CS6700: Reinforcement Learning - Tutorial 4 (Q-Learning and SARSA)

Your tasks are as follows:

1. Complete code for ϵ-greedy and softmax action selection policy
2. Complete update equation for SARSA - train and visualize an agent
3. Analyze performance of SARSA - Plot total reward & steps taken per episode (averaged across 5 runs)
4. Complete update equation for Q-Learning - train and visualize an agent
5. Analyze performance of Q-Learning - Plot total reward & steps taken per episode (averaged across 5 runs)

```
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
from IPython.display import clear_output
%matplotlib inline
```

Problem Statement

In this section we will implement tabular SARSA and Q-learning algorithms for a grid world navigation task.

Environment details

The agent can move from one grid coordinate to one of its adjacent grids using one of the four actions: UP, DOWN, LEFT and RIGHT. The goal is to go from a randomly assigned starting position to goal position.

Actions that can result in taking the agent off the grid will not yield any effect. Lets look at the environment.

```
DOWN = 0
UP = 1
LEFT = 2
RIGHT = 3
actions = [DOWN, UP, LEFT, RIGHT]
```

Let us construct a grid in a text file.

```
!cat grid_world2.txt
```

```
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

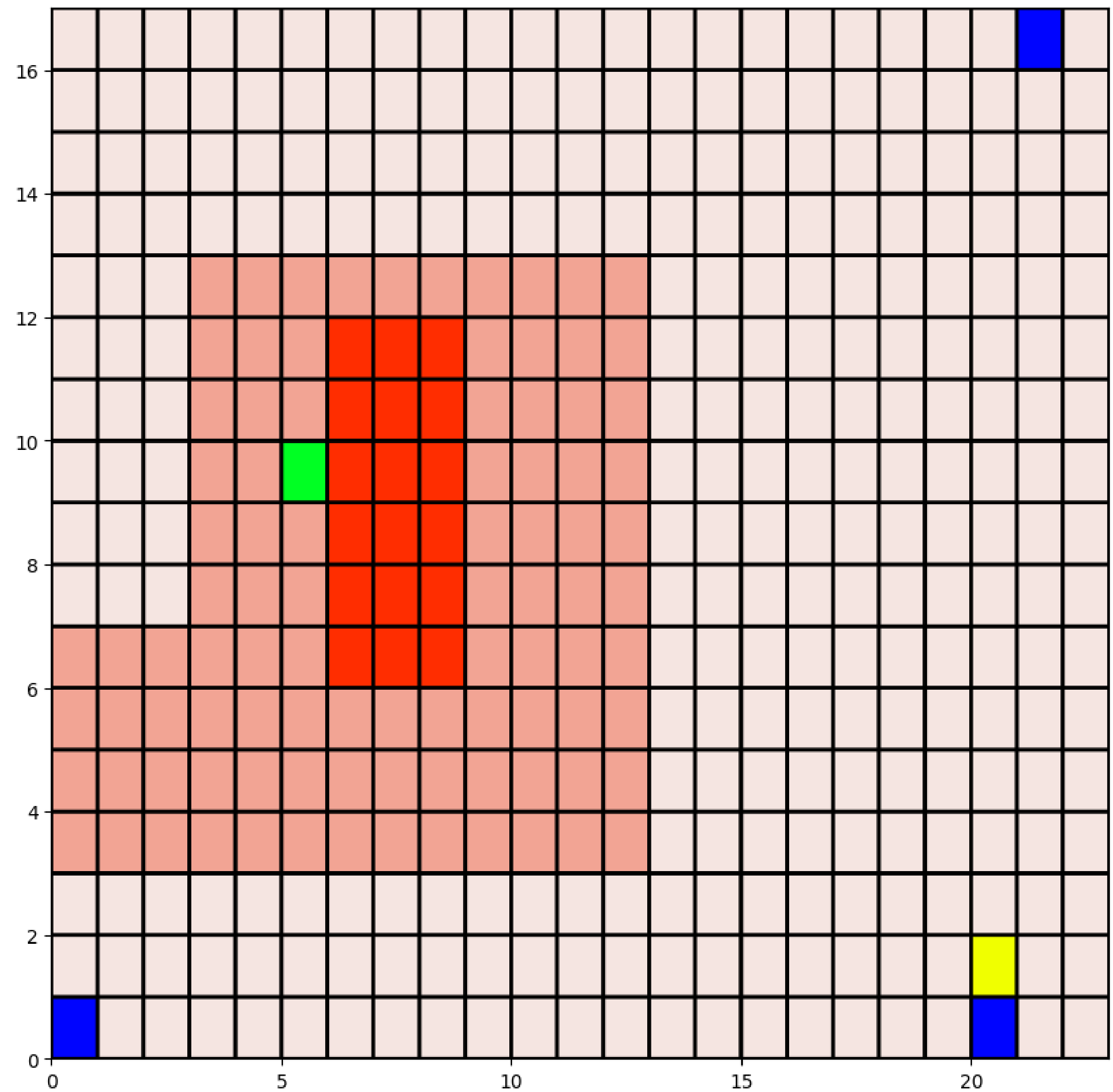
```
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 2 2 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 1 1 1 1 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
```

This is a 17×23 grid. The reward when an agent goes to a cell is negative of the value in that position in the text file (except if it is the goal cell). We will define the goal reward as 100. We will also fix the maximum episode length to 10000.

Now let's make it more difficult. We add stochasticity to the environment: with probability 0.2 agent takes a random action (which can be other than the chosen action). There is also a westerly wind blowing (to the right). Hence, after every time-step, with probability 0.5 the agent also moves an extra step to the right.

Now let's plot the grid world.

```python
from grid_world import GridWorldEnv, GridWorldWindyEnv
world = 'grid_world2.txt'
goal_reward = 100
start_states = [(0, 0), (0, 20), (16, 21)]
goal_states = [(9, 5)]
max_steps = 10000


env = GridWorldEnv(world, goal_reward=goal_reward,
start_states=start_states, goal_states=goal_states,
                   max_steps=max_steps, action_fail_prob=0.2)
plt.figure(figsize=(10, 10))
# Go UP
env.step(UP)
env.render(ax=plt, render_agent=True)
```



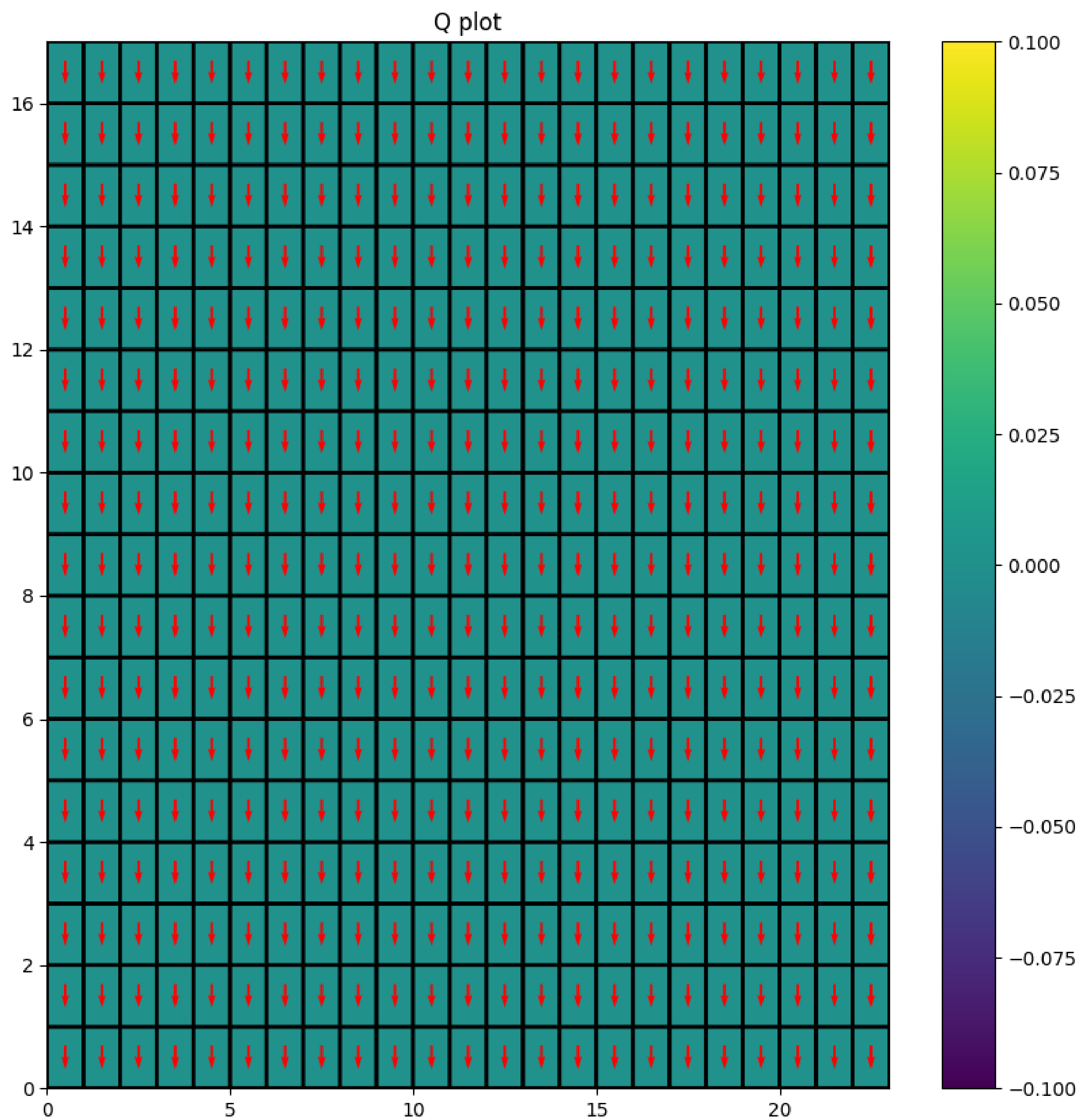
Legend

- *Blue* is the **start state**.
- *Green* is the **goal state**.
- *Yellow* is current **state of the agent**.
- *Redness* denotes the extent of **negative reward**.

Q values

We can use a 3D array to represent Q values. The first two indices are X, Y coordinates and last index is the action.

```python
from grid_world import plot_Q

Q = np.zeros((env.grid.shape[0], env.grid.shape[1],
len(env.action_space)))

plot_Q(Q)

Q.shape
```




```
(17, 23, 4)
```

Exploration strategies

1. Epsilon-greedy
2. Softmax

```
from scipy.special import softmax

seed = 42
rg = np.random.RandomState(seed)

# Epsilon greedy


def choose_action_epsilon(Q, state, epsilon=0.8, rg=rg):
    if np.random.rand() < epsilon:  # TODO: eps greedy condition
        return np.random.randint(len(Q[state[0]][state[1]]))
    else:
        return np.argmax(Q[state[0]][state[1]])  # TODO: return best
action

# Softmax

def choose_action_softmax(Q, state, rg=rg):
    logits = Q[state[0]][state[1]]
    probs = softmax(logits)
    action = rg.choice(len(probs), p=probs)

    return action  # TODO: return random action with selection
probability
```

SARSA

Now we implement the SARSA algorithm.

Recall the update rule for SARSA: \begin{equation} Q(s_t,a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \end{equation}

Hyperparameters

So we have som hyperparameters for the algorithm:

- α
- number of *episodes*.
- ϵ: For epsilon greedy exploration

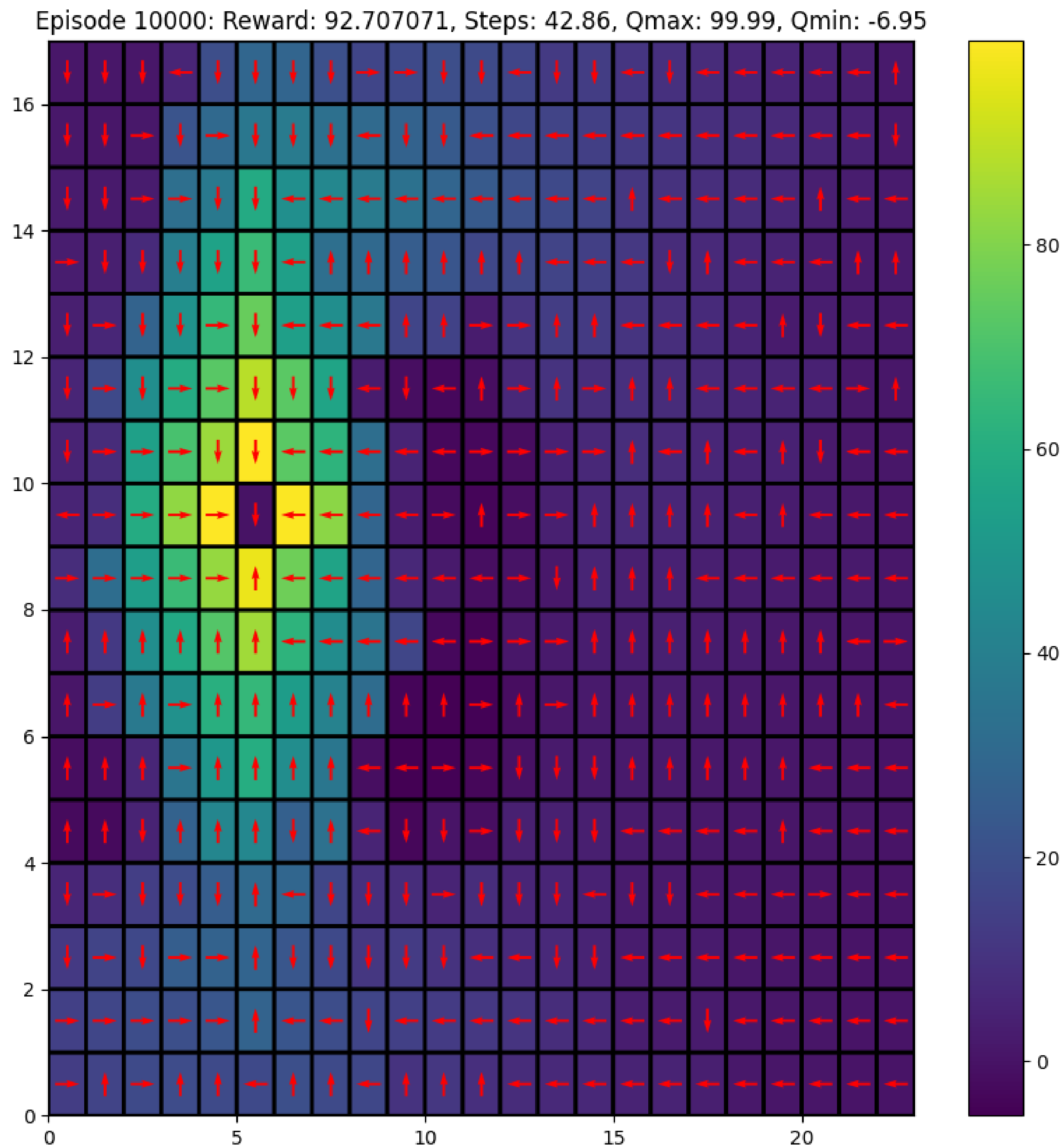
```
# initialize Q-value
Q = np.zeros((env.grid.shape[0], env.grid.shape[1],
len(env.action_space)))

alpha0 = 0.4
gamma = 0.9
```

```
episodes = 10000
epsilon0 = 0.1
```

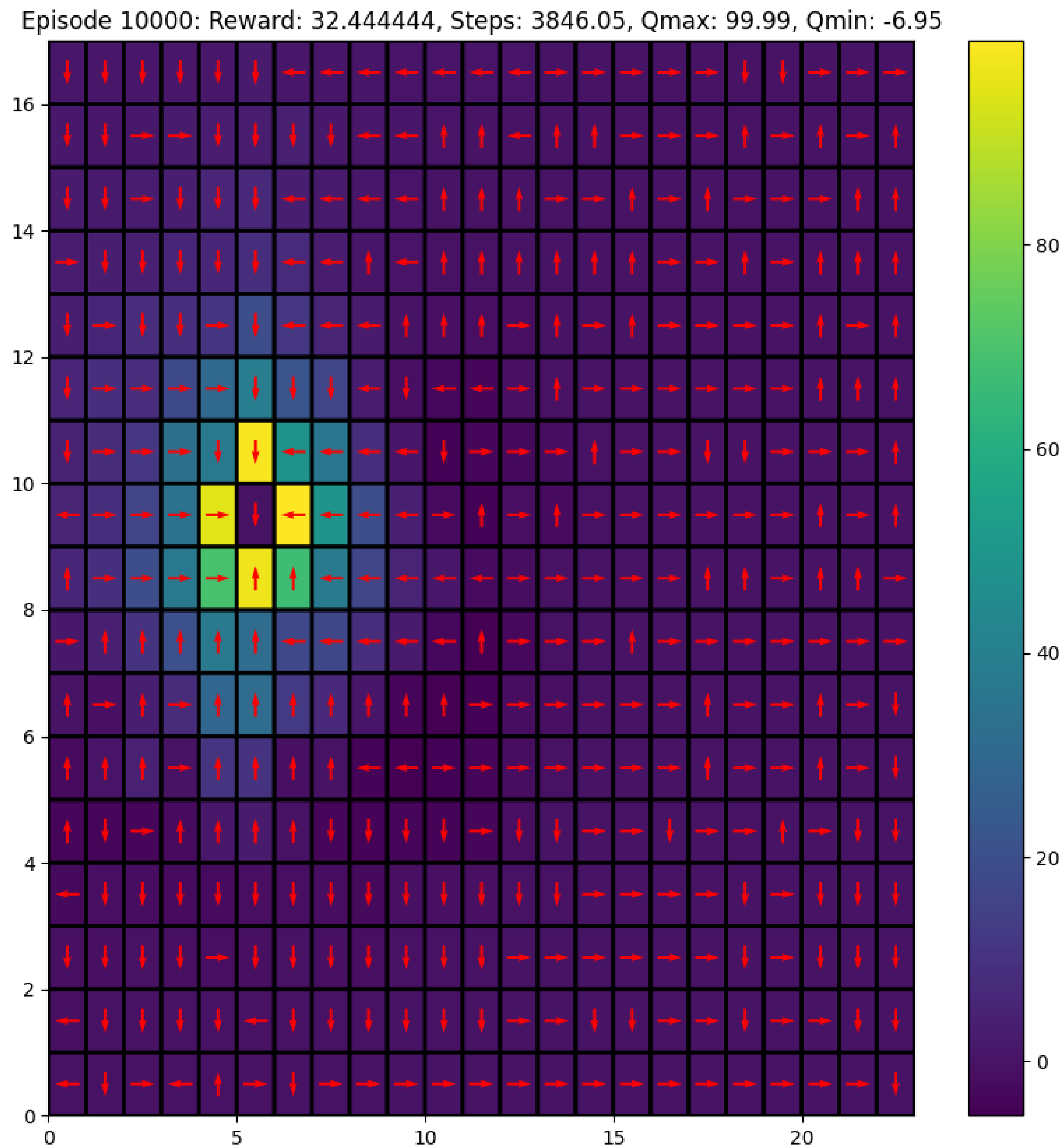
Let's implement SARSA

```
print_freq = 100


def sarsa(env, Q, gamma=0.9, plot_heat=False,
choose_action=choose_action_softmax):

    episode_rewards = np.zeros(episodes)
    steps_to_completion = np.zeros(episodes)
    if plot_heat:
        clear_output(wait=True)
        plot_Q(Q)
    epsilon = epsilon0
    alpha = alpha0
    for ep in tqdm(range(episodes)):
        tot_reward, steps = 0, 0

        # Reset environment
        state = env.reset()
        action = choose_action(Q, state)
        done = False
        while not done:
            state_next, reward, done = env.step(action)
            action_next = choose_action(Q, state_next)

            # TODO: update equation
            if state_next[0] == env.goal_states[0][0] and
state_next[1] == env.goal_states[0][1]:
                Q[state_next[0]][state_next[1]] = 0
            Q[state[0]][state[1]][action] += alpha*(reward +
gamma*Q[state_next[0]][state_next[1]][action_next] - Q[state[0]]
[state[1]][action])

            tot_reward += reward
            steps += 1

            state, action = state_next, action_next

        episode_rewards[ep] = tot_reward
        steps_to_completion[ep] = steps

        if (ep+1) % print_freq == 0 and plot_heat:
            clear_output(wait=True)
            plot_Q(Q, message="Episode %d: Reward: %f, Steps: %.2f,
Qmax: %.2f, Qmin: %.2f" % (ep+1, np.mean(episode_rewards[ep-
print_freq+1:ep]),
```

```
np.mean(

steps_to_completion[ep-print_freq+1:ep]),

Q.max(), Q.min()))

    return Q, episode_rewards, steps_to_completion

Q, rewards, steps = sarsa(
    env, Q, gamma=gamma, plot_heat=True,
choose_action=choose_action_softmax)
```




```
100%|██████████| 10000/10000 [00:33<00:00, 294.44it/s]

Q, rewards, steps = sarsa(
    env, Q, gamma=gamma, plot_heat=True,
choose_action=choose_action_epsilon)
```



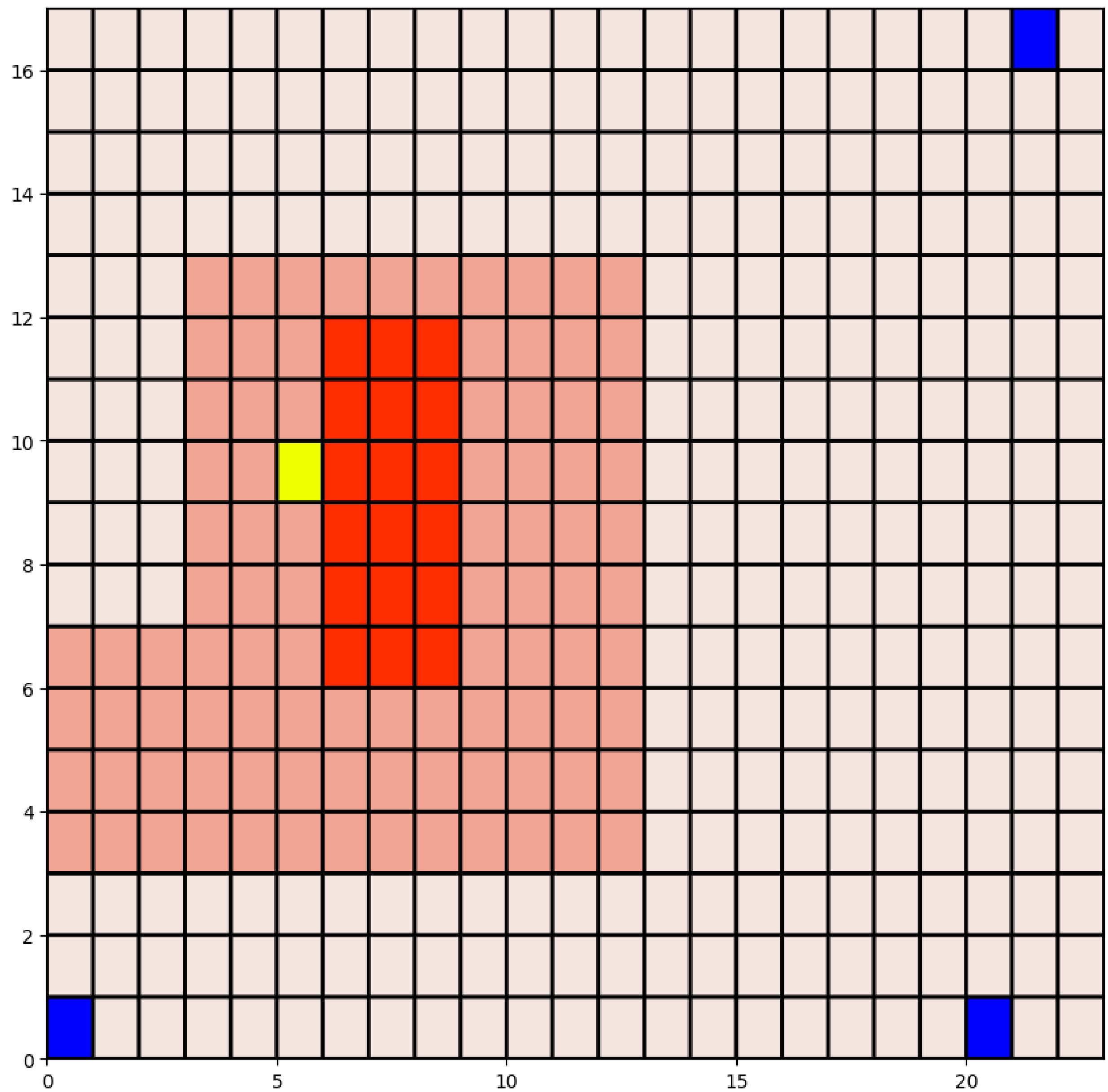

```
100%|██████████| 10000/10000 [04:24<00:00, 37.83it/s]
```

Visualizing the policy

Now let's see the agent in action. Run the below cell (as many times) to render the policy;

```
from time import sleep

state = env.reset()
```

```python
done = False
steps = 0
tot_reward = 0
while not done:
    clear_output(wait=True)
    state, reward, done = env.step(Q[state[0], state[1]].argmax())
    plt.figure(figsize=(10, 10))
    env.render(ax=plt, render_agent=True)
    plt.show()
    steps += 1
    tot_reward += reward
    sleep(0.2)
print("Steps: %d, Total Reward: %d" % (steps, tot_reward))
```




```
Steps: 16, Total Reward: 91
```

Analyzing performance of the policy

We use two metrics to analyze the policies:

1. Average steps to reach the goal
2. Total rewards from the episode

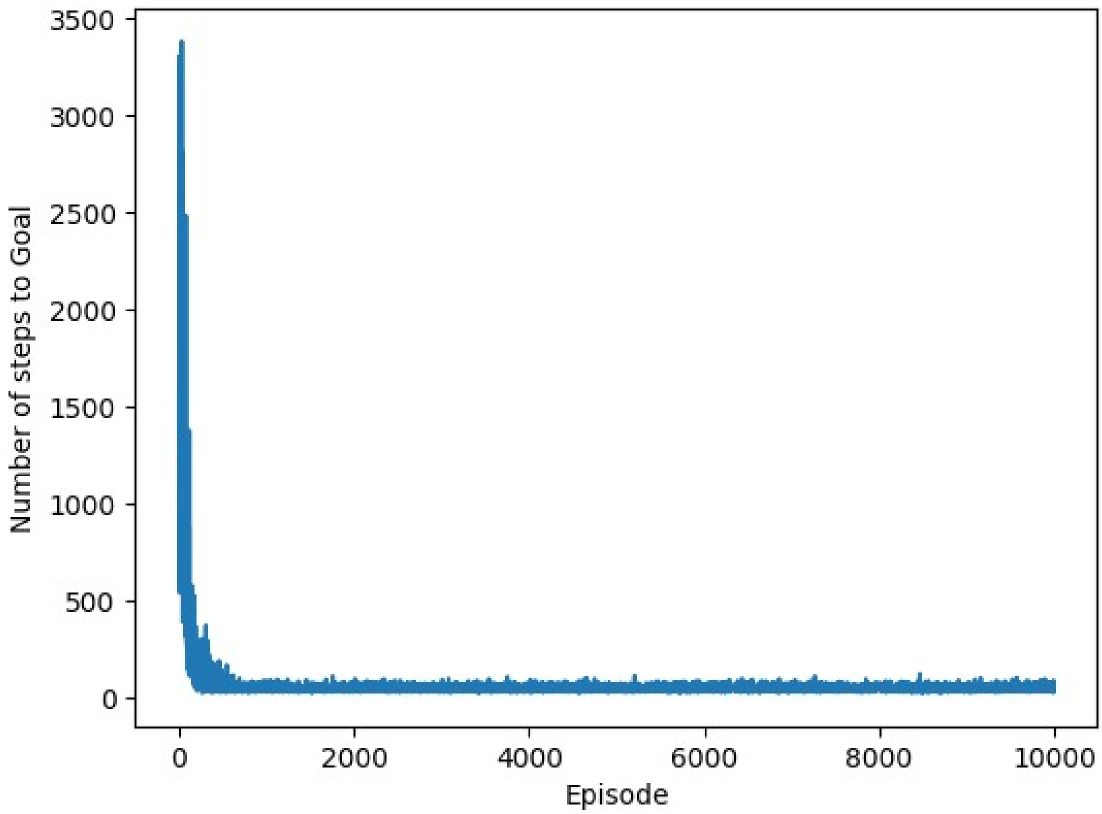
To ensure, we account for randomness in environment and algorithm (say when using epsilon-greedy exploration), we run the algorithm for multiple times and use the average of values over all runs.

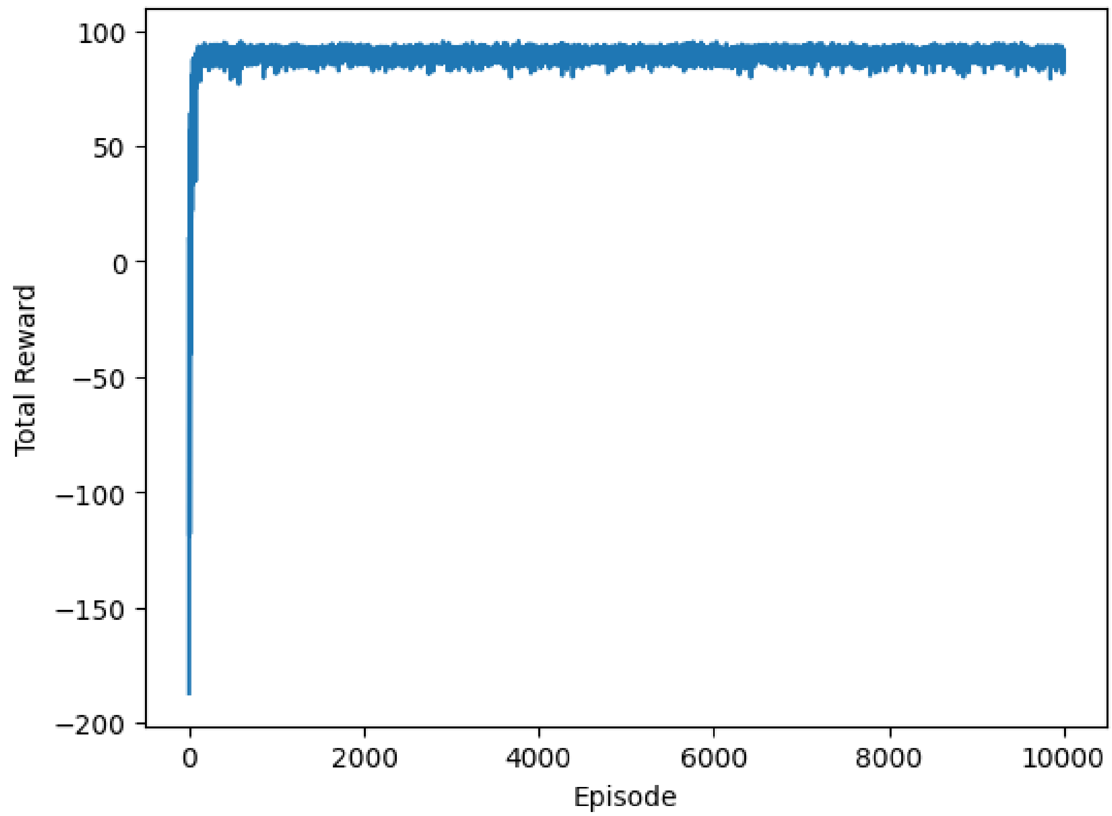
```
num_expts = 5
reward_avgs, steps_avgs = [], []

for i in range(num_expts):
    print("Experiment: %d" % (i+1))
    Q = np.zeros((env.grid.shape[0], env.grid.shape[1],
len(env.action_space)))
    rg = np.random.RandomState(i)

    # TODO: run sarsa, store metrics
    Q, rewards, steps = sarsa(
    env, Q, gamma=gamma, plot_heat=False,
choose_action=choose_action_softmax)
    reward_avgs.append(rewards)
    steps_avgs.append(steps)

reward_avgs = np.mean(reward_avgs,axis = 0)
steps_avgs = np.mean(steps_avgs,axis=0)
```

```
Experiment: 1

100%|██████████| 10000/10000 [00:19<00:00, 511.50it/s]

Experiment: 2

100%|██████████| 10000/10000 [00:20<00:00, 493.35it/s]

Experiment: 3

100%|██████████| 10000/10000 [00:18<00:00, 529.13it/s]

Experiment: 4

100%|██████████| 10000/10000 [00:21<00:00, 463.95it/s]

Experiment: 5

100%|██████████| 10000/10000 [00:21<00:00, 475.90it/s]
```

```
# TODO: visualize individual metrics vs episode count (averaged across
multiple run(s))

plt.figure()
plt.plot(steps_avgs)
plt.xlabel('Episode')
plt.ylabel('Number of steps to Goal')
plt.show()

plt.figure()
plt.plot(reward_avgs)
plt.xlabel('Episode')
```

```
plt.ylabel('Total Reward')
plt.show()
```





Q-Learning

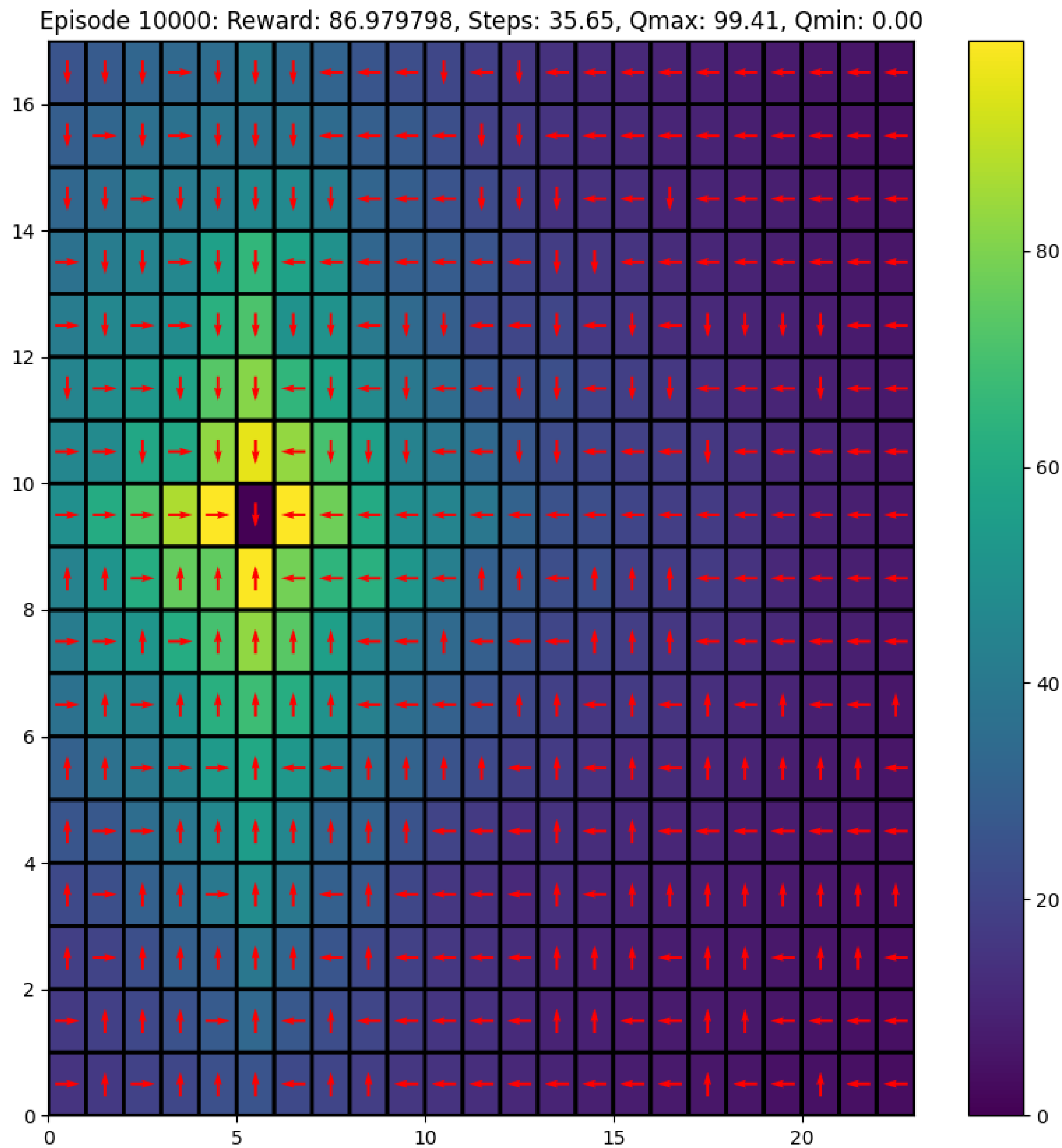
Now, implement the Q-Learning algorithm as an exercise.

Recall the update rule for Q-Learning: \begin{equation} Q(s*t,a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_a Q(s*{t+1}, a) - Q(s_t, a_t)] \end{equation}

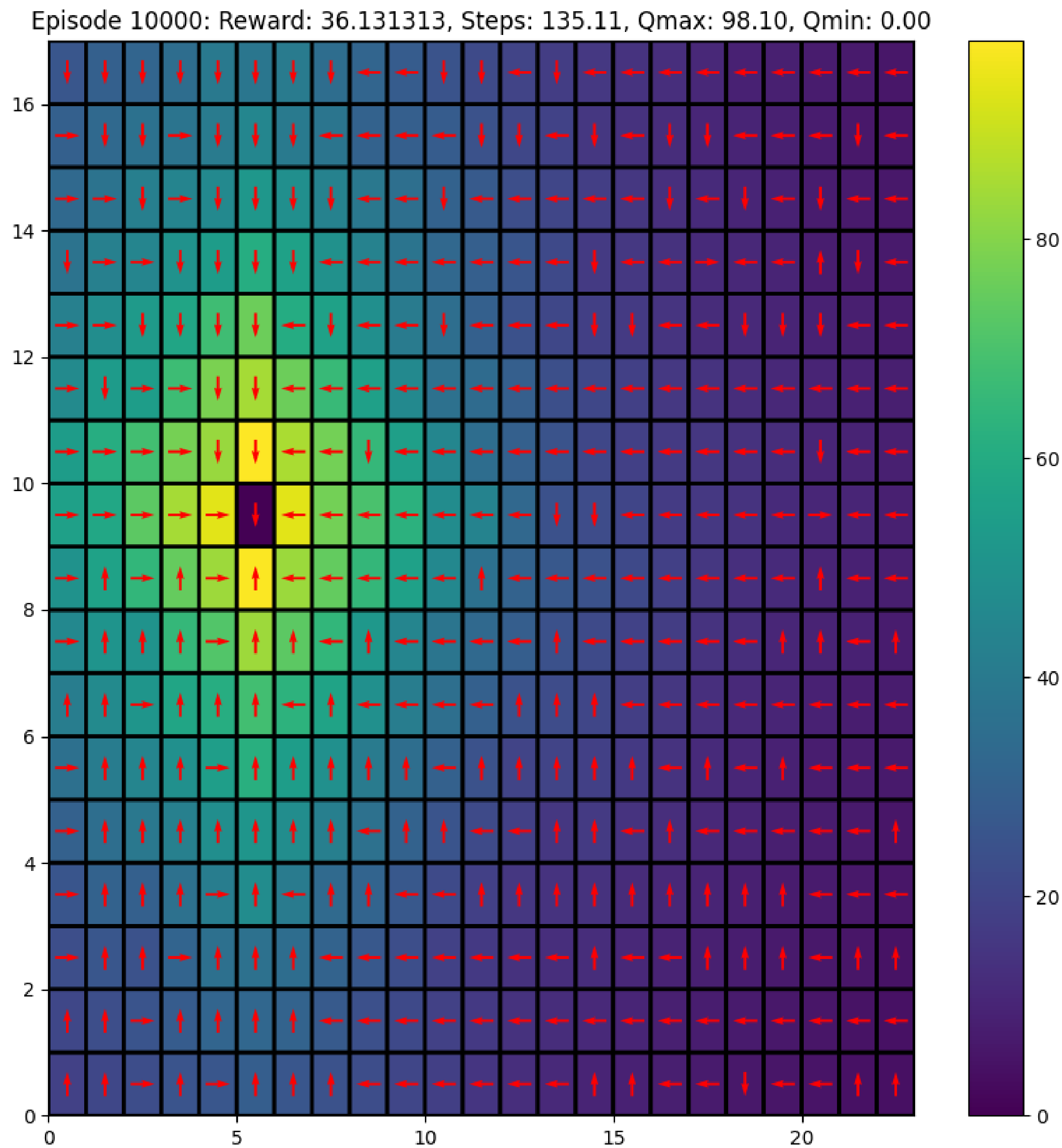
Visualize and compare results with SARSA.

```
# initialize Q-value
Q = np.zeros((env.grid.shape[0], env.grid.shape[1],
len(env.action_space)))

alpha0 = 0.4
gamma = 0.9
episodes = 10000
epsilon0 = 0.1

print_freq = 100


def qlearning(env, Q, gamma=0.9, plot_heat=False,
choose_action=choose_action_softmax):

    episode_rewards = np.zeros(episodes)
```

```
    steps_to_completion = np.zeros(episodes)
    if plot_heat:
        clear_output(wait=True)
        plot_Q(Q)
    epsilon = epsilon0
    alpha = alpha0
    for ep in tqdm(range(episodes)):
        tot_reward, steps = 0, 0

        # Reset environment
        state = env.reset()
        action = choose_action(Q, state)
        done = False
        while not done:
            state_next, reward, done = env.step(action)
            action_next = choose_action(Q, state_next)

            # TODO: update equation
            if state_next[0] == env.goal_states[0][0] and
state_next[1] == env.goal_states[0][1]:
                Q[state_next[0]][state_next[1]] = 0
            Q[state[0]][state[1]][action] += alpha*(reward +
gamma*np.max(Q[state_next[0]][state_next[1]]) - Q[state[0]][state[1]]
[action])

            tot_reward += reward
            steps += 1

            state, action = state_next, action_next

        episode_rewards[ep] = tot_reward
        steps_to_completion[ep] = steps

        if (ep+1) % print_freq == 0 and plot_heat:
            clear_output(wait=True)
            plot_Q(Q, message="Episode %d: Reward: %f, Steps: %.2f,
Qmax: %.2f, Qmin: %.2f" % (ep+1, np.mean(episode_rewards[ep-
print_freq+1:ep]),

np.mean(

steps_to_completion[ep-print_freq+1:ep]),

Q.max(), Q.min()))

    return Q, episode_rewards, steps_to_completion

Q, rewards, steps = qlearning(
    env, Q, gamma=gamma, plot_heat=True,
choose_action=choose_action_softmax)
```

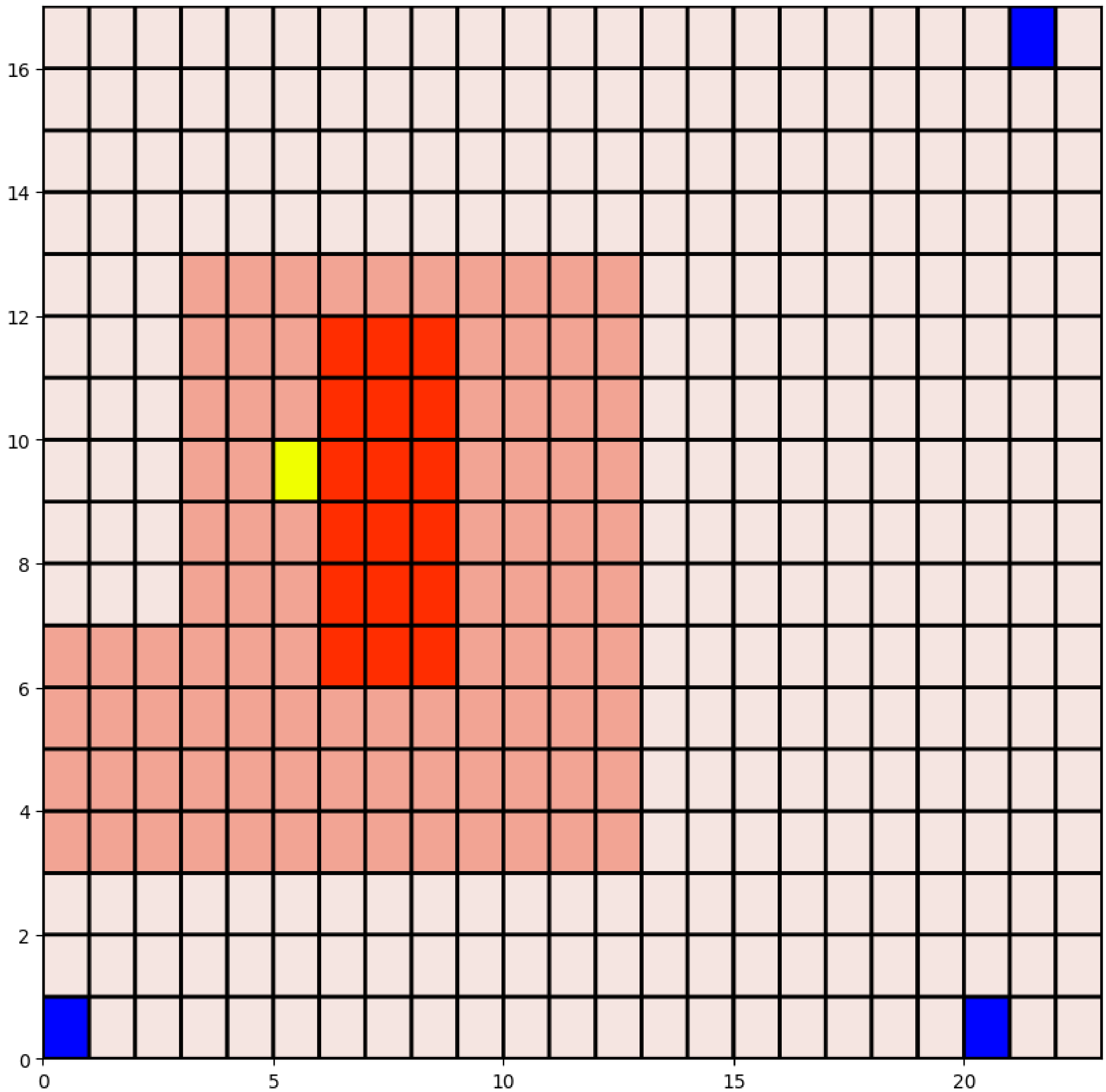



```
100%|██████████| 10000/10000 [00:29<00:00, 343.14it/s]

Q, rewards, steps = qlearning(
    env, Q, gamma=gamma, plot_heat=True,
choose_action=choose_action_epsilon)
```




```
100%|██████████| 10000/10000 [00:30<00:00, 331.71it/s]

from time import sleep

state = env.reset()
done = False
steps = 0
tot_reward = 0
while not done:
```

```
    clear_output(wait=True)
    state, reward, done = env.step(Q[state[0], state[1]].argmax())
    plt.figure(figsize=(10, 10))
    env.render(ax=plt, render_agent=True)
    plt.show()
    steps += 1
    tot_reward += reward
    sleep(0.2)
print("Steps: %d, Total Reward: %d" % (steps, tot_reward))
```



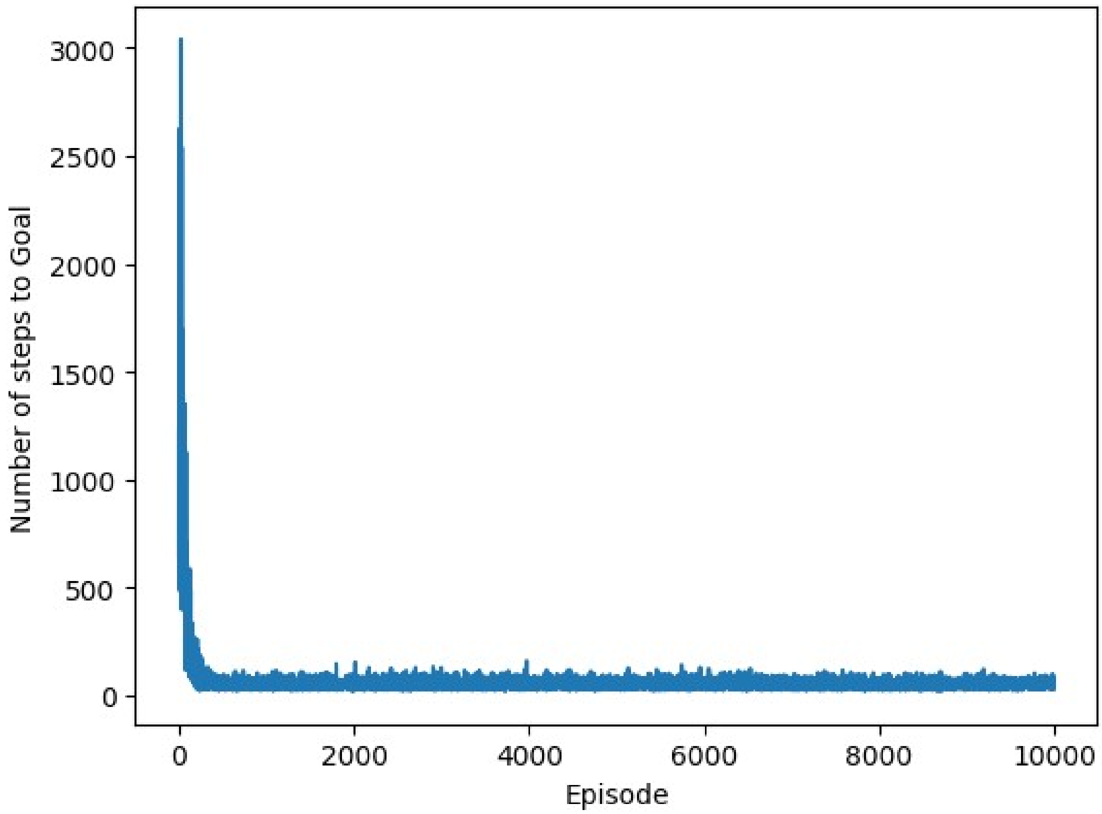

```
Steps: 22, Total Reward: 84
```

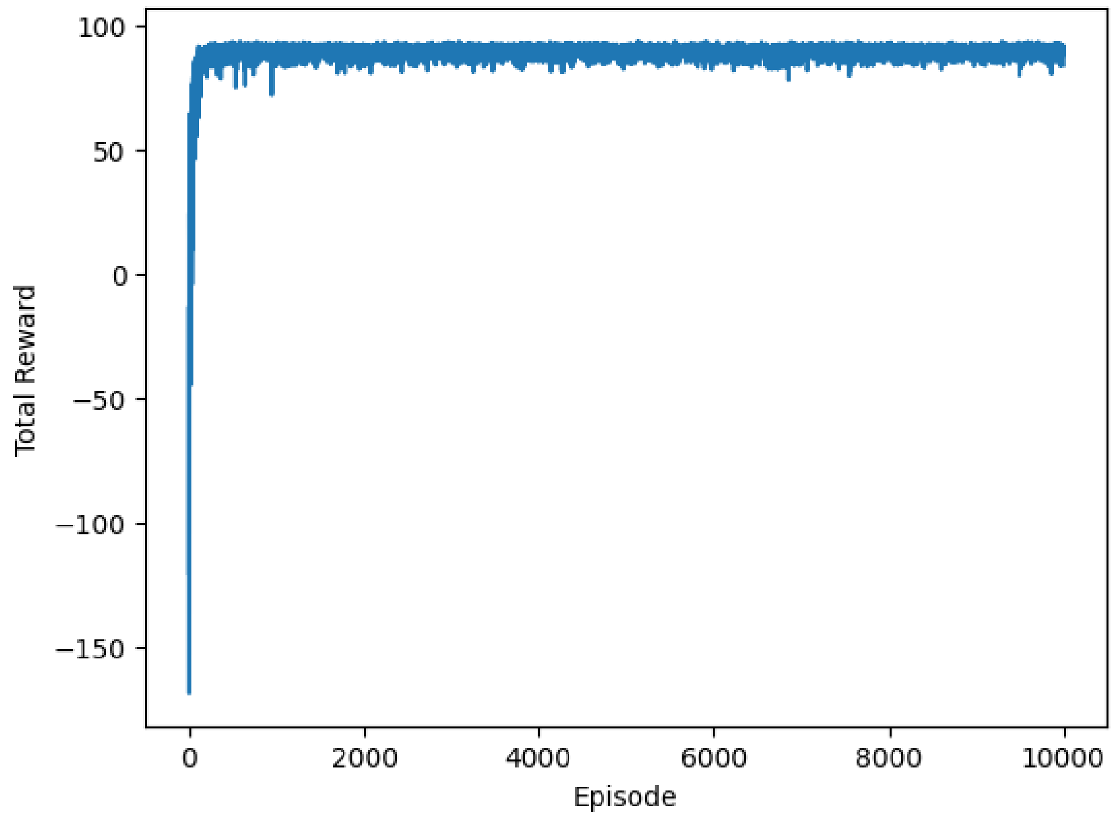
```
num_expts = 5
reward_avgs, steps_avgs = [], []

for i in range(num_expts):
    print("Experiment: %d" % (i+1))
    Q = np.zeros((env.grid.shape[0], env.grid.shape[1],
len(env.action_space)))
    rg = np.random.RandomState(i)

    # TODO: run qlearning, store metrics
    Q, rewards, steps = qlearning(
        env, Q, gamma=gamma, plot_heat=False,
choose_action=choose_action_softmax)
    reward_avgs.append(rewards)
    steps_avgs.append(steps)

reward_avgs = np.mean(reward_avgs,axis = 0)
steps_avgs = np.mean(steps_avgs,axis=0)
```

```
Experiment: 1

100%|██████████| 10000/10000 [00:29<00:00, 336.90it/s]

Experiment: 2

100%|██████████| 10000/10000 [00:16<00:00, 611.66it/s]

Experiment: 3

100%|██████████| 10000/10000 [00:24<00:00, 404.38it/s]

Experiment: 4

100%|██████████| 10000/10000 [00:20<00:00, 485.03it/s]

Experiment: 5

100%|██████████| 10000/10000 [00:22<00:00, 446.15it/s]
```

```
# TODO: visualize individual metrics vs episode count (averaged across
multiple run(s))

plt.figure()
plt.plot(steps_avgs)
plt.xlabel('Episode')
plt.ylabel('Number of steps to Goal')
plt.show()

plt.figure()
plt.plot(reward_avgs)
plt.xlabel('Episode')
```

```
plt.ylabel('Total Reward')
plt.show()
```





TODO: What differences do you observe between the policies learnt by Q Learning and SARSA (if any).

For the Q-learning implementation the epsilon greedy policy adapts well with a fixed epsilon value, while as the SARSA with a fixed epsilon value isn't able to optimize the result to reach the goal in a well manner, where as the softmax policy performed well in both the cases while applying it with the SARSA and Q-learning. The Q-learning updating the policy is learned through the greedy approach usualy, while for SARSA it learns through the policy that it takes during the learning phase.

```
!pip install nbconvert
!sudo apt-get install texlive-xetex texlive-fonts-recommended texlive-plain-generic

!jupyter nbconvert --to html "/content/drive/MyDrive/Colab Notebooks/CS6700_Tutorial_4_QLearning_SARSA_ROLLNUMBER.ipynb"
```