Going further in reinforcement learning

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Q-Learnin: the basics

- Iterative update on (State, Action) interest.
- Q-value equation:

$$Q(s^t, a) = (1 - \alpha)Q(s^t, a) + \alpha \left(r + \gamma \max_{a^* \in A} Q(s^{t+1}, a^*) \right)$$

- Parrameters:

α - learning rate ; ϵ - thexploration-Exploitation ratio ; γ - discount factor

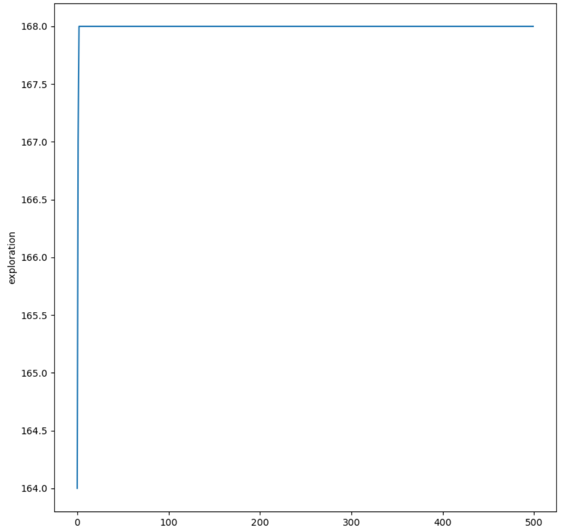
Q-Learnin: Game 421 (Single PLayer)

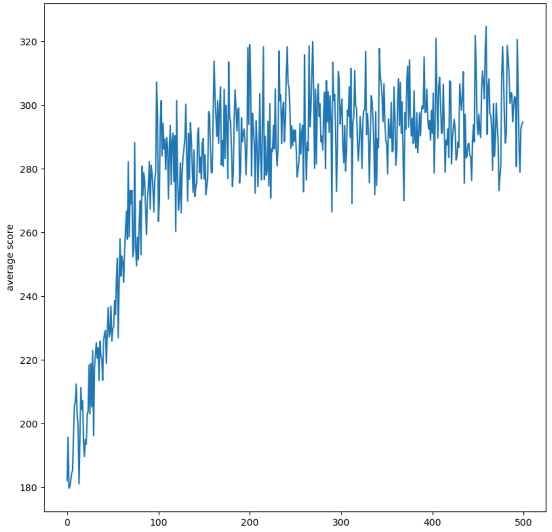
- State Space: Horizon $\in [2, 0]$, Dice $\in [1, 6] \times 3$: (~ 168 états)
- Action Space: **Keep** or **Roll** each dice 2^3 : (8 actions)
- Potentially $168 \times 8 \times 168$ Transition.
- Game score (unique final reward): [0 (*2-2-1*), 800 (*4-2-1*)]
- Random policy score : **~170**

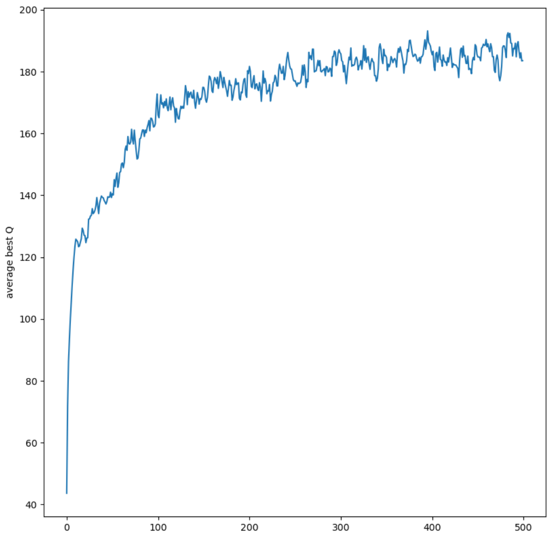
- Correction: playerQ.py (raw file)

Q-Learnin: Game 421 (Single PLayer)

- With **500** steps of **500** games:



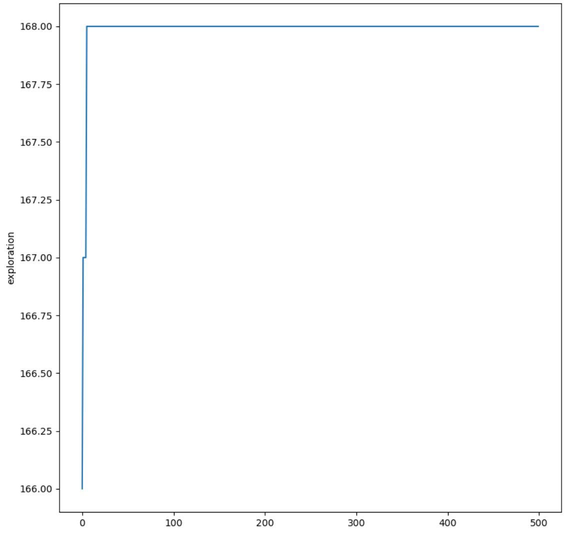


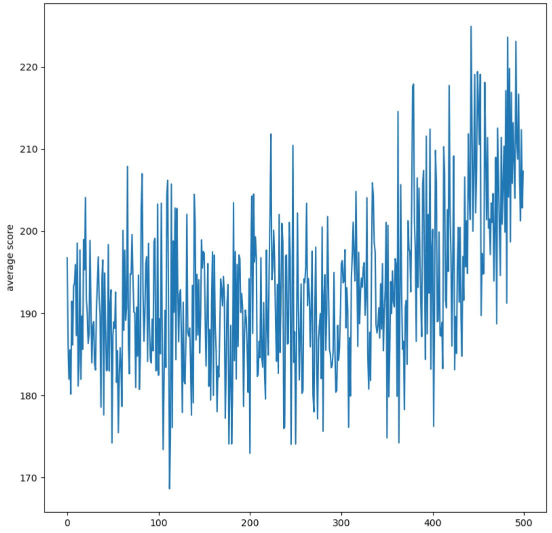


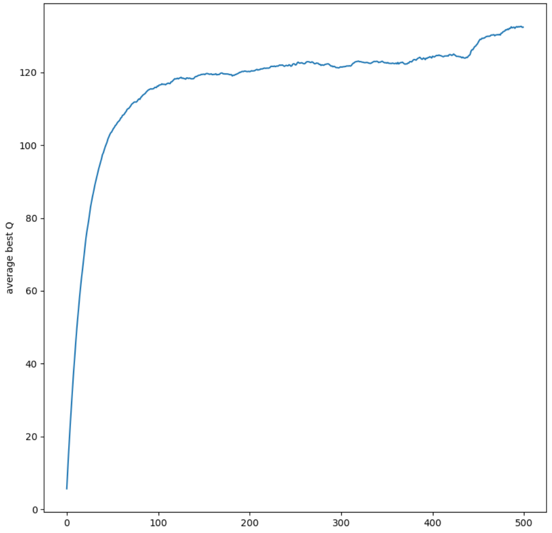
- α : 0.1 ; ϵ : 0.1 ; γ : 0.99

Convergence: effect of the learning rate

- With **500** steps of **500** games:



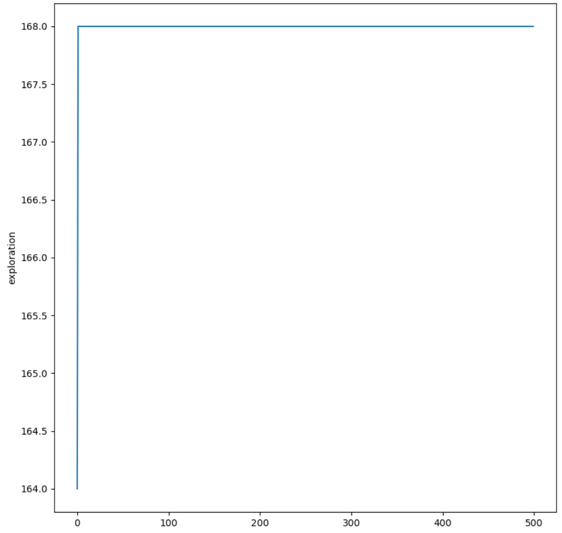


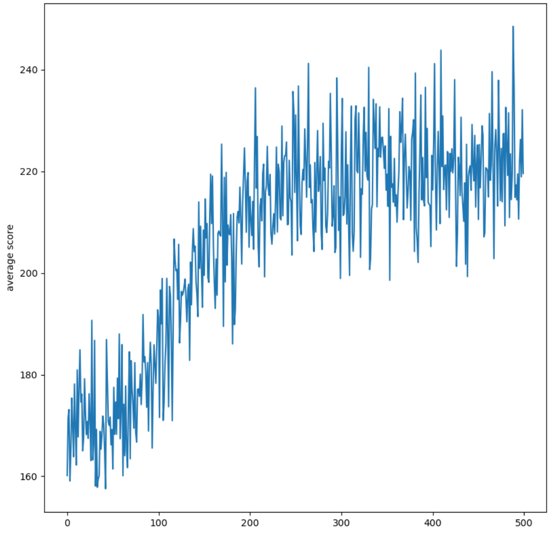


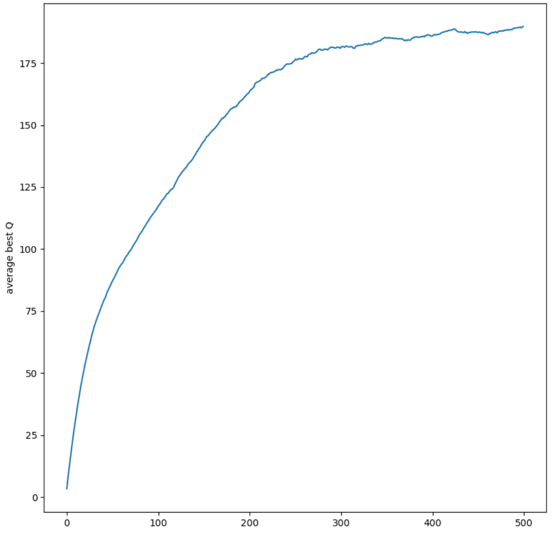
- α : 0.01 ; ϵ : 0.1 ; γ : 0.99

Convergence: effect of the exploration ratio

- With **500** steps of **500** games:







- α : 0.01 ; ϵ : 0.6 ; γ : 0.99

Playing with the parameters:

- Generated rapidly "good" policies
- Converge on maximal and stable Q values
  (an indicator for optimal policy)

- Be reactive to system modification (recovery)
  (no more equiprobable dice for instance)

Optimize Q-Learning:

A first solution: use dynamic parameters

- Balance **learning rate** and **exploration ratio** by taking into account known and unknown areas:

Typically: Count the number of performed transitions, for each couple of (state, action)

Problem: The dynamic will depend on other parameters

Danger: Quid of the recovery mode

Optimize Q-Learning:

A second solution: use expert kownledge

- Drive the exploration with an expert knowledge.

Typically: initialize the Q(s, a) with coherent value to take advantage of exploitation from the very beginning.

Problem: calibrate the "weight" of the initial knowledge.

Danger: Wrong initialization could slow down the learning process.

Model-based learning (the other RL technic)

Main Idea:

- Random trajectories (a lot)
- Until each transition is visited several times.
- Compute an optimal policy.

Potentially:

- Require driving exploration
- Only incomplete exploration can be performed

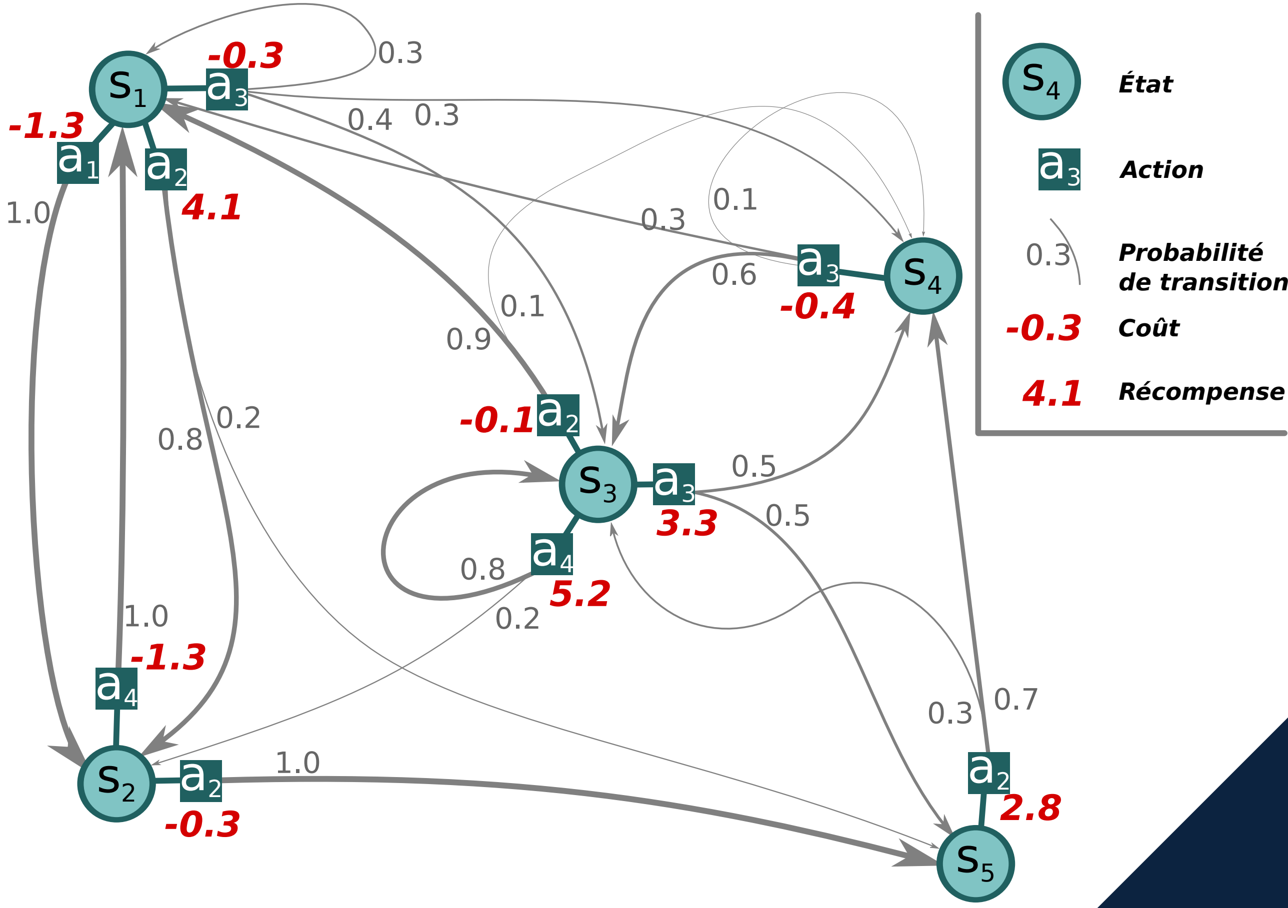
Markov Decision Process

MDP: $\langle S, A, T, R \rangle$:

S : set of system's states
A : set of possible actions
T : S × A × S → [0, 1] : transitions
R : S × A → R : cost/rewards

Optimal policy:

The policy π^* maximizing Bellman



Solving MDP: Value Iteration

Input: an **MDP:** $\langle S, A, T, R \rangle$; precision error: ϵ ; discount factor γ ; initial $V(s)$

1. Repeat until the **maximal delta** < ϵ

   For each state $s \in S$

   - Search the action a^* maximizing the Bellman Equation
   - Update $\pi(s)$ and $V(s)$ by considering action a^*
   - Compute the delta value between the previous and the new $V(s)$

Output: an optimal π^* and associated **V-values**.

$$V^{\pi}(s) = R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \times V^{\pi}(s')$$

Application to 421

- Python implementation - playerMDP.py :

```
solver= MDP()
solver.learnModel( Engine() )
solver.valueIteration()

player= PiPlayer( solver.policy() )
```

- Learning phase: Estimate **t** and **r**:
  - *10 000* simulations for each couple (s, a)
- Value iteration:
  - *3* iterations (directed and finit game)
- Average score (100 000 games): **~338**

(To notice: decreasing the learning phase impact the average score)

Let's play to a more complicated game: Zombie Dice....