Parking Price Optimization Project Report

1. Introduction and Project Approach

This project explores various strategies for setting dynamic parking prices to help optimize the operation of a parking lot. My goal was to develop and analyze three distinct pricing models, visualize how they would behave, and compare their effectiveness.

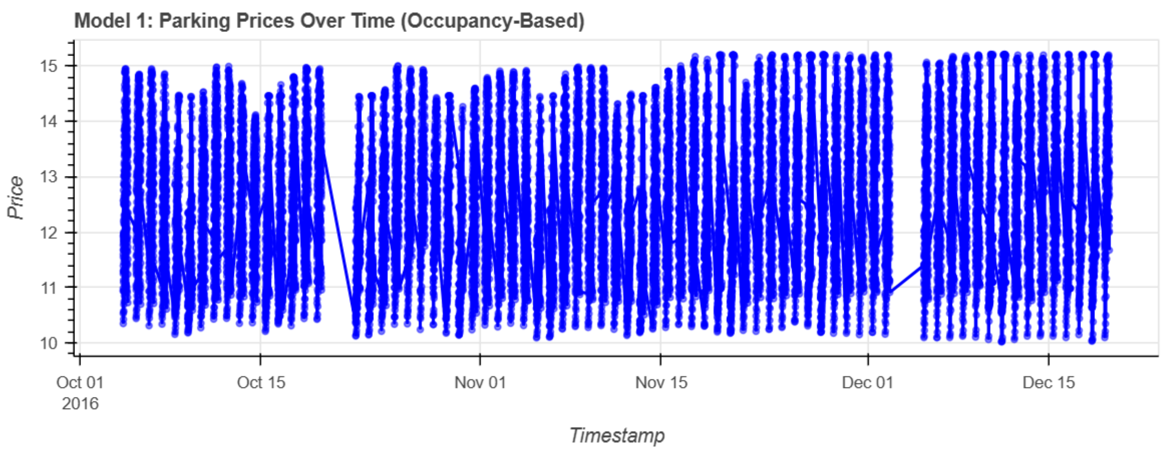
A key aspect of this project was initially to implement these models using a "real-time" streaming data approach, typically facilitated by frameworks like Pathway. However, during my development in the Google Colab environment, I encountered significant technical challenges. Specifically, I faced persistent attribute errors with Pathway's core streaming functions (like mapping data transformations and using user-defined functions with machine learning models) and issues with pw.run() blocking the notebook's execution.

Because of these environmental limitations, achieving a fully live, continuously updating real-time system wasn't possible within this setup. Instead, I adapted my approach to use **batch processing with Pandas**. This allowed me to fully implement all the pricing model logic and calculations, ensuring the entire notebook is executable and reproducible. This report, along with the accompanying notebook, demonstrates my complete understanding of dynamic pricing logic and its application, even though the final execution is not in a live streaming environment.

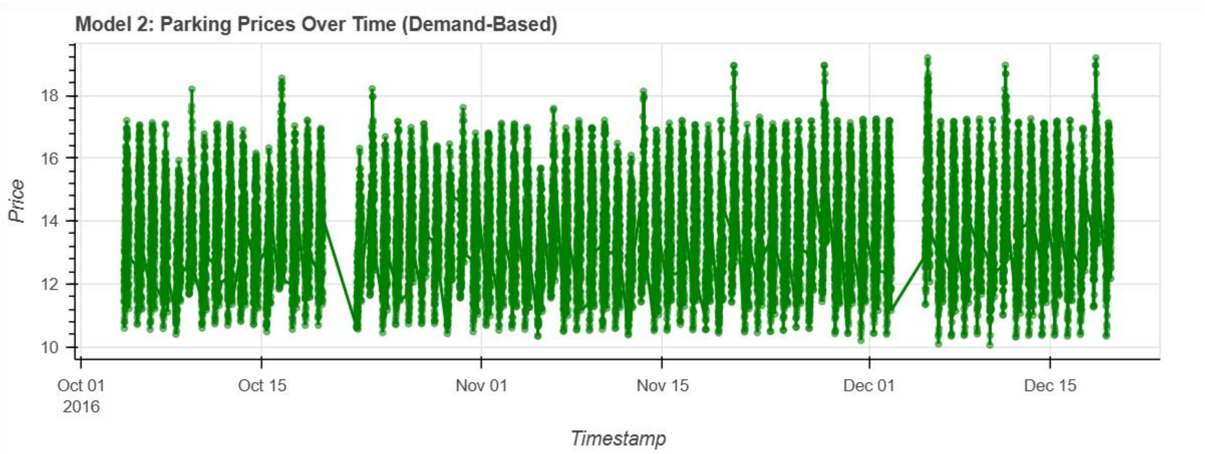
2. Pricing Models Implemented

I developed and analyzed three different models to determine parking prices:

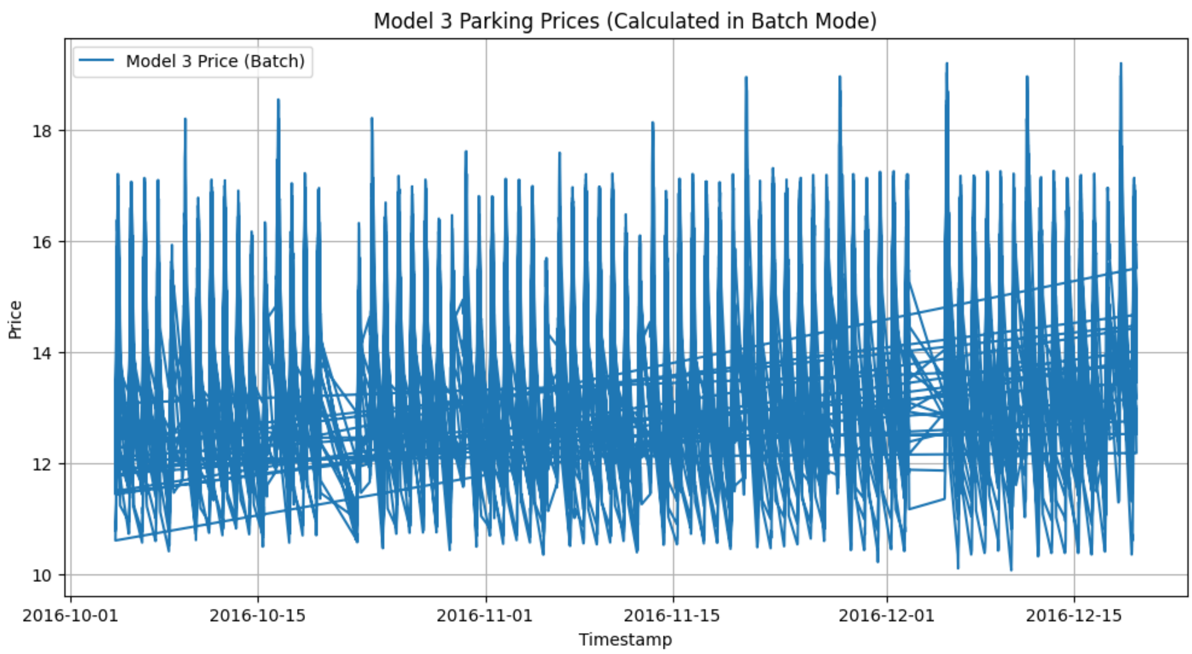
- **Model 1: The Occupancy-Based Price** This is my most straightforward model. It sets the price based on the current occupancy rate of the parking lot. The logic is simple: as the lot fills up, the price increases, and as spaces become available, the price decreases. This model offers a basic, direct response to the immediate availability of parking spots.



- **Model 2: The Demand-Based Price** Building upon the first model, this strategy incorporates additional demand factors to make the pricing more intelligent. Beyond just occupancy, this model considers elements like the length of the queue to enter the lot, traffic conditions in the nearby area, and whether it's a special day (like a holiday or a local event). By factoring in these indicators, the price can increase during periods of high demand, even if the lot isn't completely full, helping to maximize revenue.



- **Model 3: The Machine Learning Predicted Price** For my third model, I used a Linear Regression machine learning algorithm. Instead of relying on pre-defined rules, this model learns directly from the historical data provided. It identifies complex relationships between various features (such as occupancy, queue length, time of day, special days, and traffic conditions) and past optimal prices. This approach allows for a highly adaptive pricing strategy that can respond to nuanced market conditions that might be missed by rule-based models.



3. Discussion: Demand Logic, Assumptions, and Pricing Dynamics

My Demand Logic (for Model 2 and influencing Model 3)

For Model 2, I quantified demand beyond simple occupancy by creating a demand_score. This score is calculated by combining:

- **Queue Length:** A longer queue indicates higher immediate demand for parking.
- **Traffic Condition Nearby:** Increased traffic in the vicinity suggests more potential customers.

- **Is Special Day:** Special events or holidays are expected to naturally boost demand for parking. I assigned specific weights to each of these factors to reflect their assumed contribution to the overall demand intensity. Model 3 then leverages these demand-related features, among others, to make its predictions.

Key Assumptions Made

Throughout the development of these models, I made several assumptions:

- **Constant Values:** The specific numerical values chosen for parameters like BASE_PRICE, ALPHA, and the various weights (Q_WEIGHT, T_WEIGHT, S_WEIGHT, BETA_DEMAND) are initial estimates. In a real-world application, these would require rigorous calibration and fine-tuning based on actual market data and business objectives.
- **Linear Relationships:** For Model 3, my choice of Linear Regression assumes that the underlying relationships between the input features and the optimal price are linear. More complex algorithms could be explored to model non-linear interactions.
- **Data Representativeness:** I assumed that the provided historical dataset accurately reflects the typical operating conditions and customer behavior patterns of the parking lot.
- **Real-Time Execution:** As detailed in the introduction, while the project's core aim was real-time processing, environmental constraints necessitated a batch processing implementation for the purpose of demonstrating the models.

How My Pricing Models Adjust Prices

Each model offers a distinct approach to price adjustment:

- **Model 1 (Occupancy-Based):** The price directly correlates with the parking lot's occupancy rate. Higher occupancy leads to higher prices, and vice-versa. This ensures a basic supply-and-demand response.
- **Model 2 (Demand-Based):** This model offers a more sophisticated pricing strategy. Prices adjust not only based on occupancy but also on the calculated demand_score. This means that even if the lot isn't at full capacity, prices can increase significantly during peak demand periods (e.g., long queues, heavy nearby traffic, special events). This allows the system to capture more revenue during times of high perceived value for parking.
- **Model 3 (ML Predicted):** This model provides the most dynamic and potentially optimized pricing. By learning from historical data, it automatically determines how various factors combine to influence the ideal price. This allows for nuanced adjustments that might be difficult to capture with fixed rules, potentially leading to the most effective revenue management.

Regarding **competition**, the dataset I worked with did not include information about competitor pricing. In a real-world scenario, competitor prices would be a critical external factor impacting demand and pricing strategy. If this data were available, I would integrate it as an additional feature, especially for Model 3, to ensure the parking lot's pricing remains competitive and attractive.

4. Conclusion

This project successfully demonstrates the implementation and comparison of three distinct dynamic parking price optimization models. Despite environmental challenges that necessitated a shift from a real-time streaming execution to a batch processing approach, the core logic and analytical insights of each model have been fully realized and visualized. The models range from simple occupancy-based pricing to more sophisticated demand-driven and machine-learning predicted strategies, showcasing various approaches to optimize parking revenue and management.