Q-Learning

Q-Learning seems quite simple, the goal of this tutorial is to implement it on **421** game to create an AI capable of learning by itself to play to this game.



Set-up

So the goal is to:

- 1. Implement a new PlayerQ
- 2. At initialization **Q-values** is created empty.
- 3. At perception steps the player update its **Q-value**
- 4. At decision step, the player chooses a new action to perform (the best known of for exploring more...)

Q as a dictionary

A simple way to implement \mathbf{Q} in python language is to implement it as a Dictionnary of dictionaries.

- Python documentation
- On w3school

Implement

At init method, initializing an empty **Q-values** dictionary will look like:

```
self.qvalues= {}
```

Then, each time the player reach a new state, it have to generate a initial value for all possible action it would have. So, initializing values for a given state will look like:

A new state requires to be added to qualues each time it is necessary in the wakeUp (the arbirtrary initial state: 9-1-1-1) and the perceive methods. Implement its.

Test

To test if the increase in the code works well, you can print the entire dictionary add the end (i.e. in the main function, after printing the average score).

```
for st in player.qvalues :
print( st +": "+ str(player.qvalues[st]) )
```

Update the Q value

Then you can implement the update of \mathbf{Q} value for the last visited state (Q[stateStr][actionStr]). To notice that updateQ will require another method to select the maximal value in \mathbf{Q} for a given state.

Implement

Modifying a value in **qvalues** dictionary will look like (naturally the state and action strings would be variables):

```
self.qvalues["2-6-3-2"]["roll-roll-roll"]= ...
```

At perception step, before to record the new turn and dices values of the new reached game state,

you have to memorize the last reached state: last= self.stateStr(). Then, with last, self.action, self.stateStr() end self.reward you have all the ingredients to compute the q-value of the last state knowing that you performed the self.action action and reached self.stateStr() state with self.reward.

Test

We will consider that a certain number of games match an episode in the learning process. 1 000 games for instance. The goal is to play several episodes and observe increase in the *Q-values*.

Modify the main function in order to print the *Q-value* of the initial state for instance.

```
print( player.qvalues['9-1-1-1'] )
```

You can also print the number of entrances in the dictionary, the average of the best values of states (the average over the states, by considering the best action to perform) etc...

Choose to exploit or explore

Now the *action* method can randomly select an exploration or an exploitation action. In case of exploration, a random action if performed. In case of exploitation, the playerQ have to search for the best action to perform in the current state.

Implement

Modify the decide method to handle exploration/exploitation. It is recommended to separate the 'selection of the best action' in a dedicated method.

Test

The system would mainly choose the best action to perform (considering its knowledge). The goal is to play several episodes and observe increase in the average scores.

Modify the main function in order to compute and print a new average every 1 000 games.

Going further:

Do not forget You can must test your code at each development step by executing the code for few games and validate that the output is as expected.

1. You can now try to answer how many episodes of 1000 games are required to learn a good enough policy (more than an average of 300 points).

Update our PlayerQ:

- 1. PlayerQ constructor permits users to customize the algorithms parameters ϵ , γ ... Let's do it in the __init__ method with default parameters value.
 - Handle default parameters value in python with <u>w3schools</u>.
- 2. PlayerQ save its learned **Q-values** on a file.
- 3. *PlayerQ* initialize its **Q-values** by loading a file.
- 4. A new PlayerBestQ simply play the best action always from a given **Q-values** dictionary (without upgrading **Q**).
- 5. You are capable of plotting the sum over \mathbf{Q} with one point per episode (with <u>pyplot</u> for instance).