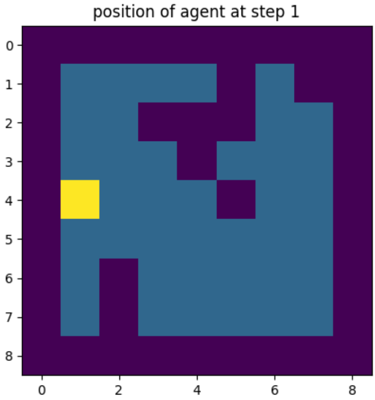
Machine learning II, unsupervised learning and agents: reinforcement learning



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

- Atari games

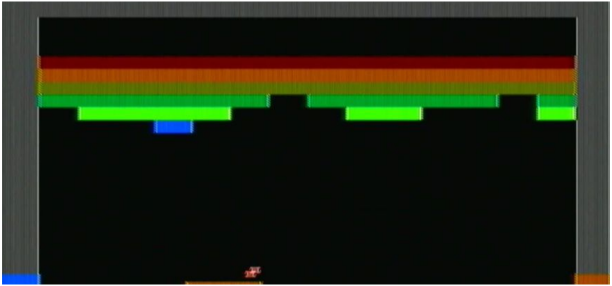


Figure – [Mnih et al., 2013]

- AlphaGo

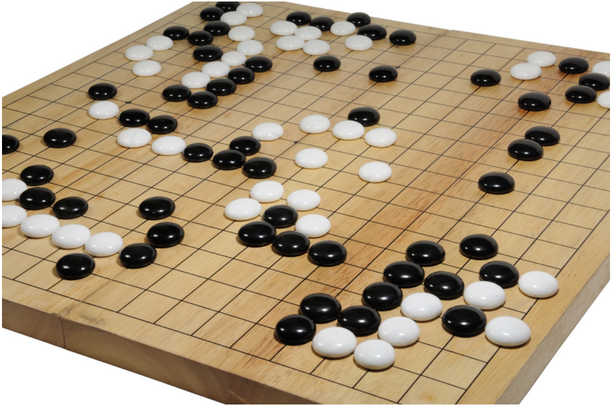


Figure – Go game, beaten by AlphaGo in 2017 [Silver et al., 2016]

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

Overview

Supervised learning and Correction

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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 give.
- The agent must then **correct its model** based on this answer.

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.

Reinforcement learning

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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.
- Most of the time, the objective of the agent will be to optimize the **agregation of rewards**.

Reinforcement learning

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Reinforcement learning

- 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

Formalization

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- We will consider **discrete spaces** :
  - the time will be discrete
  - the number of possible states will be **finite**
  - the number of possible actions will be **finite**
- Continuous spaces are also available for RL. In those cases the objects are slightly different, and the optimization procedures also differ. For an introductory course, discrete spaces are more suitable.

Question

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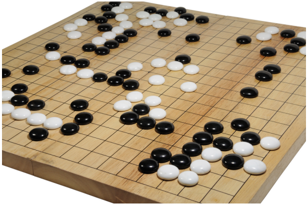
- Are these hypotheses valid in the case of AlphaGo ?



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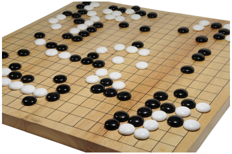

- Yes ! This shows that discrete spaces can still describe very complex problems.

Formalization

- we will write :
  - S_t : state at time t
  - R_t : reward received at time t
  - A_t : action performed at time t
- the actions are chosen according to a **policy** π

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- 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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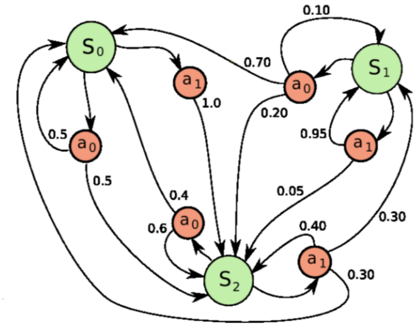
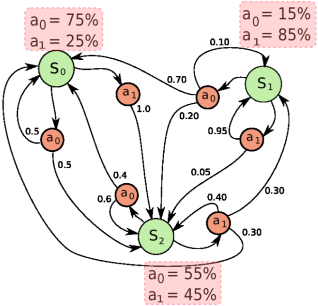


Figure – A stochastic policy with a stochastic transition function.

Exercice 1 :

- What is the probability of staying in state s when performing an action from s ? 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.**
- There are several ways to agregate the rewards.

Returns

We introduce the **return** G_t.

- Episodic case (finite number of steps) :

$$G_t = R_{t+1} + R_{t+2} + \cdots + R_{t+N} \tag{1}$$

- Continuiing tasks :

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \tag{2}$$

$\gamma \in [0, 1[$ is the **discount factor**

Value function

Given a fixed policy π, the value function $v_\pi(s)$ quantities how good a state s is.

$$v_\pi(s) = E[G_t | S_t = s] \tag{3}$$

(the expectation is taken over the next actions, following the policy π).

The Bellman equation

Given a fixed policy π, and a state s, we can write a recursive relationship between $v_\pi(s)$ and the values v_π of the next possible successor states (see the Sutton book for the general form of the equation 3.12 page 85).

More considerations

- The Markov hypothesis
- Exploitation exploration compromise

ϵ-greedy policy

A way to tackle the exploitation-exploration compromise.

- with probability $1 - \epsilon$: go to the best known reward (exploitation).
- with probability ϵ : perform a random action (exploration).

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
- Deterministic transition function.

World

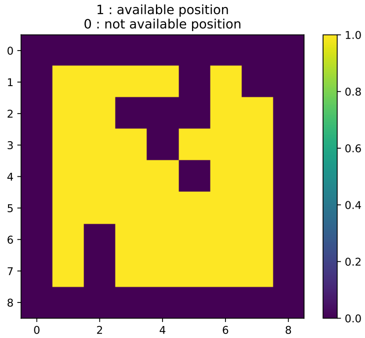


Figure – 2 dimensional world.

Reward

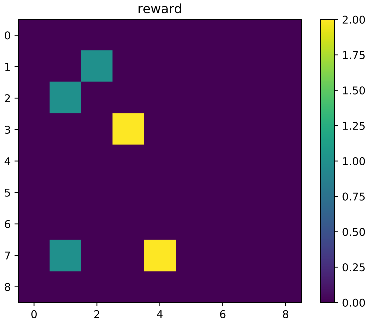


Figure – Reward function.

2D world

- Our agent can move in the 4 directions, one step at a time.

Optimal value functions

We look for the value of the **optimal policy** π^*, defined by the fact that it has the best value function among all policies.

$$
\begin{aligned}
v_*(s) &= \max_{a \in \text{available actions}} E[G_t | S_t = s, A_t = a] \\
&= \max_{a \in \text{available actions}} E[\sum_{k \geq 0} \gamma^k R_{t+k+1} | S_t = s, A_t = a] \\
&= \max_{a \in \text{available actions}} E[R_{t+1} + \gamma \sum_{k \geq 1} \gamma^{k-1} R_{t+k+1} | S_t = s, A_t = a] \\
&= \max_{a \in \text{available actions}} E[R_{t+1} + \gamma \sum_{k \geq 0} \gamma^k R_{t+k+2} | S_t = s, A_t = a] \\
&= \max_{a \in \text{available actions}} E[R_{t+1} + \gamma v_*(S_{t+1}) | S_t = s, A_t = a]
\end{aligned} \tag{4}
$$

Bellman optimality equation

In the case of our simple 2D deterministic world, the Bellman optimality equation 4 takes a simpler form !

$$v_*(s) = \max_{a \in \text{available actions}} R_{t+1} + \gamma v_*(S_{t+1}) \tag{5}$$

The expected values are replaced by deterministic values.

Value Iteration

- Value iteration belongs to dynamic programming methods. They are a specific case of RL where a perfect model of the environment is assumed.
- In value iteration, equation 4 is used as an update urle at each time step.

Value Iteration

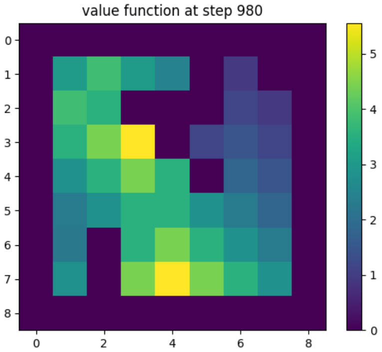
- First, the initial Value function for all the states is 0.
- Then we propagate the information about the rewards between the states, in order to **update the value function** (sweep)

$$\forall s \in V(s) \leftarrow \max_a \left(R_{t+1} + \gamma V(s_{t+1}) | S_t = s, A_t = a \right) \tag{6}$$

- In parallel, we explore the world to learn about the distribution of rewards.

Value iteration

- After learning, we will obtain a value function



- **cd reinforcement_learning/**
- Use the file **create_world.py** in order to generate your own environment.
- You can also use the one that is already there if you prefer.
- We store the data about the world in **.npy** files.

Exercice 2 :

- In **value_iteration.py**, modify the function **move_agent()** so that the agent is randomly moved at each time step.

Exercice 3 :

- In **value_iteration.py**, modify the function **update_value_function()** in order to update the value function according to the Bellman equation, and run the algorithm until convergence of the value function.

Optimal policy

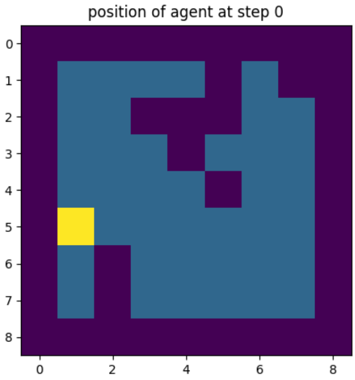
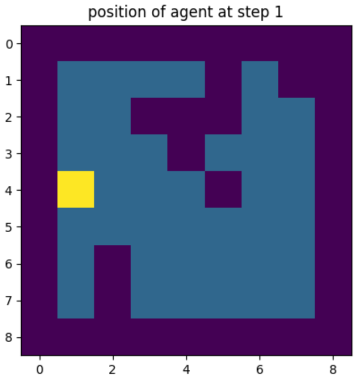


Figure – After learning hte optimal policy, the agent can go to the reward.

Optimal policy



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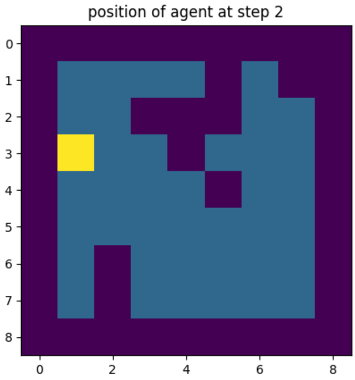

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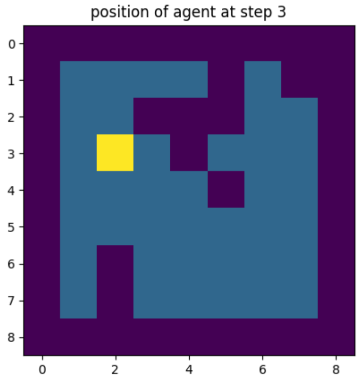

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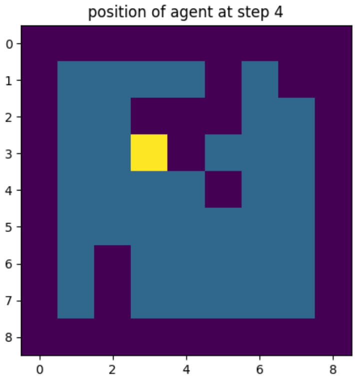

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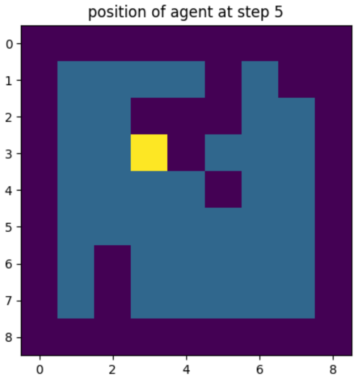

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Multiple paradigms

- Reinforcement learning has many variants.
- In the ones we studied, a model of the consequence of our actions was known.
- This is not always the case.

Temporal difference learning

- In temporal difference learning, the agent does not know a **model** of its world.
- But it can still learn the value function with the **TD updates**

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- But it can still learn the value function with the **TD updates**

$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)] \tag{7}$$

Monte Carlo methods

Monte Carlo methods can be used in Reinforcement Learning to estimate the expected values of some random variables (such as the expected reward in a given state).

Actor critic methods

- Sometimes you can use **two** policies
  - the **behavior policy** provides actions and guarantees exploration
  - the **target policy** is the optimal policy learned in parallel by the agent, that would be used in exploitation mode.

Tabular case and continous case

- We studied **finite** (and thus discrete situations).
- However, RL can also be applied to continuous state / discrete action spaces (DQN).

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- We studied **finite** (and thus discrete situations).
- However, RL can also be applied to continuous state / discrete action spaces (DQN)
- And even to continous state / continous action spaces (DDPG) [Bengio, 2009] .

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