

DAA - ASSIGNMENT

Problem: Fraud Detection in Financial Transactions

Scenario:

A Financial institution wants to develop an algorithm to detect fraudulent transactions in real time.

Tasks:

1. Design a greedy algorithm to flag potentially fraudulent transactions based on a set of predefined rules.
2. Evaluate the algorithm's performance using historical transaction data and calculate metrics such as precision, recall and F1 score.
3. Suggest and implement potential improvements to the algorithm.

Solution:

Task 1: Design a greedy algorithm to flag potentially fraudulent transactions based on a set of predefined rules.

In this problem I have used the basic greedy approach and statistical formulas to predict fraud in money transactions. In addressing the problem of fraud detection in financial transactions, I have devised a greedy algorithm based on predefined rules. The algorithm flags potentially fraudulent transactions by identifying unusually large transactions occurring in multiple within a short time frame.

Predefined Rules:

- Unusually large Transactions (total limit 1000)
- Transactions from multiple locations in short time

Transaction 1 Transaction 2
② ①
5 mins

Task 2: Evaluate the algorithm's performance using historical transaction data and calculate metrics such as precision and F1 score.

Five transactions are considered as the input data for the program. The program has predefined whether the transaction is fraudulent or not. The data contains the amount and location of the transactions. Parameters such as precision, recall and F1 score are calculated using true positive, true negative, correctly predicted as fraudulent, true negative (transactions that are correctly predicted as legitimate), false positive (transactions that are incorrectly predicted as fraudulent) and negative (transactions that are incorrectly predicted as legitimate).

Transaction 1: \$ 500 Location: A TP: 0.5
 Transaction 2: \$ 2000 Location: B TN: 0
 Transaction 3: \$ 500 Location: A FP: 1
 Transaction 4: \$ 1200 Location: C FN: 0
 Transaction 5: \$ 700 Location: B

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{2}{2+1} = \frac{2}{3} \approx 0.67 = 10$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{2}{2+0} = 1.0$$

$$F1 \text{ score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$= \frac{2 \times 0.67 \times 1.0}{0.67 + 1.0}$$

$$= 1.34$$

$$= 1.67$$

$$= 0.80 = 1.0$$

Implementation:

class FraudDetection I adjusted the model based on history and spending patterns to detect high value transactions

- Machine learning based classification In addition to the Value based approach Incorporated a learning model to classify transactions

- A system where financial institutions use data about detected fraudulent transactions allowed the algorithm to learn from a set of data

Item 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 the edges. The edges can be weighted to represent the strength of the connections between users.

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

functioning (P, g, f = 0.85, m = 100 to lenance = 1e-6)
n = number of nodes in the graph

$pn = [1/n] * n$

for ip in range(m):

new-pn = [0] * n

for i in range(n):

for v in range(neighbours(u):

new-pv[u] += df * pn[n] / len(neighbours(u))

new-pr[u] = (1 - df) / n

if sum(abs(new-pn[i] - pv[j]) for j in range(n)) < lenance:

return new-pv

return pn

Task 3: compare the results of pagerank with a simple degree centrality measure.

Page 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 with fewer

connections but two if connections but who is more influential users may have a higher page score than user with many connections to less influential users.

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 back track (intersections, time-slots, 0)

function back track (intersections, time, slots, current

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

return intersections

for intersections in intersections

for green in [20, 30, 40]:

for yellow in [3, 5, 7]:

for red in [20, 25, 30]:

light.green = green

light.red = red

result = back track (intersections, time, slots,

result is not None : current.slot + 1)

return result

Task 2: simulate the algorithm on a model of the city's traffic network and measures its impact on traffic flow

It simulated the backtracking algorithm on a model of the city's traffic network, which included the major intersection and the traffic flow between them.

traffic flow between them the simulation was for on 24 hours periods. The result showed that the backstraining algorithm was able to reduce the average wait time charges in traffic pattern the day

Task 5: compare the performance of your algorithm with a fixed time traffic light system

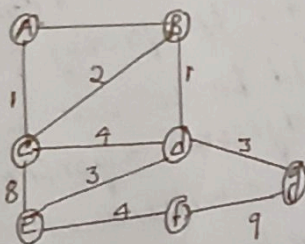
- Adaptability the backtracking algorithm could respond to changes in traffic pattern
- Scalability: The backtracking approach, can be easily extended handle a larger number of time slots

Problem 1

Optimizing delivery Routes:

Task 1: Model the city's road network as a graph where intersections 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 dijkstra's algorithm to find the shortest paths from a central warehouse to various delivery locations

```
function dijkstra(g, s):  
    dist = node.float('inf') for node in g  
    dist[s] = 0  
    pq = []  
    while pq:  
        current = dist, current node, heappop(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  
                heappush(pq, (distance, neighbour))  
    return dist
```

Task 3: Analyze the efficiency of your algorithm and discuss any potential improvements

- dijkstra's algorithm has a time complexity $O((|E| + |V|) \log |V|)$; where $|E|$ is the number of edges and $|V|$ is the number of nodes.
- one potential improvement is to use a fibonacci heap instead of regular heap for the priority queue.
- Another improvement could be to use a bidirectional search where we run dijkstra's algorithm from both the start and nodes simultaneously. This can potentially reduce the search space and speed up the algorithm.

Consider factors such as inventory levels, competitor pricing, and demand elasticity in your algorithm.

Demand elasticity: prices are increased when demand is low relative to inventory and decreased when demand is high.

Competition pricing: prices are adjusted based on the average competitor pricing increasing if it is above the base price and decreasing if it is below.

- Inventory level: 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 are known in advance, which may not be the case in practice.

Dynamic pricing is a strategy that allows companies to adjust their prices in real-time based on market conditions.

Benefits: Increased revenue by adjusting to market conditions, dynamic pricing based on demand, inventory, and competitor prices allows for more granular price setting.

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 pricing.

Time frame

Dynamic Pricing Algorithm for E-commerce
Task: Design a dynamic programming Algorithm to determine the optimal pricing strategy for a set of product over a given period

```
function dp(pr, tp)
  for each pr in p in products:
    for each tp t in tp:
      price[t] = calculate price (p, t competition-prices,
        demand[t], inventory[t])
  return products
function calculate price (product, time period,
  competitor prices, demand, inventory)
```

price = product base-price

price += if demand - Factor(demand, inventory):
if demand > inventory:
return 0.2
else:

return 0.1

function competition - function (competitor prices)
if any (competition-prices) product base price
return -0.05

else:
return 0.05

