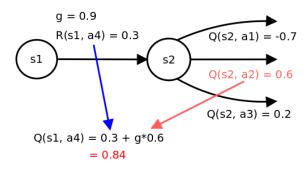
Deep Q networks

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1 Q-learning



$$Q(s,a) = R + \gamma \max_{\alpha'} Q(s', \alpha') \tag{1}$$

where s is state a is action s' is next state a' is best action in next state R is reward function $\gamma \in \langle 0, 1 \rangle$ is discount factor

2 Deep Q network - DQN

Approximate Q(s,a) using neural network as $\hat{Q}(s,a;w)$, where w are learnable network parameters resulted Q value using 1

$$\hat{Q}(s, a; w) = R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w)$$
(2)

error to minimize

$$E = R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w) - \hat{Q}(s, a; w)$$
target value

(3)

weights gradient

$$\Delta w = \eta E \nabla_w \hat{Q}(s, \alpha, w) \tag{4}$$

There is changing target value, $\hat{Q}(s, a; w)$ depends on w which is changing and leads to unstable learning. **Solution - fix** w, using temporary network with w' weights. This leads to deep Q learning equation

$$\hat{Q}(s, a; w) = R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w')$$
(5)

and every K steps update $w' \leftarrow w$, usually after training epoch. For agent decission making, the network w' is used.

3 Dueling deep Q network - DDQN

$$\hat{Q}(s,a,w) = \hat{V}(s,w) + \hat{A}(s,a,w)$$
value for being in state s advantage of taking action a at state s (6)

to avoid identifiability we substract average value of A truth all actions

$$\hat{Q}(s, a, w) = \hat{V}(s, w) + \hat{A}(s, a, w) - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s, \alpha', w)$$
(7)

using equation 5 we obtain dueling deep Q network equation

$$\hat{Q}(s,a;w) = R + \gamma \left(\hat{V}(s',w') + \max_{\alpha'} \hat{A}(s',\alpha',w') - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s',\alpha',w') \right)$$
(8)

and finally the weights learning rule

$$\Delta w = \eta \left(R + \gamma \left(\hat{V}(s', w') + \max_{\alpha'} \hat{A}(s', \alpha', w') - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s', \alpha', w') \right) - \hat{Q}(s, a; w) \right) \nabla_w \hat{Q}(s, a; w)$$
(9)