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Biscotti and Cannoli

An Initial Exploration into Machine Learning for the Purposes of Finding Bugs in Source Code

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Oracle Labs

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Project Overview

- Imagine if machine learning could detect bugs for us in software
  - With good precision
  - With good recall
  - With good performance
  - And beat Parfait and other static code analysis tools at finding bugs in software

- This Friday Project is an investigation into what is feasible in this space
  - Project started in February 2016

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Machine Learning is the subfield of computer science that “gives computers the ability to learn without being explicitly programmed” (Arthur Samuel, 1959)

– Wikipedia

Machine Learning Approaches

Supervised Learning

- The learning algorithm is given example inputs and their desired outputs, with the goal to learn a general rule that maps inputs to outputs

Unsupervised Learning

- The learning algorithm infers structure in its inputs to produce the outputs of interest

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Machine Learning Approaches

Supervised Learning

- The learning algorithm is given example inputs and their desired outputs, with the goal to learn a general rule that maps inputs to outputs
- Two tools
  - Biscotti
  - Cannoli

Unsupervised Learning

- The learning algorithm infers structure in its inputs to produce the outputs of interest

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Supervised Learning – Classifiers and Decision Trees

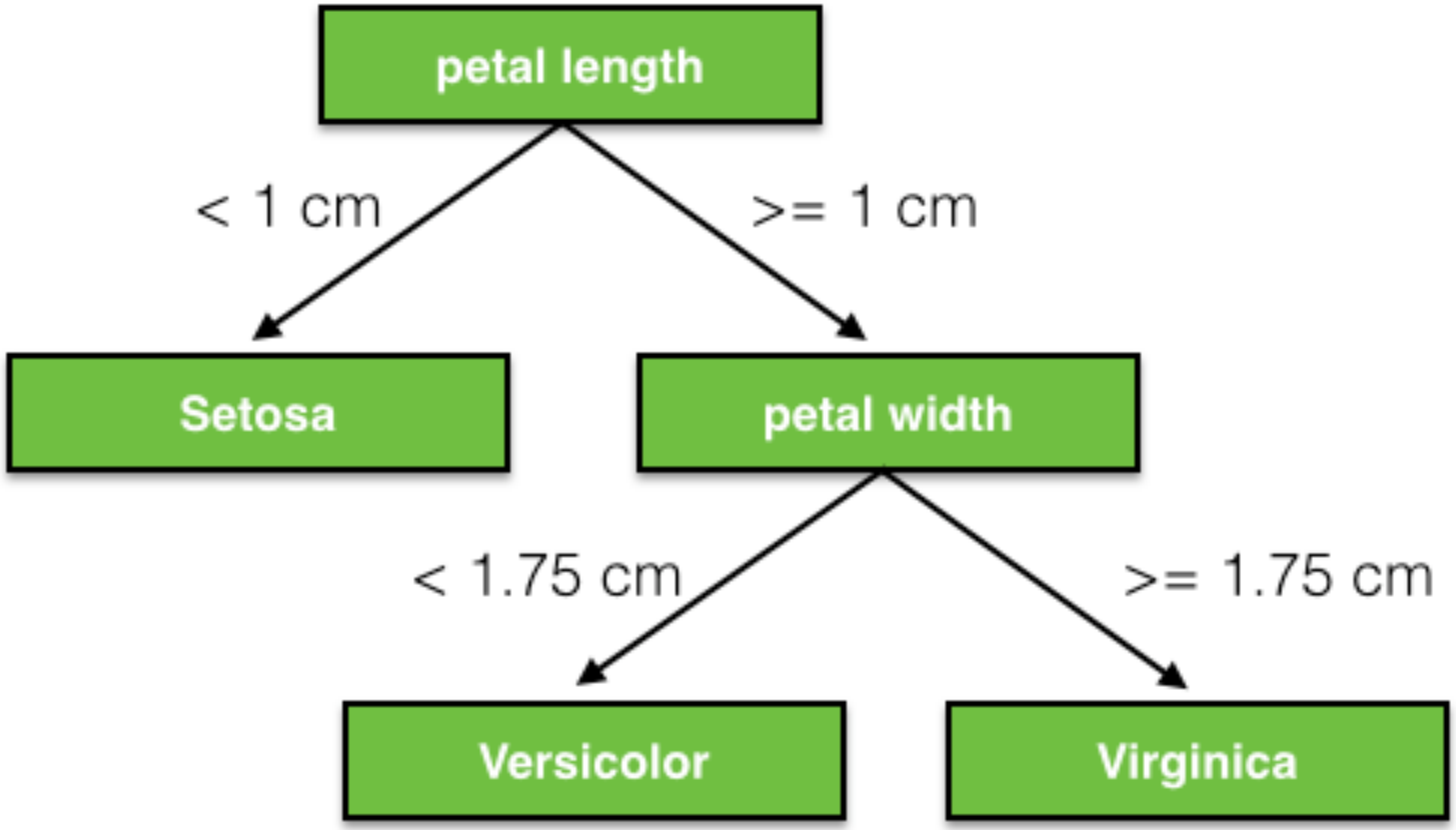
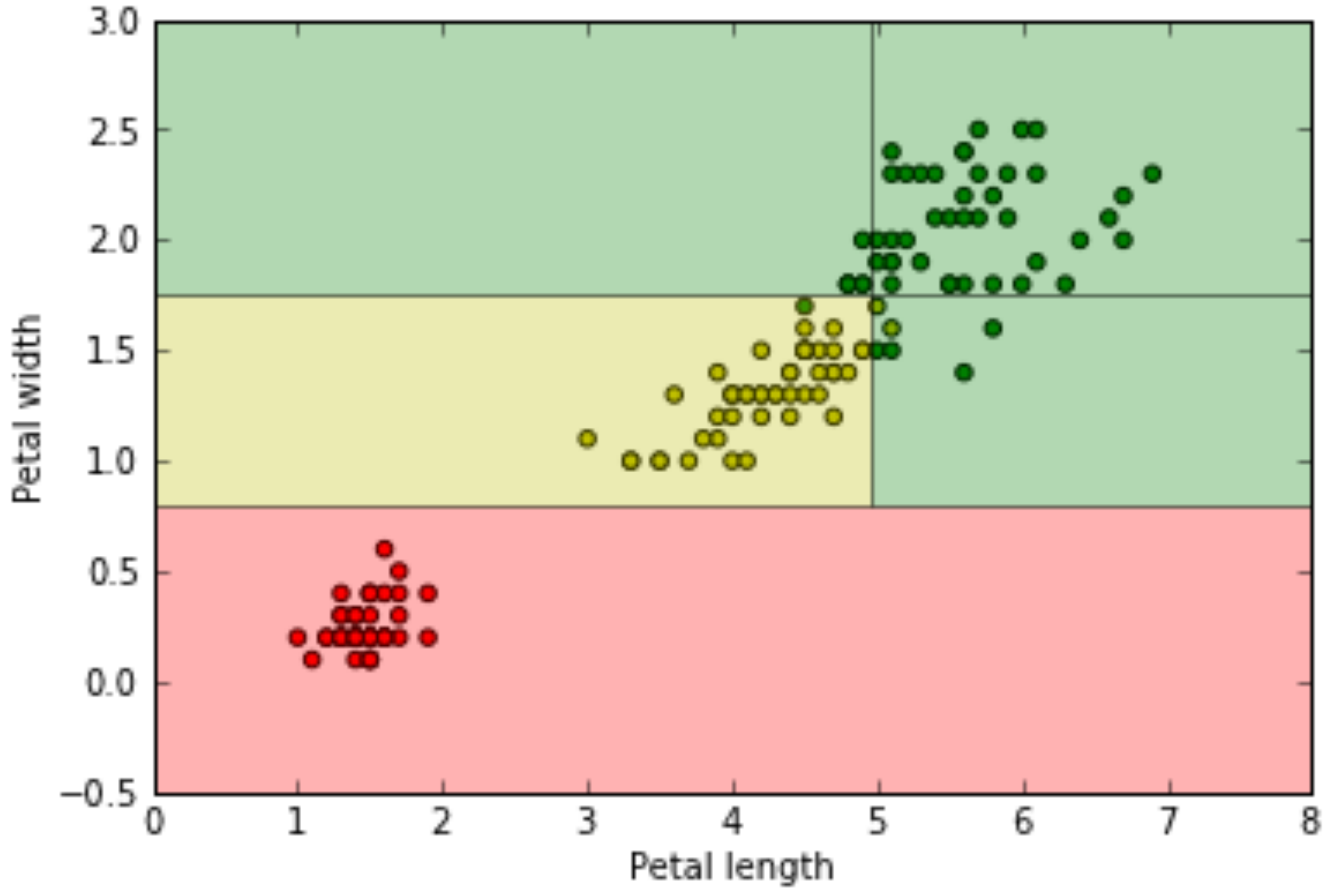


Diagram from: http://sebastianraschka.com/images/blog/2014/intro_supervised_learning/decision_tree_1.png

2D Decision Boundary



http://statweb.stanford.edu/~jtaylo/courses/stats202/_images/trees_fig_03.png

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Iris Dataset Example

- Made use of two petal **features** (length and width)
- Classified into three **classes** of Irises (setosa, versicolor, virginica)

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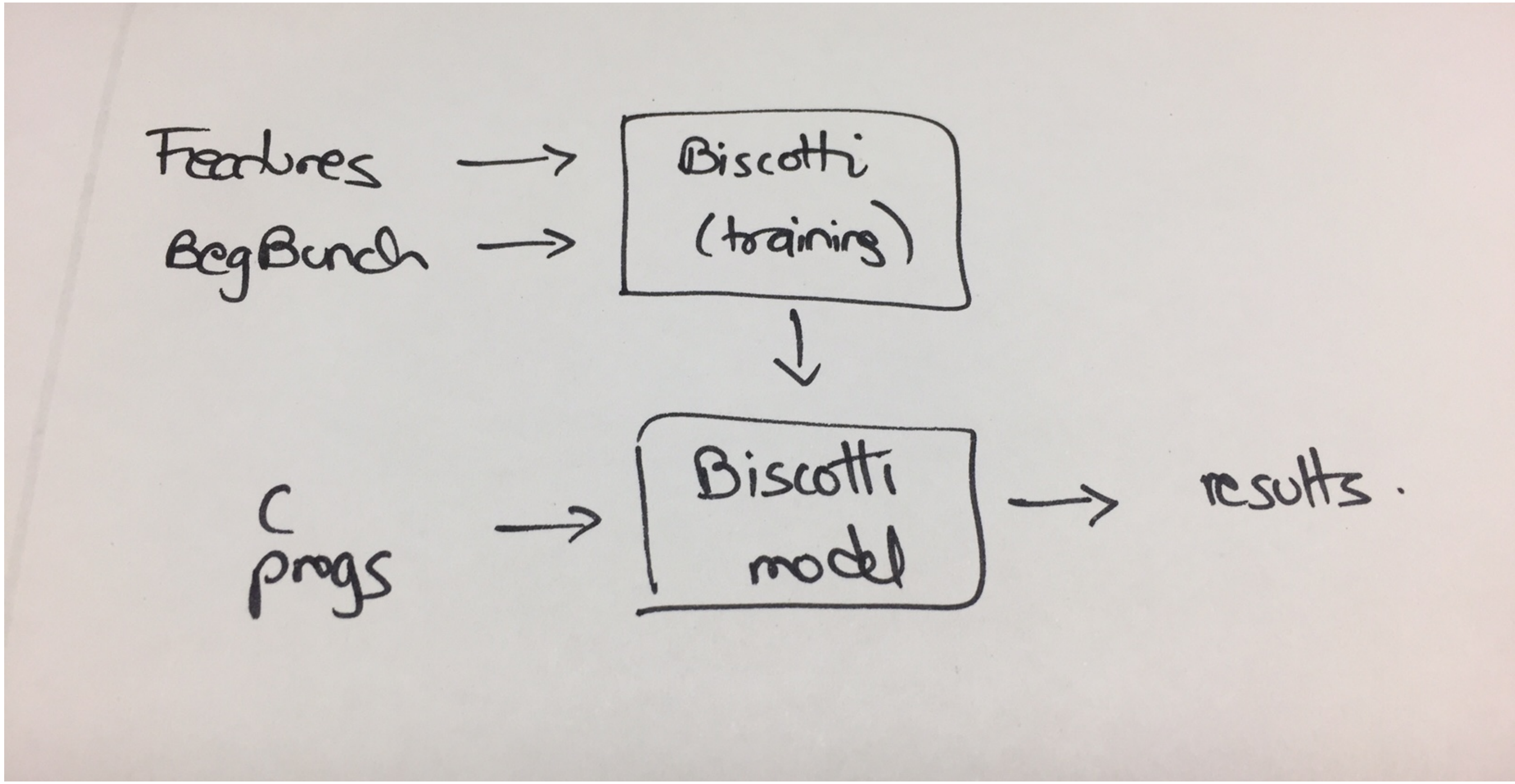
Abstracting The Iris Dataset Example

- **Features** are inputs
- **Classes** are outputs
- Dataset needs to contain features and classes

Abstracting The Iris Dataset Example

- **Features** are inputs
- **Classes** are outputs
- Dataset needs to contain features and classes
- For bugs in source code
  - Features == ?
  - Classes == bug type

Biscotti


Features
BegBunch
Biscotti
(training)
Biscotti
model
C
progs
results.

Biscotti's Feature Selection

- Complexity of the code
  - Cyclomatic complexity
  - Def-use chains
  - # edges
  - # knots
  - Length of code
  - Line count
  - Nesting level
  - Vocabulary
  - Function start line
  - Function end line
  - …

- Text features
  - !
  - (
  -)
  - ,
  - 00
  - 1
  - …
  - FILE
  - …
  - Input
  - Logged
  - …

- Intermediate Code instruction frequency
  - add
  - alloca
  - and
  - ashr
  - bitcast
  - br
  - call
  - extractvalue
  - fadd
  - …

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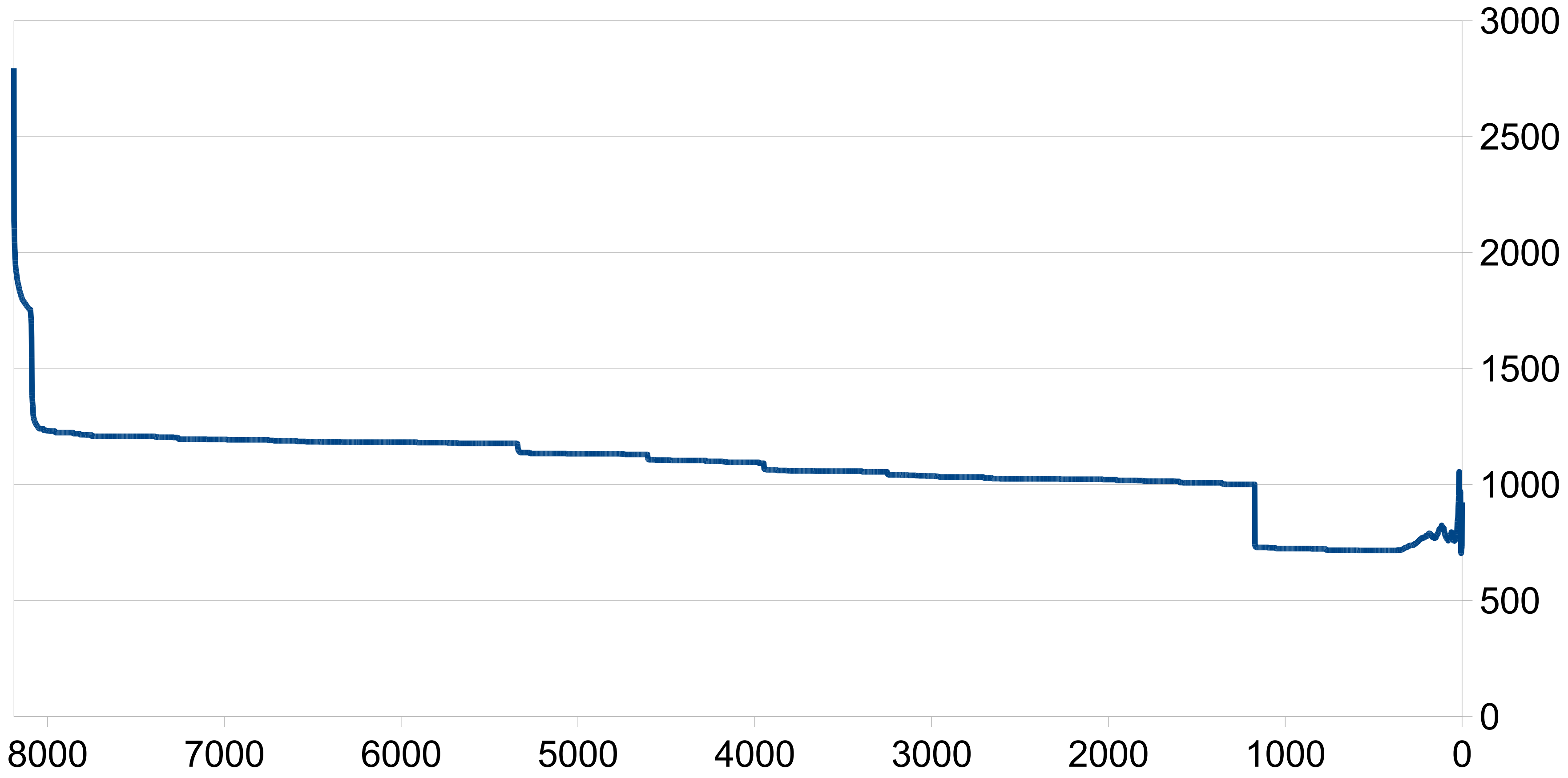
Biscotti's Feature Selection

- Intermediate Code 2-grams
  - alloca-alloca
  - store-store
  - store-br
  - br-load
  - load-icmp
  - icomp-br
  - br-br
  - …

- Clang –analyze output
  - Array-subscript-is-undefined
  - Bad-free
  - Dead-assignment
  - Dead-increment
  - Dereference-of-null-pointer
  - Double-free
  - Function-call-argument-is-an-uninitialized-value
  - Memory-leak
  - Out-of-bound-array-access
  - …

- Output from other Static Code Analysis tools
  - Parfait
  - Splint
  - UNO

Feature Selection – Dimensionality Reduction



8,190 features reduced to 500

Feature Selection – Dimensionality Reduction

- LOONNE: leave one out nearest neighbour error
  - Removes the least distinguishing feature at each step by minimising the global error

Given a feature set FS,

GlobalError(FS) = Sum of all misclassifications for FS

LOONNE removes feature f if

for all other features f’, GlobalError(FS-{f}) > GlobalError(FS-{f’})

Biscotti's Classification Algorithm

- Random Forests
  - Forest of 100 randomly-seeded decision trees using random subsets of the feature set
  - The outcomes of the decision trees are combined to produce a single outcome for each result
  - Useful when no natural probabilistic distribution amongst features
- Granularity of analysis: function level
  - Line number level too fine for initial experimentation

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Training and Test Datasets: BegBunch's Accuracy Suites

Bugs are marked up in the suites

BegBunch Suite	Type of Benchmark	Average Non-Commented Lines of Code	# Functions	# and Types of Bugs
Cigital	Synthetic	15	50	Buffer overruns: 1709 Memory leaks: 196 Uninitialised vars: 131
Samate	Synthetic	20	2,366	
Iowa	Synthetic	31	1,686	
OracleLabs*	Real	917	547	

Trained with 4-fold cross-validation over test datasets

* These bug kernels were extracted from open source code, including relevant flow of control.

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Results ML (Biscotti) vs Static Code Analysis Tools

Type of Bug	Splint		Parfait		Biscotti 500 features	
Buffer overrun	581/999 TP (58%)	343 FP	885/999 (89%)	14 FP	910/999 (91%)	262 FP
Memory leak	-		9/42 (21%)	10 FP	17/42 (40%)	3 FP
Uninitialised variable	12/15 TP (80%)	54 FP	13/15 (87%)	11 FP	8/15 (53%)	0 FP

Evaluated using 4-fold cross-validation over BegBunch dataset

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What Did Biscotti Learn?

- Top 10 features
  - [Parfait] buffer overflow
  - [Parfait] read outside array bounds
  - [Splint] fresh storage not released before return
  - [Text] ,
  - [Complexity] function end line
  - [Parfait] uninitialised variable
  - [Splint] function exported but not used outside
  - [Splint] for body not block
  - [Text] contents
- Training datasets have high number of synthetic benchmarks
  - Biscotti learnt to rely on features that don't make sense (e.g., end of line)
- None of the features are representative of a bug

Results ML (Biscotti) vs Static Code Analysis Tools

Type of Bug	Splint		Parfait		Biscotti			
					500 features		1-&2-grams + complexity features (553 features)	
Buffer overrun	581/999 TP (58%)	343 FP	885/999 (89%)	14 FP	910/999 (91%)	262 FP	23/999 (2%)	5 FP
Memory leak	-		9/42 (21%)	10 FP	17/42 (40%)	3 FP	5/42 (12%)	0 FP
Uninitialised variable	12/15 TP (80%)	54 FP	13/15 (87%)	11 FP	8/15 (53%)	0 FP	0/15 (0%)	0 FP

Evaluated using 4-fold cross-validation over BegBunch dataset

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Biscotti Conclusions

- Need more datasets of representative bugs; marked up
  - I.e., not synthetic benchmarks

- The crux of supervised learning is determining the **right set of features**
  - What features make a bug a bug?

“Deep Learning succeeds when it’s difficult to figure out what features you want to use in your classifier”

Machine Learning Approaches

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Unsupervised Learning

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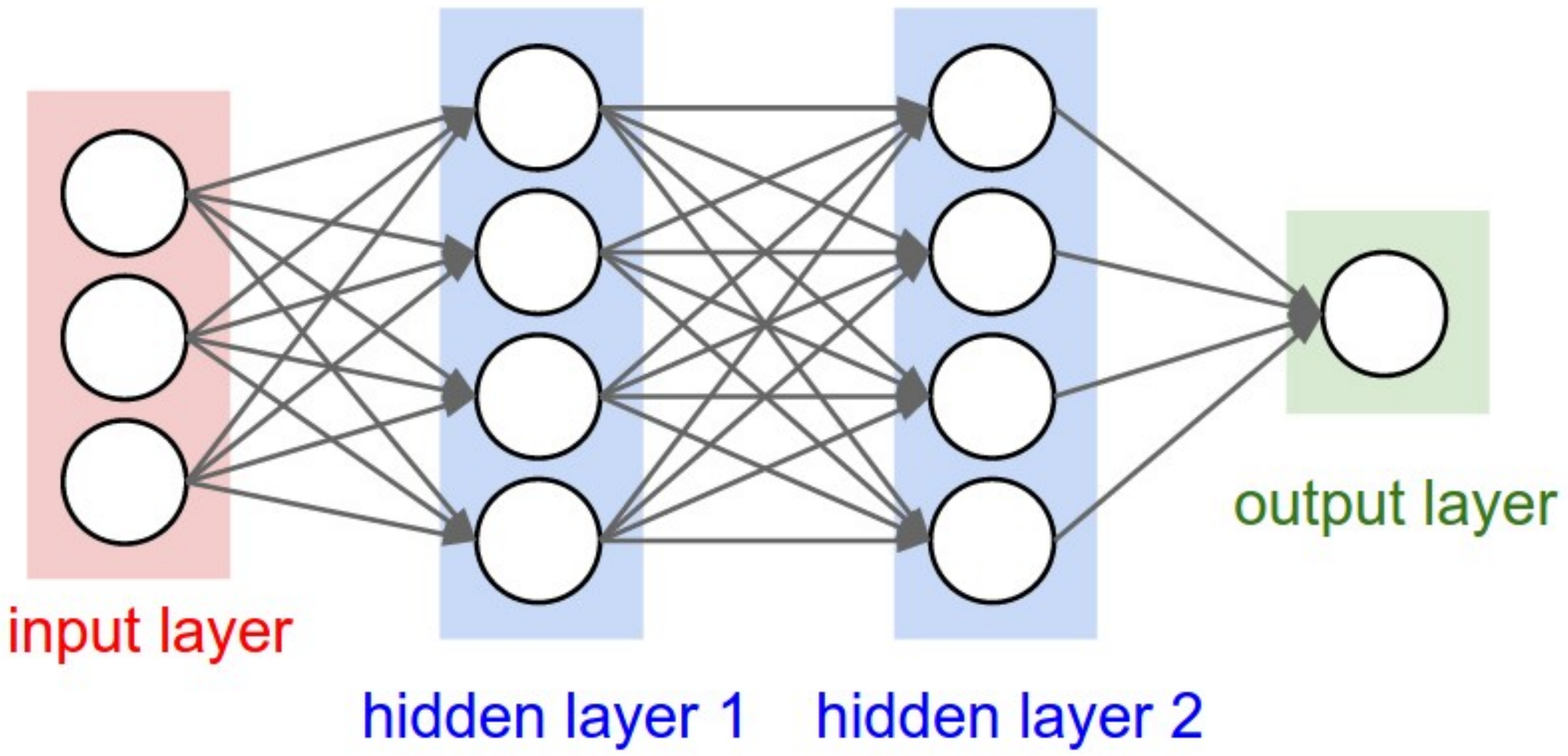
Supervised Learning – Convolutional Neural Networks

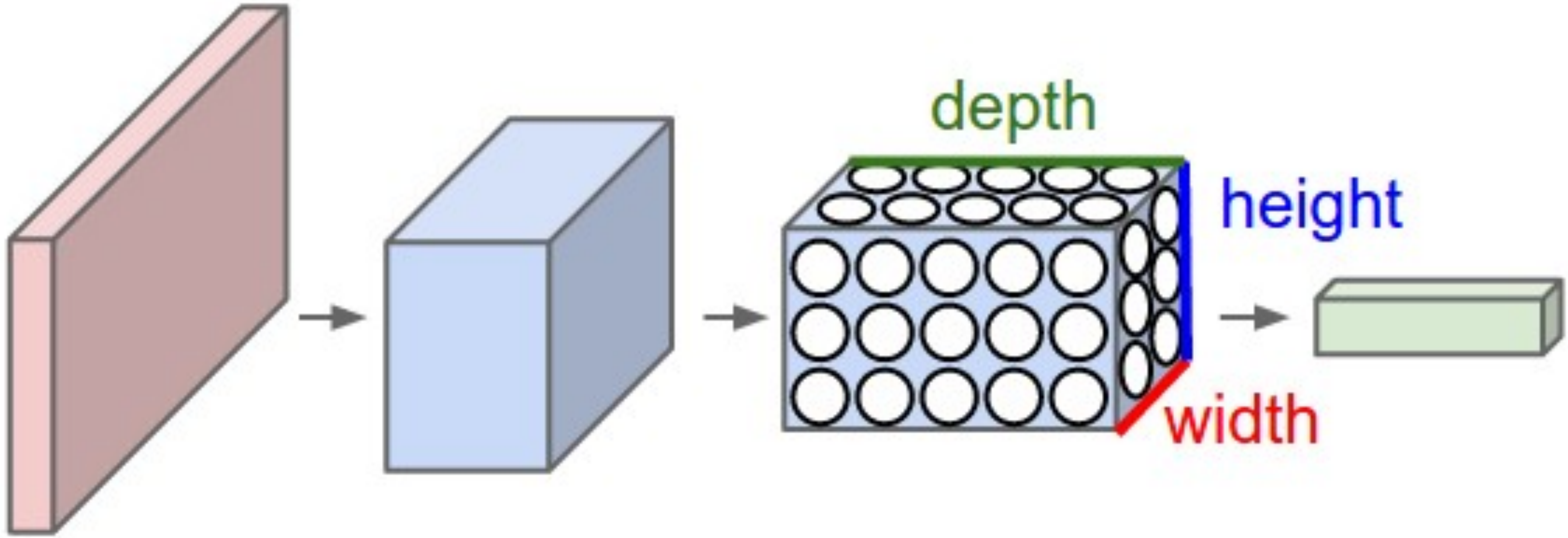
3-layer neural network



http://cs231n.github.io/assets/nn1/neural_net2.jpeg

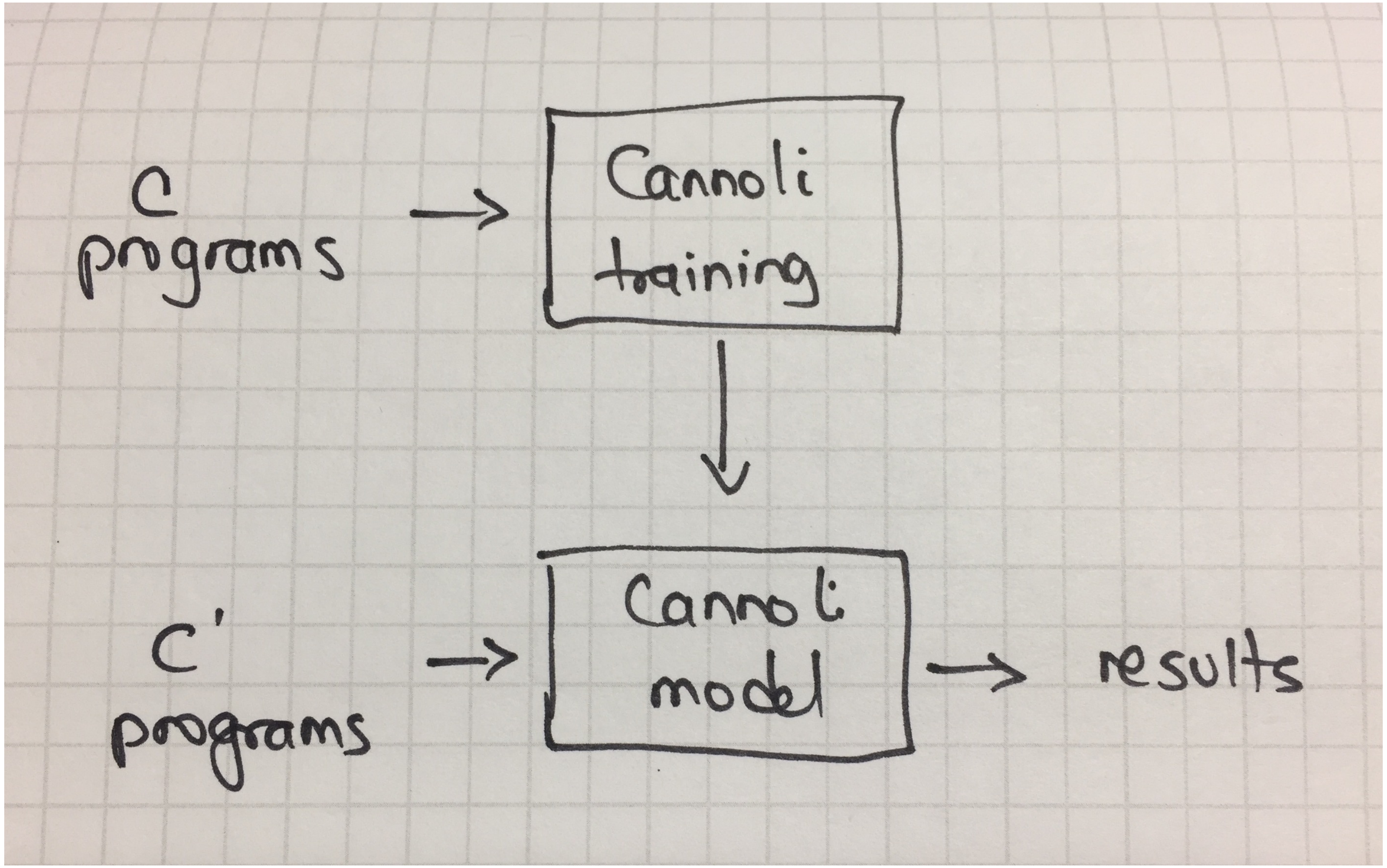
Supervised Learning – Convolutional Neural Networks

Convolutional neural network

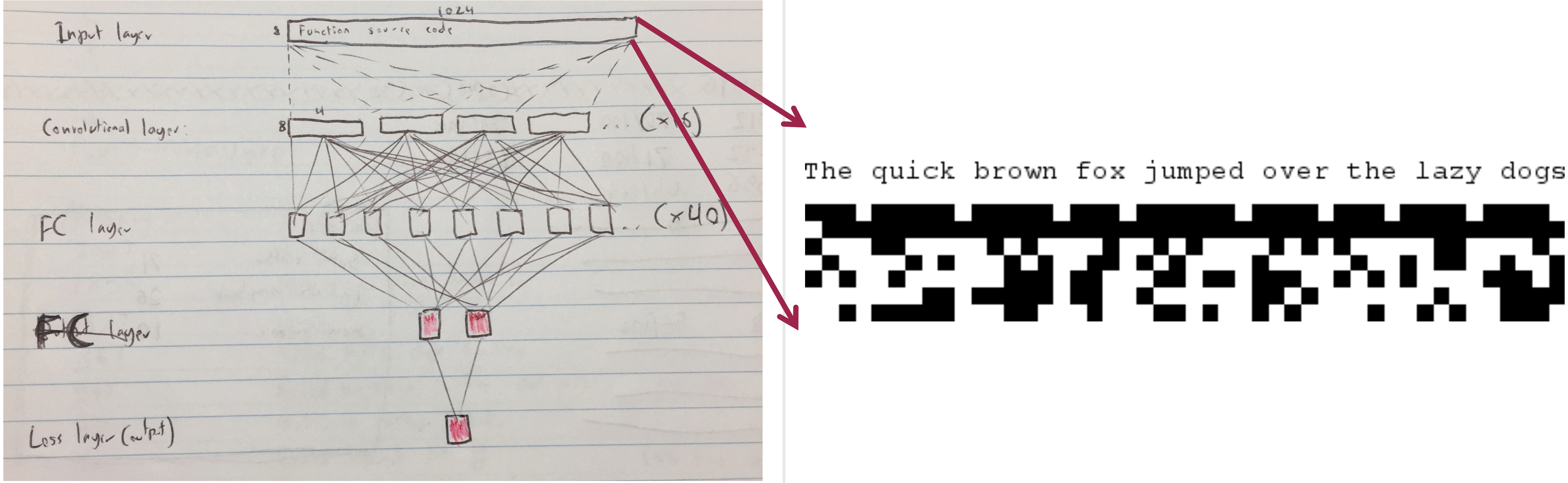


http://cs231n.github.io/assets/cnn/cnn.jpeg

Cannoli


C
programs
Cannoli
training
C'
programs
Cannoli
model
results

Cannoli's Architecture



Training Dataset: BegBunch’s Scalability Suites

Bugs are not marked up in these suites

BegBunch Suite	Average Non-Commented Lines of Code	# Functions
Calysto	87,636	11,214
OracleLabs	394,739	53,448

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Results ML (Cannoli) vs Static Code Analysis Tools

Training on Scalability Suite (50/50 split), testing on OpenSolaris ONNV b93* (no split)

Type of Bug	Parfait v0.4.1	Cannoli
Buffer overrun	221 TP, 81 FP	213/221 TP, 56095 FP
Memory leak	506 TP, 94 FP	497/506 TP, 47414 FP

Training on Scalability Suites using Parfait v1.7.1.3 results as ground truth

* 168,666 functions

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Results ML (Cannoli) vs Static Code Analysis Tools

Training on BegBunch's Accuracy Suites (no split), testing on OpenSolaris ONNV b93*

Type of Bug	Parfait v0.4.1	Cannoli
Buffer overrun	221 TP, 81 FP	23/221 TP, 9146 FP
Memory leak	506 TP, 94 FP	0/506 TP, 174 FP
Uninitialised variable	30 TP, 16 FP	0/30 TP, 153 FP

Training on Scalability Suites using Parfait v1.7.1.3 results as ground truth

* 168,666 functions

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What Did Cannoli Learn?

?

Cannoli Conclusions

- Image recognition techniques not ideal for source code analysis

- Results from black-box techniques are not very useful for bug detection
  - No bug traces can be derived for developers to understand the results of the tool

Summary Of The State Of The Art

Paper	Venue-Year	Summary
Brun, Ernst	ICSE-04	Properties inferred using both buggy and fixed code
Yamaguchi et al.	ACSAC-12	Extrapolate vulnerabilities from known vulnerabilities using AST representations
ALETHEIA	CCS-14	Statistical analyses to predict "rare" vulnerabilities; tunable to focus on FP elimination/TP detection. Basic features (per Biscotti)
JSNice	POPL-15	Use program dependence graphs and statistical prediction to deobfuscate JavaScript code
Mou et al.	AAAI-16	Convolutional Neural Networks using AST representation to identify code similarities
Wang et al.	ICSE-16	Use Deep Belief Networks and AST representation to detect within project and cross project defects
Greico et al.	CODASPY-16	Use static and dynamic features (state of memory) to detect vulnerabilities

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Summary

- Two ML approaches were implemented to find bugs in C code
  - Biscotti: supervised learning using a random forest of decision trees and LOONNE
  - Cannoli: supervised learning using a convolutional neural network
- Both learned "something"
  - But results are tied to the datasets used; i.e., doesn't learn to find bugs in unseen code
- Biscotti captures syntactic features of the program
  - ***Need to capture semantic features***
- **Need a lot more representative data**

Future Plans

1. Create enough data for datasets
   – Representative proportion of buggy vs non-buggy code
   – Representative number of bugs for each bug type of interest
   – Fixed version of each buggy example
2. Explore different approaches to encode semantics
   – Use of buggy vs fixed code to determine features of interest [Ernst'04]
   – Use of recurrent neural network with long short-term memory (LSTM) [Tristan'16]

Q&A

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