$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \lambda \max_{a} Q(s_{t+1}, a) - Q(s_t, a_t)]$$

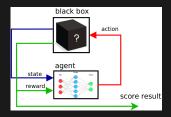
(The New Action Value = The Old Value) + The Learning Rate × (The New Information - the Old Information)



Output

Reinforcement learning

- obtain state
- choose action
- execute action
- obtain reward
- learn from experiences
- function Q(s, a), how good is action a in state s



- playing Atari
- playing Doom
- playing GO

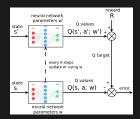


Deep Q network

- correlated states : experience replay buffer
- unstable training: non-stationary target value $\hat{Q}(s, a; w)$, depends on w, use temporary fixed weights w'
- lacktriangle unknow gradients values : clip or normalise rewards, Q values and gradients into $\langle -1,1 \rangle$

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

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



Networks architecture

Following modern **State of the art** networks : 3x3 convolutions, 2x2 pooling, ELU activation

- Atari
 - input : 48x48x12 (rgb x 4 last frames)
 - network: C3x3x32 P2x2 C3x3x32 P2x2 C3x3x32 P2x2
 C3x3x32 P2x2 FC256 FCactions count



- DOOM
 - input: 80x80x24 (rgb x 8 last frames)
 - network : C3x3x64 P2x2 C3x3x64 P2x2 C3x3x64 P2x2
 C3x3x64 P2x2 FC256 FC_{actions_count}



GO Network architecture

we need to go much deeper for GO

- 28, 35 layers
 dense blocks + feature pooling layer
- input
 4 matrices 19x19: black stones, white stones, empty fields, active player
- output
 recommended moves 19x19 + 1 for pass = 362 outputs



All programmed from scratch in C++, Cuda and Python - about 40 000 lines of code :

- Rysy CNN framework : https://github.com/michalnand/rysy
- RL framework :
 https://github.com/michalnand/rl_examples



michal chovanec (michal.nand@gmail.com)
www.youtube.com/channel/UCzVvP2ou8v3afNiVrPAHQGg