Deep Q networks

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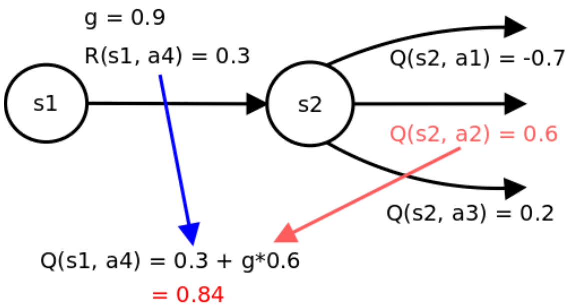
1 Q-learning



Obr. 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

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

error to minimize

$$E = \underbrace{R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w)}_{\text{target value}} - \underbrace{\hat{Q}(s,a;w)}_{\text{predicted value}} \tag{3}$$

weights gradient

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

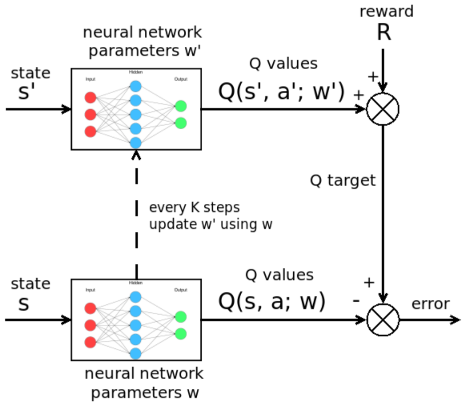
There is changing target value, $\hat{Q}(s,a;w)$ depends on w which is also changing during training, and leads to unstable learning. **Solution - fix** w, using temporary network with w' weights. This leads to deep Q learning equation

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

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

$$E = R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w') - \hat{Q}(s,a;w) \tag{6}$$

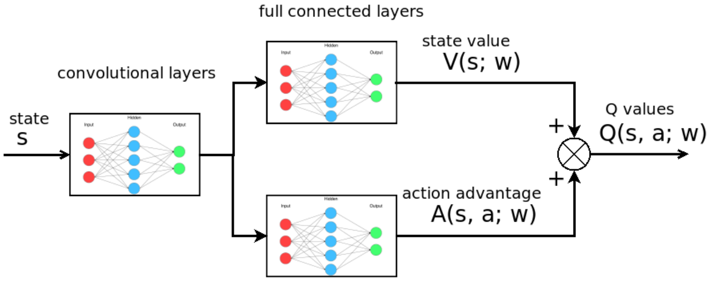
Principle of DQN can be demostrated on image 2 (Q-learning γ and max operator are removed for simplicity).



Obr. 2: basic DQN principle

3 Dueling deep Q network - DDQN

$$\hat{Q}(s,a,w) = \underbrace{\hat{V}(s,w)}_{\text{value for being in state s}} + \underbrace{\hat{A}(s,a,w)}_{\text{advantage of taking action a at state s}} \tag{7}$$



Obr. 3: dueling DQN principle

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

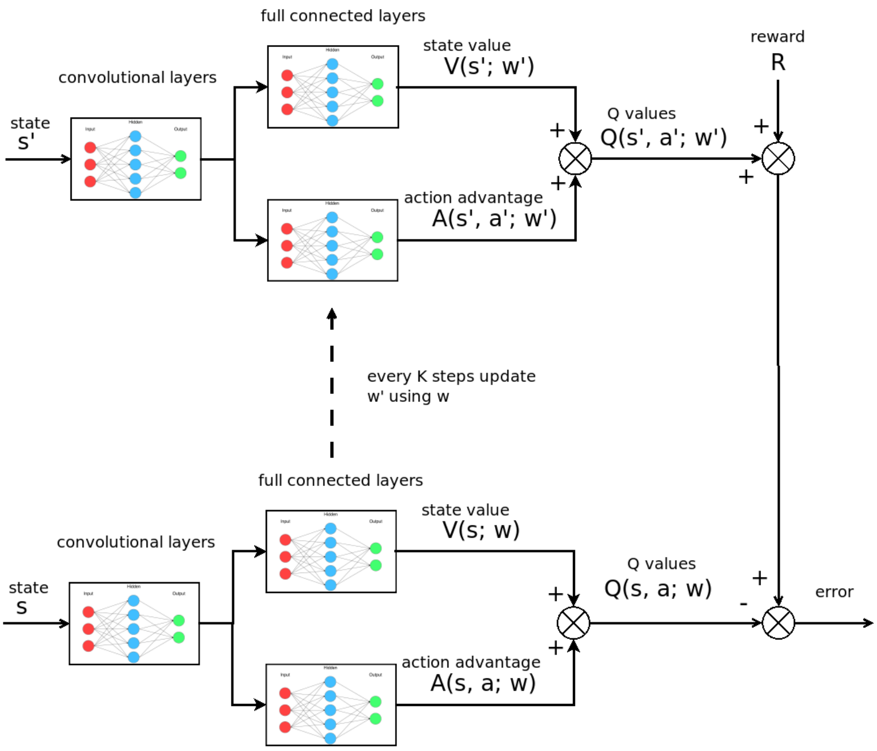
$$\hat{Q}(s,a,w) = \hat{V}(s,w) + \hat{A}(s,a,w) - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s,\alpha',w) \tag{8}$$

using equation 5 we obtain dueling deep Q network equation

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

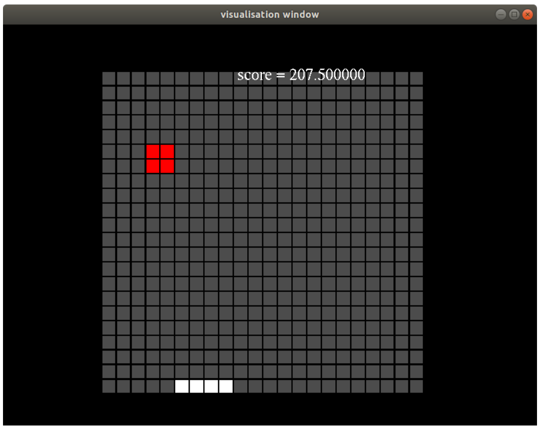
and finally the weights learning rule

$$\Delta w = \eta \left(R + \gamma \left(\hat{V}(s',w') + \max_{\alpha'} \hat{A}(s',\alpha',w') - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s',\alpha',w') \right) - \hat{Q}(s,a;w) \right) \nabla_w \hat{Q}(s,a;w) \tag{10}$$



Obr. 4: dueling DQN principle, full

4 Experiments



Obr. 5: example of testing game

Network hyperparameters

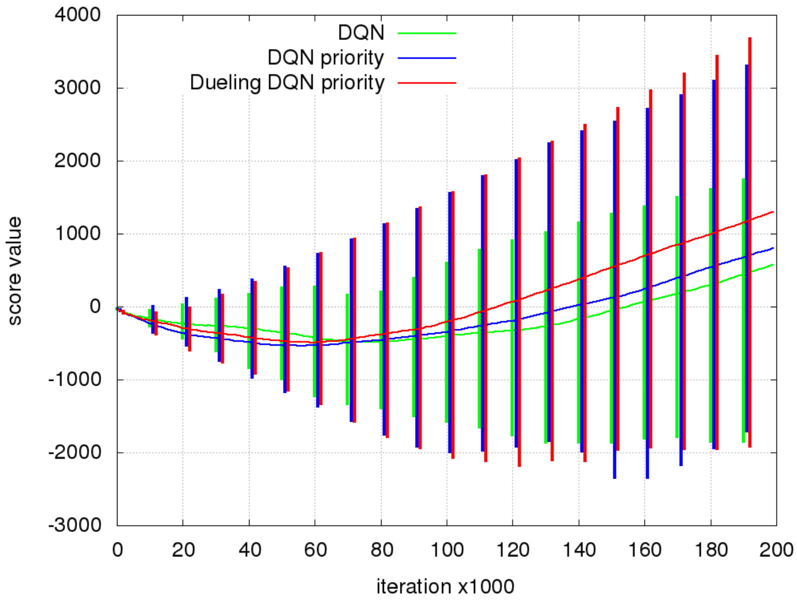
- init weights : XAVIER
- learning rate : 0.0005
- L1 regularization : 0.0000001
- L2 regularization : 0.0000001
- dropout : 0.2
- minibatch size : 32

RL hyperparameters

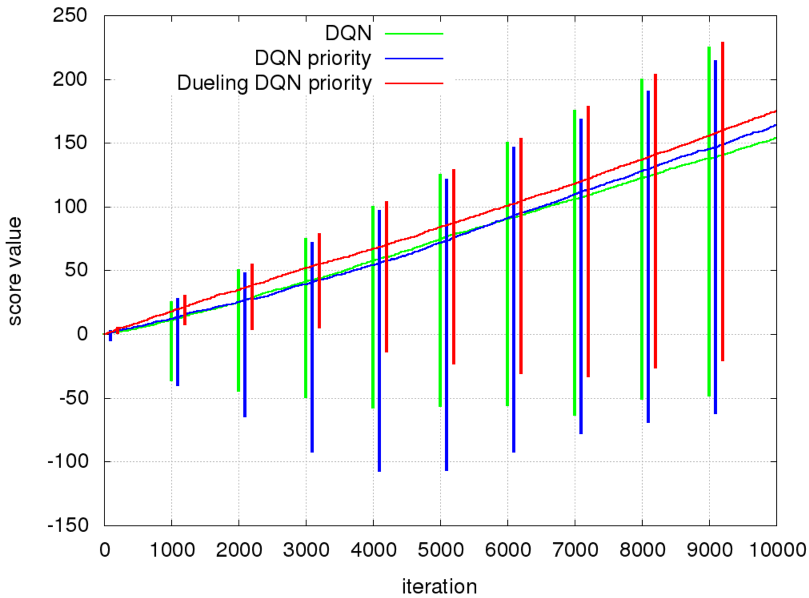
- experience buffer size : 1024
- gamma : 0.95
- epsilon training : 0.1
- epsilon testing : 0.05

layer type	input dimensions	kernel dimensions
dense convolution	22x22x1	3x3x8
dense convolution	22x22x9	3x3x8
dense convolution	22x22x17	3x3x8
dense convolution	22x22x25	3x3x8
convolution	22x22x33	3x3x32
full connected	22x22x32	actions_count

Tabul'ka 1: testing network architecture



Obr. 6: training score progress



Obr. 7: testing score progress