Conditional Program Generation for Bimodal Program Synthesis

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(Joint work with Chris Jermaine, Vijay Murali, and Letao Qi)

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RICE Unconventional Wisdom

Program synthesis

[Simon 1963, Summers 1977, Manna-Waldinger 1977, Pnueli-Rosner 1989]

Specification

↓

Synthesizer

↓

Program
+
Correctness Certificate

Specification: Logical constraint that must be satisfied exactly

Algorithm: Search for a program that satisfies the specification.

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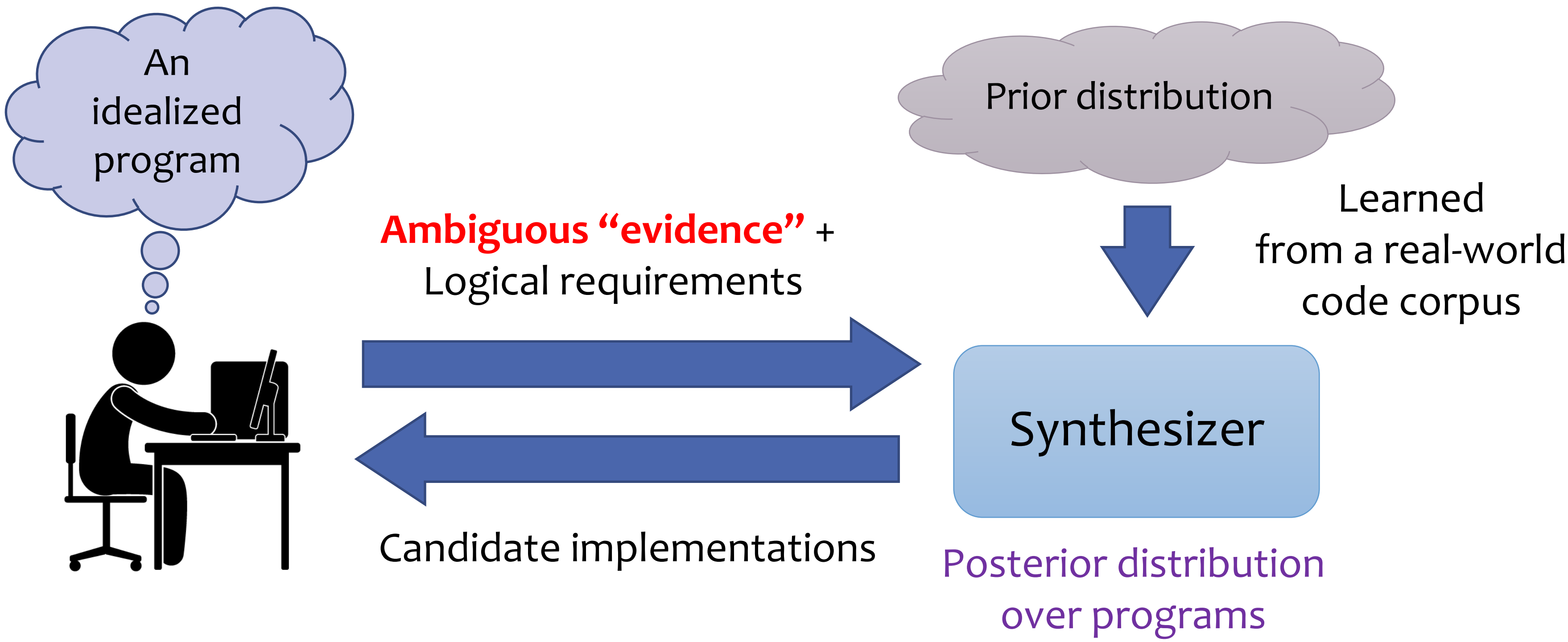
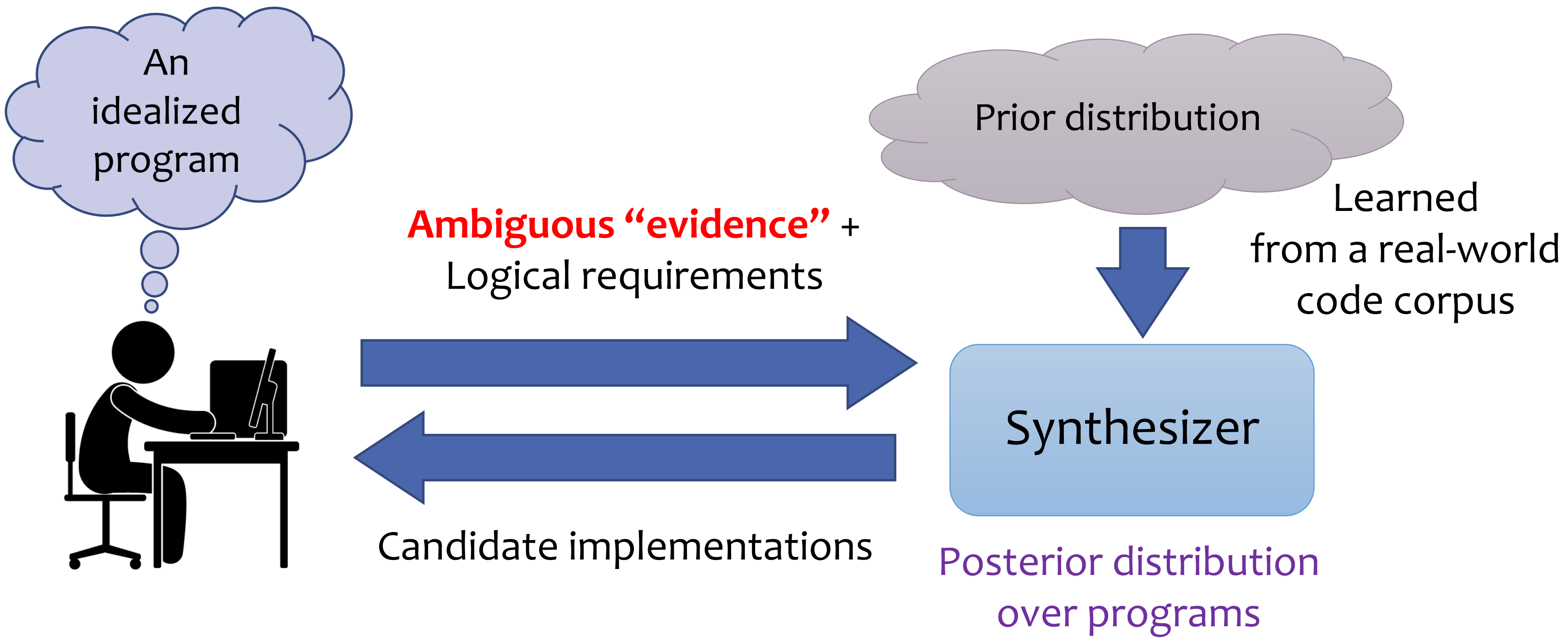
“Bimodal” program synthesis



Neural Sketch Learning for Conditional Program Generation. Murali, Qi, Chaudhuri, and Jermaine. Arxiv 2017.

"Bimodal" program synthesis



- API calls or types that the program uses
- "Soft" I/O examples or constraints
- Natural language description of what the program does
- …

The Bayou synthesizer: A demo

http://bit.ly/2zgP5fj

Conditional program generation

Assume random variables X and $Prog$, over **labels** and **programs** respectively, following a joint distribution $Q(X, Prog)$.

Offline:

- You are given a set $\{(X_i, Prog_i)\}$ of samples from $Q(X, Prog)$. From this, learn a function g that maps evidence to programs.
- Learning goal: maximize $E_{(X,Prog)\sim Q}[I]$, where

$$I = \begin{cases} 1 & \text{if } g(X) \equiv Prog \\ 0 & \text{otherwise.} \end{cases}$$

Online: Given X, produce $g(X)$.

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In what we actually do

The map g is probabilistic.

Learning is maximum conditional likelihood estimation:

- Given $\{(X_i, Prog_i)\}$, solve $\arg\max_\theta \sum_i \log P(Prog_i | X_i, \theta)$.

Programs

Language capturing the essence of API usage in Java.

$$
\begin{array}{lcl}
\mathsf{Prog} & ::= & \mathbf{skip} \mid \mathsf{Prog}_1 ; \mathsf{Prog}_2 \mid \mathbf{call}\ \mathsf{Call} \mid \\
 & & \mathbf{let}\ x = \mathsf{Call} \mid \\
 & & \mathbf{if}\ \mathsf{Exp}\ \mathbf{then}\ \mathsf{Prog}_1\ \mathbf{else}\ \mathsf{Prog}_2 \mid \\
 & & \mathbf{while}\ \mathsf{Exp}\ \mathbf{do}\ \mathsf{Prog}_1 \mid \mathbf{try}\ \mathsf{Prog}_1\ \mathsf{Catch} \\
\mathsf{Exp} & ::= & \mathsf{Sexp} \mid \mathsf{Call} \mid \mathbf{let}\ x = \mathsf{Call} : \mathsf{Exp}_1 \\
\mathsf{Sexp} & ::= & c \mid x \\
\mathsf{Call} & ::= & \mathsf{Sexp}_0.a(\mathsf{Sexp}_1, \ldots, \mathsf{Sexp}_k) \\
\mathsf{Catch} & ::= & \mathbf{catch}(x_1)\ \mathsf{Prog}_1\ \ldots\ \mathbf{catch}(x_k)\ \mathsf{Prog}_k
\end{array}
$$

API call

API method name

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Labels

Set of API calls

- readline, write,…

Set of API datatypes

- BufferedReader, FileReader,…

Set of keywords that may appear while describing program actions in English

- read, file, write,…
- Obtained from API calls and datatypes through a camel case split

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Challenges

Directly learning over source code simply doesn't work

- Source code is full of low-level, program-specific names and operations.
- Programs need to satisfy structural and semantic constraints such as type safety. Learning to satisfy these constraints is hard.

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Language abstractions to the rescue!

Learn not over programs, but typed, syntactic models of programs.

Sketches

The sketch of a program is obtained by applying an **abstraction function** α.

From sketch Y to program $Prog$: a fixed **concretization distribution** $P(Prog \mid Y)$.

Learning goal changes to

- Given $\{(X_i, Y_i)\}$, solve $\arg\max_{\theta} \sum_i \log P(Y_i | X_i, \theta)$.

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Sketches

Sketch

$$
\begin{array}{lcl}
\mathsf{Y} & ::= & \mathsf{Call} \mid \textbf{skip} \mid \textbf{while}\ \mathsf{Cond}\ \textbf{do}\ \mathsf{Y}_1 \mid \mathsf{Y}_1 ; \mathsf{Y}_2 \mid \\
 & & \textbf{try}\ \mathsf{Y}_1\ \mathsf{Catch} \mid \textbf{if}\ \mathsf{Cond}\ \textbf{then}\ \mathsf{Y}_1\ \textbf{else}\ \mathsf{Y}_2 \\
\mathsf{Catch} & ::= & \textbf{catch}(\tau_1)\ \mathsf{Y}_1\ \ldots\ \textbf{catch}(\tau_k)\ \mathsf{Y}_k \\
\mathsf{Cond} & ::= & \{\mathsf{Call}_1, \ldots, \mathsf{Call}_k\} \\
\mathsf{Call} & ::= & a(\tau_1, \ldots, \tau_k)
\end{array}
$$

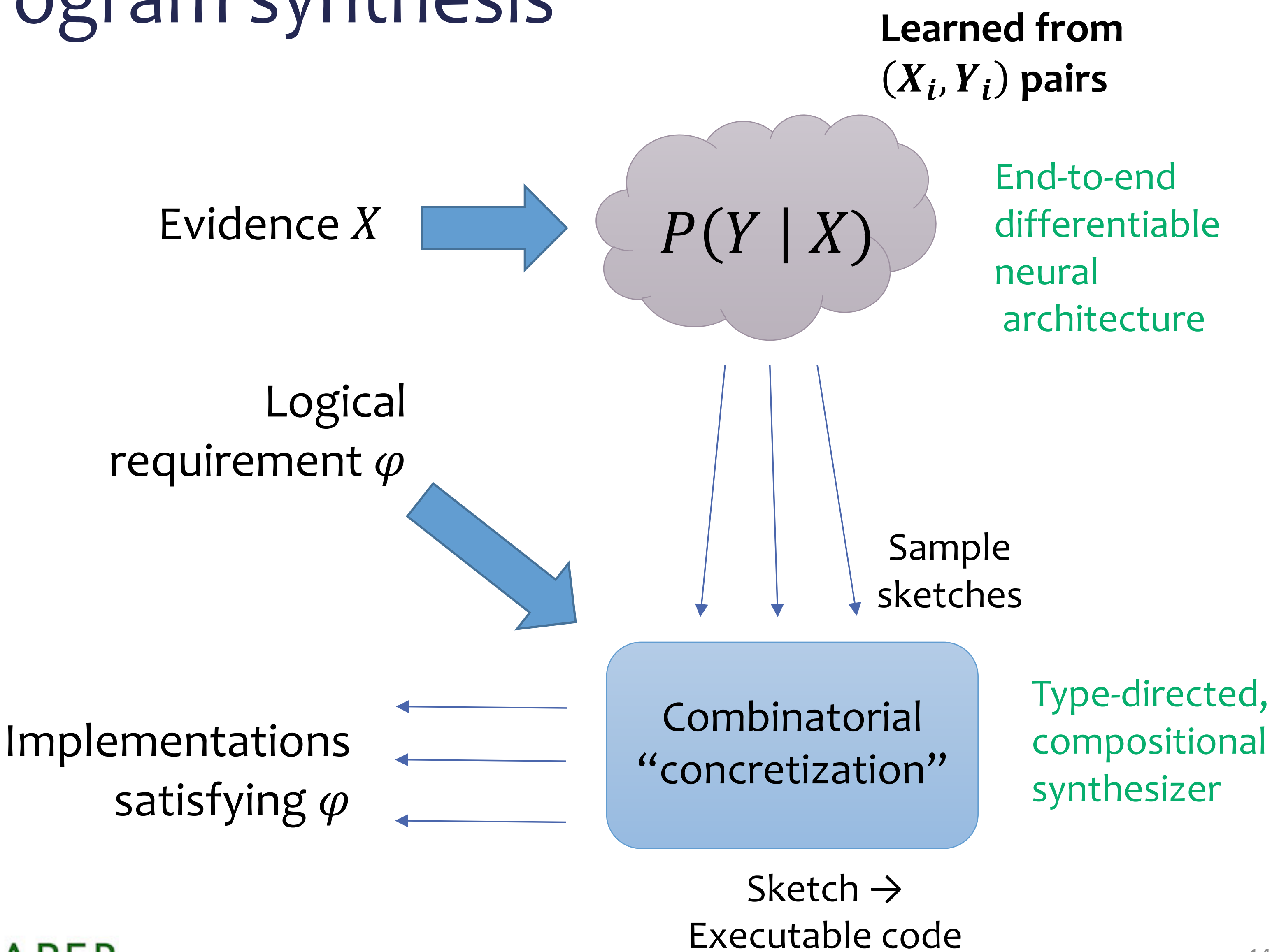
Conditions replaced by sets of abstract API calls

Abstract API call

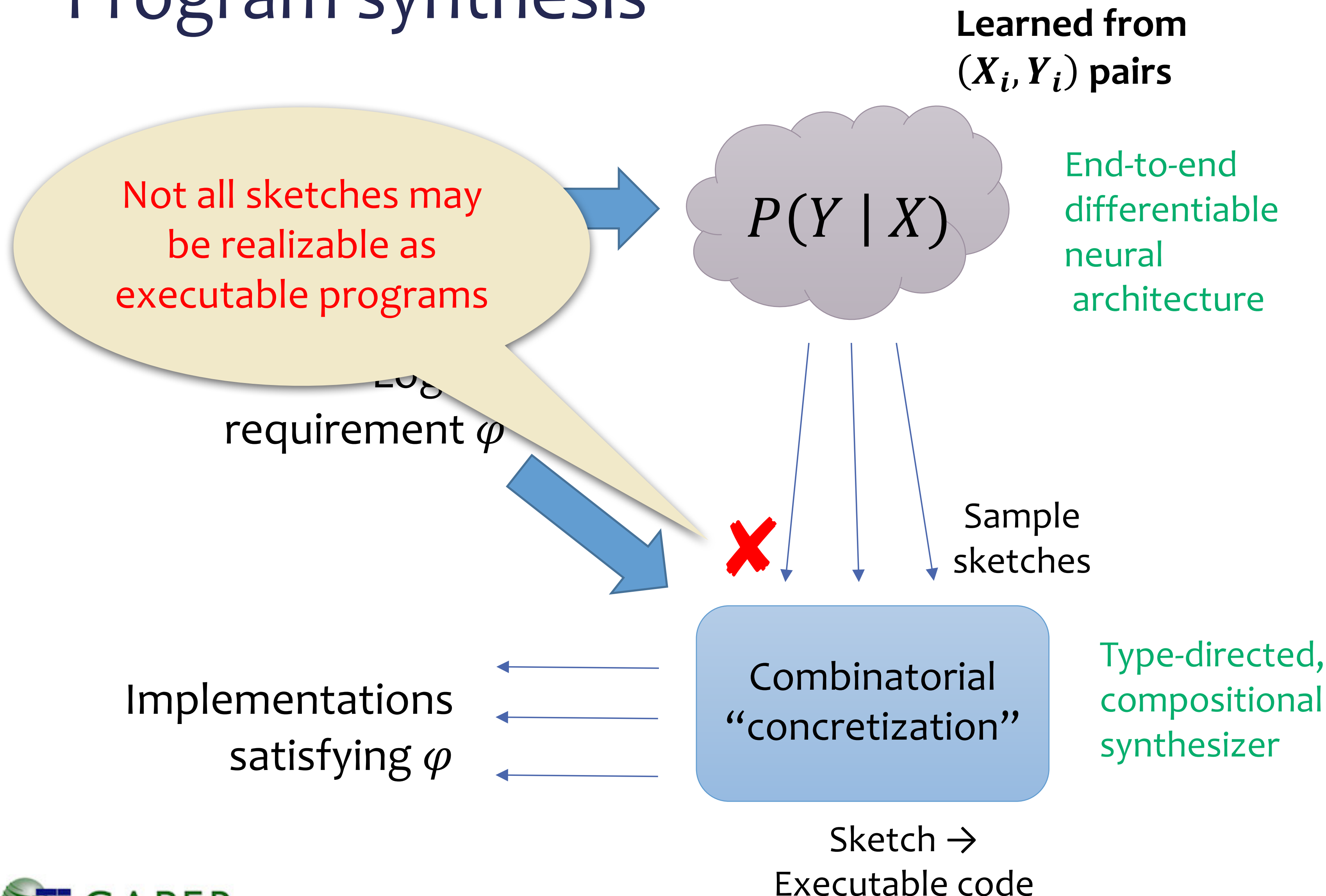
API method name

Types

Program synthesis



Program synthesis



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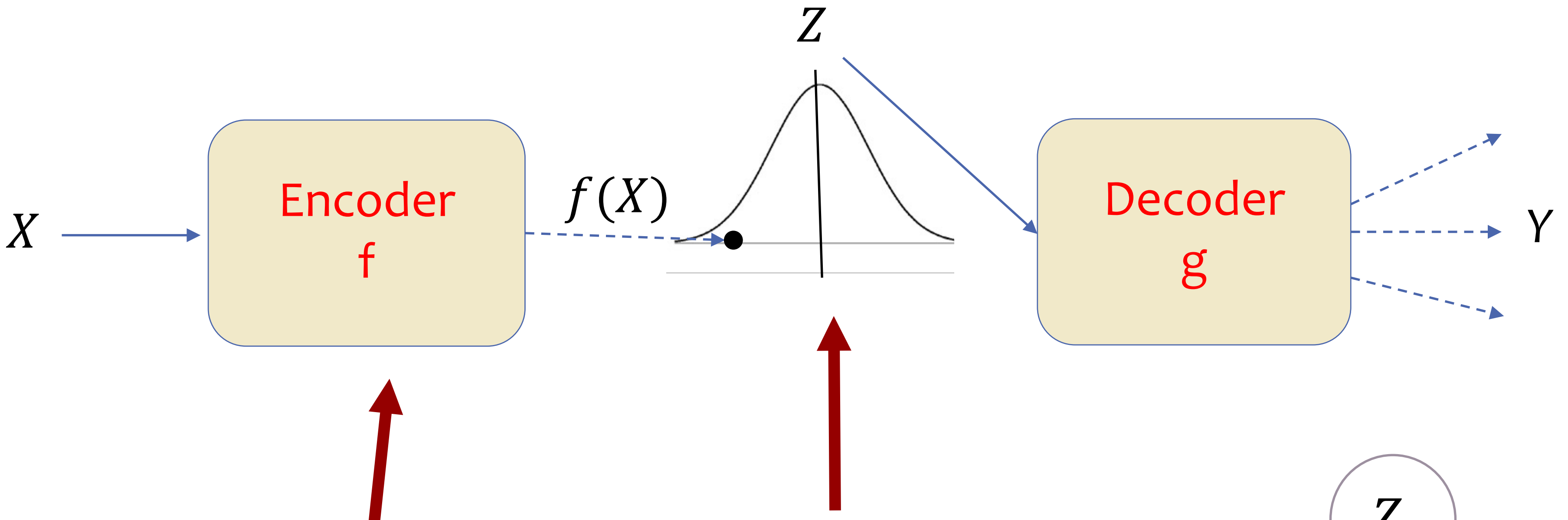
Learning using a probabilistic encoder-decoder

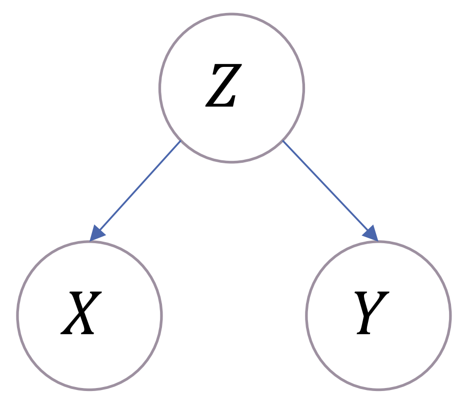
X: Evidence
Y: Sketches
Z: Latent "intent"



Feedforward neural net

Representation of hidden intent

Prior for regularization



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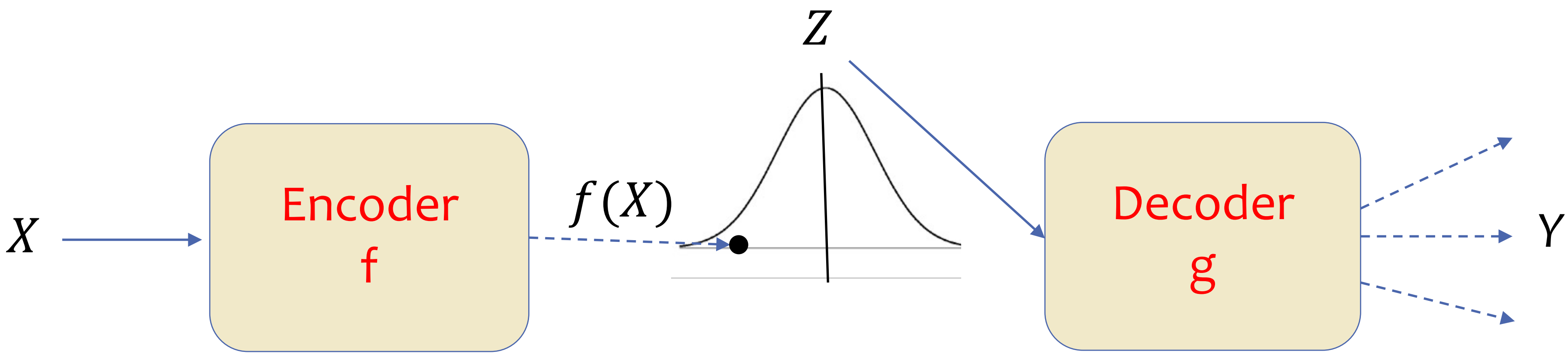

$$P(Z) = \ Normal(0, I)$$

$$P(f(X) \mid Z) = \ Normal(Z, \sigma^2 I)$$

During learning, use Jensen's inequality to get smooth loss function

Learning using a probabilistic encoder-decoder

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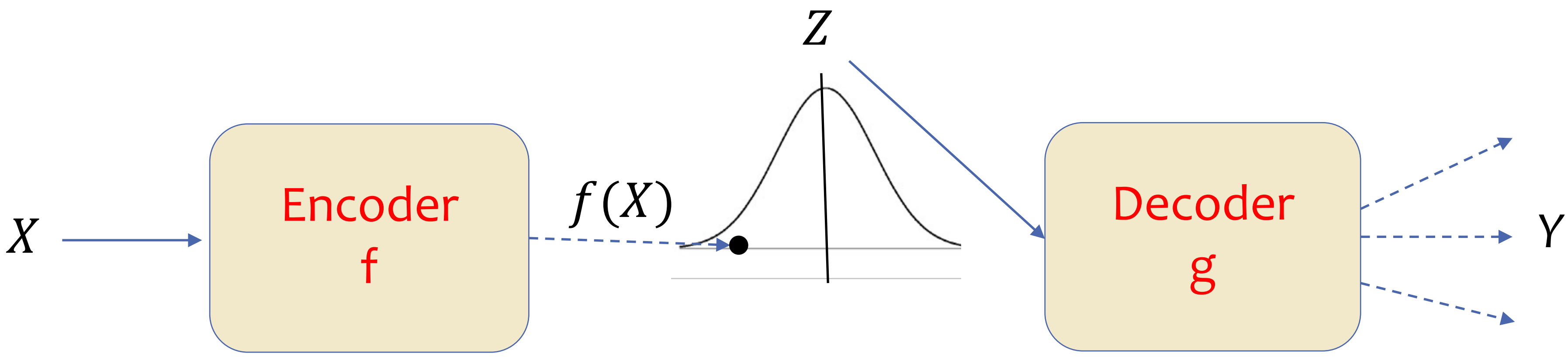


$$P(Z) = Normal(0, I)$$

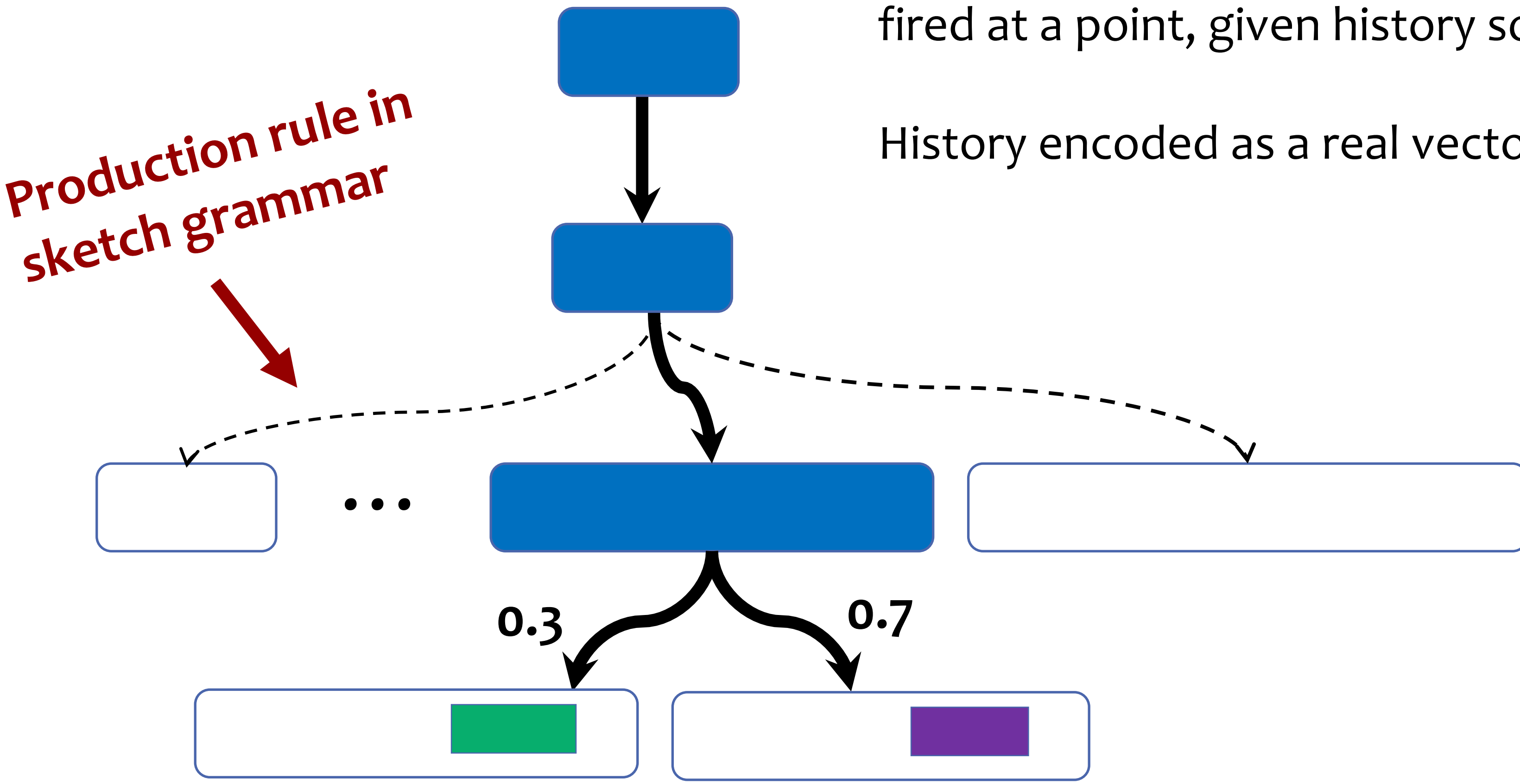
$$P(f(X) \mid Z) = Normal(Z, \sigma^2 I)$$

During inference, get P(Z | X) using normal-normal conjugacy

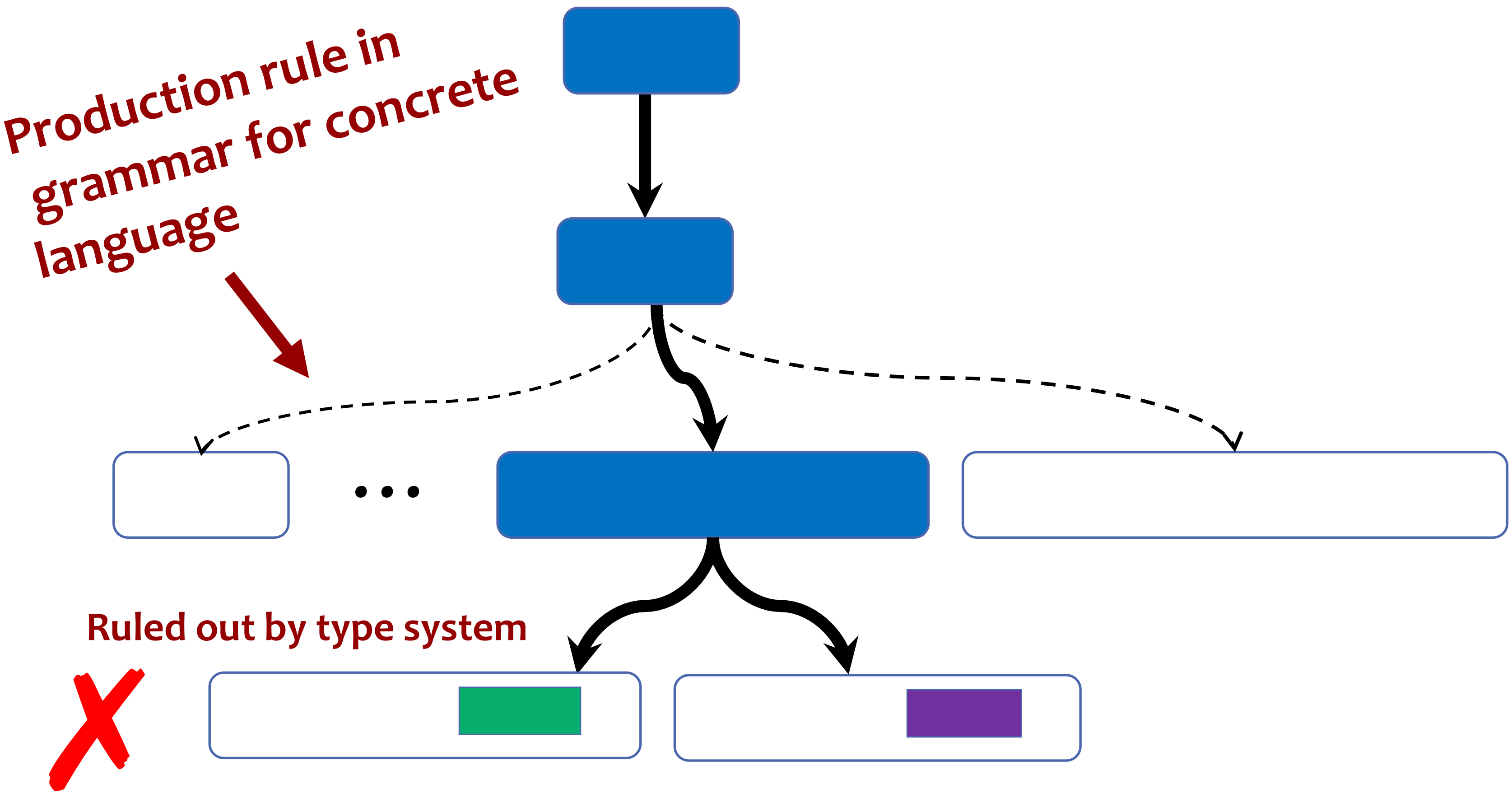
Neural decoder

Distribution on rules that can be fired at a point, given history so far.

History encoded as a real vector.



Concretization



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Results

- Trained method on 100 million lines of Java/Android code. ~2500 API methods, ~1500 types.
- Synthesis of method bodies from scratch, given 2-3 API calls and types.
- Sketch learning critical to accuracy.
- Good performance compared to GSNNs (state of the art conditional generative model).
- Good results on label-sketch pairs not encountered in training set.

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Thank you!

Questions?

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