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 :

Time Complexity :-

* Initialization $O(1)$
* While loop :
  - → visited : $O(1)$
  - → Iterating over neighbors : $O(E)$ per node, where E is the number of edges
  - → Updating 'shortest_path : $O(1)$ per neighbor

    $O(V)$ 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 paths Dictionary : $O(V)$

→ Visited set $O(V)$

$= O(V+E)$

Pseudocode:

```
function Dijkstra (graph, start, goal)
   sq. <- 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 :

TimeComplexity -

→ Priority Queue Operations: Using a priority queue, each insertion and extraction operation takes $O(\log V)$ times

→ Edge Relaxtion : Each edge is relaxed at most once. Relaxation involves updating the priority queue, which also take $O(\log V)$ times.

Thus, the total time complexity is:

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

* 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 once, 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:

Time Complexity:-

→ Priority Queue Operation:

* Each insertion and extraction in the priority queue $O(\log V)$ times.
* for v nodes, the total time for extraction is $V \cdot O(\log V)$.
* 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 up to 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:

2.1 Analysis.

Time Complexity:-

→ The time Complexity is dominated by the nested loops iterating over time steps ('T'), products ('N'), and prices ('k' where 'k' is the average number of prices per product). Therefore, the time complexity is approximately O(T*N*k)

Space Complexity:-

→ The Space Complexity is O(T*N), Primarily due to the 'Dp' array storing maximum profits for each product up to each time step.

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:

2.2 Analysis.

→ Time Complexity :-

→ The time complexity is approxiamately $O(T^*N^*I^*k)$

→ 'T' is the time horizon

→ 'N' is the number of products.

→ 'I' is the maximum inventory capacity among all products.

→ 'k' is the average number of prices per product.

Space Complexity :-

→ The space complexity is $O(T^*N^*I)$, Primarily due to the 'DP' array storing maximum profits for each product, time step, and inventory state

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:

2.3 Analysis :-

Time Complexity :-

update_demand_trends (Products): O(n)

update_competitor_prices (Products): O(n)

Calculate_new_price: O(1)

Simulate_sales (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:

3.1 Analysis :-

→ The steps to step analysis of program identify users as nodes.

→ Determine connection btw users as edges.

→ Decide if edges are directed or undirected decide if edges are assign edge weight or properties if applicable.

→ 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:

3.2 : Analysis :-

→ Model social network as directed graph with users as nodes and connections as directed graphs.

→ Intialize the score of each node to uniform value eg:- 1/N where

N: total nodes and iteratively calculated

$PR(A) = (1-d)/N + d(PR(T_1)/C(T_1) + \dots PR(T_n$

formula using node.

→ Select the node with top page rank scores to identify 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.

TASK-3:

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:

33 Analysis :-

→ Comparethe top k most influential nodes identified by page rank algorithm and degree certainly measure

- Recognize the pagerank can identify the influent node may not have most connectie.

→ Evaluate measure better identies the bully inflaties basedon specific goals and requirement of social network analysis task.

→ Consider Factors like computational complexity interpreted and ~~algo~~ alignment with analysis objections when decide btw two approaches

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:

4.1 Analysis:-

Time Complexity:-

→ Initializing structure $O(1)$

→ iterating through transaction $O(n)$

∴ The time 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:

4) Analysis:-

Time Complexity:-

→ Flagging transactions: $O(N)$, N is the number of transaction.

→ Evaluating algorithm. $O(N)$, same as above

→ Overall time complexity: $O(N)$

Space Complexity:-

→ Additional space for storing flagged transactions and user transactions.

→ Space complexity is primarily $O(N)$ due to storing transaction detail and flagged transactions.

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:

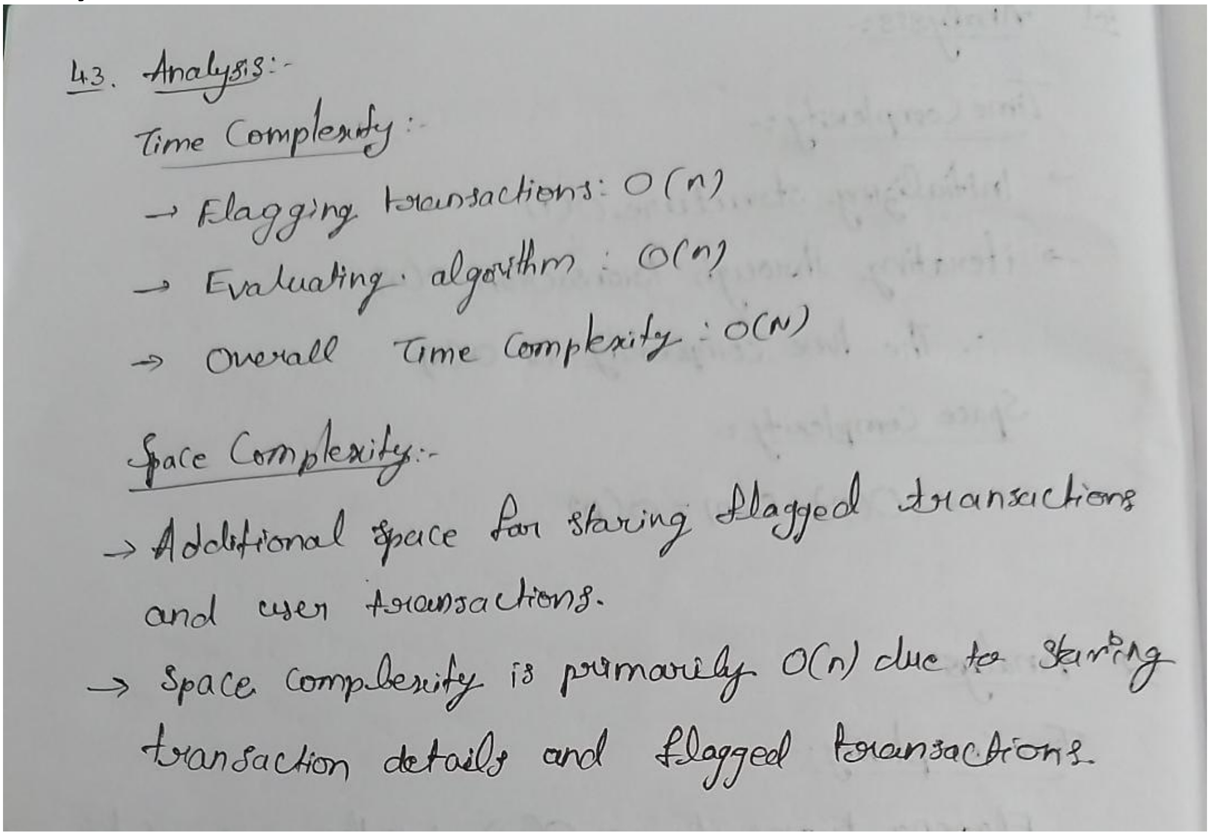
1.Reduce Redundant Checks:Instead of repeatedly filtering transactions for each user, maintain a sliding window of recent transactions.Use efficient data structures like a deque to maintain the recent transactions within the given time threshold.

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:



43. Analysis:-

Time Complexity:-

→ Flagging transactions: $O(n)$

→ Evaluating algorithm: $O(n)$

→ Overall Time Complexity: $O(N)$

Space Complexity:-

→ Additional space for storing flagged transactions and user transactions.

→ Space complexity is primarily $O(n)$ due to storing transaction details and flagged transactions.

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
```

Time Complexity: O(n*k)

Space Complexity: O(n)

Result: The program runs successfully.

PROBLEM-5: Real-Time Traffic Management System

<u>TASK-1:</u>

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

AIM:

To create a class Traffic Light that represents a traffic light and provides methods to manage its colour 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:

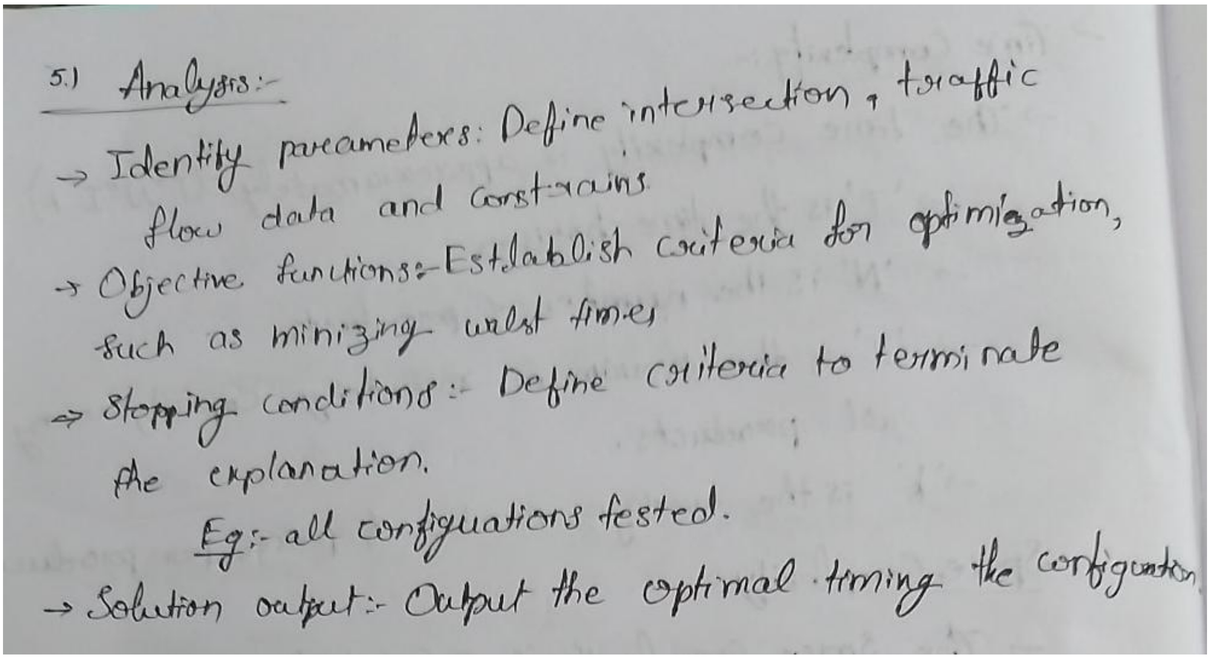
Class TrafficLight:

```
   // 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.) Analysis:-

→ Identify parameters: Define intersection, traffic flow data and constrains.

→ Objective functions:- Establish criteria for optimization, such as minizing wait times

→ Stopping conditions:- Define criteria to terminate the explanation.

Eg:- all configuations tested.

→ Solution output:- Output the optimal timing the configuration

TIME COMPLEXITY: O(1)

SPACE COMPLEXITY: O(1)

OUTPUT: red

RESULT: code is successfully executed

<u>TASK-2:</u>

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:

5.2 Analysis:-

Time Complexity:-

→ Exponenental in number of intersections and the traffic light phases due to combinational and nature of back tracking.

Space analysis:-

→ Linear in the number of configurations. Sorting current states and best configuration found.

→ Overall impact:- Directly related to complexity of traffic network and no. of configurations tested.

TIME COMPLEXITY: O(1)

OUTPUT:[19,57,37]

RESULT: code is successfully executed

TASK-3:

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:

5.3 Analysis:-

Time Complexity:- Exponential dependent on intersection and phases, slower due to exploring the multiple Configuration.

Space Complexity:- Linear, sorting Configuration recursive stack and optimal solution

TIME COMPLEXITY: O (1)

SPACE COMPLEXITY: O (1)

OUTPUT: Implementing algorithm-based traffic light system..

RESULT: code is successfully executed