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Artificial Intelligence

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A Mini-Project Report on

"Autonomous Robot Path Planning with Reinforcement Learning"

23CSE514

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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1. Introduction

Autonomous robots require the ability to navigate from a starting point to a destination while avoiding obstacles and optimizing the chosen path. Traditional path-planning algorithms such as BFS, and Dijkstra rely on predefined heuristics and complete knowledge of the environment. However, in real-world scenarios, robots must learn to make decisions based on experience and feedback.

Reinforcement Learning (RL) provides a framework where an agent interacts with an environment, receives rewards or penalties, and learns an optimal policy over time. In this project, a Q-Learning based approach is used to train a robot to navigate a grid-world environment and reach the goal while avoiding obstacles.

This project demonstrates how RL can be applied to path planning and shows the learning process, policy convergence, and final optimal path chosen by the agent.

2. Review (Prior Study / Literature Review)

Several studies have explored the use of reinforcement learning for navigation:

1. **Bernard et al. (2016)** demonstrated the use of Q-Learning for navigation tasks in discrete grid environments, showing effective convergence when reward shaping is applied.
2. **Sutton & Barto (2018)** introduced foundational reinforcement learning methods, explaining how agents can learn optimal actions via temporal-difference learning.
3. **Kober, Bagnell & Peters (2013)** explored the application of RL in robotics, highlighting the benefits of experience-based learning for navigation, manipulation, and control tasks.
4. **DeepMind (Mnih et al., 2015)** extended Q-Learning into Deep Q-Networks (DQN), showing how neural networks can solve more complex navigation problems such as Atari games and continuous control.

These studies highlight that RL is effective for autonomous decision-making without requiring full knowledge of the environment, making it suitable for robotic path-planning.

3. Project Details

3.1 Problem Statement

To design and implement a reinforcement learning agent capable of autonomously navigating a grid-world environment, avoiding obstacles, and reaching a goal position using Q-Learning. The system should learn from interaction and improve its performance over time based on rewards.

3.2 Dataset / Environment Details

Unlike supervised learning, reinforcement learning does not use a traditional dataset.
Instead, the **agent generates its own experience** through exploration.
Environment characteristics:

- Grid Size: **10 × 10**
- State Representation: robot's position (x, y)
- Actions: **up, down, left, right**
- Obstacles: randomly generated or fixed blocks
- Start position: user-defined
- Goal position: user-defined
- Reward structure:
- **+10** for reaching goal
- **–1** per step (to encourage shorter paths)
- **–5** for hitting an obstacle or invalid move

This environment acts as the "dataset" by providing state transitions and rewards.

3.3 Methodology

Step 1: Environment Setup

A 10×10 grid-world is created where cells may contain obstacles. The agent interacts with this environment by choosing actions.

Step 2: Q-Learning Algorithm

Q-Learning is a model-free RL algorithm that updates Q-values using:

[

Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s,a)]

]

Where:

- (s) = current state
- (a) = action taken
- (r) = reward
- (s') = next state
- (\alpha) = learning rate
- (\gamma) = discount factor

Step 3: Exploration vs Exploitation

An **epsilon-greedy** strategy is used:

- With probability ε → explore
- With probability (1–ε) → exploit the best action

Epsilon decays over time to encourage exploitation in later episodes.

Step 4: Training

The agent:

1. Starts at the initial state
2. Chooses an action using the Q-table
3. Receives reward
4. Updates its Q-value
5. Repeats until goal is reached or max steps reached

The Q-table gradually converges to an optimal policy.

Step 5: Policy Extraction

After training, the agent follows the greedy policy:

[

\pi(s) = \arg\max_a Q(s,a)

]

This produces the final optimal path.

3.4 Code Summary (Colab Implementation)

The complete code consists of:

- GridWorld environment class
- Q-Learning implementation
- Training loop
- Reward plotting
- Policy visualization
- Optimal path extraction

The main modules are:

1. **Environment Setup**

```
env = GridWorld(size=10)
```

1. **Initialize Q-table**

```
Q = np.zeros((env.size * env.size, 4))
```

1. **Training**

```
for episode in range(episodes):
    ...
```

1. **Visualization**

- Grid with obstacles
- Learned policy arrows
- Final path

1. **Saving Q-table**

```
np.save("q_table.npy", Q)
```

3.5 Results

✔ Reward Curve

Shows improvement across episodes, indicating learning and convergence.

✔ Learned Policy Map

Arrows show the best action from each state.

✔ Optimal Path

The robot successfully navigates from start to goal using the trained policy.

✔ Robustness

The model avoids obstacles and adapts to different grid configurations.

3.6 Summary

- Reinforcement Learning was successfully used for autonomous robot navigation.
- Q-Learning learned an optimal policy without using any labelled dataset.
- The agent improves performance over time through reward feedback.
- Results validate that RL is suitable for discrete path-planning tasks.

4.Code Implementation

Create GridWorld Environment

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

class GridWorld:
    def __init__(self, size=10, obstacles_prob=0.2):
        self.size = size
        self.obstacles_prob = obstacles_prob
        self.actions = [(0,1),(1,0),(0,-1),(-1,0)]  # R,D,L,U
        self.n_actions = 4

        self.reset_env()

    def reset_env(self):
        self.grid = np.zeros((self.size, self.size))
        for i in range(self.size):
            for j in range(self.size):
                if random.random() < self.obstacles_prob:
                    self.grid[i][j] = -1  # obstacle

        self.start = (0, 0)
        self.goal = (self.size-1, self.size-1)

        self.grid[self.start] = 0
        self.grid[self.goal] = 0

    def reset(self):
        self.agent = self.start
```

```
        return self._state(self.agent)

    def _state(self, pos):
        return pos[0] * self.size + pos[1]

    def step(self, action):
        dx, dy = self.actions[action]
        x, y = self.agent
        nx, ny = x + dx, y + dy

        if 0 <= nx < self.size and 0 <= ny < self.size and self.grid[nx][ny] != -1:
            self.agent = (nx, ny)

        reward = -0.01
        done = False

        if self.agent == self.goal:
            reward = 1
            done = True

        return self._state(self.agent), reward, done
```

Q-Learning Agent

```
class QLearningAgent:
    def __init__(self, n_states, n_actions, lr=0.7, gamma=0.99, eps=1.0, eps_min=0.05,
eps_decay=0.995):
        self.q = np.zeros((n_states, n_actions))
        self.lr = lr
        self.gamma = gamma
        self.eps = eps
        self.eps_min = eps_min
        self.eps_decay = eps_decay
        self.n_actions = n_actions

    def choose_action(self, state):
        if random.random() < self.eps:
            return random.randint(0, self.n_actions-1)
        return np.argmax(self.q[state])

    def update(self, s, a, r, s2, done):
        target = r if done else r + self.gamma * np.max(self.q[s2])
        self.q[s][a] += self.lr * (target - self.q[s][a])
        self.eps = max(self.eps_min, self.eps * self.eps_decay)
```

Train the Agent

env = GridWorld(size=10, obstacles_prob=0.2)

```
agent = QLearningAgent(env.size * env.size, env.n_actions)

episodes = 2000
rewards = []

for ep in range(episodes):
    s = env.reset()
    total_r = 0

    for _ in range(200):
        a = agent.choose_action(s)
        s2, r, done = env.step(a)
        agent.update(s, a, r, s2, done)

        s = s2
        total_r += r
        if done:
            break

    rewards.append(total_r)
plt.plot(rewards)
plt.title("Training Reward per Episode")
plt.xlabel("Episode")
plt.ylabel("Reward")
plt.show()
```

Visualize Learned Path

```
def extract_path(env, agent):
    s = env.reset()
    path = [env.start]

    for _ in range(200):
        a = np.argmax(agent.q[s])
        s, _, done = env.step(a)
        pos = (s // env.size, s % env.size)
        path.append(pos)
        if done:
            break

    return path
```

```
path = extract_path(env, agent)
path
```

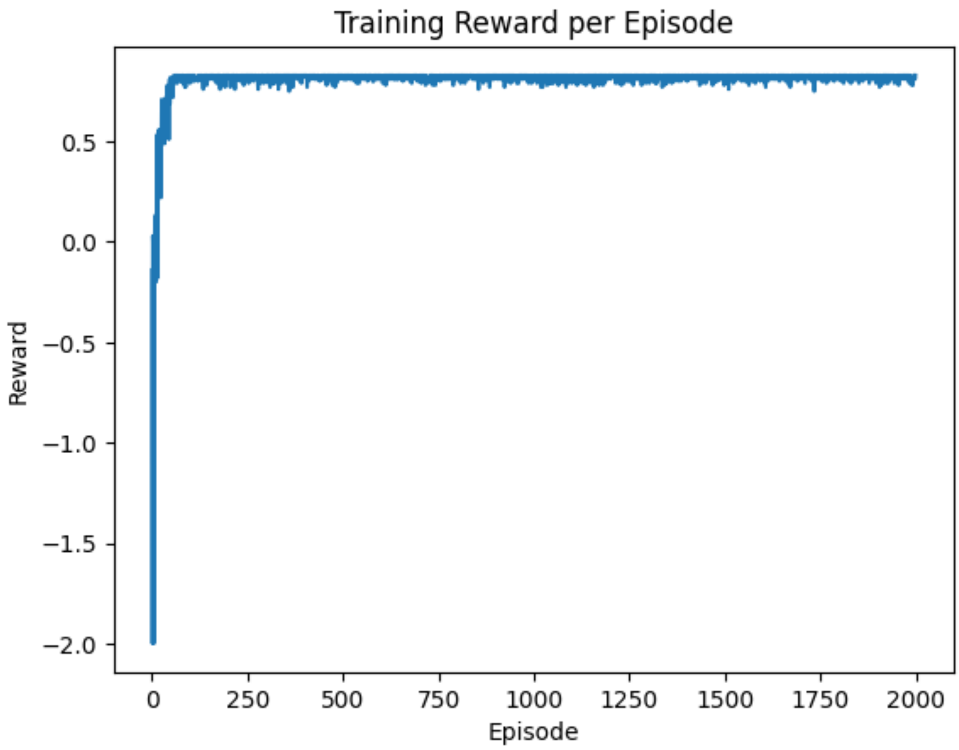
Draw the Grid with the Path

```
def plot_path(env, path):
    grid = env.grid.copy()
    plt.figure(figsize=(6,6))
    plt.imshow(grid == -1, cmap='gray')
    px = [p[1] for p in path]
    py = [p[0] for p in path]
    plt.plot(px, py, marker='o')
    plt.scatter(env.goal[1], env.goal[0], c='red', label="GOAL")
    plt.scatter(env.start[1], env.start[0], c='green', label="START")
    plt.legend()
    plt.title("Learned Path by RL Agent")
    plt.show()

plot_path(env, path)
```

Output:

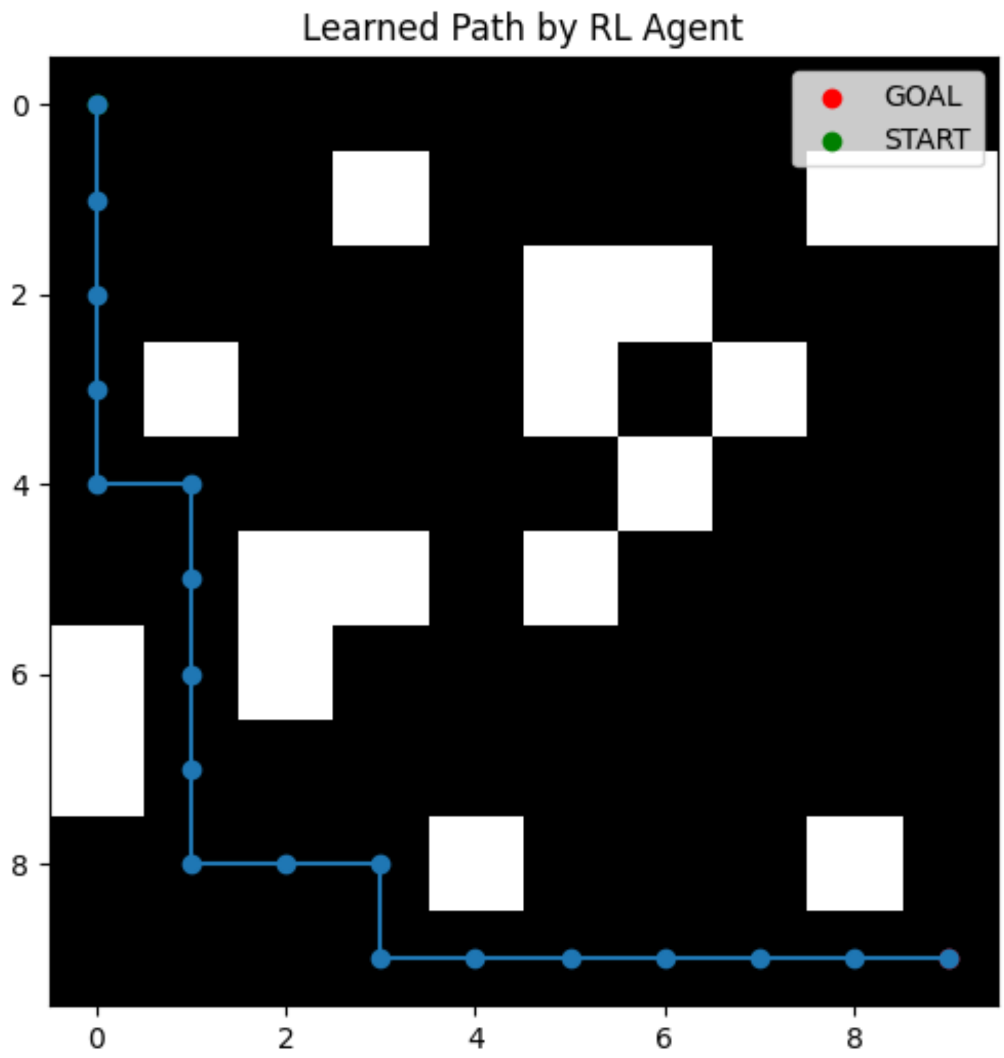
#3



#4

[(0, 0),
(1, 0),
(2, 0),
(3, 0),
(4, 0),
(4, 1),
(5, 1),
(6, 1),
(7, 1),
(8, 1),
(8, 2),
(8, 3),
(9, 3),
(9, 4),
(9, 5),
(9, 6),
(9, 7),
(9, 8),
(9, 9)]

#5



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