**LECTURER: TAI LE QUY** 

# INTRODUCTION TO REINFORCEMENT LEARNING

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Dynamic Programming	3
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### UNIT 3

# **DYNAMIC PROGRAMMING**

### **STUDY GOALS**

- Explain the importance of policies and actions in Reinforcement Learning (RL)
- Evaluate and compare policies using value functions
- Describe how dynamic programming is applied to RL
- Utilize Bellman equations to optimize a RL problem and assess their effectiveness in finding an optimal policy

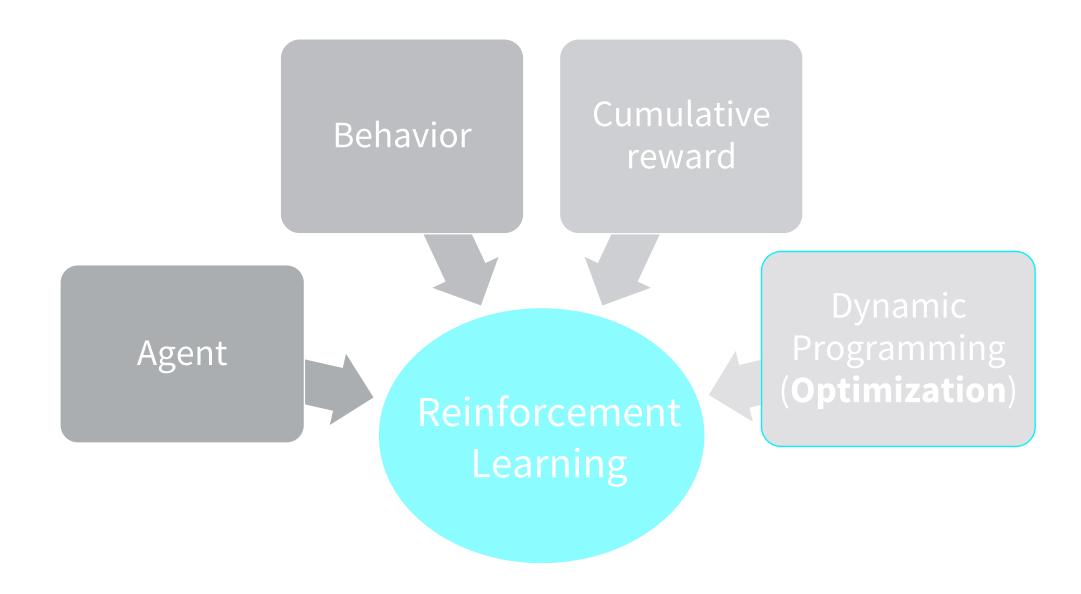


1. Explain the role of policies and actions in Reinforcement Learning

2. Describe how Bellman equations are used to compute state values and how they enable the iterative process of finding an optimal policy

3. Discuss the benefits of policy and value iteration in solving Reinforcement Learning problems

### REINFORCEMENT LEARNING AND DYNAMIC PROGRAMMING

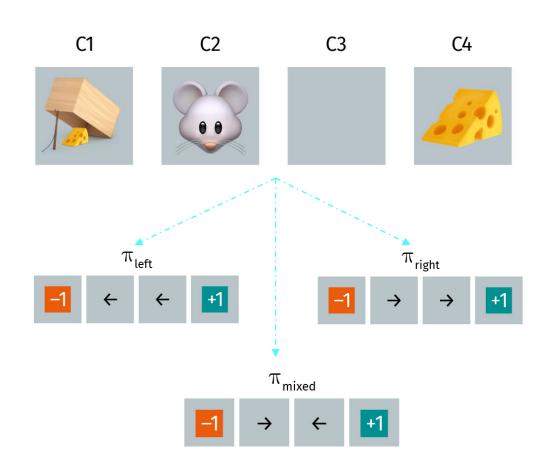




## Policy is a mapping from states to actions

Optimal policy = highest cumulative reward

- Defines agent's state actions
- Agent learns policies by experience



### **Deterministic**



- Map each state to one action
- Execute same action in a state
- Simpler, but prone to local optima

# Stochastic



- Map state to multiple actions
- Sample action from probability distribution
- Complex, but promote exploration and better solutions

VS



# Compute state or state-action pair value for achieving goal state

- Used to compare policies
- Assign value to states based on expected return from policy
- Return is sum of discounted rewards over trajectory

$$G_t = r_t + \gamma \cdot r_{t+1} + \gamma^2 \cdot r_{t+2} + \cdots$$
$$= \Sigma_{t=0}^{\infty} (\gamma^t \cdot r_t)$$



# Value function measures how **good** state or action is

State-value function: measure state value under policy

$$V^*(s_t) = \max_{\pi} E[G_t \mid s_0 = s_t]$$

Action-value function: measure value of state-action pair

$$Q^*(s_t, a_t) = \max_{\pi} E[G_t \mid s_0 = s_t, a_0 = a_t]$$

### **BELLMAN EQUATIONS**



# Bellman equations are the cornerstone of Reinforcement Learning

Recursive value function

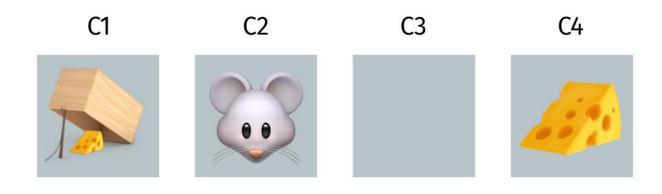
$$V^{\pi}(s_t) = E[r_t + \gamma \cdot V^{\pi}(s_{t+1}) | s_0 = s_t]$$

Estimate value based on future rewards

$$Q^{\pi}(s_t, a_t) = E[r_t + Q^{\pi}(s_{t+1}, a_{t+1}) \mid s_0 = s_t, a_0 = a_t]$$

Evaluate policies

#### **ENVIRONMENT AS A MARKOV DECISION PROCESS**



MDP <S, A, R, P>

State space  $S = \{C1, C2, C3, C4\}$ 

Reward: R

Action space  $A = \{left, right\}$ 

Transition:  $P = p(s_{t+1} | s_t, a_t)$ 



## Evaluate and improve policies for optimal rewards

# Policy evaluation

Initialize value of state V(S)

Update V(s) using Bellman equation

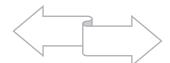
Repeat until convergence

# Policy improvement

Get best estimate for each state

Look ahead to find best policy

Pick action with highest reward





# Value iteration is a *greedy* variant of policy iteration

 Combine policy improvement and truncated policy evaluation

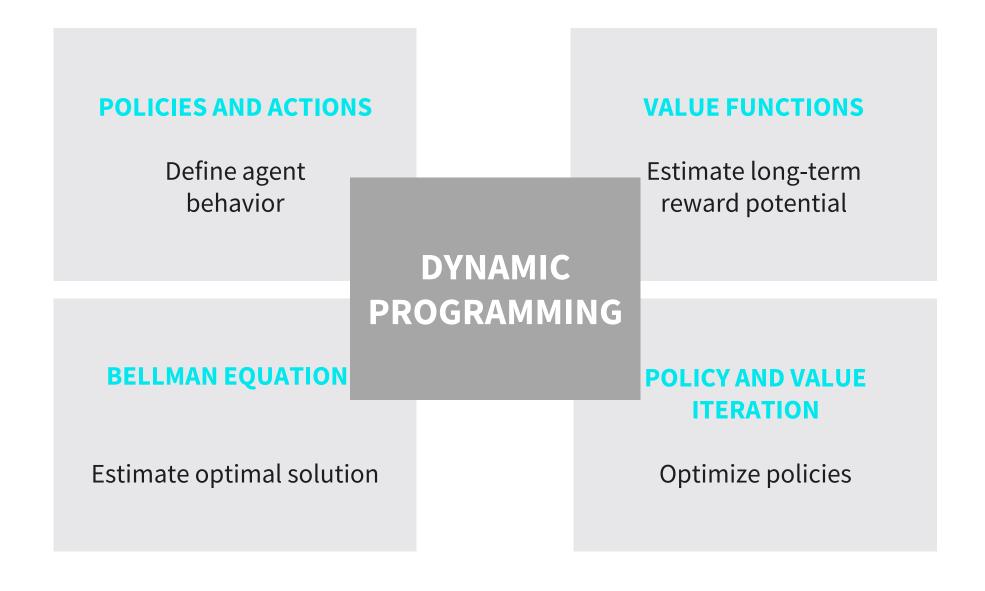
 Select actions using the value from a pass of policy evaluation Initialize V(s)

Repeat until convergence

for each state s, update V(s) using Bellman optimality

Update policy to be greedy with respect to V(s)

#### **DYNAMIC PROGRAMMING**



### **REVIEW STUDY GOALS**



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### SESSION 3

# **TRANSFER TASK**

### **Case study**

A company is designing a robot to navigate in a maze-like environment. The robot must make decisions at each intersection to reach the destination

### **Task**

Using dynamic programming concepts, design an optimal policy for the robot to navigate the maze. Discuss how value functions Bellman equations can be used to estimate rewards, and policy and value iteration to find the optimal policy

# TRANSFER TASK PRESENTATION OF THE RESULTS

Please present your results.

The results will be discussed in plenary.





- Dynamic programming is a \_\_\_\_\_ for solving complex problems
  - a) Programming language
  - b) Genetic algorithm
  - c) Optimization method
  - d) Machine learning method



- 2. Policy iteration consists of two parts: policy evaluation and \_\_\_\_\_
  - a) Policy improvement
  - b) Policy update
  - c) Value improvement
  - d) Value update



- 3. The Bellman equations for v and q are \_\_\_\_\_\_relationships
  - a) Optimal
  - b) Recursive
  - c) Numerical
  - d) Inequality

### **LIST OF SOURCES**

### <u>Images</u>

Nair, 2023.

