Deep Reinforcement Learning

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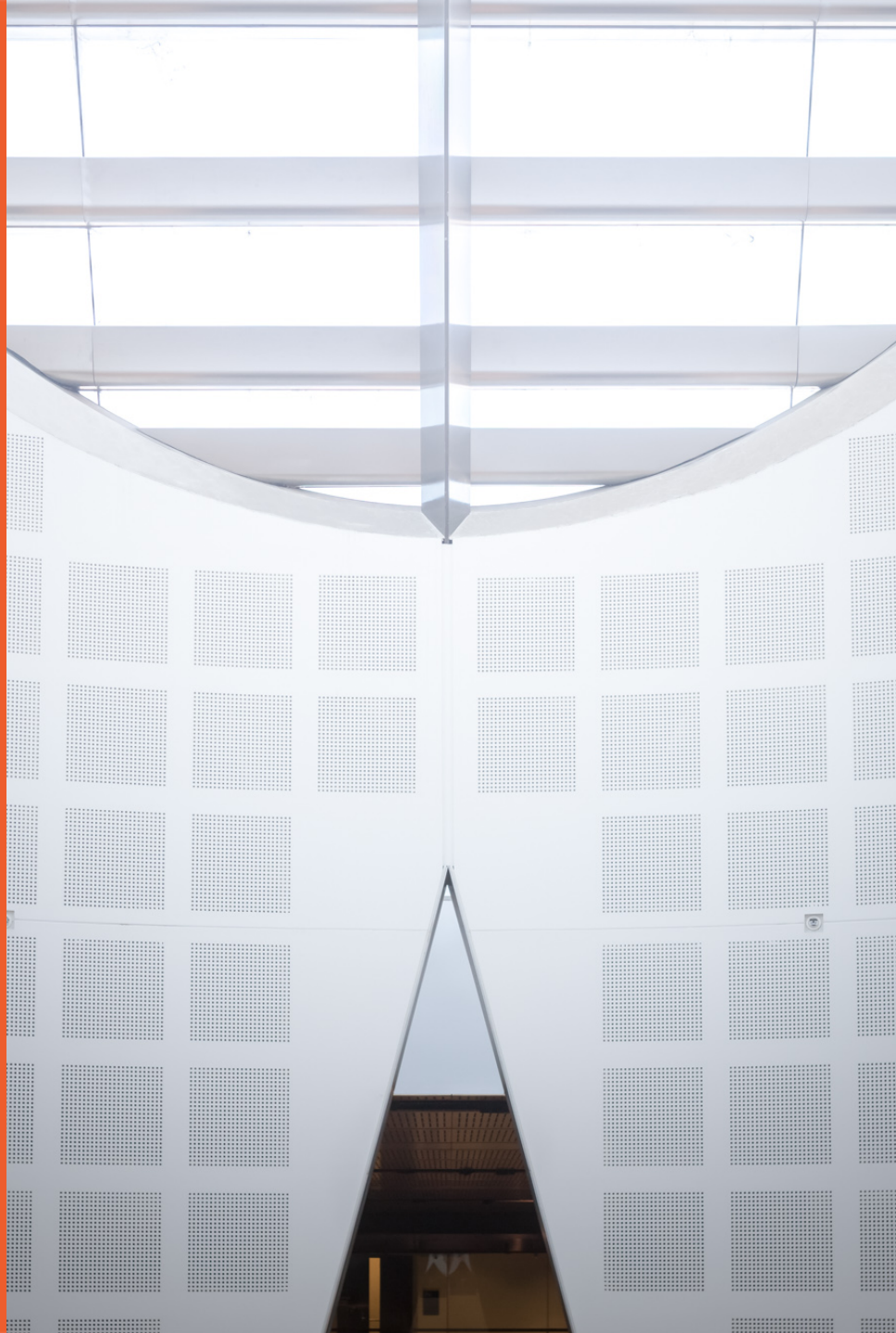
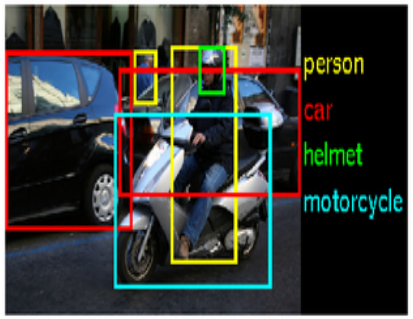


Background

- Deep learning methods are making major advances in solving many low-level perceptual tasks.



See (visual object recognition)

Read (text understanding)

Hear (speech recognition)

From the talk *Introduction to Deep Reinforcement Learning From Theory to Applications* by Siyi Li (HKUST)

Background

- More sophisticated tasks that involve decision and planning require a higher level of intelligence.
- Real Artificial Intelligence system also requires the ability of reasoning, thinking and planning.

Playing Atari game

Robotic navigation

From the talk *Introduction to Deep Reinforcement Learning From Theory to Applications* by Siyi Li (HKUST)

Reinforcement Learning (RL) in a nutshell

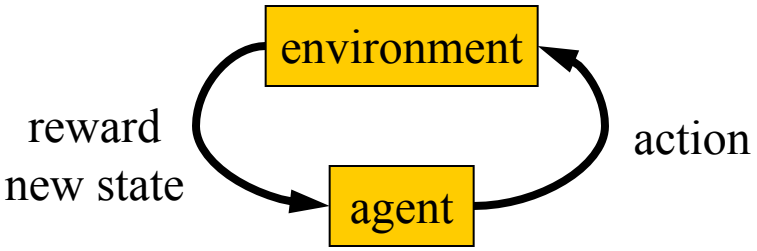
- RL is a general-purpose framework for decision making
  - RL is for an agent to act with an environment
  - Each action influences the agent's future state
  - Feedback is given by a scalar reward signal
  - Goal: select actions to maximize future reward

Actions: muscle contractions
Observations: sight, smell
Rewards: food

From the talk *Introduction to Deep Reinforcement Learning From Theory to Applications* by Siyi Li (HKUST)

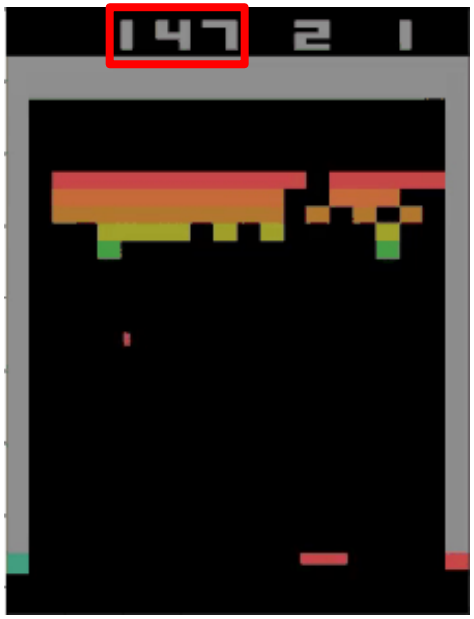
Markov Decision Process (MDP)

- set of states S, set of actions A, initial state S_0
- transition model P(s, a, s')
  - P($frame_{(t)}$, right, $frame_{(t')}$) = 0.8
- reward function r(s)
  - r($frame_{(t)}$) = +1
- goal: maximize cumulative reward in the long run

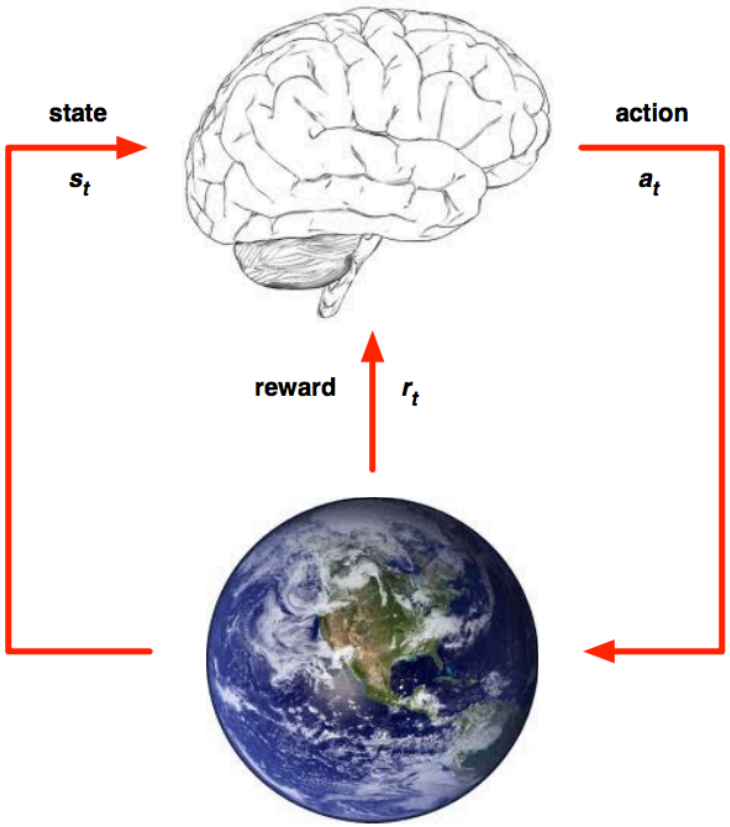


- policy: mapping from S to A
  - a=π(s) or π(s, a) (deterministic vs. stochastic)

- reinforcement learning
  - transitions and rewards usually not available
  - how to change the policy based on experience
  - how to explore the environment



Markov Decision Processes (MDPs)



- At each step t the agent:
  - Receives state s_t
  - Receives scalar reward r_t
  - Executes action a_t
- The environment:
  - Receives action a_t
  - Emits state s_t
  - Emits scalar reward r_t

From the *Tutorial: Deep Reinforcement Learning* by David Silver, Google DeepMind

Computing return from rewards

- episodic (vs. continuing) tasks
  - "game over" after N steps
  - optimal policy depends on N; harder to analyze

- additive rewards
  - $V(s_0, s_1, \ldots) = r(s_0) + r(s_1) + r(s_2) + \ldots$
  - infinite value for continuing tasks

- discounted rewards
  - $V(s_0, s_1, \ldots) = r(s_0) + \gamma * r(s_1) + \gamma^2 * r(s_2) + \ldots$
  - value bounded if rewards bounded

The goal of RL is to find the policy which maximizes the expected return.

Value Function

- A value function is the prediction of the future return
- Two definitions exist for the value function
  - State value function
  - "How much reward will I get from state s?"
  - expected return when starting in s and following π

$$V^{\pi}(s) = \mathbb{E}\left\{ \sum_{k=0}^{\infty} \gamma^k r_k \middle| s_0 = s, \pi \right\}$$

$$V^{\pi}(s) = \mathbb{E}\left\{ Q^{\pi}(s,a) \middle| a \sim \pi(s,\cdot) \right\}$$

  - State-action value function
  - "How much reward will I get from action a in state s?"
  - expected return when starting in s, performing a, and following π

$$Q^{\pi}(s,a) = \mathbb{E}\left\{ \sum_{k=0}^{\infty} \gamma^k r_k \middle| s_0 = s, a_0 = a, \pi \right\}$$

Bellman Equation and Optimality

- Value functions decompose into Bellman equations, i.e. the value functions can be decomposed into

  immediate reward plus *discounted value of successor state*

$$V^{\pi}(s) = \mathbb{E}\left\{ \sum_{k=0}^{\infty} \gamma^k r_k \,\middle|\, s_0 = s, \pi \right\} \longrightarrow V^{\pi}(s) = \mathbb{E}\left\{ R(s,a,s') + \gamma V^{\pi}(s') \right\}$$

$$Q^{\pi}(s,a) = \mathbb{E}\left\{ \sum_{k=0}^{\infty} \gamma^k r_k \,\middle|\, s_0 = s, a_0 = a, \pi \right\} \longrightarrow$$

$$Q^{\pi}(s,a) = \mathbb{E}\left\{ R(s,a,s') + \gamma Q^{\pi}(s',a') \right\}$$

- An optimal value function is the maximum achievable value.

$$V^*(s) = \max_{\pi} V^{\pi}(s) \quad Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a)$$

Bellman Optimality Equation

- Optimality for value functions is governed by the Bellman optimality equations.

- Two equations:

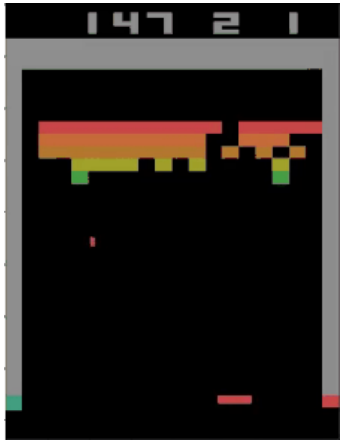
$$V^*(s) = \max_a \mathbb{E}\left\{R(s,a,s') + \gamma V^*(s')\right\}$$

$$Q^*(s,a) = \mathbb{E}\left\{R(s,a,s') + \max_{a'} \gamma Q^*(s',a')\right\}$$

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

Q-Learning

Initializing the Q(s, a) function



states

actions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Noop	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Right	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Left	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Q-Learning

$$Q^*(s,a) = \mathbb{E}\left\{ R(s,a,s') + \max_{a'} \gamma Q^*(s',a') \right\}$$

Initialize $Q(s,a)$ arbitrarily.

Start with s.

Before taking action a, we calculate the current expected return as

$$Q(s,a)$$

After taking action a, and observing r and s', we calculate the target expected return as

$$R(s,a,s') + \max_{a'} \gamma Q(s',a')$$

$$\Delta Q(s,a) = R(s,a,s') + \max_{a'} \gamma Q(s',a') - Q(s,a)$$

$$Q(s,a) \leftarrow Q(s,a) + \alpha \Delta Q(s,a)$$

Q-Learning

$$Q^*(s,a) = \mathbb{E}\left\{ R(s,a,s') + \max_{a'} \gamma Q^*(s',a') \right\}$$

Initialize Q(s, a) arbitrarily.

Repeat (for each episode)

Initialize *s*

Repeat (for each step of the episode)

Choose *a* from *s* using a policy

Take action *a*, observe *r, s'*

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

$$s \leftarrow s'$$

Exploration and Exploitation

Initialize Q(s, a) arbitrarily.

Repeat (for each episode)

Initialize s

Repeat (for each step of the episode)

Choose a from s using a policy

Take action a, observe r, s'

Update Q and s….

Random policy; Exploration

Greedy policy; Exploitation

$$\pi(s) = \arg\max_a Q(s, a)$$

ϵ-greedy policy: With probability ϵ select a random action

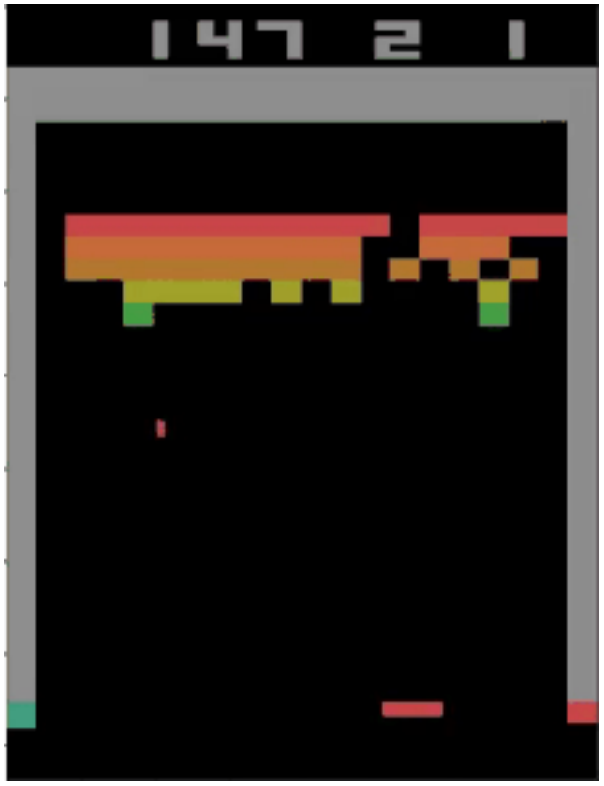
Deep RL: Deep Learning + RL

- Traditional RL
- low-dimensional state spaces
- handcrafted features

- DL's representation power + RL's generalization ability
  - RL defines the objective
  - Deep Learning learns the representation

Deep Q-Learning

Deep Q-Learning



states

actions	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Noop	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Right	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Left	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

$$\#\text{states} = 256^{210\times160}$$

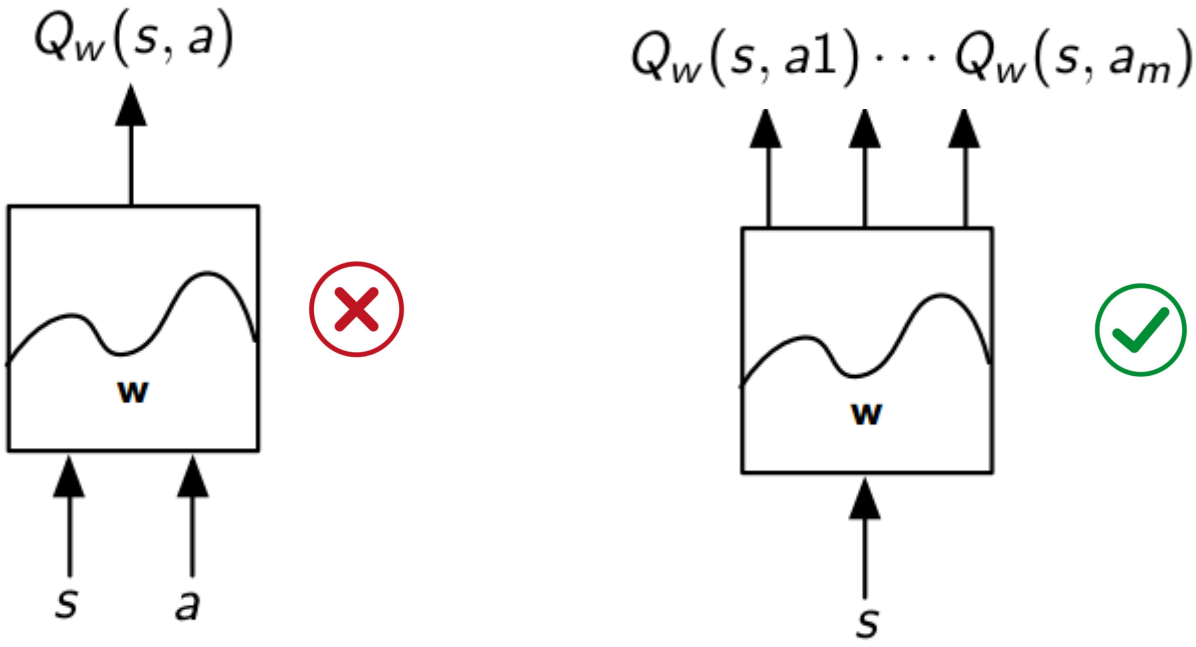
Value Function Approximation

$$Q(s,a) = f(s,a,w)$$

Q-Networks

- Represent the state-action value function （discrete actions） by Q-network with weights w

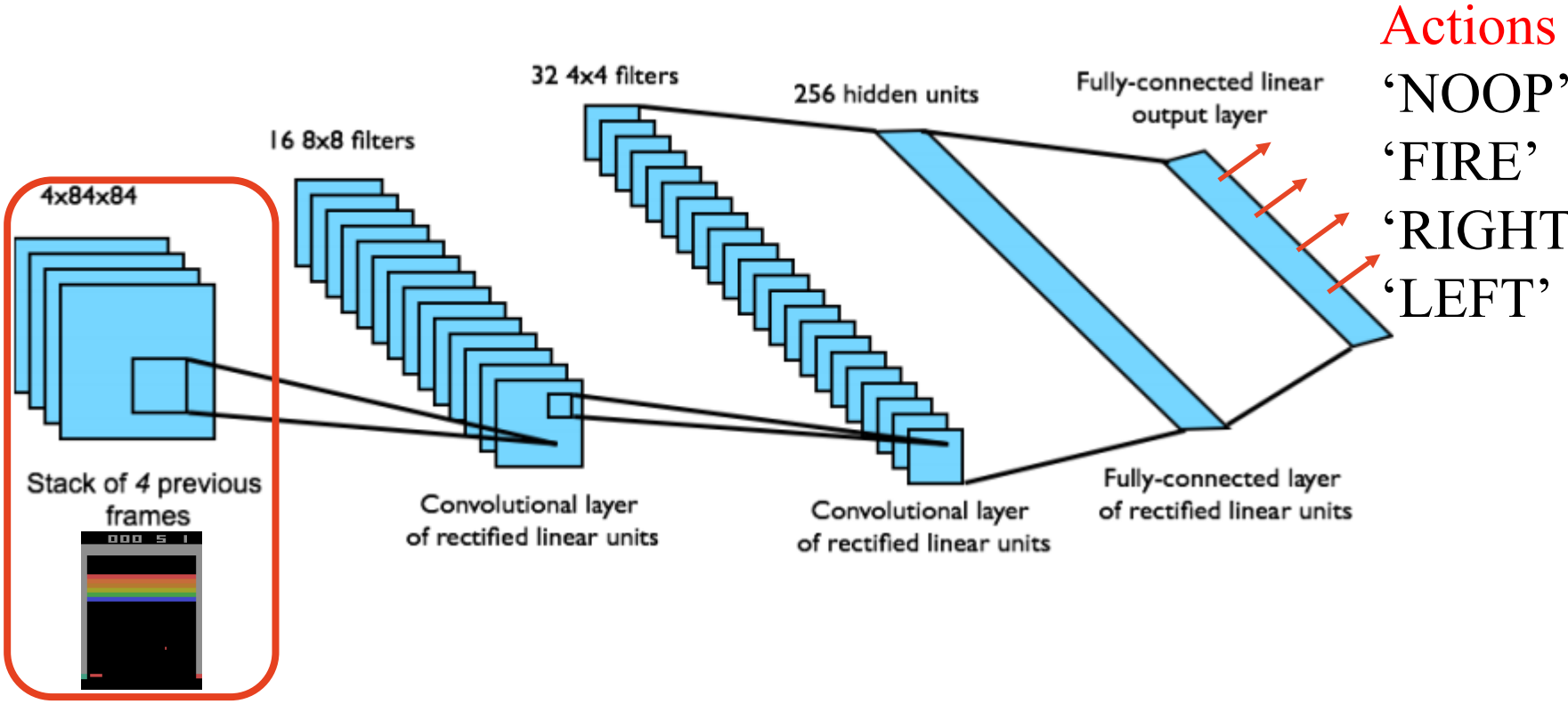
$$Q_w(s, a) \approx Q^*(s, a)$$



From the *Tutorial: Deep Reinforcement Learning* by David Silver, Google DeepMind

Deep Q-Learning

- End-to-end learning of state-action values from raw pixels
- Input state is stack of raw pixels from last 4 frames
- Output are state-action values from all possible actions



From the *Tutorial: Deep Reinforcement Learning* by David Silver, Google DeepMind

Deep Q-Networks (DQN)

- Optimal Q-values obey Bellman equation

$$Q^*(s,a) = \mathbb{E}_{s'}\left\{ r + \gamma \max_{a'} Q(s',a') | s,a \right\}$$

- Treat right-hand size as a target and minimize MSE loss by SGD

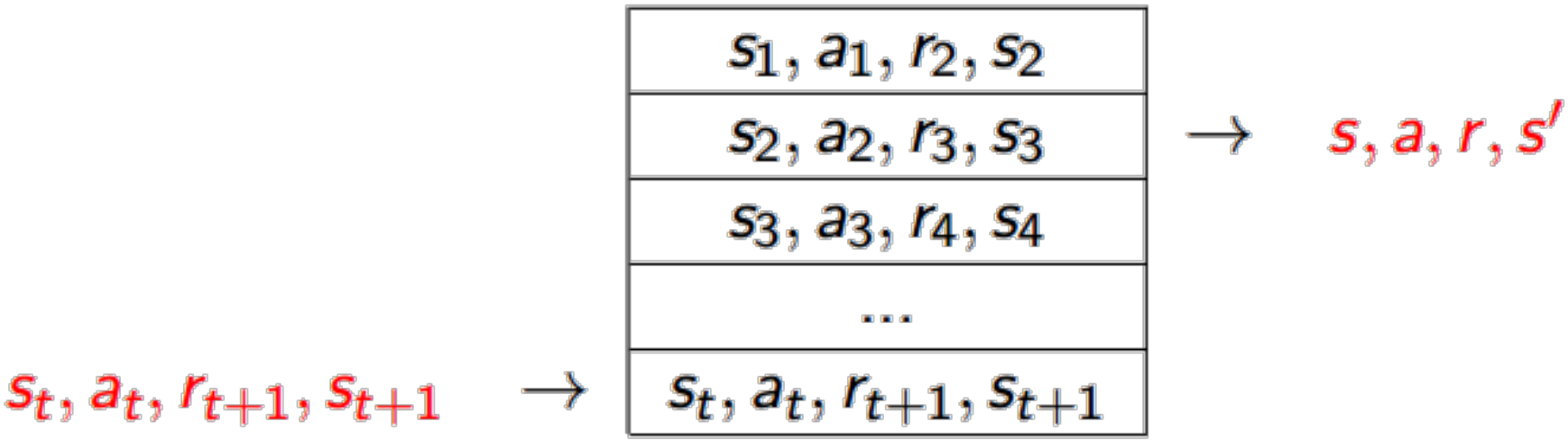
$$I = \left(\underbrace{r + \gamma \max_{a'} Q_w(s',a')}_{\text{Target}} - Q_w(s,a) \right)^2$$

- Divergence issues using neural networks due to
  - Correlations between samples
  - Non-stationary targets

From the *Tutorial: Deep Reinforcement Learning* by David Silver, Google DeepMind

Experience replay

- Build data set from agent's own experience
- Sample experiences uniformly from data set to remove correlations



Algorithm

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to
  end for
end for

ϵ-greedy

Improvements: Target Network

- To deal with non-stationarity, target parameters $\hat{w}$ are held fixed

$$I = \left(r + \gamma \max_{a'} Q_w(s', a') - Q_w(s, a) \right)^2$$

$$I = \mathbb{E}_{(s,a,r,s') \sim U(D)} \left\{ \left(r + \gamma \max_{a'} Q_{\hat{w}}(s', a') - Q_w(s, a) \right)^2 \right\}$$

Improvements: Double DQN

- Q-learning is known to overestimate state-action values
  - The max operator uses the same values to select and evaluate an action

$$Q^*(s,a) = \mathbb{E}_{s'}\left\{ r + \gamma \max_{a'} Q(s',a') | s,a \right\}$$

- The upward bias can be removed by decoupling the selection from the evaluation
  - Current Q-network is used to select actions
  - Older Q-network is used to evaluate actions

$$l = \mathbb{E}_{(s,a,r,s')\sim U(D)}\left\{ \left(r + \gamma Q_{\hat{w}_i}(s', \arg\max_{a'} Q_{w_i}(s',a')) - Q_{w_i}(s,a) \right)^2 \right\}$$

From the talk *Introduction to Deep Reinforcement Learning From Theory to Applications* by Siyi Li (HKUST)

Improvements: Prioritized Replay

- Uniform experience replay samples transitions regardless of their significance
- Can weight experiences according to their significance
- Prioritized replay stores experiences in a priority queue according to the TD error

- Use stochastic sampling to increase sample diversity

$$|r + \gamma \max_{a'} Q_{\hat{w}}(s', a') - Q_w(s, a)|$$

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

$$p_i = |\delta_i| + \epsilon$$

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Thanks!