جامعة عبد المالك السعدي
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Université Abdelmalek Essaadi

Université Abdelmalek Essaadi
Faculté des sciences et techniques de Tanger
Département génie informatique
Cycle d'ingénieur Logiciels et systèmes intelligents « LSI »
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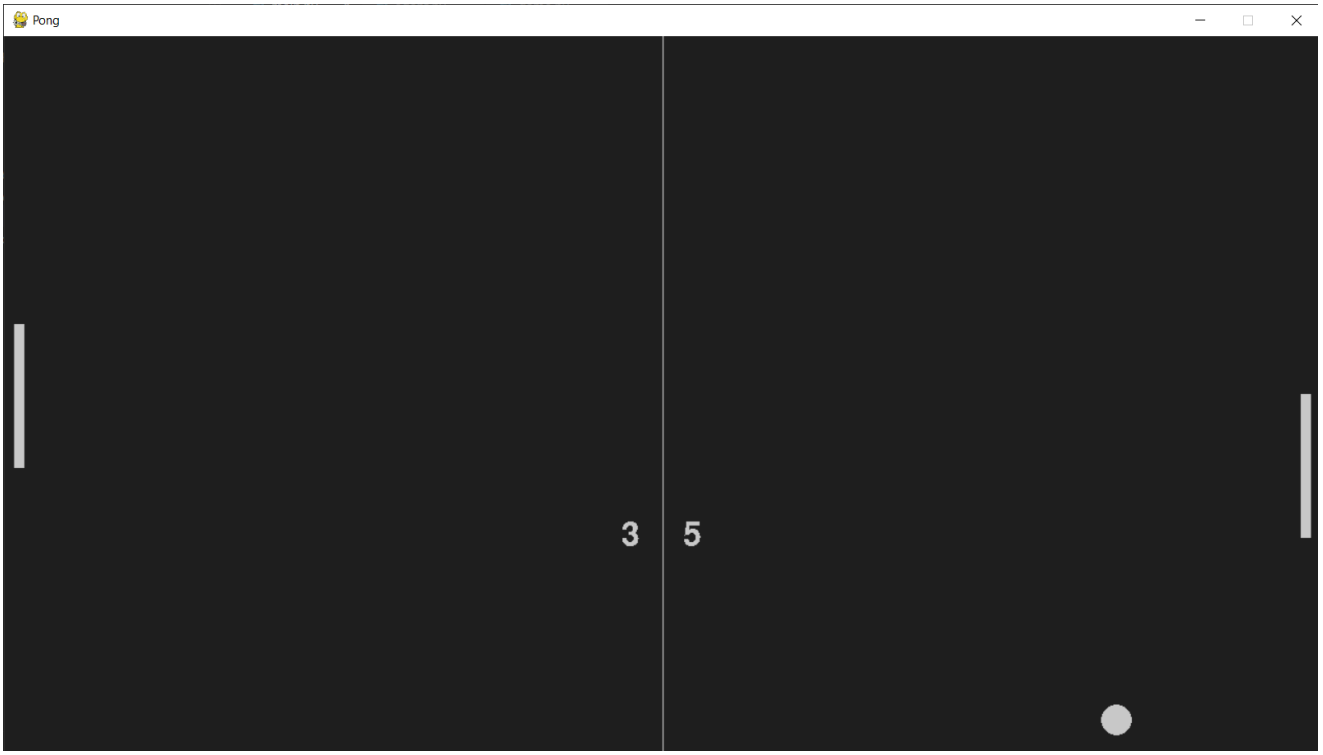
كلية العلوم و التقنيات بطنجة
ⵜⴰⵖⵣⵓⵍⵜ ⵏ ⵜⵣⵣⵓⵖⵜ ⴰ ⵜⵓⵙⵙⵔⵜⵉⵡⵉⵏ ⵏ ⵟⴰⵏⵊⴰ
Faculté des Sciences et Techniques de Tanger

Machine Learning
Atelier 4: «Q Learning / PONG »



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Objective:
l'objectif principal de cet atelier est d'implémenter l'algorithme Q-learning dans un agent qui va contrôler la barre player du jeu PONG.

Outils:
Python ,Pygame, matplotlib, Qlearning, Numpy, Matplotlib

Etape 1: Développement de la classe Agent

```
def get_action(self, s):
        return np.argmax(self.Q[s, :])

    def calculate_reward(rect, bar, ball):
        if bar.top <= ball.centery <= bar.bottom:
            return 1
        else:
            return -1

    def centre_to_state(self, centre, screen_height, bar_height):
        a = 0
        b = bar_height
        s = 0
        for i in range(int(screen_height/bar_height)):
            if a < centre < b:
                s = (b / bar_height) - 1
            else:
                a += bar_height
                b += bar_height
        return int(s)

    def update(self, s, bar, ball, screen_height, ball_speed_x,
is_permanent):
        s_ = s
        position_cal = bar.right+10
        speed = ball_speed_x*(-1)
        ballX = ball.x
        if not is_permanent:
            position_cal = bar.left - 10 - ball.width
            speed = ball_speed_x
            ballX = position_cal
            position_cal = ball.x
        if position_cal <= ballX and speed > 0:
            reward = self.calculate_reward(bar, ball)
            self.rewards.append(reward)
            self.action = self.get_action(s)
            if self.action != 0:
                s_ = self.centre_to_state(ball.centery, screen_height,
```

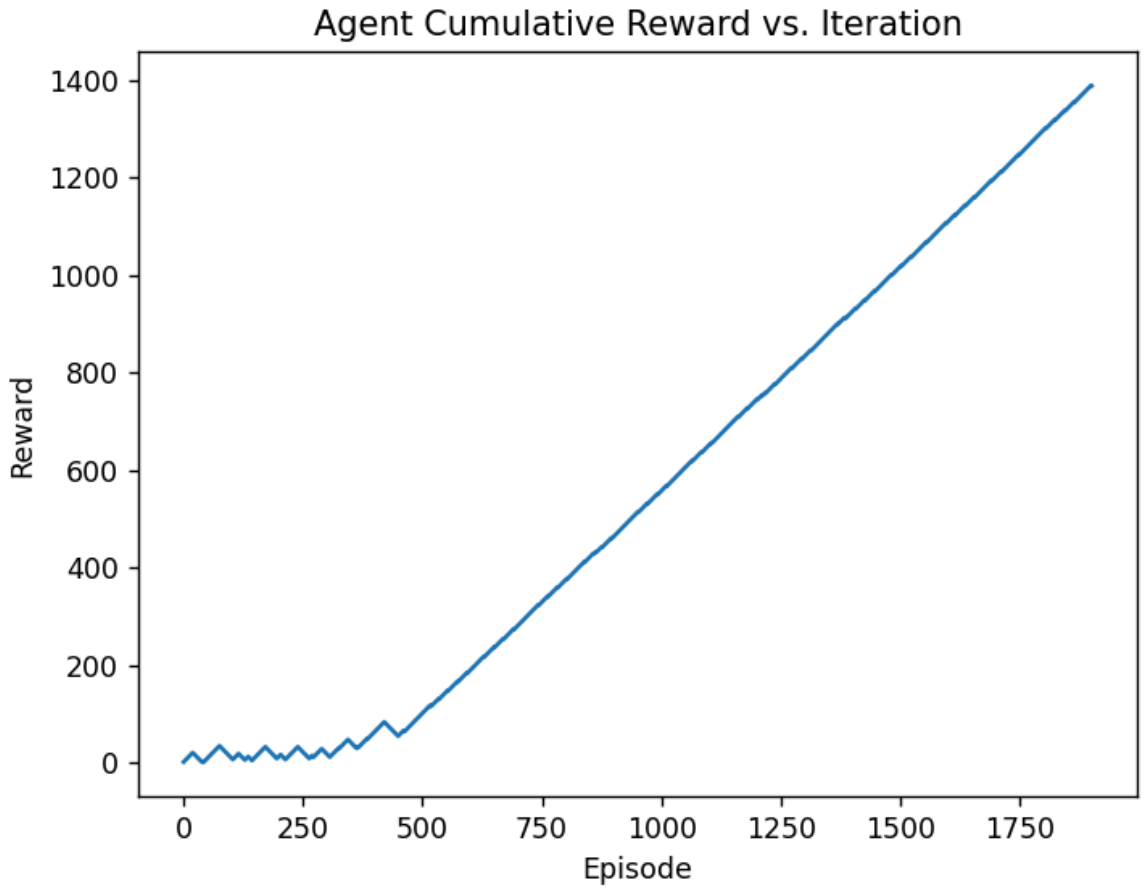
```
bar.height)
            else:
                s_ = s
            if s_ < 0:
                s_ = 0
            elif s_ > int(screen_height/bar.height)-1:
                s_ = int(screen_height/bar.height)-1
            self.state = s_
            self.Q[s, self.action] += self.alpha * (reward + self.gamma *
np.max(self.Q[s_, :]) - self.Q[s, self.action])
        return s_ * bar.height
```

Etape 2: L'intégration d'agent au niveau de jeu

```
class GameLearning:

    def __init__(self):
        while True:
            print('\n--- Choose a mode: --- ')
            type = input('1. AgentRL vs AgentAI \n2. AgentRL vs Human \n3.
AgentRL vs AgentRL\nMode nº = ')
            if type == '1' or type == '2' or type == '3':
                break
        if type == '1':
            self.game = g.Game('agentAI')
        elif type == '2':
            self.game = g.Game('human')
        else:
            self.game = g.Game('agentRL')

    def beginPlaying(self):
        self.game.play()

if __name__ == '__main__':
    gl = GameLearning()
    gl.beginPlaying()
```

Etape 3: Le graphe reward

L'agent commence sans connaissance de l'environnement. En explorant de nouveaux épisodes, son apprentissage progresse, conduisant à une augmentation des rewards. Ajustant ses actions en fonction de cette expérience, l'agent améliore ses performances au fil du temps.


Agent Cumulative Reward vs. Iteration
Reward
Episode
0
200
400
600
800
1000
1200
1400
0
250
500
750
1000
1250
1500
1750