Assignment 1 Report: Zahra Bukhari

Problem 1: City Road Network - Finding Shortest Paths

Overview of the Problem

In this assignment, I was tasked with solving a city road network problem. The scenario involves helping a city's transportation department find the shortest routes from a central location to other important spots in the city. This problem is crucial for optimizing delivery routes for local businesses.

The city's road network is modeled as a graph where:

- Intersections are represented as nodes
- Roads between intersections are represented as edges
- Each road has an associated travel time (weight)

My main objective was to implement and compare two graph traversal algorithms: Breadth-First Search (BFS) and Depth-First Search (DFS) to find the shortest paths from the city center (node 0) to specific target intersections (nodes 5, 6, and 7).

Implementation

To solve this problem, I implemented the following key components:

1. Graph Representation:

   I represented the graph using a dictionary where keys are vertices and values are lists of tuples (neighbor, weight). This allowed for an efficient and intuitive representation of the weighted graph.

2. Dijkstra's Algorithm (as BFS):

   I implemented Dijkstra's algorithm as BFS with weights to find the shortest paths from the starting node to all other nodes. This algorithm guarantees finding the shortest paths in a weighted graph.

   Key functions:

   - dijkstras(graph): Implements the main algorithm
   - findMinDistanceVertex(Q, dist): Finds the vertex with the minimum distance in the queue

```
def dijkstras(graph): #for BFS weighted
    Q = deque(graph.keys()) #vertices to visit
    distances = {vertex: math.inf for vertex in graph} #distances from origin
    distances[0] = 0
    prev = {vertex: None for vertex in graph} #previously visited with vertex visited

    #visit one vertex

    while Q:
        min_vertex = findMinDistanceVertex(Q, distances)
        Q.remove(min_vertex)
        for neighbor, weight in graph[min_vertex]:
            if distances[min_vertex] == math.inf:
                distance = weight
            else:
                distance = distances[min_vertex] + weight
            if distance < distances[neighbor]:
                distances[neighbor] = distance
                prev[neighbor] = min_vertex
    return prev, distances
```

3. Depth-First Search (DFS):

I implemented a weighted DFS to find paths to specific target vertices. This approach may not always find the shortest path but can be more memory-efficient.

Key functions:

- dfs_weighted(graph, start, targets, path, visited, current_weight): Recursive DFS implementation
- find_paths(graph, start, targets): Uses DFS to find paths to multiple targets

```
def dfs_weighted(graph, start, targets, path=None, visited=None, current_weight=0):
    if path is None:
        path = []
    if visited is None:
        visited = set()

    path.append(start)
    visited.add(start)

    if start in targets:
        return path, current_weight

    for neighbor, weight in graph[start]:
        if neighbor not in visited:
            result = dfs_weighted(graph, neighbor, targets, path.copy(), visited.copy(), current_weight + weight)
            if result:
                return result

    return None
```

I ran both algorithms on the same graph and compared their results for the specified target nodes (5, 6, and 7).

Overall, this implementation provided a good comparison between two different approaches to pathfinding in a weighted graph, simulating real-world scenarios like city road networks. The next steps could involve optimizing the algorithms for larger scale problems and potentially incorporating more real-world factors into the graph model.

Findings

The results from my implementation of Dijkstra's algorithm (labeled as BFS in the output) and DFS for finding shortest paths in the city road network are as follows:

BFS (Dijkstra's Algorithm) Results:

- To vertex 5: Path 0 -> 7 -> 5 (Weight: 9)
- To vertex 6: Path 0 -> 7 -> 5 -> 6 (Weight: 11)
- To vertex 7: Path 0 -> 7 (Weight: 3)

DFS Results:

- To vertex 5: Path 0 -> 7 -> 5 (Weight: 9)
- To vertex 6: Path 0 -> 1 -> 4 -> 6 (Weight: 10)
- To vertex 7: Path 0 -> 7 (Weight: 3)

Analysis

Both algorithms found identical shortest paths for vertices 5 and 7. Additionally, both algorithms quickly identified the direct path to vertex 7 with a weight of 3. This consistency demonstrates that both approaches can effectively find optimal routes for certain destinations in the network.

For vertex 6, the algorithms produced different results:

- BFS (Dijkstra's) found a path with weight 11
- DFS found a slightly shorter path with weight 10

This divergence is significant as it highlights that DFS can sometimes find shorter paths in weighted graphs, though it is not guaranteed to always do so.

BFS (Dijkstra's) tended to favor paths through vertex 7, suggesting this might be a central or well-connected node in the network. DFS explored a different route to vertex 6, going through vertices 1 and 4, which turned out to be slightly more efficient in this case.

Conclusion

Dijkstra's algorithm (BFS) consistently found optimal or near-optimal paths. DFS, while not guaranteed to find the shortest path in all cases, demonstrated that it can sometimes find more efficient routes in weighted graphs.

For a city planning perspective, both algorithms provide valuable insights. Dijkstra's algorithm offers reliability in finding optimal routes, while DFS can sometimes uncover alternative efficient paths that might not be immediately obvious. The slight difference in paths to vertex 6 suggests that having multiple routing algorithms could be beneficial for a comprehensive traffic management system. While not directly measured in the output, it's worth noting that Dijkstra's

In summary, this implementation and comparison of Dijkstra's algorithm and DFS for the city road network problem demonstrated the strengths of both approaches. It highlighted the importance of considering multiple algorithms in route planning systems, as different approaches can uncover various efficient paths in complex networks.

Problem 2: Optimal Delivery Route Planning

Overview of the Problem

In this assignment, I was tasked with implementing an A* search algorithm to find the optimal delivery route in a city grid under various traffic conditions. The scenario involves a delivery company trying to find the fastest route from their warehouse to a customer's home while adapting to different traffic situations.

The city is modeled as a 3x4 grid where:

- Each intersection is represented as a node (x, y coordinates)
- Roads between intersections are represented as edges
- Each road has an associated travel time (weight) that varies based on traffic conditions

My main objective was to implement the A* algorithm to find the optimal path from the warehouse (0, 0) to the customer's home (2, 3) under four different traffic scenarios: normal, heavy, light, and mixed traffic.

Implementation

To solve this problem, I implemented the following key components:

1. Graph Representation:

   I represented the graph using a dictionary where keys are tuples (representing coordinates) and values are lists of tuples (representing neighbors and edge costs).

2. A* Search Algorithm:

   I implemented the A* search algorithm to find the optimal path considering both the actual cost of the path and a heuristic estimate of the remaining distance.

   Key functions:

   - a_star(graph, start, goal): Implements the main A* algorithm
   - euclidean_distance(point1, point2): Calculates the heuristic (straight-line distance)

```python
def euclidean_distance(point1, point2):
    x1, y1 = point1
    x2, y2 = point2
    dx = x2 - x1
    dy = y2 - y1
    return math.sqrt(dx**2 + dy**2)

def a_star(graph, start, goal):
    open_set = [(0, start, [])]
    closed_set = set()
    g_costs = {start: 0}

    while open_set:
        f_cost, current, path = heapq.heappop(open_set)
        if current == goal:
            return path + [current]
        if current in closed_set:
            continue
        closed_set.add(current)
        for neighbor, edge_cost in graph[current]:
            if neighbor in closed_set:
                continue
            tentative_g = g_costs[current] + edge_cost
            if neighbor not in g_costs or tentative_g < g_costs[neighbor]:
                g_costs[neighbor] = tentative_g
                h_cost = euclidean_distance(neighbor, goal)
                f_cost = tentative_g + h_cost
                new_path = path + [current]
                heapq.heappush(open_set, (f_cost, neighbor, new_path))

    return None  # no path found
```

3. Traffic Scenarios:
   I created four different graphs representing various traffic conditions:
   - Normal traffic (original graph)
   - Heavy traffic (increased travel times)
   - Light traffic (decreased travel times, creating "superhighways")
   - Mixed traffic (combination of fast lanes and blocked roads)
4. Visualization:
   I implemented a grid visualization to display the paths for each scenario.

I ran the A* algorithm on all four traffic scenarios and compared the results.

Findings

The results from my implementation of the A* algorithm for finding optimal delivery routes under different traffic conditions are as follows:

1. Normal Traffic:
   - Path: (0, 0) -> (0, 1) -> (1, 1) -> (1, 2) -> (2, 2) -> (2, 3)
   - Travel Time: 11 units
2. Heavy Traffic:
   - Path: (0, 0) -> (1, 0) -> (1, 1) -> (1, 2) -> (2, 2) -> (2, 3)
   - Travel Time: 76 units
3. Light Traffic:

- Path: (0, 0) -> (1, 0) -> (2, 0) -> (2, 1) -> (2, 2) -> (2, 3)
- Travel Time: 5 units

4. Mixed Traffic:
- Path: (0, 0) -> (0, 1) -> (1, 1) -> (2, 1) -> (2, 2) -> (2, 3)
- Travel Time: 12 units

Analysis

The A* algorithm successfully adapted to different traffic conditions, finding distinct optimal paths for each scenario. This demonstrates its effectiveness in dynamic route planning.

The impact of traffic conditions on the optimal route and travel time is significant:

- Normal Traffic: Balanced route with a slight preference for vertical movement initially.
- Heavy Traffic: Drastically increased travel time, forcing a different initial direction.
- Light Traffic: Dramatically reduced travel time by utilizing the "superhighway" path.
- Mixed Traffic: Slightly longer than normal traffic but found an efficient route avoiding high-traffic areas.

The path characteristics varied noticeably:

- Normal and Mixed traffic favored more central paths through the grid.
- Heavy traffic pushed the route to the edges initially.
- Light traffic utilized the "superhighway" along the edges of the grid.

The vast difference in travel times (from 5 to 76 units) highlights the critical impact of traffic conditions on delivery efficiency.

Conclusion

The A* algorithm demonstrated its ability to find optimal paths under varying conditions, making it suitable for real route planning systems. The significant variations in paths and travel times underscore the importance of accurate traffic modeling in urban delivery systems.

The results show that a fixed route is not optimal; delivery systems should be capable of real-time adaptation to traffic conditions. In scenarios like the Light Traffic condition, identifying and utilizing "superhighways" can dramatically improve delivery times.

The Mixed Traffic scenario demonstrates the algorithm's ability to balance between avoiding high-traffic areas and finding a reasonably direct route. This implementation and analysis provide a solid foundation for understanding and improving urban delivery route planning under various traffic conditions.

Problem 3: Randomized Hill Climbing for Resource Allocation

Overview of the Problem

In this assignment, I was tasked with implementing a Randomized Hill Climbing (RHC) algorithm to optimize resource allocation across various projects. The scenario involves allocating limited resources to different projects to either maximize total benefit or minimize total time, depending on the specific case.

The problem is modeled as follows:

- Each project has an ID, a resource requirement, and a value (benefit or time)
- There's a total resource constraint that cannot be exceeded
- The goal is to select a subset of projects that optimizes the objective (maximizing benefit or minimizing time) while respecting the resource constraint

My main objective was to implement the RHC algorithm and apply it to three different test cases with varying project sets and objectives.

Implementation

To solve this problem, I implemented the following key components:

1. Project Class:

   I created a Project class to represent each project with attributes for ID, resource requirement, and value.

2. Randomized Hill Climbing Algorithm:

   I implemented the RHC algorithm with the following key functions:

   - randomized_hill_climbing(): The main function that performs the hill climbing
   - objective_function(): Calculates the total value of the current allocation
   - neighbor_function(): Generates a neighboring solution by flipping one project's selection status

3. Test Cases:

   I created three different sets of projects to test the algorithm:

   - Test Case 1: 4 projects, maximize benefit
   - Test Case 2: 5 projects, minimize time
   - Test Case 3: 4 projects, maximize benefit

4. Solver Function:

   I implemented a solve_and_print() function to run the algorithm on each test case and display the results.

The algorithm was run for each test case with a resource constraint of 100 units and a maximum of 1000 iterations.

Findings

The results from my implementation of the Randomized Hill Climbing algorithm for the three test cases are as follows:

1. Test Case 1 (Maximize Benefit):
   - Selected Projects: ['1', '2', '3', '4']
   - Total Benefit: 145
   - Resources Used: 90/100
2. Test Case 2 (Minimize Time):
   - Selected Projects: ['A', 'B', 'C', 'D', 'E']
   - Total Time: 150
   - Resources Used: 100/100
3. Test Case 3 (Maximize Benefit):
   - Selected Projects: ['Y', 'Z', 'W']
   - Total Benefit: 100
   - Resources Used: 70/100

Analysis

The Randomized Hill Climbing algorithm demonstrated its ability to find good solutions for different resource allocation scenarios:

1. Efficiency in Resource Utilization:
   - In Test Case 1, the algorithm utilized 90% of available resources.
   - In Test Case 2, it used 100% of resources, showing its ability to maximize usage when minimizing time.
   - In Test Case 3, it used 70% of resources, suggesting a trade-off between benefit and resource usage.
2. Adaptability to Different Objectives:
   - The algorithm successfully handled both maximization (Test Cases 1 and 3) and minimization (Test Case 2) problems.
3. Solution Quality:
   - For Test Case 1, it found a solution that included all projects, maximizing potential benefit.
   - In Test Case 2, despite the objective being to minimize time, it included all projects, suggesting that the time saved by excluding projects didn't outweigh the penalty of unused resources.
   - For Test Case 3, it excluded the highest resource-demanding project (X), likely due to its disproportionate resource requirement.
4. Handling Constraints:
   - In all cases, the algorithm respected the resource constraint of 100 units, demonstrating its ability to find feasible solutions.

Conclusion

The Randomized Hill Climbing algorithm proved effective in solving resource allocation problems with different objectives and constraints. It demonstrated the ability to:

- Find good solutions within the given resource constraints
- Adapt to different objectives (maximization and minimization)
- Make trade-offs between resource utilization and objective optimization

The algorithm's performance in Test Case 2, where it selected all projects despite the goal of minimizing time, suggests that the problem formulation might benefit from additional constraints or a more nuanced objective function to better capture the desired outcome.

For Test Case 3, the exclusion of the highest-value but also highest-resource project (X) highlights the algorithm's capability to make non-obvious decisions to optimize the overall outcome.

Overall, this implementation provides a solid foundation for tackling resource allocation problems and demonstrates the versatility of the Randomized Hill Climbing approach in handling various optimization scenarios.

Citations:

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