SCHOOL OF DATA AND COMPUTER SCIENCE, SUN YAT-SEN UNIVERSITY

E15 Reinforcement Learning (C++/Python)

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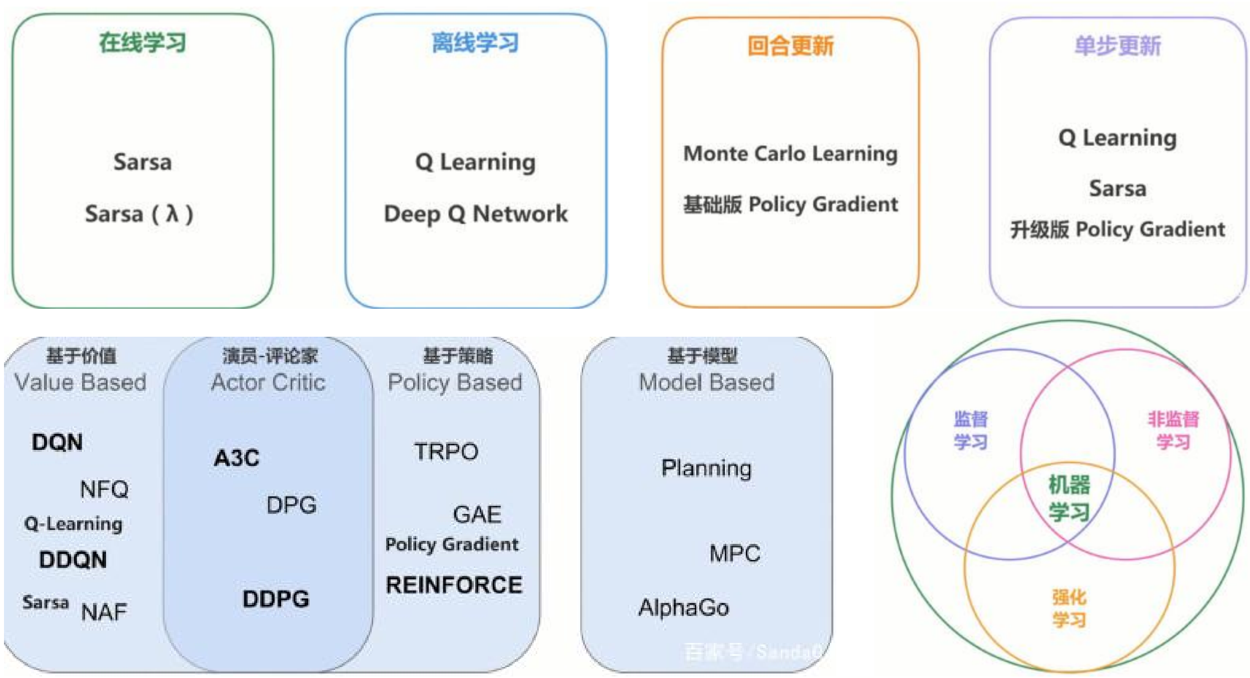
目录

1 Overview



2 Tutorial

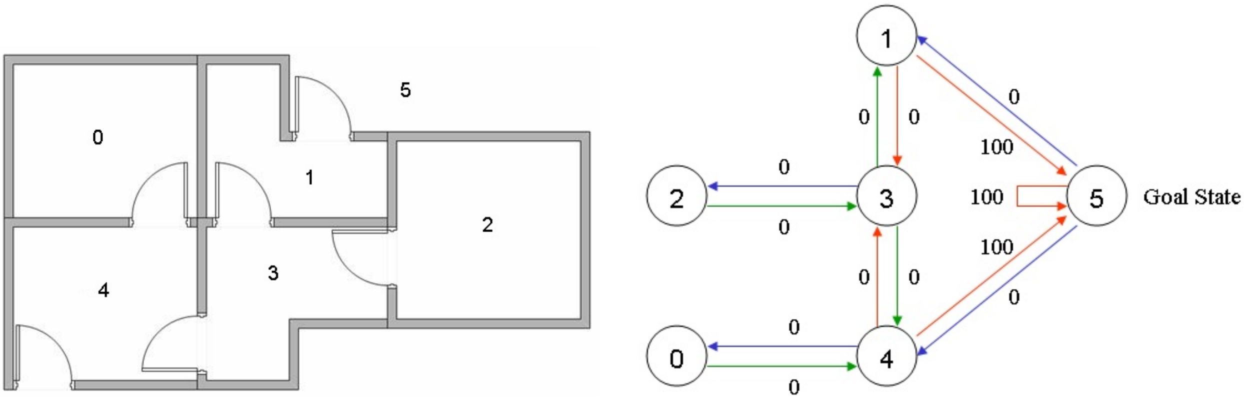
English version: `http://mnemstudio.org/path-finding-q-learning-tutorial.htm`
Chinese version: `https://blog.csdn.net/itplus/article/details/9361915`

2.1 Step-By-Step Tutorial

Suppose we have 5 rooms in a building connected by doors as shown in the figure below. We'll number each room 0 through 4. The outside of the building can be thought of as one big room (5). Notice that doors 1 and 4 lead into the building from room 5 (outside). We can represent the rooms on a graph, each room as a node, and each door as a link.

For this example, we'd like to put an agent in any room, and from that room, go outside the building (this will be our target room). In other words, the goal room is number 5. To set this room as a goal, we'll associate a reward value to each door (i.e. link between nodes). The doors that lead immediately to the goal have an instant reward of 100. Other doors not directly connected to the target room have zero reward. Because doors are two-way (0 leads to 4, and 4 leads back to 0), two arrows are assigned to each room. Each arrow contains an instant reward value, as shown below:

Of course, Room 5 loops back to itself with a reward of 100, and all other direct connections to



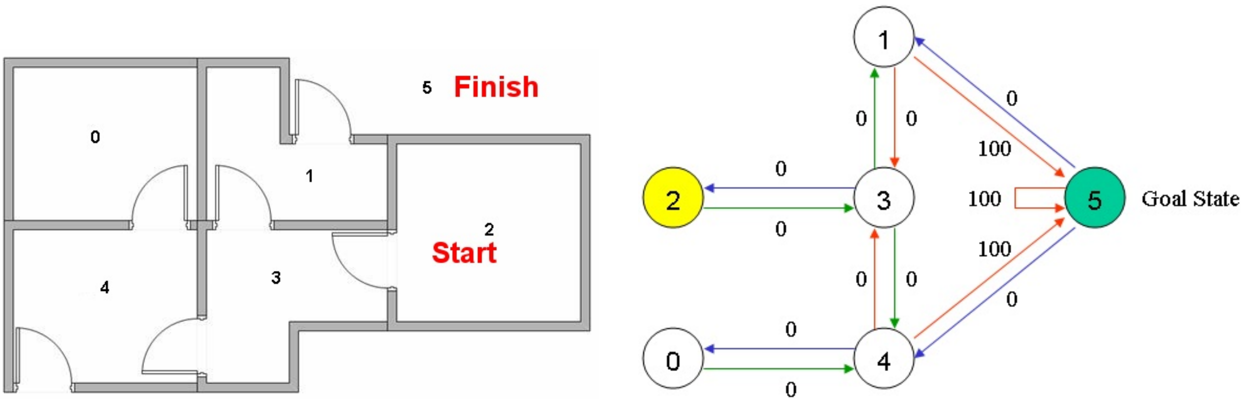
the goal room carry a reward of 100. In Q-learning, the goal is to reach the state with the highest reward, so that if the agent arrives at the goal, it will remain there forever. This type of goal is called an "absorbing goal".

Imagine our agent as a dumb virtual robot that can learn through experience. The agent can pass from one room to another but has no knowledge of the environment, and doesn't know which sequence of doors lead to the outside.

Suppose we want to model some kind of simple evacuation of an agent from any room in the building. Now suppose we have an agent in Room 2 and we want the agent to learn to reach outside the house (5).

The terminology in Q-Learning includes the terms "state" and "action".

We'll call each room, including outside, a "state", and the agent's movement from one room to another will be an "action". In our diagram, a "state" is depicted as a node, while "action" is represented by the arrows.



Suppose the agent is in state 2. From state 2, it can go to state 3 because state 2 is connected to 3. From state 2, however, the agent cannot directly go to state 1 because there is no direct door connecting room 1 and 2 (thus, no arrows). From state 3, it can go either to state 1 or 4 or back to 2 (look at all the arrows about state 3). If the agent is in state 4, then the three possible actions are to go to state 0, 5 or 3. If the agent is in state 1, it can go either to state 5 or 3. From state 0, it can only go back to state 4.

We can put the state diagram and the instant reward values into the following reward table, "matrix R".

$$\begin{array}{ccc} & & \text{Action} \\ & \text{State} & \begin{matrix} 0 & \;\;1 & \;\;2 & \;\;3 & \;\;4 & \;\;5 \end{matrix} \\ R= & \begin{matrix}0\\1\\2\\3\\4\\5\end{matrix} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix} \end{array}$$

The -1's in the table represent null values (i.e.; where there isn't a link between nodes).

Now we'll add a similar matrix, "Q", to the brain of our agent, representing the memory of what the agent has learned through experience. The rows of matrix Q represent the current state of the agent, and the columns represent the possible actions leading to the next state (the links between the nodes).

The agent starts out knowing nothing, the matrix Q is initialized to zero. In this example, for the simplicity of explanation, we assume the number of states is known (to be six). If we didn't know how many states were involved, the matrix Q could start out with only one element. It is a simple task to add more columns and rows in matrix Q if a new state is found.

The transition rule of Q learning is a very simple formula:

$$Q(state, action) = (1-\alpha) * Q(state, action) + \alpha * (R(state, action) + \gamma \max[Q(nextstate, allactions)])$$

According to this formula, a value assigned to a specific element of matrix Q, is equal to the sum of the corresponding value in matrix R and the learning parameter γ, multiplied by the maximum value of Q for all possible actions in the next state. Here the α is a hyper-parameter similar to γ, which is used to **assure the convergence** of Q-learning.

Our virtual agent will learn through experience, without a teacher (this is called unsupervised learning). The agent will explore from state to state until it reaches the goal. We'll call each exploration an episode. Each episode consists of the agent moving from the initial state to the goal state. Each time the agent arrives at the goal state, the program goes to the next episode.

The Q-Learning algorithm goes as follows:

Set the gamma parameter, and environment rewards in matrix R;

Initialize matrix Q to zero;

foreach *episode* **do**

  Select a random initial state;

  while *the goal state hasn' t been reached* **do**

    Select one among all possible actions for the current state;

    Using this possible action, consider going to the next state;

    Get maximum Q value for this next state based on all possible actions;

    Compute:

$$Q(state, action) = (1 - \alpha) * Q(state, action)$$

$$+\alpha * (R(state, action) + \gamma \max[Q(nextstate, allactions)])$$

    ;

    Set the next state as the current state;

  end

end

Algorithm 1: The Q-Learning Algorithm

The algorithm above is used by the agent to learn from experience. Each episode is equivalent to one training session. In each training session, the agent explores the environment (represented by matrix R), receives the reward (if any) until it reaches the goal state. The purpose of the training is to enhance the 'brain' of our agent, represented by matrix Q. More training results in a more optimized matrix Q. In this case, if the matrix Q has been enhanced, instead of exploring around, and going back and forth to the same rooms, the agent will find the fastest route to the goal state.

The γ parameter has a range of 0 to 1 ($0 \leq \gamma < 1$). If γ is closer to zero, the agent will tend to consider only immediate rewards. If γ is closer to one, the agent will consider future rewards with greater weight, willing to delay the reward.

To use the matrix Q, the agent simply traces the sequence of states, from the initial state to goal state. The algorithm finds the actions with the highest reward values recorded in matrix Q for current state:

Algorithm to utilize the Q matrix:

1. Set current state = initial state.
2. From current state, find the action with the highest Q value.
3. Set current state = next state.
4. Repeat Steps 2 and 3 until current state = goal state.

The algorithm above will return the sequence of states from the initial state to the goal state.

2.2 Q-learning Example By Hand

To understand how the Q-learning algorithm works, we'll go through a few episodes step by step. The rest of the steps are illustrated in the source code examples. **In this illustration, we ignore the hyper-parameter α, because the algorithm can convergence in this simple case without α. Maybe you need to add it in our task2 flappy bird.**

We'll start by setting the value of the learning parameter $\gamma = 0.8$, and the initial state as Room 1. Initialize matrix Q as a zero matrix. Look at the second row (state 1) of matrix R. There are two possible actions for the current state 1: go to state 3, or go to state 5. By random selection, we select to go to 5 as our action.

Now let's imagine what would happen if our agent were in state 5. Look at the sixth row of the reward matrix R (i.e. state 5). It has 3 possible actions: go to state 1, 4 or 5.

$$Q(state, action) = R(state, action) + \gamma \max[Q(nextstate, allactions)]$$

$$Q(1, 5) = R(1, 5) + 0.8 \times \max[Q(5, 1), Q(5, 4), Q(5, 5)] = 100 + 0.8 \times 0 = 100$$

$$
Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}
\qquad
R = \begin{array}{c} \text{State} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c} \text{Action} \\ \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix} \end{array}
$$

Since matrix Q is still initialized to zero, Q(5, 1), Q(5, 4), Q(5, 5), are all zero. The result of this computation for Q(1, 5) is 100 because of the instant reward from R(5, 1).

The next state, 5, now becomes the current state. Because 5 is the goal state, we've finished one episode. Our agent's brain now contains an updated matrix Q as:

$$
Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}
$$

For the next episode, we start with a randomly chosen initial state. This time, we have state 3 as our initial state.

Look at the fourth row of matrix R; it has 3 possible actions: go to state 1, 2 or 4. By random selection, we select to go to state 1 as our action.

Now we imagine that we are in state 1. Look at the second row of reward matrix R (i.e. state 1). It has 2 possible actions: go to state 3 or state 5. Then, we compute the Q value:

$$Q(state, action) = R(state, action) + \gamma \max[Q(nextstate, allactions)]$$

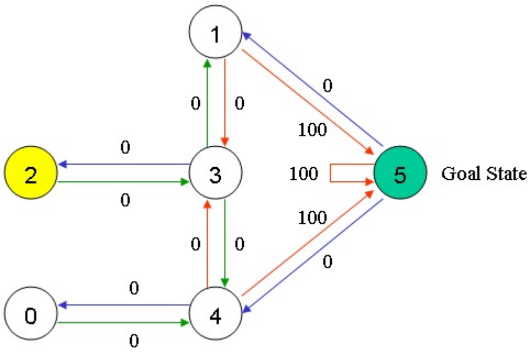
$$Q(3,1) = R(3,1) + 0.8 \times \max[Q(1,2), Q(1,5)] = 0 + 0.8 \times \max(0,100) = 80$$

We use the updated matrix Q from the last episode. Q(1, 3) = 0 and Q(1, 5) = 100. The result of the computation is Q(3, 1) = 80 because the reward is zero. The matrix Q becomes:

The next state, 1, now becomes the current state. We repeat the inner loop of the Q learning algorithm because state 1 is not the goal state.

$$Q = \begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 80 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

So, starting the new loop with the current state 1, there are two possible actions: go to state 3, or go to state 5. By lucky draw, our action selected is 5.



Now, imaging we're in state 5, there are three possible actions: go to state 1, 4 or 5. We compute the Q value using the maximum value of these possible actions.

$$Q(state, action) = R(state, action) + \gamma \max[Q(nextstate, allactions)]$$

$$Q(1,5) = R(1,5) + 0.8 \times \max[Q(5,1), Q(5,4), Q(5,5)] = 100 + 0.8 \times 0 = 100$$

The updated entries of matrix Q, Q(5, 1), Q(5, 4), Q(5, 5), are all zero. The result of this computation for Q(1, 5) is 100 because of the instant reward from R(5, 1). This result does not change the Q matrix.

Because 5 is the goal state, we finish this episode. Our agent's brain now contain updated matrix Q as:

$$Q = \begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 80 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

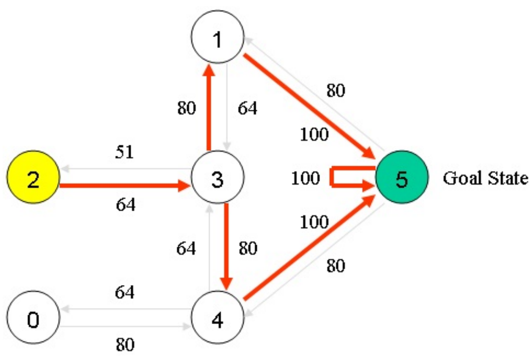
If our agent learns more through further episodes, it will finally reach convergence values in matrix Q like:

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 400 & 0 \\ 0 & 0 & 0 & 320 & 0 & 500 \\ 0 & 0 & 0 & 320 & 0 & 0 \\ 0 & 400 & 256 & 0 & 400 & 0 \\ 320 & 0 & 0 & 320 & 0 & 500 \\ 0 & 400 & 0 & 0 & 400 & 500 \end{bmatrix} \end{array}$$

This matrix Q, can then be normalized (i.e.; converted to percentage) by dividing all non-zero entries by the highest number (500 in this case):

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 80 & 0 \\ 0 & 0 & 0 & 64 & 0 & 100 \\ 0 & 0 & 0 & 64 & 0 & 0 \\ 0 & 80 & 51 & 0 & 80 & 0 \\ 64 & 0 & 0 & 64 & 0 & 100 \\ 0 & 80 & 0 & 0 & 80 & 100 \end{bmatrix} \end{array}$$

Once the matrix Q gets close enough to a state of convergence, we know our agent has learned the most optimal paths to the goal state. Tracing the best sequences of states is as simple as following the links with the highest values at each state.



For example, from initial State 2, the agent can use the matrix Q as a guide:

From State 2 the maximum Q values suggests the action to go to state 3.

From State 3 the maximum Q values suggest two alternatives: go to state 1 or 4. Suppose we arbitrarily choose to go to 1.

From State 1 the maximum Q values suggests the action to go to state 5.

Thus the sequence is 2 - 3 - 1 - 5.

3 Flappy Bird

Flappy Bird was a side-scrolling mobile game, the objective was to direct a flying bird, named "Faby", who moves continuously to the right, between sets of Mario-like pipes. Note that the pipes always have the same gap between them and there is no end to the running track. If the player touches the pipes, they lose. Faby briefly flaps upward each time that the player taps the screen; if the screen is not tapped, Faby falls because of gravity; each pair of pipes that he navigates between earns the player a single point, with medals awarded for the score at the end of the game. Android devices enabled the access of world leaderboards, through Google Play. You can also play this game on-line: `http://flappybird.io/`.

4 Tasks

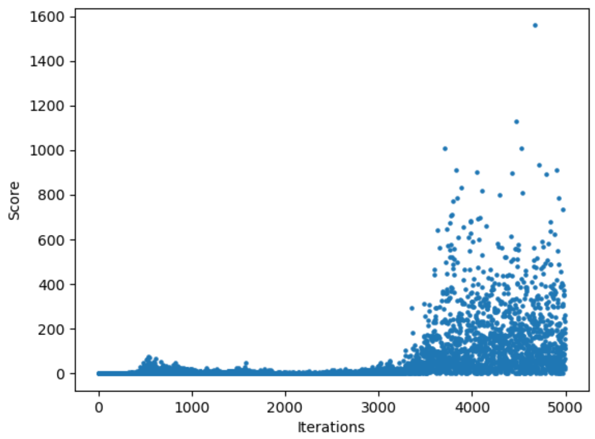
1. **Implement the algorithm in the tutorial example , and output the Q-matrix and the path with the highest values.**
2. Now here is a flappy bird project (Python3) for you, and the file `bot.py` is incomplete. You should implement a flappy bird bot who learns from each game played via Q-learning.

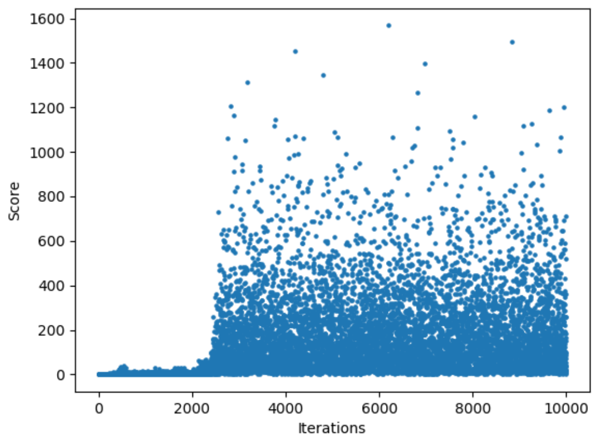
   Please pay attention to the following points:

   - The state of the bird is defined by the horizontal and vertical distances fro the next pip and the velocity of the bird.
   - In order to understand the state space, you have You need to briefly understand the following sizes: `SCREENWIDTH=288,SCREENHEIGHT=512, PIPEGAPSIZE=100, BASEY=SCREENHEIGHT*0.79, PIPE=[52,320],PLAYER=[34,24],BASE=[336,112], BACKGROUND=[288,512],etc.`
   - The Q values are dumped to the local JSON file `qvalues.json`.

- `initialize_qvalues.py` is an independent file, and we can run `python initialize_qvalues.py` to initialize the Q values. Of course, this file has been initialized.
- You can run `python learn.py --verbose 5000` to update the Q values dumped to `qvalues.json` with 5000 iterations, and then run `python flappy.py` to observe the performance the bird.

Please complete the function `update_scores()` in `bot.py`, and run `python learn.py --verbose 5000` and `python learn.py --verbose 10000` to get the following figures, respectively,:





3. Please submit a file named `E14_YourNumber.pdf` and send it to `ai_2020@foxmail.com`

5 Codes and Results

Task1 code

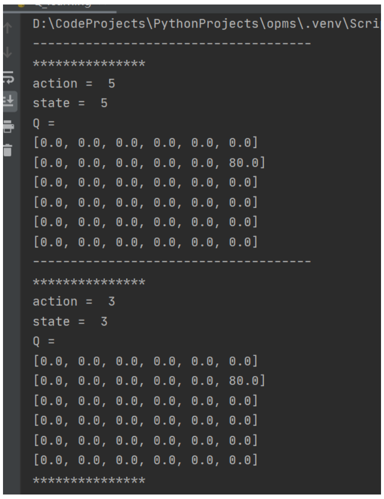
```
"""孙新梦
        18340149
      Q-learning.py实现实验要求上的机器人走房间的
      Q-算法learning
"""
import numpy as np
import random

# 奖励函数R
R = [
```

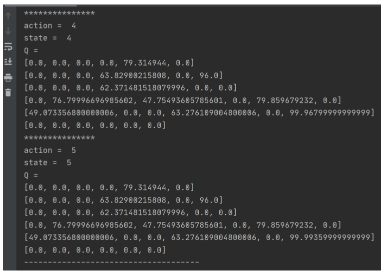
```
    [-1, -1, -1, -1, 0, -1],
    [-1, -1, -1, 0, -1, 100],
    [-1, -1, -1, 0, -1, -1],
    [-1, 0, 0, -1, 0, -1],
    [0, -1, -1, 0, -1, 100],
    [-1, 0, -1, -1, 0, 100]
]
# 参数alpha
alpha = 0.8
# 参数gamma
gamma = 0.8


# 大循环开始根据随机选R返回操作的数字,
def random_select_state():
    return random.randint(0, 5)


# 是不是到了号房5
def Goal(state):
    return state == 5


# 根据当前状态随机选择可能动作返回动作编号（数字去到几号房,
def random_select_action(state):
    not_zeros = [i for i in range(6) if R[state][i] != -1]
    action = random.sample(not_zeros, 1)
    return action[0]


# 大学习函数，进行外循环
def Q_learning(Q):
    epoches = 0
```

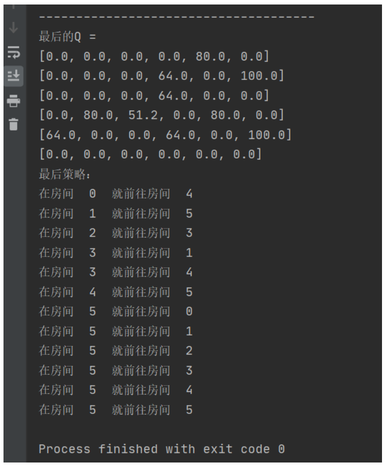
```python

    # 大循环开始
    while epoches < 100:
        epoches += 1
        print("-------------------------------------------")
        count = 0
        state = random_select_state()  # 是初始哪个房间的动作编号state
        while not Goal(state):
            print("**************")
            action = random_select_action(state)
            print("action = ", action)
            next_state = action  # 相当于做了动作到了对应房间

            # 找到对应可做动作的最大值，直接看对应那一行的最大值就是，next_stateQQ
            # 因为如果不是可行的话，不会被更新，不会是最大值
            pre_Q = Q[state][action]
            Q[state][action] = (1 - alpha) * Q[state][action] + alpha * (R[state][action] + gamma * max(Q[next_state]))

            if pre_Q != Q[state][action]:
                count += 1
            state = next_state  # 状态更新
            # 输出显示
            print("state = ", state)
            print("Q = ")
            for i in Q:
                print(i)


if __name__ == '__main__':
    # 矩阵初始化Q
```

```
    Q = np.zeros((6, 6))
    Q = Q.tolist()

    Q_learning(Q)

    # 输出Q
    print("————————————————————————————————————————")
    print最后的("Q = ")
    for i in Q:
        print(i)
    print最后策略：("")
    for row in range(6):
        for i in range(6):
            if Q[row][i] == max(Q[row]):
                print在房间(" ", row," 就前往房间 ", i )
```

Task1 Result 我在每一步更新迭代Q额度过程中，让程序打印出当前的state，当前选择的action，







开始的时候输出了开始的Q矩阵，之后的迭代过程可以明显看到学习出的Q是在不断变化的，具体是越接近正确路线（走出房间）越高期望值。

最后输出了最后的Q矩阵，可以看到最后一行是没有更新过得，原因是在我们迭代过程中，是先判断是否到5号房间，如果已经到了5号房间，认为已经到达目标，因此不进入Q的更新阶段，因此Q的第五行是不被更新的，一直是0，因此我的最后输出的策略中，5号房间由于Q都是0，所以取max的时候是一样大，输出的就是去哪里都可以，但其实我们知道是呆在5号房间不动是最优策

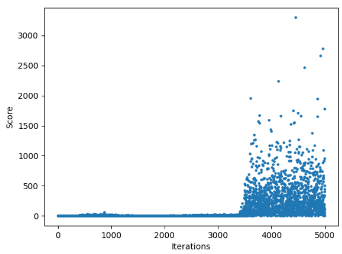
略。

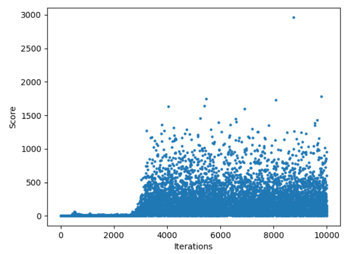
Task2 code

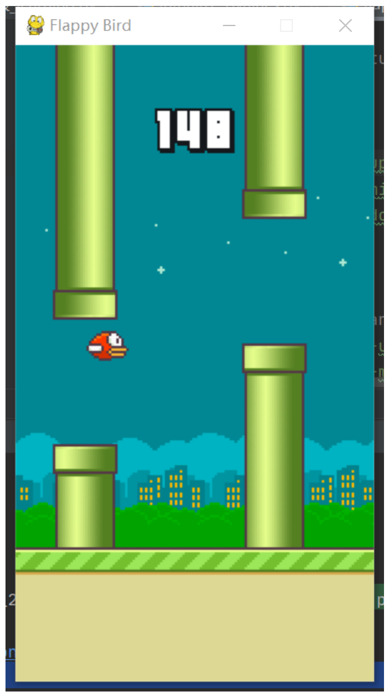
```
    def update_scores(self, dump_qvalues=True):
        """
        Update qvalues via iterating over experiences
        """
        history = list(reversed(self.moves))

        # Flag if the bird died in the top 表示即将撞上边pipe
        high_death_flag = True if int(history[0][2].split("_")[1])
            > 120 else False

        # Q-learning score updates
        t = 1 # 这里的表示一个参数，其实表两个含义，一个是最后t

        for h in history:
            state, action, next_state = h # 获取三元组
            # 找到最大的值Q
            max_Q = max(self.qvalues[next_state])

            # Select reward 最后个步骤快要死去，得是tReward，或者如果即
                将撞到上面，就给−1000为Reward，如果不是最后这几个，就
                给−10001
            if t < 3 or (high_death_flag and action):
                R = self.r[1]
            else:
                R = self.r[0]

            # 这里因为已经超出了的范围，也就是步之后不再考虑影响，置高危
                为ttflagFalse
            if t >= 3 and high_death_flag and action:
                high_death_flag = False


```

```
            # Update self.qvalues[state][act更新]值Q
            self.qvalues[state][action] = (1-self.lr)*self.qvalues
                [state][action]+ self.lr*(R+self.discount*max_Q)
            t += 1

        self.gameCNT += 1  # increase game count
        if dump_qvalues:
            self.dump_qvalues()  # Dump q values (if game count %
                DUMPING_N == 0)
        self.moves = []  # clear history after updating strategies
```

Task2 Result 前面两幅图在运行之前需要执行 python initialize qvalues.py才可以把Q重新归







为0，要不然就是基于之前的经验已经学习过的，就像是大学生再重回幼儿园。得到运行5000和10000次之后的分值，看到学习之后的分值是逐渐提升的。

第三幅图是运行了一下flappy bird，感到人工智能的强大了哈哈，我自己最高纪录是10个，但是我的AI可以玩几百个，真厉害。