# Neural Program Synthesis: Learning to Program from Trees

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## A familiar situation

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i.e., a **target language** and a **specification**.

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3. **Cannot Execute the Program:** What went wrong? What doesn't work yet?

# What is Program Synthesis?

| | A | B |
|---|---|---|
| 1 | Email | Column 2 |
| 2 | Nancy.FreeHafer@fourthcoffee.com | nancy freehafer |
| 3 | Andrew.Cencici@northwindtraders.com | andrew cencici |
| 4 | Jan.Kotas@litwareinc.com | jan kotas |
| 5 | Mariya.Sergienko@gradicdesigninstitute.com | mariya sergienko |
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(a) Specification by examples

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\begin{aligned}
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Figure: A program

- Find solution by enumerating (possibly all) programs from the **grammar** and check them against the **specification**.

# Why Program Synthesis?

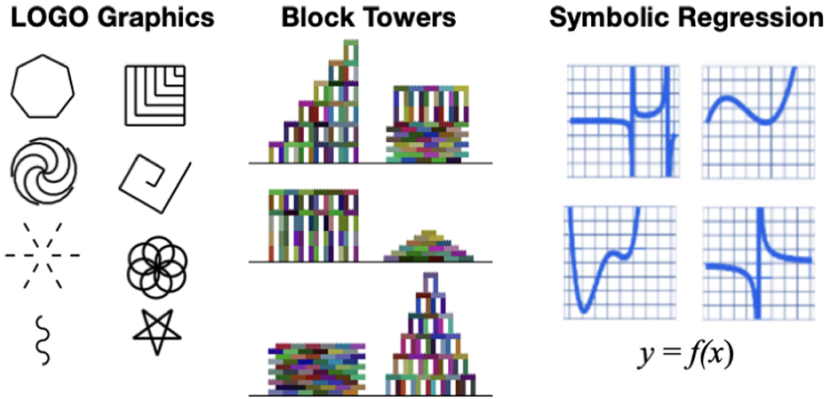


Figure: Examples of tested domains in DreamCoder [2].

[2] Ellis, K. et al. *DreamCoder: Building interpretable hierarchical knowledge representations with wake-sleep Bayesian program learning* (2020).

# Why Program Synthesis in this Seminar?

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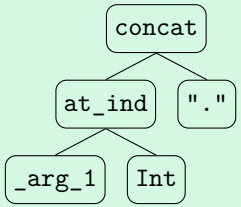


Program as an AST

Figure: A program is not just a string: it has tree structure.

# The gap we want to bridge

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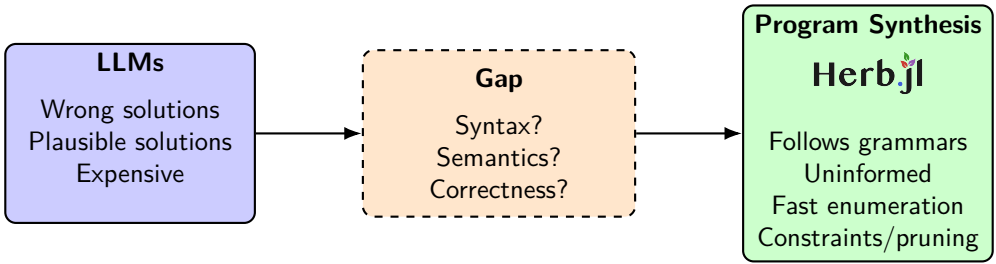


## Goal

Keep the **guidance** from LLMs, but recover the **discipline** of synthesis.

# Problem statement

## Input

- an LLM
- a target language, via a grammar $\mathcal{G}$
- a specification $\mathcal{S}$

## Question

How can we follow the **guidance** of the LLM, while still following the **grammar** and finding a **satisfying program**?

# NeuGuS: Learning Neural Guidance for Synthesis

## Definition (Learning heuristics)

Given data $\mathcal{D} = \{(i, o, p) | p(i) = o, i \in \mathcal{E}\}$,

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## Learning from trees

Given

- specification $\mathcal{E}$/the grammar $\mathcal{G}$/program-so-far $p_0$/....

predict which grammar rule $i \in [|\mathcal{G}|]$ to pick.

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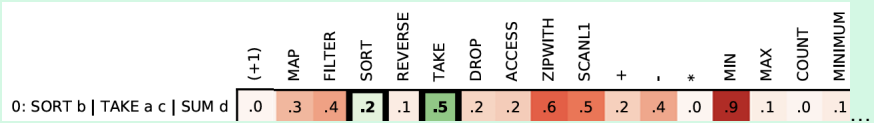
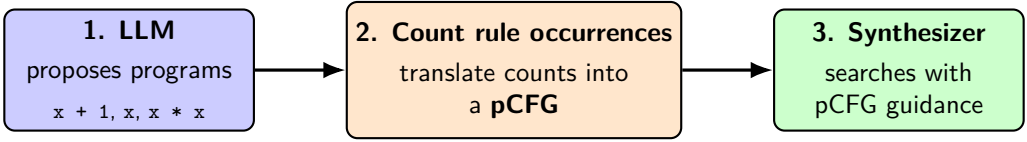



Figure: Heuristic values over grammar functions

# The common bridge: probabilistic grammars

## Most common idea

Use an LLM to produce a multiple programs, estimate grammar-rule probabilities from them, and guide synthesis with the resulting **pCFG**.



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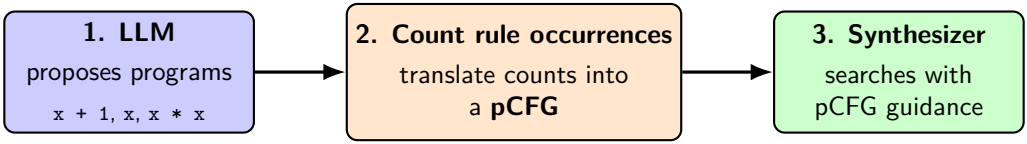


## Interpretation

Likely programs are explored earlier. Unlikely rules and programs are delayed.

# Why pCFGs are not the full answer

## Key limitation

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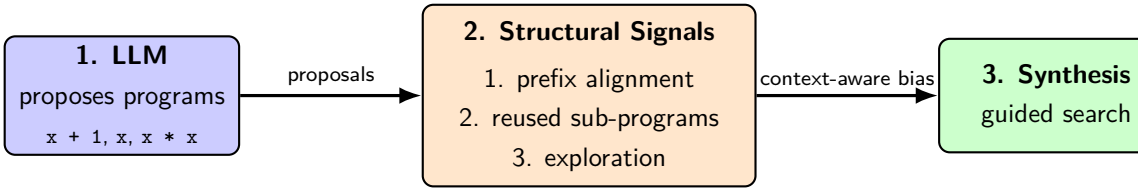
## Intuition

An LLM can prefer a rule *because of the program-so-far*. A plain pCFG usually cannot express that well.

# 1. Narcissus: Context-Aware LLM Guidance

## Goal

Inject **structural bias** into LLM guidance, while keeping correctness in the synthesizer.



# 1. Narcissus: What guidance do we want?

## Combined guidance

Let $\pi$ be the current partial program, and let $r$ be the possible next rule.

$$s(r \mid \pi) = \lambda_1 s_{\text{pref}}(r \mid \pi) + \lambda_2 s_{\text{sub}}(r \mid \pi) + \lambda_3 s_{\text{expl}}(r \mid \pi)$$

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**Example:** Suppose 8 proposals contain prefix $\pi$, and in 6 of them the previous rules were $Int \to Int + 1$. Then

$$s_{\text{pref}}(Int \to Int + Int \mid \pi) = \frac{6}{8} = 0.75.$$

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**Intuition:** The LLM proposals may be faulty. Thus, give some chance to less-used rules (regularization term).
**Example:** If $Int \to x$ has already been heavily favored many times, then $Int \to Int * Int$ may get an exploration bonus, so search still checks an alternative region.

# Search intuition

## Rule of thumb

Change weights $\lambda_i$ according to these rules of thumb:

- near the root: use strong contextual guidance
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## Interpretation

We want to approximate the LLM proposals, without getting getting stuck in local minima.

# Narcissus Conclusion: Current state + ongoing work

## What we do want

Cheap, context-aware guidance for reliable program synthesis.

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## Ongoing work:

- Formalize $\lambda$ dependency
- Study on LLM proposal quality
- Evaluation on other benchmarks

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## Constraints!

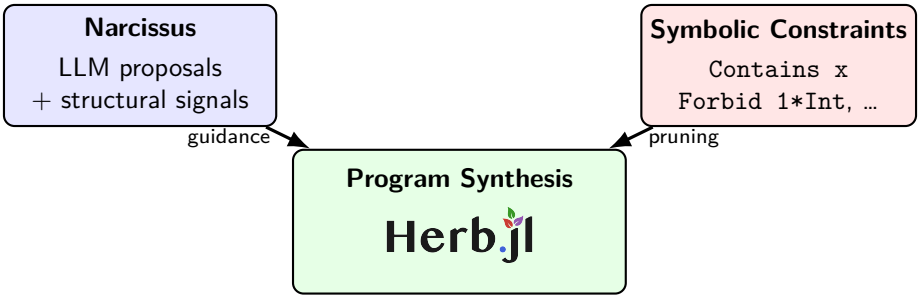
We introduce a

- language of constraints over programs,
  - `Forbid 1*Int`, `Contains x`, `Forbid 0+Int`, ...
- a constraint solver, to propagate these efficiently (called BART)

# 3. Neuro-Symbolic Program Synthesis

## Idea

Combine **LLM guidance** with **symbolic pruning**.



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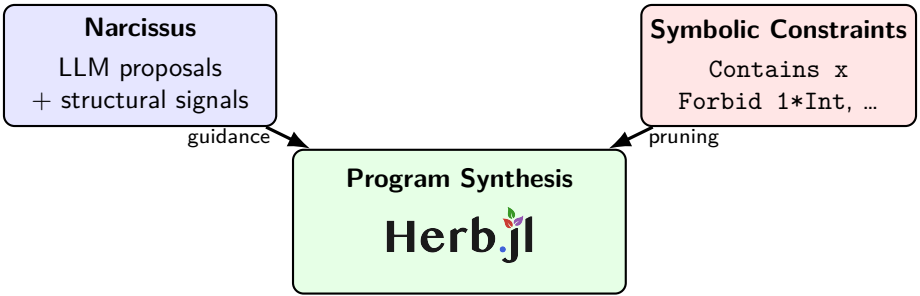


LLMs guide search toward **plausible** programs, symbolic constraints prune **undesirable** ones.

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## Talk to me!

If you are tired of writing

- code,
- differential equations, or
- process models

yourself, come talk to me afterwards.

Why LLMs do/do not work

What is Program Synthesis?

Neural Program Synthesis via LLM guidance: Narcissus

Symbolic Program Synthesis