Advanced Topics in Deep Reinforcement Learning

Exploration

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=> Exploration increases data quality

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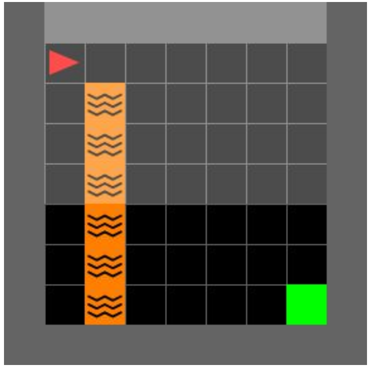
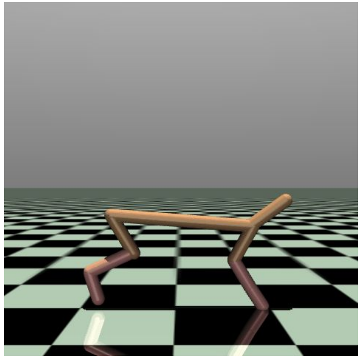
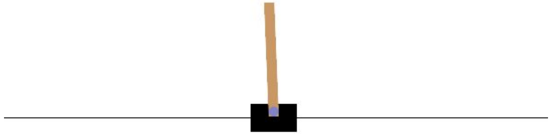
Examples:







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  Exploration around current policy, high computational overhead, not ideal for state coverage

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- Option 1: take random action with a certain probability
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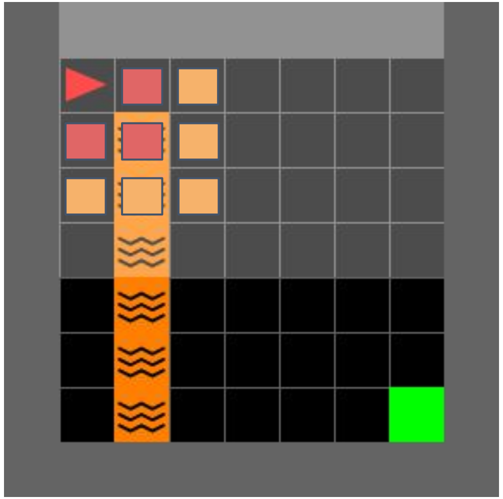
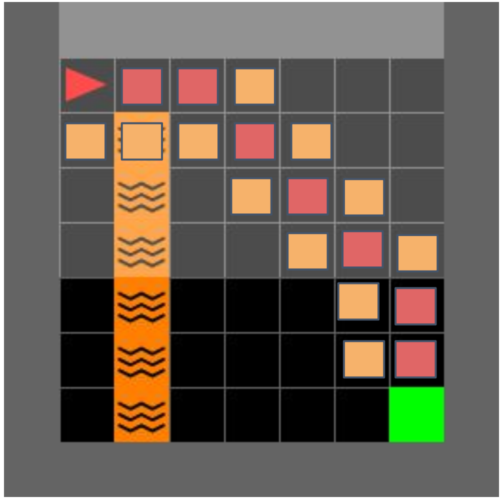
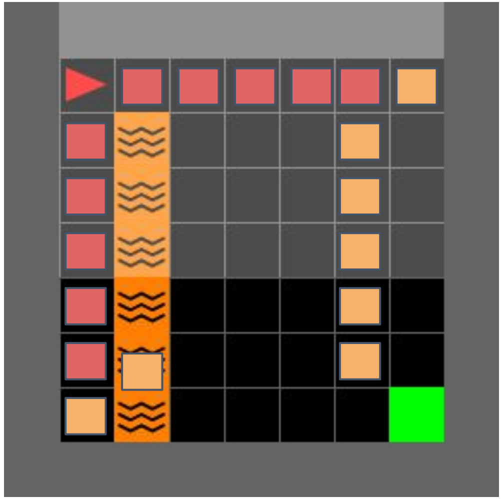


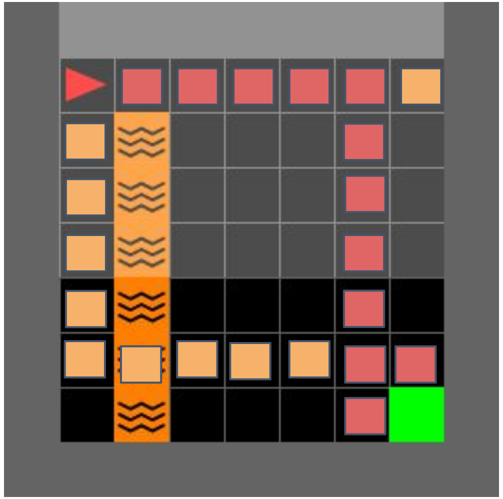


Exploration via Random Sequences

Instead of sampling a step sample a full sequence of steps

Example assuming we sample the same action for 5 steps:





Exploration via State Novelty

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Why does it work?

- Avoids spending time in mediocre states
- Still helps cover the state space

Measuring State Novelty

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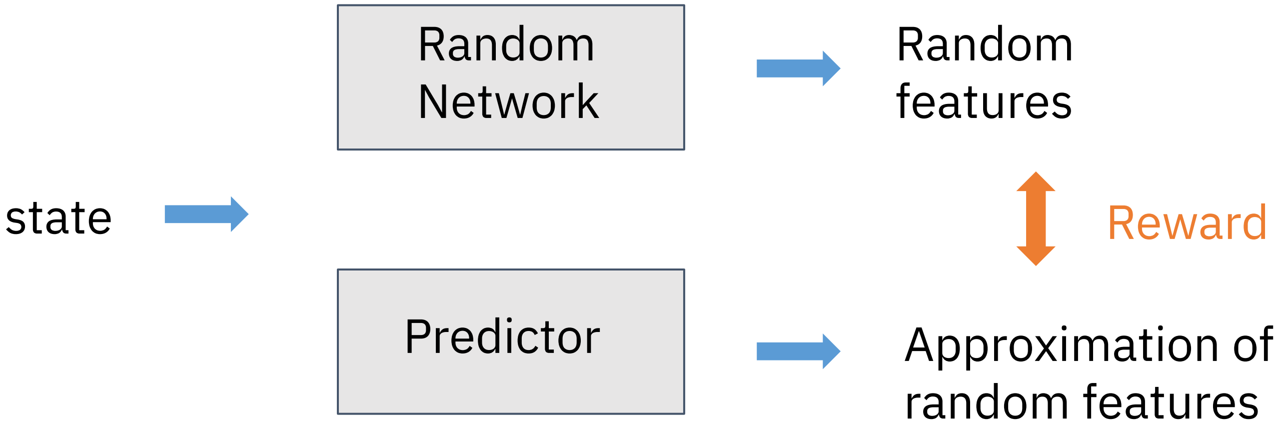
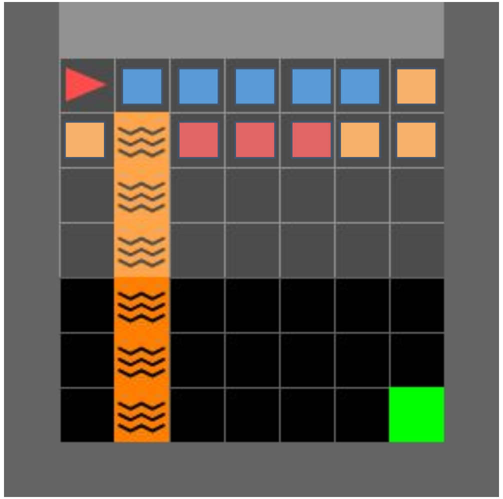


Exploration via State Novelty

Assume we learned to walk along the border to the goal:



Exploration via Intrinsic Rewards

We alter the rewards instead of the policy:

- The agent will learn exploration through the rewards
- No need to choose an explicit exploration strategy
- Algorithm-agnostic
- Can encode very specific exploration behavior

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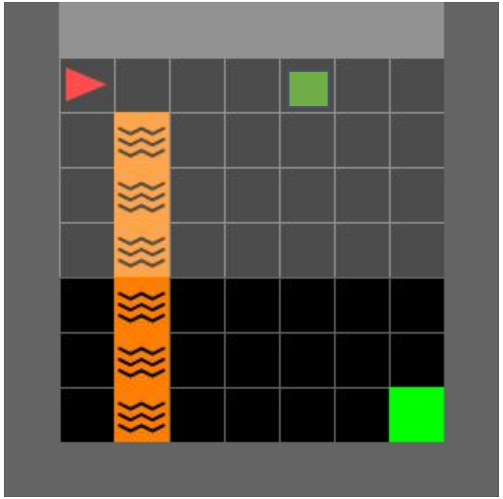
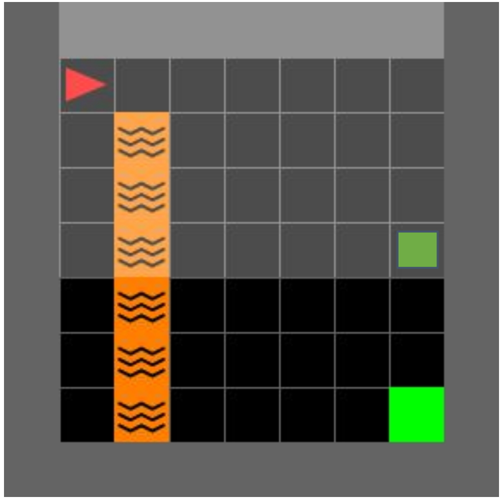
Teacher proposes sub-goal



Difficulty increases over time



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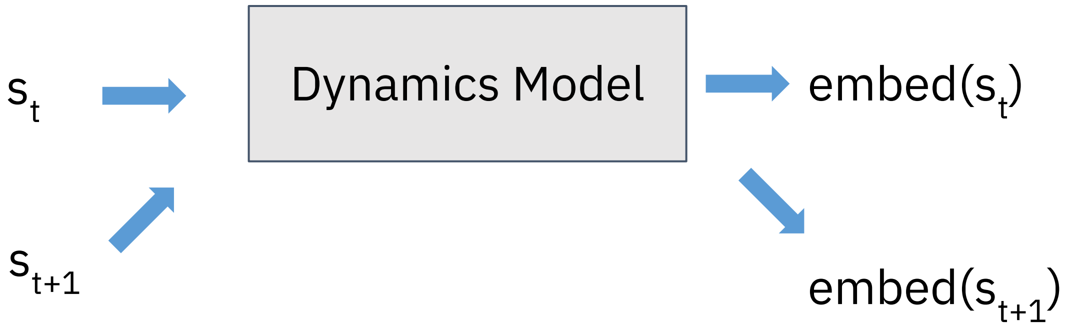

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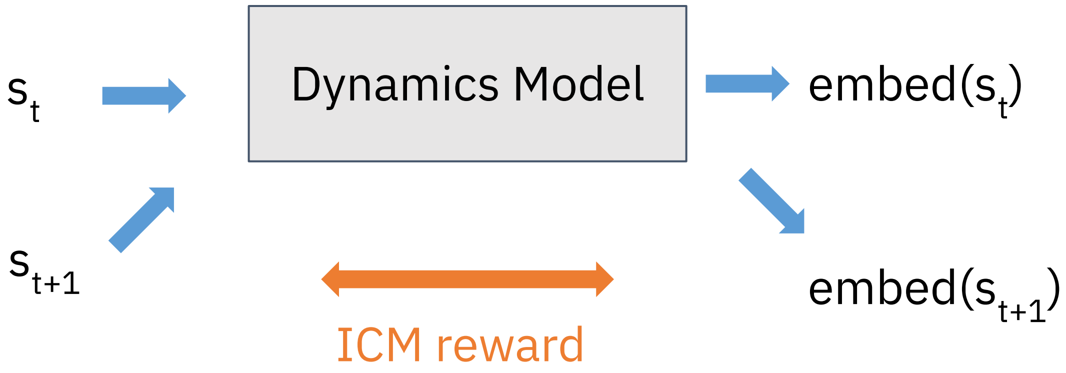

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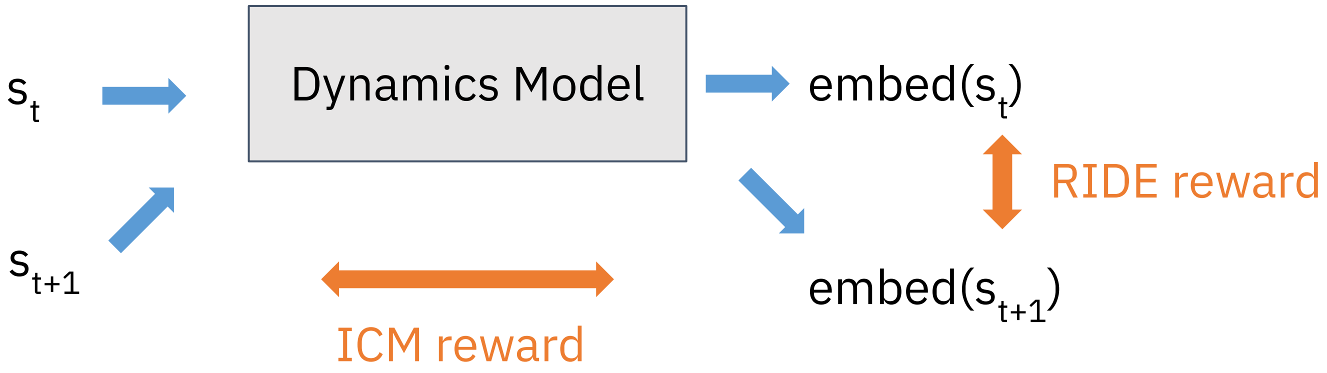

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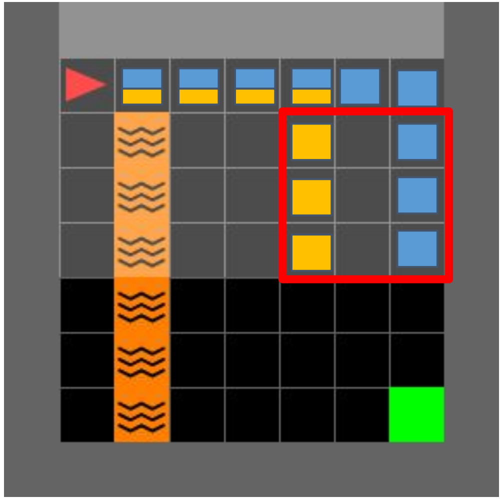
Designing intrinsic rewards is very hard and often domain-specific!

Exploration via Ensembles

Idea: if we train multiple policies on the same data, disagreement between the predictions can be a useful signal that data is insufficient



Region of Disagreement

My Understanding of RL Algorithms

- ❑ I understand what exploration accomplishes
- ❑ I can describe at least 3 ways of exploring
- ❑ I could implement at least one exploration algorithm

- ❑ I can describe each exploration idea
- ❑ I know the pros and cons of different exploration methods

- ❑ I can describe one algorithm per idea
- ❑ I can compare exploration algorithms
- ❑ I can explain which idea would work for a given problem