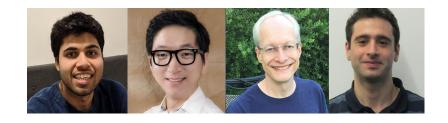




Learning to Generalize from Sparse and Underspecified Rewards

Rishabh Agarwal, Chen Liang, Dale Schuurmans, Mohammad Norouzi



Motivation

Reinforcement learning has enabled remarkable advances:





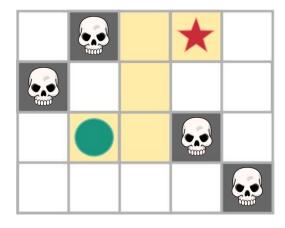




- These advances hinge on the availability of high-quality and dense rewards.
- However, many real-world problems involve sparse and underspecified rewards.
- Language understanding tasks provide a natural way to investigate RL algorithms in such settings.

Instruction Following

Instruction: "Right Up Up Right"





: Blindfolded agent



: Goal



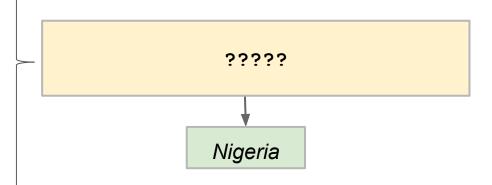
: Death

Possible Actions: \leftarrow , \uparrow , \rightarrow , \downarrow

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

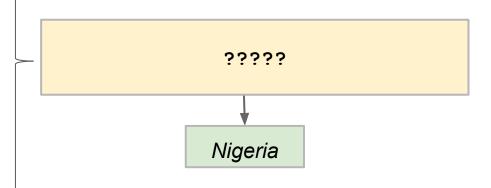
Weakly-supervised Semantic Parsing

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
1.0	Tanzania	0	0	1	1
16	Uganda	0	0	1	1

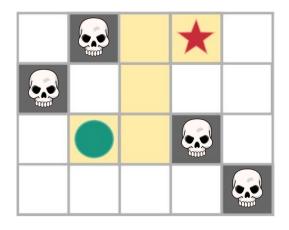


Challenges: (1) Exploration, (2) Generalization

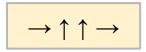
Rank	Nation	Gold	Silver	Bronze	Total
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16	Tanzania	0	0	1	1
16	Uganda	0	0	1	1



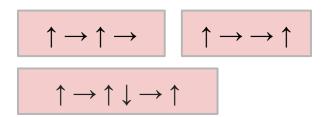
Instruction: "Right Up Up Right"



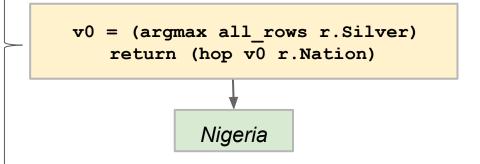
Correct Action Sequence:



Spurious Action Sequences:



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
1.0	Tanzania	0	0	1	1
16	Uganda	0	0	1	1

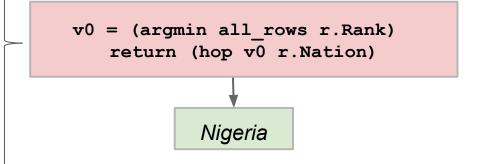


Rank	Nation	Gold	Silver	Bronze	Total
1	Nigeria	13	16	9	38
2	Kenya	12	10	7	29
3	Ethiopia	4	3	4	11
15	Madagascar	0	0	2	2
1.6	Tanzania	0	0	1	1
16	Uganda	0	0	1	1

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

Nigeria
```

Rank	Nation	Gold	Silver	Bronze	Total
1	Nigeria	13	16	9	38
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3	Ethiopia	4	3	4	11
15	Madagascar	0	0	2	2
16	Tanzania	0	0	1	1
16	Uganda	0	0	1	1





Recent interest in automated reward learning using expert demonstrations.

Learning Rewards without Demonstration



Recent interest in automated reward learning using expert demonstrations.

What if we don't have demonstrations?

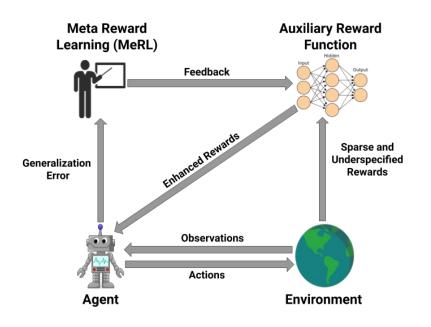
Learning Rewards without Demonstration



Recent interest in automated reward learning using expert demonstrations.

Key idea: Use generalization error as the supervisory 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.

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)	
МАРОХ	74.2 (± 0.4)	43.3 (± 0.4)	

Results

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

Method	WikiSQL	WikiTable	
MAPO	72.4 (± 0.3)	42.9 (± 0.5)	
MAPOX	74.2 (± 0.4)	43.3 (± 0.4)	
BoRL	74.2 (± 0.2)	43.8 (± 0.2)	

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 upon prior work by 1.2% and 2.4% respectively.

Method	WikiSQL	WikiTable
MAPO	72.4 (± 0.3)	42.9 (± 0.5)
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)

Poster #49 tonight @Pacific Ballroom

bit.ly/merl2019