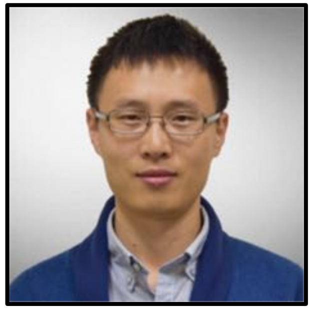
Tencent AI Lab

NeurIPS

Synthesized Policies for Transfer and Adaptation across Tasks and Environments



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Transfer Learning in RL

mop the floor

wash dishes

cooking

In this work we decompose environments and tasks, and consider three progressively more difficult transfer settings

A good household robot needs to complete multiple tasks

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Image Credits: retrieved from: http://twomaverix.com/?p=14570, https://www.stufftoblowyourmind.com/blogs/robots-will-cook-you-dinner.htm, http://www.mehmetari.com/blog/time-da-yayinlanan-yeni-nesil-robot-goruntuleri/

Transfer Learning in RL

A's home

B's home

C's home

In this work we decompose environments and tasks, and consider three progressively more difficult transfer settings

A good household robot needs to complete multiple tasks in multiple environments

Image Credits: retrieved from: http://v1.escapistmagazine.com/news/view/100397-Humanoid-Dishbot-Will-Force-You-to-Do-Chores, https://www.stufftoblowyourmind.com/blogs/robots-will-cook-you-dinner.htm, https://spielraum.xing.com/2015/03/kollege-roboter-ist-schon-da/

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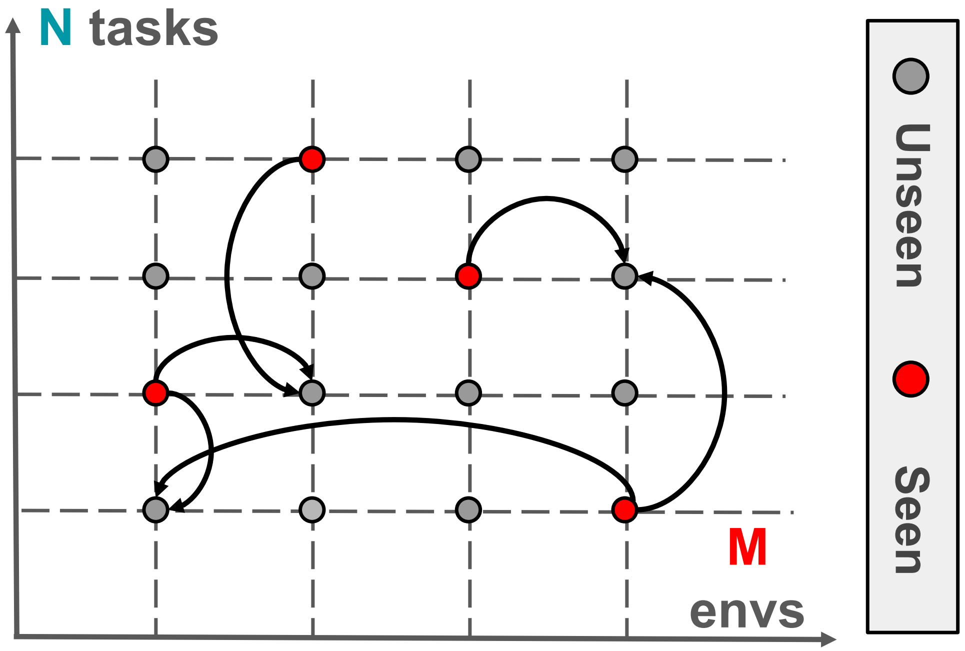
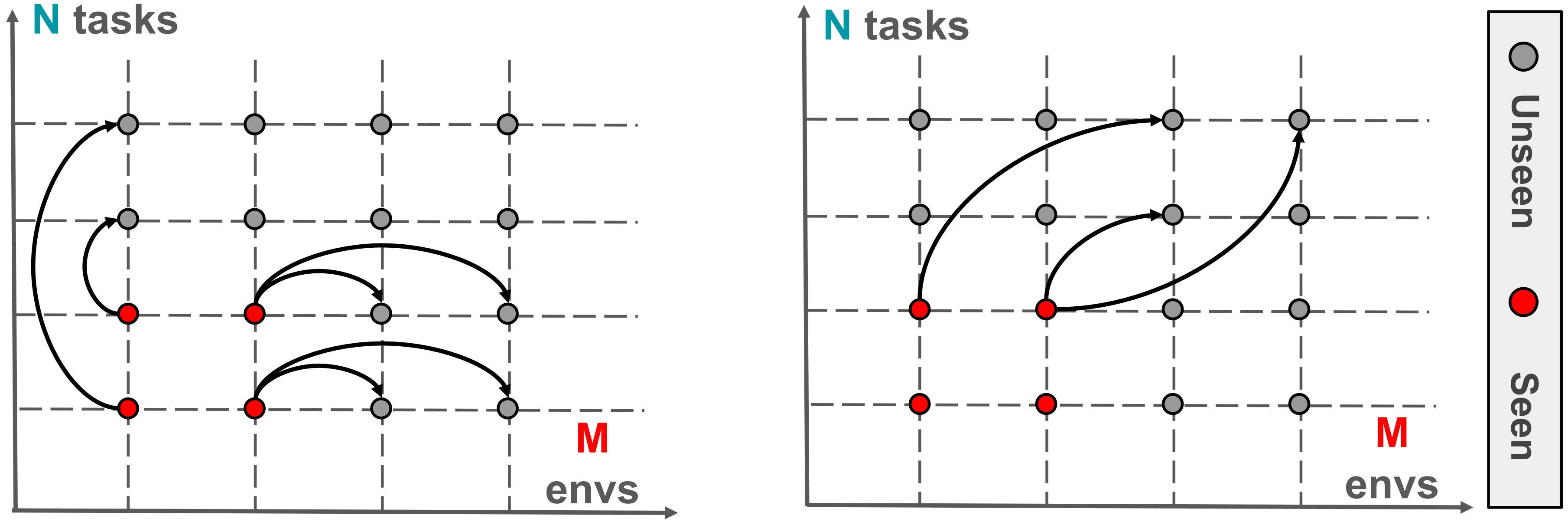
Transfer Settings I



- Transfer to a new (env, task) pair, with seen environment and seen task

Transfer Settings 2 & 3



- Transfer to a seen environment and unseen task, or unseen environment and seen task, or unseen environment and unseen task

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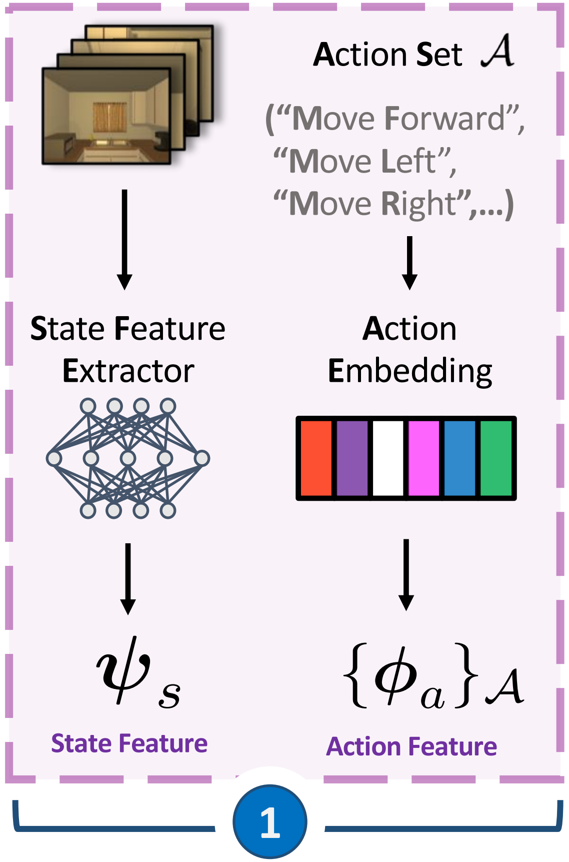
Our Method

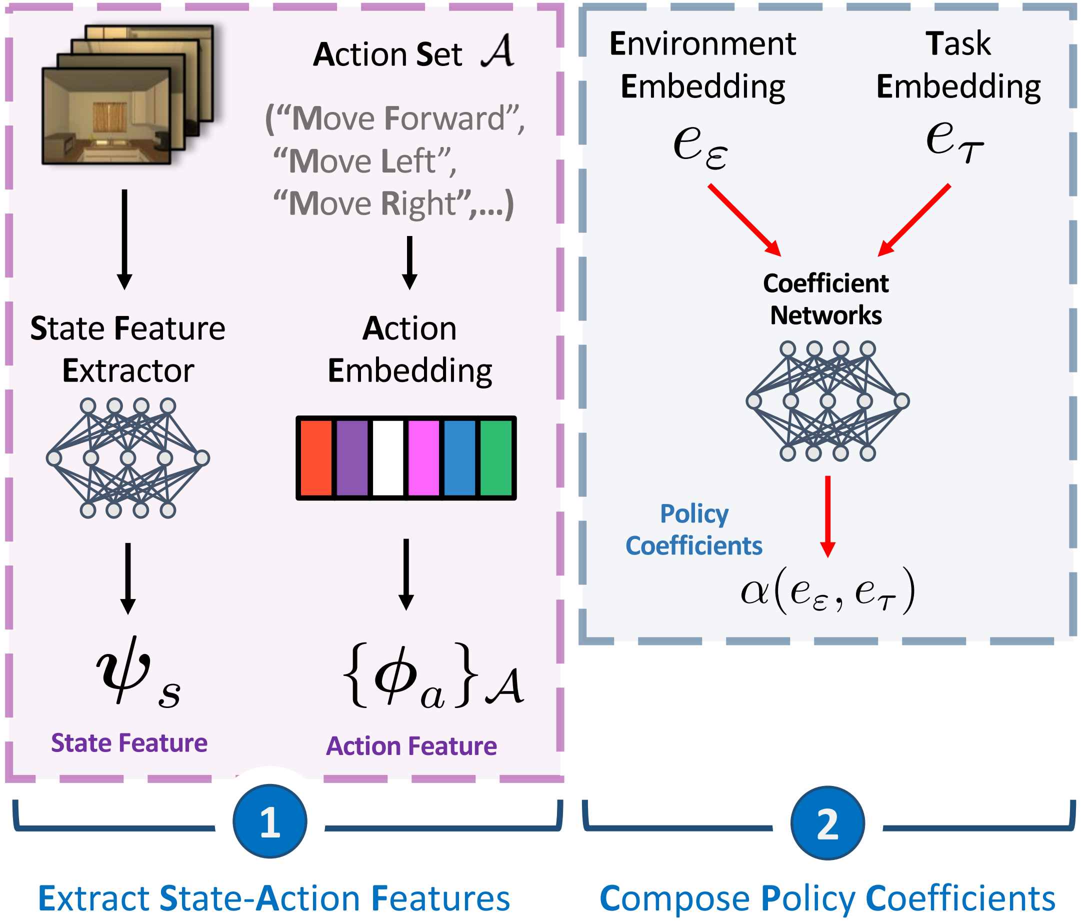
State, action features and policy basis are learned across all seen (env, task) comb.



Extract State-Action Features

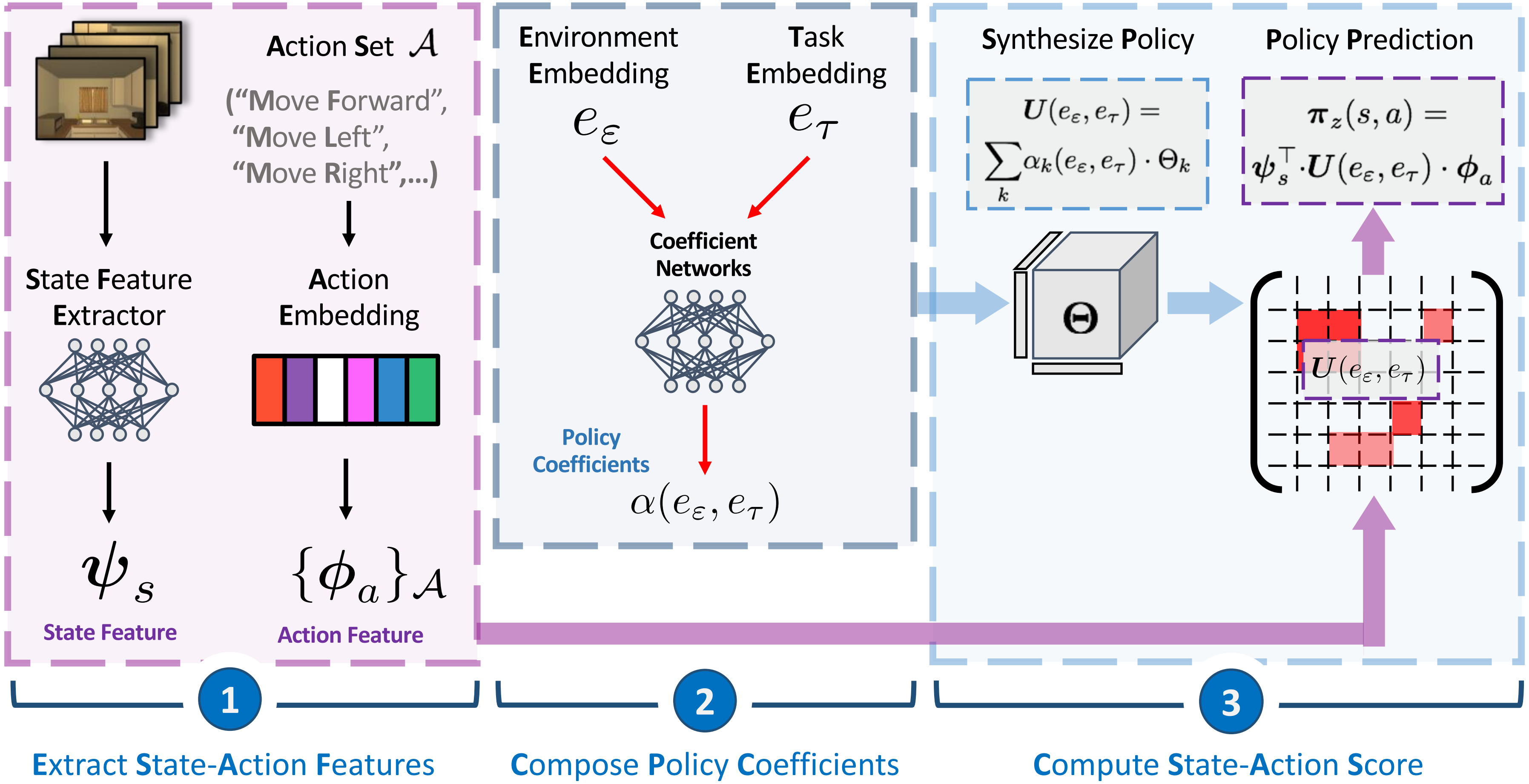
Our Method

Environment and task embeddings are learned via training on corresponding combinations.



Our Method

Both components are then used to compute state action compatibility score.



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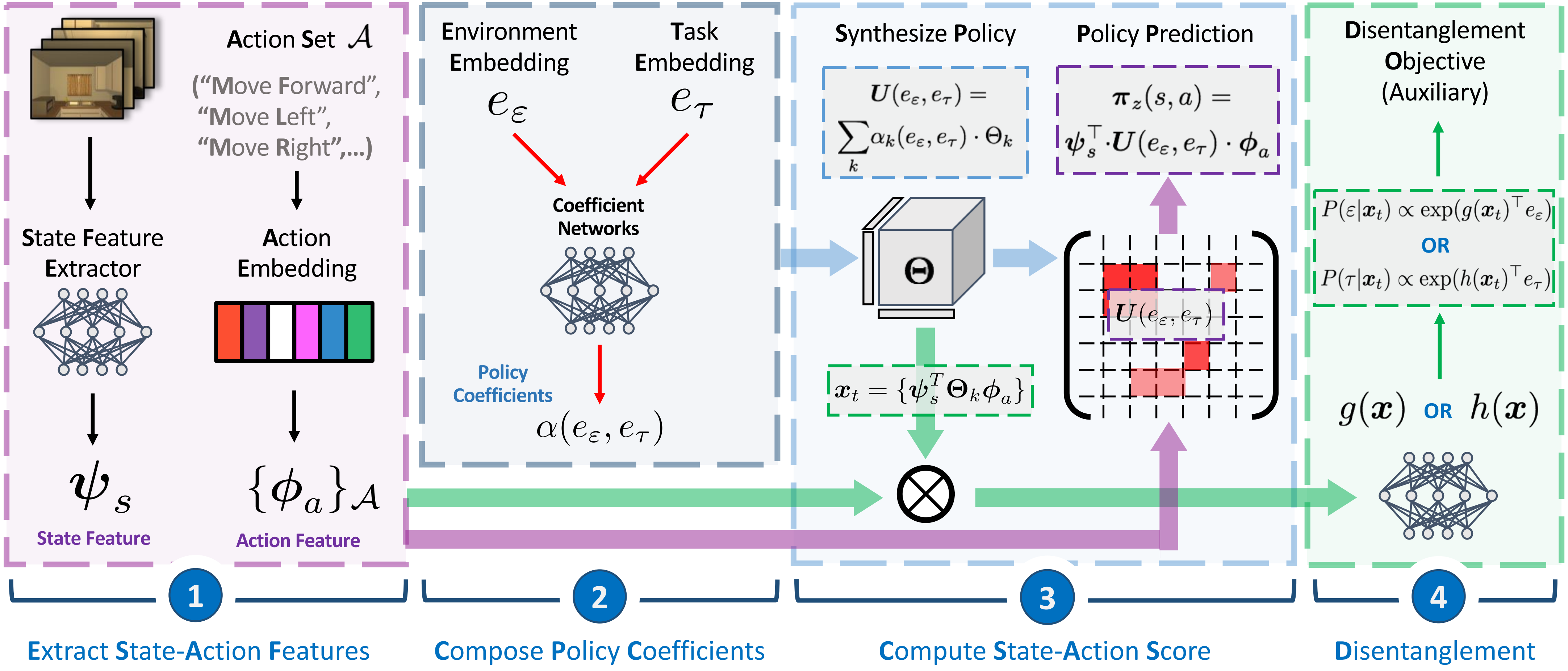
Our Method

A disentanglement objective is used as auxiliary loss term



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Experimental Setup

We experiment our approach on two different simulators, with **many different map** and **many tasks** (of **finding objects sequentially)**

GridWorld: 20 maps 20 tasks (144 SEEN & 256 UNSEEN)

THOR: 19 scenes 21 tasks (144 SEEN & 199 UNSEEN)

GridWorld Simulator

World

Agent's View

Thor [1]

Agent's View

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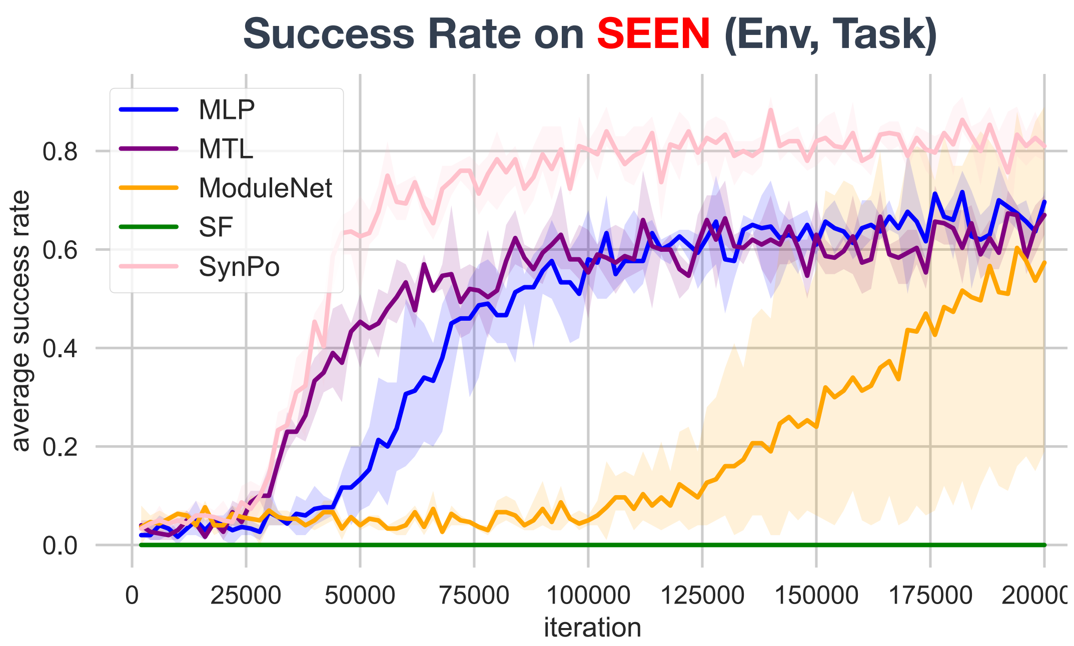
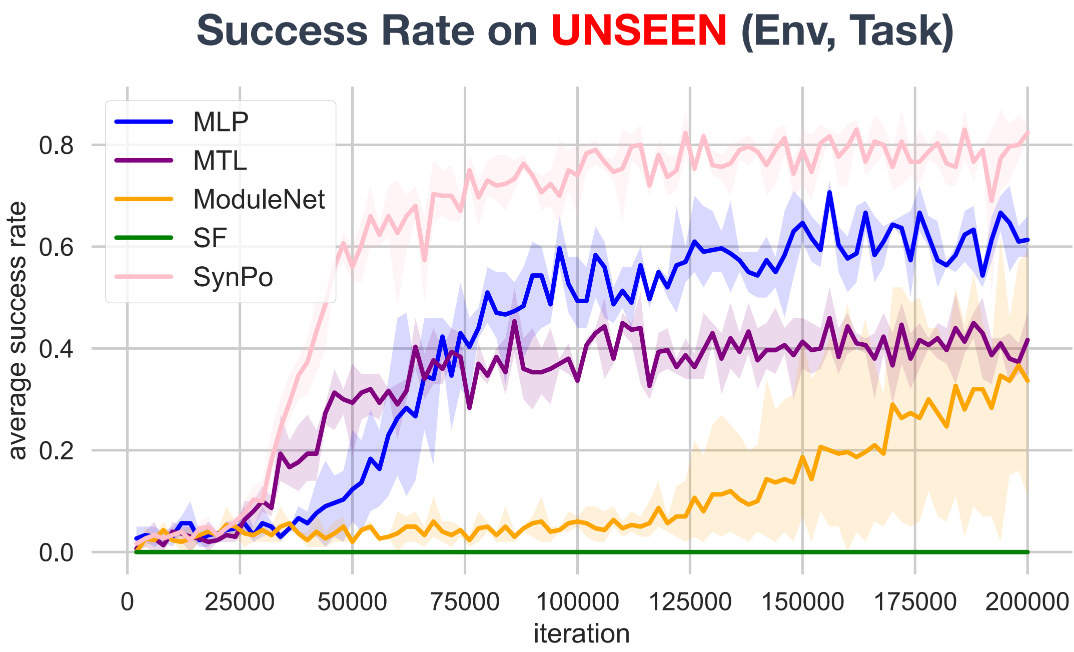
Experimental Results (Setting 1)

Performances on GridWorld





Performances on THOR[1]

Table 3: Performance of each method on THOR (SEEN/UNSEEN=144/199)

Method	ModuleNet	MLP	MTL	SYNPO
AvgSR. (SEEN)	51.5 %	47.5%	52.2%	**55.6%**
AvgSR. (UNSEEN)	14.4 %	25.8%	33.3%	**35.4%**

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Experimental Results (Setting 2 and 3)

- **On P Set**: We train policies basis and embeddings for P's task, env
- **Setting 2**: We incrementally learn new task, environment embeddings, on **purple sets**
- **Setting 3**: We directly learn new task, environment embeddings on **Q set**

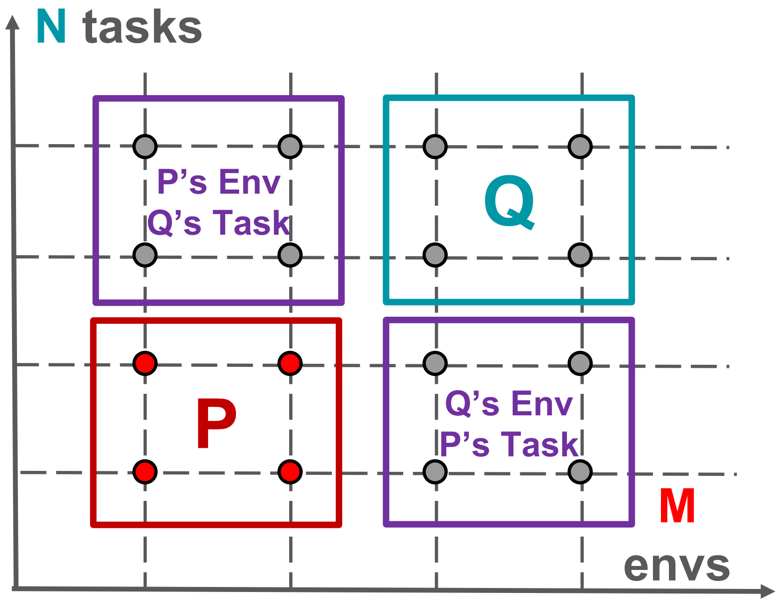

Table 2: Performance of transfer learning in the settings 2 and 3 on GRIDWORLD

Setting	Method	Cross Pair (Q's ε, P's τ)	Cross Pair (P's ε, Q's τ)	Q Pairs
Setting 2	MLP	13.8%	20.7%	6.3%
	SYNPO	**50.5%**	**21.5%**	**13.5%**
Setting 3	MLP	14.6%	18.3%	7.2%
	SYNPO	**42.7%**	**19.4%**	**12.9%**

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Thank You!

Come to our poster (#155) for more details

(Wed Dec 5th 10:45 AM – 12:45 PM @ Room 210 & 230 AB #155)

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