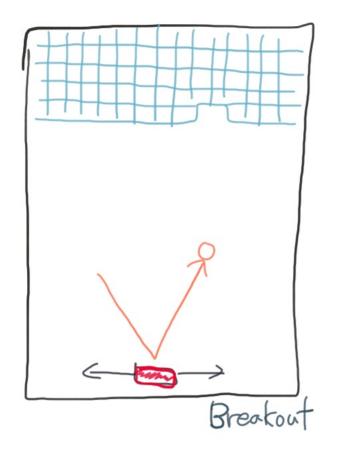
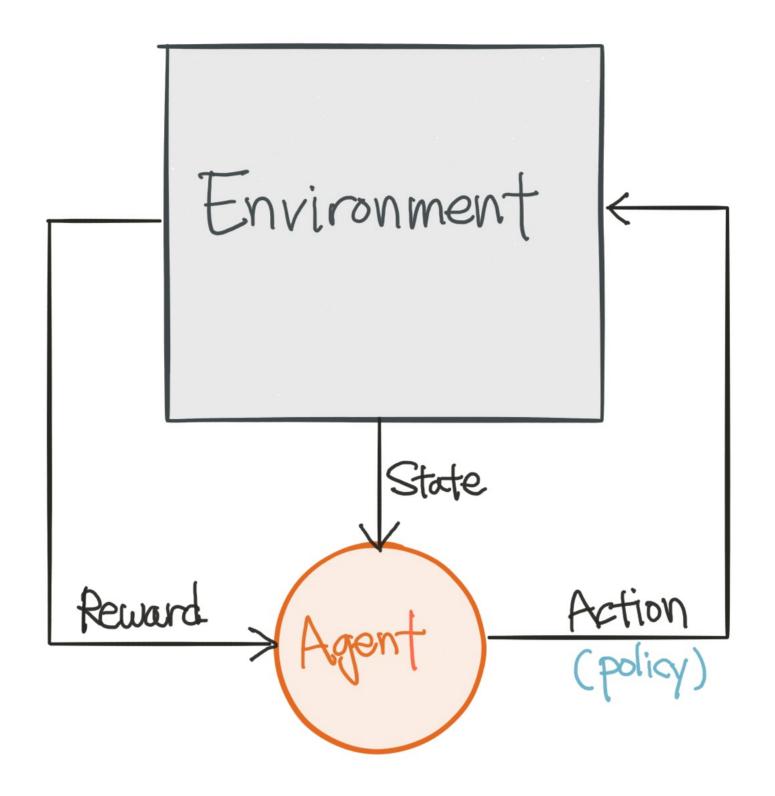
# Reinforcement Learning



Each time you hit a brick, your score increases. (Reward)

The good of RL is to find on optimal policy that maximizes the expected sum of reward.

#### Reinforcement Learning



#### Markov Decision Process

State World modelling s ES Action Possible actions a  $\in A$ Reward R(s,a): SxA -> R Policy TCS): 3->A Transition model T(s,a,s): 5xA->5 Q function Q(s,a): SXA->1R Value function V(S): 5->1 Episode So, ao, to, Si, ai, ri, ... Stat, rt

#### **Markov Decision Process**

## Terminology

To perform well in the long-term, we need to take into account the future rewards we are going to get

$$R = r_t + r_{2+} + r_n$$

$$R_t = r_t + r_{t+1} + \cdots + r_n$$

But, our world is stochastic!

So we give more emphasis on corrent reward.

#### Discounted Future Reward

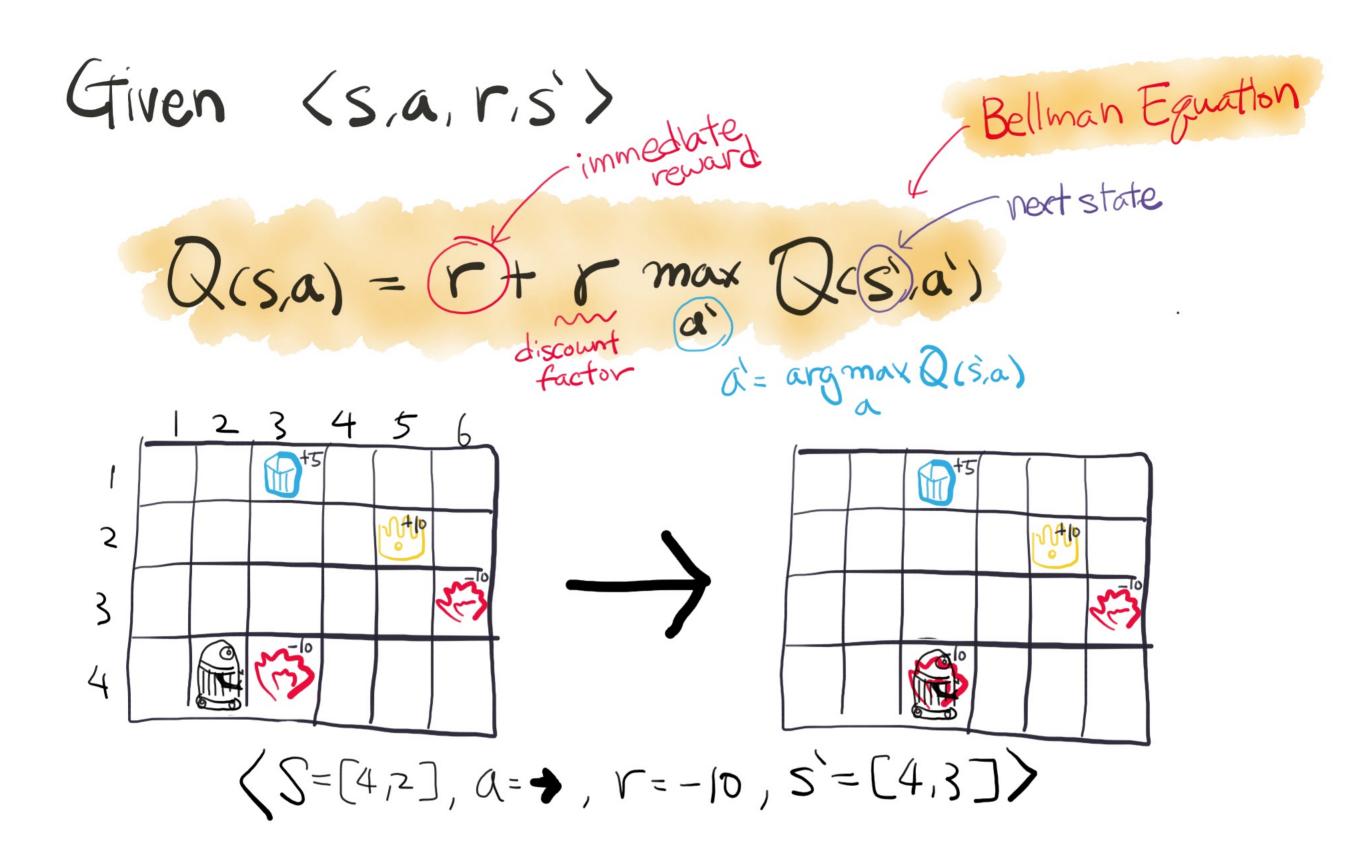
Q Learng

(Stiat) = max Reti = max (resit + & reszt ...)

- Q function is 1) Maximum discounted future reward when we perform action a in state S.
  - 2) The best possible score at the end of the game.
  - 3) The quality of certain action ingiven state

TT(S) = arg max Q(S,a)

## **Q** Learning



#### Bellman Equation

Initialize Q(s,a)Observe initial state Srepeat

Select and carry out an action aobserve reward r and new state s'  $Q(s,a) = Q(s,a) + \alpha(r + r) \max_{a'} Q(s,a') - Q(s,a)$  S = S'

until terminated

## Q Learning Algorithm

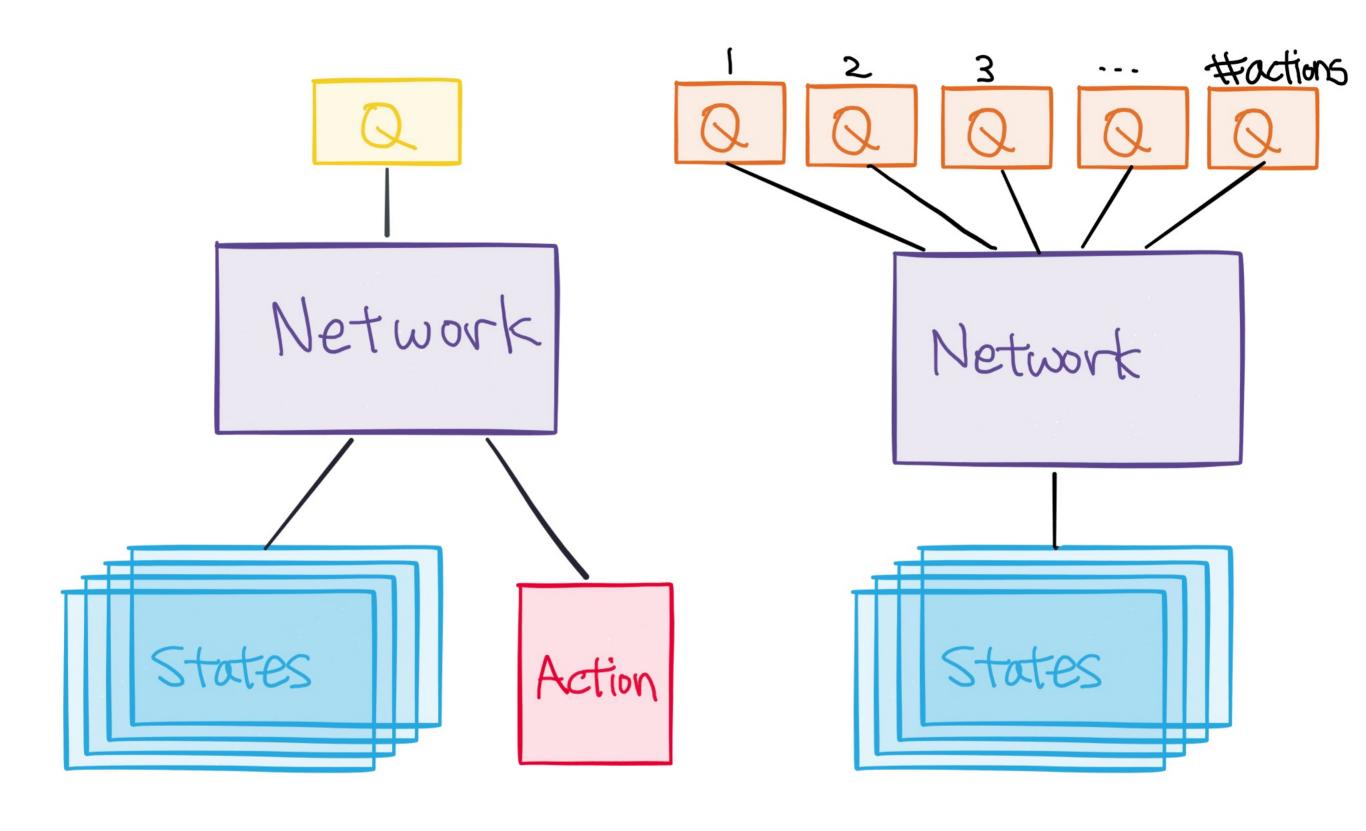
Initialize Q(s,a)Observe initial state Srepeat

Randomly

Select and carry out an action a comes from some grade observe reward r and new state s  $Q(s,a) = Q(s,a) + \alpha(r + r) \max_{a} Q(s,a) - Q(s,a)$  S=S'Learning discount tootor

until terminated

## Q Learning Algorithm

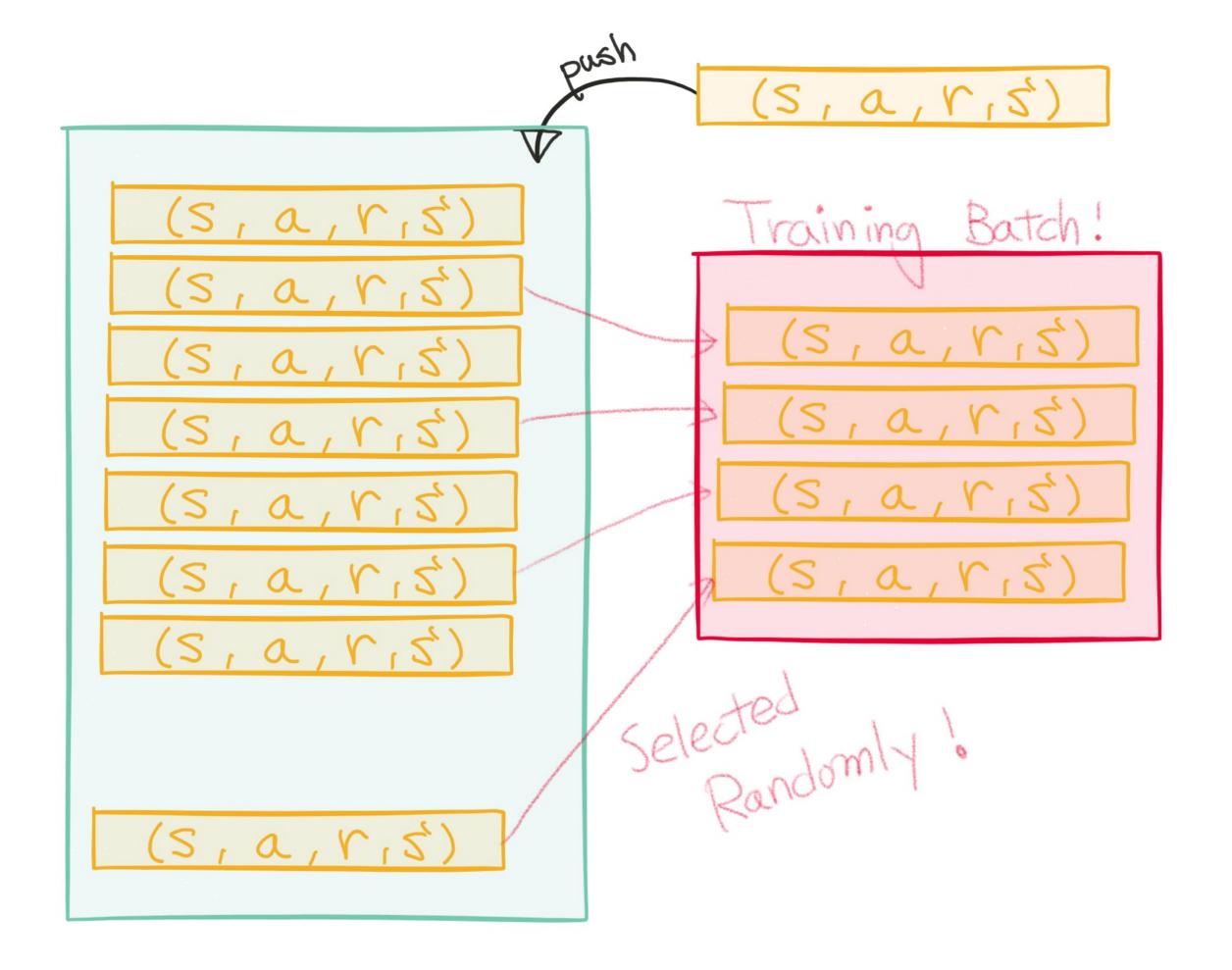


### Deep Q Learning

(S, a, r, 5')

(S, a, r, 5') (S, a, r, 5) (S, a, r, s') (S, a, r, s')

#### Experience Replay



#### Experience Replay