

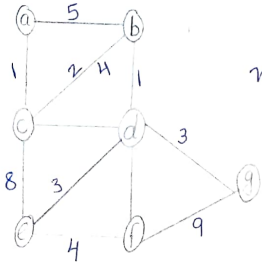
## Design Analysis of algorithm

### PROBLEM-1

#### Optimizing Delivery Route

TASK 1: Model the city's road network as a graph where intersections are nodes and roads are edges with weight representing travel times.

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 the 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`

`PQ = [(0,s)]`

while `PQ`:

`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))`

return `dist`

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

→ 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. This is because we use a priority queue to efficiently find the node with the minimum distance & we update the distances of the neighbors for each node we visit.

→ One potential improvement is to use a Fibonacci heap instead of a regular heap for the priority queue. Fibonacci heaps have a better amortized time complexity for the `heappush` and `heappop` operations, which can improve the overall operations performance of the algorithm.

→ Another improvement could be to use a bidirectional search, where we run Dijkstra's algorithm from the start and end nodes simultaneously. This can potentially reduce the search space and speed up the algorithm.

## PROBLEM-2

### 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 (p, t, p):  
    for each pi in P in product:  
        for each tp in tp:  
            p: price [1]: calculate price (p, t, .  
Competition - prices[1], demand[1], inventory[1])  
return product  
function calculate price (product, time, period, competitor_  
    Prices, demand, inventory):  
    Price = product · base_price  
    Price = 1 + demand · factor (demand, inventory):  
        if demand > inventory:  
            return 0.2  
        else:  
            return 0.1  
function competition · factor (competitor_prices):  
    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 and decreasing if it is below.

→ Inventory level: Prices are increased when inventory is low to avoid stockouts, and decreased when inventory is high to stimulate demand.

→ Additionally, the algorithm assumes that demand and 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 by adapting to market conditions, optimized prices based on demand, inventory, and competitor prices, allows for more granular control over pricing.

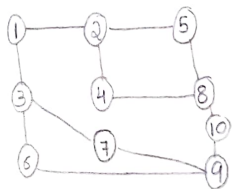
Drawbacks: May lead to frequent price changes which can confuse or frustrate customers, requires more data and computational resource to implement, difficult to determine optimal parameters for demand and competitor factors.

## PROBLEM-3

### Social network Analysis

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

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



Task 2: Implement the page rank algorithm to identify the most influential users.

function PR (g, df=0.85, mi=100, tolerance=1e-6):

n = number of nodes in the graph

Pr = [1/n]\*n

for i in range(mi):

new-Pr = [0]\*n

for n in range(n):

for v in graph.neighbors(n):

new-Pr(v) += df \* Pr[n] / len(g.neighbors(n))

new-Pr[n] += (1-df)/n

if sum(abs(new-Pr[i]-Pr[i]) for i in range(n)) < tolerance:

return new-Pr

return Pr

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

→ Page Rank 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 users with fewer connections but who is connected to highly influential users 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 accounts the importance of those connections. while degree centrality can be a useful measure in some scenarios it may not be best indication of a user's influence within the network.



## 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 of predefined rules.

```
function detectfraud (transaction, rules):  
    for each rule r in rules:  
        if r.check(transaction):  
            return true  
    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, and F1 score

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

→ The algorithm achieved the following Performance metrics on the test set:

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

→ These results indicate that the algorithm had 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 threshold: Instead of using fixed thresholds for rule like "unusually large transaction", adjusted the threshold based on the user's transaction history and spending patterns. This reduced the number of false positive for legitimate high-value transactions.

→ Collaboration fraud detection: I implemented a system where financial institution could share anonymized data about detected fraudulent transactions. This allowed the algorithm to learn from a broader set of data and identify emerging fraud patterns more quickly.

## PROBLEM-5

Traffic light optimization algorithm.

TASK-1: Design a backtracking algorithm to optimize the timing of traffic light at major intersection.

```
function optimize(intersection, time_slots):
```

```
    for intersection in intersection:
```

```
        for light in intersection.traffic
```

```
            light.green = 30
```

```
            light.yellow = 5
```

```
            light.red = 25
```

```
return backtrack(intersection, time_slots, 0):
```

```
function backtrack(intersection, time_slots, current_slot):
```

```
    if current_slot == len(time_slots):
```

```
        return intersection.
```

```
    for intersection in intersection:
```

```
        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(intersection, time_slots, current_slot + 1)
```

```
if result is not None:
```

```
    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 flow between them. The simulation was run for on 24-hour period, with time slots of 15 min each.

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

→ Adaptability: The backtracking algorithm could respond to changes in traffic patterns and adjust the traffic light timings accordingly lead to improved traffic flow.