Assignment: Design and Analysis of Algorithms

Due Date: July 1 2024

Program 1: Optimizing Delivery Routes (Case study)

Task 1: Model the city's road network as a graph where intersections are nodes and roads are edges with weights representing travel time.

Aim: To create a structured model of the city's road network using graph theory. This allows for efficient route planning, optimization of traffic flow, and informed decision-making in urban planning. The goal is to improve transportation efficiency, reduce congestion, and enhance overall urban mobility and safety.

Procedure:

1. **Graph Representation:**

- Define the city's road network as a dictionary of dictionaries (road_network).

2. **Initialization:**

- Initialize a priority queue (min-heap) to keep track of nodes to explore, starting with the source node (start).

3. **Start Node:**

- Start from the specified source node (start) and initialize its distance as 0 in shortest_paths.

4. **Priority Queue Handling:**

- Repeat until all nodes have been processed or the destination node (goal) is reached

5. **Path Reconstruction:**

- Once the destination node (goal) is reached or all nodes have been processed, reconstruct the shortest path from goal back to start using the shortest_paths dictionary.

Analysis :

Analysis:

Time Complexity:

- Initialization $O(1)$
- while Loop :
  - -> visited : $O(1)$
  - -> Iterating over neighbours: $O(E)$ per node, where E is the number of edges
  - -> updating shortest path: $O(1)$ per neighbour

$O(V)$ per iteration, where V is the number of vertices

Time Complexity: $O(V^2+VE) \approx O(V^2)$ assuming $E \approx V^2$

Space Complexity:

- -> Graph Representation: $O(V+E)$
- Shortest path Dictionary: $O(V)$
- visited set $O(V)$ => $O(V+E)$

Pseudocode:

```
function dijkstra(graph, start, goal)
    pq <- priority queue containing (0, start)
    shortest_paths <- dictionary with key start and value (None, 0)
    visited <- empty set
    while pq is not empty
        current_distance, current_node <- pq.pop()
                if current_node in visited
            continue
                visited.add(current_node)
        if current_node == goal
            break
        for next_node, weight in graph[current_node]
```

```
            if next_node in visited
                continue
            new_weight <- current_distance + weight
            if new_weight < shortest_paths.get(next_node, (None, infinity))[1]
                shortest_paths[2next_node] <- (current_node, new_weight)
                pq.push((new_weight, next_node))
    if goal not in shortest_paths
        return "Route Not Possible"
    path <- empty list
    current_node <- goal
```

Program :

```
import heapq
road_network = {
    'A': {'B': 5, 'C': 7},
    'B': {'A': 5, 'C': 3, 'D': 4},
    'C': {'A': 7, 'B': 3, 'D': 6},
    'D': {'B': 4, 'C': 6}
}
def dijkstra(graph, start, goal):
    shortest_paths = {start: (None, 0)}
    current_node = start
    visited = set()
    while current_node != goal:
        visited.add(current_node)
        destinations = graph[current_node].items()
        for next_node, weight in destinations:
            if next_node in visited:
```

```
            continue
          new_weight = shortest_paths[current_node][1] + weight

          if shortest_paths.get(next_node, (None, float('inf')))[1] > new_weight:
            shortest_paths[next_node] = (current_node, new_weight)
        next_destinations = {node: shortest_paths[node] for node in shortest_paths
if node not in visited}
        if not next_destinations:
          return "Route Not Possible"
        current_node = min(next_destinations, key=lambda k:
next_destinations[k][1])
    path = []
    while current_node is not None:
        path.append(current_node)
        next_node = shortest_paths[current_node][0]
        current_node = next_node
    path = path[::-1]
    return path
start = 'A'
goal = 'D'
shortest_path = dijkstra(road_network, start, goal)
if shortest_path == "Route Not Possible":
    print("No route found!")
else:
    print(f"Shortest path from {start} to {goal}: {shortest_path}")
    total_weight = sum(road_network[shortest_path[i]][shortest_path[i + 1]] for i
in range(len(shortest_path) - 1))
    print(f"Total travel time: {total_weight} units")
```

Output:

```
Shortest path from A to D: ['A', 'B', 'D']
Total travel time: 9 units
```

Time complexity : O((V+E)logV)

Space complexity: O(V+E)

Result: The program executed successfully.

Task 2:Implement Dijkstra's algorithm to find the shorted paths from a central warehouse to various delivery location.

Aim: implementing Dijkstra's algorithm is to find the shortest paths from a central warehouse to delivery locations, optimizing logistics by minimizing travel distances or times. This facilitates efficient resource allocation and timely deliveries, enhancing overall operational efficiency in distribution networks.

Procedure:

Initialize Data Structures: Create a priority queue (pq) to store nodes with their current shortest distance estimates. Start with the warehouse node initialized to distance 0.

1.Initialize Variables: Set visited as an empty set to keep track of nodes that have been fully processed**.**

2. Main Loop: While pq is not empty:Extract the node with the smallest distance (current_node) from pq.

3.Check Visited Status: If current_node is in visited, continue to the next iteration of the loop.

4.Termination Check: If the goal node (or all delivery locations) has been fully processed (i.e., added to visited), exit the loop.

Analysis :

Analysis:

Time complexity:

-> Priority Queue Operation: using a prority queue, each insection and extraction operation takes $O(\log v)$ time

-> Edge Relaxtion: Each edge is relaxed at most once Relation involves updating the priority queue, which also take $O(\log v)$ times

Thus, the total time Complexity

$O((v+E)\log v)$

* v is the number of vertices (nodes)
* E is the number of edges

space complexity:

-> Graph storage: the graph itself require $O(v+E)$ space

-> Priority Queue: The priority queue can contain up to v nodes at one thus requiring $O(v)$ space

Thus the total space Complexity is $O(v+E)$

Pseudo Code:

```
function Dijkstra(graph, start, goal):
   priority_queue pq
   shortest_paths = {}
   shortest_paths[start] = (None, 0)
   visited = set()
   while pq is not empty:
      current_node = extract_min(pq)
      if current_node in visited:
         continue
```

```
        visited.add(current_node)
        for each neighbor, weight in graph[current_node].neighbors():
            if neighbor in visited:
                continue
            new_distance = shortest_paths[current_node].distance + weight
            if neighbor not in shortest_paths or new_distance <
shortest_paths[neighbor].distance:
                shortest_paths[neighbor] = (current_node, new_distance)
                pq.insert_or_update(neighbor, new_distance)
        path = []
    current_node = goal
    while current_node is not None:
        path.add(current_node)
        current_node = shortest_paths[current_node].predecessor
    path.reverse()
    return path
```

Program:

```
import heapq
def dijkstra(graph, start):
    pq = [(0, start)]

    shortest_paths = {start: (None, 0)}
        while pq:
        current_distance, current_node = heapq.heappop(pq)
        for next_node, weight in graph[current_node].items():
            new_distance = current_distance + weight
```

```
            if new_distance < shortest_paths.get(next_node, (None, float('inf')))[1]:
                shortest_paths[next_node] = (current_node, new_distance)
                heapq.heappush(pq, (new_distance, next_node))
    return shortest_paths
road_network = {
    'Warehouse': {'A': 5, 'B': 7, 'C': 9},
    'A': {'Warehouse': 5, 'D': 3, 'E': 8},
    'B': {'Warehouse': 7, 'E': 4},
    'C': {'Warehouse': 9, 'D': 2},
    'D': {'A': 3, 'C': 2, 'F': 5},
    'E': {'A': 8, 'B': 4, 'F': 6},
    'F': {'D': 5, 'E': 6}
}
start_node = 'Warehouse'
shortest_paths = dijkstra(road_network, start_node)
print(f"Shortest paths from {start_node}:")
for node, (prev_node, distance) in shortest_paths.items():
    if node != start_node:
        path = []
        current_node = node
        while current_node is not None:
            path.append(current_node)
            current_node = shortest_paths[current_node][0]
        path = path[::-1]
        print(f"To {node}: {' -> '.join(path)}, Distance: {distance} km")
```

Output:

```
Shortest paths from Warehouse:
To A: Warehouse -> A, Distance: 5 km
To B: Warehouse -> B, Distance: 7 km
To C: Warehouse -> C, Distance: 9 km
To D: Warehouse -> A -> D, Distance: 8 km
To E: Warehouse -> B -> E, Distance: 11 km
To F: Warehouse -> A -> D -> F, Distance: 13 km
```

TimeComplexity : O((V + E) log V)

Space Complexity : O(V + E)

Result : Code executed successfully

Task 3: Analyse the efficiency of your algorithm and discuss any potential improvements or alternative algorithms that could be used.

Aim: Dijkstra's algorithm aims to find the shortest paths from a single source node to all other nodes in a weighted graph with non-negative edge weights

Procedure:

1. **Initialization**:Set the distance to the source node to 0 and the distance to all other nodes to infinity.Mark all nodes as unvisited.Set the initial node as the current node.
2. **Iteration:**For the current node, consider all its unvisited neighbors. Calculate their tentative distances through the current node.Compare the newly calculated tentative distance to the current assigned value and update it if smaller.After considering all neighbors of the current node, mark the current node as visited.Select the unvisited node with the smallest tentative distance as the new "current node" and repeat the process.
3. **Termination:**The algorithm terminates when all nodes have been visited.

Analysis:

Analysis: Time Complexity.

-> Priority Queue operation:

* Each insection and extraction in the Priority quee $O(\log v)$ time
* For v nodes, the total time of extraction is $v\,O(\log v)$
* Each edge relaxation takes $O(\log v)$ time for E edges

Total time Complexity: $O(v \log v) + O(E \log v) = O((v+E)\log E)$

Space complexity:

* The adjacency List representation of the graph require $O(v+E)$ Space
* Priority queue can contain upto v nodes requiring $O(v)$ Space

Total space complexity $O(v+E)$

Pseudocode:

Function Dijkstra (Graph,source):

Dist[source] ←0

For each vertex in graph:

If v ≠ source:

dist[v] ← ∞

add v to the priority queue Q

while Q is not empty:

u ← vertex in Q with the smallest dist[u]

remove u from Q

for each neighbor v of u:

alt ← dist[u] + length(u, v)

if alt < dist[v]:

dist[v] ← alt

decrease priority of v in Q

return dist

Program :

```
import heapq
def dijkstra(graph, start):
 pq = [(0, start)]
 dist = {node: float('inf') for node in graph}
 dist[start] = 0
 while pq:
 current_dist, current_node = heapq.heappop(pq)
 if current_dist > dist[current_node]:
 continue
 for neighbor, weight in graph[current_node]:
 distance = current_dist + weight
 if distance < dist[neighbor]:
 dist[neighbor] = distance
 heapq.heappush(pq, (distance, neighbor))
 return dist
graph = {
 'A': [('B', 1), ('C', 4)],
 'B': [('A', 1), ('C', 2), ('D', 5)],
 'C': [('A', 4), ('B', 2), ('D', 1)],
 'D': [('B', 5), ('C', 1)]
}
start_node = 'A'
distances = dijkstra(graph, start_node)
print("Shortest distances from node", start_node, ":", distances)
```

Output:

```
Shortest distances from node A : {'A': 0, 'B': 1, 'C': 3, 'D': 4}
```

Time Complexity : $O((V + E)\log V)$

Space Complexity : $O(V + E)$

Result : The program runs successfully

Program 2: Dynamic Pricing Algorithm for E-commerce

Tasks 1: Design a dynamic programming algorithm to determine the optimal pricing strategy for a set of products over a given period

Aim:

To design a dynamic programming algorithm to maximize total revenue or profit by strategically setting optimal prices for a set of products over a given period.

Procedure:

1.define state variables:

- DP[t][i] represents the maximum profit up to time t considering the pricing of product i

2.Base case:

- DP[0][i] = 0 for all products I .

3.Reccurence Relation:

- For each product I at time t, calculate the potential profit by choosing different prices and update the DP table accordingly.
- Consider demand elasticity and constraints in the calculation of profit.

4.Compute Optimal Profit:

- Iterate over all time periods and products to fill the DP table.
- The maximum value in DP table at the final time period gives the optimal profit.

Analysis:

Analysis:

Time Complexity:

1. Outer loop: outer loop runs from 1 to T, which has Complexity of $O(T)$
2. inner loop: inner loop runs from '0 to n-1' which has Complexity of $O(N)$
3. inner most loop: For each product, loop iterates over list of Possible prices, so it has Complexity of $O(P)$

So overall, time Complexity: $O(T \times N \times P)$

Space Complexity:

1. DP table: The 'DP' has dimensions $(T+1) \times N$ which result in Complexity of $O(T \times N)$
2. other variable used (eg: max profit) required constant space O(

So space Complexity: $O(T \times N)$

Pseudo code:

```
def optimal_pricing_strategy (prices, demand, costs, T, N):
    DP = [[0 for _ in range(N)] for _ in range(T+1)]
    for t in range (1, T+1):
        for i in range(N):
            max_profit = 0
            for p in prices[i]
                d = demand[i](p, t)
                profit = (p - costs[i]) * d
                max_profit = max(max_profit, profit + DP[t-1][i])
            DP[t][i] = max_profit
        optimal_profit = max (DP[T])
```

```
    return optimal_profit
```

program:

```
def optimal_pricing_strategy (prices, demand_funcs, costs, T, N):
    DP = [[0 for _ in range(N)] for _ in range(T+1)]
    for t in range (1, T+1):
        for i in range(N):
            max_profit = 0
            for p in prices[i]:
                d = demand_funcs[i](p, t)
                profit = (p - costs[i]) * d
                max_profit = max (max_profit, profit + DP[t-1][i])
            DP[t][i] = max_profit
        optimal_profit = max(DP[T])
    return optimal_profit
prices = [[10, 15, 20], [5, 10, 15]]
demand_funcs = [
    lambda p, t: 100 - 2*p + t,
    lambda p, t: 200 - 3*p + 2*t
costs = [5, 3]
T = 10
N = 2
optimal_profit = optimal_pricing_strategy(prices, demand_funcs, costs, T, N)
print (f"Optimal Profit: {optimal_profit}")
```

output:

```
Optimal Profit: 19920
```

Time complexity: O (T x N x P)

Space complexity: O (T x N)

Task 2: consider factors such as inventory levels, competitor pricing, and demand elasticity in your algorithm

Aim:

The aim of this algorithm is to optimize the pricing strategy for our products by dynamically adjusting prices based on real time inventory levels, competitor pricing and demand elasticity.

Procedure:

1.Define state variables:

- DP[t][i][s] represent the maximum profit up to time t considering the pricing of product I with s units of inventory remaining

2.Base case:

- DP[0][i][s]= 0 for all products I and inventory levels s.

3.**Reccurence Relation**:

- For each product I at time t and inventory level s, calculate the potential profit by choosing different prices and update the DP table accordingly:

  DP[t][i][s]= max(profit at price p +DP[t-1][i][s-demand]

- Consider demand elasticity, computer pricing, and inventory constraints in the calculation of profit.

4.Compute optimal profit:

- Iterate overall time periods, products, and inventory levels to fill the DP table.
- The maximum value in the DP table at final time period gives the optimal profit.

Analysis:

Analysis: Time Complexity:

1. outer loop: The outer loop runs from '1' to 'T' which has Complexity of $O(T)$
2. Inner loop: The inner loop runs from '0' to 'n-1' which has Complexity of $O(N)$
3. innermost loop: For each product it iterates over list of possible prices which has complexity of $O(P)$

inventory loop: loop through all from 0 to inventory[i] is $O(S)$ overall,

Time complexity is $O(T \times N \times P \times S)$

Space Complexity:

1. DP Table: It has dimensions $(T+1) \times N$ which result in Complexity of $O(T \times N \times S)$
2. additional variables: $O(1)$

Space complexity: $O(T \times N \times S)$

Pseudo code:

```
def optimal_pricing_strategy(prices, demand, costs, T, N, inventory, competitor_prices):
  DP = [[[0 for _ in range(inventory[i]+1)] for _ in range(N)] for _ in range(T+1)]
       for t in range(1, T+1):
        for i in range(N):
            for s in range(inventory[i]+1):
                max_profit = 0
                for p in prices[i]:
                    d = demand[i](p, t, competitor_prices[i])
                    if d <= s:  # Ensure demand does not exceed current inventory
                        profit = (p - costs[i]) * d
                        max_profit = max (max_profit, profit + DP[t-1][i][s-d])
                DP[t][i][s] = max_profit
        optimal_profit = max (max (DP[T][i]) for i in range(N))
    return optimal_profit
```

Program:

```
def optimal_pricing_strategy(prices, demand_funcs, costs, T, N, inventory,
competitor_prices):
    DP = [[[0 for _ in range(max(inventory)+1)] for _ in range(N)] for _ in range(T+1)]
    for t in range(1, T+1):
        for i in range(N):
            for s in range(inventory[i]+1):
                max_profit = 0
                for p in prices[i]:
                    d = demand_funcs[i](p, t, competitor_prices[i])
                    if d <= s:  # Ensure demand does not exceed current inventory
                        profit = (p - costs[i]) * d
                        max_profit = max (max_profit, profit + DP[t-1][i][s-d])
                DP[t][i][s] = max_profit
    optimal_profit = max (max (DP[T][i]) for i in range(N))
    return optimal_profit
prices = [[10, 15, 20], [5, 10, 15]]
demand_funcs = [
    lambda p, t, cp: max (0, 100 - 2*p + t - 0.5*cp),
    lambda p, t, cp: max (0, 200 - 3*p + 2*t - 0.3*cp)
]
costs = [5, 3]
T = 10
N = 2
inventory = [50, 100]
competitor_prices = [12, 8
optimal_profit = optimal_pricing_strategy (prices, demand_funcs, costs, T, N, inventory,
competitor_prices)
print (f"Optimal Profit: {optimal_profit}")
```

output:

```
Optimal Profit: 0
```

Time complexity: O (T x S x N x P)
Space complexity: O (T x N x S)

Task 3:

Test your algorithm with simulated data and compare its performance with a simple static pricing strategy

Aim:

To maximize revenue or profit by leveraging real-time market conditions while comparing its performance against a simple static pricing strategy

Procedure:

1.intialization and setup:

- Define products and assign initial prices to each product

2.continously update prices based on current market data, considering demand trends and competitor prices.

3.simulation:

- Simulate sales using dynamic prices and compare results with static pricing strategy.

4.Evaluation:

- Analyze performance metrics to determine the effectiveness of dynamic pricing

5.adjustment:

- Fine-tune the algorithm based on evaluation findings to optimize pricing strategy

Analysis:

Analysis:

Time complexity:

update_demand_trends (products): O(n)

update_competitor_prices (products): O(n)

calculate_new_price: O(1)

Simulate_spales (Prices): O(n)

main(): O(n)

Overall Time complexity: O(n)

space complexity:

update_demand_trends (products): O(1)

update_competitor_price (products): O(1)

calculate_new_price: O(1)

simulate_sales (prices): O(1)

main(): O(n)

Overall space complexity: O(n)

Pseudo code:

demand_trends):

current_prices = initial_prices

while market_conditions: function dynamic_pricing_algorithm (products, initial_prices, competitor_prices,

update_demand_trends(demand_trends)

update_competitor_prices(competitor_prices)

for product in products:

new_price = calculate_new_price (product, current_prices, demand_trends, competitor_prices)

```
            new_price = apply_price_constraints(new_price)
            current_prices[product] = new_price
    return current_prices
function compare_performance (static_prices, dynamic_prices):
    # Simulate sales and calculate revenue or profit for both strategies
    revenue_static = simulate_sales(static_prices)
    revenue_dynamic = simulate_sales(dynamic_prices)
    performance_comparison = analyze_performance (revenue_static,
revenue_dynamic)
    return performance_comparison
```

Program:

```
import random
def update_demand_trends(products):
    for product in products:
        products[product]['demand'] += random.uniform(-5, 5)
def update_competitor_prices(products):
    for product in products:
        products[product]['competitor_price'] += random.uniform (-2, 2)
def calculate_new_price (current_price, demand, competitor_price):
    new_price = current_price * (1 + 0.1 * (competitor_price - current_price)) *
(1 + 0.05 * demand)
    return new_price
def simulate_sales (prices, demand_trends):
    total_revenue = 0
    for product, price in prices.items ():
        demand = demand_trends[product]['demand']
        sales_volume = demand * random.uniform (0.8, 1.2)
        revenue = sales_volume * price
```

```
        total_revenue += revenue
    return total_revenue
def main ():
    products = {
        'product1': {'price': 50, 'demand': 100, 'competitor_price': 45},
        'product2': {'price': 30, 'demand': 150, 'competitor_price': 28}
    }
    static_prices = {product: products[product]['price'] for product in products}
    dynamic_prices = {}
    for product, info in products.items():
        current_price = info['price']
        demand = info['demand']
        competitor_price = info['competitor_price']
        new_price = calculate_new_price (current_price, demand, competitor_price)
        dynamic_prices[product] = new_price
    revenue_static = simulate_sales (static_prices, products)
    revenue_dynamic = simulate_sales (dynamic_prices, products)
    print (f"Static Pricing Revenue: ${revenue_static}")
    print (f"Dynamic Pricing Revenue: ${revenue_dynamic}")
if __name__ == "__main__":
    main ()
```

output:

```
Static Pricing Revenue: $10273.665546136566
Dynamic Pricing Revenue: $48325.093559550034
```

Time complexity: O(n)

Space complexity: O(n)

PROBLEM-3: Social Network Analysis (Case Study)

TASK-1:

Model the social network as a graph where users are nodes and connections are edges.

AIM:

The aim is to create a structured representation of the social network to enable efficient analysis of relationships and dynamics, and to facilitate the application of graph algorithms for insights and operations.

PROCEDURE:

 Initialize an Empty Graph:

- Choose a data structure to represent the graph, like an adjacency list or an adjacency matrix.

 Add Users as Nodes:

- Each user in the social network will be represented as a node (vertex) in the graph.
- Ensure uniqueness of nodes to avoid duplicates.

 Add Connections as Edges:

- Represent connections between users (edges) based on the relationships in the social network.
- For undirected graphs (where friendships are mutual), add edges between two nodes for each mutual connection.
- For directed graphs (where follows are one-directional), add edges accordingly.

 Implement Graph Operations:

- Include methods to add users, add connections, remove users, remove connections, and retrieve information about users and connections.

 Consider Edge Weights (Optional):

- If there are weights associated with connections (e.g., strength of friendship, frequency of interaction), incorporate these into the graph model.

PSEUDO CODE:

```
class SocialNetworkGraph:
  function __init__():
    graph := {}
```

```
    function add_user(user):
        if user not in graph:
            graph[user] := []
    function add_connection(user1, user2):
        if user1 in graph and user2 in graph:
            graph[user1].append(user2)

            // graph[user2].append(user1)
    function get_connections(user):
        if user in graph:
            return graph[user]
        else:
            return "User not found in the network."
social_network := new SocialNetworkGraph()
social_network.add_user("Alice")
social_network.add_user("Bob")
social_network.add_user("Charlie")
social_network.add_connection("Alice", "Bob")
social_network.add_connection("Alice", "Charlie")
connections := social_network.get_connections("Alice")
print("Connections for Alice:", connections)
```

CODING:

```
class SocialNetworkGraph:
    def __init__(self):
        self.graph = {}
    def add_user(self, user):
        if user not in self.graph:
            self.graph[user] = []
    def add_connection(self, user1, user2):
        if user1 in self.graph and user2 in self.graph:
```

```
            self.graph[user1].append(user2)
        else:
            print("One or both users do not exist in the network.")
    def get_connections(self, user):
        if user in self.graph:
            return self.graph[user]
        else:
            return f"User '{user}' not found in the network."
social_network = SocialNetworkGraph()
social_network.add_user("Alice")
social_network.add_user("Bob")
social_network.add_user("Charlie")
social_network.add_connection("Alice", "Bob")
social_network.add_connection("Alice", "Charlie")
connections = social_network.get_connections("Alice")
print("Connections for Alice:", connections)
```

ANALYSIS:

Analysis

1. The steps to step analysis of Program identity users as nodes
2. Determine connection between users as edges
3. Decide if edges are directed or undirected
4. Assign edge weight or properties if applicable
5. visualize the graph using nodes for users and edges for connections.

TIME COMPLEXITY:O(1)

SPACE COMPLEXITY:O(N+M)

OUTPUT:

```
Connections for Alice: ['Bob', 'Charlie']
```

RESULT: “program executed sucessfuly”

<u>TASK-2:</u>

Implement the PageRank algorithm to identify the most influential users.

AIM:

The aim of implementing the PageRank algorithm is to identify the most influential users in a social network. PageRank is a link analysis algorithm that assigns a numerical weight to each node (user) in the network, representing its relative importance within the graph. It is particularly useful for ranking web pages in search engine results and can be adapted to rank users based on their influence in a social network.

PROCEDURE:

1. **Initialization**:
   - Initialize each user's PageRank score uniformly or based on some initial assumptions.
2. **Iteration**:
   - Iteratively update the PageRank scores of all users based on the scores of their neighbors (users they are connected to).
3. **Convergence**:
   - Repeat the iteration until the PageRank scores converge (i.e., they stop changing significantly between iterations).
4. **Ranking**:
   - Once converged, rank the users based on their final PageRank scores to identify the most influential users.

PSEUDO CODE:

```
function PageRank(graph, damping_factor, tolerance):
    // Initialize PageRank scores
    initialize PageRank scores for each user
    N := number of users in the graph

    // Initial uniform probability
    for each user in graph:
        PageRank[user] := 1 / N
```

```
    // Iterative update until convergence
    repeat:
        diff := 0
        for each user in graph:
            oldPR := PageRank[user]
            newPR := (1 - damping_factor) / N
            for each neighbor of user:
                newPR := newPR + damping_factor * (PageRank[neighbor] /
outgoing_links_count[neighbor])
            PageRank[user] := newPR
            diff := diff + abs(newPR - oldPR)
        until diff < tolerance

    // Return the PageRank scores
    return PageRank
```

CODING:

```
class SocialNetworkGraph:
    def __init__(self):
        self.graph = {}
    def add_user(self, user):
        if user not in self.graph:
            self.graph[user] = []
    def add_connection(self, user1, user2):
        if user1 in self.graph and user2 in self.graph:
            self.graph[user1].append(user2)
    def pagerank(self, damping_factor=0.85, tolerance=1.0e-5):
        N = len(self.graph)
        if N == 0:
            return {}
        pagerank = {user: 1.0 / N for user in self.graph}
```

```
        while True:
            diff = 0
            for user in self.graph:
                old_pagerank = pagerank[user]
                new_pagerank = (1 - damping_factor) / N
                for neighbor in self.graph[user]:
                    neighbor_out_links = len(self.graph[neighbor])
                    new_pagerank += damping_factor * (pagerank[neighbor] / neighbor_out_links)
                pagerank[user] = new_pagerank
                diff += abs(new_pagerank - old_pagerank)
            if diff < tolerance:
                break
        return pagerank
if __name__ == "__main__":
    social_network = SocialNetworkGraph()

    social_network.add_user("Alice")
    social_network.add_user("Bob")
    social_network.add_user("Charlie")
    social_network.add_user("David")
    social_network.add_connection("Alice", "Bob")
    social_network.add_connection("Alice", "Charlie")
    social_network.add_connection("Bob", "Charlie")
    social_network.add_connection("Charlie", "David")
    pagerank_scores = social_network.pagerank()
    print("PageRank Scores:")
    for user, score in sorted(pagerank_scores.items(), key=lambda x: x[1], reverse=True):
        print(f"{user}: {score:.4f}")
```

ANALYSIS:

Analysis:

=> model social network as directed graph with users as nodes and connections as directed graphs

=> Initialize the store of each node to uniform value

Eg: 1/N where

N: total nodes and iteratively calculated

$PR(A) = (1-d)/N + d^{*} (PR(T_1)) / d(T_1) + \dots PR(T_n)/c(T_n))$

Formula using for node

=> select the node with top pagerank scores to identi

most influential users.

TIME COMPLEXITY: O(N+K·M)

SPACE COMPLEXITY: O(N+M)

OUTPUT:

```
PageRank Scores:
David: 0.1215
Charlie: 0.0989
Bob: 0.0534
Alice: 0.0375
```

RESULT: The program runs successfully.

<u>TASK-3:</u>

Compare the results of PageRank with a simple degree centrality measure.

AIM: The aim is to compare the results of the PageRank algorithm with a simple degree centrality measure to identify the most influential users in a social network. Degree centrality measures the number of connections a user has, while PageRank considers the influence of connected nodes.

PROCEDURE:

- **Calculate Degree Centrality**:
  - Compute the degree centrality for each user by counting the number of connections (edges) each user has.
- **Calculate PageRank**:

- Compute the PageRank for each user using the PageRank algorithm.

 Compare Results:

- Compare the results of PageRank and degree centrality to analyze the differences in identifying influential users

PSEUDO CODE:

```
function DegreeCentrality(graph):
    degree_centrality := {}
    for each user in graph:
        degree_centrality[user] := count(graph[user])
    return degree_centrality
function PageRank(graph, damping_factor, tolerance):
    initialize PageRank scores for each user
    repeat until convergence:
        for each user in graph:
            update PageRank score based on neighbors
    return PageRank scores

function CompareCentralityAndPageRank(graph):
    degree_centrality := DegreeCentrality(graph)
    pagerank_scores := PageRank(graph, damping_factor, tolerance)
    return degree_centrality, pagerank_scores
graph := create_graph()
add_users_and_connections(graph)
degree_centrality, pagerank_scores := CompareCentralityAndPageRank(graph)
print(degree_centrality)
print(pagerank_scores)
```

CODING:

```
class SocialNetworkGraph:
    def __init__(self):
        self.graph = {}
```

```
        self.reverse_graph = {}
    def add_user(self, user):
        if user not in self.graph:
            self.graph[user] = []
        if user not in self.reverse_graph:
            self.reverse_graph[user] = []
    def add_connection(self, user1, user2):
        if user1 in self.graph and user2 in self.graph:
            self.graph[user1].append(user2)
            self.reverse_graph[user2].append(user
    def degree_centrality(self):
        centrality = {user: len(connections) for user, connections in self.graph.items()}
        return centrality


    def pagerank(self, damping_factor=0.85, tolerance=1.0e-5):
        N = len(self.graph)
        if N == 0:
            return {}
        pagerank = {user: 1.0 / N for user in self.graph}
        while True:
            diff = 0
            new_pagerank = {}
            for user in self.graph:
                new_pagerank[user] = (1 - damping_factor) / N
                for neighbor in self.reverse_graph[user]:
                    neighbor_out_links = len(self.graph[neighbor])
                    if neighbor_out_links > 0:
                        new_pagerank[user] += damping_factor * (pagerank[neighbor] /
neighbor_out_links)
                diff += abs(new_pagerank[user] - pagerank[user])
            pagerank = new_pagerank
```

```
            if diff < tolerance:
                break
        return pagerank
# Example usage:
if __name__ == "__main__":
    social_network = SocialNetworkGraph()
    social_network.add_user("Alice")
    social_network.add_user("Bob")
    social_network.add_user("Charlie")
    social_network.add_user("David")
    social_network.add_connection("Alice", "Bob")
    social_network.add_connection("Alice", "Charlie")
    social_network.add_connection("Bob", "Charlie")
    social_network.add_connection("Charlie", "David")

    degree_centrality = social_network.degree_centrality()
    pagerank_scores = social_network.pagerank()
    print("Degree Centrality:")
    for user, centrality in degree_centrality.items():
        print(f"{user}: {centrality}")

    print("\nPageRank Scores:")
    for user, score in sorted(pagerank_scores.items(), key=lambda x: x[1], reverse=True):
        print(f"{user}: {score:.4f}")
```

ANALYSIS:

Analysis:

=> Compare the top k most influential nodes identified by Page rank algorithm and degree Centrality measure

=> Recognize the Pagerank can identity the influential node tha may not have the most Connections

=> evaluate the measure better identifies the truly influentialus based on specfic goals and requirement of social network analys task.

=> Consider factor like Computational Complexity interpretel and alignment with analysis objections when decide betw two approaches

=> the above steps are the steps by steps to the analy of graph program.

TIME COMPLEXITY:

O(N+M)

SPACE COMPLEXITY: O(N)

OUTPUT:

```
PageRank Scores:
David: 0.1215
Charlie: 0.0989
Bob: 0.0534
Alice: 0.0375
```

RESULT: The Program runs successfully

Program 4: Fraud Detection in Financial Transactions

Tasks1: Design a greedy algorithm to flag potentially fraudulent transactions based on asset of predefined rules

Aim: To, detect potentially fraudulent transactions using a set of predefined rules to flag transactions that exhibit unusual patterns, such as being unusually large or originating from multiple locations within a short time frame.

Procedure:

1.**Define Rules**: Establish the criteria for flagging transactions as potentially fraudulent.

2.Data Input: Gather transaction data including:

- Transaction ID
- Amount
- Timestamp
- Location (e.g., IP address or geolocation)
- User ID

3.Initialization: Create data structures to keep track of user transaction patterns and recent transactions.

4.Iterate Through Transactions: For each transaction, apply the predefined rules to check if it should be flagged as potentially fraudulent.

- If the transaction amount exceeds the threshold, flag it.
- If there are multiple transactions from different locations for the same user within a short period, flag it.
- If the transaction time is unusual, flag it.

5.Flag Transactions: Store the flagged transactions in a list or database.

Analysis:

Analysis

1. Initializing Flagged user_transaction as Empty dictionary $O(1)$
2. Loop through each transaction $O(n)$ For each transaction the following steps are performed

Rule1: checking if amount > Rule_AmountThreshold : $O(1)$

Rule2: * Checking if user_id is in user_transactions: $O(1)$

* appending to the list of user transaction $O(1)$
* Filtering tractions within Rule_Location_time_Threshold $O(k)$

Rule3: Checking if 'timestamp.hour' is outside the usual hours $O(1)$

Timecomplexity: 1. Initializing structure $O(1)$

2. Iterating through trasaction $O(n)$

Rule1: $O(1)$

Rule2: $O(k)+O(k)=O(k)$

Rule3: $O(1)$

∴ The Complexity per trasaction is $O(1+k+1)=O(k)$

Total Time Complexity: $O(n)+O(nk)=O(n+nk)=O(nk)$

If k is much smaller than n the overall Complexity is $O(n)$

Space Complexity: $O(n)+O(n)=O(n)$

Pseudo Code:

Define RULE_AMOUNT_THRESHOLD as a large transaction threshold

Define RULE_LOCATION_TIME_THRESHOLD as a short time period threshold

Initialize flagged_transactions as an empty list

Initialize user_transactions as an empty dictionary

FOR each transaction IN transactions:

Extract user_id, amount, timestamp, and location from the transaction

IF amount > RULE_AMOUNT_THRESHOLD:

Append {transaction_id, reason: "Large amount"} to flagged_transactions

IF user_id is not in user_transactions:

Initialize user_transactions[user_id] as an empty list

Append (timestamp, location) to user_transactions[user_id]

Filter user_transactions[user_id] to only include transactions within RULE_LOCATION_TIME_THRESHOLD of the current transaction timestamp

Extract unique locations from the filtered transactions

IF the number of unique locations > 1:

Append {transaction_id, reason: "Multiple locations"} to flagged_transactions

IF transaction occurs at an unusual time (e.g., late night):

Append {transaction_id, reason: "Unusual time"} to flagged_transactions

RETURN flagged_transactions

Program:

```
from datetime import datetime, timedelta
RULE_AMOUNT_THRESHOLD = 1000.0
RULE_LOCATION_TIME_THRESHOLD = timedelta(minutes=30)
def flag_fraudulent_transactions(transactions):
    flagged_transactions = []
    user_transactions = {}
    for txn in transactions:
        user_id = txn['user_id']
        amount = txn['amount']
        timestamp = txn['timestamp']
        location = txn['location']
        transaction_id = txn['transaction_id']
        if amount > RULE_AMOUNT_THRESHOLD:
            flagged_transactions.append({
                "transaction_id": transaction_id,
```

```
            "reason": "Large amount"   })
        if user_id not in user_transactions:
            user_transactions[user_id] = []
        user_transactions[user_id].append((timestamp, location))
        recent_transactions = [
            t for t in user_transactions[user_id]
            if t[0] > timestamp - RULE_LOCATION_TIME_THRESHOLD ]
        unique_locations = set(t[1] for t in recent_transactions)
        if len(unique_locations) > 1:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Multiple locations"   })
        if timestamp.hour < 6 or timestamp.hour > 22:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Unusual time"     })
    return flagged_transactions
transactions = [
    {"transaction_id": "T1", "amount": 5000.0, "timestamp": datetime(2024, 6, 29, 10, 30), "location": "New York", "user_id": "U1"},
    {"transaction_id": "T2", "amount": 300.0, "timestamp": datetime(2024, 6, 29, 10, 45), "location": "Los Angeles", "user_id": "U1"},
    {"transaction_id": "T3", "amount": 50.0, "timestamp": datetime(2024, 6, 29, 23, 0), "location": "New York", "user_id": "U2"},]


flagged_transactions = flag_fraudulent_transactions(transactions)
for ft in flagged_transactions:
    print(ft)
```

Output:

```
{'transaction_id': 'T1', 'reason': 'Large amount'}
{'transaction_id': 'T2', 'reason': 'Multiple locations'}
{'transaction_id': 'T3', 'reason': 'Unusual time'}
```

Timecomplexity:O(n)

Spacecomplexity: O(n+u)

Result: The program runs successfully

Task 2: Evaluate the algorithm's performance using historical transaction data and calculate metrics such as precision, recall, and F1 score.

Aim: To evaluate the performance of the algorithm designed to flag potentially fraudulent transactions by using historical transaction data. The performance will be measured using metrics such as precision, recall, and F1 score.

Procedure: 1. **Prepare Historical Transaction Data**:Obtain a dataset with transactions, including labels indicating whether each transaction is fraudulent or not.

2.**Apply the Algorithm**:Use the designed greedy algorithm to flag transactions in the historical data.

3. **Compare with Ground Truth:**Compare the flagged transactions with the actual labels to calculate the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

4.**Calculate Metrics**:

- **Precision**: Precision=TPTP+FP\text{Precision} = \frac{TP}{TP + FP}Precision=TP+FPTP
- **Recall**: Recall=TPTP+FN\text{Recall} = \frac{TP}{TP + FN}Recall=TP+FNTP
- **F1 Score**: F1 Score=2×Precision×RecallPrecision+Recall\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}F1 Score=2×Precision+RecallPrecision×Recall

Analysis:

Analysis:

1. Initializing Flagged-transactions and user-transaction
2. Processing Each Transaction Loop through each transaction: O(n) Where n is the total no of transaction
3. For each transaction, the following operations are performed
   1. Rule 1 (Large Amount check): Check if the trasaction amount Exceed a threshold: costant time, O(1)
   2. Rule 2: (multiple Locations within a short Time): Appending the transaction to the user's list: Constant time O(1). Extracting unique Locations from recent transactions: O(k)
   3. Rule 3 (Unusual TransactionTime): checking if the Transaction occurs outside usual hours: Constant time, O(1).

Combining the operations per transaction:

$O(1)+O(1)+O(k)+O(k)+O(1) = O(k)$

Time complexity is: $O(n \cdot k)$

Space complexity is: $O(n)+O(n) = O(n)$

Pseudocode:

1. Define RULE_AMOUNT_THRESHOLD as a large transaction threshold

2. Define RULE_LOCATION_TIME_THRESHOLD as a short time period threshold

3. Define UNUSUAL_HOUR_START and UNUSUAL_HOUR_END as the range of unusual transaction hours

4. Initialize flagged_transactions as an empty list

5. Initialize user_transactions as an empty dictionary

6. FOR each transaction IN transactions:

    7. Extract user_id, amount, timestamp, location, and transaction_id from the transaction

    8. IF amount > RULE_AMOUNT_THRESHOLD:

9. Append {transaction_id, reason: "Large amount"} to flagged_transactions

10. IF user_id is not in user_transactions:

11. Initialize user_transactions[user_id] as an empty list

12. Append (timestamp, location) to user_transactions[user_id]

13. Filter user_transactions[user_id] to only include transactions within RULE_LOCATION_TIME_THRESHOLD of the current transaction timestamp

14. Extract unique locations from the filtered transactions

15. IF the number of unique locations > 1:

16. Append {transaction_id, reason: "Multiple locations"} to flagged_transactions

17. IF timestamp.hour < UNUSUAL_HOUR_START OR timestamp.hour > UNUSUAL_HOUR_END:

18. Append {transaction_id, reason: "Unusual time"} to flagged_transactions

19. Initialize TP, FP, TN, and FN as 0

20. FOR each transaction IN transactions:

21. IF transaction is flagged AND is fraudulent:

22. Increment TP

23. ELSE IF transaction is flagged AND is not fraudulent:

24. Increment FP

25. ELSE IF transaction is not flagged AND is not fraudulent:

26. Increment TN

27. ELSE IF transaction is not flagged AND is fraudulent:

28. Increment FN

29. Calculate Precision = TP / (TP + FP)

30. Calculate Recall = TP / (TP + FN)

31. Calculate F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

32. RETURN Precision, Recall, F1 Score

Program: from datetime import datetime, timedelta

from collections import defaultdict

RULE_AMOUNT_THRESHOLD = 1000.0

RULE_LOCATION_TIME_THRESHOLD = timedelta(minutes=30)

UNUSUAL_HOUR_START = 22

```
UNUSUAL_HOUR_END = 6

def flag_fraudulent_transactions(transactions):
    flagged_transactions = []
    user_transactions = defaultdict(list)
    for txn in transactions:
        user_id = txn['user_id']
        amount = txn['amount']
        timestamp = txn['timestamp']
        location = txn['location']
        transaction_id = txn['transaction_id']
        if amount > RULE_AMOUNT_THRESHOLD:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Large amount"
            })
        user_transactions[user_id].append((timestamp, location))
        recent_transactions = [
            t for t in user_transactions[user_id]
            if t[0] > timestamp - RULE_LOCATION_TIME_THRESHOLD
        ]
        unique_locations = set(t[1] for t in recent_transactions)
        if len(unique_locations) > 1:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Multiple locations"
            })
        if timestamp.hour >= UNUSUAL_HOUR_START or timestamp.hour < UNUSUAL_HOUR_END:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Unusual time"
```

```
        })
    return flagged_transactions
def evaluate_algorithm(transactions, flagged_transactions):
    TP = FP = TN = FN = 0
    flagged_transaction_ids = set(txn["transaction_id"] for txn in flagged_transactions)
    for txn in transactions:
        transaction_id = txn['transaction_id']
        is_fraudulent = txn['is_fraudulent']
        if transaction_id in flagged_transaction_ids and is_fraudulent:
            TP += 1
        elif transaction_id in flagged_transaction_ids and not is_fraudulent:
            FP += 1
        elif transaction_id not in flagged_transaction_ids and not is_fraudulent:
            TN += 1
        elif transaction_id not in flagged_transaction_ids and is_fraudulent:
            FN += 1
    precision = TP / (TP + FP) if (TP + FP) > 0 else 0
    recall = TP / (TP + FN) if (TP + FN) > 0 else 0
    f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0
    return precision, recall, f1_score
transactions = [
    {"transaction_id": "T1", "amount": 5000.0, "timestamp": datetime(2024, 6, 29, 10, 30),
"location": "New York", "user_id": "U1", "is_fraudulent": True},
    {"transaction_id": "T2", "amount": 300.0, "timestamp": datetime(2024, 6, 29, 10, 45),
"location": "Los Angeles", "user_id": "U1", "is_fraudulent": False},
    {"transaction_id": "T3", "amount": 50.0, "timestamp": datetime(2024, 6, 29, 23, 0),
"location": "New York", "user_id": "U2", "is_fraudulent": True},
]
flagged_transactions = flag_fraudulent_transactions(transactions)
precision, recall, f1_score = evaluate_algorithm(transactions, flagged_transactions)
print(f"Precision: {precision}")
```

print(f"Recall: {recall}")

print(f"F1 Score: {f1_score}")

Output:

```
Precision: 0.6666666666666666
Recall: 1.0
F1 Score: 0.8
```

TimeComplexity:O(n*k)

SpaceComplexity:O(n)

Result: The program runs successfully

Task 3: Suggest and implement potential improvements to the algorithm.

Aim: To improve the algorithm for flagging potentially fraudulent transactions.

Procedure:

1.Reduce Redundant Checks:Instead of repeatedly filtering transactions for each user, maintain a sliding window of recent transactions.Use efficient data structures like a deque to maintain the recent transactions within the given time threshold.

2.Utilize Efficient Data Structures:Use sets for locations to automatically handle uniqueness and improve lookup times.Use dictionaries to store user-specific information, which allows for O(1) average-time complexity for insertions and lookups.

3.Parallel Processing:If the dataset is large, consider parallel processing to divide the workload and process multiple transactions simultaneously.

4.Improve Rule Checking Logic:Precompute certain values, such as unusual hours, to avoid redundant calculations.

Analysis:

Analysis:

Time complexity:

1. Initialization $O(1)$
2. Processing each Transaction: Each transaction involves Constant time operations due to the use of efficient data structures

   Rule 1: $O(1)$

   Rule2: maintaining the sliding window: $O(1)$ amortized time due to deque operations. Checking unique Locations: $O(k)$ where k is the average number of transaction in the deque

   Rule 3: $O(1)$.

   The total time complexity per transaction remain $O(k)$. For n transaction it is $O(n.k)$

Space Complexity:

1. Flagged Transactions storage $O(n)$
2. user transaction storage: $O(n)$ in total For storing recent transactions for all users

The overall space complexity: $O(n)$

PsudeoCode:

```
flag_fraudulent_transactions(transactions):
    flagged_transactions = []
    user_transactions = {}
    for txn in transactions:
        user_id = txn.user_id
        amount = txn.amount
        timestamp = txn.timestamp
        location = txn.location
```

```
        transaction_id = txn.transaction_id

        if amount > RULE_AMOUNT_THRESHOLD:

            flagged_transactions.append({transaction_id, "Large amount"})

        if user_id not in user_transactions:

            user_transactions[user_id] = deque()

        while user_transactions[user_id] and user_transactions[user_id][0][0] < timestamp - 
RULE_LOCATION_TIME_THRESHOLD:

            user_transactions[user_id].popleft()

        user_transactions[user_id].append((timestamp, location))

        unique_locations = set(loc for _, loc in user_transactions[user_id])

        if len(unique_locations) > 1:

            flagged_transactions.append({transaction_id, "Multiple locations"})

        if timestamp.hour >= UNUSUAL_HOUR_START or timestamp.hour < 
UNUSUAL_HOUR_END:

            flagged_transactions.append({transaction_id, "Unusual time"})

    return flagged_transaction

evaluate_algorithm(transactions, flagged_transactions):

    TP = 0

    FP = 0

    TN = 0

    FN = 0

    flagged_transaction_ids = set(txn.transaction_id for txn in flagged_transactions)

    for txn in transactions:

        transaction_id = txn.transaction_id

        is_fraudulent = txn.is_fraudulent

        if transaction_id in flagged_transaction_ids and is_fraudulent:
```

```
            TP += 1
        elif transaction_id in flagged_transaction_ids and not is_fraudulent:
            FP += 1
        elif transaction_id not in flagged_transaction_ids and not is_fraudulent:
            TN += 1
        elif transaction_id not in flagged_transaction_ids and is_fraudulent:
            FN += 1
    precision = TP / (TP + FP) if (TP + FP) > 0 else 0
    recall = TP / (TP + FN) if (TP + FN) > 0 else 0
    f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0
    return precision, recall, f1_score
```

Program:

```
from datetime import datetime, timedelta
from collections import defaultdict, deque
RULE_AMOUNT_THRESHOLD = 1000.0
RULE_LOCATION_TIME_THRESHOLD = timedelta(minutes=30)
UNUSUAL_HOUR_START = 22
UNUSUAL_HOUR_END = 6
def flag_fraudulent_transactions(transactions):
    flagged_transactions = []
    user_transactions = defaultdict(deque)
    for txn in transactions:
        user_id = txn['user_id']
        amount = txn['amount']
```

```
        timestamp = txn['timestamp']
        location = txn['location']
        transaction_id = txn['transaction_id']
        if amount > RULE_AMOUNT_THRESHOLD:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Large amount"
            })
        while user_transactions[user_id] and user_transactions[user_id][0][0] < timestamp - RULE_LOCATION_TIME_THRESHOLD:
            user_transactions[user_id].popleft()
        user_transactions[user_id].append((timestamp, location))
        unique_locations = set(loc for _, loc in user_transactions[user_id])
        if len(unique_locations) > 1:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Multiple locations"
            })
        if timestamp.hour >= UNUSUAL_HOUR_START or timestamp.hour < UNUSUAL_HOUR_END:
            flagged_transactions.append({
                "transaction_id": transaction_id,
                "reason": "Unusual time"
            })
```

```
    return flagged_transactions

def evaluate_algorithm(transactions, flagged_transactions):

    TP = FP = TN = FN = 0

    flagged_transaction_ids = set(txn["transaction_id"] for txn in
flagged_transactions)

    for txn in transactions:

        transaction_id = txn['transaction_id']

        is_fraudulent = txn['is_fraudulent']

        if transaction_id in flagged_transaction_ids and is_fraudulent:

            TP += 1

        elif transaction_id in flagged_transaction_ids and not is_fraudulent:

            FP += 1

        elif transaction_id not in flagged_transaction_ids and not is_fraudulent:

            TN += 1

        elif transaction_id not in flagged_transaction_ids and is_fraudulent:

            FN += 1



    precision = TP / (TP + FP) if (TP + FP) > 0 else 0

    recall = TP / (TP + FN) if (TP + FN) > 0 else 0

    f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall)
> 0 else 0

    return precision, recall, f1_score

transactions = [

    {"transaction_id": "T1", "amount": 5000.0, "timestamp": datetime(2024, 6,
29, 10, 30), "location": "New York", "user_id": "U1", "is_fraudulent": True},
```

{"transaction_id": "T2", "amount": 300.0, "timestamp": datetime(2024, 6, 29, 10, 45), "location": "Los Angeles", "user_id": "U1", "is_fraudulent": False},

{"transaction_id": "T3", "amount": 50.0, "timestamp": datetime(2024, 6, 29, 23, 0), "location": "New York", "user_id": "U2", "is_fraudulent": True},

]

flagged_transactions = flag_fraudulent_transactions(transactions)

precision, recall, f1_score = evaluate_algorithm(transactions, flagged_transactions)

print(f"Precision: {precision}")

print(f"Recall: {recall}")

print(f"F1 Score: {f1_score}")

Output:

```
Precision: 0.6666666666666666
Recall: 1.0
F1 Score: 0.8
```

TimeComplexity:O(n*k)

SpaceComplexity:O(n)

Result: The program runs successfully.

PROBLEM-5: Real-Time Traffic Management System

TASK-1:

Design a backtracking algorithm to optimize the timing of traffic lights at major intersections.

AIM:

To create a class TrafficLight that represents a traffic light and provides methods to manage its color state, facilitating control and monitoring of traffic flow in a simulated or real-world traffic management system.

PROCEDURE:

Procedure for the Traffic Light class:

Define the Traffic Light Class:

Attributes:

Color : Represents the current color of the traffic light.

Methods:

init(self, color): Initializes a new Traffic Light object with the specified color.

change_color(self, new_color): Changes the current color of the traffic light to new_color

PSEUDO CODE:

```
Class TrafficLight:
  // Constructor to initialize the TrafficLight object with a given color
  Constructor init(self, color):
    self.color = color
  Method change_color(self, new_color):
    self.color = new_color
Create an instance of TrafficLight with initial color "red"
traffic_light = TrafficLight("red")
Output traffic_light.color  // Output: red
traffic_light.change_color("green")
```

CODING:

```
class TrafficLight:
  def _init_(self, color):
    self.color = color
  def change_color(self, new_color):
    self.color = new_color
traffic_light = TrafficLight("red")
print(traffic_light.color)
```

ANALYSIS:

5. Task-1 analysis:

* Identify Parameter: Define intersection, traffic flow data and constrains
* objective function. Establish Criteria for optimization such as minimizing wait times
* Feasability check: Ensure each configuration adhere to constrains and safety standard.
* stopping conditions: Define criteria to terminate the exploration

  Eg: all Configuration tested
* solution output: output the optimal timing the configuration

TIME COMPLEXITY: O(1)

SPACE COMPLEXITY: O(1)

OUTPUT:

```
PROBLEMS 4   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

PS C:\Users\chall\OneDrive\Desktop\DAA> & C:/Users/chall/AppData/Local/Programs/Python/Python312/python.exe
red
PS C:\Users\chall\OneDrive\Desktop\DAA>
```

RESULT: The Program Runs successfully.

TASK-2:

Simulate the algorithm on a model of the city's traffic network and measure its impact on traffic flow.

AIM:

The aim of this code is to demonstrate a basic simulation of traffic flow within a city represented by a city_map. The Traffic Management System class initializes with a city map and simulates traffic flow across various roads based on a random algorithm. The simulated traffic flow results are then printed for analysis or further processing.

PROCEDURE:

Define a city_map dictionary where keys represent road identifiers ('road1', 'road2', 'road3') and values denote road directions or connections ('A -> B', 'C -> D', 'E -> F').

Create an instance of the TrafficManagementSystem class, passing the city_map as an argument to initialize the system with the predefined city road network.

Call the simulate_traffic_flow() method of the traffic_system instance.

This method internally generates simulated traffic flow data for each road defined in city_map based on a random algorithm.

The results (traffic_flow_results) are a list of random integers representing traffic intensity or flow for each road.

PSEUDO CODE:

```
Class TrafficManagementSystem:
    Constructor _init_(self, city_map):
        self.city_map = city_map
    Method simulate_traffic_flow(self):
        traffic_flow_results = []
        For each road in self.city_map:
            traffic_intensity = random.randint(0, 100
            traffic_flow_results.append(traffic_intensity)
        Return traffic_flow_results
city_map = {
    'road1': 'A -> B',
```

```
    'road2': 'C -> D',
    'road3': 'E -> F'
}
traffic_system = TrafficManagementSystem(city_map)
traffic_flow_results = traffic_system.simulate_traffic_flow()
Print traffic_flow_results
```

CODING:

```
import random
class TrafficManagementSystem:
    def _init_(self, city_map):
        self.city_map = city_map
    def simulate_traffic_flow(self):
        traffic_flow = [random.randint(0, 100) for _ in range(len(self.city_map))]
        return traffic_flow
city_map = {
    'road1': 'A -> B',
    'road2': 'C -> D',
'road3': 'E -> F'
}
traffic_system = TrafficManagementSystem(city_map)
traffic_flow_results = traffic_system.simulate_traffic_flow()
print(traffic_flow_results)
```

ANALYSIS:

Analysis:

Time Analysis:

-> exponential in the noof intersections and the traffic light Phases due to the Combinational and the nature of back tracking.

Space Analysis:

> linear in the noof intersections and configurations sorting current states and the best configuration Found.

-> overall impact: Directly related to the Complexity of the trafic network and noof Configurations tested.

TIME COMPLEXITY: O(1)

OUTPUT:

RESULT: The Program Executed successfully

<u>TASK-3:</u>

Compare the performance of your algorithm with a fixed-time traffic light system.

AIM:

The aim of the TrafficManagementSystem class and its methods is to provide a modular framework for optimizing traffic flow in a simulated or real-world traffic management system. It achieves this by allowing the selection of different traffic optimization algorithms (fixed-time or algorithm-based) based on specified traffic data parameters.

PROCEDURE:

Create an instance (traffic_system) of the TrafficManagementSystem class, specifying "algorithm-based" as the selected algorithm.

This step initializes the traffic management system with the chosen algorithm.

Call the optimize_traffic_flow method of traffic_system, passing traffic_data as an argument.

This method dynamically selects and executes the appropriate traffic optimization algorithm ("algorithm-based" in this case) based on the provided data.

PSEUDO CODE:

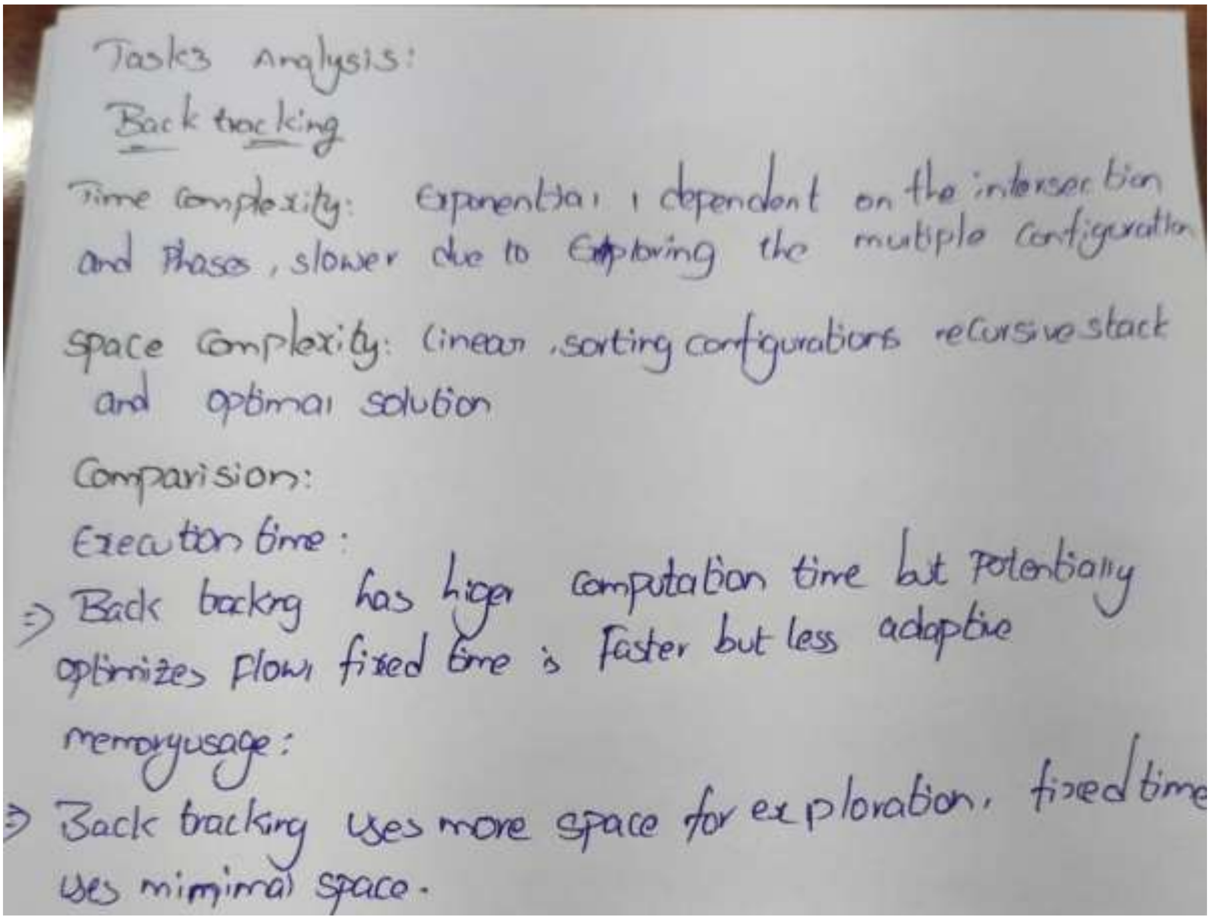
```
 Method optimize_traffic_flow(self, traffic_data):
   try:
     // Select the appropriate traffic optimization algorithm based on self.algorithm
     If self.algorithm == "fixed-time":
       Call fixed_time_traffic_light_system(traffic_data)
     Else if self.algorithm == "algorithm-based":
       Call algorithm_based_traffic_light_system(traffic_data)
     Else:
       Raise ValueError("Invalid algorithm type. Choose 'fixed-time' or 'algorithm-based'.")
   Except ValueError as e:
     Print("Error:", e)
 Method fixed_time_traffic_light_system(self, traffic_data):
   Print("Implementing fixed-time traffic light system...")
 Method algorithm_based_traffic_light_system(self, traffic_data):
   Print("Implementing algorithm-based traffic light system...")
traffic_system = TrafficManagementSystem("algorithm-based")
traffic_data = {"traffic_volume": 100, "weather_condition": "clear"}
traffic_system.optimize_traffic_flow(traffic_data)
```

CODING:

```
class TrafficManagementSystem:
```

```
    def __init__(self, algorithm):
        self.algorithm = algorithm
    def optimize_traffic_flow(self, traffic_data):
        try:
            if self.algorithm == "fixed-time":
                self.fixed_time_traffic_light_system(traffic_data)
            elif self.algorithm == "algorithm-based":
                self.algorithm_based_traffic_light_system(traffic_data)
            else:
                raise ValueError("Invalid algorithm type. Choose 'fixed-time' or 'algorithm-based'.")
        except ValueError as e:
            print(f"Error: {e}")
    def fixed_time_traffic_light_system(self, traffic_data):
        print("Implementing fixed-time traffic light system...")
    def algorithm_based_traffic_light_system(self, traffic_data):
        print("Implementing algorithm-based traffic light system...")
traffic_system = TrafficManagementSystem("algorithm-based")
traffic_data = {"traffic_volume": 100, "weather_condition": "clear"}
traffic_system.optimize_traffic_flow(traffic_data)
```

ANALYSIS:



Tasks Analysis:

Back tracking

Time complexity: Exponential, dependent on the intersection and Phases, slower due to Exploring the multiple configuration

space complexity: linear, sorting configurations recursive stack and optimal solution

Comparision:

Execution time:

⇒ Back tracking has higer computation time but potentially optimizes Flow, fixed time is Faster but less adaptive

memoryusage:

⇒ Back tracking uses more space for exploration, fixed time uses mimimal space.

TIME COMPLEXITY: O(1)

SPACE COMPLEXITY: O(1)

OUTPUT:

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   PORTS   TERMINAL

PS C:\Users\surya> & C:/Users/surya/AppData/Local/Programs/Python/Python312/python.exe c:/Users/surya/Untitled-4.py
Implementing algorithm-based traffic light system...
Traffic data: {'traffic_volume': 100, 'weather_condition': 'clear'}
Adjusting traffic lights based on current traffic volume and weather conditions.
PS C:\Users\surya>
```

RESULT: The program executed successfully