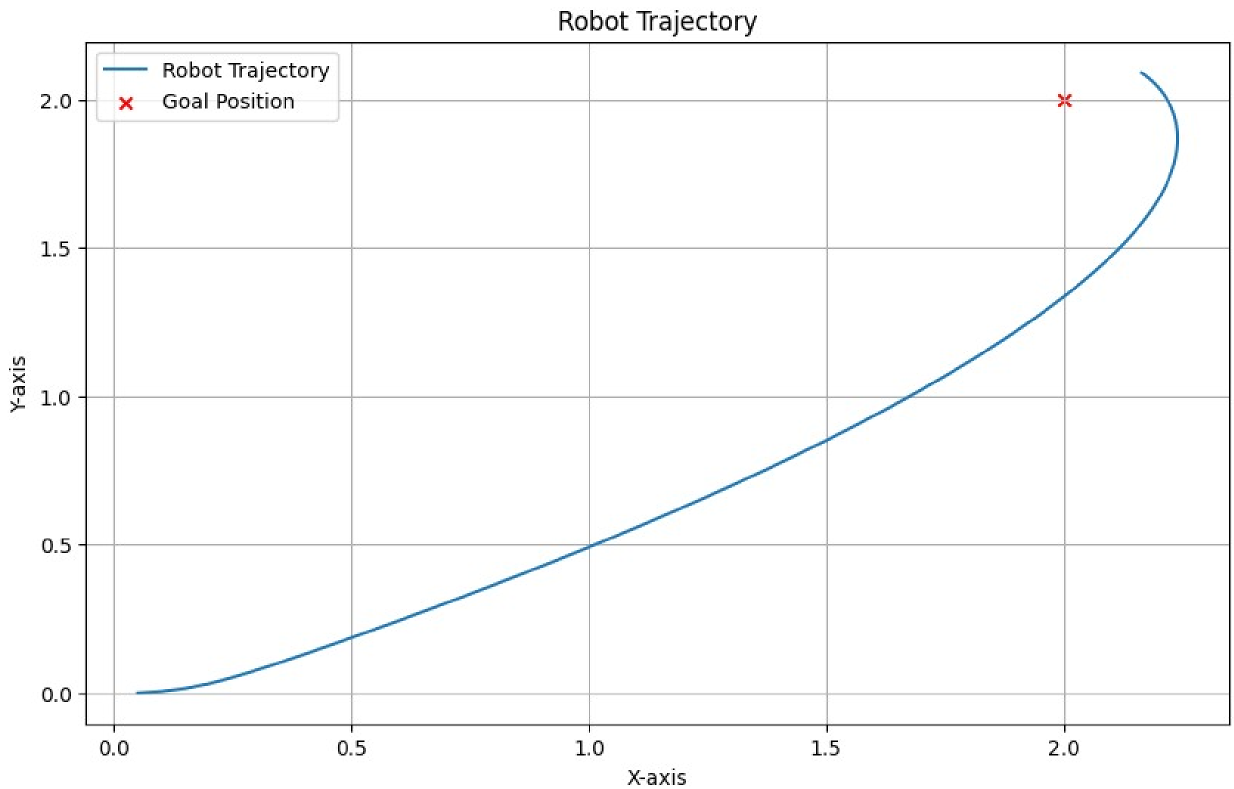
```python
#Ques - 02: Pose Stabalization Full Ques in Assignment Copy
import typing as T
import numpy as np
from utils import wrapToPi

# command zero velocities once we are this close to the goal
RHO_THRES = 0.05
ALPHA_THRES = 0.1
DELTA_THRES = 0.1

class PoseController:
    """ Pose stabilization controller """
    def __init__(self, k1: float, k2: float, k3: float,
                 V_max: float = 0.5, om_max: float = 1) -> None:
        self.k1 = k1
        self.k2 = k2
        self.k3 = k3

        self.V_max = V_max
        self.om_max = om_max

        self.x_g = 0.0
        self.y_g = 0.0
        self.th_g = 0.0

    def load_goal(self, x_g: float, y_g: float, th_g: float) -> None:
        """ Loads in a new goal position """
        self.x_g = x_g
        self.y_g = y_g
        self.th_g = th_g

    def compute_control(self, x: float, y: float, th: float, t: float)
-> T.Tuple[float, float]:
        """
        Inputs:
            x, y, th: Current state
            t: Current time (you shouldn't need to use this)
        Outputs:
            V, om: Control actions

        Hints: You'll need to use the wrapToPi function. The np.sinc
function
        may also be useful, look up its documentation
        """
        ########## Code starts here ##########
        # Calculate errors
        dx = self.x_g - x
        dy = self.y_g - y
        dtheta = wrapToPi(self.th_g - th)
```

```
        # Control law
        rho = np.sqrt(dx**2 + dy**2)
        alpha = wrapToPi(np.arctan2(dy, dx) - th)
        delta = wrapToPi(alpha - th)

        V = self.k1 * rho * np.cos(alpha)
        om = self.k2 * alpha + self.k1 * np.sinc(alpha/np.pi) *
np.cos(alpha) * delta + self.k3 * delta

        ########## Code ends here ##########

        # apply control limits
        V = np.clip(V, -self.V_max, self.V_max)
        om = np.clip(om, -self.om_max, self.om_max)

        return V, om

# Output
# Create an instance of PoseController
controller = PoseController(k1=1.0, k2=0.5, k3=0.1, V_max=0.5,
om_max=1.0)

# Set a goal
controller.load_goal(x_g=2.0, y_g=2.0, th_g=0.0)

# Example current state
x_current = 0.0
y_current = 0.0
th_current = 0.0
t_current = 0.0

# Compute control actions
V_control, om_control = controller.compute_control(x_current,
y_current, th_current, t_current)

# Display the results
print("Control Actions:")
print(f"V: {V_control}")
print(f"omega: {om_control}")


# Output as Graph
import matplotlib.pyplot as plt

# Function to simulate the robot's movement and plot the trajectory
def simulate_and_plot(controller, initial_state, total_time, dt=0.1):
    times = np.arange(0, total_time, dt)
    states = np.zeros((len(times), 3))
    controls = np.zeros((len(times), 2))
```

```python
    state = np.array(initial_state)

    for i, t in enumerate(times):
        V, om = controller.compute_control(*state, t)
        state += np.array([V * np.cos(state[2]), V * np.sin(state[2]),
om]) * dt

        states[i, :] = state
        controls[i, :] = [V, om]

    # Plotting the trajectory
    plt.figure(figsize=(10, 6))
    plt.plot(states[:, 0], states[:, 1], label='Robot Trajectory')
    plt.scatter(controller.x_g, controller.y_g, color='red',
marker='x', label='Goal Position')
    plt.xlabel('X-axis')
    plt.ylabel('Y-axis')
    plt.title('Robot Trajectory')
    plt.legend()
    plt.grid(True)
    plt.show()

# Set initial state
initial_state = [0.0, 0.0, 0.0]

# Create an instance of PoseController (replace k1, k2, k3 with actual
values)
controller = PoseController(k1=1.0, k2=1.0, k3=1.0)

# Set the goal position
controller.load_goal(2.0, 2.0, 0.0)

# Simulate and plot the trajectory for 10 seconds
simulate_and_plot(controller, initial_state, total_time=10.0, dt=0.1)
```

```
Control Actions:
V: 0.5
omega: 0.9712388980384691
```



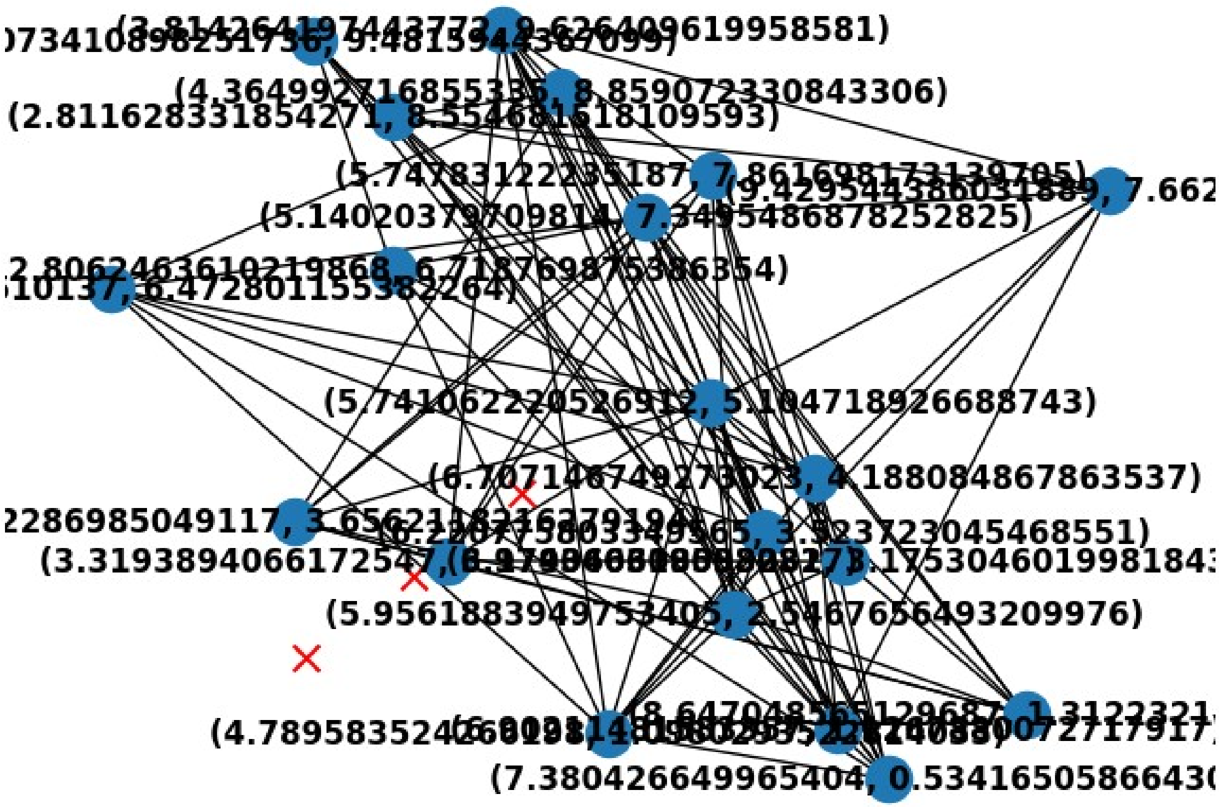

```
# Only the main code of Ques 04: Describe step by step (in words) the
A* grid-based search algorithm. What are cons of this method?
open = []
closed = []

# Add the starting node to the open list
open.append(start)

while open:
    # Find the node with the least f value in the open list
    current = min(open, key=lambda node: node.f)

    # Remove current from the open list
    open.remove(current)

    # Add current to the closed list
    closed.append(current)

    # Check if the current node is the goal state
    if current == goal:
        # Reconstruct the path from the start node to the goal node
        path = []
        while current:
            path.append(current)
            current = current.parent
```

```
        path.reverse()
        return path

    # Generate all possible successors of current
    successors = generate_successors(current)

    for successor in successors:
        # Calculate the g value
        successor.g = current.g + distance(current, successor)

        # Calculate the h value (using the Manhattan heuristic)
        successor.h = manhattan_distance(successor, goal)

        # Calculate the f value
        successor.f = successor.g + successor.h

        # Check if a node with the same position as successor is
already in the open list
        # and has a lower f value
        if successor in open and successor.f < successor.f:
            continue

        # Check if a node with the same position as successor is
already in the closed list
        # and has a lower f value
        if successor in closed and successor.f < successor.f:
            continue

        # Add successor to the open list
        open.append(successor)

# In Words
'''
1. Initialization:

Create two empty lists: open and closed.
Add the starting node to the open list. Set its g value to 0 and its h
value to the estimated distance to the goal using a heuristic function
(e.g., Manhattan distance). The f value, which is the sum of g and h,
represents the estimated total cost to reach the goal from the current
node.
2. Exploration and Path Building:

While the open list is not empty:
a. Select the Best Node:
Find the node with the lowest f value in the open list. This node is
considered the most promising candidate for reaching the goal.
b. Expand and Evaluate Successors:
Remove the selected node from the open list and add it to the closed
list.
```

```
Generate all possible successors of the selected node. These
successors represent the potential next steps in the path towards the
goal.
For each successor:
Calculate the g value, which is the cost of reaching the successor
from the starting node. This is typically the distance between the
successor and its parent node.
Calculate the h value, which is an estimate of the cost of reaching
the goal state from the successor. This can be done using various
heuristic functions (e.g., Manhattan distance, Euclidean distance).
Calculate the f value, which is the sum of g and h.
Check if a node with the same position as the successor is already in
the open list and has a lower f value. If so, skip this successor, as
there is a more promising path available.
Check if a node with the same position as the successor is already in
the closedlist and has a lowerf` value. If so, skip this successor, as
this path has already been explored and found to be less efficient.
If neither of the above conditions is met, add the successor to the
open list.
3. Goal Reached or Exhausted:

If the goal node is found (i.e., a node with the same position as the
goal is in the open or closed list), retrace the path from the goal
node back to the starting node by following the parent pointers of
each node. This is the shortest path from the start to the goal.
If the open list is empty, the algorithm has explored all possible
paths without finding the goal. The goal is either unreachable or the
heuristic function is not accurate enough.
'''

# Only the main code of Ques 05: Describe step by step (in words) the
Probabilis3c Road Map (PRM) sampling-based mo3on planning
# method. What are the cons of this method?
import numpy as np
import matplotlib.pyplot as plt
import networkx as nx
import random

# This function generates a random configuration (2D point) within the
given space_size.
def generate_random_configuration(space_size):
    return np.random.rand(2) * space_size

# This function checks if a given configuration q is collision-free
with respect to a list of obstacles. It returns True if the distance
from q to all obstacles is greater than 0.1.
def is_collision_free(q, obstacles):
    return all(np.linalg.norm(q - obstacle) > 0.1 for obstacle in
obstacles)
```

```
''' PRM START '''
# This function builds the PRM. It initializes an empty graph G using
the networkx library.
def build_prm(space_size, num_nodes, num_neighbors, obstacles):
    G = nx.Graph()
# This loop generates num_nodes random configurations, checks if they
are collision-free, and adds them as nodes to the graph G.
    for _ in range(num_nodes):
        q = generate_random_configuration(space_size)
        if is_collision_free(q, obstacles):
            G.add_node(tuple(q), config=q)
# This nested loop connects nodes in the graph by adding edges between
them if they are collision-free and within a certain distance (0.1 in
this case).
    for node1 in G.nodes():
        for node2 in random.sample(list(G.nodes()), min(num_neighbors,
len(G.nodes()))):
            if node1 != node2 and is_collision_free(np.array(node1),
obstacles) and is_collision_free(np.array(node2), obstacles):
                G.add_edge(node1, node2)
    return G
''' PRM END '''


# This function plots the PRM graph using matplotlib and positions the
nodes based on their configurations.
def plot_prm(G, obstacles):
    pos = {tuple(config): config for config in G.nodes()}
    nx.draw(G, pos=pos, with_labels=True, font_weight='bold')

    for obstacle in obstacles:
        plt.scatter(obstacle[0], obstacle[1], color='red', marker='x',
s=100)

    plt.show()

def main():
    space_size = 10
    num_nodes = 20
    num_neighbors = 5
    obstacles = np.array([[2, 2], [3, 3], [4, 4]])

    prm = build_prm(space_size, num_nodes, num_neighbors, obstacles)
    plot_prm(prm, obstacles)

if __name__ == "__main__":
    main()

'''
Cons of Probabilistic Roadmap (PRM) method:
```

```
1) Computational Complexity:
Time complexity of building the roadmap is influenced by factors such
as the number of nodes, number of neighbors, and collision checking
computations.

2) Memory Requirements:
Roadmap can be substantial, particularly in environments with a large
number of nodes which may limit the applicability of PRM

3) Sensitivity to Parameters:
PRM performance can be sensitive to the choice of parameters, such as
the number of sampled nodes, the connection radius, and the number of
neighbors to connect. Selecting appropriate parameters may require
experimentation and tuning.

4) Not Guaranteed to Find a Solution
5) Lack of Optimality: May not necessarily find the shortest or most
efficient path between the start and goal configurations. Additional
post-processing, such as path smoothing, may be needed to improve path
quality.
6) Dependency on Collision Checking Accuracy:If the collision checking
is not precise, the algorithm may produce paths that collide with
obstacles. Achieving accurate collision checking may require
sophisticated methods and can contribute to increased computational
costs.
7) Difficulty Handling Narrow Passages:Algorithm relies on random
sampling, and there's a chance that the randomly generated
configurations do not adequately explore such challenging areas.
8) Static Roadmap: PRM constructs a roadmap based on a snapshot of the
environment, assuming it is static. If the environment changes
dynamically, the pre-built roadmap may become obsolete, and the robot
may need to rebuild the roadmap in real-time.
'''
```



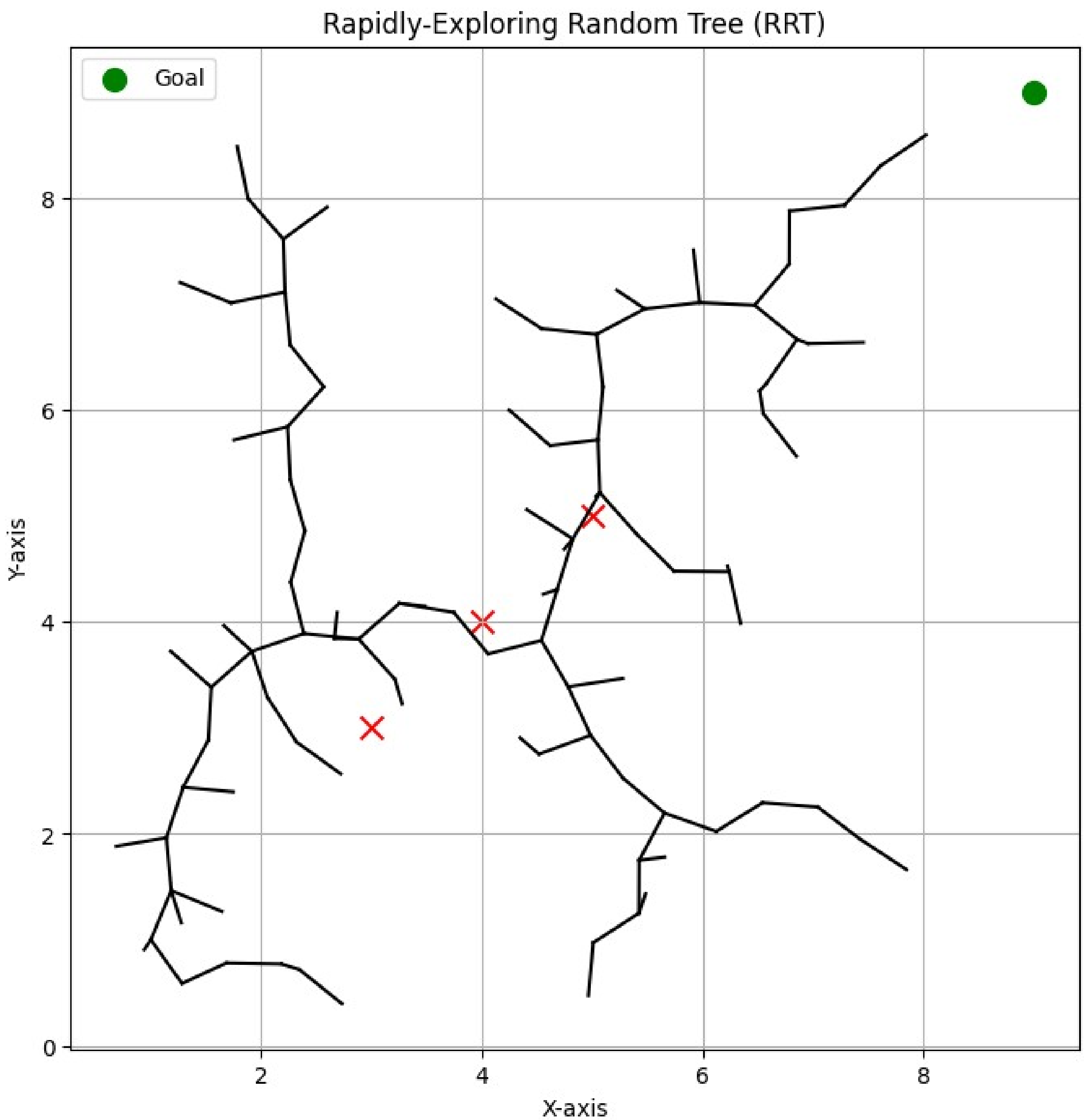

```
"\nCons of Probabilistic Roadmap (PRM) method:\n1) Computational
Complexity:\nTime complexity of building the roadmap is influenced by
factors such as the number of nodes, number of neighbors, and
collision checking computations.\n\n2) Memory Requirements:\nRoadmap
can be substantial, particularly in environments with a large number
of nodes which may limit the applicability of PRM\n\n3) Sensitivity to
Parameters:\nPRM performance can be sensitive to the choice of
parameters, such as the number of sampled nodes, the connection
radius, and the number of neighbors to connect. Selecting appropriate
parameters may require experimentation and tuning.\n\n4) Not
Guaranteed to Find a Solution\n5) Lack of Optimality: May not
necessarily find the shortest or most efficient path between the start
and goal configurations. Additional post-processing, such as path
smoothing, may be needed to improve path quality.\n6) Dependency on
Collision Checking Accuracy:If the collision checking is not precise,
the algorithm may produce paths that collide with obstacles. Achieving
accurate collision checking may require sophisticated methods and can
contribute to increased computational costs.\n7) Difficulty Handling
Narrow Passages:Algorithm relies on random sampling, and there's a
chance that the randomly generated configurations do not adequately
explore such challenging areas.\n8) Static Roadmap: PRM constructs a
```

```
roadmap based on a snapshot of the environment, assuming it is static.
If the environment changes dynamically, the pre-built roadmap may
become obsolete, and the robot may need to rebuild the roadmap in
real-time.\n"

# Only the main code of Ques 06: Describe step by step (in words)
theRapidly-exploring Random Tree (RRT) sampling-based motion planning
# method. What are the cons of this method?
import numpy as np
import matplotlib.pyplot as plt

class Node:
    def __init__(self, state):
        self.state = state
        self.parent = None

def generate_random_configuration(space_size):
    return np.random.rand(2) * space_size

def find_nearest_node(tree, q):
    # Find the nearest node in the tree to the given configuration q
    distances = [np.linalg.norm(np.array(node.state) - q) for node in
tree]
    nearest_node_index = np.argmin(distances)
    return tree[nearest_node_index]

def is_collision_free(q, obstacles):
    # Check if a configuration q is collision-free with respect to the
obstacles
    for obstacle in obstacles:
        if np.linalg.norm(q - obstacle) < 0.1:
            return False  # Collision
    return True  # Collision-free

def extend_tree(t, q, step_size, obstacles):
    # Extend the tree towards the random configuration q
    nearest_node = find_nearest_node(t, q)
    direction = np.array(q) - np.array(nearest_node.state)
    distance = np.linalg.norm(direction)
    if distance > step_size:
        direction = (direction / distance) * step_size

    new_state = np.array(nearest_node.state) + direction

    if is_collision_free(new_state, obstacles):
        new_node = Node(new_state)
        new_node.parent = nearest_node
        t.append(new_node)
        return True
    return False
```

```
def rrt(start, goal, space_size, num_nodes, step_size, obstacles):
    # Initialize the tree with the start node
    tree = [Node(start)]

    for _ in range(num_nodes):
        q = generate_random_configuration(space_size)

        # Extend the tree towards the random configuration q
        extended = extend_tree(tree, q, step_size, obstacles)

        # Check if the goal is reached
        if np.linalg.norm(np.array(tree[-1].state) - goal) <
step_size:
            goal_node = Node(goal)
            goal_node.parent = tree[-1]
            tree.append(goal_node)
            return tree

    return tree

def extract_path(tree):
    # Extract the path from the tree by backtracking from the goal
node to the start node
    path = []
    current_node = tree[-1]
    while current_node is not None:
        path.append(current_node.state)
        current_node = current_node.parent
    return path[::-1]

def plot_rrt(tree, goal, obstacles):
    # Plot the RRT graph
    plt.figure(figsize=(8, 8))
    for node in tree:
        if node.parent is not None:
            plt.plot([node.parent.state[0], node.state[0]],
[node.parent.state[1], node.state[1]], color='black')

    # Plot the goal
    plt.scatter(goal[0], goal[1], color='green', marker='o', s=100,
label='Goal')

    # Plot the obstacles
    for obstacle in obstacles:
        plt.scatter(obstacle[0], obstacle[1], color='red', marker='x',
s=100)

    plt.title('Rapidly-Exploring Random Tree (RRT)')
    plt.xlabel('X-axis')
```

```python
    plt.ylabel('Y-axis')
    plt.legend()
    plt.grid(True)
    plt.show()

def main():
    start = [1, 1]
    goal = [9, 9]
    space_size = 10
    num_nodes = 100
    step_size = 0.5
    obstacles = np.array([[3, 3], [4, 4], [5, 5]])

    # Run RRT algorithm
    tree = rrt(start, goal, space_size, num_nodes, step_size,
obstacles)

    # Extract and print the path
    path = extract_path(tree)
    print("Path:", path)

    # Plot the RRT graph
    plot_rrt(tree, goal, obstacles)

if __name__ == "__main__":
    main()


'''
1) Non-Optimal Paths: The randomness in the tree expansion process can
lead to suboptimal paths, especially in scenarios where a more
structured approach might find a shorter path.
2) Sensitivity to Parameters: Sensitive to the choice of parameters
such as step size, the number of nodes, and exploration strategy.
3) Difficulty in Narrow Spaces: Random nature of the tree expansion
may lead to nodes being placed in less informative areas of the
configuration space.
4) Limited Exploration in High-Dimensional Spaces: due to the "curse
of dimensionality." making it challenging to find valid paths.
5) Vulnerability to Local Minima: The randomness may not always lead
the tree towards unexplored or more promising regions.
6) Lack of Guarantee for Completeness: The algorithm's success depends
on random sampling and the probability of reaching the goal
configuration.
7) Dependency on Steering Function: The steering function should be
carefully designed to balance exploration and exploitation.
8) Difficulty Handling Dynamic Environments: Adapting the algorithm to
handle dynamic environments or changes in obstacle configurations may
require additional considerations and modifications.
'''
```

```
Path: [[1, 1], array([1.1849622 , 1.46453093]), array([1.14142113,
1.96263149]), array([1.2928247 , 2.43915742]), array([1.52121818,
2.88394548]), array([1.54742606, 3.38325815]), array([1.9153672,
3.7218129]), array([2.38660117, 3.88896118]), array([2.88391884,
3.83723949]), array([3.25281921, 4.17474878]), array([3.7453891 ,
4.08887153]), array([4.05626205, 3.69726201]), array([4.53994206,
3.82396498]), array([4.68191229, 4.30338594]), array([4.82428265,
4.78268822]), array([5.06974301, 5.21829035]), array([5.05241945,
5.71799015]), array([5.09738883, 6.2159638 ]), array([5.0391366 ,
6.71255888]), array([5.4769235 , 6.95410108]), array([5.22148883,
7.12957281])]
```



```
'\n1) Non-Optimal Paths: The randomness in the tree expansion process
can lead to suboptimal paths, especially in scenarios where a more
structured approach might find a shorter path.\n2) Sensitivity to
Parameters: Sensitive to the choice of parameters such as step size,
the number of nodes, and exploration strategy.\n3) Difficulty in
Narrow Spaces: Random nature of the tree expansion may lead to nodes
being placed in less informative areas of the configuration space.\n4)
Limited Exploration in High-Dimensional Spaces: due to the "curse of
dimensionality." making it challenging to find valid paths.\n5)
Vulnerability to Local Minima: The randomness may not always lead the
tree towards unexplored or more promising regions.\n6) Lack of
Guarantee for Completeness: The algorithm\'s success depends on random
sampling and the probability of reaching the goal configuration.\n7)
Dependency on Steering Function: The steering function should be
carefully designed to balance exploration and exploitation.\n8)
Difficulty Handling Dynamic Environments: Adapting the algorithm to
handle dynamic environments or changes in obstacle configurations may
require additional considerations and modifications.\n'
```