Learning Symbols and Abstractions in Robot Planning

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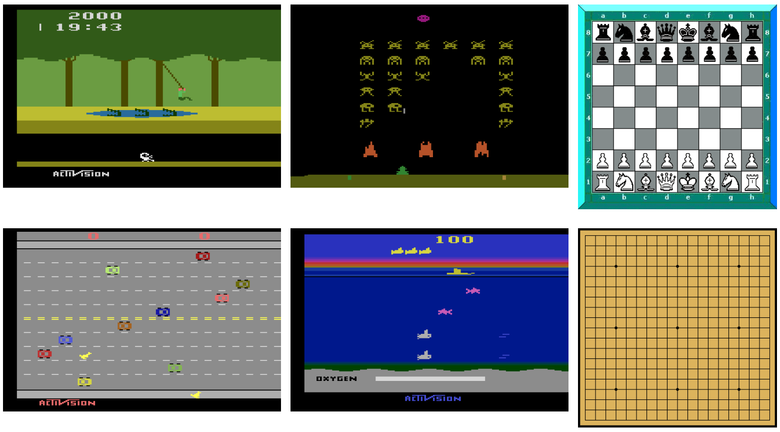
Contents

Abstract Concepts [Slide 1]

- Abstract concepts organize the world in a *small parameter space*, intrinsically generalizing and simplifying learning and reasoning.

- We parse visual scenes into *structure* in terms of generally-useful concepts (elements, relations, ...).
- We *reason* about structure in abstract ways.

Game Play [Slide 2]



[Chess by MG and Go by Katpatuka, CC BY-SA 3.0; Atari from Bellemare et al. 2013]

ML systems require a lot of training data and generalize poorly.

Humans apply real-world concepts in the game worlds.

Technical Problem-Solving Skills [Slide 3]

[Photo by Greg Rosenke on Unsplash]

How to learn to adjust a bicycle dérailleur?

- Randomly playing with screws won't generalize to other dérailleurs.
- Learn about the structure and function of the ***mechanism***?

  Current ML methods are unable to discover such mechanisms.

Knowledge of such a mechanism allows you to solve many other tasks as well!

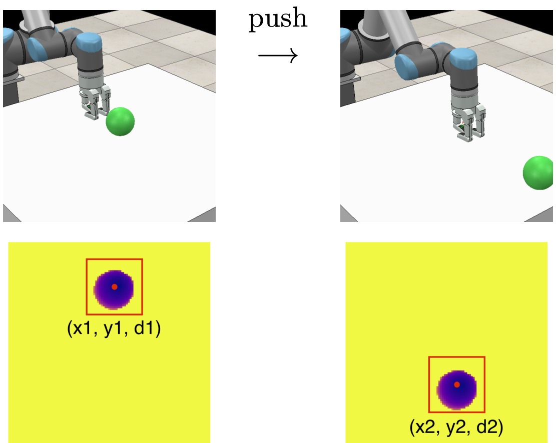
1 Learn how the world behaves

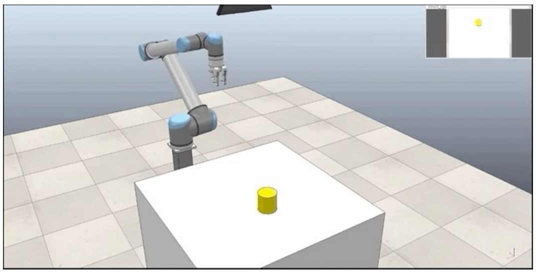
DeepSym: Deep Symbol Generation and Rule Learning for Planning [Ahmetoglu et al. 2022]

Joint work with Boğaziçi Üniversitesi, Istanbul

(I) Interaction With Objects Using Predefined Actions [Slide 4]

- Input: depth image
- Actions: push-front, push-left, push-top
- Effect: $(\Delta x, \Delta y, \Delta d, \Delta F)$
- Objects: sphere, cube, upright cylinder, sideways cylinder, cup

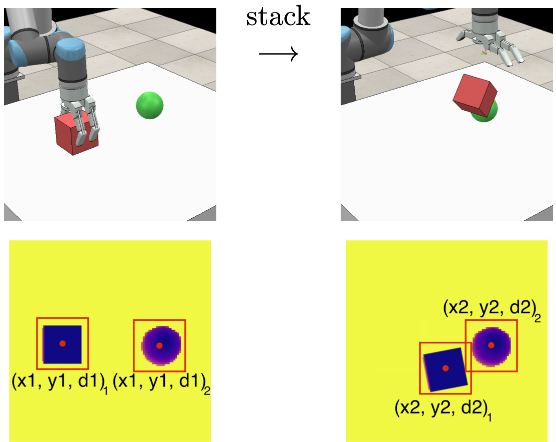


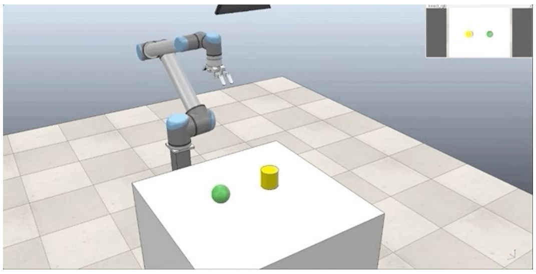


[Ahmetoglu et al. 2022]

(I) Interaction With Objects Using Predefined Actions [Slide 5]

- Input: depth image
- Action: stack
- Effect: $(\Delta x, \Delta y, \Delta d)_1, (\Delta x, \Delta y, \Delta d)_2$
- Objects: sphere, cube, upright cylinder, sideways cylinder, cup

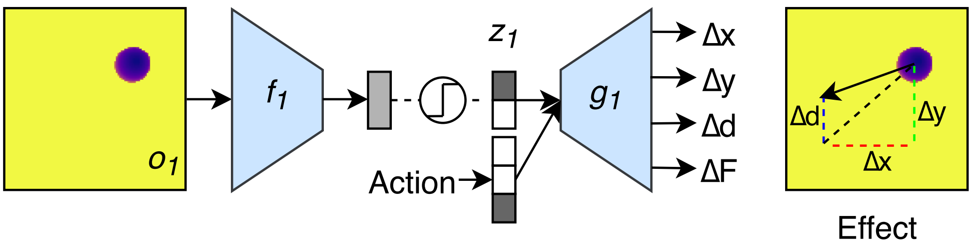




[Ahmetoglu et al. 2022]

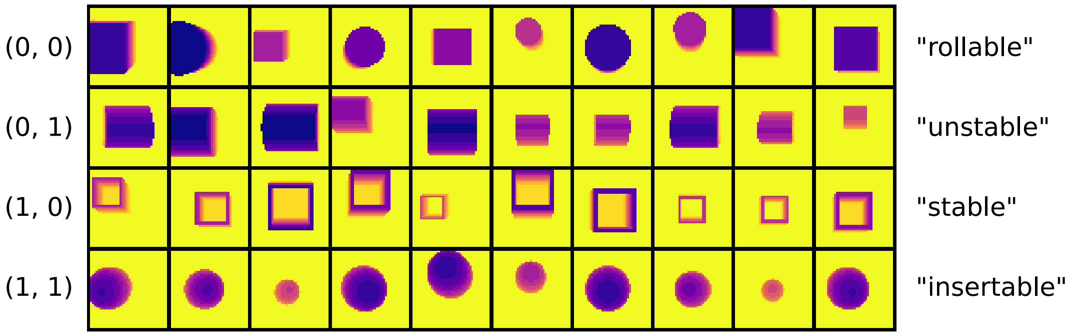
(II) Symbol Formation: Single Objects [Slide 6]

- deep encoder-decoder neural network
- Input: depth image
- Output: predicted action effect
- Gumbel softmax as binary hidden units for learning a discrete latent space via backprop
- latent layer combines info from observation, action, and effect



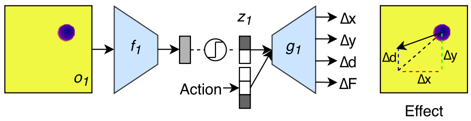
(II) Symbol Formation: Example [Slide 7]

- Object categories found with two binary units
- Unsupervised; only based on observed effects



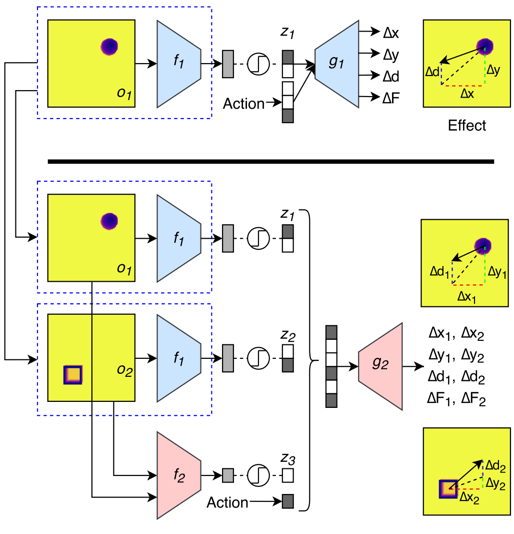
(II) Symbol Formation: Pairs of Objects [Slide 8]

- Symbols are discovered from actions on single objects.
- Freeze the trained encoder.

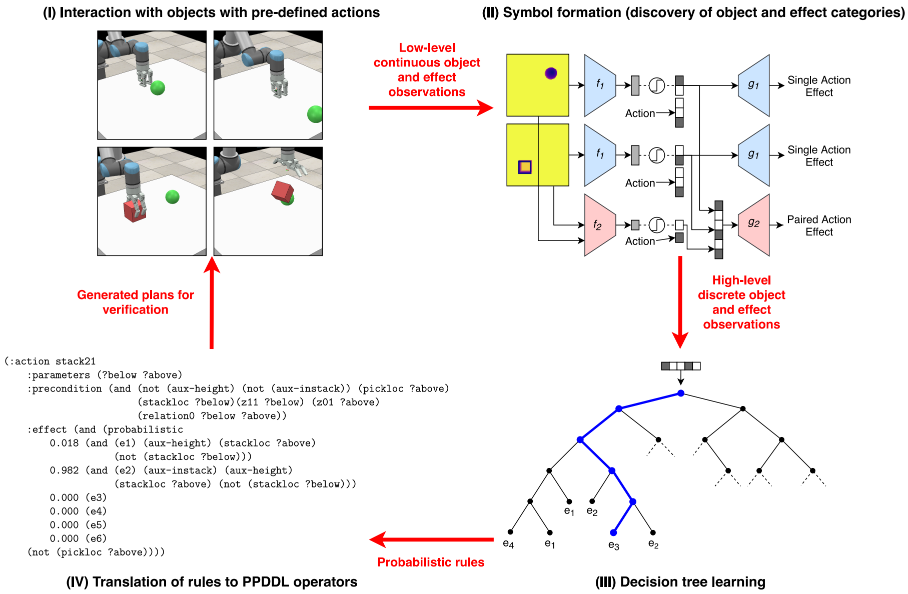


(II) Symbol Formation: Pairs of Objects [Slide 9]

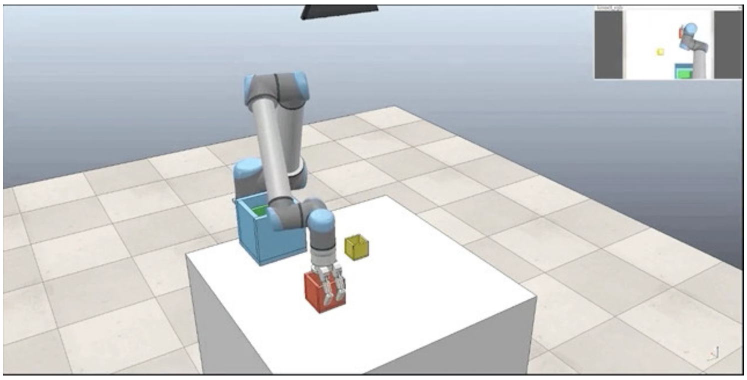
- Symbols are discovered from actions on single objects.
- Freeze the trained encoder.
- One more encoder for paired-object categories.
- Concatenate single-object and object-pair (action) vectors.
- Predict the effect.



[Slide 10]

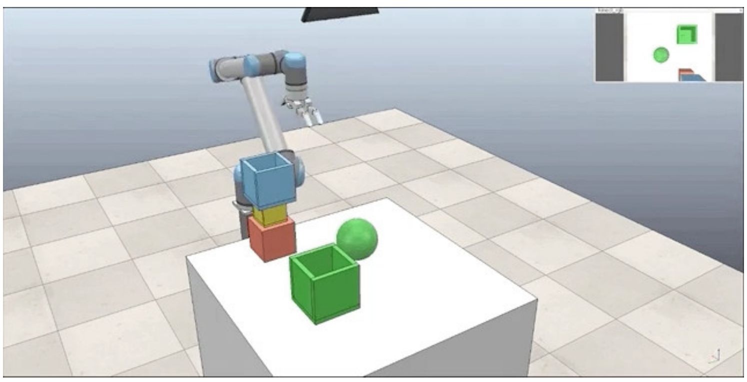


Build a Tower of Height 1! [Slide 11]



[Ahmetoglu et al. 2022]

Build a Tower of Height 5! [Slide 12]



[Ahmetoglu et al. 2022]

2 References

References [Slide 13]

Ahmetoglu, Alper, M. Seker, Justus Piater, Erhan Oztop, and Emre Ugur (Nov. 2022). "DeepSym: Deep Symbol Generation and Rule Learning for Planning from Unsupervised Robot Interaction." In: *Journal of Artificial Intelligence Research* 75, pp. 709–745. DOI: 10.1613/jair.1.13754. URL: https://jair.org/index.php/jair/article/view/13754/26858.

Bellemare, M., Y. Naddaf, J. Veness, and M. Bowling (June 2013). "The Arcade Learning Environment: An Evaluation Platform for General Agents." In: *Journal of Artificial Intelligence Research* 47, pp. 253–279. DOI: 10.1613/jair.3912. URL: http://doi.org/10.1613/jair.3912.