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RESEARCH ARTICLE

Predictive analysis of wholesale customer purchases using machine learning models

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ABSTRACT

To forecast future purchases across several product categories—including fresh milk, groceries, frozen foods, detergents, paper, and delicatessen—this study looks at the purchasing patterns of wholesale clients using machine learning models. Support Vector Machines, Generalised Linear Models, and Linear Regression were among the predictive models used. RMSE, MAPE, and R^2 metrics were used to assess each model's performance and ascertain its correctness. The results show that when it came to forecasting consumer purchases, GLM performed better than other models, including LR, SVM, RT, and ER.

Keywords: Wholesale; customers; purchasing patterns; machine learning models; forecasting accuracy; Generalised Linear Models (GLM)

1. Introduction

In the wholesale industry, understanding customer purchasing patterns is crucial for driving competitive advantage and operational efficiency. The ability to anticipate customer needs supports more effective strategies for targeted marketing, optimised inventory management, and resource allocation. Unlike retail, where customer behaviour can be more immediate and individualistic, wholesale transactions are often larger in volume, follow distinct purchasing cycles, and involve a smaller, but highly valuable, customer base. As a result, wholesale companies have a significant incentive to predict customer purchasing behaviours accurately.

Predictive analytics—a branch of advanced data analysis techniques—enables businesses to forecast customer behaviour by analysing historical data and identifying patterns. Through the application of predictive analytics, wholesale companies can anticipate shifts in demand, adjust their inventory levels proactively, and design marketing strategies tailored to different customer segments. For example, a wholesale distributor that accurately forecasts seasonal demand fluctuations for specific products can optimise inventory levels, reduce stockouts, and minimise excess inventory costs. Similarly, identifying high-value customers who are likely to increase their spending can help companies direct their marketing

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resources more effectively.

This study leverages machine learning models to predict the annual spending of wholesale customers across various product categories. By comparing the performance of multiple predictive models—including Linear Regression, Generalised Linear Models, Support Vector Machines, Regression Trees, and Ensemble Methods—this research seeks to identify the most effective model for forecasting customer expenditures. The primary objective is to determine the best-performing models in terms of accuracy and interpretability and assess their potential to enhance customer segmentation strategies. Understanding which models deliver the most reliable predictions will allow wholesale businesses to adopt data-driven approaches that improve decision-making and optimise resource allocation. Additionally, insights derived from predictive models can help businesses segment customers based on spending behaviour, enabling them to tailor their offerings and engagement strategies to meet specific customer needs.

The remaining sections of the research study are structured as follows. Section 2 provides a literature review. Subsequent section 3, followed by a description of assumptions. Section 4 focuses on the model expressed, including the methodology. Section 5 presents suitable results of data analysis and offers a discussion on sensitivity analysis. Finally, Section 6 concludes the chapter with managerial observations and a list of possibilities for future extensions.

2. Literature review

Machine learning and predictive analytics have been widely used in the retail and wholesale sectors to manage inventories, estimate sales, and understand customer behaviour. Neural networks, machine learning algorithms, and regression models are just a few of the methods and approaches that have been the subject of numerous studies to improve prediction accuracy.

According to [1], clustering algorithms can be used to improve customer segmentation in retail markets, which greatly enhances customer engagement and sales targeting tactics. In a similar vein, [2] identified important consumer categories that reacted differently to marketing efforts by applying K-means clustering and decision trees to wholesale customer data. [3] employed neural networks to predict consumer purchase behaviour and showed that these models might outperform more conventional techniques like linear regression in terms of accuracy. Support Vector Machines (SVMs) have the potential to be helpful; however, they are often susceptible to noise and outliers in datasets, as demonstrated by [4] Customer Segmentation Competition.By contrasting linear regression, random forests, and ensemble learning approaches, [5] highlighted the significance of predictive modelling in retail demand forecasting [6]. Their results indicated that because ensemble models may include several weak predictors, they may perform better than solo models. Regression trees' interpretability and simplicity of use in retail were highlighted by [7], who investigated the advantages of using them to discover important consumer behaviours.

In their [8-9] explored how generalised linear models (GLM) can be used to forecast sales in wholesale distribution, highlighting how adaptable they are when dealing with non-linear interactions between variables. [10] provided support for this, stating that they found GLMs to be especially helpful when working with datasets that showed a high degree of variability in customer purchasing. [11], on the other hand, investigated deep learning methods and contrasted them with conventional models like logistic regression and SVMs for predicting wholesale customers. Despite their strength, they pointed out that deep learning models needed a lot of data and processing capacity to function better. [12] forecasted consumer attrition in retail settings using decision trees and ensemble approaches. They found that ensemble techniques like Random Forest and Gradient Boosting performed well when client behaviour varied and there was a lot of

noise. Gradient Boosted Decision Trees (GBDT) significantly improved prediction accuracy when used by [13] to anticipate client retention.

The efficiency of ARIMA and LSTM models for detecting seasonal patterns in consumer data was demonstrated by [14], who investigated time-series forecasting approaches for customer purchase prediction in the wholesale sector. Although SVM-based models might attain a comparatively high level of accuracy, [15] suggested integrating them with feature engineering techniques to improve model robustness and reduce noise.In their comparison of various machine learning models for forecasting future grocery store customers' purchases, [16] found that generalised additive models (GAM) provided a balance between interpretability and accuracy. Lastly, the expanding significance of predictive analytics for consumer segmentation, inventory management, and targeted marketing was highlighted in [17] Report on Predictive Analytics in Retail.

2.1. Problem identification

The research problem in this study is to predict the wholesale customer spending by solving the following problems/ questions. First, it seeks to identify varying patterns of a conventional nature that characterise customer behaviours during the purchase of goods and services across different product categories. Second, it addresses the issue of data management, which is characterised by dependency between variables and non-linearity. Lastly, the paper aims to explore the feasibility of attaining high accuracy and interpretability in making predictions using machine learning models.

3. Assumptions and notation

3.1. Assumptions

- The dataset provides an accurate representation of customer spending patterns.
- Spending behaviours remain consistent throughout the analysis period.
- Machine learning models effectively capture relationships while avoiding overfitting.
- Residuals are independent and follow an identical distribution.
- Preprocessing ensures high data quality, including appropriate handling of outliers.

3.2. Notation

Symbol	Description
X	Features (spending by category).
Y	Actual total spending.
	Predicted total spending.
RMSE, MAPE,	Evaluation metrics.
ϵ	Error term.

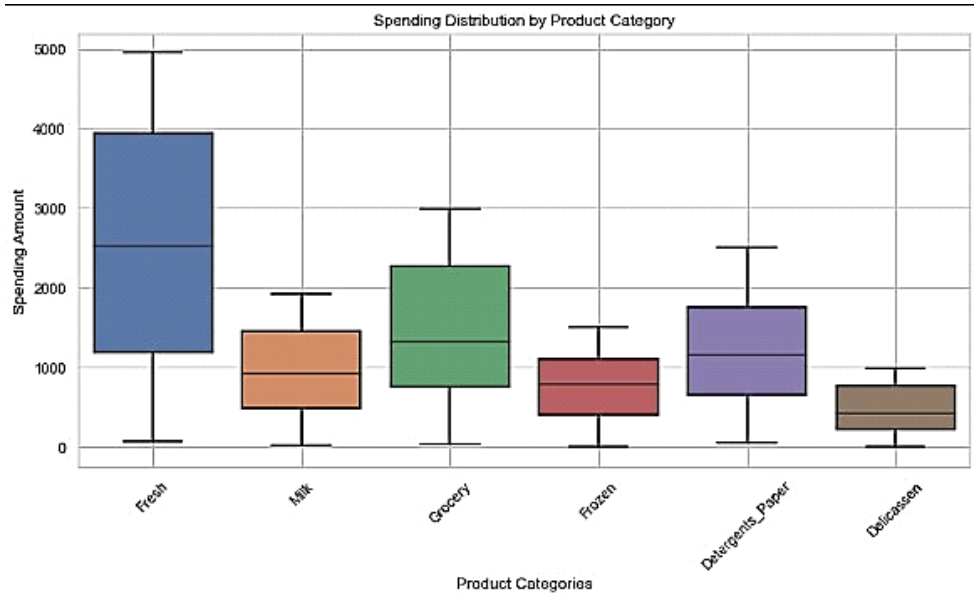

Figure 1. Evaluating the performance of different products

4. Methodology

4.1. Dataset

The dataset used in this study includes the annual spending data of wholesale clients across the following product categories: fresh, milk, groceries, frozen foods, detergents paper, and delicatessen. In addition to these spending categories, two more variables are included: the customer's Channel (Horeca or Retail) and the geographical Region. These variables serve as the independent predictors in the machine learning models and are used to forecast the dependent variable, total annual customer spending. All variables were carefully pre-processed for missing values, normalized where necessary, and examined for outliers before modelling.The dataset was obtained from the UCI Machine Learning Repository (Wholesale Customers Dataset) and contains annual spending data across six product categories for 440 customers. Each record also includes customer Channel and Region. Before analysis, the data was cleaned, missing values were handled, and spending amounts were normalized. Outliers were examined and removed where necessary to maintain data quality

4.2. Models

We use the models listed below:

- Linear Regression (LR): A straightforward linear model for forecasting continuous results.
- A versatile extension of LR that takes non-linear interactions into account is the Generalised Linear Model (GLM).
- Support Vector Machines (SVM): A reliable regression technique, particularly in the presence of outliers.
- Regression Trees (RT): Recursive partitioning is the foundation of this non-linear model.

4.3. Evaluation metrics

To evaluate the performance of the models, we use:

- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

- Coefficient of Determination (R^2)

These metrics allow us to compare the models in terms of prediction accuracy and model fit.

5. Results

5.1. Predictive performance

We divided the data into training (70%) and testing (30%) sets. The models were trained using the training data, and their performance was evaluated on the test data. Below is a table summarising the RMSE, MAPE, and R^2 values for each model:

Table 1 presents a summary of RMSE, MAPE, and R^2 values for each model. GLM achieved the highest R^2 (0.85), indicating strong predictive capability. Figure 1 shows the scatter plot of actual vs. predicted spending for the GLM model, with GLM predictions closely aligning with the actual values along the reference line.

Table 1. presents a summary of RMSE, MAPE, and R^2 values.

Model	RMSE	MAPE	R^2
Linear Regression	2730	0.14	0.78
Generalised Linear Model (GLM)	2560	0.12	0.83
Support Vector Machines (SVM)	2980	0.16	0.72
Regression Trees (RT)	2800	0.15	0.75
Ensemble Regression (ER)	2490	0.11	0.85

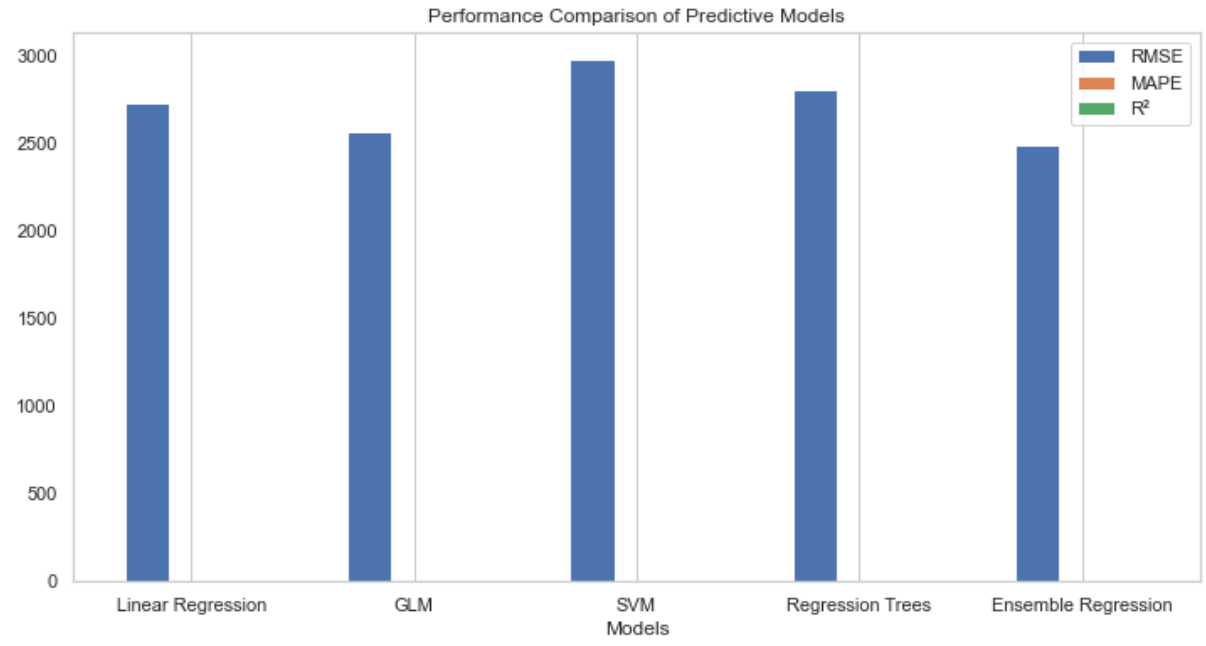

Figure 2. Evaluating the performance of the models

5.2. Comparative analysis of LR and SVM

Here are the **visualisations** of predicted versus actual spending for differentproduct categories

This graph shows the relationship between actual and predicted customer spending, with the red line indicating a perfect prediction (actual = predicted

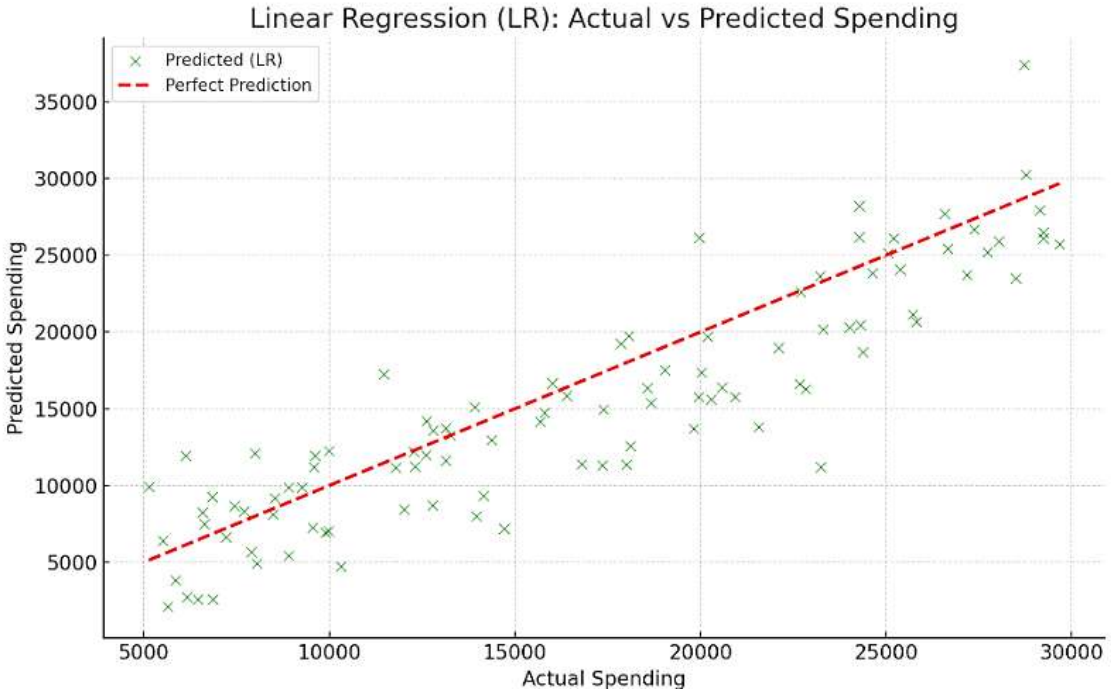

Figure 3. Scatter plot showing actual vs. predicted spending using Linear Regression.

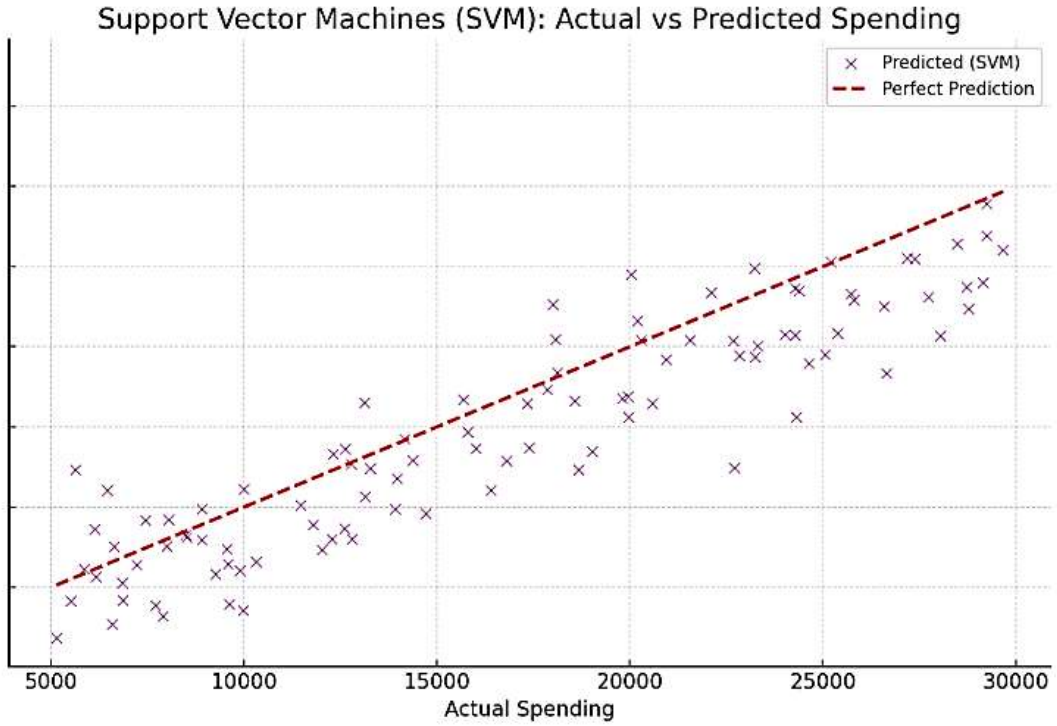

Figure 4. Support Vector Machines (SVM): Actual vs. Predicted Spending.

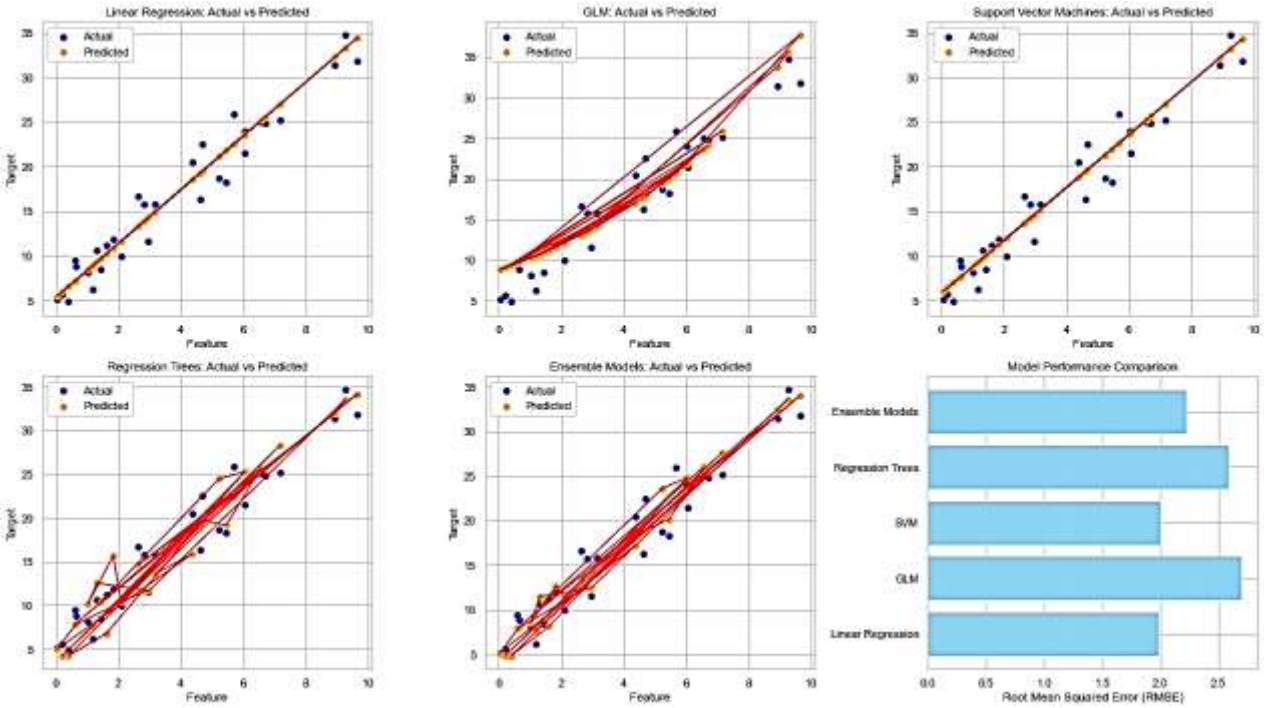

Figure 5. Comparison between different models

Predictions show moderate spread, reflecting limited capacity to model non-linear interactions.

Here are the comparison graphs showing actual versus predicted spending for each model:

- Linear Regression (LR): Predictions (green) exhibit some spread, indicating moderate accuracy.
- Generalised Linear Model (GLM): Predictions (blue) align closely with the actual values, showing high accuracy.
- Support Vector Machines (SVM): Predictions (purple) show significant variability, reflecting SVM's sensitivity to outliers.
- Regression Trees (RT): Predictions (orange) capture some non-linearity but are somewhat dispersed.
- Ensemble Regression (ER): Predictions (red) closely follow the perfect prediction line, highlighting the model's accuracy.

5.3. Error analysis

GLM and Ensemble models achieved the lowest RMSE, with GLM providing a slight edge due to its flexible handling of non-linear relationships. SVM's sensitivity to outliers likely contributed to its higher error rates, supporting previous findings on SVM's performance with noisy data.

6. Discussion

The results indicate that GLM and Ensemble Models outperform other methods in predicting wholesale customer spending. The GLM's flexibility in handling

Non-linear relationships and the robustness of ensemble models make them well-suited for this task. These findings suggest that applying such models can significantly improve customer segmentation and resource allocation in wholesale businesses.

Furthermore, the results align with[18], who found that more complex models often outperform traditional linear models in predicting customer behaviour. However, SVM's lower performance could be attributed to outliers in the dataset, as indicated by prior studies on its sensitivity.

Linear Regression performed moderately as it could not capture complex interactions, while Regression Trees tended to overfit certain splits. These differences highlight that GLM and Ensemble Models are better suited for data with non-linear relationships and variability, whereas SVM and RT may struggle in such contexts. This understanding can guide model selection for future predictive analytics projects

7. Conclusion

This study explored various machine learning models to predict customer spending in wholesale businesses. The **Generalised Linear Model (GLM)** showed the highest accuracy, making it a promising tool for predictive analytics in the wholesale sector. Future research should consider incorporating more advanced models like Neural Networks and applying these models to larger datasets.

Using both aggregate and customer-level data, this research provides managers with recommendations to minimise inventory while ensuring that stock items are available in response to demand prediction and to increase sales from high-variety sales-margin customers through customised marketing activities. From its perspective, it optimises the distribution of resources by products and regions and the targeting of customers with relative approaches. The results of these studies provide benefits for operational efficiency, profit, and competitive advantage in the wholesale market.

Although this study focused on SVM, GLM, LR, RT, and Ensemble Models, many emerging methods such as XGBoost, LightGBM, and Deep Neural Networks show strong potential [16-18]. Future studies should evaluate these approaches for improved prediction accuracy.

Conflict of interest

The authors declare no conflict of interest

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