Discrete Unicycle Environment and Q-Learning Agent

Introduction

This notebook defines a custom discrete grid-based environment for a unicycle agent and implements a Q-learning agent to learn navigation towards a goal while avoiding obstacles.

Environment Class Definition

The DiscreteUnicycleEnv class defines a grid-based environment where the agent navigates to a goal while avoiding obstacles.

Rewards:

Reach Destination = +100

Distance to Target= -distance

Collide with obstacles = -100

number of steps = -number

End Episode:

Reach Target

Collide with obstacles

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from tqdm import tqdm
4 from collections import deque
5 from matplotlib.patches import Rectangle, Arrow
6 from IPython.display import display, clear_output
7 import gym
8
```

```
1
 2 class DiscreteUnicycleEnv(gym.Env):
       def __init__(self, grid_size=10, obstacles=None):
          super(DiscreteUnicycleEnv, self).__init__()
          self.grid_size = grid_size
 6
          self.max x = grid size
          self.max_y = grid_size
 8
 9
          self.action_space = gym.spaces.Discrete(8) # 8 possible directions
10
          self.observation space = gym.spaces.Dict({
11
              'state': gym.spaces.Box(low=0, high=grid_size, shape=(3,), dtype=np.int32),
12
               'obstacles': gym.spaces.Box(low=0, high=1, shape=(grid_size, grid_size), dtype=np.int32)
13
          })
14
15
           self.initial_state = np.array([0, 0, 0], dtype=np.int32) # Initial state
16
          self.goal = np.array([grid_size - 1, grid_size - 1, 7]) # Goal state
17
18
           self.state = self.initial_state.copy()
```

```
20
21
          self.obstacles = np.zeros((grid_size, grid_size), dtype=np.int32)
22
          if obstacles:
23
              for obs in obstacles:
24
                 self.obstacles[obs] = 1
25
26
          self.path = []
27
          self.fig, self.ax = plt.subplots()
28
          self.max_steps_per_episode = 50  # Maximum steps per episode
29
30
      def reset(self):
31
          self.state = self.initial_state.copy() # Reset to initial state
32
33
          self.relative_state = self.get_relative_state()
34
          self.path = [self.state[:2].copy()]
35
          return {'state': self.state, 'obstacles': self.obstacles}
37
      def step(self, action):
38
          x, y, theta = self.state
39
          if action == 0: # Move right
40
41
          elif action == 1: # Move up-right
42
             x += 1
             y += 1
43
44
          elif action == 2: # Move up
45
              y += 1
46
          elif action == 3: # Move up-left
47
             x -= 1
48
             y += 1
          elif action == 4: # Move left
49
50
51
          elif action == 5: # Move down-left
52
53
             y -= 1
54
          elif action == 6: # Move down
55
             y -= 1
56
          elif action == 7: # Move down-right
57
             x += 1
58
              y -= 1
59
60
          x = np.clip(x, 0, self.grid_size - 1)
61
          y = np.clip(y, 0, self.grid_size - 1)
62
          self.state = np.array([x, y, theta])
63
          self.relative state = self.get relative state()
64
65
          self.path.append(self.state[:2].copy())
66
67
          done = self.is done()
68
          reward = self.get_reward()
69
          return {'state': self.state, 'obstacles': self.obstacles}, reward, done, {}
70
71
72
      def get_relative_state(self):
73
          x, y, theta = self.state
74
          goal_x, goal_y, goal_theta = self.goal
75
          dx = goal_x - x
76
          dy = goal y - y
          ex = (np.cos(theta * np.pi / 4) * dx + np.sin(theta * np.pi / 4) * dy) * 2
77
78
          ey = (-np.sin(theta * np.pi / 4) * dx + np.cos(theta * np.pi / 4) * dy) * 2
79
          ex = np.rint(ex)
80
          ey = np.rint(ey)
81
          etheta = (goal_theta - theta) % 8
82
          return np.array([ex, ey, etheta], dtype=np.int16)
```

Self.relative_State = Self.get_relative_State()

19

```
84
       def get_reward(self):
85
           x, y, theta = self.state
86
           if self.obstacles[x, y] == 1: # Collision with obstacle
87
           distance = np.sqrt((x - self.goal[0])**2 + (y - self.goal[1])**2)
88
 89
           reward = -distance
 90
           if self.is_done():
91
               reward += 100
92
93
               reward -= 1 # Penalty for each step
94
           return reward
96
       def is_done(self):
97
           x, y, theta = self.state
98
           if self.obstacles[x, y] == 1: # Collision with obstacle
99
100
           return np.array_equal(self.state[:2], self.goal[:2])
101
102
       def render(self, mode='human'):
103
           x, y, theta = self.state
104
           goal_x, goal_y, goal_theta = self.goal
105
           self.ax.clear()
           buffer = 1
106
107
           self.ax.set xlim(-buffer, self.max x + buffer)
108
           self.ax.set ylim(-buffer, self.max y + buffer)
109
           self.ax.add patch(Rectangle((-buffer, -buffer), self.max x + 2*buffer, self.max y + 2*buffer, fill=None, edgecolor='gray', linestyle='-', linewidth=1))
110
           self.ax.plot(goal_x, goal_y, 'ro', label='Goal')
111
           self.ax.add_patch(Arrow(goal_x, goal_y, np.cos(goal_theta * np.pi / 4), np.sin(goal_theta * np.pi / 4), width=0.5, color='r'))
112
           self.ax.plot(self.path[0][0], self.path[0][1], 'go', label='Start')
114
           # Plot obstacles
115
           for i in range(self.grid size):
               for j in range(self.grid_size):
116
117
                  if self.obstacles[i, j] == 1:
                      self.ax.add_patch(Rectangle((i, j), 1, 1, color='gray'))
118
119
120
           path = np.array(self.path)
121
           self.ax.plot(path[:, 0], path[:, 1], 'k--', label='Path')
122
           width, height = self.max_x / 20, self.max_x / 30
123
           robot = Rectangle((x - 0.5 * width, y - 0.5 * height), width, height, angle=np.degrees(theta * np.pi / 4), edgecolor='b', facecolor='b')
124
           self.ax.add patch(robot)
125
           self.ax.add_patch(Arrow(x, y, np.cos(theta * np.pi / 4), np.sin(theta * np.pi / 4), width=0.5, color='b'))
           self.ax.set_aspect('equal', adjustable='box')
126
127
           self.ax.legend()
128
           self.ax.grid(True)
129
           clear_output(wait=True)
130
           display(self.fig)
131
           plt.pause(0.001)
132
133
134
       def close(self):
135
           plt.close(self.fig)
137 # Define obstacles
138 obstacles = [(0,1),(1,1),(2,1),(3,1),(2,7),(4,3),(5,6),(7,3),(8,5),(6,3),(8,5),(7,6),(7,5),(4,7),(7,4),(1,7),(1,6),(1,5)]
140 # Create environment instance
141 env = DiscreteUnicycleEnv(obstacles=obstacles)
```

Q-Learning Agent Class Definition

The QLearningAgent class defines an agent that uses Q-learning to learn to navigate the DiscreteUnicycleEnv environment.

```
1 class OLearningAgent:
       def init (self, state size, action size, learning rate=0.1, discount factor=0.95, epsilon=1.0, epsilon decay=0.995, epsilon min=0.01):
           self.state_size = state_size
          self.action_size = action_size
          self.learning rate = learning rate
 6
          self.discount_factor = discount_factor
          self.epsilon = epsilon
          self.epsilon decay = epsilon decay
 9
          self.epsilon_min = epsilon_min
10
           self.q_table = np.zeros(state_size + (action_size,))
11
12
      def choose_action(self, state):
13
          if np.random.rand() <= self.epsilon:</pre>
14
              return np.random.choice(self.action size)
15
          return np.argmax(self.q_table[state['state'][0], state['state'][1], state['state'][2]])
16
17
       def learn(self, state, action, reward, next_state, done):
18
          q_update = reward
19
          if not done:
              q_update += self.discount_factor * np.max(self.q_table[next_state['state'][0], next_state['state'][1], next_state['state'][2]])
20
21
           self.q_table[state'][0], state['state'][1], state['state'][2], action] += self.learning_rate * (q_update - self.q_table[state'][0], state['state'][1], state['state'][2], action
22
          if self.epsilon > self.epsilon_min:
23
              self.epsilon *= self.epsilon_decay
24
25 # Define state and action sizes
26 state_size = (env.grid_size, env.grid_size, 8)
27 action_size = env.action_space.n
28
29 # Create Q-learning agent instance
30 agent = QLearningAgent(state_size, action_size)
31
```

Training the Q-Learning Agent

Train the Q-learning agent on the DiscreteUnicycleEnv environment for a specified number of episodes.

```
1 \text{ episodes} = 5000
 2 \text{ max steps} = 50
 4 average_rewards = []
 6 for e in tqdm(range(episodes), desc="Training Episodes"):
       state = env.reset()
       total reward = 0
 8
 9
       for _ in range(max_steps):
10
           action = agent.choose_action(state)
11
           next_state, reward, done, _ = env.step(action)
12
           agent.learn(state, action, reward, next_state, done)
13
           state = next_state
14
           total reward += reward
15
           if done:
16
               break
       average rewards.append(total reward / max steps)
```

→ Evaluating the Trained Agent

Run the trained Q-learning agent in the environment to visualize its performance.

```
1 # Render environment for visual display
2 state = env.reset()
3 done = False
4 while not done:
5     action = agent.choose_action(state)
6     next_state, reward, done, _ = env.step(action)
7     env.render()
8     state = next_state
9 env.close()
```



