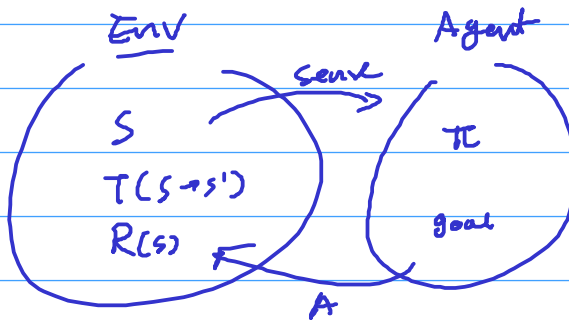
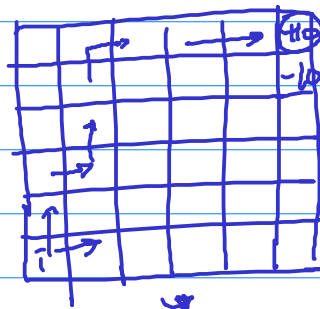


AI



finite, ~~discrete~~ discrete state-action space

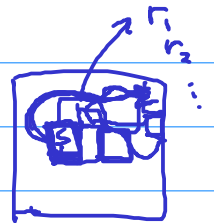


MDP

$$\begin{Bmatrix} T(s, a, s') \\ R(s) \end{Bmatrix} \rightarrow DP$$

RL

$$\begin{Bmatrix} T \times \\ R \times \end{Bmatrix} \rightarrow$$



RL $\left\{ \begin{array}{l} \text{model-based: } \hat{T}, \hat{R} \rightarrow DP \begin{Bmatrix} VI \\ PI \end{Bmatrix} \\ \text{model-free:} \end{array} \right.$

Passive RL : evaluate $\pi \rightarrow V$ $\left\{ \begin{array}{l} MC \text{ (Direct sampling)} \\ TD \text{ (temporal-difference)} \\ = \text{moving average} \end{array} \right.$

active RL π

$\left\{ \begin{array}{l} MC \text{ control: } Q(s, a) \\ TD \text{ control: } Q \end{array} \right.$

$$\underline{\underline{V_{k+1}^{(s)} \leftarrow V_k^{(s)} + \alpha [R_k + \gamma V_k^{(s')} - V_k^{(s)}]}}$$

$\left\{ \begin{array}{l} \text{on-policy: } \epsilon\text{-greedy} \\ \text{off-policy: } \pi \end{array} \right. \left\{ \begin{array}{l} \epsilon \\ 1-\epsilon: \text{explore} \end{array} \right. \pi$

Q-learning : off-policy, TD-control

SARSA : on-policy

SARSA

vs

Q-learning

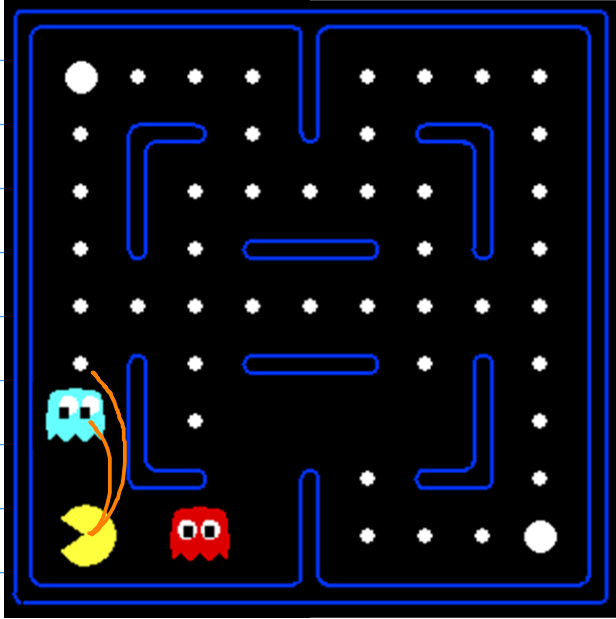
\checkmark A from s using ϵ -greedy Q;
A' from s' " "

b: A from s using ϵ -greedy

$$Q(s, a) \leftarrow Q(s, a) + \alpha [R + \gamma \overbrace{Q(s', a')}^{\pi} - Q(s, a)]$$

$$Q(s, a) \leftarrow Q(s, a) + \alpha [R + \gamma \max_a Q(s', a) - Q(s, a)]$$

Approximation Method ~



$$V = \sum_j W_j \cdot f_j(s)$$

$$Q = \sum_j W_j \cdot f_j(s, a)$$

$$Q \leftarrow Q^{\text{old}} + \alpha (\text{difference})$$

$$Q_{\text{target}} - \hat{Q}$$

$$W_j \leftarrow W_j + \alpha \left(\frac{\partial \mathcal{L}}{\partial W_j} \right)$$

$$\mathcal{L} = \frac{1}{2} (Q_t - \hat{Q})^2$$

$$\left((Q_t - \hat{Q}) \cdot \frac{\partial \hat{Q}}{\partial W_j} \right)$$

$$W_j \leftarrow W_j + \alpha \cdot (Q_t - \hat{Q}) \cdot f_j(s, a)$$

1. Non-linear model → ?

2. Q_{true}

3. Deep RL

ML

Supervised learning $\mathcal{L}(y, \hat{y})$

Parametric model $\hat{y} = f_{\theta}(x) \quad \{\theta\}, \text{ gradient desc}$

non-parametric: $\hat{y} = f(x) \quad \text{dis ent}$

1) MC → $E(r) \rightarrow Q(s, a) = Q_t$

2) Bootstrapping $\left[r + \gamma \max_{a'} Q_{\theta}(s', a') \right] \rightarrow$ Semi-gradient method

$Q_t - \hat{Q} \quad \frac{\partial \hat{Q}}{\partial \theta}$

$$W_j \leftarrow W_j + \alpha \frac{\partial \hat{\phi}_w}{\partial W_j}(s_i, a_i) \left(\underbrace{Q_t - \hat{Q}_w(s_i, a_i)}_{r(s, a) + \gamma \max_{a'} \hat{\phi}_w(s', a')} \right)$$

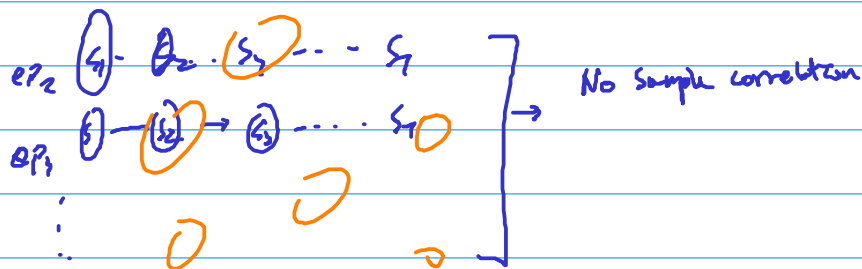
Q-learning / f.A

- 1) sample (a) $s, a \rightarrow s', r$ #1 Samples are correlated ✓
- 2) $Q_t = r(s, a) + \gamma \max_{a'} \hat{Q}_w(s', a')$ #2 off-policy, bootstrapped ✓
- 3) $w \leftarrow w + \alpha \frac{\partial \hat{Q}(s, a)}{\partial w} (Q_t - \hat{Q}(s, a))$ #3 semi-gradient descent

Deep Q-Network 2015

1. F.A \rightarrow DQN
2. off-policy \rightarrow never converges!
3. Bootstrapping

P1. Correlated samples. \rightarrow replay buffer



#2,3: Regression target not stable

$$w' \leftarrow w$$

$$\{s_i, a_i, s'_i, r_i\} \rightarrow \text{RB}$$

$$w \leftarrow w + \alpha \sum_i \frac{\partial \hat{Q}_w}{\partial w} (r(s_i, a_i) + \gamma \max_{a'} \hat{Q}_w(s'_i, a') - \hat{Q}_w(s_i, a_i))$$

$v' = w$

\rightarrow Stable regression

$N = 1000 \sim 10000$

$$w' \leftarrow \tau w' + (1 - \tau) w$$