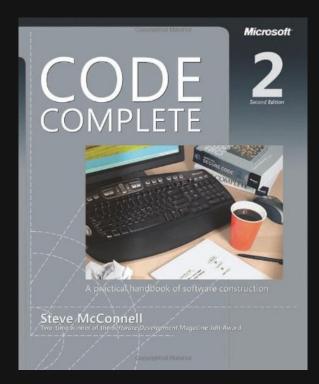
DeepBugs: A Learning Approach to Name-based Bug Detection

Michael Pradel and Koushik Sen Presented at OOPSLA 2018

Software has bugs

Software has bugs



0.5-25/KLoC in delivered software

Static Bug Detection

- Lightweight static analysis
- General framework & set of checkers for specific bug patterns



The Problem

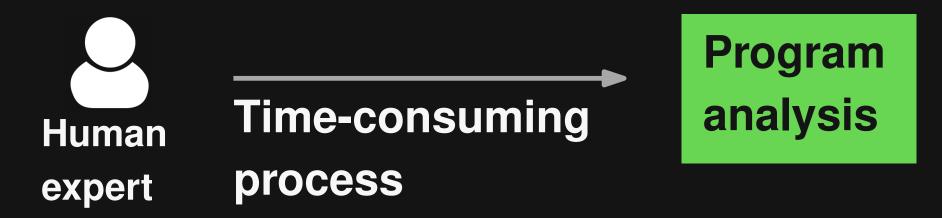
Existing bug detectors miss most bugs (see our ASE'18 paper)

Main reasons:

- □ Bugs are domain-specific
- Bug detectors cover only a small fraction of all bug patterns

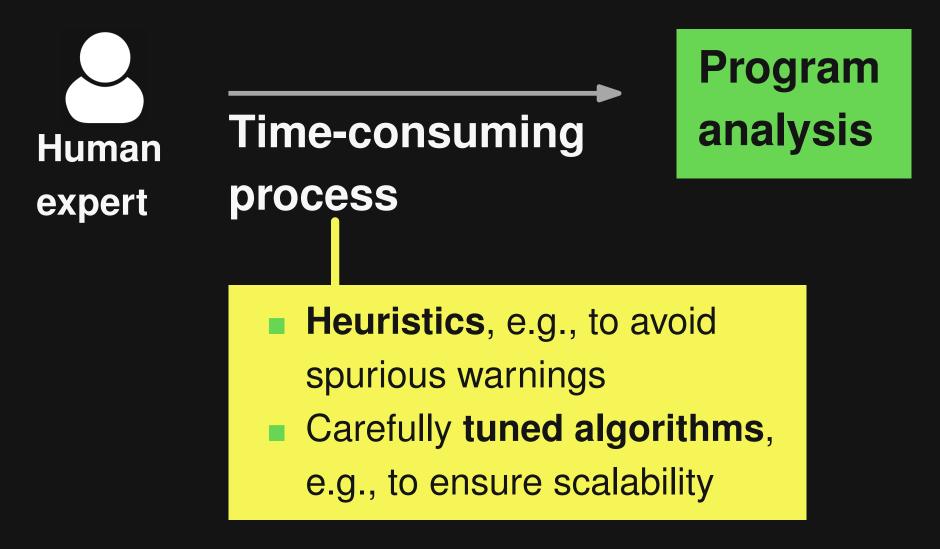
Traditional Approach

How to create a new bug detector?



Traditional Approach

How to create a new bug detector?



Learning to Find Bugs

Train a model to distinguish correct from buggy code

 Buggy code →
 Train machine

 Train machine
 ↓

 Learning model
 ↓

 Buggy/Okay

Learning to Find Bugs

Train a model to distinguish correct from buggy code

Buggy code → Train machine learning model → Classifier Buggy/Okay

How to get training data?

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

Learning to Find Bugs

Train a model to distinguish correct from buggy code

Buggy code → Train machine learning model Correct code →

How to represent code?

- Here: Embeddings of natural language elements in code
- Other options, e.g., token-based, graph-based

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

What's wrong with this code?

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

var x_dim = 23; var y_dim = 5; setPoint(y_dim, x_dim);

What's wrong with this code?

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

Incorrect order of arguments

Name-related Bugs (2)

What's wrong with that code?

}

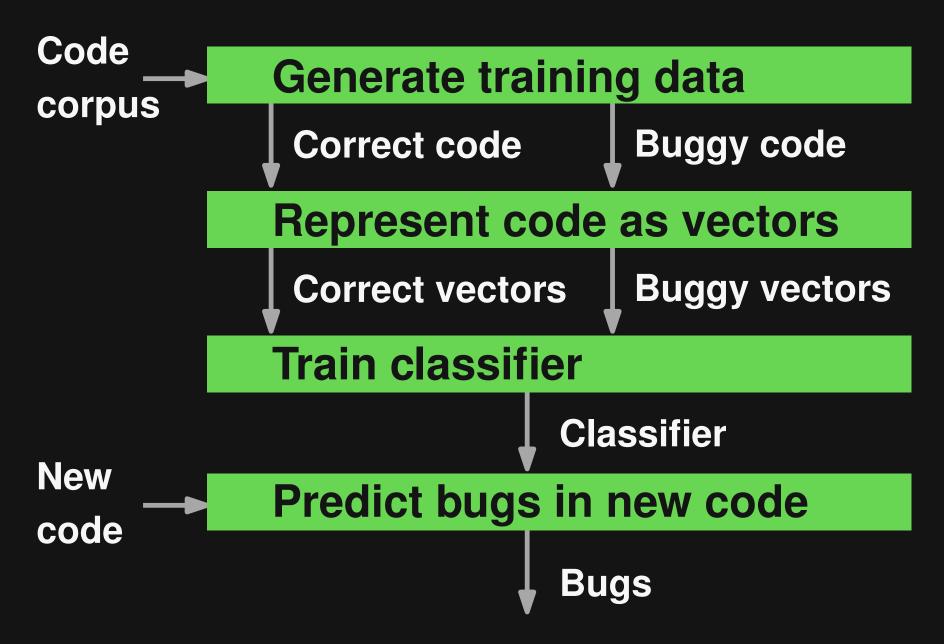
}

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) -> setPoint(y, x)

Simple code transformations to inject artifical bugs into given corpus

2) Wrong binary operator

Simple code transformations to inject artifical bugs into given corpus

3) Wrong binary operand
bits << 2 bits << next</p>
Randomly selected operand
that occurs in same file

Representing Code as Vectors

Insight: Natural language in identifiers conveys semantics of code

Compute word embeddings of identifier names

Train Word2Vec* on corpus of code
 Tokens \approx words

Efficient Estimation of Word Representations in Vector Space (Mikolov et al., 2013)

Word Embeddings

Known problem in natural language processing

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

Word2Vec

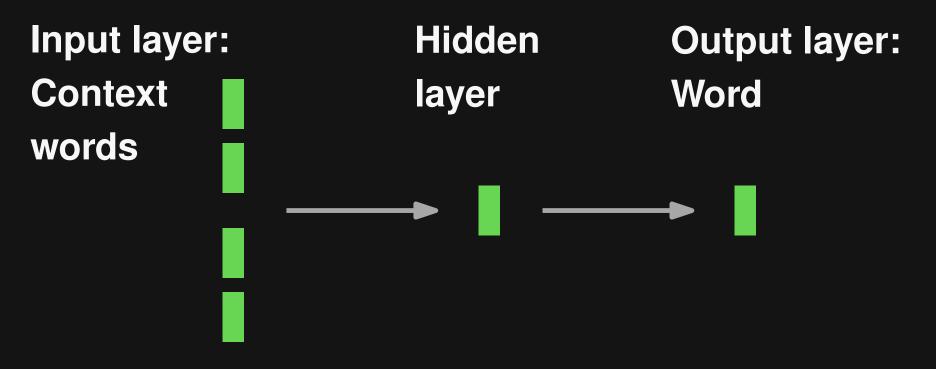
Learn embeddings from corpus of text

- "You shall know a word by the company it keeps"
- Context: Surrounding words in sentences

Word2Vec

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Word2Vec for Source Code

NaturalProgramminglanguagelanguageSentencesProgramWordsTokens

Word2Vec for Source Code

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

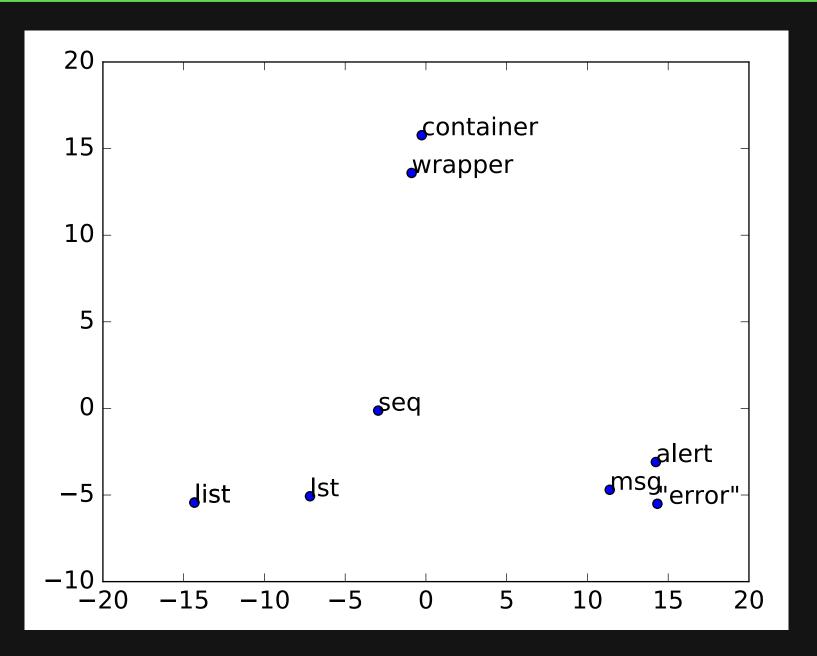
var x_dim = 23; var y_dim = 5; setPoint(y_dim, x_dim);

Word2Vec for Source Code

NaturalProgramminglanguagelanguageSentencesProgramWordsTokens

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

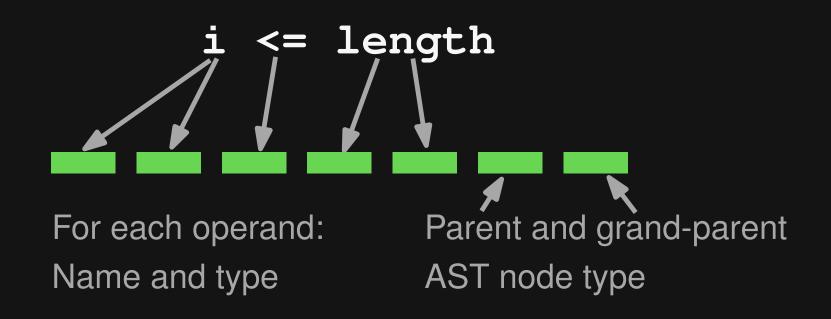
someObj.someFun(arg1, arg2)

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 Hidden layer

Hidden layer: size=200, dropout=0.2 RMSprop optimizer with binary cross-entropy as loss function

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	

Accuracy of Classifier

Bug detector	Validation accuracy
Swapped arguments	94.70%
Wrong binary operator	92.21%
Wrong binary operand	89.06%

// 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);

// 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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Total	150	95	7	48

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

Importance of Embeddings

How many true positives do we miss with random embeddings?

- Misses 11 out of 102 true positives
- Example:

transform = is(obj, value) | is(func, value);

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How many true positives do we miss with random embeddings?

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transform = is(obj, value) | is(func, value);
Bitwise OR for logical OR of booleans:
Inefficient and error-prone

Efficiency

Data extraction and learning:
 28 minutes – 59 minutes
 (depending on bug detector)

 Prediction of bugs: Less than 20ms per JavaScript file

48 Intel Xeon E5-2650 CPU cores, 64GB of memory, 1 NVIDIA Tesla P100 GPU

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
- A single model for multiple bug patterns

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

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