CNRS - Toulouse INP - UT3 - UT Capitole - UT2

Institut de Recherche en Informatique de Toulouse

Lecture 1: Introduction

N8EN18B - Contrôle et Apprentissage

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Contents

Course Organization

Class Info

- Contact: guilherme.ricardo@irit.fr
- Moodle: Announcements, lecture slides, and additional material
- No official textbook – Recommended reading:
  - An Introduction to Reinforcement Learning, Sutton and Barto (2020).
  - Algorithms for Reinforcement Learning, Szepesvari (2010).
- Assessment:
  - 25% TP
  - 75% Final Exam
- Slides are based on Prof. Silver's course [Silver, 2015]

Schedule

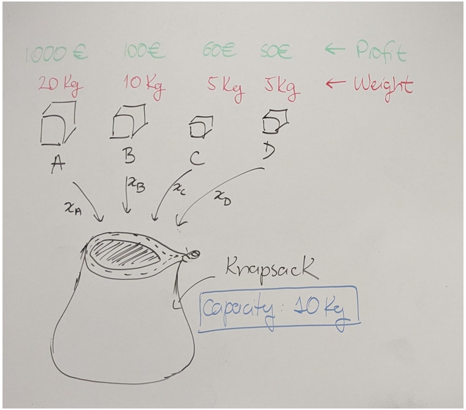
Class	Date	Time	Topic
CM1	29/03/2024	10h15 - 12h00	Introduction
CM2	02/04/2024	16h15 - 18h00	MDP
CM3	04/04/2024	10h15 - 12h00	Dynamic Programming
CM4	23/04/2024	10h15 - 12h00	Q-Learning
TP	26/04/2024	A: 08h00 - 09h45	T.B.A.
		R: 10h15 - 12h00	T.B.A.
CM5	14/05/2024	08h00 - 09h45	Deep Q-Learning
Final Exam			

Table: Tentative Schedule

What is this course about?

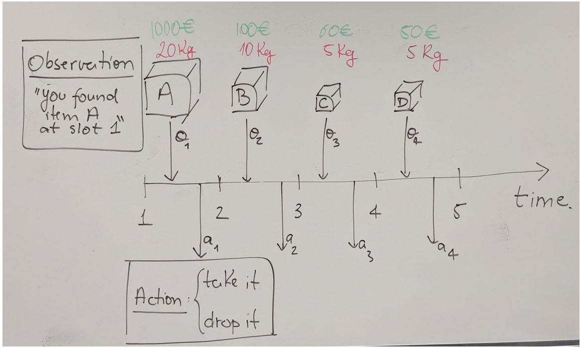
Control and Learning

Control = Optimization



Control and Learning

Learning = Sequential decision making under uncertainty



Reinforcement Learning

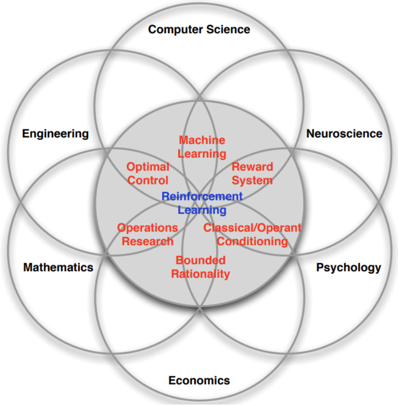


Figure: RL according to different areas.

Reinforcement Learning

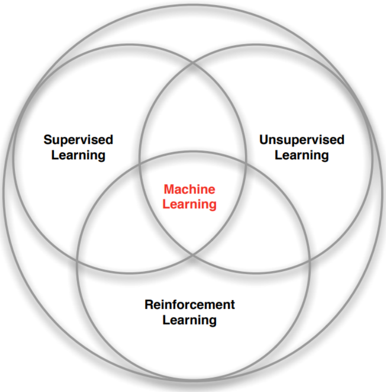


Figure: RL as a Machine Learning paradigm.

Characteristics of RL

What makes RL different from other ML paradigms?

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- There is no supervisor, only a reward signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non-i.i.d. data)
- Agent’s actions affect the subsequent data it receives

Example of RL Applications

- Fly stunt manoeuvres in a helicopter

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- Defeat the world champion at Backgammon
- Manage an investment portfolio
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- Make a humanoid robot walk
- Play many different video games better than humans

Example of RL Applications in Networking

5G Drone Relay [Gangula et al., 2018]

The RL Problem

The RL Problem

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Definition (Reward Hypothesis)

All goals can be described by the maximization of expected cumulative reward.

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Do you agree with this statement?

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  - -ve reward for falling over
- Play many different Atari games better than humans
  - +ve/-ve reward for increasing/decreasing score

Examples of Rewards

What are the rewards for the 5G relay example?

Sequential Decision Making

- Goal: select actions to maximize total future reward
- Actions may have long-term consequences
- Reward may be delayed
- It may be better to sacrifice immediate reward to gain more long-term reward
- Examples:
  - A financial investment (may take months to mature)
  - Refuelling a helicopter (might prevent a crash in several hours)
  - Blocking opponent moves (might help winning chances many moves from now)

The RL Problem

Agent and Environment

Agent

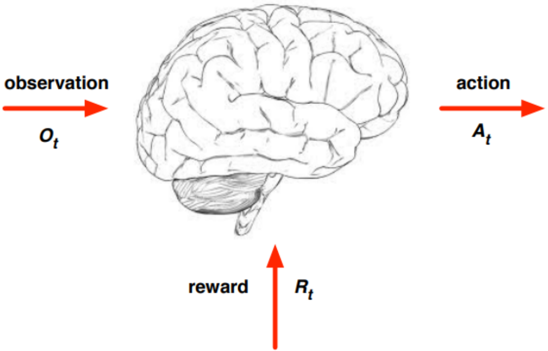

Figure: Agent Abstraction

Agent and Environment

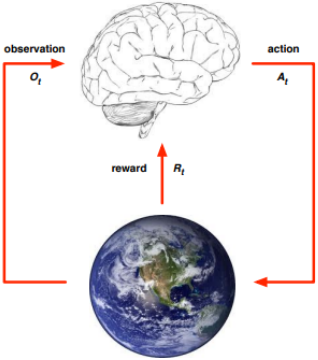

Figure: Agent-Environment cycle

At each step t,

- the agent:
  - Executes action A_t
  - Receives observation O_t
  - Receives scalar reward R_t
- the environment:
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}
- t increments at environment step

The RL Problem

State

History and State

- The *history* is the sequence of observations, actions, rewards:

$$H_t = O_1, R_1, A_1, \ldots, A_{t-1}, O_t, R_t \tag{1}$$

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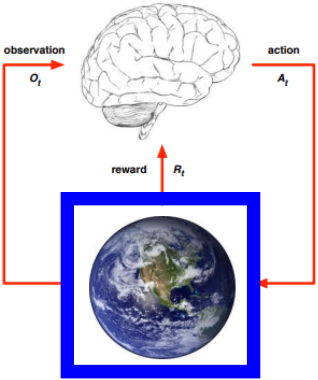
- What happens next depends on the history:
  - The agent selects actions
  - The environment selects observation/rewards
- *State* is the information used to determine what happens next
- Formally, the state S_t at time t is a function of the history:

$$S_t = f(H_t) \tag{2}$$

Environment State



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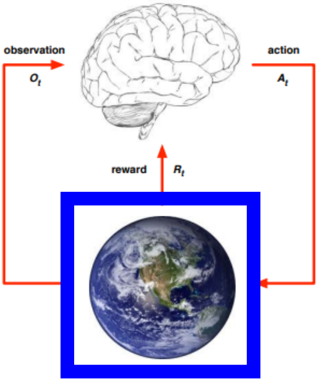

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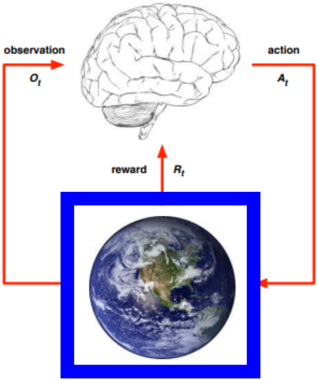

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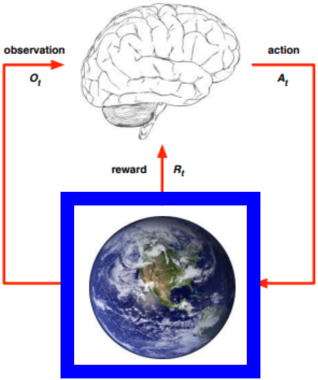

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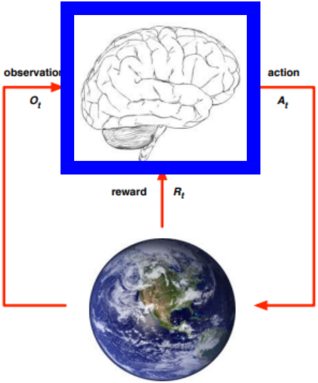
- The environment state is not usually visible to the agent
- Even if S_t^e is visible, it may contain irrelevant information

Agent State



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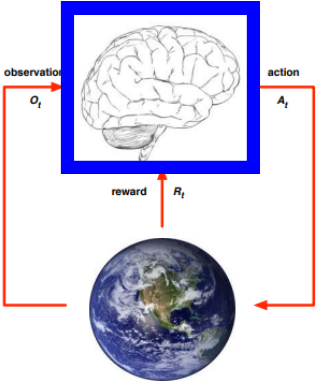

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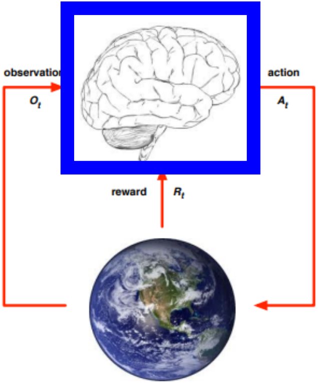

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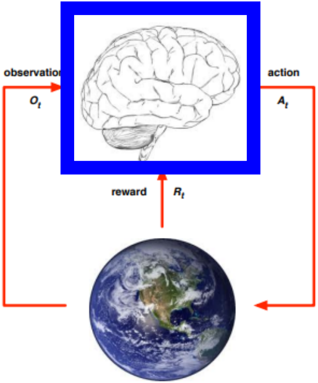

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- It can be any function of history:

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Rat Example

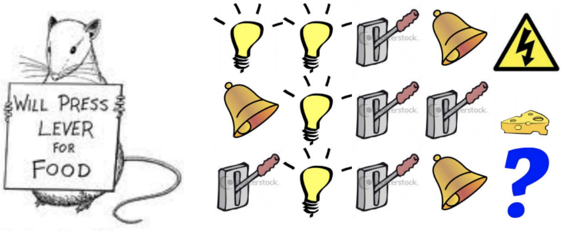

Figure: Cognitive Experiment with Rats

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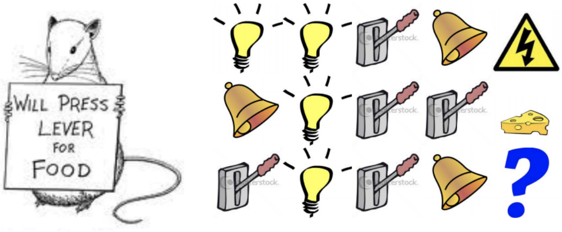

Figure: Cognitive Experiment with Rats

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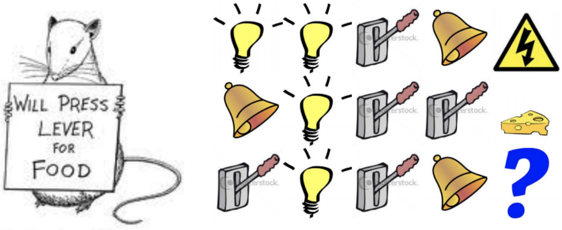

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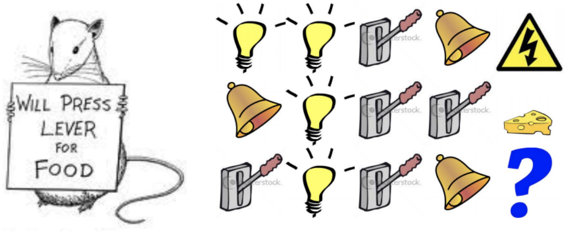

Figure: Cognitive Experiment with Rats

- What if agent state = "last 3 items in sequence"?
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- What if agent state = "complete sequence"?

Fully Observable Environments

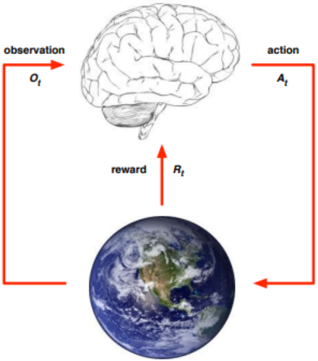

Figure: Agent-Environment cycle

Full observability: agent directly observes environment state

$$O_t = S_t^a = S_t^e \tag{6}$$

- Agent state = environment state = information state
- Formally, this is a **Markov Decision Process (MDP)**

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  - **Beliefs** of environment state: $S_t^a = (\mathbb{P}(S_t^e = s^1), \ldots, \mathbb{P}(S_t^e = s^n))$

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  - Recurrent neural network: $S_t^a = \sigma(S_{t-1}^a W_s + O_t W_o)$

The RL Problem
Inside An RL Agent

Major Components of an RL Agent

An RL agent may include one or more of these components:

- *Policy*: agent's behavior function
- *Value function*: how good is each state and/or action
- *Model*: agent's representation of the environment

Policy

- A **policy** is the agent's behavior
- It is a map from state to action, e.g.,
- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = \mathbb{P}(A_t = a | S_t = s)$

Value Function

- **Value function** is a prediction of future reward
- Used to evaluate the goodness/badness of states
- And therefore to select between actions, e.g.,

$$v_\pi(s) = \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots | S_t = s] \tag{7}$$

Model

- A **model** predicts what the environment will do next
- Transitions: $\mathcal{P}$ predicts the next state
- Rewards: $\mathcal{R}$ predicts the next (immediate) reward, e.g.,

$$\mathcal{P}^a_{ss'} = \mathbb{P}(S_{t+1} = s' | S_t = s, A_t = a) \tag{8}$$

$$\mathcal{R}^a_{ss'} = \mathbb{E}(R_{t+1} | S_t = s, A_t = a) \tag{9}$$

Maze Example

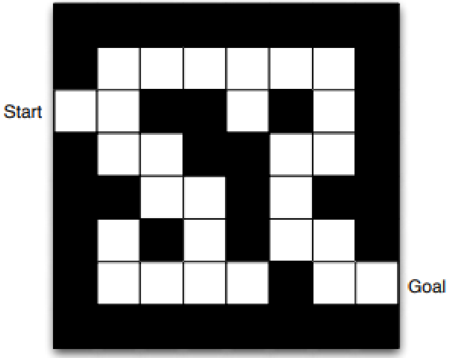


Figure: Maze Example

- Rewards: -1 per time step
- Actions: N, S, E, W
- States: Agent's location

Maze Example: Policy and Value Function

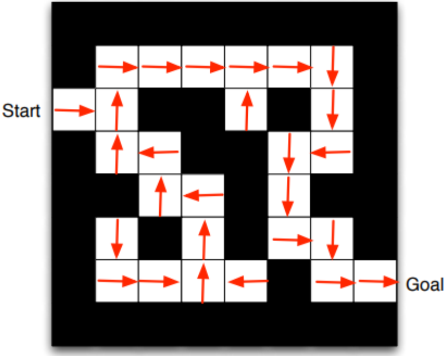


Figure: Arrows represent **policy** $\pi(s)$ for each state s

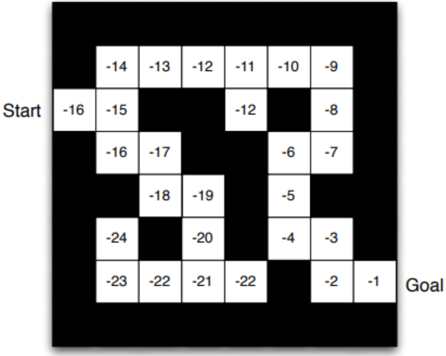
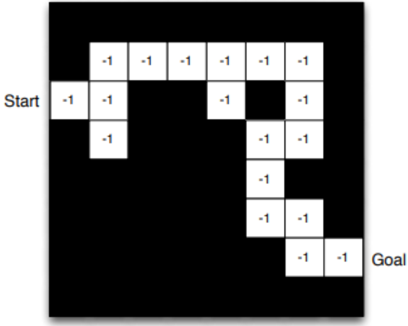


Figure: Numbers represent **value** $v_\pi(s)$ for each state s

Maze Example: Model



- Agent may have an internal model of the environment
- Dynamics: how actions change the state
- Rewards: how much reward from each state
- The model may be imperfect

- Grid layout represents transition model $\mathcal{P}^a_{ss'}$
- Numbers represent immediate reward $\mathcal{R}^a_s$ from each state s (same for all a)

The RL Problem
Problems within RL

Exploration and Exploitation

- RL is like trial-and-error learning
- The agent should discover a good policy
- From its experiences of the environment
- Without losing too much reward along the way

- Exploration finds more information about the environment
- Exploitation exploits known information to maximize reward
- **It is usually important to explore as well as exploit**

Exploration and Exploitation: Examples

- Restaurant Selection
  Exploitation: Go to your favorite restaurant every time
  Exploration: Try a new restaurant
- Online Banner Advertisements
  Exploitation: Show the most successful advertisement
  Exploration: Show a different advertisement
- Oil Drilling
  Exploitation: Drill at the best known location
  Exploration: Drill at a new location
- Game Playing
  Exploitation: Play the move you believe is best
  Exploration: Play an experimental move

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