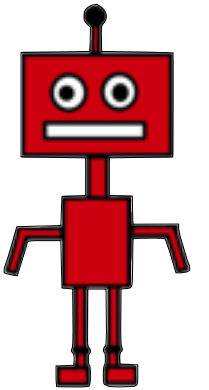


# Toward Affordance-Aware Planning



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# Outline

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# Problem Statement

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Enable Autonomous Agents to learn to plan effectively in massive stochastic state-spaces.

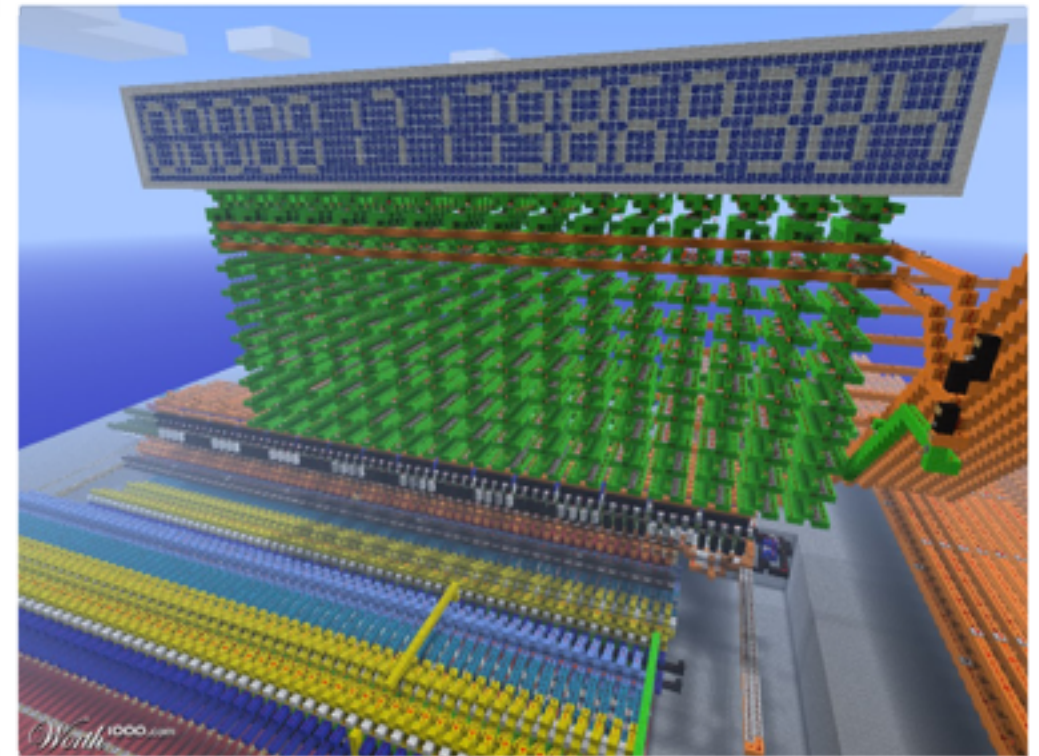
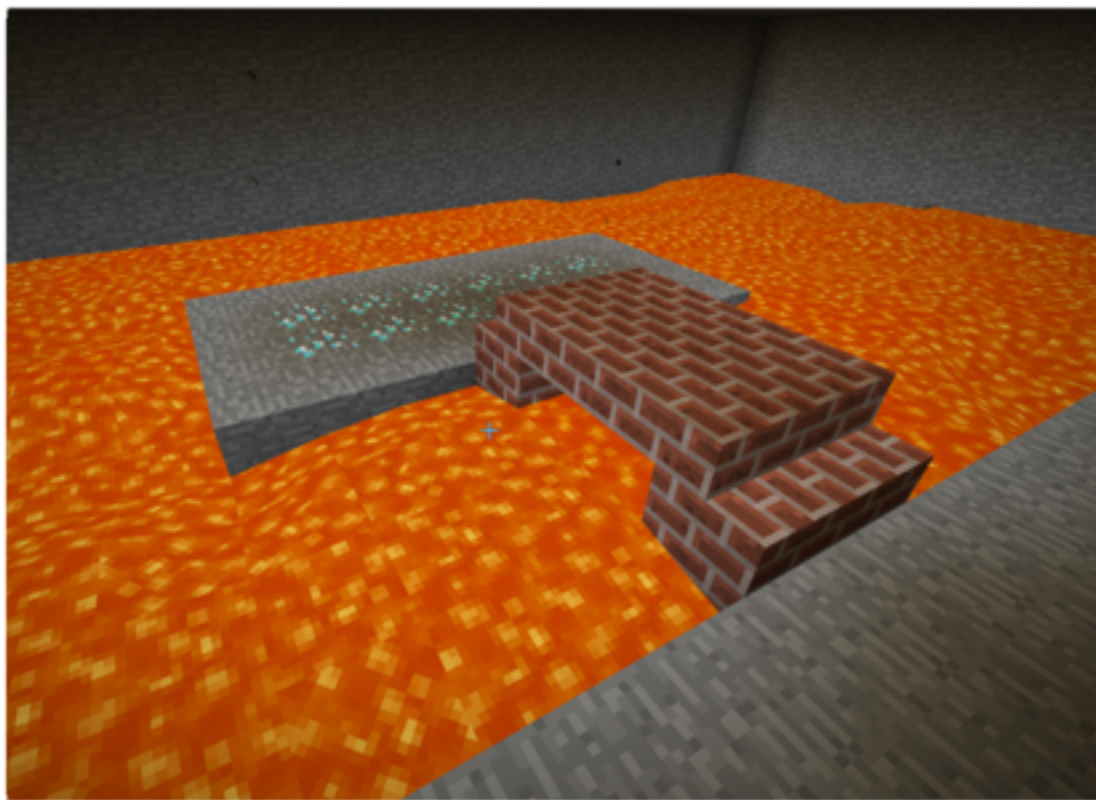
# Minecraft

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Insert video (Have it already, didn't push b/c file size)

*≈ Turing Complete LEGO*

# Minecraft & Robotics

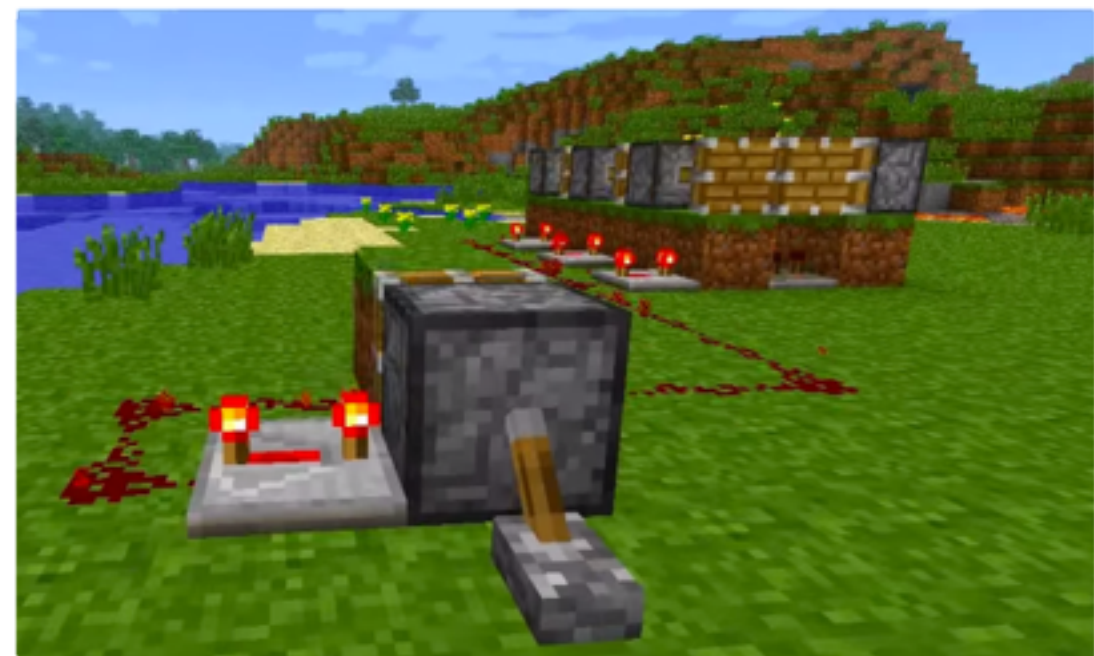
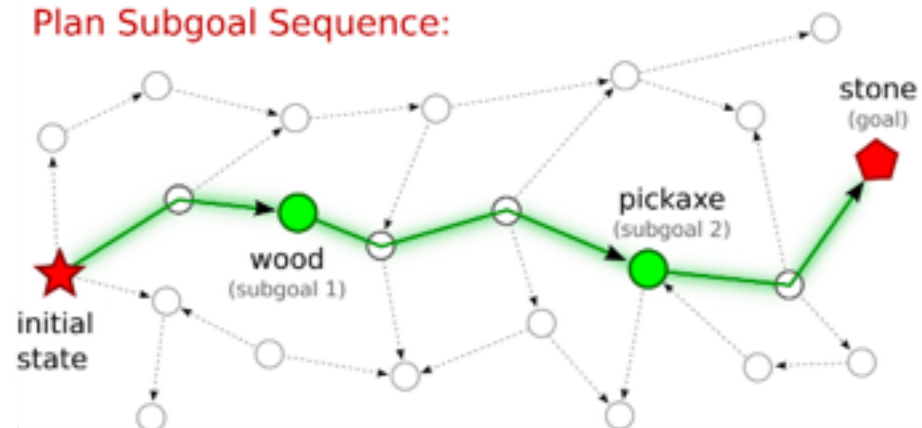


Precondition Relations:

wood  $\rightarrow$  pickaxe

pickaxe  $\rightarrow$  stone

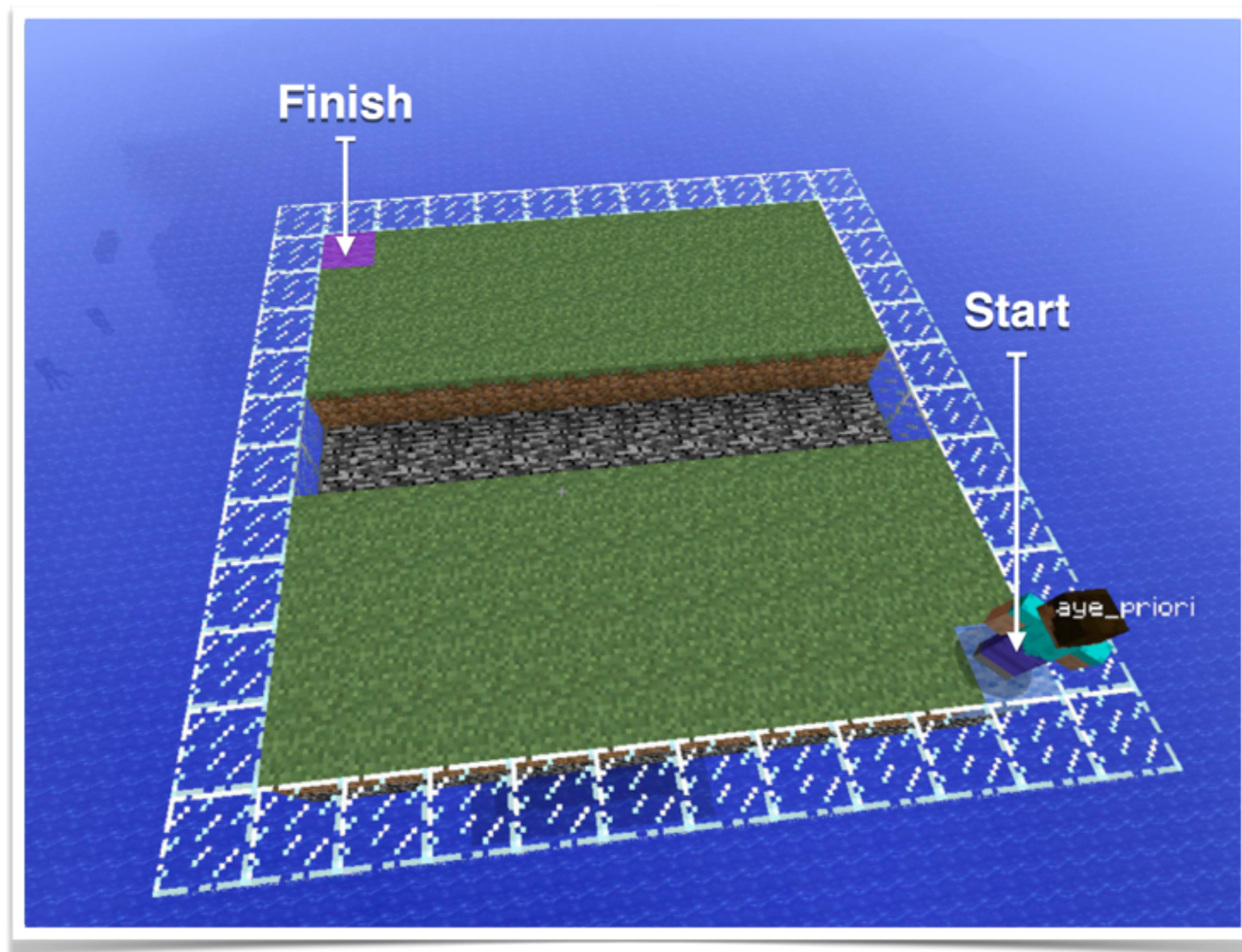
Plan Subgoal Sequence:





# Minecraft: The Problem

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## ACTIONS

- Move
- Place
- Destroy
- Use
- Jump
- Rotate
- Look
- Craft
- ...

# Affordance Formalism

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We formalise an affordance as:

$$\Delta = \langle p, g \rangle \mapsto \mathcal{A}'$$

Where:

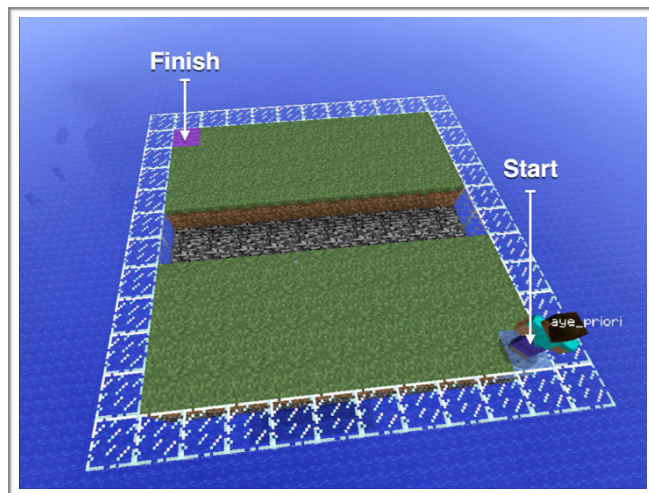
$p$  = a predicate on states

$g$  = a lifted goal description

$\mathcal{A}'$  = a set of relevant actions

# Affordance Formalism Intuition

Idea: Affordances focus the agent on *relevant action possibilities* by pruning irrelevant actions on a state by state basis



(OO)-MDP

Policy

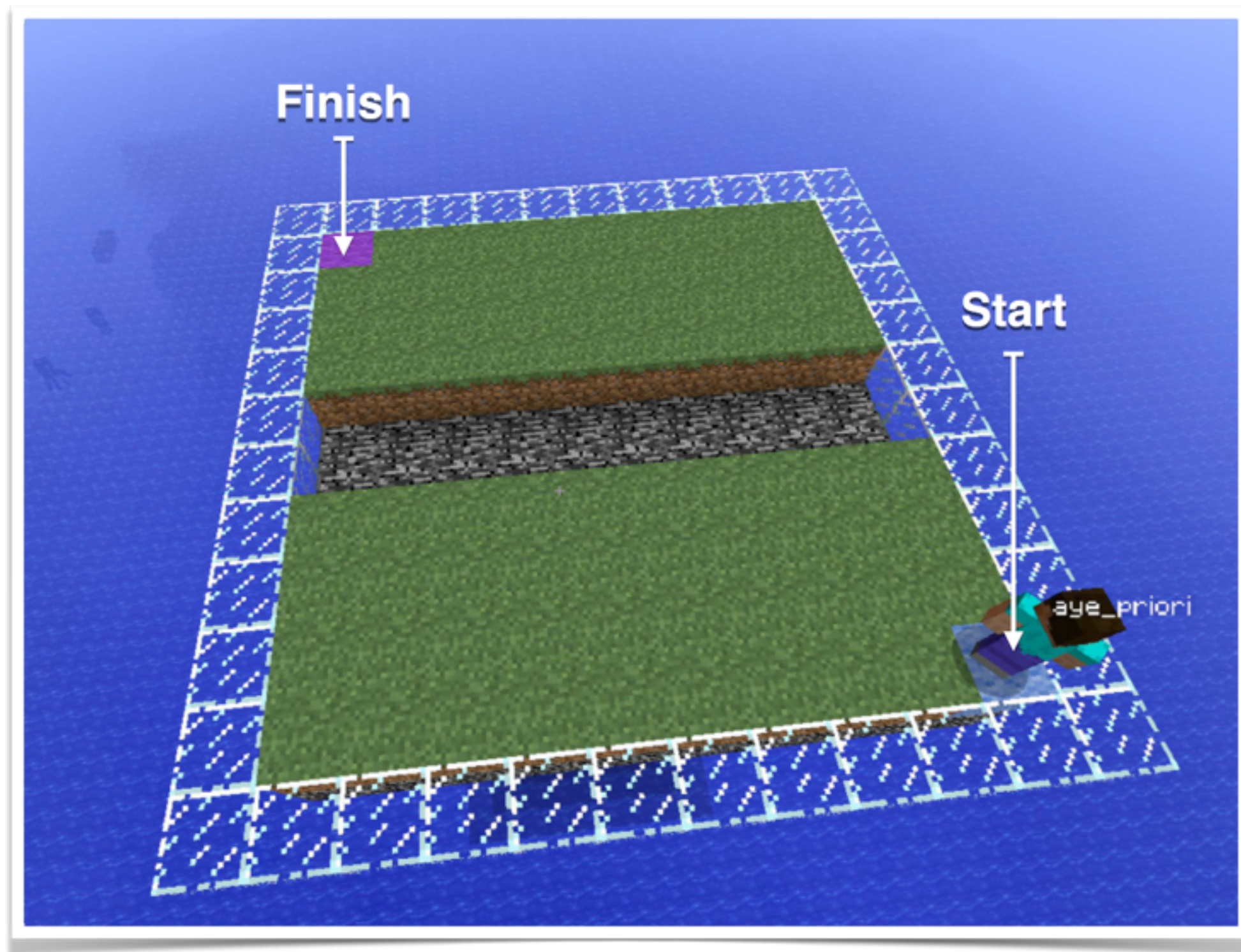
$$\Delta_1 = \langle nearTrench, AtGoal \rangle \mapsto \{place, jump\}$$

$$\Delta_2 = \langle nearPlane, AtGoal \rangle \mapsto \{move, rotate\}$$



# Affordances In Planning

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# Demo

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Insert video (Have it already, didn't push b/c file size)

# Learning Framework

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Goal: For each reachable state in the MDP,  $s$ , infer:

$$\Pr(\mathcal{A}^* \mid s, \Delta_1 \dots \Delta_K)$$

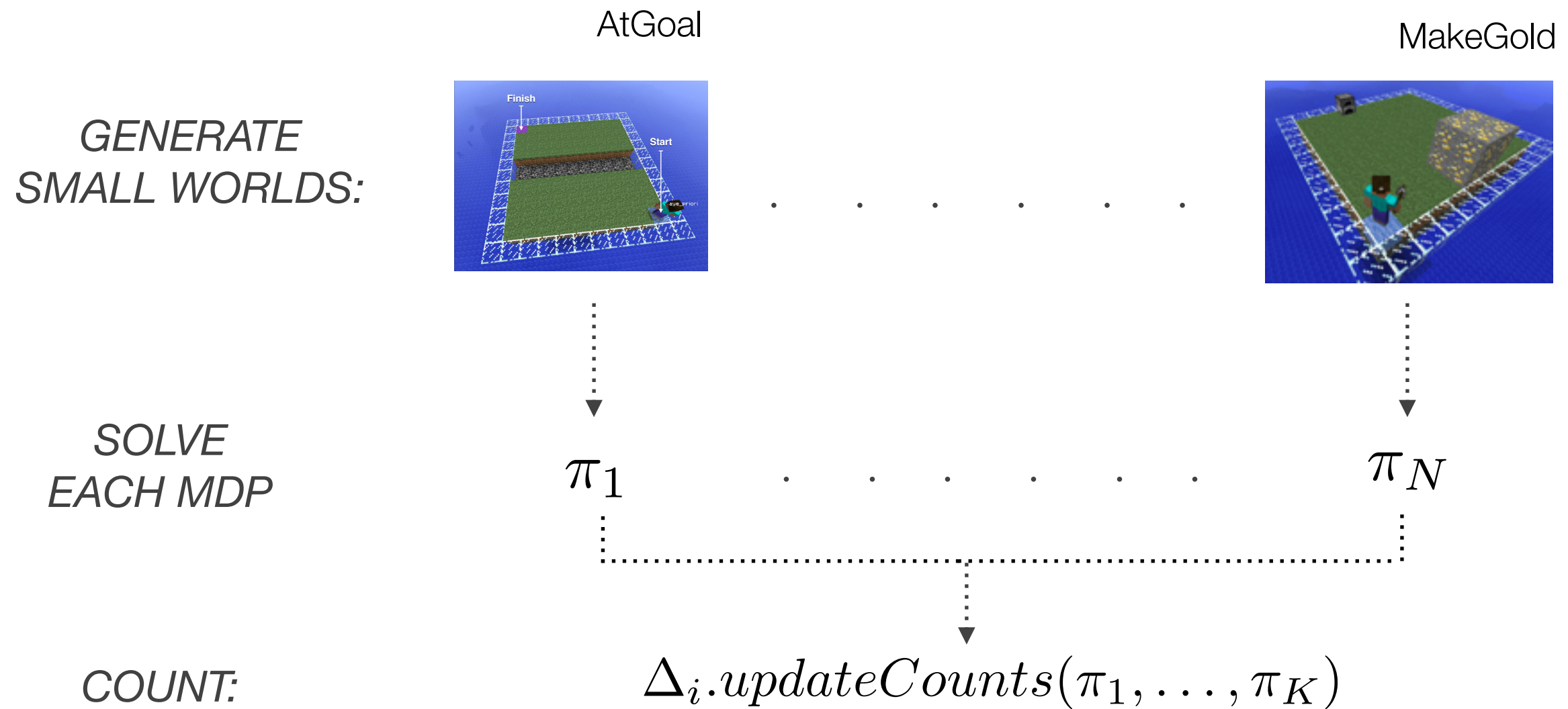
$\approx$  Probability that an action set contains the optimal action for that state

Where:

$$\mathcal{A}^* = \bigcup_{i=1}^K \mathcal{A}'_i$$

# Full Learning Process

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# Counts

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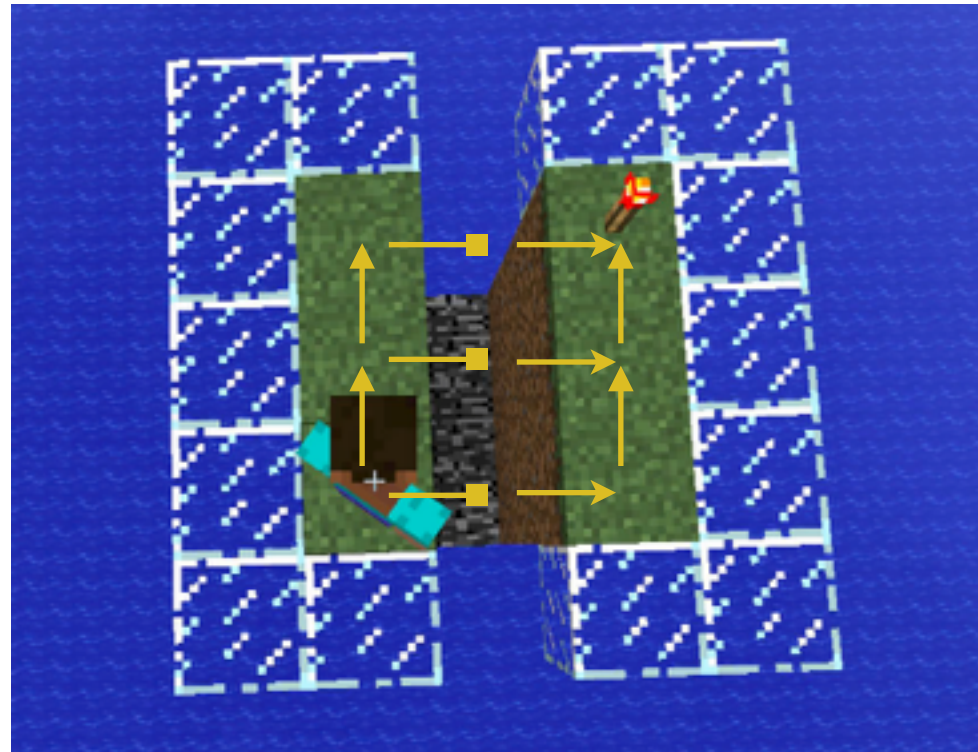
$\Delta_i.\alpha =$  number of worlds in which each action was used

$\Delta_i.\beta =$  number of unique actions used in each world



$$\Delta_i.updateCounts(\pi_1, \dots, \pi_K)$$


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$\rightarrow$  = *move*  
 $\rightarrow$ ■ = *place*

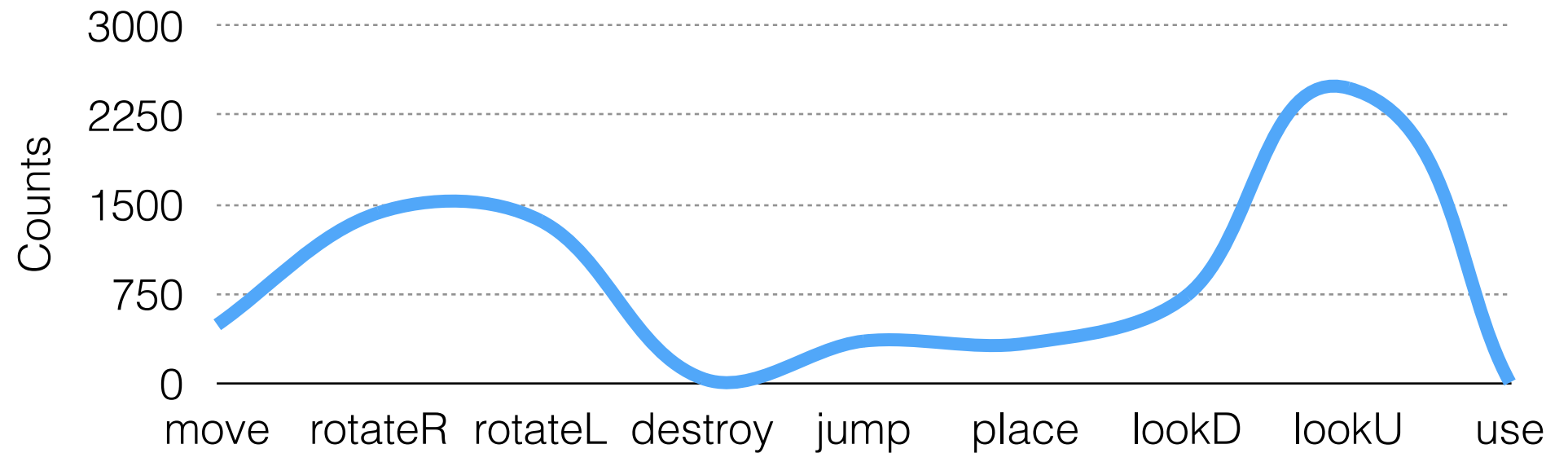
$$\Delta_1 = \langle \checkmark nearTrench, \checkmark atGoal \rangle$$

$$\Delta_1.\alpha.moveRight++, \Delta_1.\alpha.moveForward++, \Delta_1.\alpha.placeRight++$$

$$\Delta_1.\beta.3++$$

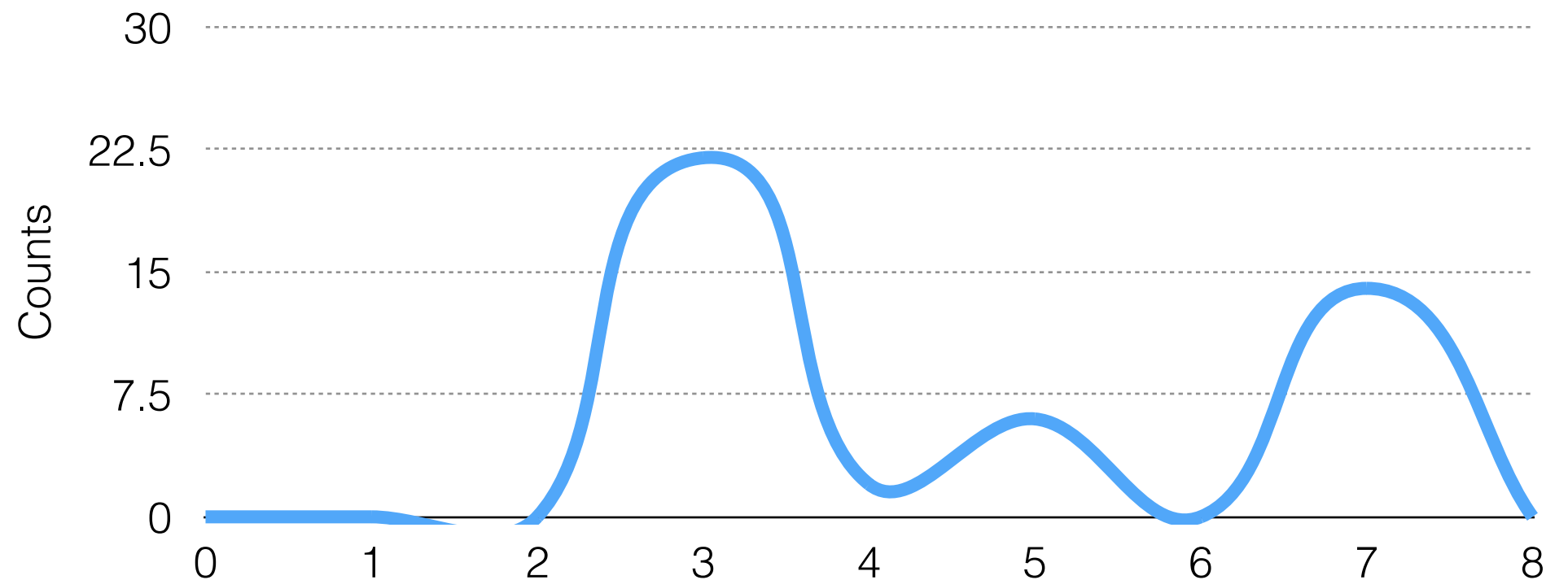
# Learning Example

$\alpha$  counts



$p = \text{trenchFrontOfAgent}$   
 $g = \text{AtGoal}$

$\beta$  counts



# Learning Results

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## Average # Bellman Updates Per Converged Policy



# Current Work

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- Extending predicates to logical expressions
- Clustering problem types
- Incorporating perception
- Pragmatic natural language extensions (e.g. “bridge”)
- Subgoal Planning
- Deploy on robots, other domains (cooking, javascript, Atari)

# In Summary

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- Proposed **Affordance-Aware Planning**
- Proposed complete learning framework for Affordances
- Demonstrated speedups in planning in large stochastic state spaces



# References

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