Language as an Abstraction for Hierarchical Deep Reinforcement Learning

Paper Authors: Yiding Jiang, Shixiang Gu, Kevin Murphy, Chelsea Finn

Problem Overview

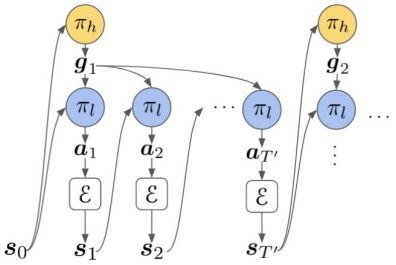
- Learning a variety of **compositional**, **long horizon** skills while being able to **generalize** to novel concepts remains an open challenge.

- Can we leverage the compositional and generalizable structure of **language** as an abstraction for goals to help decompose problems?

Learning Sub-Goals

Hierarchical Reinforcement Learning:

- High-level policy: $\pi_h(g \mid s)$
- Low-level policy: $\pi_l(a \mid s, g)$



Language as an abstraction for goals

Hierarchical Reinforcement Learning:

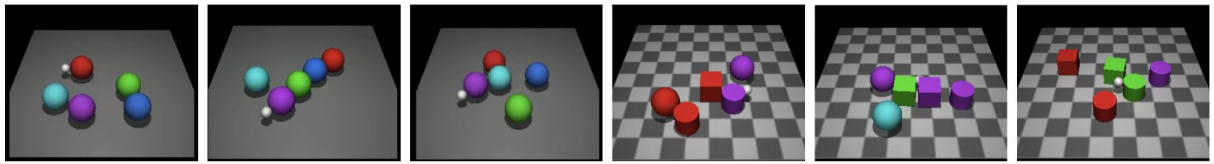
- High-level policy: $\pi_h(g \mid s)$
- Low-level policy: $\pi_l(a \mid s, g)$

What if g is an sentence in human language? Some motivations in paper:

1) High-level policies would generate interpretable goals
2) An instruction can represent a region of states that satisfy some abstract criteria
3) Sentences have a compositional and generalizable structure
4) Humans use language as an abstraction for reasoning, planning, and knowledge acquisition

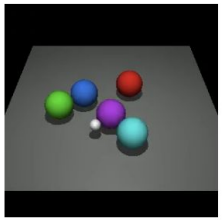
Concrete Examples Studied

High Level:



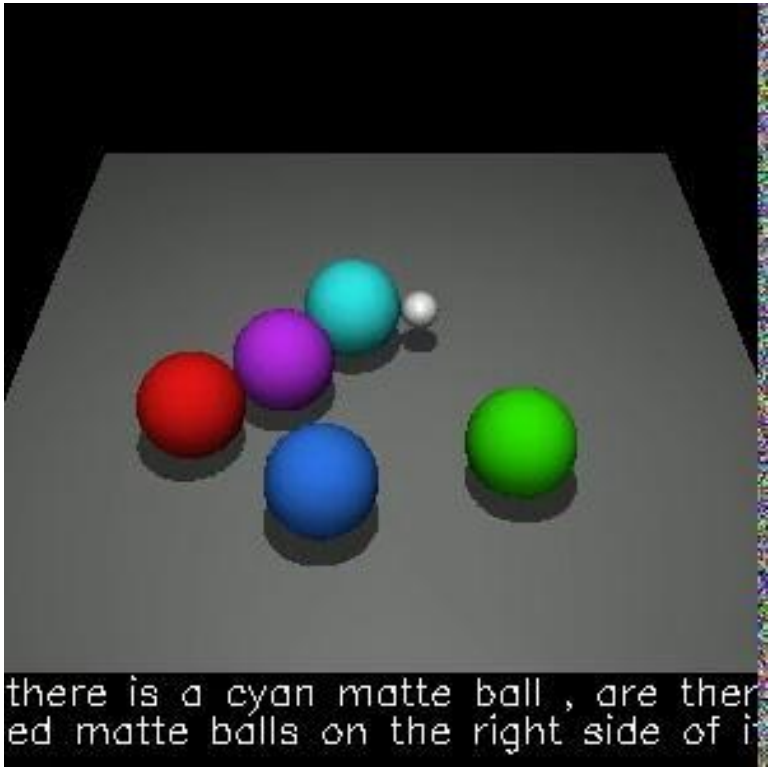
(a) Object arrangement | (b) Object ordering | (c) Object sorting | (d) Color ordering | (e) Shape ordering | (f) Color & shape ordering

Low level:



(a) Goal is g_0: "*There is a **red** ball; are there any matte **cyan** sphere **right** of it?*".

Environment



- New environment using MuJoCo physics engine and CLEVR language engine.
- Binary reward function, only if all the constraints are met
- State-based observation:

$$\boldsymbol{s} \in \mathbb{R}^{10} \qquad |\mathcal{A}| = 40$$

- Image-based observation:

$$\boldsymbol{s} \in \mathbb{R}^{64\times64\times3} \qquad |\mathcal{A}| = 800$$

Methods

Low-Level Policy

$$\pi_l(a|g, s_t)$$

Language to state mapping

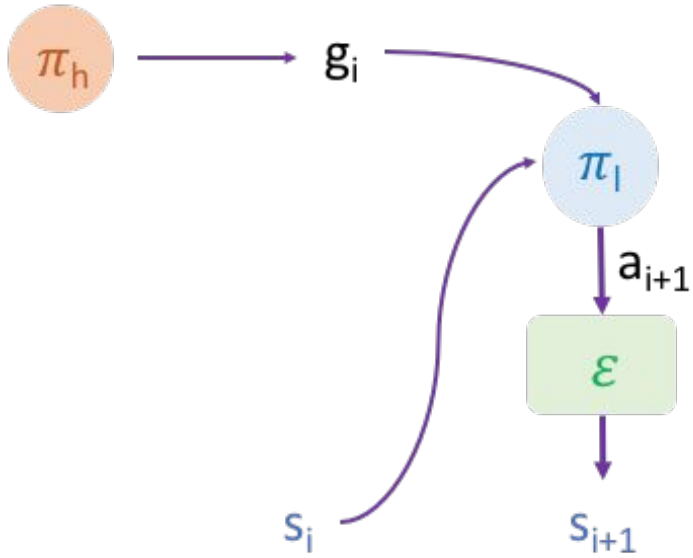
$$\omega(g|s) \rightarrow \Omega(s) = \{g \mid \omega(g|s) > 0\}$$

Checking if a state satisfies an instruction

$$\Psi : \mathcal{S} \times \mathcal{G} \rightarrow \{0, 1\}$$

Trained on sampled language instructions

$$\boldsymbol{g} \sim \mathcal{U}(\{\boldsymbol{g} \in \Omega(\boldsymbol{s}_{t+1}) \mid \Psi(\boldsymbol{s}_{t+1}, \boldsymbol{g}) = 0\})$$



Low-Level Policy

$$\pi_l(a|g, s_t)$$

Reward Function

$$R(s_t, a_t, s_{t+1}, g) = \begin{cases} 0 & \text{if } \Psi(s_{t+1}, g) = 0 \\ \Psi(s_{t+1}, g) \oplus \Psi(s_t, g) & \text{if } \Psi(s_{t+1}, g) = 1 \end{cases}$$

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Can be very **sparse** → **Hindsight Instruction Relabeling (HIR)**

- Similar to Hindsight Experience Replay (HER)
- HIR is used to relabel the goal with an instruction that was satisfied.
- Enable the agent to learn from many different language goals at once

High-Level Policy

- Double Q-Learning Network [1]
- Reward given only if all constraints were satisfied from the environment
- Instructions (goals) are pick, not generated.
- Uses extracted visual features from the low-level policy and then extract salient spatial points with spatial softmax. [2]

[1] Hado van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning, 2015.

[2] Sergey Levine, Chelsea Finn, Trevor Darrell, and Pieter Abbeel. End-to-end training of deep visuomotor policies. *The Journal of Machine Learning Research*, 17(1):1334–1373, 2016.

Experiments

Experimentation Goals

- **Compositionality:** How does language compare with alternative representations?
- **Scalability:** How well does this framework scale?
  - With **instruction diversity**
  - With **state dimensionality**
- **Policy Generalization:** Can the policy systematically generalize by leveraging the structure of language?
- **Overall,** how does this approach compare to state-of-the-art hierarchical RL approaches?

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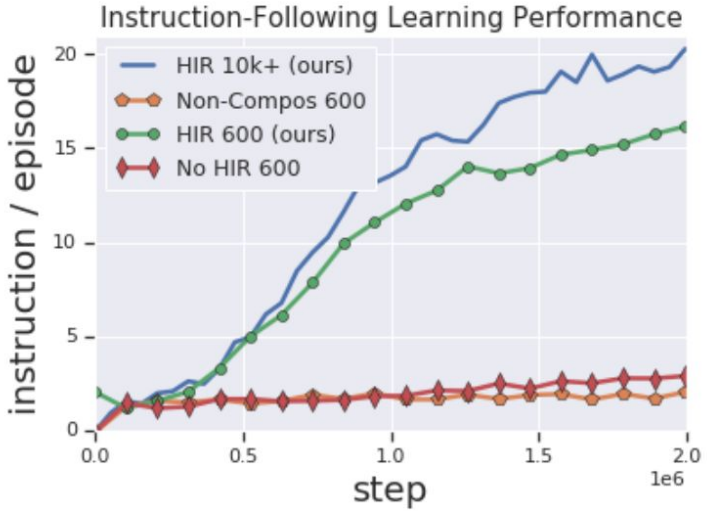
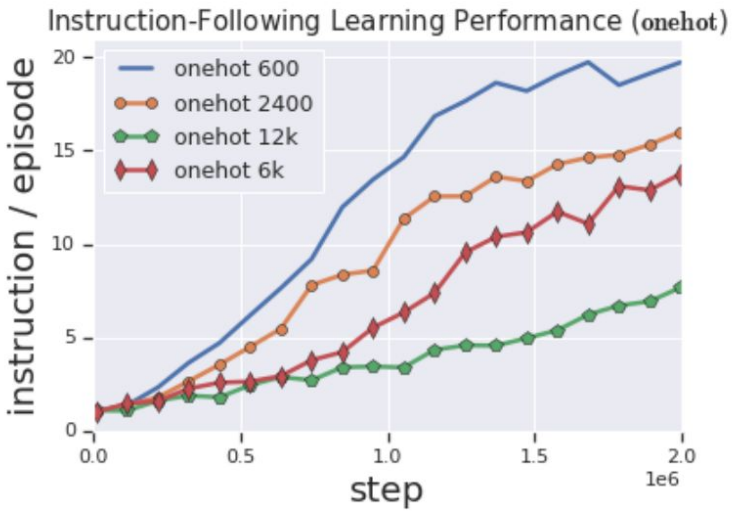
Compositionality: How does language compare to alternative representations?

- One-hot instruction encoding
- Non-compositional Representation: loss-less autoencoder for instructions.





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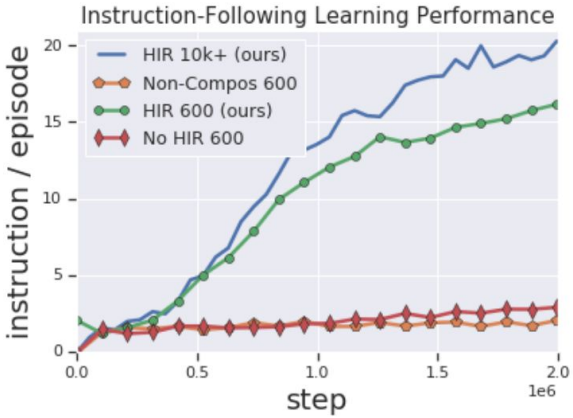

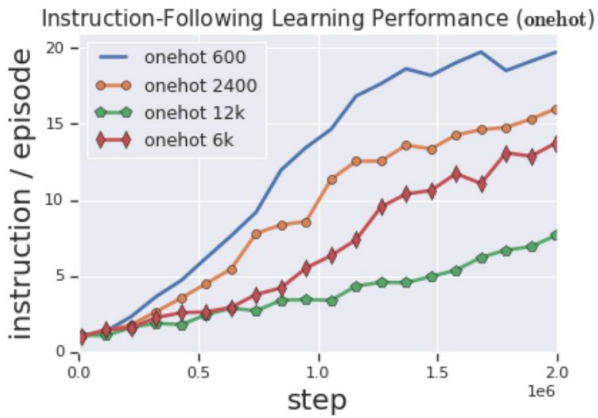

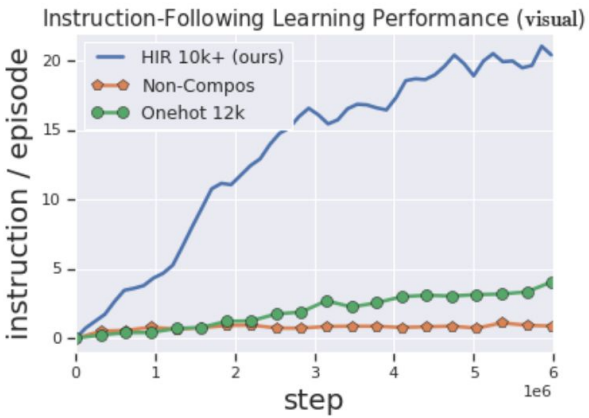

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Policy Generalization: Can the policy systematically generalize by leveraging the structure of language?

	Standard train	Standard test	Standard gap	Systematic train	Systematic test	Systematic gap
Language	**21.50 ± 2.28**	**21.49 ± 2.53**	**0.001**	**20.09 ± 2.46**	**8.13 ± 2.34**	**0.596**
Non-Compos	6.26 ± 1.18	5.78 ± 1.44	0.077	7.54 ± 1.14	0.76 ± 0.69	0.899
Random	0.17 ± 0.20	0.21 ± 0.17	-	0.11 ± 0.19	0.18 ± 0.22	-

Random: 70/30 random split of the instruction set.

Systematic: Training set doesn't include "red" in the first half of instructions, and Test set is the complement. => **Zero-shot Adaptation**

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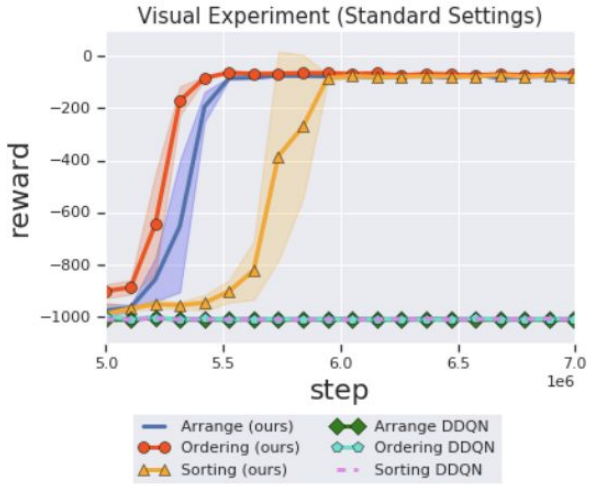
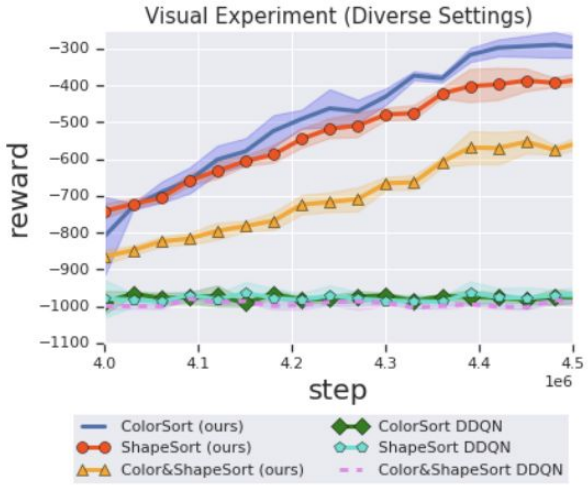
High-Level Policy Experiments

DDQN: non-hierarchical

HIRO and OC: hierarchical, non-language based

High Level Policy Experiments (Visual)





Takeaways

- Strengths:
  - High-level policies are human-interpretable
  - Low-level policy can be re-used for different high-level objectives
  - Language abstractions generalized over a region of goal states, instead just an individual goal state
  - Generalization to high dimensional instruction sets and action spaces
- Weakness:
  - Low-level policy depends on the performance of another system for its reward
  - HIR is dependent on the performance of another system for its new goal label
  - The instruction set is domain-specific
  - The number of subtasks are fixed

Future Work

- Instead of picking instructions, generate them
- Dynamic or/and learned number of substeps
  - Curriculum learning by decreasing the number of substeps as the policies are training
  - Study how does the parameter effects the overall performance of the model
- Finetune policies to each other, instead just training them separately
- Concern about practicality: for any problem need both a set of sub-level instructions and a language oracle which can validate their fulfilment
- Other ways to validate low-level reward

Potential Discussion Questions

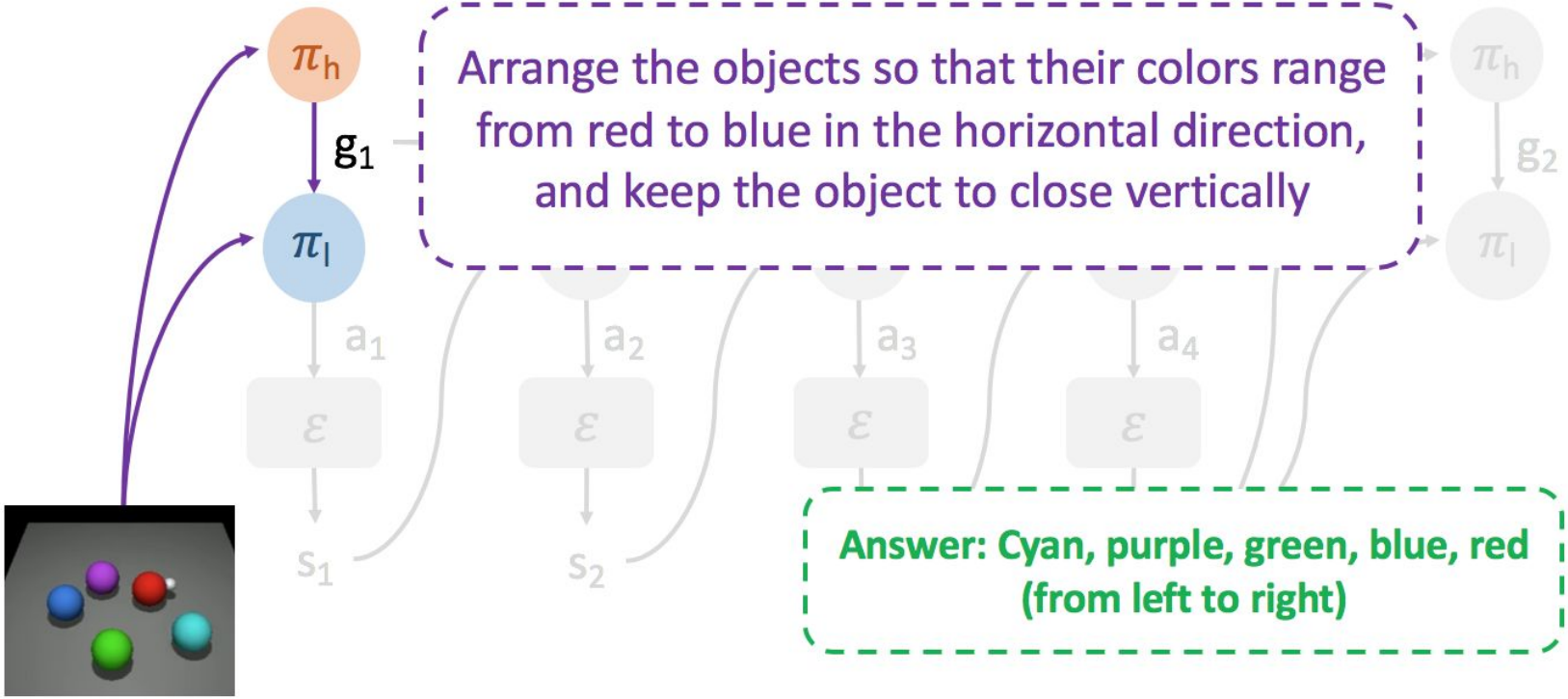
- Is it prideful to try to use language to try to impose language structure on these subgoals instead of looking for less human-motivated solutions?

- In two equally performing models, one with language interpretability seems inherently better due to interpretability. Does this make these types of abstractions likely for the future?

- Can you think of any other situations in which this hierarchical model could be implemented? Would language always be appropriate?

Appendix

Overall Approach: Object Ordering



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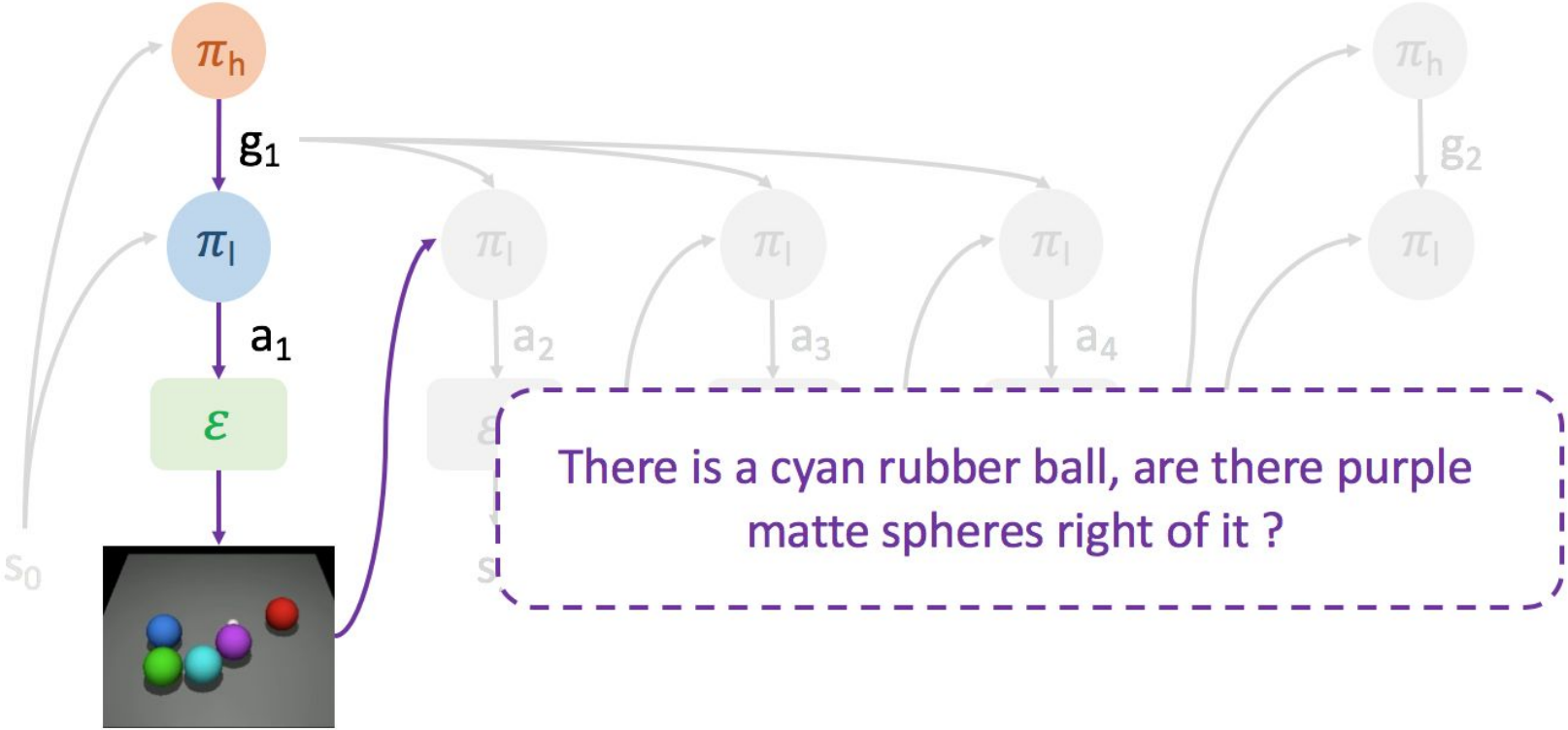

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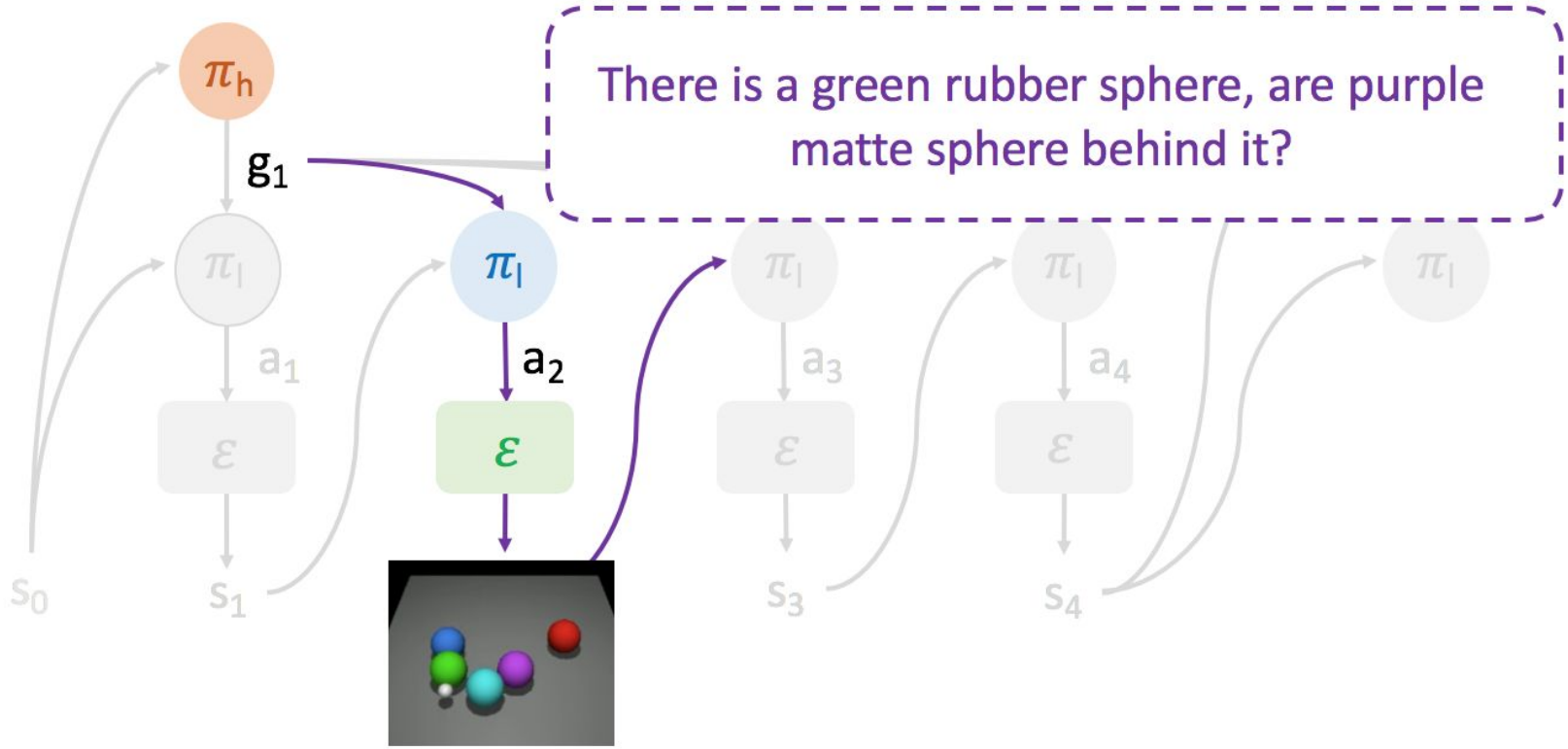

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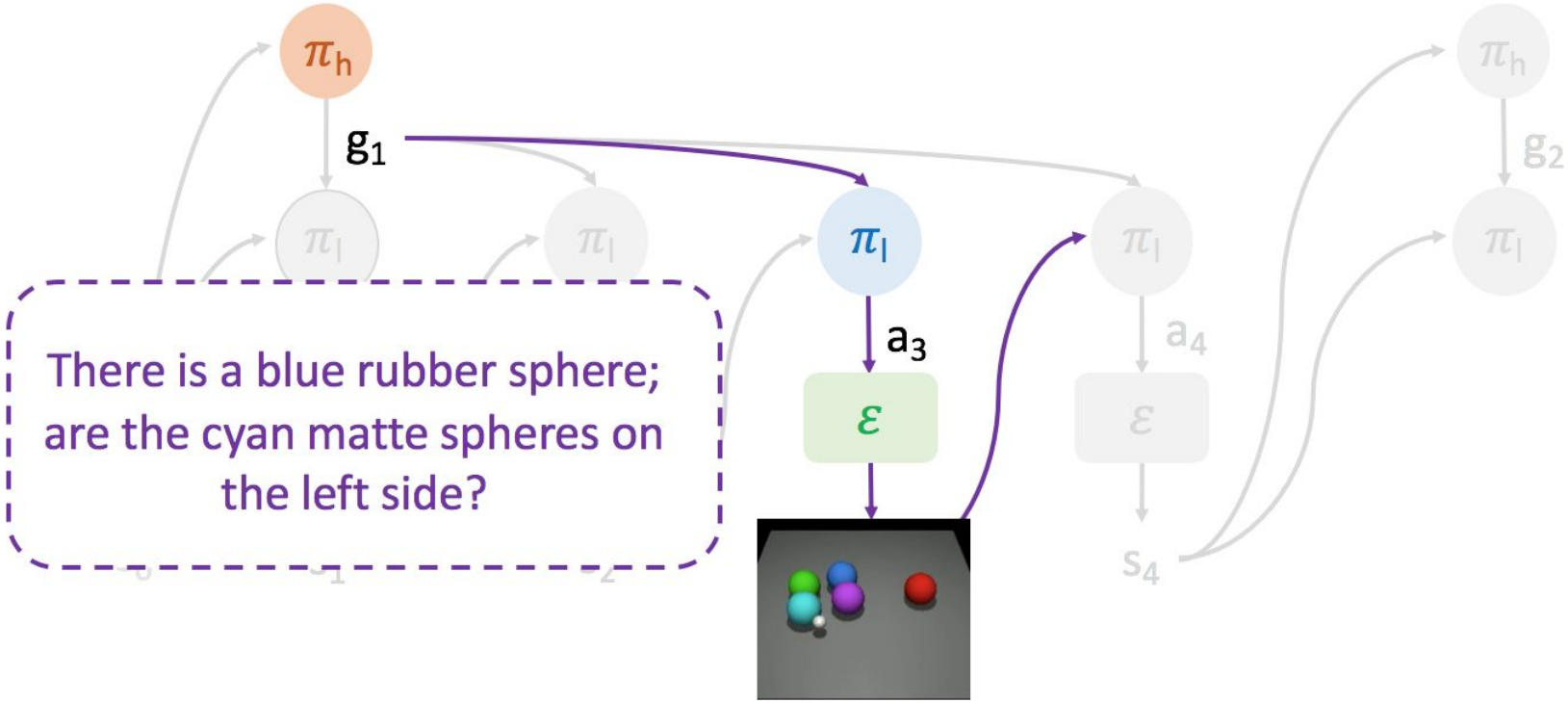

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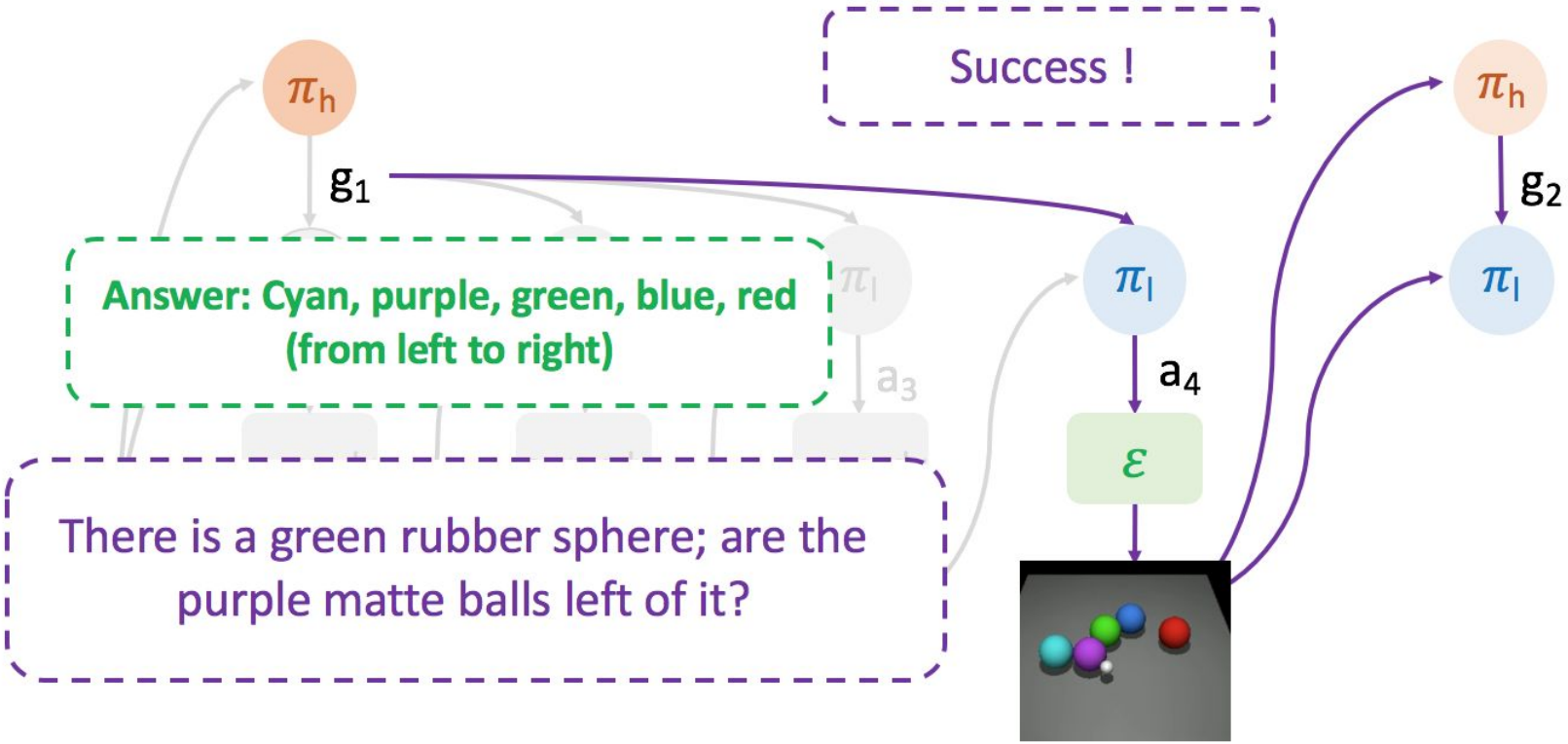
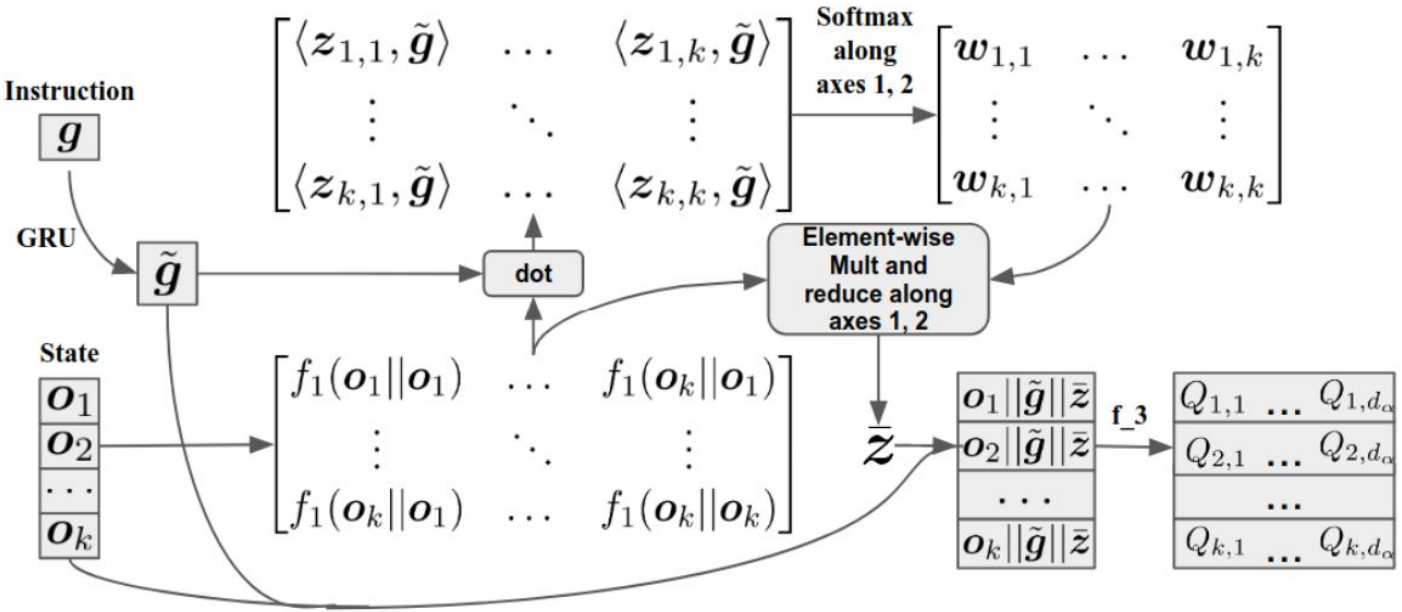


State-based Low-Level Policy



Vision-based Low-Level Policy