

minimax-tree
rollouts
MCTS

Planning
Bellman equations

V, Q, π

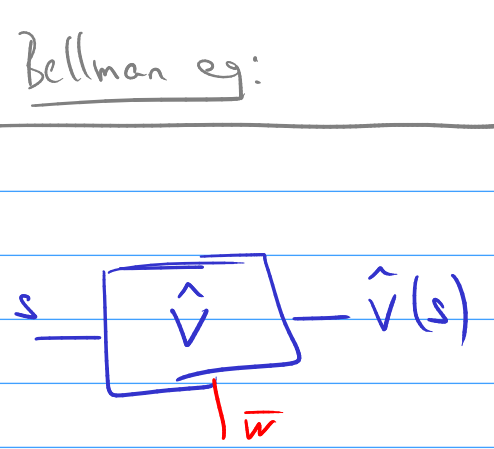
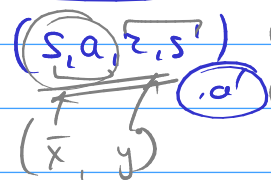
Experience replay

Direct RL
MC-methods
TD-systems

Experience

Model learning
 $p(r, s' | s, a)$

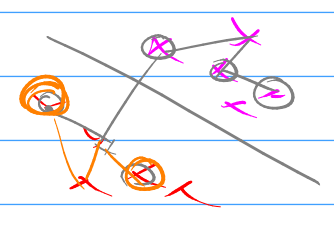
Model



Approximate RL

local, approx. memory
memory, compression

$$L(\bar{w}) = \sum_{s \in \mathcal{S}} \mu(s) (V(s) - \hat{V}(s, \bar{w}))^2$$



$$\nabla_{\bar{w}} L = -2 \sum_s \mu(s) (V(s) - \hat{V}(s, \bar{w})) \nabla_{\bar{w}} \hat{V}(s, \bar{w})$$

\hat{Q}_t : $\bar{w} := \bar{w} + \alpha (V(s_t) - \hat{V}(s_t, \bar{w})) \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$] stochastic GD

$\approx U_t$

\hat{Q}_t : $\bar{w} := \bar{w} + \alpha (U_t - \hat{V}(s_t, \bar{w})) \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$

$\mathbb{E}[U_t | S_t = s] = V(s)$

$U_t = G_t \Rightarrow$ Gradient MC

evaluation

control
on-policy

off-policy

$\pi, V_\pi(s) = ?$

- generate $s_0, A_0, R_1, s_1, \dots, s_T$

- $\forall t = T-1, \dots, 0$

- $\bar{w} := \bar{w} + \alpha (G_t - \hat{V}(s_t, \bar{w})) \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$

$p_t = \frac{\pi(A_t | s_t)}{b(A_t | s_t)}$

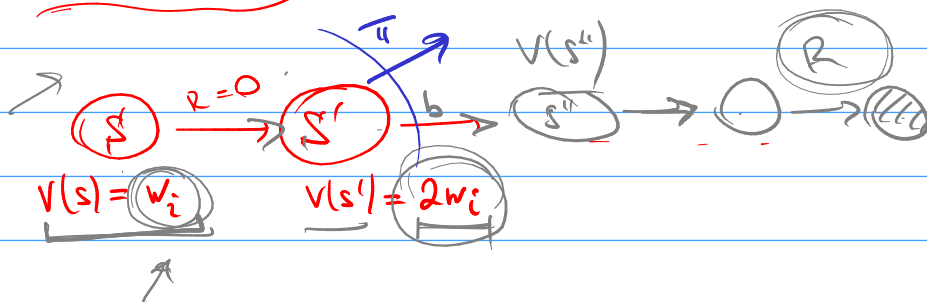
Approximate TD

$$\bar{w} := \bar{w} + \alpha \left(R + \gamma \hat{V}(s' | \bar{w}) - \hat{V}(s, \bar{w}) \right) \cdot \nabla_{\bar{w}} \hat{V}(s, \bar{w})$$

Semi-gradient TD

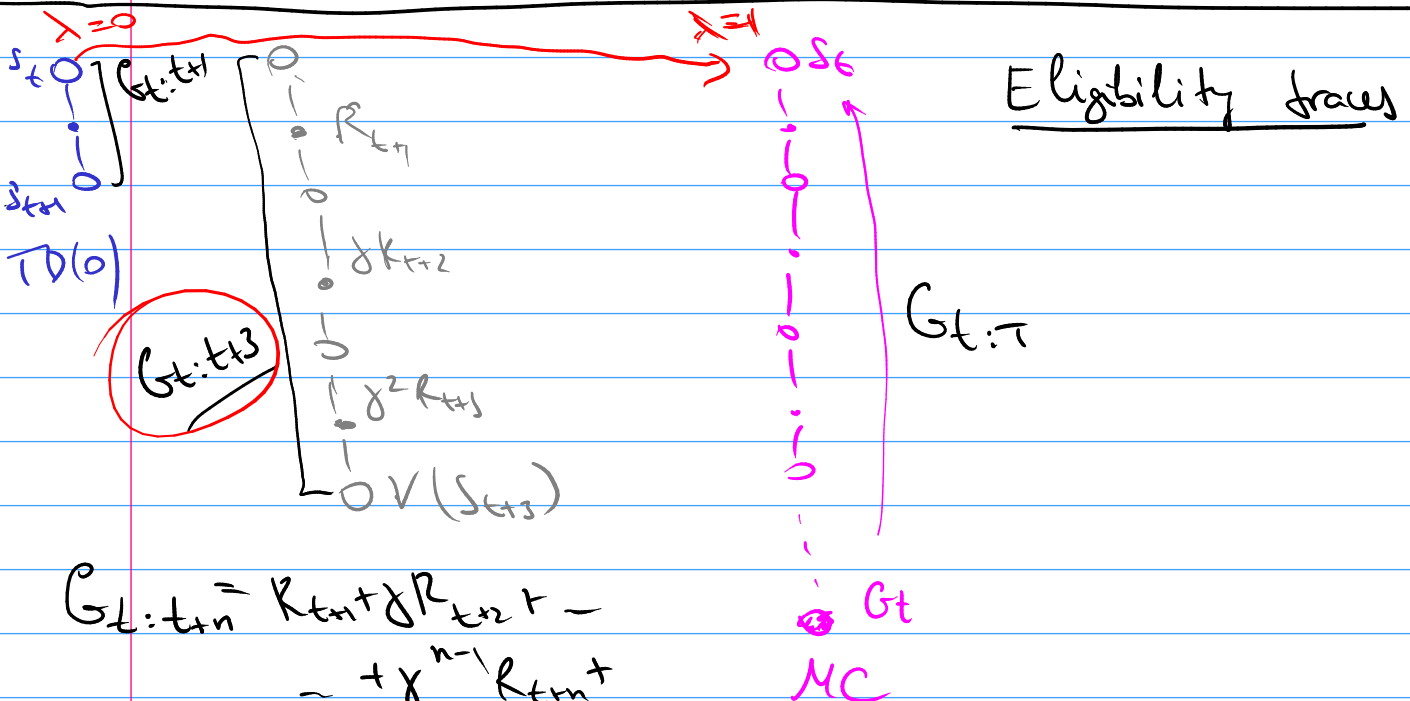
~~Gradient TD~~

off-policy TD



The deadly triad:

- 1) approximation
- 2) bootstrapping
- 3) off-policy



$$G_{t:t+n} = R_{t+n} + \gamma R_{t+n-1} + \gamma^2 R_{t+n-2} + \dots + \gamma^n V(s_{t+n})$$

$$G_t^\lambda = (1-\lambda) G_{t:t+1} + (1-\lambda)\lambda G_{t:t+2} + (1-\lambda)\lambda^2 G_{t:t+3} + \dots$$

$$\bar{w} := \bar{w} + \alpha (\bar{G}_t - \hat{V}(s_t, \bar{w})) \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$$

Semi-gradient TD(λ):

- init $s_0, \bar{z}_1 = 0$

- $\forall t = 0, \dots, T$:

- $\text{obs} \supset A, \text{next} \supset R, s'$ & s

- $\bar{z} := \gamma \cdot \lambda \bar{z} + \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$

- $\bar{w} := \bar{w} + \alpha (R + \gamma \hat{V}(s', \bar{w}) - \hat{V}(s, \bar{w})) \bar{z}$

$\lambda = 0 \Rightarrow$ TD
 $\lambda = 1 \Rightarrow$ MC

Policy gradient

~~Q, V (state-value / action-value methods)~~

$s \rightarrow \boxed{\pi} \rightarrow a$

$$\pi(a|s, \theta) = P_r[A_t = a | S_t = s, \theta]$$

$$J(\theta) = ?$$

$$\bar{\theta} := \bar{\theta} + \alpha \nabla_{\theta} J(\bar{\theta})$$

$s \rightarrow \boxed{\pi} \rightarrow a$
 $\pi(a|s, \theta)$

Actor-critic methods

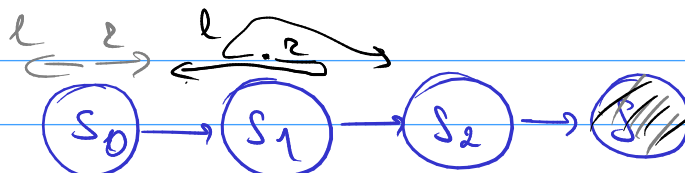
$$\pi(a|s, \bar{\theta}) + V(s, \bar{w})$$

$s \rightarrow \boxed{\pi} \rightarrow a$

$$h(a, s, \theta) = \boxed{\text{softmax}} = \pi(a|s, \theta) = \frac{e^{h(a, s, \theta)}}{\sum_{a'} e^{h(a', s, \theta)}}$$

$s \rightarrow \boxed{Q_*} \rightarrow a$

$$Q_*(s, a) \Rightarrow \pi = \arg\max_a Q_*(s, a)$$



$$J(\theta) = V_{\pi_{\theta}}(s_0)$$

$$\nabla_{\theta} J(\theta) = ?$$

$$V_{\pi_{\theta}}(s) = \sum_a \pi(a|s, \theta) Q_{\pi_{\theta}}(s, a)$$

$$\nabla_{\theta} V_{\pi_{\theta}}(s) = \sum_a \left((\nabla_{\theta} \pi(a|s, \theta)) \cdot Q_{\pi_{\theta}}(s, a) + \pi(a|s, \theta) \cdot \nabla_{\theta} Q_{\pi_{\theta}}(s, a) \right) =$$

$$= \sum_a \left[\nabla_{\theta} \pi \cdot Q_{\pi}(s, a) + \pi(a|s, \theta) \cdot \nabla_{\theta} \sum_{s', z} p(s', z|s, a) (r + \gamma V_{\pi_{\theta}}(s')) \right] =$$

$$= \sum_a \left(\nabla_{\theta} \pi \cdot Q_{\pi}(s, a) + \pi(a|s, \theta) \cdot \sum_{s', z} p(s', z|s, a) (r + \gamma \nabla_{\theta} V_{\pi_{\theta}}(s')) \right) =$$

$$= \sum_a \left(Q_{\pi}(s, a) \cdot \nabla_{\theta} \pi(a|s) + \pi(a|s, \theta) \cdot \sum_{s', z} p(s', z|s, a) (r + \gamma \sum_{a'} (\nabla_{\theta} \pi(a'|s') \cdot Q_{\pi}(s', a') + \pi(a'|s', \theta) \cdot \nabla_{\theta} Q_{\pi}(s', a')) \right) =$$

$$= \sum_{s' \in \mathcal{S}} \sum_{k=0}^{\infty} \Pr[s \rightarrow s' \text{ in } k \text{ steps} \mid \pi] \left(\sum_a \nabla_{\theta} \pi(a|s') Q_{\pi}(s', a) \right)$$

$$\nabla_{\theta} J(\theta) = \nabla_{\theta} V_{\pi}(s_0) = \sum_s \left(\sum_{t=0}^{\infty} \Pr[s_0 \rightarrow s \text{ in } t \text{ steps} \mid \pi] \right) \left[\sum_a \nabla_{\theta} \pi \cdot Q_{\pi} \right]$$

$$= \sum_s \eta(s) \cdot \sum_a \nabla_{\theta} \pi(a|s) \cdot Q_{\pi}(s, a) \propto$$

$$= \mathbb{E}[\# \text{ non-zero } Q \text{ at } s]$$

$$\propto \sum_s \mu(s) \cdot \sum_a \nabla_{\theta} \pi(a|s) Q_{\pi}(s, a)$$

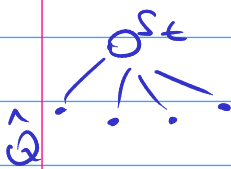
done non-zero count. s

Policy gradient theorem

$$\left[\nabla J(\bar{\theta}) \propto \sum_s \mu(s) \sum_a Q_{\pi}(s, a) \cdot \nabla_{\theta} \pi(a|s, \theta) \right] =$$

$$= \mathbb{E}_{\pi} \left[\sum_a \underline{Q_{\pi}(s, a)} \nabla_{\theta} \pi(a|s, \theta) \right]$$

① All-actions

$$\bar{\theta} := \bar{\theta} + \alpha \sum_a \hat{Q}(s_t, a, \bar{\theta}) \cdot \nabla_{\bar{\theta}} \pi(a|s_t, \bar{\theta})$$


② REINFORCE

$$\begin{aligned} \nabla J(\bar{\theta}) &\propto \mathbb{E}_{\pi} \left[\sum_a Q_{\pi}(s_t, a) \nabla_{\theta} \pi(a|s_t, \theta) \right] = \\ &= \mathbb{E}_{\pi} \left[\left(\sum_a \frac{\pi(a|s_t)}{\pi(a|s_t)} \right) \cdot \frac{1}{\pi(a|s_t)} Q_{\pi}(s_t, a) \nabla_{\theta} \pi(a|s_t, \theta) \right] = \end{aligned}$$

$$\begin{aligned} [A_t \sim \pi] &= \mathbb{E}_{\pi} \left[\underbrace{Q_{\pi}(s_t, A_t)} \cdot \frac{\nabla_{\theta} \pi(A_t|s_t, \theta)}{\pi(A_t|s_t, \theta)} \right] = \\ Q_{\pi}(s_t, A_t) &= \mathbb{E}_{\pi} [\underline{G_t} | s_t, A_t] \end{aligned}$$

$$J(\theta) \propto \mathbb{E}_{\pi} \left[\underline{G_t} \cdot \frac{\nabla_{\theta} \pi(A_t|s_t, \theta)}{\pi(A_t|s_t, \theta)} \right]$$

$$\bar{\theta} := \bar{\theta} + \alpha G_t \cdot \frac{\nabla_{\theta} \pi(A_t|s_t, \theta)}{\pi(A_t|s_t, \theta)} = \bar{\theta} + \alpha G_t \nabla_{\theta} \ln \pi(A_t|s_t, \theta)$$

REINFORCE:

- loop
- gen. ep. $S_0, A_0, R_1, S_1, \dots, S_T$
- & $t = 0, \dots, T-1$:
 - $G_t := R_{t+1} + \gamma V_{t+2} + \dots + \gamma^{T-t-1} R_T$

$$-\theta := \theta + \alpha \gamma^t \cdot G \nabla_{\theta} \ln \pi(A_t | S_t, \theta)$$

$$\nabla J(\bar{\theta}) \propto \sum_s \mu(s) \sum_a \underline{Q_{\pi}(s, a)} \cdot \nabla_{\theta} \pi(a | s, \theta)$$

$b(s)$ - baseline

$$\sum_s \mu(s) \sum_a (Q_{\pi}(s, a) - b(s)) \nabla_{\theta} \pi(a | s, \theta) =$$

$$= \sum_s \mu(s) \left(\sum_a Q \nabla_{\pi} - \sum_a \cancel{b(s)} \nabla_{\theta} \pi(a | s, \theta) \right)$$

$$b(s) \cdot \nabla_{\theta} \left(\sum_a \pi(a | s, \theta) \right)$$

REINFORCE w/ baseline:

$$-\theta := \theta + \alpha \left(G_t - \underbrace{b(s_t)}_{\hat{V}(s_t, \bar{w})} \right) \cdot \nabla_{\theta} \ln \pi(A_t | S_t, \theta)$$

$$-\bar{w} := \bar{w} + \alpha' \left(\underbrace{G_t}_{R_{t+1} + \gamma \hat{V}(s_{t+1}, \bar{w})} - \hat{V}(s_t, \bar{w}) \right) \nabla_{\bar{w}} \hat{V}(s_t, \bar{w})$$