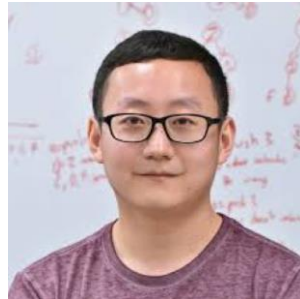


Discovering Generalizable Spatial Goal Representations via Graph-based Active Reward Learning



Aviv Netanyahu*



Tianmin Shu*



Josh Tenenbaum

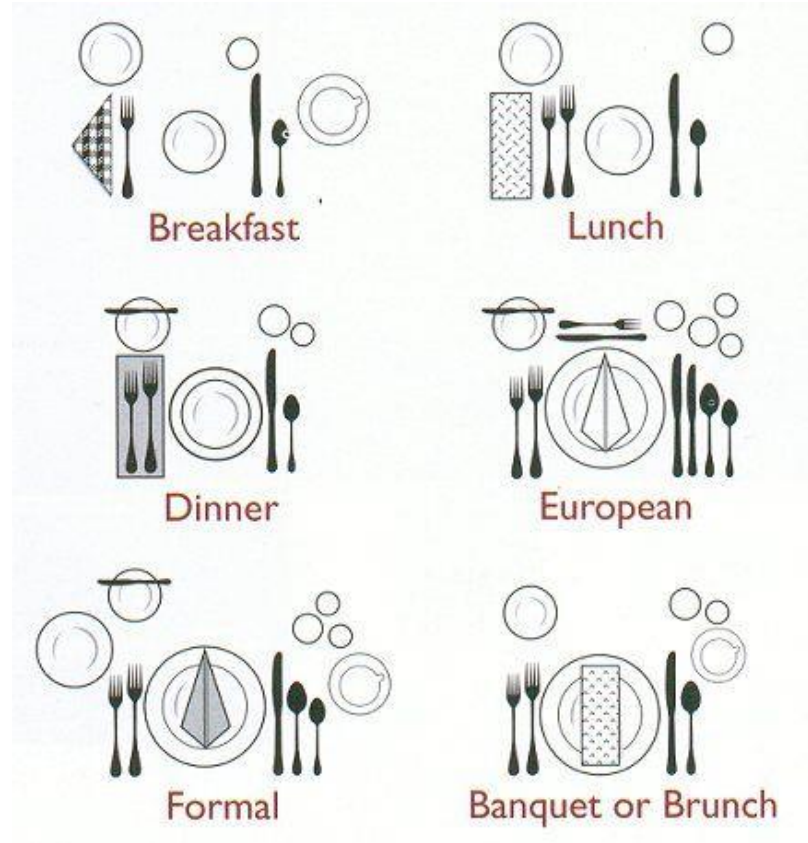


Pulkit Agrawal

Massachusetts Institute of Technology

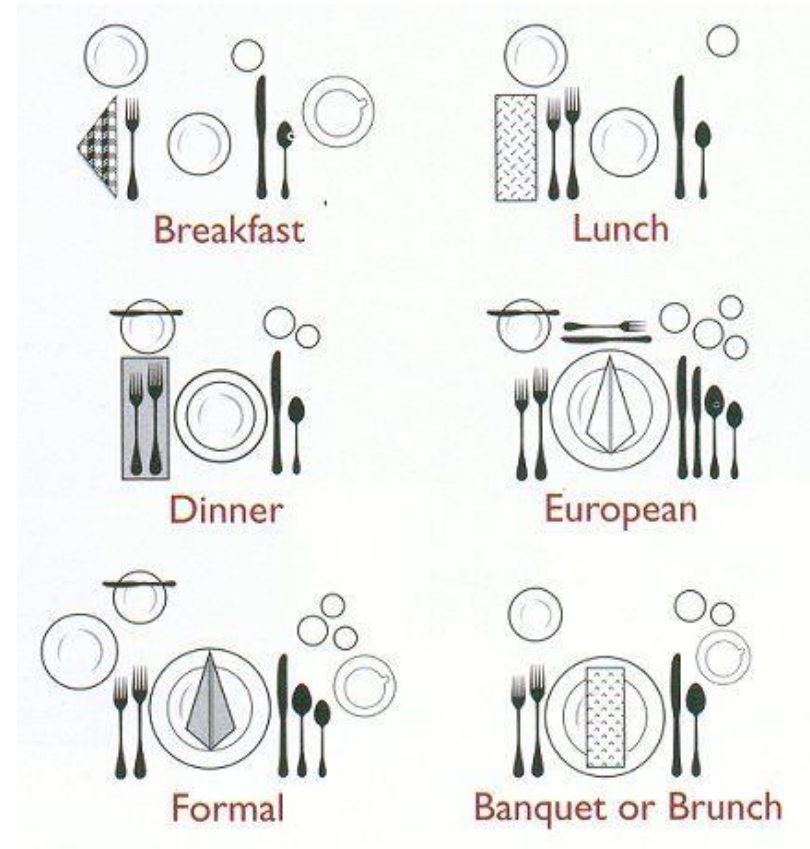
(* equal contribution)

AI assistants need to adapt to *any* task



AI assistants need to adapt to *any* task

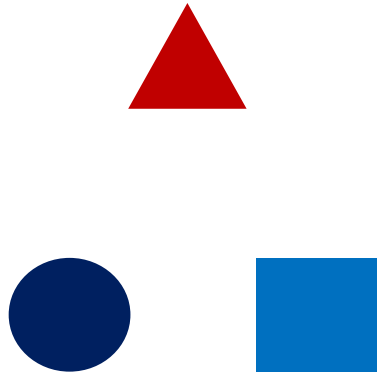
Key: Learn the goal specification for any new task



This work

Spatial goals for object rearrangement tasks

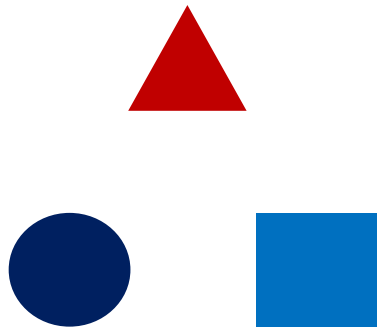
A Expert Demonstration



This work

Spatial goals for object rearrangement tasks

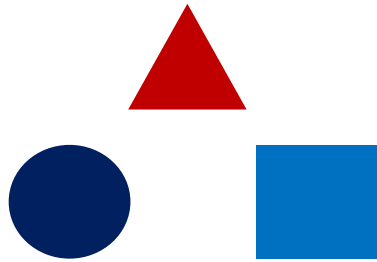
A Expert Demonstration



This work

Spatial goals for object rearrangement tasks

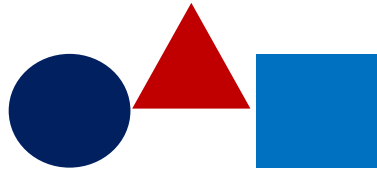
A Expert Demonstration



This work

Spatial goals for object rearrangement tasks

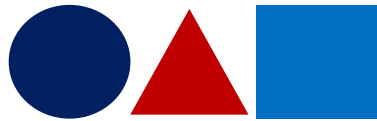
A Expert Demonstration



This work

Spatial goals for object rearrangement tasks

A Expert Demonstration

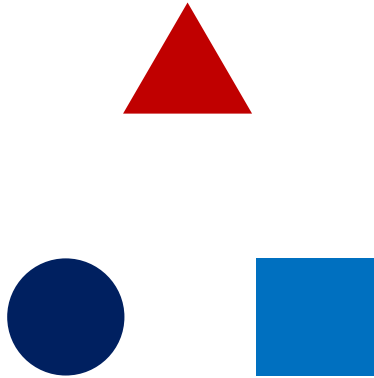


This work

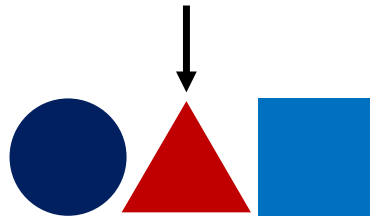
Spatial goals for object rearrangement tasks

A Expert Demonstration

Initial state



Final state

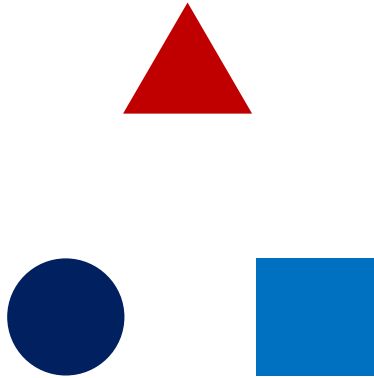


This work

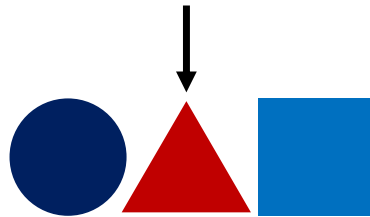
Spatial goals for object rearrangement tasks

A Expert Demonstration

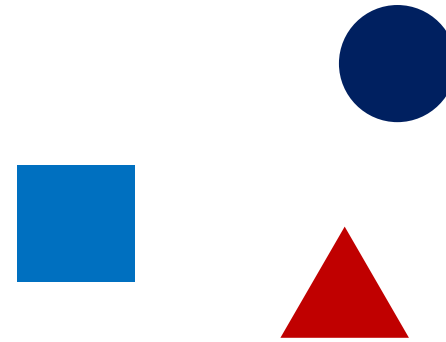
Initial state



Final state



B Testing Environment

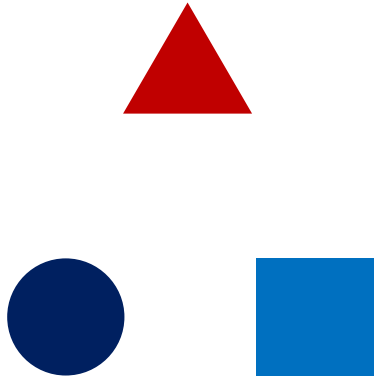


This work

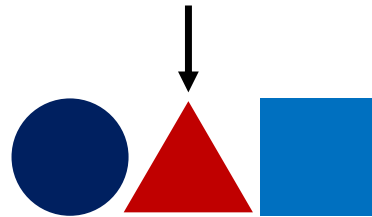
Spatial goals for object rearrangement tasks

A Expert Demonstration

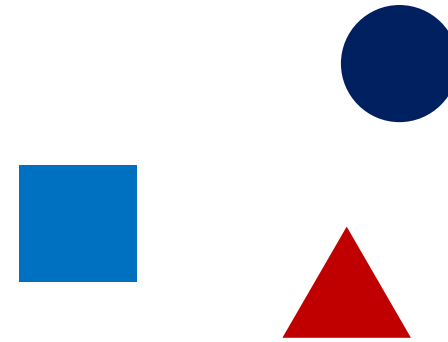
Initial state



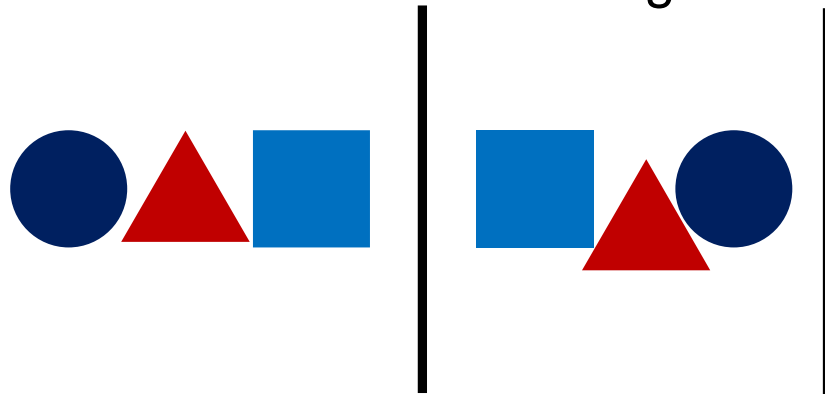
Final state



B Testing Environment



C Final states in the testing environment based on different interpretations

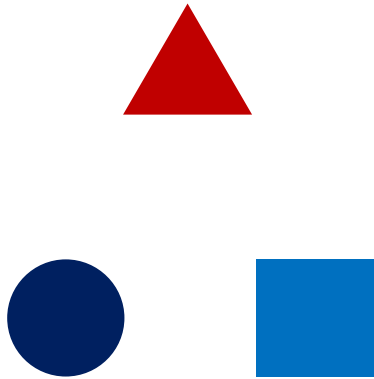


This work

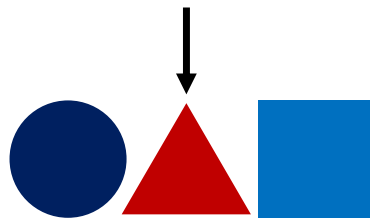
Spatial goals for object rearrangement tasks

A Expert Demonstration

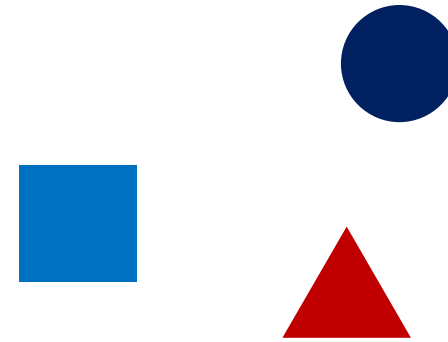
Initial state



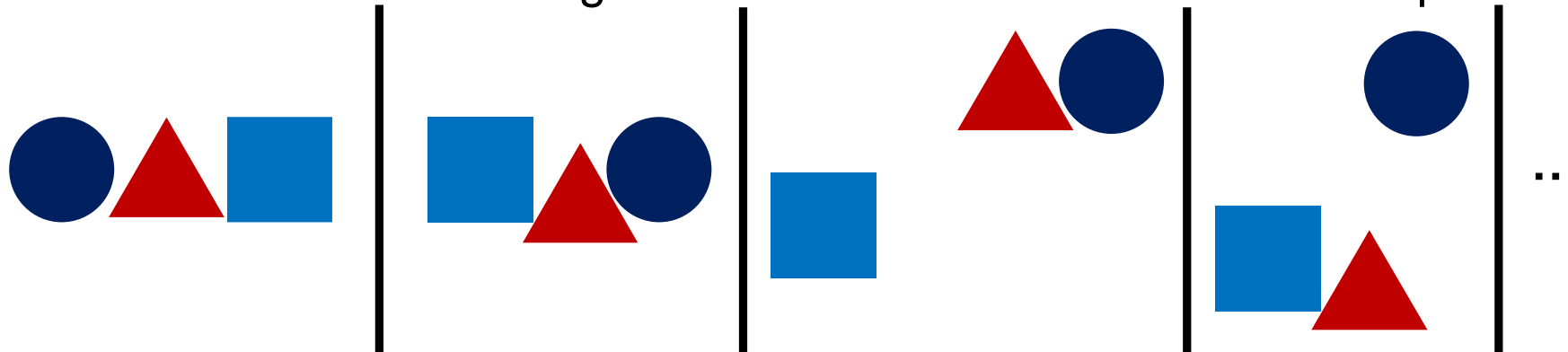
Final state



B Testing Environment

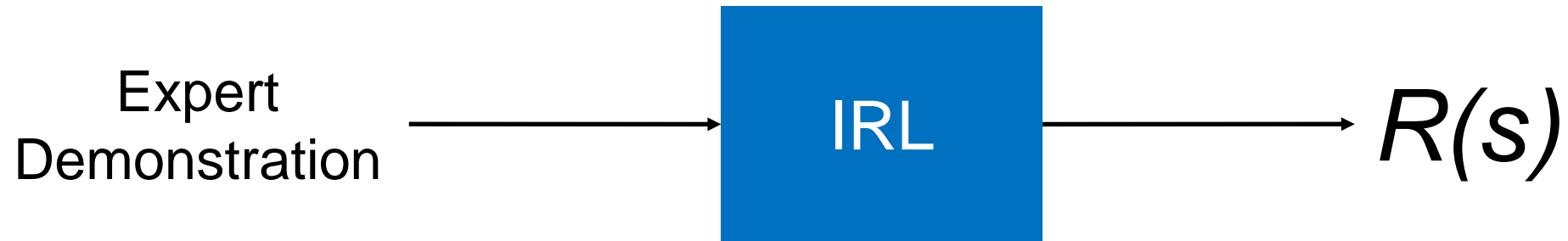
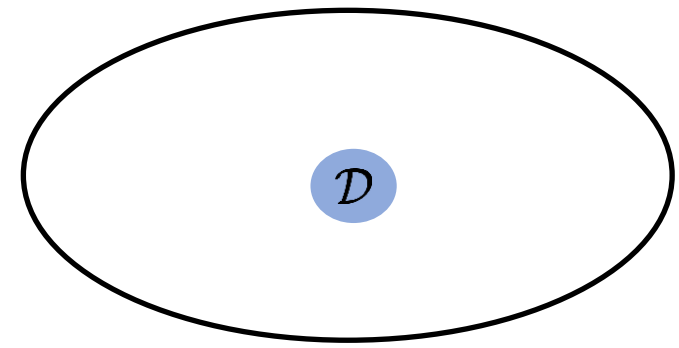


C Final states in the testing environment based on different interpretations



Prior work

Inverse Reinforcement Learning (IRL)

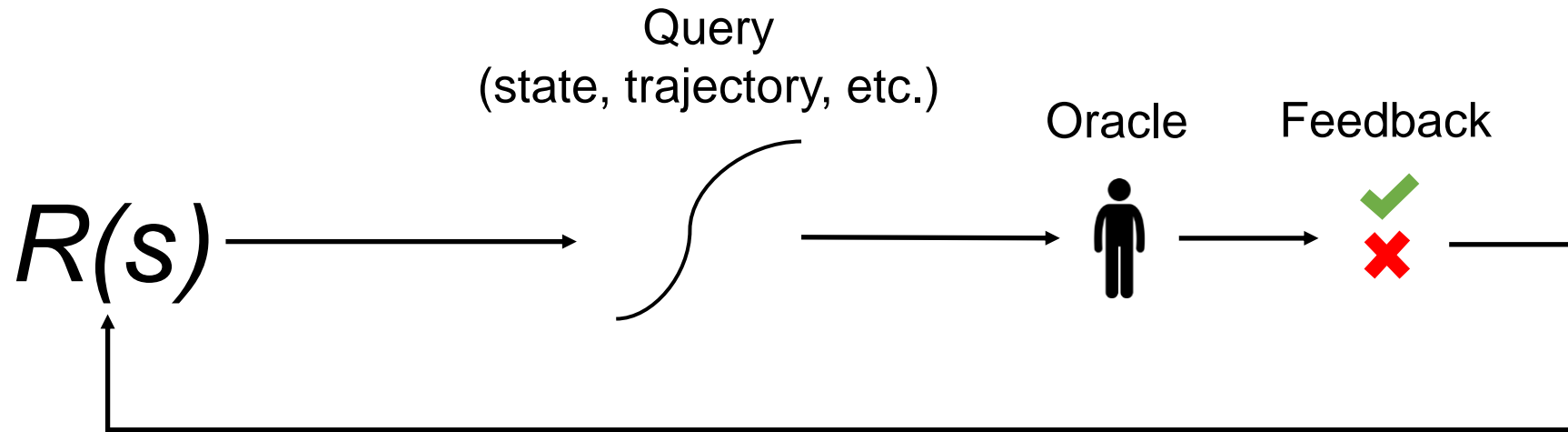
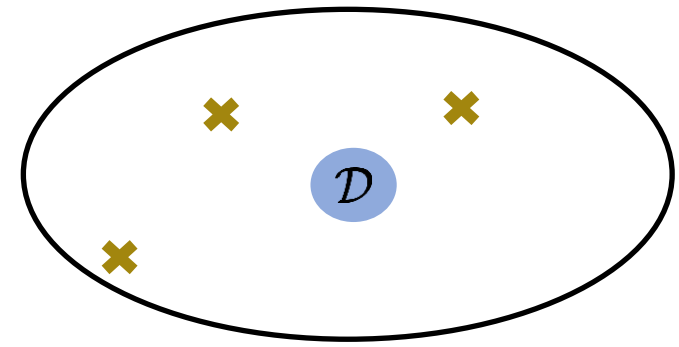


Learn $R(s)$ from demos

Approximates the rewards for states **in the demo**

Prior work

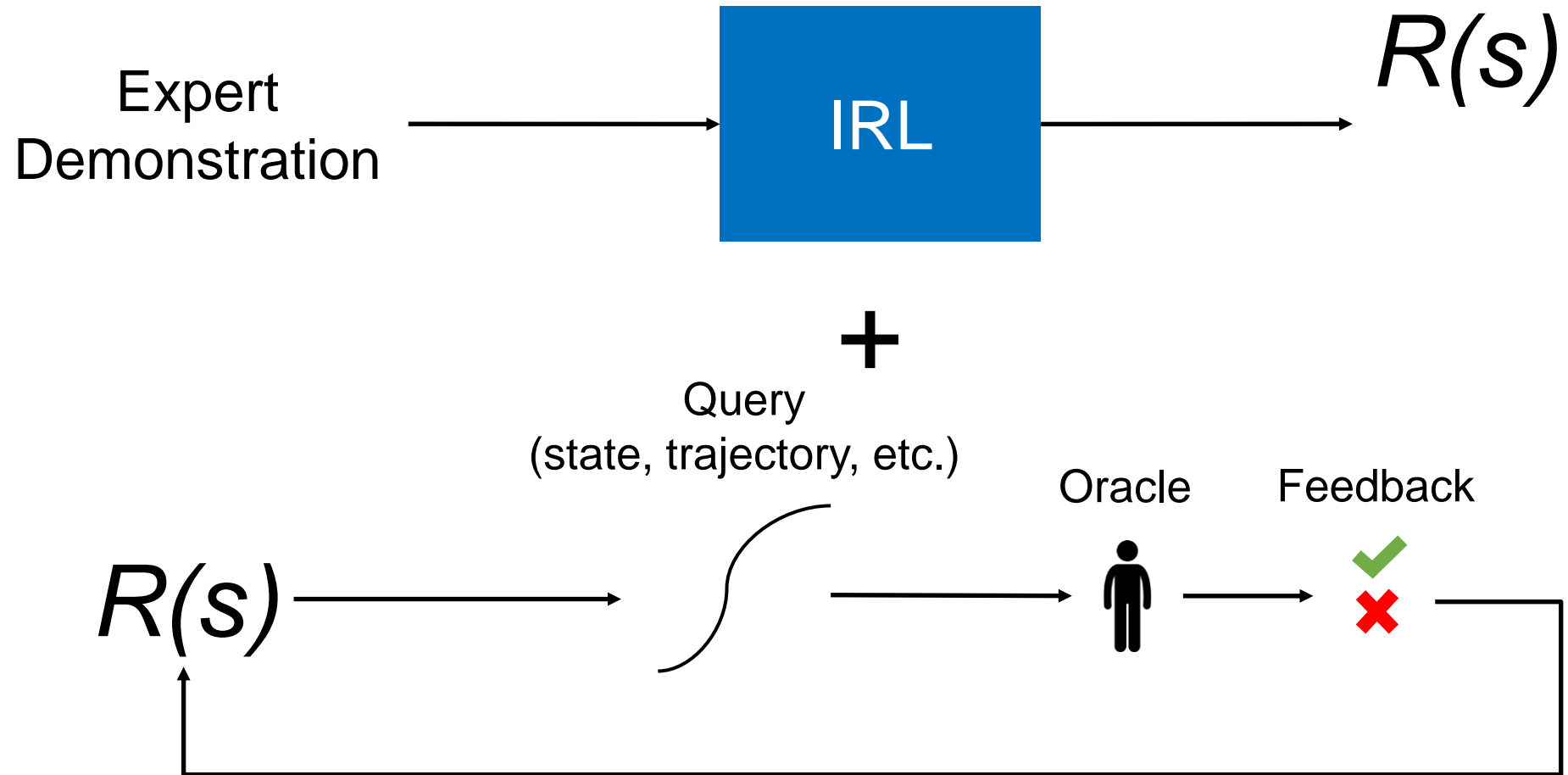
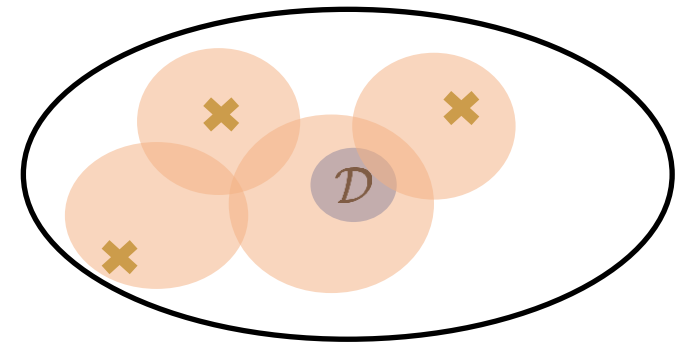
Active reward learning



Collect additional training data from oracle feedback
Each query provides **one data point**

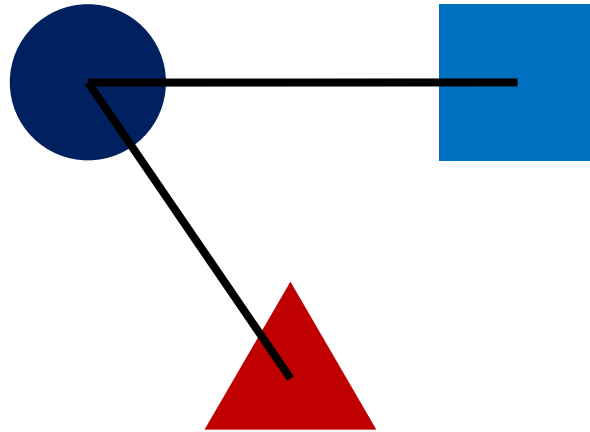
Our approach

Combine IRL and active reward learning



Graph-based rewards for spatial goals

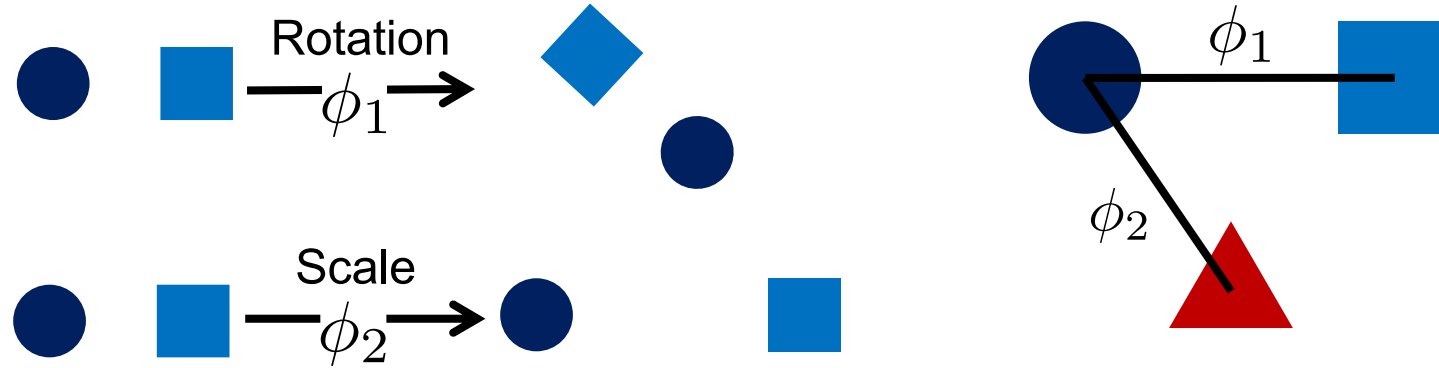
Graph structure: *which* relations?



$$R(\text{●}, \text{■}, \text{▲}, G) = r(\text{●}, \text{■}) + r(\text{●}, \text{▲})$$

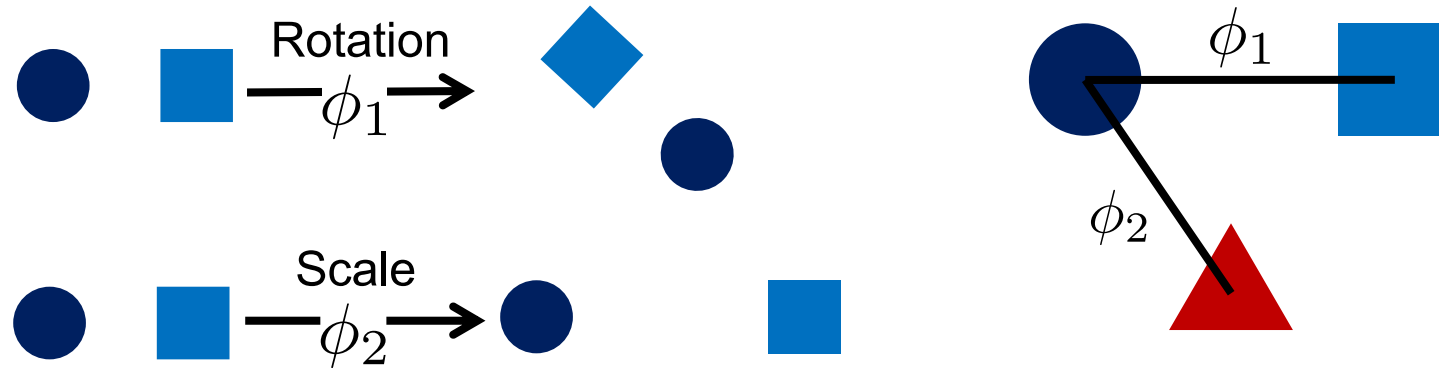
Equivalence mappings for data augmentation

Equivalence mappings: *what* relations?



Equivalence mappings for data augmentation

Equivalence mappings: *what* relations?

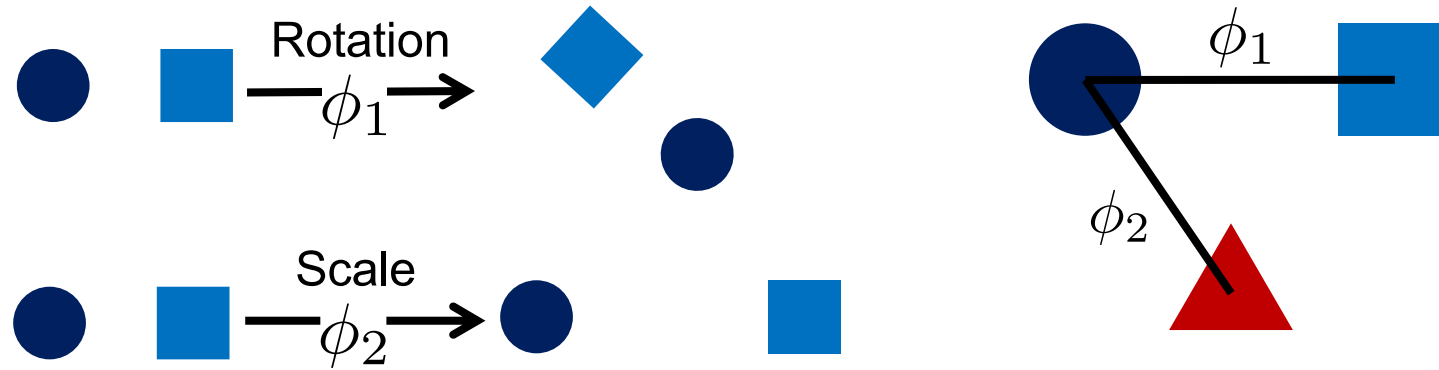


Edge equivalence \rightarrow same reward for transformed edge

$$r(\bullet, \blacksquare) = r(\phi_k(\bullet, \blacksquare))$$

Equivalence mappings for data augmentation

Equivalence mappings: *what* relations?



Edge equivalence \rightarrow same reward for transformed edge

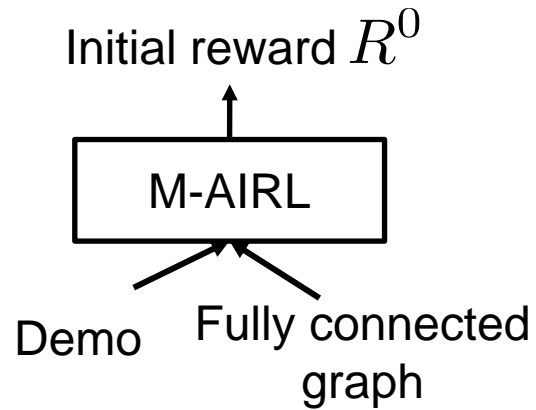
$$r(\bullet, \blacksquare) = r(\phi_k(\bullet, \blacksquare))$$

This enables data augmentation

GEM: Graph-based Equivalence Mappings

Reward function initialization

via **model-based** adversarial **inverse RL** (M-AIRL), an extension of Fu et al. (2018)

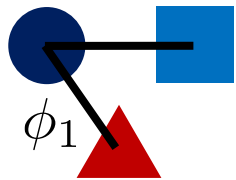


GEM: Graph-based Equivalence Mappings

Active reward refinement

Discover the **graph** and **equivalence mappings** for data augmentation

Current state, graph, and
mapping assignment

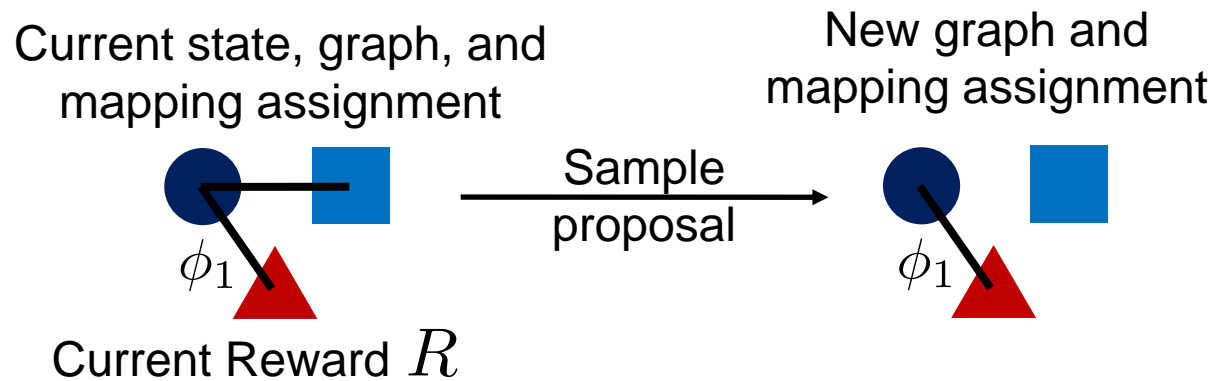


Current Reward R

GEM: Graph-based Equivalence Mappings

Active reward refinement

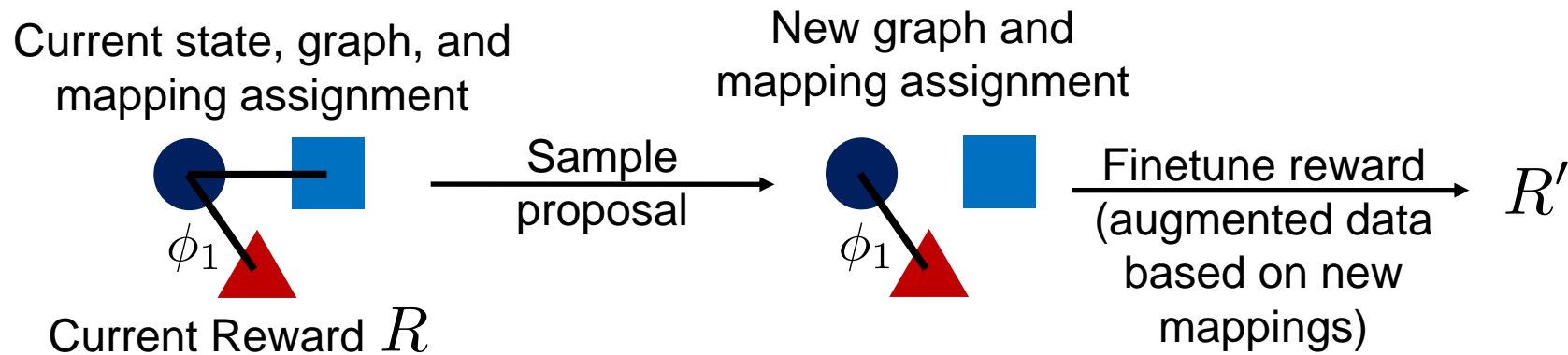
Discover the **graph** and **equivalence mappings** for data augmentation



GEM: Graph-based Equivalence Mappings

Active reward refinement

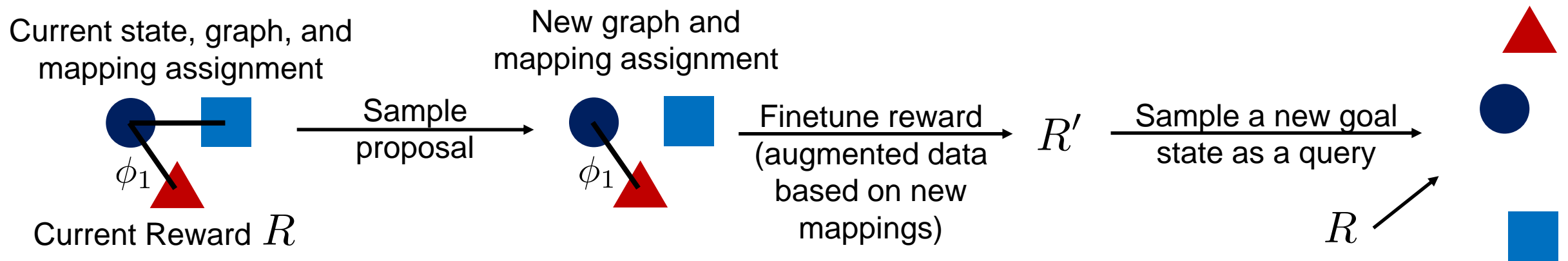
Discover the **graph** and **equivalence mappings** for data augmentation



GEM: Graph-based Equivalence Mappings

Active reward refinement

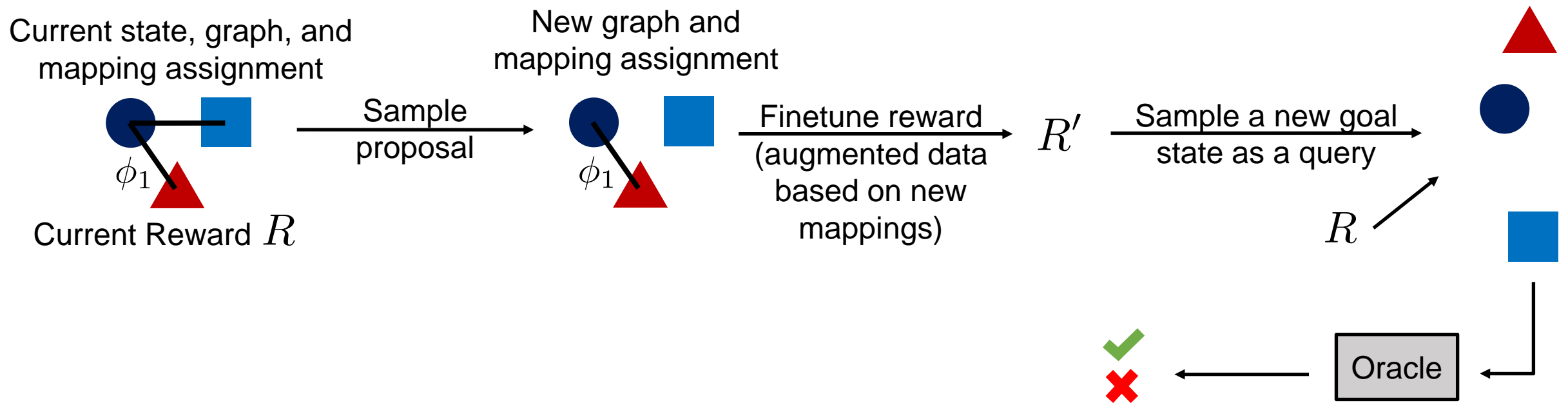
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GEM: Graph-based Equivalence Mappings

Active reward refinement

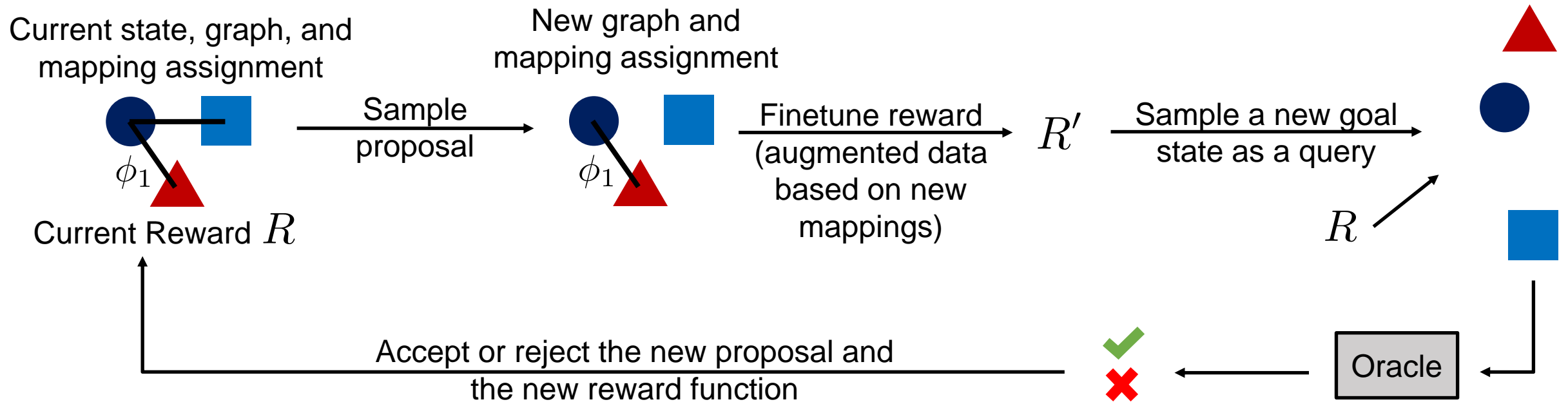
Discover the **graph** and **equivalence mappings** for data augmentation



GEM: Graph-based Equivalence Mappings

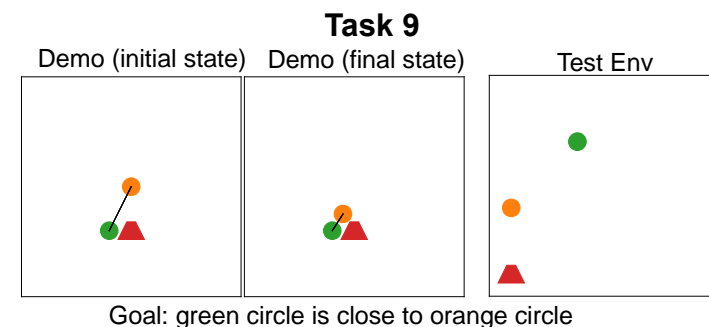
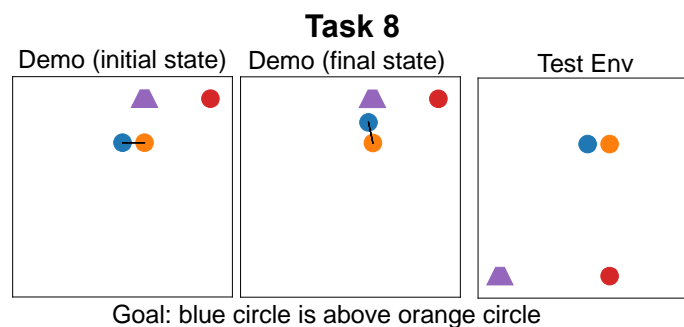
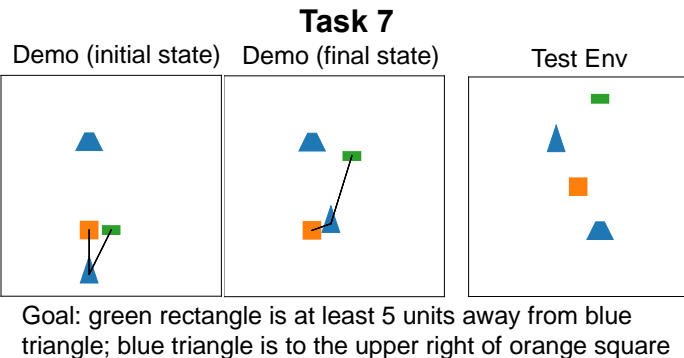
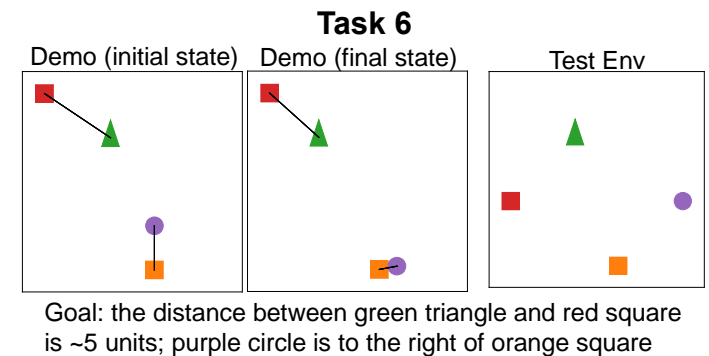
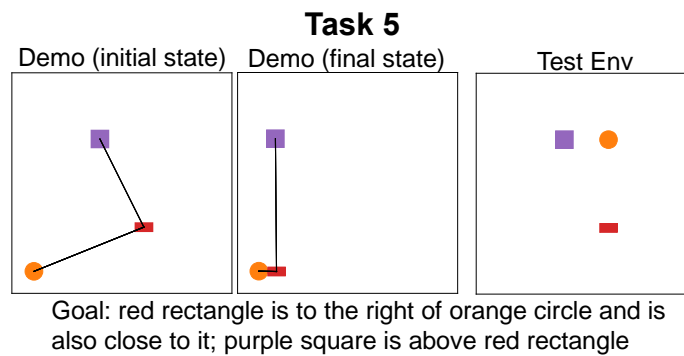
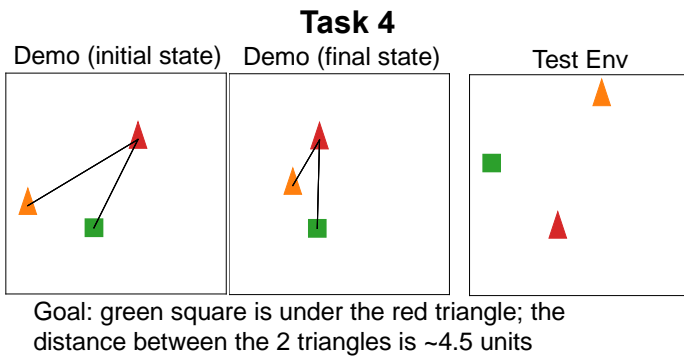
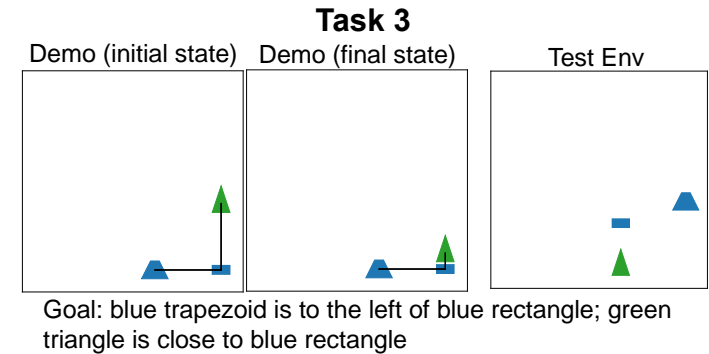
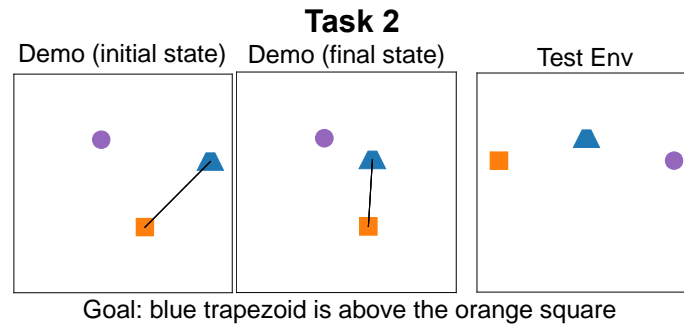
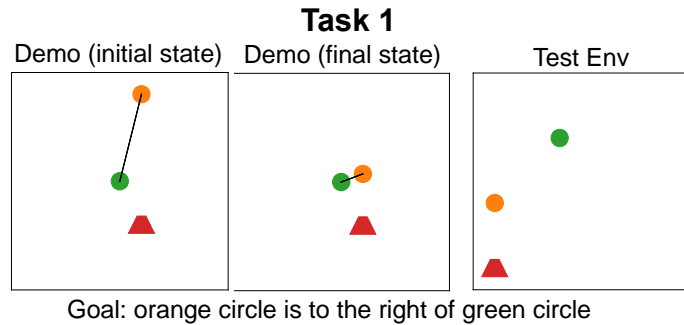
Active reward refinement

Discover the **graph** and **equivalence mappings** for data augmentation



Watch&Move tasks

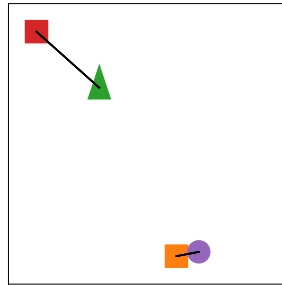
Object rearrangement tasks in a physics simulation from a single demonstration
Evaluation in an unseen environment



Results with a **simulated** oracle

Task 6

Demo (final state)

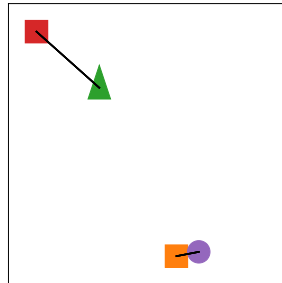


Goal: the distance between green triangle and red square is ~ 5 , and purple circle is to the right of orange square

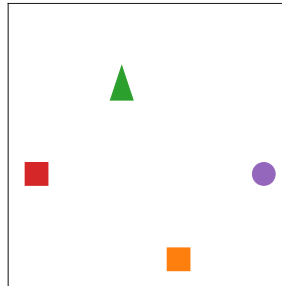
Results with a simulated oracle

Task 6

Demo (final state)



Test Env

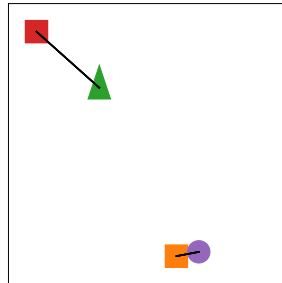


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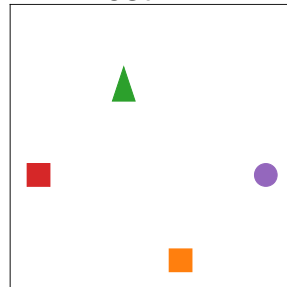
Results with a simulated oracle

$$R_{\text{eval}} = \underbrace{\mathbf{1}(s^T \text{ satisfies the goal})}_{\text{Task completion}} - \underbrace{0.02 d(s^0, s^T)}_{\text{Cost (displacement)}}$$

Task 6
Demo (final state)



Test Env



Goal: the distance between green triangle and red square is ~ 5 , and purple circle is to the right of orange square

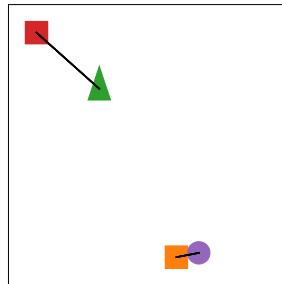
R eval

Number of queries

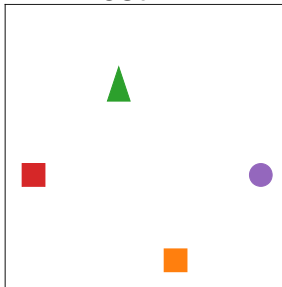
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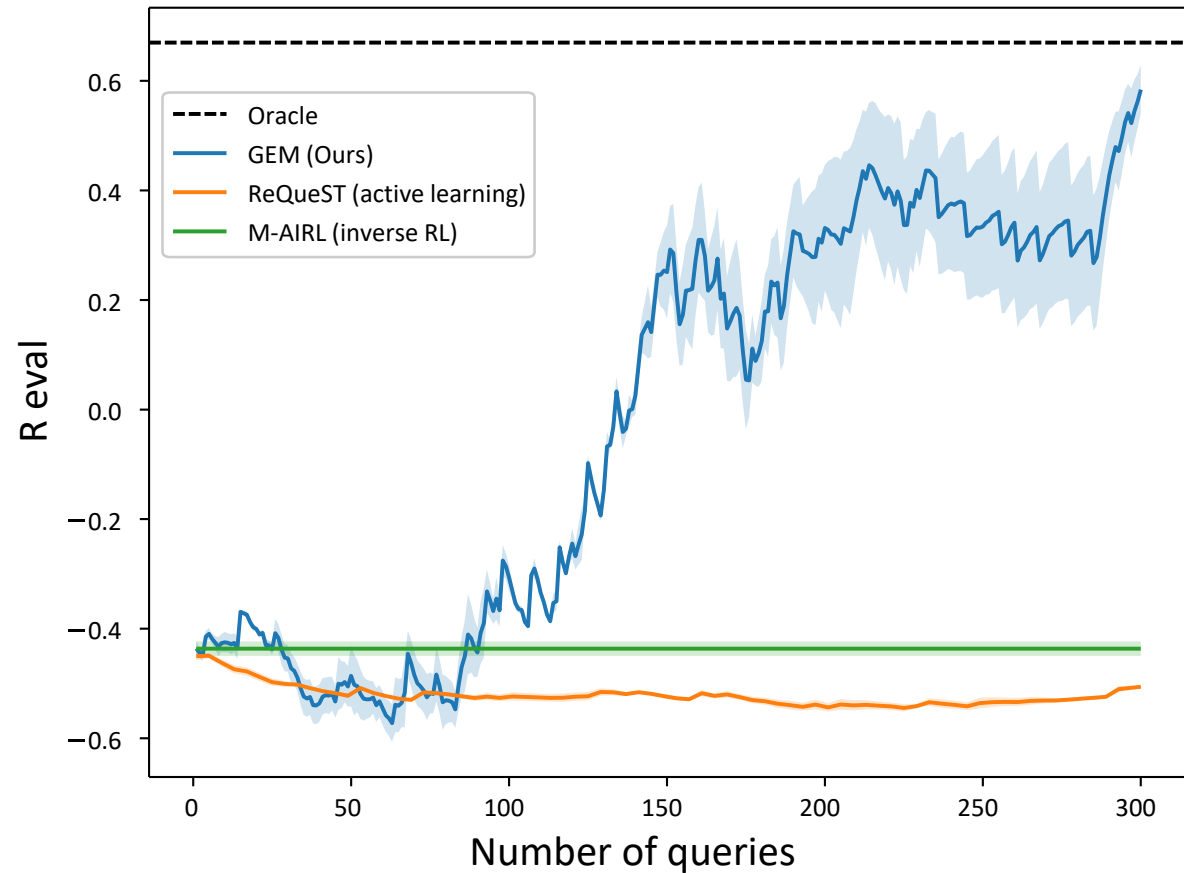
Task 6
Demo (final state)



Test Env

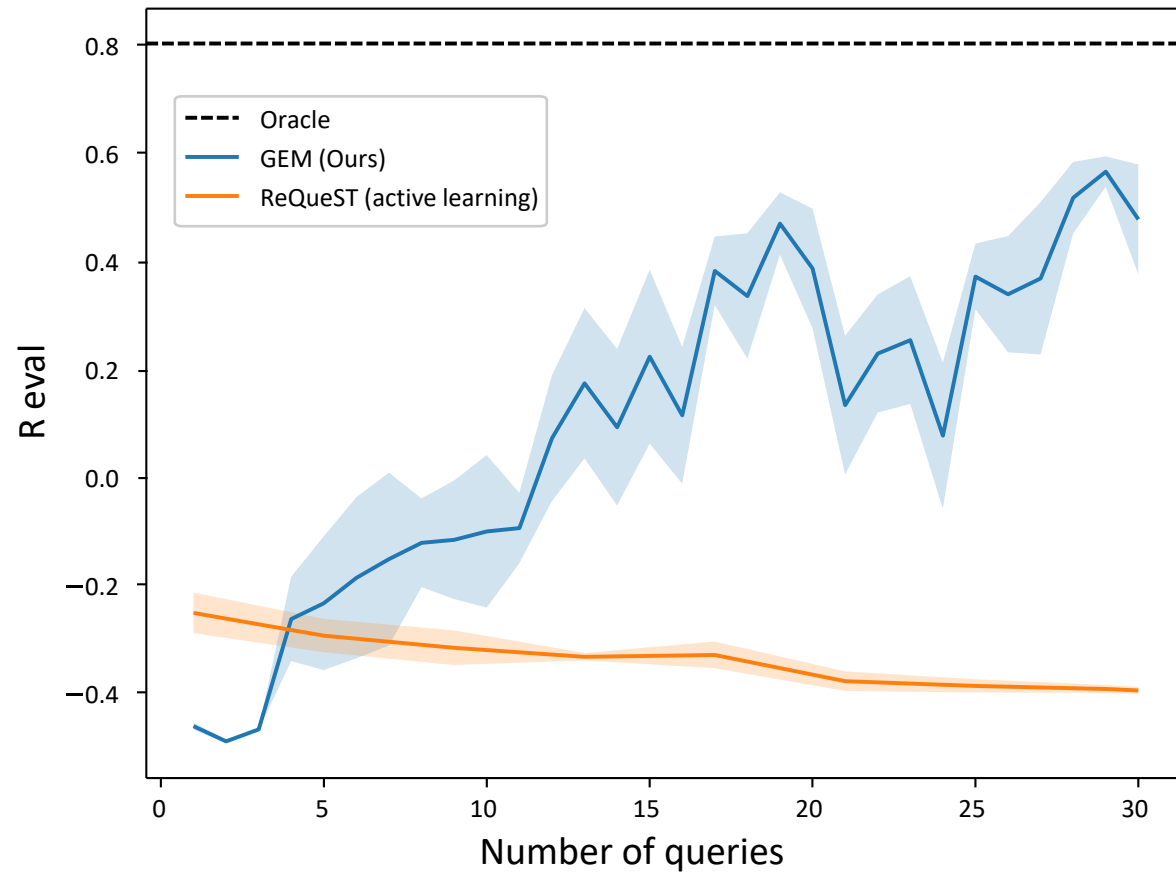
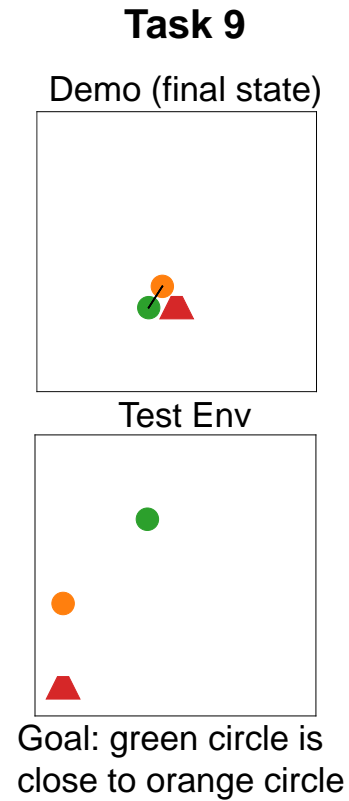


Goal: the distance between green triangle and red square is ~ 5 , and purple circle is to the right of orange square



Results with a human oracle

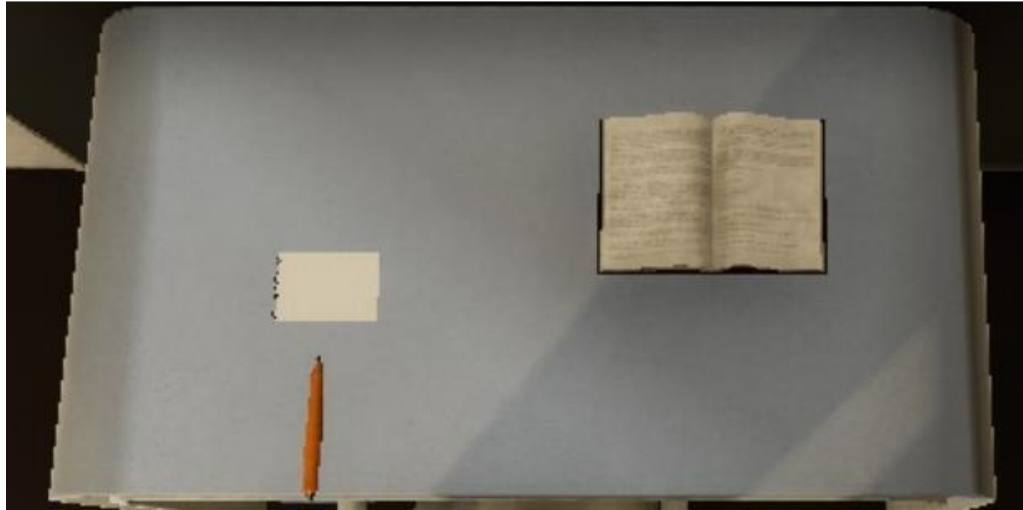
$$R_{\text{eval}} = \underbrace{\mathbf{1}(s^T \text{ satisfies the goal})}_{\text{Task completion}} - \underbrace{0.02 d(s^0, s^T)}_{\text{Cost (displacement)}}$$



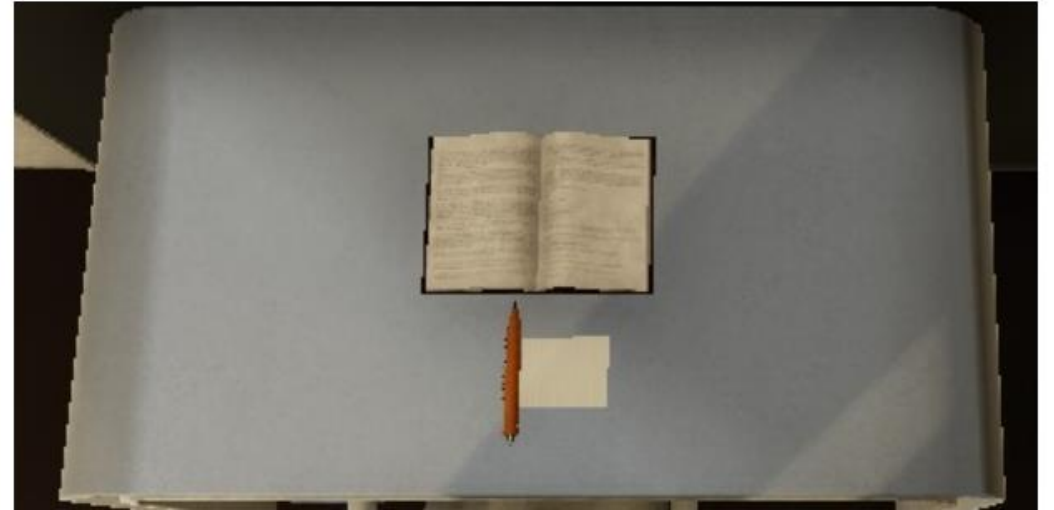
Results on a **real-life** task

Virtual home simulator

Initial State of the Testing Environment

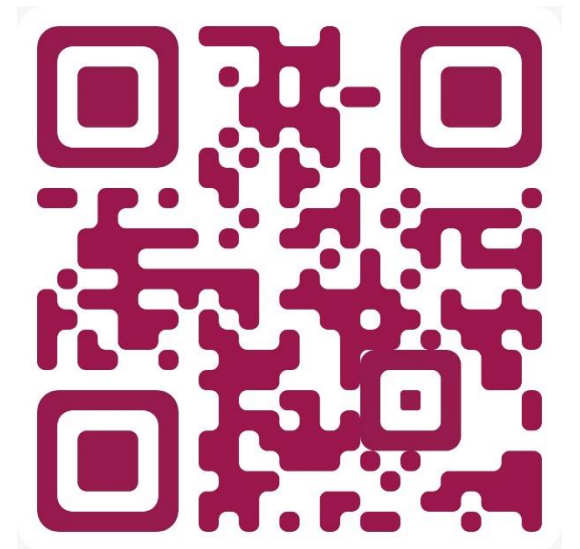


A Sampled Goal State Using the Learned Reward



Summary

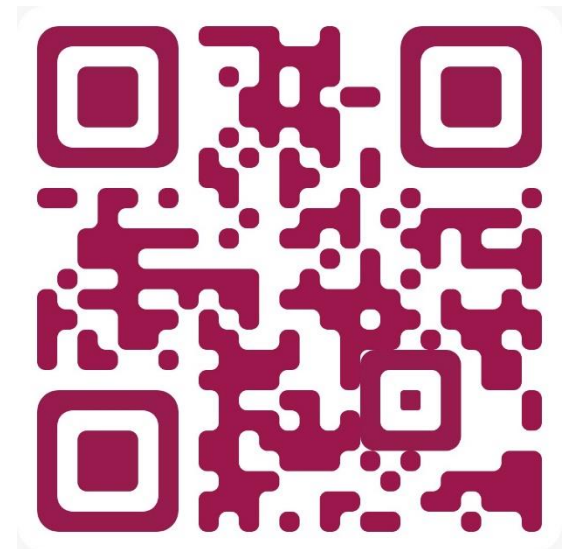
A **graph-based active reward learning** algorithm, GEM, for learning **spatial goals** from a **single demonstration** and **oracle feedback**



Summary

A **graph-based active reward learning** algorithm, GEM, for learning **spatial goals** from a **single demonstration** and **oracle feedback**

GEM achieves much greater success in learning **generalizable spatial goal specification** compared to SOTA IRL and active reward learning baselines

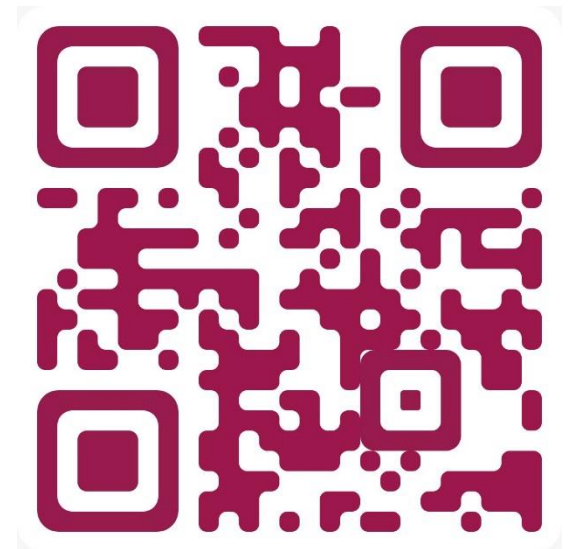


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GEM can also **learn from human users**



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GEM achieves much greater success in learning **generalizable spatial goal specification** compared to SOTA IRL and active reward learning baselines

GEM can also **learn from human users**

Project website: <https://www.tshu.io/GEM/>

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