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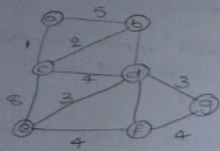
## DAA

## Assignment

### Problem-1 Optimizing delivery routes

Task-1: Model the city's road network as a graph where intersection 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 weight of the edges can represent the travel time b/w 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 neighbours, 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 algorithm that could be used.

→ dijkstra's algorithm has a time complexity of  $O((|E|+|V|)\log|V|)$ , where  $|E|$  is the No. of edges and  $|V|$  is the No. of nodes in graph. This is because we use a priority queue of efficiency find the node with the minimum distance and we update the distance of the neighbors of each node we visit.

→ One potential improvement is use to fibonacci heap instead for a regular heap of the priority queue fibonacci operations.

→ Another improvement could be to use a bi-directional 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.

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## Problem-2

### Dynamic pricing Algorithm for E-commerce

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

```
function dp(p, tp);  
    for each pr in p in products:  
        for each tp t in tp:  
            P.price[t] = calculateprice(P, t,  
                competitor-price[t], demand[t], inventory[t])  
    return products;  
  
function calculateprice(product, time period, competitor-  
    prices, demand, inventory)  
    Price = product-base-price  
    Price = H * demand-factor(demand, inventory);  
    if demand > inventory;  
        return 0.2  
    else  
        return 0.1  
  
function competition_factor(competitions-prices);  
    if avg(competitor-prices) < product-base-price;  
        return 0.05  
    else  
        return 0.05
```

**TASK 2:** consider factors such as inventory level, competitor pricing, and demand elasticity in your algorithm

→ Demand elasticity: prices are increased when demand is high relative to inventory, and decreasing 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 levels: prices are increased when inventory is low to avoid stockouts, and decreased when inventory is high to simulate 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, optimizes prices based on demand, inventory, and competitive prices.

→ Drawbacks: may lead to frequent price changes which can confuse or frustrate customers, requires more data and computational resource to implement

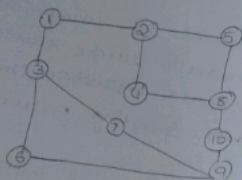


### Problem - 3

#### Social network analysis

Task-3: Model the social network as a graph where users are nodes and connection are edges.

The social network can be model as a directed graph where each users it represented as a node, and the connections b/w users are represented as edges. The edge can weight to represent the strength edge connections b/w users



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

function PR( $g$ ,  $df=0.85$ ,  $min=100$ ,  $tolerance=1e-6$ );

$n = \text{no. of nodes in the graph}$

$pr = [1/n]^n$

for  $i$  in range( $min$ );

$\text{new\_pr} = [0]^n$

    for  $n$  in range( $n$ ):

        for  $v$  in graph.neighbors( $u$ );

$\text{new\_pr}[v] = df * pr[u] / \text{len}(g.\text{neighbors}(u))$   
 if  $\text{sum}(\text{abs}(\text{new\_pr}[j] - pr[j]) \text{ for } j \text{ in range}(n)) < \text{tolerance}$ :  
 return new-pr

Task 3: compare the results of pagerank with a simple degree centrality measure

→ Pagerank is an effective measure for identify influential in a social network because it catches it takes into account not only the numbers of connections a users they are connected to, this means that a 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 No. of connections a user has, without taking into account the importance of those connections. While degree centrality can be useful measure in some scenarios, it may not be best indicator of a user's influence within the network.

#### Problem: 4

**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 (transaction, rules):

  for each transaction t in transactions:

    if detectFraud(t, rules)

      flag t as potentially fraudulent

  return transaction.

**Task-2:** Evaluate the algorithm performance using historical data and calculate metrics such as Precision, recall and f1 score

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

• 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 users transactions history and spending patterns.

→ Machine learning based classification: I implemented addition a machine learning model to classify transactions.

→ Collaborative fraud detection: I implemented a system where financial institution could share anonymized data about detected fraudulent transactions. We allowed algorithm to learn from broader set of data.



#### Problem-5:

Traffic lights optimization algorithm

Task-1: Design a backtracking algorithm to optimize the timing lights at major intersections

function optimize (intersection, time\_slots):

for intersection in intersections:

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)

if current\_slot == len(time\_slots):

return intersection

for intersections in intersections:

for light in intersections

for yellow in [3, 5, 7]:

light.green = green

light.yellow = yellow

light.red = red

result = backtrack

return result;

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

→ If simulated the backtracking algorithm on a model of the city's traffic network, which included the major intersections and the traffic flow blew them. The simulation was run for an 24-hours period.

→ The result showed that the backtracking algorithm was able to reduce the average wait time at intersections, by 20%, compared fixed. Optimizing the traffic light timings accordingly.

Task-3: - compare the performance of your

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

→ Optimization: The algorithm was able to find the optimal traffic light timings for each-intersections.