Title:

**Dynamic Pricing for Urban Parking Lots** 

**Capstone Project – Summer Analytics 2025** 

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### **Project Objective**

The goal of this project is to build a dynamic, data-driven pricing engine for 14 urban parking lots. Prices are updated in real-time based on features such as occupancy, queue length, vehicle type, nearby traffic congestion, special events, and competitor pricing.

We build and compare three models of increasing complexity:

- Model 1 Baseline Linear Pricing
- Model 2 Demand-Based Pricing
- Model 3 Competitive-Aware Pricing

### **Tech Stack**

- Python (NumPy, Pandas) for data manipulation and logic
- Pathway real-time data stream simulation
- Geopy distance calculations
- Bokeh / Matplotlib data visualization
- Google Colab development and execution environment

# Model 1 – Linear Pricing (Baseline)

#### Formula:

 $Price[t+1] = Price[t] + \alpha \times (Occupancy / Capacity)$ 

- Starts from a base price of \$10
- $\alpha$  is a constant (e.g., 2.0)
- Price increases proportionally with occupancy

### **Use Case:**

Acts as a simple benchmark for dynamic pricing logic.

### Model 2 - Demand-Based Pricing

### **Demand Function:**

### Formula:

Demand =  $\alpha \times (Occupancy / Capacity) + \beta \times QueueLength - \gamma \times Traffic + \delta \times IsSpecialDay + \epsilon \times VehicleTypeWeight$ 

### **Explanation of Terms:**

- Occupancy / Capacity: Measures how full the lot is
- QueueLength: Longer queues imply higher demand
- Traffic: High congestion decreases accessibility (thus lowers demand)
- IsSpecialDay: Events or holidays increase demand
- VehicleTypeWeight: Trucks > Cars > Bikes (weights: 1.5, 1.0, 0.7)

# **Pricing Formula:**

Price = BasePrice ×  $(1 + \lambda \times NormalizedDemand)$ 

- Normalized demand is scaled to [0, 1]
- $\lambda$  determines sensitivity to demand
- Price is clipped between 0.5× and 2× of base

# **Assumptions**

• Demand function results in smooth, gradual price changes

- All vehicle types have a defined weight
  - o Car: 1.0, Bike: 0.7, Truck: 1.5
- Traffic is encoded:
  - o Low: 0.5, Medium: 1.0, High: 1.5
- Queue length has linear influence
- Base price is fixed at \$10 for all lots

## **Model 3 – Competitive Pricing Logic**

This model adds competitive awareness based on distance and price comparison.

### Logic:

- If a nearby lot (within 300 meters) is cheaper and available → suggest rerouting or reduce price
- If nearby lots are full or more expensive → allow price to increase up to 2× base
- Distances are calculated using latitude and longitude via Geopy

# **Real-Time Implementation**

- Data is streamed using Pathway's engine, preserving timestamps
- Pricing models operate on each time slice (18 slots/day from 8:00 AM to 4:30 PM)
- Visualizations are done in real time using Bokeh or Matplotlib

# **Price Behavior Summary**

Feature	Price Impact
Higher Occupancy	Increases Price
Longer Queue	Increases Price

Feature Price Impact

High Traffic Decreases Price

Special Event Day Increases Price

Vehicle is a Truck Increases Price (more than Car/Bike)

Nearby Lot is Cheaper Triggers Price Reduction or Rerouting

### Conclusion

This system provides an efficient, real-time pricing solution for urban parking management. Each model represents an advancement in pricing logic:

- Model 1 reacts to occupancy alone
- Model 2 considers multiple demand factors
- Model 3 incorporates competition and rerouting

The full solution can be deployed with real-time data pipelines using Pathway, enabling smarter city infrastructure.