

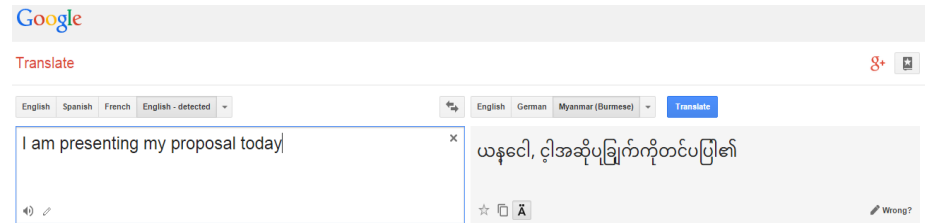
Machine Learning for Programming

Martin Vechev

ETH Zurich and DeepCode.ai

Learning and probabilistic models based on Big Data have **revolutionized** entire fields

Natural Language Processing
(e.g., machine translation)

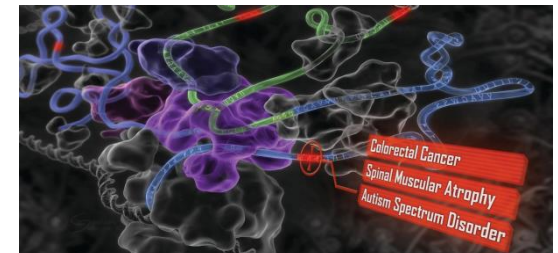


Computer Vision
(e.g., image captioning)



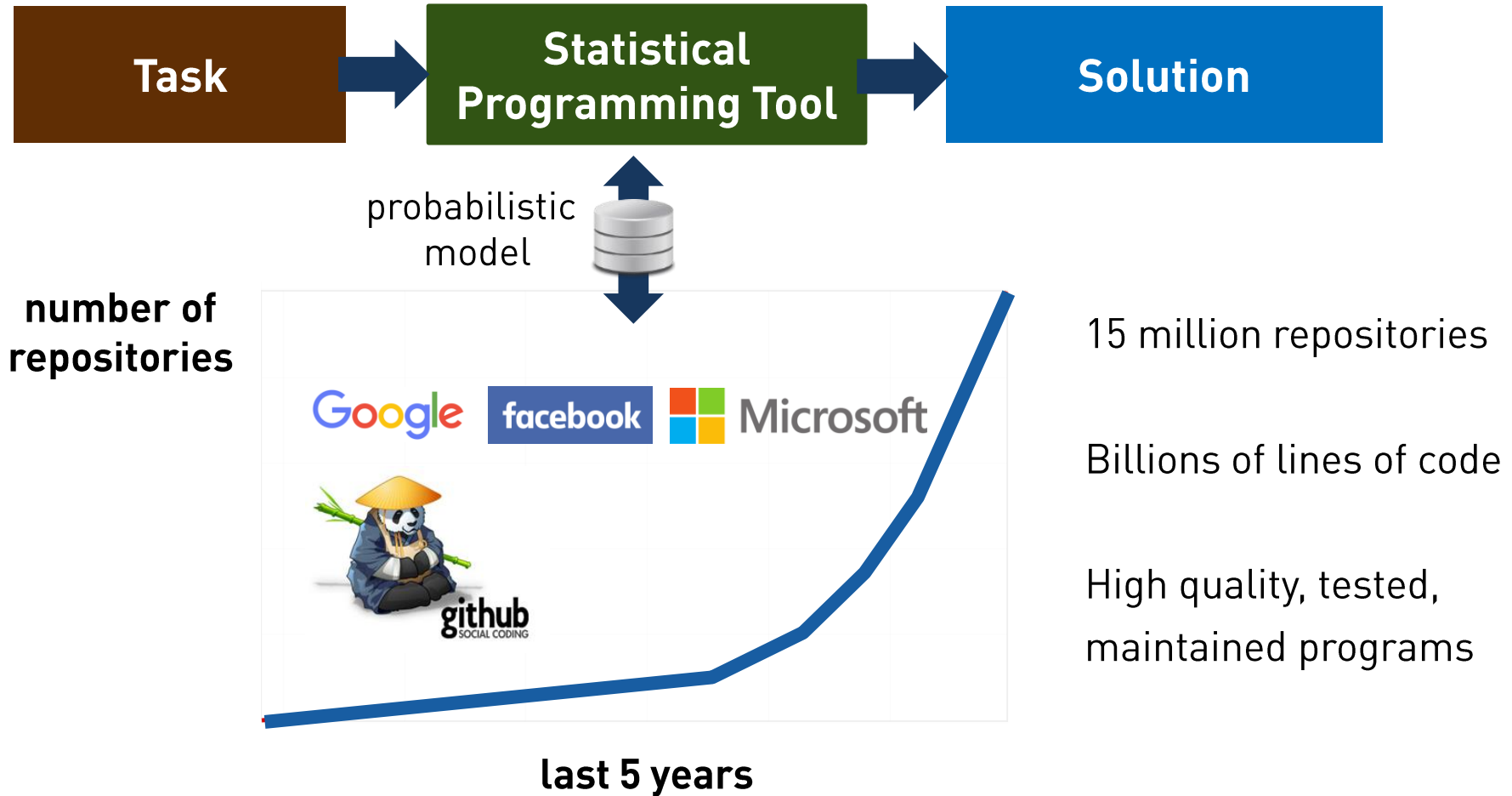
A group of people shopping
at an outdoor market.
There are many vegetables
at the fruit stand.

Medical Computing
(e.g., disease prediction)



Can we bring this revolution to programmers?

Machine Learning for Programs



Why now?

Advances in Programming Languages
[Automated Reasoning, Synthesis, Constraint Solving]

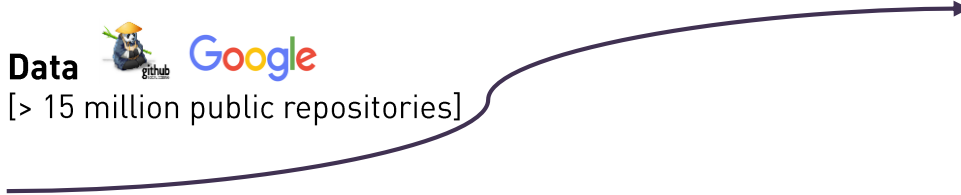
Confluence of streams



Advances in Machine Learning
[Deep Learning, Graphical Models, Language Models]



Data
[> 15 million public repositories]



**machine learning-based
programming tools**
new rules, new ideas, new opportunities

Machine Learning for Programs

Probabilistically likely solutions to problems hard to solve otherwise

Joint work with :



Veselin
Raychev



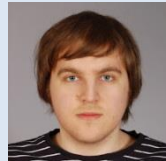
Andreas
Krause



Pavol
Bielik



Christine
Zeller



Svetoslav
Karaivanov



Pascal
Roos



Benjamin
Bichsel



Timon
Gehr



Petar
Tsankov



Mateo
Panzacchi

Publications

- Program Synthesis for Character Level Language Modeling, **ICLR'17**
- Learning a Static Analyzer from Data, **CAV'17**
- Statistical Deobfuscation of Android Applications, **ACM CCS'16**
- Probabilistic Mode for Code with Decision Trees, **ACM OOPSLA'16**
- PHOG: Probabilistic Mode for Code, **ACM ICML'16**
- Learning Programs from Noisy Data, **ACM POPL'16**
- Predicting Program Properties from “Big Code”, **ACM POPL'15**
- Code Completion with Statistical Language Models, **ACM PLDI'14**
- Machine Translation for Programming Languages, **ACM Onward'14**

Statistical Engines

apk-deguard.com



DEEP3

jsnice.org



SLANG

nice2predict.org



more: <http://plml.ethz.ch>

Dimensions:

Machine Learning for Programming

Applications

Intermediate
Representation

Analyze Program
(PL)

Train Model
(ML)

Query Model
(ML)

Dimensions:

Machine Learning for Programming

Applications	Code completion Deobfuscation	Program synthesis	Feedback generation	Translation
Intermediate Representation	Sequences (sentences)	Trees	Translation Table	Graphical Models (CRFs) Feature Vectors
Analyze Program (PL)	typestate analysis scope analysis	control-flow analysis	alias analysis	
Train Model (ML)	Neural Networks N-gram/back-off	SVM PCFG	Structured SVM	
Query Model (ML)	$\operatorname{argmax}_{y \in \Omega} P(y \mid x)$		Greedy MAP inference	

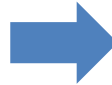
Statistical Code Synthesis

[Code Completion with Statistical Language Models, ACM PLDI 2014

Veselin Raychev, Eran Yahav, M.V.]

```
Camera camera = Camera.open();  
camera.setDisplayOrientation(90);
```

SLANG



```
Camera camera = Camera.open();  
camera.setDisplayOrientation(90);  
  
camera.unlock();  
SurfaceHolder holder = getHolder();  
holder.addCallback(this);  
holder.setType(SurfaceHolder.STP);  
MediaRecorder r = new MediaRecorder();  
r.setCamera(camera);  
r.setAudioSource(MediaRecorder.AS);  
r.setVideoSource(MediaRecorder.VS);  
r.setOutFormat(MediaRecorder.MPEG4);
```

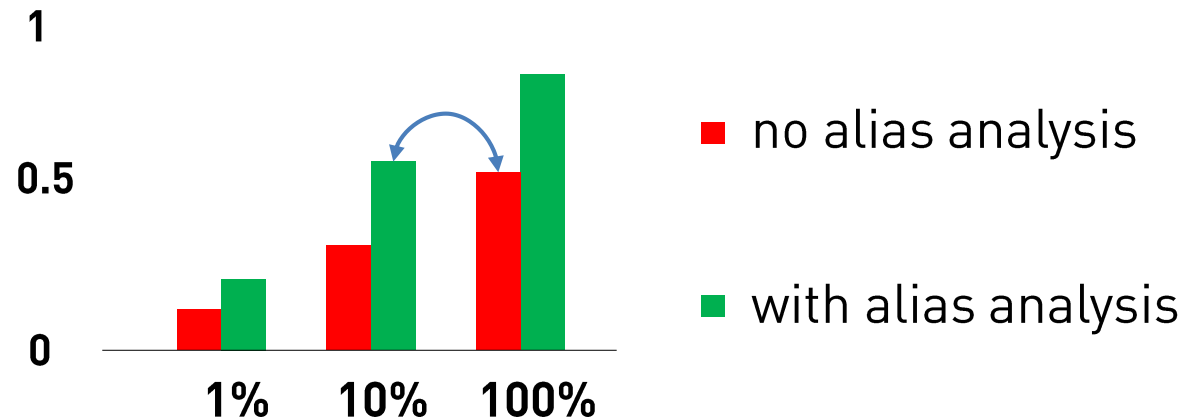
Statistical language models
Recurrent neural networks

+

Typestate analysis
Alias analysis

Importance of Static (Semantic) Analysis

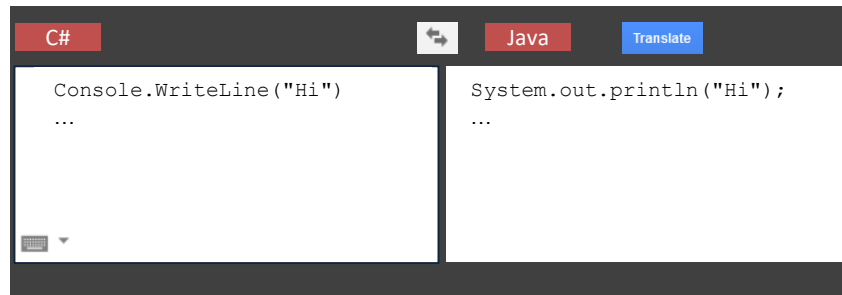
precision vs. % of data used



static analysis benefit = 10x more data

Statistical Language Translation

[ACM Onward'14, Svetoslav Karaivanov, Veselin Raychev, M.V.]



Phrase-based Statistical
Machine Translation

+

Prefix Parsing of
Context-Free Grammars

Statistical Program de-obfuscation

Predicting program properties from “Big Code”
Veselin Raychev, Andreas Krause, M.V.

ACM POPL'15

SIGPLAN and ACM Research Highlight

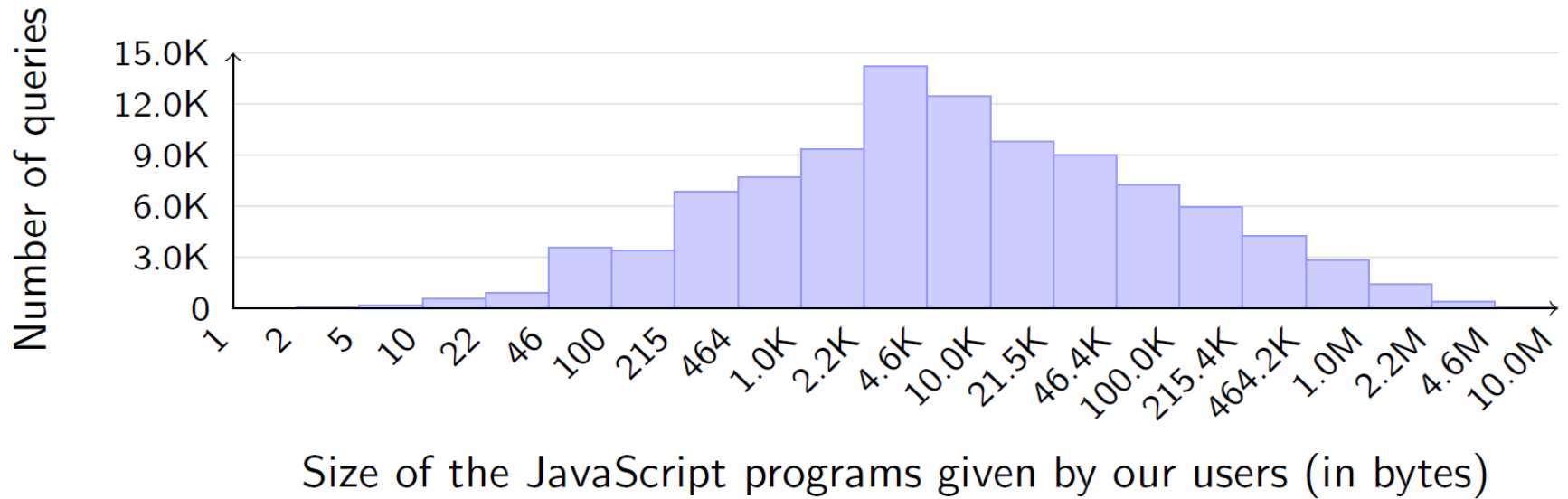
```
function FZ(e, t) { var n = [];  
var r = e.length; var i = 0;  
for (; i < r; i += t) if (i + t <  
r) n.push(e.substring(i, i +  
t)); else  
n.push(e.substring(i, r));  
return n;  
}
```



```
function chunkData(str, step) {  
var colNames = [];  
var len = str.length;  
var i = 0;  
for (; i < len; i += step)  
if (i + step < len)  
colNames.push(str.substring(i, i + step));  
else  
colNames.push(str.substring(i, len));  
return colNames;  
}
```


JSNice: over a year of usage

May 2015 – May 2016



Total: 12GB of code

JSNice

```
function chunkData(e, t)
  var n = [];
  var r = e.length;
  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



```
function chunkData(str, step)
  var colNames = [];
  var len = str.length;
  var i = 0;
  for (; i < len; i += step)
    if (i + step < len)
      colNames.push(str.substring(i, i + step));
    else
      colNames.push(str.substring(i, len));
  return colNames;
```

Key Challenges

Facts to be predicted are **dependent**

Prediction should be **fast** (real-time)
(hard, **millions of possible choices**)

Key Idea

Phrase the problem of predicting program facts as

Structured Prediction for Programs

MAP inference

```
function chunkData(e, t)
  var n = [];
  var r = e.length;
  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```

MAP inference

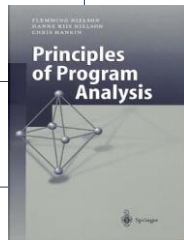
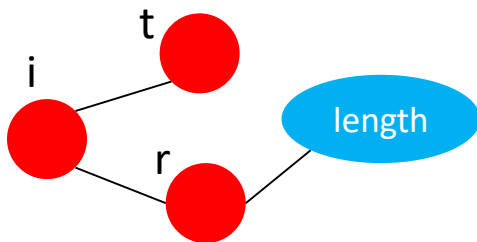
```
function chunkData(e, t)
  var n = [];
  var r = e.length;
  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



Unknown facts:



Known facts:



MAP inference

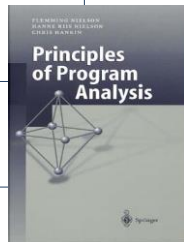
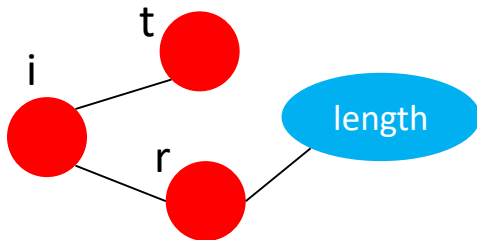
```
function chunkData(e, t)
  var n = [];
  var r = e.length;
  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



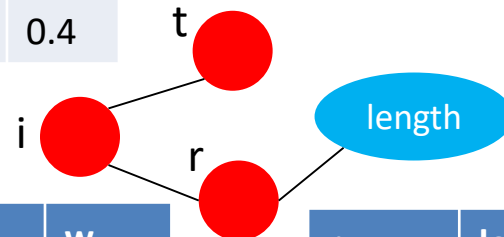
Unknown facts:



Known facts:



i	t	w
i	step	0.5
j	step	0.4



i	r	w
i	len	0.6
i	length	0.3

r	length	w
length	length	0.5
len	length	0.3

MAP inference

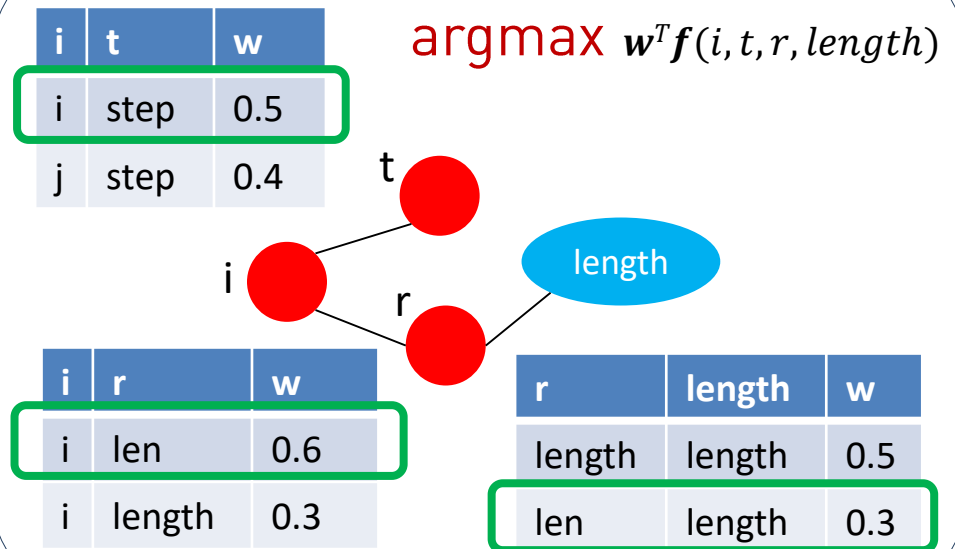
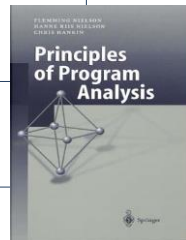
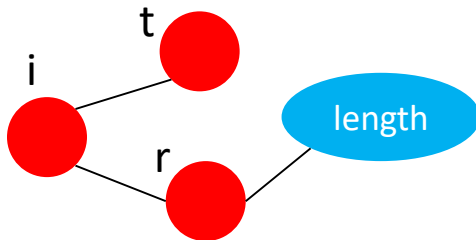
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  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



Unknown facts:



Known facts:



MAP inference

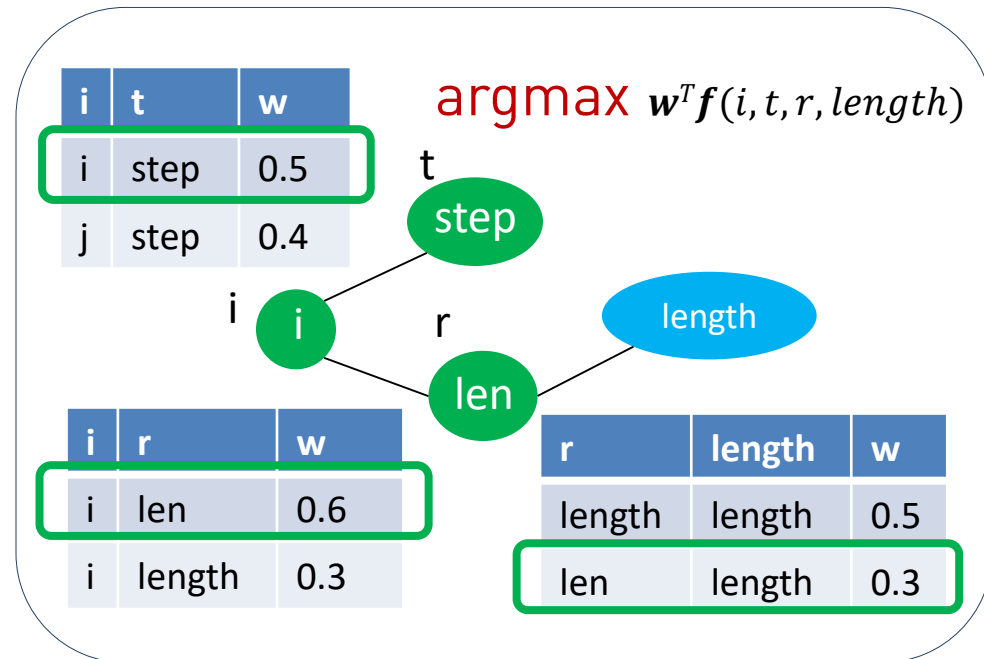
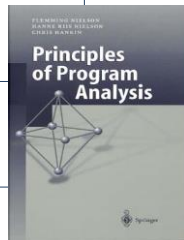
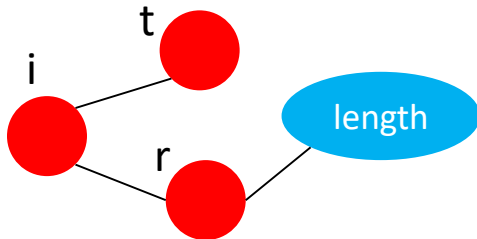
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  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



Unknown facts:



Known facts:



MAP inference

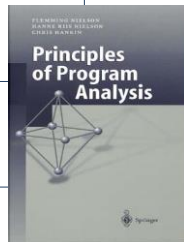
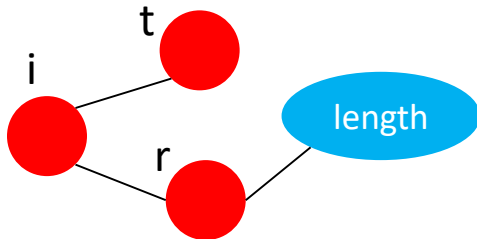
```
function chunkData(e, t)
  var n = [];
  var r = e.length;
  var i = 0;
  for (; i < r; i += t)
    if (i + t < r)
      n.push(e.substring(i, i + t));
    else
      n.push(e.substring(i, r));
  return n;
```



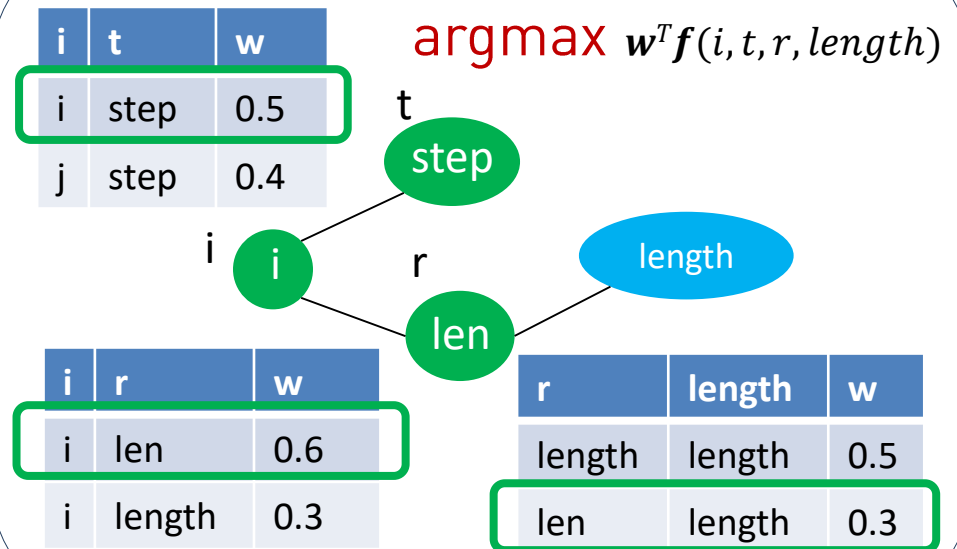
Unknown facts:



Known facts:



```
function chunkData(str, step)
  var colNames = [];
  var len = str.length;
  var i = 0;
  for (; i < len; i += step)
    if (i + step < len)
      colNames.push(str.substring(i, i + step));
    else
      colNames.push(str.substring(i, len));
  return colNames;
```



A glimpse of learning...

[N. Ratliff, J. Bagnell, M. Zinkevich, AISTATS 2007]

$$P(\textcolor{red}{y} \mid \textcolor{blue}{x}) = \frac{1}{Z(\textcolor{blue}{x})} \exp(\mathbf{w}^T \mathbf{f}(\textcolor{red}{y}, \textcolor{blue}{x}))$$

Given a data set: $D = \{ \mathbf{x}^j, \mathbf{y}^j \}_{j=1..n}$ learn weights $\mathbf{w}^T$

Optimization objective (max-margin training):

The diagram shows the optimization objective equation with three blue curly braces underneath the terms $\sum w_i f_i(\mathbf{x}^{(j)}, \mathbf{y}^{(j)})$, $\sum w_i f_i(\mathbf{x}^{(j)}, \mathbf{y})$, and $\Delta(\mathbf{y}, \mathbf{y}^{(j)})$. Three blue arrows point from the text 'Given prediction is better than any other prediction by a margin' to these three terms. A brown arrow points from the text 'for all samples' to the quantifiers $\forall j \forall \mathbf{y}$.

$$\forall j \forall \mathbf{y} \underbrace{\sum w_i f_i(\mathbf{x}^{(j)}, \mathbf{y}^{(j)})}_{\text{Given prediction is better than any other prediction by a margin}} \geq \underbrace{\sum w_i f_i(\mathbf{x}^{(j)}, \mathbf{y})}_{\text{Given prediction is better than any other prediction by a margin}} + \underbrace{\Delta(\mathbf{y}, \mathbf{y}^{(j)})}_{\text{Given prediction is better than any other prediction by a margin}}$$

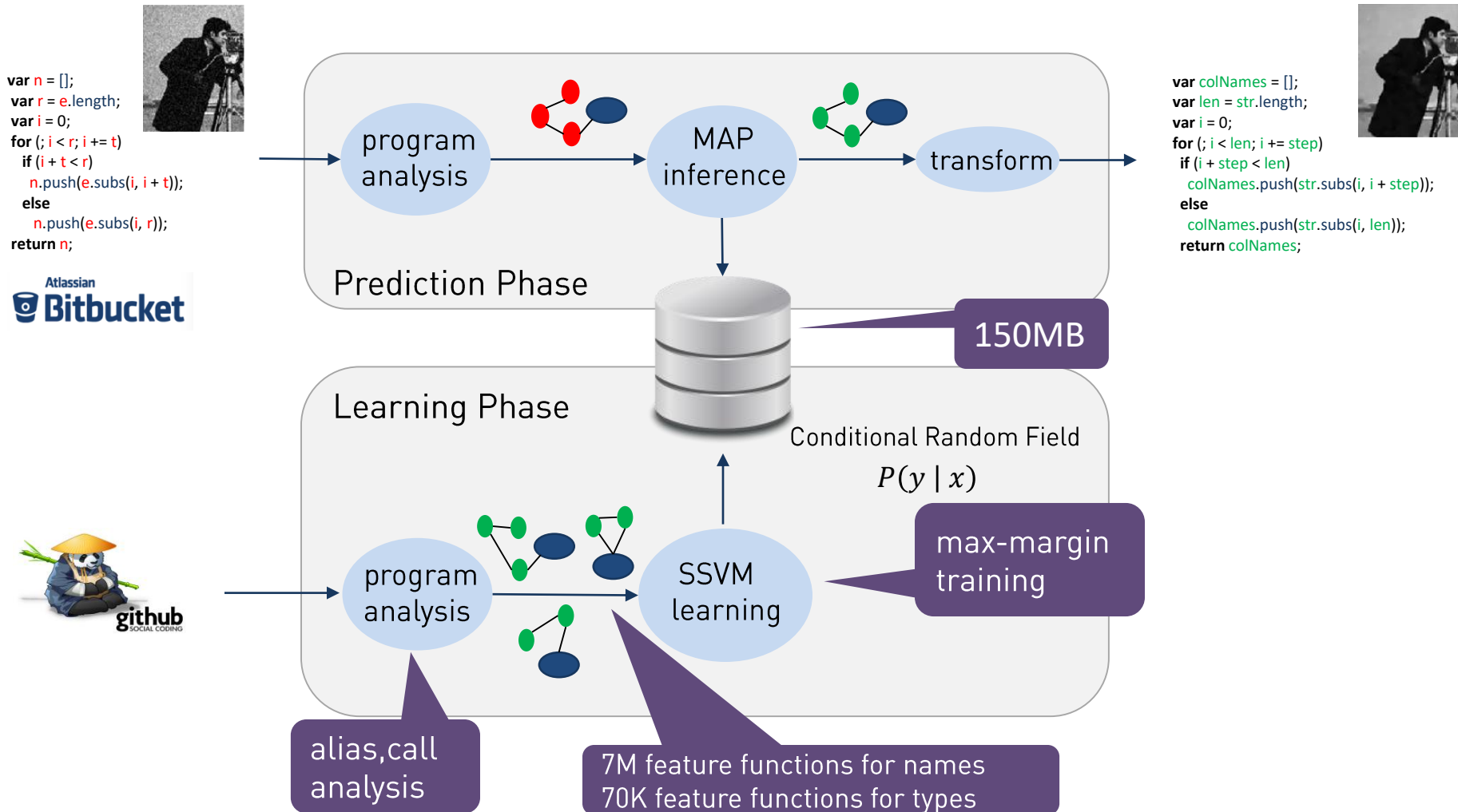
for all samples

Given prediction is better than any other prediction by a margin

Avoids expensive computation of the partition function $Z(\mathbf{x})$

JSNice

[Predicting program properties from Big Code, ACM POPL 2015]



Statistical Program de-obfuscation

[ACM CCS'16, Benjamin Bichsel, Petar Tsankov, Veselin Raychev, M.V.]

```
package a.b.c
class a extends SQLiteHelper
{
    SQLiteDatabase b; public
a(Context ctx) { b =
getWritableDatabase(); }
Cursor c(String str) {
return b.rawQuery(str); }}
```



```
package com.example.dbhelper

class DBHelper extends
SQLiteHelper {
    SQLiteDatabase db;

    public DBHelper(Context ctx) {
        db = getWritableDatabase();
    }

    Cursor execSQL(String str) {
        return db.rawQuery(str);
    }
}
```



Funny Reddit post/comment



[–] **Tycon712** • 3 points 2 days ago



Can someone tell me **what the point of using Proguard** is if there are tools out there like this?

[permalink](#) [embed](#) [pocket](#)



[–] **theheartbreakpug** • 6 points 2 days ago



As far as I know, this is brand new. I asked the creator of ProGuard a week ago how hard it is to unobfuscate code after it's run through proguard. He said it strips all the names out of the code so it's essentially impossible. **I'm super impressed by what they've done here.**

Nice2Predict.org:

scalable structured prediction framework

[Pavol Bielik, Veselin Raychev, Matteo Panzacchi, Nick Baumann, M.V.]

fully, **open sourced**,
Apache license

used by **various**
groups worldwide

JS **NICE**

DEGUARD

Your System
Here

NICE 2 Predict

Fast, Approximate
MAP inference

Fast, Parallel, Structured SVM
and Pseudo-Likelihood Training

Arbitrary factors and
indicator functions

Fundamental Problem

Data

Learning

Model



Probabilistic
Model



Widely
Applicable

Efficient
Learning

High
Precision

Explainable
Predictions

Training dataset ***D***

```
f.open("f2" | "r");  
f.read();
```

```
f.open("f2" | "w");  
f.write("c");
```

```
f.open("f1" | "r");  
f.read();
```

query:

```
f.open("file" | "r");
```

```
f.?
```

Training dataset ***D***

```
f.open("f2" | "r");  
f.read();
```

```
f.open("f2" | "w");  
f.write("c");
```

```
f.open("f1" | "r");  
f.read();
```

query:

```
f.open("file" | "r");  
f. ?
```

3-gram model on tokens

Hindle et. al., ACM ICSE'12

P(open		f.)	~ 3/6
P(read		f.)	~ 2/6
P(write		f.)	~ 1/6


context γ

Training dataset ***D***

```
f.open("f2" | "r");  
f.read();
```

```
f.open("f2" | "w");  
f.write("c");
```

```
f.open("f1" | "r");  
f.read();
```

query:

```
f.open("file" | "r");  
f. open
```

3-gram model on tokens

Hindle et. al., ACM ICSE'12

P(open		f. 	)	~ 3/6
P(read		f. 	)	~ 2/6
P(write		f. 	)	~ 1/6

context γ

Training dataset ***D***

```
f.open("f2" | "r");  
f.read();
```

```
f.open("f2" | "w");  
f.write("c");
```

```
f.open("f1" | "r");  
f.read();
```

probabilistic model on APIs

Raychev et. al., ACM PLDI'14

$P(\text{read} \mid$	$\text{open}) \sim 2/3$
$P(\text{write} \mid$	$\text{open}) \sim 1/3$

context γ

query:

```
f.open("file" | "r");  
f. ?
```

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Hindle et. al., ACM ICSE'12

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$P(\text{write} \mid$	$\text{f.}) \sim 1/6$

context γ

Training dataset ***D***

```
f.open("f2" | "r");  
f.read();
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f.open("f2" | "w");  
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context γ

Training dataset D

```
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```

probabilistic model on APIs

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context γ

query:

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$P(\text{open} \mid$	$\text{f.}) \sim 3/6$
$P(\text{read} \mid$	$\text{f.}) \sim 2/6$
$P(\text{write} \mid$	$\text{f.}) \sim 1/6$

context γ

What should the context be?



“...All problems in computer science can be solved
by **another level of indirection...**”

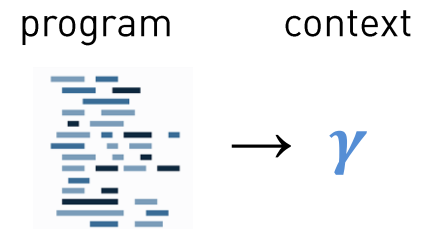
-- David Wheeler



“...All problems in computer science can be solved
by **another level of indirection...**”

-- David Wheeler

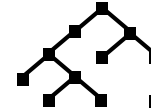
key idea: **synthesize a function** f :



Creating probabilistic models: our method

[“Learning Programs from Noisy Data”, ACM POPL’16, “PHOG: Probabilistic Model for Code”, ACM ICML’16,
“Probabilistic Model for Code with Decision Trees”, ACM OOPSLA’16, “Synthesis for Char. Level Language Modeling, ICLR’17]

1. Pick a structure of interest, e.g., ASTs:



2. Define a DSL for expressing functions:
(can be Turing complete)

DSL

3. Synthesize $f_{best} \in \text{DSL}$ from Dataset $\mathbf{D}$:

$$f_{best} = \underset{f \in \text{DSL}}{\operatorname{argmin}} \operatorname{cost}(\mathbf{D}, f)$$

4. Use f_{best} to compute context and predict:

$$f_{best} \left(\begin{array}{c} \text{AST diagram} \end{array} \right) \rightarrow \gamma$$

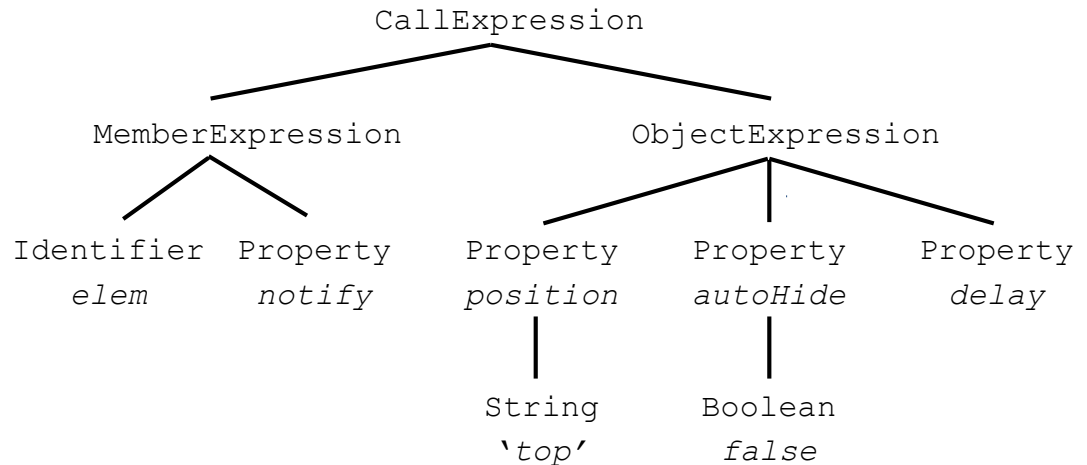
Step 1: Pick Structure of Interest

Let it be abstract syntax trees (ASTs) of programs

JavaScript program

```
elem.notify({  
  position: 'top',  
  autoHide: false,  
  delay: 100  
});
```

AST



Step 2: Define a DSL over structure

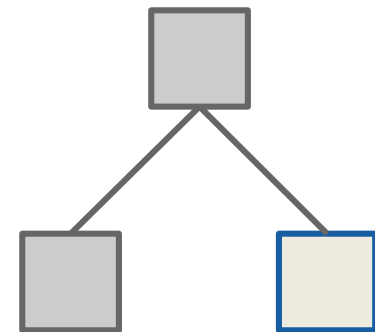
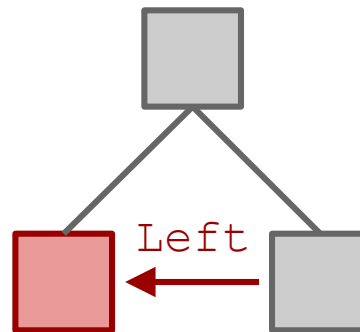
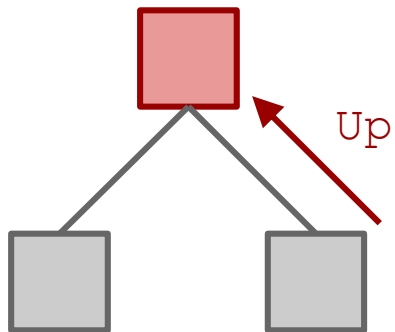
Syntax

`TCond ::=  $\epsilon$  | WriteOp TCond | MoveOp TCond`

`MoveOp ::= Up, Left, Right, DownFirst, DownLast,
NextDFS, PrevDFS, NextLeaf,
PrevLeaf, PrevNodeType, PrevNodeValue, PrevNodeContext`

`WriteOp ::= WriteValue, WriteType, WritePos`

Semantics



`WriteValue`

$\gamma \leftarrow \gamma \cdot \square$

Step 3: synthesize f_{best}

$$f_{best} = \operatorname{argmin}_{f \in \text{DSL}} \text{cost}(\mathbf{D}, f)$$

Step 3: synthesize f_{best}

DSL

```
TCond  ::=  ε | WriteOp TCond | MoveOp TCond  
MoveOp ::=  Up, Left, Right, ...  
WriteOp ::= WriteValue, WriteType, ...
```

Synthesizer

generate candidate f

$$f_{best} = \operatorname{argmin}_{f \in \text{DSL}} \text{cost}(\mathbf{D}, f)$$

Build Probabilistic Model P

dataset $\mathbf{D}$



millions ($\approx 10^8$)

use $\mathbf{D}$ and f to compute

$$P(\text{element} \mid f(\text{tree}))$$

to scale: iterative synthesis
on fraction of examples

$$\text{cost}(\mathbf{D}, f) = \text{entropy}(P)$$

$$O(|D|)$$

Step 4: use f_{best} to predict

program

```
elem.notify(  
  ... ,  
  ... ,  
  {  
    position: 'top',  
    hide: false,  
    ?  
  }  
);
```

f_{best}

Left
WriteValue
Up
WritePos
Up
DownFirst
DownLast
WriteValue

Context γ

{ }
{hide}
{hide}
{hide, 3}
{hide, 3}
{hide, 3}
{hide, 3}
{hide, 3, notify}



{Previous Property, Parameter Position, API name}

Deep3: Experimental Results

[Probabilistic Model of JavaScript]

Dataset **D**: 150,000 files Training Time: ~**100** hours $f_{best} \sim$ **50,000** instr.

Probabilistic Model	Accuracy (APIs)
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%
<i>Deep3</i>	66.6%

Details in: “Probabilistic Model for Code with Decision Trees”, ACM OOPSLA'16

Applying the Concept to Natural Language

[Program Synthesis for Character Level Language Modeling, **ICLR'17**]

Dataset **D**:

Hutter Prize Wikipedia Dataset

Training Time: ~ **8** hours

$f_{best} \sim \mathbf{9,000}$ instr

uses a char-level DSL with state

Interpretable model, browse here:

<http://www.srl.inf.ethz.ch/charmmodel.html>

Probabilistic Model

Bits-per-Character

7-gram (best)	1 . 94
Stacked LSTM (Graves 2013)	1 . 67
Char-based DSL synthesis	1 . 62
MRNN (Sutskever 2011)	1 . 60
MI-LSTM (Wu et al. 2016)	1 . 44
HM-LSTM* (Chung et al. 2016)	1 . 40

Learning a Static Analyzer from Data

[Pavol Bielik, Veselin Raychev, M.V., CAV'17]

```
function isBig(v) {  
  return v < this.length  
}  
[12, 5].filter(isBig);
```

```
VarPtsTo("global", h)  
checkIfInsideMethodCall  
checkMethodCallName  
checkReceiverType  
checkNumberOfArguments ...
```

```
VarPtsTo(this, h)
```

Can be understood by experts

Found issues in Facebook's Flow



More Resources

Learning from Large Codebases,

PhD Thesis, ETH Zurich, 2016

ACM Doctoral Dissertation, Honorable Mention Award



Veselin
Raychev

- <http://plml.ethz.ch>
- Dagstuhl Seminar on Big Code Analytics, Nov 2015
- Data sets, tools, challenges: <http://learningfrombigcode.org>

Summary

OPPORTUNITY

Advances in Programming Languages
[Automated Reasoning, Synthesis, Constraint Solving]

Advances in Machine Learning

[Deep Learning, Graphical Models, Language Models]

Data 
[> 15 million public repositories]

Learning-based programming tools
new rules, new ideas, new opportunities

RICH PROBLEM SPACE

Applications	Code completion Deobfuscation	Program synthesis	Translation Feedback generation
Intermediate Representation	Sequences (sentences)	Translation Table Trees	Graphical Models (CRFs) Feature Vectors
Analyze Program (PL)	typestate analysis scope analysis	control-flow analysis	alias analysis
Train Model (ML)	Neural Networks N-gram language model	PCFGs SVM	Structured SVM
Query Model (ML)	$\arg\max_{y \in \Omega} P(y x)$		Greedy MAP inference

NEW PROBABILISTIC MODELS

1. **Pick** a structure of interest, e.g., trees:



2. **Define** a DSL for expressing functions:
(can be Turing complete)

```
TCond ::=  $\epsilon$  | WriteOp TCond | MoveOp TCond
MoveOp ::= Up, Left, Right, DownFirst, DownLast,
NextDFS, PrevDFS, NextLeaf, PrevLeaf,
PrevNodeType, PrevNodeValue,
WriteOp ::= WriteValue, WriteType, WritePos
```

3. **Synthesize** $f_{best} \in \text{DSL}$ from Dataset D:

$$f_{best} = \operatorname{argmin}_{f \in \text{DSL}} \text{cost}(D, f)$$

4. **Use** f_{best} on new structures:

$$f_{best} \left(\text{tree diagram} \right) \rightarrow \gamma$$

PRACTICAL IMPACT



more: <http://plml.ethz.ch>