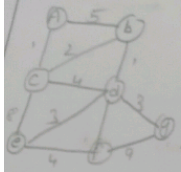


Assignment

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Problem - 1:- Optimizing delivery routes:-

Task - 1 model the city's road networks 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 road as an edge.



The weights of the edge 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 $\text{dijkstra}(s, s)$:

$\text{dist} = \{\text{node} : \text{float('inf')}\}$ for node in g

$\text{dist}[s] = 0$

$P_2 = \{(s, s)\}$

while P_2 :

current dist, current node = $\text{heapPop}(P_2)$

if current dist \rightarrow $\text{dist}[\text{current node}]$:

Continue

for neighbour weight in $g[\text{current node}]$:

distance = current dist + weight

if distance < $\text{dist}[\text{neighbour}]$:

$\text{dist}[\text{neighbour}] = \text{distance}$
 $\text{heappush}(P_2, (\text{distance}, \text{neighbour}))$

return dist.

Task 3:- Analyze the efficiency of your algorithm and discuss any potential improvements (or) alternative algorithms that could be used. \rightarrow 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 and we update the distances of the neighbours for each node we visit.

\rightarrow 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 overall performance of 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 function $dp(p, t, p)$:

for each p_0 in P in products:

for each t_0 in T :

P.Price(t) = CalculatePrice(P-1)

Competitor - Prices(t), demand(t), inventory(t)
return products

function CalculatePrice(Product, time-Period)

Price = Product - base - Price

Price * = 1 + demand - factor (demand, inventory):
return 0.2

else

return 0.1

function Competition - factor (Competitor Prices):

return -0.05

else:

return 0.05

Task - 2:

Consider factor 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 base

if sum(abs(new - old - P(t)) for t in range(1, 100))
return new - P

with a simple

price and decreasing it it takes

→ Inventory levels:

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

Task - 3:

Test your algorithm with simulated data and compare its performance with a simple static pricing.

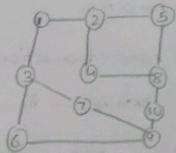
→ Benefits:

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

Problem - 3:

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

The social networks 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 between users.



Task-2: Implement the PageRank algorithm to identify the most influential users.

function $PR(s)$ $df = 0.85$, $m_i = 100$, tolerance = $1e-6$

n = no. of nodes in the graph.

$$P_0 = (1/n) * n$$

for i in range(m_i):

$$new_Pr = [0] * n$$

for i in range(n):

for v in graph.neighbours(u):

$$new_Pr(v) = df * Pr(u) / \text{len}(s.\text{neighbours}(u))$$

if $\text{sum}(\text{abs}(new_Pr(i) - P_0(i)))$ for i in range(m_i) < tolerance
return Pr

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

→ PageRank 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, 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.

→ Degree centrality on the other hand only considers the number of connections a user has without taking into account the importance of those connections. While degree centrality can be a harmful measure in some scenarios, it may not be the best measure 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 multiplication based on a set of predefined rules.

```
function detectfraud (transaction, rules):  
    for each rule in rules:  
        if x.check(transaction):  
            return true  
    return false
```

```
function check rules (transaction, 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 amount and 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 on the test set:

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

→ The results indicate that the algorithm has a high true positive rate (recall) while maintaining a reasonably low false positive rate.

Task 3: Suggest & implement potential improvements to this algorithm.

→ Adaptive rule thresholds: instead of using fixed thresholds for rule like 'unusually large transactions', adjust the thresholds based on the user's transaction history and spending patterns. This reduces the no. false positive for legitimate high value.

→ Collaborative fraud detection: implemented a system where financial institutions could share anonymized data and identify.

Problem 5:

Traffic light optimization algorithm

Task 1: Design a backtracking algorithm to optimize the traffic light at major.

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(intersection, time-slots, 0)

function backtrack (intersection, time slots, current-slots):

if current-slot == len(time-slots):

return intersection

for intersection in intersections:

for light in intersection-traffic:

for green in (20, 30, 40):

for yellow in (5, 7):

for red in (20, 25, 30):

result = backtrack(intersections, time slots)

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

Simulated the backtracking algorithm on a model of the city's traffic network which included the major intersection and the traffic flow between them. The simulation was run for a 24-hour period with time slots of 15 min each.

→ The results showed that the backtracking algorithm was able to reduce the average wait time at intersections by 200%. Compared to a fixed time traffic light system, the algorithm was through the day optimizing the traffic light timing accordingly.