# Deep Reinforcement Learning Homework #1

# - Random Policy Evaluation

- 1. Implementation
  - (1) Data format
    - Matrix (to state, from state, 方向)
      - 方向:0=上、1=左、2=下、3=右
      - Ex. Matrix (1, 2, 3): 從 state2 向左走到 state1

```
Matrix[1][2]
[0. 1. 0. 0.]
```

- (2) Process Initialization
  - traverse 整個 grid world,得到 Matrix (16\*16\*4)

```
# traverse all grid world
for row in range(4):
    for col in range(4):
        now_state = row * 4 + col
        ## 0 == move up
        Matrix[:, now_state, 0] = traverse_state(now_state, 0).flatten()
        ## 1 == move left
        Matrix[:, now_state, 1] = traverse_state(now_state, 1).flatten()
        ## 2 == move down
        Matrix[:, now_state, 2] = traverse_state(now_state, 2).flatten()
        ## 3 == move right
        Matrix[:, now_state, 3] = traverse_state(now_state, 3).flatten()
```

## Example

```
Matrix[:,1,:]:
[[0. 1. 0. 0.]
 [1. 0. 0. 0.]
 [0. 0. 0. 1.]
 [0. 0. 0. 0.]
 [0. 0. 0. 0.]
 [0. 0. 1. 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. 0.]
 [0. 0. 0. 0.]]
```

Matrix[:,1,:]的 Column 依序為上左下右

- 從 state1 往上走會撞到牆壁,所以 [0,1] 是 1
- 単 從 state1 往左走到 state0
- 從 state1 往下走到 state5
- 從 state1 往右走到 state2

```
Matrix[1, :, :]的 Column 依序為上左下右
Matrix[1,:,:]:
[[0. \ 0. \ 0. \ 1.]
                     從 statel 往上走會撞到牆壁,所以
[1. 0. 0. 0.]
[0. 1. 0. 0.]
                     [0,1] 是 1
[0. 0. 0. 0.]
[0. 0. 0. 0.]
                    從 state5 往上走到 state1
[1. 0. 0. 0.]
[0. 0. 0. 0.]
                     從 state2 往左走到 state1
[0. 0. 0. 0.]
[0. 0. 0. 0.]
                     從 state0 往右走到 state1
[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.]]
```

#### ● Function traverse state 的設計細節

依照 spec 的規定,如果 agent 撞到牆壁,會停留在原地到下個 timestamp,故先將 map 從 4\*4 padding 成 6\*6,所有值初始為 0,接著根據移動方向(上下左右)來更新 map 的值,最後更新至 Matrix。

Example:如果方向是上 (dir=1)

```
if dir == 0:
                                               ** dir == 0 **
   Map[Map_row-1, Map_col] = 1
                                               now_state: 1
elif dir == 1:
                                               Map:
   Map[Map\_row, Map\_col-1] = 1
                                               [[0. 0. 1. 0. 0. 0.]
elif dir == 2:
                                                 [0. 0. 0. 0. 0. 0.]
   Map[Map_row+1, Map_col] = 1
                                                 [0. 0. 0. 0. 0. 0.]
elif dir == 3:
                                                 [0. 0. 0. 0. 0. 0.]
   Map[Map\_row, Map\_col+1] = 1
                                                 [0. 0. 0. 0. 0. 0.]
   print(str(dir) + "is not a valid direction.")
                                                [0. 0. 0. 0. 0. 0.]]
```

要特別處理撞到牆壁的情況, Example:

```
Map[:,0]: [0. 1. 0. 0. 0. 0.]
                                  idx: 1
if np.max(Map[:,0]) > 0:
                                  Map[idx,0]: 1.0
   idx = np.argmax(Map[:,0])
                                  Before Map[idx,1]: 0.0
   Map[idx,1] += Map[idx,0]
                                  After Map[idx,1]: 1.0
if np.max(Map[:,5]) > 0:
   idx = np.argmax(Map[:,4+1])
   Map[idx,4] += Map[idx,4+1]
if np.max(Map[0,:]) > 0:
   idx = np.argmax(Map[0,:])
   Map[1,idx] += Map[0,idx]
if np.max(Map[5,:]) > 0:
   idx = np.argmax(Map[4+1,:])
   Map[4,idx] += Map[4+1,idx]
```

另外,要將 Matrix 中 from state 為 terminal state (state0 和 state15) 設為 1。

```
## state 0 and 15 is terminal, set the value as 1
state0 = np.zeros([16,4])
state0[0,:] = 1
Matrix[:,0,:] = state0

state15 = np.zeros([16,4])
state15[15,:] = 1
Matrix[:,15,:] = state15
```

```
Matrix[:,state_0,:] Matrix[:,state_15,:] [[1. 1. 1. 1.] [[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.] [[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.] [[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.] [[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.] [[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.] [[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.]] [[0. 0. 0. 0.]] [[0. 0. 0. 0.]]
```

# (3) Process Iteration

Iterative Policy Evaluation

按照 pseudo code 的步驟更新 value function, 直到 converge

```
Input \pi, the policy to be evaluated Initialize an array V(s)=0, for all s\in \mathbb{S}^+ Repeat \Delta \leftarrow 0 For each s\in \mathbb{S}: v\leftarrow V(s) V(s)\leftarrow \sum_a \pi(a|s)\sum_{s',r} p(s',r|s,a)\big[r+\gamma V(s')\big] \Delta \leftarrow \max(\Delta,|v-V(s)|) until \Delta < \theta (a small positive number) Output V\approx v_\pi
```

```
# iterate policy evaluation
while delta > theta:
    func_value_now = func_value.copy()
    for state in range(1,15):
        ## p(s',r|s,a)
        prob_next_state = prob * Matrix[:, state, :]
        ## r + gamma * V(s')
        future_reward = func_reward + gamma * func_value_now
        ## sum( prob_next_state * future_reward)
        func_value[state] = np.sum(np.matmul(np.transpose(prob_next_state), future_reward))
    delta = np.max(np.abs(func_value - func_value_now))
```

● 毎跑一次 while loop 更新一次 state value, 直到收斂 下圖以 gamma = 0.9 為例, 印出 Iter1-5 和 Iter17-21 的 state value

```
Iter 1
 [ 0. -0.75 -1. [-0.75 -1. -1.
[[ 0.
                               -1.
                     -1.
                              -0.75]
                     -0.75 0. ]]
 [-1.
            -1.
Iter 2
 [ 0. -1.37 -1.84 -1.9 ]
[-1.37 -1.79 -1.9 -1.84]
[[ 0.
 [-1.84 -1.9 -1.79 -1.37]
[-1.9 -1.84 -1.37 0. ]]
Iter 3
 [ 0. -1.88 -2.58 -2.68]
[-1.88 -2.47 -2.63 -2.58]
[[ 0.
 [-2.58 -2.63 -2.47 -1.88]
[-2.68 -2.58 -1.88 0. ]]
```

## 2. Result

- (1) Output the learned (converged)  $V\pi$  for state 1-14
- $\bullet$  gamma = 0.9

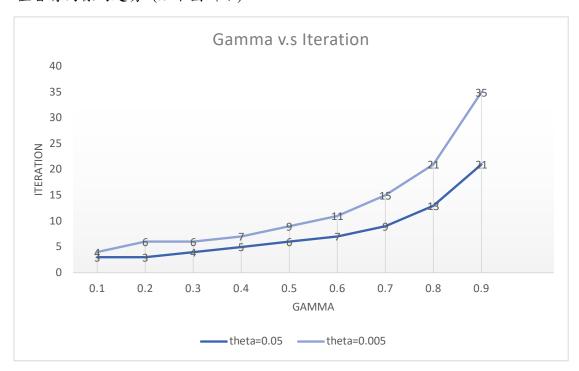
• gamma = 0.1

3. How does the iteration stop?

當 delta 小於或等於 theta (設為 0.05) 的時候結束 while 迴圈

4. How does the discount factor gamma affect the results?

當 discount factor (gamma) 越大,需要越多個 iteration 才能 converge,實驗了兩個不同的 theta 值皆有同樣的趨勢 (如下圖所示)。



# = \ Compare Q-Learning with SARSA

1. Environment design: 共設計了兩個 environment, 如下:

## (1) Environment 1

Start		
	Black Hole	
Goal	Tiole	

Reward

Start	-1	-1	-1
-1	-500	-1	-1
-1	-200	-1	-1
Goal	-1	-1	-1

## (2) Environment 2

Map

1.14P										
		Small	Bomb		Small	Bomb	Small	Bomb		
Start	Big Bomb						Goal			

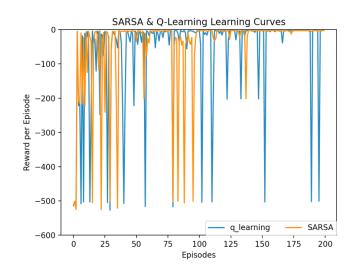
#### Reward:

-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-100	-100	-1	-100	-100	-1	-100	-100	-1	-1
Start	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	Goal

(3) Action:上下左右

# 2. Behaviors of these algorithms

# (1) Environment 1 - Learning Rate



執行 200 個 episodes, 左圖的 計算方式為把當回合的所有 reward 加總, 初期兩個方法皆有 蠻多極端值, 到後期 SARSA 逐漸 趨近於穩定, Q-Learning 仍有一 些回合得到負值較大的回饋。

此圖也反映 SARSA 較保守、 考慮未來的 action、避免負值較大 的回饋, Q-Learning 較敢於嘗試、 尋找最佳路線。

# (2) Environment 1 - Q-Learning 路徑

註:\*為走過的路徑、X 是黑洞、0 是沒有經過但可以走的路徑、S 是起點、G 是終點 可觀察到 Q-Learning 在第 100 個 episode 附近,有時仍會找到非最佳解的路線,但到第 200 個 episode 時,已經可以穩定走到最 optimal 的路徑了。

Q-learning ep 100	Q-learning ep 197
S   0   0   0     *   X   0   0     *   X   0   0     G   0   0   0   Q-learning ep 101	S   0   0   0     *   X   0   0     *   X   0   0     G   0   0   0   Q-learning ep 198

## (3) Environment 1 - SARSA 路徑

可觀察到 SARSA 在第 100 或到第 200 個 episode 都盡量走距離負分較遠的路線,避免負值的 reward。

Sarsa ep 100	Sarsa ep 197
	   S   *   *   *     0   X   *   *     0   X   0   *     G   *   *   *     Sarsa ep 198
	   S   *   *   *     0   X   *   0     0   X   *   *     G   *   *   *     Sarsa ep 199
	   S   *   *   *     0   X   0   *     0   X   0   *   <u> </u> G   *   *   *

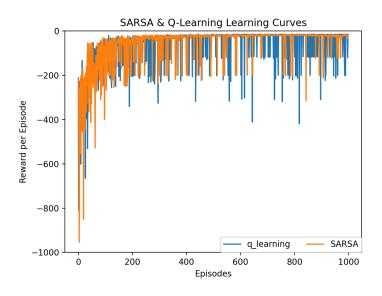
# (4) Environment 1 - 將兩個方法的路徑放在一起比較

註:淺藍色是 Q-Learning、深藍色是 SARSA

St	art	-1	-1	-1
-1		-100	-1	-1
-1		-100	-1	-1
Go	Al	-1	-1	-1

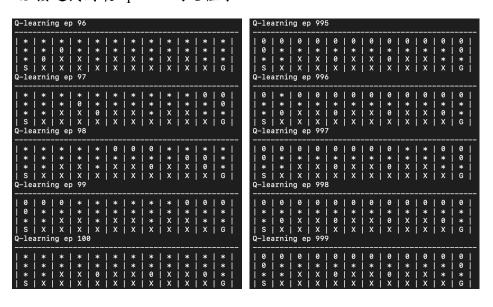
# (5) Environment 2 - Learning Rate

嘗試 1000 個 episodes,下圖的計算方式為把當回合的所有 reward 加總,初期兩個方法皆有蠻多極端值,到中後期 SARSA 逐漸趨近於穩定,Q-Learning 仍有一些回合得到負值較大的回饋。此圖也反映 SARSA 較保守、考慮未來的 action、避免負值較大的回饋,Q-Learning 較敢於嘗試、尋找最佳路線。



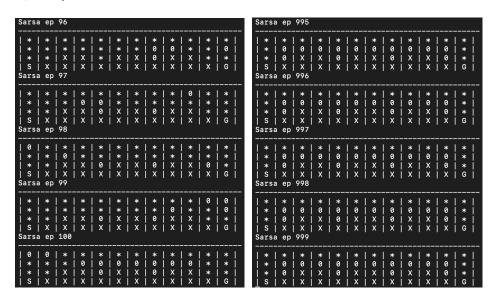
## (6) Environment 2 - Q-Learning 路徑

註: \*為走過的路徑、X 是炸彈、0 是沒有經過但可以走的路徑、S 是起點、G 是終點可觀察到 Q-Learning 在第 100 個 episode 仍在尋找最佳解,但到第 1000 個 episode 時,已經接近找到最 optimal 的路徑了。



## (7) Environment 2 - SARSA 路徑

可觀察到 SARSA 在第 100 或到第 1000 個 episode 都盡量走距離炸彈最遠的路線,避免負值較大的 reward。另外,有嘗試跑 5000 個 episodes 結果還是類似,無法像 Q-Learning 找到最佳路線。



#### (8) Environment 2 - 將兩個方法的路徑放在一起比較

註:淺藍色是 Q-Learning、深藍色是 SARSA

-	·1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	
-	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	
-	1	-1	-100	-100	-1	-100	-100	-1	-100	-100	-1	-	1
St	art	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	Go	al

#### 3. Implementation

(1) Q-learning 和 SARSA 分別的更新方式

```
# Q(S, A) - Q(S, A) + α [R + γ max Q(S', A) - Q(S, A)]
if method == 'qlearning':
    update_value = alpha * (reward + gamma * np.max(action_value[next_state,:]) - now_value)
# Q(S, A) - Q(S, A) + α [R + γ Q(S', A') - Q(S, A)]
elif method == 'sarsa':
    next_action = record[4]
    update_value = alpha * (reward + gamma * action_value[next_state, next_action] - now_value)
```

```
def qlearn(action_value, reward, steps, gamma, alpha, epsilon):

# initialize setting
record = []
state = 36
for step in range(steps):

# get next information
action = GetAction(action_value, epsilon, state)

next_state = TransMat(state, action)
record.append(istate, action), reward[next_state], next_state]

# update action value
action_value(state, action) = ValueUpdate('qlearning', action_value, record[step], alpha, gamma)

# update for next_state
state = next_state
if state > 36:
    break

# episode reward
record = np.array(record,dtype=object)
map(record[:,8])
epi_reward = np.sum(record[:,2])
return action_value, rej_reward

def sarsa(action_value, reward, steps, gamma, alpha, epsilon):

# initialize setting
record = []
state = 36
action = GetAction(action_value, epsilon, state)
for step in range(steps):

# get next information
next_state = ransMat(state, action), reward[next_state), next_state)
next_action = GetAction(action_value, epsilon, next_state)
record = app.sarbate(state, action, reward[next_state], next_state
action_value(state, action) = ValueUpdate('sarsa', action_value, record[step], alpha, gamma)
# update for next_state
state = next_state
action = GetAction(action_value, epsilon, next_state)
record = np.sur(record(action_value, epsilon, next_state)
record = np.sur(record(action_value, epsilon, next_state)
record = np.sur(record(action_value, eps
```

## (2) Reward 設計 (同 1.的地圖)

#### • Environment 1

```
ActionValue = np.zeros([16, 4])
# design map
Reward = np.full(16, -1)
Reward[5] = -500
Reward[9] = -200

| Reward[9] = -200
```

```
Reward

[-1 -1 -1 -1]

[ -1 -500 -1 -1]

[ -1 -200 -1 -1]

[-1 -1 -1 -1]
```

#### • Environment 2

```
ActionValue = np.zeros([48, 4])
# design map
Reward = np.full(48, -1)
Reward[26:28] = -100
Reward[29:31] = -100
Reward[32:34] = -100
Reward[37:-1] = -200
```

#### (3) 跑 Episode 迴圈

```
# Execute
if method == 'qlearning':
    for episode in range(episodes):
        print("Q-learning ep "+str(episode))
        ActionValue, Epi_Reward = qlearn(ActionValue, Reward, Steps, Gamma, Alpha, Epsilon)
        EpisodeReward.append(Epi_Reward)
    #print("QLearn ActionValue:")
        #print(ActionValue)
elif method == 'sarsa':
    for episode in range(episodes):
        print("Sarsa ep "+str(episode))
        ActionValue, Epi_Reward = sarsa(ActionValue, Reward, Steps, Gamma, Alpha, Epsilon)
        EpisodeReward.append(Epi_Reward)
        #print("Sarsa ActionValue:")
        #print(ActionValue)
```

## (4) 執行 200 / 1000 個 episodes, 並把 reward 分別存起來

(Environment 2 有嘗試不同的 ep 數,但 1000 個在比較兩者差異時的效果最好)

```
if __name__ == '__main__':
    q_reward = main(1000, 'qlearning')
    s_reward = main(1000, 'sarsa')

np.save('q-episode-reward.npy', q_reward)
    np.save('s-episode-reward.npy', s_reward)

# show plot
show()
```

# 三、Tic-tac-toe (3x3)

1. Implementation: Q-learning training procedure

(1) 先定義 MDP 問題的各個元素

● Action:下一步的位置

● States:目前盤面狀態

• Reward:

■ 赢: R(s, a) = 1

■ 輸: R(s, a) = -1

■ 平手: R(s, a) = 0

● Goal:最大化 Reward

# (2) 可調整參數

• Learning rate  $(\alpha)$ 

• Discount factor  $(\gamma)$ 

Exploration probability (ε): Explore (選擇 random action) 和 Exploit (根據 Q (s,a) 決定 action)
 的比例,一開始設為 1 會逐漸遞減,並設定下界。

● Iteration: 跑幾個 episode

(3) Q-learning 實作

對每個 episode 中的每一步

•  $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max Q(S', A) - Q(S, A)]$ 

newQ = currentQ + self.learning\_parameter \* (self.agent.rewardFunction(state, action)
+ self.discount\_factor \* max\_nextQ - currentQ)

#### 2. Experiment

(1) Iteration: 嘗試改變 Iteration為 500,000、1,000,000,如下表淺藍色網底的實驗,1,000,000個 Iter和 500,000個 Iter相比, 500,000個 Iter的勝率較高。

註:表格中的數值為每 100 個 episode 中,# col win, # col lose, # tie

Iteration	500,000	1,000,000		
500,000	37, 38, 26	0, 0, 0		
1,000,000	<b>49</b> , 0, 51	36, 36, 28		

(2) Learning rate ( $\alpha$ ) :實驗  $\alpha=0.1$ 、0.5,可觀察到在下表淺藍色網底的實驗中,learning rate 設為 0.1 較的勝率比 0.5 高一倍,故推測 learning rate 設為 0.1 較恰當。

註:表格中的數值為每 100 個 episode 中,# col win, # col lose, # tie

Learning rate	0.1	0.5
0.1	37, 38, 26	25, <b>50</b> , 25
0.5	0, 0, 100	35, 36, 29

(3) Discount factor (γ): 改變 γ 為  $0.9 \times 0.5$ ,可觀察到在下表淺綠色網底的實驗中,當  $\gamma = 0.9$  與 0.5 對戰時,0.9 的勝率比較高。

註:表格中的數值為每 100 個 episode 中,#col win,#col lose,#tie

discount factor	0.5	0.9		
0.5	39, 38, 23	<b>25</b> , 0, 75		
0.9	0, 1, 99	37, 38, 26		

(4) Exploration probability ( $\epsilon$ ):  $\epsilon$  的初始值皆為 1.0, 每個 episode 依序遞減 1 / Iteration,直到設定的  $\epsilon$ \_lower\_bound,依序使用  $\epsilon$ \_lower\_bound =  $0.2 \times 0.5$  做訓練,訓練好後相互對戰,觀察勝率變 化。結果如下表,可觀察到相同 lower bound 的 agent 對戰勝率皆為 1:1,若不同 lower bound 的 agent 相比, $\epsilon$  lower bound = 0.5 的勝率比較高。

註:表格中的數值為每 100 個 episode 中# col win, # col lose, # tie

ε lower bound	0.2	0.5
0.2	37, 38, 25	<b>50,</b> 25, 25
0.5	0, 0, 100	41, 42, 17

以上實驗其他參數 default 為 Iteration =  $500,000 \times \alpha = 0.1 \times \gamma = 0.9 \times \epsilon$  lower bound = 0.2

- 3. Implementation: environment
- (1) Class Agent:

```
symbol: 1
current_state: [[-1 0 0]
  [ 0 0 0]
  [ 0 0 0]]
actions: [[1 2]
  [2 0]]
action_history: [array([0, 0]), array([2, 1]), array([2, 2]), array([1, 1])]
```

- symbol (1 或-1,代表 agent 是 X 或 O)、current\_state、actions(空的位置)、action\_history (agent 當局下過的位置)
- function: getPossibleActions、updatePossibleActions、performAction、
   performRandomAction、revertLastAction、getActionHash、getActionHashFromState、
   rewardFunction、assignState、getBestAction(選擇 reward 最高的)、saveTrainer、LoadTrainer
- performAction(): 更新 Q (實作 Q learning, 詳細寫在三 1.) → 執行 action → 把 action 記在 action\_history → 更新空的位置 (available\_pos)

```
def performAction(self, action, state = None, updateQ = False):
    if action.shape != (2,):
        print("Wrong shape " + str(action))

if state == None:
        state = self.current_state

# Read action
        x = action[0]
        y = action[1]

# Update Q as part of Q-learning in the Trainer class
    if updateQ is True:
        self.trainer.updateQ(state, action)

# Make move
    state.setPosition(x, y, self.symbol)
    self.action_history.append(action)

# Update possible actions
    self.updatePossibleActions()
```

● getBestAction():找到 expected return 最大的 action。

```
def getBestAction(self):
    self.updatePossibleActions()

# Get hash key for state and actions
    state_hash, actions_hash = self.getActionHashFromState()

# Return best move (if all are equally good, then it picks one at random)
    return self.trainer.getBestAction(state_hash, actions_hash, self.actions)
```

(2) Class Board:模擬圈圈叉叉 3x3 的棋盤

```
state:
[[-1 1 -1]
  [-1 -1 1]
  [ 1 -1 1]]
rows: 3
cols: 3
win_threshold: 3
```

- state (紀錄盤面)、rows=3、cols=3、win threshold=3
- function: getState、getPosition、setPosition、getAvailablePos(尋找空的位置)、getStateHash、checkWinner(判斷是否有玩家獲勝)、checkGameEnded(判斷是否有空位置,若無則平手、遊戲結束)、checkWinPossible、resetGame、getInvertedState
- checkWinner():判斷現在的盤面是否有贏家,依序檢查 row、col、對角線。

```
def checkWinner(self):
    symbols = np.unique(self.state)
    symbols = list(symbols[np.nonzero(symbols)])

for sym in symbols:
    # Check rows
    row= np.any((np.all(self.state == sym, axis=1)))

# Check columns
    col = np.any((np.all(self.state == sym, axis=0)))

# Check diagonals
    diag1 = np.array([self.state[0,0], self.state[1,1], self.state[2,2]])
    diag1 = np.all(diag1 == sym)

diag2 = np.array([self.state[0,2], self.state[1,1], self.state[2,0]])
    diag2 = np.all(diag2 == sym)

# Check if state has winner and return winner in that case
    if row or col or diag1 or diag2:
        return sym

return 0 # No winner found
```

#### (3) Class Trainer:

learning\_parameter 和 discount\_factor 參數的相關實驗在上頁,Q 是用 dictionary 的資料型別實作,儲存訓練過成中儲存的 Q function

- agent \ learning\_parameter \ \ discount\_factor \ \ Q
- getStatePairKey \ getValueQ \ setValueQ \ getMaxQ \ getBestAction \ updateQ
- getBestAction():在所有可行的 action 中,找Q最大的。

#### (4) function simulate():

因為 Q-learning 訓練的方式為一部分的機率(exploration\_probability)為 random、其他為使用從過去的經驗(Q function)找最佳解, exploration\_probability 逐 episode 遞減 1 / Iter, 實作方式如下:

```
#Explore
if explore_only is True or random.random() < exploration_probability:
    a.performRandomAction(updateQ=True)
# Exploit
else:
    best_action = a.getBestAction()
    a.performAction(best_action, updateQ=(True))

# Reduce probability to explore during training
# Do not remove completely
exploration_probability_lower_bound = 0.2
if exploration_probability > exploration_probability_lower_bound:
    exploration_probability -= 1/iterations
```

(5) training 時執行順序: simulate() → 初始化 Board 和兩個 agent → for loop{checkGameEnded() → updatePossibleActions → 根據 exploration\_probability 選擇 explore-performRandomAction()或 exploit-getBestAction()-performAction() → 更新 exploration\_probability → checkWinner() → 換另一個 agent}

- 4. Implement: Testing procedure
- (1) 實作找Q最大、決定 action 的部分和訓練差不多,惟不用再更新Q值。
- (2) 讀入 input 檔,用 for loop 依照行讀取,放入 board 內,用訓練好的 agent 尋找 Q 最大的 Action, 最後寫入 output 檔。

```
if input state[0] == '1':
__init__(self):
                                                                           self.current_player = playerX
trained_agent = "hw1_3_data"
                                                                           self.current_player = player0
for line in input_file.readlines():
    input_state = line.rstrip("\n").split(" ")
                                                                       self.agent = Agent(self.current_player, self.board, load_trainer = trained_agent)
    playerX = Board.playerX
                                                                       self.agent_symbol = self.agent.symbol
    player0 = Board.player0
                                                                       if self.current_player == self.agent_symbol:
    if len(input_state[1:10]) == 9:
                                                                           self.agentMove()
        state = input_state[1:10]
                                                                  input_file.close()
                                                                  output_file.close()
        print("Error State!")
                                                              def playMove(self, x, y):
    self.board = Board(rows=3, cols=3, win_threshold=3)
                                                                  # print("Output move - x:
print(str(x)+" "+str(y))
    index = 0
    for i in range(BOARD_ROWS):
                                                                  output_file.write("%d " % x)
        for j in range(BOARD_COLS):
   if int(state[index]) == 1:
                                                                   output_file.write("%d\n" % y)
                self.board.setPosition(i, j, 1)
                                                              def agentMove(self):
            elif int(state[index]) == -1:
                                                                  move = self.agent.getBestAction()
                self.board.setPosition(i, j, -1)
                                                                  self.playMove(move[1], move[0])
```

(3) 讀檔、寫檔、印結果

```
input_file = open("hw1-3_sample_input","r")
cutput_file = open("hw1-3_output","w")
Play()
```

(4) 測試 sample input

```
[(base) NKUSTde-MacBook-Pro:RL_HW1 nkust$ python 106070038_hw1_3_test.py
1 2
2 1
```

## 四、Tic-tac-toe (4x4x4)

1. Implementation: MCTS training procedure

不像 minimax tree 需要建出完整的樹,MCTS 可以在只有部分的樹的情況下找到最佳解,步驟: Selection → Expansion → Simulation → Backpropagation, Explore 和 Exploit 兩者之間的 tradeoff 採用 UCT (Upper Confidence Bounds to Trees,上限信賴區間演算法),公式如下:

最大化 
$$\frac{w_i}{n_i} + c\sqrt{\frac{\ln t}{n_i}}$$

 $W_i$ : 第 i 次移動後獲勝次數,  $n_i$ : 第 i 次移動後仿真次數, c: 探索參數, t:  $\sum n_i$ 

- (1) Selection:從 Root 開始,遞歸選擇最優的子節點,直到到達葉節點
- (2) Expansion: 創建一個或者更多的字子節點
- (3) Simulation: 運行一個模擬的輸出,直到博弈遊戲結束
- (4) Backpropagation:用模擬的結果輸出更新當前行動序列 但因為效果不佳,後來採用 Q-learning 的方法做優化,訓練 50,000 個 episodes。

- 實驗後發現,除了 episodes 的次數以外, states 做 hashing 的方式也會顯著影響到 model 的大小,為了避免超過 10MB,有將 hashing 的方式做了些調整。
- $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max Q(S', A) Q(S, A)]$

```
newQ = currentQ + self.learning_parameter * (self.agent.rewardFunction(state, action)
+ self.discount_factor * max_nextQ - currentQ)
```

- 架構與上題類似,先初始化 Board 和兩個 agent → 跑迴圈→ 更新 Action → 根據 ε 選擇隨機的 Action 或用過去的 Q 尋找最佳解→ 更新 ε → 判斷是否產生贏家
- 2. Implementation: Environment

類似上題 3x3 的實作方式,但因為維度增加一維,所以在檢查是否有贏家時,先檢查 col、row、height,再考慮對角線是否有四點連線,對角線共有 24 種情況 (8x3)。

```
row = np.any((np.all(self.state == sym, axis=1)))
# Check colum
col = np.any((np.all(self.state == sym, axis=0)))
height = np.any((np.all(self.state == sym, axis=2)))
 Check diagonal
diag1 = np.array([self.state[0,0,0], self.state[1,1,0], self.state[2,2,0], self.state[3,3,0]])
diag1 = np.all(diag1 == sym)
diag2 = np.array([self.state[0,0,1], self.state[1,1,1], self.state[2,2,1], self.state[3,3,1]])
diag2 = np.all(diag2 == sym)
diag3 = np.array([self.state[0,0,2], self.state[1,1,2], self.state[2,2,2], self.state[3,3,2]])
diag3 = np.all(diag3 == sym)
diag4 = np.array([self.state[0,0,3], self.state[1,1,3], self.state[2,2,3], self.state[3,3,3]])
diag4 = np.all(diag4 == sym)
diag5 = np.array([self.state[0,3,0], self.state[1,2,0], self.state[2,1,0], self.state[3,0,0]])
diag5 = np.all(diag5 == sym)
diag6 = np.array([self.state[0,3,1], self.state[1,2,1], self.state[2,1,1], self.state[3,0,1]])
diag6 = np.all(diag6 == sym)
```

- 3. Implementation: 4x4x4 testing procedure
- (1) 類似上題 3x3 的實作方式,但要修改維度,讀入 input 檔,用 for loop 依照行讀取,放入 board 內,用訓練好的 agent 尋找 Q 最大的 Action,最後寫入 output 檔。

```
def __init__(self):
   trained_agent = "hw1_4_data"
   for line in input_file.readlines():
       input_state = line.rstrip("\n").split(" ")
       playerX = Board.playerX
       player0 = Board.player0
       if len(input_state[1:65]) == 64:
           state = input_state[1:65]
           print("Error State!")
       # Start game
       self.board = Board(rows=4, cols=4, heights=4, win_threshold=4)
        for i in range(BOARD_ROWS):
            for j in range(BOARD_COLS):
               for k in range(BOARD_HEIGHTS):
                   if int(state[index]) == 1:
                       self.board.setPosition(i, j, k, 1)
                    elif int(state[index]) == -1:
                       self.board.setPosition(i, j, k, -1)
                    index+=1
```

```
if input_state[0] == '1':
    self.current_player = playerX
else:
    self.current_player = player0

self.agent = Agent(self.current_player, self.board, load_trainer = trained_agent)
self.agent_symbol = self.agent.symbol

if self.current_player == self.agent_symbol:
    self.agentMove()

input_file.close()
output_file.close()
```

(2) 讀檔、寫檔、印結果

(3) 測試 sample input

[(base) NKUSTde-MacBook-Pro:~ nkust\$ python 106070038\_hw1\_4\_test.py
1 2 0