Introduction to reinforcement learning

October 5, 2019

Introduction

- 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

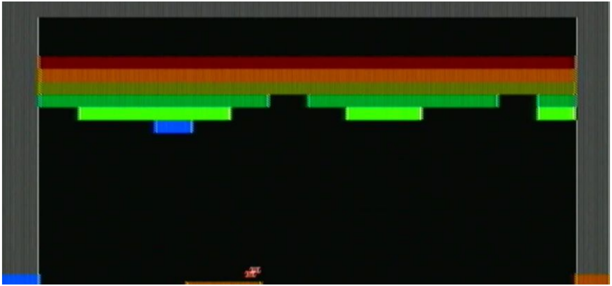

Figure: Atari game

Applications of Deep Reinforcement Learning II

- AlphaGo

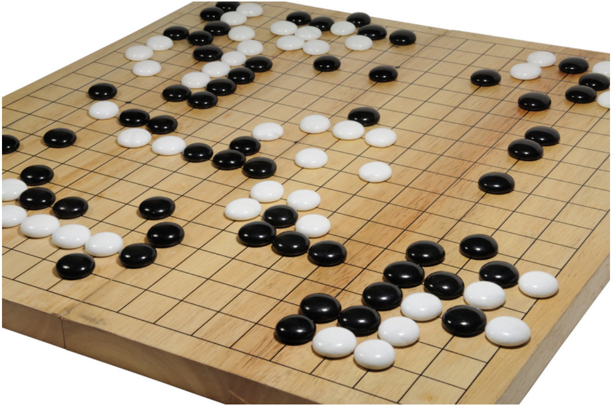

Figure: Go game, beaten by AlphaGo in 2017 [Silver et al., 2016]

Applications of Reinforcement Learning III

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

References

- General Reinforcement Learning : [Andrew and Sutton, 1998]

Overview

Supervised learning and Correction

- In **supervised learning**, the supervisor indicates the **expected answer** the agent should answer.
- With our mnist digit classification example, the action 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.

Reinforcement learning

- First, the agent does **not** know if a reward is good or bad per se.
- A reward of -10 good be good or bad depending on the other rewards that are possible to obtain.

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

- The agent lives in a world E, and can be in several states s. The agent performs **actions** a and receives rewards r.

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** :
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  - the number of possible actions will be **finite**

Question

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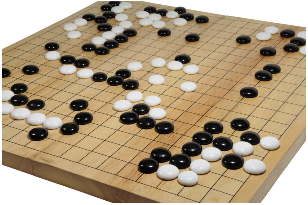
- Are these hypothesis valid in the case of AlphaGo ?



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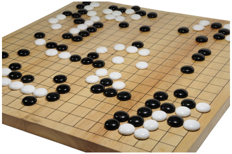

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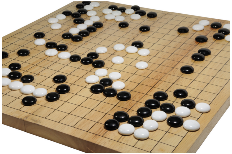

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- Yes.
- However, please note that this is not always the case. Sometimes the possible actions are continuous, the available psitions are continuous, etc.

Let us continue with the formalization

- we will write :
  - s_t : state at time t
  - a_t : action performed at time t
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- we will write :
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  - r_t : reward received at time t
- 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

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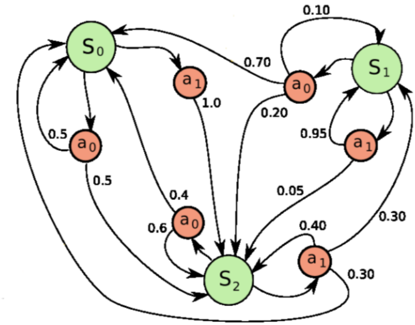
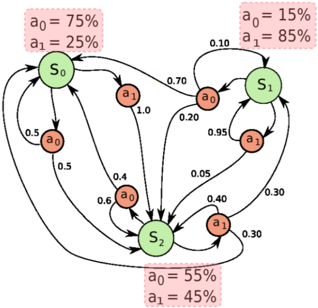


Figure: A stochastic policy with a stochastic transition function.

Exercice 1 : **Computing a probability.**

- 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

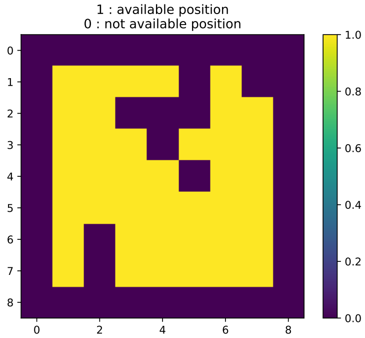


Figure: 2 dimensional world.

Reward

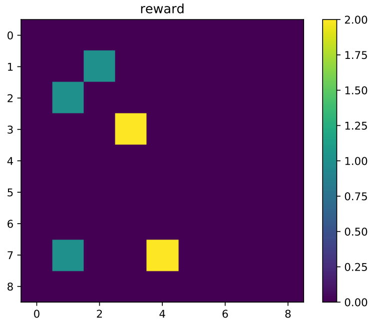


Figure: Reward function.

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**.
-
$$V(s_0) = r_0 + \gamma r_1 + \gamma^2 r_2 \ldots \tag{5}$$

States and rewards.

Exercice 2 : **Bellman equation.**

- For each state (=position in the 2D world), we want to compute the **value function**.
- $$V(s_0) = r_0 + \gamma r_1 + \gamma^2 r_2 \ldots \tag{6}$$
- 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.

Value Iteration

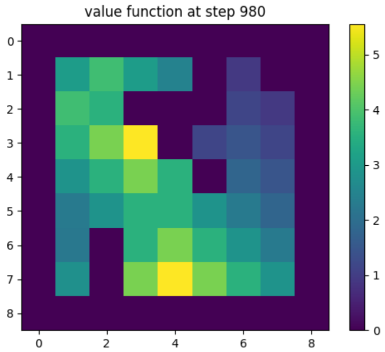
- First, the initial Value function for all the states is 0.
- Then we propagate the information about the rewards between the states, in order to **update the value function**
- We can find an optimal policy in the following way :

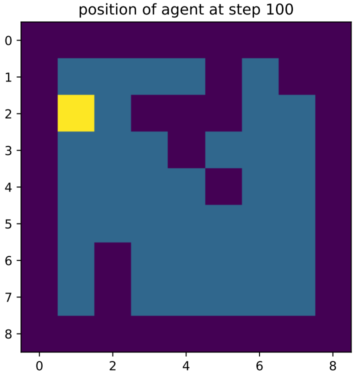
$$\forall s \in V(s_t) \leftarrow \max_{a_t} \left(r_{s_t} + \gamma V(s_{t+1}) \right) \tag{7}$$

(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

World

Exercice 3 : **Creating the environment.**

- **cd ./reinforcement_learning**
- 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.

Random policy

Exercice 4 : **Moving agent**

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

Bellman update

Exercice 4 : **Update value**

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

Optimal value

Exercice 4 : **Update value**

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

Optimal policy

Exercice 5 : **Choosing a policy**

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

Optimal policy

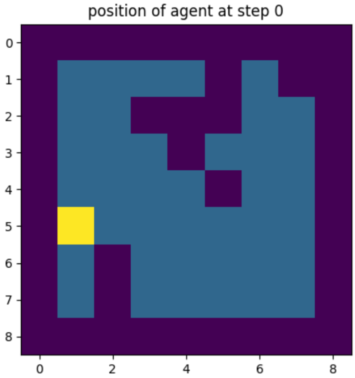


Figure: After learning, the agent can go to the reward.

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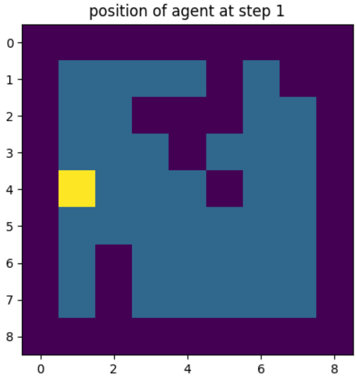

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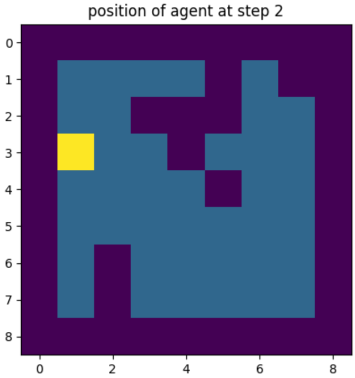

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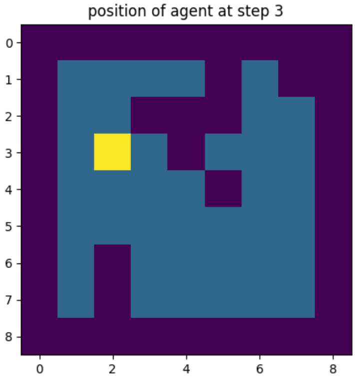

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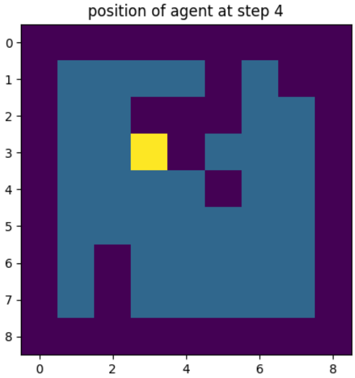

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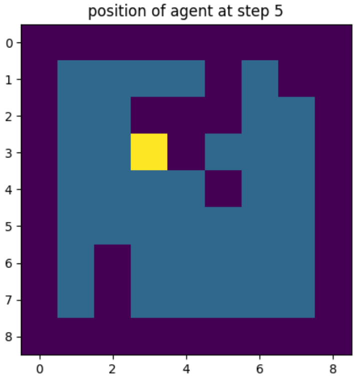

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Remark

- Before going closer to RL, let us do another example of **dynamic programming.**

Policy Iteration

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  - **Policy improvement**

Policy Iteration

Exercice 6 : **Implementing the algorithm**

- Pease use the file **policy_iteration.py** in order to perform the algorithm.

Policy Iteration

Exercice 6 : **Implementing the algorithm with randomness**

- Pease use the file **policy_iteration.py** in order to perform the algorithm.
- Add randomness to the actions of the agent to **guarantee exploration**.

Multiple paradigms

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

Temporal difference learning

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$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)] \quad (8)$$

Monte Carlo methods

- Monte Carlo methods can be used in Reinforcement Learning.

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- For instance in episodic games, we can do statistics on the values of the states.

Actor critic methods

- Sometimes you can use **two** policies

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.

Bias variance compromise

- Very generally speaking, the complexity of your model influences the bias and the variance.

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- Very generally speaking, the complexity of your model influences the bias and the variance.
  - more complex : less bias, more variance
  - less complex : more bias, less variance

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- However, RL can also be applied to continuous state / discrete action spaces (DQN) [Mnih et al., 2013]
- And even to continous state / continous action spaces (DDPG) [Bengio, 2009] .

References I

Andrew, A. M. and Sutton, R. S. (1998).
Reinforcement Learning: An Introduction.

Bengio, Y. (2009).
CONTINUOUS CONTROL WITH DEEP REINFORCEMENT LEARNING.
Foundations and Trends® in Machine Learning.

Mnih, V., Silver, D., and Riedmiller, M. (2013).
Deep Q Network (Google).
Arxiv.

References II

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., and Hassabis, D. (2016).
Mastering the Game of {Go} with Deep Neural Networks and Tree Search.
Nature, 529(7587):484–489.