Introduction to reinforcement learning

July 9, 2019

Introduction

- This morning we will study an important AI paradigm : **Reinforcement learning (RL)**

Applications of RL

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- RL has many applications and is quite a hot topic.
- Especially **Deep Reinforcement Learning** has received a lot of attention recently.

Applications of Deep Reinforcement Learning I

- Atari games

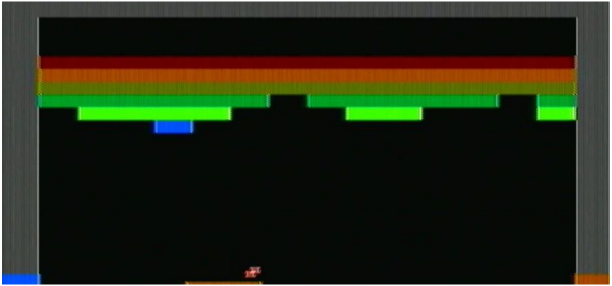

Figure: Atari game

Applications of Deep Reinforcement Learning II

- AlphaGo

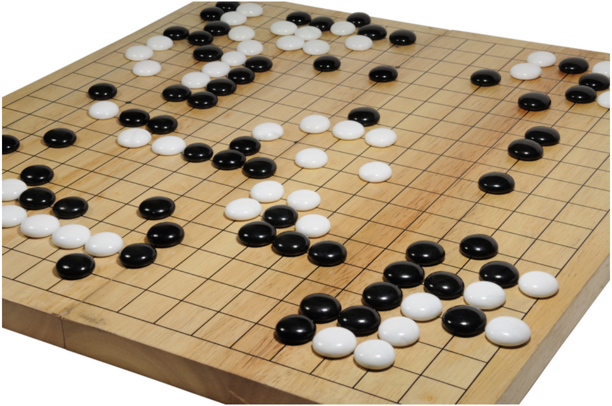

Figure: Go game, beaten by AlphaGo in 2017 [Silver et al., 2016]

Applications of Reinforcement Learning III

- Reinforcement Learning is also begin used in the community of **Computationnal neuroscience.**

Ressources

- `https://github.com/nlehir/summerschool` contains our slides and exercices.
- When doing exercises, we will be using **python 3**

References

- [Andrew and Sutton, 1998]

Overview

Supervised learning

- Let us first recall what supervised learning is.

Supervised learning

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- MNIST demo

Supervised learning and Correction

- In **supervised learning**, the supervisor indicates the **expected answer** the agent should answer.
- With our mnist digit classificatino example, the actin of the agent is the **prediction of the class**.

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- The feedback does not depend on the action performed by the agent (for instance the prediction from the agent)
- We say that the agent receives an **instructive feedback**

Supervised learning Correction

- In **supervised learning**, the supervisor indicates the **expected answer** the agent should answer.
- The agent must then **correct its model** based on this answer.

Cost sensitive learning

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Cost sensitive learning

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- The agent receives an **evaluative feedback**. The feedack depends on the action performed by the agent.
- **Examples :**
  - AI playing a game and receiving "victory" or "defeat" as a feedback.
  - Child playing with an animal.

Reinforcement learning

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- In reinforcement learning, the feedback is a **real number**
- **Example :** amount of coins won after a poker turn.

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Reinforcement learning

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- A reward of -10 good be good or bad depending on the other rewards that are possible to obtain.
- The objective of the agent will be to optimize the **agregation of rewards**

Reinforcement learning

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Reinforcement learning

- The idea is that the agent lives in a world E, and can be in several states s. The agent performs **actions** a and receives rewards r.
- **Examples :**
  - world $= \mathbb{R}^2$
  - state $=$ position
  - actions $=$ moving somewhere
  - reward $=$ amount of food found

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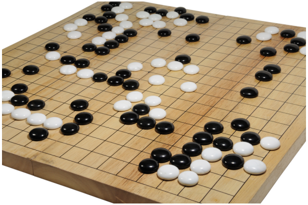
- Are these hypothesis valid in the case of AlphaGo ?



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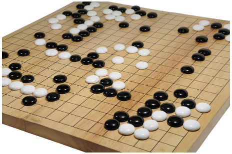

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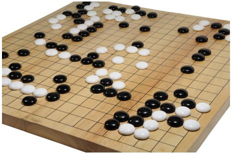

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- Yes ! So you can do crazy stuff in discrete spaces.
- However, please note that this is not always the case. Sometimes the possible actions are continuous, the available psitions are continuous, etc.

Let us continue with the formalization

- we will write :
  - s_t : state at time t
  - a_t : action performed at time t
  - r_t : reward received at time t
- how is the action chosen ?

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  - s_t : state at time t
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- the actions are chosen according to a **policy** π

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- It can be **deterministic :** the action chosen is chosen with probability 1
- Or **stochastic :** the action performed in a given state is drawn from a **distribution**

Two levels of randomness

- The policy can be deterministic or stochastic.
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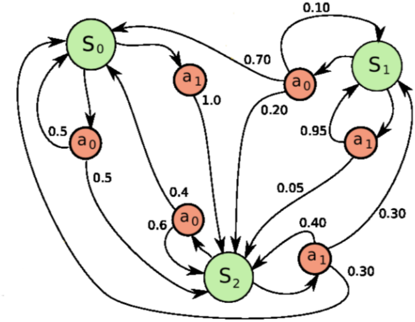
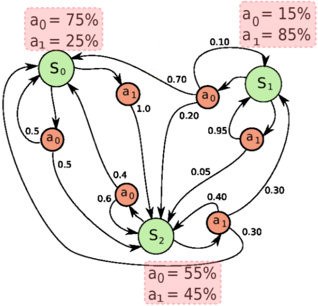


Figure: A stochastic policy with a stochastic transition function.

Exercise

- What is the probability of staying in state S_0 when performing an action from S_0 ? and from S_1 and S_2 ?



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Agregation of rewards

- Remember that our agent want to optimize the **agregation of the rewards.**
- However, what exactly does the agent maximise ?

Agregation of rewards

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- However, what exactly does the agent maximise ?
- There are several ways to agregate the rewards.

Agregation of rewards

- If the horizon is finite, we can take the sum

$$V^{\pi}(s_0) = r_0 + \cdots + r_N \tag{1}$$

Agregation of rewards

- If the horizon is finite, we can take the sum

$$V^{\pi}(s_0) = r_0 + \cdots + r_N \tag{2}$$

- We could also average a window. For instance a window of size 3 :

$$V^{\pi}(s_0) = \frac{r_0 + r_1 + r_2}{3} \tag{3}$$

Agregation of rewards : discount factor

- the **discount factor** $\gamma \in [0, 1]$ allows you to weight the rewards r_k

$$V^{\pi}(s_0) = \sum_{t=t_0}^{+\infty} \gamma^{t-t_0} r_t \tag{4}$$

More considerations

- The Markov hypothesis
- Exploitation exploration compromise

Art

"RL is a science, but dealing with the exploration-exploitation compromise is an art" (Sutton)

Dynamic programming

- Today we will study a simple case of Reinforcement learning
- In that case, the result of our actions is deterministic.

World

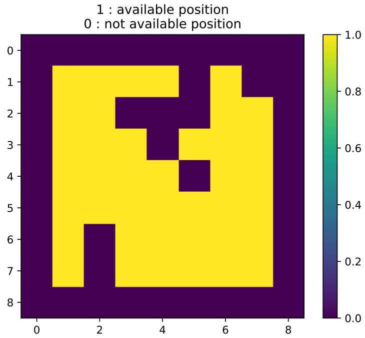

Figure: 2 dimensional world.

Reward

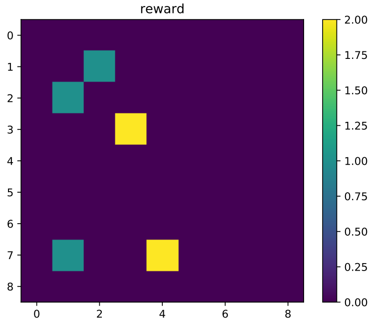

Figure: Reward function.

2D world

- Our agent can move in the 4 directions, one step at a time.
- We will progressively build an agent that learns to evaluate the states and then learns how to go to the best state.

Value function

- For each state (=position in the 2D world), we want to compute the **value function**.
-
$$V(s_0) = r_0 + \gamma r_1 + \gamma^2 r_2 \dots \tag{5}$$

Exercise

- For each state (=position in the 2D world), we want to compute the **value function**.
- $$V(s_0) = r_0 + \gamma r_1 + \gamma^2 r_2 \dots \tag{6}$$
- Can you express $V(s_0)$ as a function of $V(s_1)$?

Bellman equation

- This equation is the Bellman equation.

Value Iteration

- First, the initial Value function for all the states is 0.

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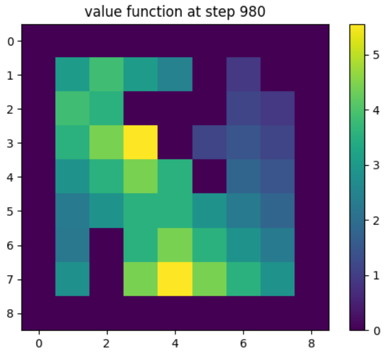
- First, the initial Value function for all the states is 0.
- Then we propagate the information about the rewards between the states, in order to **update the value function**
- We can find an optimal policy in the following way :

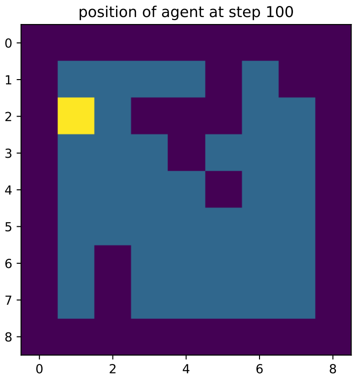
$$\forall s \in V(s_t) \leftarrow \max_{a_t} \left(r_{s_t} + \gamma V(s_{t+1}) \right) \tag{7}$$

(s_{t+1} depends on a_t).

Value iteration

- After learning, we will obtain a value function




position of agent at step 100
0
1
2
3
4
5
6
7
8
0
2
4
6
8

Exercise 2A

- in the **reinforcement learning folder**
- Please use the file **create_world.py** in order to generate your own environment.
- You can use the one that is already there if you prefer.
- We store the data about the world in **.npy** files.

Exercise 2B

- In **value_iteration.py**, modify the function **move_agent** so that the agent is randomly moved.

Exercise 2C

- In **value_iteration.py**, modify the function **update_value_function** in order to modify the value function according to the Bellman equation.

Exercise 2D

- Finally, make the alrogithm run in order to **converge to the optimal value function.**

Exercise 3

- Please use the file **value_iteration_policy** in order to design an optimal policy for our agent.

Optimal policy

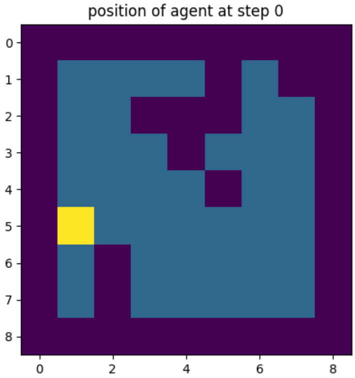


Figure: After learning, the agent can go to the reward.

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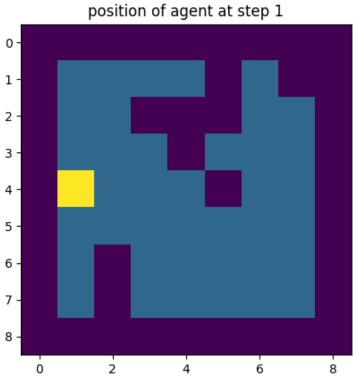

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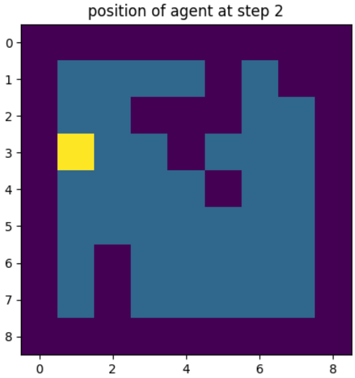

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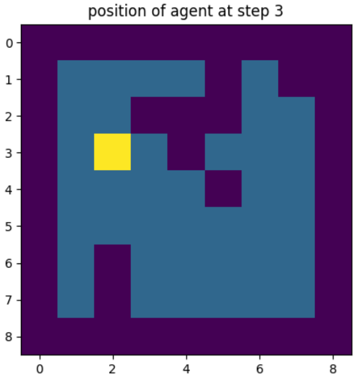

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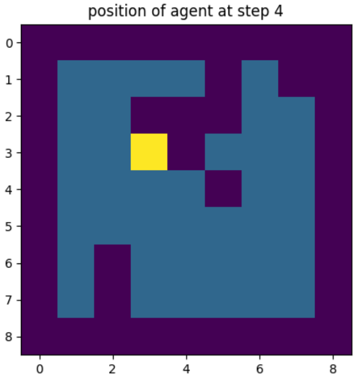

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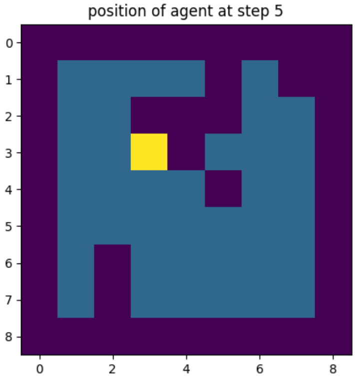

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