FrozenLake-v0 Excercise □

`1BM120: Tutorial 3 - Deep reinforcement learning` This tutorial will introduce you with Gym library and deep reinforcement learning framework. Solve the `tasks` given in each part below

Part 0: Load libraries

We begin by installing the dependcies on google colab.

In [5]:
```
!pip install gym
```

```
Requirement already satisfied: gym in c:\users\20204841\anaconda3\lib\site-packages (0.18.0)
Requirement already satisfied: numpy>=1.10.4 in c:\users\20204841\anaconda3\lib\site-packages (from gym) (1.19.2)
Requirement already satisfied: scipy in c:\users\20204841\anaconda3\lib\site-packages (from gym) (1.6.2)
Requirement already satisfied: Pillow<=7.2.0 in c:\users\20204841\anaconda3\lib\site-packages (from gym) (7.2.0)
Requirement already satisfied: pyglet<=1.5.0,>=1.4.0 in c:\users\20204841\anaconda3\lib\site-packages (from gym) (1.5.0)
Requirement already satisfied: cloudpickle<1.7.0,>=1.2.0 in c:\users\20204841\anaconda3\lib\site-packages (from gym) (1.6.0)
Requirement already satisfied: future in c:\users\20204841\anaconda3\lib\site-packages (from pyglet<=1.5.0,>=1.4.0->gym) (0.18.
2)
```

Import the neccary packages. We will use four libraries:

- `Numpy` for our Qtable
- `OpenAI Gym` for our FrozenLake Environment
- `Random` to generate random numbers
- `Deque` to record cumulative reward over multiple episodes
- `MatPlotlib` to generate plots

In [1]:
```
import numpy as np
import gym
import random
from collections import deque
import matplotlib.pyplot as plt
%matplotlib inline
```

Part 1: Explore FrozenLake-v0 🎮

Task 1:

- Create an instance of the environment
- Render the environment
- Print the state and action space

In [2]:
```
env = gym.make('FrozenLake-v0') # Create an  instance of the envrionment
```

In [3]:
```
env.render()# render the envrionment
```

```
SFFF
FHFH
FFFH
HFFG
```

The agent moves through a 4×4 gridworld

The agent has 4 potential actions:

```
UP = 0
RIGHT = 1
DOWN = 2
LEFT = 3
```

Thus, $\mathcal{S}^+ = \{0, 1, \ldots, 15\}$, and $\mathcal{A} = \{0, 1, 2, 3\}$.

In [4]:
```
print(env.reset())
```

```
0
```

In [5]:
```
action_space = env.action_space.n#Get number of actions in an environment
state_space = env.observation_space.n#Get number of states in an environment
print('Action space', action_space)
print('State space', state_space)
```

```
Action space 4
State space 16
```

Other important points of the environvment:

- The episode ends when you reach the goal or fall in a hole.
- Agent receives a reward of 1 if it reach the goal, and zero otherwise.
- FrozenLake-v0 is considered "solved" when the agent obtains an average reward of at least **0.78 over 100** consecutive episodes.

Task 2:

- Sample an action from the environment.
- Call the step function and inspect the outputs.

In [6]:
```
action = env.action_space.sample()# sample an action from the env instance
print(action)
```

```
2
```

In [7]:
```
env.step(action)# call the step function of the env. and inspect quadruple of (state, reward, done, info)
```

Out[7]:
```
(4, 0.0, False, {'prob': 0.3333333333333333})
```

Task 3:

- Randomly interact with the envrionment for two episodes.

In [8]:

```
for episode in range(2):
    state = env.reset()# get the starting state from the env.
    step = 0
    done = False
    print("EPISODE ", episode)
    for step in range(99):
        action = env.action_space.sample()# sample an action from the environment
        new_state, reward, done, info = env.step(action) #give the action to environment to obtain reward, and next state,
        if done: #if the goal state is reached or agent fall into hole.
            env.render() #print the last stay
            if new_state == 15:
                print("We reached our Goal 🏆")
            else:
                print("We fell into a hole ☠")

            # We print the number of step it took.
            print("Number of steps", step)

            break
        state = new_state
env.close()
```

```
EPISODE  0
  (Down)
SFFF
FHFH
FFFH
HFFG
We fell into a hole ☠
Number of steps 12
EPISODE  1
  (Right)
SFFF
FHFH
FFFH
HFFG
We fell into a hole ☠
Number of steps 1
```

Part 2: Q-Table 🗄

We will implement Q-learning algorithm to devise optimal policy for FrozenLake environment.

Task 4

- Create Q-table with `state space` as rows and `action space` as columns. state =16 action=4

In [9]:
```
qtable = np.zeros((state_space, action_space))
print(qtable)
```

```
[[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.]]
```

Part 3: The Q learning algorithm 🧠

It is fine if you do not understand all the details at this point. Q-learning will be introduced in Lecture 3 of DRL part.

Q learning is a off-policy algorithm. Meaning that the actions that are executed are different from the target actions that are used for learning. Epsilon-greedy policy – most likely selects the `greedy actions` but can select `random actions` too

- Ensures explorations
- Choose greedy action with 1- ϵ (epsilon)
- Choose random action with ϵ (epsilon)

In [10]:
```python
def epsilon_greedy_policy(Q, state, epsilon):
      # Q:          : state-action pair
      # State (int) : current state
      # eps (float): epsilon
    action = 0
    if random.uniform(0, 1) > epsilon: #exploitation
        action = np.argmax(Q[state,:])
    else: #exploration
        action = env.action_space.sample()
    return action
```

The algorithm takes nine arguments:

- `env` : This is an instance of an OpenAI Gym environment.
- `total_episodes` : This is the number of episodes that are generated through agent-environment interaction.
- `max_step` : This is the max number of interactions between agent and env. within a single episode.
- `epsilon` : This is to encourage exploration. Epsilon is decayed over time to discourage explortation and encourage exploitation once agent has explored different state.
- `max_epsilon` : This is the maximum value of epsilon.
- `min_epsilon` : This is the minimum value of epsilon.
- `decay_rate` : This is the decay rate for epsilon.
- `gamma` : This is the discount rate. It must be a value between 0 and 1, inclusive (default value: `1`).
- `plot_every` : This is additional argument to plot the cumulative reward against episodes.

The algorithm returns as output:

- `qtable` : This is an ndarray where `qtable[s][a]` is the estimated action value corresponding to state `s` and action `a` .

Task 5

- Fill the missing code to complete the Q-learning implementation.
- Write a condition to break the loop as soon as agent receives a reward of 0.78 or higher in 100 consecutive episodes.

```
In [12]: def q_learning(env, total_episodes, max_steps = 99, epsilon = 1.0, max_epsilon = 1.0, min_epsilon = 0.01, decay_rate = 0.005,  gamma
             rewards = []   # List of rewards
             tmp_scores = deque(maxlen=plot_every)     # deque for keeping track of scores
             avg_scores = deque(maxlen=total_episodes)   # average scores over every plot_every episodes
             for episode in range(total_episodes):
                 state = env.reset()#Reset the environment to the starting state
                 #step = 0
                 done = False
                 total_rewards = 0 # collected reward within an episode
                 if episode % 100 == 0: #monitor progress
                     print("\rEpisode {}/{}".format(episode, total_episodes), end="")

                 for step in range(max_steps):
                     action = epsilon_greedy_policy(qtable, state, epsilon)# call the epsilon greedy policy to obtain the actions
                     new_state, reward, done, info = env.step(action) #take the action and observe resulting reward and state.

                     # Update Q(s,a):= Q(s,a) + lr [R(s,a) + gamma * max Q(s',a') - Q(s,a)]
                     # qtable[new_state,:] : all the actions we can take from new state
                     qtable[state, action] = qtable[state, action] + learning_rate * (reward + gamma * np.max(qtable[new_state, :]) - qtable[

                     total_rewards += reward # sum the rewards collected within an episode
                     state = new_state # Our new state is state
                     if done == True: #done is true when agent fall into hole or reached the goal state
                         tmp_scores.append(total_rewards)  #for plot
                         break
                 if (episode % plot_every == 0): #for plot
                     avg_scores.append(np.mean(tmp_scores))

                     #....  #break the loop as soon as agent obtain the reward of 0.78 or higher in 100 consective episodes.
                 epsilon = min_epsilon + (max_epsilon - min_epsilon)*np.exp(-decay_rate*episode) # Reduce epsilon value to encourage expoitat
                 rewards.append(total_rewards)

             # plot performance
             plt.plot(np.linspace(0,total_episodes,len(avg_scores),endpoint=False), np.asarray(avg_scores))
             plt.xlabel('Episode Number')
             plt.ylabel('Average Reward (Over %d Episodes)' % plot_every)
             plt.show()
             # print best 100-episode performance
             print(('Best Average Reward over %d Episodes: ' % plot_every), np.max(avg_scores))
             return qtable
```

Part 4: Train the agent

Here comes the real part.

- We will train our agent using Q-learning algorithm defined above.

Task 6

- Call the Q-learning algorithm with appropriate hyperparameter setting.
- Find the hyper-parameters configuration to solve the environment in fewer than 5000 training episodes.

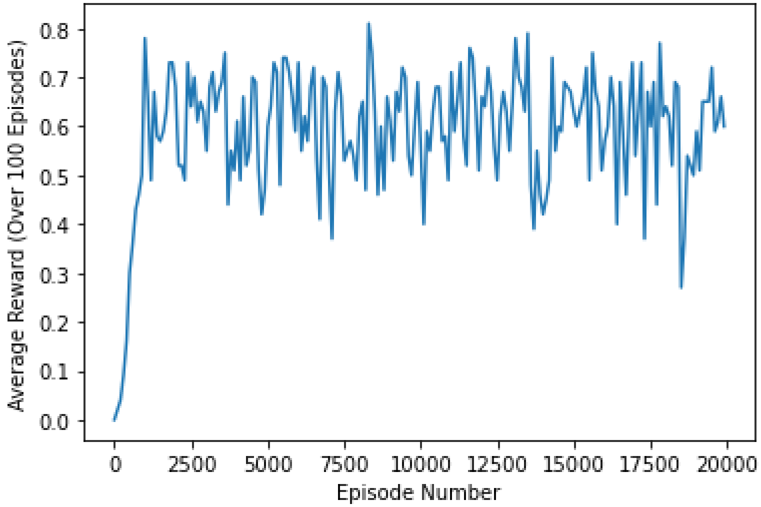
In [14]:

```
total_episodes = 20000        # Total episodes
learning_rate = 0.2#7           # Learning rate
max_steps = 99                # Max steps per episode
gamma = 0.95                  # Discounting rate

# Exploration parameters
epsilon = 1.0                  # Exploration rate
max_epsilon = 1.0              # Exploration probability at start
min_epsilon = 0.01             # Minimum exploration probability
decay_rate = 0.005             # Exponential decay rate for exploration prob
```

In [15]:
```
q_learning(env, total_episodes, epsilon = 1.0, gamma=0.95, plot_every=100)
```

```
Episode 19900/20000
```




```
Best Average Reward over 100 Episodes:  0.81
```

Out[15]:
```
array([[0.11285265, 0.1127035 , 0.12081788, 0.11258996],
       [0.0804557 , 0.08539748, 0.09183846, 0.10746259],
       [0.13313935, 0.08570335, 0.08118435, 0.08630615],
       [0.05659425, 0.        , 0.00628647, 0.00925518],
       [0.16011468, 0.09791253, 0.1149572 , 0.11499648],
       [0.        , 0.        , 0.        , 0.        ],
       [0.04374923, 0.02346374, 0.20086058, 0.02190949],
       [0.        , 0.        , 0.        , 0.        ],
       [0.12795146, 0.1078945 , 0.14285891, 0.24651516],
       [0.11899803, 0.39883064, 0.25187464, 0.23929691],
       [0.37072458, 0.14950281, 0.09749314, 0.20894068],
       [0.        , 0.        , 0.        , 0.        ],
       [0.        , 0.        , 0.        , 0.        ],
       [0.33624029, 0.32113925, 0.58188388, 0.19891305],
       [0.55960173, 0.81811091, 0.5142551 , 0.52468939],
       [0.        , 0.        , 0.        , 0.        ]])
```

Part 5: Action in Action! 🕹️

- After training, the agent has develop a Q-table can be used to play FrozenLake. The Q-table tells agent which action to take in each state.
- Run the code below to see our agent playing FrozenLake.

In [18]:

```python
env.reset()

for episode in range(5):
    state = env.reset()
    step = 0
    done = False
    print("********************")
    print("EPISODE ", episode)
    for step in range(max_steps):
        action = np.argmax(qtable[state,:])# Take the action (index) with maximum expected future reward given that state
        new_state, reward, done, info = env.step(action)
        if done:
            env.render()
            if new_state == 15:
                print("Goal 🏅")
            else:
                print("Hole 💀")
            # We print the number of step it took.
            print("Number of steps", step)
            break
        state = new_state
env.close()
```

```
********************
EPISODE  0
  (Down)
SFFF
FHFH
FFFH
HFFG
Goal 🏅
Number of steps 19
********************
EPISODE  1
  (Down)
SFFF
FHFH
FFFH
HFFG
Goal 🏅
Number of steps 87
********************
EPISODE  2
```

```
  (Down)
SFFF
FHFH
FFFH
HFFG
Goal 🏅
Number of steps 37
********************
EPISODE  3
  (Down)
SFFF
FHFH
FFFH
HFFG
Goal 🏅
Number of steps 29
********************
EPISODE  4
  (Right)
SFFF
FHFH
FFFH
HFFG
Hole 💀
Number of steps 23
```

```
In [ ]:
```