CarMDP Environment, which is provided for your convenience. You should not change code of this environment. This Jupyter notebook is prepared by Kui Wu

You have implemented a model-based solution in Assignment 2, and a model-free solution in Assignment 3. In this assignment, we assume that the agent initially knows nothing about the environment but gradually learns the environment and uses the learned knowledge for planning. We build the solution based on the Dyna framework.

In [1]:

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

from gym import Env

class CarMDP(Env):
    """
    Car MDP with simple stochastic dynamics.
    The states are tuples with two elements:
        - a position index (i, j)
        - an integer from (0, 1, 2, 3) representing absolute orientation (se
    For example, the state
        s = (0, 1, 2)
    represents the car in the cell with indices (0, 1) and oriented to face
    """
    def __init__(self, width, height, obstacles, goal_transition, initial_st
                 collision_reward=-5., goal_reward=10., stagnation_penalty=-
        self.width = width
        self.height = height
        self.grid_map = np.ones((width, height))
        for cell in obstacles:
            self.grid_map[cell[0], cell[1]] = 0.
        self.obstacles = obstacles
        self.orientations = {0: 'North', 1: 'East', 2: 'South', 3: 'West'}
        self.A = {0: 'Forward', 1: 'Left', 2: 'Right', 3: 'Brake'}
        self.goal_transition = goal_transition  # Tuple containing start and

        self.p_corr = p_corr
        self.p_err = (1. - p_corr)/2.

        self.base_reward = base_reward
        self.collision_reward = collision_reward
        self.goal_reward = goal_reward
        self.stagnation_penalty = stagnation_penalty
        self.state_history = []
        self.action_history = []
        self.reward_history = []

        assert initial_state[0] >= 0 and initial_state[1] >= 0 and initial_s
               initial_state[2] in self.orientations, "ERROR: initial state
        self.state_history = [initial_state]
        self.action_history = []
        self.reward_history = []
        self.init_state=initial_state


    def reset(self):
        self.state_history = [self.init_state]
        self.action_history = []
        self.reward_history = []

    def is_collision(self, state):
        is_out_of_bounds = state[0] < 0 or state[0] >= self.width or state[1
            state[1] >= self.height
        return is_out_of_bounds or (state[0], state[1]) in self.obstacles
```

```
    def transition_dynamics(self, state, action):
        assert not self.is_collision(state), "ERROR: can't take an action f
        delta = 1
        orientation = state[2]

        if self.orientations[orientation] == 'North':
            left = (state[0] - delta, state[1] - delta)
            forward = (state[0], state[1] - delta)
            right = (state[0] + delta, state[1] - delta)
        elif self.orientations[orientation] == 'West':
            left = (state[0] - delta, state[1] + delta)
            forward = (state[0] - delta, state[1])
            right = (state[0] - delta, state[1] - delta)
        elif self.orientations[orientation] == 'South':
            left = (state[0] + delta, state[1] + delta)
            forward = (state[0], state[1] + delta)
            right = (state[0] - delta, state[1] + delta)
        elif self.orientations[orientation] == 'East':
            left = (state[0] + delta, state[1] - delta)
            forward = (state[0] + delta, state[1])
            right = (state[0] + delta, state[1] + delta)

        # p gives categorical distribution over (state, left, forward, righ
        if self.A[action] == 'Forward':
            p = np.array([0., self.p_err, self.p_corr, self.p_err])
        elif self.A[action] == 'Right':
            p = np.array([0., 0., 2.*self.p_err, self.p_corr])
        elif self.A[action] == 'Left':
            p = np.array([0., self.p_corr, 2. * self.p_err, 0.])
        elif self.A[action] == 'Brake':
            p = np.array([self.p_corr, 0., 2. * self.p_err, 0.])

        candidate_next_state_positions = (state, left, forward, right)
        next_state_position = candidate_next_state_positions[categorical_sa

        # Handle orientation dynamics (deterministic)
        new_orientation = orientation
        if self.A[action] == 'Right':
            new_orientation = (orientation + 1) % 4
        elif self.A[action] == 'Left':
            new_orientation = (orientation - 1) % 4

        return next_state_position[0], next_state_position[1], new_orientat


    def step(self, action):
        assert action in self.A, f"ERROR: action {action} not permitted"
        terminal = False
        current_state = self.state_history[-1] # -1 means the current eleme
        next_state = self.transition_dynamics(current_state, action)
        if self.is_collision(next_state):
            reward = self.collision_reward
            terminal = True
        elif (current_state[0], current_state[1]) == self.goal_transition[0
                (next_state[0], next_state[1]) == self.goal_transition[1]:
            reward = self.goal_reward
            terminal = True  # TODO: allow multiple laps like this?
        elif current_state == next_state:
            reward = self.stagnation_penalty
```

```
            terminal = False
        else:
            reward = self.base_reward
            terminal = False

        self.state_history.append(next_state)
        self.reward_history.append(reward)
        self.action_history.append(action)

        return next_state, reward, terminal, []

    def render(self, title):
        self._plot_history(title)

    def _plot_history(self, title):
        """
        Plot the MDP's trajectory on the grid map.
        :param title:
        :return:
        """
        fig = plt.figure()
        plt.imshow(self.grid_map.T, cmap='gray')
        plt.grid()
        x = np.zeros(len(self.state_history))
        y = np.zeros(x.shape)
        for idx in range(len(x)):
            x[idx] = self.state_history[idx][0]
            y[idx] = self.state_history[idx][1]
            if self.state_history[idx][2] == 0:
                plt.arrow(x[idx], y[idx], 0., -0.25, width=0.1)
            elif self.state_history[idx][2] == 1:
                plt.arrow(x[idx], y[idx], 0.25, 0., width=0.1)
            elif self.state_history[idx][2] == 2:
                plt.arrow(x[idx], y[idx], 0., 0.25, width=0.1)
            else:
                plt.arrow(x[idx], y[idx], -0.25, 0., width=0.1)

        plt.plot(x, y, 'b-')  # Plot trajectory
        plt.xlim([-0.5, self.width + 0.5])
        plt.ylim([self.height + 0.5, -0.5])
        plt.title(title)
        plt.xlabel('x')
        plt.ylabel('y')
        plt.show()
        return fig


def categorical_sample_index(p: np.ndarray) -> int:
    """
    Sample a categorical distribution.

    :param p: a categorical distribution's probability mass function (i.e.,
              returning idx for an integer 0 <= idx < len(p)). I.e., np.sum
    :return: index of a sample weighted by the categorical distribution des
    """
    P = np.cumsum(p)
    sample = np.random.rand()
    return np.argmax(P > sample)
```

Below is the skeleton code of your agent. Your solution should be filled here. You may need to introduce new functions and/or new data structure here.

In [2]:

```
class ReinforcementLearningAgent:
    """
    Your implementation of a reinforcement learning agent.
    Feel free to add additional methods and attributes.
    """
    def __init__(self):
        ### STUDENT CODE GOES HERE
        # Set any parameters
        # You can add arguments to __init__, so long as they have default va
        self.gamma = 1
        self.epsilon = 0.05
        self.alpha = 0.05
        self.Q = np.zeros((9*6, 4))
        self.shape = (9,6)
        self.model = {}
        self.state_history = []
        self.action_history = []

    def reset(self, init_state) -> int:
        """
        Called at the start of each episode.

        :param init_state:
        :return: first action to take.
        """
        ### STUDENT CODE GOES HERE
        action = 0
        self.state_history = []
        self.action_history = []

        self.state_history.append(init_state)

        state = (init_state[0], init_state[1])
        state = np.ravel_multi_index(tuple(state), self.shape)

        if np.random.random() < self.epsilon:
            action = np.random.randint(4)
        else:
            action = np.argmax(self.Q[state,:])

        self.action_history.append(action)

        return action

    def next_action(self, reward: float, state: int, terminal: bool) -> int
        """
        Called during each time step of a reinforcement learning episode

        :param reward: reward resulting from the last time step's action
        :param state: state resulting from the last time step's action
        :param terminal: bool indicating whether state is a terminal state
        :return: next action to take
        """
        ### STUDENT CODE GOES HERE
        # Produce the next action to take in an episode as a function of the
        # You may find it useful to track past actions, states, and rewards
        # Additionally, algorithms that learn during an episode (e.g., tempo
#         if terminal:
```

```
#             print(state)
#             return 0

        prev_state = self.state_history[-1]
        prev_state = (prev_state[0], prev_state[1])
        prev_action = self.action_history[-1]
        prev_state = np.ravel_multi_index(tuple(prev_state), self.shape)

        if terminal:
            next_state = -1
            self.Q[prev_state, prev_action] += self.alpha*(reward - self.Q[p
            self.model_learning(prev_state, prev_action, next_state, reward
            self.planning(5)
            return 0

        self.state_history.append(state)
        next_state = (state[0], state[1])
        next_state = np.ravel_multi_index(tuple(next_state), self.shape)

        eps_action = 0
        if np.random.random() < self.epsilon:
            eps_action = np.random.randint(4)
        else:
            eps_action = np.argmax(self.Q[next_state,:])

        self.action_history.append(eps_action)

#         prev_q_value = self.Q[prev_state, prev_action]
#         next_q_value = self.Q[next_state, eps_action]
#         prev_q_value += self.alpha*(reward + self.gamma*next_q_value - pr
        self.Q[prev_state, prev_action] += self.alpha*(reward + self.gamma*s

        self.model_learning(prev_state, prev_action, next_state, reward)

        self.planning(5)
        #print(self.model)
        #print(self.Q)

        return eps_action

    def planning(self, planningStep):
        ### STUDENT CODE GOES HERE
        # Set any parameters
        # You can add other arguments to planning
        for i in range(planningStep):
            state_action, l = random.choice(list(self.model.items()))
            prev_state = state_action[0]
            prev_action = state_action[1]

            total_count = 0
            for j in l:
                total_count += j[2]

            # Do an expected update instead of sample update
            update = 0
            for k in l:
                next_state = k[0]
                reward = k[1]
                freq = k[2]
```

```
                prob = freq/total_count

                if next_state == -1:
                    value = prob*reward
                    update += value
                else:
                    next_action = 0
                    if np.random.random() < self.epsilon:
                        next_action = np.random.randint(4)
                    else:
                        next_action = np.argmax(self.Q[next_state,:])

                    value = prob*(reward + self.gamma*self.Q[next_state,nex
                #value = prob*(reward + self.gamma*np.max(self.Q[next_state
                    update += value

            self.Q[prev_state,prev_action] = update

    def model_learning(self, prev_state, prev_action, next_state, reward):
        ### STUDENT CODE GOES HERE
        # Set any parameters
        # You can add other arguments to model_learning
        # model stores the state-action pair as key and [next_state, reward
        state_action = tuple((prev_state,prev_action))
        if state_action not in self.model:
            l = [[next_state,reward,1]]
            self.model.update({state_action : l})
        else:
            l = self.model[state_action]
            found = 0
            for i in l:
                if i[0] == next_state:
                    found = 1
                    i[1] = i[1] + (1/i[2])*(reward-i[1])
                    i[2] += 1
                    break
            if found == 0:
                temp = [next_state,reward,1]
                l.append(temp)
                #print("hi")
            self.model.update({state_action : l})


    def finish_episode(self):
        """
        Called at the end of each episode.
        :return: nothing
        """
        ### STUDENT CODE GOES HERE
        # Algorithms that learn from an entire episode (e.g., Monte Carlo) i
        pass
```

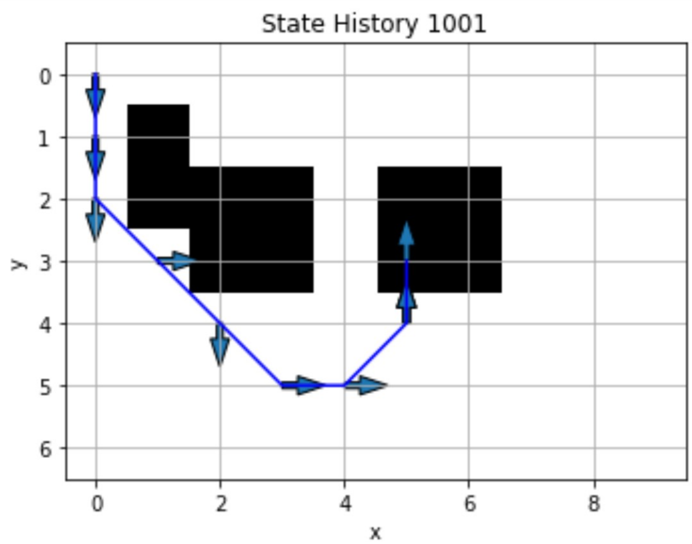
Below is the sample test code. In the final print out you need to print out the correct policy name (It is random so far). Note that

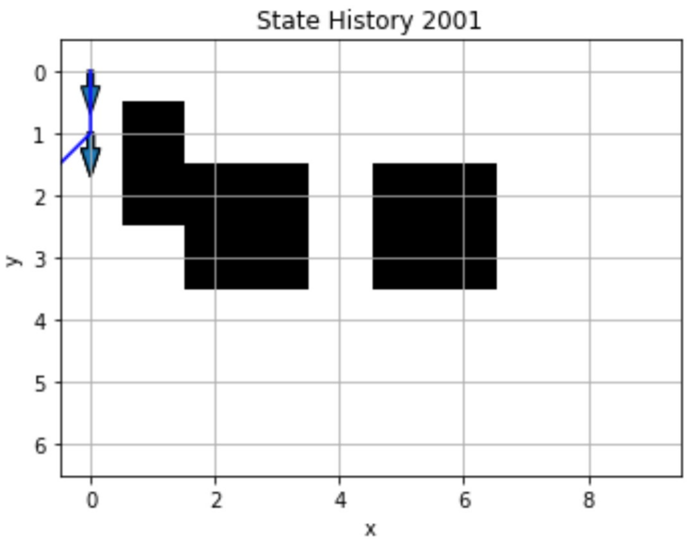
policy name (it is random so far). Note that

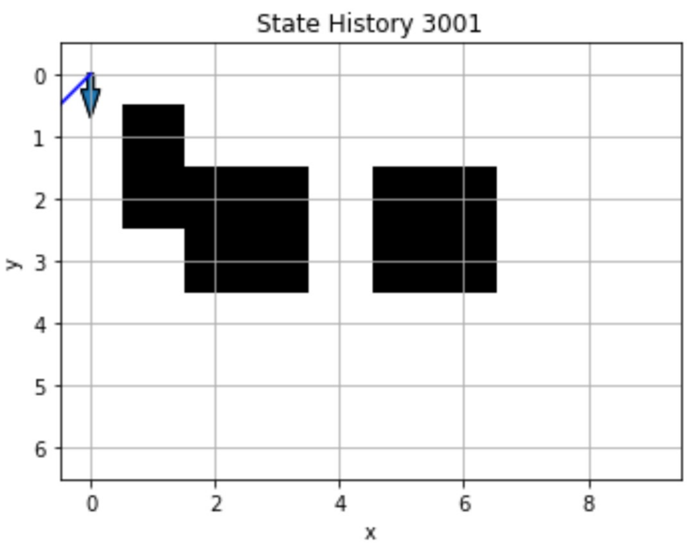
In [3]:

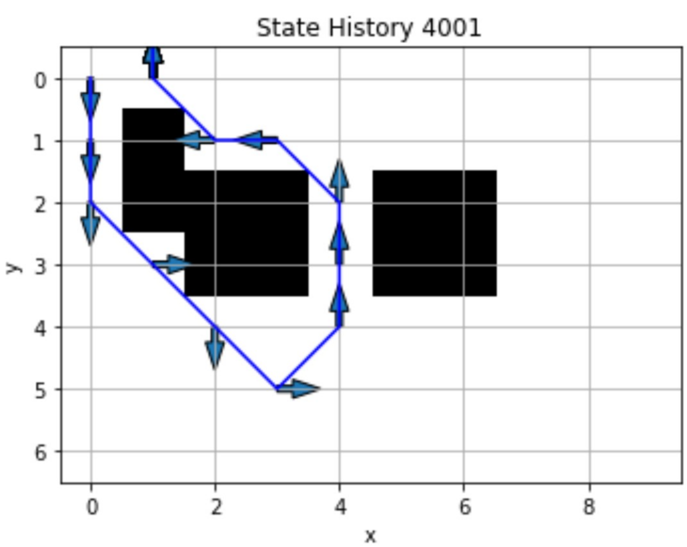
```
def test_rl_algorithm(rl_agent, car_mdp, initial_state, n_episodes=10000, n_
    """
    Code that will be used to test your implementation of ReinforcementLearn
    As you can see, you are responsible for implementing three methods in Re
        - reset (called at the start of every episode)
        - next_action (called at every time step of an episode)
        - finish_episode (called at the end of each episode)

    :param rl_agent: an instance of your ReinforcementLearningAgent class
    :param car_mdp: an instance of CarMDP
    :param init_state: the initial state
    :param n_episodes: number of episodes to use for this test
    :param n_plot: display a plot every n_plot episodes
    :return:
    """
    returns = []
    for episode in range(n_episodes):
        G = 0.  # Keep track of the returns for this episode (discount fact
        # Re-initialize the MDP and the RL agent
        car_mdp.reset();
        action = rl_agent.reset(initial_state)
        terminal = False
        while not terminal:  # Loop until a terminal state is reached
            next_state, reward, terminal, [] = car_mdp.step(action)
            G += reward
            action = rl_agent.next_action(reward, next_state, terminal)
        rl_agent.finish_episode()
        returns += [G]

        # Plot the trajectory every n_plot episodes
        if episode % n_plot == 0 and episode > 0:
            #print(n_plot)
            #print(episode)
            car_mdp.render('State History ' + str(episode + 1))

    return returns


if __name__ == '__main__':

    # Size of the CarMDP map (any cell outside of this rectangle is a termi
    width = 9
    height = 6
    initial_state = (0, 0, 2)  # Top left corner (0, 0), facing "Down" (2)
    obstacles = [(2, 2), (2, 3), (3, 2), (3, 3),  # Cells filled with obsta
                 (5, 2), (5, 3), (6, 2), (6, 3),
                 (1, 1), (1, 2)]
    goal_transition = ((1, 0), (0, 0))  # Transitioning from cell (1, 0) to
    p_corr = 0.95  # Probability of actions working as intended

  # Create environment
    car_mdp = CarMDP(width, height, obstacles, goal_transition, initial_stat

 # Create RL agent. # You must complete this class in your solution, it is
 # the first agent (rl_agent) is just to track the agent to see if it is le

    rl_agent = ReinforcementLearningAgent()
```

```
student_returns = test_rl_algorithm(rl_agent, car_mdp, initial_state, n_


# Example plot. You need to change it according to the assignment requi
n_runs = 10
n_episodes = 10000
returns = np.zeros((n_runs, n_episodes))
for run in range(n_runs):
    rl_agentnew = ReinforcementLearningAgent()
    returns[run, :] = test_rl_algorithm(rl_agentnew, car_mdp, initial_s



# Plot one curve like this for each parameter setting - the template co
# returns a random action, so this example curve will just be noise. Wh
# should increase as the number of episodes increases. Feel free to cha
rolling_average_width = 100
# Compute the mean (over n_runs) for each episode
mean_return = np.mean(returns, axis=0)
# Compute the rolling average (over episodes) to smooth out the curve
rolling_average_mean_return = np.convolve(mean_return, np.ones(rolling_a
plt.figure()
plt.plot(rolling_average_mean_return, 'b-')  # Plot the smoothed averag
plt.grid()
plt.title('Learning Curve')
plt.xlabel('Episode')
plt.ylabel('Average Return')
plt.legend(['alpha = 0.05, epsilon = 0.05, planning steps = 5'])
plt.show()
```

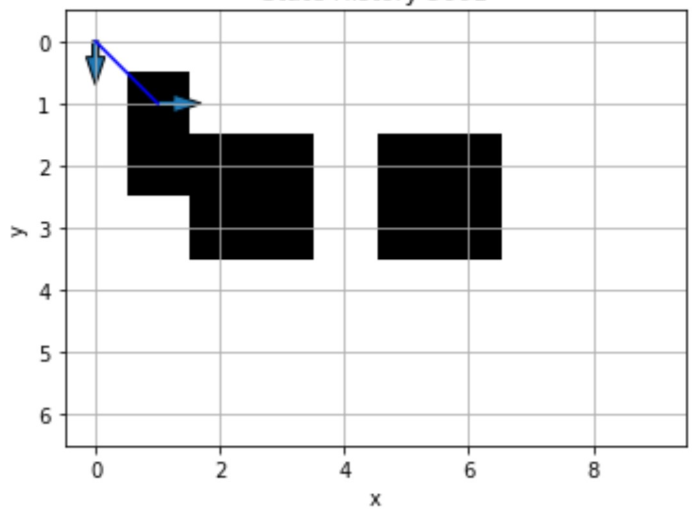



State History 2001
y
x
0
1
2
3
4
5
6
0
2
4
6
8

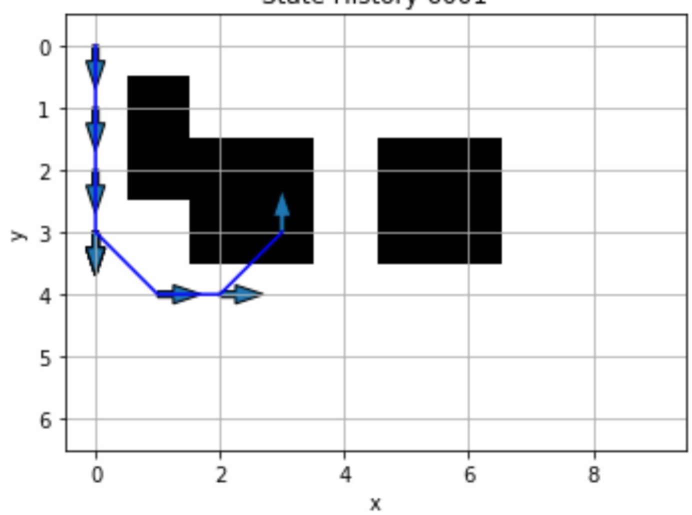

State History 3001
y
x
0
1
2
3
4
5
6
0
2
4
6
8


State History 4001
y
x
0
1
2
3
4
5
6
0
2
4
6
8

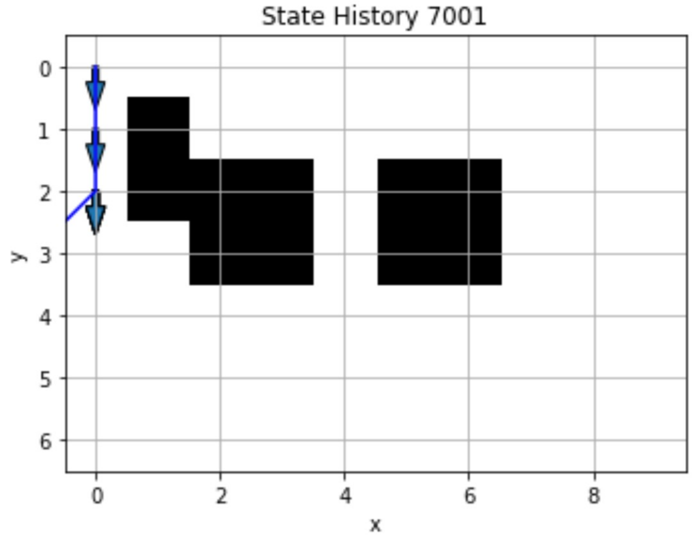
State History 5001

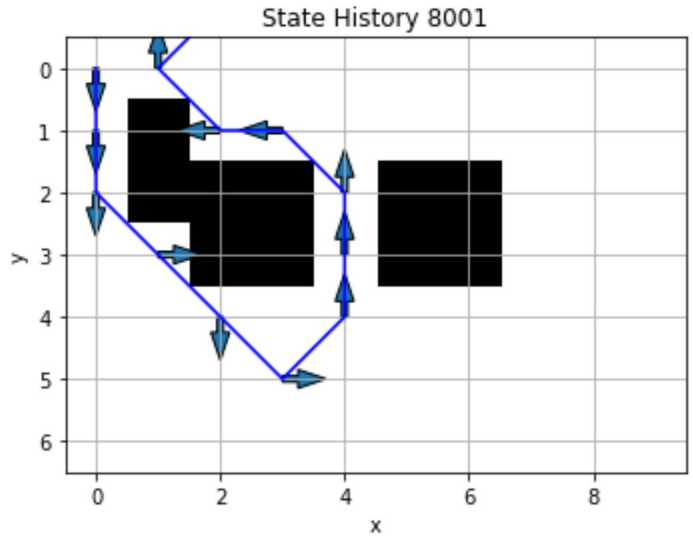


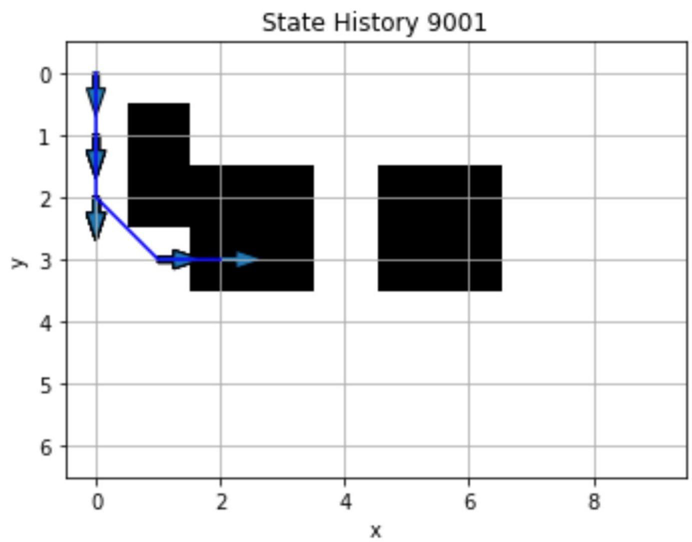
State History 6001

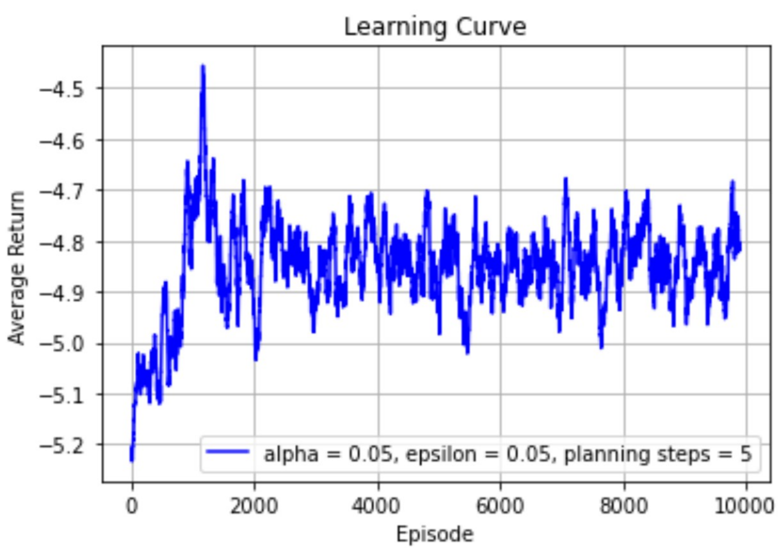


State History 7001




State History 8001
y
x


State History 9001
y
x


Learning Curve
Average Return
Episode
alpha = 0.05, epsilon = 0.05, planning steps = 5

In [ ]:

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