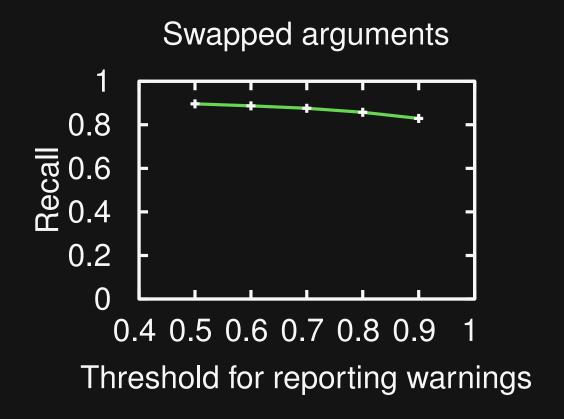
Swapped arguments	94.70%
Wrong binary operator	92.21%
Wrong binary operand	89.06%

Accuracy of Classifier

Validation accuracy (after training)

	Embedding	
	Random	Learned
Swapped arguments	93.88%	94.70%
Wrong binary operator	89.15%	92.21%
Wrong binary operand	84.79%	89.06%

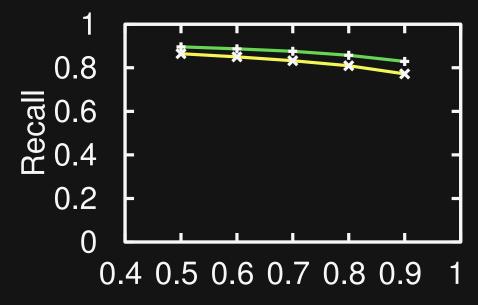
How many of all seeded bugs are found?



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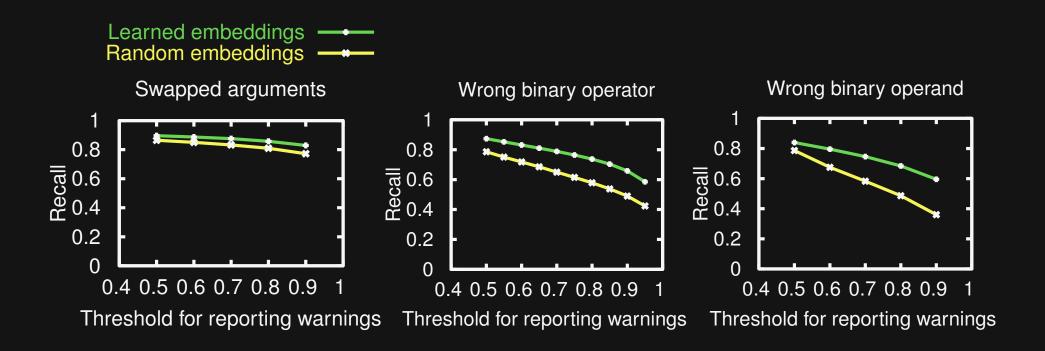
Learned embeddings ——
Random embeddings ——

Swapped arguments

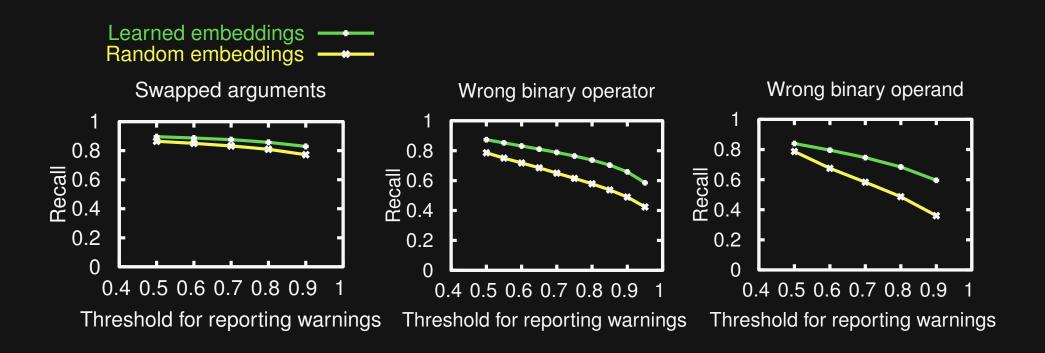


Threshold for reporting warnings

How many of all seeded bugs are found?



How many of all seeded bugs are found?



Embeddings enable generalization across similar names

Efficiency

- Data extraction and learning:
 28 minutes 59 minutes
 (depending on bug detector)
- Prediction of bugs:Less than 20ms per JavaScript file

Open Challenges

Bug detection based on other code representations

- Token-based, graph-based, etc.
- One representation for many bug patterns

Support more bug patterns

- Learn code transformations from version histories
- Train one model per bug pattern

Conclusion

Bug detection as a learning problem

Classify code as buggy or correct

DeepBugs: Name-based bug detector

- Exploit natural language information to detect otherwise missed bugs
- Learning from seeded bugs yields classifier that detects real bugs

OOPSLA'18: DeepBugs: A Learning Approach to Name-based Bug Detection (Pradel & Sen)

ASE'18: How Many of All Bugs Do We Find? A Study of Static Bug Detectors (Habib & Pradel)