Title:

Prediction of customer demand for perishable products in retail inventory management, using the hybrid Prophet-XGBoost model during the post-COVID-19 period

Abstract:

Retail inventory management (IM) presents challenges in decision-making, especially in determining the optimal inventory level to align with future customer demand. This study focuses on the prediction of demand for dairy products experienced by a significant European retail company, using historical order data from the pre- and post-COVID-19 periods. As dairy products are perishable and constitute a significant portion of retail trade volume, accurate IM is crucial for the prevention of wastage and meeting customer needs. However, external factors like COVID-19 may impact demand volatility and seasonal patterns. To tackle these challenges, the research employs two predictive models, Prophet and XGBoost, known for their superior performance in the prediction of demand. Moreover, a hybrid approach combining both models is proposed to enhance prediction accuracy by leveraging the capacity of the Prophet model to handle seasonal and holiday-period effects and XGBoost's regularisation to prevent overfitting. The results demonstrate the feasibility of historical imputation and the hybrid model approach, optimised through Optuna, improving significantly individual model performance. The study provides retail practitioners with valuable insight, assisting in IM decision-making and extending the applicability of the proposed approach to predict the shipment of other products, and ultimately contributing towards more effective IM practices.

Keywords:

Inventory Management, XGBoost, Prophet, Customer Demand Prediction, COVID-19

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I. Introduction

Inventory management (IM) presents a complex situation with regard to decision-making on the part of retail practitioners (Perez *et al.*, 2021). Its main challenge is to identify an optimal inventory which will coordinate replenishment and future customer demand (Ehrenthal *et al.*, 2014). Therefore, sales prediction plays a major role in the decision-making process of warehouse managers (Deng and Liu, 2021) and the accuracy of the forecast is thus a critical factor in determination of an optimal inventory.

In this study, we predict future customer demand for products pertaining to the dairy food category of a significant European retail company. We focus on the stores that receive its inventory from one of the company's largest warehouses and use historical order data from the pre- and post-COVID-19 periods. The selection of this product category is not trivial. On the one hand, it is essential to have an optimal IM in the case of perishable items that have a limited shelf life and may go to waste if the inventory exceeds demand (Perez *et al.*, 2021). On the other hand, the food category in question has seen the highest number of units shipped from the European retailer warehouse over the last few years. Moreover, macroeconomic events, such as COVID-19, significantly influence the volatility of demand for essential goods, impacting the seasonality of the category (Deng and Liu, 2021; Ehrenthal *et al.*, 2014).

Sales prediction has been widely studied in literature. In recent years, machine-learning (ML) based models have acquired significant importance with respect to the classical time series methodologies. In this paper, we use Prophet and XGBoost, which are now used increasingly frequently due to their good performance results (Kramar and Alchakov, 2023; Srinivas and Katarya, 2022). Moreover, following Wang, Du and Qi (2022), we have also developed the hybridisation of both models.

Our contribution to the literature occurs in two principal ways: (i) only articles analysing the impact of COVID-19 on households have been identified (Madeira, 2020), but no scientific studies that predict the sales of perishable products after the post-COVID-19 era have been undertaken; (ii) the use of Prophet and XGBoost as a hybrid model, which, to the best of our knowledge, has not been implemented in this scenario.

II. Methodology

This section describes the methodology of our research. Figure 1 illustrates the procedure flow used in this paper.

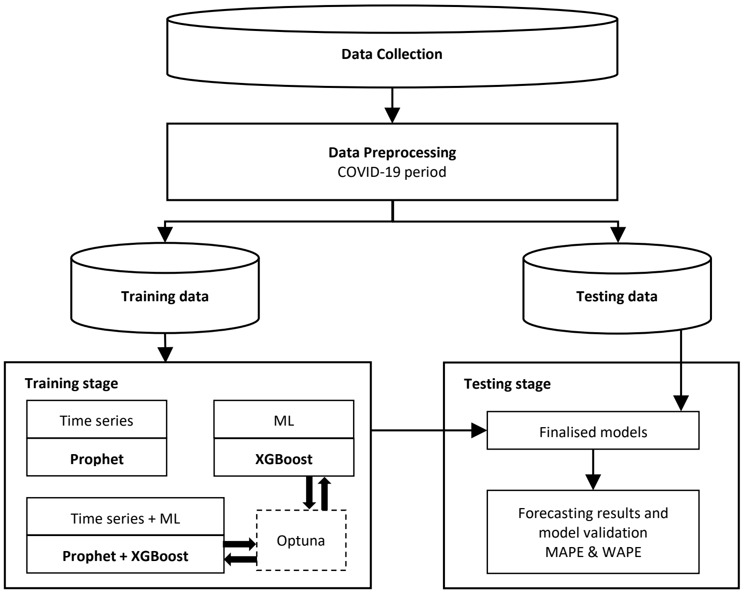

Figure 1. The procedure flow used in this paper.

The retail company provided historical order data recorded on a daily basis at one of its largest warehouses and, that is, the data corresponding to the units of dairy products shipped from the warehouse to the stores according to the customers' daily demand.

The data is stored in the database in the raw form, so preprocessing and filtering are required. The data referred to in our study were recorded from March 2019 to April 2023, however the data corresponding to the years 2020 and 2021 were tainted by the impact of the pandemic. This is why it makes sense to omit the data related to the COVID-19 pandemic, as it was an extraordinary situation that affected household consumption, especially in the case of essential products (Sleiman *et al.*, 2022). By omitting these two years, there is a break in the time series. Due to this, two different alternatives have been proposed:

- Option 1: exclude the 2019 data from the analysis and use data starting from 2022 so that we have a time series of 535 days.
- Option 2: considering the homogeneous patterns observed in data from 2019, 2022 and 2023 (Figure 2) and assuming that 2021 would have followed a similar trend if the pandemic had not occurred (Eurostat, 2020); it may be reasonable to develop a historical imputation using the 2019 data as a proxy for the missing data from 2021. As a result, we establish a time series that presents 837 daily observations (302 from 2021, 365 from 2022, and 170 from 2023).

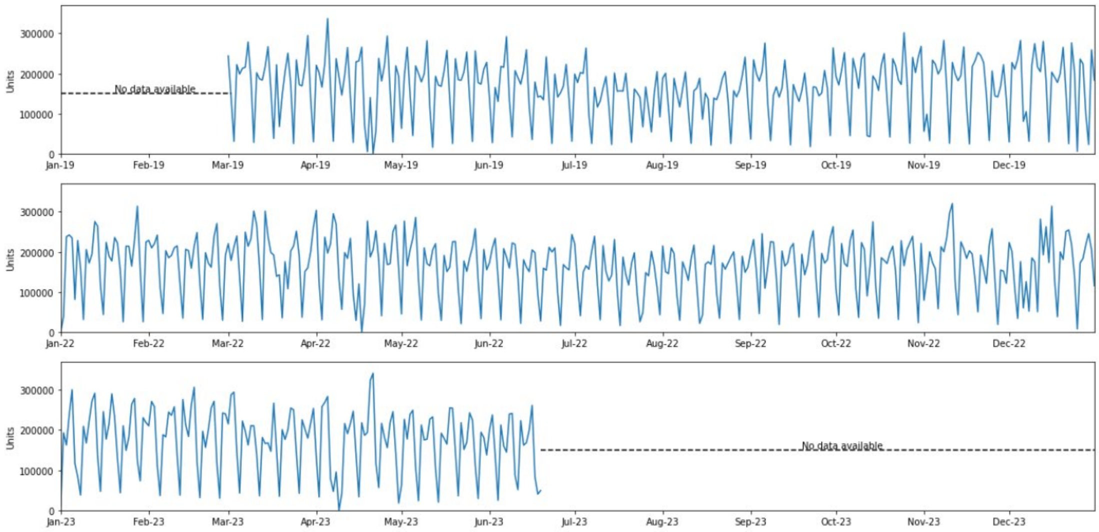

Figure 2. Evolution of units shipped. Years: 2019, 2022, 2023.

For the evaluation of a prediction algorithm each time series is split at the same time point into two parts, with the first part chronologically becoming the train dataset (to train the model) and the second part forming the test dataset (120 days).

Different models were adopted in order to form the predictive model: Prophet, XGBoost and the hybridisation of these two models.

Prophet is an open-source forecasting procedure for time series data. It was presented by Taylor and Letham (2018). It utilises an additive regression model to capture non-linear trends, and the yearly, weekly, daily, seasonality, and holiday effects. The method performs well with the time series, presenting strong seasonal patterns and multiple seasons of historical data. The selection of model parameters is fully automated, simplifying the model-building process. At its core is the sum of three functions of time, plus an error term:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{1}$$

where $g(t)$ is the trend function that models non-periodic changes in the value of the time series, $s(t)$ represents periodic changes, $h(t)$ represents the effects of holidays that occur on potentially irregular schedules over one or more days, and ε_t represents any idiosyncratic changes that are not accommodated by the model and follows a normal distribution with a mean of 0.

XGBoost is a tree-based ML forecasting method developed by Chen and Guestrin (2016). This model is a more regularised form of Gradient boosting which improves the generalisation by adding regularisation terms to prevent the model from overfitting. The objective is to identify the optimal value that will minimise total loss function. The most commonly used loss function for a regression problem is:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{2}$$

where $l(\cdot)$ represents a second-order derivable loss function, which measures the difference between the actual value y_i and the predicted value $\hat{y}_i^{(t-1)}$, and $\Omega(\cdot)$ denotes the regularisation term.

Moreover, the study proposes a hybrid prediction model which combines the advantages of the two methods to achieve improved prediction accuracy (Wang *et al.*, 2022). Firstly, the series is modelled using Prophet; secondly, the features obtained from the model are added to the first dataframe. Once this merge is completed, the new dataframe is used to make predictions using XGBoost.

Furthermore, efficient hyperparameter tuning is crucial for performance improvement. Optuna is a trending method known for achieving better optimisation results by finding the best combination of available hyperparameters for a model (Srinivas and Katarya, 2022). To determine hyperparameters using Optuna, the steps include entering the hyperparameters, defining types and search ranges (Table 1), setting the objective function, determining the optimisation direction (minimum in this research), and specifying the number of trials (100 in this research) (Lai *et al.*, 2023).

Table 1. List of hyperparameters using the Optuna library.

Hyperparameters	Types	Search Ranges
n_estimators	Integer	[50-10000]
max_depth	Integer	[3-10]
subsample	Float	[0-1]
reg_alpha	Float	[0-180]
reg_lambda	Float	[0-1]
learning_rate	Float	[0.01-0.3]
colsample_bytree	Float	[0.3-1]
min_child_weight	Float	[0.3-10]

III. Results

After fitting the training data set to all models, the MAPE (Mean Absolute Percentage Error) and WAPE (Weighted Average Percentage Error) metrics are utilised for an evaluation of the performance of the proposed models:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100 \quad (3)$$

$$WAPE = \sum_{t=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100 \quad (4)$$

Table 2 depicts the optimal hyperparameters determined by Optuna, minimising the loss function, for each model in this research.

Table 2. Optimal hyperparameters found in this research.

Hyperparameters	Option 1		Option 2	
	XGBoost	Prophet-XGBoost	XGBoost	Prophet-XGBoost
n_estimators	10000	10000	10000	10000
max_depth	3	3	5	6
subsample	0.2543169829653345	0.8594670338248664	0.26301110161619823	3.1700668339312976
reg_alpha	128.63737076135752	80.07827416262859	75.32845685226198	51.031196369728974
reg_lambda	0.8712359724199028	0.9366151735683103	0.4119943600117272	0.4715915820485001
learning_rate	0.22986312235879872	0.18373536800838014	0.17089767571718673	0.12035222634314197
colsample_bytree	0.6785461002750619	0.49026962305533395	0.9581853464118388	0.5702877386615345
min_child_weight	8.51977627806604	0.5538135251601395	6.889114934913907	6.558575847783384

Table 3 presents the prediction outcomes of the models. A comparison of Option 1 and Option 2 reveals that selecting a historical imputation approach is well-founded when confronted with a time series break that exhibits a discernible pattern across different years. This assertion is substantiated by the consistently lower values observed in Option 2 across all three models. Moreover, the proposed hybrid model is the most accurate for the case study, achieving a WAPE of 13.10%.

Table 3. Performance evaluation summary.

Models	Option 1		Option 2	
	MAPE	***WAPE***	***MAPE***	***WAPE***
Prophet	24.47%	14.71%	22.91%	13.87%
XGBoost	27.51%	15.25%	25.84%	15.09%
Prophet-XGBoost	25.60%	15.10%	19.48%	**13.10%**

Additionally, Figure 3 provides the real and predicted values of Options 1 and 2 of the daily shipping of dairy product units for the three models. When analysing Table 3 and Figure 3, it can be observed that Prophet presents a higher degree of accuracy than XGBoost. This is because Prophet is specifically designed to address seasonal patterns and holidays in time series data, e.g., during the Easter holiday, the date of which varies each year, the Prophet model demonstrates higher accuracy than XGBoost. However, the proposed hybrid approach, which combines the strengths of both models, presents even better performance.

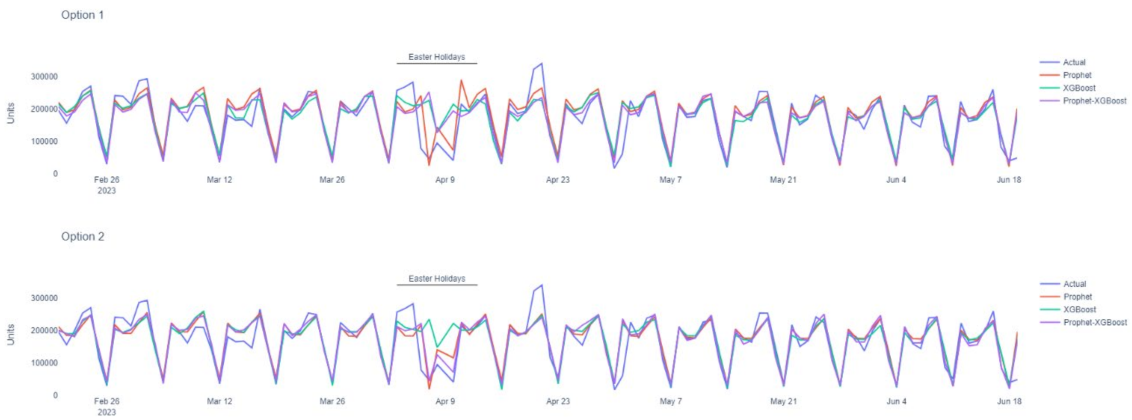

Figure 3. Shipped Units forecasts (120 days). Models: Prophet, XGBoost and Prophet-XGBoost.

IV. Conclusions

In the retail sector, warehouse managers need accurate sales forecasts to make the right decisions. To achieve this goal, it is essential to have reliable historical data and select the proper methodology.

In the research, we predict dairy customer demands received by a European retailer. To avoid the impact of the COVID-19 pandemic, which affected household consumption during the period 2020-2021 (especially in the case of essential products), we propose two options regarding the year 2021: removal or historical imputation. With regard to the methodology adopted, we use two models (Prophet and XGBoost) and the hybridisation of the same, which has recently proven its capacity to achieve a good level of accuracy in other contexts.

In this study, two valuable insights are identified: (i) historical imputation leads to better accuracy; (ii) the hybrid model approach is better than both single models. These results provide a guide for practitioners working with data to improve IM decisions.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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