Learning to Generalize from Sparse and Underspecified Rewards

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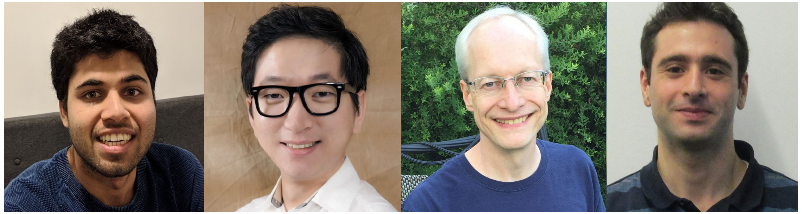

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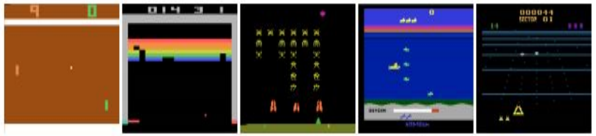
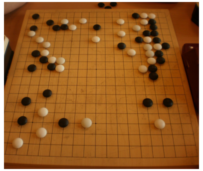
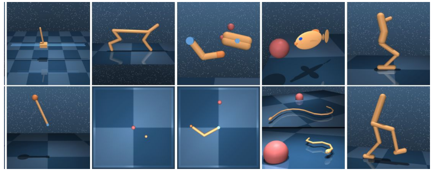
Motivation

- Reinforcement learning has enabled remarkable advances:


- These advances hinge on the availability of high-quality and dense rewards.
- However, many real-world problems involve sparse and underspecified rewards.
- Language understanding tasks provide a natural way to investigate RL algorithms in such settings.

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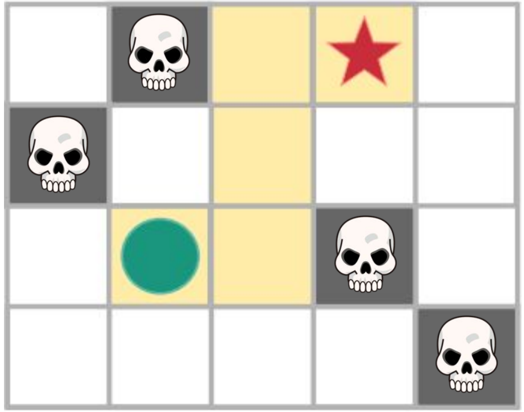
Instruction Following

Instruction: “Right Up Up Right”



: Blindfolded agent

: Goal

: Death

Possible Actions: ←, ↑, →, ↓

The reward is +1 if the goal is reached and 0 otherwise.

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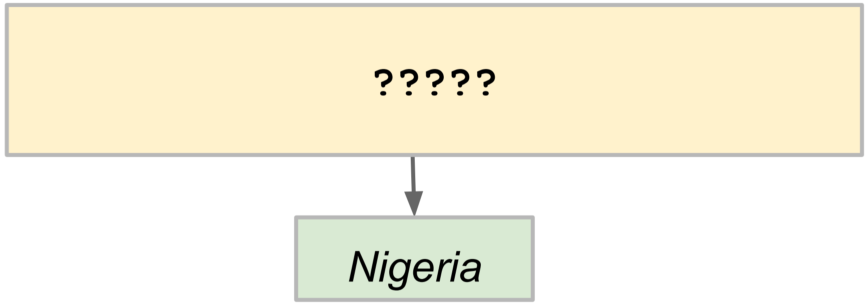
Weakly-supervised Semantic Parsing

Question: Which nation won the most number of Silver medals?

Rank	Nation	Gold	Silver	Bronze	Total
1	Nigeria	13	16	9	38
2	Kenya	12	10	7	29
3	Ethiopia	4	3	4	11
...	...	...	...	...	...
15	Madagascar	0	0	2	2
16	Tanzania	0	0	1	1
	Uganda	0	0	1	1



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Challenges: (1) Exploration, (2) Generalization

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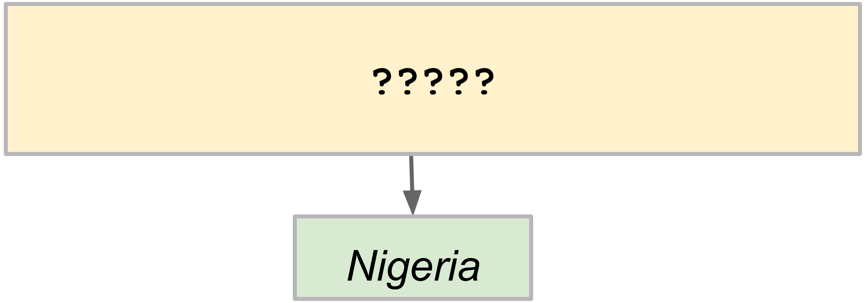

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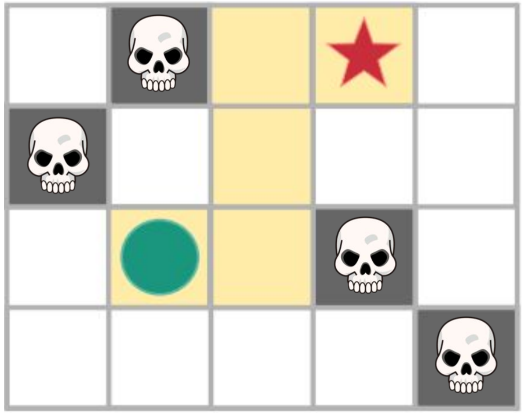
Underspecified Rewards

Instruction: “Right Up Up Right”



Correct Action Sequence:

→ ↑ ↑ →

Spurious Action Sequences:

↑ → ↑ →

↑ → → ↑

↑ → ↑ ↓ → ↑

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Underspecified Rewards

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```
v0 = (argmax all_rows r.Silver)
return (hop v0 r.Nation)
```

Nigeria

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Underspecified Rewards

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Nigeria

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v0 = (argmin all_rows r.Rank)
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Nigeria

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Underspecified Rewards

Recent interest in automated reward learning using expert demonstrations.

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Learning Rewards without Demonstration

Recent interest in automated reward learning using expert demonstrations.

What if we don't have demonstrations?

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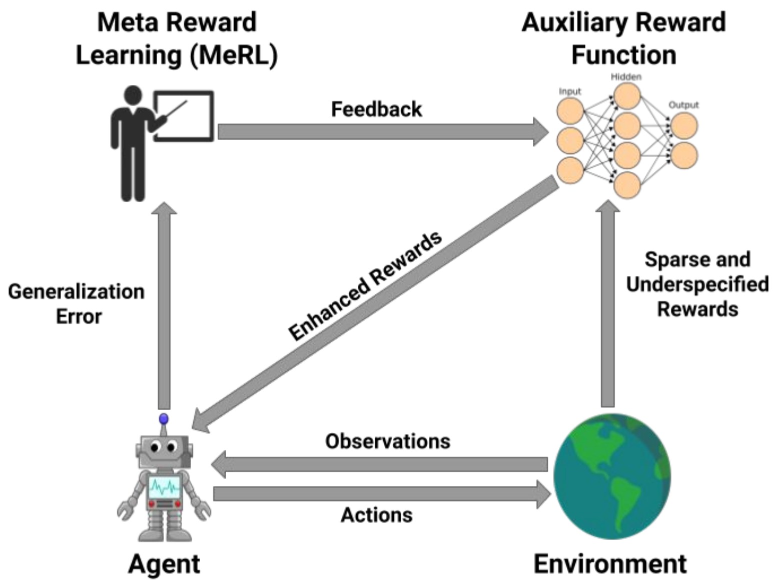
Learning Rewards without Demonstration

Recent interest in automated reward learning using expert demonstrations.

Key idea: Use generalization error as the training signal for learning rewards.

Meta Reward Learning (MeRL)



The auxiliary rewards R_ϕ are optimized based on the generalization performance O_{val} of a policy π_θ trained using the auxiliary rewards:

$$\theta' = \theta - \alpha \nabla_\theta O_{\text{train}}(\pi_\theta, R_\phi)$$

$$\phi' = \phi - \nabla_\phi O_{\text{val}}(\pi_{\theta'})$$

Tackling Sparse Rewards

- ➢ Disentangle exploration from exploitation.
- ➢ Mode covering direction of KL divergence to collect successful sequences .
- ➢ Mode seeking direction of KL divergence for robust optimization.

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Results

- *MAPOX* uses *our mode covering* exploration strategy on top of prior work (*MAPO*).

Method	WikiSQL	WikiTable
MAPO	72.4 (± 0.3)	42.9 (± 0.5)
MAPOX	**74.2** (± 0.4)	**43.3** (± 0.4)

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Results

- ➢ *MAPOX* uses *our mode covering* exploration strategy on top of prior work (*MAPO*).
- ➢ *BoRL* is our Bayesian optimization approach for learning rewards.

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BoRL	**74.2 (± 0.2)**	**43.8 (± 0.2)**

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Results

➢ *MAPOX* uses *our mode covering* exploration strategy on top of prior work (*MAPO*).

➢ *BoRL* is our Bayesian optimization approach for learning rewards.

➢ *MeRL achieves* state-of-the-art results on *WikiTableQuestions* and *WikiSQL*, improving the upon *prior work* by **1.2%** and **2.4%**.

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MAPOX	74.2 (± 0.4)	43.3 (± 0.4)
BoRL	74.2 (± 0.2)	43.8 (± 0.2)
MeRL	**74.8** (± 0.2)	**44.1** (± 0.2)

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Poster **#49** tonight @Pacific Ballroom

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