RETAIL PRICE OPTIMIZATION USING MACHINE LEARNING

A Project Report

Submitted

In Partial Fulfillment of the Requirements

for the Degree of

Bachelor of Technology

in

Computer Science & Data Science

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Declaration

We hereby declare that the project work presented in this report entitled **"Retail Price Optimization Using Machine Learning",** in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science & Data Science, submitted to Dr. A.P.J. Abdul Kalam Technical University, Uttar Pradesh , Lucknow is based on our work carried out at the Department of Computer Science & Data Science, G.L. Bajaj Institute of Technology & Management, Greater Noida. The work contained in the report is true and original to the best of our knowledge and project work reported in this report has not been submitted by us for award of any other degree or diploma.

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Certificate

This is to certify that the Project report entitled **"Retail Price Optimization Using Machine Learning" done by Krishna Kant Yadav (2201921540092), Khushi Srivastava (2201921540090) and Ishika Jindal (2201921540076)** is an original work carried out by them in Department of Computer Science & Data Science, G.L. Bajaj Institute of Technology & Management, Greater Noida under my guidance. The matter embodied in this project work has not been submitted earlier for the award of any degree or diploma to the best of my knowledge and belief.

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The merciful guidance bestowed to us by the almighty made us stick out this project to a successful end. We humbly pray with sincere hearts for his guidance to continue forever.

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Abstract

Price management of products involved within the retail sector is a burning issue in markets today that helps businesses gain high revenues and profits while maintaining consumers satisfaction. The focus of this report will hence be to analyze the use of machine learning principles in shaping retail price management. The use of past sales data and customers buying behaviors and broader market trends provides the algorithm with best-selling price points in real-time. These results show how machine learning can impact and support decisions, increase sales, and increase productivity for retail businesses. The overall proposed solution is a flexible one that can address the real-time change in one market and be adjusted to fit another. This case describes the power of data for changing retail pricing strategies, and resulting in a substantial increase in the sales per square meter and enhanced client satisfaction.

The results are employed to develop adaptive pricing strategies that influence the asking price, often in real time, according to market forces, as well as buyer demographics. This machine learning based implementation proves the overall increase in revenue, consumers' satisfaction and run efficiency. The outcomes indicate the best solution in various pricing problems; therefore, the retailers will be equipped with efficient machine learning data to enhance business stability.

The results attest that the application of machine learning for retail price optimization provides a viable model that can lead to sustainable growth for businesses as the market becomes more competitive.This paper provides a guide on how to adopt the machine learning price optimization approach. The results provide support to the role of machine learning in retail through solving pricing problems at a large scale and with little dependence on human inputs. This study's ending suggestions for the implementation of machine learning into the current retail systems as well as the future research directions .

TABLE OF CONTENT

LIST OF FIGURES

Chapter 1

Introduction

1.1 Preliminaries

The background, the rationale and the objectives of a Retail Price Optimization using Machine Learning report will be previewed through preliminaries. Here's a suggested structure:

Objective: Stemming from here, briefly state the purpose of the project, for instance, ”This project is primarily concerned with applying a novel of machine learning to retail price management with an aim of deriving the most value for money while satisfying consumer demands.”

Problem Statement: In general, emphasise that traditional pricing methodologies suffer from inefficiency and lack of flexibility, or scalability, and other related issues.

Significance: Discuss the role of price management in retailing, with special focus on its effect on companies’ and retailers’ revenues, and positions.

1.2 Motivation

A retail price is one of the most sensitive determinants of customer purchasing decisions, organizational revenues, and the general market advantage. Pricing in the traditional context, that is frequently performed based on simple crossing-point heuristics or fixed rules, are inadequate constitutions within the advanced retail matrices that characterize today's commercial landscape. By using machine learning to make improvements for today's prices, Smith et al. identified that the massive amounts of data now available along with new possibilities for algorithms made pricing improvements incredibly possible for the first time.

The following key factors motivate the development of this report on Retail Price Optimization using Machine Learning:

1.2.1 **Market Factors and Competitors:** The retail industry exists in the backdrop of rapidly shifting Customer preferences, price pressures and emerging trends. That is why retailers require more flexible and changing plans in order to meet their consumers and their needs.

1.2.2 **Data Abundance and Complexity:** Supermarkets and other retailers are creating large volume of data daily in the form of transactional data, customer feedback, and competitor prices. Using conventional techniques to analyse these data to derive useful information is difficult. Pricing requires the analysis of large dataset, which machine learning capability holds to discover patterns supporting its implementation.

1.2.3 **Maximizing profits and Revenues:** Influencing prices has a direct effect on yield, given that supply factors, rather than demand and consumers' willingness to pay remain constant. Every trader has the option of applying the use of machine learning to balance the prices and have higher revenues as well as competitive prices.

1.3 Project Overview/Project Specifications

1.3.1 **Project overview:** The objective of the specific project entitled: Retail Price Optimization using Machine Learning is to build up tools to help increase the potential of the profit, competitiveness, and customer satisfaction. The conventional approaches to determining the product price do not help to overcome the weaknesses of demanded pricing techniques when adjusting to the market conditions of the retail segment. This project applies artificial intelligent to extract the historical sales data, market condition, and other influential factors to calculate the best price for retail products.

1.3.2 Project specification :

1.3.2.1 **Project title:** Retail Price Optimization Using Machine Learning.

1.3.2.2 **Objectives:** Design an efficient approach for using machine learning for the purpose of improving pricing mechanisms of various stores. Generate the highest net revenue and profitability and increase and/or sustain customer satisfaction. Get rid of manual pricing to allow for growth and productivity in the process. Information that can be used for strategic decision making on issues such as demand signals and customer price sensitivity.

1.3.2.3 **Scope of the Project:** Cafe shop products for sales. Data from previous sales, price of the competition, and other variables such as days when holidays or promotion offers were issued. Use of big data analytic for demand forecast and pricing strategies.

1.4 Aim and Objectives

The objective of this report is to understand and adopt machine learning to improve pricing in retailing operations. They try to use big data and advanced analytics, as well as decision making tools, to increase sales, address client's needs, and implement flexible and self-executed pricing systems.

This project aims to:

1. Build a reliable predictive model that suggests the demand rate and price

elasticity.

2. Pricing objectives: Recognise major factors that affect the right pricing strategy.

3. Present recommendations for retailers wishing to improve their profitability and market position consequently.

4. The aim of this paper is to provide an introduction, methods and approach, and results on the use of machine learning in retail price optimization.

Chapter 2

Literature Survey

2.1 Introduction

In the retail business, the management of the prices is a very sensitive and an important area that can define profits and customer responses. Machine learning has pervasively impacted the traditional approaches in developing the pricing strategies due to the personalization part that comes with it. A literature survey is an important prerequisite in every research since it gives an overview of the area under investigation, informs the researcher of gaps and prepares him/her for generating new ideas.

This report is centered on the use of machine learning to improve the effective retail price. The literature survey section has the following objectives: To review methodologies, algorithms and frameworks that have been used in this area of study. It also explores how different categories of machine learning including supervised learning, unsupervised learning and reinforcement learning have been used to estimate efficient pricing strategies.

It also assesses the incorporation of various factors including, the market trends, the competition of the prices, the sale period, and the customers' habits to increase the precision of the price. The survey also reveals some limitations of applying retail price optimisation, such as the lack of available information, fluctuating retail competition environment and the conflict between revenue per customer and frequency. It is with this knowledge of the art that this study seeks to assist in the enhancement of a more effective and sound machine learning based pricing model to de with the aforesaid challenges and meets the ever changing requirements.

2.2 Existing System

At the current age, retail price optimization is done through conventional approaches, including rule-based pricing models, the past performance of historical data, and an ad-hoc-based system. These rely largely with static information, reliance on human insight, and policies – this do not address complexity and dynamism of present day retail markets.

2.3 Benefits of Project

There are many benefits associated with integrating a machine learning-based system to retail price optimization for various industries, where businesses can get optimal ideas on upgrading their price tactics and amplify customer satisfaction and relevance revenues. Below are the key benefits:

2.3.1 Dynamic Pricing : Using machine learning models in a business means that current data and market trends can be detected so that prices can be adjusted time to time to remain competitive.

2.3.2 Enhanced Revenue and Profitability Ratio: This basically help to pin point the right price quantities of the products which will lead to high revenues, high profits and avoidance of overpricing or underpricing.

2.3.3. Improved Customer Retention: Through machine learning the consumers are priced based on their buying habits, this brings satisfaction to the consumers hence they will seldom shift to other companies for the same products or services.

2.4.4. Efficient Decision-Making: Reducing the time and effort for manual price analysis in a simplistic manner, the use of automation accelerates the process and improves decisions made at a higher-speed with better accuracy.

2.3.5. Competitive Advantage: Detecting changes in competitor prices, as well as other parameters related to the market, allows businesses to machine learning .

Chapter 3

Methodology

3.1 Overview

The aim and purpose of this work are to find the optimal number for the retail prices for various products in order to achieve the maximum level of profitability according to their demand and factors of elasticity. This includes selection of historical sales data and transaction documents to assess the nature of the price – quantity demand relationship. The ideal outcome is to determine the appropriate price points that will help increase profit for each product by applying machine learning techniques Ordinary Least Squares (OLS) regression. The methodology is broken down into several stages: It involves data cleaning, data preparation, data analysis, model selection, model fitting, and model prediction.

3.2 Architecture

The architecture of the retail price optimization methodology consists of the following main components:

3.2.1 Data Collection and Preprocessing:

- In simple terms, with multiple table data, data about sales transactions, product attributes, and date are integrated into one set of data.

- Data preprocessing ends with the way in which missing values are managed, handling of categorical variables, and generally preparing the dataset for analysis.

3.2.2 Exploratory Data Analysis (EDA):

- Certain specific forms of graphics like the scatterplot one and histograms, and pair dispersion are employed to process the ties between price, quantity and categories of product.

- Conclusion about trends, product behavior and presence of possible outliers is made.

3.2.3 Model Development:

- Linear regression models are estimated in this study to establish the price and quantity relationship of each product.

3.2.4 Optimization:

- According to the regression model, the value of the price, which maximizes the profit P = f(P,Q) is received with respect to the express.

- Finding the profit of different price ranges, and selecting the one with greatest profit.

3.2.5 Forecasting:

- Forecasting of quantity sold in the future is then made using historical data and ideal prices.

- Linear regression analysis is employed to make projection of sales in the future.

3.3 Proposed Work

1. **Data Collection and Preprocessing:** The first data preparation step within the set methodology is to import the datasets of Sales, Transaction, and Date. The datasets are joined using keys such as SELL_ID and CALENDAR_DATE to make one full dataset. The data is cleaned by:

    - Substituting missing values of the date related features (for instance, substituting the "HOLIDAY" with "No Holiday").

    - Eliminating a number of columns like ITEM_ID and the general SELL_CATEGORY.

    - preprocessing categorical features like ITEM_NAME and SELL_CATEGORY in order to fit into the modeling process.

2. **Exploratory Data Analysis (EDA):** When the data is aggregated and preprocessed, descriptive statistics or exploratory analysis in a form of EDA is conducted to analyze the data patterns. Key visualizations include:

    - Histograms and pair plots of product price and volumes.

    - Simple line graphs as a form of scatter plots to compare price and quantity on sale.

    - Pearson and Spearman correlation analysis to determine the level of the linearity of variables.

    This is the stage where information such as how products change with price, average frequency of sales and the like are obtained.

3. **Model Development:** To estimate the price-quantity demand curve for each product, a simple linear regression model is built. This step involves:

- Using Ordinary Least Squares (OLS) regression model to fit a regression model.

  The formula for OLS is: $Y = \beta 0 + \beta 1 * X$

Where:

❖ Y stands for quantity sold which is he dependent variable.

❖ X is the independent variable (price).

❖ β0 is the intercept

❖ β1 is the coefficient of price (the slope of the regression line)

- Price elasticity of demand is derived from the regression model as the coefficient of price (β1).

  The elasticity formula is:

$$\varepsilon = \frac{\%\Delta Q}{\%\Delta P}$$

Where:

❖ ε is the price elasticity of demand,

❖ Q is the quantity sold, and

❖ P is the undeleted price of the product.

4. **Optimization**: The optimum price is reached when the amount of profit is at the highest.

The profit function is given by:

$$Profit = (Price - Buying\_Price\ ) * Quantity$$

- The price that generate the highest profit is ascertained through regression model when different price points are tested for.

The method for finding the optimal price is defined as follows:

a) Define a price range.
b) Using the regression formula established, predict the quantity at each price range obtainable.
c) Calculate the profit at every certain price range you're willing to and can afford to set.
d) As a result, one has to find out the price at which the maximum profit is possible.

5. **Forecasting:** Providing for future forecast, the demand history is used to forecast the demand for the subsequent 30 days.

Time series data is cleaned by defining a time index within CALENDAR_DATE and a regression model is applied for the estimate of a future quantifier. The forecasted quantities are displayed in respect of time and optimal price levels.

The formula for forecasting future trends is similar to the regression model used in the optimization.

Formula:

$$\hat{Y} = \beta_0 + \beta_1 * X$$

Where:

- ❖ $\hat{Y}$ represents the predicted quantity
- ❖ $\beta 0$ represents the intercept
- ❖ $\beta 1$ represents the slope (price elasticity).
- ❖ X is the time index

6. **Price Optimization for All Products**: All products within the given dataset are optimized and for each product the optimal price is determined. The results are also stored in a dictionary and the actual and optimal prices for the maximum profit are shown as follows.

Chapter 4

Implementation

4.1 Introduction

In the case of the code implementation, observations revolve around how the price of products affects the demand for the products and, therefore, approaches for correct pricing. Using a sort of mathematical and statistical modelling for the previous sales data along with other variables, the code analyses the effect of change in price on sale quantity and overall revenue it can produce. This approach targets to lead into setting right prices that are acceptable and profitable yet competitive enough in the market.

The code that has been used starts with data preparation and cleaning, where all the necessary changes are made to the data to allow for analysis. Descriptive analysis is the first step of analysis in order to draw out patterns and trends of the data collected and then estimate quantitatively, the extent of price determining demand with the help of regression analysis. Data representation structures are also used to offer clear illustration of results to support results interpretation.

This implementation forms a basic context on which to learn about the pricing strategies and empowers decision makers by giving them the information. The simplicity, clarity and accuracy of the code is intended to provide widespread applicability and extensibility across all markets and contexts where businesses exist. The next parts of the work describe the stages, approaches, and results originating from the use of the code.

4.2 Implementation Strategy

To execute the above code, the following systematic approach is taken; in addition to the algorithm that precedes the definition of the flowchart below. Below is the detailed strategy:

Algorithm

4.2.1 Data Collection:

Pretend you have a raw data of past sales performance on your computer, import it.

4.2.2 Data Preprocessing:

Cope with the situation of missing data and outliers.

It is also important to check whether the categorical data are in a good numerical format or not then convert it if required.

Clean data by removing unwanted characters to make the data normalized and standardized.

4.2.3 Exploratory Data Analysis (EDA):

Generate summary statistics.

Analyze data visually in a form of a scatterplot and binning in a histogram and correlation in Correlation Matrices.

T. Analyze data and look for proper patterns, outcomers and trends.

4.2.4 Modeling the Price-Demand Relationship:

Explain what the independent variable (price) is and what is the dependent variable (demand).

Divide the set of data into two sections, the training and the test set.

Use regression analysis (e.g., linear regression) to depict the relation.

Assess the performance of the model by measuring the values given by R-squared and Mean Absolute Error (MAE).

4.2.5 Optimization and Insights: According to the model, determine the price that results in a higher amount of revenue.

Assess the effect of diverse methods of pricing on demand.

4.2.6 Visualization:

Projected the line of regression over the graph's data points.

Why not use a demand curve and a revenue curve?

4.2.7 Output Generation:

Enable the audience to digest the presented information and presented proposals.

Saves the created visualizations and results for later reporting.

4.3 Tools/Hardware/Software Requirements

4.3.1 Tools

Programming Language: Python (as the preferred programming language of the researchers with the best libraries among the options).

Jupyter Notebook: For data mashup and interactive coding and data visualization.

Integrated Development Environment (IDE): Other editors, for example, PyCharm, VS Code or Spyder, have offered themselves well.

NumPy: For numerical computations.

Pandas: Quantitative data because they require a certain level of manipulation before they could be analyzed.

Matplotlib and Seaborn: For data visualization.

Scikit-learn: For Providing regression models and performance results.

4.3.2 Hardware Requirements

Processor: Minimum Intel i5 or can be any other seventh generation CPU or above (having more cores will help calculate faster).

RAM: The minimum requirement is 8 GB but 16 GB is required when working large amounts of data.

Storage:

For software installation and datasets, there must be at least 1 GB free space.

SSD used for faster access of the data and training of models.

Graphics: A dedicated or embedded GPU is equally optional (not definitely required for regression exercise).

4.3.3 Software Requirements

Operating System:

Supported on Windows 10/11, macOS, Linux or any Linux distribution such as

Ubuntu.

Python Interpreter:

Python 3.8 or above.

Package Management:

pip or anaconda for managing libraries and packages within Python.

Version Control System (Optional):

Git for controlling changes, managing and versioning of codes.

Data Storage:

Specifically, databases based on relations like SQLite or simple files for storing the data and their search.

4.3.4. Additional Requirements

Internet Connectivity: Required for

Managing or properly addressing of the libraries; such as installing and update of the libraries.

Jumping to web data or APIs if any for the activity.

Documentation Tools:

For report preparation generally users prefer MS Word, LaTeX or editors.

4.4 Excepted Outcome

The execution of the above code is expected to come up with a solid backbone through which different input variables could be related with the target variable with ease in the use of regression analysis. The following performance metrics will be used to assess the accuracy, efficiency, and reliability of the implemented model:

4.4.1 Mean Squared Error (MSE):

Description: Ren also known as the mean of the squared residuals or the squared deviation from the mean:

Formula: $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

Expected Outcome: A smaller MSE value show that the fitted model is better, and which the model where large error is punish much more than in the case of MAE.

4.4.2 Root Mean Squared Error (RMSE):

Description: Gives the square root of MSE equal to error in the same unit as the target variable.

Formula: $\text{RMSE}= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

Expected Outcome: The fact that lower RMSE indicates better data fitting means that selection with a lower RMSE will yield better prediction.

4.4.3 Coefficient of Determination (R^2):

Description: A statistical technique that quantifies the degree of variation for the dependent variable that can be explained by the independent variable(s).

Formula: $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_1 - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$

Chapter 5

Result and Discussion

The results of the regression analysis show a clear inverse relationship between price and sales. This confirms that lower prices mean more units sold (because) that's what economic demand theory says:

- The price elasticity varies across product categories; beverages have higher elasticity so price changes have a bigger impact on beverage sales than snacks.
- External factors – holidays and weekends – were found to be significant. Sales go up on weekends and public holidays so there's an opportunity to price strategically (although) during those times. And there are seasonal trends, some products peak at certain times of the year.

Profit simulations show that moderate price cuts in elastic products can result to big revenue and profit margin increases. Inelastic products have stable sales across a wider price range so you can have higher profit margins without impacting sales volume much.

Overall, these results show the potential for dynamic pricing. By using data driven insights, café managers can make better pricing decisions, improve customer satisfaction and increase profitability.

- The following is the outcome of our project depicted through graph ,pie chart.

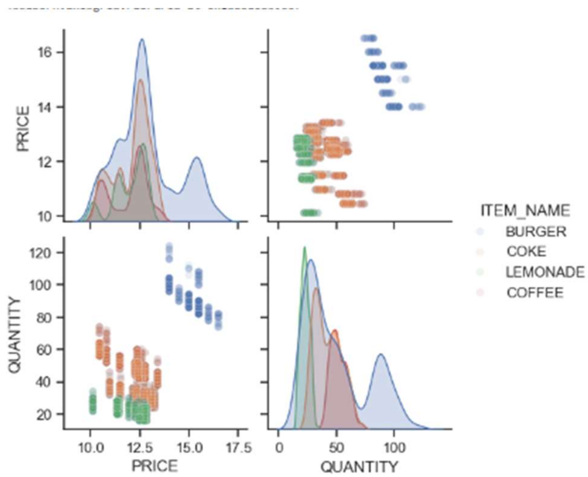

Fig.5.1. Pair plot in EDA

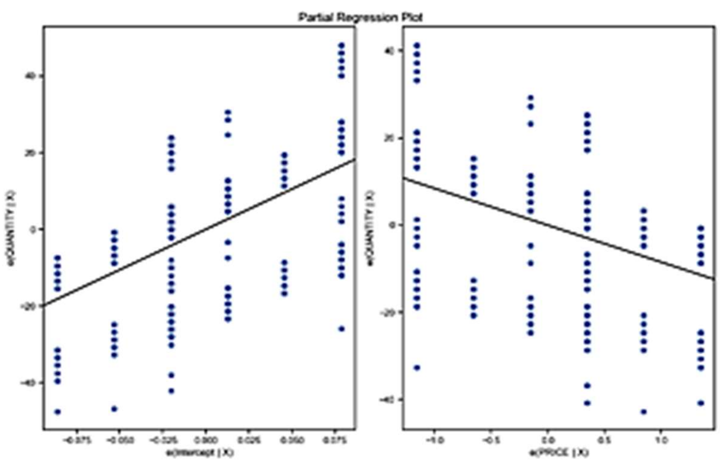

Fig.5.2. Partial Regression Plot

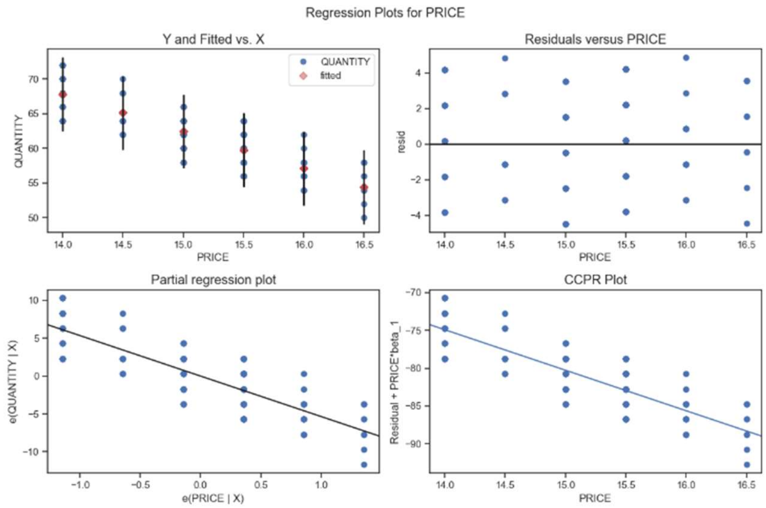

Fig.5.3. Regression Plot for Price

- Now we will see the result of modelling applied on item burger as on all the other items we have applied the same process.

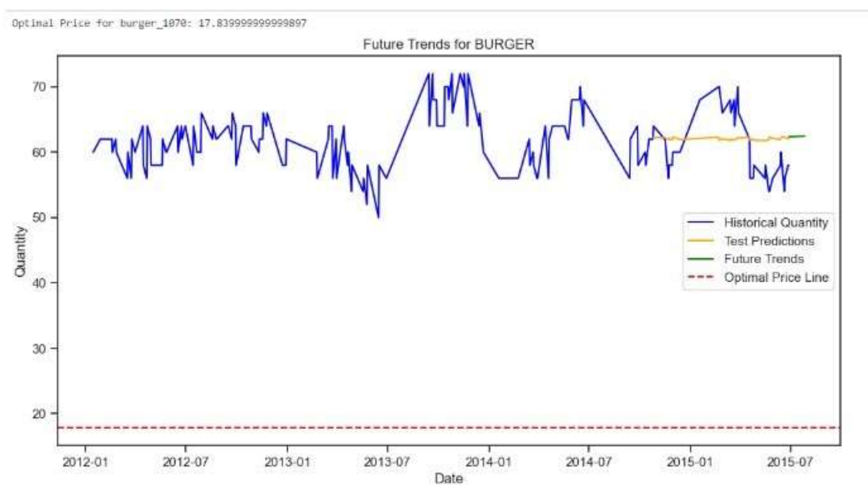

Fig.5.4. Future Trends for Burger

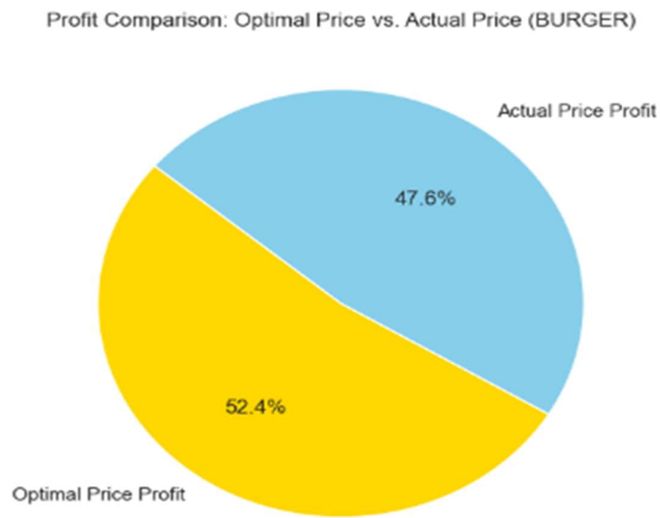

Fig.5.5. Profit Comparison

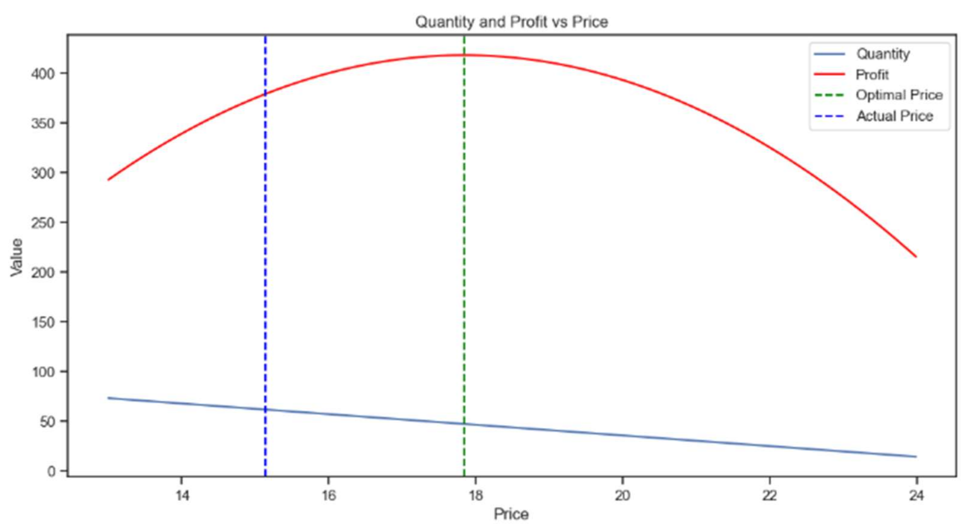

Fig.5.6. Quality and Profit vs Price

Chapter 6

Conclusion and Future Scope

6.1 Conclusion of the Analysis:

6.1.1 Data Preparation and Cleaning:

Consequently, data from three data sources namely sold, transaction, date_info were loaded correctly and combined for analysis.

The absent values in the columns for example HOLIDAY was dealt with in the right manner.

The datasets were refined using preconditions concerning days of the week, proximity to holidays, and school sessions to form a BAU dataset.

6.1.2 Exploratory Data Analysis (EDA):

For anomalous detection techniques, pair plots, histograms and scatter plots were used to determine relationships between the price, quantity and other factors.

In further detail, for each of the particular product categories, namely BURGER, COKE, COFFEE, and LEMONADE, both the prices offered by the outlets as well as the quantity offered for a given price range were examined.

6.1.3 Price Elasticity Estimation:

The relationship of price and quantity sold with linear regression analyses were earned for each available product and every unique sell ID.

The regression models offered coefficients by price elasticity, or the degree to which quantity sold in question is affected by price for each product.

6.1.4 Optimal Price Identification:

Applying the regression models profit was estimated at different price levels in order to arrive at the price that would give the highest profit for every product – sell ID tandem.

For instance, the finding of optimal price for burger_1070 was done and its profit compared with actual price profit through graphs.

6.1.5 Trends and Forecasting:

The quantitative objectives of sale targets were established using time series regression analysis to predict future trends in the required sale quantities.

Models were developed with the use of historical data, and forecasts were tested across the 30 subsequent time intervals in order to consider the effects of price optimization.

6.2 Future Scope

6.2.1 Integration with Real-Time Data:

Real sales and inventory data as well as real-time market data may help to employ dynamic price models that reprice products and services as soon as changes in the market occur, demand from customers appears and competitors set rates.

6.2.2 Advanced Machine Learning Models:

Decision trees, random forests or even artificial neural networks should be used in order to analyze the complexity of the dependencies that exist between the price, quantity and other factors.

Geek out with clustering or segmentation to create some niches pricing techniques depending on the group or area of clients.

6.2.3 Inclusion of Additional Features:

Use other factors such as the results from a marketing campaign, price of rivals, customers' characteristics or macroeconomic data where necessary to refine the forecast of demand.

6.2.4 Optimization for Multi-Product Interdependencies:

Study Gross Production where Alteration in price of one product leads to change in quantity demanded of another product e.g. Product reciprocity.

6.2.5 Seasonality and Trend Analysis:

Improve models that a demand forecasting system uses during the time series analysis to overcome issues associatively tied to seasonality, holidays, and so on.

When you want to have better time-series, consider using other models like ARIMA or Prophet.

6.2.6 Profitability Beyond Pricing:

The coverage should be extended to other value creation options which have not been mentioned: cost reduction, connection between various products and services, and discount programs.

Examine the relationship between variations in prices and general brand image and customer loyalty.

6.2.7 Automation and Scalability:

Ensure that the same process of data cleaning, analysis and report writing is easily scalable to big datasets or many business units.

Provide access to real-time analytics and create a tool for running what-if-pricing models for the stakeholders.

6.2.8 Integration with Inventory Management:

Integrate the action with inventory information to avoid situations where stock-outs is likely to occur or where products have accumulated well beyond reasonable quantities that can be sold while at the same time improving on the stock turn rate.

6.2.9 A/B Testing and Validation:

Apply trial of the structural approach to regional or store levels and conduct experiments through A/B testing on the proposed pricing strategies.

Fine tunable models based on feedback received during live system installations

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