



Xi'an Jiaotong-Liverpool University

西交利物浦大学

INT305 Machine Learning

Lecture 11

Reinforcement Learning

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Supervised Learning

So far... Supervised Learning

Data: (x, y)

x is data, y is label

Goal: Learn a *function* to map $x \rightarrow y$

Examples: Classification,
regression, object detection,
semantic segmentation, image
captioning, etc.



→ Cat

Classification

Unsupervised Learning

So far... Unsupervised Learning

Data: x

Just data, no labels!

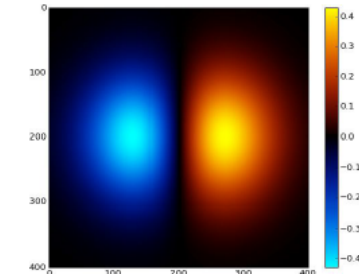
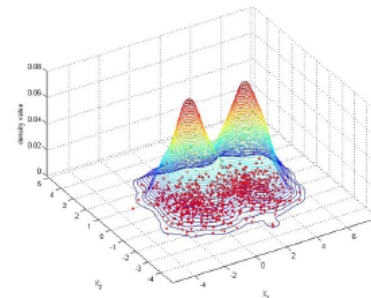
Goal: Learn some underlying hidden *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.



Figure copyright Ian Goodfellow, 2016. Reproduced with permission.

1-d density estimation



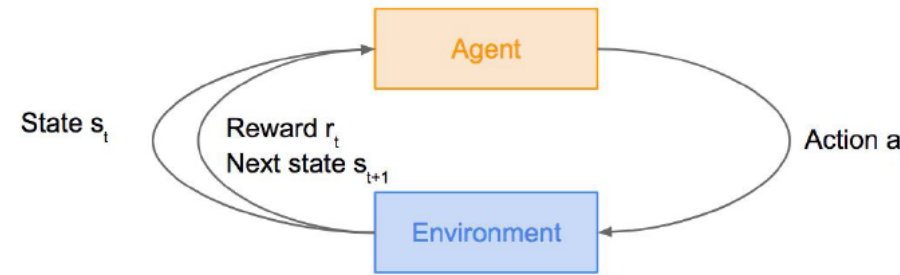
2-d density estimation

Reinforcement Learning

Today: Reinforcement Learning

Problems involving an **agent** interacting with an **environment**, which provides numeric **reward** signals

Goal: Learn how to take actions in order to maximize reward



Overview

Overview

- What is Reinforcement Learning?
- Markov Decision Processes
- Q-Learning

Reinforcement Learning

Reinforcement Learning

Agent



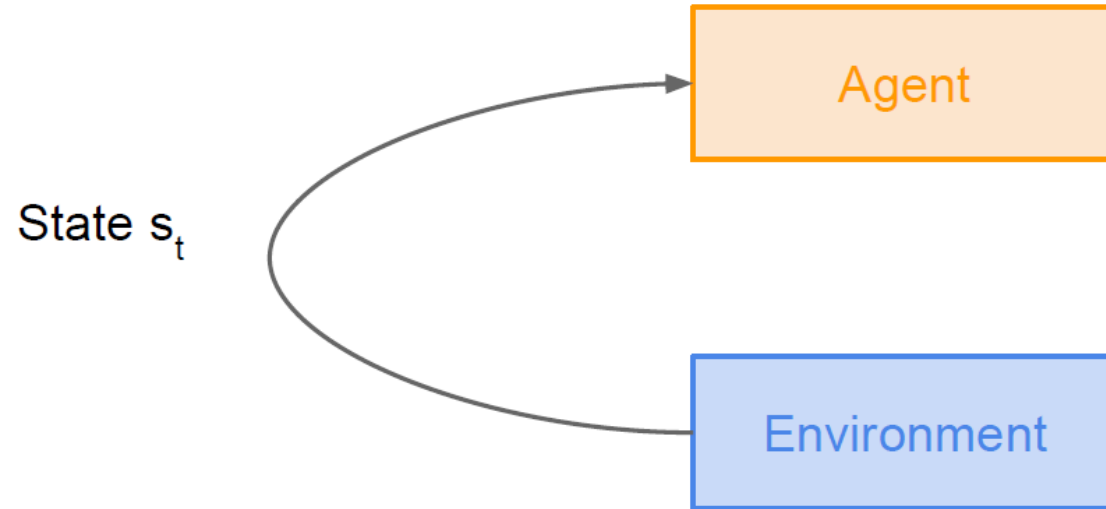
```
graph TD; Agent[Agent] --- Environment[Environment];
```

The diagram illustrates the basic components of Reinforcement Learning. It consists of two rectangular boxes stacked vertically. The top box is light orange with an orange border and contains the word "Agent" in orange text. The bottom box is light blue with a blue border and contains the word "Environment" in blue text. A vertical line connects the two boxes, representing the interaction between the agent and the environment.

Environment

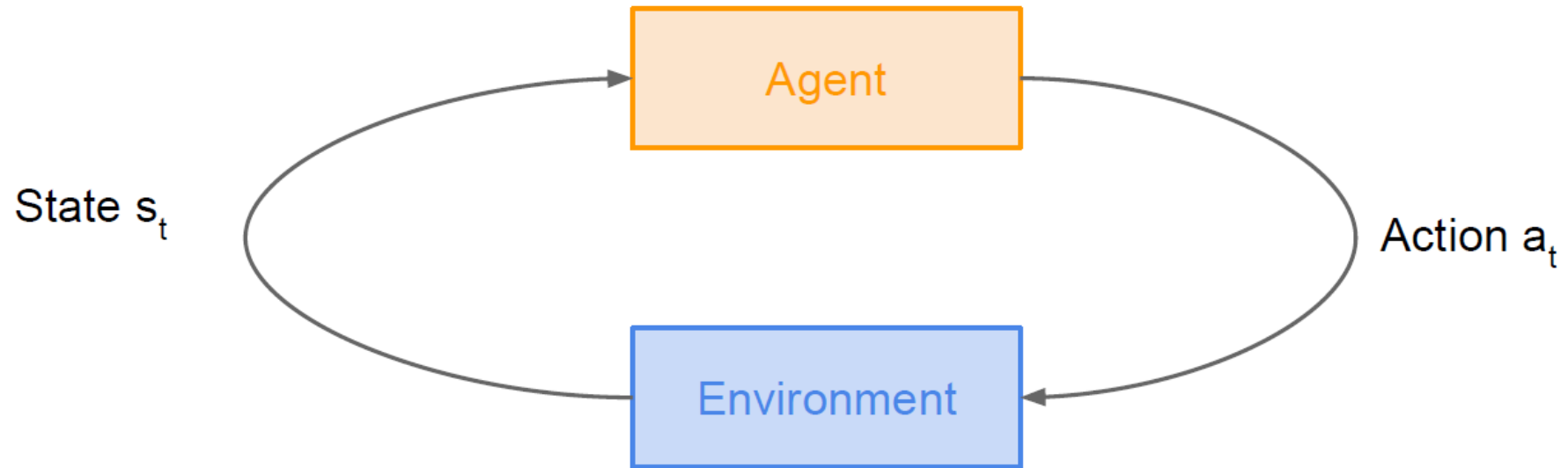
Reinforcement Learning

Reinforcement Learning



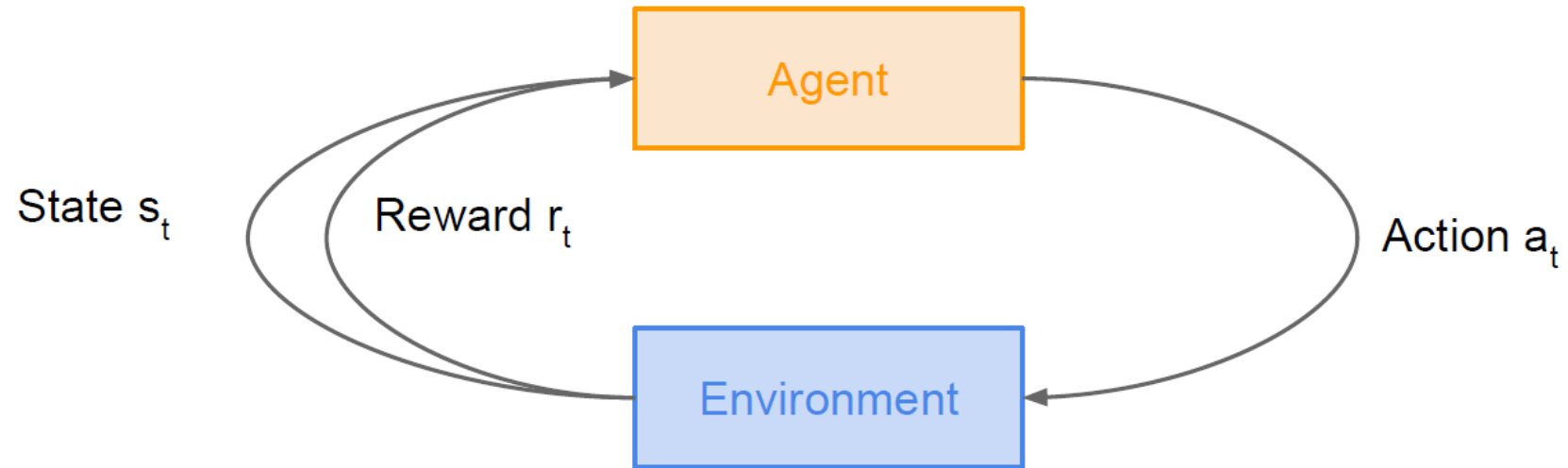
Reinforcement Learning

Reinforcement Learning



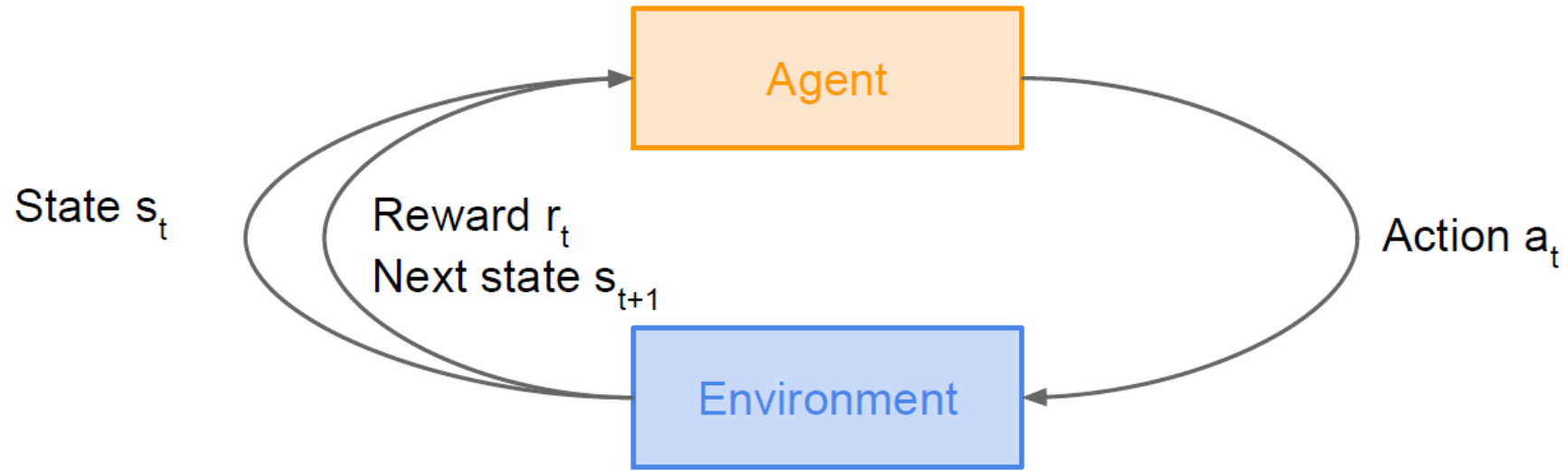
Reinforcement Learning

Reinforcement Learning



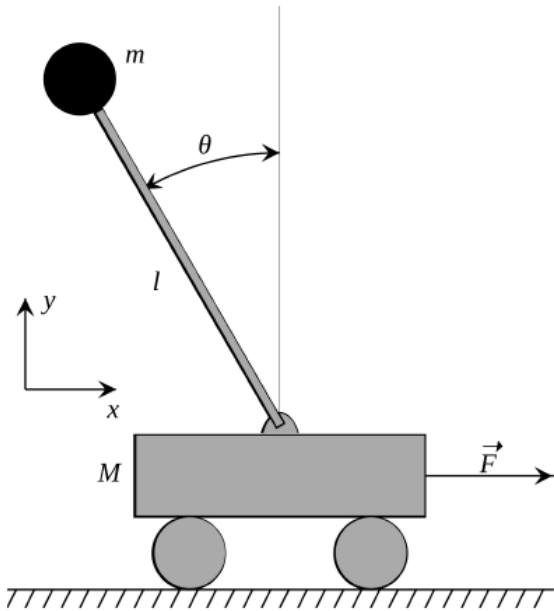
Reinforcement Learning

Reinforcement Learning



Examples

Cart-Pole Problem



Objective: Balance a pole on top of a movable cart

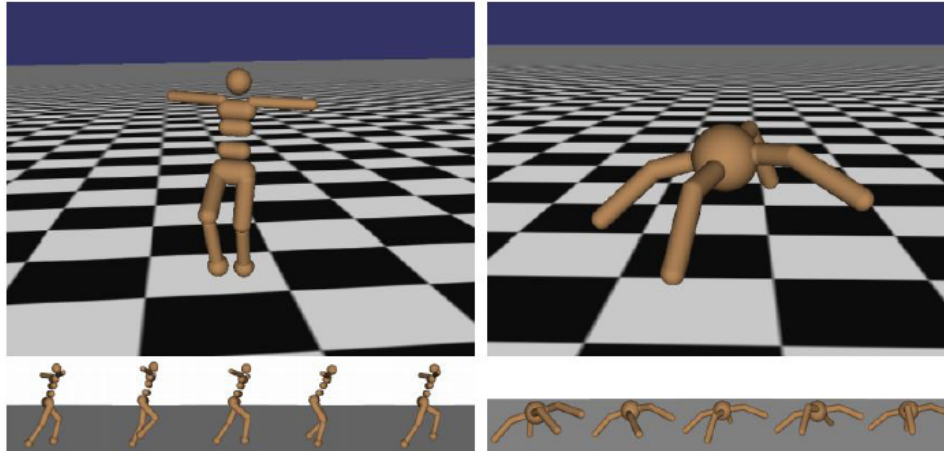
State: angle, angular speed, position, horizontal velocity

Action: horizontal force applied on the cart

Reward: 1 at each time step if the pole is upright

Examples

Robot Locomotion



Objective: Make the robot move forward

State: Angle and position of the joints

Action: Torques applied on joints

Reward: 1 at each time step upright + forward movement

Examples

Atari Games



Objective: Complete the game with the highest score

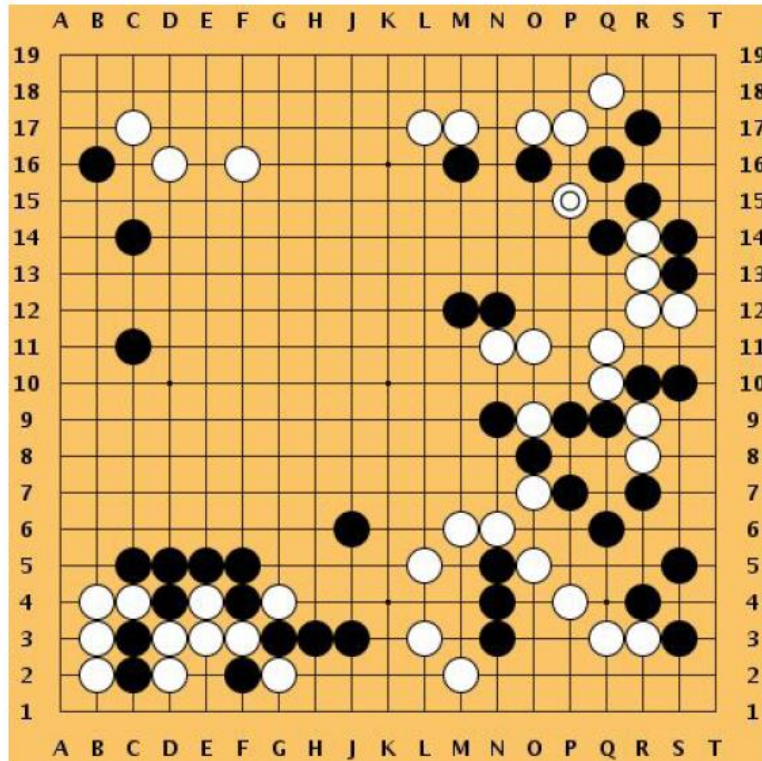
State: Raw pixel inputs of the game state

Action: Game controls e.g. Left, Right, Up, Down

Reward: Score increase/decrease at each time step

Examples

Go



Objective: Win the game!

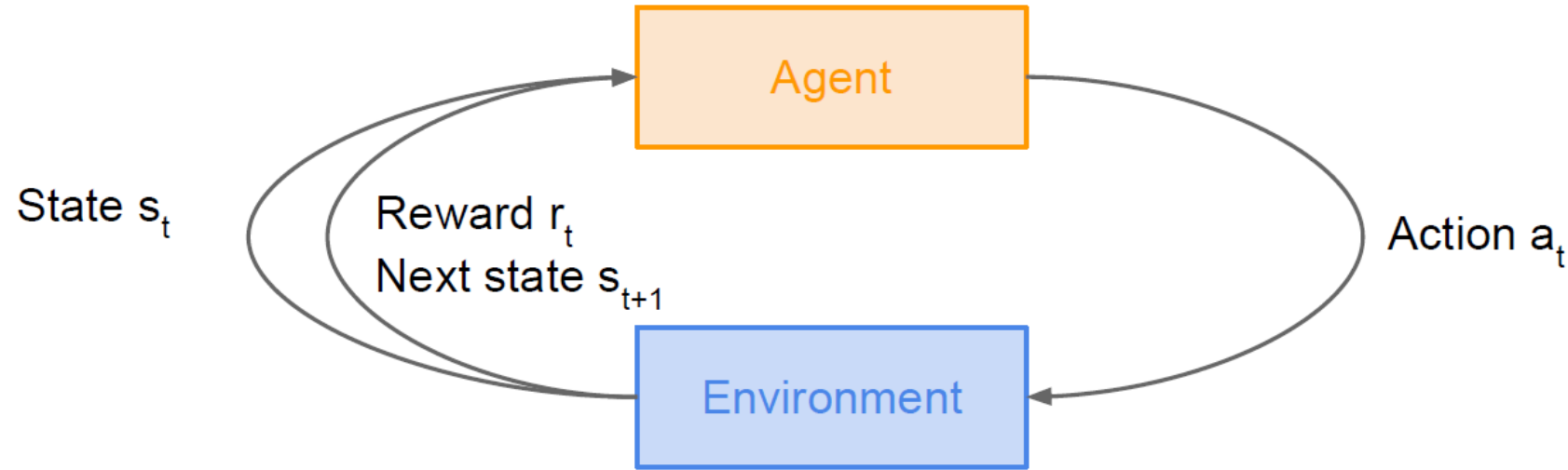
State: Position of all pieces

Action: Where to put the next piece down

Reward: 1 if win at the end of the game, 0 otherwise

Markov Decision Process

How can we mathematically formalize the RL problem?



Markov Decision Process

Markov Decision Process

- Mathematical formulation of the RL problem
- **Markov property**: Current state completely characterises the state of the world

Defined by: $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathbb{P}, \gamma)$

\mathcal{S} : set of possible states

\mathcal{A} : set of possible actions

\mathcal{R} : distribution of reward given (state, action) pair

\mathbb{P} : transition probability i.e. distribution over next state given (state, action) pair

γ : discount factor

Markov Decision Process

Markov Decision Process

- At time step $t=0$, environment samples initial state $s_0 \sim p(s_0)$
- Then, for $t=0$ until done:
 - Agent selects action a_t
 - Environment samples reward $r_t \sim R(\cdot | s_t, a_t)$
 - Environment samples next state $s_{t+1} \sim P(\cdot | s_t, a_t)$
 - Agent receives reward r_t and next state s_{t+1}
- A policy π is a function from S to A that specifies what action to take in each state
- **Objective**: find policy π^* that maximizes cumulative discounted reward: $\sum_{t \geq 0} \gamma^t r_t$

A simple MDP: Grid World

A simple MDP: Grid World

actions = {

1. right →

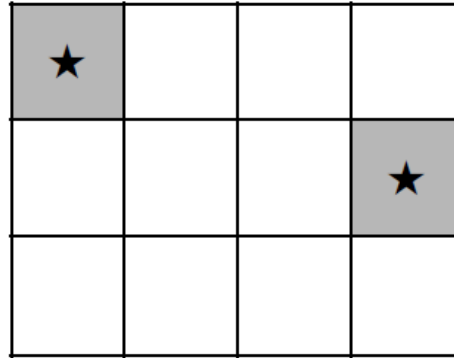
2. left ←

3. up ↑

4. down ↓

}

states

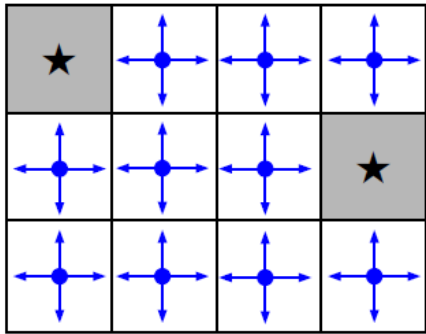


Set a negative “reward”
for each transition
(e.g. $r = -1$)

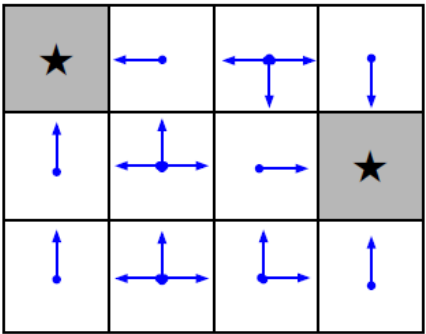
Objective: reach one of terminal states (greyed out) in
least number of actions

A simple MDP: Grid World

A simple MDP: Grid World



Random Policy



Optimal Policy

Optimal policy

The optimal policy π^*

We want to find optimal policy π^* that maximizes the sum of rewards.

How do we handle the randomness (initial state, transition probability...)?

Optimal policy

The optimal policy π^*

We want to find optimal policy π^* that maximizes the sum of rewards.

How do we handle the randomness (initial state, transition probability...)?

Maximize the **expected sum of rewards!**

$$\text{Formally: } \pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_{t \geq 0} \gamma^t r_t | \pi \right] \text{ with } s_0 \sim p(s_0), a_t \sim \pi(\cdot | s_t), s_{t+1} \sim p(\cdot | s_t, a_t)$$

Value function

Definitions: Value function and Q-value function

Following a policy produces sample trajectories (or paths) $s_0, a_0, r_0, s_1, a_1, r_1, \dots$

Value function

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How good is a state?

The **value function** at state s , is the expected cumulative reward from following the policy from state s :

$$V^\pi(s) = \mathbb{E} \left[\sum_{t \geq 0} \gamma^t r_t \mid s_0 = s, \pi \right]$$

Value function

Definitions: Value function and Q-value function

Following a policy produces sample trajectories (or paths) $s_0, a_0, r_0, s_1, a_1, r_1, \dots$

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How good is a state-action pair?

The **Q-value function** at state s and action a , is the expected cumulative reward from taking action a in state s and then following the policy:

$$Q^\pi(s, a) = \mathbb{E} \left[\sum_{t \geq 0} \gamma^t r_t \mid s_0 = s, a_0 = a, \pi \right]$$

Bellman equation

Bellman equation

The optimal Q-value function Q^* is the maximum expected cumulative reward achievable from a given (state, action) pair:

$$Q^*(s, a) = \max_{\pi} \mathbb{E} \left[\sum_{t \geq 0} \gamma^t r_t \mid s_0 = s, a_0 = a, \pi \right]$$

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Q^* satisfies the following **Bellman equation**:

$$Q^*(s, a) = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a \right]$$

Intuition: if the optimal state-action values for the next time-step $Q^*(s', a')$ are known, then the optimal strategy is to take the action that maximizes the expected value of $r + \gamma Q^*(s', a')$

Bellman equation

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The optimal policy π^* corresponds to taking the best action in any state as specified by Q^*

Solving the optimal policy

Solving for the optimal policy

Value iteration algorithm: Use Bellman equation as an iterative update

$$Q_{i+1}(s, a) = \mathbb{E} \left[r + \gamma \max_{a'} Q_i(s', a') | s, a \right]$$

Q_i will converge to Q^* as $i \rightarrow \text{infinity}$

Solving the optimal policy

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What's the problem with this?

Not scalable. Must compute $Q(s, a)$ for every state-action pair. If state is e.g. current game state pixels, computationally infeasible to compute for entire state space!

Solving the optimal policy

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What's the problem with this?

Not scalable. Must compute $Q(s, a)$ for every state-action pair. If state is e.g. current game state pixels, computationally infeasible to compute for entire state space!

Solution: use a function approximator to estimate $Q(s, a)$. E.g. a neural network!

Solving the optimal policy

Solving for the optimal policy: Q-learning

Q-learning: Use a function approximator to estimate the action-value function

$$Q(s, a; \theta) \approx Q^*(s, a)$$

Solving the optimal policy

Solving for the optimal policy: Q-learning

Q-learning: Use a function approximator to estimate the action-value function


$$Q(s, a; \theta) \approx Q^*(s, a)$$

If the function approximator is a deep neural network => **deep q-learning!**

Solving the optimal policy

Solving for the optimal policy: Q-learning

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function parameters (weights)

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Q-Learning

Solving for the optimal policy: Q-learning

Remember: want to find a Q-function that satisfies the Bellman Equation:

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

Forward Pass

Loss function: $L_i(\theta_i) = \mathbb{E}_{s, a \sim \rho(\cdot)} [(y_i - Q(s, a; \theta_i))^2]$

where $y_i = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) | s, a \right]$

Q-learning

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Backward Pass

Gradient update (with respect to Q-function parameters θ):

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s, a \sim \rho(\cdot); s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) - Q(s, a; \theta_i) \right] \nabla_{\theta_i} Q(s, a; \theta_i)$$

Q-Learning

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Case Study

Case Study: Playing Atari Games



Objective: Complete the game with the highest score

State: Raw pixel inputs of the game state

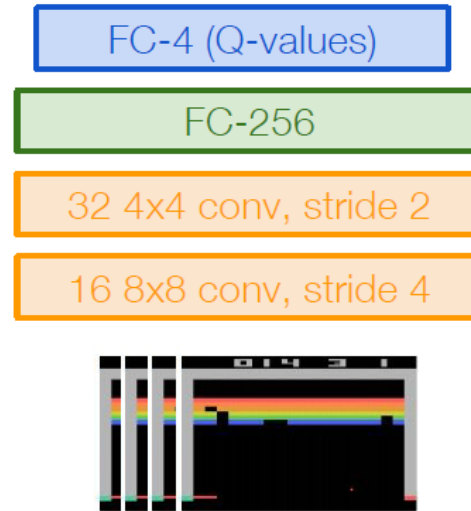
Action: Game controls e.g. Left, Right, Up, Down

Reward: Score increase/decrease at each time step

Case Study

Q-network Architecture

$Q(s, a; \theta)$:
neural network
with weights θ

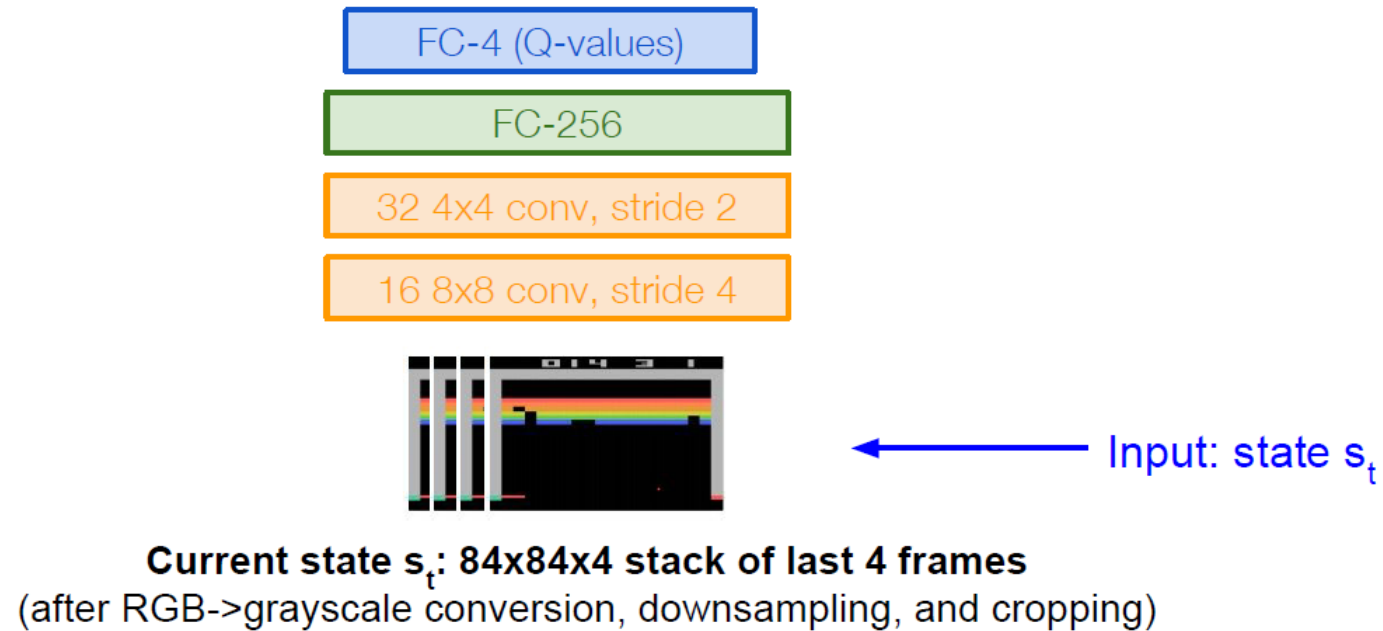


Current state s_t : 84x84x4 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)

Case Study

Q-network Architecture

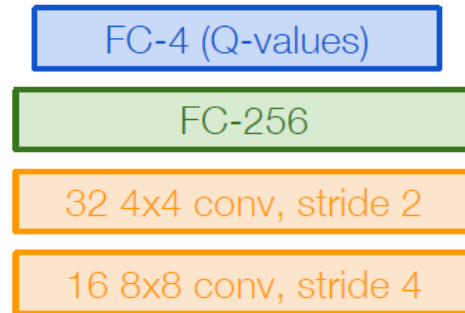
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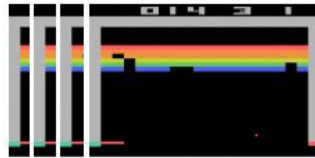
Case Study

Q-network Architecture

$Q(s, a; \theta)$:
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← Familiar conv layers,
FC layer

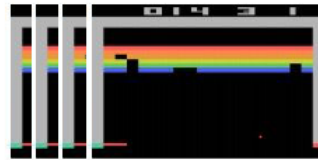
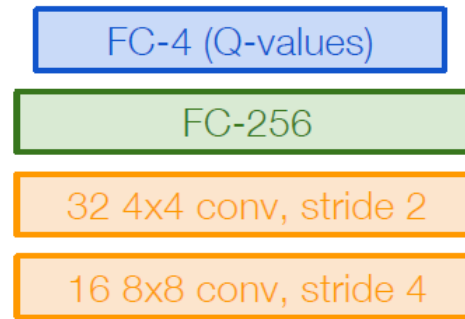


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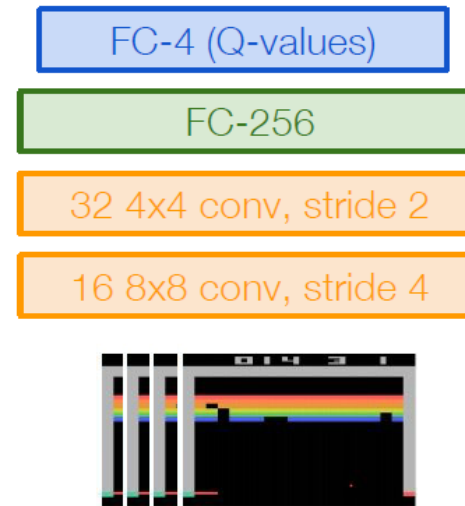
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← Last FC layer has 4-d
output (if 4 actions),
corresponding to $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$,
 $Q(s_t, a_4)$

Case Study

Q-network Architecture

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Number of actions between 4-18
depending on Atari game

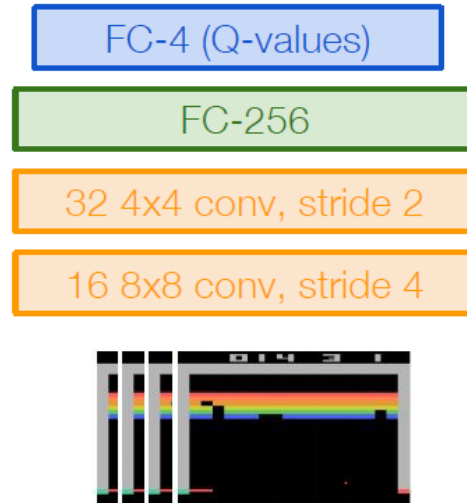
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Case Study

Q-network Architecture

$Q(s, a; \theta)$:
neural network
with weights θ

A single feedforward pass
to compute Q-values for all
actions from the current
state => efficient!



← Last FC layer has 4-d
output (if 4 actions),
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Case Study

Training the Q-network: Loss function (from before)

Remember: want to find a Q-function that satisfies the Bellman Equation:

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

Forward Pass

Loss function: $L_i(\theta_i) = \mathbb{E}_{s, a \sim \rho(\cdot)} [(y_i - Q(s, a; \theta_i))^2]$

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Backward Pass

Gradient update (with respect to Q-function parameters θ):

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Experience Replay

Training the Q-network: Experience Replay

Learning from batches of consecutive samples is problematic:

- Samples are correlated => inefficient learning
- Current Q-network parameters determines next training samples (e.g. if maximizing action is to move left, training samples will be dominated by samples from left-hand size) => can lead to bad feedback loops

Experience Replay

Training the Q-network: Experience Replay

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Address these problems using **experience replay**

- Continually update a **replay memory** table of transitions (s_t, a_t, r_t, s_{t+1}) as game (experience) episodes are played
- Train Q-network on random minibatches of transitions from the replay memory, instead of consecutive samples

Experience Replay

Training the Q-network: Experience Replay

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- Train Q-network on random minibatches of transitions from the replay memory, instead of consecutive samples

Each transition can also contribute
to multiple weight updates
=> greater data efficiency

Experience Replay

Putting it together: Deep Q-Learning with Experience Replay

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  $\epsilon$  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 equation 3
  end for
end for
```

Algorithm

Putting it together: Deep Q-Learning with Experience Replay

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory \mathcal{D} to capacity N

Initialize action-value function Q with random weights

← Initialize replay memory, Q-network

for episode = 1, M **do**

 Initialize 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 equation 3

end for

end for

Algorithm

Putting it together: Deep Q-Learning with Experience Replay

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**

 Initialize 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 $\phi_{t+1} = \phi(s_{t+1})$

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end for

end for

← Play M episodes (full games)

Algorithm

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 Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3

end for

end for

← Initialize state
(starting game
screen pixels) at the
beginning of each
episode

Algorithm

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end for

end for

← For each timestep t
of the game

Algorithm

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 Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3

end for

end for

← With small probability,
select a random
action (explore),
otherwise select
greedy action from
current policy

Algorithm

Putting it together: Deep Q-Learning with Experience Replay

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 Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3

end for

end for

← Take the action (a_t),
and observe the
reward r_t and next
state s_{t+1}

Algorithm

Putting it together: Deep Q-Learning with Experience Replay

Algorithm 1 Deep Q-learning with Experience Replay

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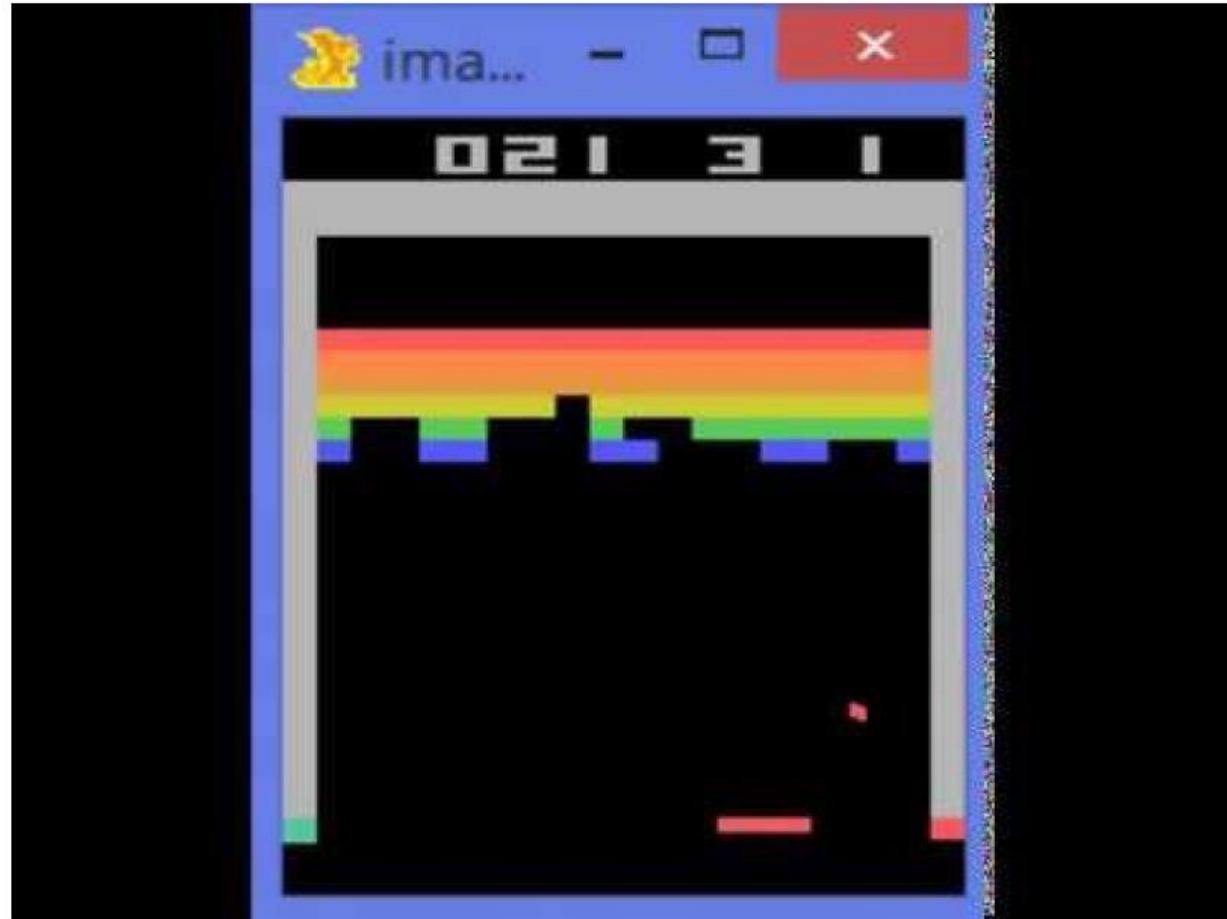
end for

end for

Store transition in
replay memory



Demo



<https://www.youtube.com/watch?v=V1eYniJ0Rnk>