Reinforcement Learning:
Rollout

BIOE 498/598 PJ

Spring 2022

Review

The *value function* is the expected sum of future rewards

$$V(s_i) = \mathbb{E}\{r_i + r_{i+1} + \cdots + r_T\}.$$

At any state s_i, the optimal policy follows the objective

$$\begin{aligned}
&\max_{a_i} \mathbb{E}\{r_i + r_{i+1} + \cdots + r_T\} \\
=&\max_{a_i} \mathbb{E}\{r_i\} + \mathbb{E}\{r_{i+1} + \cdots + r_T\} \\
=&\max_{a_i} \mathbb{E}\{r_i\} + V(s_{i+1})
\end{aligned}$$

Optimal policies can be found with a value function.

The optimal RL policy balances the immediate reward r_i with future rewards $V(s_{i+1})$:

$$\pi^*(s_i) = \arg\max_{a_i} \left\{ \mathbb{E}[r_i] + V(s_{i+1}) \right\}.$$

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If we know the value function, the optimal policy is to be greedy with respect to it. However, we rarely know V:

- Monte Carlo estimation of V is only approximate even with many simulations.
- If the state space is very large, we may never visit every state to estimate V by tabular methods.

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Instead, we use an *approximate value function* $\widetilde{V}(s)$ to find a sub-optimal policy $\pi(s)$.

Approximate value functions.

There are two classes of methods for approximating a value function.

1. **Parametric approximation** trains a model that predicts value from previous visits to states. The model predicts the value for *all* states, even those that have not been visited.
   - Any type of model can be used to predict value: Linear models, Gaussian Process Regression, Artificial Neural Networks ("Deep RL").
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2. **Monte Carlo approximation** uses a model of the MDP to simulate the rewards following a state.
   - Monte Carlo methods work well *online* by simulating states just ahead of the agent in the MDP.
   - These methods are *sample efficient* but require a computational model of the MDP.

Rollout

- Rollout is a Monte Carlo method frequently used for online RL.
- Rollout "looks ahead" to estimate the value of states the agent is likely to visit next.
- Rollout is robust and works with many RL problems. Variants of rollout (e.g. MCTS) power AlphaGo, AlphaZero, and other top game engines.
- Rollout can be used for policy iteration, but we will limit our discussion to a single pass through an MDP.

The rollout algorithm

Rollout requires

- A *simulator* that generates sequences

$$s_i, a_i, r_i, \ldots, s_{T-1}, a_{T-1}, r_{T-1},\ s_T, r_T$$

  given a policy π.
- A *base policy* π_{base} to use with the simulator. A random base policy works.

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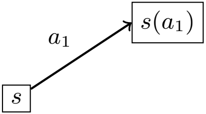

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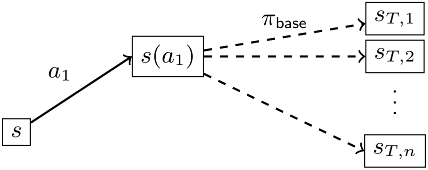

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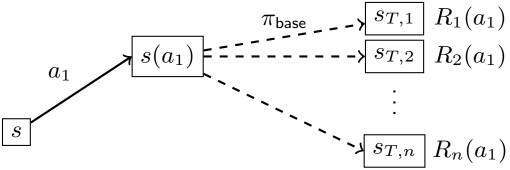

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$$\boxed{s} \xrightarrow{a_1} \boxed{s(a_1)}\ \ \widetilde{V}\left(s(a_1)\right) = \tfrac{1}{n}(R_1 + R_2 + \cdots + R_n)$$

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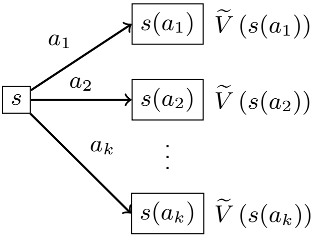

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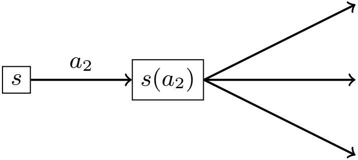
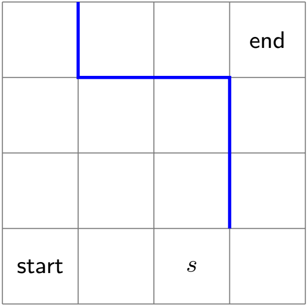


Rollout in Gridworld



- Imagine we are in the middle of the maze at state s.

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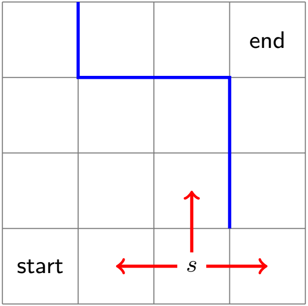

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- There are three available actions: {left, up, down}.

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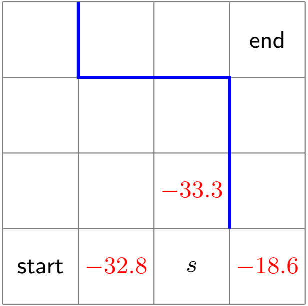

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- We use random walks to estimate $\widetilde{V}$ after each action.

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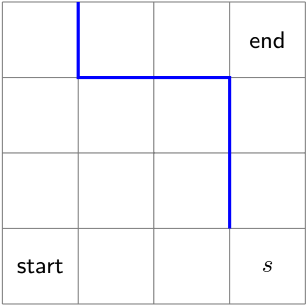

- Imagine we are in the middle of the maze at state s.
- There are three available actions: $\{$left, up, down$\}$.
- We use random walks to estimate $\widetilde{V}$ after each action.
- We select the action that leads to the best estimated value.

Policy improvement with rollout

- The online policy we are finding is called the *rollout policy*.
- The rollout policy has the *policy improvement property* — it will be equal to or better than the base policy.
- We can repeat the process with another trip through the MDP using the rollout policy as the new base policy.
- However, iterating in this way requires us to add exploration to our policies.

Summary

- **Rollout** is an online method that reduces simulation by focusing on local starts.
- A single pass with a random base policy provides good, but not necessarily optimal, behavior.
- Iteration and exploration are required to find optimal policies.