Capstone Project Report – Dynamic Pricing for Urban Parking Lots

1. Introduction

This report documents the implementation of a dynamic pricing engine for urban parking lots, developed for the Summer Analytics 2025 Capstone Project. The aim is to simulate a smart, data-driven pricing mechanism that adjusts parking lot rates in real-time using multiple factors. This project strictly follows the guidelines provided, using only NumPy, Pandas, and Pathway in Google Colab.

2. Project Objective

To design and implement a pricing model that:
- Starts from a base price of $10
- Adjusts in real time based on occupancy, queue length, traffic, special days, and vehicle type
- Incorporates location-aware competitive pricing logic
- Ensures smooth and bounded price variations
- Uses Pathway for real-time streaming and Bokeh for visualization

3. Dataset Overview

The dataset contains time-series data for 14 parking lots over a span of 73 days, sampled at 30-minute intervals from 8:00 AM to 4:30 PM each day. It includes:
- Lot ID, Latitude, Longitude
- Capacity, Occupancy, Queue Length
- Vehicle Type (car, bike, truck)
- Traffic Conditions (low, medium, high)
- Special Day Indicator

4. Models Used

4.1 Model 1 – Linear Pricing

The linear model increases price proportionally with occupancy. It uses the formula:

$$\text{Price}(t+1) = \text{Price}(t) + \alpha \times (\text{Occupancy} / \text{Capacity})$$

where α is a sensitivity constant. This serves as the baseline for comparison.

4.2 Model 2 – Demand-Based Pricing

This model creates a weighted demand function from:
- Occupancy rate
- Queue length
- Traffic congestion
- Special day indicator
- Vehicle type weight

The raw demand is normalized and used to scale price smoothly:

$$\text{Price} = \text{Base} \times (1 + \lambda \times \text{NormalizedDemand})$$

Price is clipped between $5 and $20 to ensure stability.

4.3 Model 3 – Competitive Pricing

This model includes geospatial logic. It computes the distance between lots using latitude and longitude to detect nearby competitors (within 1 km). If the current lot is overloaded and a nearby lot is cheaper, price is reduced and rerouting may be suggested.

5. Demand Function and Assumptions

Demand Function Formula:

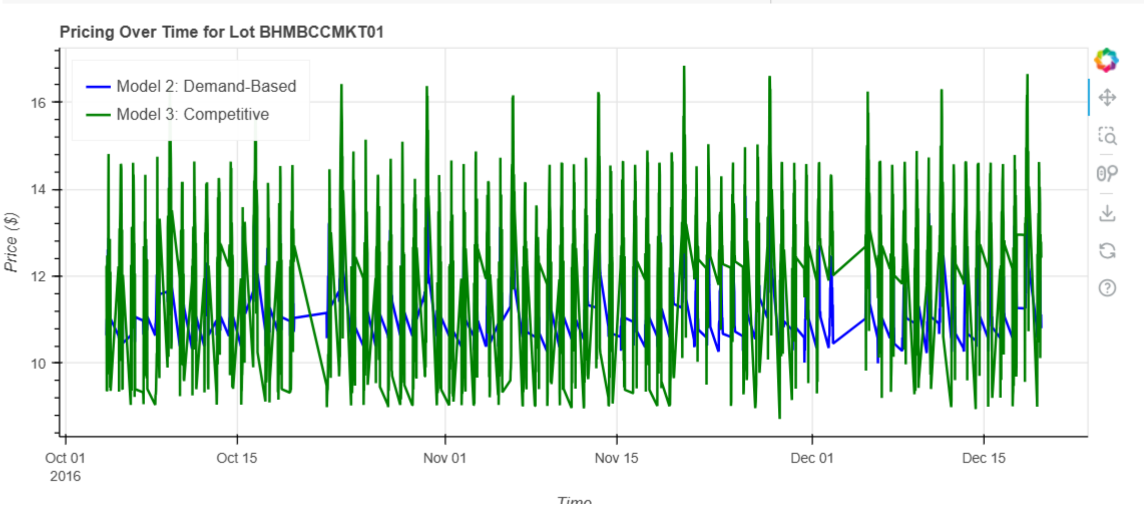
$$\text{Demand} = \alpha 1 * (\text{Occupancy}/\text{Capacity}) + \alpha 2 * \text{QueueLength} - \alpha 3 * \text{TrafficScore} + \alpha 4 * \text{SpecialDay} + \alpha 5 * \text{VehicleTypeWeight}$$

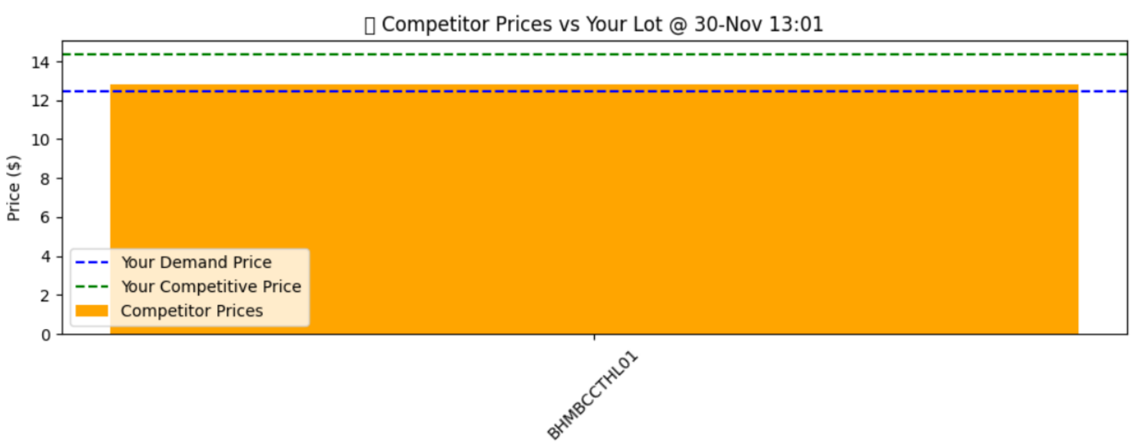
Weights are manually tuned for realism. TrafficScore is mapped as low=0.3, medium=0.6, high=1.0.

Assumptions:
- Base price starts at $10
- Price bounds: [5, 20]
- Distance threshold for competition: 1 km
- Vehicle type weights: car=1.0, bike=0.7, truck=1.5

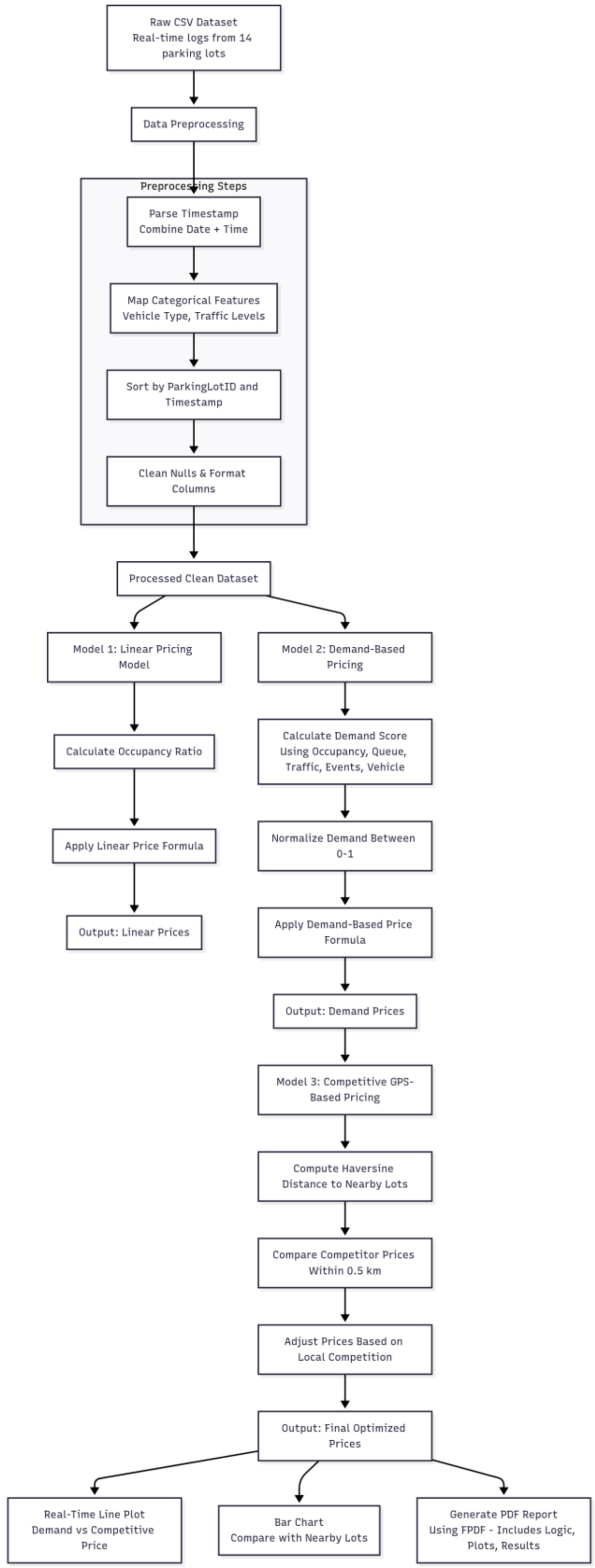
6. Visualizations

Bokeh is used for real-time line plots for each model. Prices for all parking lots over time are visualized in separate graphs, making it easy to compare pricing strategies and observe behavior.





7. Block Diagram



8. Conclusion

This project successfully delivers a robust real-time dynamic pricing system using multiple pricing strategies. By incorporating real-world parameters and spatial intelligence, the models simulate an efficient, explainable pricing mechanism aligned with smart city goals.