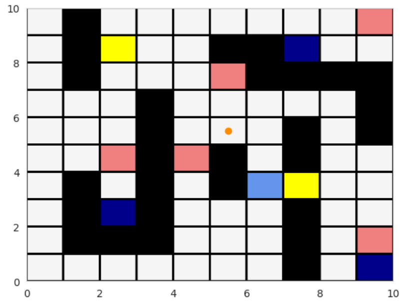
CS6700 Programming Assignment 1

ME19B179 and ME19B177

Structure of the assignment:



1. Approach
2. Observations
3. Training Notebook (code)
4. Plots of the Results

Approach

The given environment was quite similar to that in the tutorials that we solved. In this case, with changes in indexing and a glue function, we were able to reuse most of our code from the tutorial for the actual implementation of SARSA and QLearning.

The major technical challenge in the assignment was the sheer number of scenarios to work out. There were a grand total of 32 configurations. For each configuration, we needed to tune the three different hyperparameters. Combining this with the considerable runtime for a single experiment (around two minutes on our machine) made us realize that manual parameter tuning and experiment running would not be feasible.

We had two approaches:

1. Tune the hyperparameters for a configuration and apply them to all 31 other configurations. This approach still suffered from a vast number of manual runs (32 + the runs required to tune the hyperparameters).
2. Automate the problem and use exhaustive search to find the optimal hyperparameters for each configuration. We selected the experiments that gave the maximal reward after training. With our chosen parameter space this would require a mind blowing 4000 runs. However with automation, we felt that this would be more efficient overall in man hours. We went with this technique.

We first defined a sample space for each of the configuration variables and parameters. Then, as the training process was CPU bound, we acquired access to a relatively powerful machine with 20 cpu cores. Finally, we launched our code to run overnight on that machine. The results were saved to the filesystem. This notebook is in the third section of our report.

After that, we took the generated data, chose the runs with the optimal hyperparameters and displayed the plots for those runs. This notebook is in the fourth section of our report.

Overall, more than just the algorithms involved, this assignment showed us how tedious the job of actually training and tuning a reinforcement learning algorithm is. We realized how important it is to have intuition on the meaning of each hyper-parameter and how to tune them for optimal performance. However, in today's day and age, much of that can be brute forced away by more computationally powerful machines (or more time.

Observations

SARSA

- In almost all cases, the policy was an almost direct path to the goal location. The cells on the route to the path had a high Q value. The cells near environmental hazards had lower Q values. This is especially evident in more stochastic and windy environments.
- When evaluated, the agent would attempt to follow the determined path to the goal location.
- In cases with stochasticity and wind, the agent may switch to another goal if it gets blown off the path.

- In configurations with stochastics or wind, the algorithm may take a slightly longer path to avoid areas where it might accidently move into Bad and Restart states.
    - For the start state (0,4), there was minimal effect of the wind
    - For the second start state, the agent often chose a different goal to path to if the wind was enabled.
    - In general, with higher stochasticism, the agent chose a “safer” path.
        - We saw one case with stochasticism, where the agent would **attempt to move into a wall** to reduce their chances of moving into the restart state. This made us understand how the agent weighs all the available actions, even those that may seem nonsensical to us.

- The configurations with greater stochasticity tended to explore more cells and have a lot higher variance in reward and steps taken.

- The epsilon greedy exploration function tended to perform better than the softmax exploration function. They converged more strongly and converged faster
    - The rewards were higher when a lower epsilon value was provided to the function.
    - In the given scenarios, we do not require a significant amount of exploration. The most direct path is often the optimal path

QLearning

- QLearning had similar overall behavior to SARSA
- QLearning tended to **converge more strongly onto the best path**.
- The cells not on the optimal path had a much, much lower Q value.
- Despite this, we noticed that overall, the QLearning agents visited a larger variety of states during training.
- For the given scenario, we would choose QLearning as our metric of comparison was the agent's performance after training.

Hyperparameter Choice

As mentioned in the approach section, due to the sheer number of different configurations, we decided to find the optimal hyperparameters by brute force search over the parameter space.

We graded the different experiments based on the reward when using the final learned policy.

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Code for Training

In [2]:

```
from math import floor
import numpy as np
from IPython.display import clear_output
import seaborn as sns
sns.set_style('whitegrid')
from typing import Tuple, Optional
```

Grid World Simulation

In [3]:

```
# From the tutorial

def row_col_to_seq(row_col, num_cols):  # Converts row_column format to state
    return row_col[:,0] * num_cols + row_col[:,1]

def seq_to_col_row(seq, num_cols): # Converts state number to row_column forma
    r = floor(seq / num_cols)
    c = seq - r * num_cols
    return np.array([[r, c]])

class GridWorld:
    """
    Creates a gridworld object to pass to an RL algorithm.
    Parameters
    ----------
    num_rows : int
        The number of rows in the gridworld.
    num_cols : int
        The number of cols in the gridworld.
    start_state : numpy array of shape (1, 2), np.array([[row, col]])
        The start state of the gridworld (can only be one start state)
    goal_states : numpy arrany of shape (n, 2)
        The goal states for the gridworld where n is the number of goal
        states.
    """
    def __init__(self, num_rows, num_cols, start_state, goal_states, wind = Fa
        self.num_rows = num_rows
        self.num_cols = num_cols
        self.start_state = start_state
        self.goal_states = goal_states
        self.obs_states = None
        self.bad_states = None
        self.num_bad_states = 0
        self.p_good_trans = None
        self.bias = None
        self.r_step = None
        self.r_goal = None
        self.r_dead = None
        self.gamma = 1 # default is no discounting
        self.wind = wind
```

```python
    def add_obstructions(self, obstructed_states=None, bad_states=None, restar

        self.obs_states = obstructed_states
        self.bad_states = bad_states
        if bad_states is not None:
            self.num_bad_states = bad_states.shape[0]
        else:
            self.num_bad_states = 0
        self.restart_states = restart_states
        if restart_states is not None:
            self.num_restart_states = restart_states.shape[0]
        else:
            self.num_restart_states = 0

    def add_transition_probability(self, p_good_transition, bias):

        self.p_good_trans = p_good_transition
        self.bias = bias

    def add_rewards(self, step_reward, goal_reward, bad_state_reward=None, res

        self.r_step = step_reward
        self.r_goal = goal_reward
        self.r_bad = bad_state_reward
        self.r_restart = restart_state_reward


    def create_gridworld(self):

        self.num_actions = 4
        self.num_states = self.num_cols * self.num_rows# +1
        self.start_state_seq = row_col_to_seq(self.start_state, self.num_cols)
        self.goal_states_seq = row_col_to_seq(self.goal_states, self.num_cols)

        self.R = self.r_step * np.ones((self.num_states, 1))
        self.R[self.goal_states_seq] = self.r_goal

        for i in range(self.num_bad_states):
            if self.r_bad is None:
                raise Exception("Bad state specified but no reward is given")
            bad_state = row_col_to_seq(self.bad_states[i,:].reshape(1,-1), sel
            self.R[bad_state, :] = self.r_bad
        for i in range(self.num_restart_states):
            if self.r_restart is None:
                raise Exception("Restart state specified but no reward is give
            restart_state = row_col_to_seq(self.restart_states[i,:].reshape(1,
            self.R[restart_state, :] = self.r_restart

        if self.p_good_trans == None:
            raise Exception("Must assign probability and bias terms via the ac

        self.P = np.zeros((self.num_states,self.num_states,self.num_actions))
        for action in range(self.num_actions):
            for state in range(self.num_states):
                row_col = seq_to_col_row(state, self.num_cols).reshape(1, -1)
                if self.obs_states is not None:
                    end_states = np.vstack((self.obs_states, self.goal_states)
                else:
                    end_states = self.goal_states
```

```
            if any(np.sum(np.abs(end_states-row_col), 1) == 0):
                self.P[state, state, action] = 1
            else:
                for dir in range(-1,2,1):
                    direction = self._get_direction(action, dir)
                    next_state = self._get_state(state, direction)
                    if dir == 0:
                        prob = self.p_good_trans
                    elif dir == -1:
                        prob = (1 - self.p_good_trans)*(self.bias)
                    elif dir == 1:
                        prob = (1 - self.p_good_trans)*(1-self.bias)

                    self.P[state, next_state, action] += prob
            if self.restart_states is not None:
                if any(np.sum(np.abs(self.restart_states-row_col),1)==0):
                    next_state = row_col_to_seq(self.start_state, self.num
                    self.P[state,:,:] = 0
                    self.P[state,next_state,:] = 1
        return self

    def _get_direction(self, action, direction):
        left = [2,3,1,0]
        right = [3,2,0,1]
        if direction == 0:
            new_direction = action
        elif direction == -1:
            new_direction = left[action]
        elif direction == 1:
            new_direction = right[action]
        else:
            raise Exception("getDir received an unspecified case")
        return new_direction

    def _get_state(self, state, direction):

        row_change = [-1,1,0,0]
        col_change = [0,0,-1,1]
        row_col = seq_to_col_row(state, self.num_cols)
        row_col[0,0] += row_change[direction]
        row_col[0,1] += col_change[direction]

        # check for invalid states
        if self.obs_states is not None:
            if (np.any(row_col < 0) or
                np.any(row_col[:,0] > self.num_rows-1) or
                np.any(row_col[:,1] > self.num_cols-1) or
                np.any(np.sum(abs(self.obs_states - row_col), 1)==0)):
                next_state = state
            else:
                next_state = row_col_to_seq(row_col, self.num_cols)[0]
        else:
            if (np.any(row_col < 0) or
                np.any(row_col[:,0] > self.num_rows-1) or
                np.any(row_col[:,1] > self.num_cols-1)):
                next_state = state
            else:
                next_state = row_col_to_seq(row_col, self.num_cols)[0]
```

```
        return next_state

    def reset(self) -> int:
      return int(self.start_state_seq)

    def step(self, state, action) -> Tuple[int, float, bool]:
        p, r = 0, np.random.random()
        for next_state in range(self.num_states):
            p += self.P[state, next_state, action]
            if r <= p:
                break

        if(self.wind and np.random.random() < 0.4):
          arr = self.P[next_state, :, 3]
          next_next = np.where(arr == np.amax(arr))
          next_state = next_next[0][0]

        done = state in self.goal_states_seq

        return next_state, self.R[next_state], done


    def rowcol_to_seq(self, row_col: np.ndarray) -> int:  # Converts row_colum
        return row_col[:,0] * self.num_cols + row_col[:,1]

    def seq_to_rowcol(self, seq: int) -> np.ndarray: # Converts state number t
        r = floor(seq / self.num_cols)
        c = seq - r * self.num_cols
        return np.array([r, c])
```

In [4]:

```
from time import time
from sys import stderr
```

In [5]:

```
def sarsa_final(env, Q, gamma, choose_action, alpha, episodes, t_limit=60*3):

    episode_rewards = np.zeros(episodes)
    steps_to_completion = np.zeros(episodes)
    visited_states = np.zeros(shape=Q.shape[0:2])

    t_start = time()

    for ep in range(episodes):
        tot_reward, steps = 0, 0

        state_seq = env.reset()
        state_rowcol = env.seq_to_rowcol(state_seq)
        action = choose_action(Q, state_rowcol)

        done = False
        while not done:
            # Iterate the simulation
            state_next_seq, reward, done = env.step(state_seq, action)
            tot_reward += reward
            steps += 1
            visited_states[state_rowcol[0], state_rowcol[1]] += 1

            # Find the next action
            state_next_rowcol = env.seq_to_rowcol(state_next_seq)
```

```
            action_next = choose_action(Q, state_next_rowcol)

            # Update the Q Value
            Q[state_rowcol[0], state_rowcol[1], action] += alpha * (
                reward +
                gamma * Q[state_next_rowcol[0], state_next_rowcol[1], action_r
                Q[state_rowcol[0], state_rowcol[1], action]
            )

            state_seq, action = state_next_seq, action_next
            state_rowcol = state_next_rowcol

            if steps > 100 or time() > t_start + t_limit:
                False, None, None, None, None

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

    return True, Q, episode_rewards, steps_to_completion, visited_states
```

In [6]:

```
def qlearning_final(env, Q, gamma, choose_action, alpha, episodes, t_limit=60*
    episode_rewards = np.zeros(episodes)
    steps_to_completion = np.zeros(episodes)
    visited_states = np.zeros(shape=Q.shape[0:2])
    t_start = time()

    for ep in range(episodes):
        tot_reward, steps = 0, 0

        # Reset environment
        state_seq = env.reset()
        state_rowcol = env.seq_to_rowcol(state_seq)

        action = choose_action(Q, state_rowcol)

        done = False
        while not done:
            visited_states[state_rowcol[0], state_rowcol[1]] += 1
            state_next_seq, reward, done = env.step(state_seq, action)
            state_next_rowcol = env.seq_to_rowcol(state_next_seq)

            tot_reward += reward
            steps += 1

            action_next = choose_action(Q, state_next_rowcol)

            # Update Equation
            Q[state_rowcol[0], state_rowcol[1], action] += alpha * (
                reward
                + gamma * max(Q[state_next_rowcol[0], state_next_rowcol[1]])
                - Q[state_rowcol[0], state_rowcol[1], action]
            )

            state_seq, state_rowcol, action = state_next_seq, state_next_rowcc

            if steps > 100 or time() > t_start + t_limit:
                False, None, None, None, None

        episode_rewards[ep] = tot_reward
```

```python
        steps_to_completion[ep] = steps

    return True, Q, episode_rewards, steps_to_completion, visited_states
```

In [7]:

```python
from dataclasses import dataclass
from typing import Literal

import numpy as np
from scipy.special import softmax


def epsilon_greedy(self, Q, state):
    epsilon = self.explore_param
    rg = self.rg
    actions = range(len(Q[state[0], state[1]]))
    if rg.rand() < epsilon:
        return rg.choice(actions)
    else:
        return max(actions, key=lambda x: Q[state[0], state[1], x])


def final_choose_action_softmax(self, Q, state):
    tau = self.explore_param
    rg = self.rg
    pis = softmax(Q[state[0], state[1]] / tau)
    assert abs(pis.sum() - 1) < 1e-8
    return rg.choice(range(len(Q[state[0], state[1]])), p=pis)


# All possible test configurations
configs = {
    "method": ("sarsa", "qlearning"),
    "exploration_method": ("EpsilonGreedy", "Softmax",),
    "wind": (False, True),
    "start_state": ((0, 4,), (3, 6,)),
    "alpha": (0.1, 0.2, 0.3, 0.4, 0.5,),
    "gamma": (0.8, 0.9, 0.95, 0.99, 0.999),
    "exploration_value_id": (0, 1, 2, 3, 4),
    "p": (1, 0.7),
}

explore_values_epgreedy = (0, 0.025, 0.05, 0.075, 0.1,)
explore_values_softmax = (0.01, 0.5, 1, 2, 5,)


@dataclass
class Params:
    method: Literal["sarsa", "qlearning"]
    exploration_method: Literal["EpsilonGreedy", "Softmax"]
    wind: bool
    start_state: Literal[(0, 4,), (3, 6,)]

    alpha: float
    gamma: float
    p: float

    exploration_value_id: int
```

```python
    def init(self):
        self.explore = self.epsilon_greedy if self.exploration_method == "Epsi
        self.explore_param = explore_values_epgreedy[
            self.exploration_value_id] if self.exploration_method == "EpsilonG
            self.exploration_value_id]
        self.init_env()
        self.method_func = sarsa_final if self.method == "sarsa" else qlearnin
        self.rg = np.random.RandomState(42)

        self.dir_name = f"AA_{self.method}_{self.wind}_{self.start_state[0]}_{
        self.filename = f"AA_{self.alpha}_{self.gamma}_{self.exploration_value

    def epsilon_greedy(self, Q, state):
        epsilon = self.explore_param
        rg = self.rg
        actions = range(len(Q[state[0], state[1]]))
        if rg.rand() < epsilon:  # TODO: eps greedy condition
            return rg.choice(actions)
        else:
            return max(actions, key=lambda x: Q[state[0], state[1], x])

    def softmax(self, Q, state):
        tau = self.explore_param
        rg = self.rg
        pis = softmax(Q[state[0], state[1]] / tau)
        assert abs(pis.sum() - 1) < 1e-8
        return rg.choice(range(len(Q[state[0], state[1]])), p=pis)

    def __str__(self):
        pass


    def init_env(self):
        # specify world parameters
        num_cols = 10
        num_rows = 10

        obstructions = np.array([[0,7],[1,1],[1,2],[1,3],[1,7],[2,1],[2,3],
                                [2,7],[3,1],[3,3],[3,5],[4,3],[4,5],[4,7],
                                [5,3],[5,7],[5,9],[6,3],[6,9],[7,1],[7,6],
                                [7,7],[7,8],[7,9],[8,1],[8,5],[8,6],[9,1]])

        bad_states = np.array([[1,9],[4,2],[4,4],[7,5],[9,9]])
        restart_states = np.array([[3,7],[8,2]])

        start_state = np.array([self.start_state])
        goal_states = np.array([[0,9],[2,2],[8,7]])

        # create model
        gw = GridWorld(num_rows=num_rows,
                    num_cols=num_cols,
                    start_state=start_state,
                    goal_states=goal_states, wind = self.wind)
        gw.add_obstructions(obstructed_states=obstructions,
                            bad_states=bad_states,
                            restart_states=restart_states)
        gw.add_rewards(step_reward=-1,
                    goal_reward=10,
                    bad_state_reward=-6,
                    restart_state_reward=-10)
```

```python
        gw.add_transition_probability(p_good_transition=self.p,
                                      bias=0.5)
        self.env = gw.create_gridworld()
```

In [9]:

```python
import os
import numpy as np
from pathlib import Path
def write_data(params, r: float, r_s, s_s, visits, q):
    dirs = Path(params.dir_name)
    dirs.mkdir(parents=True, exist_ok=True)
    r = np.array((r,))
    fl = params.dir_name + "/" + params.filename
    if os.path.exists(fl):
        os.remove(fl)
    np.savez(fl, r=r, r_s=r_s, s_s=s_s, visits=visits, q=q)
```

In [10]:

```python
def run(parameters: Params):
    # Train the model
    episodes = 1000
    method_func = parameters.method_func
    explore_function = parameters.explore
    gamma = parameters.gamma
    alpha = parameters.alpha
    env = parameters.env

    t_limit = 60 * 3


    def train(t_limit):
        Q = np.zeros((env.num_rows, env.num_cols, env.num_actions))
        success, Q, episode_rewards, steps_to_completion, visited = method_fur
        return success, Q, episode_rewards, steps_to_completion, visited


    # Test the model
    def test(Q, t_limit=10):
        state_seq = env.reset()
        state_rowcol = env.seq_to_rowcol(state_seq)
        action = explore_function(Q, state_rowcol)
        done = False
        steps = 0
        tot_reward = 0
        t_start = time()
        while not done:
            state_seq, reward, done = env.step(state_seq, Q[state_rowcol[0], s
            state_rowcol = env.seq_to_rowcol(state_seq)
            steps += 1
            tot_reward += reward
            if steps > 100 or time() > t_start + t_limit:
                return None
        return tot_reward

    success, Q, episode_rewards, steps_to_completion, visited = train(t_limit)
    if not success:
        stderr.write(f"Train Failed: {parameters.dir_name}/{parameters.filenam
        return None
```

```
    total_reward = test(Q, 10)
    if total_reward is None:
        stderr.write(f"Test Failed: {parameters.dir_name}/{parameters.filename
        return None

    write_data(parameters, total_reward, episode_rewards, steps_to_completion,

    return total_reward
```

In [11]:

```
# Test the params object

c = {
    "method": "qlearning",
    "exploration_method": "EpsilonGreedy",
    "wind": False,
    "start_state": (0, 4,),
    "alpha": 0.1,
    "gamma": 0.9,
    "exploration_value_id": 4,
    "p": 0.7,
}

p = Params(**c)
p.init()
run(p)
```

Out[11]:

```
array([-3.])
```

In [12]:

```
import itertools
from functools import reduce
import operator
from multiprocessing import Pool, cpu_count
import tqdm

def product_dict(**kwargs):
    keys = kwargs.keys()
    vals = kwargs.values()
    for instance in itertools.product(*vals):
        yield dict(zip(keys, instance))

def get_all_params():
    for args in product_dict(**configs):
            pp = Params(**args)
            pp.init()
            yield pp

N = reduce(operator.mul, map(len, configs.values()))

nproc = cpu_count() - 5
print(f"Running with {nproc} cpus")
with Pool(processes=nproc) as p:
    with tqdm.tqdm(total=N) as pbar:
        for _ in p.imap_unordered(run, get_all_params()):
            pbar.update()

print("done")
```

```
Running with 15 cpus
```

```
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5_0.95_3_AA.npzTest Failed: AA_sarsa_False_3_6_1_EpsilonGreedy_AA/AA_0.3_0.9
99_3_AA.npzTest Failed: AA_sarsa_False_3_6_1_EpsilonGreedy_AA/AA_0.4_0.999_2
_AA.npzTest Failed: AA_sarsa_False_3_6_1_EpsilonGreedy_AA/AA_0.5_0.99_2_AA.n
pzTest Failed: AA_sarsa_False_3_6_1_EpsilonGreedy_AA/AA_0.5_0.999_3_AA.npzTe
st Failed: AA_sarsa_True_0_4_1_EpsilonGreedy_AA/AA_0.2_0.95_4_AA.npzTest Fai
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sa_True_0_4_1_EpsilonGreedy_AA/AA_0.5_0.999_1_AA.npzTest Failed: AA_sarsa_Tr
ue_0_4_0.7_EpsilonGreedy_AA/AA_0.5_0.999_4_AA.npzTest Failed: AA_sarsa_True_
3_6_1_EpsilonGreedy_AA/AA_0.5_0.99_2_AA.npzTest Failed: AA_sarsa_True_3_6_1_
EpsilonGreedy_AA/AA_0.5_0.999_3_AA.npzTest Failed: AA_sarsa_False_0_4_0.7_So
ftmax_AA/AA_0.4_0.8_3_AA.npzTest Failed: AA_sarsa_False_0_4_1_Softmax_AA/AA_
0.5_0.8_4_AA.npzTest Failed: AA_sarsa_True_3_6_0.7_EpsilonGreedy_AA/AA_0.5_
0.8_1_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.1_0.8_4_AA.npzT
est Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.1_0.8_2_AA.npzTest Failed: A
A_sarsa_True_0_4_0.7_Softmax_AA/AA_0.1_0.8_3_AA.npzTest Failed: AA_sarsa_Tru
e_0_4_1_Softmax_AA/AA_0.2_0.8_3_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softm
ax_AA/AA_0.2_0.8_4_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.3_
0.8_4_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.3_0.8_3_AA.npzT
est Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.4_0.8_3_AA.npzTest Failed: A
A_sarsa_True_0_4_0.7_Softmax_AA/AA_0.4_0.8_3_AA.npzTest Failed: AA_sarsa_Tru
e_0_4_1_Softmax_AA/AA_0.5_0.9_3_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softm
ax_AA/AA_0.5_0.9_4_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.5_
0.8_4_AA.npzTest Failed: AA_sarsa_True_0_4_1_Softmax_AA/AA_0.5_0.8_3_AA.npzT
est Failed: AA_sarsa_True_3_6_0.7_Softmax_AA/AA_0.1_0.8_1_AA.npzTest Failed:
AA_sarsa_True_3_6_0.7_Softmax_AA/AA_0.5_0.8_4_AA.npzTest Failed: AA_qlearnin
g_False_0_4_0.7_EpsilonGreedy_AA/AA_0.4_0.8_1_AA.npzTest Failed: AA_qlearnin
g_True_0_4_1_Softmax_AA/AA_0.1_0.8_3_AA.npzTest Failed: AA_qlearning_True_0_
4_1_Softmax_AA/AA_0.1_0.8_4_AA.npzTest Failed: AA_qlearning_True_0_4_1_Softm
ax_AA/AA_0.2_0.8_3_AA.npzTest Failed: AA_qlearning_True_0_4_1_Softmax_AA/AA_
0.2_0.8_4_AA.npzTest Failed: AA_qlearning_True_0_4_1_Softmax_AA/AA_0.3_0.8_4
_AA.npzTest Failed: AA_qlearning_True_0_4_0.7_Softmax_AA/AA_0.3_0.8_3_AA.npz
Test Failed: AA_qlearning_True_0_4_0.7_Softmax_AA/AA_0.3_0.8_4_AA.npzTest Fa
iled: AA_qlearning_True_0_4_1_Softmax_AA/AA_0.5_0.8_4_AA.npzTest Failed: AA_
qlearning_True_0_4_0.7_Softmax_AA/AA_0.5_0.8_4_AA.npz
```

```
done
```

In [ ]:

```

```

In [14]:

```
!du -sh ./
```

```
108M	./
```

ME19B79 and ME19B177

Data Analysis and Plots

Code

In [1]:
```
filename = "CS6700_PA1_Data.tar.xz"
```

In [2]:
```
!ls -lh {filename} || gdown --fuzzy 'https://drive.google.com/file/d/1_jP8Ec6IpMdB10aJde
```

```
-rw-r--r-- 1 suraj suraj 13M Feb 24 22:54 CS6700_PA1_Data.tar.xz
```

In [3]:
```
!ls data > /dev/null || tar xf {filename}
```

In [4]:
```
!ls -1 data | wc -l
```

```
32
```

In [5]:
```
!ls -1 data/AA_qlearning_False_0_4_1_EpsilonGreedy_AA | wc -l
```

```
125
```

We have data from 32 different configurations.
Each configuration should have data from 125 different hyperparameter combinations.

In [6]:
```
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
from IPython.display import display, Markdown, Latex
%matplotlib inline
```

In [7]:
```
from pathlib import Path

path = Path('./data')
best_expt_by_id = {}  # stores expt name, maps to object
for config_id, config in enumerate(path.iterdir()):
    best_expt_by_id[config_id] = []
    reward = -np.inf

    for expt in config.iterdir():
        data = np.load(expt)

        temp = str(expt).split('_')
        algorithm = temp[1]
        wind = temp[2] == "True"
        start_coord = np.fromiter(map(int, [temp[3], temp[4]]), int)
        p = float(temp[5])
        strategy = temp[6]
        alpha = float(temp[8])
        gamma = float(temp[9])
        heat_or_eps = float(temp[10])

        # tot_rewards = data['r_s'].sum()
```

```python
        r = data['r'].sum()

        if r > reward:
            reward = r
            path = config / expt
            best_expt_by_id[config_id] = [algorithm, strategy, wind, start_coord, p, alp
```

In [8]:

```python
def sort_order(item):
    key, (algorithm, strategy, wind, start_coord, p, alpha, gamma, heat_or_eps, path, to
    return algorithm == "sarsa", start_coord.sum(), p, wind,
best_expt_by_id = dict(sorted(best_expt_by_id.items(), key=sort_order))
```

In [9]:

```python
len(best_expt_by_id)
```

Out[9]: 32

In [10]:

```python
DOWN , UP, LEFT, RIGHT = 0, 1, 2, 3
x_direct = np.array((0, 0, -1, 1))
y_direct = np.array((-1, 1, 0, 0))

def plot_Q(Q, ax, vmax=None):
    sns.heatmap(Q.max(-1), edgecolors='k', linewidths=0.5, ax=ax)

    policy = Q.argmax(-1)
    policyx = x_direct[policy]
    policyy = y_direct[policy]
    idx = np.indices(policy.shape)
    ax.quiver(idx[1].ravel() + 0.5, idx[0].ravel() + 0.5, policyx.ravel(), policyy.ravel
```

In [11]:

```python
visits_max = 4000
q_max = 1000

def print(algo):
    tick = 1
    for key in best_expt_by_id.keys():

        expt_info = best_expt_by_id[key]
        [algorithm, strategy, wind, start_coord, p, alpha, gamma, heat_or_eps, path, tot
        if algorithm != algo:
            continue

        display(Markdown(f'# Configuration {tick}'))
        outputs = (
            "| Reward | Algorithm | Exploration Strategy | Wind | Start Coors | P | . |
            "| :-: | :-: | :-: | :-: | :-: | :-: | :-: | :-: | :-: | :-: |",
            f"| {tot_rewards} | {algorithm} | {strategy} | {wind} | {start_coord} | {p}
        )
        display(Markdown("\n".join(outputs)))

        data = np.load(path)
        Q = data['q']
        Q = Q[::-1, :, :]
        visits = data['visits']
        visits = visits[::-1, ::]

        fig, axs = plt.subplots(2, 2, figsize=(10, 6))

        # Plot Optimal Policy
        plot_Q(Q, axs[0, 0], vmax=q_max)
        axs[0, 0].set_title('Q values with optimal policy')
```

```
        # Plotting Reward Curve
        episodes = np.arange(data['r_s'].shape[0])
        axs[0, 1].plot(episodes, data['r_s'])
        axs[0, 1].set_title('Rewards vs No of Episodes')
        axs[0, 1].set_xlabel('Episode')
        axs[0, 1].set_ylabel('Rewards')
        axs[0, 1].set_ylim(-200, 10)

        fig.show()

        # Plotting Steps Curve
        axs[1, 1].plot(episodes, data['s_s'])
        axs[1, 1].set_title('Steps to Steps vs No of Episodes')
        axs[1, 1].set_xlabel('Episode')
        axs[1, 1].set_ylabel('Steps')
        axs[1, 1].set_ylim(0, 100)

        # Plotting Heatmap of visited states
        sns.heatmap(visits, ax=axs[1, 0], vmax=visits_max)
        axs[1, 0].set_title('Heatmap of Visited States')

        fig.show()

        plt.pause(0.001)
        tick += 1
```

SARSA

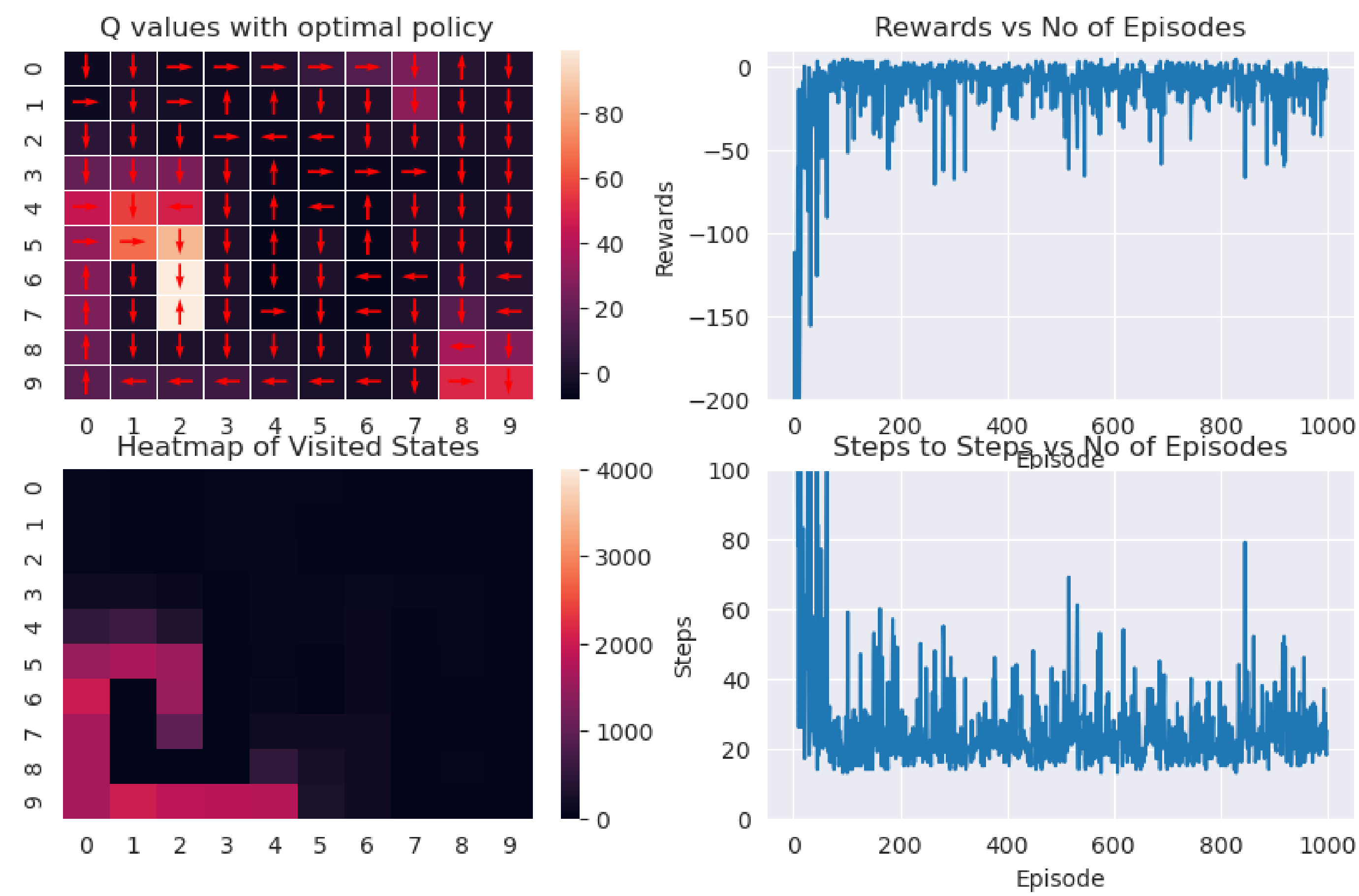
In [12]:

```
print("sarsa")
```

Configuration 1

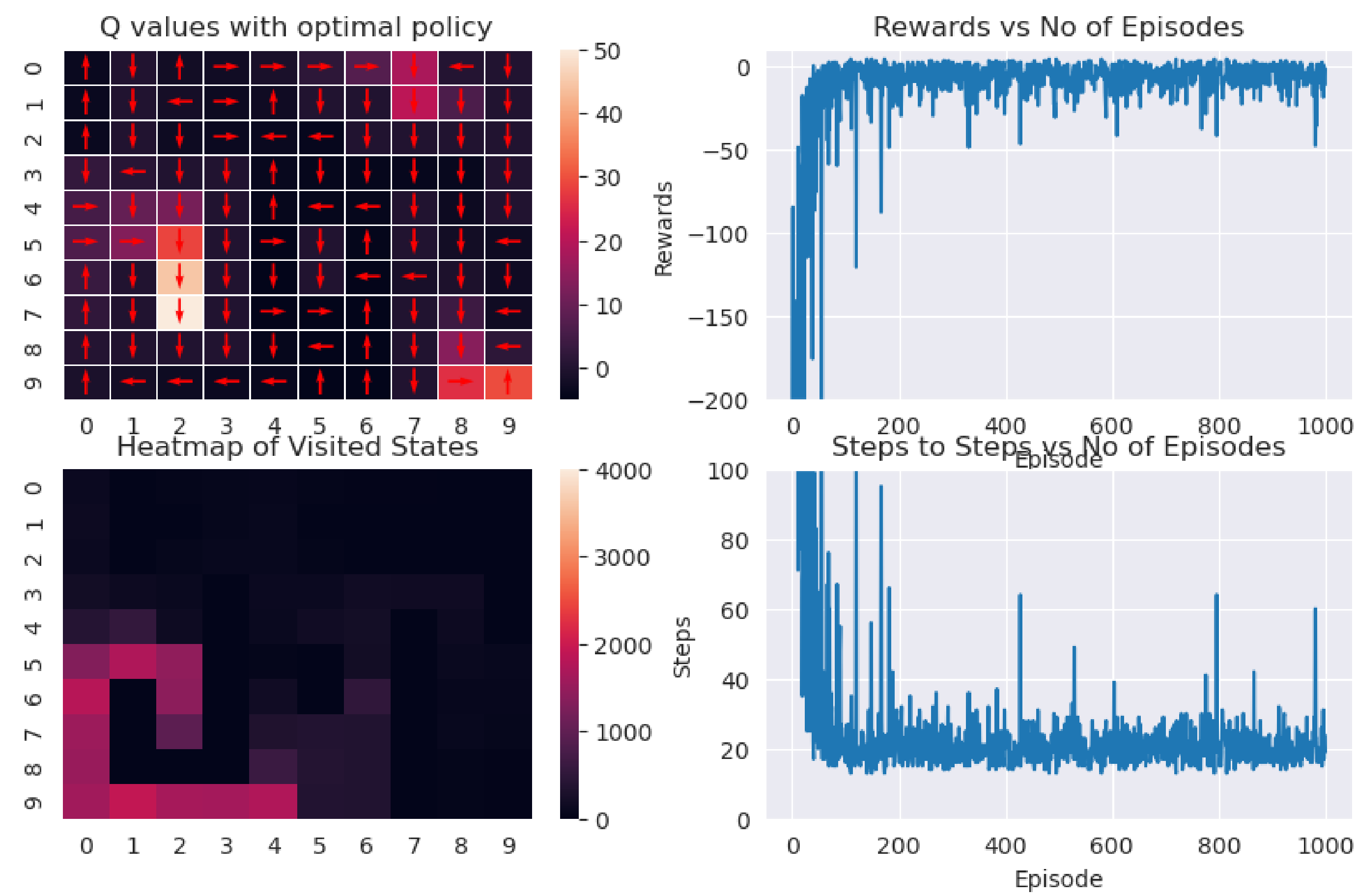
Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	sarsa	EpsilonGreedy	False	[0 4]	0.7	.	0.9	0.5	2.0

```
/tmp/ipykernel_8072/2852134997.py:41: UserWarning: Matplotlib is currently using modul
e://matplotlib_inline.backend_inline, which is a non-GUI backend, so cannot show the fig
ure.
  fig.show()
/tmp/ipykernel_8072/2852134997.py:54: UserWarning: Matplotlib is currently using modul
e://matplotlib_inline.backend_inline, which is a non-GUI backend, so cannot show the fig
ure.
  fig.show()
```



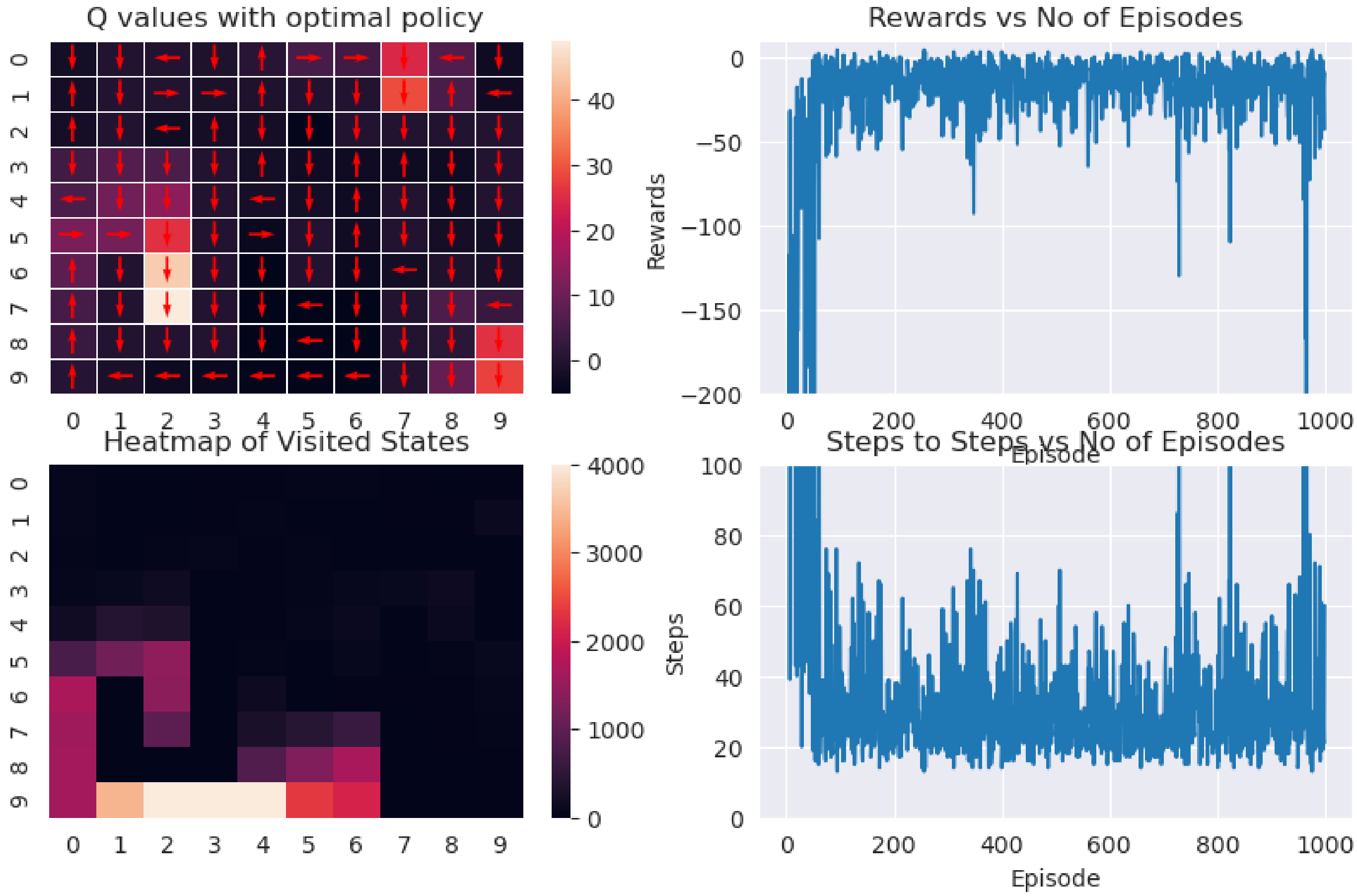
Configuration 2

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	sarsa	Softmax	False	[0 4]	0.7	.	0.8	0.2	0.0



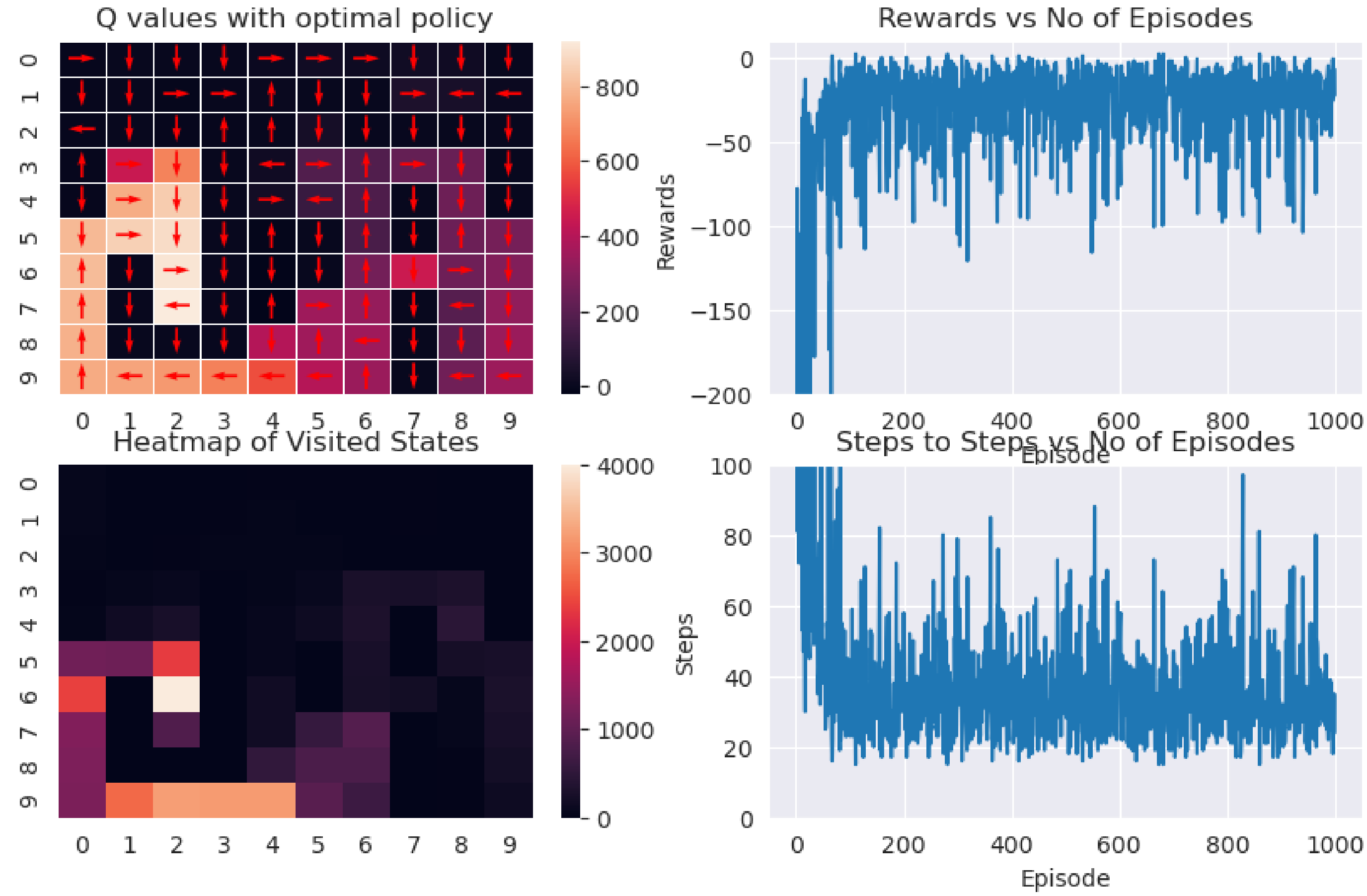
Configuration 3

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
2.0	sarsa	EpsilonGreedy	True	[0 4]	0.7	.	0.8	0.2	1.0



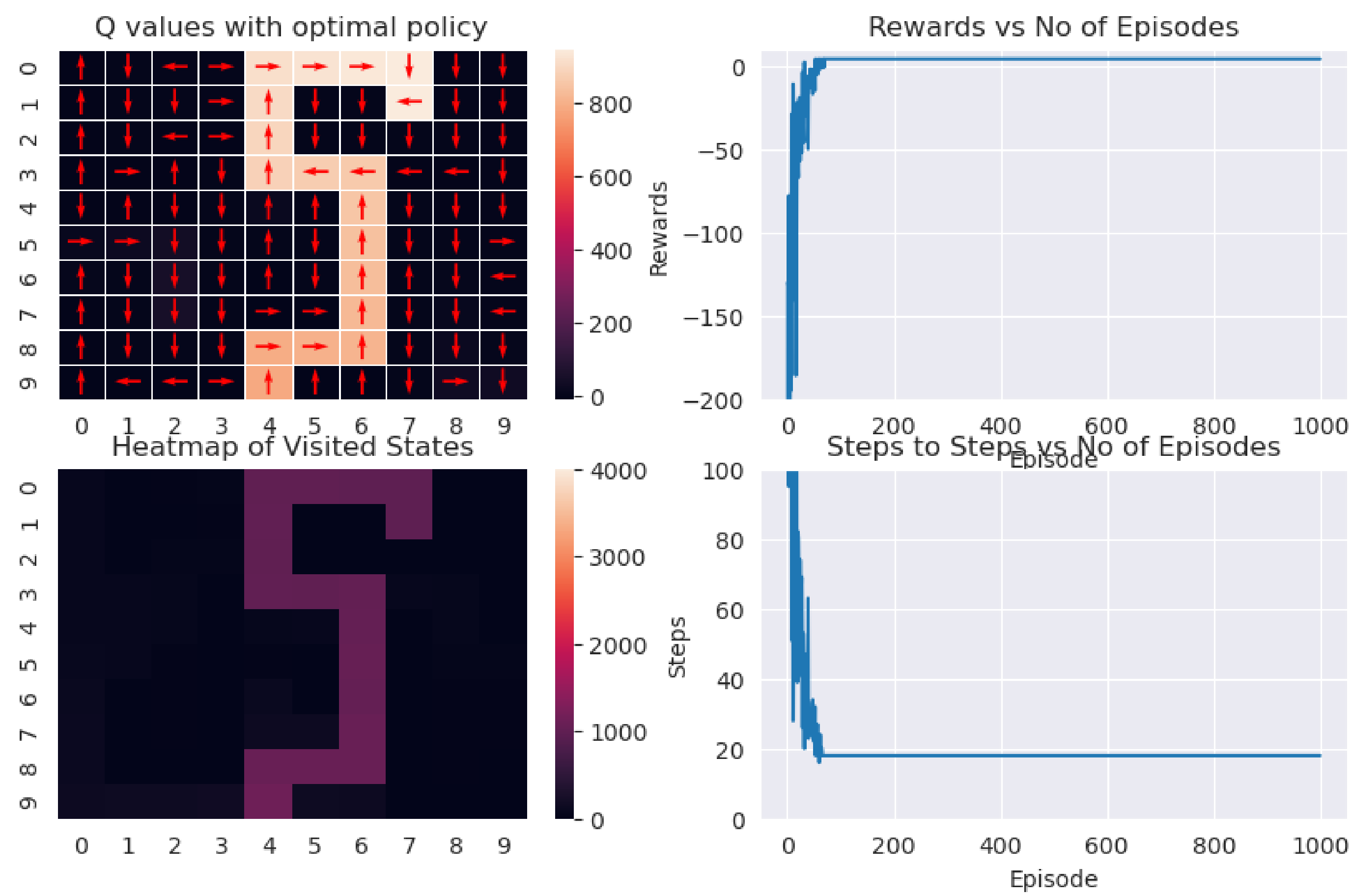
Configuration 4

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
2.0	sarsa	Softmax	True	[0 4]	0.7	.	0.99	0.3	0.0



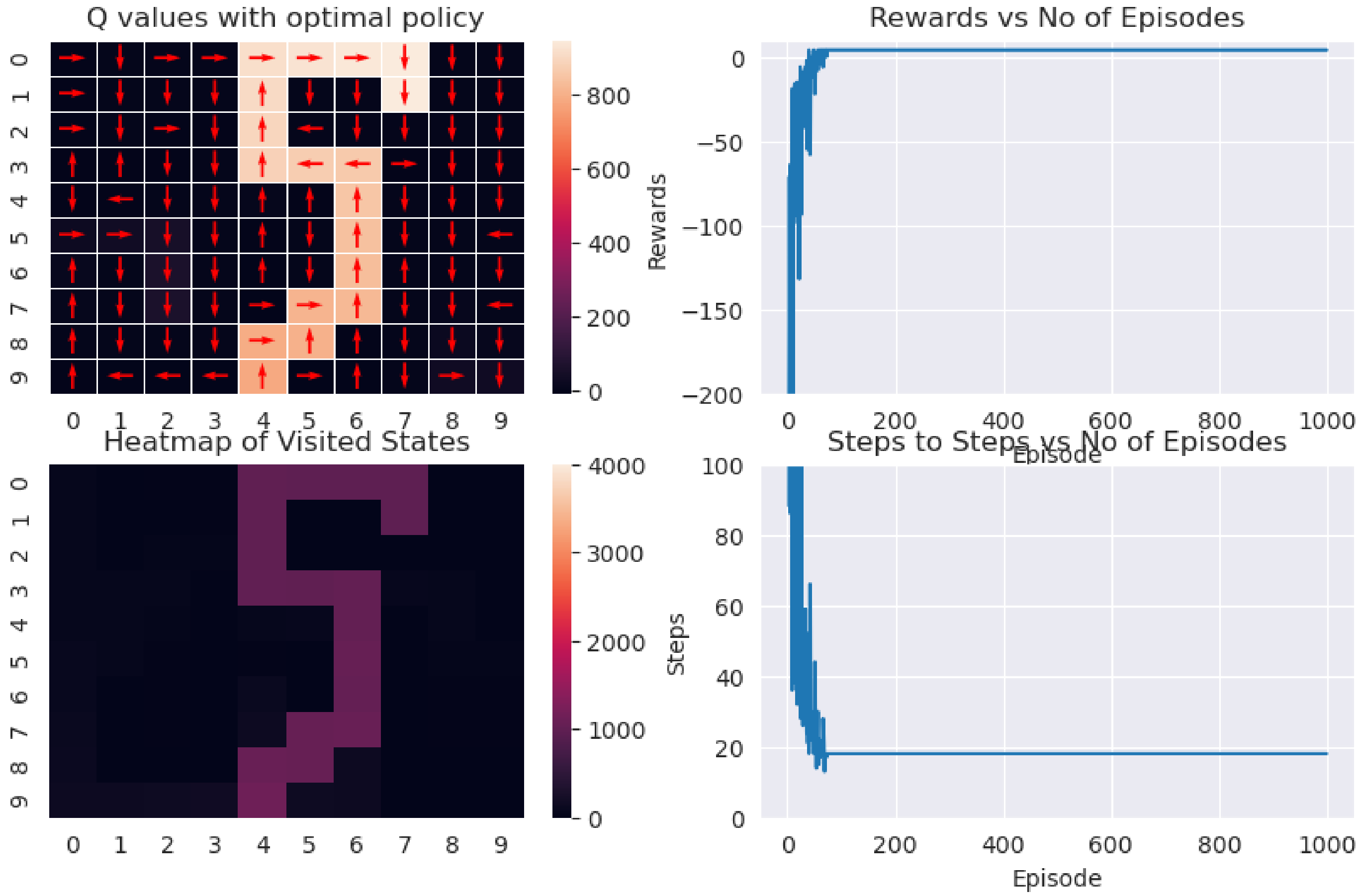
Configuration 5

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	sarsa	Softmax	False	[0 4]	1.0	.	0.99	0.3	0.0



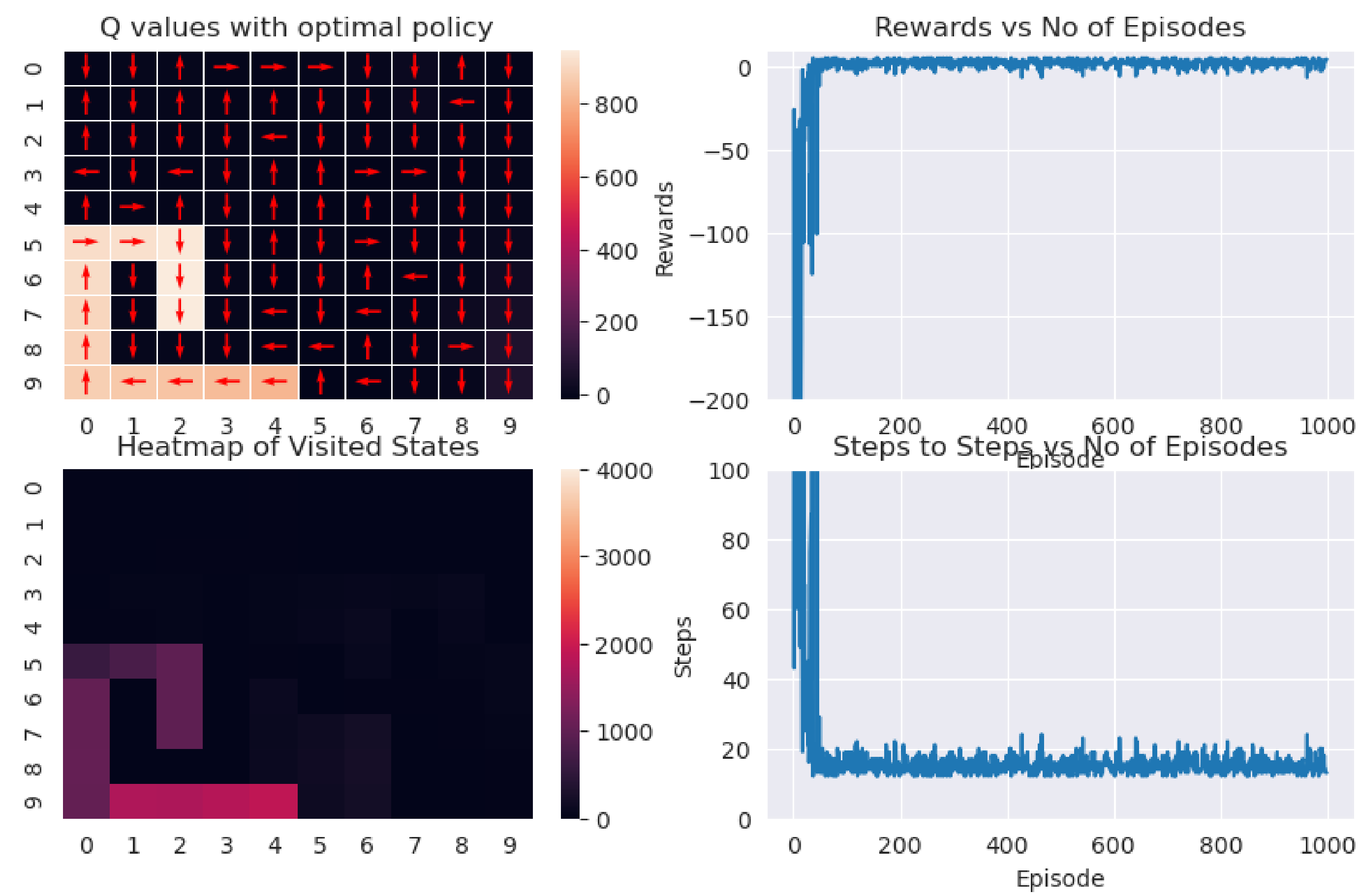
Configuration 6

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	sarsa	EpsilonGreedy	False	[0 4]	1.0	.	0.99	0.3	0.0



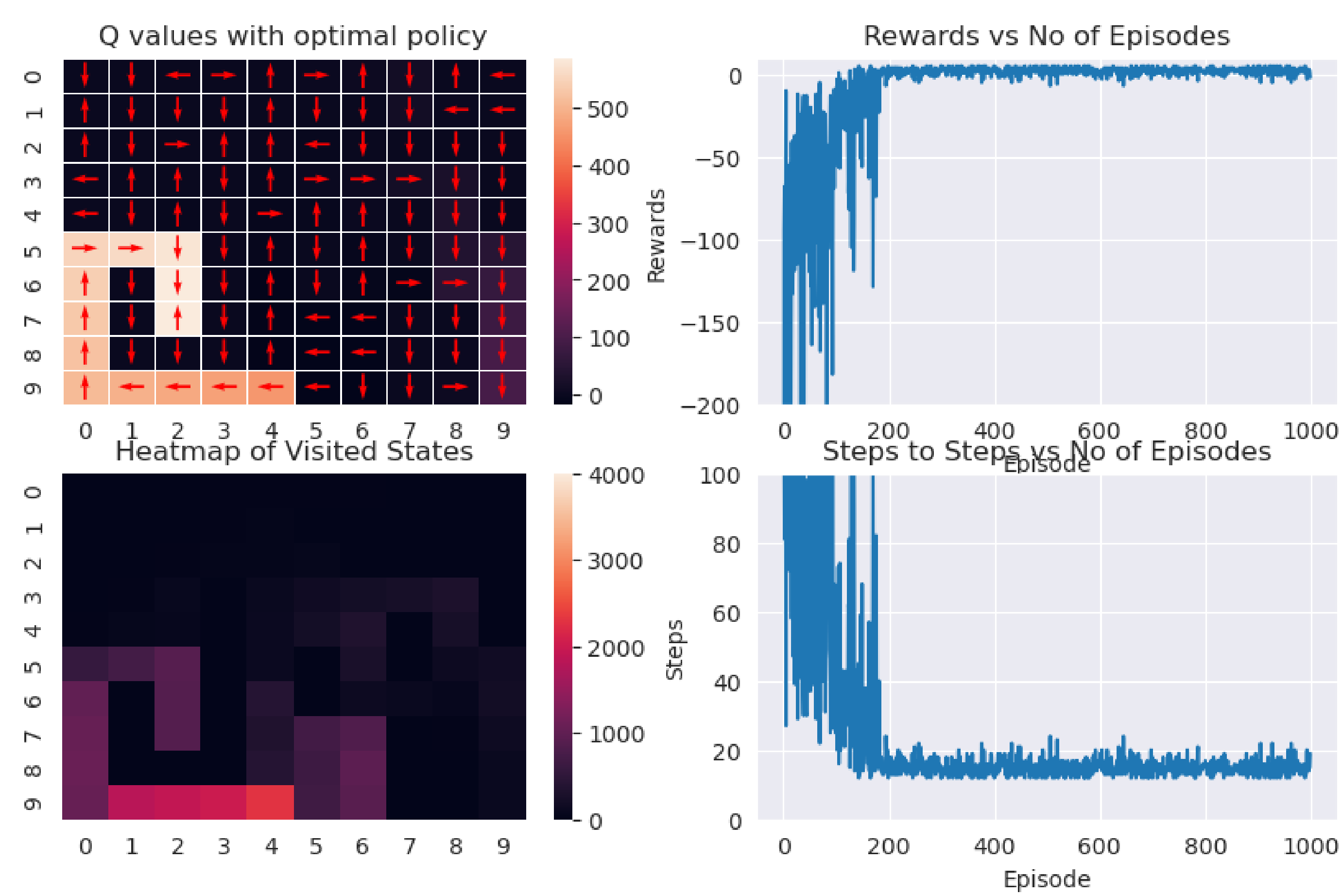
Configuration 7

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
5.0	sarsa	EpsilonGreedy	True	[0 4]	1.0	.	0.99	0.3	0.0



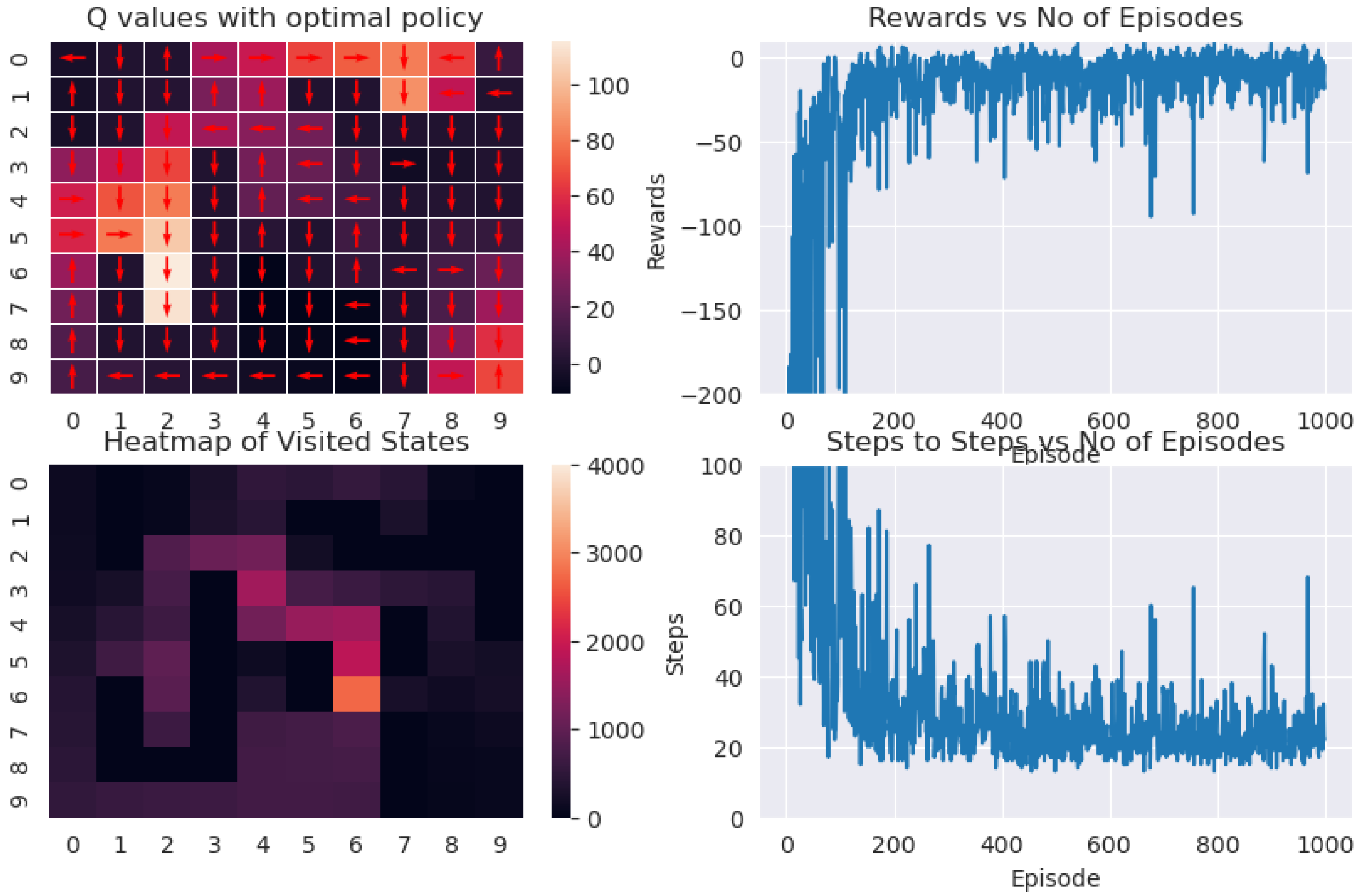
Configuration 8

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
5.0	sarsa	Softmax	True	[0 4]	1.0	.	0.99	0.1	1.0



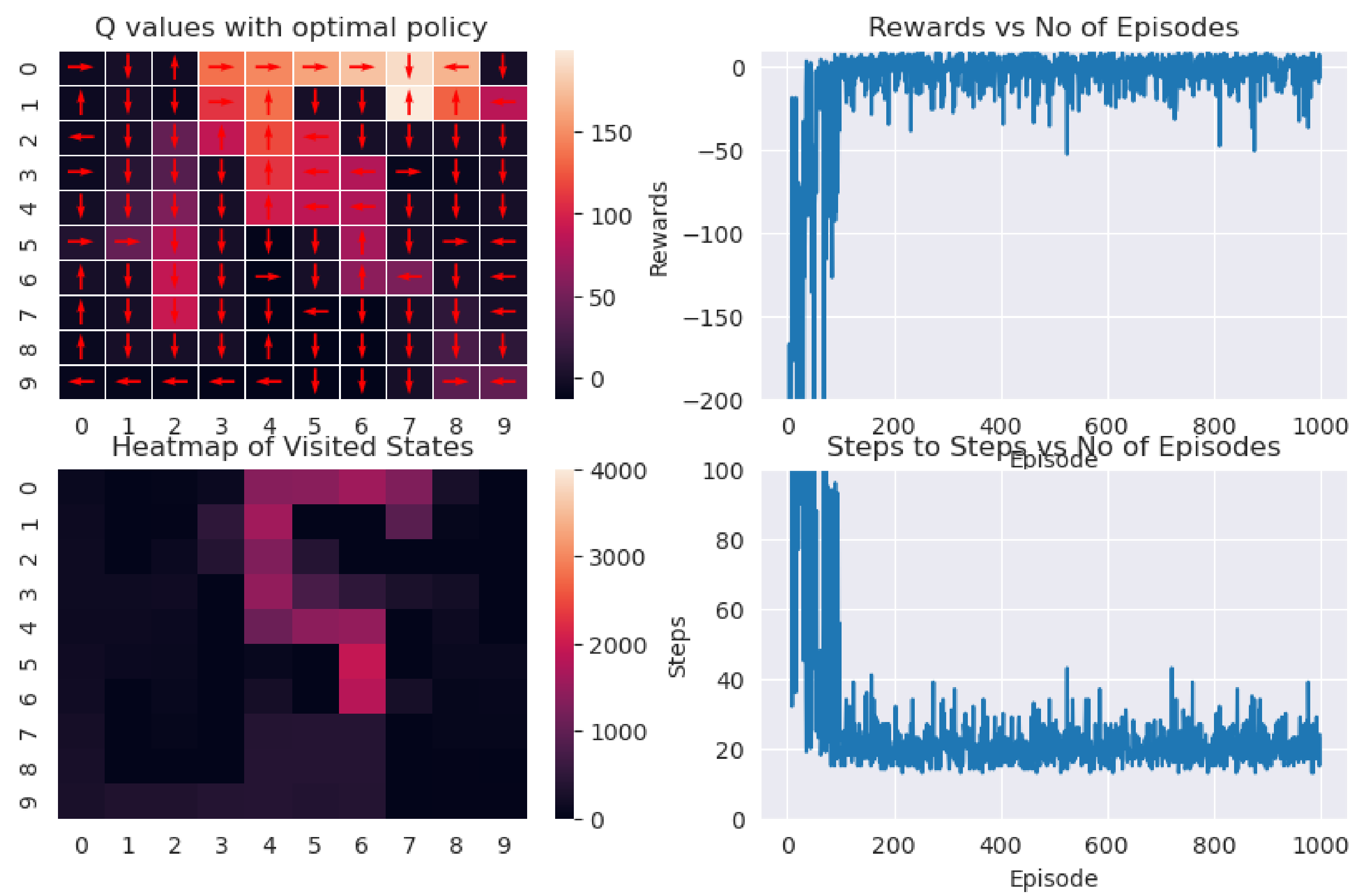
Configuration 9

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	EpsilonGreedy	False	[3 6]	0.7	.	0.95	0.1	3.0



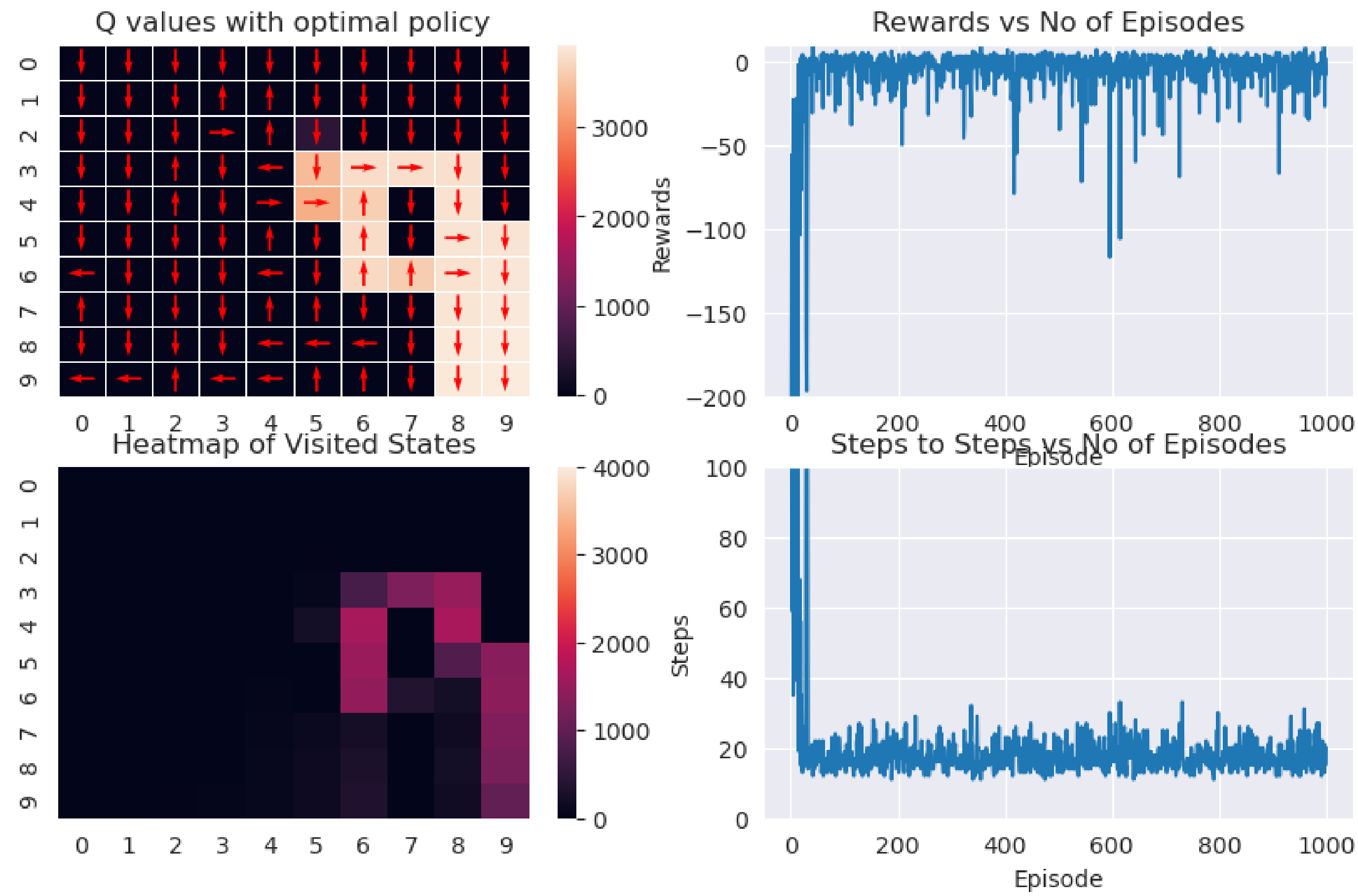
Configuration 10

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	Softmax	False	[3 6]	0.7	.	0.95	0.2	1.0



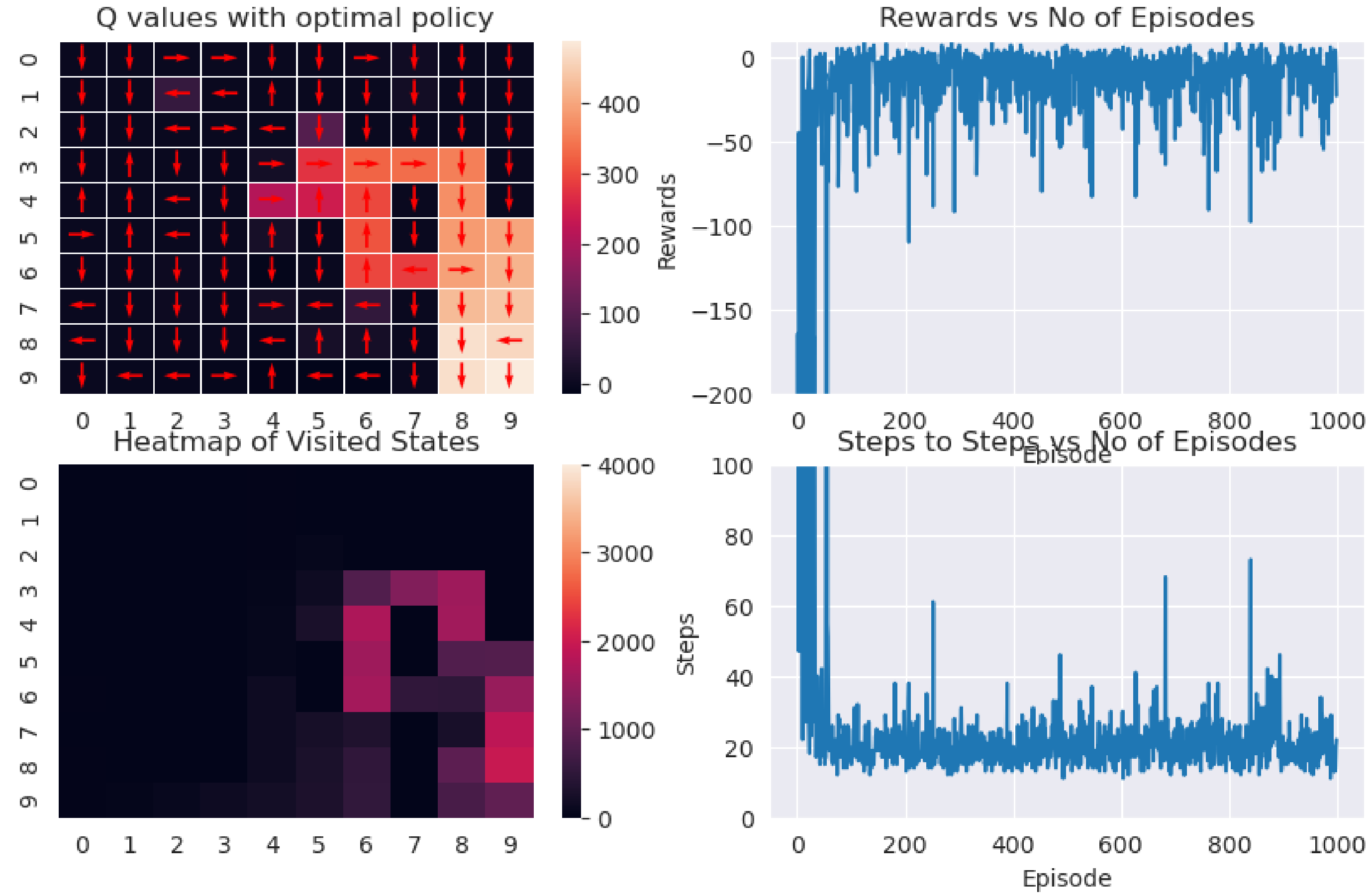
Configuration 11

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
6.0	sarsa	Softmax	True	[3 6]	0.7	.	0.999	0.5	3.0



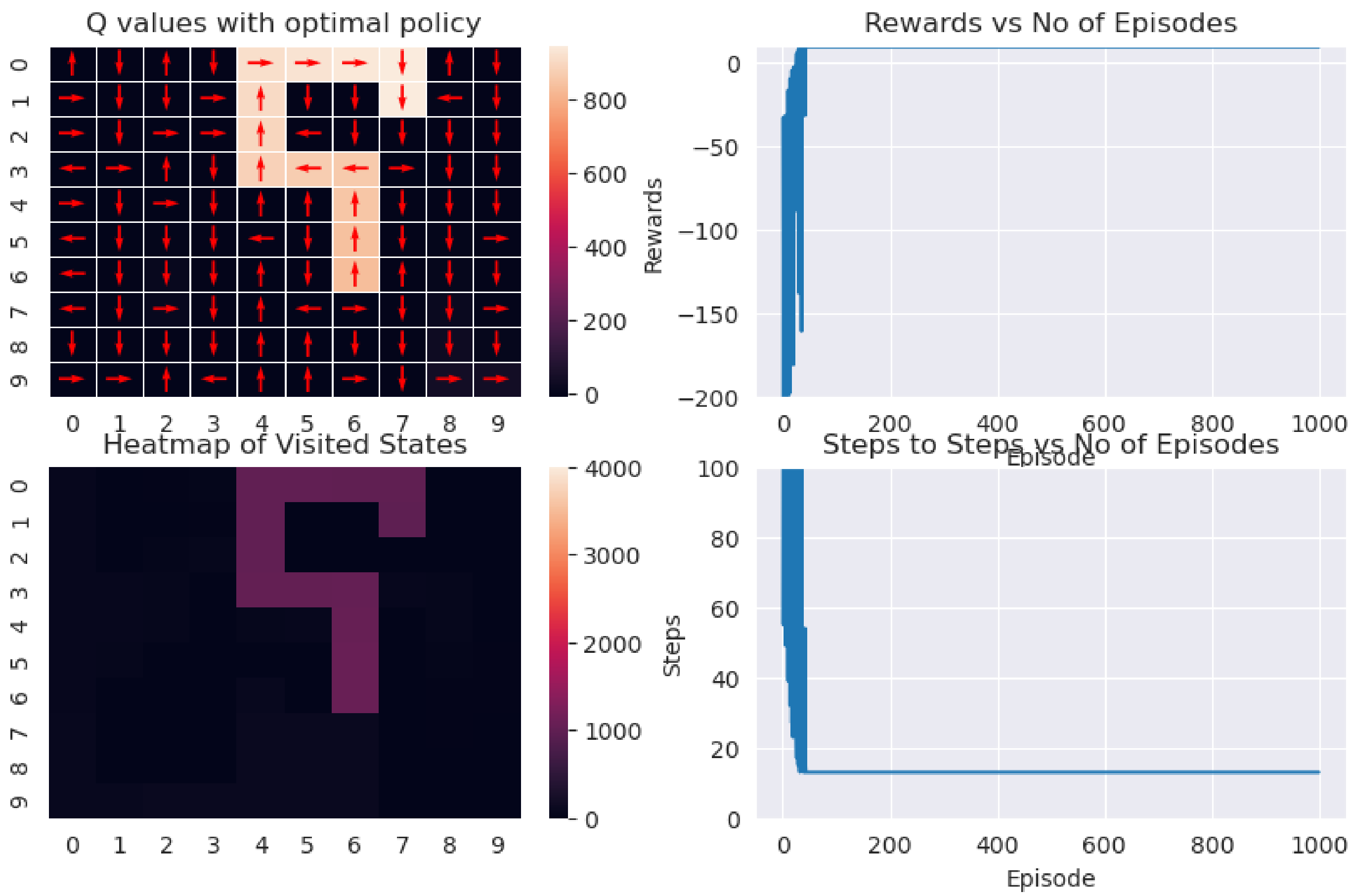
Configuration 12

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	EpsilonGreedy	True	[3 6]	0.7	.	0.99	0.2	1.0



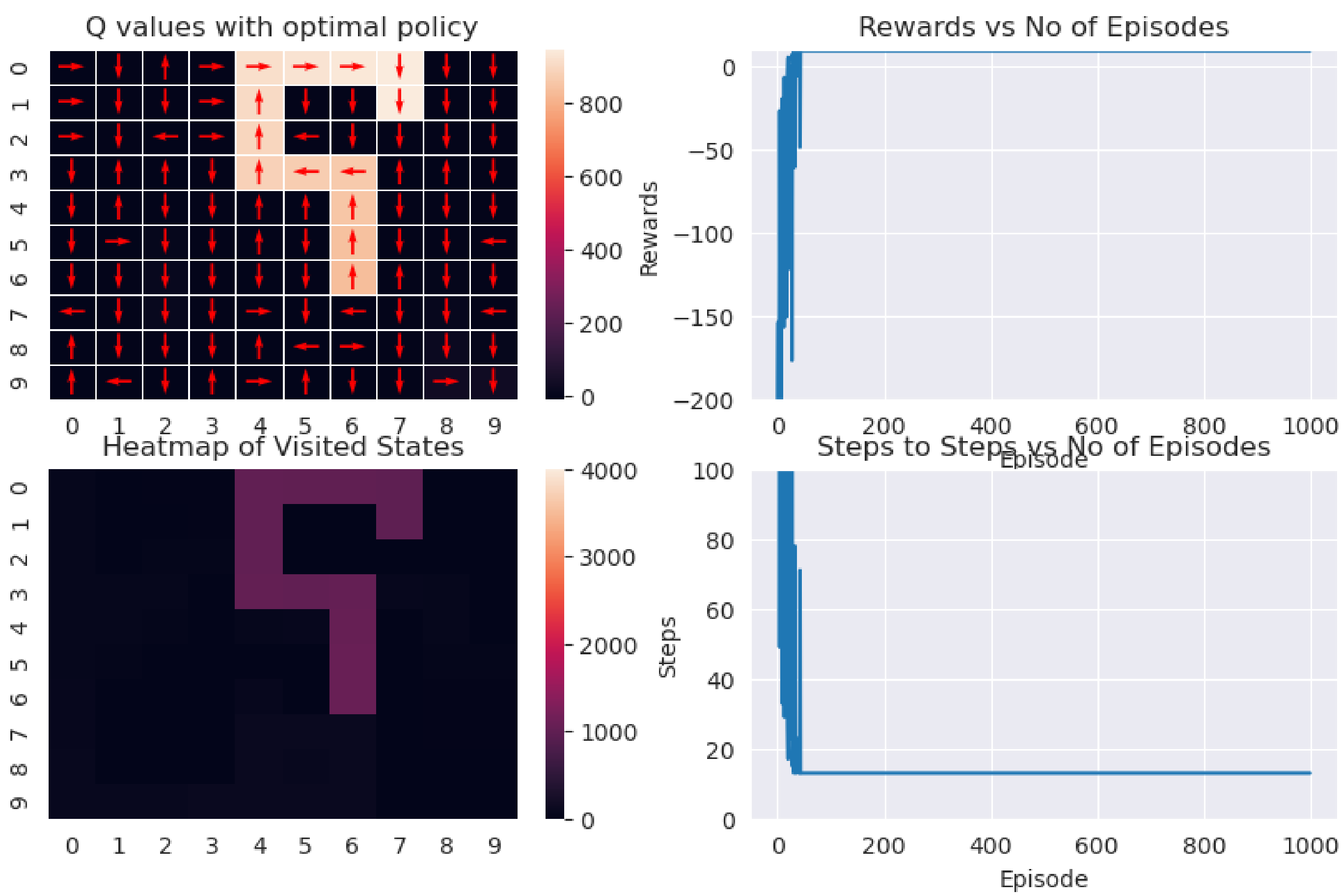
Configuration 13

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	Softmax	False	[3 6]	1.0	.	0.99	0.3	0.0



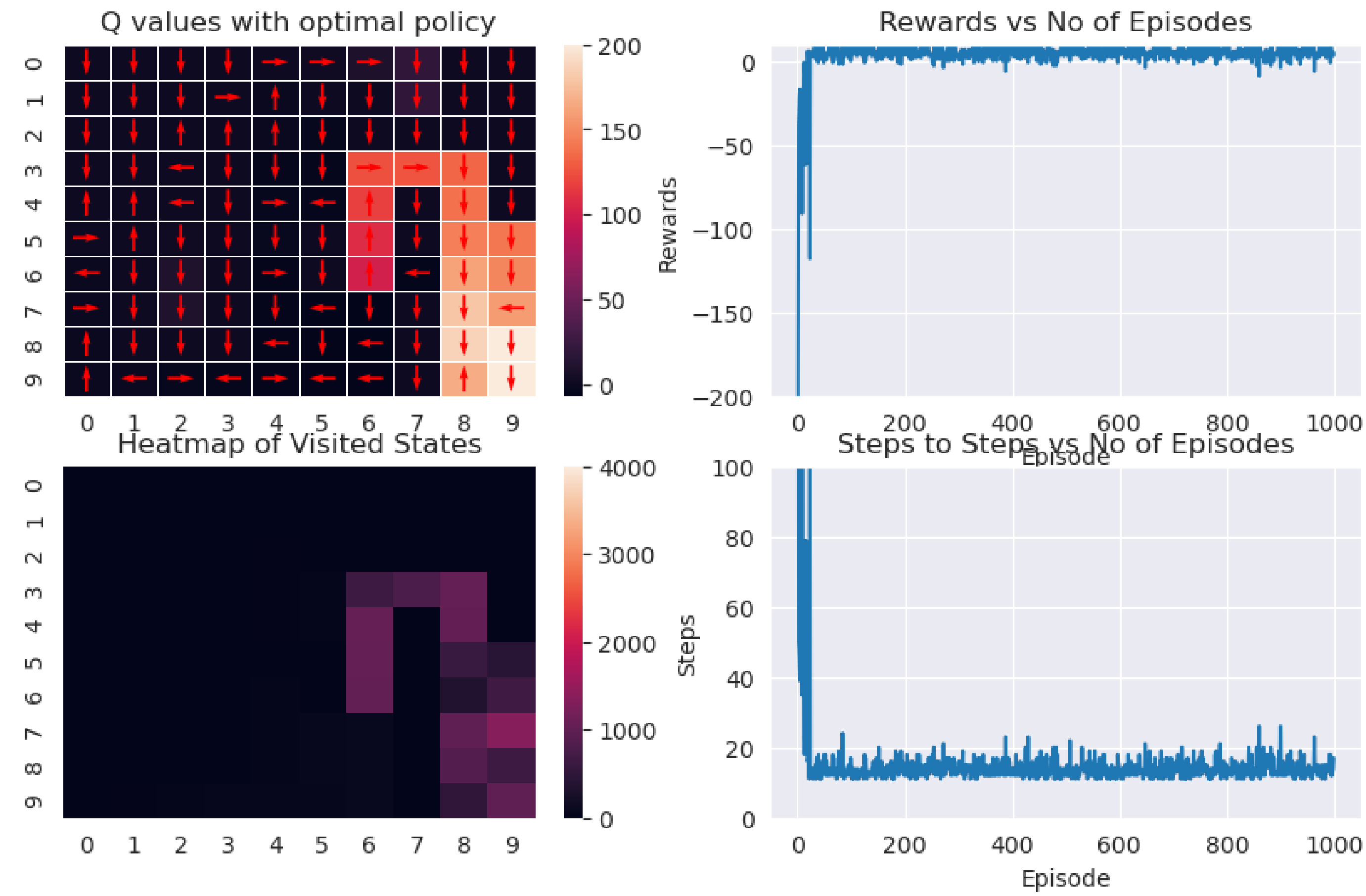
Configuration 14

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	EpsilonGreedy	False	[3 6]	1.0	.	0.99	0.3	0.0



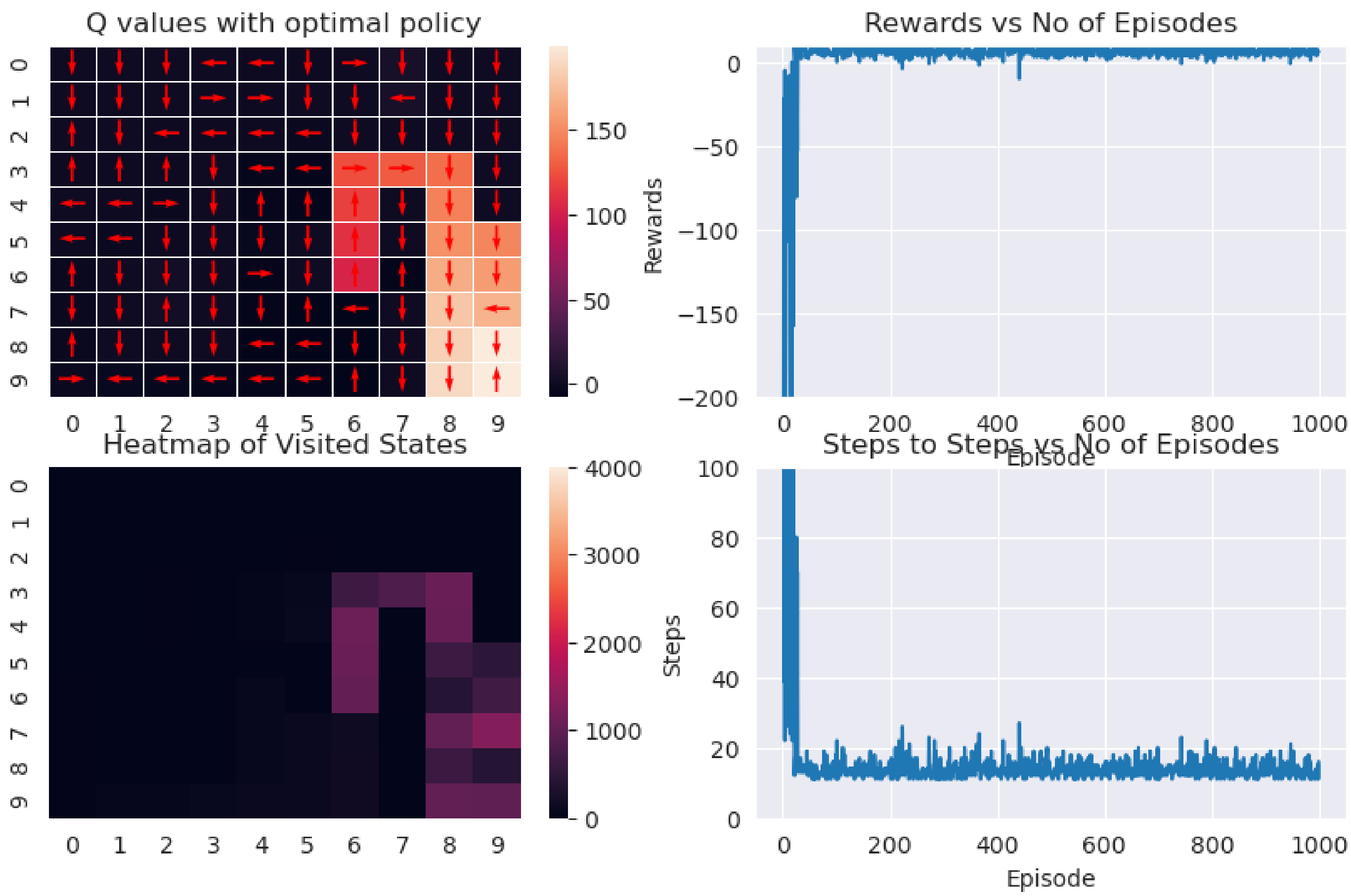
Configuration 15

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
10.0	sarsa	EpsilonGreedy	True	[3 6]	1.0	.	0.95	0.5	0.0



Configuration 16

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	sarsa	Softmax	True	[3 6]	1.0	.	0.95	0.3	0.0



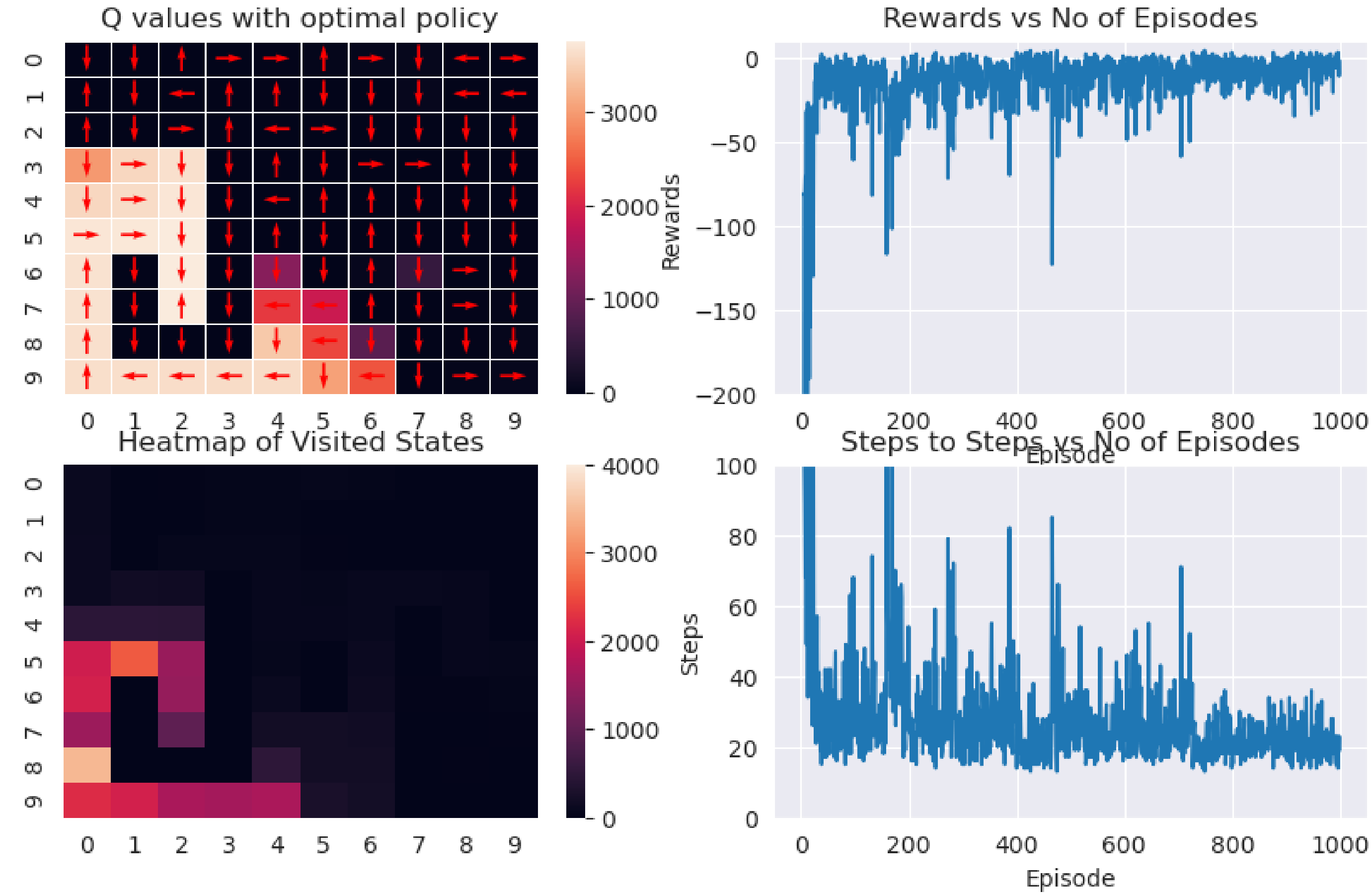
QLearning

In [13]:
```python
print("qlearning")
```

Configuration 1

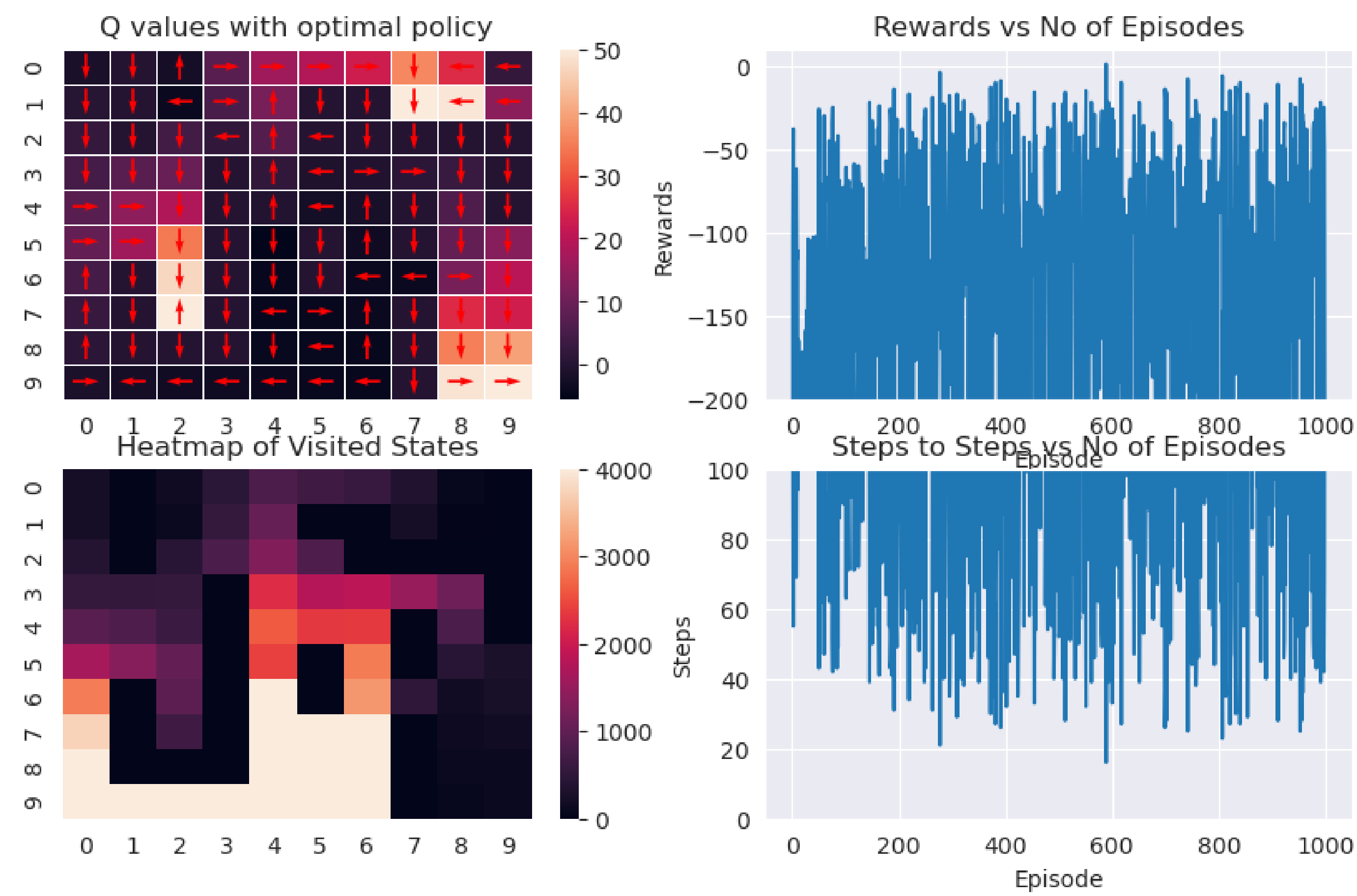
Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
3.0	qlearning	EpsilonGreedy	False	[0 4]	0.7	.	0.999	0.5	2.0

```
/tmp/ipykernel_8072/2852134997.py:41: UserWarning: Matplotlib is currently using modul
e://matplotlib_inline.backend_inline, which is a non-GUI backend, so cannot show the fig
ure.
  fig.show()
/tmp/ipykernel_8072/2852134997.py:54: UserWarning: Matplotlib is currently using modul
e://matplotlib_inline.backend_inline, which is a non-GUI backend, so cannot show the fig
ure.
  fig.show()
```



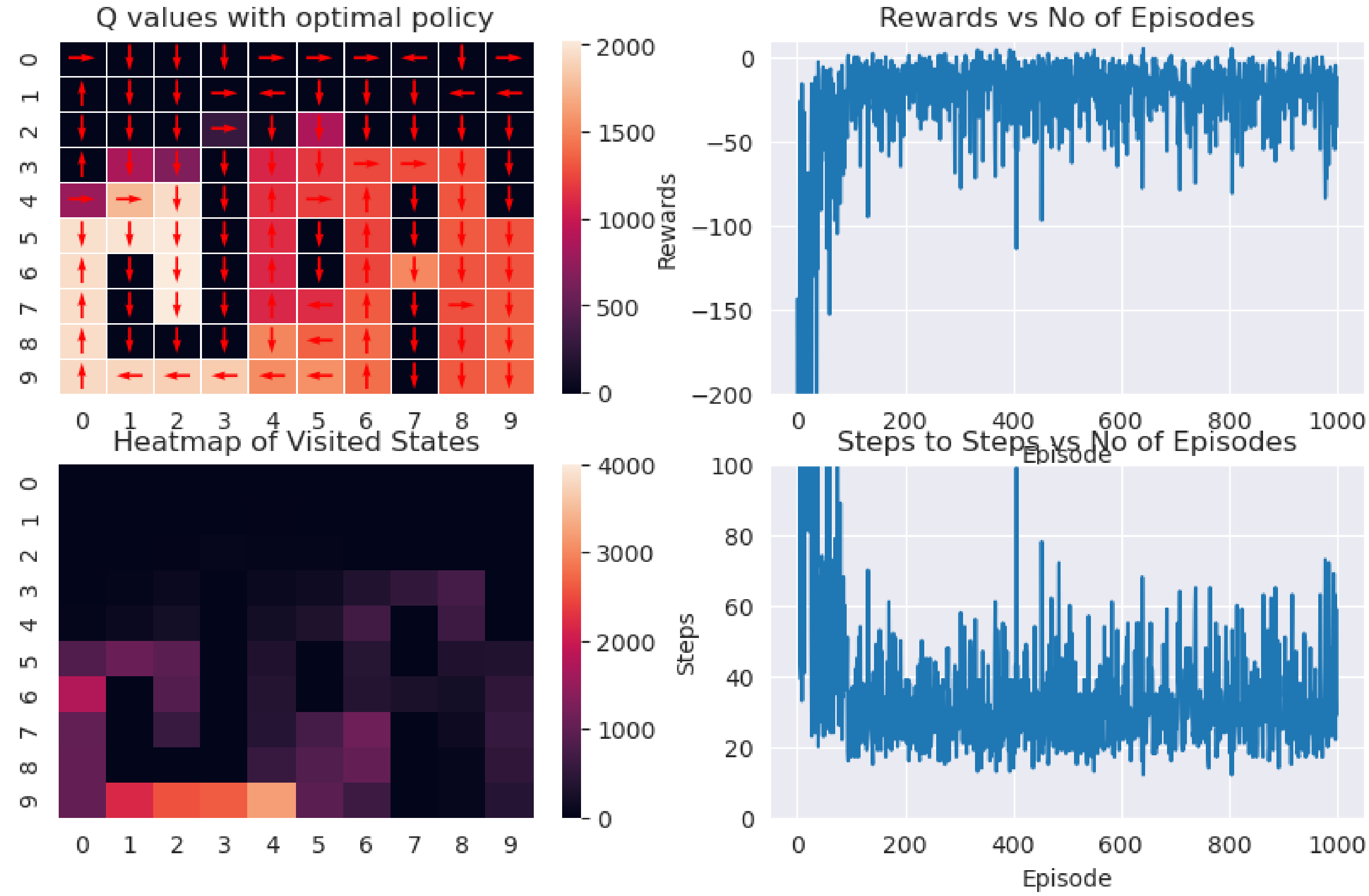
Configuration 2

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	qlearning	Softmax	False	[0 4]	0.7	.	0.8	0.4	4.0



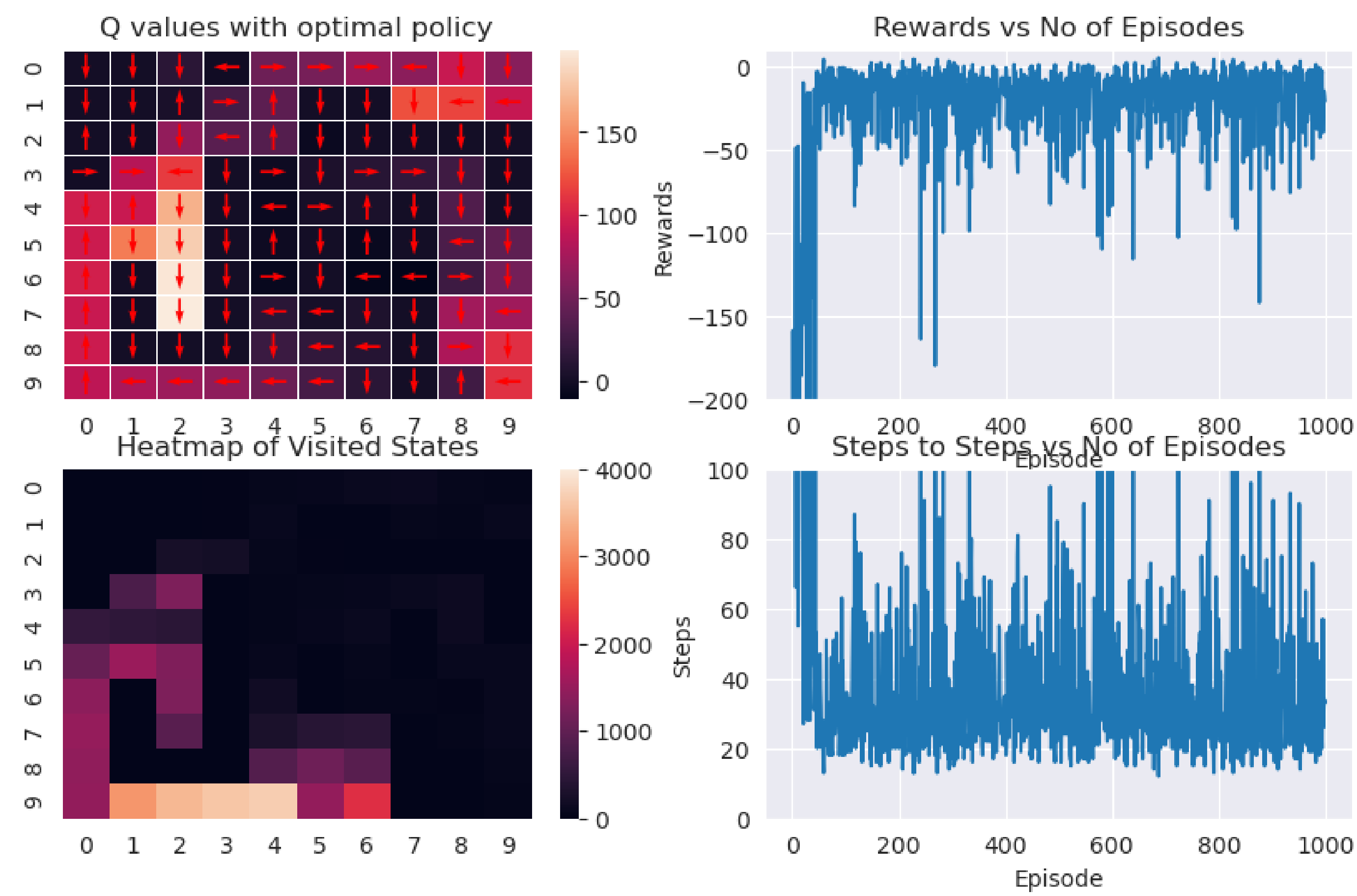
Configuration 3

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
3.0	qlearning	EpsilonGreedy	True	[0 4]	0.7	.	0.999	0.4	3.0



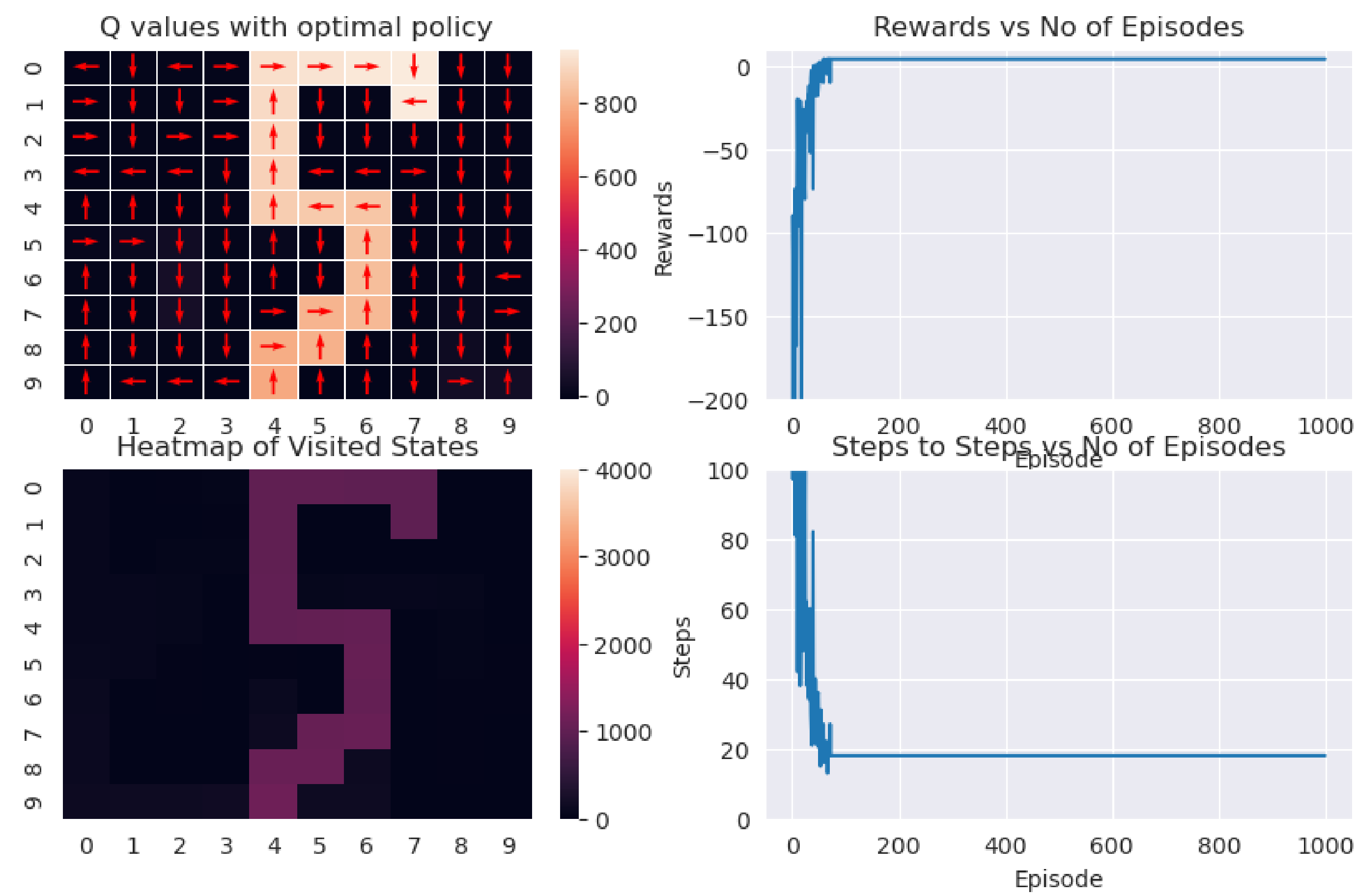
Configuration 4

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
3.0	qlearning	Softmax	True	[0 4]	0.7	.	0.95	0.4	0.0



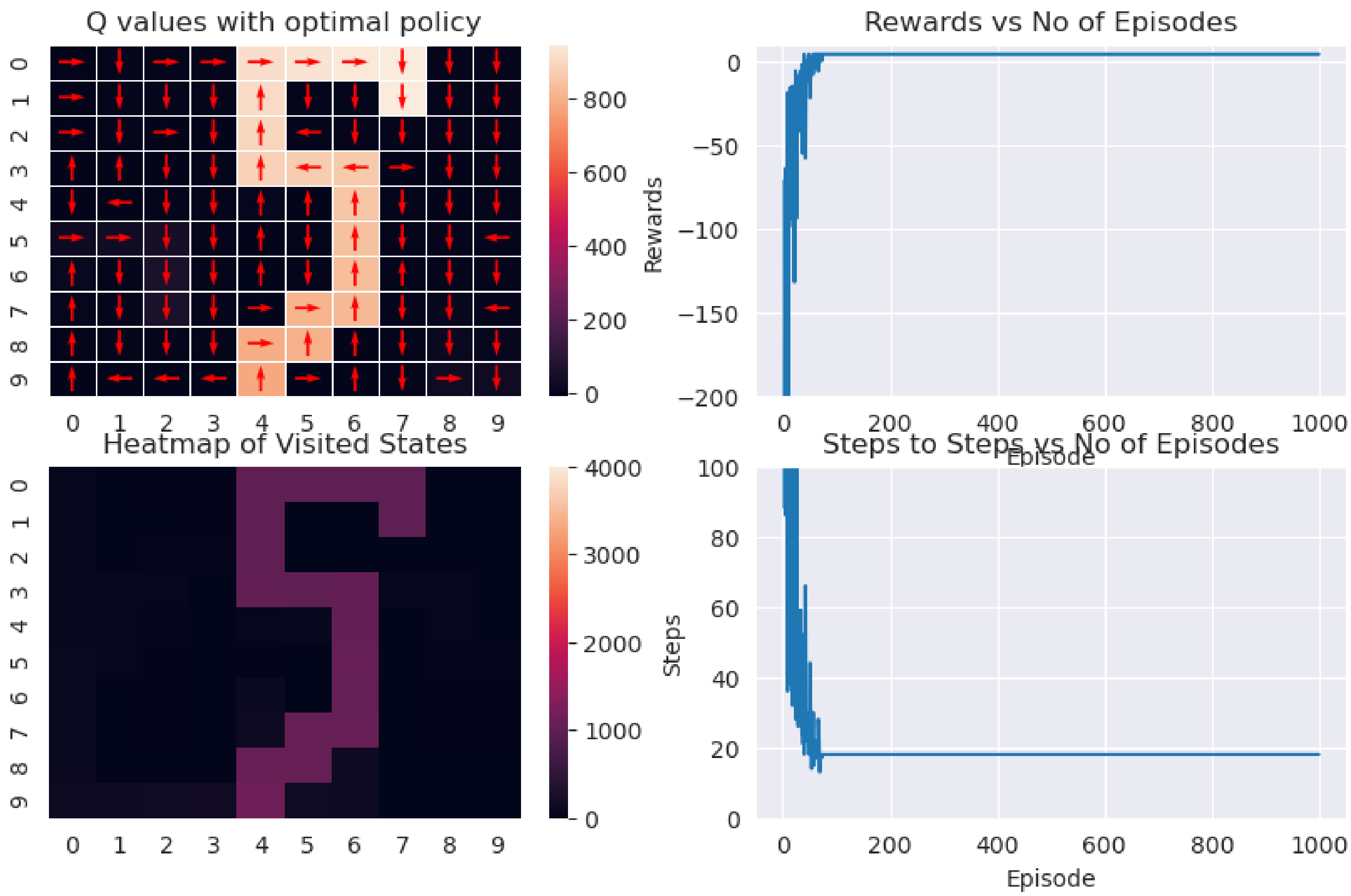
Configuration 5

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	qlearning	Softmax	False	[0 4]	1.0	.	0.99	0.3	0.0



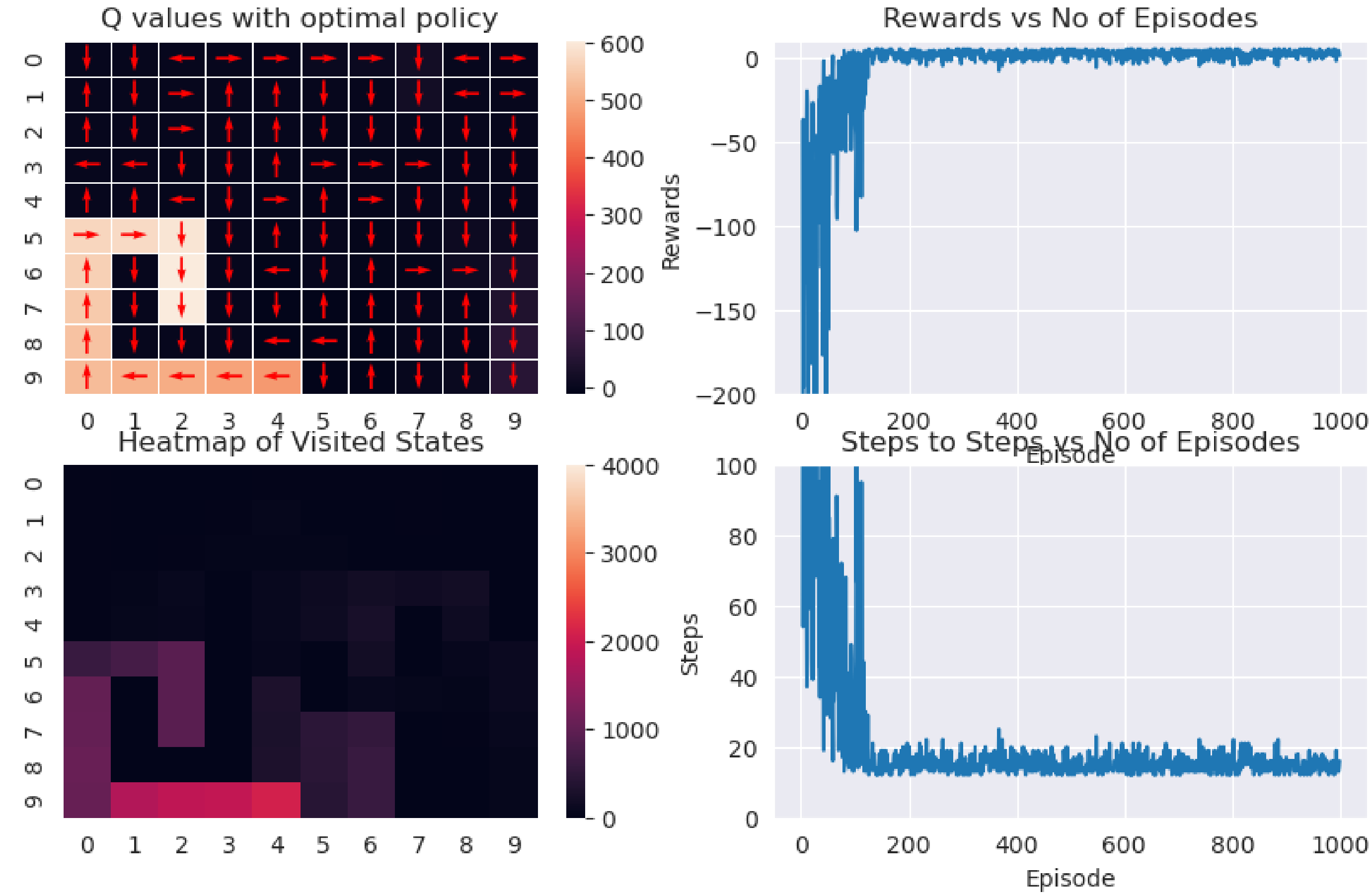
Configuration 6

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
4.0	qlearning	EpsilonGreedy	False	[0 4]	1.0	.	0.99	0.3	0.0



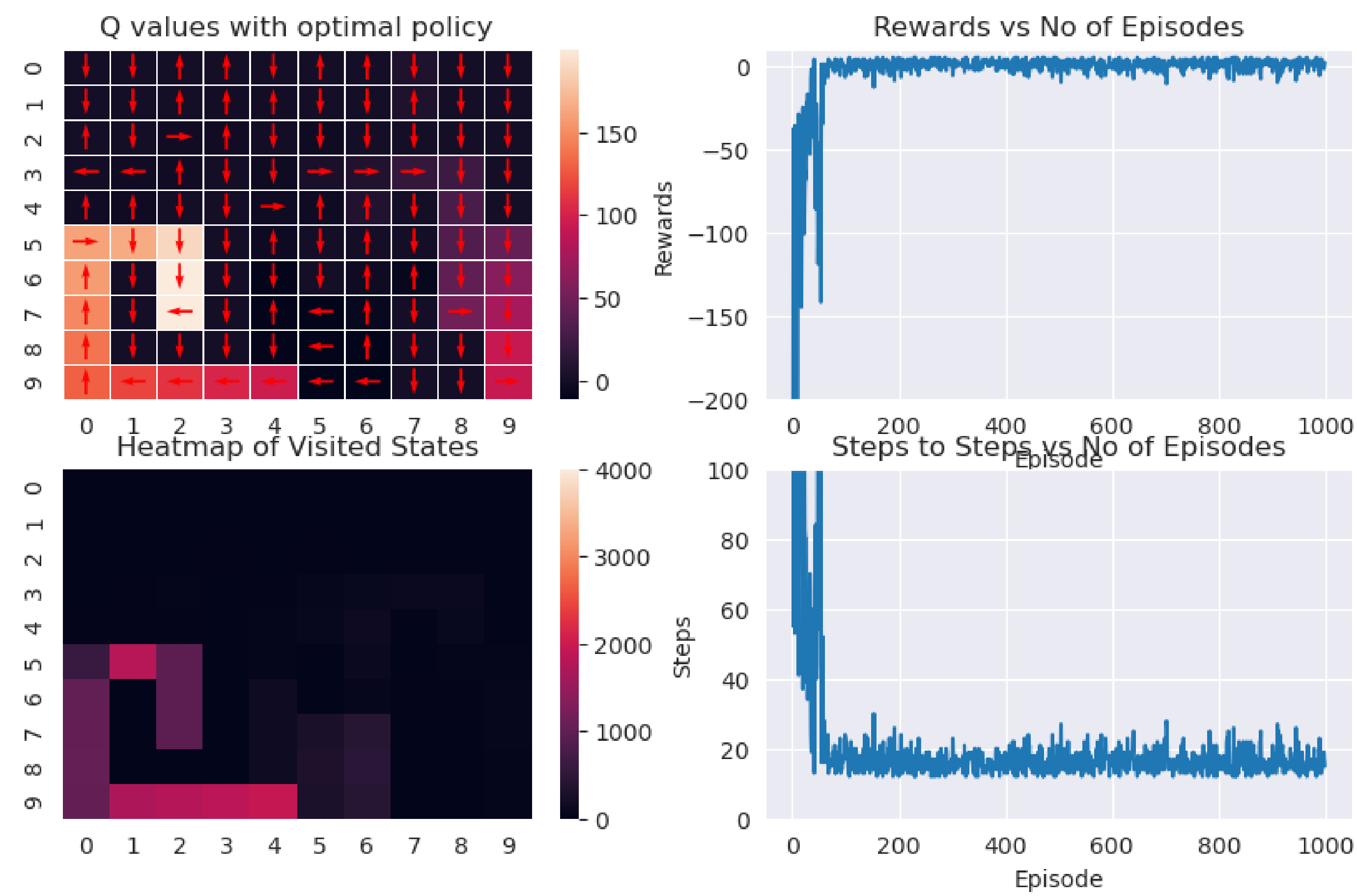
Configuration 7

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
5.0	qlearning	EpsilonGreedy	True	[0 4]	1.0	.	0.99	0.1	0.0



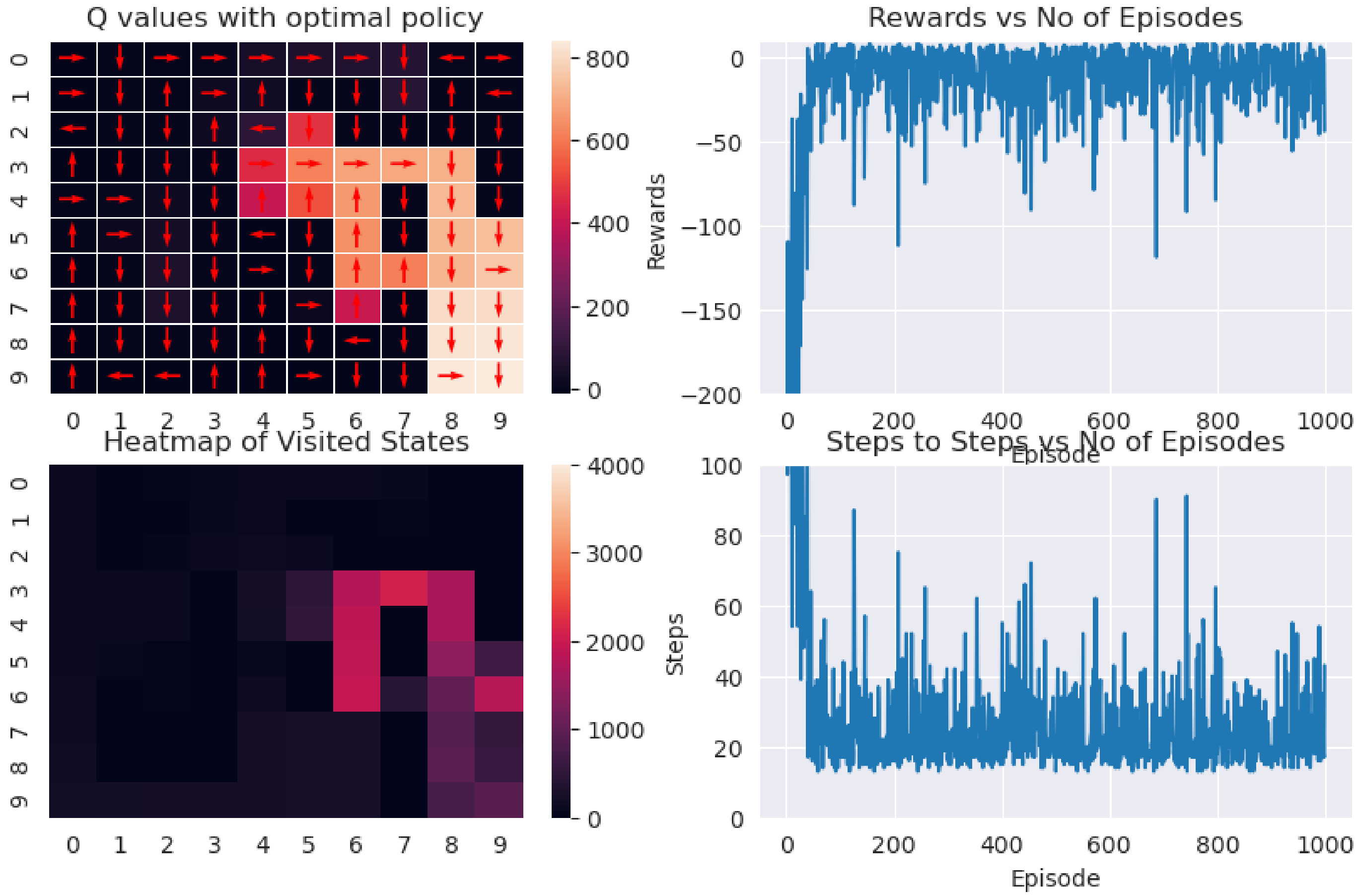
Configuration 8

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
5.0	qlearning	Softmax	True	[0 4]	1.0	.	0.95	0.3	1.0



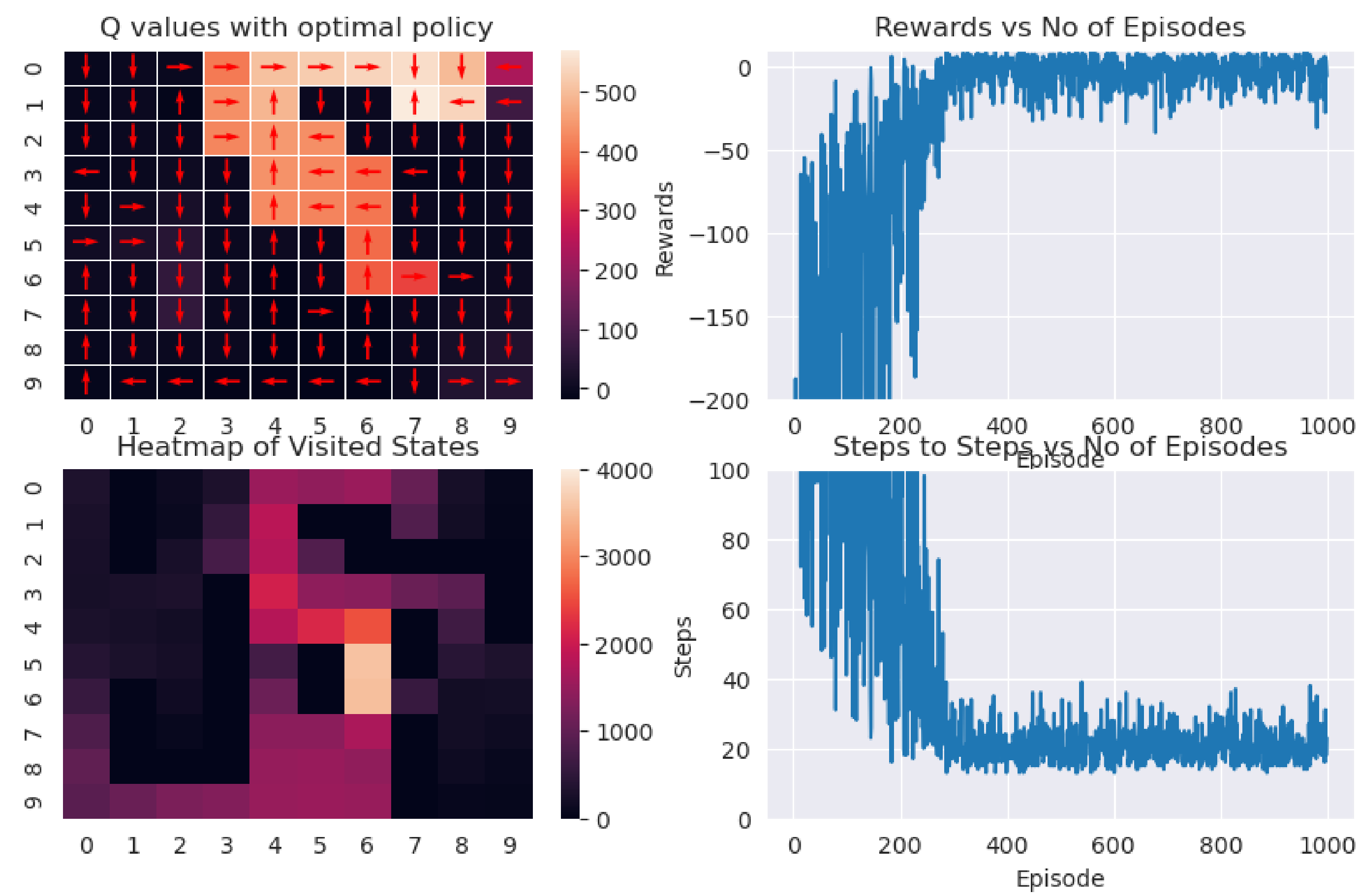
Configuration 9

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
8.0	qlearning	EpsilonGreedy	False	[3 6]	0.7	.	0.99	0.2	1.0



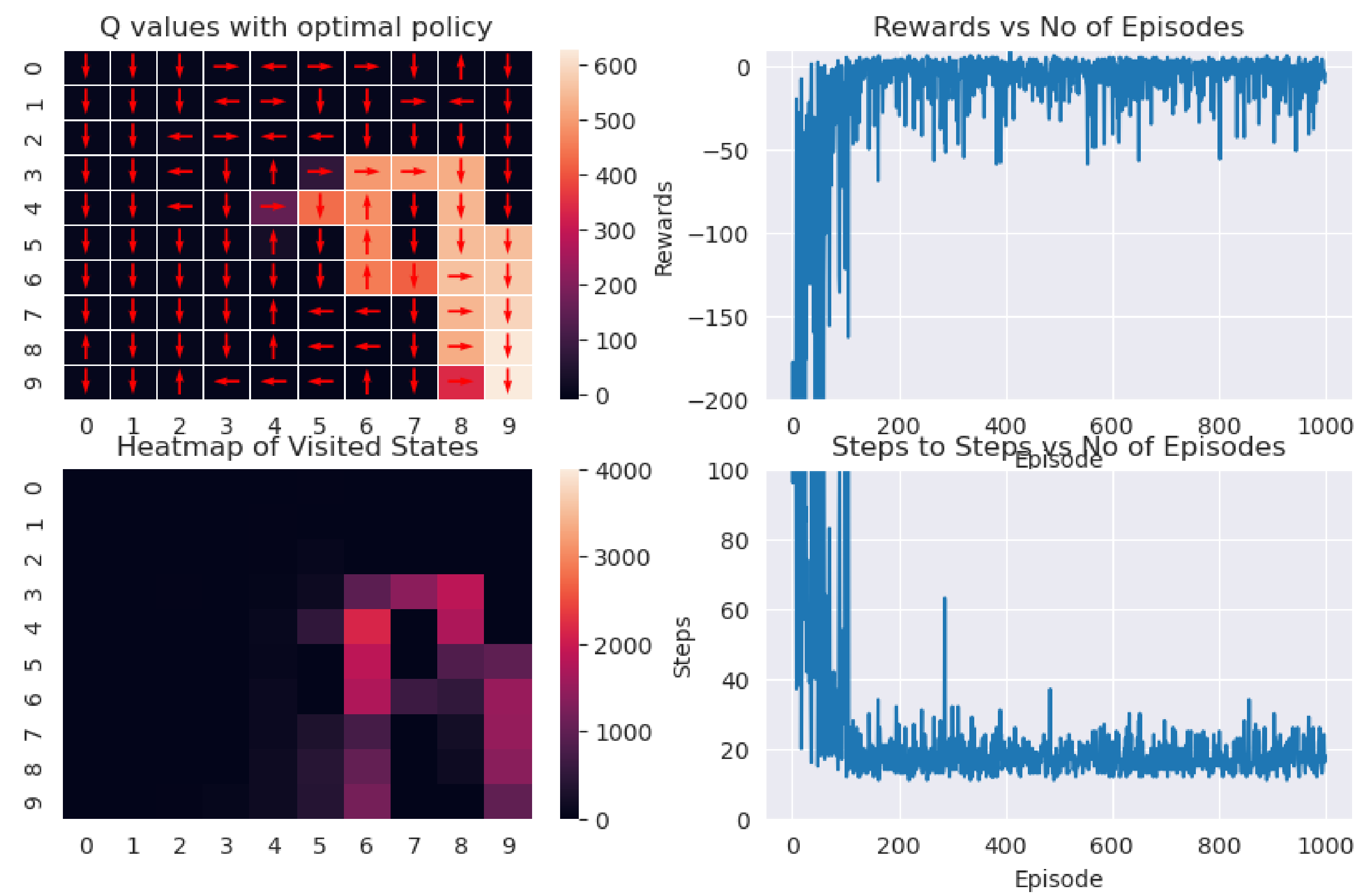
Configuration 10

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	qlearning	Softmax	False	[3 6]	0.7	.	0.99	0.1	4.0



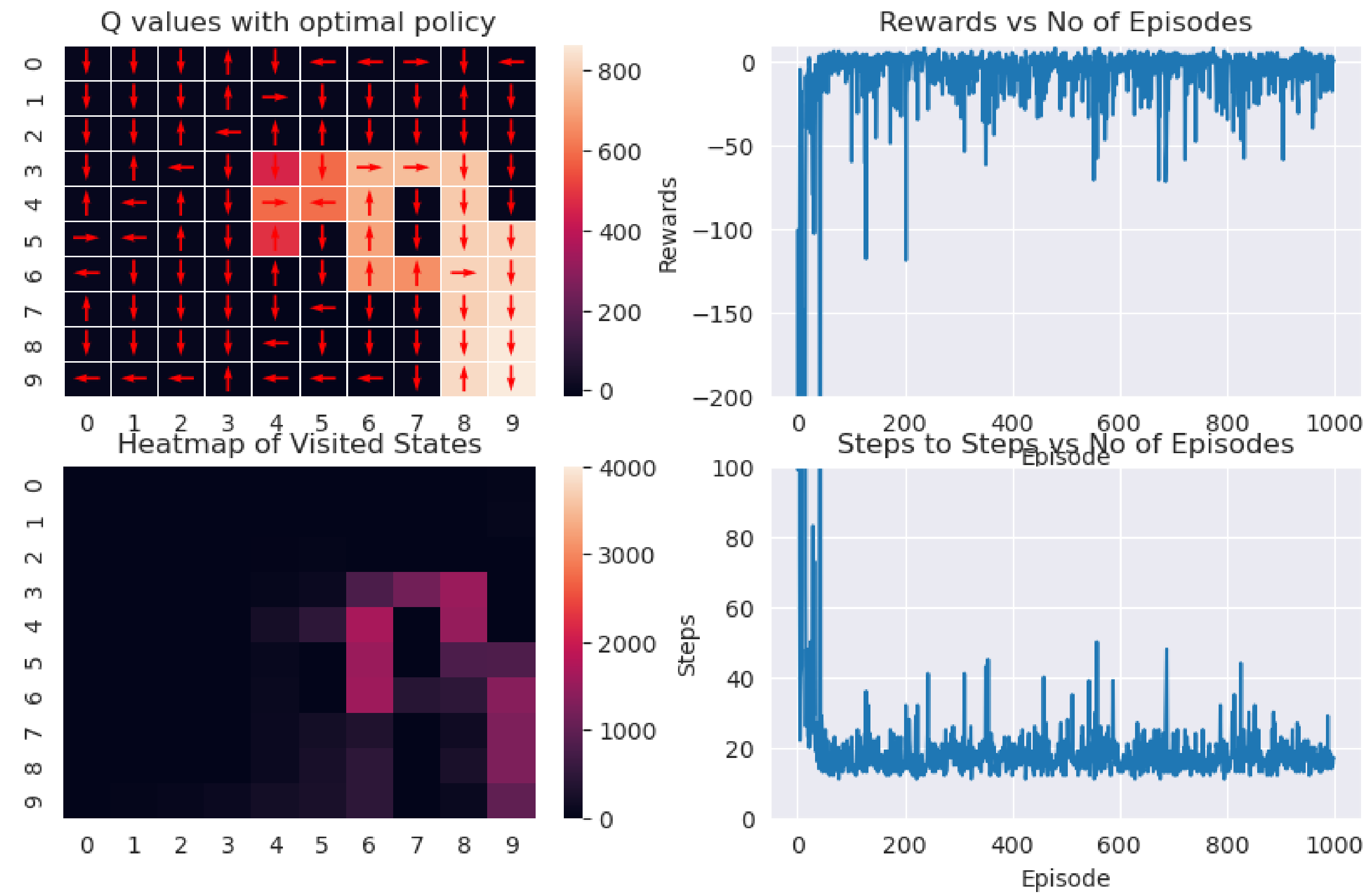
Configuration 11

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
5.0	qlearning	Softmax	True	[3 6]	0.7	.	0.99	0.1	3.0



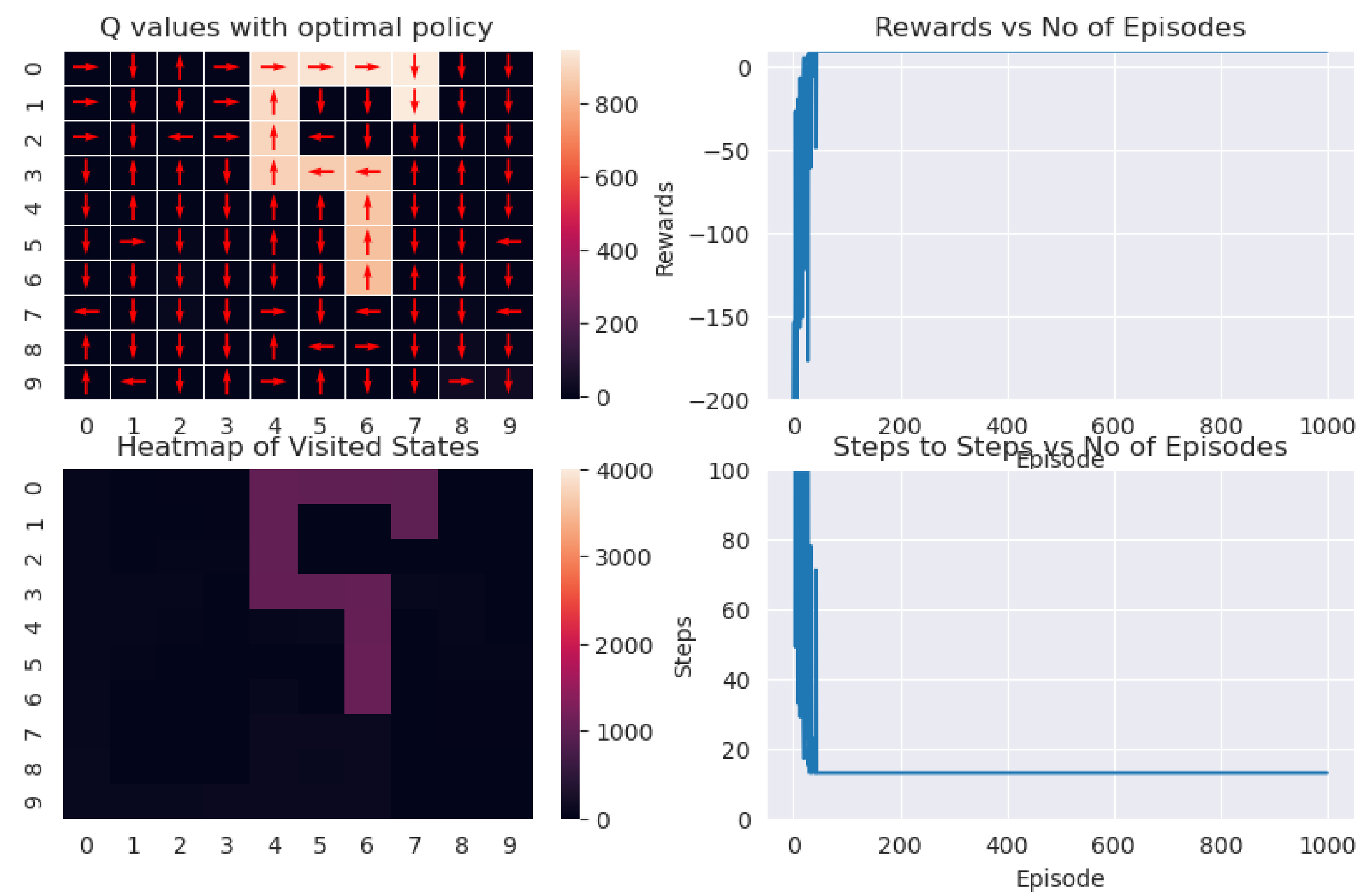
Configuration 12

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
10.0	qlearning	EpsilonGreedy	True	[3 6]	0.7	.	0.99	0.2	0.0



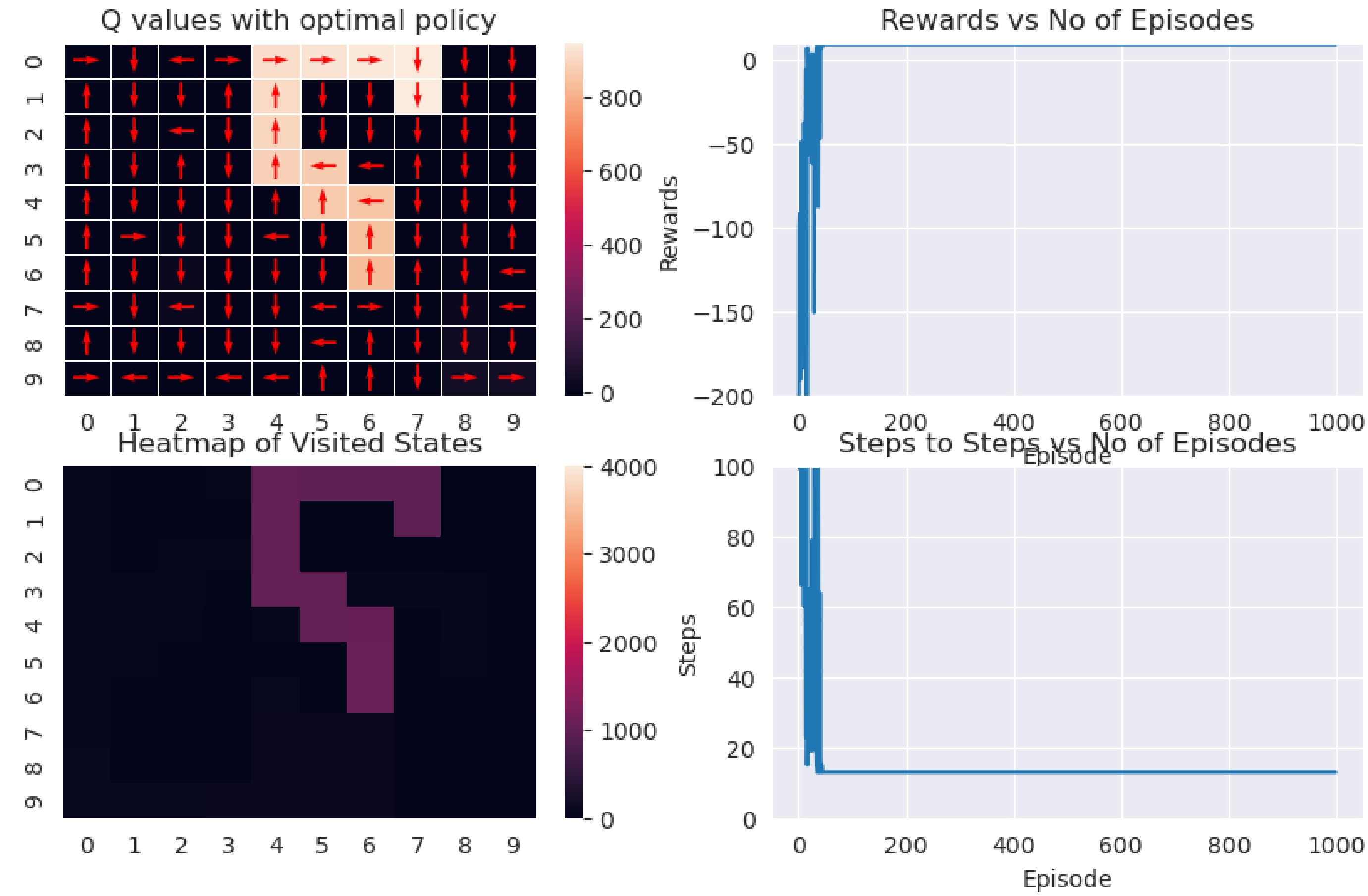
Configuration 13

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	qlearning	EpsilonGreedy	False	[3 6]	1.0	.	0.99	0.3	0.0



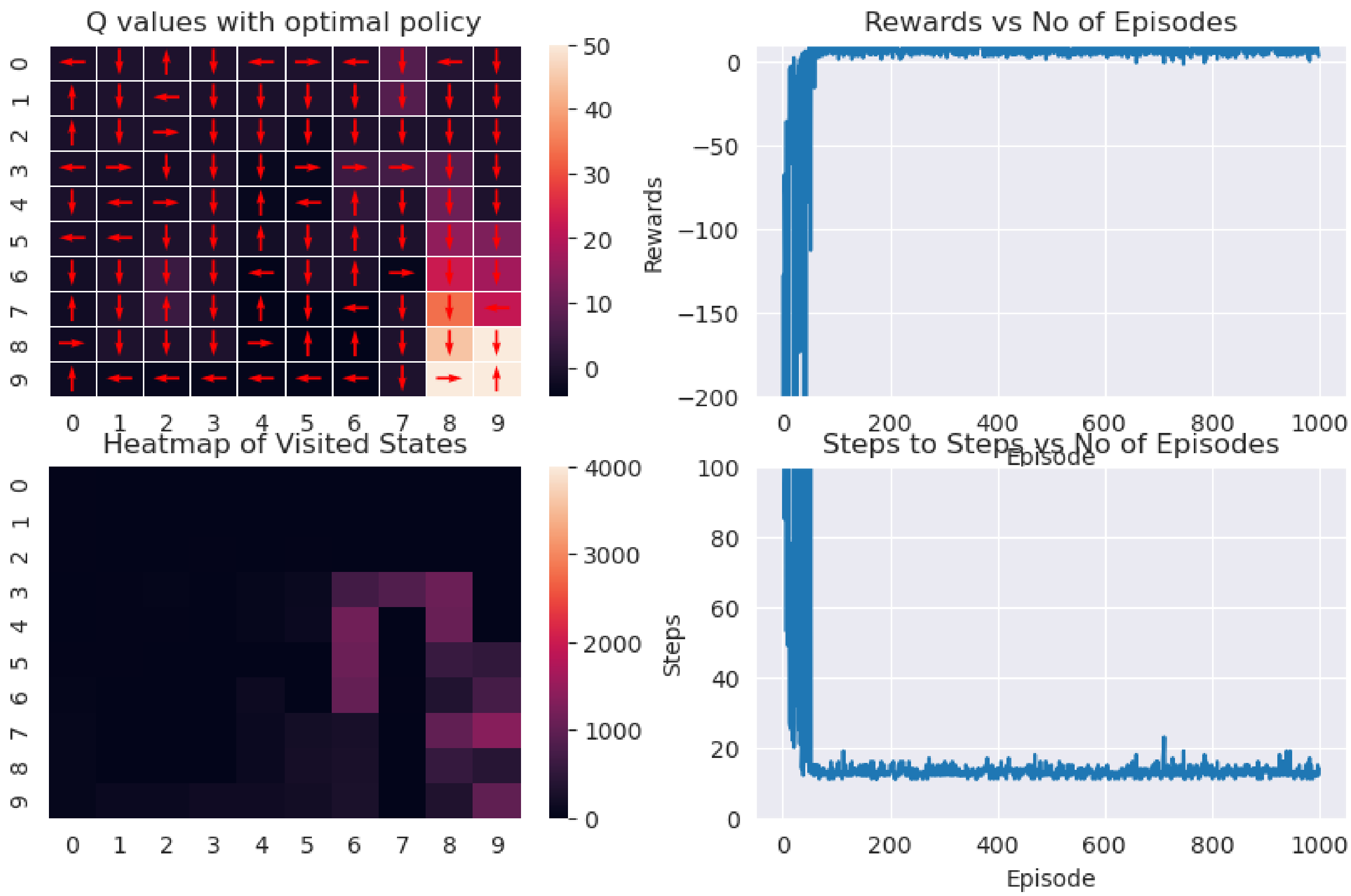
Configuration 14

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	qlearning	Softmax	False	[3 6]	1.0	.	0.99	0.3	0.0



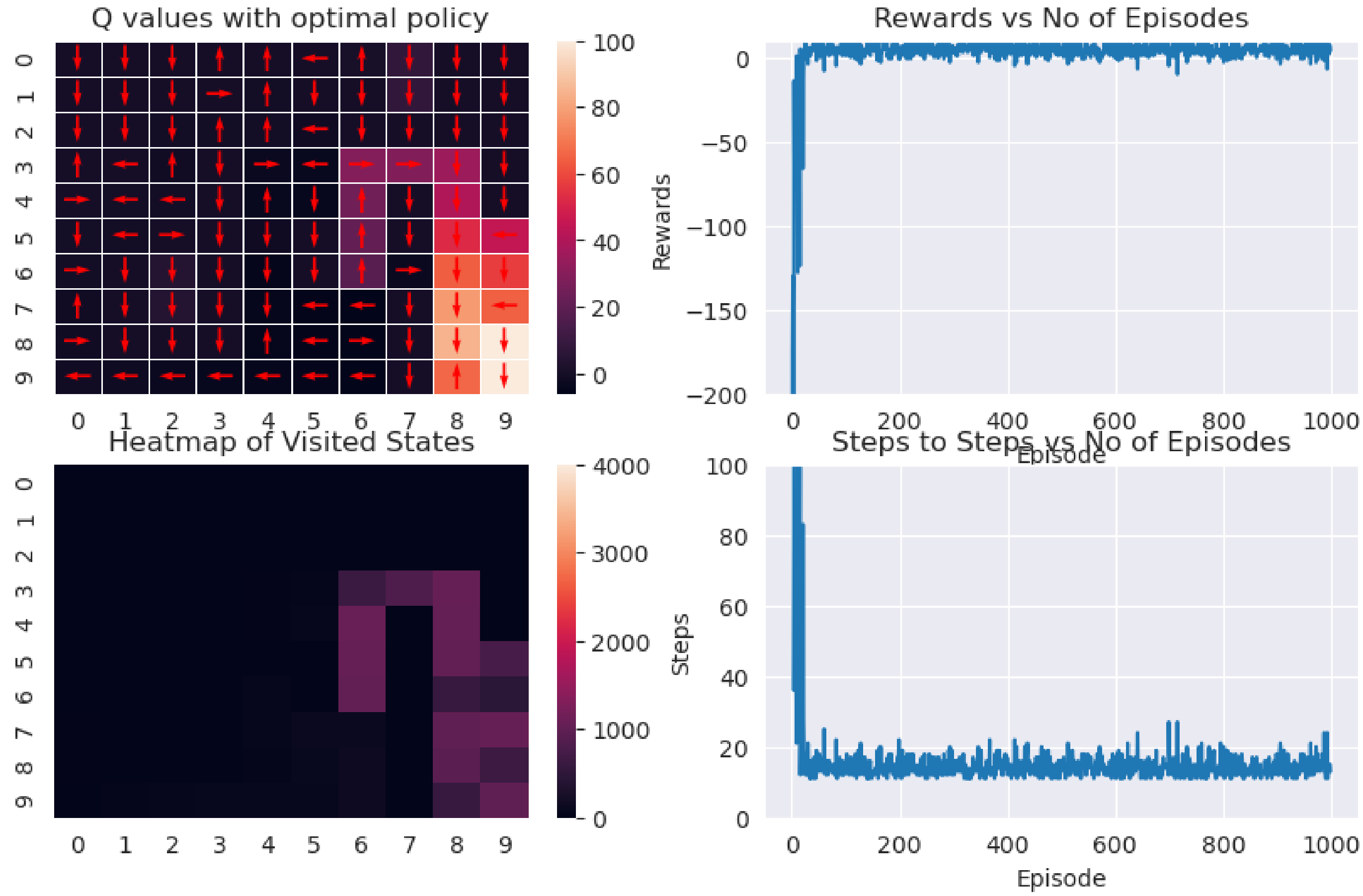
Configuration 15

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
9.0	qlearning	Softmax	True	[3 6]	1.0	.	0.8	0.2	0.0



Configuration 16

Reward	Algorithm	Exploration Strategy	Wind	Start Coors	P	.	Gamma	Alpha	Exploration Param
11.0	qlearning	EpsilonGreedy	True	[3 6]	1.0	.	0.9	0.4	0.0



Q values with optimal policy
Rewards vs No of Episodes
Rewards
Episode
Heatmap of Visited States
Steps to Steps vs No of Episodes
Steps
Episode

In [ ]: