Q Learning applied to 421

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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

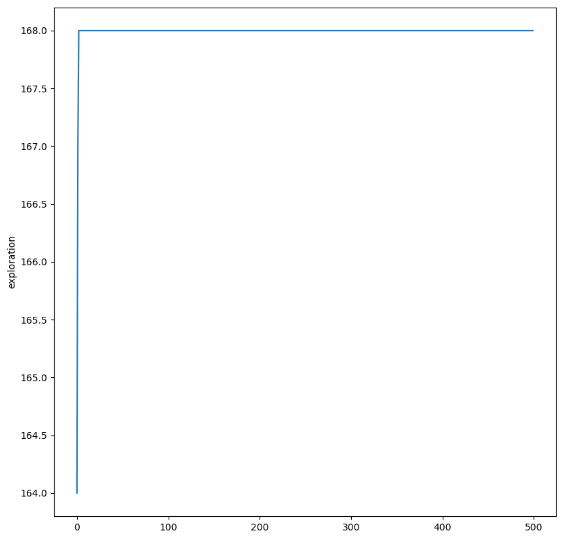
Q-Learnin: Game 421 (Single PLayer)

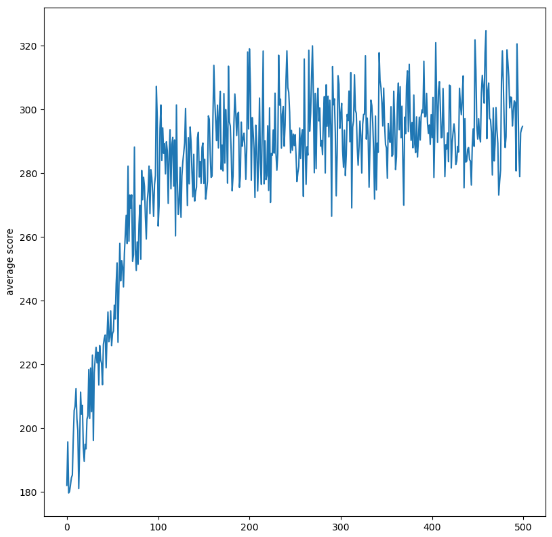
- State Space: Horizon $\in [2, 0]$, Dice $\in [1, 6] \times 3$: (~ 168 états)
- Action Space: **Keep** or **Roll** each dice 2^3 : (8 actions)
- Potentially $168 \times 8 \times 168$ Transition.
- Game score (unique final reward): [0 (*2-2-1*), 800 (*4-2-1*)]
- Random policy score : **~170**

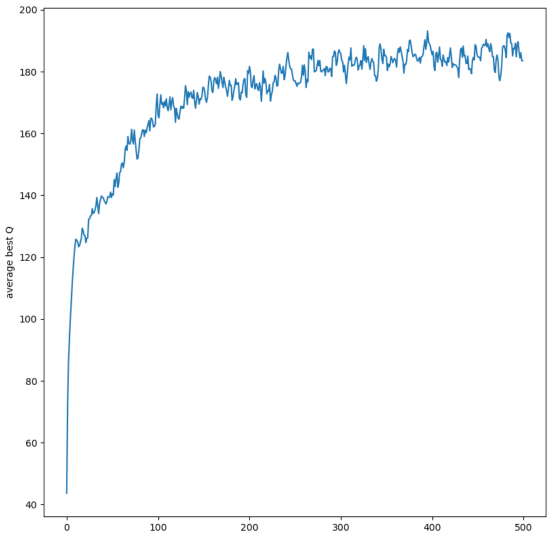
- Correction: playerQ.py (raw file)

Q-Learnin: Game 421 (Single PLayer)

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



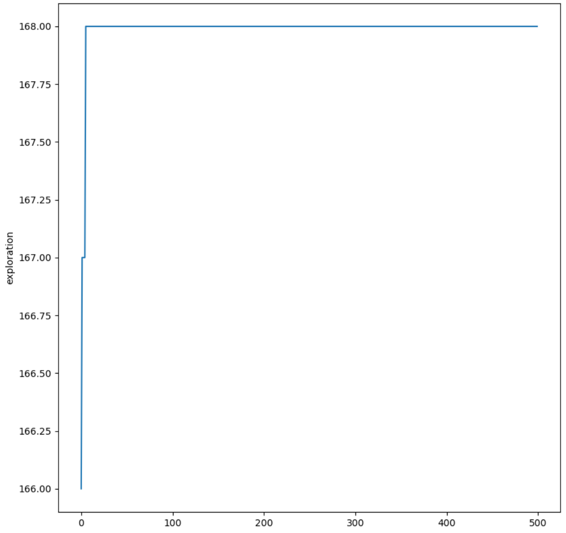


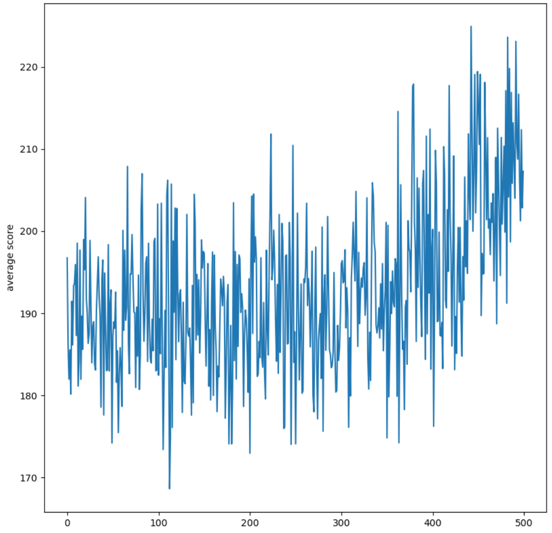


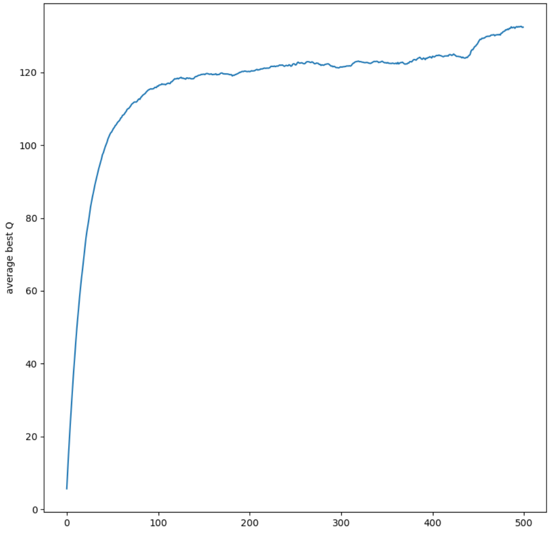
- α : 0.1 ; ϵ : 0.1 ; γ : 0.99

Convergence: effect of the learning rate

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



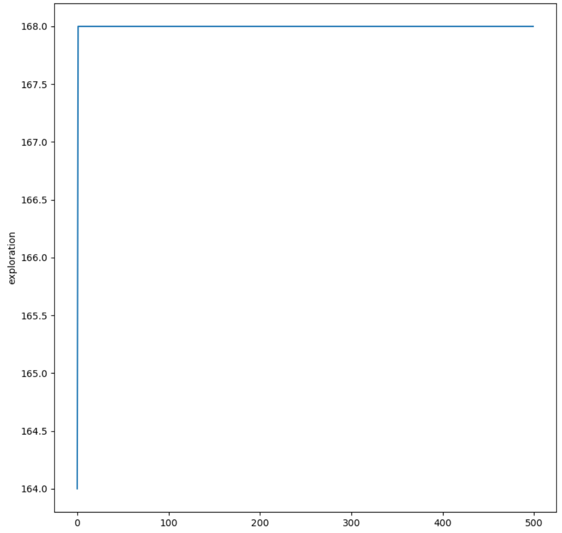


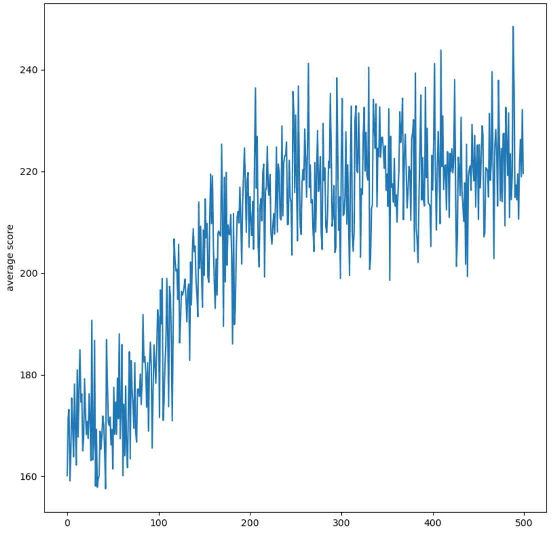


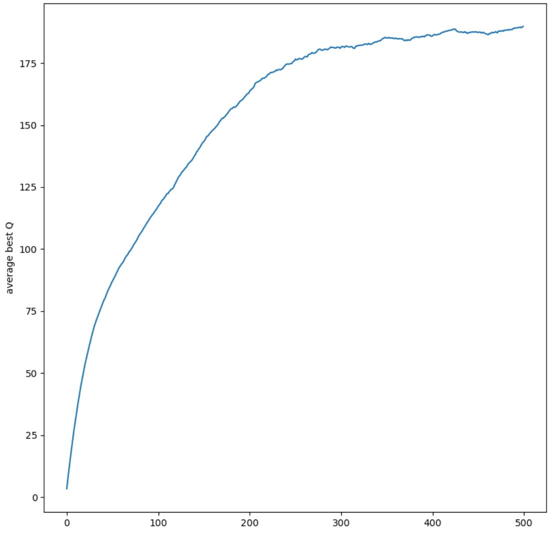
- α : 0.01 ; ϵ : 0.1 ; γ : 0.99

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.

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