hw4_Q2

April 4, 2021

[4]:
```python
import numpy as np
import copy
import math

ACTION_MEANING = {
    0: "UP",
    1: "RIGHT",
    2: "LEFT",
    3: "DOWN",
}

SPACE_MEANING = {
    1: "ROAD",
    0: "BARRIER",
    -1: "GOAL",
}


class MazeEnv:

    def __init__(self, start=[6,3], goals=[[1, 8]]):
        """Deterministic Maze Environment"""

        self.m_size = 10
        self.reward = 10
        self.num_actions = 4
        self.num_states = self.m_size * self.m_size

        self.map = np.ones((self.m_size, self.m_size))
        self.map[3, 4:9] = 0
        self.map[4:8, 4] = 0
        self.map[5, 2:4] = 0

        for goal in goals:
            self.map[goal[0], goal[1]] = -1

        self.start = start
```

```python
        self.goals = goals
        self.obs = self.start

    def step(self, a):
        """ Perform a action on the environment

            Args:
                a (int): action integer

            Returns:
                obs (list): observation list
                reward (int): reward for such action
                done (int): whether the goal is reached
        """
        done, reward = False, 0.0
        next_obs = copy.copy(self.obs)

        if a == 0:
            next_obs[0] = next_obs[0] - 1
        elif a == 1:
            next_obs[1] = next_obs[1] + 1
        elif a == 2:
            next_obs[1] = next_obs[1] - 1
        elif a == 3:
            next_obs[0] = next_obs[0] + 1
        else:
            raise Exception("Action is Not Valid")

        if self.is_valid_obs(next_obs):
            self.obs = next_obs

        if self.map[self.obs[0], self.obs[1]] == -1:
            reward = self.reward
            done = True

        state = self.get_state_from_coords(self.obs[0], self.obs[1])

        return state, reward, done

    def is_valid_obs(self, obs):
        """ Check whether the observation is valid

            Args:
                obs (list): observation [x, y]

            Returns:
                is_valid (bool)
```

```python
        """

        if obs[0] >= self.m_size or obs[0] < 0:
            return False

        if obs[1] >= self.m_size or obs[1] < 0:
            return False

        if self.map[obs[0], obs[1]] == 0:
            return False

        return True

    @property
    def _get_obs(self):
        """ Get current observation
        """
        return self.obs

    @property
    def _get_state(self):
        """ Get current observation
        """
        return self.get_state_from_coords(self.obs[0], self.obs[1])

    @property
    def _get_start_state(self):
        """ Get the start state
        """
        return self.get_state_from_coords(self.start[0], self.start[1])

    @property
    def _get_goal_state(self):
        """ Get the start state
        """
        goals = []
        for goal in self.goals:
            goals.append(self.get_state_from_coords(goal[0], goal[1]))
        return goals

    def reset(self):
        """ Reset the observation into starting point
        """
        self.obs = self.start
        state = self.get_state_from_coords(self.obs[0], self.obs[1])
        return state
```

```python
    def get_state_from_coords(self, row, col):
        state = row * self.m_size + col
        return state

    def get_coords_from_state(self, state):
        row = math.floor(state/self.m_size)
        col = state % self.m_size
        return row, col


class ProbabilisticMazeEnv(MazeEnv):
    """ (Q2.3) Hints: you can refer the implementation in MazeEnv
    """

    def __init__(self, goals=[[2, 8]], p_random=0.05):
        """ Probabilistic Maze Environment

            Args:
                goals (list): list of goals coordinates
                p_random (float): random action rate
        """

        pass

    def step(self, a):
        pass
```

[6]:
```python
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
# from qlearning import *
# from maze import *

#  UTILITY FUNCTIONS


color_cycle = ['#377eb8', '#ff7f00', '#a65628',
               '#f781bf','#4daf4a',  '#984ea3',
               '#999999', '#e41a1c', '#dede00']

def plot_steps_vs_iters(steps_vs_iters, block_size=10):
    num_iters = len(steps_vs_iters)
    block_size = 10
    num_blocks = num_iters // block_size
    smooted_data = np.zeros(shape=(num_blocks, 1))
    for i in range(num_blocks):
        lower = i * block_size
```

```
        upper = lower + 9
        smooted_data[i] = np.mean(steps_vs_iters[lower:upper])

    plt.figure()
    plt.title("Steps to goal vs episodes")
    plt.ylabel("Steps to goal")
    plt.xlabel("Episodes")
    plt.plot(np.arange(1,num_iters,block_size), smooted_data,␣
 ↪color=color_cycle[0])

    return

def plot_several_steps_vs_iters(steps_vs_iters_list, label_list, block_size=10):
    smooted_data_list = []
    for steps_vs_iters in steps_vs_iters_list:
        num_iters = len(steps_vs_iters)
        block_size = 10
        num_blocks = num_iters // block_size
        smooted_data = np.zeros(shape=(num_blocks, 1))
        for i in range(num_blocks):
            lower = i * block_size
            upper = lower + 9
            smooted_data[i] = np.mean(steps_vs_iters[lower:upper])
        smooted_data_list.append(smooted_data)

    plt.figure()
    plt.title("Steps to goal vs episodes")
    plt.ylabel("Steps to goal")
    plt.xlabel("Episodes")
    index = 0
    for label, smooted_data in zip(label_list, smooted_data_list):
        plt.plot(np.arange(1,num_iters,block_size), smooted_data, label=label,␣
 ↪color=color_cycle[index])
        index += 1
    plt.legend()

    return


# this function sets color values for
# Q table cells depending on expected reward value
def get_color(value, min_val, max_val):

    switcher={
                0:'gray',
                1:'indigo',
                2:'darkmagenta',
```

```
                3:'orchid',
                4:'lightpink',
             }

    step = (max_val-min_val)/5
    i = 0
    color='lightpink'

    for limit in np.arange(min_val, max_val, step):
        if limit <= value < limit+step:
            color = switcher.get(i)
        i+=1
    return color



# get first cell out of the start state
def get_next_cell(x1,x2,heatmap,policy_table,xlim=9,ylim=9):
    up_reward=-10000
    down_reward=-10000
    left_reward=-10000
    right_reward=-10000

    if (x1<ylim):
        if (policy_table[x1-1][x2]!=3):
            up_reward = heatmap[x1-1][x2]
    else:
        up_reward = -1000

    if (x1>0):
        if (policy_table[x1+1][x2]!=0):
            down_reward = heatmap[x1+1][x2]
    else:
        down_reward = -1000

    if (x2>0):
        if (policy_table[x1][x2-1]!=1):
            left_reward = heatmap[x1][x2-1]

    else:
        left_reward = -1000

    if (x2<xlim):
        if (policy_table[x1][x2+1]!=2):
            right_reward = heatmap[x1][x2+1]

    else:
```

```
        right_reward = -1000

    rewards = np.array([up_reward, down_reward, left_reward, right_reward])
    idx = np.argmax(rewards)
    next_cell = [(x1-1,x2), (x1+1,x2), (x1,x2-1), (x1,x2+1)][idx]
    choice = ['up', 'down', 'left', 'right']
    #print ('picking ',choice[idx])
    return next_cell




# get coordinates of the cells
# on the way from the start to goal state
def get_path(x1,x2, policy_table):
    x_coords = [x1]
    y_coords = [x2]
    x1_new = x1
    x2_new = x2

    i=0
    num_steps = 0
    total_cells = len(policy_table)*len(policy_table[0])
    while (policy_table[x1][x2]!='G') and num_steps < total_cells:
        if (policy_table[x1][x2]==1): # right
            x2_new=x2+1
            #print(i, ' - moving right')

        elif (policy_table[x1][x2]==0):
            x1_new=x1-1
            #print(i, ' - moving up')

        elif (policy_table[x1][x2]==3):
            x1_new=x1+1
            #print(i, ' - moving down')

        elif (policy_table[x1][x2]==2):
            x2_new=x2-1
            #print(i, ' - moving left')

        x1 = x1_new
        x2 = x2_new
        x_coords.append(x1)
        y_coords.append(x2)
        num_steps += 1
    return x_coords, y_coords
```

```
# plot Q table
# optimal path is highlighted and cells colored by their values
def plot_table(env, table_data, heatmap, goal_states, start_state, max_val,␣
↪min_val, x_coords, y_coords):
    fig = plt.figure(dpi=80)
    ax = fig.add_subplot(1,1,1)
    plt.figure(figsize=(10,10))

    width = len(table_data[0])
    height = len(table_data)

    new_table = []

    for i in range(height):
        new_row = []

        for j in range(width):
            if env.map[i][j] == 0:
                new_row.append('')
            else:
                digit = table_data[i][j]
                if (digit==0):
                    new_row.append('\u2191') # up
                elif (digit==1):
                    new_row.append('\u2192') # right
                elif (digit==2):
                    new_row.append('\u2190') # left
                elif (digit==3):
                    new_row.append('\u2193') # down
                elif (digit=='G'):
                    new_row.append('G') # goal state
                elif (digit=='S'):
                    new_row.append('S') # goal state
                elif (digit==-1):
                    new_row.append('+') # All four directions
                else:
                    new_row.append('x') # unknown

        new_table.append(new_row)

    table = ax.table(cellText=new_table, loc='center',cellLoc='center')

    table.scale(1,2)

    for i in range(height):
```

```
        new_row = []

        for j in range(width):
            if new_table[i][j] == '':
                table[i, j].set_facecolor('black')
            else:
                table[i, j].
↪set_facecolor(get_color(heatmap[i][j],min_val,max_val))

    for goal_state in goal_states:
        table[(goal_state[0], goal_state[1])].set_facecolor("limegreen")
    table[(start_state[0], start_state[1])].set_facecolor("yellow")
    ax.axis('off')
    table.set_fontsize(16)

    for i in range(len(x_coords)):
        table[(x_coords[i], y_coords[i])].get_text().set_color('red')
    plt.show()


# this function takes 3D Q table as an input
# and outputs optimal trajectory table (policy table)
# and corresponding excpected reward values of different cells (heatmap)
def get_policy_table(q_hat_3D, start_state, goal_states):
    policy_table = []
    heatmap = []

    for i in range(q_hat_3D.shape[0]):
        row = []
        heatmap_row = []
        for j in range(q_hat_3D.shape[1]):

            heatmap_row.append(np.max(q_hat_3D[i,j,:]))

            for goal_state in goal_states:
                if (goal_state[0]==i) and (goal_state[1]==j):
                    row.append('G')

            if (start_state[0]==i) and (start_state[1]==j):
                row.append('S')
            else:
                if np.max(q_hat_3D[i,j,:]) == 0:
                    row.append(-1) # All zeros
                else:
                    row.append(np.argmax(q_hat_3D[i,j,:]))
        policy_table.append(row)
        heatmap.append(heatmap_row)
```

```
    return policy_table, heatmap

def plot_policy_from_q(q_hat, env):
    q_hat_3D = np.reshape(q_hat, (env.m_size, env.m_size, env.num_actions))
    max_val = q_hat_3D.max()
    min_val = q_hat_3D.min()
    start_state = env.get_coords_from_state(env._get_start_state)
    goal_states = env._get_goal_state
    goal_states = [env.get_coords_from_state(goal_state) for goal_state in␣
 ↪goal_states]
    policy_table, heatmap = get_policy_table(q_hat_3D, start_state, goal_states)
    x,y = get_next_cell(start_state[0],start_state[1],heatmap,policy_table)
    x_coords, y_coords = get_path(x,y,policy_table)
    plot_table(env, policy_table, heatmap, goal_states,␣
 ↪start_state,max_val,min_val, x_coords, y_coords)

    return
```

[20]:

```
import numpy as np
import math
import copy

def qlearn(env, num_iters, alpha, gamma, epsilon, max_steps,␣
 ↪use_softmax_policy, init_beta=None, k_exp_sched=None):
    """ Runs tabular Q learning algorithm for stochastic environment.

    Args:
        env: instance of environment object
        num_iters (int): Number of episodes to run Q-learning algorithm
        alpha (float): The learning rate between [0,1]
        gamma (float): Discount factor, between [0,1)
        epsilon (float): Probability in [0,1] that the agent selects a random␣
 ↪move instead of
                selecting greedily from Q value
        max_steps (int): Maximum number of steps in the environment per episode
        use_softmax_policy (bool): Whether to use softmax policy (True) or␣
 ↪Epsilon-Greedy (False)
        init_beta (float): If using stochastic policy, sets the initial beta as␣
 ↪the parameter for the softmax
        k_exp_sched (float): If using stochastic policy, sets hyperparameter␣
 ↪for exponential schedule
            on beta

    Returns:
```

```
        q_hat: A Q-value table shaped [num_states, num_actions] for environment
with with num_states
            number of states (e.g. num rows * num columns for grid) and
num_actions number of possible
            actions (e.g. 4 actions up/down/left/right)
        steps_vs_iters: An array of size num_iters. Each element denotes the
number
            of steps in the environment that the agent took to get to the goal
            (capped to max_steps)
    """
    action_space_size = env.num_actions
    state_space_size = env.num_states
    q_hat = np.zeros(shape=(state_space_size, action_space_size))
    steps_vs_iters = np.zeros(num_iters)

    for i in range(num_iters):
        # TODO: Initialize current state by resetting the environment
        curr_state = env.reset()
        num_steps = 0
        done = False

        # TODO: Keep looping while environment isn't done and less than maximum
steps
        while (num_steps < max_steps) and not done:
            num_steps += 1

            # Choose an action using policy derived from either softmax Q-value
            # or epsilon greedy
            if use_softmax_policy:
                assert(init_beta is not None)
                assert(k_exp_sched is not None)
                # TODO: Boltzmann stochastic policy (softmax policy)
                beta = beta_exp_schedule(init_beta, i, k=k_exp_sched) # Call
beta_exp_schedule to get the current beta value
                action = softmax_policy(q_hat, beta, curr_state)
            else:
                # TODO: Epsilon-greedy
                action = epsilon_greedy(q_hat, epsilon, curr_state,
action_space_size)

            # TODO: Execute action in the environment and observe the next
state, reward, and done flag
            next_state, reward, done = env.step(action)

            # TODO: Update Q_value
            if next_state != curr_state:
```

```
                new_value = reward + gamma * np.max(q_hat[next_state, :]) -␣
↪q_hat[curr_state, action]
                # TODO: Use Q-learning rule to update q_hat for the curr_state␣
↪and action:
                # i.e., Q(s,a) <- Q(s,a) + alpha*[reward + gamma *␣
↪max_a'(Q(s',a')) - Q(s,a)]
                q_hat[curr_state, action] = q_hat[curr_state, action] + alpha *␣
↪new_value

                # TODO: Update the current staet to be the next state
                curr_state = next_state

        steps_vs_iters[i] = num_steps

    return q_hat, steps_vs_iters


def epsilon_greedy(q_hat, epsilon, state, action_space_size):
    """ Chooses a random action with p_rand_move probability,
    otherwise choose the action with highest Q value for
    current observation

    Args:
        q_hat: A Q-value table shaped [num_rows, num_col, num_actions] for
            grid environment with num_rows rows and num_col columns and␣
↪num_actions
            number of possible actions
        epsilon (float): Probability in [0,1] that the agent selects a random
            move instead of selecting greedily from Q value
        state: A 2-element array with integer element denoting the row and␣
↪column
            that the agent is in
        action_space_size (int): number of possible actions

    Returns:
        action (int): A number in the range [0, action_space_size-1]
            denoting the action the agent will take
    """
    # TODO: Implement your code here
    # Hint: Sample from a uniform distribution and check if the sample is below
    # a certain threshold

    q_s = q_hat[state]
    # Q values for 4 actions are all zeros
    if np.all(q_s==0):
        return np.random.randint(action_space_size)
```

```python
    # Epsilon-greedy
    if np.random.uniform(0, 1) < epsilon:
        # a random action with p_rand_move probability
        return np.random.randint(action_space_size)
    else:
        # choose the action with highest Q value for current observation
        return np.argmax(q_s)

def softmax_policy(q_hat, beta, state):
    """ Choose action using policy derived from Q, using
    softmax of the Q values divided by the temperature.

    Args:
        q_hat: A Q-value table shaped [num_rows, num_col, num_actions] for
            grid environment with num_rows rows and num_col columns
        beta (float): Parameter for controlling the stochasticity of the action
        obs: A 2-element array with integer element denoting the row and column
            that the agent is in

    Returns:
        action (int): A number in the range [0, action_space_size-1]
            denoting the action the agent will take
    """
    # TODO: Implement your code here
    # Hint: use the stable_softmax function defined below
    q_s = q_hat[state] # action using policy derived from Q
    # using softmax of the Q values divided by the temperature
    softmax_q_s = stable_softmax(beta * q_s, axis=0)

    return np.random.choice(4, p=softmax_q_s)

def beta_exp_schedule(init_beta, iteration, k=0.1):
   beta = init_beta * np.exp(k * iteration)
   return beta

def stable_softmax(x, axis=2):
    """ Numerically stable softmax:
    softmax(x) = e^x /(sum(e^x))
               = e^x / (e^max(x) * sum(e^x/e^max(x)))

    Args:
        x: An N-dimensional array of floats
        axis: The axis for normalizing over.

    Returns:
        output: softmax(x) along the specified dimension
```

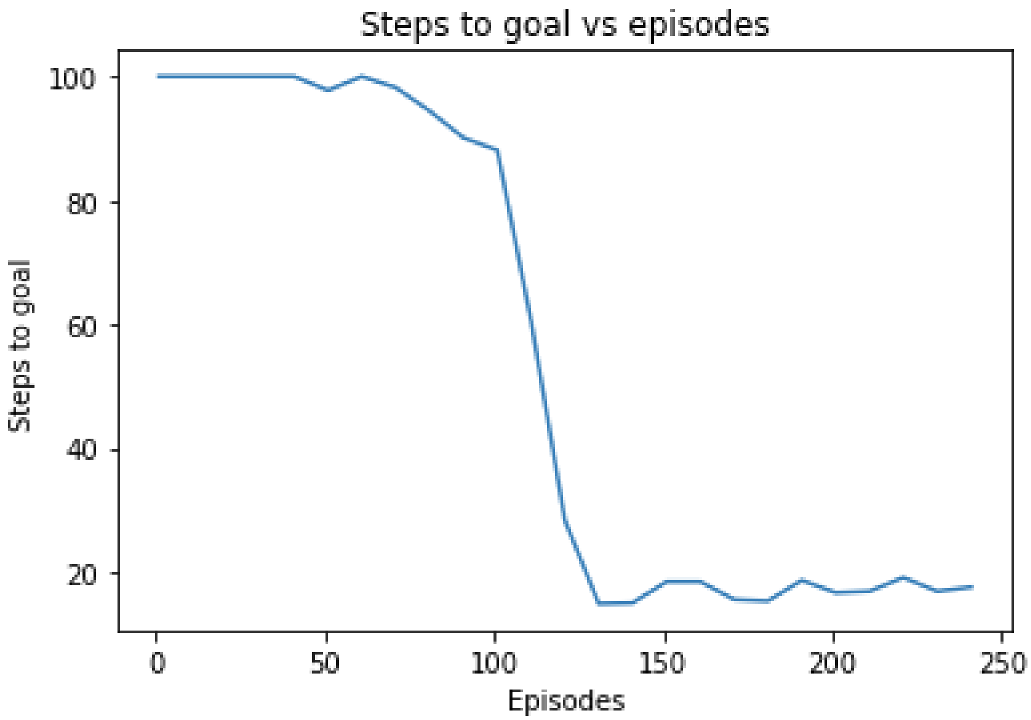
```
    """
    max_x = np.max(x, axis, keepdims=True)
    z = np.exp(x - max_x)
    output = z / np.sum(z, axis, keepdims=True)

    return output
```

2.1 You should implement a Q learning algorithm that selects moves for the agent. The algorithm should perform exploration by choosing the action with the maximum Q value 90% of the time, and choosing one of the four actions at random the remaining 10% of the time. We should "break-ties" when the Q-values are zero for all the actions (happens initially) by essentially choosing uniformly from the action. So now you have two conditions to act randomly: for amount of the time, or if the Q values are all zero.

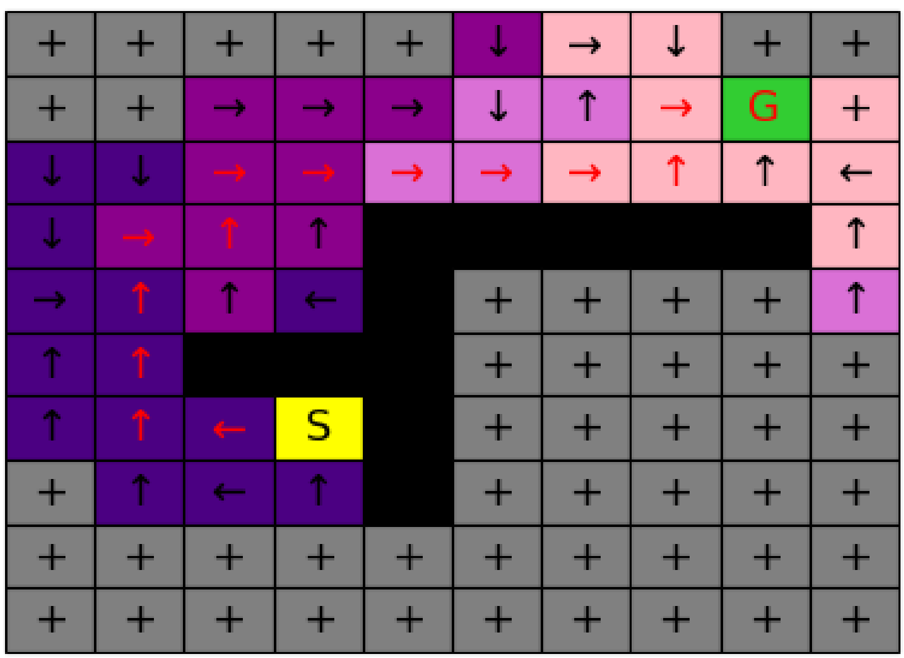
The simulation consist of a series of trials, each of which runs until the agent reaches the goal state, or until it reaches a maximum number of steps, which you can set to 100. The reward at the goal is 10, but at every other state is 0. You can set the parameter to 0.9.

[21]:
```
# TODO: Fill this in
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Instantiate the MazeEnv environment with default arguments
env = MazeEnv()

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
 ↪max_steps, use_softmax_policy)
```

[22]:
```
# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)
plot_steps_vs_iters(steps_vs_iters)
```



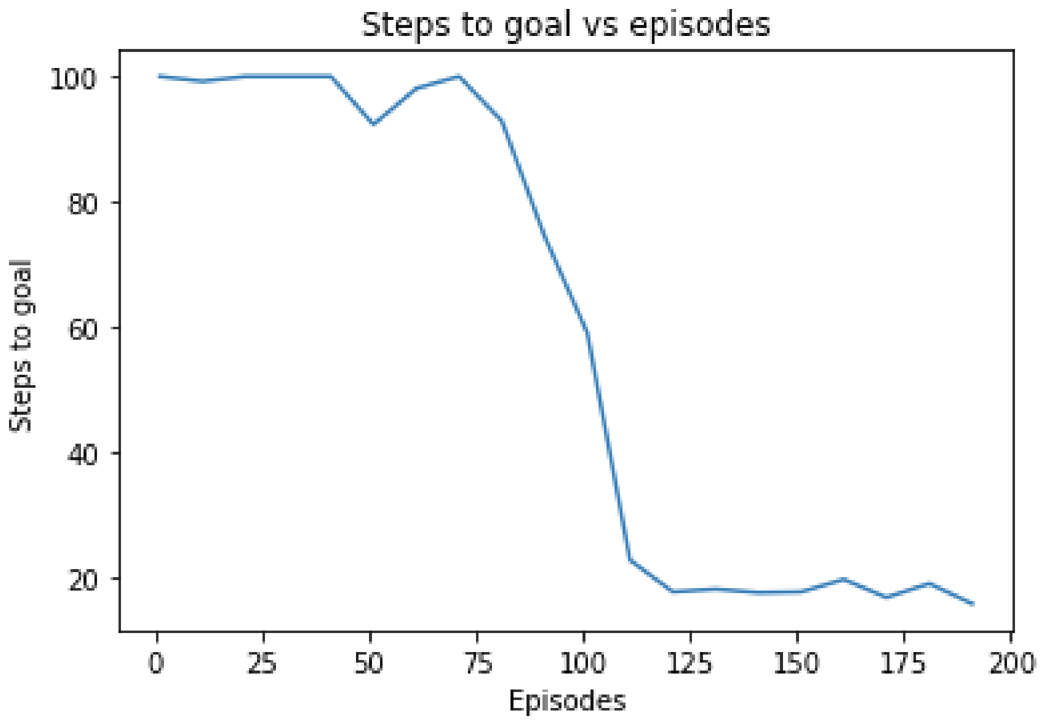
[23]:
```
# TODO: plot the policy from the Q value
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```

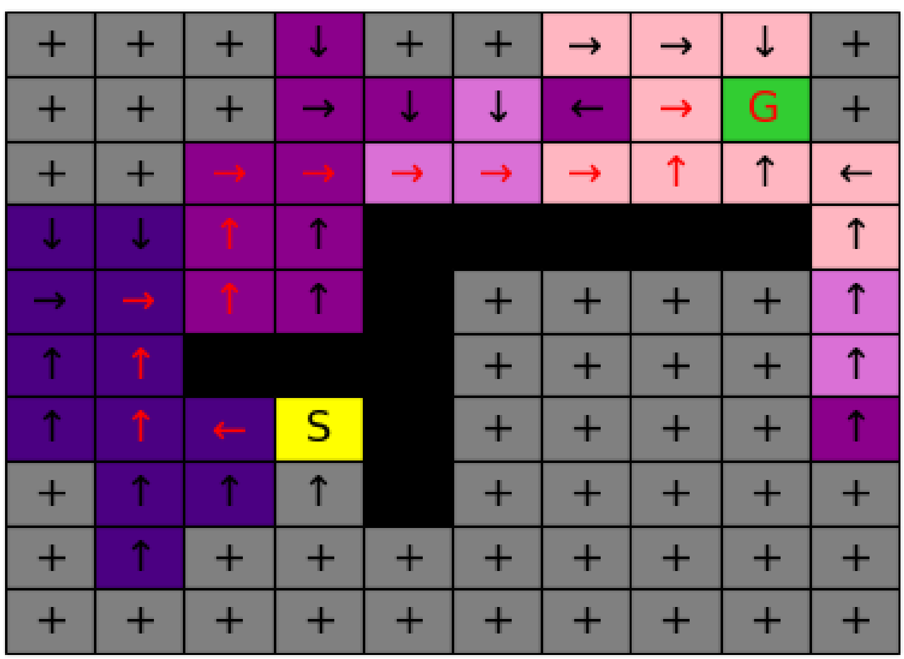


<Figure size 720x720 with 0 Axes>

2.2.1(a)Basic Q learning experiments: Run your algorithm several times on the given environment.

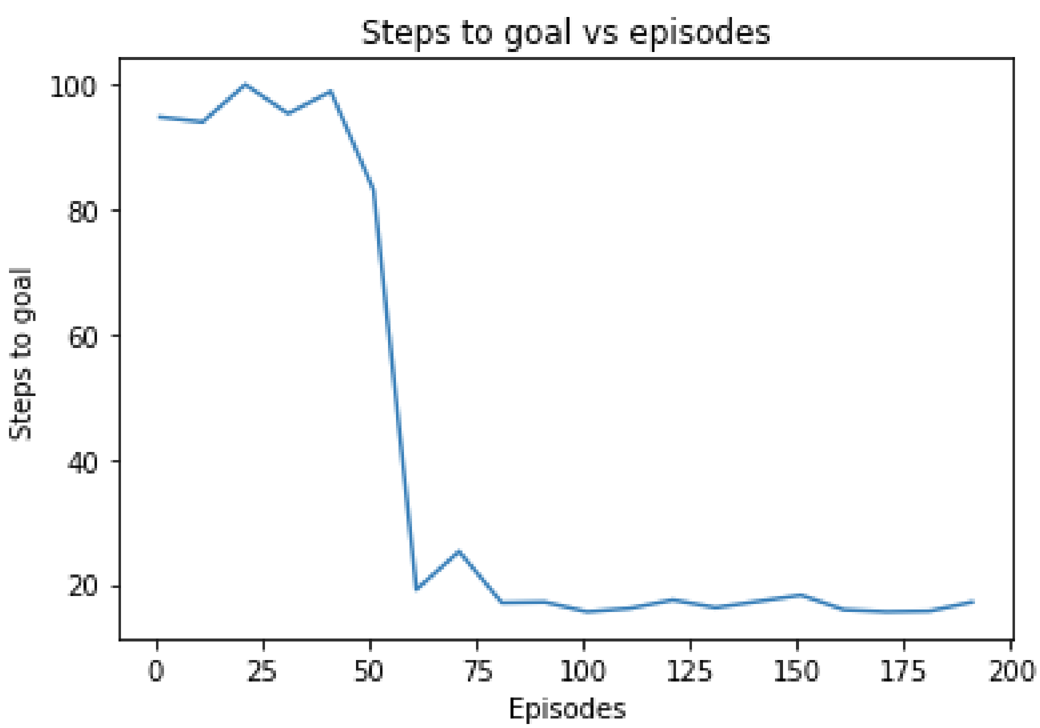
[24]:
```
# TODO: Fill this in
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Instantiate the MazeEnv environment with default arguments
env = MazeEnv()

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,
 ↪max_steps, use_softmax_policy)

# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)
plot_steps_vs_iters(steps_vs_iters)

# TODO: plot the policy from the Q value
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```

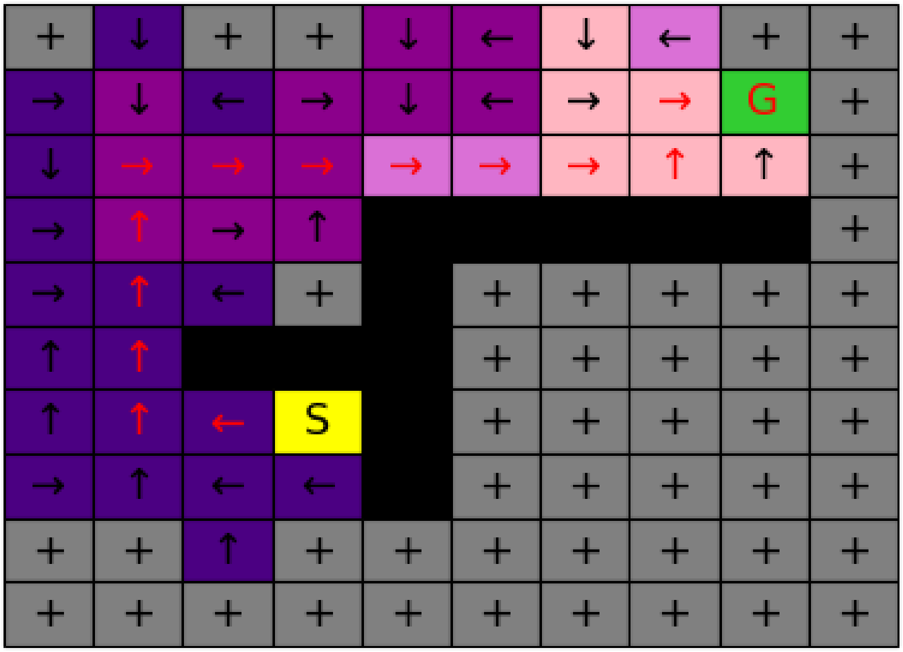





```
<Figure size 720x720 with 0 Axes>
```

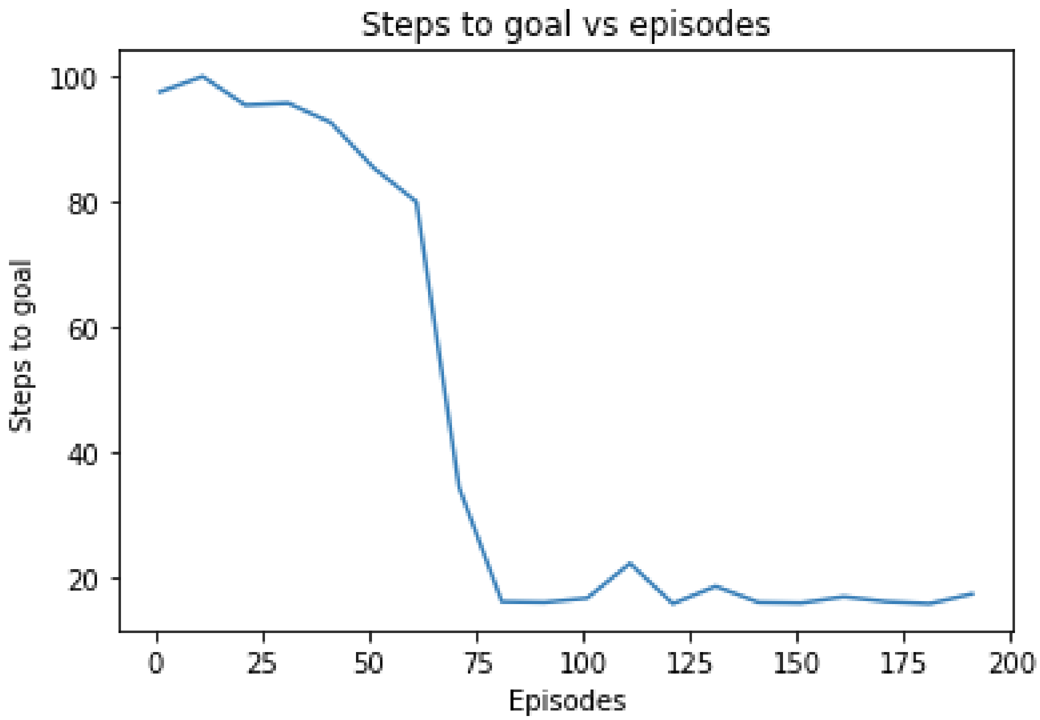
[25]:
```python
# TODO: Fill this in
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Instantiate the MazeEnv environment with default arguments
env = MazeEnv()

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
 ↪max_steps, use_softmax_policy)

# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)
plot_steps_vs_iters(steps_vs_iters)

# TODO: plot the policy from the Q value
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```

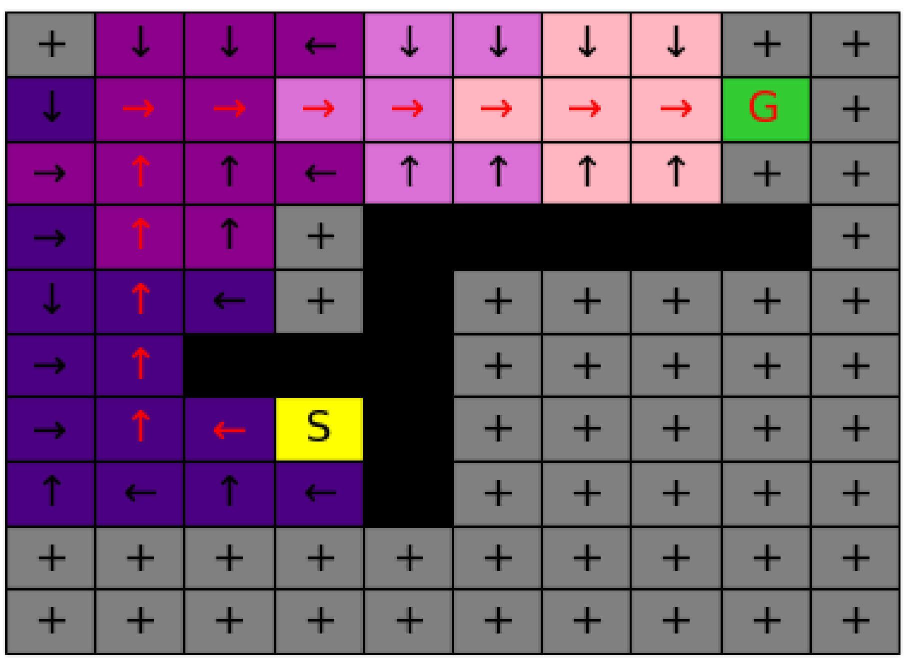




<Figure size 720x720 with 0 Axes>

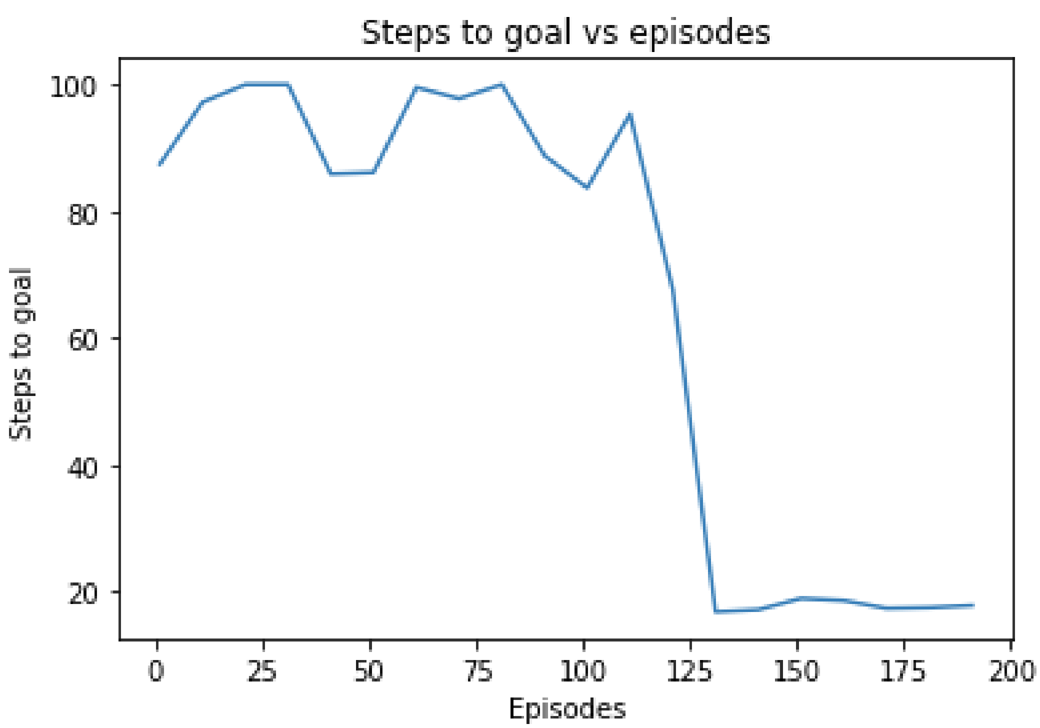
[26]:
```python
# TODO: Fill this in
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Instantiate the MazeEnv environment with default arguments
env = MazeEnv()

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,
    max_steps, use_softmax_policy)

# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)
plot_steps_vs_iters(steps_vs_iters)

# TODO: plot the policy from the Q value
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```

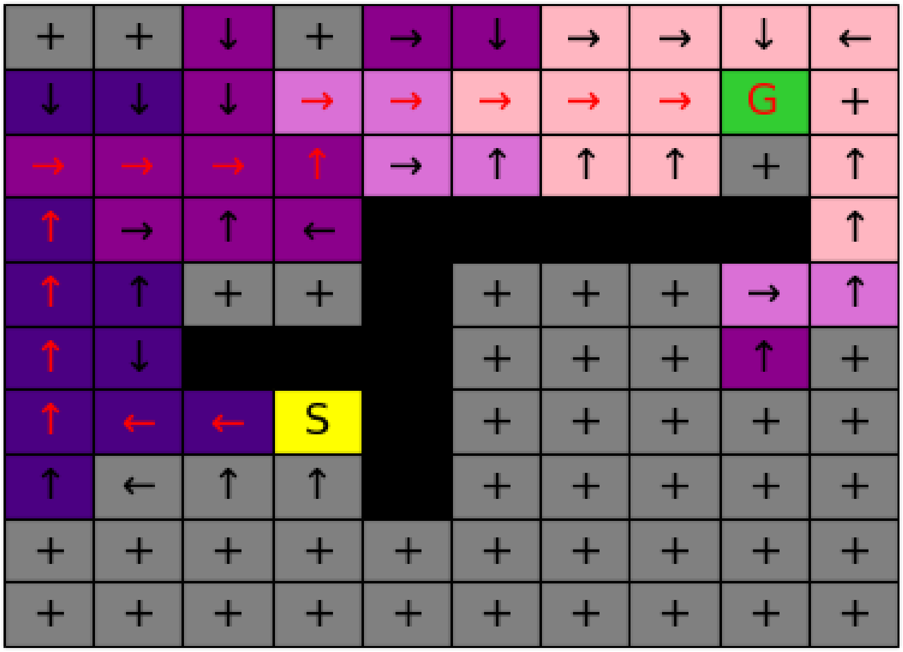




<Figure size 720x720 with 0 Axes>

[27]:
```python
# TODO: Fill this in
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Instantiate the MazeEnv environment with default arguments
env = MazeEnv()

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
↪max_steps, use_softmax_policy)

# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)
plot_steps_vs_iters(steps_vs_iters)

# TODO: plot the policy from the Q value
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```





<Figure size 720x720 with 0 Axes>

2.2.1(b) Run your algorithm by passing in a list of 2 goal locations: (1,8) and (5,6). Note: we are using 0-indexing, where (0,0) is top left corner. Report on the results.

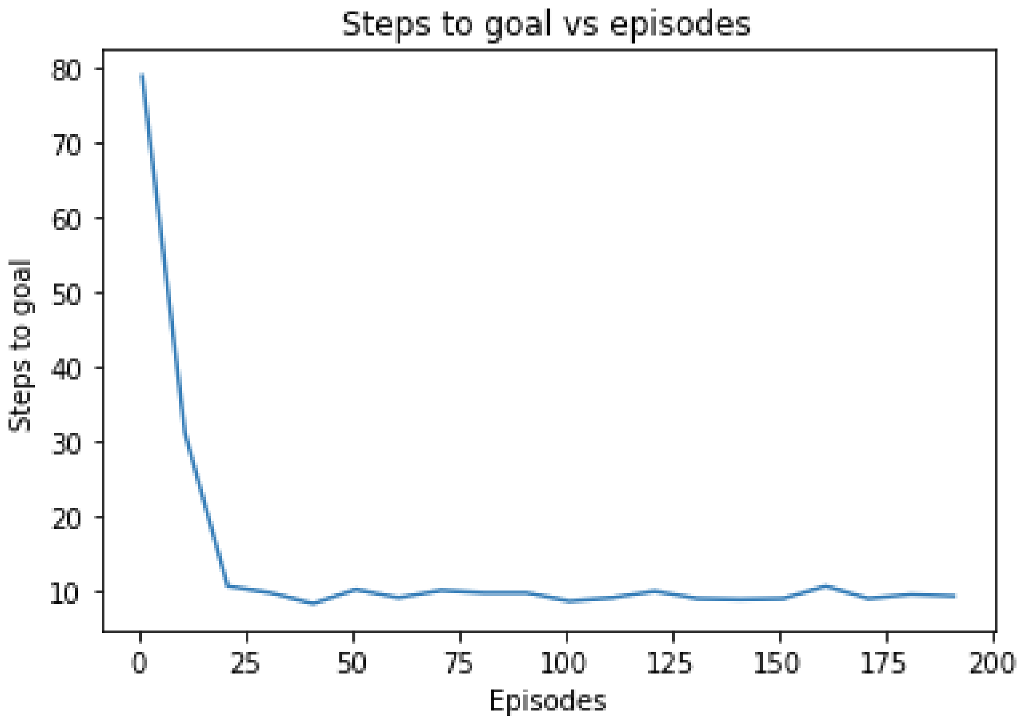
From the steps vs iterations plot, we can see that after 25 iterations, the steps to goals are near 10.

From the policy from the Q values plot, we can see that it takes 7 steps to reach the goal location (5,6).

[32]:
```
# TODO: Fill this in (same as before)
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: Set the goal
goal_locs = [[1,8], [5,6]]
env = MazeEnv(start=[6,3], goals=goal_locs) # starting point S

# TODO: Run Q-learning:
q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
↪max_steps, use_softmax_policy)
```

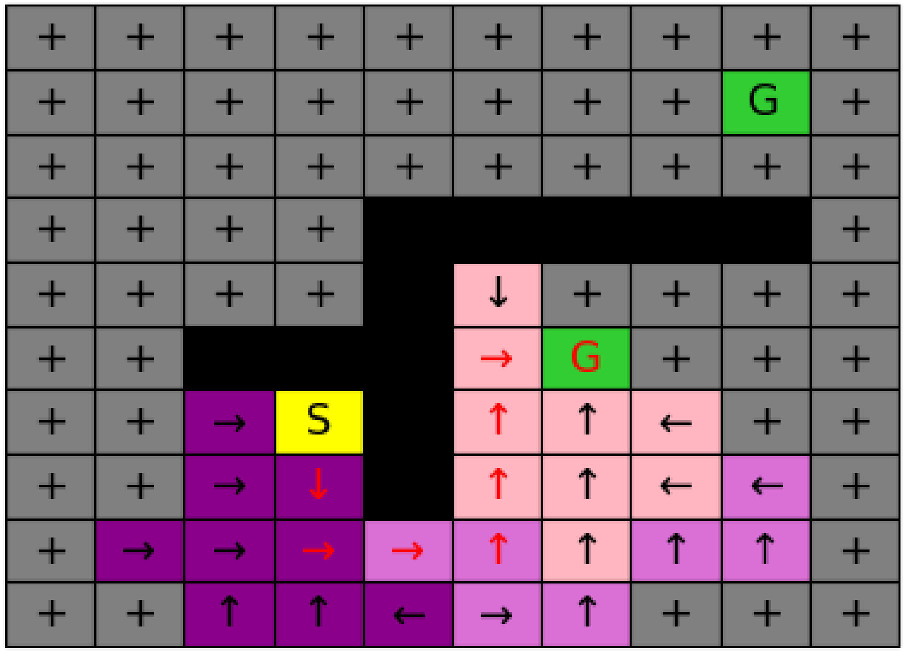
[33]:

```
# TODO: Plot the steps vs iterations
# plot_steps_vs_iters(...)

plot_steps_vs_iters(steps_vs_iters)
```



[34]:

```
# TODO: plot the policy from the Q values
# plot_policy_from_q(...)

plot_policy_from_q(q_hat, env)
```



<Figure size 720x720 with 0 Axes>

2.2.2(a) Try different values in -greedy exploration: We asked you to use a rate of =0.1, but try also 0.5 and 0.01. Graph the results (for the 3 -values) and discuss the costs and benefits of higher and lower exploration rates.

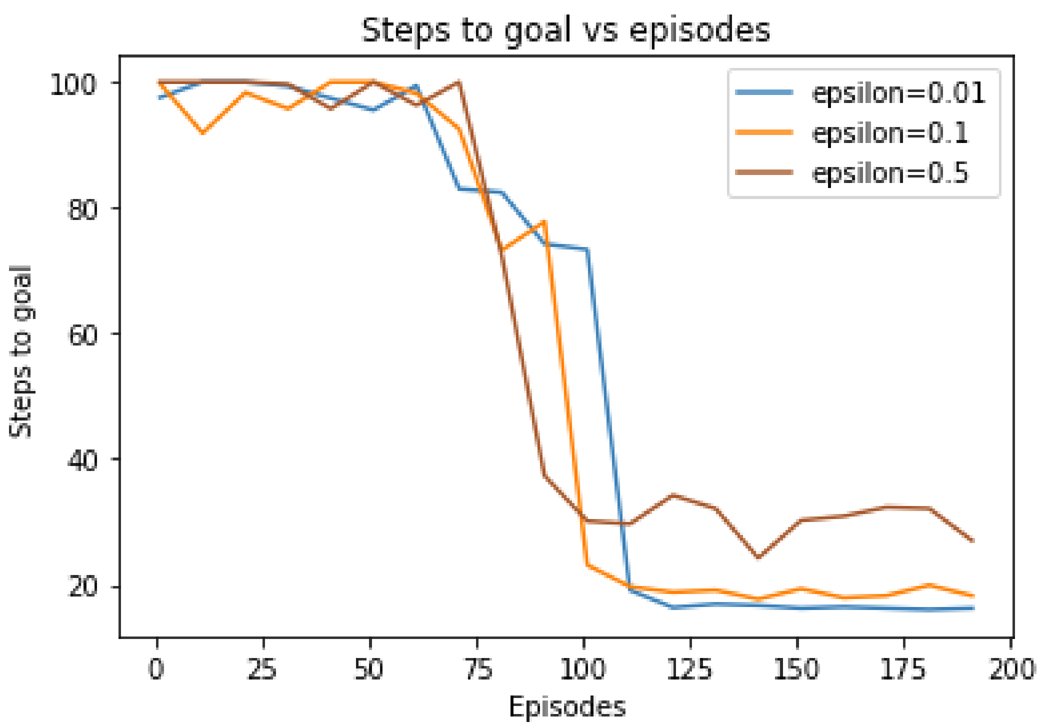
For lower exploration rates, the cost is that we need more iterations to be converged and the benefit is that we can reach the goal with less steps.

For higher exploration rates, the benefit is that we need less iterations to be converged and the cost is that we will reach the goal with more steps.

[35]:
```
# TODO: Fill this in (same as before)
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# TODO: set the epsilon lists in increasing order:
epsilon_list = [0.01, 0.1, 0.5]

env = MazeEnv()

steps_vs_iters_list = []
for epsilon in epsilon_list:
```

```
    q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon, max_steps, use_softmax_policy)
    steps_vs_iters_list.append(steps_vs_iters)
```

[36]:
```
# TODO: Plot the results
# plot_several_steps_vs_iters(...)
label_list = ["epsilon={}".format(eps) for eps in epsilon_list]
plot_several_steps_vs_iters(steps_vs_iters_list, label_list)
```

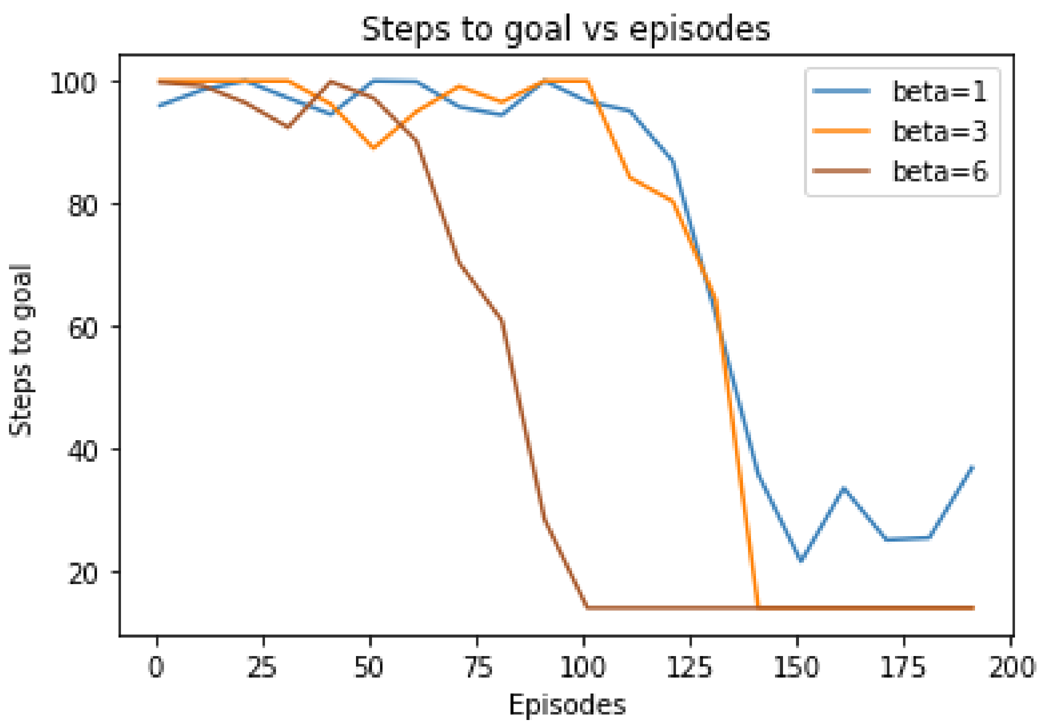


2.2.2(b) Try exploring with policy derived from the softmax of Q-values described in the Q learning lecture. Use the values $\{1,3,6\}$ for your experiment, keeping fixed throughout the training.

[53]:
```
# TODO: Fill this in for Static Beta with softmax of Q-values
num_iters = 200
alpha = 1.0
gamma = 0.9
epsilon = 0.1
max_steps = 100

# TODO: Set the beta
beta_list = [1,3,6]
use_softmax_policy = True
k_exp_schedule = 0 # (float) choose k such that we have a constant beta during training
```

```
env = MazeEnv()
steps_vs_iters_list = []
for beta in beta_list:
    q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
 ↪max_steps, use_softmax_policy, beta, k_exp_schedule)
    steps_vs_iters_list.append(steps_vs_iters)
```

[54]:
```
label_list = ["beta={}".format(beta) for beta in beta_list]
# TODO:
# plot_several_steps_vs_iters(...)

plot_several_steps_vs_iters(steps_vs_iters_list, label_list)
```



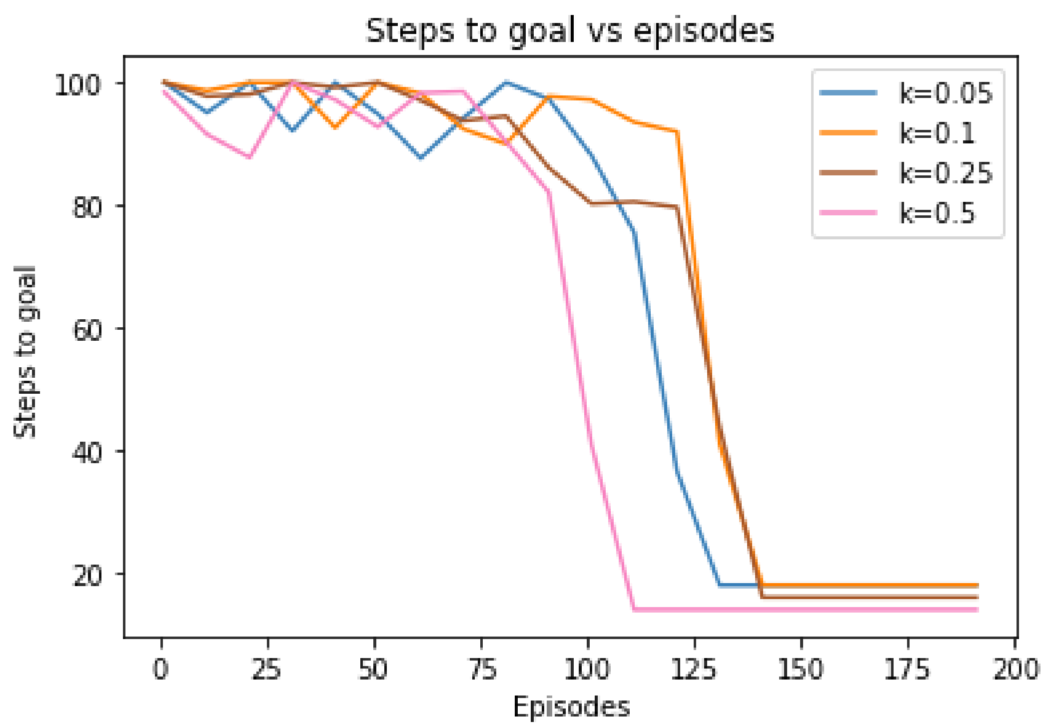
2.2.2(c) Run the training again for different values of k {0.05, 0.1, 0.25, 0.5}, keeping 0 = 1.0. Compare the results obtained with this approach to those obtained with a static value.

A dynamic may have better performance than a static . A static value may not converge to a very small steps to goal, while for a dynamic value, it will always converge to a small steps to goal. The iterations taken to reach the smallest steps to goal for both values are similar.

[55]:
```
# TODO: Fill this in for Dynamic Beta
num_iters = 200
alpha = 1.0
```

```
gamma = 0.9
epsilon = 0.1
max_steps = 100

# TODO: Set the beta
beta = 1.0
use_softmax_policy = True
k_exp_schedule_list = [0.05, 0.1, 0.25, 0.5]
env = MazeEnv()

steps_vs_iters_list = []
for k_exp_schedule in k_exp_schedule_list:
    q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
 ↪max_steps, use_softmax_policy, beta, k_exp_schedule)
    steps_vs_iters_list.append(steps_vs_iters)
```

[56]:
```
# TODO: Plot the steps vs iterations
label_list = ["k={}".format(k_exp_schedule) for k_exp_schedule in␣
 ↪k_exp_schedule_list]
# plot_several_steps_vs_iters(...)

plot_several_steps_vs_iters(steps_vs_iters_list, label_list)
```



2.2.3(a) Make the environment stochastic (uncertain), such that the agent only has say a 95%

chance of moving in the chosen direction, and a 5% chance of moving in a random direction.

[57]:
```python
# TODO: Implement ProbabilisticMazeEnv in maze.py

class ProbabilisticMazeEnv(MazeEnv):
    """ (Q2.3) Hints: you can refer the implementation in MazeEnv
    """

    def __init__(self, goals=[[2, 8]], p_random=0.05):
        """ Probabilistic Maze Environment

            Args:
                goals (list): list of goals coordinates
                p_random (float): random action rate
        """
        super(ProbabilisticMazeEnv, self).__init__(goals=goals)
        self.p_random = p_random


        def step(self, a):
            """ Perform a action on the environment

                Args:
                    a (int): action integer

                Returns:
                    obs (list): observation list
                    reward (int): reward for such action
                    done (int): whether the goal is reached
            """
            done, reward = False, 0.0
            next_obs = copy.copy(self.obs)

            # Make the environment stochastic with random action rate
            if np.random.uniform(0, 1) < self.p_random:
                a = np.random.randint(self.num_actions)

            if a == 0:
                next_obs[0] = next_obs[0] - 1
            elif a == 1:
                next_obs[1] = next_obs[1] + 1
            elif a == 2:
                next_obs[1] = next_obs[1] - 1
            elif a == 3:
                next_obs[0] = next_obs[0] + 1
            else:
                raise Exception("Action is Not Valid")
```

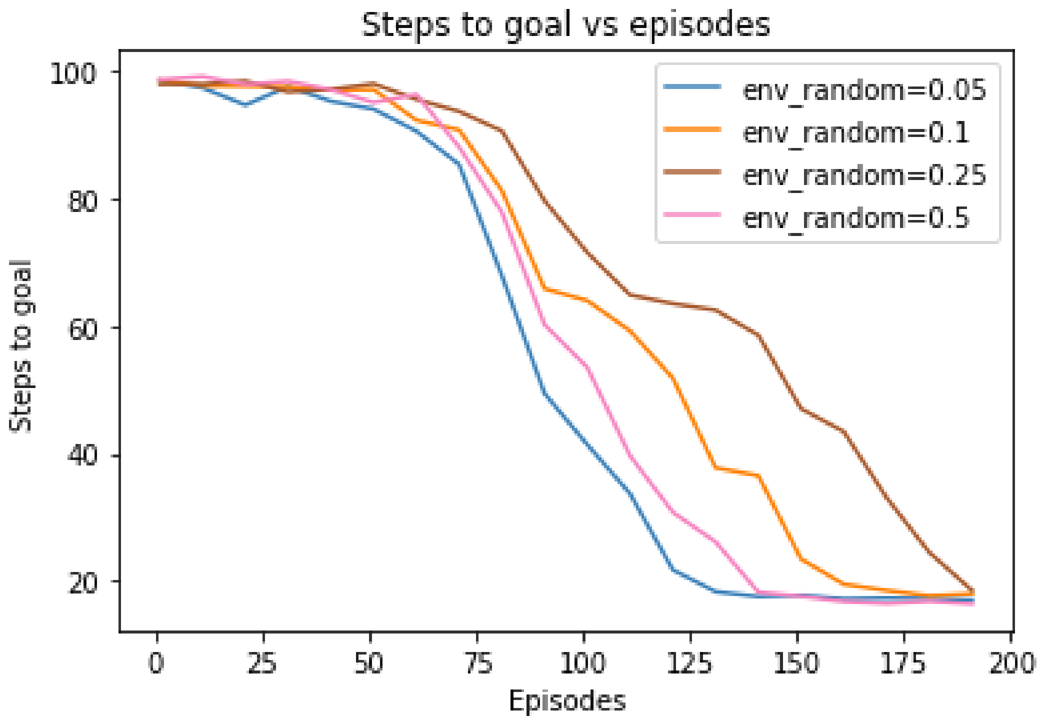
```
            if self.is_valid_obs(next_obs):
                self.obs = next_obs

            if self.map[self.obs[0], self.obs[1]] == -1:
                reward = self.reward
                done = True

            state = self.get_state_from_coords(self.obs[0], self.obs[1])

            return state, reward, done
```

2.2.3(b) Change the learning rule to handle the non-determinism, and experiment with different values of the probability that the environment performs a random action prand {0.05,0.1,0.25,0.5} in this new rule. How does performance vary as the environment becomes more stochastic?

The performance does not seem to follow a trend as the environment becomes more stochastic. We will always reach to the same minimum steps to goal. However, the number of iterations taken to reach the minimum steps to goal is very different. From the plot, we can see that it takes least iterations to reach the minimum with 0.05 p_random, follwed by 0.5, 0.1, 0.25, respectively.

[62]:
```
# TODO: Use the same parameters as in the first part, except change alpha
num_iters = 200
alpha = 0.5
gamma = 0.9
epsilon = 0.1
max_steps = 100
use_softmax_policy = False

# Set the environment probability of random
env_p_rand_list = [0.05, 0.1, 0.25, 0.5]

steps_vs_iters_list = []
for env_p_rand in env_p_rand_list:
    # Instantiate with ProbabilisticMazeEnv
    env = ProbabilisticMazeEnv(p_random=env_p_rand)

    # Note: We will repeat for several runs of the algorithm to make the result␣
 ↪less noisy
    avg_steps_vs_iters = np.zeros(num_iters)
    for i in range(10):
        q_hat, steps_vs_iters = qlearn(env, num_iters, alpha, gamma, epsilon,␣
 ↪max_steps, use_softmax_policy)
        avg_steps_vs_iters += steps_vs_iters
    avg_steps_vs_iters /= 10
    steps_vs_iters_list.append(avg_steps_vs_iters)
```

[63]:
```
label_list = ["env_random={}".format(env_p_rand) for env_p_rand in␣
 ↪env_p_rand_list]
# plot_several_steps_vs_iters(...)

plot_several_steps_vs_iters(steps_vs_iters_list, label_list)
```



Hand in a brief summary of your experiments. For each sub-section, this summary should include a one paragraph overview of the problem and your implementation. It should include a graph showing number of steps required to reach the goal as a function of learning trials (one trial is one run of the agent through the environment until it reaches the goal or maximum number of steps). You should also make a figure showing the policy of your agent for the first 2.1.1 section. The policy can be summarized by making an array of cells corresponding to the states of the environment, and indicating the direction (up, down, left,right) that the agent is most likely to move if it is in that state.