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A Machine Learning-Based Data Analytics Framework for Retail Sales Prediction

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Abstract-- **The swift development of digital retail and e-commerce has led to the creation of substantial amounts of sales and transactional data. Proper analysis of this data can be beneficial for retailers wishing to enhance their demand appraisals, inventory control, promotion-related planning, and business performance. Nevertheless, forecasting retail sales is not a straightforward process, as there are many parameters that can impact the sales number, such as the previous demand patterns, seasonal factors, the nature of the product sold, prices, sales promotions, holidays, regional factors, and the evolving demands of customers.**

This study proposes the implementation of Machine Learning-Based Data Analytics Framework for Retail Sales Forecasting. The implementation of this framework includes collecting data, processing it, conducting exploratory data analysis, creating features, making machine learning models, and building visuals. The historical data in retail industry will be processed in order to obtain meaningful prediction features (e.g. lagged sales, rolling averages, calendar features, product types, promotion and price features). The paper compares four different machine learning algorithms for solving the forecasting issue – Linear Regression, Random Forest, Gradient Boosting, and XGBoost. The performance of each algorithm is measured in terms of Mean Absolute Error (MAE), Root Mean Squared Error

The framework provides functionalities for making predictions as well as analytics. In addition to forecasting sales on the basis of historical sales data, it can identify crucial factors affecting sales and provide useful insights that can be utilized in inventory planning, product management, promotions, and supply chain operations. The proposed framework thus serves as a platform for developing intelligent retail sales forecasting systems.

I. INTRODUCTION

Over the past ten years, retail has undergone a tremendous digital revolution. Retail outlets gather information from cash register systems, e-commerce, inventory systems, customer loyalty programs, and advertising campaigns. This big data makes it possible to develop smart technologies that allow historical data analysis and reliable forecasts of outcomes.

Sales forecasting is one of the most significant areas of retail analytics. The accuracy of the sales predictions allows businesses to find out the quantities of goods to be purchased, which products should be dispatched, dates of promotions, and distribution of resources.

The incorrect forecasting process can result in two major issues – overestimation can lead to surplus of goods and increases in warehouse expenses, while underestimation can provoke out-of-stock problems, dissatisfaction among customers, and decrease in profits.

Traditional forecasting techniques such as moving average, exponential smoothing, and autoregressive modeling have been successfully employed in forecasting processes. The above-mentioned techniques are effective only under the conditions of stable historical trends. At the same time, modern retail sectors deal with multiple variables and nonlinear relationships within the dataset. For instance, the impact of discounts may differ depending on the product category, season, shop, etc.

Machine learning offers another method, which model is based on the concept of historical observations in relation to future sales. Random Forest, Gradient Boosting, XG Boost algorithms are able to recognize complicated relationships and dependencies between various parameters. Using feature engineering techniques, the forecast accuracy can be improved as well due to generation of lag and rolling variables reflecting how demands were predicted in the past.

The goal of the conducted work is to create a machine learning-based analytical framework for retail sales forecasting and obtaining valuable business insights.

Problem Statement

There are many internal and external factors that have an impact on retail sales. In order to ensure a correct prediction system is created, we need to have proper data processing, feature engineering methods, as well as the right algorithm and useful evaluation.

The research problem could be phrased in the following terms:

The task is to find a way to combine historical retail sales data with significant business variables into an analytics framework using machine learning algorithms in order to predict retail sales correctly.

Research Objectives

The primary goals of this research are:

Creating a framework for forecasting retail sales using machine learning approach.

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- Processing and analyzing past retail sales data.
- Identifying main factors affecting retail sales.
- Designing features related to time and business.
- Comparing various machine learning models.
- Measuring performance of the models with help of standard criteria.
- Giving understandable conclusions based on the forecast results.
- Showing how the forecast can be used in the retail business.

II. Literature Review

Retail sales forecast has become a major area of study as accurate forecasts influence directly stocking, supply chain functionality, sales promotion, and financial planning. Prior research in this domain has concentrated on statistical techniques like exponential smoothing, autoregressive models, and moving averages.

Fildes, Ma and Kolassa reviewed retail forecasting literature and pointed out the complex nature of forecasting process due to the presence of large number of products, outlets, promotions, and different aggregation levels.

This obviously implies that retail forecasting requires methodologies capable of working with massive and heterogeneous data.

With the advent of machine learning technology, the application of supervised learning algorithms to forecasting of sales and demand has become popular. Machine learning models can process numerous explanatory variables together and recognize nonlinear relationships.

Random Forest is an example of ensemble algorithm based on a number of decision trees which makes it possible to model nonlinear relationships between the variables. It offers some measures of the importance of the explanatory variables too.

Gradient Boosting methods are built incrementally, where each new learner works on fixing the faults that the previous learner left behind. XGBoost is a specific application of gradient boosting which is optimized to deliver efficient training and good results on structured data.

Deep learning has become a relevant method in the field of retail forecasting. For example, RNNs and LSTMs can model temporal relationships in sales data.

In the latest approaches, transformer architecture is being evaluated for long-term predictions.

Nonetheless, complicated models can impose restrictive requirements on the size of the dataset as well as computational resources and interpretability.

Several structured retail datasets are suitable for the use of machine learning models together with relevant feature engineering techniques enabling a good compromise in terms of efficacy, computational cost, and explainability.

Research Gap

Prior studies have proved the feasibility of ML strategies in sales predictions, however in numerous cases the emphasis is simply put on accuracy of predictions only. For the project to be viewed as an effective retail analytics tool it should be more than just a quantitative forecast.

There are several components to be incorporated into a universal framework, such as:

- Data preprocessing
- Exploratory data analysis
- Temporal feature engineering
- Machine learning
- Model comparison
- Performance evaluation
- Importance of features
- Business visualization

This research aims at solving the issue by developing a holistic analytical framework instead of concentrating on the development of the models.

III. Proposed Methodology

The recommended framework consists of multiple interlinked phases:

Data Acquisition → Data Preparation → Data Exploration → Feature Creation → Modeling → Evaluation of the Model → Forecasting → Visualization of the Business

3.1 Data Collection

The model may be implemented using past transaction data from the retail sector. The appropriate dataset may involve information about sales at three dimensions: product level, store level, and date level.

The possible variables could be the following:

- *Date:* the date of sales or any other transactions made by customers.
- *Store_ID:* distinctive identifier of a store.
- *Product_ID:* distinctive identifier of a product.
- *Category:* category of the product.
- *Sales:* quantity of the sold products.
- *Price:* the price at which product has been sold.
- *Promotion:* indicator of promotions made with the help of a product.

Holiday: indicator of holidays.

Inventory: information about the products available to be sold.

Region: stores' geographical location.

M5 retail forecasting dataset can be used for its implementation or any other recommendation can be referred to as required.

3.2 Data Preparation

Raw data provided by retail sector may contain empty data, duplication, inconsistent types of data and exceptional data points.

Preprocessing

During preprocessing, some of the tasks that require attention are listed below:

- Dealing with the null values.
- Removing duplicates.
- Fixing data types.
- Changing the format of dates to an appropriate format.
- Identifying outliers and studying them.
- Encoding the categorical variables.
- Ensuring consistency in data.

In addition, one must be careful to avoid data leakage. Future data must not be used in creating features of past data.

3.3 Exploratory Data Analysis

Exploratory Data Analysis is concerned with the characteristics of the data. Key analyses include:

- Daily sales data analysis.
- Monthly sales data analysis.
- Analysis based on the product.
- Analysis based on the shops.
- Performance data on the categories.
- Promotional data.
- Seasonality.
- Effect of holidays.
- Distribution of sales.

Visualization techniques like line graph, bar graph, histogram, box plot, and correlation matrix can be applied.

3.4 Feature Engineering

This aspect of feature engineering is essential for implementation of the suggested model.

Temporal Features

Variable of date can be processed into:

- Day.
- Week.
- Month.
- Quarter.
- Year.
- Day of the week.
- A sign of weekend.
- A sign of holiday.

Lag Features

The quantity of sales can be used as a basis for creation of lagged indicators:

Lag_1 = Sales_{t-1}

Lag_7 = Sales_{t-7}

Lag_30 = Sales_{t-30}

These variables reflect previous trend.

Rolling Features

The rolling means can be used to discover current demand:

- 7-day mean.
- 14-day mean.
- 30-day mean.
- Rolling deviation.
- Rolling minimum.
- Rolling maximum.

Price and Promotion Features

It is possible to add extra variable of:

- Current pricing.
- Previous pricing.
- Change in price.
- Discount number.
- State of promotion.
- Duration of promotion.

IV. Machine Learning Models

Four machine learning algorithms are suggested for comparison.

4.1 Linear Regression

Linear Regression is taken as the baseline model and it is assumed that there exists a linear relationship between the target variable and the input variables.

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The main pros are that this model is simple and easy to understand. Nonetheless, this method does not provide the opportunity to represent complicated nonlinear relationships.

4.2 Random Forest

Random Forest is one of the ensemble learning techniques where a number of decision trees is used in order to get the overall decision. The advantages of Random Forest are:

The ability to work with nonlinear relationships.

The possibility to model interaction between features.

Relative robustness to noise.

Provision of feature importance.

Its efficiency with respect to structured datasets.

4.3 Gradient Boosting

Gradient Boosting is based on the idea of creating a model as a series of decision trees where every next tree is trained to correct the mistakes made by the previous one.

Gradient Boosting performs well if the parameters of the model are well chosen.

4.4 XGBoost

XGBoost is a gradient-boosting method that has been implemented for effective and fast machine learning.

XGBoost works well for retail sales prediction because it can

V. Experimental Design And Assessment

5.1 Dataset

For testing the suggested framework, one can use a well-known retail transaction dataset like the M5 forecasting dataset or another relevant dataset. When implementing the system, it is important to mention: - source of dataset - number of records - number of products - number of shops - date range - number of features - target variable

5.2 Experimental Environment

The complete implementation can be executed in Python. Potential technologies can be: - Python - Pandas - NumPy - Matplotlib - Scikit-learn - XGBoost - Jupyter Notebook - Power BI for the dashboard design.

5.3 Evaluation Metrics

For evaluating the proposed implementation, it is suggested to use: Mean Absolute Error (MAE) MAE indicates average prediction error. Root Mean Squared Error (RMSE) RMSE puts more weight on the bigger errors.

Mean Absolute Percentage Error (MAPE) MAPE proves to be effective when measuring and forecasting sales as it shows forecast error in form of percentage and should be used with caution in cases when real sales contain values that are zero. R^2 Score A higher value of R^2 means better explanatory capability of the model.

VI. Results And Discussion

The experiment presented evaluates the four different types of machine learning model based on similar dataset and testing duration. The obtained results after the completion of the experiment must be documented using the following format.

Model	MAE	RMSE	MAPE	R^2
Linear Regression	Actual Value	Actual Value	Actual Value	Actual Value
Random Forest	Actual Value	Actual Value	Actual Value	Actual Value
Gradient Boosting	Actual Value	Actual Value	Actual Value	Actual Value
XGBoost	Actual Value	Actual Value	Actual Value	Actual Value

6.1 Actual and Expected Sales

The chart comparing the actual and expected data for all the periods must be created for the test period. The chart should include the X-axis showing the date, Y-axis indicating sales, actual sales numbers, as well as the expected sales.

A capable explanatory model must reflect the main tendencies in the actual sales numbers.

6.2 Comparison of the models

The models can be compared on the basis of:

Accuracy of the prediction

Need for computing resources.

Time necessary for training.

Understandability.

Ability to be scaled.

Stability.

If referring to the case of XGBoost, if it gives the lowest RMSE and MAE, then it would be the best model for this data set. However, one should wait until running the experiment in question.

6.3 Feature importance

Feature importance is the ability to identify the factors crucial for sales forecasts. A number of important factors can be identified, including:

- The amount of sales for the previous day.
- The sales for the previous week.
- The average sales.
- The type of product.
- The shop.
- The price.
- Promotional activities.
- The month.
- The day of the week.
- Holidays.

The actual score for importance must be taken from the given model.

6.4 Explainability

SHAP (SHapley Additive exPlanations) could be helpful for explaining predictions of machine learning algorithms.

In answer to the following questions it might help to get the answers:

- What is the reason for high predicted sales?
- What feature has the negative impact on the prediction?
- What is the influence of promotion on prediction?
- What is the importance of previous sales?
- What products or shops played the most role for prediction?

Explainability is of the highest importance when the predictions of machine learning algorithms are used for business making decisions.

VII. Business Applications and Dashboard

This framework can be used together with the business intelligence dashboard to turn the predictions of machine learning algorithms into essential business data.

7.1 Sales Forecasting

This algorithm can give the following results:

- Daily sales forecasts
- Weekly sales forecasts
- Monthly sales forecasts
- Product level forecasts
- Store level forecasts

7.2 Inventory Optimization

Predicted demand is useful for retailers to understand the needed level of inventory.

The system can distinguish:

- High-demand products
- Low demand products
- Products that can run out of stock
- Slowly selling products

This helps to minimize both losses from lack of inventory and excessive stock levels.

7.3 Product Evaluation

Utilizing the dashboard will allow for:

- Sales of products from highest to lowest figures.
- Poorly performed products in terms of sales.
- Sales breakdown by category.
- Analysis of product growth rates.
- Forecasting of sales on the product level.

7.4 Store Evaluation

Stores' performance can be evaluated in terms of:

- Total sales figures.
- Average sales statistics.
- Changes in sales.
- Ranking of stores based on sales.
- Forecasting of sales at store level.

7.5 Promo Analysis

Retail stores can analyze sales data for promo and normal periods in order to:

- Determine promo efficiency.
- Find products most sensitive to discounts.
- Study the effect of campaigns on sales figures.
- Find promising promo opportunities.

7.6 Dashboard Layout

The suggested layout can include:

Executive Summary

- Total sales results.
- Expected sales.
- Growth of sales values.
- Best-selling product.
- Best store.

Sales Forecast

- Sales figures and expectations.

Product Analysis

- Categories' performance.
- Top products.

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Store Analysis

Store ranking.

Sales by store.

Forecasting

Predictions for sales.

Promo Analysis

Sale analysis of promo vs. non-promo sales.

VIII. Limitations And Future Scope

Limitations

There are many drawbacks of the presented framework.

First, the accuracy of the forecasts heavily relies on the quality and availability of the data used for forecasting. If historical data is incorrect or missing, the forecasting model may fail.

Second, the sudden events that cannot be predicted using historical data, e.g., changes in economy, disruptions of supply chains, bad weather conditions, or performance of competitors, cannot be covered.

Third, proper feature engineering and hyper-specificing of hyper-parameters are crucial to train machine learning models properly.

Fourth, very advanced models sometimes might turn out to be hard to explain for business users.

And lastly, a model created from one retail case does not automatically become applicable for other retailers due to significant differences in goods sold, customers, and their behavior.

Future Scope

Research in this area can take many forms in the future.

Deep Learning

Both traditional machine learning algorithms and LSTM, GRU and other deep-learning models can be compared and contrasted.

Additional Data

The algorithm can be supplemented with the information about:

Weather forecast.

Economic statistics.

Prices of competitors.

Social media trends.

Customer feedback and reviews.

Local events in the area.

Real

Explainable AI

The dashboard can easily incorporate SHAP and methods that provide information about how decisions are made.

Hybrid Forecasting

Statistical forecasting methods can be combined with machine learning models to create hybrid forecasting methods.

IX. Conclusion

The present research introduced a Data Analytics Framework based on Machine Learning aimed at Retail Sales Prediction. The framework unites data acquisition, data processing, exploratory data analysis, feature engineering, machine learning, evaluation, interpretability, and visual analytics into an all-embracing system.

Retail sales forecasting is rather complicated since demand depends on a number of variables, including past sales volumes, product and prices features, promotional activity, holidays, seasonality effects, and factors which relate to the store.

In the framework, Linear Regression, Random Forest, Gradient Boosting, and XGBoost are considered as prediction models. Feature engineering, which is based on lagged sales, rolling averages, calendar variables, information about prices, promotions, characteristics of products, and store information, can enhance the models' ability to capture the patterns of retail demand.

The framework highlights that forecasting must not be confined to forecasting accuracy alone. Feature importance and explainability enable business users to gain understanding about future forecasts, while visual dashboards assist in transforming forecasts into sound input for stock management, product planning, store operations, and planning of promotions.

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