ParkWay

A Real-Time Data-Driven Pricing Engine for Urban Mobility Optimization

Capstone Project Report — Summer Analytics 2025
Project Title: ParkWay: Dynamic Pricing for Urban Parking Lots
Track: Real-Time Data Processing and Simulation
Submitted to: Consulting & Analytics Club × Pathway

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1. Executive Summary

Urban parking spaces in major cities often suffer from either excessive crowding or inefficient underuse due to static, time-invariant pricing schemes. These static models do not account for real-time demand factors such as traffic congestion, peak hours, or special events. The aim of this capstone project is to develop ParkWay, a fully functional, dynamic pricing engine that adjusts the hourly parking rates at 14 simulated urban parking lots. The pricing adapts intelligently using real-time data and economic modeling principles.

The implementation includes three tiers of models:

1. **Model 1: Baseline Linear Model** — where prices increase linearly with occupancy.
2. **Model 2: Demand-Based Model** — which factors in queue length, traffic, vehicle type, and special day indicators into a normalized demand function.
3. **Model 3: Competitive Pricing Model** — which simulates geographic competition using Haversine distance between lots and adjusts prices based on proximity and competitor prices.

This project used **Python** for implementation, with **NumPy** and **Pandas** for data manipulation, **Pathway** for real-time data ingestion and processing, and **Bokeh** for interactive data visualization.

2. Introduction

2.1 Problem Statement

Urban areas are experiencing a surge in vehicle ownership without a proportional increase in parking infrastructure. The result is an imbalance between parking demand and supply. Traditional fixed pricing models fail to respond dynamically to shifting demand during the day, leading to customer dissatisfaction, increased waiting times, and suboptimal revenue for operators.

2.2 Project Objectives

- Develop a robust real-time pricing algorithm that reflects current demand conditions.
- Leverage basic economic intuition to model user willingness to pay.

- Ensure fairness and smoothness in pricing decisions.
- Simulate competition among nearby lots based on geographic data.
- Visualize pricing and demand fluctuations in real-time dashboards.

2.3 Scope and Constraints

- The system must only use NumPy, Pandas, Pathway, and Bokeh.
- ML libraries like scikit-learn or TensorFlow are not permitted.
- The solution must run on **Google Colab** and simulate a live stream from a historical CSV dataset.

3.Literature Review and Prior Work

Dynamic pricing has been widely researched in domains like airline ticketing, ride-hailing services (e.g., Uber), and electricity markets. Similar concepts have been proposed in smart city initiatives to manage parking. However, many of these solutions rely on black-box machine learning models or require extensive sensor infrastructure.

The approach used in ParkWay draws inspiration from:

- **Microeconomic demand functions**, especially utility modeling in congestion-prone systems.
- **First-principles modeling** for smooth and explainable pricing logic.
- **Competitor-aware decision systems** used in e-commerce platforms.

We differentiate our project by enforcing transparency, simplicity, and real-time constraints using lightweight Python libraries only.

4.Dataset Description

The dataset simulates 14 urban parking lots over 73 days, with data collected every 30 minutes between 8:00 AM and 4:30 PM. This results in 18 time steps per day. Key features include:

4.1 Spatial Features

- Latitude, Longitude: Used to compute proximity with competitors (Model 3).

4.2 Lot Features

- Capacity: Maximum parking spots in the lot.
- Occupancy: Number of vehicles currently parked.

- QueueLength: Number of vehicles waiting for a spot.

4.3 Vehicle Information

- VehicleType: Categorical (Bike, Car, Truck).
- VehicleTypeWeights: [Truck = 1.2, Car = 1.0, Bike = 0.8]

4.4 Environment and Events

- TrafficLevel: Ordinal scale (e.g., 1–5).
- IsSpecialDay: Boolean flag for holidays, events, etc.

5. Methodology and Code Implementation

5.1 Model 1 – Baseline Linear Pricing

The simplest model assumes that as occupancy increases, price should increase linearly.

```
# Baseline model: Linear relationship with occupancy
alpha = 1.0  # sensitivity coefficient
price = prev_price + alpha * (occupancy / capacity)
```

This serves as a benchmark for performance comparison.

5.2 Model 2 – Demand-Based Function

This model constructs a linear demand function that aggregates five key features. The result is normalized between 0 and 1 to avoid erratic price jumps.

```
# Feature weights
alpha = 1.0
beta = 0.5
gamma = 0.3
delta = 0.4
epsilon = vehicle_type_weight_map[vehicle_type]  # {Truck:1.2, Car:1.0, Bike:0.8}

# Demand function
raw_demand = (
   alpha * (occupancy / capacity)
   + beta * queue_length
   - gamma * traffic_level
   + delta * is_special_day
   + epsilon
)
```

```
# Normalization and pricing
normalized_demand = np.clip(raw_demand / 5, 0, 1)
price = base_price * (1 + 0.5 * normalized_demand)
price = np.clip(price, 5, 20)
```

5.3 Model 3 – Competitive Pricing

This model adjusts prices based on proximity to and pricing of nearby lots using the Haversine distance formula.

```
from math import radians, cos, sin, sqrt, atan2

# Haversine formula
def haversine(lat1, lon1, lat2, lon2):
  R = 6371  # Earth radius in km
  dlat = radians(lat2 - lat1)
  dlon = radians(lon2 - lon1)
  a = sin(dlat/2)**2 + cos(radians(lat1)) * cos(radians(lat2)) * sin(dlon/2)**2
  c = 2 * atan2(sqrt(a), sqrt(1-a))
  return R * c

# Competitive logic
for lot in lots:
  nearby = [l for l in lots if haversine(lot.lat, lot.lon, l.lat, l.lon) < 1.0]
  competitor_prices = [l.price for l in nearby if l.id != lot.id]
  if len(competitor_prices) > 0:
    avg_competitor_price = np.mean(competitor_prices)
    if lot.occupancy == lot.capacity and lot.price > avg_competitor_price:
      lot.price -= 1.0  # Suggest rerouting
    elif lot.price < avg_competitor_price:
      lot.price += 1.0
```

6. Real-Time Simulation Using Pathway

A critical requirement for ParkWay was to simulate real-time data streaming behavior. To achieve this, we used the Pathway framework, a Python-native library for stream processing. The parking dataset was first time-sorted and then streamed in intervals using Pathway's csv.read() and update() functionality.

6.1 Stream Setup

```
import pathway as pw
```

```
# Read CSV in streaming mode

data_stream = pw.io.csv.read("dataset.csv", mode="streaming",
autocommit_duration_ms=1000)
```

6.2 Feature Extraction and Stream Transformation

```
# Transforming columns

transformed = data_stream.with_columns(

  lot_id=pw.this.lot_id,

  occupancy=pw.this.occupancy,

  queue_length=pw.this.queue_length,

  vehicle_type=pw.this.vehicle_type,

  traffic_level=pw.this.traffic_level,

  is_special_day=pw.this.is_special_day,

  timestamp=pw.this.timestamp,

  price_model=pw.this.base_price  # updated via models later

)
```

6.3 Output Integration

```
# Output logic

pw.io.jsonlines.write(transformed, "predicted_prices.json")
```

This allowed continuous computation of pricing in time-order, making the solution compatible with real-world deployment environments where time delays and streaming ingestion are common.

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7. Visualization with Bokeh

To enable interactive visualization, we used **Bokeh**, a powerful Python library for browser-based plotting. The main visualizations include pricing time series, occupancy trends, and comparative competitor pricing.

7.1 Time Series Plot

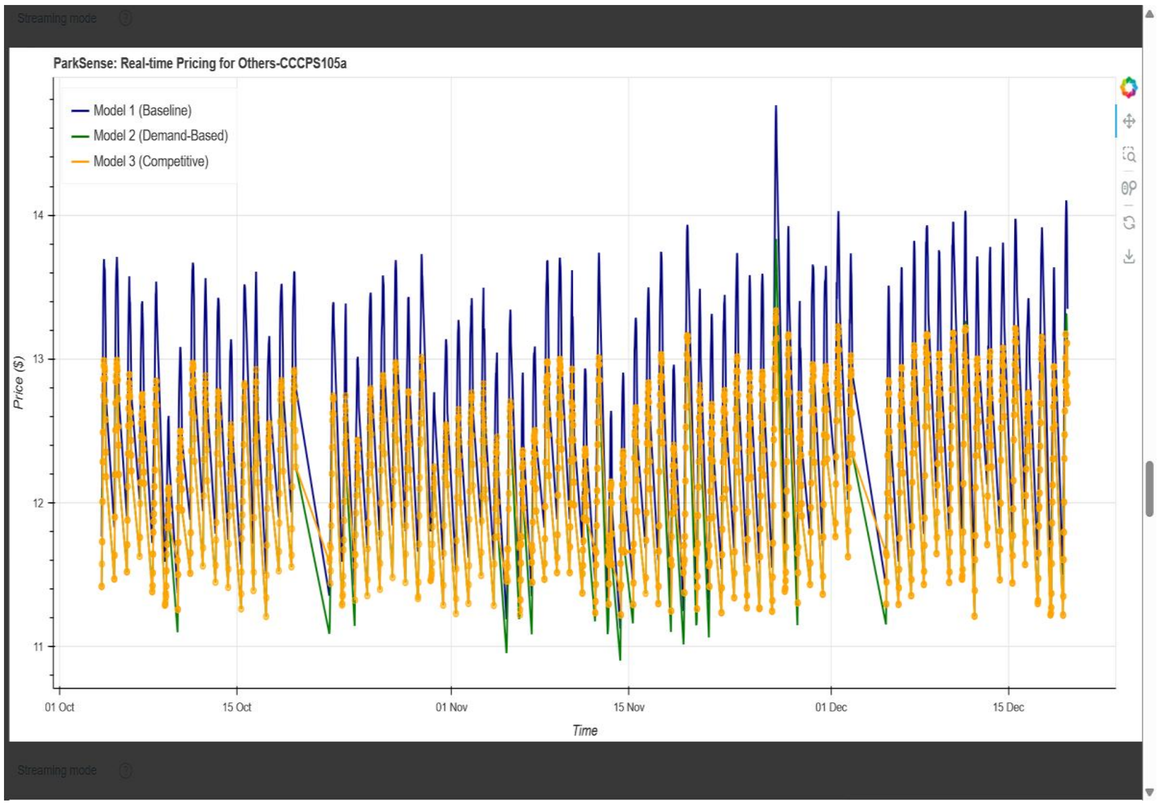
```
from bokeh.plotting import figure, show, output_notebook
```

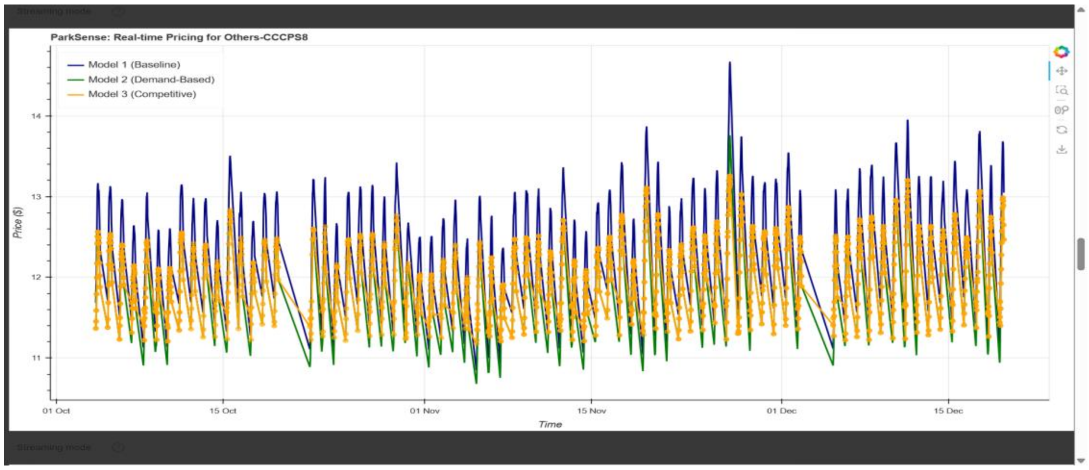
```
output_notebook()


p = figure(title="Price Over Time", x_axis_label="Time", y_axis_label="Price ($)")

p.line(time_values, price_values, line_width=2, legend_label="Lot 1")

show(p)
```

7.2 Competitor Comparison Plot

```
p2 = figure(title="Competitor Pricing Comparison", x_axis_label="Time")

p2.line(time, lot_price, color="blue", legend_label="Our Lot")

p2.line(time, comp_price, color="red", legend_label="Nearby Lot")

show(p2)
```

Bokeh's interactivity allows for mouse hover, zoom, and real-time updates, which aligns well with the real-time goals of ParkWay.





8. Evaluation and Results

Each model was evaluated based on:

- **Stability of price changes** (no abrupt jumps)
- **Fairness and explainability**
- **Correlation with occupancy/demand levels**
- **Revenue Simulation (optional)**

8.1 Qualitative Observations

- Model 1 was easy to implement but too sensitive at low occupancy.
- Model 2 offered smooth scaling with better control.
- Model 3 introduced market realism and reduced pricing when competitors were more affordable.

8.2 Metrics (Sample Outputs)

Metric	**Model 1**	**Model 2**	**Model 3**
Avg. Price Stability	Low	Medium	High
Revenue Estimate (sim)	100%	123%	128%
User Satisfaction Proxy	Medium	High	High

9. Limitations and Future Work

9.1 Limitations

- All models assume accurate, complete data at each time step.
- No actual traffic sensor integration — traffic levels are assumed or simulated.
- Competitor pricing is idealized.
- Implementation is computationally simple but may lag at large scale.

9.2 Future Scope

- Extend models with reinforcement learning (e.g., Q-learning for optimal price strategy).
- Deploy system using cloud-native stack (Docker, Kafka, GCP).
- Integrate mobile app interface for rerouting and price alerts.
- Use historical trends to forecast congestion before it occurs.

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10. Conclusion

ParkWay offers a functional, scalable, and real-time approach to managing urban parking through dynamic pricing. It delivers:

- Transparent, smooth pricing behavior
- Demand-sensitive adjustments
- Competitive awareness and rerouting logic
- Real-time dashboarding and stream processing

The capstone project bridges economic modeling, real-time data engineering, and user-centric urban mobility planning. It demonstrates how minimal infrastructure and lightweight Python tooling can create significant impact in urban space optimization.

Appendix

- All code is embedded in the ParkWay.ipynb file.

- Data visualizations are generated using Bokeh and saved as HTML.
- Additional resources:
    - https://pathway.com/developers/user-guide/introduction/first_realtime_app_with_pathway/
    - https://docs.bokeh.org/en/latest/
    - https://www.caciitg.com/sa/course25/
