Computational Models for Learning to Code

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Overview

Preliminaries

Please interrupt me.

Let's begin with the most perilous part of any talk

https://aravart.github.io/speech-games/

Live Demo

(Google Chrome only, probably)

Behavior

A simple language

Consider a simple language that can be used to control a “turtle” program. We have three instructions:

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Program graph

Imagine the student traversing a *state space* of the possible programs in an editor.

$\emptyset$

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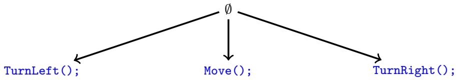

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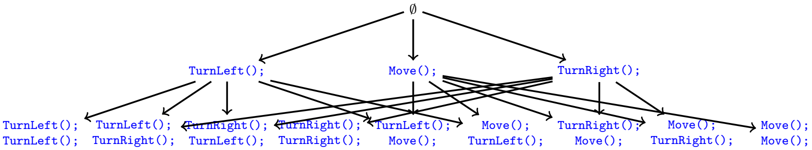
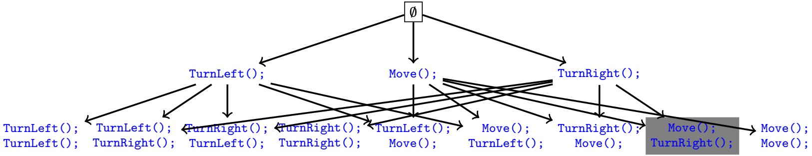


Programming as graph search

Given a goal node v and a graph G, we can model the task of programming as a search over G for v. Breadth-first search would look like:



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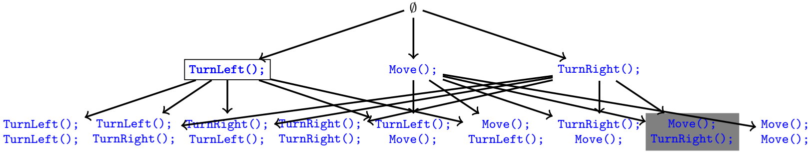

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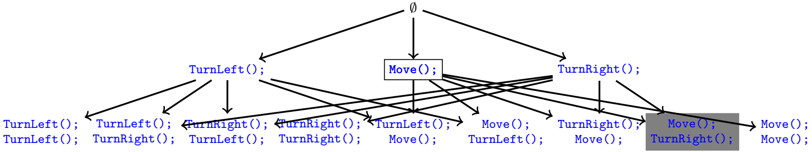

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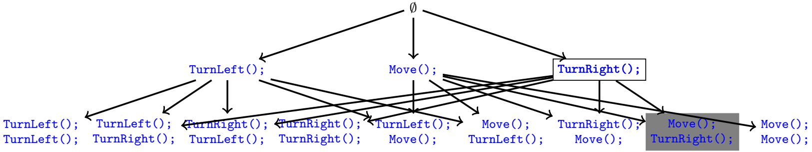

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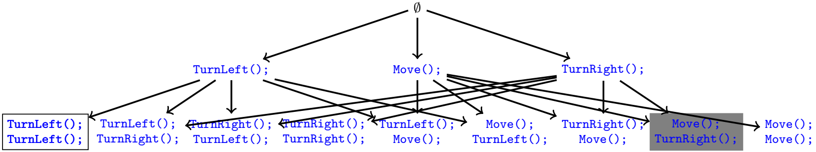

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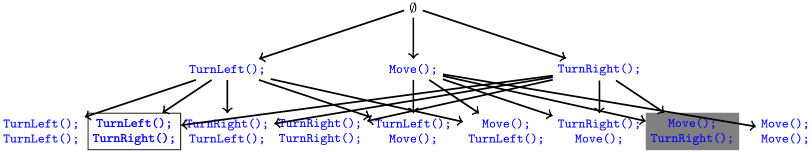

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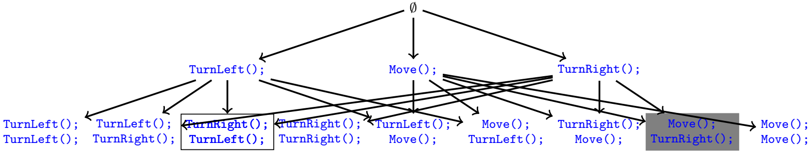

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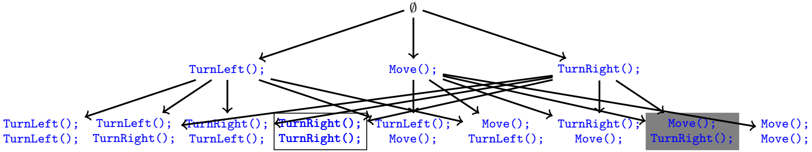

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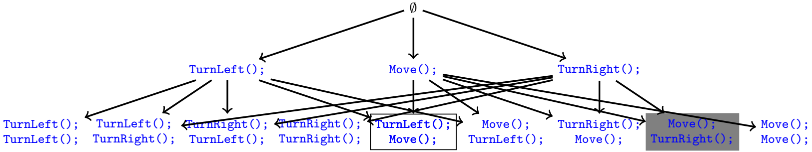

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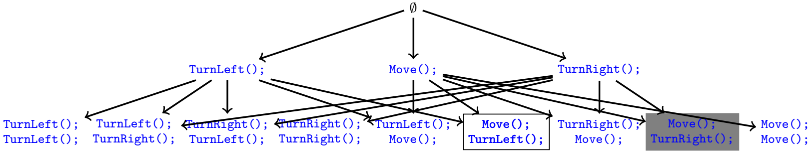

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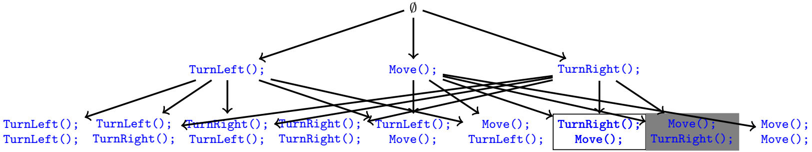

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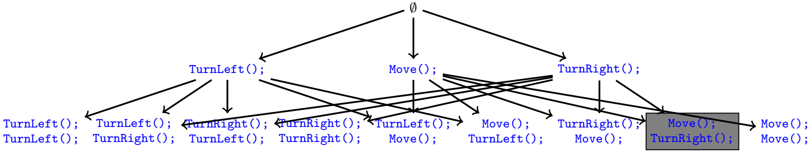

Now imagine a perfect programmer...

A perfect programmer performs the operation above flawlessly, terminating after finding the goal node (with probability 1).

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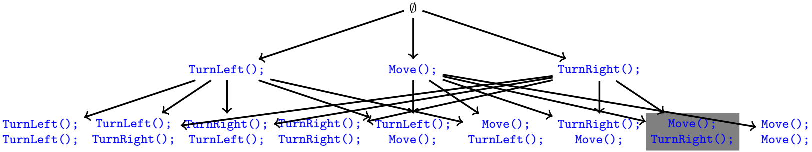

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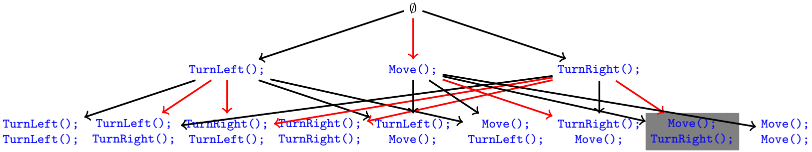

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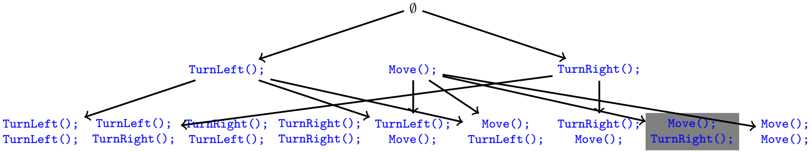

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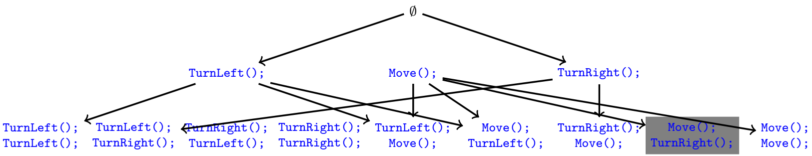

And there is no path to the goal. Search comes up empty.

Intuition

If we knock out each edge with some probability p, then for any goal node v we have some (hard to compute) probability that v is reachable from the root of G. Let's call this probability of r_v.

Two ways to think about this

Here's plain old breadth-first search...

Algorithm 1 Breadth-First Search

procedure BFS
Input: Program graph G, source node u, goal node v.
Output: Whether v was found.
    Create a queue Q; Enqueue u onto Q
    Create a set V; Add u to V
    while Q is not empty **do**
        Dequeue an item from Q into n
        If n is u **then return** True
        for each edge e incident on n **do**
            Let m be the other end of e
            if m not in V **then**
                Add m to V
                Enqueue m onto Q
    return False

Two ways to think about this

Here's breadth-first search with-forgetting...

Algorithm 2 Breadth-First Search With Forgetting

procedure BFSWithForgetting
Input: Program graph G, source node u, goal node v, forgetting probability p.
Output: Whether v was found.

```
    Create a queue Q; Enqueue u onto Q
    Create a set V; Add u to V
    while Q is not empty do
        Dequeue an item from Q into n
        If n is u then return True
        for each edge e incident on n do
            Let m be the other end of e
            if m not in V then
                Add m to V
                With probability 1 − p, enqueue m onto Q
    return False
```

Two ways to think about this

Alternatively, we can remove the edges from G and then pass this modified G into plain old breadth-first search.

Estimating the probability of finding v

Algorithm 3 Monte Carlo Estimation of r_v

```
procedure MonteCarloR
Input: Program graph G, goal node v, forgetting probability p, budget b.
Output: Estimate r̂_v.
    Set r to 0
    for i in 1 to b do
        Copy G into G'
        for each edge e in G' do
            Remove e from G' with probability p
        Call Procedure: BFS(G',∅,v) [Algorithm 1]
        Increment r if BFS found v
    Return: r/b
```

A tangent: Plato was a computer scientist?

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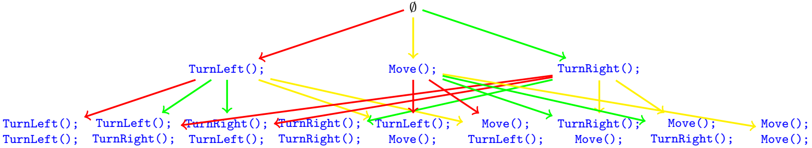
Meno: And how are you going to search for [the nature of virtue] when you don't know at all what it is, Socrates? Which of all the things you don't know will you set up as target for your search? And even if you actually come across it, how will you know that it is that thing which you don't know?

Making things more interesting: edge types

In our story so far, we have one probability p for forgetting an edge, but different operations (edges) might be more difficult to follow:



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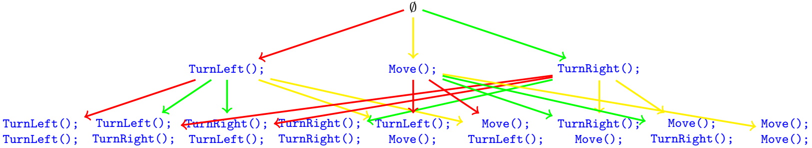
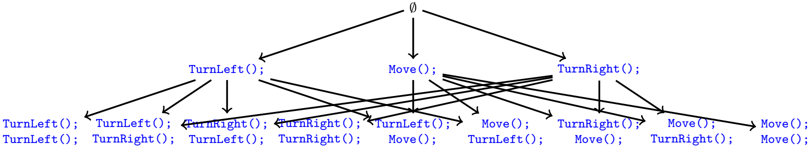


Here we've colored the edges based on which instruction *type* was inserted. More generally:

$$p : \mathit{SourceFeatures} \times \mathit{InsertionFeatures} \times \mathit{InsertionPosition} \rightarrow [0, 1]$$

Modularity

How can we express the idea that the student learns reusable fragments or idioms?



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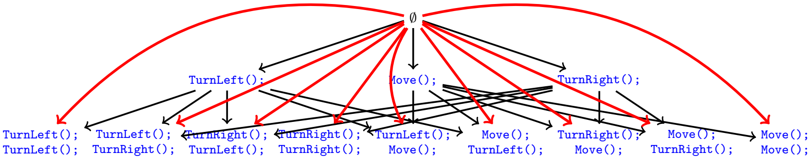

Think of these as composite edges.

Modularity

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- The most promiscuous construction would fix some basic graph G and then add an edge between any pair of vertices u, v where there is a path from u to v in G.
- More conservatively, fix some basic graph G and then add an edge between any pair of vertices u, v where v is the result of inserting some program w into u at a single position.

Learning

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- So A is some function $A : \mathcal{S} \to \Theta$.

Experiences?

An experience $X_i = \{X_{i1}, \ldots, X_{im}\}$ is a particular path through the program graph.

$\emptyset$

```
TurnLeft();
```

```
TurnLeft();
Move();
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Learning

A learns by reducing its probability of forgetting in proportion to the number of edges of that type it has seen in training.

Algorithm 4 Learn

```
procedure LEARN
    Input: Example programs X_1, X_2, ..., X_n, learning rate 0 ≤ γ ≤ 1.
    Output: A learner characterized by p.
    Initialize p(t) for each t in the domain of p to 1
    for i in 1 to n do
        for each subseqence l = {X_ij, ..., X_ik} of {X_i1, ..., X_im} do
            if t(l) is defined then
                p(t(l)) ← γp(t(l))
    return p
```

Here t is a type function that takes an edge to its type.

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- So what's teaching?

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- Think of this as a *cheating* strategy of teaching.

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- But now let's say there isn't a single v state but a large set of states $v_1, \ldots, v_n$, all of which we want to teach reasonably well and say we had a limited budget for the number of items we could teach with. What would we do?

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- Conjecture: we'd extract common, re-usable patterns and teach those.
- Think of this as a *curriculum* strategy of teaching.

Formalize this!

For a single v:

$$\begin{aligned} \min_{S \in \mathcal{S}} \quad & \epsilon(S) \\ \text{st} \quad & \mathbb{P}(R(v, A(S)) = 1) \geq \alpha. \end{aligned}$$

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But if $V \sim F_V$:

$$\begin{aligned} \min_{S \in \mathcal{S}} \quad & \epsilon(S) \\ \text{st} \quad & \mathbb{E}[R(V, A(S))] \geq \alpha. \end{aligned}$$

- Here ϵ is a *teacher's effort* function.
- And R is the Bernoulli random variable representing the success of $A(S)$ at finding V.

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- We can take $\epsilon(S) = \sum_{X \in S} |X|$ to express a preference for the smallest sequence of paths.
- Over a graph with no composite edges, this is equivalent to the number of instructions in a program.
- But we can be creative here...

Questions?