# Dynamic Pricing for Urban Parking Lots

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**Author:** Ujjwal Singh
**Email:** vireshsingh04@gmail.com

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## 1. Objective

This project aims to develop data-driven pricing strategies for urban parking lots that adapt dynamically based on real-time factors such as lot occupancy, traffic conditions, vehicle types, queue lengths, and local competition. The primary objective is to optimize pricing in a manner that balances user demand with revenue maximization while improving overall efficiency and accessibility.

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## 2. Dataset Description

- **Number of Records:** Approximately 5,000+ time-stamped entries
- **Key Features:**
- `SystemCodeNumber`: Unique identifier for each parking lot
- `Latitude`, `Longitude`: Geographical coordinates
- `Capacity`, `Occupancy`: Lot capacity and current utilization
- `TrafficConditionNearby`: Traffic conditions categorized as Low, Average, or High
- `QueueLength`: Number of vehicles waiting
- `VehicleType`: Classification of vehicles (e.g., Car, Bike)
- `IsSpecialDay`: Binary flag indicating holidays or special events
- `LastUpdatedDate`, `LastUpdatedTime`: Timestamps for data collection

The dataset captures temporal variations across several parking lots, providing a comprehensive foundation for modeling dynamic pricing.

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## 3. Pricing Models Implemented

### Model 1: Linear Occupancy-Based Pricing

**Concept:**
Pricing increases proportionally with occupancy to reflect demand pressure.

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

- **Base Price:** ₹10
- **α (Occupancy Weight):** 2.0

While intuitive, this model neglects external variables and assumes demand scales linearly with occupancy.

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### Model 2: Multi-Factor Demand-Based Pricing

**Concept:**
Incorporates multiple contextual features to estimate demand and adjust prices accordingly.

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

- **Final Price:**

$$\text{Price} = 10 \cdot (1 + \lambda \cdot \text{Normalized Demand})$$

- **Parameter Weights:**
- $\alpha = 1.2$, $\beta = 0.5$, $\gamma = 1.0$, $\delta = 1.0$, $\varepsilon = 1.5$, $\lambda = 0.5$

This model better captures behavioral and contextual influences on parking demand, smoothing sudden fluctuations.

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### Model 3: Competitor-Aware Dynamic Pricing

**Concept:**
Adjusts pricing based on the availability and rates of neighboring lots within a 1 km radius.

- **Rules:**
- If the current lot is full and neighboring lots are cheaper: **reduce price**
- If nearby lots are full or more expensive: **increase price**
- **Price Boundaries:** ₹5 (minimum) to ₹20 (maximum)
- **Distance Calculation:** Haversine formula based on GPS coordinates

This model mimics a competitive market, encouraging price alignment based on supply and nearby alternatives.

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## 4. Real-Time Simulation Using Pathway (Experimental)

A real-time implementation using the **Pathway** streaming library was attempted:

- Utilized `pw.io.csv.read()` to ingest real-time data
- Applied pricing logic in a streaming pipeline
- Attempted output to `real_time_prices.jsonl`

**Technical Challenges:** Due to compatibility constraints in Google Colab, especially with `.reduce()` operations and schema propagation in Pathway, the output pipeline could not be finalized. However, all implemented logic and intermediate results are available in the shared notebook.

## 5. Visualizations

All models were visualized using the **Bokeh** interactive plotting library. Key visual insights include:

- Model 1: Price trends vs. time
- Model 2: Demand and pricing variation over time
- Model 3: Comparative pricing across models for a selected parking lot

These visual tools enhance interpretability and highlight the impact of individual features on pricing outcomes.

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## 6. Observations

- **Model 1:** Overly simplistic and fails in congested environments
- **Model 2:** Captures nuanced demand factors and adapts more realistically
- **Model 3:** Responds intelligently to local market competition
- **Additional Insight:** Traffic conditions and special events significantly influence demand dynamics

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## 7. Conclusion

This project illustrates the application of data science for optimizing urban parking infrastructure through adaptive pricing strategies. The models evolve in complexity—from basic linear responses to multi-factor and competition-aware mechanisms. Although real-time deployment using Pathway faced technical hurdles, the initiative reflects a forward-looking approach suited for integration in smart city ecosystems.

The dynamic pricing framework developed herein demonstrates practical potential for reducing congestion, increasing revenue, and enhancing user satisfaction in urban mobility systems.

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**End of Report**