

## 1. Randomness in return: 折扣回報.

Discounted Return.

$$U_t = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots$$

$U_t$  的隨機性由 Action, state 決定

策略函數.

1. Action can be randomness.  $P(A=a | S=s) = \pi(a|s)$
2. New state can be randomness.  $P(S'=s' | S=s, A=a) = P(s' | s, a)$

將態狀移函數.

## 2. Action Value Function, 動作價值函數

對未來折扣獎勵求期望, 因是連續型隨機變數  
積分去除了折扣獎勵之隨機性.

$$Q_{\pi}(s_t, a_t) = E[U_t | \overset{\downarrow}{s_t=s}, \overset{\downarrow}{A_t=a}]$$

給動作打分

$$Q^*(s_t, a_t) = \max_{\pi} Q_{\pi}(s_t, a_t)$$

## 3. State value Function: 狀態價值函數

評價當前狀態好壞

$$\begin{aligned} V_{\pi}(s_t) &= E_A[Q_{\pi}(s_t, \overset{\downarrow}{A})] = \sum_a \pi(a|s_t) \cdot Q_{\pi}(s_t, a) \\ &= \int \pi(a|s_t) \cdot Q_{\pi}(s_t, a) da \end{aligned}$$

## 一、價值學習：

- 動作價值函數，會依當下情況給動作打分

$$Q_{\pi} = E[U_t | S_t = s_t, A_t = a_t]$$

$$Q^*(s_t, a_t) = \max_{\pi} Q_{\pi}(s_t = s_t, A_t = a_t)$$

↗ 上 0.1  
↘ 右 0.2  
→ 左 0.1

$$a = \operatorname{argmax} Q^*(s_t, a_t)$$

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- 利用神經網路近似 Q 函數 DQN

↳  $Q(s_t, a_t; w)$  to approximate  $\overset{\text{"先知"}}{Q^*(s, a)}$ .