Capstone Project Report

Title: Dynamic Pricing for Urban Parking Lots
Program: Summer Analytics 2025
Hosted by: Consulting & Analytics Club, IIT Guwahati

🧠 Project Objective

The objective of this project is to simulate a real-time pricing engine for urban parking spaces using data-driven logic. The model dynamically adjusts parking prices based on:

- Occupancy levels
- Queue lengths
- Traffic congestion
- Vehicle types
- Special days or events
- Competitive conditions (optional, Model 3)

This system helps balance supply and demand by preventing overcrowding and underutilization in city parking lots.

📊 Dataset Overview

- **Duration:** 73 days
- **Time granularity:** 18 time slots per day (every 30 mins from 8:00 AM to 4:30 PM)
- **Parking lots:** 14 urban locations
- **Features:**
    - Occupancy, Capacity, QueueLength
    - TrafficConditionNearby (low, average, high)
    - VehicleType (car, bike, truck)
    - IsSpecialDay (0 or 1)
    - Latitude, Longitude
    - Date, Time (combined to Timestamp)

🧩 Models Implemented

✅ Model 1: Baseline Linear Pricie

Formula:

price t + 1 =

price $t + \alpha \cdot$ (Occupancy Capacity) Price t+1=Price t+α·(Capacity Occupancy)

- Increases price linearly as occupancy grows
- Uses simple logic to demonstrate baseline behavior
- Alpha value is tunable to control sensitivity

✅ Model 2: Demand-Based Pricing

Step 1: Demand Calculation

Demand = $\alpha \cdot$ (Occupancy Capacity) + $\beta \cdot$ Queue Length $- \gamma \cdot$ Traffic + $\delta \cdot$ IsSpecialDay + $\epsilon \cdot$ VehicleType Weight Demand=α·(Capacity Occupancy)+β·Queue Length−γ·Traffic+δ·IsSpecialDay+ϵ·VehicleType Weight Price t = 10 · (1 + $\lambda \cdot$ Normalized Demand) Price t=10·(1+λ·Normalized Demand)

Takes into account:

- Vehicle weights: Car = 1.0, Bike = 0.5, Truck = 1.5
- Traffic mapped: Low = 1, Average = 2, High = 3
- Base price: $10
- Prices clipped between $5 and $20
- λ controls price sensitivity to demand

📈 Visualization

- Plotted time-series graphs for Model 1 and Model 2
- Compared trends of pricing over time for selected lots
- Observed smoother transitions and more logical variation in Model 2

(Optional in original problem: Model 3 - Competitive Pricing based on location proximity and price comparison)

📌 Assumptions

- Base price is fixed at $10 per slot
- Data is clean and no missing values for core features
- Each parking lot is treated independently in baseline and demand models
- No rerouting logic is included in this version
- Demand components are weighted based on intuition and tuned manually

---

🧠 Key Learnings

- Built pricing models from scratch using only Pandas and Numpy
- Engineered features to simulate demand in a time-sensitive environment
- Created normalized demand scores to scale pricing effectively
- Learned how to simulate real-time pricing behavior using time-series logic
- Visualized impact of pricing logic using Matplotlib

📎 Tools Used

- Python
- Pandas
- Numpy
- Matplotlib
- Google Colab

✅ Conclusion

The project successfully demonstrates a real-time pricing strategy that can adapt to various real-world conditions and provide balanced, intelligent pricing decisions for urban parking lots. The modular design allows for further expansion such as rerouting logic, competitor analysis, and real-time APIs.