Machine Learning Lab Assignment 5

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Mountain Climbing

Output:-

\$ python3 Mountain.py

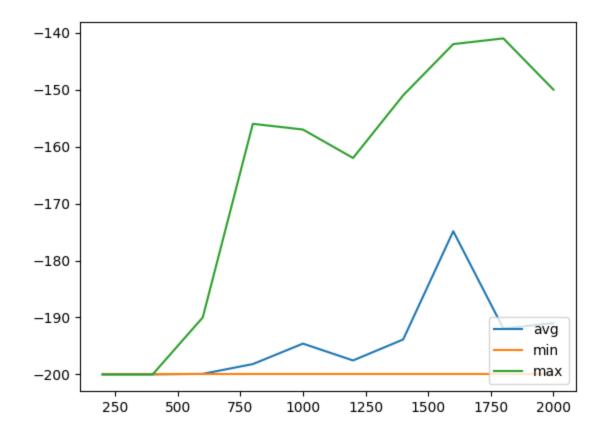
best reward: -141.0 best episode: 1756

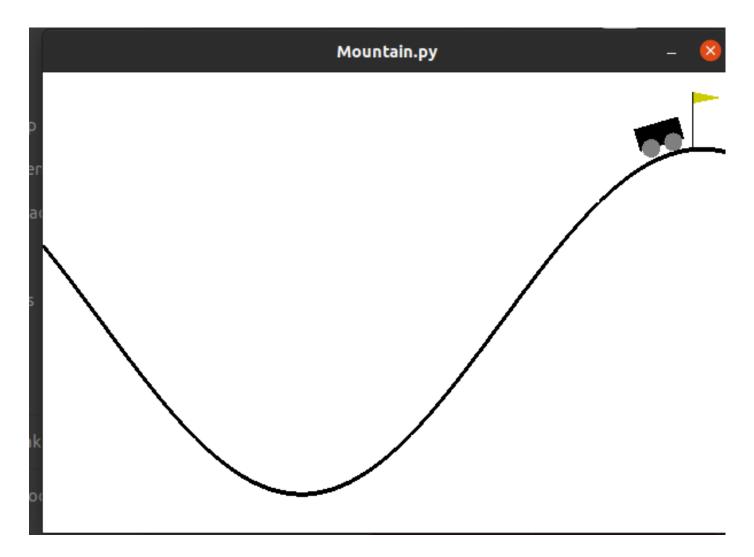
Mountain.py:32: DeprecationWarning: `np.int` is a deprecated alias for the builtin `int`. To silence this warning, use `int` by itself. Doing this will not modify any behavior and is safe. When replacing `np.int`, you may wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you wish to review your current use, check the release note link for additional information.

Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations

return tuple(discrete_state.astype(np.int))

episode: 200, avg: -200.0, min: -200.0, max: -200.0 episode: 400, avg: -200.0, min: -200.0, max: -200.0 episode: 600, avg: -199.905, min: -200.0, max: -190.0 episode: 800, avg: -198.19, min: -200.0, max: -156.0 episode: 1000, avg: -194.595, min: -200.0, max: -157.0 episode: 1200, avg: -197.55, min: -200.0, max: -162.0 episode: 1400, avg: -193.87, min: -200.0, max: -151.0 episode: 1600, avg: -174.86, min: -200.0, max: -142.0 episode: 1800, avg: -191.94, min: -200.0, max: -141.0 episode: 2000, avg: -191.0, min: -200.0, max: -150.0





Code:-

import gym import matplotlib.pyplot as plt import numpy as np

env = gym.make("MountainCar-v0")
env.reset()

LEARNING_RATE = 0.1 DISCOUNT = 0.95 EPISODES = 2000

SHOW_EVERY = 200 RENDER_EVERY = 100

DISCRETE_OS_SIZE = [20] * len(env.observation_space.high)

```
discrete os win size = (env.observation space.high - env.observation space.low) / DISCRETE OS SIZE
epsilon = 0.2
START EPSILON DECAYING = 1
END_EPSILON_DECAYING = EPISODES // 2
epsilon decay value = epsilon/(END EPSILON DECAYING - START EPSILON DECAYING)
q table = np.random.uniform(low=-2, high=0, size=(DISCRETE OS SIZE + [env.action space.n]))
ep_rewards = []
aggr_ep_rewards = {'ep': [], 'avg': [], 'min': [], 'max': []}
def get_discrete_state(state):
      discrete_state = (state - env.observation_space.low) / discrete_os_win_size
      return tuple(discrete state.astype(np.int))
best_episode_reward = -200
best_episode = -1
best_q_table = q_table
for episode in range(1, EPISODES + 1):
      episode success = False
      episode_reward = 0
      if not episode % SHOW_EVERY:
      average_reward = sum(ep_rewards[-SHOW_EVERY:])/len(ep_rewards[-SHOW_EVERY:])
      aggr_ep_rewards['ep'].append(episode)
      aggr_ep_rewards['avg'].append(average_reward)
      aggr_ep_rewards['min'].append(min(ep_rewards[-SHOW_EVERY:]))
      aggr ep rewards['max'].append(max(ep rewards[-SHOW EVERY:]))
      print(f"episode: {aggr_ep_rewards['ep'][-1]}, avg: {aggr_ep_rewards['avg'][-1]}, "
             + f"min: {aggr_ep_rewards['min'][-1]}, max: {aggr_ep_rewards['max'][-1]}")
      except Exception as e:
      print(e)
      discrete state = get discrete state(env.reset())
      done = False
      while not done:
      if np.random.random() > epsilon:
      action = np.argmax(q_table[discrete_state])
      action = np.random.randint(0, env.action_space.n)
```

```
new_state, reward, done, _ = env.step(action)
      episode_reward += reward
      new discrete state = get discrete state(new state)
      if RENDER_EVERY > 1:
      if not episode % RENDER_EVERY:
             env.render()
      if not done:
      max_future_q = np.max(q_table[new_discrete_state])
      current_q = q_table[discrete_state + (action, )]
      new_q = (1 - LEARNING_RATE) * current_q + LEARNING_RATE * (reward + DISCOUNT *
max future q)
      q_table[discrete_state + (action, )] = new_q
      elif new_state[0] >= env.goal_position:
      episode success = True
      q table[discrete_state + (action, )] = 0
      discrete_state = new_discrete_state
      if END_EPSILON_DECAYING >= episode >= START_EPSILON_DECAYING:
      epsilon -= epsilon_decay_value
      if episode_reward >= best_episode_reward:
      best episode reward = episode reward
      best_episode = episode
      best_q_table = q_table
      ep_rewards.append(episode_reward)
      env.close()
print(f"best reward: {best_episode_reward}")
print(f"best episode: {best_episode}")
plt.plot(aggr_ep_rewards['ep'], aggr_ep_rewards['avg'], label="avg")
plt.plot(aggr_ep_rewards['ep'], aggr_ep_rewards['min'], label="min")
plt.plot(aggr_ep_rewards['ep'], aggr_ep_rewards['max'], label="max")
plt.legend(loc=4)
plt.show()
```

Roulette

Output:-

\$ python3 Roulette.py

Number of actions available: 38 Number of states defined: 1

Therefore, Q-Table with 38 columns and 1 rows will be created

Q-Table shape: (1, 38)

Episode: 2280 Round: 1 Action: 33 Reward: 1.0

Total reward so far: 1.0

Episode: 2280 Round: 2 Action: 33 Reward: 1.0

Total reward so far: 2.0

Episode: 2280 Round: 3 Action: 33 Reward: 1.0

Total reward so far: 3.0

Episode: 2280 Round: 4 Action: 33 Reward: 1.0

Total reward so far: 4.0

Episode: 2280 Round: 5 Action: 33 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 6 Action: 33

Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 7 Action: 33

Reward: -1.0

Total reward so far: 3.0

Episode: 2280 Round: 8 Action: 33 Reward: 1.0

Total reward so far: 4.0

Episode: 2280 Round: 9 Action: 33 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 10 Action: 33 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 11 Action: 33 Reward: -1.0

Total reward so far: 5.0

Episode: 2280

Round: 12 Action: 33 Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 13 Action: 16 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 14 Action: 33 Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 15 Action: 33 Reward: -1.0

Total reward so far: 3.0

Episode: 2280 Round: 16 Action: 33 Reward: -1.0

Total reward so far: 2.0

Episode: 2280 Round: 17 Action: 16 Reward: 1.0

Total reward so far: 3.0

Episode: 2280 Round: 18 Action: 16 Reward: 1.0

Total reward so far: 4.0

Episode: 2280 Round: 19 Action: 16 Reward: -1.0

Total reward so far: 3.0

Episode: 2280 Round: 20 Action: 16 Reward: -1.0

Total reward so far: 2.0

Episode: 2280 Round: 21 Action: 16 Reward: 1.0

Total reward so far: 3.0

Episode: 2280 Round: 22 Action: 16 Reward: 1.0

Total reward so far: 4.0

Episode: 2280 Round: 23 Action: 16 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 24 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 25 Action: 16 Reward: -1.0

Total reward so far: 5.0

Episode: 2280 Round: 26 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 27 Action: 16 Reward: -1.0

Total reward so far: 5.0

Episode: 2280 Round: 28 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 29 Action: 16 Reward: 1.0

Total reward so far: 7.0

Episode: 2280 Round: 30 Action: 16 Reward: 1.0

Total reward so far: 8.0

Episode: 2280 Round: 31 Action: 16 Reward: -1.0

Total reward so far: 7.0

Episode: 2280 Round: 32 Action: 16 Reward: -1.0

Total reward so far: 6.0

Episode: 2280 Round: 33 Action: 16 Reward: 1.0

Total reward so far: 7.0

Episode: 2280 Round: 34 Action: 16 Reward: -1.0

Total reward so far: 6.0

Episode: 2280 Round: 35 Action: 16 Reward: 1.0

Total reward so far: 7.0

Episode: 2280 Round: 36 Action: 16 Reward: 1.0

Total reward so far: 8.0

Episode: 2280 Round: 37 Action: 16 Reward: -1.0

Total reward so far: 7.0

Episode: 2280 Round: 38 Action: 16 Reward: -1.0

Total reward so far: 6.0

Episode: 2280 Round: 39 Action: 16 Reward: -1.0

Total reward so far: 5.0

Episode: 2280 Round: 40 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 41 Action: 16 Reward: -1.0

Total reward so far: 5.0

Episode: 2280 Round: 42 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 43 Action: 16 Reward: -1.0 Total reward so far: 5.0

Episode: 2280 Round: 44 Action: 16 Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 45 Action: 16 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 46 Action: 16 Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 47 Action: 16 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 48 Action: 31 Reward: -1.0

Total reward so far: 4.0

Episode: 2280 Round: 49 Action: 25 Reward: 1.0

Total reward so far: 5.0

Episode: 2280 Round: 50 Action: 16 Reward: 1.0

Total reward so far: 6.0

Episode: 2280 Round: 51 Action: 16 Reward: 1.0

Total reward so far: 7.0

Episode: 2280 Round: 52 Action: 16 Reward: 1.0

Total reward so far: 8.0

Episode: 2280 Round: 53 Action: 16 Reward: -1.0

Total reward so far: 7.0

Episode: 2280 Round: 54 Action: 0 Reward: 36.0

Total reward so far: 43.0

Episode: 2280 Round: 55 Action: 0 Reward: -1.0

Total reward so far: 42.0

Episode: 2280

Round: 56 Action: 20 Reward: -1.0

Total reward so far: 41.0

Episode: 2280 Round: 57 Action: 0 Reward: -1.0

Total reward so far: 40.0

Episode: 2280 Round: 58 Action: 0 Reward: -1.0

Total reward so far: 39.0

Episode: 2280 Round: 59 Action: 0 Reward: -1.0

Total reward so far: 38.0

Episode: 2280 Round: 60 Action: 0 Reward: -1.0

Total reward so far: 37.0

Episode: 2280 Round: 61 Action: 0 Reward: -1.0

Total reward so far: 36.0

Episode: 2280 Round: 62 Action: 0 Reward: -1.0

Total reward so far: 35.0

Episode: 2280 Round: 63 Action: 0 Reward: -1.0

Total reward so far: 34.0

Episode: 2280 Round: 64 Action: 0 Reward: -1.0

Total reward so far: 33.0

Episode: 2280 Round: 65 Action: 0 Reward: -1.0

Total reward so far: 32.0

Episode: 2280 Round: 66 Action: 0 Reward: -1.0

Total reward so far: 31.0

Episode: 2280 Round: 67 Action: 0 Reward: -1.0

Total reward so far: 30.0

Episode: 2280 Round: 68 Action: 0 Reward: -1.0

Total reward so far: 29.0

Episode: 2280 Round: 69 Action: 0 Reward: -1.0

Total reward so far: 28.0

Episode: 2280 Round: 70 Action: 0 Reward: -1.0

Total reward so far: 27.0

Episode: 2280 Round: 71 Action: 0 Reward: -1.0

Total reward so far: 26.0

Episode: 2280 Round: 72 Action: 0 Reward: -1.0

Total reward so far: 25.0

Episode: 2280 Round: 73 Action: 0 Reward: 36.0

Total reward so far: 61.0

Episode: 2280 Round: 74 Action: 0 Reward: -1.0

Total reward so far: 60.0

Episode: 2280 Round: 75 Action: 0 Reward: -1.0

Total reward so far: 59.0

Episode: 2280 Round: 76 Action: 0 Reward: -1.0

Total reward so far: 58.0

Episode: 2280 Round: 77 Action: 0 Reward: -1.0

Total reward so far: 57.0

Episode: 2280 Round: 78 Action: 0 Reward: -1.0

Total reward so far: 56.0

Episode: 2280 Round: 79 Action: 0 Reward: 36.0

Total reward so far: 92.0

Episode: 2280 Round: 80 Action: 0 Reward: -1.0

Total reward so far: 91.0

Episode: 2280 Round: 81 Action: 0 Reward: -1.0

Total reward so far: 90.0

Episode: 2280 Round: 82 Action: 0 Reward: -1.0

Total reward so far: 89.0

Episode: 2280 Round: 83 Action: 0 Reward: -1.0

Total reward so far: 88.0

Episode: 2280 Round: 84 Action: 0 Reward: -1.0

Total reward so far: 87.0

Episode: 2280 Round: 85 Action: 0 Reward: -1.0

Total reward so far: 86.0

Episode: 2280 Round: 86 Action: 0 Reward: -1.0

Total reward so far: 85.0

Episode: 2280 Round: 87 Action: 0 Reward: -1.0 Total reward so far: 84.0

Episode: 2280 Round: 88 Action: 5 Reward: 1.0

Total reward so far: 85.0

Episode: 2280 Round: 89 Action: 0 Reward: -1.0

Total reward so far: 84.0

Episode: 2280 Round: 90 Action: 0 Reward: -1.0

Total reward so far: 83.0

Episode: 2280 Round: 91 Action: 0 Reward: -1.0

Total reward so far: 82.0

Episode: 2280 Round: 92 Action: 0 Reward: -1.0

Total reward so far: 81.0

Episode: 2280 Round: 93 Action: 0 Reward: -1.0

Total reward so far: 80.0

Episode: 2280 Round: 94 Action: 0 Reward: -1.0

Total reward so far: 79.0

Episode: 2280 Round: 95 Action: 0 Reward: -1.0

Total reward so far: 78.0

Episode: 2280 Round: 96 Action: 0 Reward: -1.0

Total reward so far: 77.0

Episode: 2280 Round: 97 Action: 25 Reward: -1.0

Total reward so far: 76.0

Episode: 2280 Round: 98 Action: 0 Reward: 36.0

Total reward so far: 112.0

Episode: 2280 Round: 99 Action: 0 Reward: -1.0

Total reward so far: 111.0

Episode: 2280

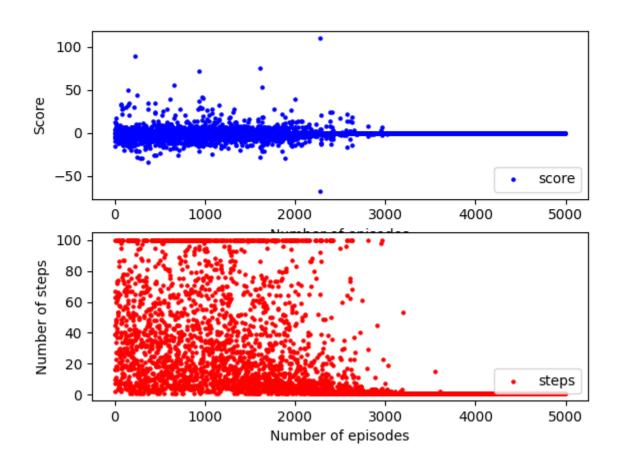
Round: 100 Action: 0 Reward: -1.0

Total reward so far: 110.0

Q-Table after 5000 episodes

[[-3.07583358e-02 -4.19334032e-02 -5.99201427e-02 -3.76336086e-02 -9.83211895e-02 -1.35208913e-02 -1.48916007e-02 -7.34094117e-02 -2.78890312e-02 -2.38599619e-02 -8.43982923e-02 -2.09545907e-02 -3.38959585e-02 -7.01535786e-02 -5.08198245e-02 -8.84553123e-03 -7.96039430e-02 -7.43652260e-02 -2.86639392e-02 -6.85138461e-02 -7.48503926e-02 -3.73022417e-02 -1.20240760e-02 -2.79969394e-02 -1.20484291e-02 -6.39220388e-02 -4.02999360e-02 -3.19100504e-03 -6.82564864e-02 -7.04195457e-02 -2.58737313e-04 -1.96667366e-02 -4.47963458e-02 -4.82113761e-02 -6.84705007e-02 -3.36668727e-02 -2.11633852e-02 1.57973762e-06]]

The best score after running 5000 episodes: 110.0



```
Code:-
import gym
import gym_toytext
import numpy as np
from IPython.display import clear_output
from time import sleep
import matplotlib.pyplot as plt
env = gym.make('Roulette-v0')
action_space_size = env.action_space.n
state space size = env.observation space.n
print(f"Number of actions available: {action_space_size}")
print(f"Number of states defined: {state_space_size}")
print(f"Therefore, Q-Table with {action_space_size} columns and {state_space_size} rows will be created")
q table = np.random.random([state space size, action space size])
#OR
# q_table = np.zeros([state_space_size, action_space_size])
print(f"Q-Table shape: {q_table.shape}")
sleep(5)
# Hyperparameters
TOTAL_EPISODES = 5_000 #Number of epsiodes to train the algorithm
MAX_STEPS = 150 #Max steps an agent can take during an episode
LEARNING_RATE = 0.1
GAMMA = 0.95 # Discount (close to 0 makes it greedy, close to 1 considers long term)
# Exploration Parameters
epsilon = 1
START_EPSILON_DECAYING = 1
END EPSILON DECAYING = TOTAL EPISODES // 2
DECAY RATE = epsilon/(END EPSILON DECAYING - START EPSILON DECAYING)
def print frames(frames):
      total reward = 0
      for i, frame in enumerate(frames):
       clear_output(wait=True)
       print('\n************')
       print(f"Episode: {frame['episode']}")
       print(f'Round: \{i + 1\}')
       print(f"Action: {frame['action']}")
```

```
print(f"Reward: {frame['reward']}")
       total_reward += frame['reward']
       print(f"Total reward so far: {total_reward}")
       sleep(0.1)
def edit reward(info):
       print(info)
env.reset()
history = {'steps': [], 'total_score': [], 'episode_number': []}
best frames = []
high\_score = 0
for episode in range(TOTAL_EPISODES):
       state = env.reset()
       step = 0
       frames = []
       current_score = 0
       done = False
       for step in range(MAX_STEPS):
       if np.random.random() > epsilon: #This is exploitation
       action = np.argmax(q_table[state, :]) #Current state, max value
       else: #This is exploration
       action = np.random.randint(0, action_space_size)
       new_state, reward, done, info = env.step(action)
       current score += reward
       frames.append({
       'episode': episode,
       'action': action,
       'reward': reward
       })
       q_table[state, action] = (1 - LEARNING_RATE) * q_table[state, action] + LEARNING_RATE * (reward
+ GAMMA * np.max(q_table[new_state, :]))
       if done:
```

```
history['steps'].append(step + 1)
       history['total_score'].append(current_score)
       history['episode_number'].append(episode)
       if current_score >= high_score:
              high_score = current_score
              best frames = frames.copy()
       break
       state = new_state
       if END EPSILON DECAYING >= episode >= START EPSILON DECAYING:
       epsilon -= DECAY_RATE
env.close()
print_frames(best_frames)
print(f"\nQ-Table after {TOTAL_EPISODES} episodes")
print(q_table)
print(f'The best score after running {TOTAL_EPISODES} episodes: {high_score}')
# Total score
plt.subplot(2, 1, 1)
plt.scatter(history['episode_number'], history['total_score'], s = 5, label = 'score', color = 'blue')
plt.xlabel('Number of episodes')
plt.ylabel('Score')
plt.legend(loc = 4)
# Number of steps
plt.subplot(2, 1, 2)
plt.scatter(history['episode_number'], history['steps'], s = 5, label = 'steps', color = 'red')
plt.xlabel('Number of episodes')
plt.ylabel('Number of steps')
plt.legend(loc = 4)
plt.show()
```