

# Reinforcement Learning Workshop

## Day 1 – Student Activities

### Topics

- Markov Decision Processes (MDPs)
  - Policy evaluation
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### 1 Activity 1: Modeling an MDP?

Consider the decision-making problem of managing an inventory system for a single type of item. Each day a certain number of orders is received that must be shipped by the next day. The manager of the facility can, each day, order a number of items. The space available for inventory is limited, and if there are not enough items to fulfill outstanding orders a penalty is incurred.

The goal of the manager is to minimize the cost of operating the system in the long term. Discuss the following questions.

- (a) What kind of costs would you expect to have in managing such system?
- (b) What important parameters would have to be specified to model this problem?
- (c) Is this an episodic task or a continuing task?

Taking into account the previous discussion, create an MDP model for this problem, specifying:

- (a) The state space  $\mathcal{S}$
- (b) The action space  $\mathcal{A}(s)$
- (c) The transition probability matrices  $P^a$  for each action  $a$ .
- (d) The reward matrices  $R^a$  for each action  $a$ .
- (e) Is this a continuing task or an episodic task?

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## 2 Activity 2: Episodic vs Continuing Tasks

Classify each task below as *episodic* or *continuing*.

- Playing a game of chess
- Controlling a thermostat
- Robot navigation with a goal state
- Stock portfolio management

For each task:

1. Does it have terminal states?
2. What is an appropriate discount factor  $\gamma$ ?

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## 3 Activity 3: Computing Returns by Hand

Consider the following trajectory:

$$(s_0, a_0, r_1 = 1), (s_1, a_1, r_2 = 2), (s_2, a_2, r_3 = -3), (s_3 \text{ terminal})$$

1. Compute the total return with  $\gamma = 1$
2. Compute the total return with  $\gamma = 0.9$

**Question:** How does the choice of  $\gamma$  change the importance of future rewards?

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## 4 Activity 4: Evaluating a Policy

A MDP has state space  $\mathcal{S} = 1, 2$  and action space  $\mathcal{A} = a, b, c$ . All actions are available in all states. The transition probability and reward matrices for each state are:

$$\begin{aligned} P^a &= \begin{bmatrix} 0.2 & 0.8 \\ 0.7 & 0.3 \end{bmatrix} & R^a &= \begin{bmatrix} 10 & 7 \\ 12 & 15 \end{bmatrix} \\ P^b &= \begin{bmatrix} 0.4 & 0.6 \\ 0.1 & 0.9 \end{bmatrix} & R^b &= \begin{bmatrix} 5 & 11 \\ 14 & 7 \end{bmatrix} \\ P^c &= \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix} & R^c &= \begin{bmatrix} 14 & 3 \\ 2 & 12 \end{bmatrix} \end{aligned}$$

Consider the deterministic policy  $\pi(1) = c, \pi(2) = b$

- (a) Write the Bellman equations for the state value function  $V^\pi(s)$  for this policy.
- (b) Write the equations in matrix form  $AV^\pi = b$
- (c) Solve linear system to find  $V^\pi$  (either by hand or using a computer).

## 5 Optional Coding Activity

Go to the GitHub repository for the course ([https://github.com/lfmartins/rl\\_cimpa\\_2026](https://github.com/lfmartins/rl_cimpa_2026)) and click on the “Day 1 Activities in Colab” link.

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