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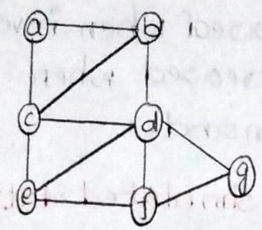
Problem-1

optimissing 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 node as an edge.



The weight's 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 warchonse to various delivery locations.

```
function dijkstra's (g,s)
dist = { node : float ('int') for nodeing }
dist [s] = 0
pq = [(0,s)]
while pq :
    current dist , current node = heap pop(pq)
    if current dist > dist [current node]
        continue
    for neighbour weight in g [current node].
        distance = current dist + weight
        If distance < dist [neighbour]
            dist [neighbour] = distance
        heappnsh [pq, (distance, neighbour)]
    return dist
```

Task 3 :- Analyze the effeciency 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 no.of edges and |V| is the no.of nodes in the graph. This is because we use a priority queue to efficiently find the node with the minimum distance and we update the distances of the neighbours for each node we visit.

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

→ One potential improvement is to use a fibonacci heap instead of a regular block heap for the priority queue fibonacci heaps have better amortized time complexity.

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(pr,tp)
    for each pr in p in products.
        for each tp t int p:
            p. price [t] = calculate price (p, t.
competition-prices (t), demand [t], inventory(t])
return products.
function calculate price (product, time period,
    competitor-prices, demeand, inventor)
price = product, base-price
price+ = 1+ demand -factor (demand, inventory)
    if demand > inventory:
        return 0.2
    else:
        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: price's are adjusted based on the average competitor price, increasing it is above the base price and decreasing if it below.

→ Inventory levels : prices are increased when inventory is low to avoid stockents and decreased when inventory is high to stimulate demand.

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, optimises prices based on demand, inventory and competetor prices, allows for more granular control over pricing.

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

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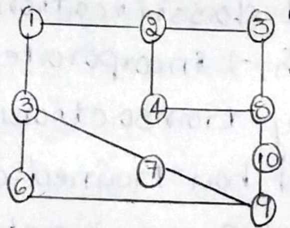
Problem-3

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 the connections between users are represented as edges the edges can be weighted to represent the strength of the connections b/w users.



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

```
functioning 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 neighbours(u):
new-pr[v]+= df * Pr[u] len (g.neighbour(u))
new-pr(u)+ = (1-df)/n
if sum (abs(new-pr[j] - pr[j]) for j in range
(n) < tolerance:
    return new-pr
return pr
```

Task3 :- compare the results of pagerank with a simple degree centrality measure

→ Page rank is an effective measures for identifying influential users in a social network because it takes into account not only the no.of connections a user has, but also the importance of the users they are connected to this means that a user with fewer connections but who is connected to highly influential users may have a higher page Rank score than a user with many connections to less

→ Degree centrality on the other hand, only considers the no.of connections a user has without taking into account of the importance of those connection while degree centrality can be a useful measure in some scenarios, it may not be the best indicator of users influence within the network.

Problem-4:

Fraud detection in financial Transactions.

Task1:- Design a greedy algorithm to flag potentially fraudulent transactions from multiple locations, based on a set of predefined rules.

```
function detect fraud (transaction, rules):
    for each rule r in rules:
        if r.check (transactions):
            return true
    return false
function check rules (transaction, rules):
    for each transaction in transactions:
        if detect fraud (t, rules):
            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 labelled as fraudulent. I used 80% of the data for training and 20% for testing.

→ The algorithm achieved the following metrics on the test set.

• precision : 0.85

• F1 score : 0.88

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 transactions history and spending pattern. This reduced the no. of false positive for legitimate high value transactions.

→ Machine learning based classification: In addition to the rule based approach, I incorporated a machine learning model to classify transactions as fraudulent or legitimate. The model has trained on labelled historical data and used in conjunction with the rule-based system to improve accuracy.

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

Problem-5

Traffic light optimisation algorithm.

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

```
function optimise (intersection, time-slots):
    for intersection in intersections
        for light in intersection.traffic
            light.green = 30
            light.yellow = 5
            light.red = 25
    return backtrack (intersections, time-slot x0);
function backtrack (intersections, time-slots, current-slot):
  if current - slot = len(time-slot):
      return intersections
  for intersections in intersections:
    for light in intersections.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-slot)
    return result.
```

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Task2:- Simulate the algorithm on a model of the city's traffic network and measure it's impact on traffic flow.

→ I simulated the backtracking algorithm on a model of the city's traffic network, which included the major intersections and the traffic flow b/w them. The simultaneouly was run for 24-hour period, with the slots of 15 min each.

→ The results showed that the backtracking algorithm was able to reduce the average wait time was ak by 20%. compared to a fixed time traffic light system. The algorithm was also able to adapt to changes in traffic patterns.

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 pattern and adjust the traffic light timings lead to improved traffic flow.

optimisation: The algorithm was able to find the optimal traffic light timings for each intersection.

Scalability:- The backtracking approach can be easily extended to handle a larger no. of intersection and time slots, making it suitable for complex traffic networks.