

LECTURER: TAI LE QUY

INTRODUCTION TO

REINFORCEMENT LEARNING

Introduction to Reinforcement Learning

1

Sequential Decision Process

2

Dynamic Programming

3

Reinforcement Learning Algorithms and their Properties

4

Deep Reinforcement Learning

5

Summary: Introduction to Reinforcement Learning

6

UNIT 5

DEEP REINFORCEMENT LEARNING



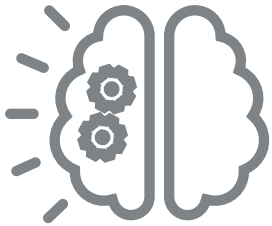
- Understand the importance of neural networks in reinforcement learning
- Analyze and evaluate the deep Q-network algorithm and its components
- Apply knowledge of deep reinforcement learning to identify and evaluate scenarios for its use



1. Explain the role of neural networks in improving the performance of reinforcement learning algorithms
2. Describe the components of deep Q-learning algorithm and how they contribute to its success?
3. Compare and contrast deep reinforcement learning with traditional reinforcement learning

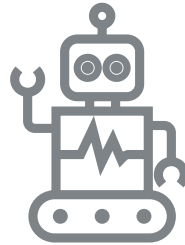


Synergy of neural networks and reinforcement learning



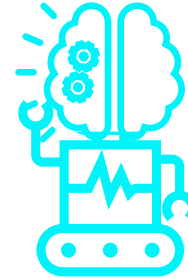
Neural
Network

+



Reinforcement
Learning

=



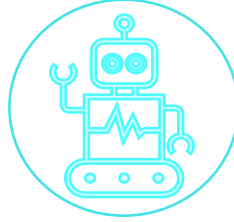
Deep Reinforcement
Learning

APPLICATIONS OF DEEP REINFORCEMENT LEARNING



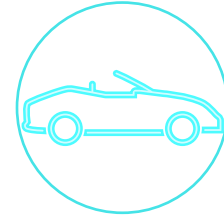
Games

- Atari games (pong, pacman)
- Go



Robotics

- Locomotion
- Grasping and navigation



Autonomous Driving

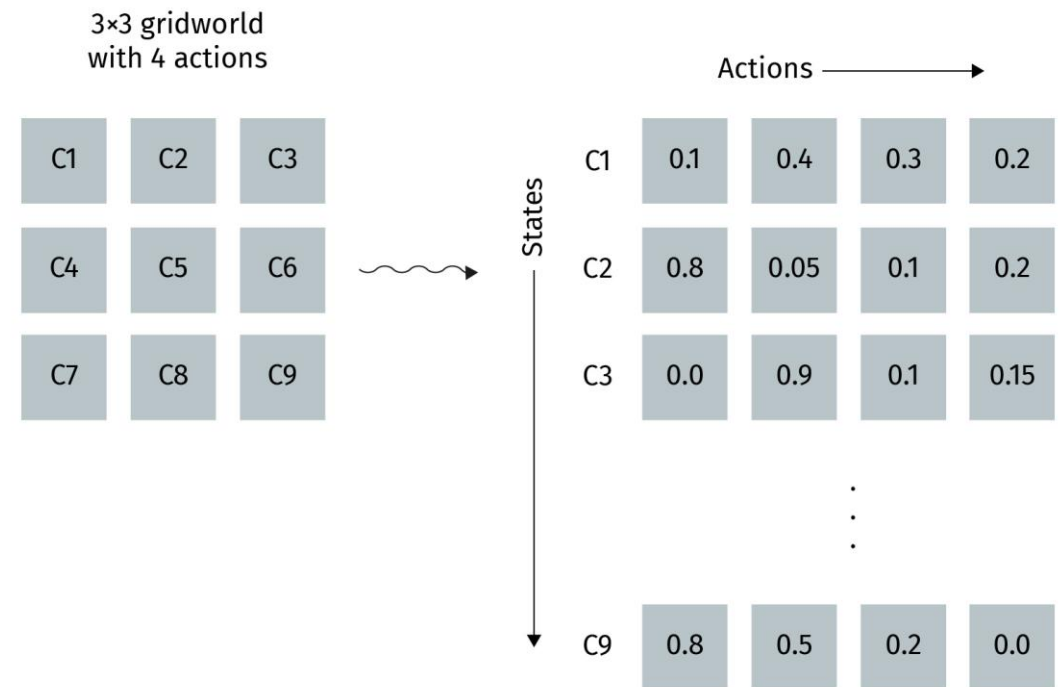
- CARLA
- Navigation tasks

Deep Reinforcement Learning



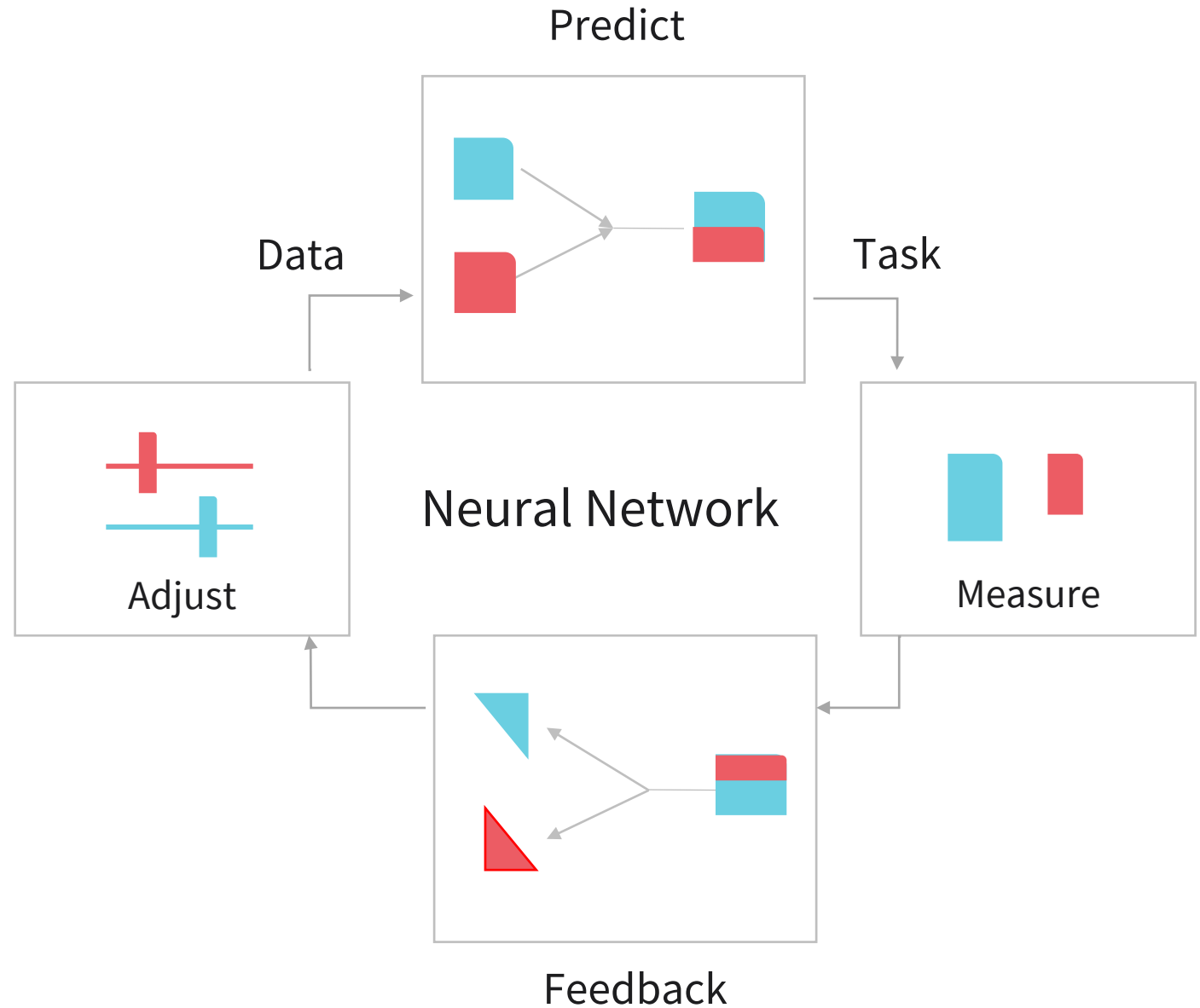
Q-learning: simple and effective RL algorithm

- Builds a lookup table
- Determines action to perform in state
- Guaranteed convergence (given enough steps)
- **Not scalable** for complex problems



FUNDAMENTAL ELEMENTS OF NEURAL NETWORKS

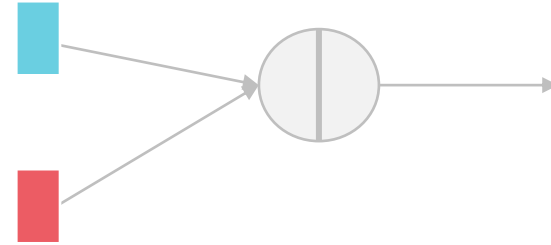
- Map features to target
- Train and test
- Adjust and repeat



FUNDAMENTAL ELEMENTS OF NEURAL NETWORKS

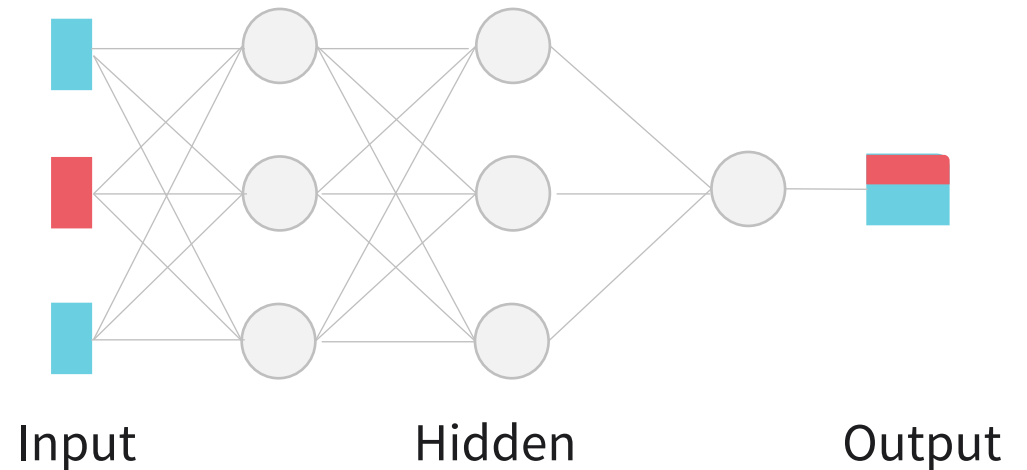
- Neuron: core computing unit
- Layers: receive input and transform it
- Model: combine layers into network

Weighted Sum | Activation



Artificial Neuron

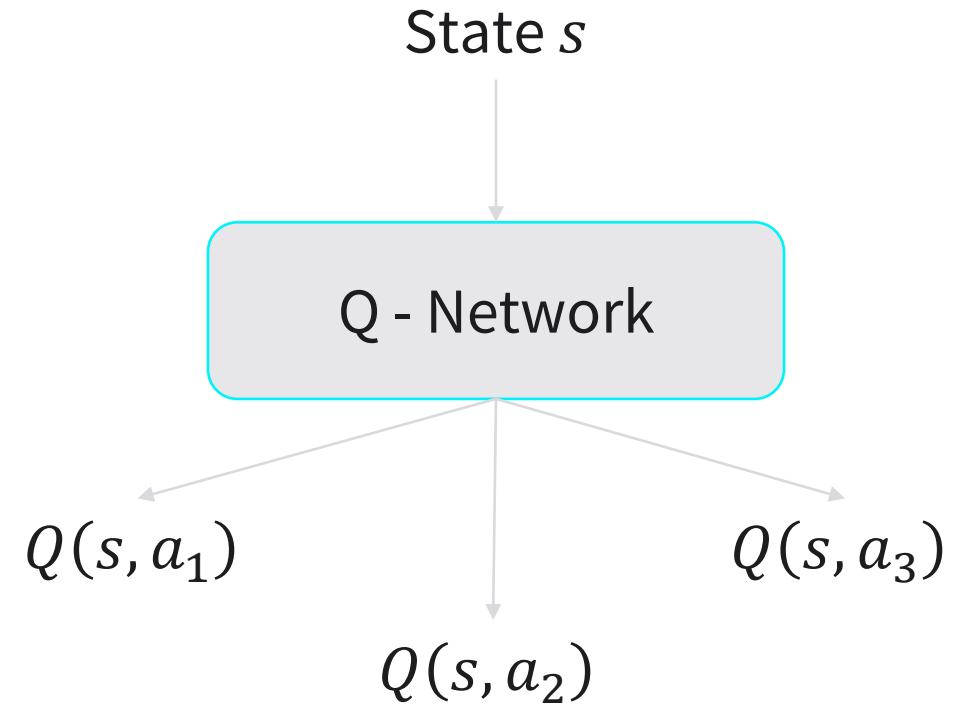
Neural Network





Efficient Q-value computation for complex environments

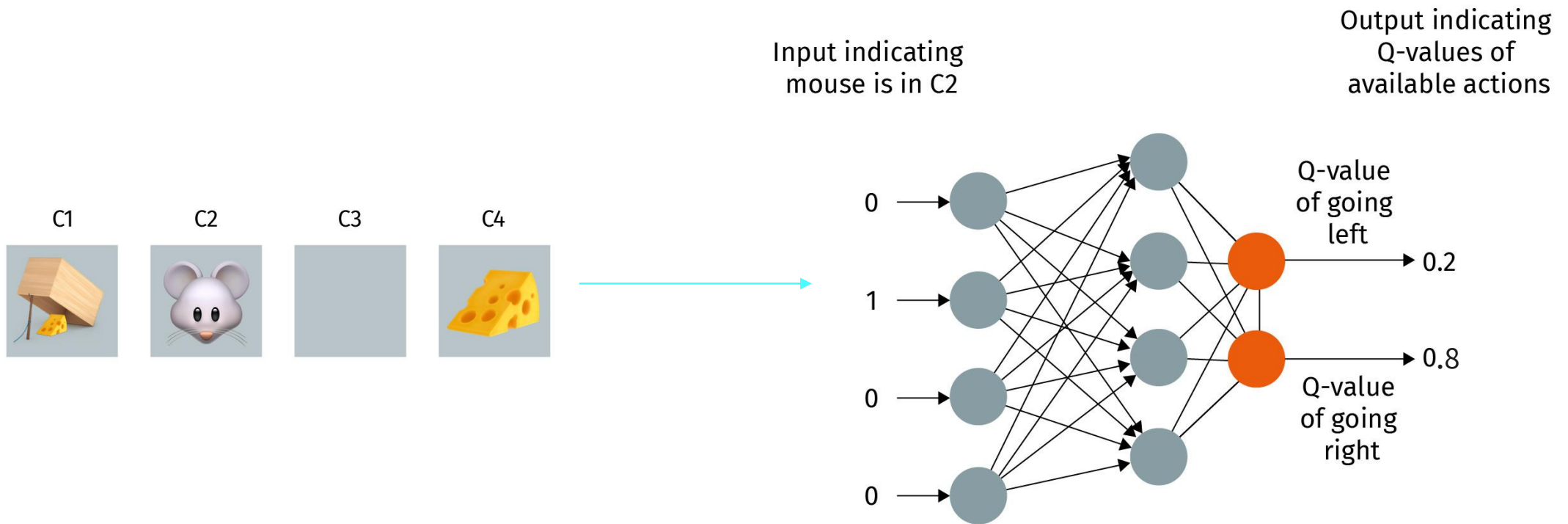
- Use neural networks instead of Q-table
- Goal: learn to compute Q-value for state-action pair $Q(s_t, a_t) \approx Q(s_t, a_t; \theta)$
- Tackle a wide range of problems and formats (image, video, text, etc.)



EXAMPLE: MOUSE GRIDWORLD



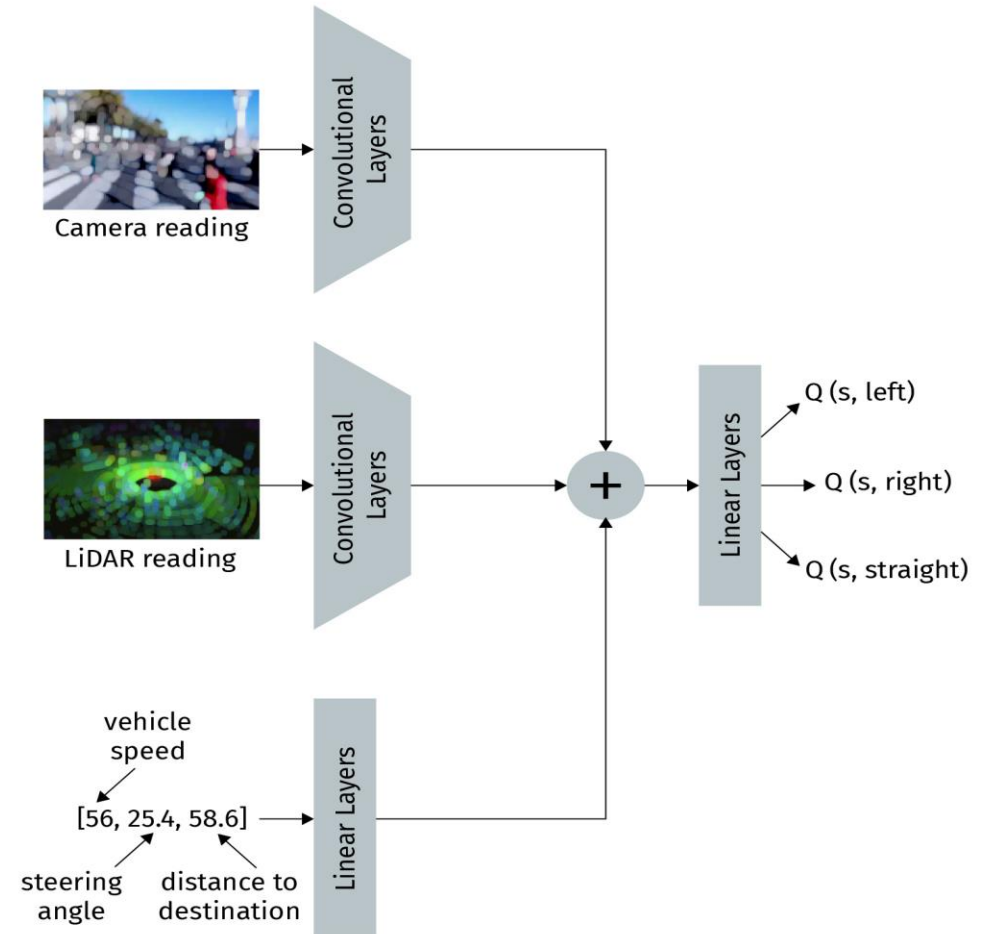
Goal: move the mouse to help it reach the destination





Leverage sensor readings and neural networks to drive autonomously

- Combination of sensors
- Several neural networks
- Goal: learn steering commands to reach goal while avoiding obstacles





Reframe reinforcement learning as supervised learning problem

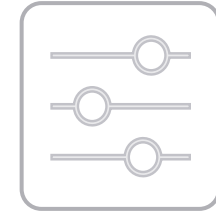
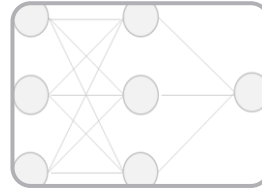
- Approximate Q-function to update Q-values
- Learn best Q-value approximation
- Use temporal differences for target Q-values

$$Q(s_t, a_t; \theta) \approx r_t + \gamma \cdot \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta) \quad \theta: \text{the parameters of the network}$$

$$\text{Loss per data sample} = \left(\left(r_t + \gamma \cdot \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta) \right) - Q(s_t, a_t; \theta) \right)^2$$

- Use optimization algorithm to train neural network

OPTIMIZING DEEP REINFORCEMENT LEARNING



Replay buffer

- Store experience in replay buffer
- Sample **mini-batch** to update weights
- Improve efficiency and stabilize learning

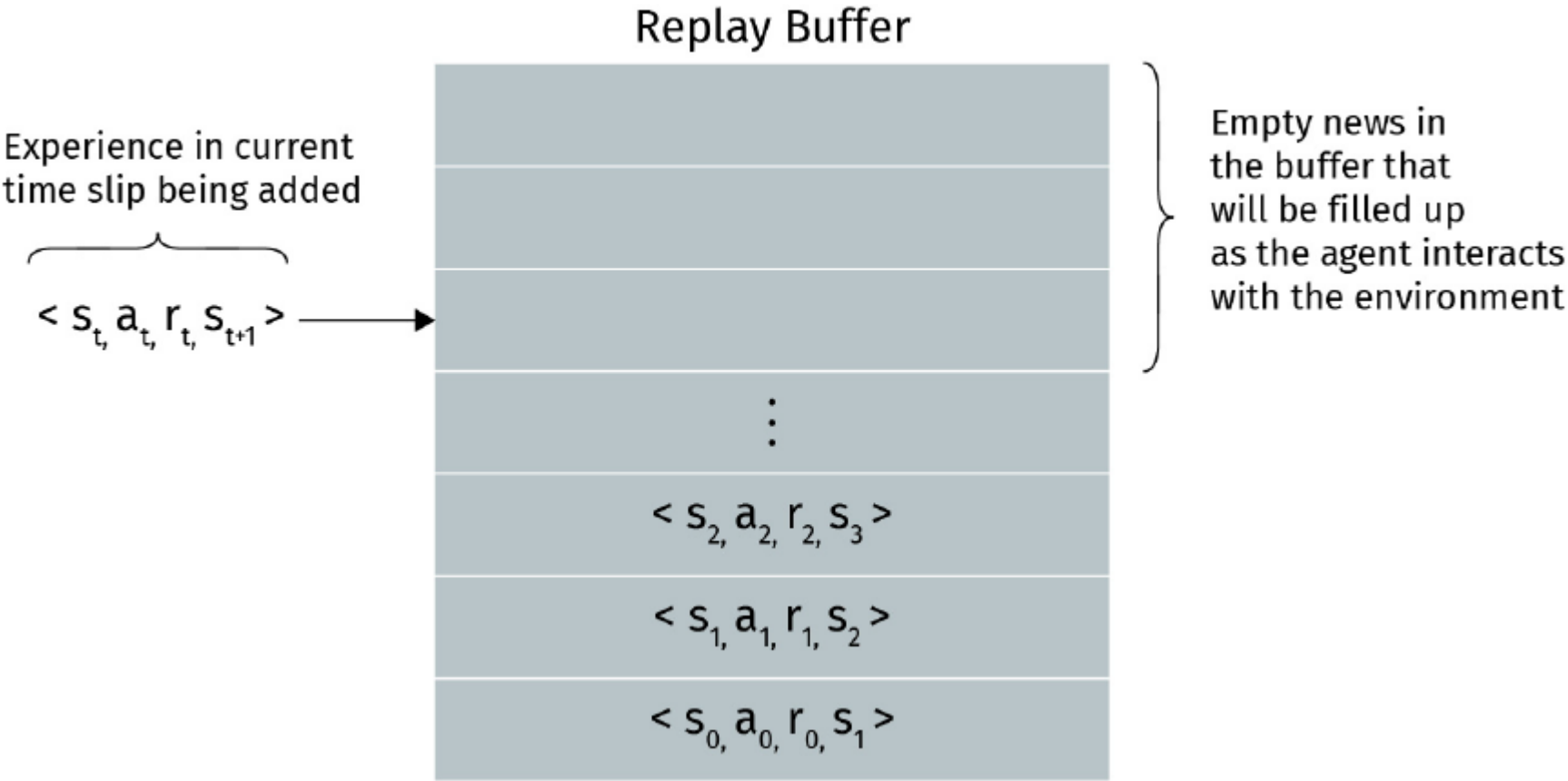
Target network

- Non-stationary targets in RL
- Target duplicates main network
- Target lags behind a few time steps

Network training

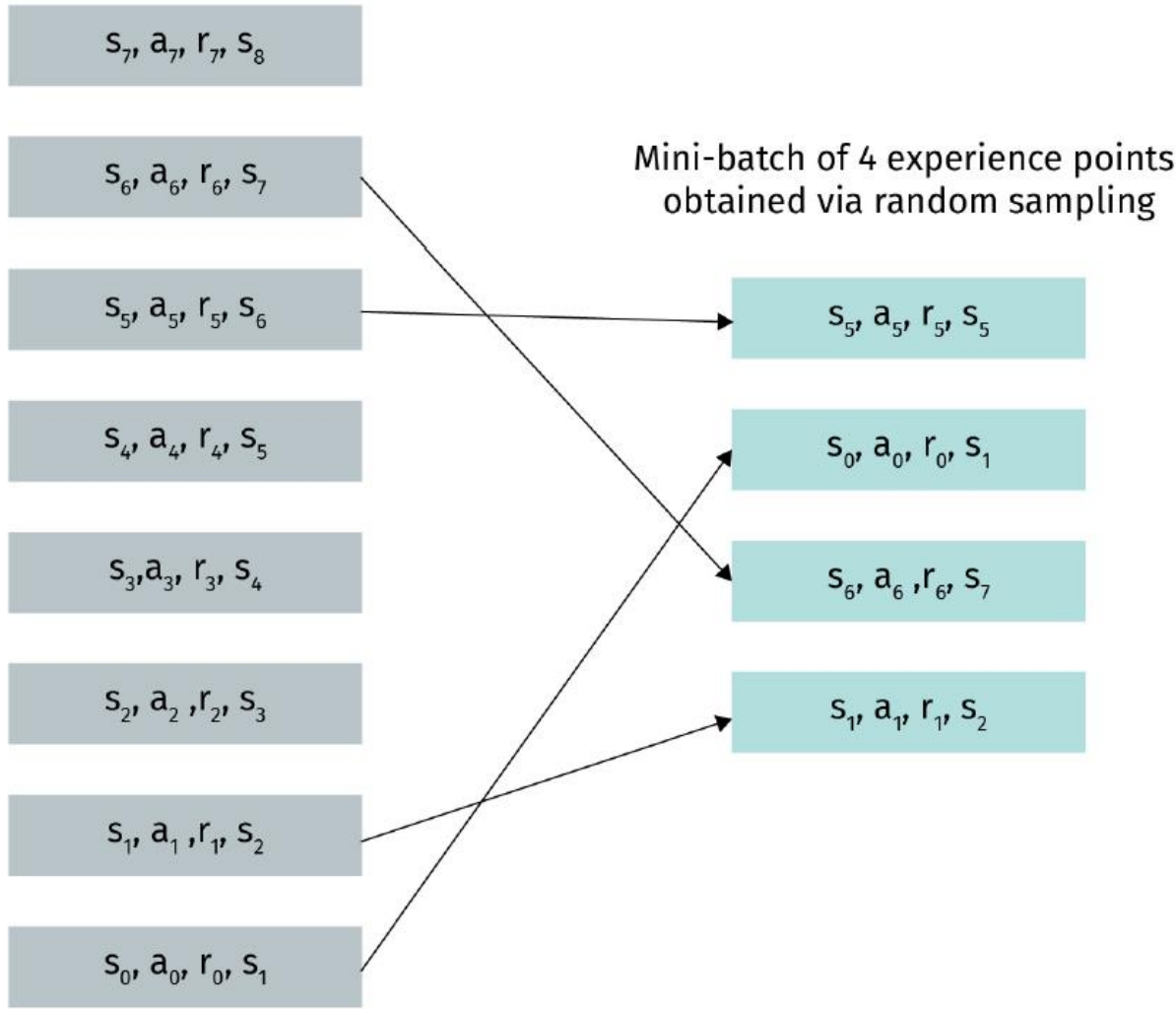
- Agents balance exploration vs exploitation
- Combine Bellman equations with greedy-epsilon strategy

REPLAY BUFFER



REPLAY BUFFER

Replay Buffer of 8 experience points





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SESSION 5

TRANSFER TASK



Case study

Your task is to develop an AI-agent that can play the Atari game Pong using deep Q-learning. Your goal is to develop an optimal policy that maximizes the game score

Task

What key steps will you consider when implementing Q-learning?
Which neural network architecture would be most appropriate?
How to optimize Q-learning? Consider factors such as experience replay and target network updates, among others

TRANSFER TASK
PRESENTATION OF THE RESULTS

Please present your
results.

The results will be
discussed in plenary.





1. The neural networks in DQN estimate
 - a) State value (V-value)
 - b) Action value (P-value)
 - c) Advantage value (A-value)
 - d) State-action value (Q-value)



2. The target network is introduced to resolve
- a) The non-IID nature of the data
 - b) The non-stationarity of targets
 - c) Sample inefficiency of RL algorithms
 - d) Break correlations between experience tuples



3. The replay buffer is used to store
- a) Q-values
 - b) Reward functions
 - c) Experience tuples
 - d) Policies

LIST OF SOURCES

Images

Plaku, 2023.

Nair, 2023.

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