

Journal

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1 RL Notes

1.1 Markov Processes

- Where the environment fully observable
- Almost all RL problems can be characterized as MDPs

1.1.1 Markov Property

- $P[S_{(t+1)} | S_t] = P[S_{(t+1)} | S_1, \dots, S_t]$
- Future is irrelevant of past, only related to present
- Given $S_{(t)}$, you don't need anything else to find to find next state s'
- Transition Matrix P defines probabilities for all successive states S'

1.1.2 Markov Chains

$M = \{S, T\}$

- Episodes are random sequences that are sampled.
- S = State Space
- T = Transition Probability or the probability of entering the next state
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1.2 Markov Reward Process

$$M = \{S, T, R\}$$

- MRP is a tuple of (S is a finite set of states, P is a state of the transition probability matrix, Reward Function R, discount factor γ)
- $R = E[R_{(t+1)} \mid S_t = s]$

$R_{(t+1)}$ is the amount of reward we get from state s

- We care about the cumulative reward

1.2.1 Return (goal)

Definition: total discounted reward from time-step t

- $G_t = R_{(t+1)} + \gamma * (R_{(t+1)}) + \dots$
- Made finite by the γ
- γ is going to have to be $[0,1]$; 0 discounted factor means you only care about present Reward, 1 factor means you care about all of them
- Discount factor is used because we don't have a perfect model, avoids infinite returns, and animals show a preference for immediate reward

1.2.2 Bellman Equation

The Bellman Equation determines value of a state. It is comprised of immediate reward ($R_{(t+1)}$) and value of next state ($\gamma * v(S_{(t+1)})$)

- Equation: $v(s) = E[G_t \mid S_t = s] = E[R_{(t+1)} + \gamma * v(S_{(t+1)}) \mid S_t = s]$

It is a linear equation and can be solved.

1.3 Markov Decision Process

$$M = \{S, A, T, R\}$$

- MDP is the same as MRP except with the addition of A (the action space)

1.3.1 Policy

$$\pi(a|s) = P[A_t = a \mid S_t = s]$$

- A policy defines the behavior of an agent. It picks the actions that get the most reward.
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