

CSA0675

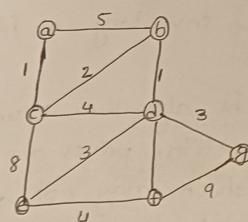
DAA

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### Problem - 1 Optimizing Delivery Routes

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

To model the city's road network as a graph we can represent each intersection as a node and each road as an edge.



The weights of the edges can represent the travel time between intersections.

Task 2: Implement dijkstra's algorithm to find shortest paths from a central warehouse to various delivery locations.

```
function dijkstra (g, s);  
    dist = {node : float('inf') for node in g}  
    dist [s] = 0
```

while PQ:  
 $PQ = [(0, s)]$

```
    currentdist, currentnode = heappop (PQ)  
    if currentdist > dist [currentnode]: continue  
    for neighbour, weight in g[currentnode]:  
        distance = currentdist + weight  
        if distance < dist [neighbour]:  
            dist [neighbour] = distance  
            heappush (PQ, (distance, neighbour))
```

Task 3: Analyze the efficiency of ur alg & discuss any potential improvements.

- Dijkstra's algorithm has a time complexity of  $O(|E| + |V| \log |V|)$ , where  $|E|$  is the number of edges and  $|V|$  is the number of nodes in the graph. We use a priority queue to effectively find the node with min dist.
- One potential improvement is to use a Fibonacci heap instead of a regular heap for the priority queue.
- Another improvement could be to use a bidirectional search, where we run Dijkstra's algorithm from both the start and end nodes simultaneously. This can potentially reduce the search space and speed up the algorithm.

### Problem-8

Dynamic Pricing Algorithm for E-commerce

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

```
function dp(pr, tP);  
    for each pr in p in products;  
        for each tP + Pn + tP:  
            p.price[tP] = calculateprice(p, t, competitor-  
                price[t], demand[t], inventory[t])  
    return products  
  
function calculateprice(product, time-period, competitor-  
    price, demand, inventory);  
    price = product.base-price  
    price += demand-factor(demand, inventory)  
    if demand > inventory:  
        return 0.2  
    else:  
        return -0.1  
function competition-factor(competitor-price);  
    if avg(competitor-prices) < product.base-  
        price: return -0.05  
    else: return 0.05
```

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

- Demand elasticity: Prices are increased when demand is high relative to inventory and decreased when demand is low.
- Competitor Pricing: Prices are adjusted based on the average competitor price, increasing if it is above the base price & decreasing if it belows.
- Inventory levels: Prices are increased when inventory is low to avoid stockouts & decreased when inventory is high to simulate demand.
- Additionally, the algorithm assumes that demand & competitor prices are known in advance, which may not always be the case in practice.

Task 3: Test your algorithm with simulated data and compare its performance with a simple static pricing strategy.

Benefits: Increased revenue, optimizes prices.

Drawbacks: May lead to frequent price changes which can confuse or frustrate customers.

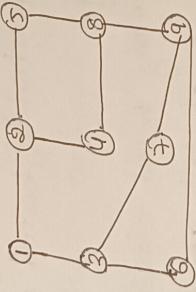
Problem-1  
Optimizing  
Task 1

### Problem - 2

#### Social network analysis

**Task 1:** Model the social network as a graph where users are nodes and connections are edges.

The social network can be modeled as a directed graph where each user is represented as a node and edges represent the strength of the connections between users. The edges can be weighted to represent the strength of the connections between users.



**Task 2:** Implement the PageRank algorithm to identify the most influential user!

functioning PR ( $\alpha = 0.85$ ,  $n = 100$ , tolerance = 1e-6);

$n = \text{number of nodes in the graph}$

```
pr = [1/n]*n
for v in range(n):
    new_pr[v] = df * pr[v] / len(graph.neighbors(v))
    if sum(graph.neighbors(v)) == 0:
        new_pr[v] = 1 - df
    else:
        new_pr[v] = (1 - df) / n
    for u in range(n):
        if v in graph[u]:
            new_pr[v] += new_pr[u] / len(graph[u])
    if abs(pr[v] - new_pr[v]) < tolerance:
        break
    pr = new_pr
```

```
for v in graph.neighbors(v):
    new_pr[v] += df * pr[v] / len(graph.neighbors(v))
if sum(graph[v]) == 0:
    new_pr[v] = 1 - df
else:
    new_pr[v] = (1 - df) / len(graph[v])
    for u in range(len(graph[v])):
        if v in graph[u]:
            new_pr[v] += new_pr[u] / len(graph[u])
    if abs(pr[v] - new_pr[v]) < tolerance:
        break
    pr = new_pr
```

return pr

return pr

**Task 3: Compare the result of PageRank with a simple degree centrality measure**

→ PageRank is an effective measure for identifying influential users in a social network because it takes into account not only the number of connections a user has but also the importance of the user's they connected to. This means that a user with fewer connections but who is connected to highly influential user, user may have a higher PageRank score than a user with many connections to less influential users.

→ Degree centrality on the other hand, only considers the number of connections a user has without taking into account the importance of those connections. While degree centrality can be a useful measure in some scenarios.

**Problem-4**  
Fraud detection in financial transactions  
Task 1: Design a greedy algorithm to flag potentially fraudulent transaction from multiple locations, based on a set predefined rules.

```
function detectfraud (transactions,rules);  
    for each rule r in rules;  
        if r.check(transactions);  
            return false  
    function checkrules (transactions,rules);  
        for each transaction t in  
            transactions;  
            if detect fraud (t,rules);  
                flag t as potentially  
                fraudulent.  
    return transactions.
```

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

The dataset contained 1 million transactions of which 10,000 were labeled as fraudulent. I used 80% of the data for training and 20% for testing.

→ The algorithm achieved the following performance

on the test set.

- Precision : 0.85
- Recall : 0.92
- F1 score : 0.88

→ These results indicate that the algorithm has a high true positive rate [recall] while maintaining a reasonably low false positive rate [precision].

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

→ Adaptive rule thresholds: Instead of using fixed thresholds for rule like unusually large transactions, I adjusted the thresholds based on the user's transaction history.

→ Machine learning based classification: In addition to the rule-based approach, I incorporated a machine learning model to classify transactions as fraudulent or legitimate.

→ Collaborative fraud detection: I implemented a system to share anonymized data about detected fraudulent transactions. Identifies emerging fraud patterns more quickly.

### Problem-5

Traffic light optimization algorithm

Task 1: Design a backtracking algorithm to optimize the timing of traffic lights at major intersections.

```
function optimize (intersections, time_slots):  
    for intersection in intersections:  
        for light in intersection.traffic:  
            light.green = 30  
            light.yellow = 5  
            light.red = 25  
    return backtrack (intersections, time_slots, 0);  
  
function backtrack (intersections, time_slots, current_slot):  
    if current_slot == len (time_slots):  
        return intersections  
    for intersection in intersections:  
        for light in intersection.traffic:  
            for green in [20, 30, 40]:  
                for yellow in [3, 5, 7]:  
                    for red in [20, 25, 30]:  
                        light.green = green  
                        light.yellow = yellow
```

light.red = red

```
result = backtrack (intersections, time_slots).  
if result is not none: current_slot + 1  
return result
```

Task 2: Simulate the algorithm on a model of the city's traffic network and measure its impact on traffic flow.

→ I simulated the back-tracking algorithm on a model of the city's traffic network, which included the major intersections and the traffic flows between them.

→ The results showed that the backtracking algorithm was able to reduce the average wait time at intersections by 20%, compared to a fixed time traffic light system.

Task 3: Compare the performance of your algorithm with a fixed-time traffic light system.

- adaptability
- optimization
- scalability

PROBLEM-2  
Dynamic traffic light system  
Task-1