Capstone Parking Pricing Model

Project Summer Analytics

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Models Used

MODEL 1

A simple model where the next price is a function of the previous price and current occupancy

MODEL 2

A more advanced model made using key features given in dataset

MODEL 3

A competitive model which takes in consideration of prices of nearby lots.

Model 1:

Introduction

In Model 1, we establish a simple dynamic pricing model where parking prices adjust based solely on the occupancy rate of each parking lot. This baseline serves as a foundation to benchmark more complex strategies. The goal is to ensure prices reflect demand without requiring extensive external factors.

Demand Function

Our demand function is defined by:

$Price = BasePrice + \alpha \times OccupancyRate$

where:

- BasePrice is set to $10 as a reasonable minimum reflecting fixed operating costs.
- OccupancyRate is calculated as Occupancy / Capacity for each lot at each timestamp.
- Alpha (price sensitivity) is set to 5 after manual tuning: this balances responsiveness to demand without excessive volatility.

Assumptions

1. The base cost of providing parking justifies a minimum price of $10.
2. Alpha was chosen by observing price trends over time to ensure smooth behavior.
3. Prices are clamped between $5 (0.5× BasePrice) and $20 (2× BasePrice), aligning with problem statement requirements to keep price changes bounded and stable.

Conclusions

Model 1 demonstrates a clear and interpretable linear relationship between occupancy and price. It provides a baseline that responds logically to parking demand while respecting operational pricing constraints. This simple model is effective in ensuring basic dynamic pricing functionality before introducing more complex factors like traffic, special days, or competitive intelligence in Models 2 and 3.

MODEL 2 – MULTI-FACTOR DEMAND-BASED PRICING WITH THRESHOLD LOGIC

INTRODUCTION

MODEL 2 EXTENDS SIMPLE OCCUPANCY-BASED PRICING BY INTRODUCING A MULTI-FACTOR DEMAND FUNCTION THAT REALISTICALLY CAPTURES URBAN PARKING DYNAMICS. IT USES THRESHOLDS TO DECIDE WHETHER SPECIFIC FACTORS MEANINGFULLY CONTRIBUTE TO INCREASING DEMAND, ALLOWING FOR NUANCED CONTROL OF PRICING RESPONSES.

THRESHOLD-BASED DEMAND LOGIC

MY MODEL 2 ALGORITHM EVALUATES KEY FEATURES INDIVIDUALLY, APPLYING CLEAR THRESHOLDS TO DETERMINE THEIR IMPACT ON DEMAND:

- VEHICLE TYPE WEIGHT:
  - IF < 0.6 → APPLY A CONCESSION (REDUCE DEMAND, LOWERING PRICE).
  - IF ≥ 0.6 → INCREASE DEMAND (HIGHER PRICE) SINCE LARGER VEHICLES TAKE MORE SPACE.
- OCCUPANCY RATE:
  - IF < 0.9 → NO PRICE IMPACT.
  - IF ≥ 0.9 → INCREASE DEMAND SCORE TO REFLECT SCARCITY.
- TRAFFIC LEVEL:
  - LOW OR AVERAGE → NO EXTRA CHARGE.
  - HIGH → ALWAYS ADD TO DEMAND SCORE TO DISCOURAGE ADDITIONAL CONGESTION.
- SPECIAL DAY (ISSPECIALDAY):
  - IF TRUE AND VEHICLE TYPE WEIGHT > 0.4 → INCREASE DEMAND SCORE FOR HIGHER PRICING DURING PEAK DAYS.
- QUEUE LENGTH:
  - IF 0 → NO IMPACT.
  - OTHERWISE → BINNED INTO INTERVALS, EACH ADDING PROGRESSIVELY TO THE DEMAND SCORE AS QUEUE LENGTH GROWS.

DEMAND SCORE CALCULATION

ONCE THRESHOLDS DECIDE WHICH FACTORS ARE ACTIVE, EACH ACTIVE FACTOR CONTRIBUTES ADDITIVELY TO A FINAL DEMAND SCORE, WHICH IS THEN NORMALIZED AND TRANSFORMED INTO A PRICE USING:

PRICE=BASEPRICE×(1+Λ×NORMALIZEDDEMANDSCORE)

THIS APPROACH MAKES SURE ONLY MEANINGFUL CONDITIONS AFFECT PRICING, AVOIDING OVERREACTING TO NOISE IN THE DATA.

ASSUMPTIONS

✅ THRESHOLDS WERE TUNED TO MATCH REALISTIC EXPECTATIONS OF DRIVER BEHAVIOR.
✅ PRICE IS CLAMPED BETWEEN $5 AND $20 TO MAINTAIN STABILITY.
✅ DEMAND NORMALIZATION ENSURES CONSISTENT SCALING ACROSS LOTS.

HOW PRICING CHANGES WITH DEMAND

- PRICING ONLY INCREASES WHEN THRESHOLDS INDICATE REAL SCARCITY OR SPECIAL CIRCUMSTANCES (E.G., VERY HIGH OCCUPANCY, QUEUES, SPECIAL DAYS).
- OTHERWISE, PRICES STAY NEAR THE BASE PRICE TO ENCOURAGE UTILIZATION.

VISUALIZATIONS

PLOTS SHOW PRICE EVOLUTION RESPONDING SHARPLY TO EVENTS CROSSING THRESHOLDS (E.G., OCCUPANCY >0.9 OR QUEUE FORMING), BUT REMAINING STABLE DURING NORMAL CONDITIONS — REFLECTING WELL-CONTROLLED, EVENT-DRIVEN DYNAMIC PRICING.

CONCLUSIONS

MODEL 2 LEVERAGES THRESHOLD-BASED DECISION-MAKING TO ENSURE PRICE CHANGES REFLECT SIGNIFICANT SHIFTS IN DEMAND, NOT RANDOM FLUCTUATIONS, RESULTING IN A MORE ROBUST AND DRIVER-FRIENDLY DYNAMIC PRICING STRATEGY.

Model 3 – Competitive and Location-Aware Pricing

Introduction

Model 3 integrates competitive intelligence and location-based considerations to reflect a realistic parking market. This model evaluates prices of nearby lots and geographic proximity to adjust pricing or recommend rerouting to drivers.

Competitive Pricing Logic

For each parking lot, the model:

- Computes ReferralScore based on occupancy, traffic, and price differences with nearby lots.
- Calculates DistanceScore to estimate the feasibility of rerouting drivers.
- Determines if a lot should recommend another lot (when ReferralScore is high) or adjust its own price to stay competitive.

Assumptions

1. Nearby lots are defined within a reasonable geographic radius.
2. ReferralScore and DistanceScore are combined with tuned weights (e.g., 0.7 referral, 0.3 distance).
3. A ReferralScore threshold determines whether to reroute or adjust price.
4. Price adjustments are bounded to avoid sudden spikes or drops.

How Pricing Changes with Demand and Competition

- If a lot is near others with lower prices and has low referral score → it lowers its price to stay attractive.
- If nearby lots are expensive → the lot can safely increase its price without losing demand.
- High referral score → suggest rerouting drivers to available, cost-effective nearby lots.

Visualizations

Plots of Model 3 decisions highlight each lot's status over time, showing when the system recommends price adjustments vs. rerouting, giving a clear view of competitive dynamics.

Conclusions

Model 3 represents a sophisticated, market-aware pricing strategy. It not only reacts to internal demand but also external competitive conditions, promoting optimal pricing and efficient parking utilization while enhancing customer experience.