

Assignment

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Subject Code: CSA0676

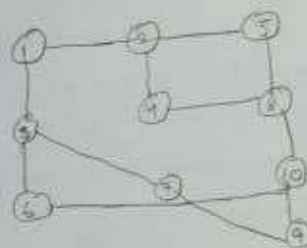
~~Course~~ 6
Subject: Design analysis of Algorithm

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 but to represent the strength of the connections between users.



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

function $PR(Lq_diff = 0.05, min_iter = 10, tolerance = 1e-6)$
 $n = \text{number of nodes in graph}$

$$pr = [1/n] * n$$

for i in range(mi):

$$\text{new-pr} = [0] * n$$

for h in range(N):

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-slot)

for intersections in intersections:

for light in intersection-traffic:

light.green = 30

light.yellow = 5

light.red = 25

return back track (intersections, time-slot, 0)

function backtrack (intersections, time-slot, current-slot):

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

return intersections

for intersections in intersections:

for light in intersection-traffic:

for green in [20, 30, 40]:

for yellow in [5, 7]:

for red in [20, 25, 30]:

light.green = green

light.yellow = yellow

light.red = red

result = backtrack (intersections, time-slot)

if result is not None:

return result

Task 1: Suggest and implement potential improvements to this algorithm.

→ Adaptive rule thresholds: Instead of using fixed thresholds for rule like "usually large transactions", I adjusted the threshold based on 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 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-4

fraud detector in financial transactions

TASK 1: Design a greedy algorithm to flag potentially fraudulent transaction from multiple locations, based on set of predefined rules.

function detectFraud (transaction rules)

for each rule r in rules

• if r check (transaction):

return true

function checkRules (transaction rules)

for each transaction t in transactions:

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 score.

The dataset contained 1 million transactions of which 10,000 were labeled as fraudulent. 70% of the data for training and 30% for testing

→ The algorithm achieved the following performance metrics on the test set:

• 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)

- 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 average competitor price, increasing it if it is above the base price and decreasing it if it is below.
- Inventory levels: prices are increased when inventory is low to avoid shortages and decreased when inventory is high to stimulate 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 performance with a simple static pricing strategy.

Benefits: Increased revenue by adapting to market conditions, optimized prices based on demand, inventory, and competitor prices, allows for 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.

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for v in graph.neighbors(u):
    new = pr[v] * dt + pr[u] / len(g.neighbors(u))
    new = pr[v] + (1 - dt) / N
    if sum(abs(new - pr[i] - pr[j] for i, j in edges
           (v, u) < tolerance):
    return new pr
    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 but also the quality of those connections. This means that a user with fewer connections may have a higher PageRank score than a user with many connections if the connections are of higher quality.

→ 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 useful measure in some scenarios it may not be the best indicator of a user's influence within the network.

Task 5: Analyze the efficiency 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 number of edges and V is the number of nodes in the graph. To efficiently find the node with the minimum distance, and we update the distances of the 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 decrease-key and extract-min operations, which can improve the overall performance of the algorithm.

→ Another improvement could be to use a bidirectional 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.

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 $dp(p, t_p)$:

for each p in P in Products:

for each t_p in T_p :

$n = price[t_p] = calculate(p, t_p)$

competitor-price[t_p] = demand + inventory

price = product.hold-price

price += 1 + demand-factor(demand, inventory)

f.f. demand > inventory

return 0.2

else:

return 0.1

function competition-factor(competitor-price):

if avg(competitor-price) > product.hold-price

price

return 0.05

else:

return 0.05

TASK 2: Consider factors such as inventory levels,

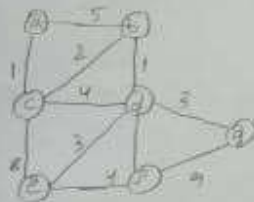
competitor pricing, and demand elasticity in your

algorithm!

PROBLEM - 1

Optimizing 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 of a node and each road as an edge.



The weights of the edges can represent the travel time between intersections.

Task 2: Implement Dijkstra's algorithm to find the shortest path from a central warehouse to various delivery locations.

function $\text{dijkstra}(g, s)$:

$\text{dist} = \text{node} \rightarrow \text{float}(\infty)$ for node in g

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

$P = [s]$

while $P \neq \emptyset$:

currentdist, currentnode = heappop(P)

if currentdist > dist[currentnode]:

continue

for neighbor, weight in $g[\text{currentnode}]$:

distance = currentdist + weight

if distance < dist[neighbor]:

dist[neighbor] = distance

heappush(P, (distance, neighbor))

return dist