Neural Guided Constraint Logic Programming for Program Synthesis

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Programing By Example

Goal: synthesize program specified in terms of input/output examples.
Approaches: enumerative type-based search methods like λ^2, Myth, Escher; Machine Learning work uses methods like conditional program generation, differentiable programming, and neural guided synthesis.
Our approach: use a ML agent to guide the search, but additionally give ML agent internal state of symbolic system.

Background

We use the constraint logic programming language miniKanren as the symbolic system.

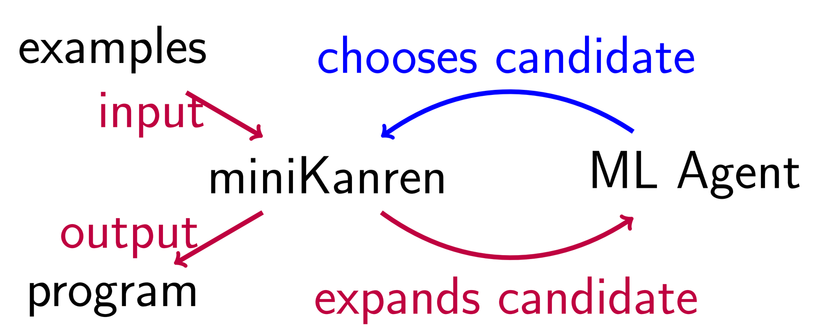
- miniKanren is flexible: can synthesize dynamically typed recursive programs
- write a **relational interpreter** in miniKanren: a relational form `(evalo P I O)` of interpreter `(eval P I) = O`
- relations like *evalo* can be thought of as constraints
- query miniKanren to find solutions to P in `(evalo P I O)` by iteratively expanding relation evalo with its definition:

```
(evalo P I O)
  ⇒ DISJ →(evalo (quote A) I O)
         →(evalo (car B) I O)
         →(evalo (cdr C) I O)
         →(evalo (cons D E) I O)
         →(evalo (var F) I O)
          ...
```

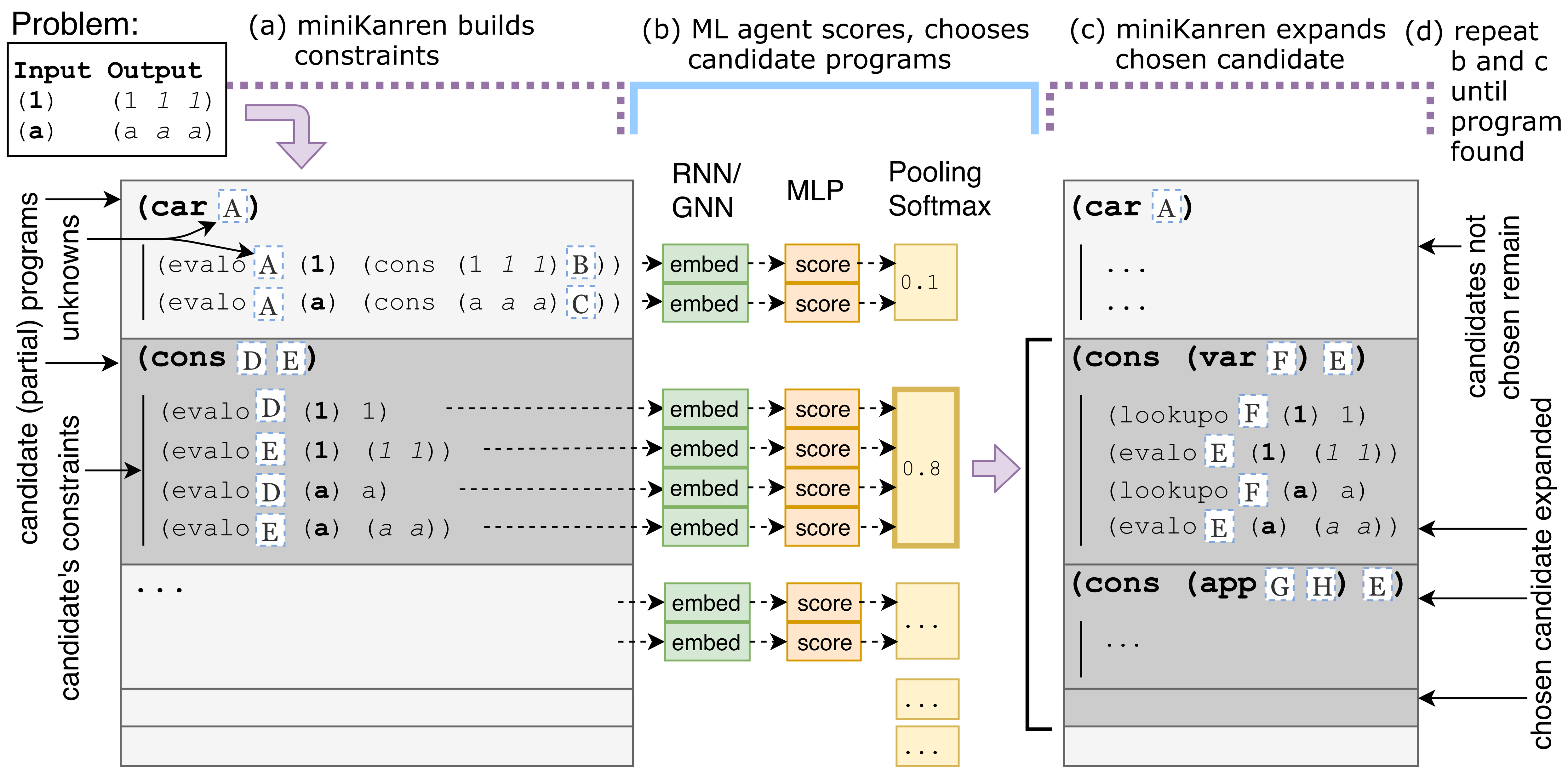
- As we choose branches of DISJ to expand, we search through possible programs P.

Our Approach: Neural Guide

Build a machine learning agent to choose branches of DISJ to expand, taking constraints as inputs.



Synthesis Steps



(a) miniKanren builds constraints representing the PBE problem; candidate programs contain unknowns, whose values are restricted by constraints: in the second candidate, the `evalo` constraints decompose the output into two portions to be synthesized independently
(b) a neural network operating on the constraints scores candidates; each constraint is embedded and scored separately, then pooled per candidate; scores determine which candidate to expand
(c) miniKanren expands the chosen candidate `(cons D E)`, so that different completions of unknown D are added to the set of candidates
(d) this process continues until a fully-specified program (with no logic variables) is found

Experimental Results

We report on two sets of results, with both experiments using the same trained weights.

- **Test Problems** Solved (%): held-out, dynamically-typed improper list construction problems.
- **Generalization**: Largest N for which synthesis of a family of programs succeeded.

Method	Test Problems Solved (%)	Generalization		
		Repeat(N)	DropLast(N)	BringToFront(N)
Naive	27%	6 (time)	2 (time)	- (time)
+Heuristics	82%	11 (time)	3 (time)	- (time)
RNN (No Constraints)	93%	9 (time)	3 (time)	2 (time)
GNN + Constraints	88%	**20+**	**6** (time)	**6** (time)
RNN + Constraints	99%	**20+**	**6** (time)	5 (time)
λ^2		4 (memory)	3 (error)	3 (error)
Escher		10 (error)	1 (oracle)	- (oracle)
Myth		**20+**	- (error)	- (error)
RobustFill beam 5000	**100%**	3	1	- (error)

- Repeat(N): repeat a token N times
- DropLast(N): drop the last element in an N element list
- BringToFront(N): bring the last element to the front in an N element list
- Failure modes: out of **time**, out of **memory**, requires **oracle**, other **error**

Model Choices

We test different models for scoring candidates:

- **RNN+Constraints** computes constraint embeddings using LSTMs, treating constraints as sequences.
- **GNN+Constraints** computes constraint embeddings using a Graph Neural Network (GNN), treating constraints as graphs.
- **RNN (No Constraints)** scores candidate programs directly by embedding the candidate program, input sequence, and output sequence using LSTMs.

Training the models:

- Autogenerate training problems: generate a program, then generate input/output examples for the program. We use miniKanren to do this.
- Since we know a ground truth program during training, we know which candidate program is correct at each step.
- Expand 2 partial programs per step during training.

Why use constraints?

- Evaluating whether a partial program is plausible should be easier than generating a program.
- ML Agent essentially learns a flavour of constraint satisfaction.
- Constraints contain relevant portions of the input/output, acting as an attentional mechanism.
- Constraints are roughly the same length, whereas programs can be long, so we should be able to scale to larger programs by using constraints.

Discussion & Future Work

- RNN with constraints performed almost perfectly in test problems.
- RNN / GNN with constraints has the potential to scale to larger programs.
- Thus far we have used a small subset of Lisp, without recursion. We would like to expand to synthesize programs in larger subsets of the Lisp language, and recursive programs.

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