# Dynamic Pricing for Urban Parking Lots

Capstone Project – Summer Analytics 2025
Consulting & Analytics Club × Pathway

## 1. Introduction

Urban parking spaces are a scarce and valuable resource. Static pricing leads to inefficiencies such as overcrowding or underutilization. This project implements a real-time, data-driven dynamic pricing engine for 14 urban parking lots using only Python, Pandas, Numpy, and Pathway. The goal is to optimize utilization and revenue, simulating a smart city parking system.

## 2. Data Preparation

- Data Source: 14 urban parking lots, 73 days, 18 time points per day.
- Features: Lot location, capacity, occupancy, queue length, vehicle type, traffic congestion, special day indicator, timestamp.
- Cleaning & Feature Engineering:
    - Traffic levels mapped to numbers: low=0.0, average=1.0, high=2.0
    - Vehicle types mapped to weights: car=1.0, bike=0.5, truck=1.5, cycle=0.25
    - Combined date and time into a single timestamp column.
    - Missing values filled appropriately.

## 3. Model 1: Baseline Linear Pricing

Logic:
Price increases linearly with occupancy rate.

$$\mathrm{Pricet+1=Pricet+}\alpha\cdot(\mathrm{OccupancyCapacity})$$

$\mathrm{Price}$

$t+1$

$=\mathrm{Price}$

$t$

$$+\alpha \cdot ($$

Capacity

Occupancy

$$)$$

- Base Price: $10
- Alpha (Sensitivity): 5
- Clipped Range: $5 to $30

Interpretation:
As occupancy increases, price rises. This encourages turnover and prevents overfilling.

## 4. Model 2: Demand-Based Dynamic Pricing

Demand Function:

$$\text{Demand} = \alpha \cdot (\text{OccupancyCapacity}) + \beta \cdot \text{QueueLength} - \gamma \cdot \text{TrafficConditionNearby} + \delta \cdot \text{IsSpecialDay} + \varepsilon \cdot \text{veh\_type\_weight}$$

$$\text{Demand} = \alpha \cdot ($$

Capacity

Occupancy

$$) + \beta \cdot \text{QueueLength} - \gamma \cdot \text{TrafficConditionNearby} + \delta \cdot \text{IsSpecialDay} + \varepsilon \cdot \text{veh\_type\_weight}$$

- Coefficients:
    - α = 2.0 (occupancy sensitivity)
    - β = 0.5 (queue sensitivity)
    - γ = 0.3 (traffic penalty)
    - δ = 1.0 (special day boost)
    - ε = 0.7 (vehicle type weight)

Price Function:

$$\text{DynamicPricet}=\text{BasePrice}\cdot(1+\lambda\cdot\text{NormalizedDemand})$$

$\text{DynamicPrice}$

$t$

$$=\text{BasePrice}\cdot(1+\lambda\cdot\text{NormalizedDemand})$$

- Lambda (Scaling): 0.6
- Demand Normalization: Min-max scaling for smooth, bounded price changes.
- Clipped Range: $5 to $30

Interpretation:
Price responds to a richer set of real-time features, allowing for smarter and more responsive pricing.

## 5. Demand Function Explanation

- Occupancy/Capacity: Higher occupancy means higher demand, so price should rise.
- QueueLength: More vehicles waiting increases demand and price.
- TrafficConditionNearby: More congestion can reduce demand (negative coefficient).
- IsSpecialDay: Special events increase demand.
- veh_type_weight: Larger vehicles (trucks) may be willing to pay more.

All features are normalized or scaled to keep price changes smooth and bounded.

## 6. Assumptions

- Base price is $10.
- Price cannot fall below $5 or rise above $30.
- Demand is a linear combination of key features.
- All models are implemented from scratch using only allowed libraries.
- No external ML libraries are used.

## 7. Price Behavior

- Model 1: Price increases with occupancy only.
- Model 2: Price responds to occupancy, queue length, traffic, special days, and vehicle type.

- Both models ensure price changes are smooth, explainable, and within realistic bounds.

## 8. Real-Time Visualization

- Used Bokeh to plot real-time pricing for each parking lot.
- Plots show both baseline and demand-based prices over time, justifying the pricing logic visually.

## 9. Real-Time Simulation with Pathway

- Pathway is used to simulate real-time data ingestion and processing.
- Pricing logic is applied in real time as new data arrives.

## 10. Conclusion

This project demonstrates a robust, explainable, and real-time dynamic pricing system for urban parking. The models are simple yet effective, and the system is ready for extension to more complex (competitive) pricing and deployment in a smart city context.

## 11. References


- Pathway Documentation: https://pathway.com/developers/
- Summer Analytics 2025: https://www.caciitg.com/sa/course25/



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