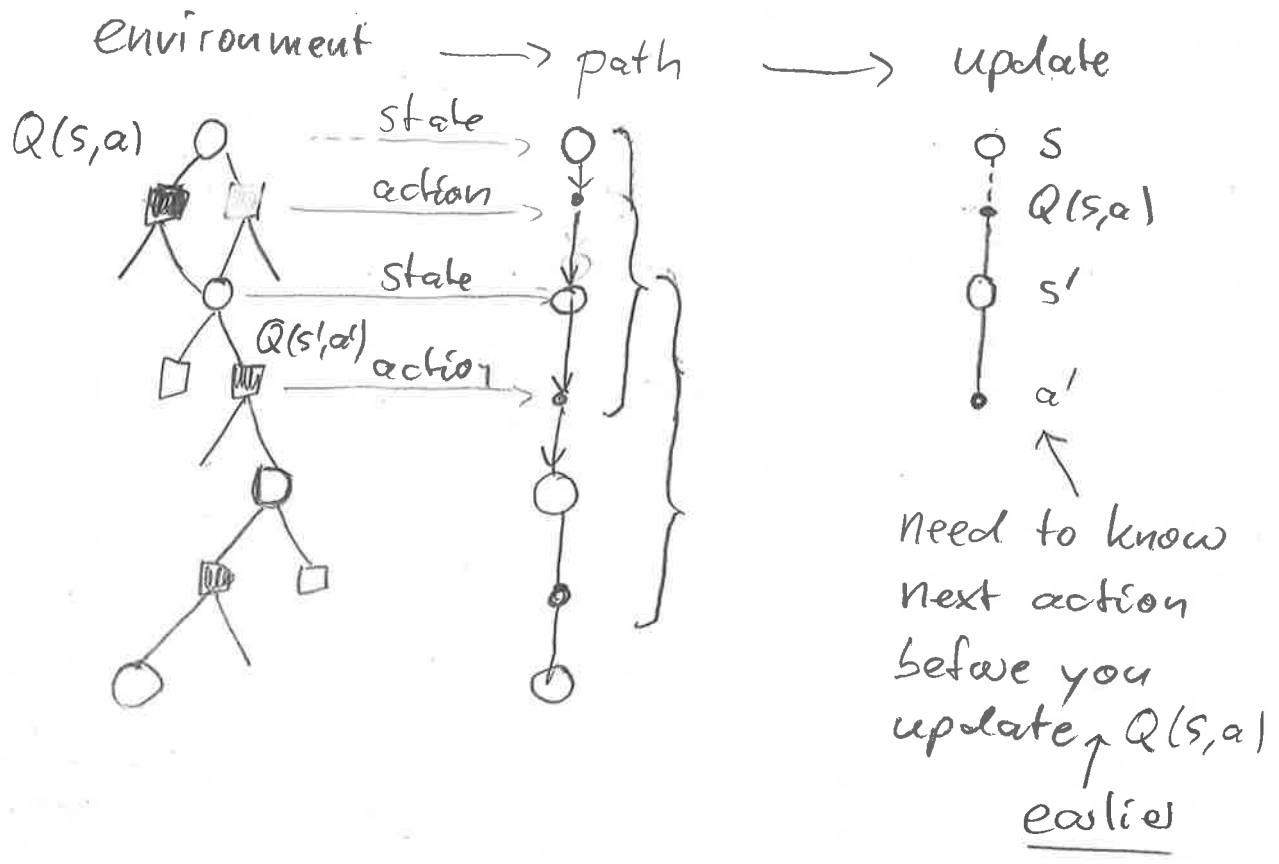


RL2 ; Blackboard1: Backup Diag



$$Q(s,a) \leftarrow Q(s,a) + d \left[r_t + \gamma Q(s',a') - Q(s,a) \right]$$

↑ earlier action ↑ next action

RL2, Exercise 1a + 1b

Blackboard 2

(\hat{s}, \hat{a}) pair	encountered in trial	Monte Carlo average return $\langle R(\hat{s}, \hat{a}) \rangle$	Bootstrap Batch-Q from Bellman
(s', a_3)	2, 4, 8	$\frac{1}{3}[1+1+1]=1$	1
(s', a_4)	1, 3, 6, 7, 9	$\frac{1}{5}[0+0+0+0.5+0.5]=\frac{1}{5}$	$\frac{1}{5}$
(s, a_1)	5, 10	$\frac{1}{2}[0+0]=0$	0
(s, a_2)	1, 9	$\frac{1}{2}[0.2+0.7]=\underline{\underline{0.45}}$	$\langle r_t \rangle + \max_{a'} Q(s', a')$ $\downarrow \qquad \qquad \downarrow$ $0.2 + 1 = \underline{\underline{1.2}}$

with same number of trials Bootstrap/Bellman/Batch-Q yields much better estimate than Monte-Carlo!

Batch-Q = Q from Bellman (without knowledge of branching ratio)

online Q-learning

$$Q(s, a) \leftarrow Q(s, a) + \eta \cdot [r_t + \underbrace{\max_{a'} \{Q(s', a')\}}_{\text{* compressed knowledge from previous trials}} - \gamma Q(s, a)]$$

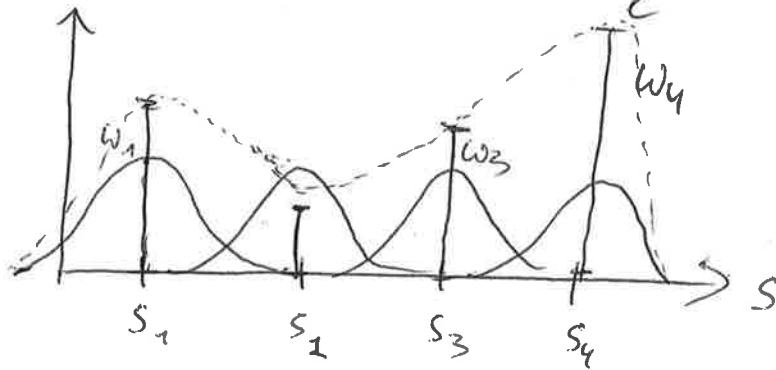
batch-Q: n trials ($1 \leq k \leq n$) starting at (s, a)

$$Q(s, a) \leftarrow Q(s, a) + \underbrace{\frac{1}{n} \left[\sum_{k=1}^n r_t(k) \right]}_{\text{average}} + \underbrace{\max_{a'} \{Q(s', a')\}}_{\text{* compressed knowledge from 0 states close to target}} - \gamma Q(s, a)$$

initialize: $Q=0$

$$Q(s, a) \leftarrow \langle r_t \rangle + \max_{a'} \{Q(s', a')\}$$

Blackboard 3, RL2



$$Q(a_1, s) = \sum_k w_k \phi(s - s_k)$$

amplitudes

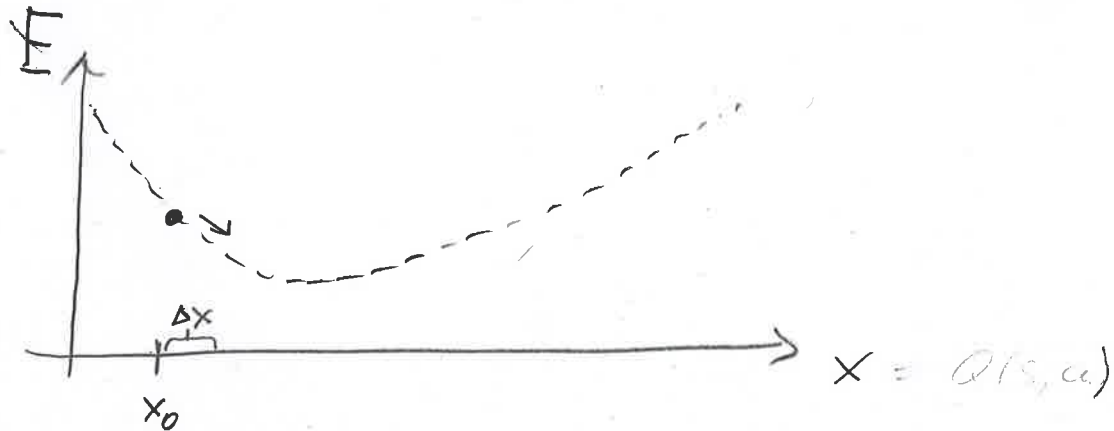
w_1 w_2 w_3 w_4

⇒ smooth function with few parameters

Blackboard 4 - RL 2: Loss function

$$\frac{\text{error}}{E} = \frac{1}{2} \left[\underbrace{r + \gamma Q(s', a')}_{\text{target}} - \underbrace{Q(s, a)}_{\substack{\text{depends on} \\ \text{parameters } x \\ \text{(the weights } w_1, w_2, \dots)}} \right]^2$$

minimize error by gradient descent



$$\Delta x_i = -\eta \cdot \frac{\partial E}{\partial x} = +\eta \cdot [r + \gamma Q(s', a') - Q(s, a)] \frac{\partial Q(s, a)}{\partial x}$$