AI-Powered Food Demand Forecasting

Bhavika Rameshwar Wagh

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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"

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 fulfillment centers. 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 center-meal combination, based on historical demand data, product features, and fulfillment center 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 fulfillment centers.

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 centers and various meal combinations.
- **Usability**: Provide actionable insights for inventory and staffing planning.

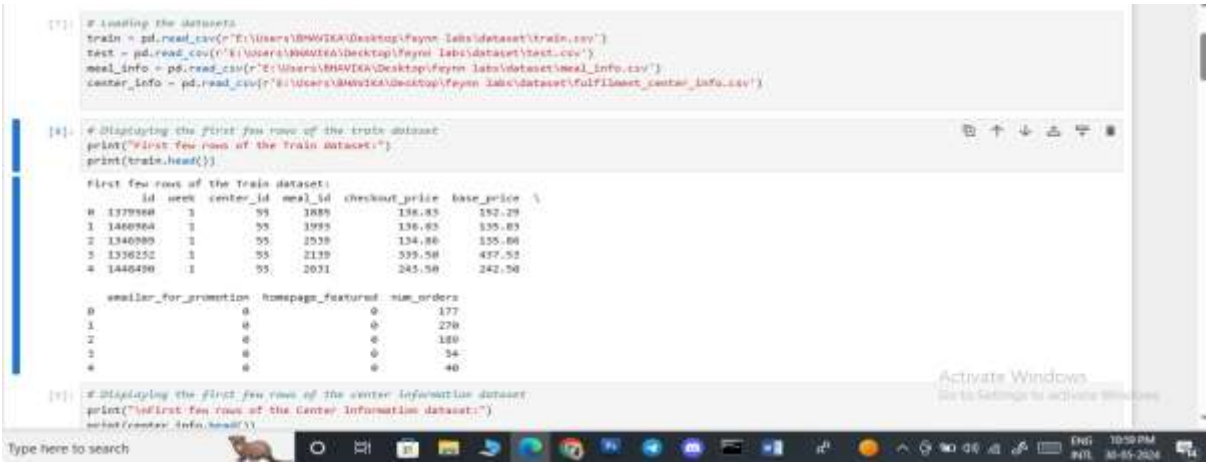
4. External Search

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 fulfillment centers. 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



```
[7]: # Loading the datasets
train = pd.read_csv(r'E:\Users\BHAVIKA\Desktop\Feynn labs\dataset\train.csv')
test = pd.read_csv(r'E:\Users\BHAVIKA\Desktop\Feynn labs\dataset\test.csv')
meal_info = pd.read_csv(r'E:\Users\BHAVIKA\Desktop\Feynn labs\dataset\meal_info.csv')
center_info = pd.read_csv(r'E:\Users\BHAVIKA\Desktop\Feynn labs\dataset\fulfilment_center_info.csv')

[8]: # Displaying the first few rows of the train dataset
print("First few rows of the Train dataset:")
print(train.head())

First few rows of the Train dataset:
        id  week  center_id  meal_id  checkout_price  base_price  \
0  1379560     1         55     1885          136.83      152.29
1  1466964     1         55     1993          136.83      135.83
2  1346989     1         55     2539          134.86      135.86
3  1338232     1         55     2139          339.50      437.53
4  1448490     1         55     2631          243.50      242.50

   emailer_for_promotion  homepage_featured  num_orders
0                      0                  0         177
1                      0                  0         270
2                      0                  0         189
3                      0                  0          54
4                      0                  0          40

[9]: # Displaying the first few rows of the center information dataset
print("\nFirst few rows of the Center Information dataset:")
print(center_info.head())
```


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

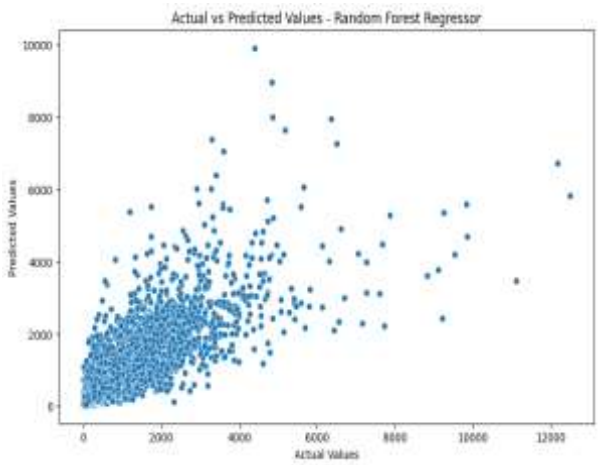
Variable	Definition
center_id	Unique ID for fulfillment center
city_code	Unique code for city
region_code	Unique code for region
center_type	Anonymized center type
op_area	Area of operation (in km^2)

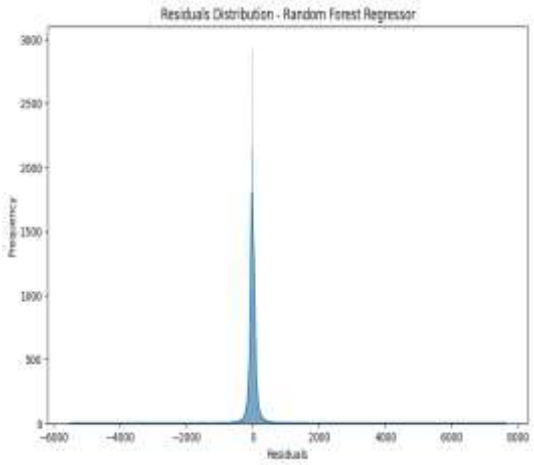
3. **meal_info.csv:** Contains information for each meal being served

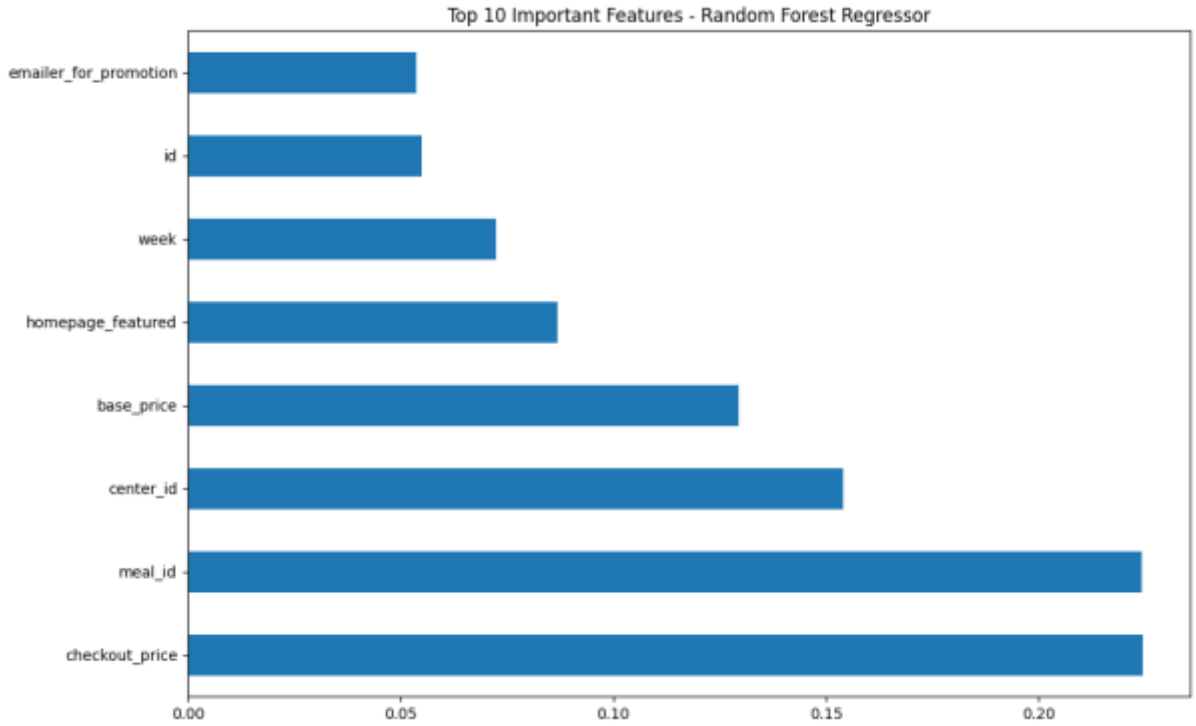
Variable	Definition
meal_id	Unique ID for the meal
category	Type of meal (beverages/snacks/soups....)
cuisine	Meal cuisine (Indian/Italian/...)

5. Benchmarking:

The benchmarking process involves exploring and transforming the data, selecting diverse models including linear regression, tree-based models, and time series models, evaluating their performance using RMSLE and cross-validation, comparing results, and iteratively refining the approach based on insights gained.







6. Final Product Prototype

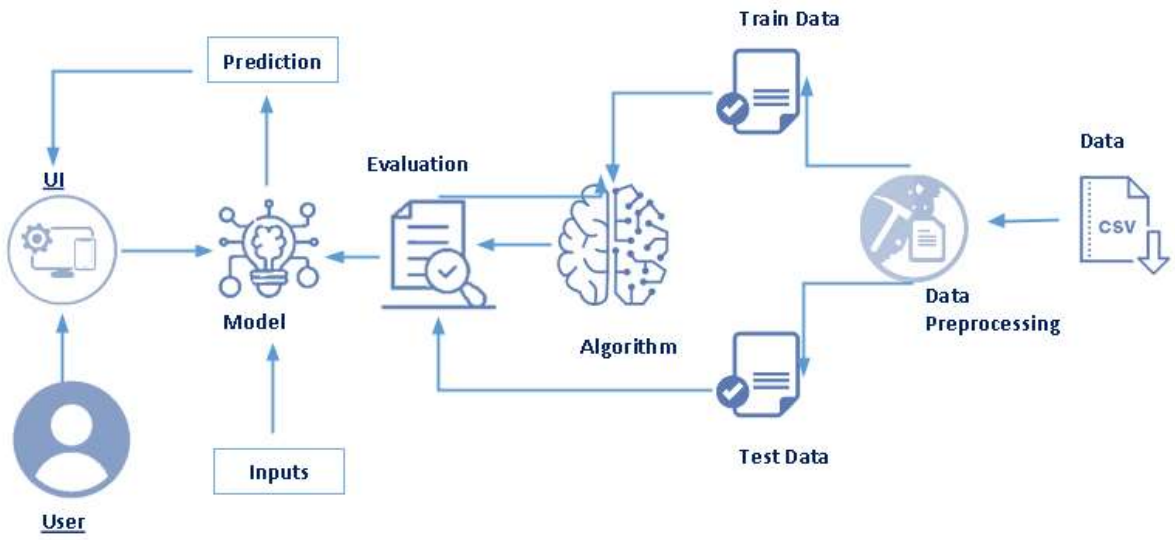
The final product prototype consists of a CatBoost regression model optimized through extensive hyper parameter tuning and feature engineering. The model incorporates:

- **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 Technical Implementation

- **Frontend**: Built with React.js for a responsive interface.
- **Backend**: Implemented using Python (Flask) to handle pre-processing, prediction, and serving results.
- **Model Integration**: Uses scikit-learn for model integration.
- **Deployment**: Hosted on cloud platform (Heroku).
- **Database**: Stores data using MySQL.

7.2 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.

12. Conclusions

This project successfully developed a robust demand forecasting model tailored to the needs of a meal delivery service. The use of CatBoost, combined with strategic feature engineering and hyperparameter tuning, resulted in a highly accurate forecasting tool. The insights gained from this model can significantly enhance the client’s ability to manage inventory, reduce waste, and maintain high customer satisfaction. Future work may involve integrating real-time data updates and expanding the model to incorporate additional external factors influencing demand.

13. References:

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