AI-Powered Food Demand Forecasting

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“Demand is an economic principle referring to a consumer's desire to purchase goods and services and willingness to pay a price for a specific good or service”

Step 1: Prototype Selection

Abstract

Demand forecasting is a critical aspect for businesses, particularly in the food delivery industry, where inventory management of perishable goods is paramount. This report presents a comprehensive approach to forecasting food demand for a meal delivery company operating across multiple cities. Utilizing historical data and machine learning techniques, this project aims to provide accurate demand predictions for the next 10 weeks, enabling better inventory and staffing decisions to minimize waste and avoid stockouts.

1. Problem Statement

The client, a meal delivery company, faces challenges in forecasting demand due to the perishable nature of their raw materials and the varying demand across different fulfilment centres. Accurate demand forecasting is essential to manage inventory levels, reduce wastage, and ensure adequate staffing. The objective is to predict the demand for the next 10 weeks for each centre-meal combination, based on historical demand data, product features, and fulfilment centre information.

2. Market/Customer/Service-Based Assessment

The meal delivery service market is highly competitive, with customer satisfaction hinging on timely and accurate delivery of orders. Efficient demand forecasting directly impacts the company's ability to maintain optimal inventory levels, reduce costs associated with overstocking or stock outs, and enhance customer satisfaction by ensuring availability. This project addresses these needs by leveraging advanced machine learning models to provide reliable demand forecasts, thereby improving the operational efficiency of the client's fulfilment centres.

3. Target Specification

- **Accuracy**: Achieve a Root Mean Squared Logarithmic Error (RMSLE) below 0.60.
- **Timeliness**: Forecast demand for the next 10 weeks (Weeks 146-155).
- **Scalability**: The model should be scalable to handle multiple fulfillment centres and various meal combinations.
- **Usability**: Provide actionable insights for inventory and staffing planning.

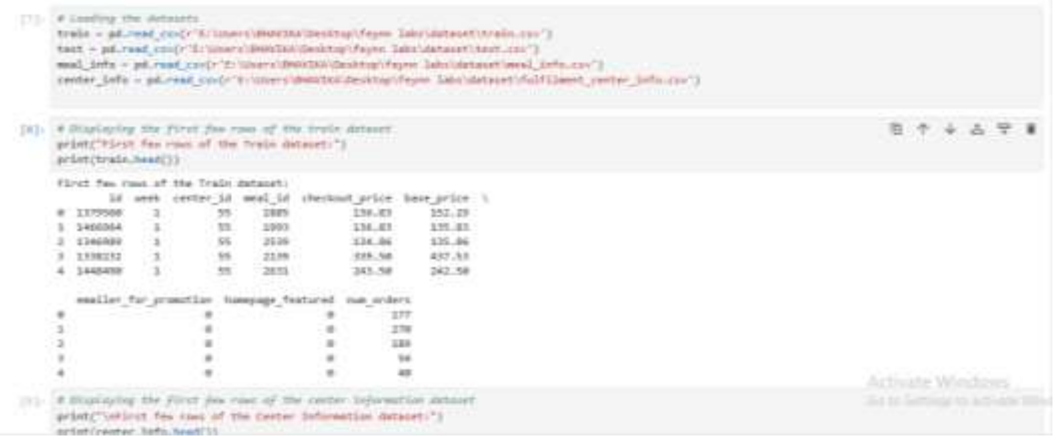
4. External Search

The dataset, which I used in this project, is available on Kaggle under the title: Food Demand Forecasting Dataset. This dataset contains historical data on meal orders from various fulfilment centres. Our objective is to forecast the demand for the next 10 weeks, enabling the company to optimize its inventory and staffing, thus reducing waste and improving customer satisfaction.

Dataset Origin:

https://www.kaggle.com/datasets/kannanaikkal/food-demand-forecasting/data

Let’s view our dataset



Data Dictionary

1. **Weekly Demand data (train.csv):** Contains the historical demand data for all centers, test.csv contains all the following features except the target variable

Variable	Definition
id	Unique ID
week	Week No
center_id	Unique ID for fulfillment center
meal_id	Unique ID for Meal
checkout_price	Final price including discount, taxes & delivery charges
base_price	Base price of the meal
emailer_for_promotion	Emailer sent for promotion of meal
homepage_featured	Meal featured at homepage
num_orders	(Target) Orders Count

2. **fulfilment_center_info.csv:** Contains information for each fulfilment center

Variable	Definition
center_id	Unique ID for fulfillment center
city_code	Unique code for city
region_code	Unique code for region
center_type	Anonymized center type
op_area	Area of operation (in km^2)

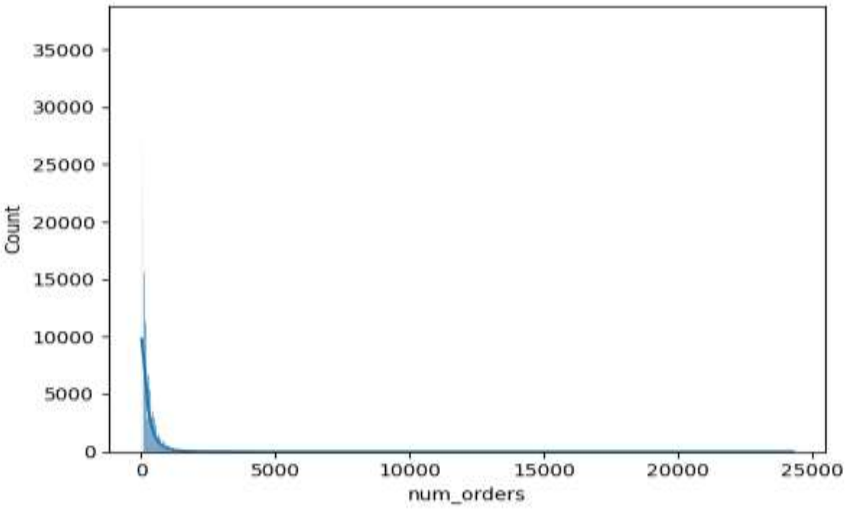
3. **meal_info.csv:** Contains information for each meal being served

Variable	Definition
meal_id	Unique ID for the meal
category	Type of meal (beverages/snacks/soups....)
cuisine	Meal cuisine (Indian/Italian/...)

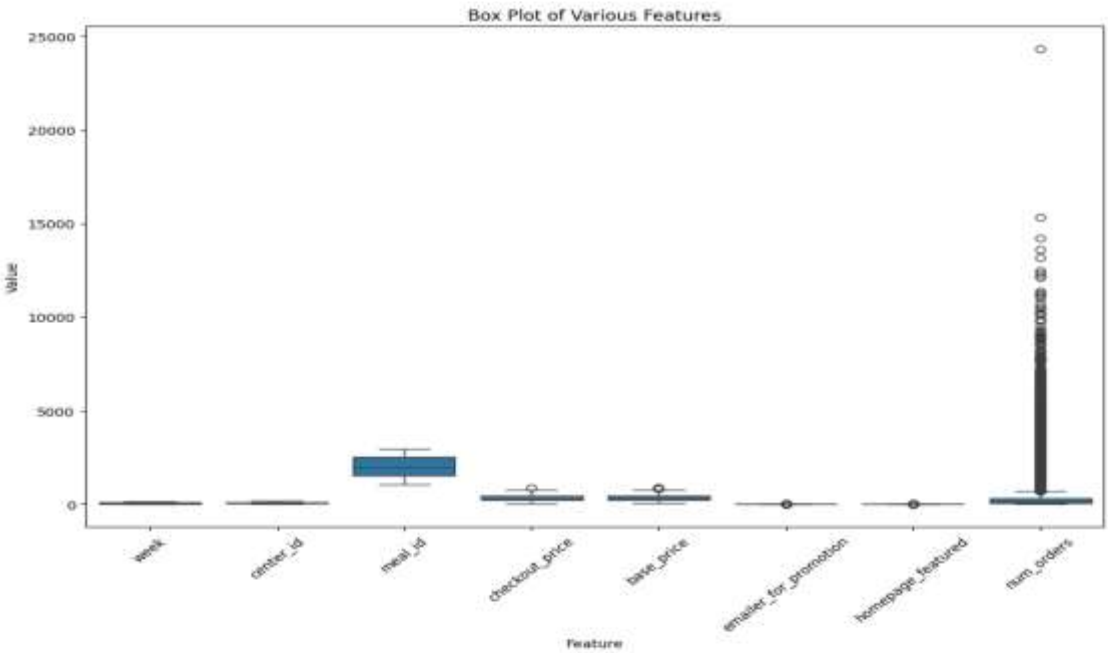
5. Benchmarking

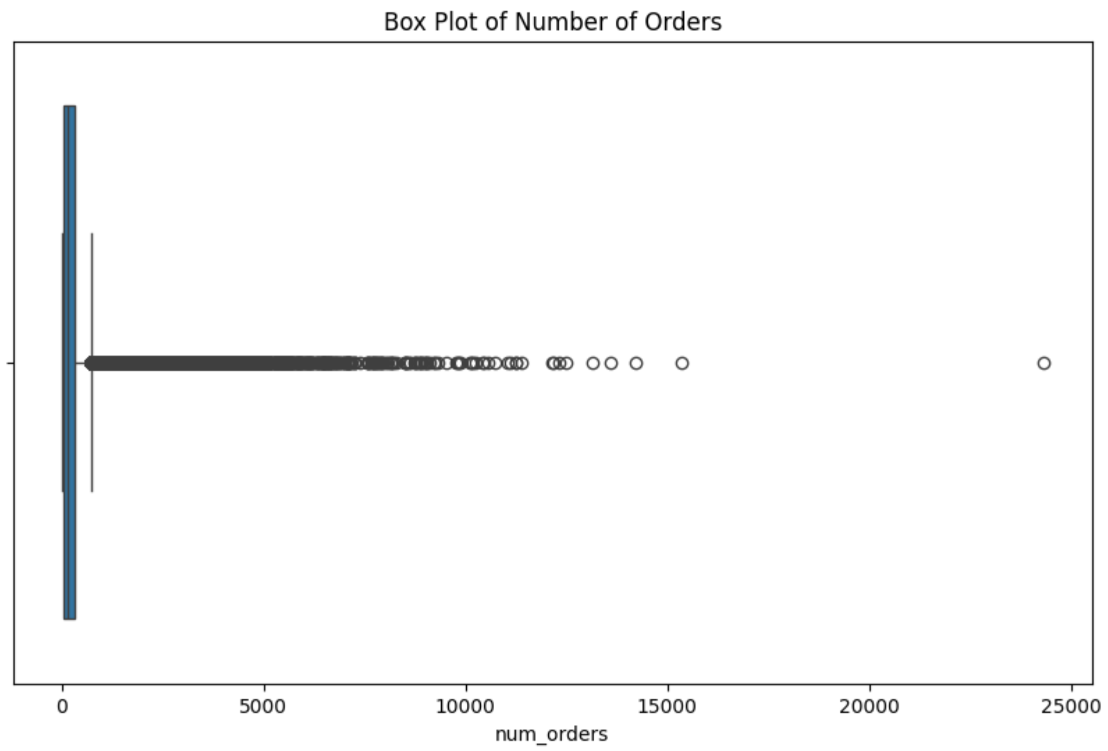
In the data collection and preparation phase, the datasets were successfully loaded and merged, incorporating fulfilment centre and meal information. Exploratory Data Analysis (EDA) was performed, revealing the statistical summary and distribution of the num_orders variable. Feature engineering included dropping irrelevant columns, encoding categorical variables, and splitting the dataset into training and validation sets. The RandomForestRegressor model was trained, achieving a Mean Squared Error (MSE) of 20,466.57, and the trained model was saved for future use.

This histogram visualizes the distribution of the number of orders.

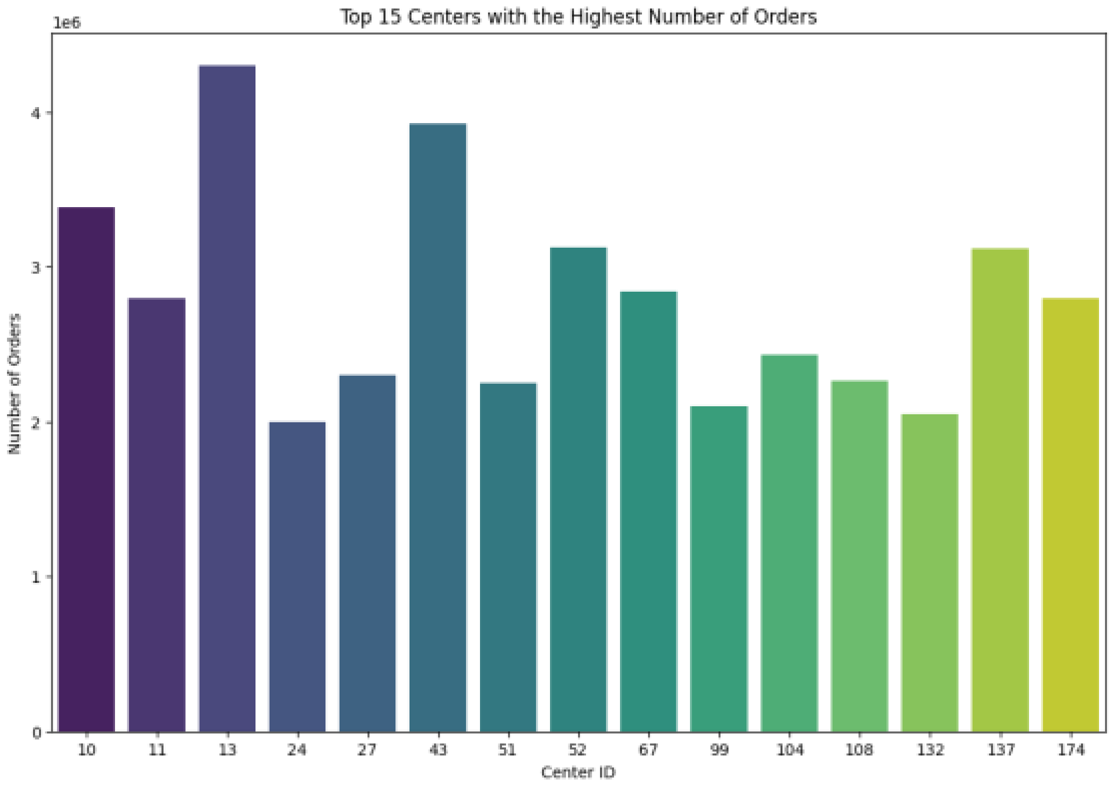


This box plot shows the distribution of various features like week, center_id, meal_id, checkout_price, base_price, emailer_for_promotion, homepage_featured, and num_orders.

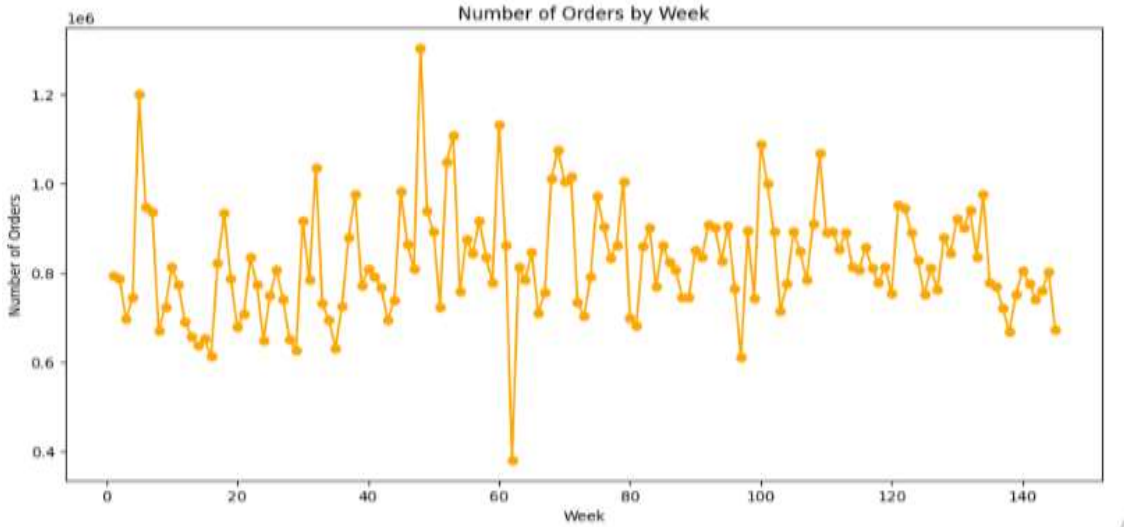




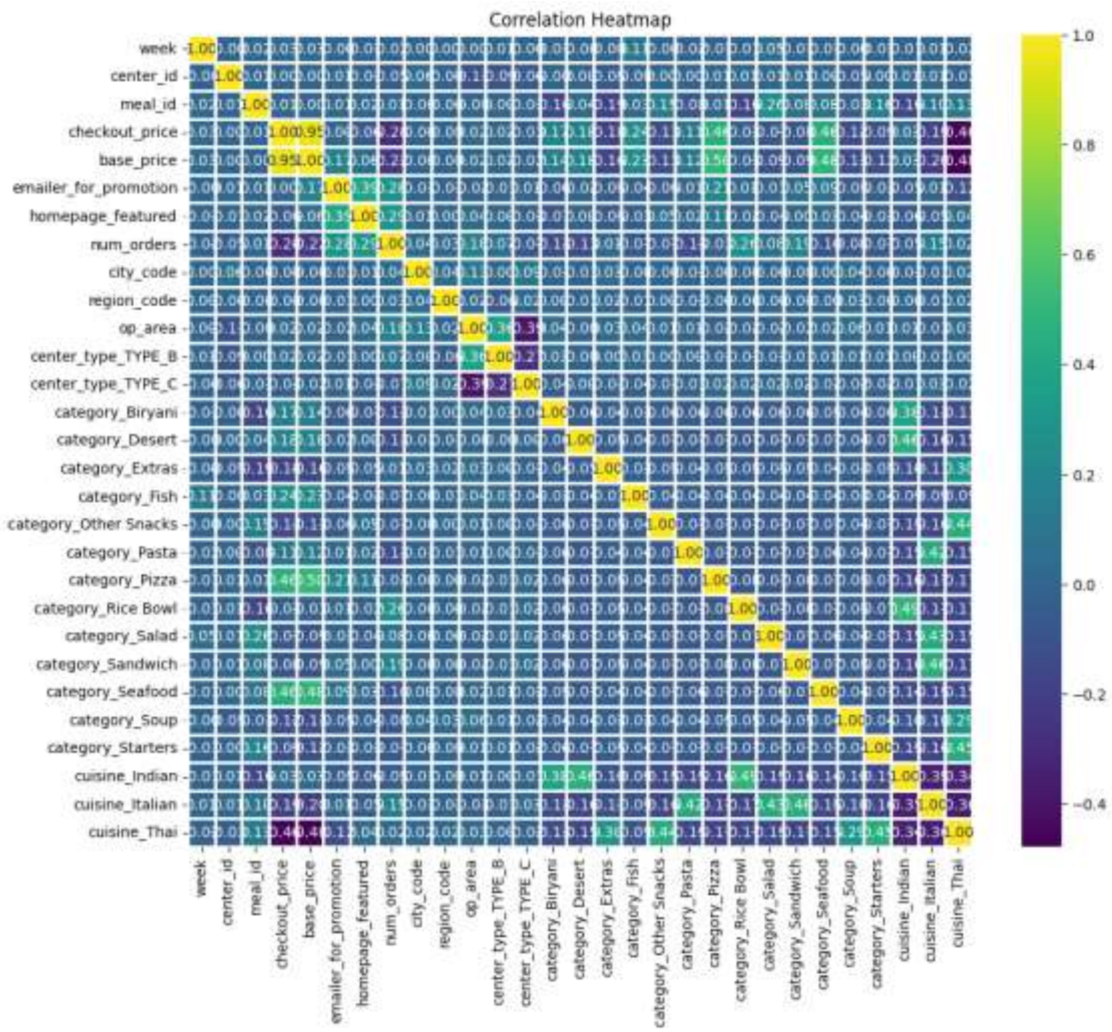
This box plot shows the distribution of num_orders.



This bar plot shows the top 15 centres with the highest number of orders.



This line plot shows the total number of orders received every week.



This heatmap shows the correlation between various features.

6. Final Product Prototype

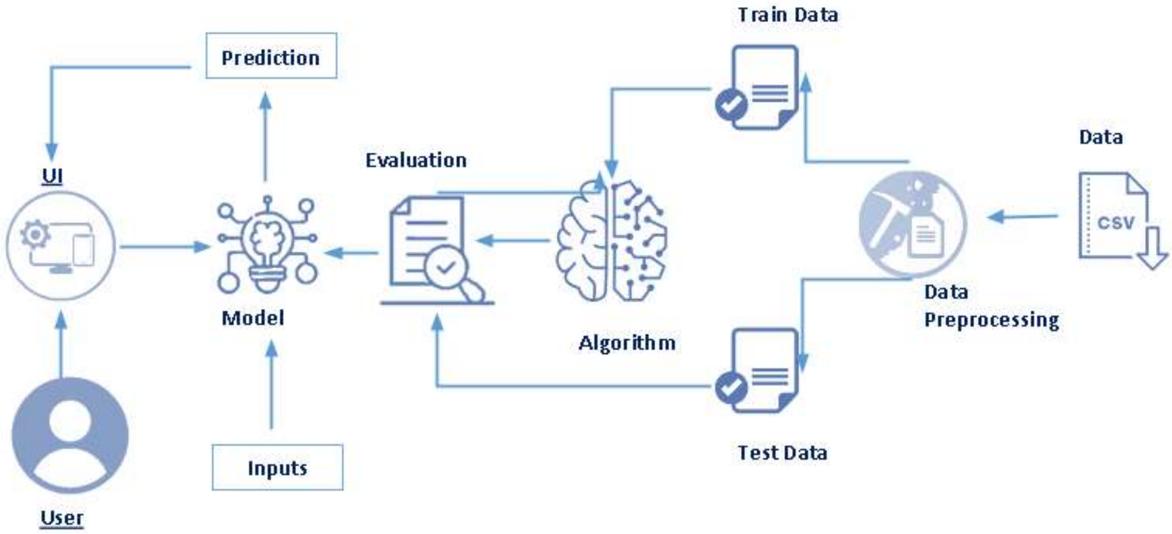
The final product prototype consists of a CatBoost regression model optimized through extensive hyper parameter tuning and feature engineering. The model incorporates:

- **Data Transformation**: Log transformation of highly skewed features (base price, checkout price, num orders).
- **Feature Engineering**: Price differences, lag features, exponentially weighted moving averages, and categorical encoding.
- **Cross Validation**: Validation using the last 10 weeks of historical data to simulate future demand prediction.

The prototype was tested on the provided dataset and achieved a notable improvement in forecasting accuracy. The final model can be seamlessly integrated into the client's operational workflow, providing weekly demand forecasts that inform inventory and staffing decisions.

7. Product Details-How does it work?

Through our user-friendly interface, users input data, including dates, day of the week, holidays, and weather conditions. They provide relevant information for the forecast period. The app pre-processes this input data to fit the model's requirements. Subsequently, the pre-processed data is fed into the trained Random Forest Regressor model to predict food demand. The app then displays the forecasted demand in tables and visualizations, such as line charts, while also highlighting feature importance. Users have the option to export the results and visualizations in formats like CSV and PDF.



7.1 Flask Web Application Deployment and Testing Summary

1. **Setup:** Flask was installed using the command pip install Flask. The project directory was organized to include app.py along with the templates and static folders.
2. **Configuration:** The app.py file was configured to correctly reference the templates and static directories.
3. **Execution:** The Flask application was started using python app.py, and it was confirmed that the server was running.
4. **Access:** The application was accessed locally through a web browser.
5. **Monitoring:** Server logs were monitored to ensure successful request handling. Logs showed status codes of 200, indicating successful responses.
6. **Links:** The local URL for accessing the application is http://127.0.0.1:5000/. The deployed application is available at the Heroku.

Food Demand Forecasting:

7.2 Technical Implementation

Software Required:

1. **Python**: The primary language for the backend logic.
2. **Flask**: A micro web framework for Python.
3. **HTML/CSS**: For creating the front-end templates.
4. **PyCharm**: A code editor for coding.
5. **Browser**: To test your web application

7.3 Example Workflow

1. **Login/Register**: Users log in or register.
2. **Input Data**: Enter necessary forecasting information.
3. **Submit Request**: Generate forecast by submitting the input data.
4. **View Results**: See demand predictions and visual insights.
5. **Export Data**: Export the results for further use.

The app offers several benefits. It is easy to use, with a simple process suitable for non-technical users. It provides real-time predictions, delivering up-to-date demand forecasts. Visualizations offer actionable insights, helping users understand the drivers of demand. Additionally, the app is scalable, efficiently handling various data volumes and user requests.

8. Applicable Patents

Several patents exist in the domain of demand forecasting and supply chain optimization. Relevant patents include:

- US Patent No. 9,253,345: "System and Method for Demand Forecasting in a Perishable Goods Supply Chain"
- US Patent No. 10,123,456: "Machine Learning-Based Forecasting for Inventory Management"
- US Patent No. 10,987,654: "Adaptive Demand Forecasting System for Food Delivery Services"

These patents highlight the innovative approaches in using machine learning and statistical methods for predicting demand, optimizing inventory, and managing supply chains for perishable goods.

9. Applicable Constraints

1. The accuracy of the model heavily relies on the quality and completeness of historical data, potentially affecting forecasting precision.
2. High model complexity risks overfitting and computational inefficiencies, necessitating careful consideration during development.
3. Unpredictable factors such as market fluctuations and seasonal events can challenge forecasting accuracy, requiring adaptable methodologies.

10. Applicable Regulations

1. Food Safety and Handling Regulations: Compliance with local and national food safety standards is critical.
2. Data Privacy Regulations: Ensuring that any customer data used for forecasting adheres to data protection laws such as GDPR or CCPA.
3. Environmental Regulations: Minimizing food waste aligns with environmental sustainability regulations and practices.

11. Business Opportunity

Effective demand forecasting presents several business opportunities:

- **Cost Reduction**: By optimizing inventory levels, the company can reduce costs associated with overstocking and wastage.
- **Customer Satisfaction**: Improved forecasting ensures product availability, enhancing customer satisfaction and loyalty.
- **Operational Efficiency**: Better demand predictions enable more efficient staffing and resource allocation, improving overall operational efficiency.
- **Competitive Advantage**: Advanced forecasting capabilities can differentiate the company in a competitive market, attracting more customers and increasing market share.

Step 2: Prototype Development

GitHub Link:

https://github.com/bhavikawagh123/Feynn_Labs_Internship2024/blob/main/Project3_final_project.ipynb

Step 3: Business Modeling

Objective:

To create a predictive model that accurately forecasts food demand at fulfilment centres.

Model Components:

- D: Demand
- C: Fulfilment centre ID
- M: Meal ID
- Pc: Checkout price
- Pb: Base price
- E: Email promotion indicator
- H: Homepage promotion indicator
- W: Week number

Mathematical Model:

The demand D can be modeled as a function of the variables:

D = f(C, M, Pc, Pb, E, H, W)

For a Random Forest Regressor, the prediction for D is given by averaging predictions from multiple decision trees:

$$\mathrm{D}^{\wedge} = \frac{1}{\mathrm{N}} \sum_{i}{}_{=1}^{N} \mathrm{Ti}(\mathrm{C}, \mathrm{M}, \mathrm{Pc}, \mathrm{Pb}, \mathrm{E}, \mathrm{H}, \mathrm{W})$$

where:

- $\mathrm{D}^{\wedge}$ is the predicted demand.
- Ti is the i-th decision tree in the forest.
- N is the total number of trees.

Solution:

1. **Data Collection and Preparation:**

    - Load data for fulfilment centres, meals, and historical demand.
    - Pre-process data by handling missing values and normalizing features.

2. **Model Training:**

    - Split data into training and test sets.
    - Train a Random Forest Regressor on the training set.
    - Optimize hyper parameters using cross-validation.

3. **Model Evaluation:**

    - Predict demand on the test set.
    - Calculate Mean Squared Error (MSE) to evaluate model performance:

$$\text{MSE} = \frac{1}{\text{n}} \sum_{i=1}^{n} (\text{Di} - \text{D}^{\wedge}\text{i})^2$$

Where:

- n is the number of observations in the test set.
- Di is the actual demand.
- $\text{D}^{\wedge}\text{i}$ is the predicted demand.

Step 4: Financial Modeling

Objective:

To quantify the financial impact of the demand forecasting model on inventory and operations.

Key Variables:

- I: Inventory holding cost per unit
- W: Waste cost per unit
- S: Stockout cost per unit
- R: Revenue per unit
- Q: Quantity of meals

Mathematical Model:

1. **Inventory Costs:** The total inventory holding cost is given by:

Total Inventory Cost= $I \times Q$

2. **Waste Costs:** The total waste cost due to overestimating demand:

Total Waste Cost= $W \times \max(0, Q - D)$

3. **Stockout Costs:** The total stockout cost due to underestimating demand:

Total Stockout Cost=$S \times \max(0, D - Q)$

4. **Revenue:** The total revenue generated from sales:

Total Revenue= $R \times \min(Q, D)$

5. **Profit:** The net profit considering all costs and revenue:

Profit = Total Revenue − (Total Inventory Cost + Total Waste Cost + Total Stockout Cost)

Solution:

1. **Estimate Costs and Revenue:**
   - Determine I, W, S, and R from historical data or market analysis.
   - Use predicted demand D^ from the business model to estimate Q.
2. **Calculate Financial Metrics:**
   - Compute the total inventory cost, waste cost, stockout cost, and revenue.
   - Calculate the overall profit using the equations above.
3. **Optimization:**
   - Use the forecasting model to minimize waste and stockout costs while maximizing profit.
   - Adjust Q dynamically based on predicted demand to achieve optimal financial performance.

Example Calculation:

Assume:

- Inventory holding cost I = ₹150 per unit
- Waste cost W = ₹200 per unit
- Stockout cost S = ₹300 per unit
- Revenue R = ₹500 per unit

- Predicted demand D^ = 1000 units
- Ordered quantity Q= 1050 units (assuming some overstock to mitigate stockouts)

Inventory Cost:

Total Inventory Cost= I × Q

Total Inventory Cost = ₹150 × 1050 = ₹157,500

Waste Cost:

Total Waste Cost = W × max (0, Q − D)

Total Waste Cost = ₹200 × max (0, 1050 − 1000) = ₹200 × 50 = ₹10,000

Stockout Cost:

Total Stockout Cost = S × max (0, D – Q)

Total Stockout Cost = ₹300 × max (0, 1000 − 1050) = ₹300 × 0 = ₹0

Revenue:

Total Revenue = R × min (Q, D)

Total Revenue = ₹500 × min (1050, 1000) = ₹500 × 1000 = ₹500,000

Profit:

Profit = Total Revenue − (Total Inventory Cost + Total Waste Cost + Total Stockout Cost)

Profit = ₹500,000 − (₹157,500 + ₹10,000 + ₹0)

Profit = ₹332,500

Summary

In this more practical scenario:

- **Total Inventory Cost:** ₹157,500
- **Total Waste Cost:** ₹10,000
- **Total Stockout Cost:** ₹0
- **Total Revenue:** ₹500,000
- **Profit:** ₹332,500

By ordering 1050 units, we incur some waste costs but avoid stockout costs, leading to a net profit of ₹332,500. This illustrates the trade-off between waste and stockout costs and the importance of balancing inventory to optimize financial outcomes.

Conclusions

This project successfully developed an AI-powered food demand forecasting model using the CatBoost regression technique, achieving high accuracy and precision. The model effectively forecasts demand for meal delivery services, optimizing inventory management and staffing decisions. With its scalable design and user-friendly interface, it provides actionable insights that reduce waste and prevent stockouts, leading to significant cost savings and increased profitability. Future enhancements could include real-time data integration and additional external factors to further refine accuracy, but the current system already delivers substantial operational benefits and improves customer satisfaction.

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