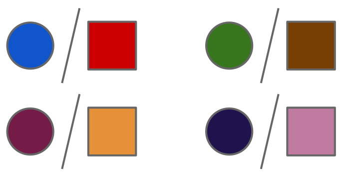
Learning Programs from Noisy Data

Veselin Raychev
Pavol Bielik
Martin Vechev
Andreas Krause

ETH Zurich

Why learn programs from examples?

Input/output
examples



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(e.g. in FlashFill)

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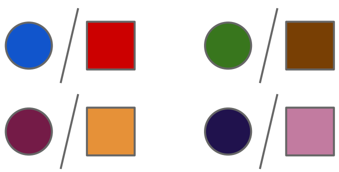

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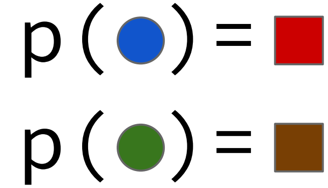

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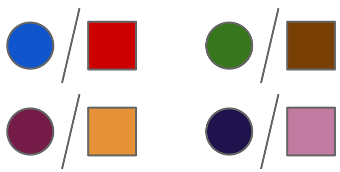

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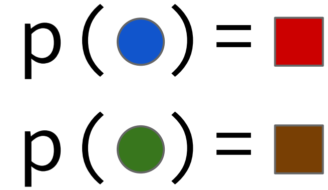

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Why learn programs from examples?

Input/output examples

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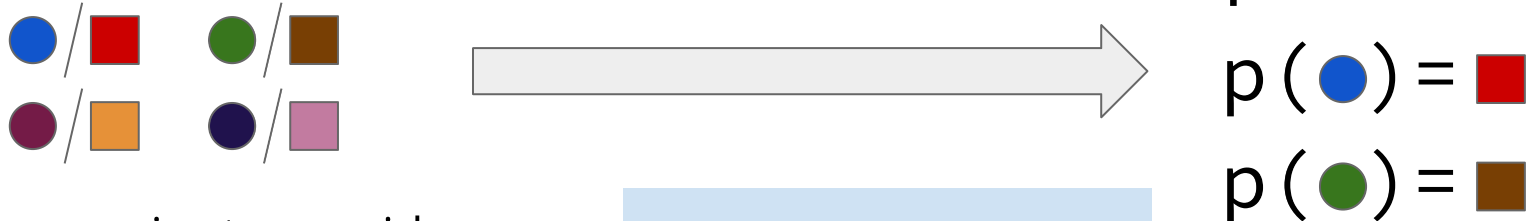

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Actual goal: produce p that the **user really wanted** and tried to specify

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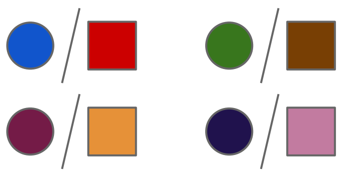

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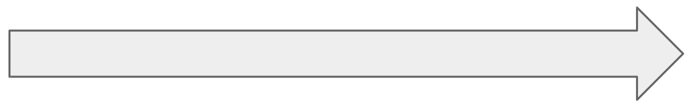
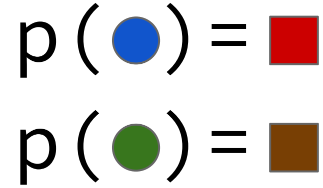
learn a function



p such that



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Key problem of synthesis: overfits, not robust to noise

Learning Programs from Data: Defining Dimensions

Handling errors in the dataset

Number of Examples

Learned program complexity

Learning Programs from Data: Defining Dimensions

	Program synthesis (PL)
Handling errors in the dataset	**no**
Number of Examples	**tens**
Learned program complexity	**interesting programs**

Learning Programs from Data: Defining Dimensions

	Program synthesis (PL)	Deep learning (ML)
Handling errors in the dataset	**no**	**yes**
Number of Examples	**tens**	**millions**
Learned program complexity	**interesting programs**	**simple, but unexplainable functions**

Learning Programs from Data: Defining Dimensions

	Program synthesis (PL)	This paper bridges a gap	Deep learning (ML)
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new state-of-the-art precision for programming tasks

Learning Programs from Data: Defining Dimensions

	Program synthesis (PL)	This paper bridges a gap	Deep learning (ML)
Handling errors in the dataset			
Number of Examples			
Learned program complexity			

Bridges gap between ML and PL

Advances both areas

expands capabilities of existing synthesizers

new state-of-the-art precision for programming tasks

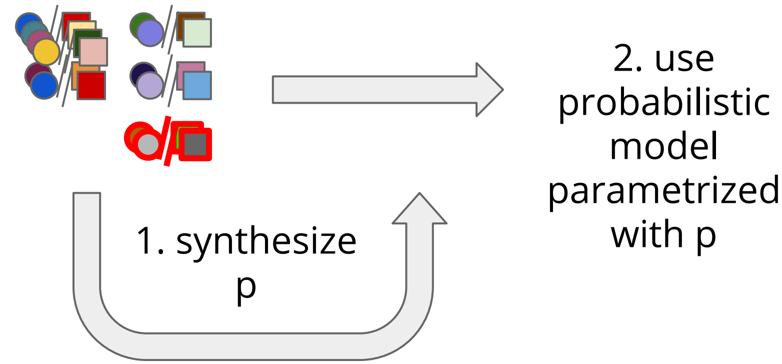
In this paper

- A general framework that handles
  - errors in training dataset
  - learns statistical models on data
  - handles synthesis with millions of examples

- Instantiated with two synthesizers
  - generalize existing works

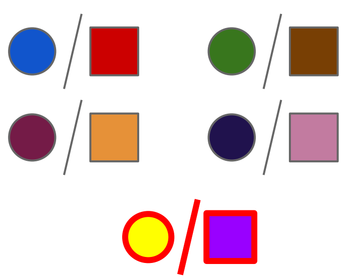
Contributions

New probabilistic models



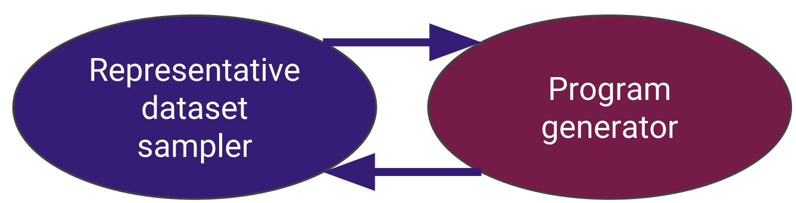
Handling noise

Input/output examples



incorrect examples

Handling large datasets



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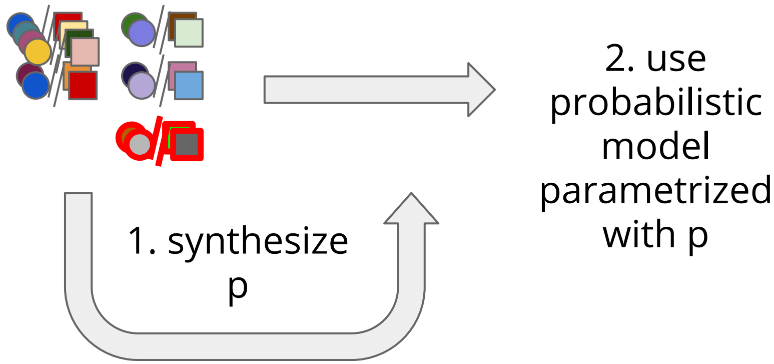

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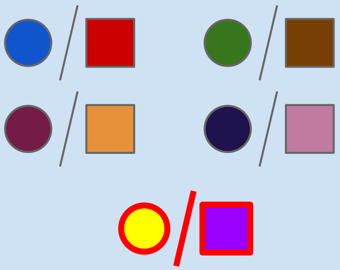

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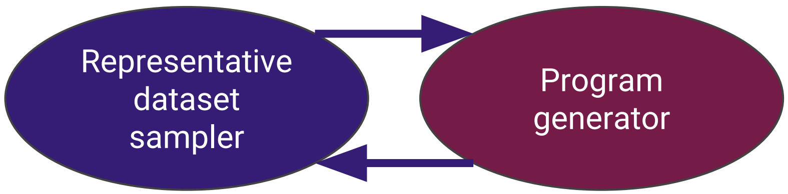
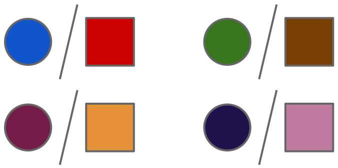


Synthesis with noise: usage model

Input/output
examples



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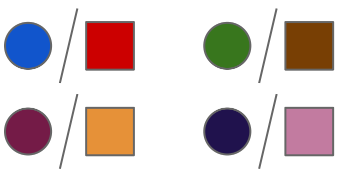
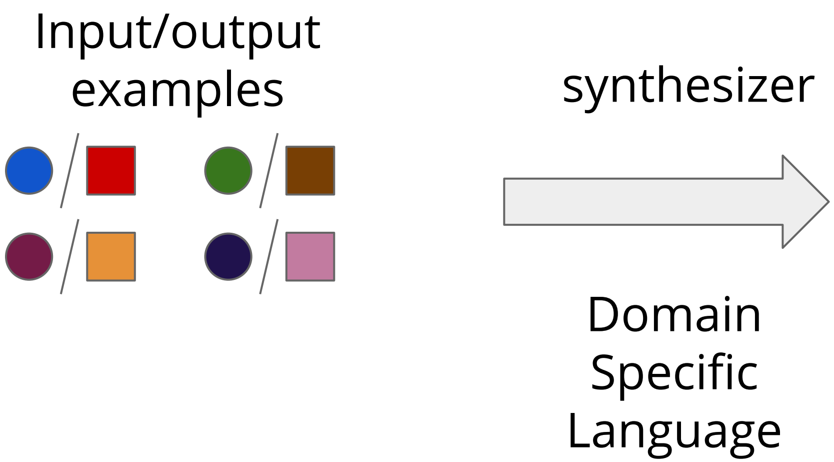


Domain Specific Language

Synthesis with noise: usage model



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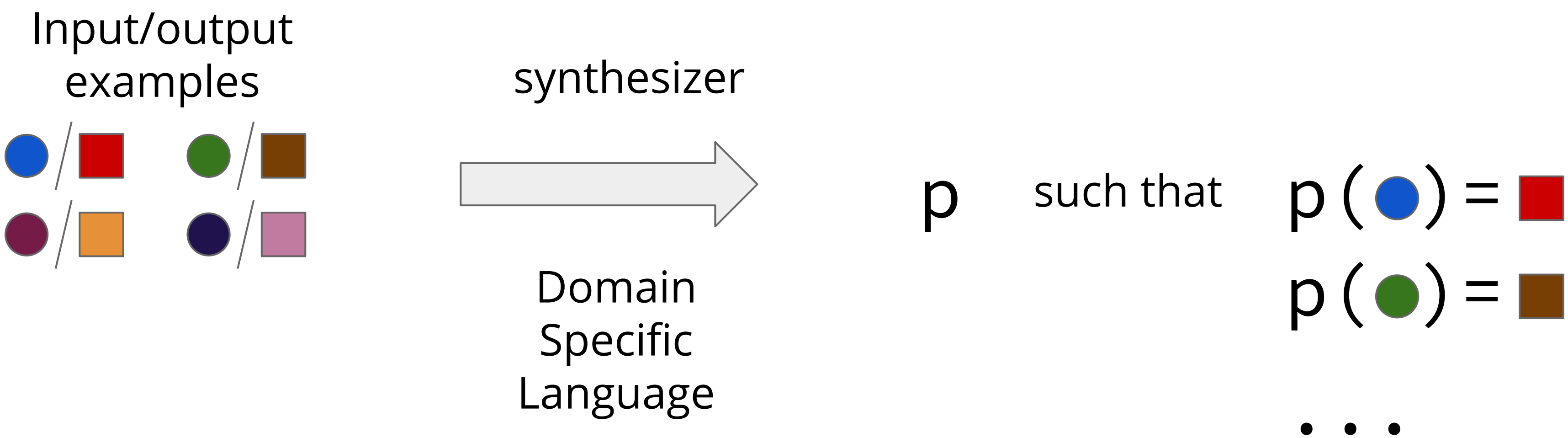

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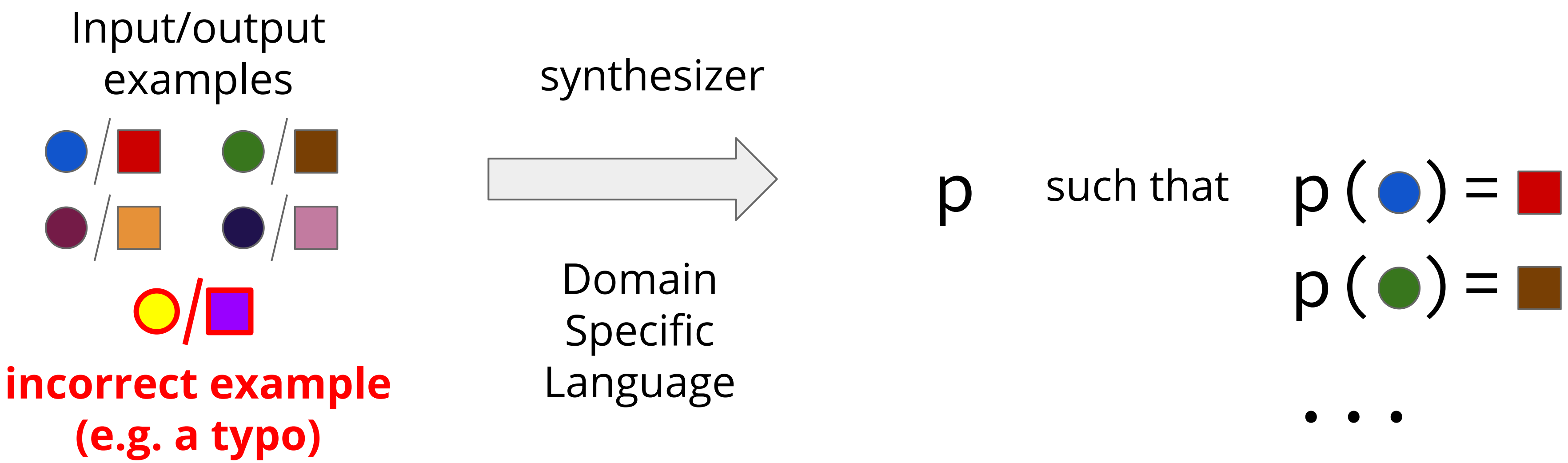

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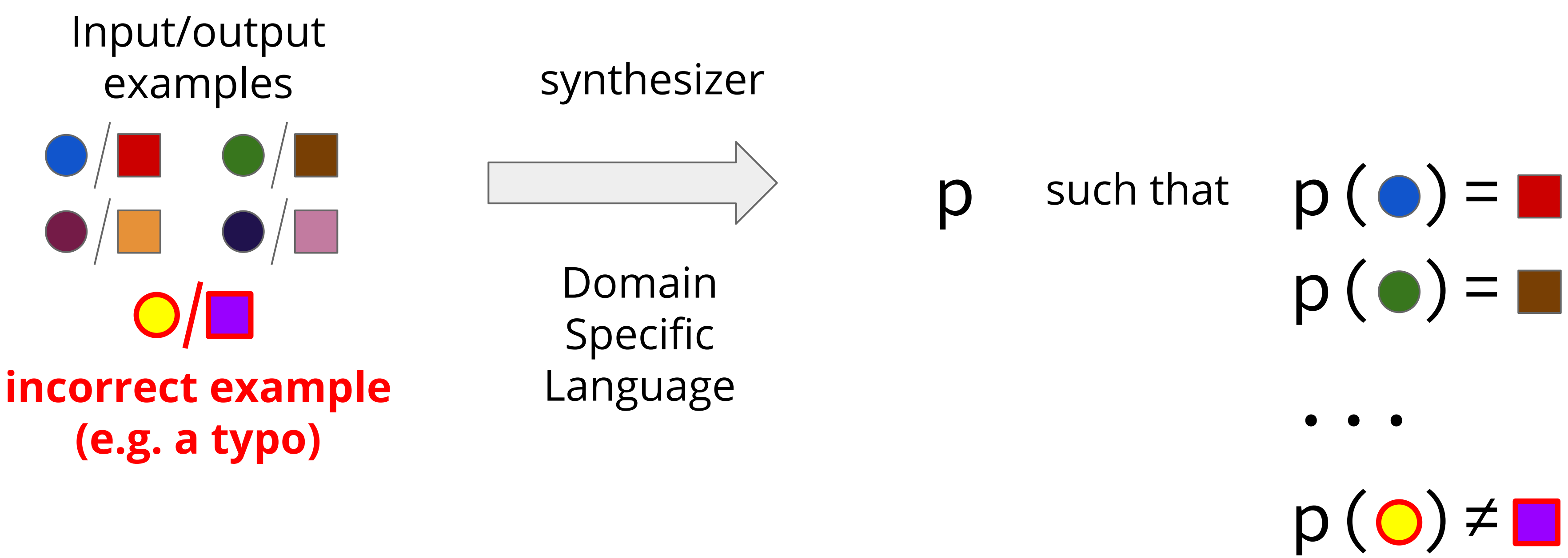

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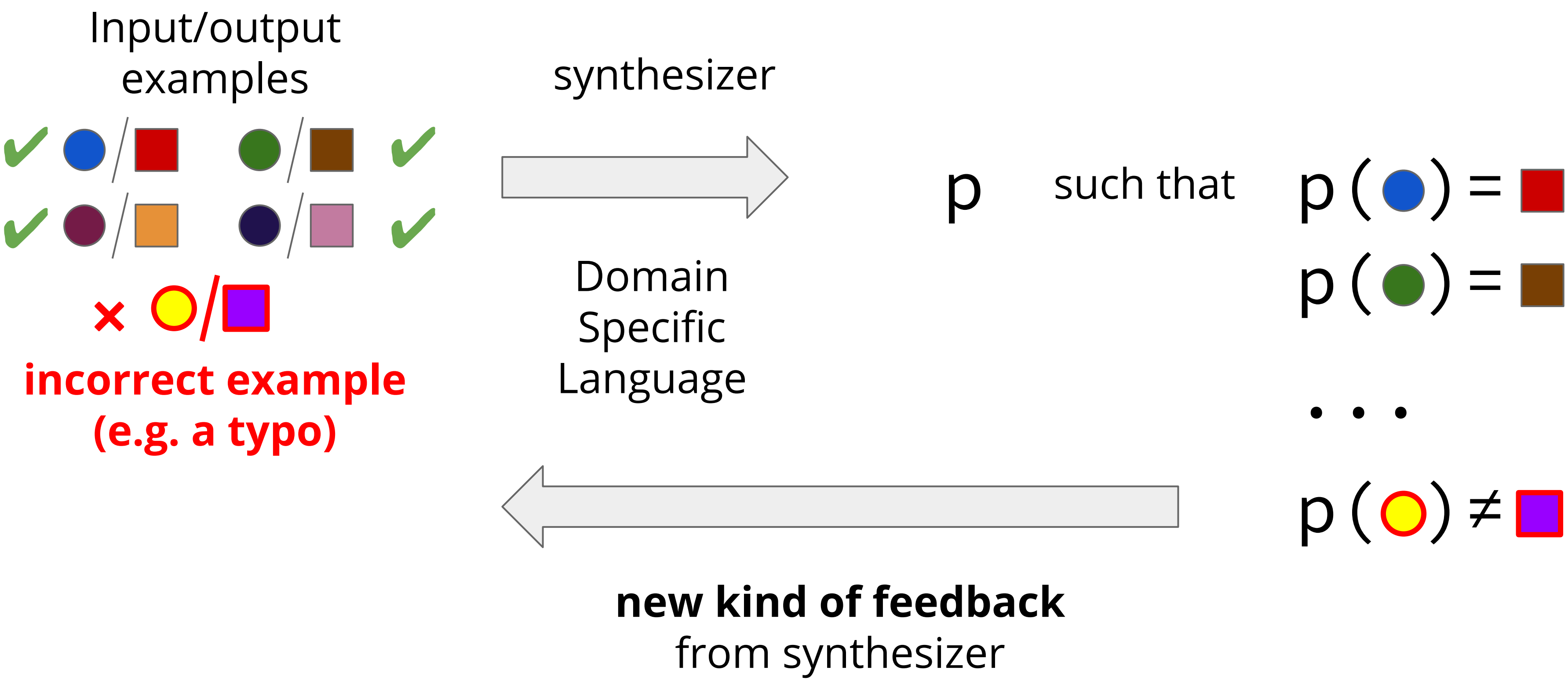

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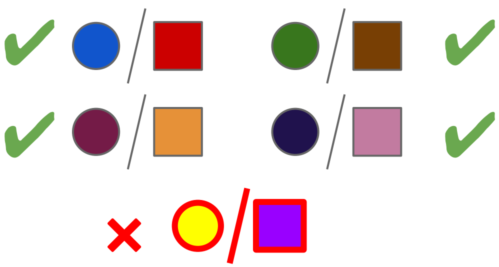
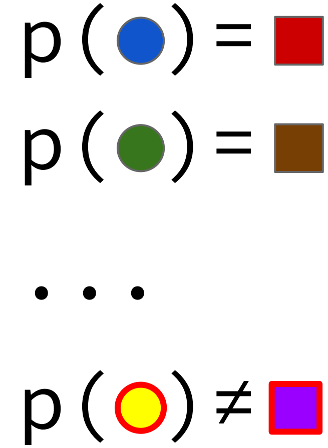


incorrect example
(e.g. a typo)

synthesizer

Domain
Specific
Language

p such that

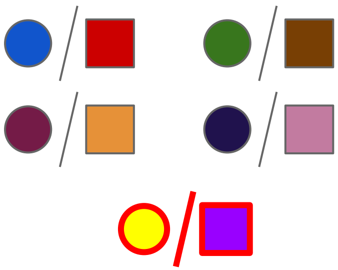


new kind of feedback
from synthesizer

- Tell user to remove **suspicious** example, or
- Ask for more examples

Handling noise: problem statement

D: Input/output examples



incorrect examples

synthesizer

dataset of input/output examples

$$p_{best} = \underset{p \in P}{\arg\min}\ \mathrm{errors}(D, p)$$

space of possible programs in DSL

Too long program, hardcodes the input/outputs.
Synthesis must penalize such answers

Our problem formulation:

regularization constant

$$p_{best} = \underset{p \in P}{\arg\min}\ \mathrm{errors}(D, p) + \lambda r(p)$$

error rate

regularizer penalizes long programs

Noisy synthesis using SMT

total solution

cost

$$p_{best} = \arg\min_{p \in P} \boxed{\text{errors}(D,\ p) + \lambda r(p)}$$

number of instructions

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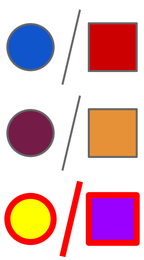

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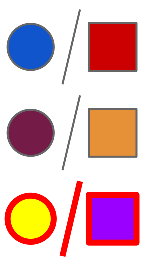

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p $\in$ P_r (with **r** instructions)

Ψ

formula given to SMT solver

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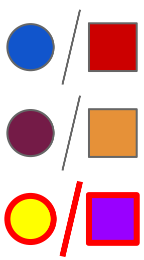

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Ask a number of SMT queries in increasing value of solution cost

e.g. for

$\lambda = 0.6$

costs are

cost		number of **errors**			
		0	1	2	3
r	1	**0.6**	**1.6**	**2.6**	**3.6**
	2	**1.2**	**2.2**	**3.2**	**4.2**
	3	**1.8**	**2.8**	**3.8**	**4.8**

Noisy synthesis using SMT

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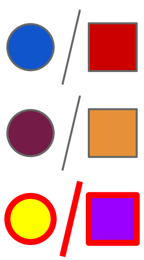

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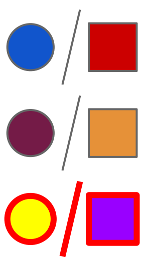

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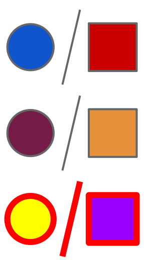

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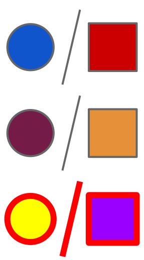

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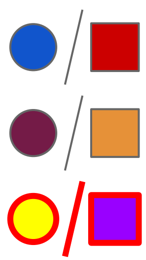

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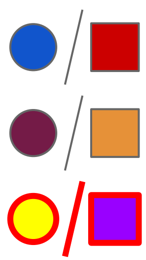

encoding

err_1 = if p(●) = ■ then 0 else 1
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best program is
with two
instructions and
makes one error

Noisy synthesizer: example

Take an actual synthesizer and
show that we can make it handle noise

Implementation: BitSyn

For BitStream programs, using Z3

similar to Jha et al.[ICSE'10] and Gulwani et al.[PLDI'11]

Example program:

```
function check_if_power_of_2(int32 x) {
    var o = add(x, 1)
    return bitwise_and(x, o)        ← synthesized, short loop-free programs
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Question: how well does our synthesizer discover noise?
(in programs from prior work)

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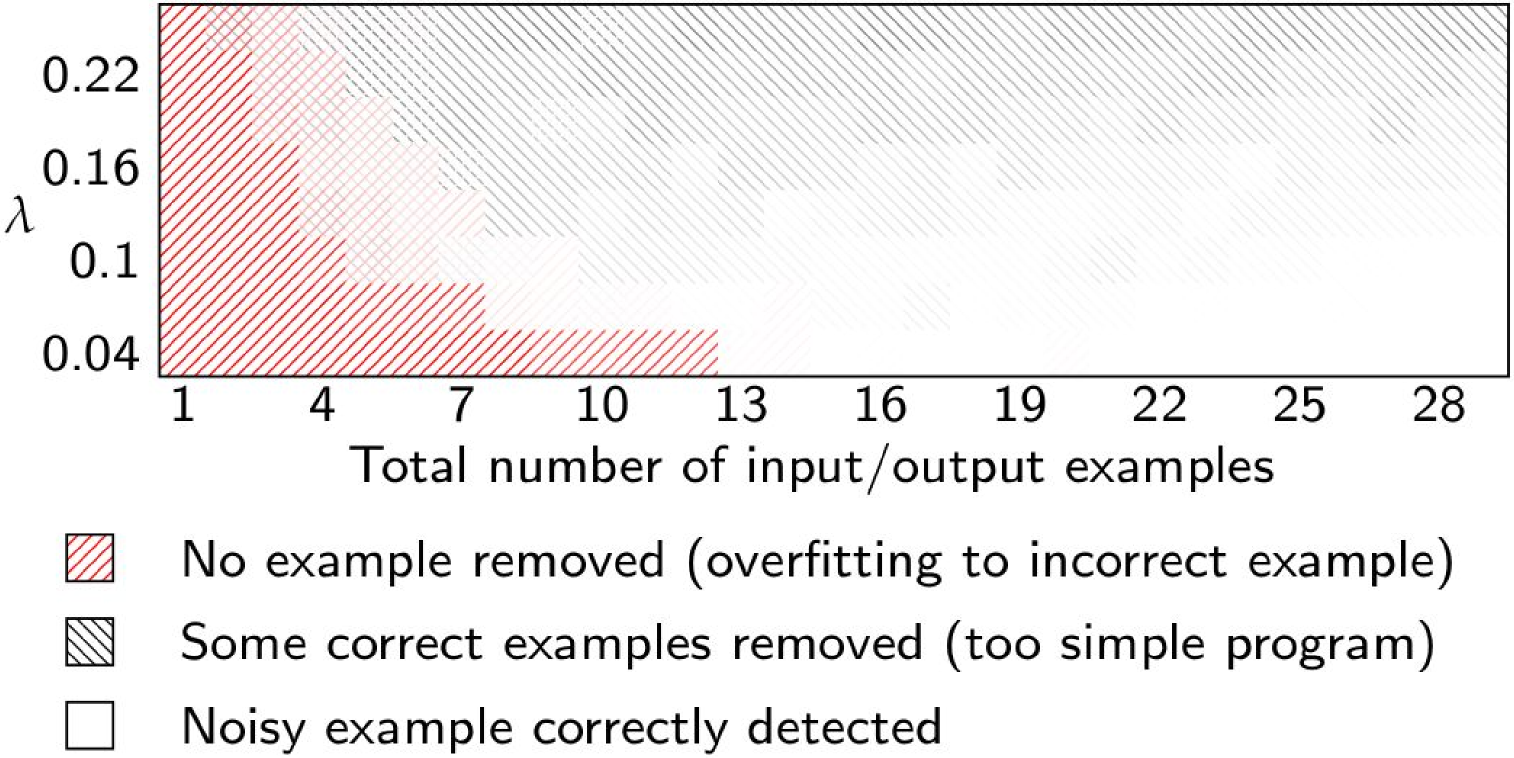

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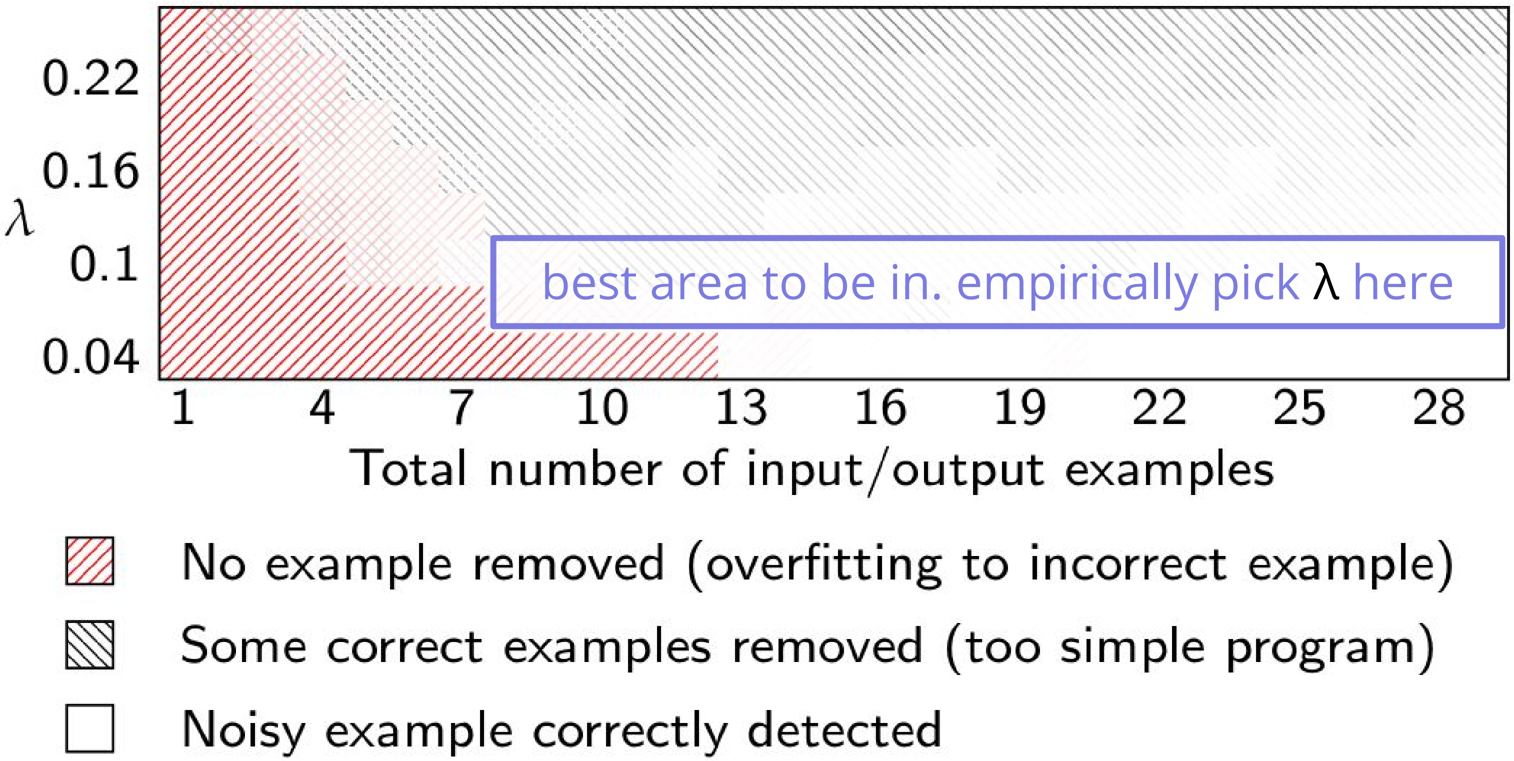

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So far... handling noise

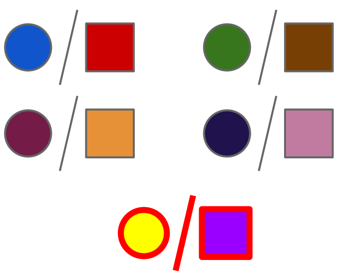
- Problem statement and regularization
- Synthesis procedure using SMT
- Presented one synthesizer

Handling noise enables us to solve new classes of problems beyond normal synthesis

Contributions

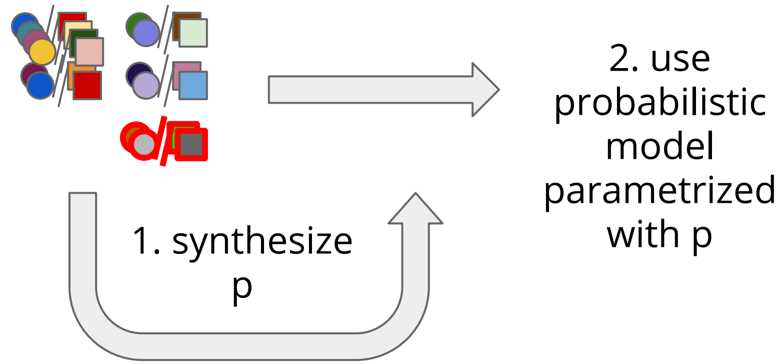
Handling noise

Input/output examples

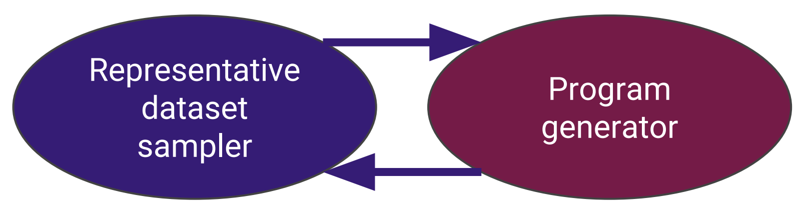


incorrect examples

New probabilistic models



Handling large datasets



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Handling noise

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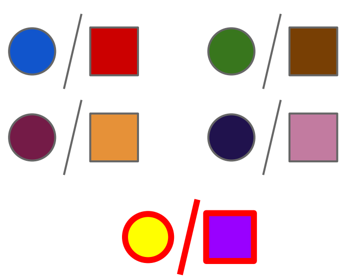
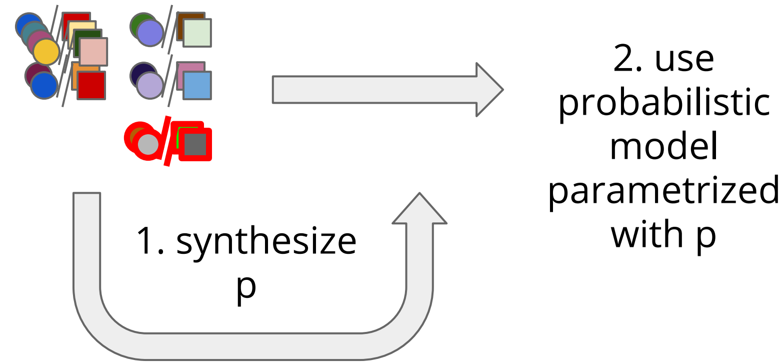
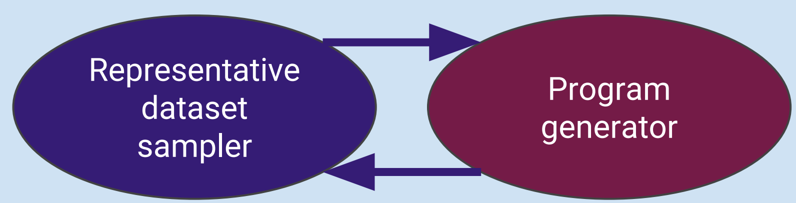


incorrect examples

New probabilistic models



Handling large datasets



Fundamental problem

Large number of examples:

$$p_{best} = \arg\min_{p \in P} \mathrm{cost}(D, p)$$

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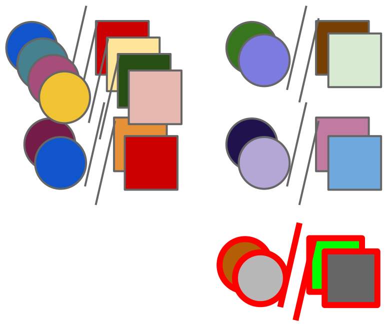

D

Millions of input/output examples

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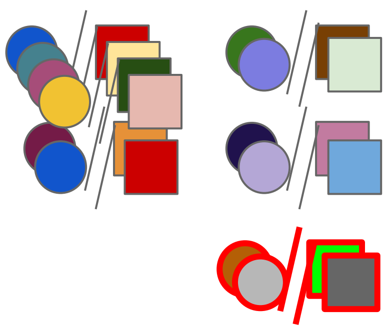

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computing cost(D, p)

O(|D|)

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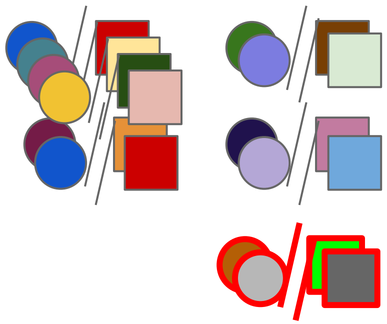

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Synthesis: practically intractable

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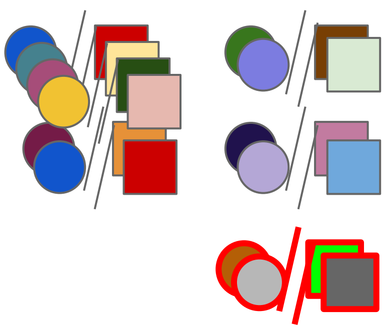

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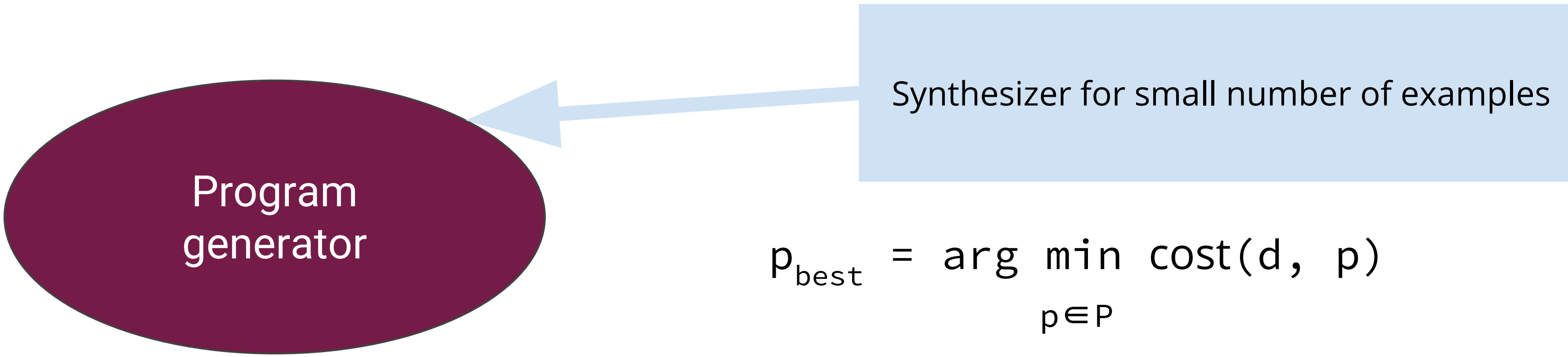
Synthesis: practically intractable

Key idea: iterative synthesis on fraction of examples

Our solution: two components



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given dataset d, finds best program

Our solution: two components

Synthesizer for small number of examples

Program generator

$$p_{best} = \arg\min_{p \in P} \mathrm{cost}(d, p)$$

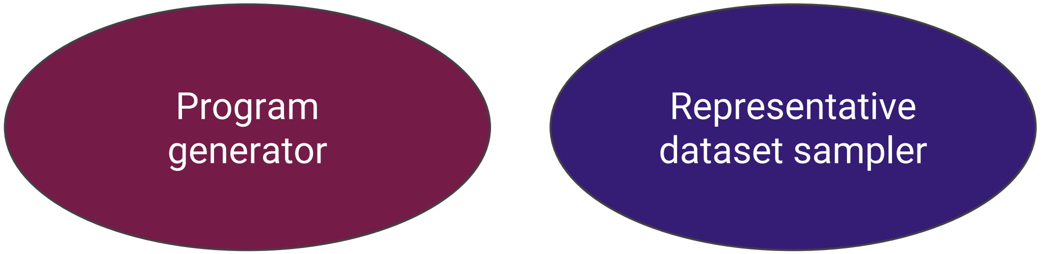
given dataset d, finds best program

Dataset sampler

Picks dataset d ⊆ D

We introduce representative dataset sampler
Generalize a user providing input/output examples

In a loop



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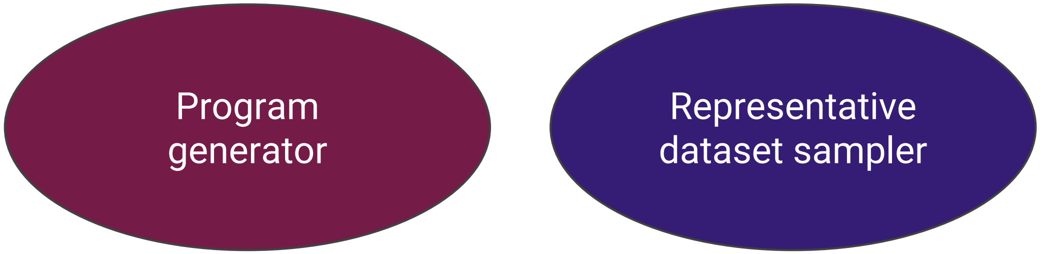
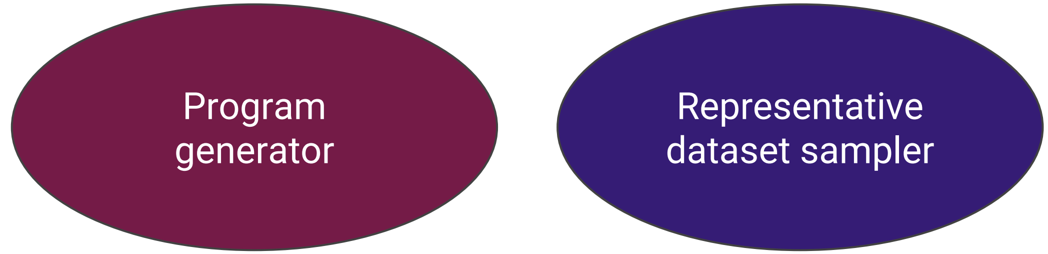


Start with a small random sample d⊆D

Iteratively generate programs and samples.

In a loop



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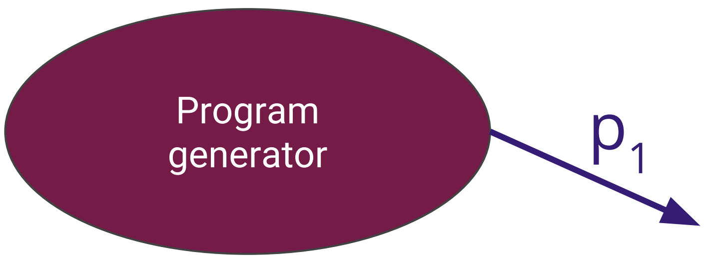

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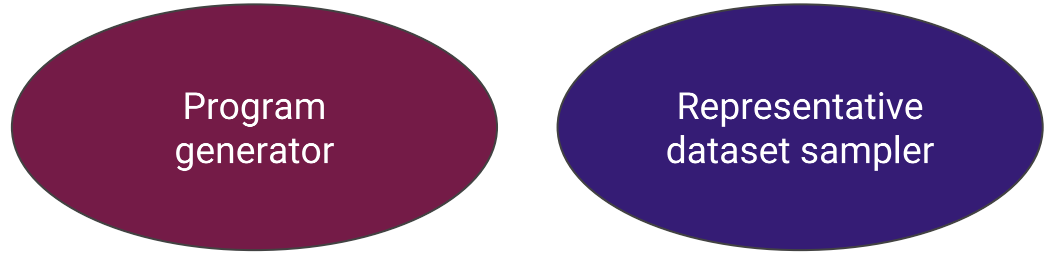

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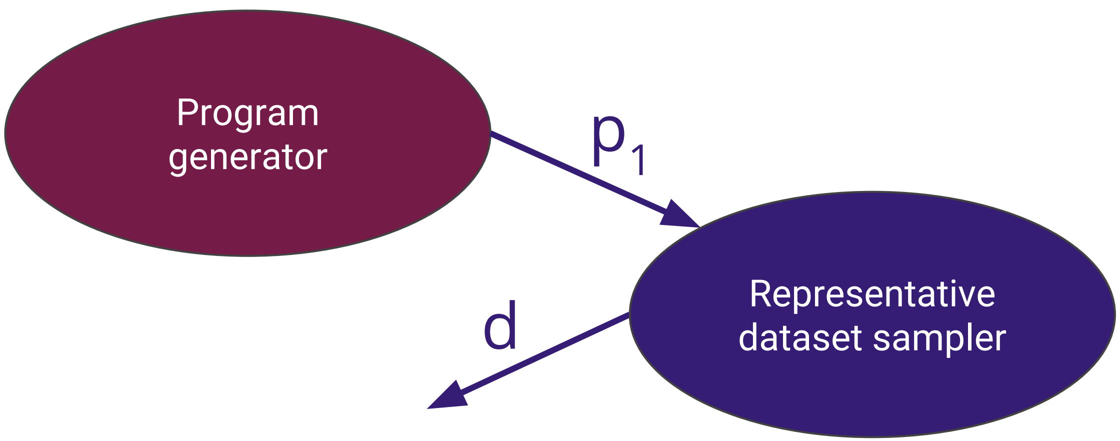

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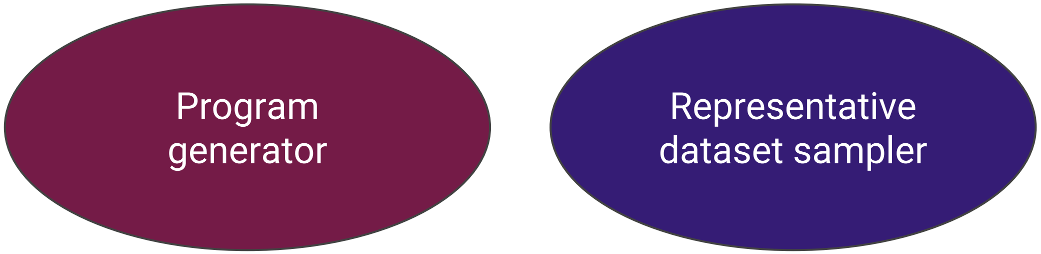

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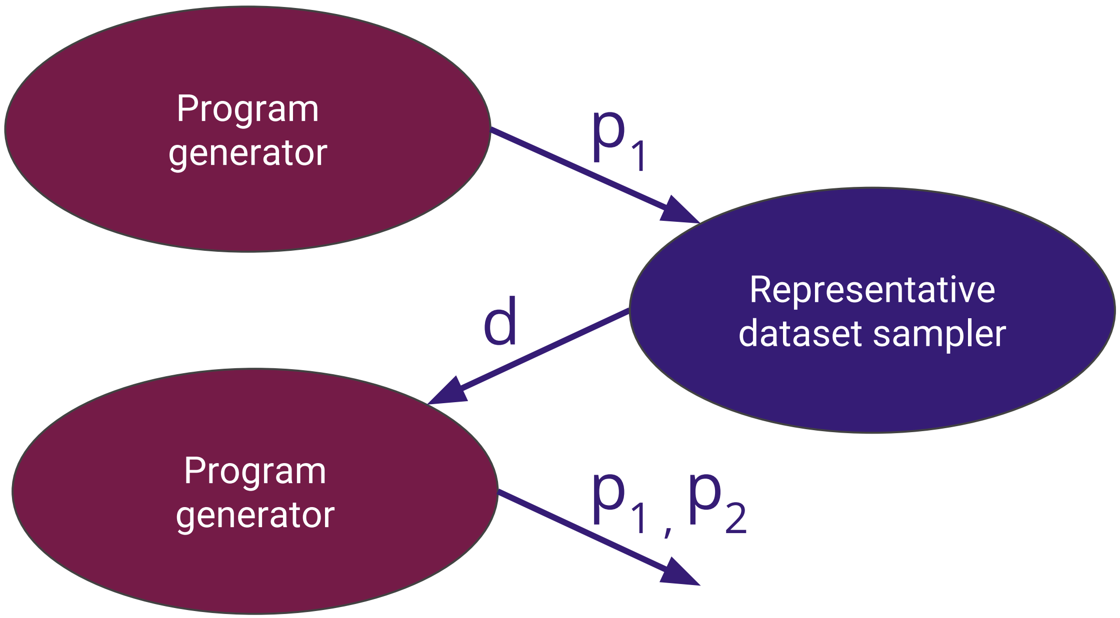

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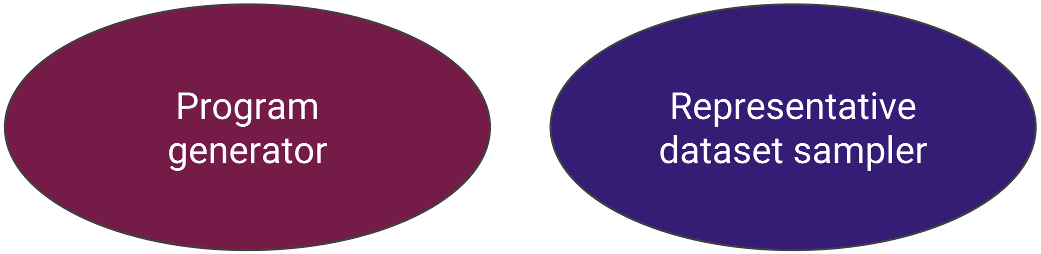

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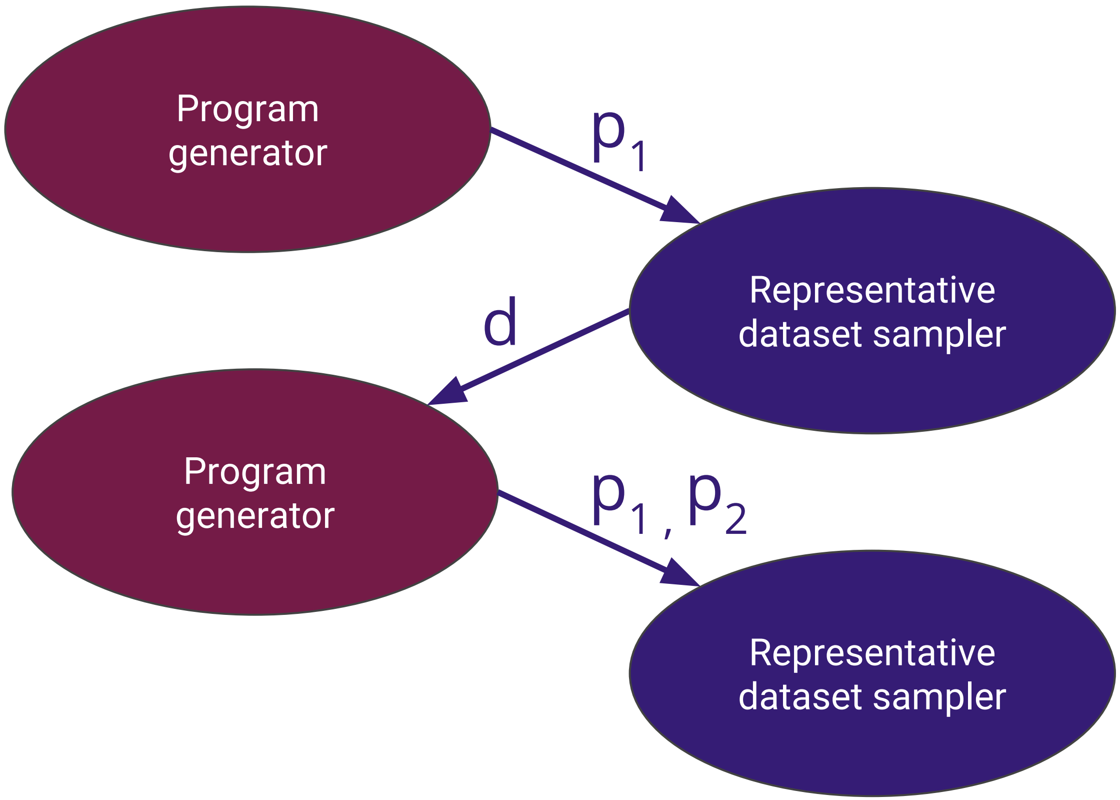

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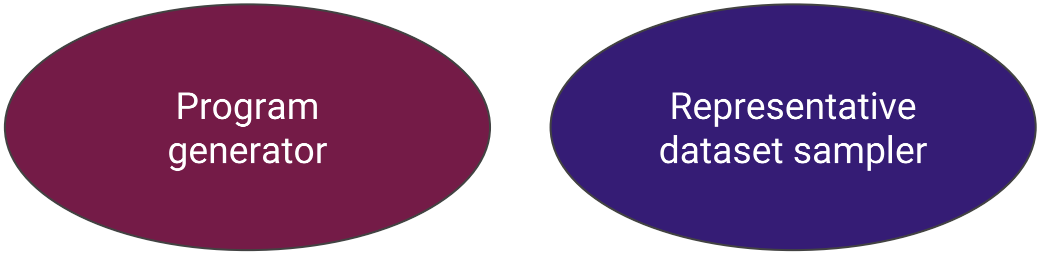

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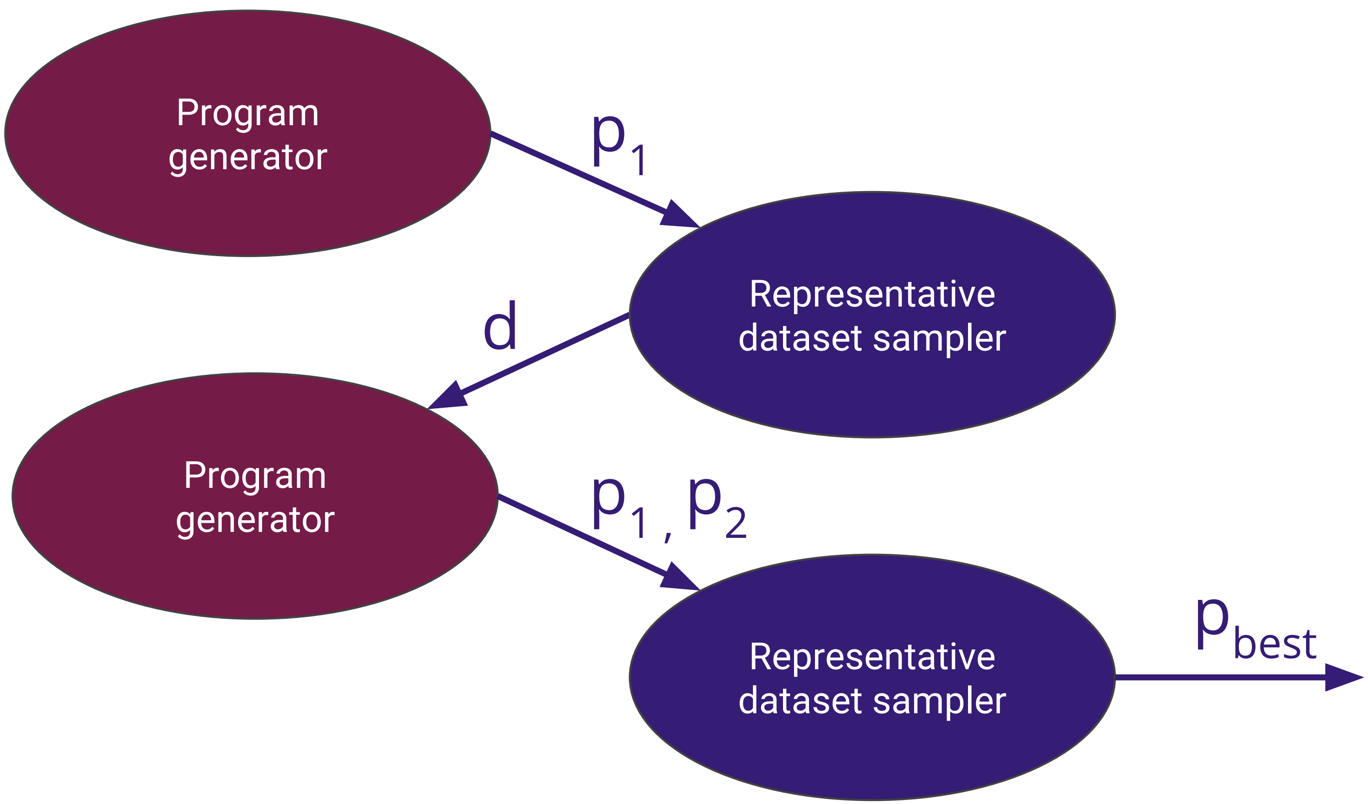

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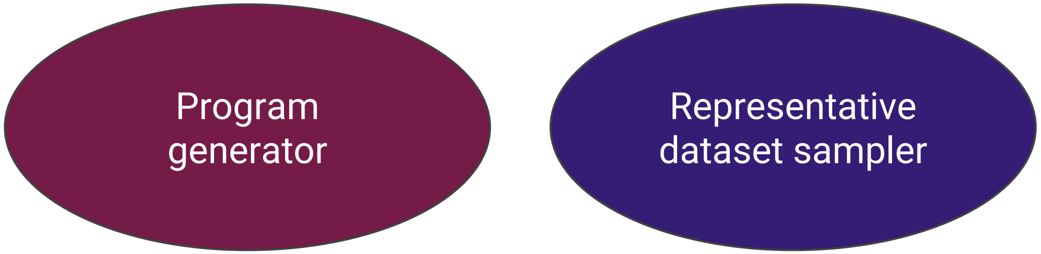

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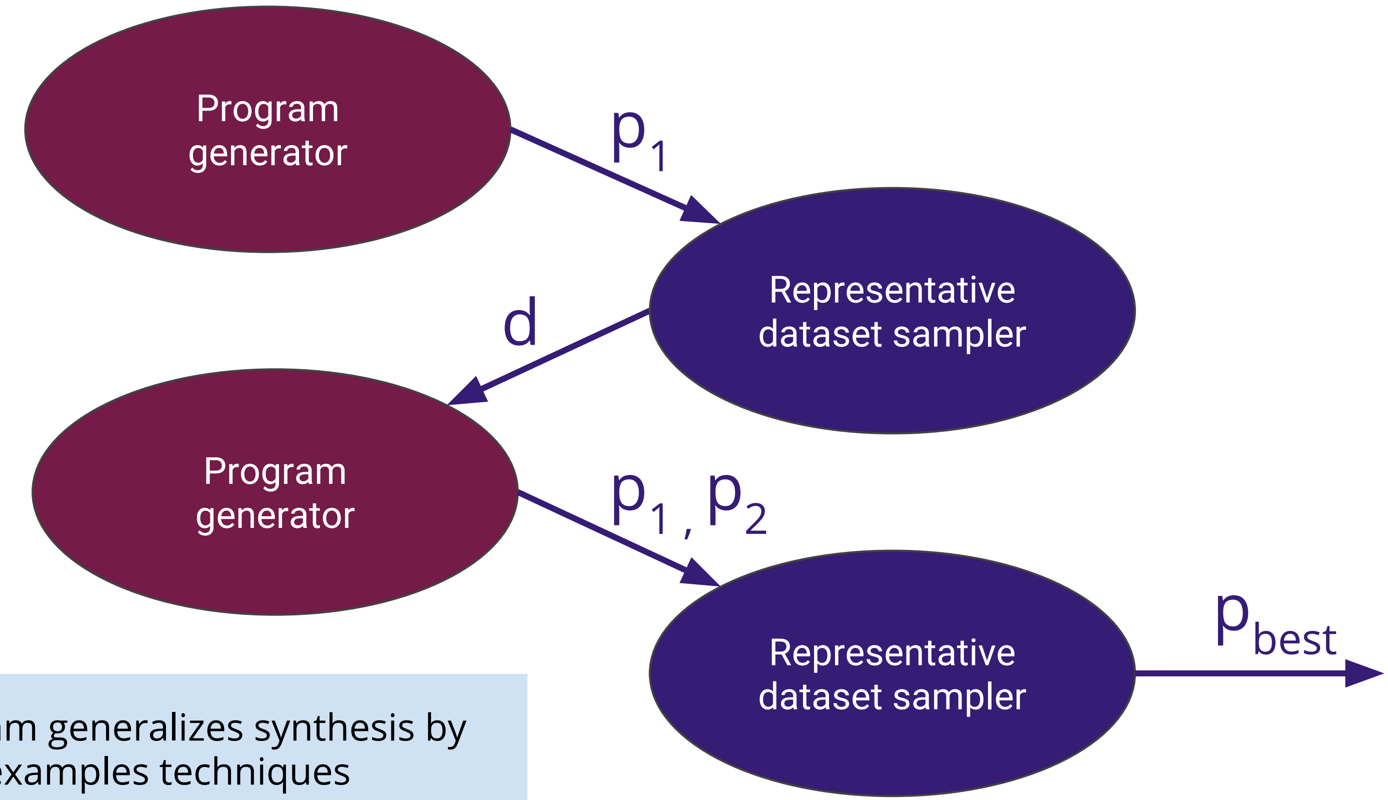

Algorithm generalizes synthesis by examples techniques

Representative dataset sampler

Idea: pick a small dataset d for which a set of already generated programs $p_1,\ldots,p_n$ behave like on the full dataset

$$d = \arg\min_{d \subseteq D} \max_{i \in 1..n} | \mathrm{cost}(d, p_i) - \mathrm{cost}(D, p_i) |$$

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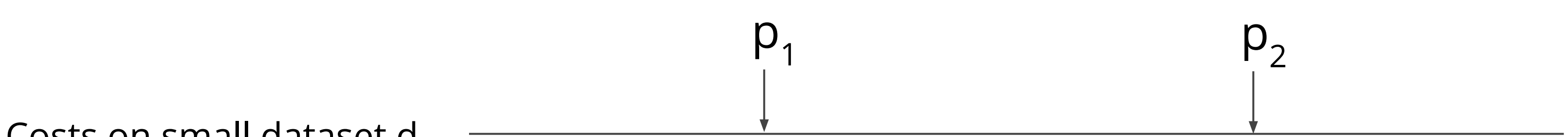

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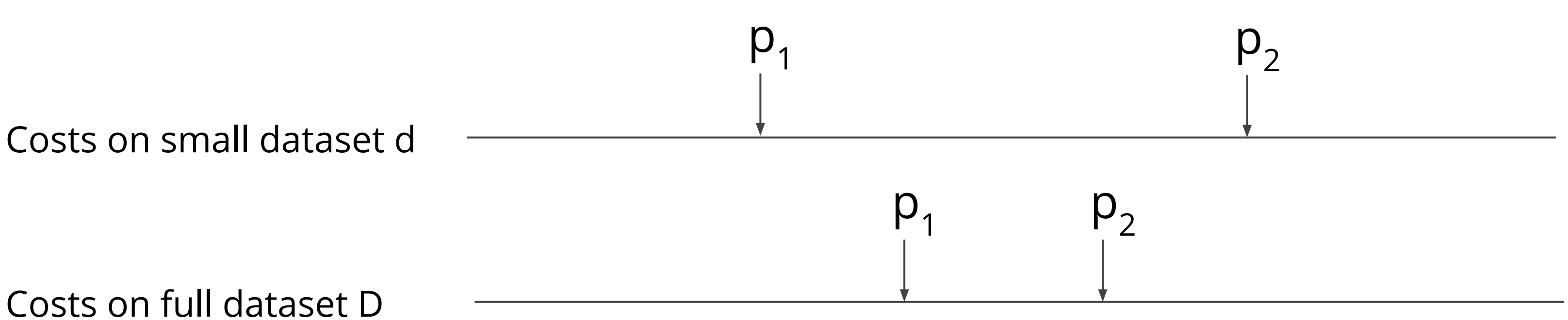

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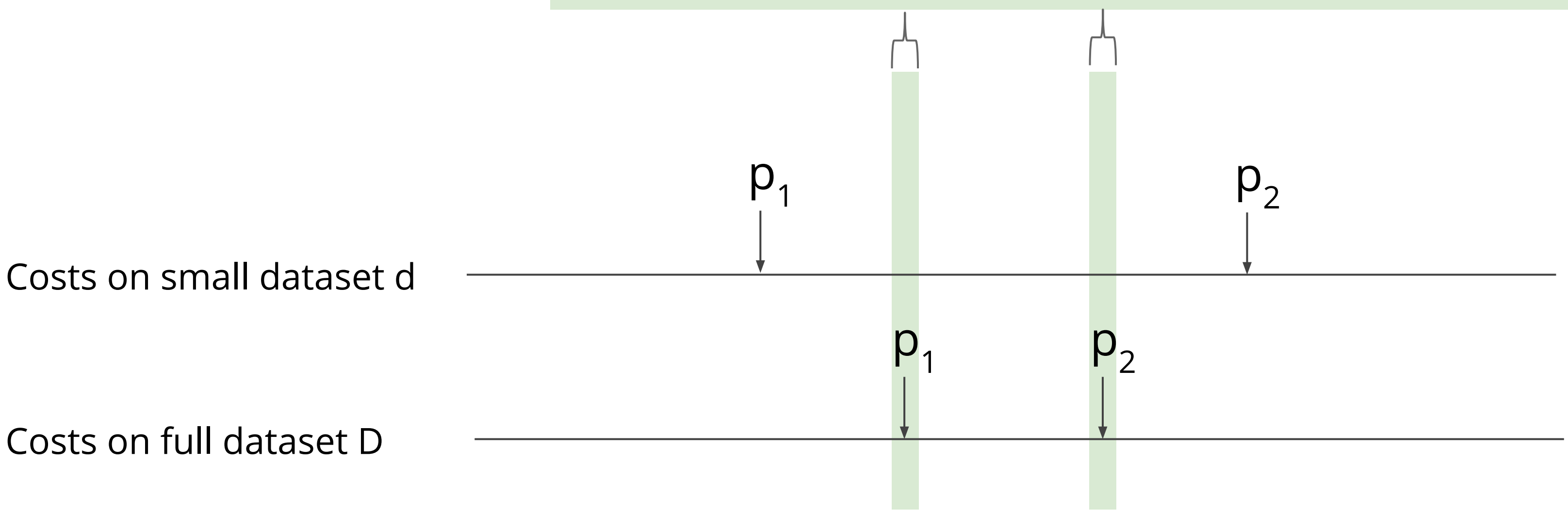

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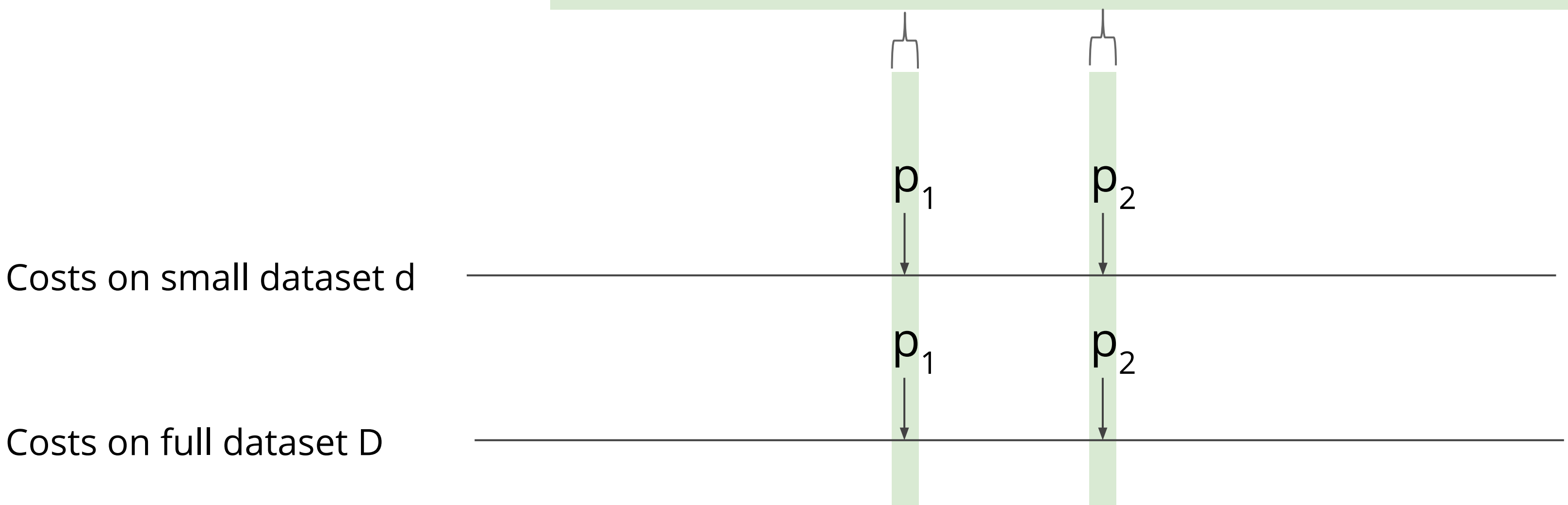

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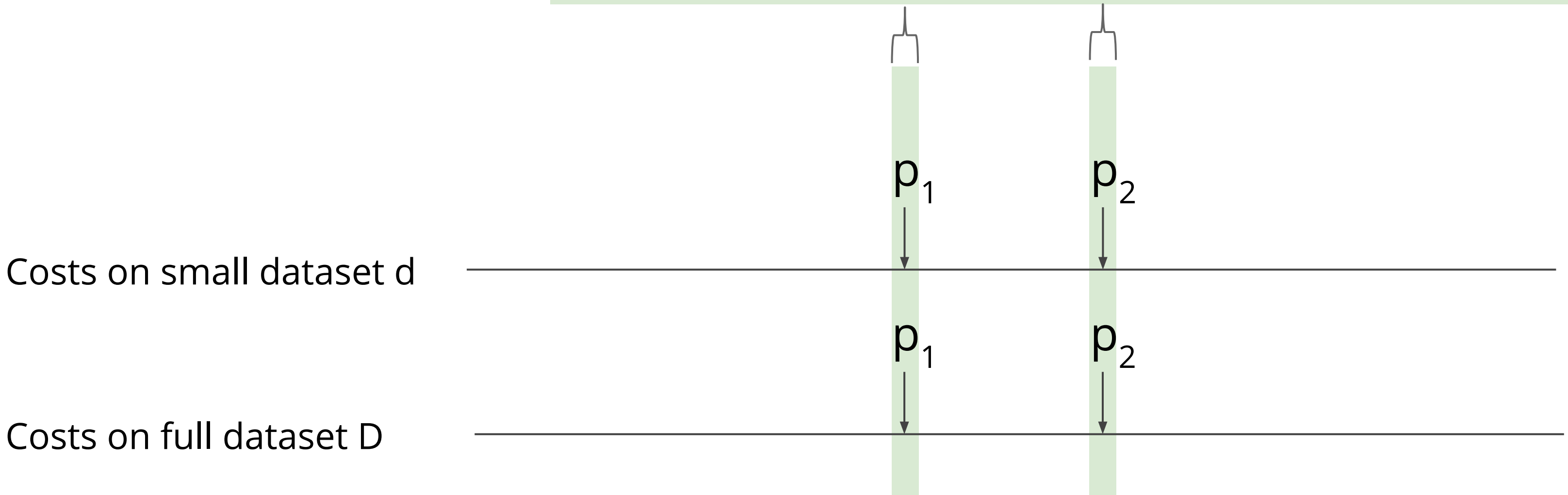


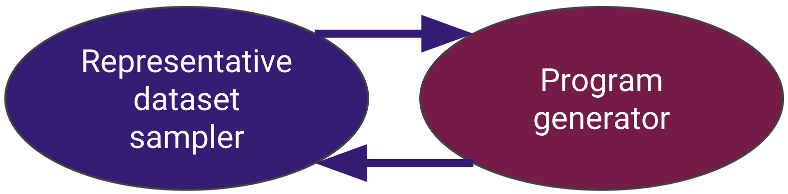
Theorem: this sampler shrinks the candidate program search space
In evaluation: significant speedup of synthesis

So far... handling large datasets

- Iterative combination of synthesis and sampling

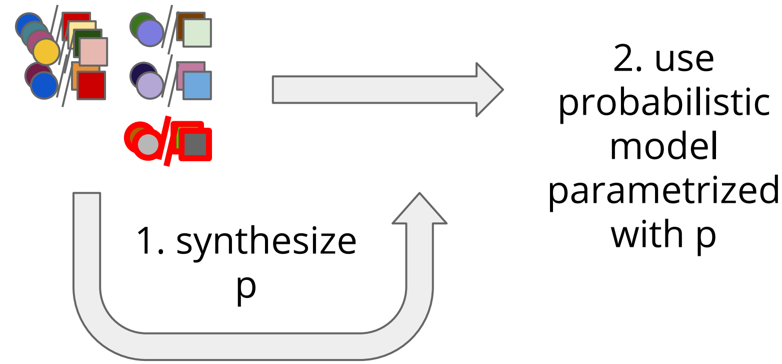
- New way to perform approximate empirical risk minimization

- Guarantees (in the paper)



Contributions

New probabilistic models



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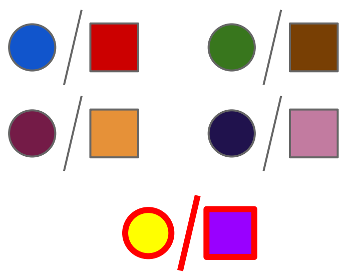

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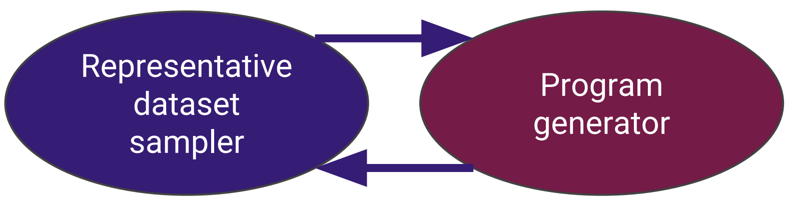

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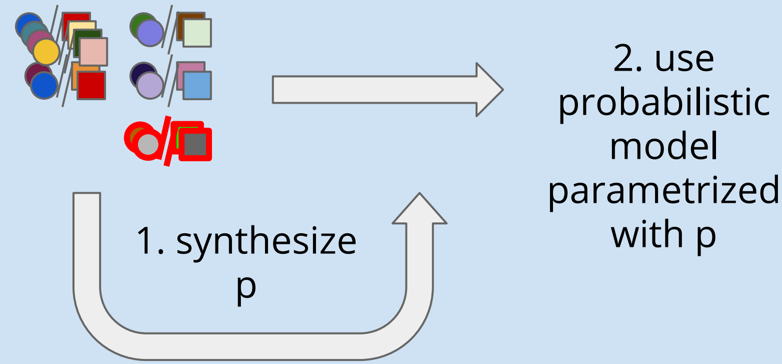

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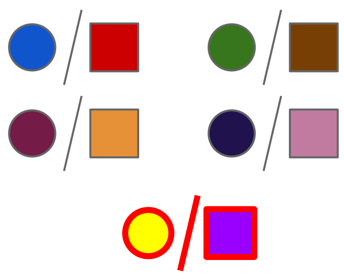

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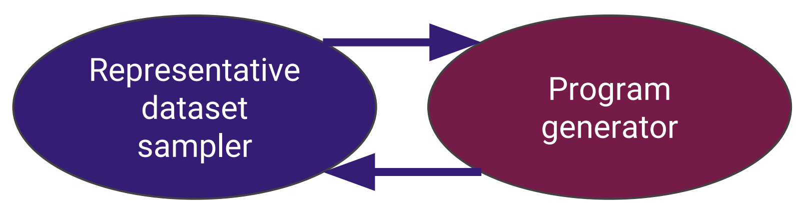

Statistical programming tools

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Learn from large existing codebases (e.g. Big Code) to make predictions about programs

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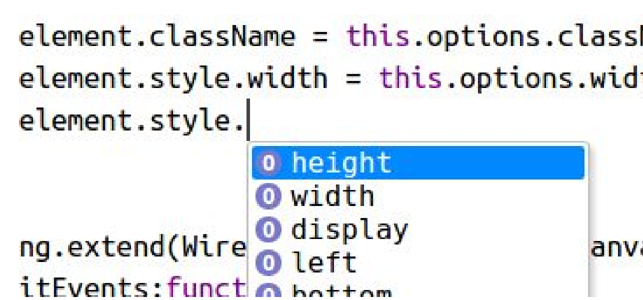

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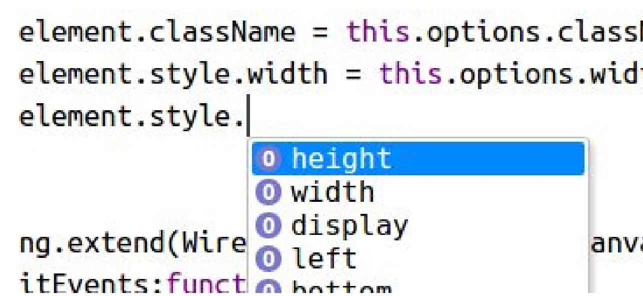

hard-coded model
low precision

Existing machine learning models

Essentially remember mapping from context in training data to prediction (with probabilities)

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Hindle et al.[ICSE'12]

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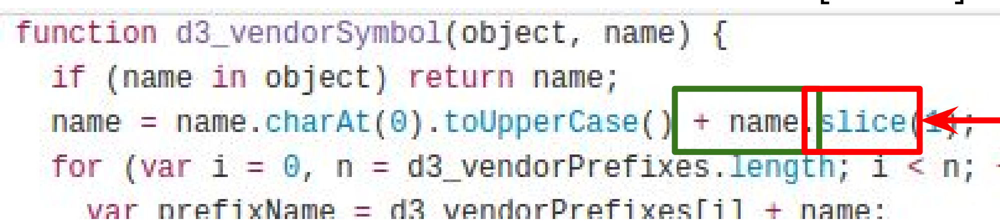

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`+ name .` → `slice`

Model will predict `slice` when it sees it after "`+ name .`"

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Learn a mapping

`charAt` → `slice`

Model will predict `slice` when it sees it after "`charAt`"
Relies on static analysis

Problem of existing systems

Precision. They rarely predict the next statement

Hindle et al.[ICSE'12]

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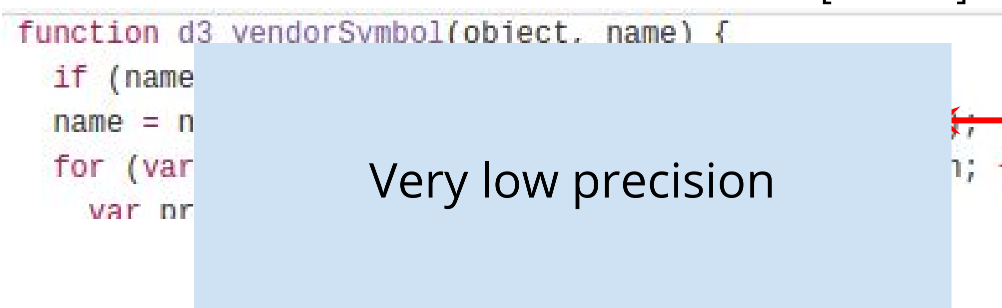

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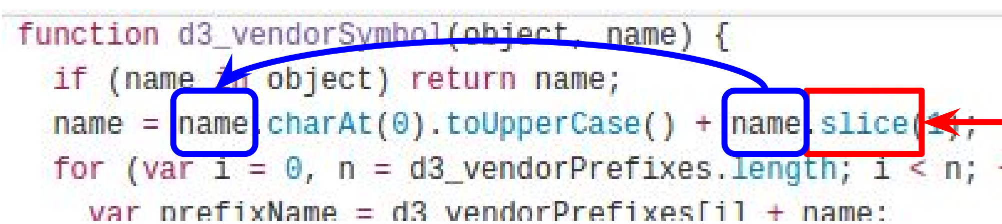

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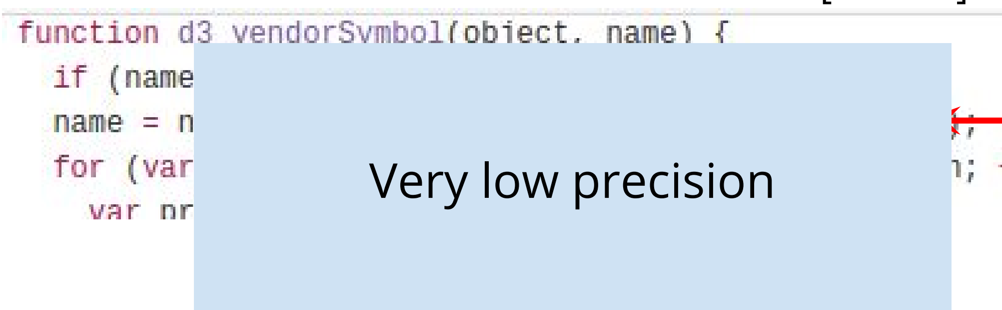
Relies on static analysis

Problem of existing systems

Precision. They rarely predict the next statement

Hindle et al.[ICSE’12]



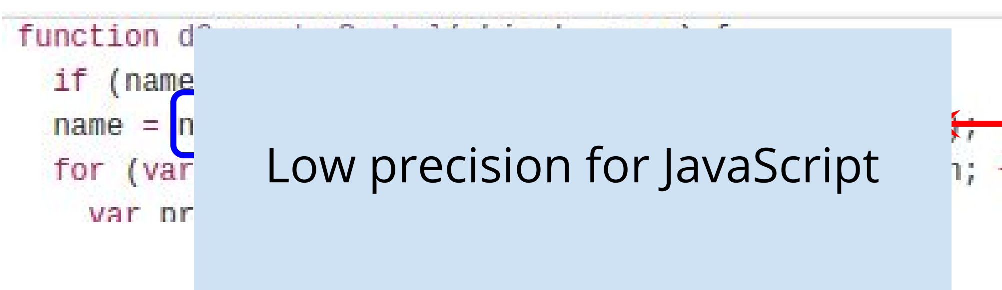
Learn a mapping

`+ name .` → `slice`

Model will predict `slice` when it sees it after “`+ name .`”

This model comes from NLP

Raychev et al.[PLDI’14]



Learn a mapping

`charAt` → `slice`

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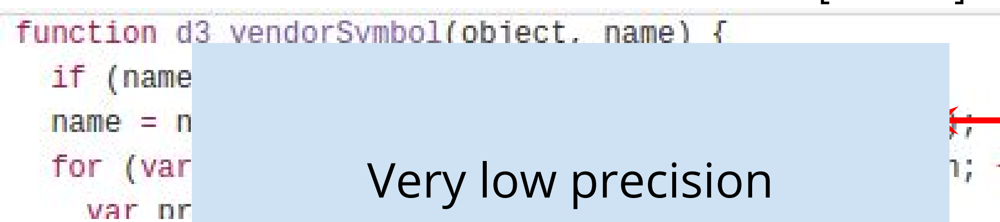
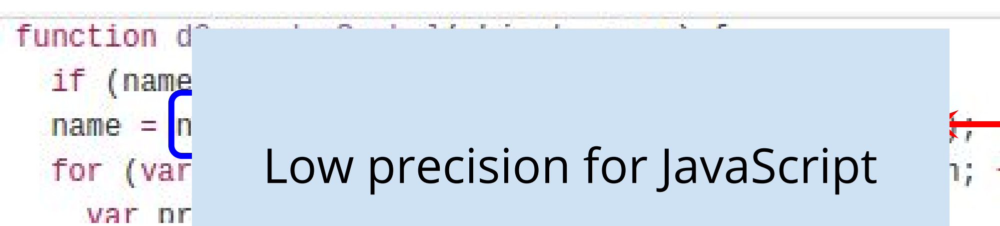


Very low precision

Raychev et al.[PLDI'14]



Low precision for JavaScript

Core problem:
Existing machine learning models are limited and not expressive enough

Key idea: second-order learning

Learn a program that parametrizes a probabilistic model that makes predictions.

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Learn a program that parametrizes a probabilistic model
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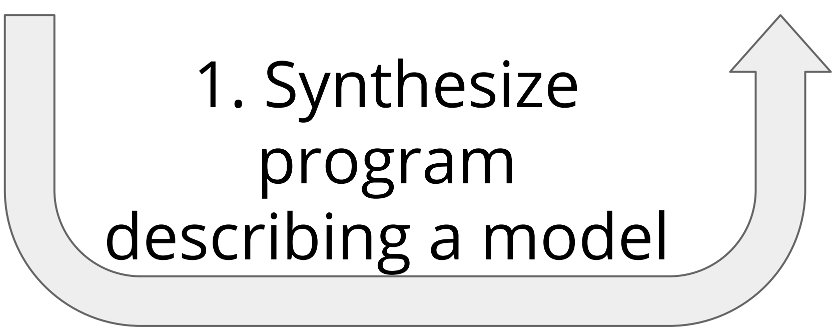

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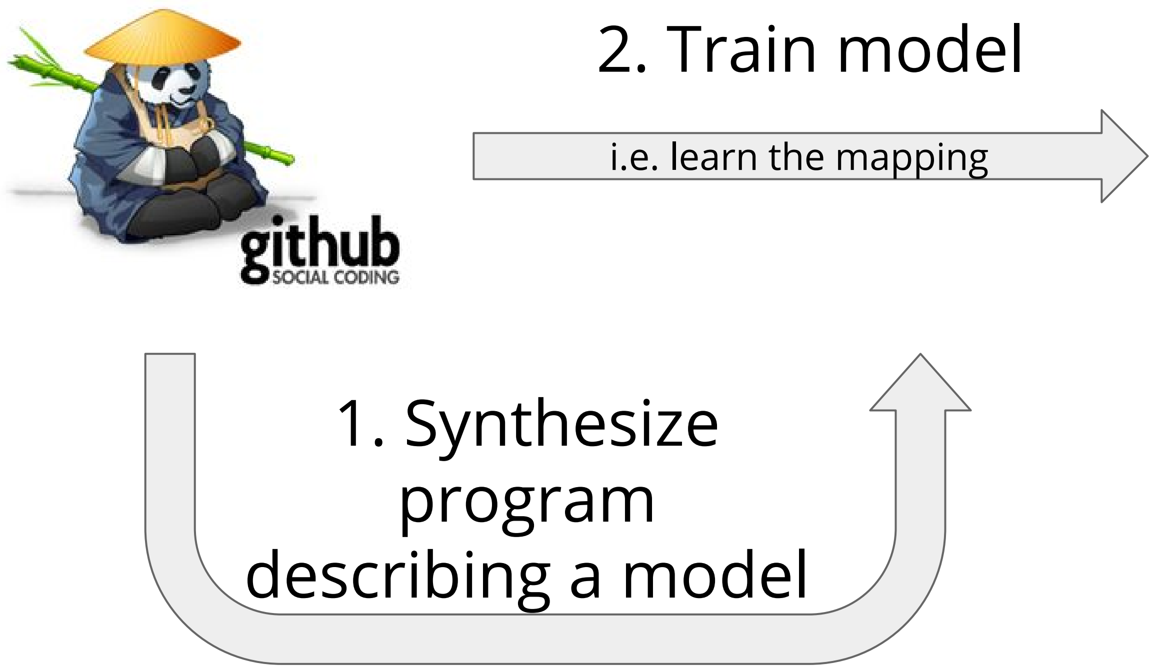

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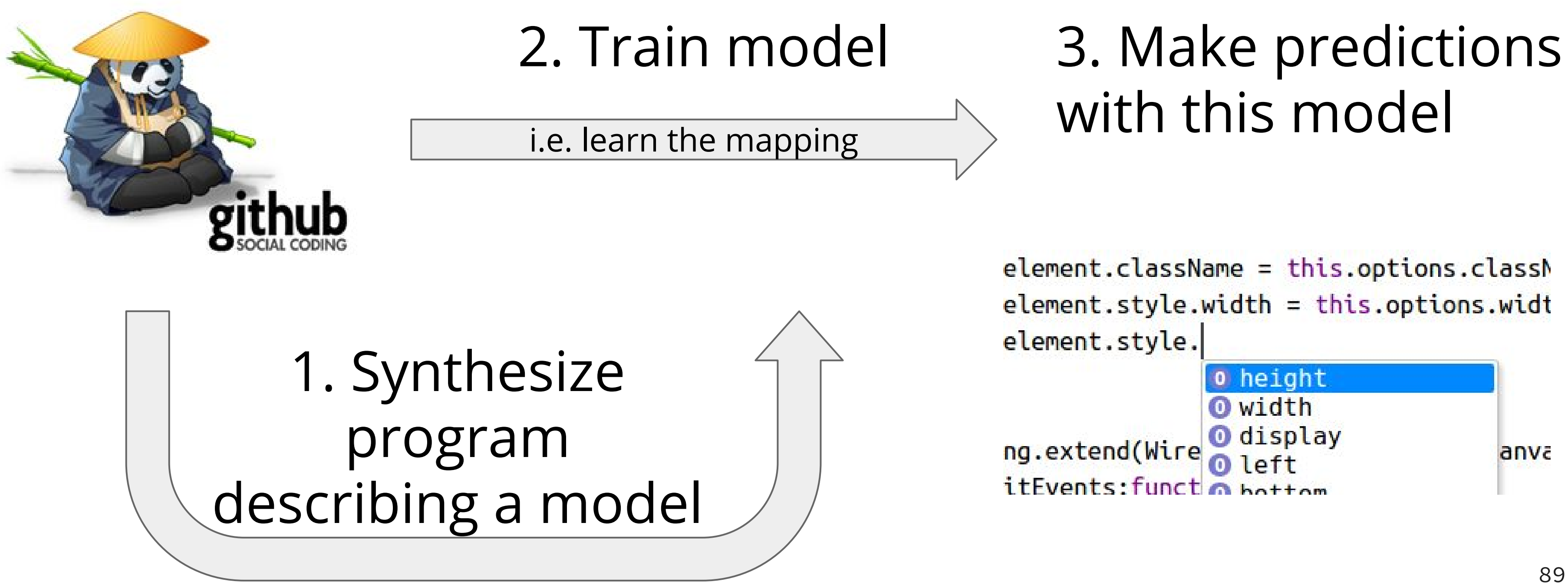


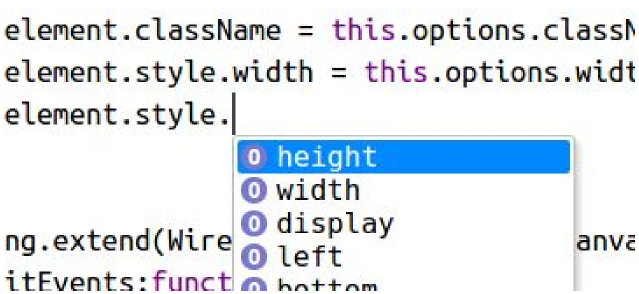
Key idea: second-order learning

Learn a program that parametrizes a probabilistic model that makes predictions.

2. Train model

i.e. learn the mapping

3. Make predictions with this model



prior models are described by simple hard-coded programs

Our approach:
learn a better program

Training and evaluation

Training example:

```
function d3_vendorSymbol(object, name) {
  if (name in object) return name;
  name = name.charAt(0).toUpperCase() + name.[redacted]
  for (var i = 0, n = d3_vendorPrefixes.length; i < n; -
    var prefixName = d3_vendorPrefixes[i] + name;
```

input

`slice`

output

Training and evaluation

Compute context with program p

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input

`slice`

Learn a mapping

`toUpperCase` → `slice`

Training and evaluation

Compute context with program p

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input

slice

Learn a mapping

toUpperCase → slice

Evaluation example:

```
/)
cc, word) => {
acc + ' ' + word[0].toUpperCase() +  word.[redacted]
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Training and evaluation

Compute context with program p

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predict completion

slice

Training and evaluation

Compute context with program p

Training example:

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input

`slice`

Learn a mapping

`toUpperCase` → `slice`

Evaluation example:

Compute context with program p

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```

predict completion

`slice` ✔

Observation

Synthesis of probabilistic model can be done with the same optimization problem as before!

evaluation data:
input/output
examples

Our problem formulation:

regularization constant

$$p_{best} = \arg\min_{p \in P} \text{errors}(D, p) + \lambda r(p)$$

regularizer
penalizes long
programs

Observation

Synthesis of probabilistic model can be done with the same optimization problem as before!

evaluation data: input/output examples

cost(D, p)

Our problem formulation:

regularization constant

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regularizer penalizes long programs

So far...

Handling noise

Synthesizing a model

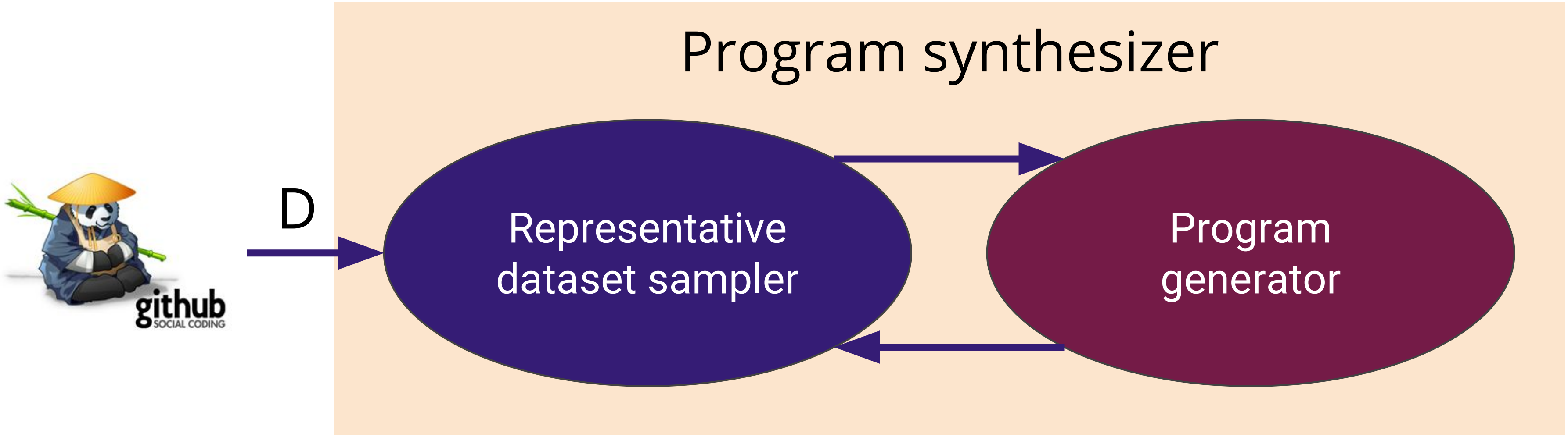
Representative dataset sampler

Techniques are generally applicable to program synthesis

Next, application for “Big Code” called DeepSyn

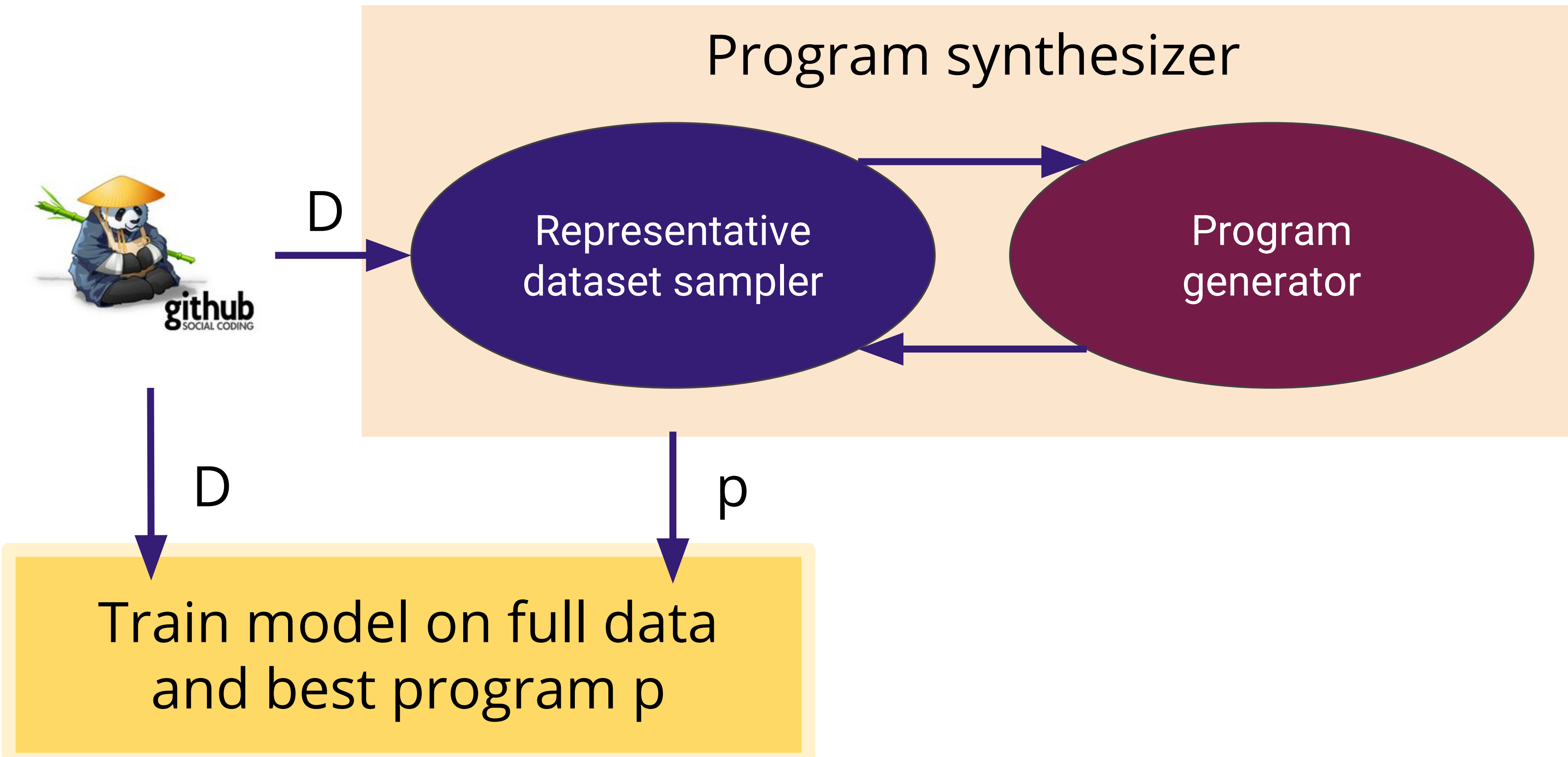
DeepSyn: Training

Trained on 100’000 JavaScript files from GitHub

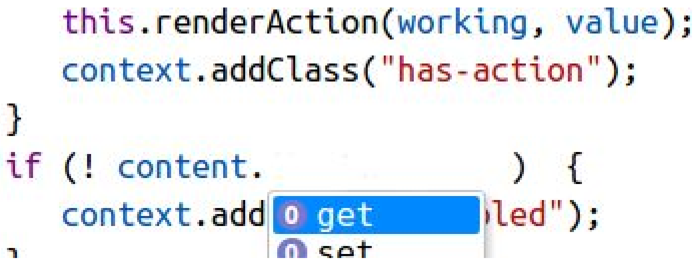


DeepSyn: Training

Trained on 100’000 JavaScript files from GitHub



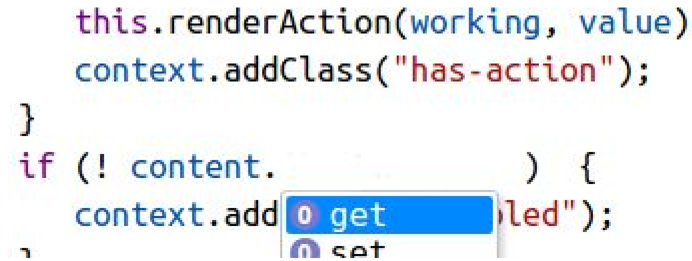
DeepSyn: Evaluation



50’000 evaluation files (not used in training or synthesis)

API completion task

DeepSyn: Evaluation



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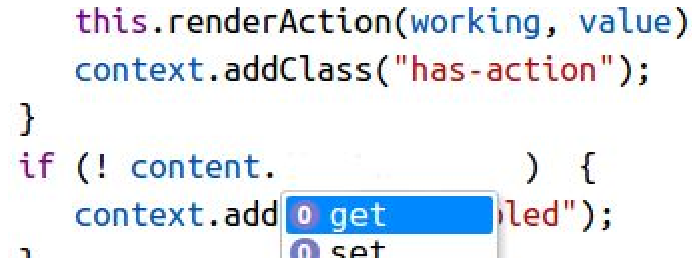
API completion task

	Conditioning program p	Accuracy
	Last two tokens, Hindle et al.[ICSE’12]	22.2%
	Last two APIs per object, Raychev et al.[PLDI’14]	30.4%
This work	**Program synthesis with noise**	**46.3%**
	Program synthesis with noise + dataset sampler	**50.4%**

DeepSyn: Evaluation



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API completion task

Conditioning program p	Accuracy
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Program synthesis with noise	**46.3%**
Program synthesis with noise + dataset sampler	**50.4%**

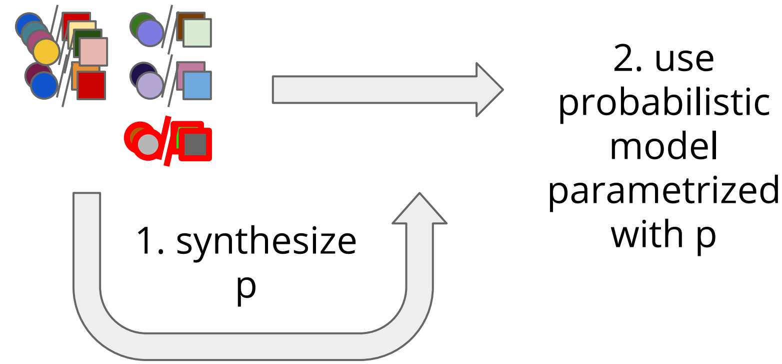
This work

We can explain best program. It looks at API preceding completion position and at tokens prior to these APIs.

Q&A

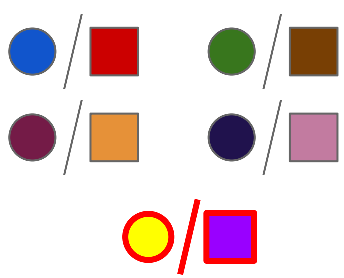
Synthesis of probabilistic models

Second-order learning



Handling noise

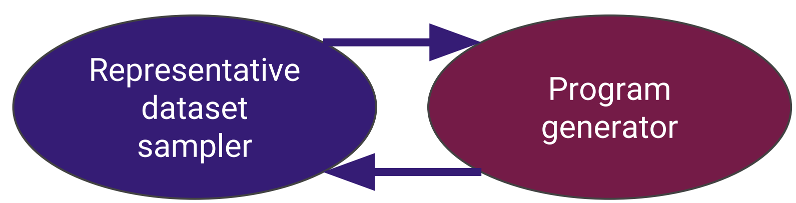
Input/output examples



incorrect examples

Extending synthesizers to handle noise

Handling large datasets

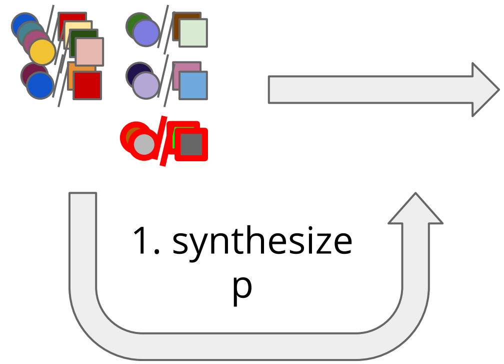


Scalability

Q&A

Synthesis of probabilistic models

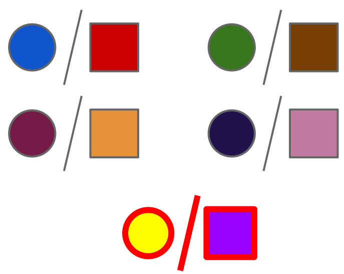
Second-order learning



2. use probabilistic model parametrized with p

Handling noise

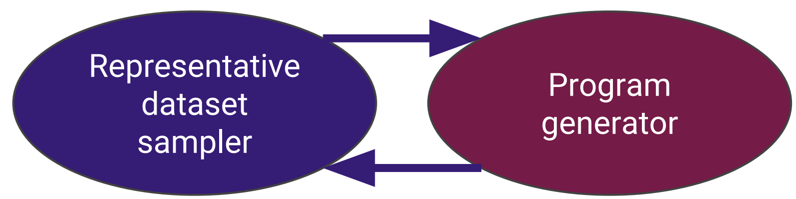
Input/output examples



incorrect examples

Bridges gap between ML and PL
Advances both areas

Handling large datasets



Extending synthesizers to handle noise

Scalability

What did we synthesize?

Left PrevActor WriteAction WriteValue PrevActor WriteAction PrevLeaf WriteValue PrevLeaf WriteValue

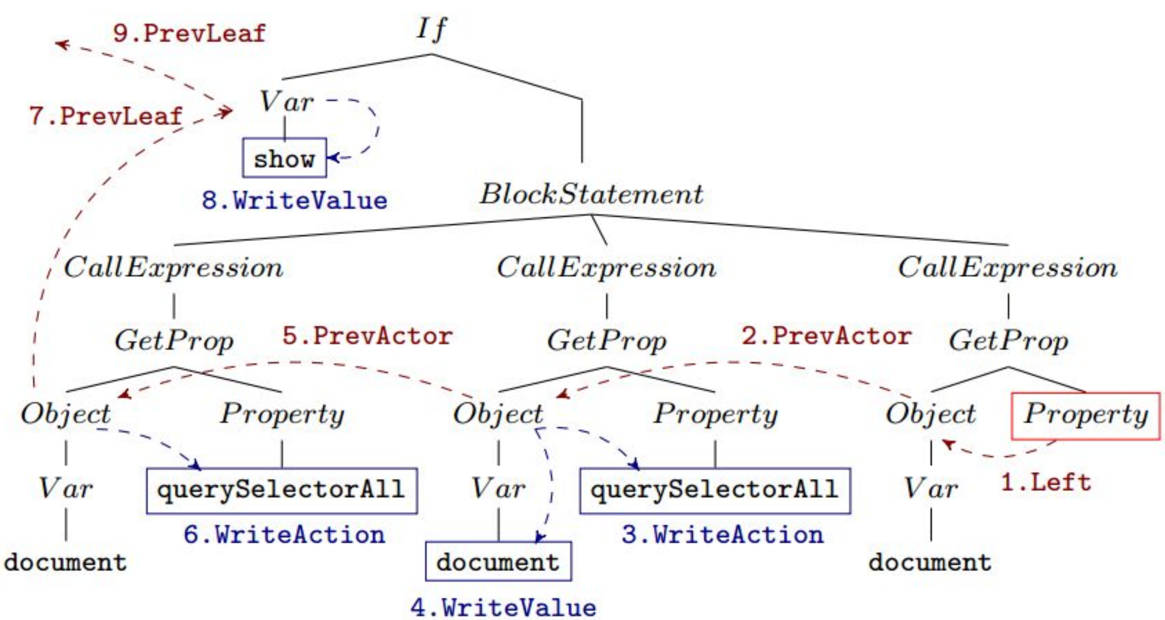
$p_{\approx best}$ =

```
Left PrevActor WriteAction WriteValue
PrevActor WriteAction PrevLeaf
WriteValue PrevLeaf WriteValue
```

(a) TCOND program

```
if (show) {
 var cws = document.querySelectorAll(...);
 for (var i = 0, slide; slide = cws[i]; i++) {
   slide.classList.add("hidden");
 }
 var iap = document.querySelectorAll(...);
 for (var i = 0, slide; slide = iap[i]; i++) {
   slide.classList.add("hidden");
 }
 var dart = document.
 ...                   └──── Completion position
}
```

(b) JavaScript code snippet



(c) Execution of $p_{\approx best}$ on the AST representation of the code snippet from (b)