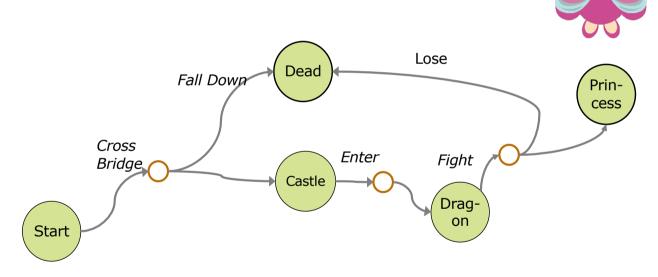


Markov Decision Processes Summary



Reinforcement Learning

October 13, 2022



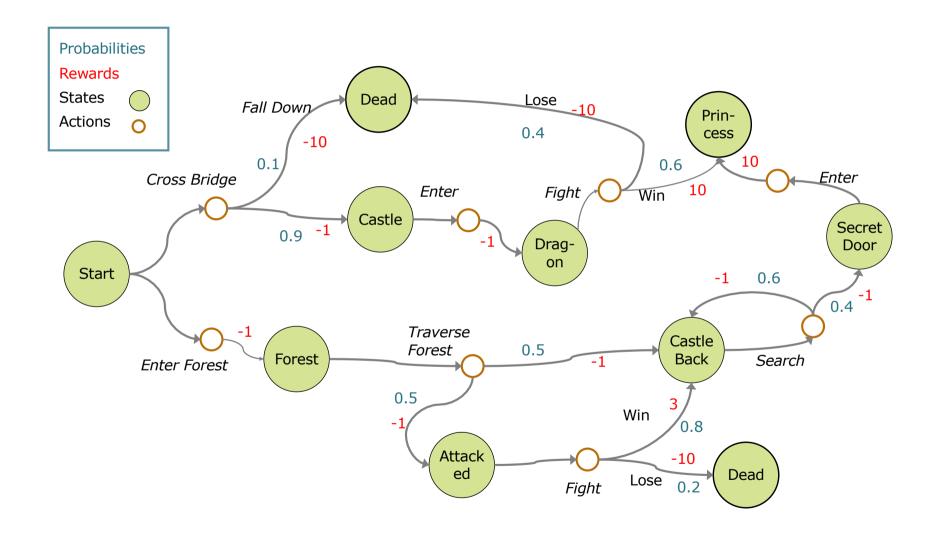
Definition of MDP

The dynamics of an MDP is defined as

$$p(s', r \mid s, a) \doteq \Pr\{S_t = s', R_t = r \mid S_{t-1} = s, A_{t-1} = a\}$$

(this can be viewed as a function of 4 parameters)

Markov Decision Process



Policy and Value Functions

A **policy** is a mapping from states to probabilities of selecting each possible action:

$$\pi(a|s) \doteq \Pr\{A_t = a|S_t = s\}$$

The **state-value function** of a state s under a policy π is the expected return by following π from s:

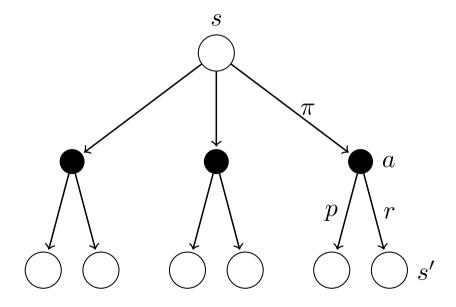
$$v_{\pi}(s) \doteq \mathbb{E}_{\pi}[G_t \mid S_t = s], \text{ for all } s \in S$$

The **action-value function** is the expected return by taking action a in state s and then following π :

$$q_{\pi}(s,a) \doteq \mathbb{E}_{\pi}[G_t \mid S_t = s, A_t = a]$$

Bellman Equation

$$v_{\pi}(s) = \sum_{a} \pi(a|s) \sum_{s',r} p(s',r|s,a) [r + \gamma v_{\pi}(s')], \text{ for all } s \in S$$



Optimal State-Value Function

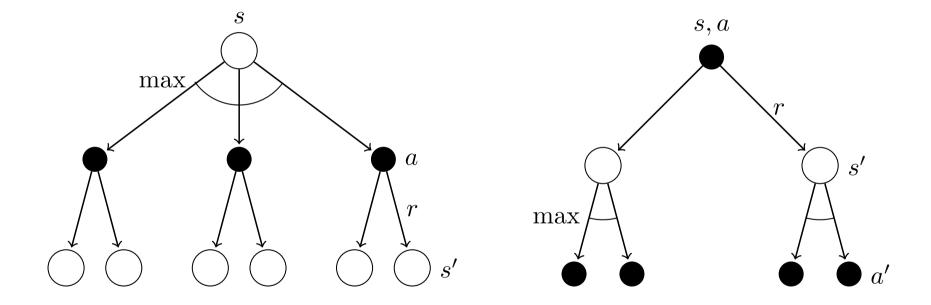
the optimal state-value function is defined as

$$v_*(s) \doteq \max_{\pi} v_{\pi}(s)$$

and the optimal action-value function as

$$q_*(s,a) \doteq \max_{\pi} q_{\pi}(s,a)$$

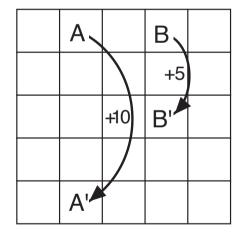
Backup diagrams for the optimal functions



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Examples of MDPs

- Grid world environment
- In state A (or B), the agent is transferred to the state A' (or B') with the indicated reward by any action
- Action that take the agent off the grid have reward -1, other actions 0



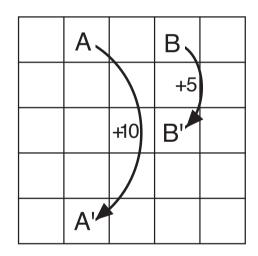


3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

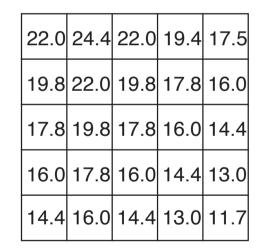
value function for random policy and discount factor 0.9

Example: Gridworld

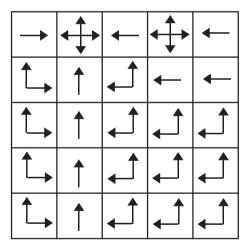
Optimal value function (and policy) for the gridworld problem, using the Bellman Equation



Gridworld



 v_*



 π_*