Pathfinding Intelligence: *Dynamic Programming, Monte Carlo, and Temporal Difference Learning in Action*

This notebook demonstrates the implementation of three Reinforcement Learning algorithms (Dynamic Programming, Monte Carlo, and Temporal Difference) for solving a maze navigation problem.

Objective:

- To implement and compare the performance of different RL algorithms in a controlled maze environment.
- To gain practical experience in applying RL concepts to a real-world problem.

Aim:

To develop and analyze RL agents that can effectively learn optimal policies for navigating a given maze environment, maximizing the cumulative reward.

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1. Introduction

Reinforcement Learning (RL) is a powerful paradigm for training agents to interact with an environment and learn optimal behaviors. In this project, we focus on solving a classic maze navigation problem using three prominent RL algorithms:

- **Dynamic Programming (DP):** Leverages knowledge of the entire environment to iteratively compute the optimal policy.
- **Monte Carlo (MC) Learning:** Learns from complete episodes of interaction with the environment.
- **Temporal Difference (TD) Learning:** Learns from incomplete episodes and bootstraps from current estimates.

This notebook provides a comprehensive implementation and analysis of these algorithms, along with visualizations and performance comparisons.

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

2. Maze Environment

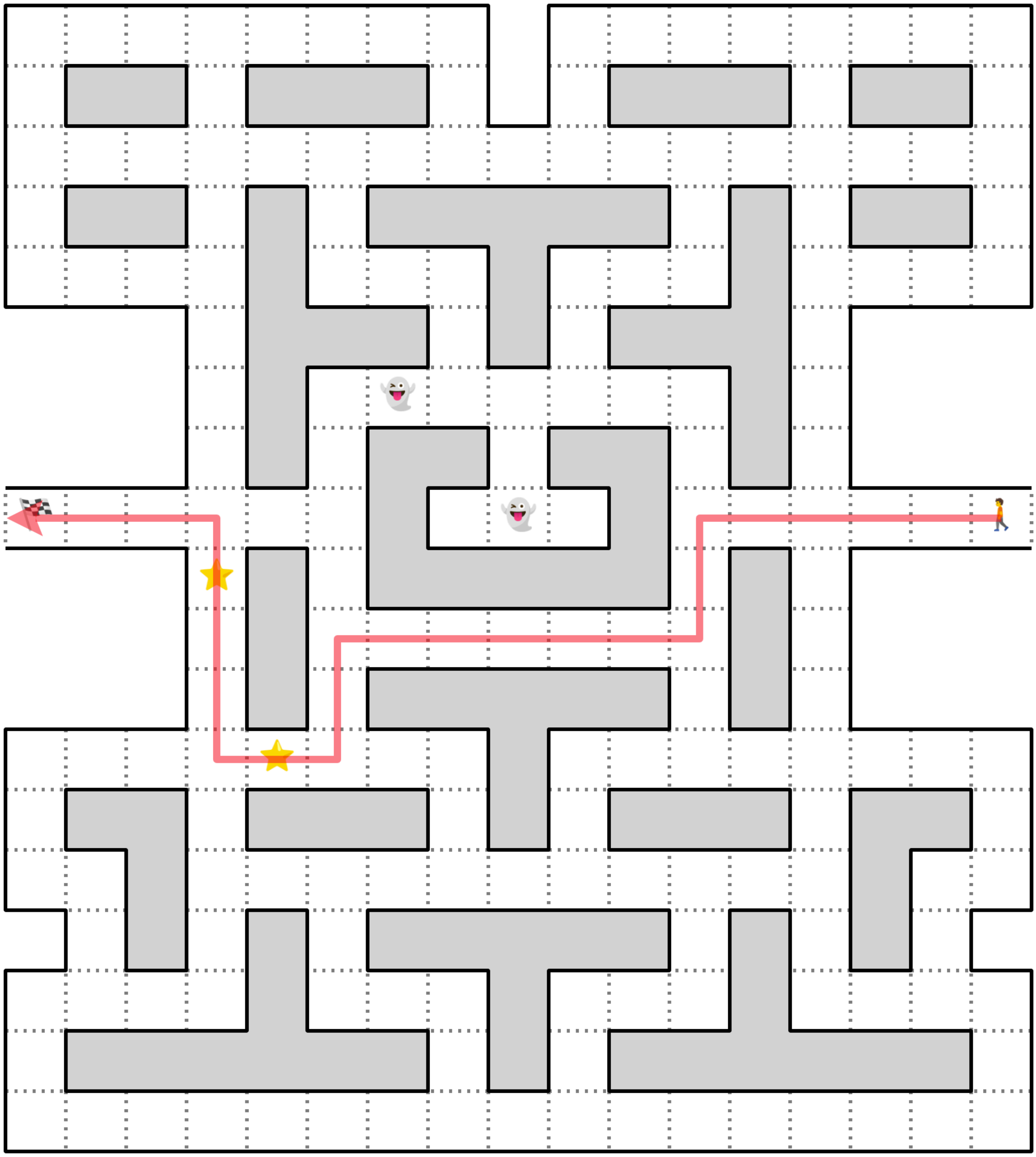
```
# 2. Maze Environment

class Maze:
    """
    Defines the maze environment with obstacles, starting locations,
    absorbing states (goal locations), and rewards.
    """

    def __init__(self):
        """
        Initializes the maze environment.
        """
        # Properties set from the CID
        cid = get_CID()
        y = int(cid[-2])
        z = int(cid[-1])
        self._prob_success = 0.8 + 0.02 * (9 - y)  # float
        self._gamma = 0.8 + 0.02 * y  # float
        self._goal = 3  # integer (0 for R0, 1 for R1, 2 for R2, 3 for R3) z%4

        # Build the maze
        self._build_maze()

        self._graphics_object = GraphicsMaze(self._shape,
                                        self._locations,
                                        self._default_reward,
                                        self._obstacle_locs,
                                        self._absorbing_locs,
                                        self._absorbing_rewards,
                                        self._absorbing)

    def _build_maze(self):
        """
        Maze initialization.
        """
```

```python
# Properties of the maze
self._shape = (13, 10)
self._obstacle_locs = [
    (1, 0), (1, 1), (1, 2), (1, 3), (1, 4), (1, 7), (1, 8), (1, 9),
    (2, 1), (2, 2), (2, 3), (2, 7),
    (3, 1), (3, 2), (3, 3), (3, 7),
    (4, 1), (4, 7),
    (5, 1), (5, 7),
    (6, 5), (6, 6), (6, 7),
    (8, 0),
    (9, 0), (9, 1), (9, 2), (9, 6), (9, 7), (9, 8), (9, 9),
    (10, 0)
]  # Location of obstacles
self._absorbing_locs = [(2, 0), (2, 9), (10, 1), (12, 9)]  # Location of absorbing states
self._absorbing_rewards = [(500 if (i == self._goal) else -50) for i in range(4)]  # Reward of absorbing states
self._starting_locs = [(0, 0), (0, 1), (0, 2), (0, 3), (0, 4), (0, 5), (0, 6), (0, 7), (0, 8), (0, 9)]
self._default_reward = -1  # Reward for each action performs in the environment
self._max_t = 500  # Max number of steps in the environment

# Actions
self._action_size = 4
self._direction_names = ['N', 'E', 'S', 'W']  # Direction 0 is 'N', 1 is 'E' and so on

# States
self._locations = []
for i in range(self._shape[0]):
    for j in range(self._shape[1]):
        loc = (i, j)
        # Adding the state to locations if it is no obstacle
        if self._is_location(loc):
            self._locations.append(loc)
self._state_size = len(self._locations)

# Neighbours - each line is a state, ranked by state-number, each column is a direction (N, E, S, W)
self._neighbours = np.zeros((self._state_size, 4))

for state in range(self._state_size):
    loc = self._get_loc_from_state(state)

    # North
    neighbour = (loc[0] - 1, loc[1])  # North neighbours location
    if self._is_location(neighbour):
        self._neighbours[state][self._direction_names.index('N')] = self._get_state_from_loc(neighbour)
    else:  # If there is no neighbour in this direction, coming back to current state
        self._neighbours[state][self._direction_names.index('N')] = state

    # East
    neighbour = (loc[0], loc[1] + 1)  # East neighbours location
    if self._is_location(neighbour):
        self._neighbours[state][self._direction_names.index('E')] = self._get_state_from_loc(neighbour)
    else:  # If there is no neighbour in this direction, coming back to current state
        self._neighbours[state][self._direction_names.index('E')] = state

    # South
    neighbour = (loc[0] + 1, loc[1])  # South neighbours location
    if self._is_location(neighbour):
        self._neighbours[state][self._direction_names.index('S')] = self._get_state_from_loc(neighbour)
    else:  # If there is no neighbour in this direction, coming back to current state
        self._neighbours[state][self._direction_names.index('S')] = state

    # West
    neighbour = (loc[0], loc[1] - 1)  # West neighbours location
    if self._is_location(neighbour):
        self._neighbours[state][self._direction_names.index('W')] = self._get_state_from_loc(neighbour)
    else:  # If there is no neighbour in this direction, coming back to current state
        self._neighbours[state][self._direction_names.index('W')] = state

# Absorbing
self._absorbing = np.zeros((1, self._state_size))
for a in self._absorbing_locs:
    absorbing_state = self._get_state_from_loc(a)
    self._absorbing[0, absorbing_state] = 1

# Transition matrix
self._T = np.zeros((self._state_size, self._state_size, self._action_size))  # Empty matrix of domension S*S*A
for action in range(self._action_size):
    for outcome in range(4):  # For each direction (N, E, S, W)
        # The agent has prob_success probability to go in the correct direction
        if action == outcome:
            prob = 1 - 3.0 * ((1.0 - self._prob_success) / 3.0)  # (theoritically equal to self.prob_success but avoid rounding
        # Equal probability to go into one of the other directions
```

```
            else:
                prob = (1.0 - self._prob_success) / 3.0

            # Write this probability in the transition matrix
            for prior_state in range(self._state_size):
                # If absorbing state, probability of 0 to go to any other states
                if not self._absorbing[0, prior_state]:
                    post_state = self._neighbours[prior_state, outcome]  # Post state number
                    post_state = int(post_state)  # Transform in integer to avoid error
                    self._T[prior_state, post_state, action] += prob

    # Reward matrix
    self._R = np.ones((self._state_size, self._state_size, self._action_size))  # Matrix filled with 1
    self._R = self._default_reward * self._R  # Set default_reward everywhere
    for i in range(len(self._absorbing_rewards)):  # Set absorbing states rewards
        post_state = self._get_state_from_loc(self._absorbing_locs[i])
        self._R[:, post_state, :] = self._absorbing_rewards[i]

    # Creating the graphical Maze world
    self._graphics = GraphicsMaze(self._shape, self._locations, self._default_reward, self._obstacle_locs, self._absorbing_locs, se

    # Reset the environment
    self.reset()

def _is_location(self, loc):
    """
    Is the location a valid state (not out of Maze and not an obstacle)
    input: loc {tuple} -- location of the state
    output: _ {bool} -- is the location a valid state
    """
    if (loc[0] < 0 or loc[1] < 0 or loc[0] > self._shape[0] - 1 or loc[1] > self._shape[1] - 1):
        return False
    elif (loc in self._obstacle_locs):
        return False
    else:
        return True

def _get_state_from_loc(self, loc):
    """
    Get the state number corresponding to a given location
    input: loc {tuple} -- location of the state
    output: index {int} -- corresponding state number
    """
    return self._locations.index(tuple(loc))

def _get_loc_from_state(self, state):
    """
    Get the state number corresponding to a given location
    input: index {int} -- state number
    output: loc {tuple} -- corresponding location
    """
    return self._locations[state]

# Getter functions used only for DP agents
# You DO NOT NEED to modify them
def get_T(self):
    return self._T

def get_R(self):
    return self._R

def get_absorbing(self):
    return self._absorbing

# Getter functions used for DP, MC and TD agents
# You DO NOT NEED to modify them
def get_graphics(self):
    return self._graphics_object

def get_action_size(self):
    return self._action_size

def get_state_size(self):
    return self._state_size

def get_gamma(self):
    return self._gamma

# Functions used to perform episodes in the Maze environment
def reset(self):
    """
    Reset the environment state to one of the possible starting states
```

```
        input: /
        output:
            - t {int} -- current timestep
            - state {int} -- current state of the envionment
            - reward {int} -- current reward
            - done {bool} -- True if reach a terminal state / 0 otherwise
        """
        self._t = 0
        self._state = self._get_state_from_loc(self._starting_locs[random.randrange(len(self._starting_locs))])
        self._reward = 0
        self._done = False
        return self._t, self._state, self._reward, self._done

    def step(self, action):
        """
        Perform an action in the environment
        input: action {int} -- action to perform
        output:
            - t {int} -- current timestep
            - state {int} -- current state of the envionment
            - reward {int} -- current reward
            - done {bool} -- True if reach a terminal state / 0 otherwise
        """

        # If environment already finished, print an error
        if self._done or self._absorbing[0, self._state]:
            print("Please reset the environment")
            return self._t, self._state, self._reward, self._done

        # Drawing a random number used for probaility of next state
        probability_success = random.uniform(0, 1)

        # Look for the first possible next states (so get a reachable state even if probability_success = 0)
        new_state = 0
        while self._T[self._state, new_state, action] == 0:
            new_state += 1
        assert self._T[self._state, new_state, action] != 0, "Selected initial state should be probability 0, something might be wrong i

        # Find the first state for which probability of occurence matches the random value
        total_probability = self._T[self._state, new_state, action]
        while (total_probability < probability_success) and (new_state < self._state_size - 1):
            new_state += 1
            total_probability += self._T[self._state, new_state, action]
        assert self._T[self._state, new_state, action] != 0, "Selected state should be probability 0, something might be wrong in the en

        # Setting new t, state, reward and done
        self._t += 1
        self._reward = self._R[self._state, new_state, action]
        self._done = self._absorbing[0, new_state] or self._t > self._max_t
        self._state = new_state
        return self._t, self._state, self._reward, self._done
```

3. Visualization



```
# 3. Helper Class for Visualization

class GraphicsMaze:
    """
    A helper class for visualizing the maze environment.
    """

    def __init__(self, shape, locations, default_reward, obstacle_locs, absorbing_locs, absorbing_rewards, absorbing):
        """
        Initializes the GraphicsMaze object.
        """
        self.shape = shape
        self.locations = locations
        self.absorbing = absorbing

        # Walls
        self.walls = np.zeros(self.shape)
        for ob in obstacle_locs:
            self.walls[ob] = 20
```

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        # Rewards
        self.rewarders = np.ones(self.shape) * default_reward
        for i, rew in enumerate(absorbing_locs):
            self.rewarders[rew] = 10 if absorbing_rewards[i] > 0 else -10

        # Print the map to show it
        self.paint_maps()

    def paint_maps(self):
        """
        Print the Maze topology (obstacles, absorbing states and rewards)
        input: /
        output: /
        """
        plt.figure(figsize=(15, 10))
        plt.imshow(self.walls + self.rewarders)
        plt.show()

    def paint_state(self, state):
        """
        Print one state on the Maze topology (obstacles, absorbing states and rewards)
        input: /
        output: /
        """
        states = np.zeros(self.shape)
        states[state] = 30
        plt.figure(figsize=(15, 10))
        plt.imshow(self.walls + self.rewarders + states)
        plt.show()

    def draw_deterministic_policy(self, Policy, state):
        """
        Draw a deterministic policy
        input: Policy {np.array} -- policy to draw (should be an array of values between 0 and 3 (actions))
        output: /
        """

        graphics = self.get_graphics()
        plt.figure(figsize=(15, 10))
        plt.imshow(self.walls + self.rewarders)  # Create the graph of the Maze
        for state, action in enumerate(Policy):
            if (self.absorbing[0, state]):  # If it is an absorbing state, don't plot any action
                continue
            arrows = [r"$\uparrow$", r"$\rightarrow$", r"$\downarrow$", r"$\leftarrow$"]
            action_arrow = arrows[Policy[state]]  # Choose the arrow based on policy for state

            location = self.locations[state]  # Access location using state
            graphics.text(location[1], location[0], action_arrow, ha='center', va='center')

            graphics.show()
           # plt.text(location[1], location[0], action_arrow, ha='center', va='center')  # Place it on graph
        plt.show()

    def draw_policy(self, Policy):
        """
        Draw a policy (draw an arrow in the most probable direction)
        input: Policy {np.array} -- policy to draw as probability
        output: /
        """
        deterministic_policy = np.array([np.argmax(Policy[row, :]) for row in range(Policy.shape[0])])
        self.draw_deterministic_policy(deterministic_policy)

    def draw_value(self, Value):
        """
        Draw a policy value
        input: Value {np.array} -- policy values to draw
        output: /
        """
        plt.figure(figsize=(15, 10))
        plt.imshow(self.walls + self.rewarders)  # Create the graph of the Maze
        for state, value in enumerate(Value):
            if (self.absorbing[0, state]):  # If it is an absorbing state, don't plot any value
                continue
            location = self.locations[state]  # Compute the value location on graph
            plt.text(location[1], location[0], round(value, 2), ha='center', va='center')  # Place it on graph
        plt.show()

    def draw_deterministic_policy_grid(self, Policies, title, n_columns, n_lines):
        """
        Draw a grid representing multiple deterministic policies
        input: Policies {np.array of np.array} -- array of policies to draw (each should be an array of values between 0 and 3 (actions)
        output: /
```

```
        """
        plt.figure(figsize=(20, 8))
        for subplot in range(len(Policies)):  # Go through all policies
            ax = plt.subplot(n_columns, n_lines, subplot + 1)  # Create a subplot for each policy
            ax.imshow(self.walls + self.rewarders)  # Create the graph of the Maze

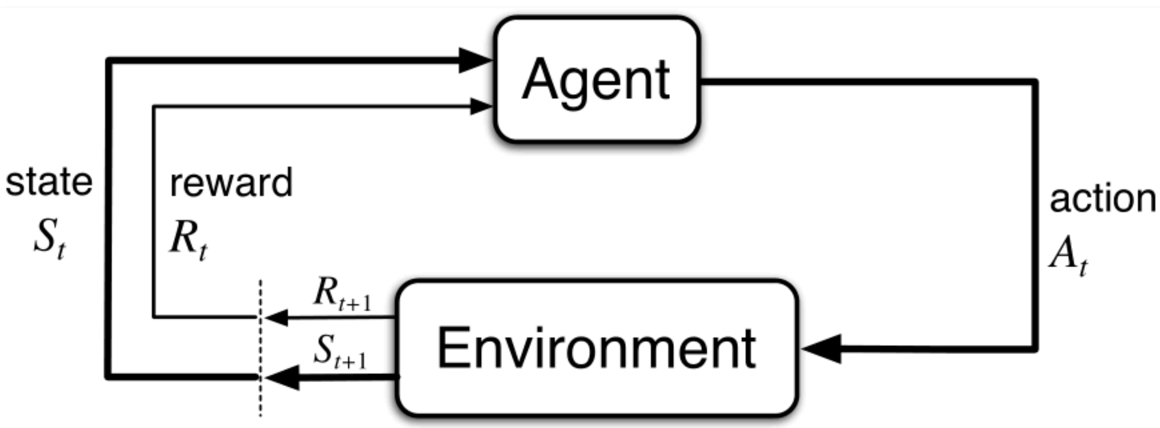
        for state, action in enumerate(Policy):
          location = self.locations[state]  # Access location using state

        for state, action in enumerate(Policies[subplot]):
                if (self.absorbing[0, state]):  # If it is an absorbing state, don't plot any action
                    continue
                arrows = [r"$\uparrow$", r"$\rightarrow$", r"$\downarrow$", r"$\leftarrow$"]  # List of arrows corresponding to each pos
                action_arrow = arrows[action]  # Take the corresponding action
                location = self.locations[state]  # Compute its location on graph
                plt.text(location[1], location[0], action_arrow, ha='center', va='center')  # Place it on graph
                ax.title.set_text(title[subplot])  # Set the title for the graph given as argument
        plt.show()

    def draw_policy_grid(self, Policies, title, n_columns, n_lines):
        """
        Draw a grid representing multiple policies (draw an arrow in the most probable direction)
        input: Policy {np.array} -- array of policies to draw as probability
        output: /
        """
        deterministic_policies = np.array([[np.argmax(Policy[row, :]) for row in range(Policy.shape[0])] for Policy in Policies])
        self.draw_deterministic_policy_grid(deterministic_policies, title, n_columns, n_lines)

    def draw_value_grid(self, Values, title, n_columns, n_lines):
        """
        Draw a grid representing multiple policy values
        input: Values {np.array of np.array} -- array of policy values to draw
        output: /
        """
        plt.figure(figsize=(20, 8))
        for subplot in range(len(Values)):  # Go through all values
            ax = plt.subplot(n_columns, n_lines, subplot + 1)  # Create a subplot for each value
            ax.imshow(self.walls + self.rewarders)  # Create the graph of the Maze
            for state, value in enumerate(Values[subplot]):
                if (self.absorbing[0, state]):  # If it is an absorbing state, don't plot any value
                    continue
                location = self.locations[state]  # Compute the value location on graph
                plt.text(location[1], location[0], round(value, 1), ha='center', va='center')  # Place it on graph
            ax.title.set_text(title[subplot])  # Set the title for the graoh given as argument
        plt.show()
```

Dynamic Programming




```
# 4. Dynamic Programming Agent

class DP_agent:
    """
    Implements the Dynamic Programming algorithm for solving the maze.
    """

    def solve(self, env):
        """
        Solves the given maze environment using Dynamic Programming.
```

```
    Args:
        env (Maze): The Maze environment object.

    Returns:
        tuple: A tuple containing the optimal policy and the corresponding
               value function.
    """
    # Initialisation (can be edited)
    policy = np.zeros((env.get_state_size(), env.get_action_size()))
    V = np.zeros(env.get_state_size())

    ####
    # Add your code here
    # WARNING: for this agent only, you are allowed to access env.get_T(), env.get_R() and env.get_absorbing()
    ####

    #### Here we are accessing the environment properties ####
    # T: Transition matrix
    # R: Reward matrix
    # absorbing: Boolean array indicating absorbing states in the environment
    # actions: Total number of possible actions
    # states: Total number of possible states
    # gamma: Discount factor

    T = env.get_T()
    R = env.get_R()
    absorbing = env.get_absorbing()
    actions = env.get_action_size()
    states = env.get_state_size()
    gamma = env.get_gamma()

    # Set threshold for convergence of the value function

    threshold = 1

    # Ensure gamma value is valid
    assert (gamma <= 1) and (gamma >= 0), "Discount factor should be in [0, 1]."

    # Initialisation
    epochs = 0
    delta = threshold  # Setting value of delta to go through the first breaking condition
    V = np.zeros(states)  # Initialise values at 0 for each state

    while delta >= threshold:
        epochs += 1  # Increment the epoch
        delta = 0  # Reinitialise delta value

        # For each state
        for prior_state in range(states):

            # If not an absorbing state
            if not absorbing[0, prior_state]:

                # Store the previous value for that state
                v = V[prior_state]

                # Compute Q value
                Q = np.zeros(4)  # Initialise with value 0
                for post_state in range(states):
                    Q += T[prior_state, post_state, :] * (R[prior_state, post_state, :] + gamma * V[post_state])

                # Set the new value to the maximum of Q
                V[prior_state] = np.max(Q)

                # Compute the new delta
                delta = max(delta, np.abs(v - V[prior_state]))

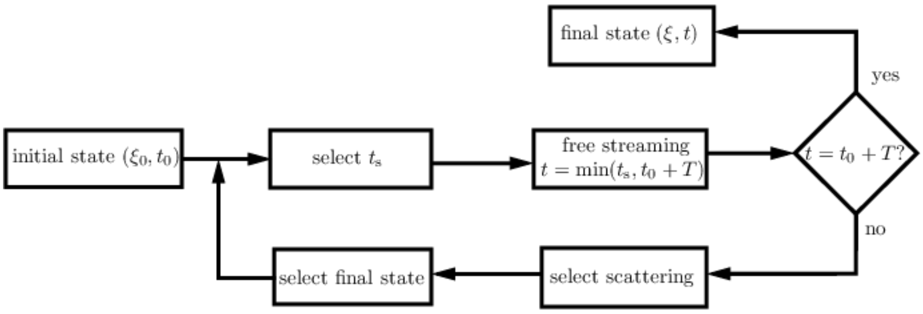
    # When the loop is finished, fill in the optimal policy
    policy = np.zeros((states, actions))  # Initialisation

    for prior_state in range(states):
        # Compute the Q value
        Q = np.zeros(4)
        for post_state in range(states):
            Q += T[prior_state, post_state, :] * (R[prior_state, post_state, :] + gamma * V[post_state])

        # The action that maximises the Q value gets probability 1
        policy[prior_state, np.argmax(Q)] = 1

    return policy, V
```

5. Monte Carlo Agent




```
# 5. Monte Carlo Agent

class MC_agent:
    """
    Implements the Monte Carlo learning algorithm for solving the maze.
    """

    def solve(self, env):
        """
        Solves the given maze environment using Monte Carlo learning.

        Args:
            env (Maze): The Maze environment object.

        Returns:
            tuple: A tuple containing the optimal policy, a list of successive
                   value functions, and a list of total rewards for each episode.
        """

        # Initialisation (can be edited)
        Q = np.random.rand(env.get_state_size(), env.get_action_size())
        V = np.zeros(env.get_state_size())
        epsilon = 0.01
        states = env.get_state_size()
        actions = env.get_action_size()
        gamma = env.get_gamma()
        policy = np.zeros((env.get_state_size(), env.get_action_size()))

        # Initialize policy based on initial Q values
        policy = initialize_policy(states, actions, Q, policy, epsilon)
        values = [V]
        total_rewards = []

        # env.reset() and env.step() methods of the Maze class, as well as env.get_action_size(),
        # env.get_state_size() and env.get_gamma().

        ####
        # Add your code here
        # WARNING: this agent only has access to env.reset() and env.step()
        # You should not use env.get_T(), env.get_R() or env.get_absorbing() to compute any value
        ####

        returns = {}

        # Set the number of episodes to run Monte Carlo algorithm

        num_episodes = 1000
        for iteration in range(num_episodes):

            G = 0  # Initialize return
            episode = generate_episode(env, actions, policy)  # Generate an episode using the current policy
            sum_rewards = 0
            epsilon = epsilon - (epsilon / num_episodes)  # Decay epsilon over time

            for i in reversed(range(0, len(episode))):

                t, s_t, a_t, r_t = episode[i]  # Time step, state, action, reward for current step
                state_action = (s_t, a_t)
                G = gamma * G + r_t  # Increment total reward by reward on current timestep
                sum_rewards += r_t

                # Check if this is the first occurrence of the state-action pair in the episode
```

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            if not state_action in [(x[1], x[2]) for x in episode[0:i]]:  # to check

                # Update returns for the state-action pair

                if returns.get(state_action):
                    returns[state_action].append(G)
                else:
                    returns[state_action] = [G]

                Q[s_t][a_t] = np.mean(returns[state_action])  # Average reward across episodes

                Q_list = Q[s_t]
                indices = np.where(Q_list == np.max(Q_list))[0]  # Get indices of max Q-values
                max_Q = np.random.choice(indices)

                A_star = max_Q  # Optimal action for the current state

                for a in range(actions):  # Update action probability for s_t in policy
                    if a == A_star:
                        policy[s_t][a] = 1 - epsilon + (epsilon / actions)
                    else:
                        policy[s_t][a] = (epsilon / actions)

        # Calculate the value function V based on current policy and Q values

        V = np.sum(policy * Q, axis=1)
        values.append(V.copy())
        total_rewards.append(sum_rewards)  # Store the total rewards for the current episode

    return policy, values, total_rewards

def generate_episode(env, actions, policy):
    """ To generate an episode based on the policy

    Args:
        env (object): The object of the maze class
        actions (int): Total number of possible actions
        policy (np.array): An array of size (number of states x number of actions)

    Returns:
        list: The generated episode
    """

    t, state, reward, done = env.reset()
    episode = []
    while not done:
        action_probs = policy[state]

        action = np.random.choice(np.arange(len(action_probs)), p=action_probs)

        t, next_state, reward, done = env.step(action)
        episode.append((t, state, action, reward))
        state = next_state

    return episode

def initialize_policy(states, actions, Q, policy, epsilon):
    """ To initialize the policy

    Args:
        states (int): Total number of states
        actions (int): Total number of possible actions
        Q (np.array): An array of state-action value function having size (number of states x number of actions)
        policy (np.array): An array of size (number of states x number of actions)
        epsilon (float): A parameter to choose the action based on a stochastic policy
    Returns:
        np.array: The initialized policy based on epsilon soft policy
    """
    for state in range(states):
        best_action = random.choice(range(actions))
        for action in range(actions):
            if action == best_action:
                policy[state][action] = 1 - epsilon + (epsilon / actions)
            else:
                policy[state][action] = (epsilon / actions)

    return policy
```
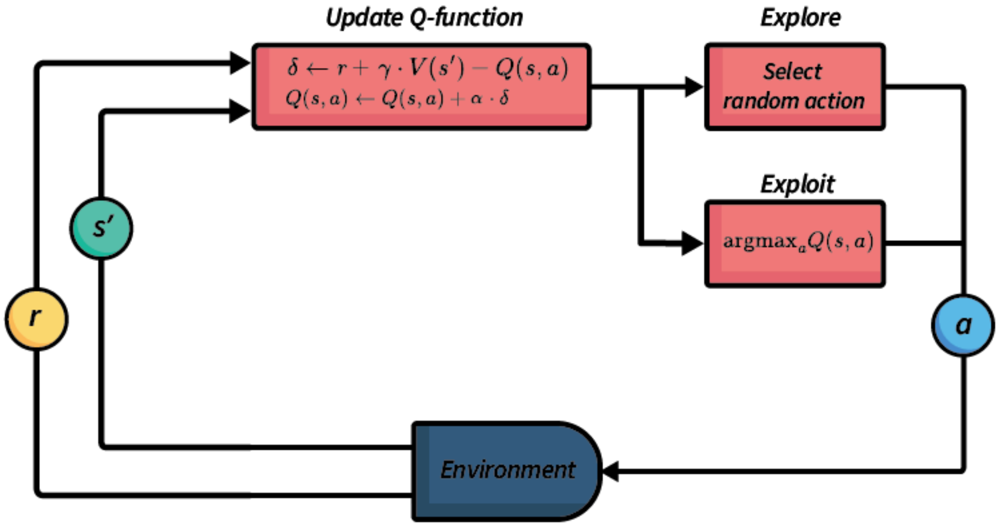

6. Temporal Difference Agent



```
# 6. Temporal Difference Agent

class TD_agent:
    """
    Implements the Temporal Difference learning algorithm for solving the maze.
    """

    def solve(self, env):
        """
        Solves the given maze environment using Temporal Difference learning.

        Args:
            env (Maze): The Maze environment object.

        Returns:
            tuple: A tuple containing the optimal policy, a list of successive
                   value functions, and a list of total rewards for each episode.
        """

        # Initialisation (can be edited)
        Q = np.random.rand(env.get_state_size(), env.get_action_size())
        V = np.zeros(env.get_state_size())
        policy = np.zeros((env.get_state_size(), env.get_action_size()))
        values = [V]
        total_rewards = []

        # Get the absorbing states

        absorbing = env.get_absorbing()[0]

        # Set the Q-values for absorbing states to zero

        for ind, state in enumerate(absorbing):
            if state != 0:
                Q[ind, :] = 0

        states = env.get_state_size()
        actions = env.get_action_size()
        gamma = env.get_gamma()

        alpha = 0.1  # 0.1  Although theory says that alpha should follow Robbins-Monro conditions, but in practice it is observed that
        epsilon = 0.4  # 0.4

        n_episodes = 1000  # Total number of episodes to run

        # Initialize the policy based on the initial Q-values

        policy = initialize_policy(states, actions, Q, policy, epsilon)

        for episode in range(n_episodes):

            epsilon = epsilon - (epsilon / n_episodes)  # Implementation of epsilon decay
            t, state, reward, done = env.reset()
            action = epsilon_greedy(state, epsilon, policy, actions)  # Select the first action using epsilon-greedy policy
            reward_sum = 0  # Track the sum of rewards for this episode

            # Loop over each step within the episode until the agent reaches a terminal state

            while not done:
```

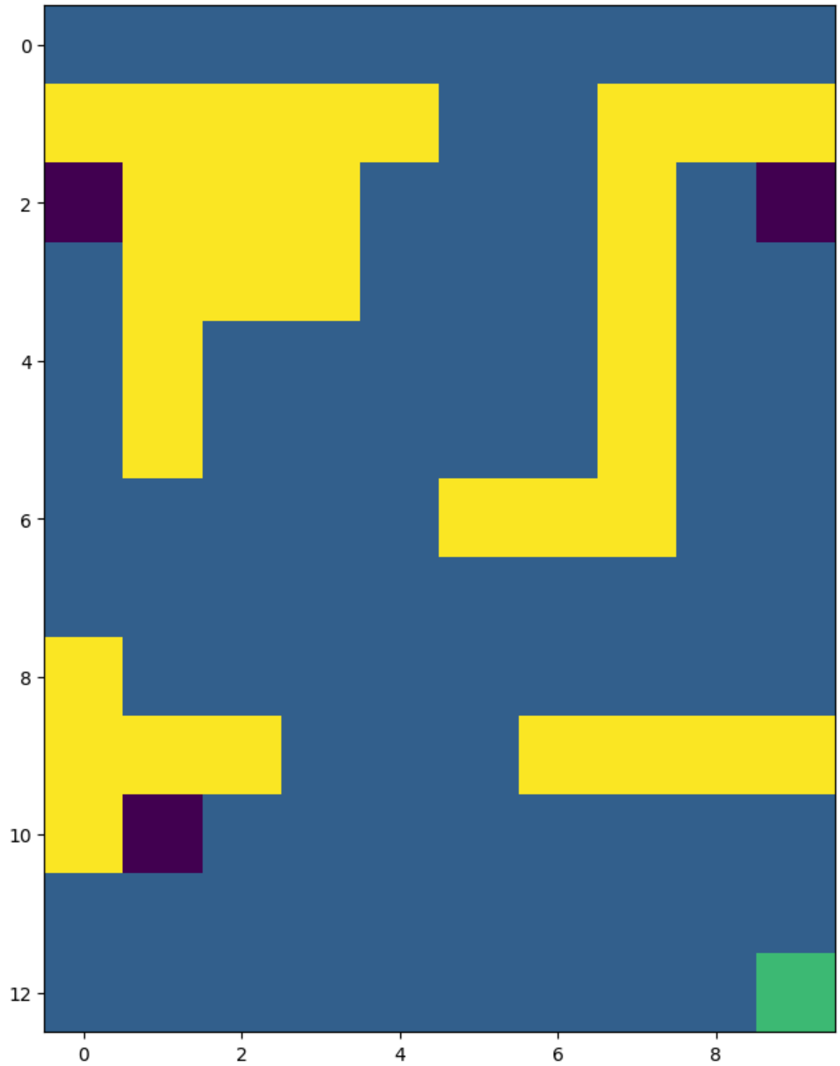
```
                # Take action and observe the next state, reward, and whether the episode is done

                t, next_state, reward, done = env.step(action)

                alpha = 1 / (t + 1)  # Implement alpha decay

                next_action = epsilon_greedy(next_state, epsilon, policy, actions)  # Select the next action using epsilon-greedy policy

                # Update the Q-value using the SARSA update rule

                Q[state, action] += alpha * (
                        reward + gamma * Q[next_state, next_action] - Q[state, action]
                )

                # Update policy to choose the action with the highest Q-value for the current state

                Q_list = Q[state]
                indices = np.where(Q_list == np.max(Q_list))[0]  # Get indices of max Q-values
                max_Q = np.random.choice(indices)
                A_star = max_Q  # choose the best action

                for a in range(actions):  # Update action probability for s_t in policy
                    if a == A_star:
                        policy[state][a] = 1 - epsilon + (epsilon / actions)
                    else:
                        policy[state][a] = (epsilon / actions)

                # Move to the next state and action

                state = next_state
                action = next_action
                reward_sum += reward

            total_rewards.append(reward_sum)

            # Calculate the value function V based on current policy and Q values

            V = np.sum(policy * Q, axis=1)
            values.append(V.copy())

        return policy, values, total_rewards

def generate_episode(env, actions, policy):
    """ To generate an episode based on the policy

    Args:
        env (object): The object of the maze class
        actions (int): Total number of possible actions
        policy (np.array): An array of size (number of states x number of actions)

    Returns:
        list: The generated episode
    """

    t, state, reward, done = env.reset()
    episode = []
    while not done:
        action_probs = policy[state]

        action = np.random.choice(np.arange(len(action_probs)), p=action_probs)

        t, next_state, reward, done = env.step(action)
        episode.append((t, state, action, reward))
        state = next_state

    return episode

def initialize_policy(states, actions, Q, policy, epsilon):
    """ To initialize the policy

    Args:
        states (int): Total number of states
        actions (int): Total number of possible actions
        Q (np.array): An array of state-action value function having size (number of states x number of actions)
        policy (np.array): An array of size (number of states x number of actions)
        epsilon (float): A parameter to choose the action based on a stochastic policy
    Returns:
        np.array: The initialized policy based on epsilon soft policy
    """
    for state in range(states):
        best_action = random.choice(range(actions))
```

```
        for action in range(actions):
            if action == best_action:
                policy[state][action] = 1 - epsilon + (epsilon / actions)
            else:
                policy[state][action] = (epsilon / actions)

    return policy
```

Driver's Code

```
# 7. Main Execution
def get_CID():
      return "06006553"  # Replace with your actual CID

if __name__ == "__main__":

    # Create the maze environment
    print("Creating the Maze:\n")
    maze = Maze()

    # Solve using Dynamic Programming
    dp_agent = DP_agent()
    dp_policy, dp_value = dp_agent.solve(maze)

    print("Results of the DP agent:\n")
    maze.get_graphics().draw_policy(dp_policy, state)  # Pass state argument
    maze.get_graphics().draw_value(dp_value)

    #print("Results of the DP agent:\n")
    #for state in range(len(dp_policy)):
    #  maze.get_graphics().draw_policy(dp_policy, state)  # Pass state as argument
    #maze.get_graphics().draw_value(dp_value)

    # Solve using Monte Carlo learning
    mc_agent = MC_agent()
    mc_policy, mc_values, total_rewards = mc_agent.solve(maze)

    print("Results of the MC agent:\n")
    maze.get_graphics().draw_policy(mc_policy)
    maze.get_graphics().draw_value(mc_values[-1])

    # Solve using Temporal Difference learning
    td_agent = TD_agent()
    td_policy, td_values, total_rewards = td_agent.solve(maze)

    print("Results of the TD agent:\n")
    maze.get_graphics().draw_policy(td_policy)
    maze.get_graphics().draw_value(td_values[-1])
```

Creating the Maze:



Results of the DP agent: