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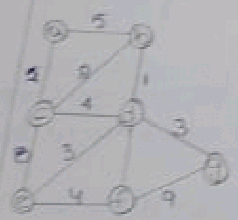
DAA - Data and Analysis of Algorithms for Back Tracking

Problem-1

Optimizing Delivery Routes

Task 1: Model the city's road network as a graph were 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 dijikstra's algorithm to find the shortest paths from a central warehourse to various delivery locations

```
function dijikstra(g,s):
    dist={node: float('inf') for node in g}
    dist[s]=0
    pq=[(0,s)]
while pq:
    current dist, currentnode,=heap pop(pq)
    if currentdist > dist [current node];
        contine
for neighbour, weight in g[currentnode]:
distance = currentdist + weight
if distance < dist[neighbour]:
    dist[neighbour]=distance
    heappush(pq,(distance, neighbor))
    return dist
```

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

→ dijikstra'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 and we update the distances of 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 performance of the algorithm

→ ~~Algori~~ Another improvement could be to use a bidirectional search, where we run dijikstra's algorithm from both 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(pr, tp);
    for each pr in p in products:
        for each tp in tp
            P.price[t]= calculateprice(p,t,competitor-
  price[t], demand[t], inventory[t]);
    return products:
function Calculateprice(product,timeperiod,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-prices
      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 incresed 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 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 cases 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

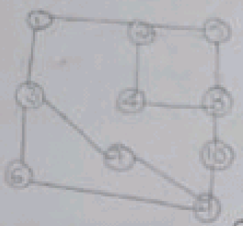
Benefits: Increased revenue by adapting to market conditions optimizing prices based on demand inventory and competitor prices allows for more granular control over pricing.

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

PROBLEM-3

Social Network Analysis

TASK-1: Model to 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 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 u in range(n)
for v in graphneighbours(u):
new-pr[v]+= df*pr[n]/len(g.neighbours(u))
new-pr[n]+= (1-df)/n
if sum(abs(new-pr[j]-pr[j]) for j in range
    (n) < tolerange :
return new-pr
```

return pr

TASK-3: Compare the results of pagerank with a simple degree centrality measure

-> PageRank is an effective measures for identifying influential user in a social network. because it takes into account not only the number of connections a user has, bus 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 pageRank score than a user with many connections to less influential users

-> Degree centrality, on the other hand, only consider 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 it may not be the indicator 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 predefined rules

```
function detectFraud(transaction, rules):
    for each rule r in rules:
        if r.check(transactions):
            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 of 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 : 0.93

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 users transaction history and spending patterns. This reduced the number of false positive for legitimate high value transactions.

→ Machine learning based classification: In addition to the rule-based approach, I incorporate a machine learning model to classify transactions as fraudulent or legitimate. The model was trained on labelled historical data and used in conjunction with the rule-based system to improve overall 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 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 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, current_slot+1)
    if result is not None:
        return result
```

TASK-2: Simulate the algorithm on a model of the city's traffic flow. 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 inter sections and the traffic flow between them. The simulation was run for an 24-hour period with time slots of 15 min each.

→ The result showed that the backtracking algorithm was able to reduce the average wait time at intersection by 20%. compared to a fixed time traffic light system. The algorithm was also able to adapt to changes in traffic patterns throughout the day optimizing the traffic light timing accordingly

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 according lead to improved traffic flow

→ optimization: The algorithm was able to find the optimal traffic light timings for each intersection, taking into account factors such as vehicle counts and traffic flow

→ Scalability: The backtracking approach can be easily extended to handle a larger number of intersection and time slots, making it suitable for complex traffic networks