

# CAPSTONE PROJECT REPORT

## **DYNAMIC PRICING FOR URBAN PARKING LOTS**

-KRITHYAA VIJAYANAND

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This report aims at providing reasoning and additional insights on the implementation of the project

- Urban parking spaces are scarce and face fluctuating demand throughout the day. Static pricing often results in either overcrowding or underutilization of these lots. Dynamic pricing allows for more efficient use by adjusting prices in response to real-time conditions and demand patterns.
- **Project Objective:** To develop an intelligent, data-driven dynamic pricing engine for 14 parking lots using real-time data streams, basic economic principles, and machine learning models implemented from scratch with Python, Pandas, and Numpy.

## Methodology

### Real-Time Data Simulation

- Used Pathway to simulate real-time streaming of parking data
- Preserved timestamp order to reflect realistic data ingestion
- Enabled continuous feature updates and price predictions

### Assumptions:

Base price fixed at \$10 for all lots initially

Linear weights ( $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$ ,  $\epsilon$ ) tuned heuristically based on domain knowledge and data analysis

### Pricing Models:

#### Model 1: Baseline Linear Pricing Model

Logic: simple, intuitive relationship between the parking lot occupancy and the price. The idea is that as the lot fills up, the price should increase linearly to reflect higher demand and discourage excessive congestion.

$$\text{Price}_{t+1} = \text{Price}_t + \alpha \cdot \left( \frac{\text{Occupancy}}{\text{Capacity}} \right)$$



Sensitivity parameter controlling how much the price changes with occupancy

- This model acts as a baseline to show how occupancy directly influences price.
  - It is easy to interpret and implement but ignores other important factors like queue length, traffic, or special events.
- However, does not take into account change patterns and can lead to sudden jump if there is sharp fluctuation.

## Model 2: Demand-Based Price Function

Logic: To capture more realistic demand dynamics, this model incorporates multiple key factors that influence parking demand and thus pricing. These factors include occupancy rate, queue length (waiting vehicles), traffic congestion, special events, and the type of incoming vehicle.

$$\text{Demand} = \alpha \cdot \left( \frac{\text{Occupancy}}{\text{Capacity}} \right) + \beta \cdot \text{QueueLength} - \gamma \cdot \text{Traffic} + \delta \cdot \text{IsSpecialDay} + \varepsilon \cdot \text{VehicleTypeWeight}$$

### **$\lambda$ : Controls the amplitude of price changes based on demand.**

- Models multiple factors affecting demand instead of just occupancy.
- Allows for a smooth, bounded price that adapts dynamically and is more reflective of real-world conditions.
- The inclusion of vehicle type and special day captures nuanced effects on demand.

## Model 3: Competitive Pricing Model

Logic: introduces competition by considering prices of nearby parking lots and their occupancy status. It mimics how customers might choose alternative parking spots based on price and availability.

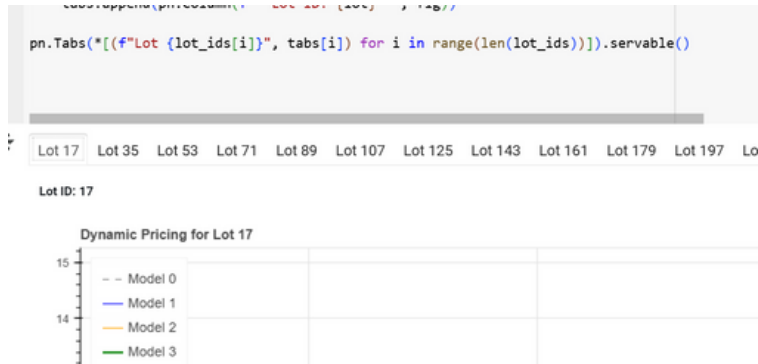
- Monitor competitor prices and availability in real-time.
- Adjust own price based on competitor prices and capacity:
  - If own lot is full and nearby lots have lower prices → lower price to attract demand or suggest rerouting vehicles to competitors.
  - If competitors are more expensive → raise price to maximize revenue while staying attractive.

Competitive Pricing Strategy:

- **Balances between maximizing revenue and maintaining customer flow.**
- Reflects real-world market dynamics where customers have alternatives.
- Helps prevent customer loss to competitors or overcrowding by rerouting.

## Visual Results

Different tabs to view different parking lots and their trends and how different pricing models works in each



Optional Suggestion for rerouting to nearby lots if current lot is overburdened.

This result shows next suggested lot for a particular lot and also shows the distance of it from current lot

```
#FOR REROUTING SUGGESTIONS
for msg in reroute_msgs[:10]:
    print("Rerouting Message:", msg)
```

Rerouting Message: Lot 17 is full. Suggest Lot 35 (0.18 km)  
Rerouting Message: Lot 35 is full. Suggest Lot 125 (0.21 km)  
Rerouting Message: Lot 53 is full. Suggest Lot 107 (0.86 km)  
Rerouting Message: Lot 71 is full. Suggest Lot 35 (0.17 km)  
Rerouting Message: Lot 89 is full. Suggest Lot 53 (0.89 km)  
Rerouting Message: Lot 107 is full. Suggest Lot 125 (0.87 km)  
Rerouting Message: Lot 125 is full. Suggest Lot 233 (0.25 km)  
Rerouting Message: Lot 143 is full. Suggest Lot 35 (0.37 km)  
Rerouting Message: Lot 161 is full. Suggest Lot 449 (0.41 km)  
Rerouting Message: Lot 179 is full. Suggest Lot 53 (0.67 km)