Learning from “Big Code”

21th PeWe, OntoParty, April 7, 2017

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Software Reliability Lab
Department of Computer Science
ETH Zurich

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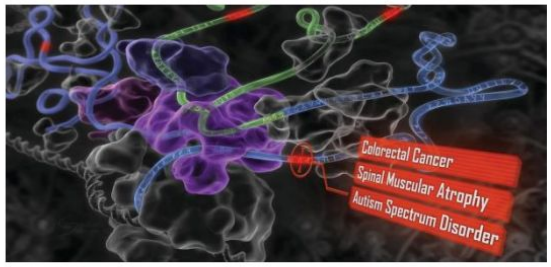
Big Data Impact

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)



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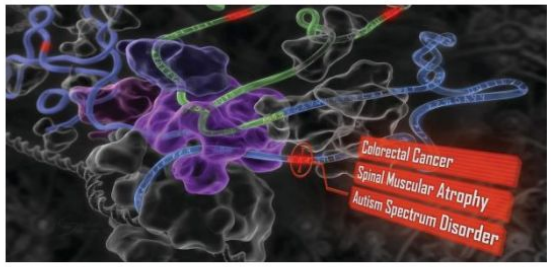


Can we bring this revolution to programmers?

Vision

Create new kinds of software tools that leverage **massive codebases** to solve problems **beyond** what is possible with traditional techniques.

number of repositories

last 8 years

15 million repositories

Billions of lines of code

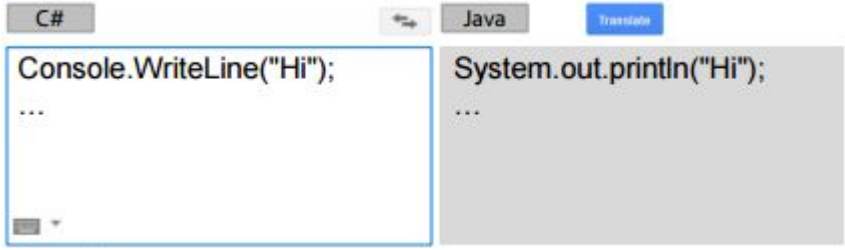
High quality, tested, maintained programs

Statistical Software Tools

Write new code:
Code Completion

```
Camera camera = Camera.open();
camera.SetDisplayOrientation(90);
                ?
```

Port code:
Programming Language Translation



Understand code/security:
JavaScript Deobfuscation
Type Prediction

JS NICE

Debug code:
Statistical Bug Detection

```
...                    likely error
for x in range(a):
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```

All of these benefit from the “Big Code” and lead to applications not possible with previous techniques

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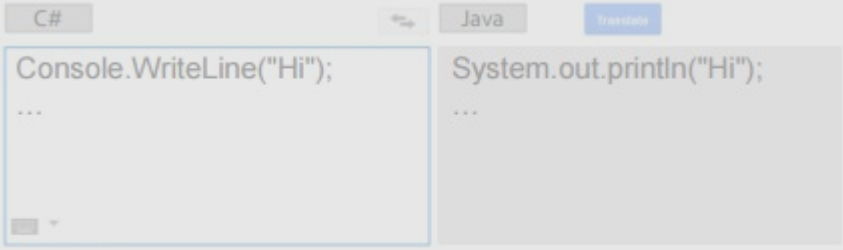

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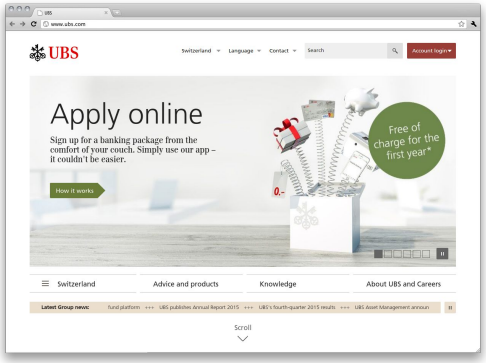

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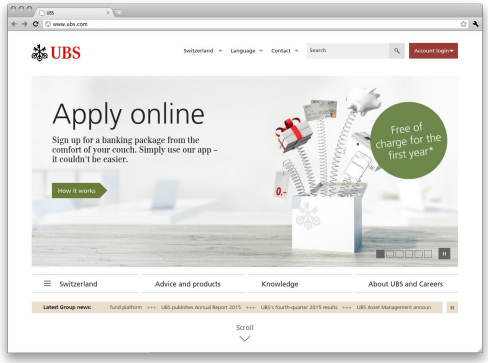
JavaScript

Code understanding/security



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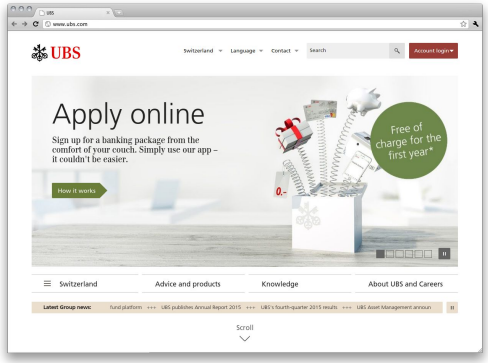
JavaScript

```
savePassword(user, password)  →  Obfuscation/ Minification  →  B(d, c)
```

Code understanding/security



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iPhone JavaScript ANDROID

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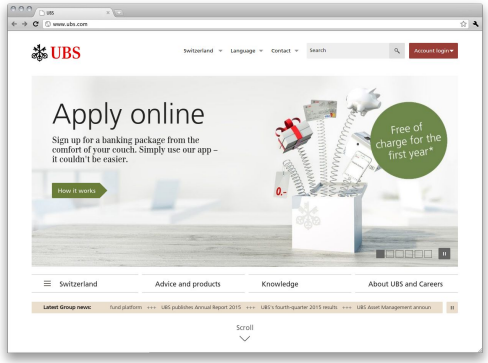

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Security Analyst

iPhone JavaScript ANDROID

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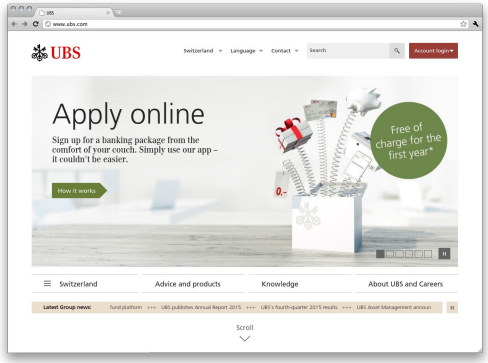

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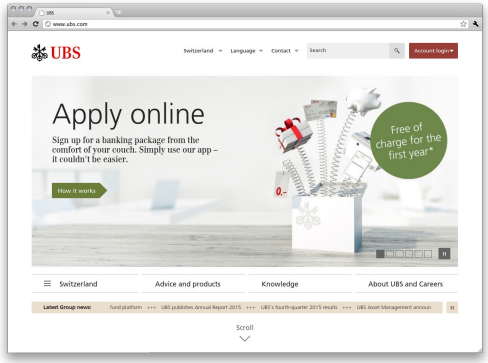
`savePassword(user, password)` ← ? ← `B(d, c)`

Code understanding/security



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iPhone JavaScript ANDROID

`savePassword(user, password)` → Obfuscation/ Minification → `B(d, c)`

`savePassword(user, password)` ← JS NICE ← `B(d, c)`

Demo

available online:

www.jsnice.org

Impact

30, 000 Users in 1st week

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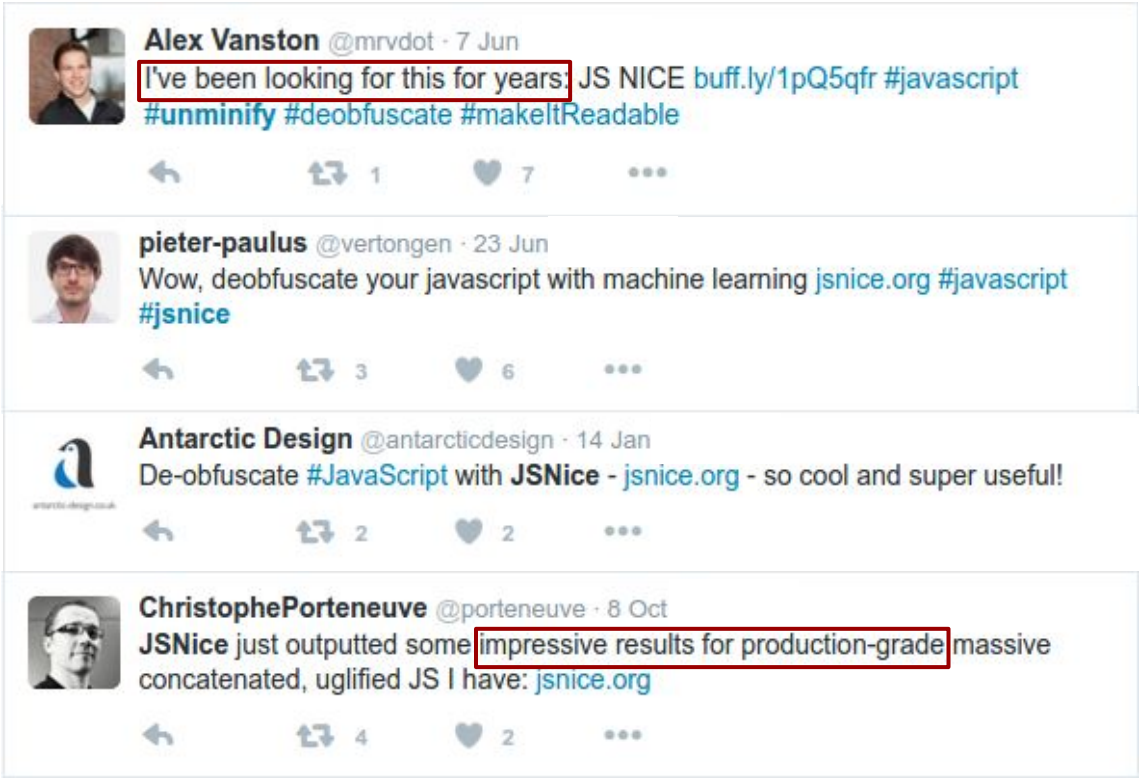

Alex Vanston @mrvdot · 7 Jun
I've been looking for this for years: JS NICE buff.ly/1pQ5qfr #javascript #unminify #deobfuscate #makeItReadable
1 7

pieter-paulus @vertongen · 23 Jun
Wow, deobfuscate your javascript with machine learning jsnice.org #javascript #jsnice
3 6

Antarctic Design @antarcticdesign · 14 Jan
De-obfuscate #JavaScript with **JSNice** - jsnice.org - so cool and super useful!
2 2

ChristophePorteneuve @porteneuve · 8 Oct
JSNice just outputted some impressive results for production-grade massive concatenated, uglified JS I have: jsnice.org
4 2

Impact

30, 000 Users in 1st week

How to build such tools?

Write new code:
Code Completion

```
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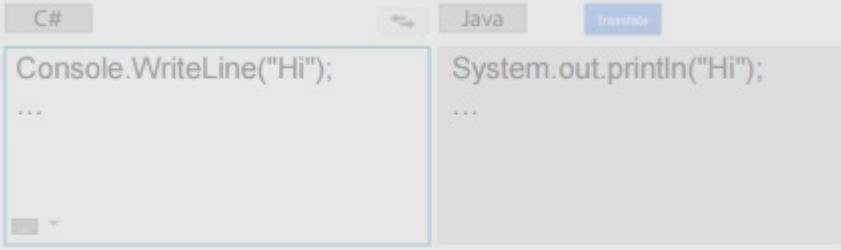
Port code:
Programming Language Translation



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```

JS NICE Statistical Type Inference and Renaming

Applications

```
function get(a, b, c) {
    b.open("GET", a, false);
    b.send(c);
}
```

Predicting types

Predicting names

```
// @param {string} url
// @param {Object} client
// @param {string} data
function get(url, client, data) {
    client.open("GET", url, false);
    client.send(data);
}
```

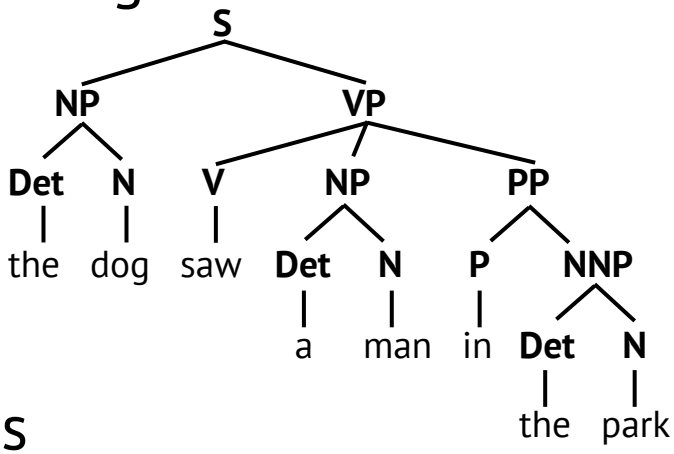
What is a suitable program representation?

Applications

Intermediate Representation

Natural Language Processing

The dog saw a man in the park →



Programming Languages

→ ?

What is a suitable program representation?

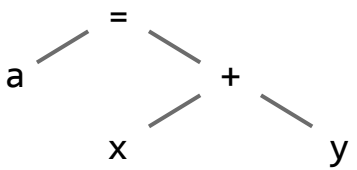
Applications

Intermediate Representation

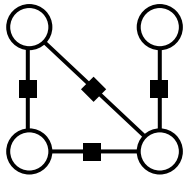
Sequences

```
req    → {<open, 0>, <send, 0>}
source → {..., <open, 2>}
```

Trees



Graphical Models



Feature Vectors

```
req    → (0,0,1,1,0)
source → (1,0,0,0,0)
...
```

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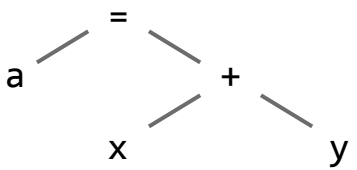

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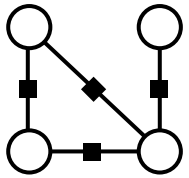

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JS NICE Representation

Applications

Intermediate Representation

```
function get(a, b, c) {
    b.open("GET", a, false);
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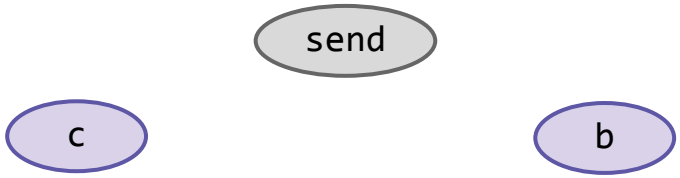

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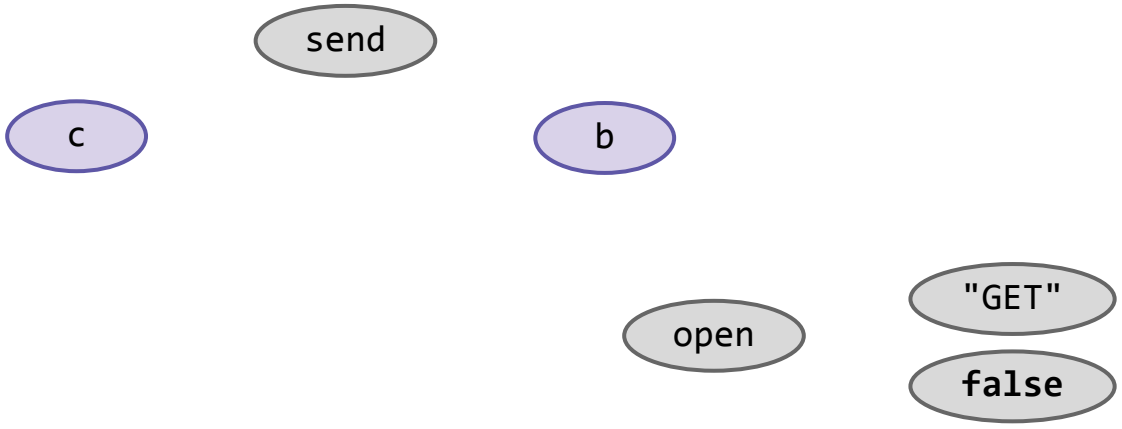

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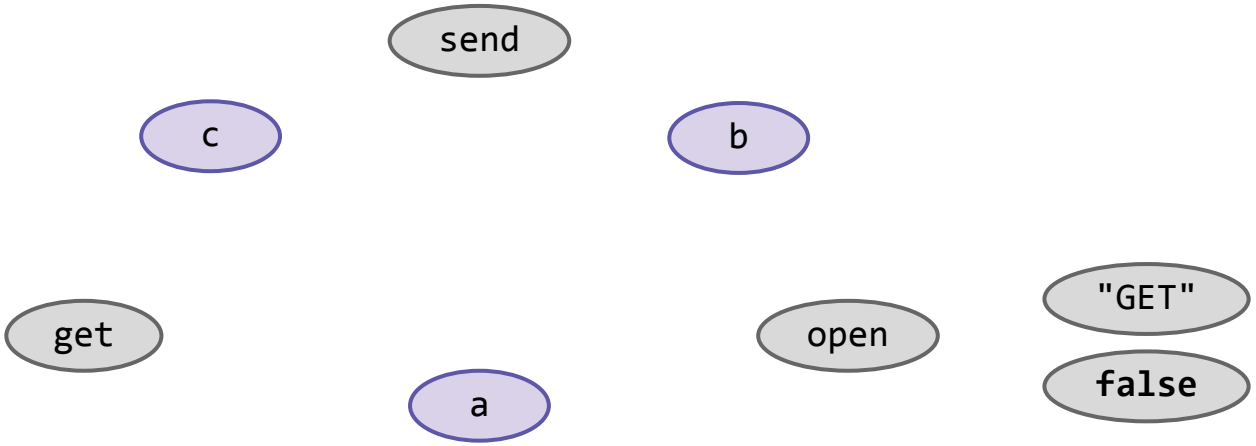

JS NICE Representation

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Intermediate Representation

Analyze Program (PL)

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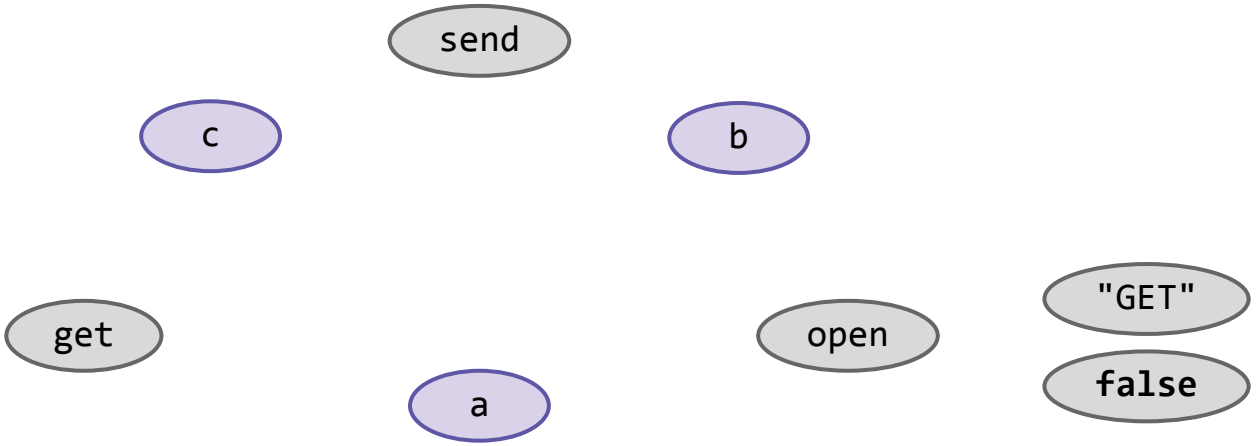

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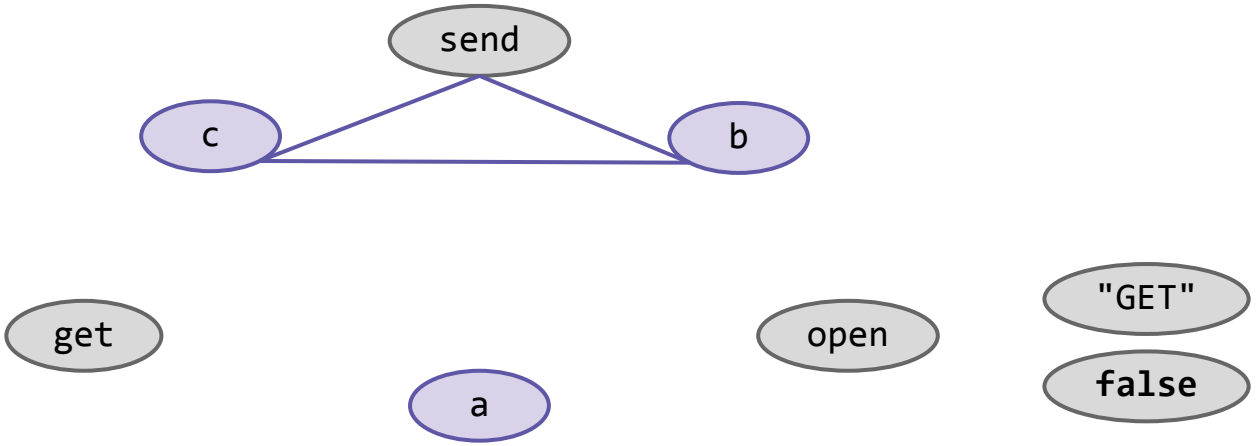

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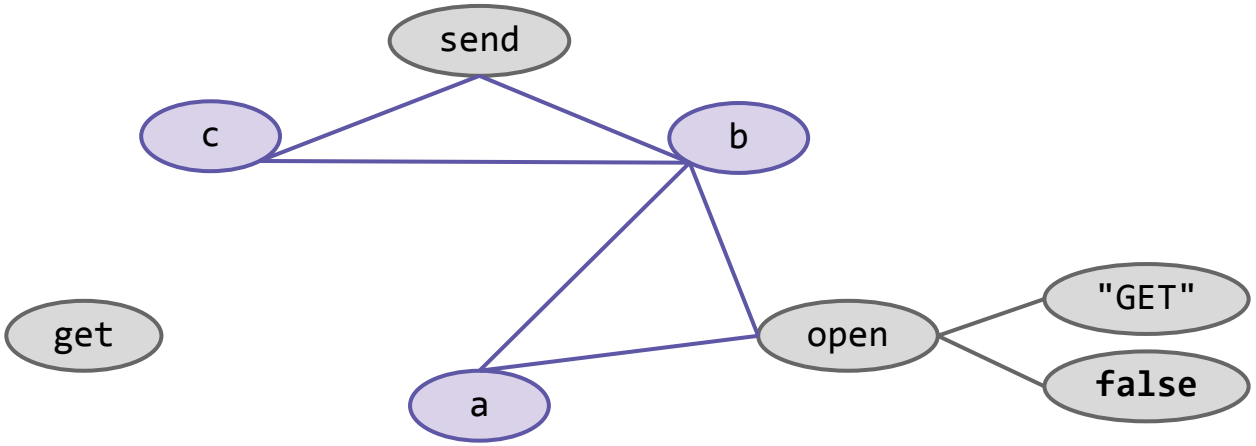

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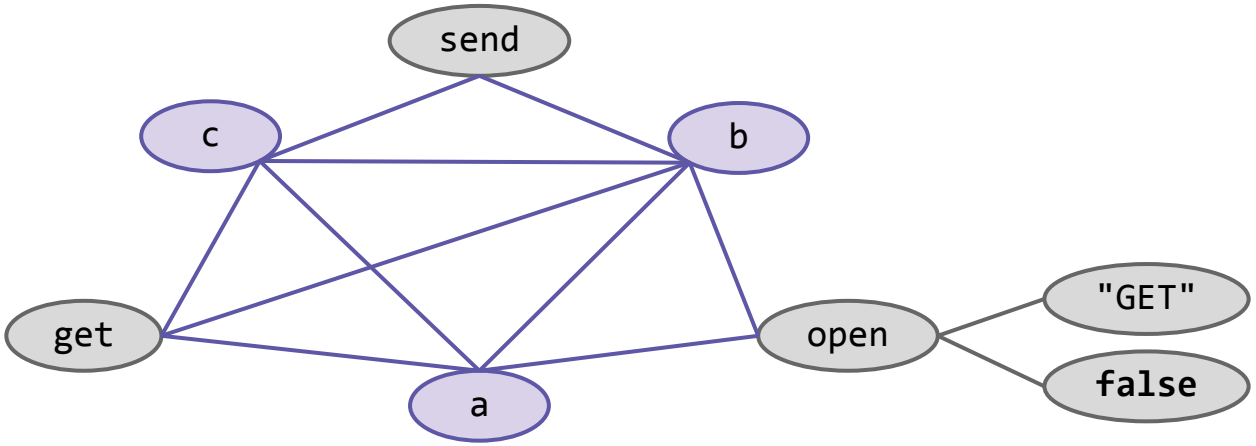

JS NICE Representation

Applications

Intermediate Representation

Analyze Program (PL)

Call graph analysis

`Who are the callers of get function?`

Alias analysis

b and c point to the same object?

```
function get(a, b, c) {
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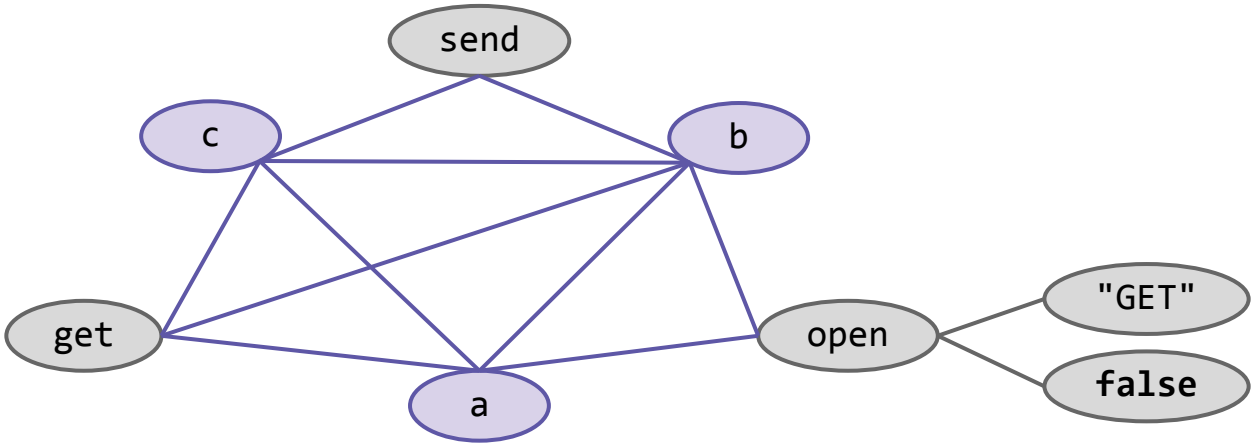
}
```

Scope analysis

`Program location where b was defined?`

Typestate analysis

`State of the object b?`

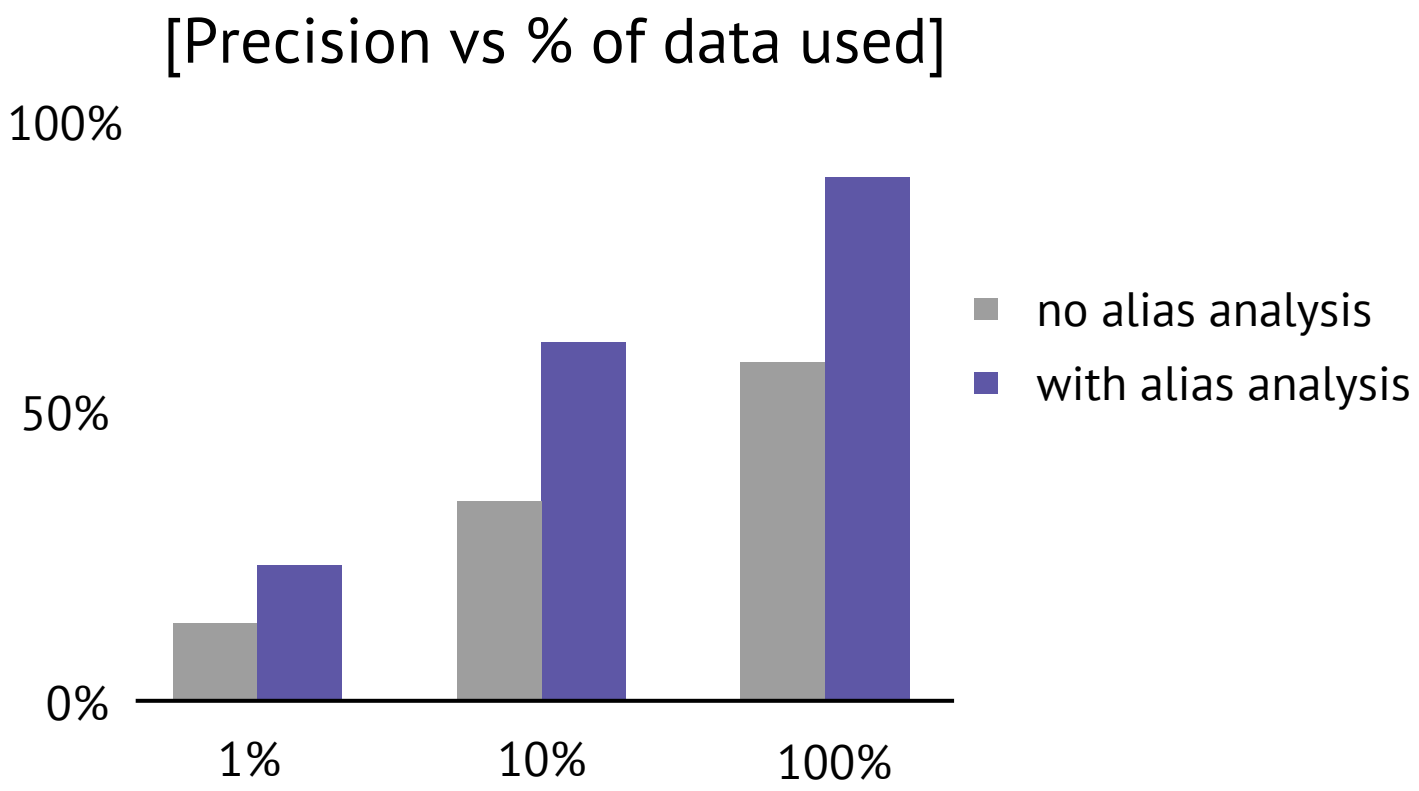


Importance of Program Analysis

Applications

Intermediate Representation

Analyze Program (PL)



Markov Network

Applications

Intermediate Representation

Analyze Program (PL)

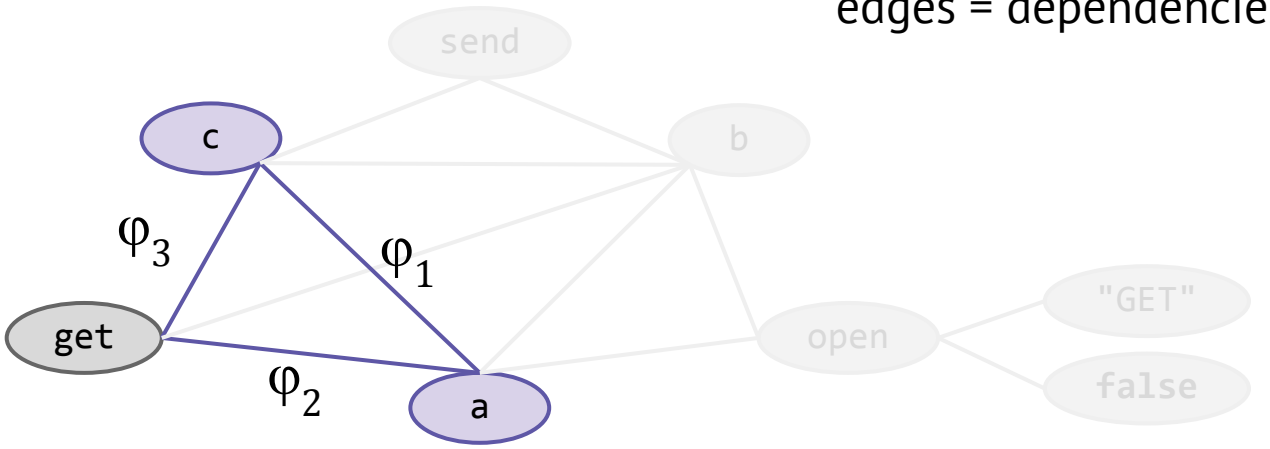
Train Model (ML)

Undirected graphical model

Captures **dependencies** between facts to be predicted

nodes = random variables

edges = dependencies



$$P(get, c, a) = \varphi_1(a, c) * \varphi_2(a, get) * \varphi_2(c, get) * \ldots / Z(get, c, a)$$

makes **P** a valid probability distribution
very expensive to compute

Conditional Random Fields

(J. Lafferty, A. McCallum, F. Pereira, ICML 2001)

Applications

Intermediate Representation

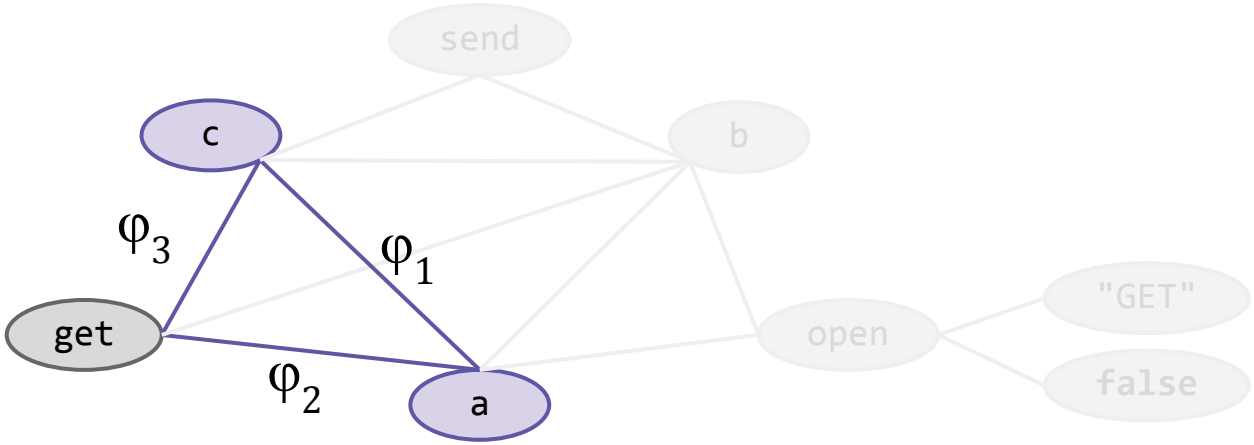
Analyze Program (PL)

Train Model (ML)

Undirected graphical model

Captures **dependencies** between facts to be predicted

Captures **conditional distribution** on known facts



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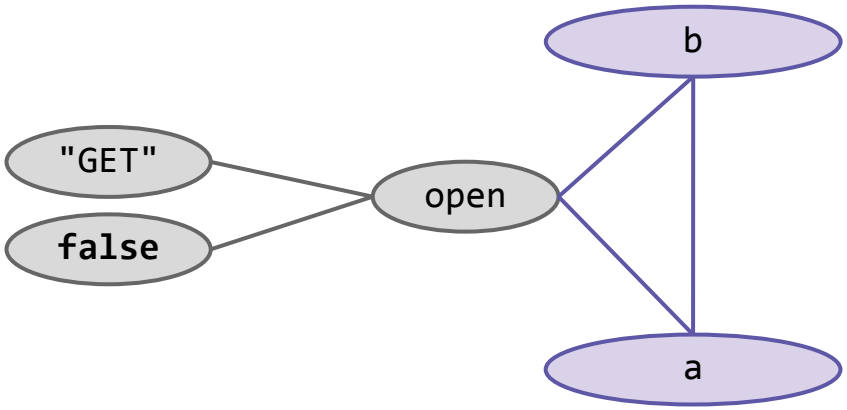
MAP inference example

$$\text{argmax}_{\mathbf{Y}} \mathbf{P}(\mathbf{Y}|\mathbf{X})$$

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MAP inference example

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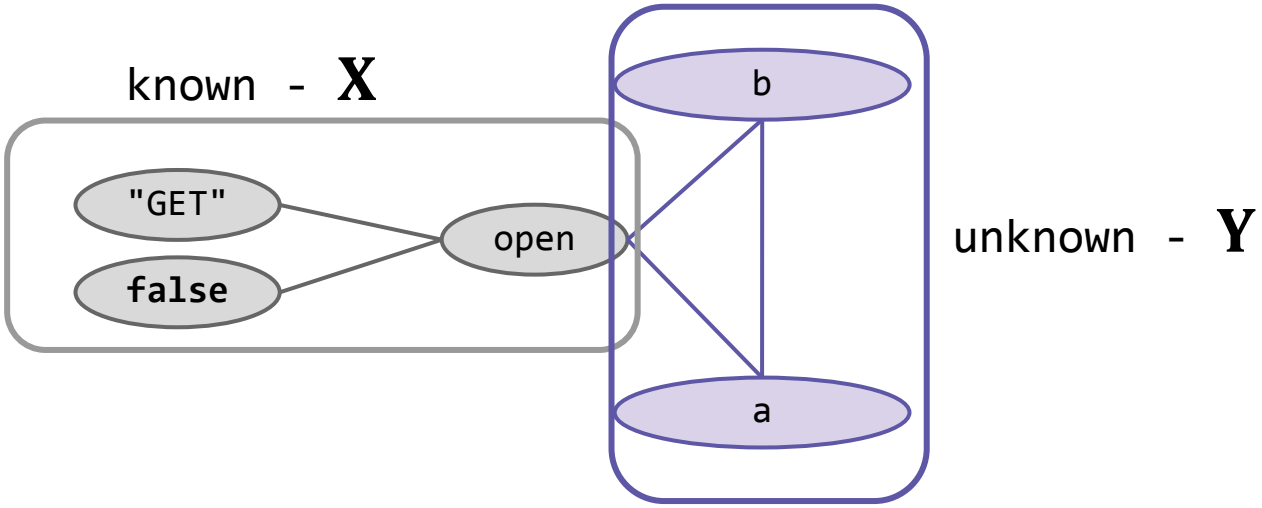


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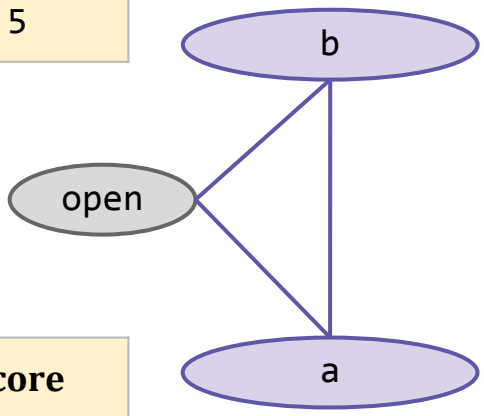
MAP inference example

$$\text{argmax}_{c,t}\ \mathbf{P}(c,t|v=\text{open})$$

φ_1

v	c	Score
open	req	6
open	client	5



t	c	Score
client	url	8
client	link	5
req	link	2

φ_2

v	t	Score
open	link	7
open	url	5
open	address	2

```
b.open("GET", a, false);
```

MAP inference example

$$\text{argmax}_{c,t}\ \mathbf{P}(c,t|v=\text{open})$$

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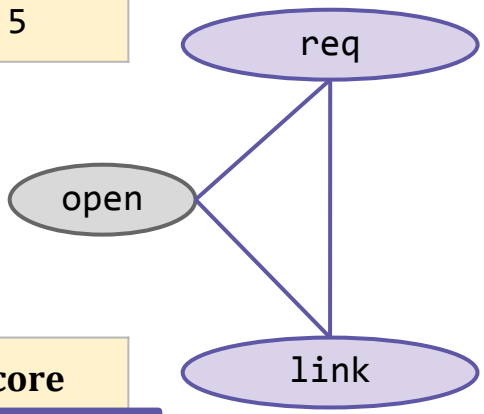

Maximize product of scores:

$$6*7*2 = 84$$

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client	url	8
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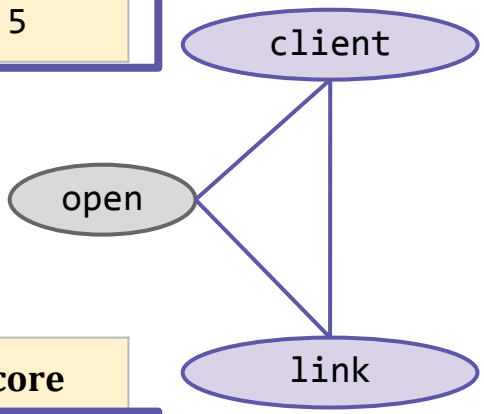

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client	url	8
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φ_2

v	t	Score
open	link	7
open	url	5
open	address	2

Maximize product of scores:

5*7*5 = 175

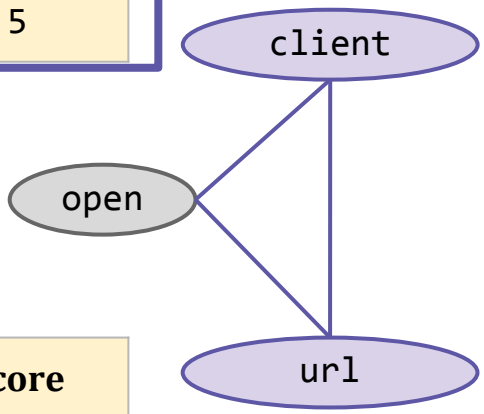
```
b.open("GET", a, false);
```

MAP inference example

$$\text{argmax}_{c,t}\ \mathbf{P}(c,t|v=\text{open})$$

φ_1

v	c	Score
open	req	6
open	client	5



Maximize product of scores:

$$5*5*8 = 200$$

t	c	Score
client	url	8
client	link	5
req	link	2

φ_2

v	t	Score
open	link	7
open	url	5
open	address	2

```
b.open("GET", a, false);
```

Query

Our goal is to find the most likely assignment of $\mathbf{y}$ that satisfies the constraints, also known as **MAP inference**:

$$\mathbf{y} = \text{argmax}_{\mathbf{y}'} \mathbf{P}(\mathbf{y}'|\mathbf{x}) = \text{argmax}_{\mathbf{y}'} 1/\mathbf{Z} \prod \varphi_i(\mathbf{x},\mathbf{y})$$

Good news:
the expensive partition function $\mathbf{Z}(\mathbf{x})$ is unnecessary

Query

Our goal is to find the most likely assignment of $\mathbf{y}$ that satisfies the constraints, also known as **MAP inference**:

$$\mathbf{y} = \text{argmax}_{\mathbf{y}'} \mathbf{P}(\mathbf{y}'|\mathbf{x}) = \text{argmax}_{\mathbf{y}'} 1/\mathbf{Z} \prod \varphi_i(\mathbf{x},\mathbf{y})$$

Good news:
the expensive partition function $\mathbf{Z}(\mathbf{x})$ is unnecessary

Bad news:
computing the argmax is still NP-hard (Max-SAT)

Query

Our goal is to find the most likely assignment of $\mathbf{y}$ that satisfies the constraints, also known as **MAP inference**:

$$\mathbf{y} = \text{argmax}_{\mathbf{y}'} \mathbf{P}(\mathbf{y}'|\mathbf{x}) = \text{argmax}_{\mathbf{y}'} 1/\mathbf{Z} \prod \varphi_i(\mathbf{x},\mathbf{y})$$

Good news:
many approximate algorithm exists (Variational Methods, EM, Gibbs sampling, Elimination Algorithm, Junction-Tree algorithm)

Query

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Good news:
many approximate algorithm exists (Variational Methods, EM, Gibbs sampling, Elimination Algorithm, Junction-Tree algorithm)

Bad news:
still too slow for learning

Query

Our goal is to find the most likely assignment of $\mathbf{y}$ that satisfies the constraints, also known as **MAP inference**:

$$\mathbf{y} = \text{argmax}_{\mathbf{y}'} \mathbf{P}(\mathbf{y}'|\mathbf{x}) = \text{argmax}_{\mathbf{y}'} 1/\mathbf{Z} \prod \varphi_i(\mathbf{x},\mathbf{y})$$

Good news:
approximate algorithms designed to fit our setting

Learning

$$\mathbf{P(y|x)} = 1/Z \quad \exp \sum \lambda_i f_i(\mathbf{x},\mathbf{y})$$

Learning finds weights λ_i from training data

$$D = \{ \mathbf{x}^{(j)}, \mathbf{y}^{(j)} \}_{j=1..n}$$

programs with facts of interest already manually annotated

Big codebase to learn from
Programmers have spent countless hours to develop, maintain and annotate

Structured SVM

Generalizes SVM, learns weights such that:

$$\forall j \; \forall \mathbf{y} \; \Sigma \lambda_i f_i(\mathbf{x}^{(j)},\mathbf{y}^{(j)}) \geq \Sigma \lambda_i f_i(\mathbf{x}^{(j)},\mathbf{y}) + \Delta(\mathbf{y},\mathbf{y}^{(j)})$$

for all training data samples

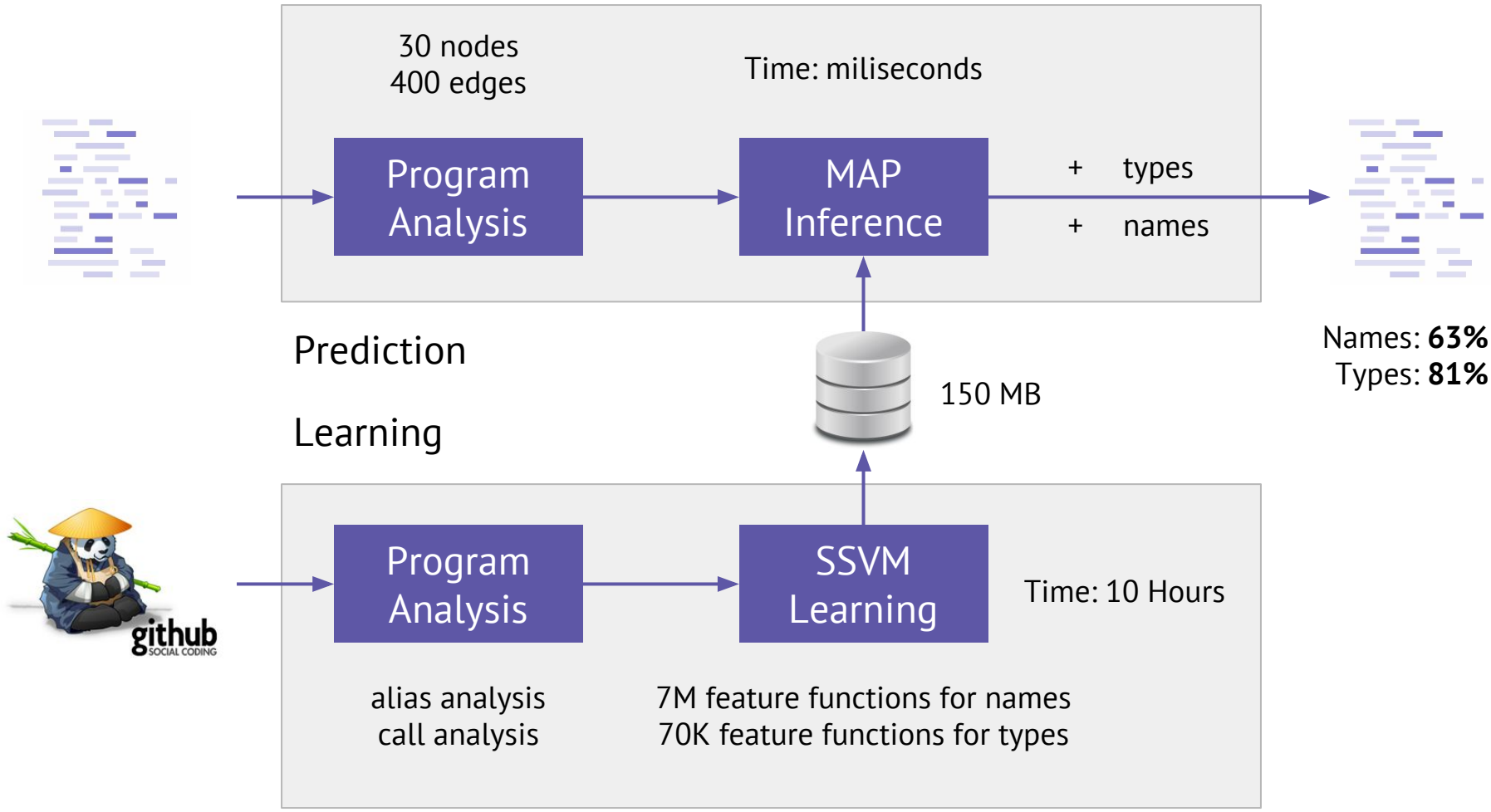
the **given prediction** is better than **any other prediction** by at least a **margin**

Training procedure:

N.Ratliff, J. Bagnell, M. Zinkevich: (Online) Subgradient Methods for Structured Prediction, AIStats'07

Memory efficient
Fast and scalable

Structured Prediction for Programs



Programming with "Big Code"

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

More information and tutorials at: http://www.nice2predict.org/ http://plml.ethz.ch/

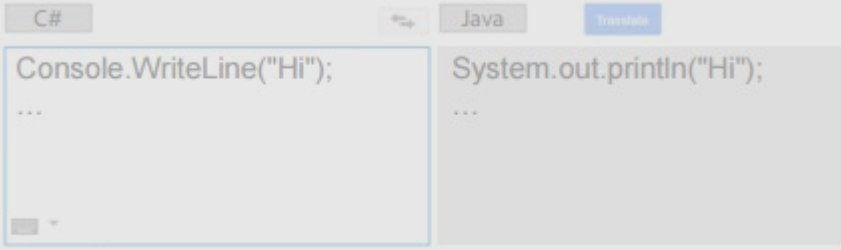
NICE 2 Predict

Statistical Software Tools

Write new code:
Code Completion

```
Camera camera = Camera.open();
camera.SetDisplayOrientation(90);
                ?
```

Port code:
Programming Language Translation



Understand code/security:
JavaScript Deobfuscation
Type Prediction

JS NICE

Debug code:
Statistical Bug Detection

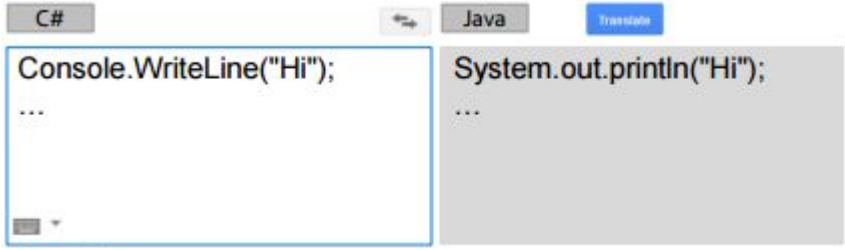
```
...                    likely error
for x in range(a):
    print a[x]
```

Statistical Software Tools

Write new code:
Code Completion

```
Camera camera = Camera.open();
camera.SetDisplayOrientation(90);
                ?
```

Port code:
Programming Language Translation



Understand code/security:
JavaScript Deobfuscation
Type Prediction

Debug code:
Statistical Bug Detection

```
...                    likely error
for x in range(a):
    print a[x]
```

Probabilistic Model for Code

Model is a key part of the Statistical Programming Tools

Goal: score programs

Select best among several candidates

Probabilistic Model for Code

Model is a key part of the Statistical Programming Tools

Goal: score programs

Select best among several candidates

Example: Which function is more likely?

(a)

```
function area(a) {
  return a.width * a.height
}
```

(b)

```
function area(a) {
  return a.width * a.close()
}
```

Statistical Code Completion

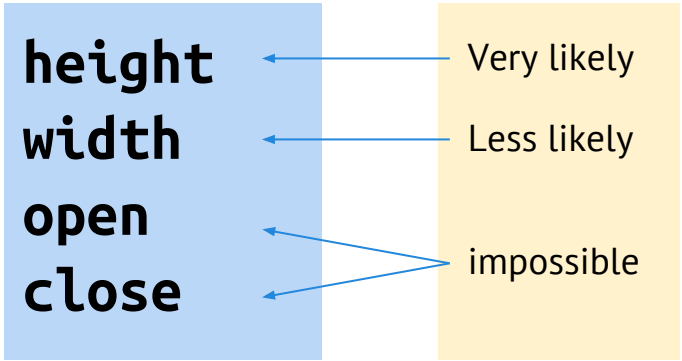
Model is a key part of Statistical Programming Tools

Goal: score programs

Select best among several candidates

Example:

```
function area(a) {
  return a.width * a.
}
```

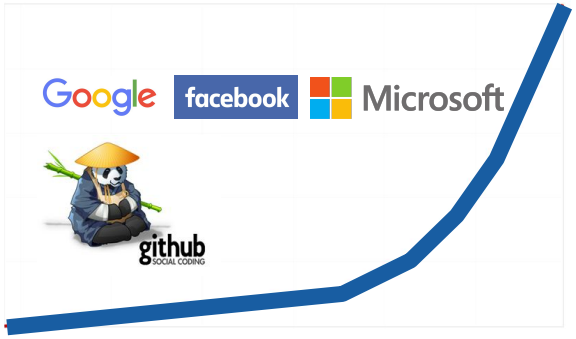


Probabilistic Model for Code

Directly applicable to code completion, but is a ***key statistical component*** for many others tasks:
e.g. natural language to code,
statistical bug localization

Model Requirements

Existing Programs



Learning

Model

Probabilistic Model

Widely Applicable	Efficient Learning	High Precision	Explainable Predictions

Observation

Regularities in code are similar
to regularities in natural language

The quick brown fox jumps over the lazy ?

Observation

Regularities in code are similar
to regularities in natural language

The quick brown fox jumps over the lazy dog

Observation

Regularities in code are similar
to regularities in natural language

The quick brown fox jumps over the lazy dog

```
file = open(filename, "r")
file.??
```

Observation

Regularities in code are similar
to regularities in natural language

The quick brown fox jumps over the lazy dog

```
file = open(filename, "r")
file.read()
```

N-gram Language Model

Conditional probability only on previous n-1 words

$$P(w_i \mid w_1 \ldots w_{i-1}) \approx P(w_i \mid \underbrace{w_{i-n+1} \ldots w_{i-1}}_{\text{n-1 words}}) \approx \frac{\#(w_{i-n+1} \ldots w_{i-1} w_i)}{\#(w_{i-n+1} \ldots w_{i-1})}$$

#(n-gram) - number of occurrences of n-gram in training data

N-gram Language Model

Conditional probability only on previous n-1 words

$$P(w_i \mid w_1 \dots w_{i-1}) \approx P(w_i \mid \underbrace{w_{i-n+1} \dots w_{i-1}}_{\text{n-1 words}}) \approx \frac{\#(w_{i-n+1} \dots w_{i-1} w_i)}{\#(w_{i-n+1} \dots w_{i-1})}$$

Training is achieved by counting n-grams (3-gram)

$$P(\text{jumped} \mid \text{The quick brown fox}) \approx P(\text{jumped} \mid \text{brown fox}) \approx \frac{\#(\text{brown fox jumped})}{\#(\text{brown fox})}$$

#(n-gram) - number of occurrences of n-gram in training data

N-gram Language Model

Training

```
return f . height * scale;

f . open (mode) ;

f . close () ;

2 * f . width;

f . close ()
```

Prediction

```
f.width + f. ?
```

N-gram Language Model

Training (3-gram model)

```
return f . height * scale;

f . open (mode) ;

f . close () ;

2 * f . width;

f . close ()
```

3-gram

Prediction

```
f.width + f. ?
```

N-gram Language Model

Training (3-gram model)

```
return f . height * scale;

f . open (mode) ;

f . close () ;

2 * f . width;

f . close ()
```

3-gram

Prediction

f.width + f. **?** **P**

close	0.4
open	0.2
width	0.2
height	0.2

N-gram Language Model

Conditioning	Accuracy
Last two tokens, Hindle et. al. [ICSE'12]	22.2%

Main Problem:

```
f.width + f. ?
```

	P
close	0.4
open	0.2
width	0.2
height	0.2

Bad context leads to bad probability estimates

Better Context

Training

```
return x.width * x.height

return y.width * y.height

area = s.width * s.height

s.width = s.width + 10

q.depth * q.width * q.height
```

Prediction

```
f.width + f.?
```

Better Context

Training

```
return x.width * x.height

return y.width * y.height

area = s.width * s.height

s.width = s.width + 10

q.depth * q.width * q.height
```

Prediction

```
f.width + f.?
```

Context: relevant for this prediction

height	0.8
width	0.2
open	0.0
close	0.0

Better Context

Conditioning	**Accuracy**
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%

JavaScript APIs

Conditioning	**Accuracy**
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
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is this the best we can do?

JavaScript APIs

Conditioning	Accuracy
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%

is this the best we can do?

Program synthesis	**66.4%**

JavaScript APIs

Conditioning	Accuracy
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%
Last three APIs	
Declaration Site + Last two APIs	
Variable Name + Method Name + Last API	
...	

How do we know that which is the best context?

JavaScript APIs

Conditioning	Accuracy
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%
Last three APIs	
Declaration Site + Last two APIs	
Variable Name + Method Name + Last API	
...	

How do we know that which is the best context?

JavaScript APIs

Identifiers

Strings

Numbers

Arguments

Properties

Statements

RegExp

Structure

Solution: Synthesise the Best Model

Synthesise a function *f* from a domain specific language that explains the data

Function Examples

$f(p_1) = \{$ $\}$

```
for (j = 0; j < groups.length; j++) {
  idsInGroup = groups[j].filter(
    function(id) { return id >= 42; }
  );
  if (idsInGroup.length == 0) {
      ?
  }
}
```

Function Examples

$f(p_1) = \{$ for, if, length==0 $\}$

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for (j = 0; j < groups.length; j++) {
  idsInGroup = groups[j].filter(
    function(id) { return id >= 42; }
  );
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      ?
  }
}
```

Function Examples

$f(p_1) = \{$ for, if, length==0 $\}$

```
for (j = 0; j < groups.length; j++) {
  idsInGroup = groups[j].filter(
    function(id) { return id >= 42; }
  );
  if (idsInGroup.length == 0) {
      ?
  }
}
```

$f(p_2) = \{ \quad \}$

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

Function Examples

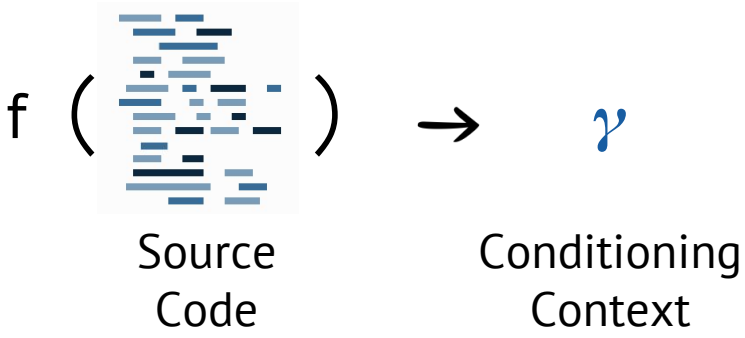
$f(p_1) = \{$ for, if, length==0 $\}$

```
for (j = 0; j < groups.length; j++) {
  idsInGroup = groups[j].filter(
    function(id) { return id >= 42; }
  );
  if (idsInGroup.length == 0) {
      ?
  }
}
```

$f(p_2) = \{$ notify, position, hide $\}$

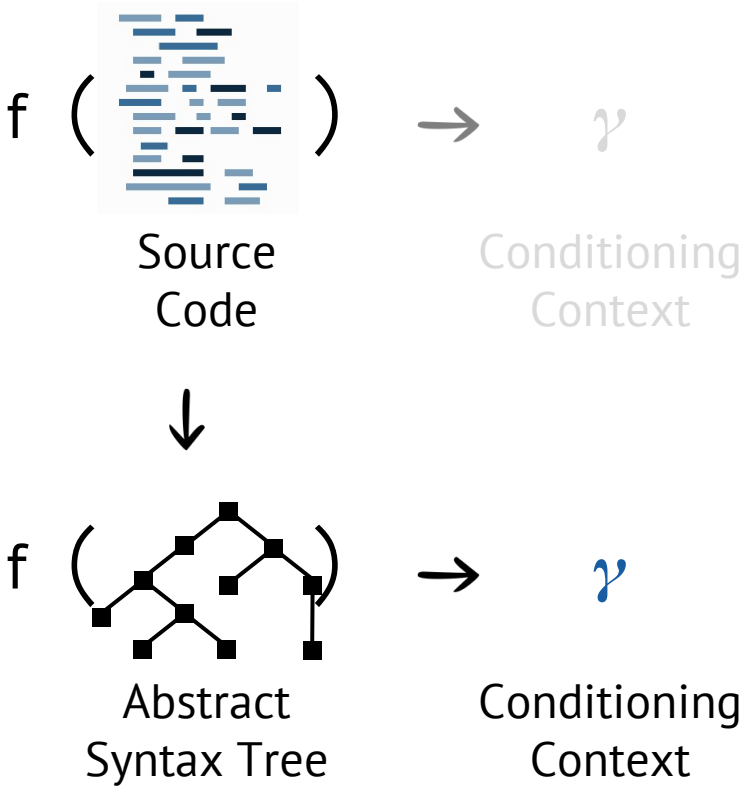
```
elem.notify( ..., {
    position: 'top',
    hide: false,
      ?
} );
```

Overview



Synthesise a function f from a domain specific language that explains the data

Overview



Synthesise a function *f* from a domain specific language that explains the data

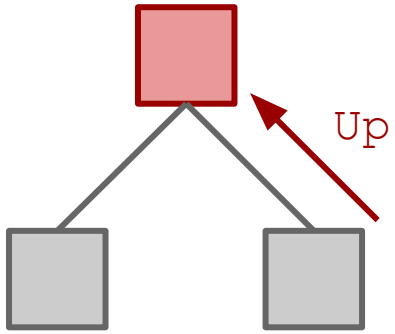
Function Representation

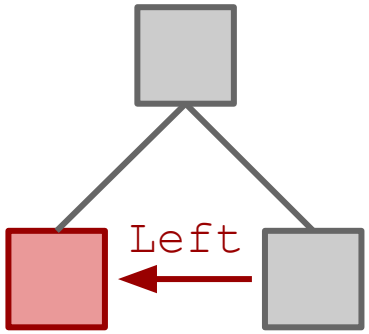
In general:
Unrestricted programs (Turing complete)

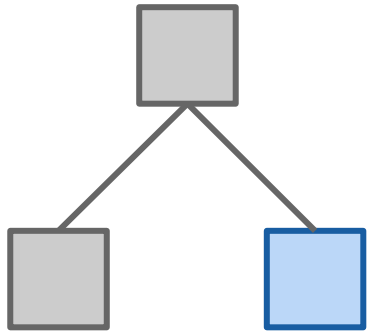
Our Work:
TCond Language for navigating over trees
and accumulating context

```
TCond       ::=  ε | WriteOp TCond | MoveOp TCond | BranchProg
BranchProg  ::=  if pred(x) then TCond else TCond
MoveOp      ::=  Up, Left, Right, DownFirst, DownLast,
                 NextDFS, PrevDFS, NextLeaf, PrevLeaf,
                 PrevNodeType, PrevNodeValue, PrevNodeContext
WriteOp     ::=  WriteValue, WriteType, WritePos
```

Expressing functions: TCond Language







WriteValue

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

```
TCond       ::=  ε | WriteOp TCond | MoveOp TCond | BranchProg
BranchProg  ::=  if pred(x) then TCond else TCond
MoveOp      ::=  Up, Left, Right, DownFirst, DownLast,
                 NextDFS, PrevDFS, NextLeaf, PrevLeaf,
                 PrevNodeType, PrevNodeValue, PrevNodeContext
WriteOp     ::=  WriteValue, WriteType, WritePos
```

Example

Query TCond γ

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

Example

Query	TCond	γ

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

Example

Query

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

TCond

Left
WriteValue
Up
WritePos

γ

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

Example

Query

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

TCond	γ
Left	{}
WriteValue	{hide}
Up	{hide}
WritePos	{hide, 3}
Up	{hide, 3}
DownFirst	{hide, 3}
DownLast	{hide, 3}
WriteValue	{hide, 3, notify}

Example

Query

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

TCond	γ
Left	{}
WriteValue	{hide}
Up	{hide}
WritePos	{hide, 3}
Up	{hide, 3}
DownFirst	{hide, 3}
DownLast	{hide, 3}
WriteValue	{hide, 3, notify}

{ Previous Property, Parameter Position, API name }

Results

Probabilistic Model of JavaScript Language

20k Learning *100k Training* *50k Blind Set*

GitHub

JavaScript APIs

Conditioning	Accuracy
Last two tokens, Hindle et. al. [ICSE'12]	22.2%
Last two APIs, Raychev et. al. [PLDI'14]	30.4%
Program synthesis	**66.4%**

JavaScript Structure

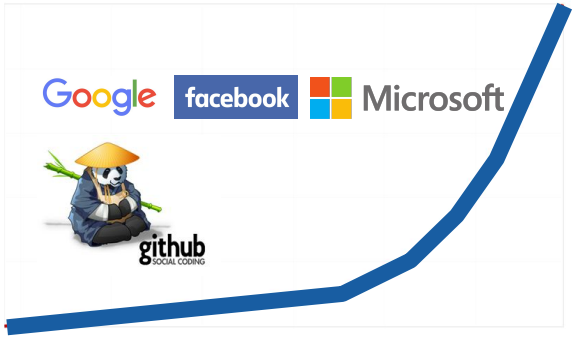
Model	Accuracy
PCFG	51.1%
N-gram	71.3%
Naïve Bayes	44.2%
SVM	70.5%
Program synthesis	**81.5%**

JavaScript Values

	Accuracy	Example
Identifier	62%	`contains = jQuery …`
Property	65%	`start = list.length;`
String	52%	`'[' + attrs + ']'`
Number	64%	`canvas(xy[0], xy[1], …)`
RegExp	66%	`line.replace(/(	)+/, …)`
UnaryExpr	97%	`if (!events || !…)`
BinaryExpr	74%	`while (++index < …)`
LogicalExpr	92%	`frame = frame || …`

Model Requirements

Existing Programs



Learning

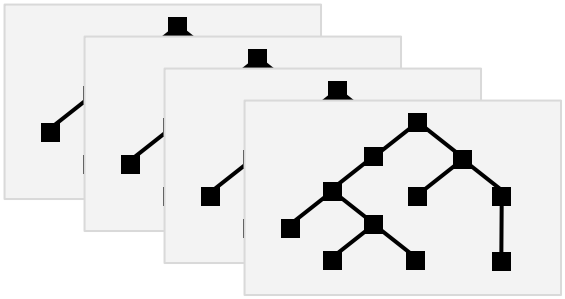
Model

Probabilistic Model

Widely Applicable	Efficient Learning	High Precision	Explainable Predictions

Learning

Dataset



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

TCond Language

Program Synthesis

Enumerative search

Genetic programming

Decision tree learning

MCMC

$$f_{best} = \arg\min cost(D, f)$$
$$f \in \text{TCond}$$

$|d| << |D|$

$|cost(d, f) - cost(D,f)| < \varepsilon$

Representative sampling

Applications

Writing new Code

Finding Bugs

Porting Code

Allocation site Analysis

Points-to Analysis

Handwriting Recognition

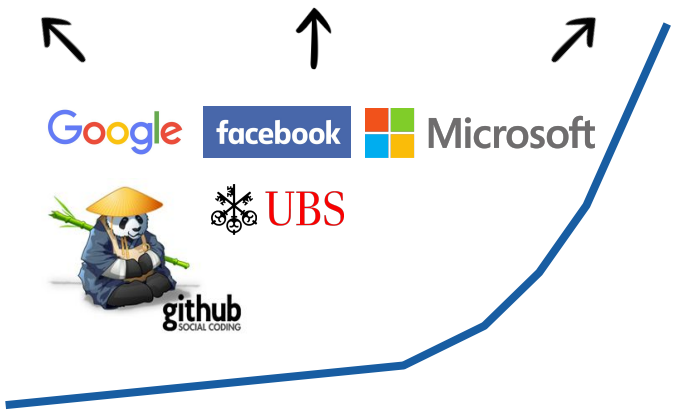
Speech Recognition

Probabilistic Model

Static Analysis

Neural Networks

Character-level Language Models



The quick brown fox jumps over the lazy dog

Work @ ETH Zurich

Prof.
Martin
Vechev

Veselin
Raychev

Pavol
Bielik

Christine
Zeller

Pascal
Roos

Benjamin
Bischel

Svetoslav
Karaivanov

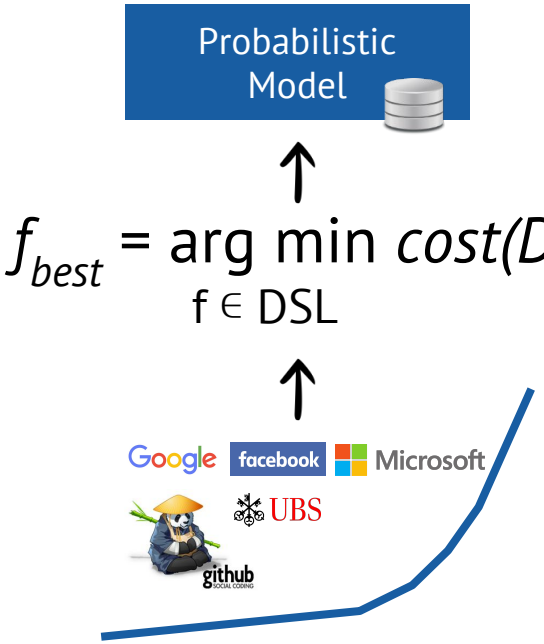
Benjamin
Mularczyk

Learning from "Big Code"

Applications	Name and Types Prediction …
Intermediate Representation	Graphical Models Feature Vectors
Analyze Program (PL)	
Train Model (ML)	Structured SVM
Query Model	Greedy MAP Inference

NICE 2 Predict

Key Idea:
Learn a function *f* that explains the data. The function dynamically obtains the best conditioning context for a given query.



http://plml.ethz.ch/