Probabilistic Model for Code with Decision Trees

  

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Big Data Revolution

Research area	Big Data	Application
Computer vision	IMAGENET COCO Common Objects in Context	Image labeling  A group of people shopping at an outdoor market. There are many vegetables at the fruit stand.
Programming languages	GitHub Bitbucket GitLab	?

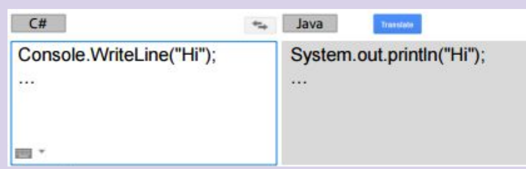
Statistical programming tools

SRL
SOFTWARE RELIABILITY LAB

Write new code [PLDI'14, POPL'16]:
Code Completion

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

Port code [ONWARD'14]:
Programming Language Translation



Understand code/security [POPL'15]:
Deobfuscation
Type Prediction

JS NICE

www.jsnice.org

Other groups

- Natural language to code
- Automatic patch generation
- Bug finding
- Code completion
- others...

All of these benefit from a good probabilistic model for code.

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.
}
```

height	Very likely
width	Less likely
open	impossible
close	impossible

Model usability

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

Existing works: naive models

Most common model: n-gram

Training (3-gram model):

3-gram

```
return a . width * a .
  + a . open (mode) ;
+ a . close () ;
      * a . height ;
  * a . close () ;
```

Count 3-grams	e.g `a.close` (2 times)

Prediction:

```
width + a .
```

a.close - 2 times
a.open - 1 times
a.width - 1 times
a.height - 1 times

	Probability
close	0.4
open	0.2
width	0.2
height	0.2

Existing works: naive models

Most common model: n-gram

Training (3-gram model):

Prediction:

Main problem:

Bad context leads to bad probability estimates

Count 3-grams | e.g `a.close` (2 times)

width + a .

Probability

`a.close` - 2 times

`a.open` - 1 times

`a.width` - 1 times

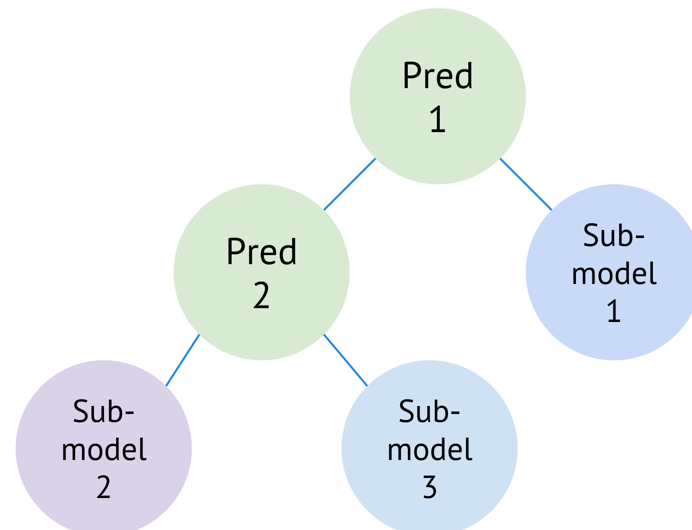
`a.height` - 1 times

close	0.4
open	0.2
width	0.2
height	0.2

1. Richer conditioning context

```
return a.width * a. ?
```

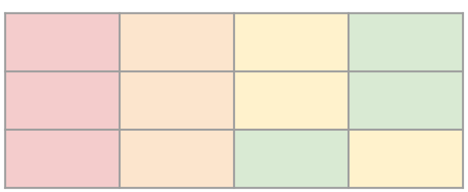
2. Domain Specific Language encoding Decision Trees



Lang ::= BasicPart | BranchPart

BranchPart ::= if pred(x) then Lang else Lang

3. Evaluation



Conditioning context

Training (3-gram model):

```
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:

```
return a.width * a. ?
```

Context: relevant for this prediction

height	0.8
width	0.2

width	→	height	4 times
width	→	width	1 time
width	→	close	0 times

Indirection

Query: x

```
return a.width * a. ?
```

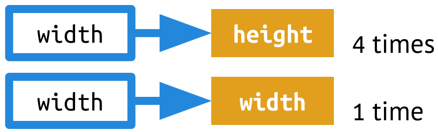
Completion: y

? = height

Context: ctx = f(x)

```
return a.width * a. ?
```

Model: P(y|f(x))



Example contexts

Query: x

```
return a.width * a. ?
```

ctx = f(x): last two tokens
3-gram language model

```
return a.width * a. ?
```

ctx = f(x): previous actions
on the same object [PLDI'14]

```
return a.width * a. ?
```

ctx = f(x): the third token
before the completion

Question:

Which context is the best?

Try many of them and evaluate

Evaluation metric: entropy

Average entropy:
~0.66667 bits

`console.` `info`	P(`info` | `console.`) = 1	0
`console.` `info`	P(`info` | `console.`) = 1	0
`a.width * a. height`	P(`height` | `a.`) = 0.5	1
`b.width * b. height`	P(`height` | `b.`) = 0.5	1
`a.right - a. left`	P(`left` | `a.`) = 0.5	1
`b.bottom - b. top`	P(`top` | `b.`) = 0.5	1

Evaluation metric: entropy

Average entropy:
~1.91 bits

`console.info`	P(`info` | `.`) = 1/3	~1.58
`console.info`	P(`info` | `.`) = 1/3	~1.58
`a.width * a.height`	P(`height` | `.`) = 1/3	~1.58
`b.width * b.height`	P(`height` | `.`) = 1/3	~1.58
`a.right - a.left`	P(`left` | `.`) = 1/6	~2.58
`b.bottom - b.top`	P(`top` | `.`) = 1/6	~2.58

Unconditional model

No conditioning in the probability distribution:
ctx=⊥

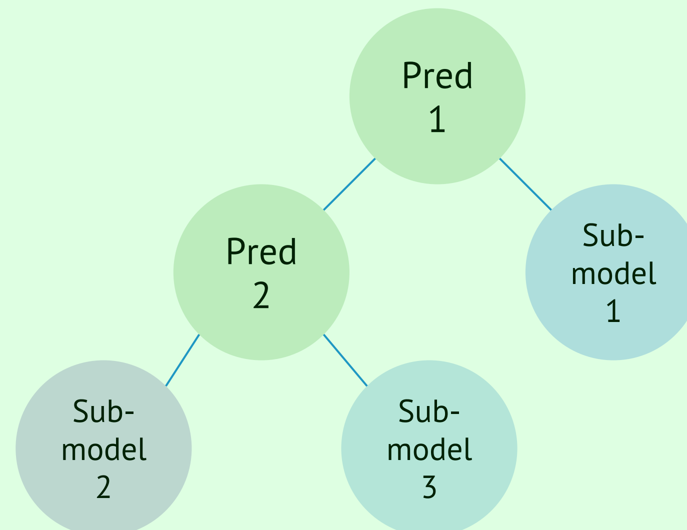
Average entropy:
~1.91 bits

`console.` $\boxed{\texttt{info}}$	P(`info`) = 1/3	~1.58
`console.` $\boxed{\texttt{info}}$	P(`info`) = 1/3	~1.58
`a.width * a.` $\boxed{\texttt{height}}$	P(`height`) = 1/3	~1.58
`b.width * b.` $\boxed{\texttt{height}}$	P(`height`) = 1/3	~1.58
`a.right - a.` $\boxed{\texttt{left}}$	P(`left`) = 1/6	~2.58
`b.bottom - b.` $\boxed{\texttt{top}}$	P(`top`) = 1/6	~2.58

1. Richer conditioning context

```
return a.width * a.    ?
```

2. Domain Specific Language encoding Decision Trees



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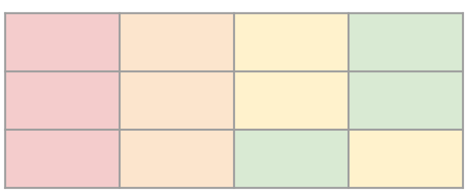
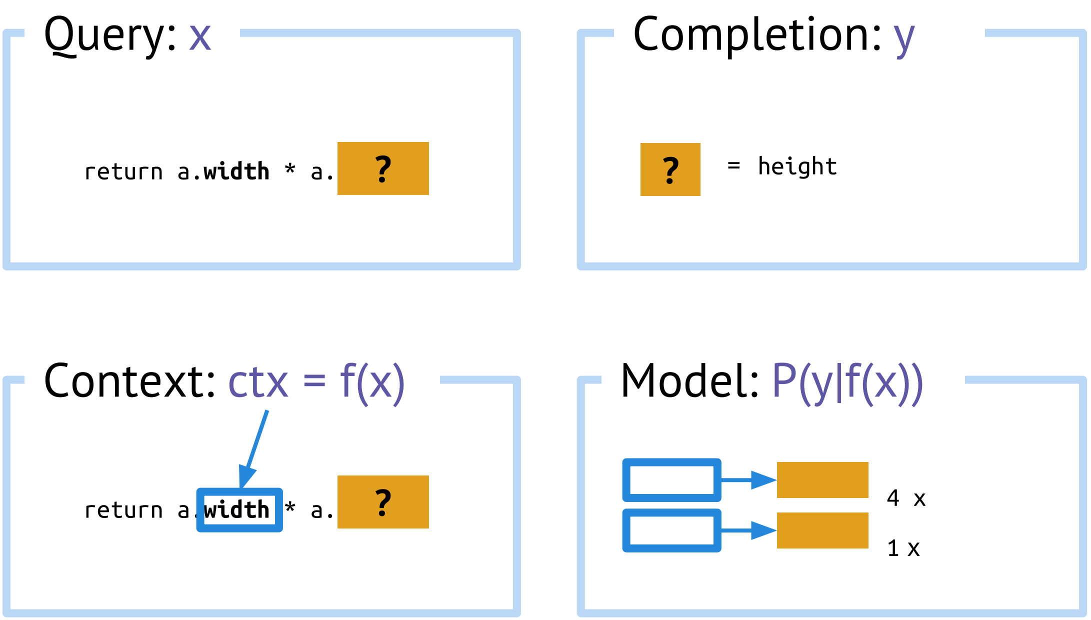


Synthesize the best model



Find function f

From a domain specific language

Same basic idea in
Learning Programs from Noisy Data [POPL'16]

Main DSL requirement

Program ::= BasicPart | **BranchPart**

BranchPart ::= if pred(x) then **Program** else **Program**

Basic part

Includes models from a simple DSL

```
return a.width * a. ?
```

ctx = f(x): last two tokens
3-gram language model

```
return a.width * a. ?
```

ctx = f(x): previous actions on the same object [PLDI'14]

```
return a.width * a. ?
```

ctx = f(x): empty
Unconditional model

Branch part

Combines programs based on predicates. Language of predicates pred

e.g. are we completing a field name?
Is there another operation on the same object?

Special empty program ε

Best program

If there is no prior field access, then use 3-gram model, otherwise prior field access

Code	Probability	Entropy (bits)
`console.info`	P(`info` | `console.`) = 1	0
`console.info`	P(`info` | `console.`) = 1	0
`a.width * a. height`	P(`height` | `a.`) = 1	0
`b.width * b. height`	P(`height` | `b.`) = 1	0
`a.right - a. left`	P(`left` | `a.`) = 1	0
`b.bottom - b. top`	P(`top` | `b.`) = 1	0

Synthesis using basic part of DSL

Involved
See POPL'16

At high level:
Search through **thousands** of candidate programs that describe conditioning.

Basic part

Includes models from a simple DSL

```
return a.width * a. ?
```

ctx = f(x): last two tokens
3-gram language model

```
return a.width * a. ?
```

ctx = f(x): previous actions on the same object [PLDI'14]

```
return a.width * a. ?
```

ctx = f(x): empty
Unconditional model

Synthesis of branch part

Space of possible programs:

BranchPart ::= if pred(x) then **Program** else **Program**

Search thousands

Search thousands

Search thousands

Billions even without nesting

Infinite with nesting

Goal: find program with best entropy

Idea 1: synthesis in parts

1. Synthesize branch with empty programs in leaves

Synthesize : if pred(x) then ε else ε

Search thousands

Until no predicate improves entropy over basic ε

Then synthesize basic part

Goal: find program with **approximately** best entropy

2. Synthesize leaves separately

Synthesize : if pred(x) then **Program** else **Program**

Recursively call 1 for branch

Recursively call 1 for branch

This is decision tree learning

Synthesis of branch part

Space of possible programs:

BranchPart ::= if pred(x) then **Program** else **Program**

Search thousands

Search thousands

Search thousands

Search for each component separately

Performance at expense of possible non-optimality

Goal: find program with **approximately** best entropy

Idea 2: synthesis in parts

1. Synthesize basic program

f' ∊ BasicPart

Search thousands

Goal: find program with **approximately** best entropy

2. Synthesize branch

Synthesize : if pred(x) then **f'** else **f'**

Search thousands

Until no predicate improves entropy over simply **f'**

If no, return **f'**

3. Synthesize leaves separately

Synthesize : if pred(x) then **Program** else **Program**

Recursively call 1 for branch

Recursively call 1 for branch

Main result

Synthesis procedure 1 is a new formulation of a known and popular algorithm for decision tree learning: ID3

In fact, we extended ID3 to support programs in decision tree leaves from the BasicPart DSL fragment

Synthesis procedure 2 is new
And also applicable to decision trees

New name:

E13

1. Richer conditioning context

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```

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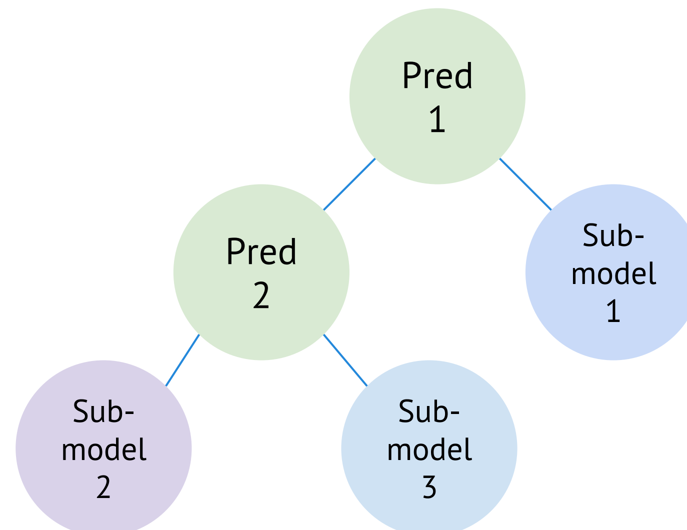

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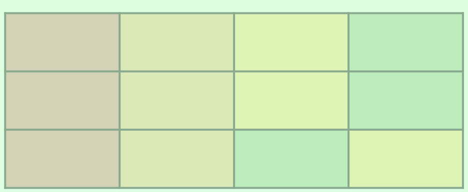

Evaluation

150’000 JavaScript files, from GitHub.com, parsed into ASTs. Public datasets.

100’000 files
Training data for synthesis

Synthesis time: ~100 hours

50’000 files
Evaluation data

Evaluation files are not on the same projects as training

Question: How well can we predict program elements?

Accuracy: JavaScript

Query time for all models is basically the same
(>10K queries per second)

Task	**PCFG**	**3-gram**	**ID3+**	**E13**
API completion	0.04%	30.0%	54%	**66.6%**
Field access completion	3.2%	32.9%	52.5%	**67.0%**
Predicting loops	0%	37.5%	**65.0%**	28.3%

Many more evaluation results in the paper.... Also for Python. Easily applicable to all languages.

Big improvement over prior methods

Both ID3+ and E13 learn useful probabilistic models