

Simultaneously Learning Transferable Symbols and Language Groundings from Perceptual Data for Instruction Following

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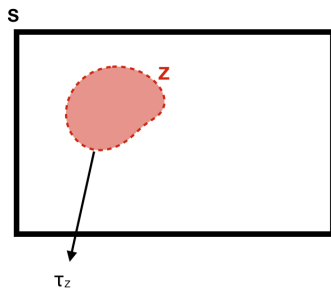
Introduction

- Problem: translate natural language to actions (policies).
- Option 1: end-to-end learning, language \rightarrow actions.
 - Data intensive
- Option 2: language \rightarrow pre-defined states.
 - Pre-defined states
- Option 3:
 - 1 Learn portable symbols as in James et al. [2]
 - 2 Map language to symbols with Seq2seq [3]

Symbols

Definition

A propositional symbol σ_Z is the name associated with a test τ_Z , and the corresponding set of states $Z = \{s \in S \mid \tau_Z(s) = 1\}$.



Symbols

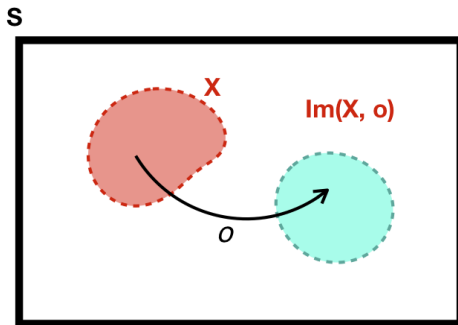


Figure: “Image” of option o from a set of states X .

Options framework

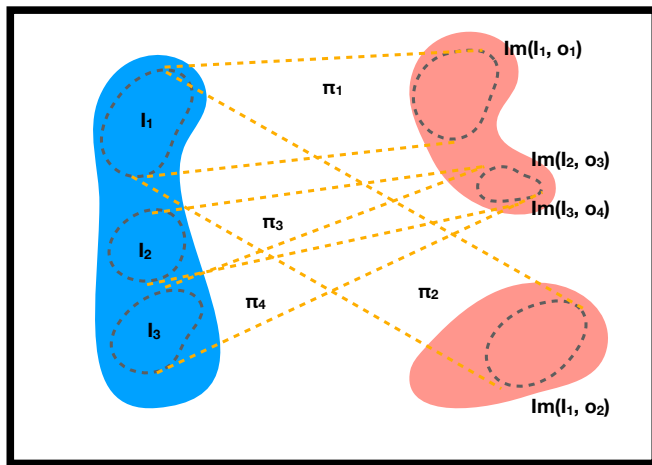


Figure: Example of options framework.

Problem with Environment Specific State Space



Figure: We cannot use the symbol learned in the left environment for the right environment. Reprinted from [2].

Symbolic Representations in Egocentric Space

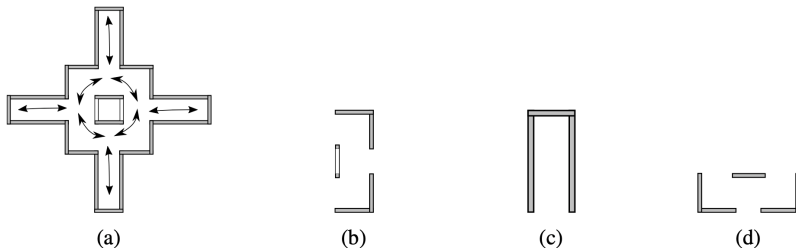


Figure: (a) Possible actions are shown with arrows. (b-d) Local egocentric observations. Reprinted from [2].

Symbolic Representations in Egocentric Space

Option	Precondition	Effect
Clockwise1	wall-junction	window-junction
Clockwise2	window-junction	wall-junction
Anticlockwise1	wall-junction	window-junction
Anticlockwise2	window-junction	wall-junction
Outward	wall-junction \vee window-junction	dead-end
Inward	dead-end	$\begin{cases} \text{window-junction w.p. 0.5} \\ \text{wall-junction w.p. 0.5} \end{cases}$

Figure: Subgoal options learned in egocentric space. Reprinted from [2].

Transferring Egocentric Symbols

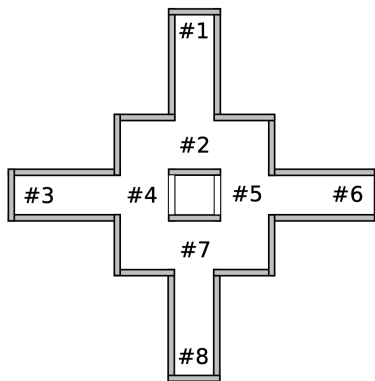


Figure: Environment-specific states are clustered. Reprinted from [2].

Portable symbol learning pipeline

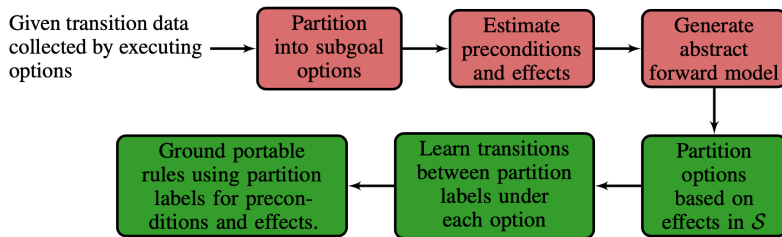
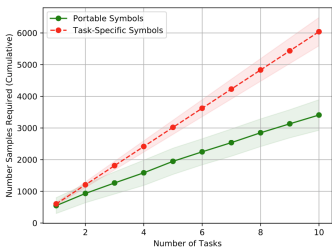
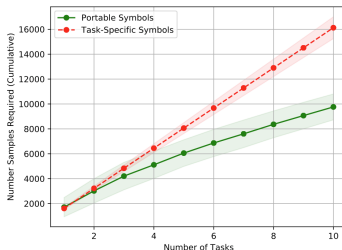


Figure: General pipeline for learning portable representations. Reprinted from [2].



(a) Results for the *Rod-and-Block* domain.



(b) Results for the *Treasure Game* domain.

Figure: The usage of egocentric state space reduces the necessary sample size. Reprinted from [2].

Method

- $\tau_j = \{(s_0, a_0), (s_1, a_1), \dots, (s_T, a_T)\}$ and $l_j = \text{"go straight and turn left"}$
- Cluster a_i with HDP-HMM.

Skill segmentation

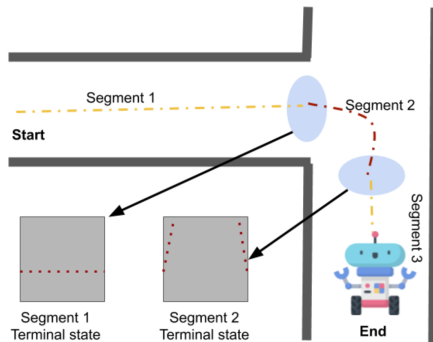


Figure: Reprinted from [1].

Seq2seq translation

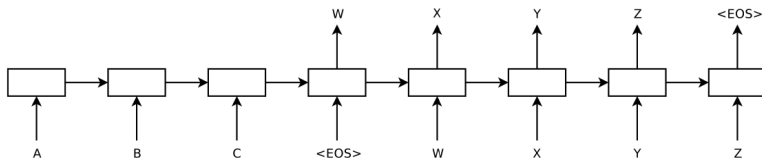


Figure: Reprinted from [3].

Method pipeline

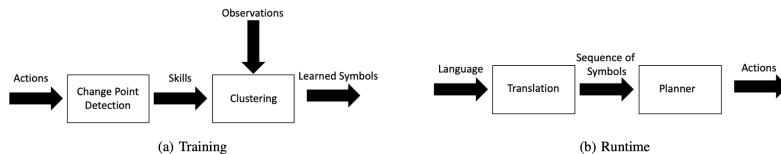


Figure: Reprinted from [1].

Data



Figure: The NPS Neighborhood dataset (left) [4], the Movo mobile manipulator (right) [1].

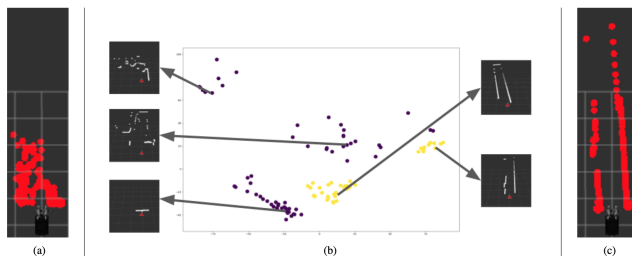


Figure: Reprinted from [1].

- No planning is done for this domain, only language translation.
- Translation exact match accuracy: 96.51 ± 0.46 .
- There are 3 output symbols with maximum sequence length of 2 (random guess probability: $\frac{1}{3^2} = 12.5$).

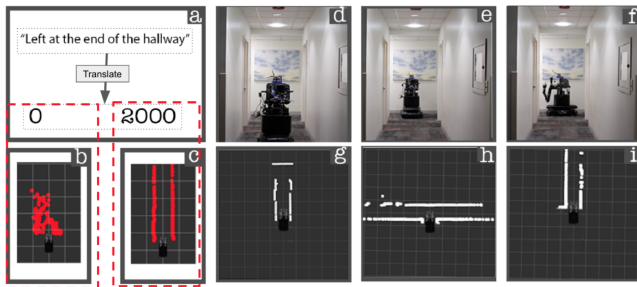


Figure: Reprinted from [1].

- Translation exact match accuracy: 75.71 ± 0.37 .
- There are 5 output symbols with maximum sequence length of 3 (random guess probability: $\frac{1}{5^3} = 0.41$).

- [1] Nakul Gopalan, Eric Rosen, George Konidaris, and Stefanie Tellex. Simultaneously learning transferable symbols and language groundings from perceptual data for instruction following. *Robotics: Science and Systems XVI*, 2020.
- [2] Steven James, Benjamin Rosman, and George Konidaris. Learning portable representations for high-level planning. *arXiv preprint arXiv:1905.12006*, 2019.
- [3] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112, 2014.
- [4] Andrew K Watson. Automated creation of labeled pointcloud datasets in support of machine-learning based perception. Technical report, Naval Postgraduate School Monterey United States, 2017.