Report: Dynamic Pricing for Urban Parking Lots

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1. Project Overview

This report documents our implementation of a dynamic pricing model for urban parking lots using data-driven logic and real-time simulation. The aim was to make pricing responsive to demand by using multiple influencing features and update them periodically.

All processing was done using Python libraries — NumPy, Pandas for data handling, and Pathway for real-time simulation. We also used Bokeh to visualize price trends over time.

2. Data Understanding and Preparation

We started by exploring the dataset that included records collected over 73 days from 14 parking spaces. Each record captured parking lot status every 30 minutes from 8:00 AM to 4:30 PM.

We performed the following preprocessing steps:

- Converted date and time fields into a combined timestamp for temporal analysis.
- Mapped traffic congestion levels to numerical values (low = 1, average = 2, high = 3).
- Assigned weights to vehicle types (e.g., truck = 1.3, car = 1.0, cycle = 0.5) based on their space and impact.
- Computed the occupancy ratio as the proportion of filled capacity.
- Converted the special day flag into binary (0 or 1).

These transformations made the dataset ready for our pricing logic.

3. Pricing Models

We developed two pricing models of increasing complexity:

Model 1: Baseline Linear Model

This model assumes that prices increase linearly with occupancy. It acts as a simple benchmark.

Formula:

```None
Price = Base Price + α × (Occupancy / Capacity)
```

Where:

- Base Price = $10
- α (alpha) = 5

It does not consider queue length, traffic, or vehicle type.

Model 2: Demand-Based Dynamic Model

This model considers multiple real-world features to estimate demand and adjusts pricing accordingly.

Demand Function:

```None
Demand = (1.5 × OccupancyRatio) + (0.8 × QueueLength)
         - (0.7 × TrafficLevel) + (1.2 × IsSpecialDay)
         + (0.6 × VehicleWeight)
```

Price Function:

```None
Price = BasePrice × (1 + λ × NormalizedDemand)
```

Where:

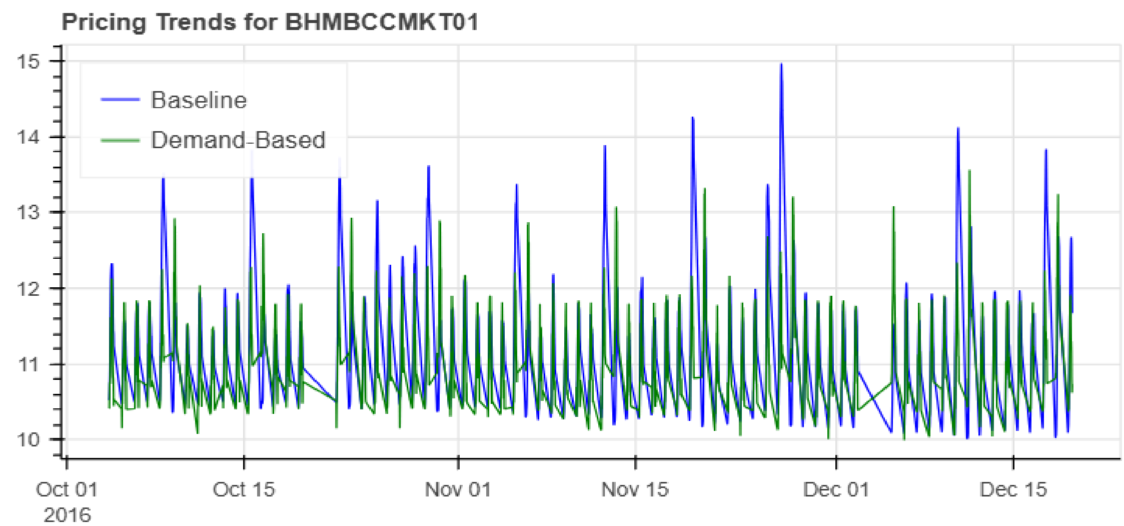
- Base Price = $10

- λ (lambda) = 0.5

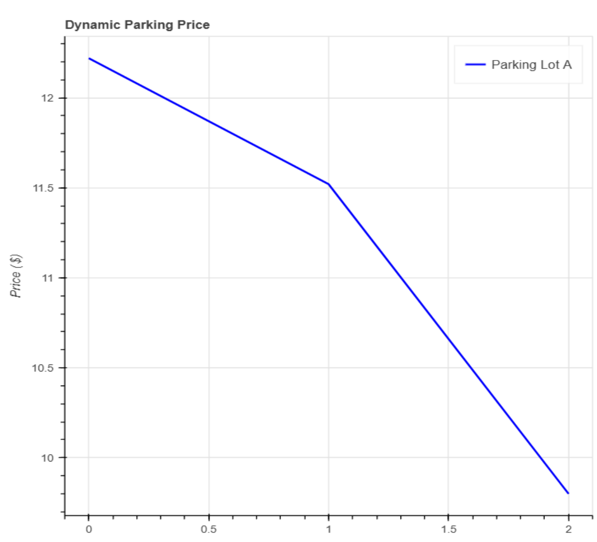
We normalized the demand to ensure price fluctuations were smooth and bounded. Prices were clipped between \$5 and \$20.

4. Visualizations

We used Bokeh to visualize the pricing outputs of both models for selected parking lots.



Pricing comparison (baseline vs. demand-based) for parking lot "BHMBCCMKT01"



Real-time dynamic price stream using output from Pathway

Key Observations:

- Demand-based pricing adapts better to real-world conditions like traffic and events.
- Prices rise during peak hours and on special days.
- The baseline model is limited and only reflects occupancy-based increases.

You can add multiple such plots using other SystemCodeNumbers as needed.

5. Demand Function Rationale

We designed the demand function as a weighted sum of relevant factors:

- Occupancy Ratio (more vehicles = higher demand)
- Queue Length (indicates incoming demand)
- Traffic (high traffic = less demand)
- Special Day (events or holidays boost demand)
- Vehicle Type (larger vehicles take more space)

Normalization was used to bring all demand values into a [0, 1] range and avoid erratic price changes.

6. Assumptions

- Traffic levels and queue lengths are accurate and timely.
- Base price of $10 is realistic.
- Price is capped within 0.5x to 2x of base to ensure fairness.
- Prices are updated every 30 minutes based on incoming data.
- Vehicle type weights reflect relative parking space consumption.

7. Insights

- The demand-based model provides smoother and more context-aware pricing.

- Queue length and special days were significant influencers.
- Prices remained within bounds while still being responsive.
- Baseline model was too simplistic for real-world deployment.