Retail Pricing Strategy Optimization

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1. Overview

This project addresses the challenge of optimizing product pricing in the retail industry using machine learning. By analyzing historical sales and product data, a predictive model was built to estimate how different pricing strategies affect sales quantity and revenue. The model is deployed in a Streamlit web application to support real-time pricing simulation.

2. Introduction

In a highly competitive retail environment, data-driven pricing is essential to maximize profitability and customer satisfaction. Traditional pricing relies on static rules or guesswork. This project aims to build a complete AI/ML solution that enables businesses to simulate pricing scenarios, forecast revenue, and evaluate demand elasticity.

3. Problem Statement

Ineffective pricing strategies result in suboptimal sales, excess inventory, and missed revenue opportunities. The objective is to leverage historical sales data to create a machine learning model that predicts the impact of price changes on sales volume and revenue, enabling optimal pricing decisions.

4. Business Value

- Maximize revenue and profit margin
- Support pricing teams with data-driven recommendations
- Reduce underpricing or overpricing risks
- Understand price sensitivity and customer behavior
- Improve stock management by forecasting demand

5. Dataset Description

Feature Name	Description
product_category_name	Product category name
unit_price	Price per unit
qty	Quantity sold
total_price	unit_price × qty
freight_price	Shipping cost
product_score	Customer rating
product_weight_g	Product weight in grams
comp_1	Competitor price
weekday/weekend/holiday	Temporal features
volume	Size-based product metric

6. Methodology

6.1 Data Preprocessing

- Removed nulls and duplicates

- Converted date strings to datetime

- Label-encoded product categories

- Scaled numerical columns

- Handled outliers using IQR

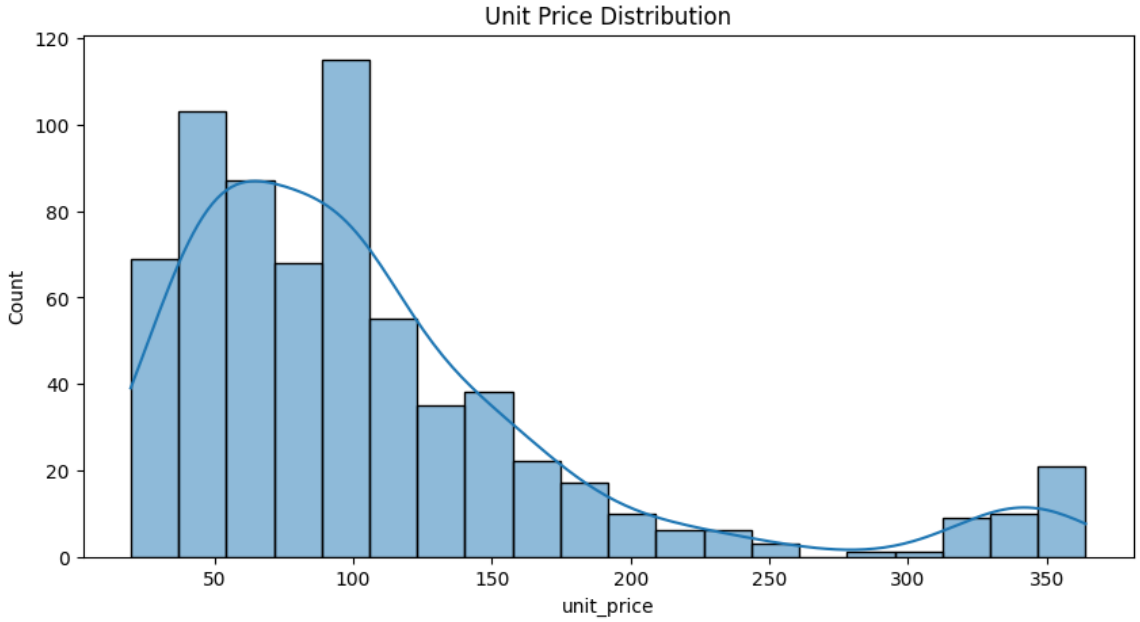
6.2 Exploratory Data Analysis (EDA)

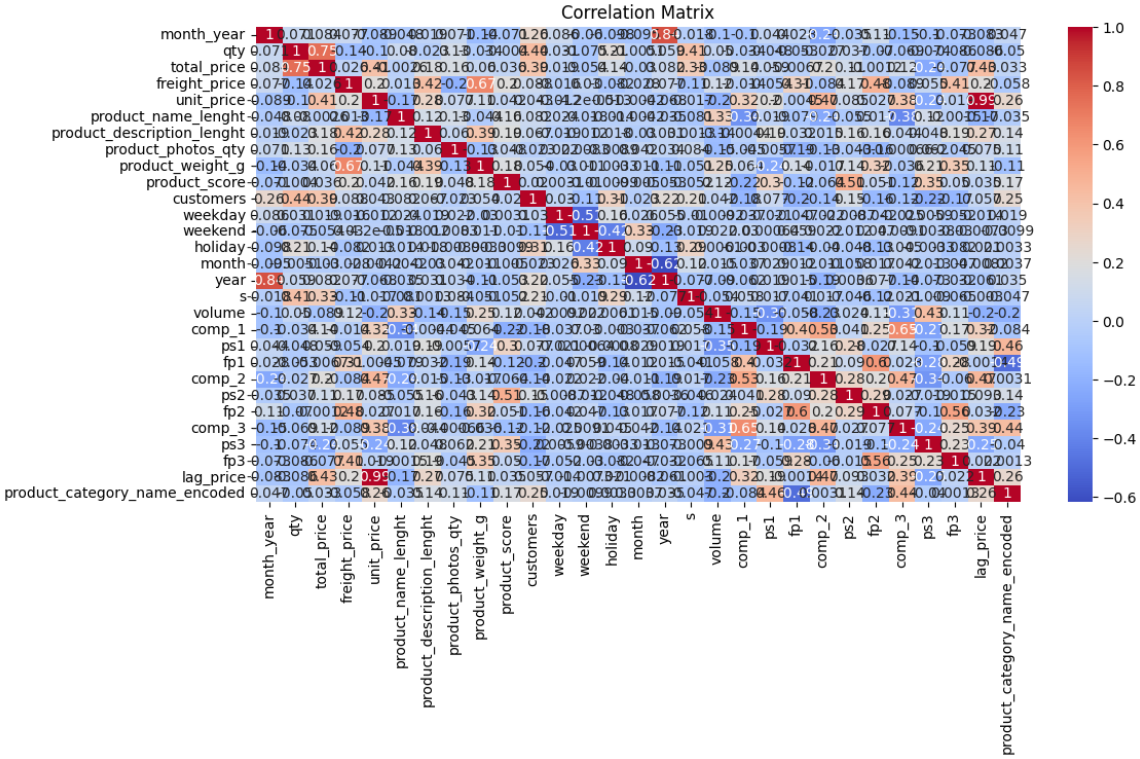
- Price vs. quantity distribution across categories

- Correlation heatmaps

- Demand trends over time

- Visual insights using Seaborn/Matplotlib


Unit Price Distribution
Count
unit_price
0
20
40
60
80
100
120
50
100
150
200
250
300
350


Correlation Matrix
month_year
qty
total_price
freight_price
unit_price
product_name_lenght
product_description_lenght
product_photos_qty
product_weight_g
product_score
customers
weekday
weekend
holiday
month
year
s
volume
comp_1
ps1
fp1
comp_2
ps2
fp2
comp_3
ps3
fp3
lag_price
product_category_name_encoded
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

6.3 Model Building

- Target: unit_price or qty

- Models: Linear Regression, Random Forest

- Feature set: volume, product_score, comp_1, category, etc.

6.4 Model Evaluation

- Metrics: MSE, RMSE, R^2

- Random Forest outperformed Linear Regression

- Feature importance: volume > score > comp_1

Evaluation

```python
def evaluate_model(name, y_true, y_pred):
    print(f"\n{name} Evaluation:")
    print("MSE:", mean_squared_error(y_true, y_pred))
    print("RMSE:", np.sqrt(mean_squared_error(y_true, y_pred)))
    print("R2 Score:", r2_score(y_true, y_pred))
```

[22] Python

```python
evaluate_model("Linear Regression", y_test, y_pred_lr)
evaluate_model("Random Forest", y_test, y_pred_rf)
```

[23] Python

```
...
Linear Regression Evaluation:
MSE: 66.23691974472548
RMSE: 8.138606744690733
R2 Score: 0.987739112487981

Random Forest Evaluation:
MSE: 43.96479326807407
RMSE: 6.630595242365052
R2 Score: 0.9918618289191814
```

6.5 Price Elasticity Analysis

- Formula: Elasticity = % change in quantity / % change in price

- Elastic categories respond significantly to price changes

- Inelastic categories are price stable

Price Elasticity of Demand

```
[24]
df['price_change_pct'] = df['unit_price'].pct_change()
df['qty_change_pct'] = df['qty'].pct_change()
df['elasticity'] = df['qty_change_pct'] / df['price_change_pct']
print("\nElasticity Sample:")
display(df[['unit_price', 'qty', 'price_change_pct', 'qty_change_pct', 'elasticity']].head(10))
```

Python

```
Elasticity Sample:
```

	unit_price	qty	price_change_pct	qty_change_pct	elasticity
0	45.950000	1	NaN	NaN	NaN
1	45.950000	3	0.000000	2.000000	inf
2	45.950000	6	0.000000	1.000000	inf
3	45.950000	4	0.000000	-0.333333	-inf
4	45.950000	2	0.000000	-0.500000	-inf
5	45.950000	3	0.000000	0.500000	inf
6	40.531818	11	-0.117915	2.666667	-22.615213
7	39.990000	6	-0.013368	-0.454545	34.003203
8	39.990000	19	0.000000	2.166667	inf
9	39.990000	18	0.000000	-0.052632	-inf

7. Deployment

- Model saved using joblib

- Interactive Streamlit dashboard for simulation

- Features: dropdown, slider, prediction output, visualization, CSV download

8. Results and Observations

- RF achieved lowest RMSE

- Elasticity and EDA aligned

- Certain categories showed strong price sensitivity

- Streamlit app allows easy simulation

9. Conclusion

This project successfully implemented an end-to-end ML solution for dynamic retail pricing. It provides actionable insights for business users and supports interactive decision-making via the Streamlit dashboard. Future improvements could include time-series forecasting and competitor scraping.

10. Tools and Technologies Used

- Python

- pandas, numpy, matplotlib, seaborn

- scikit-learn, joblib

- Streamlit

- Jupyter Notebook, VS Code

11. References

- https://scikit-learn.org

- https://docs.streamlit.io

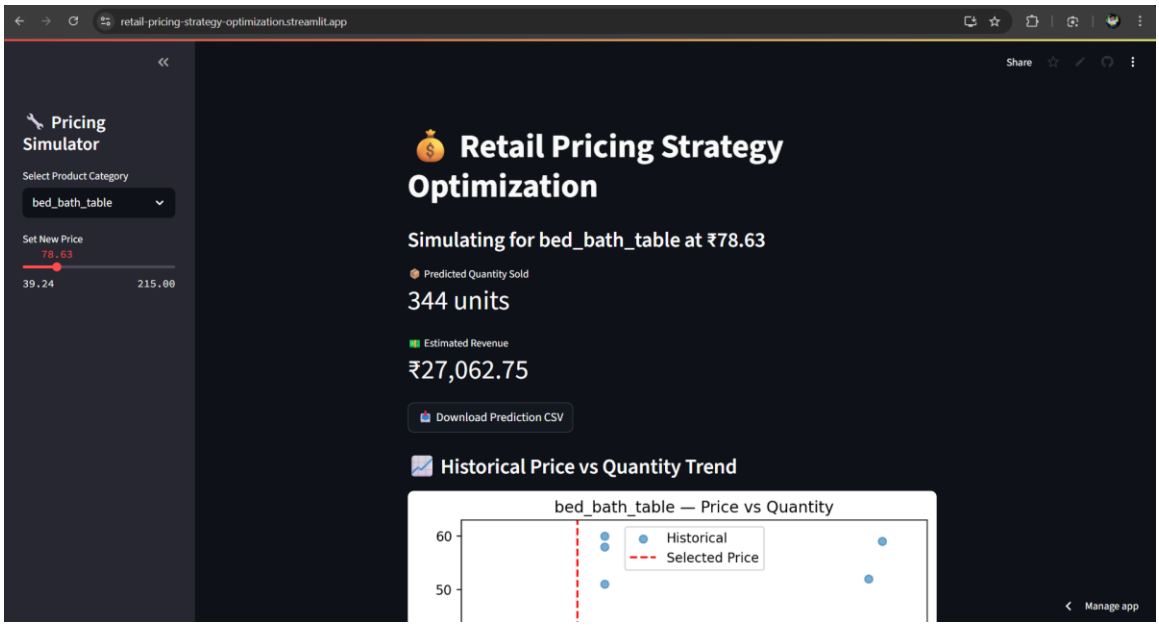
- Kaggle pricing datasets

- Industry blogs on retail optimization

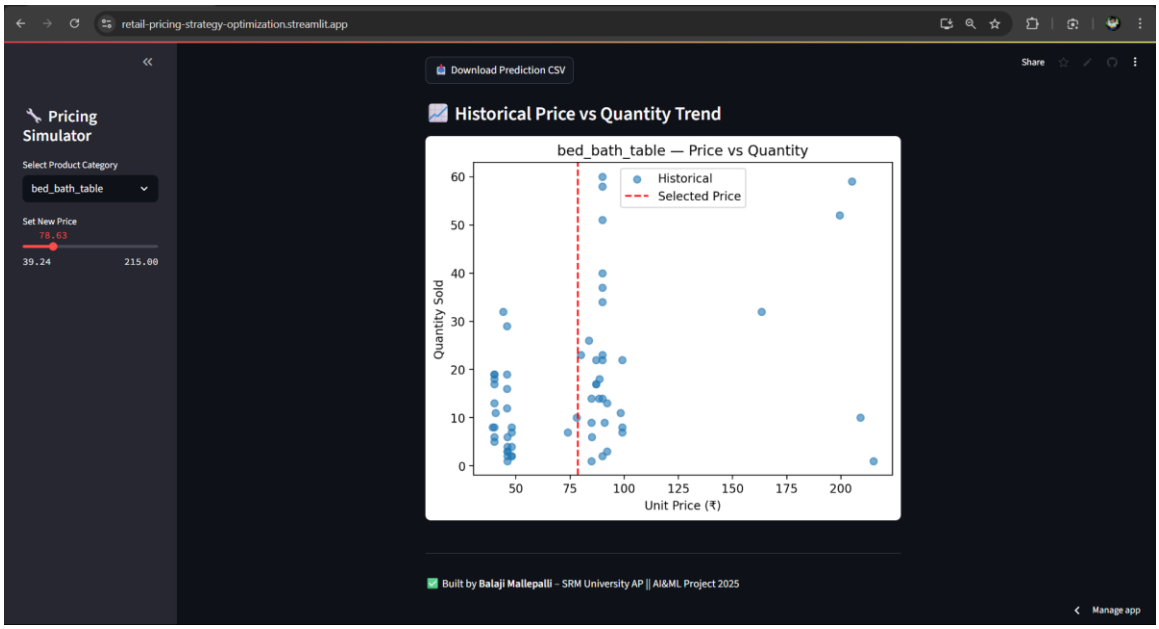
12. Appendix

- Streamlit App Link : https://retail-pricing-strategy-optimization.streamlit.app/

- Github Repo Link : https://github.com/balaji-mallepalli/Retail-Pricing-Strategy-Optimization



- Price vs Quantity Plot



13. Submitted By

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