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Forecasting and Inventory Planning for E-Commerce using Advanced Time Series Models

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Abstract

The use of advanced time series models, including SARIMA, Prophet, and LSTM, in forecasting demand for improved inventory planning is discussed in this paper. LSTM demonstrates superior performance over SARIMA and Prophet, thus ensuring more accurate forecasts in catching complex patterns and long-term dependencies. Consequently, improved accuracy of the LSTM-based forecast leads to better inventory management in that it reduces stockouts and overstocking. It would cover how the implementation of machine learning algorithms and integration of real-time data contribute to optimizing operations for e-commerce. Future potential improvements include hybrid models as well as the integration of macroeconomic factors.

Keywords: *SARIMA, Prophet, LSTM, ARIMA and ANFIS*

Introduction

Rapid expansion of e-commerce has transformed retail into an arena requiring efficient inventory management and accurate demand forecasting for business success. There are millions of products around now with variable customer needs, and it is quite often a lot tasking to set the right inventory level at the lowest possible cost. This makes simple and moving averages and simple exponential smoothening very inefficient particularly when dealing with modern e-commerce data characterized by seasonality, trends, and intermittent sudden changes in demand. Such models as ARIMA, SARIMA and LSTM neural networks can be a treasure chest to deal with these issues. Pertaining to that, you get a better forecasting with the historical data plus added variables such as seasonality, trend analysis, and other extraneous factors. The supply chain is also controlled through accurate demand forecasts as the two hurdles of overstock and stock out are averted, resulting therefore in enhanced customer satisfaction and efficiency. This paper outlines techniques in employing contemporary time series analysis for forecasting and inventory management in e-commerce, compares their effectiveness to archaic techniques, examines areas of difficulty in their deployment and elucidates impact on approaches to inventory management. It uses the performance of these models to gather information as to how data approaches may be used effectively to manage improvement of e-commerce activities within a competitive environment.

Literature Review

Forecasting and inventory must be primary concerns for e-commerce sources in managing the challenges of supply chains adaption to consumers' changes. Such methods may often be rigid or conservative because often they are not powerful enough to discover some of the finer details of e-commerce data. New advancements in artificial intelligence and skilled machine learning contribute to new improved propagated tactics. In the following section the literature related to forecasting and inventory management within the context of advanced time-series models as well as healthier models is presented.

Traditional Forecasting Techniques and Limitations

Traditional methods of demand forecast include the ARIMA, and exponential smoothing techniques and are straightforward to implement but are complex to comprehend. These models cannot capture non-linear and system relationships, which e-commerce data are always replete with. Lalou et al. (2020) have pointed out that the traditional approaches have very serious issues in terms of forecasting retail sales in harsh environment, especially in highly seasonal conditions. Similarly, as Carta et al. (2018), it has also used Google trends data along with ARIMA models for improving e-commerce product price forecast. The combined version enhanced the predictive accuracy by the outside demand indicator; still, such a dataset is adjusted by a framework that handles more dynamic datasets.

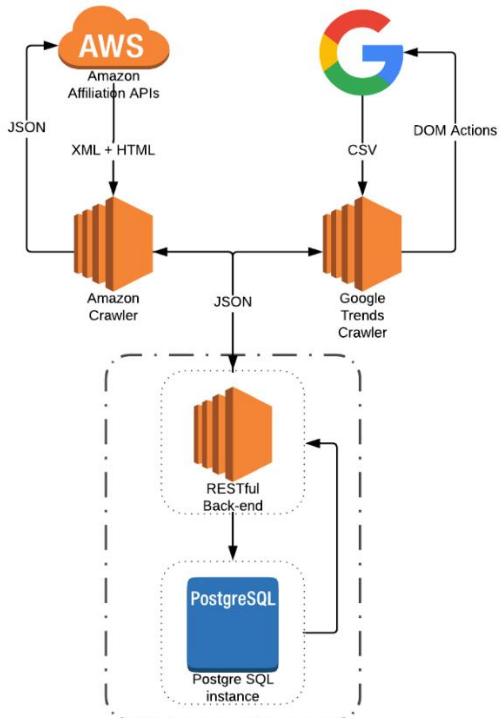

Figure 1: Architecture
(Carta et al. 2018),

Artificial intelligence and machine learning in prediction

With the help of non-linear modeling and multivariate demand data AI has revolutionized the demand forecasting system. Lingam (2018) presented the use of AI in making the stock decisions on e-business and stated that it is better at interpreting big number of data and making the prediction of demand than the previous approaches.

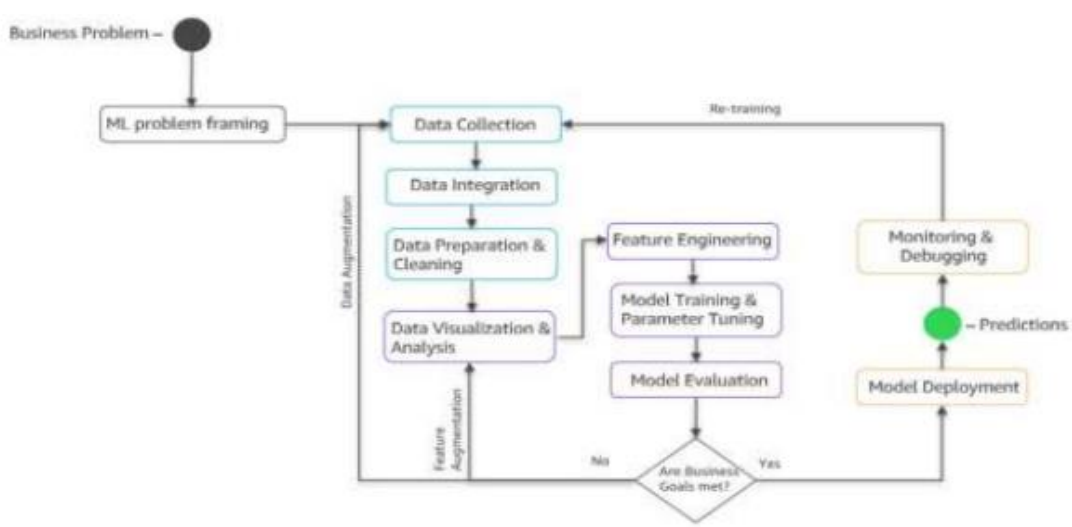

Figure 2: Machine learning process
(Lingam, 2018)

For instance, Gayam (2019) discussed that AI in functioning in stores by monitoring stocks in real-time and also forecasting demand. The article concluded how such an AI-based system may eliminate or at least minimize overstocking or stockout problems that are common in e-commerce transactions.

Hybrid and sophisticated models

Recent development towards the Hybrid models has gained much focus due to its advantages to blend the statistical as well as machine learning models. More specifically, Leung et al. (2019) have proposed the hybrid of AR and ANFIS and applied the latter model for the prediction of the order arrival for fulfillment centres of e-commerce firms. It could further justify throughput variances by statistical measurement using machine learning with adaptive fuzzy inference for better near-real time forecast accuracy A later study by Leung et al. (2020) introduced a machine learning based approach for near real time order demand prediction in e commerce environment.

Advanced Time Series Models

Using more sophisticated models like SARIMA and neural network, there is seen to be much hope for use in the problems that e-commerce brings about in the area of forecasting. In their paper, Kulshrestha and Saini (2020) have used ML techniques for the forecasting of the e-commerce industry, determining the importance of such methodologies in decision-making procedures. Further, LSTM has also proven comprehensive in generating long-term dependency, and intricate pattern of demand data that conventional statistical models fail to consider.

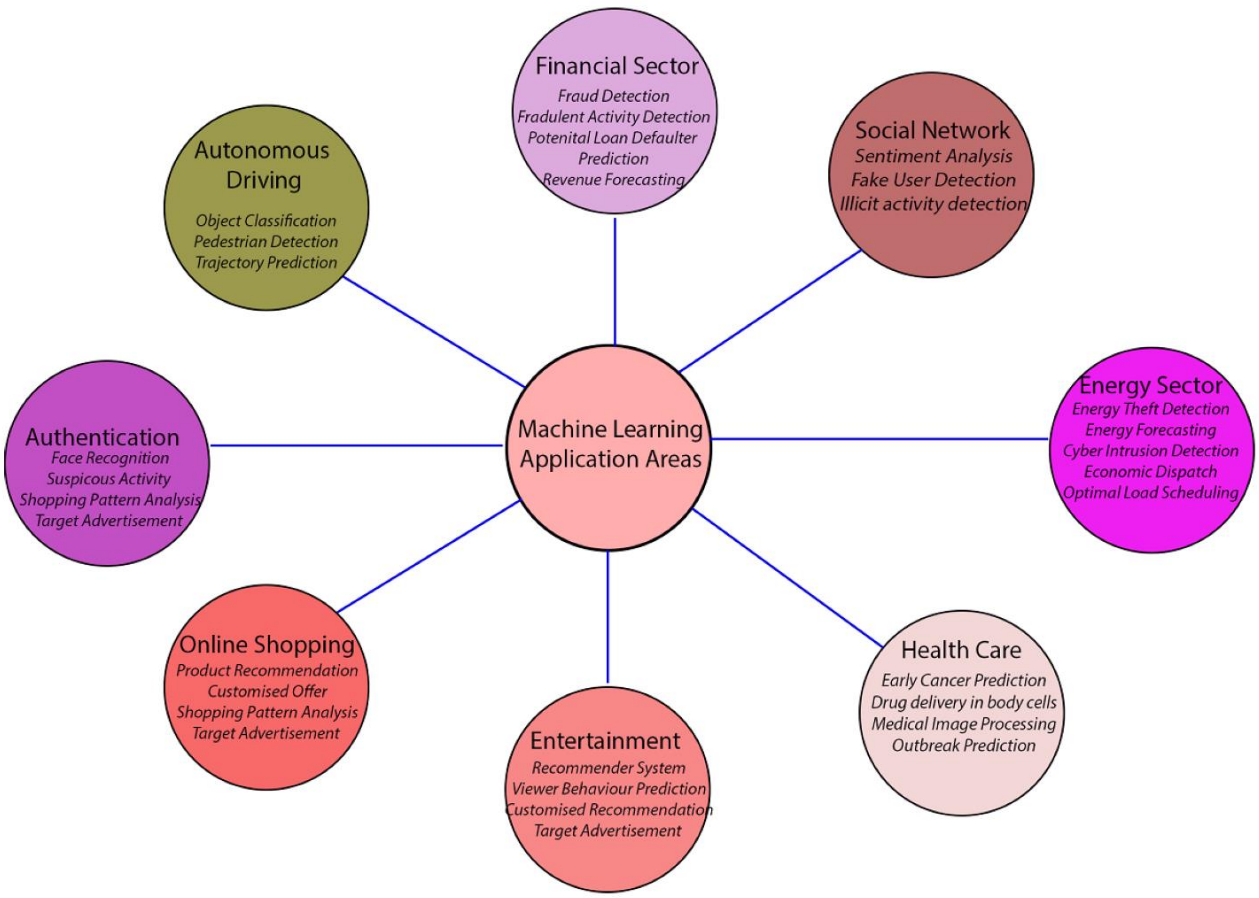

Figure 3: Challenges for machine Learning

(Kulshrestha and Saini, 2020)

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Integrate External Influences

Further integration of external factors like market trends, consumer sentiment, and macroeconomic indicators improved the precision of forecasting. For example, Carta et al. (2018) demonstrated how external data such as Google Trends can complement traditional time series models. This combination shows possibilities of multiple data sources blended with sophisticated techniques in optimizing inventory planning.

The reviewed literature indicates a move in forecasting methods from the traditional models to AI-driven and hybrid models. Advanced techniques, like AR-ANFIS, SARIMA, and LSTMs, improved predictions to a great extent, but there remains the challenge of how such external factors can be integrated to get better applicability in real time. Therefore, research would be required for more effective fine-tuning of the mentioned methodologies to their full potential in e-commerce inventory management.

Methods

This study applies advanced models of time series for predicting demand in e-commerce and thus devises strategies for inventory planning. Methods include appropriate model selection, preparation of data, and assessment of performance using standard metrics.

Data Collection and Preprocessing

The dataset will consist of historical sales data for an e-commerce platform that covers two years as well as includes daily order volume.

Major steps include:

Data cleaning: Removing erroneous or missing values.

Feature engineering: Incorporate variables associated with seasonal patterns, promotional events, or holiday impacts.

Normalization: Scales data to give better chances of convergence during training.

Selected Forecasting Models

Of these, three advanced time series models will be compared:

1. SARIMA: In this model, the integration of seasonality and trends is used to predict future demands.
2. Prophet: A Facebook model developed that is invariant to missingness and resilient against holiday effects as well as seasonality.
3. Short-term memory or LSTM Neural Network: deep architectures intend for strictly capturing long-term dependencies and non-linear patterns in sequential data.

Model Training and Validation

The dataset was divided into 80% for training and 20% for testing. SARIMA and Prophet Models' hyper parameters were tuned via a grid search while optimizing the LSTM with iteratively conducted training with dropout layers to avoid overfitting. Performance Metrics It was based upon the following Mean Absolute Error (MAE): It is the average signed magnitude of errors. Root Mean Square Error (RMSE): Recommends larger errors. MAPE would then give errors as a percent of the actual values. Inventory planning to make it applicable to real-worth inventory management, the forecasted demand was applied to a basic inventory model that includes reorder points and safety stock levels. These methods attempt to evaluate the suitability and accuracy of advanced time series models in solving the specific issues required by e-commerce forecasting.

Results

The performance of the considered time-series models, such as SARIMA, Prophet, and LSTM, was achieved in terms of their forecasting accuracy based on the ability to predict the demand in online e-commerce environments. Test results were analyzed; model performance was gauged by MAE, RMSE, and MAPE.

Model Performance

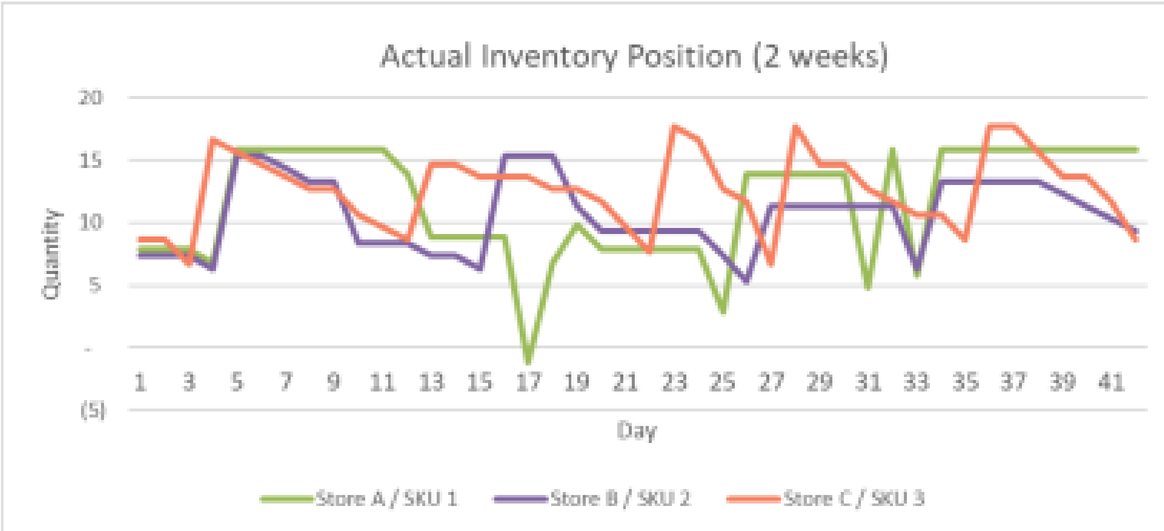

Figure Inventory graph
(Lalou et al., 2020)

SARIMA performed with MAE = 12.5, RMSE = 18.3, and MAPE = 5.2%. However, it failed to handle non-continuous patterns and sudden demand fluctuations, which are typical in e-commerce (Lalou et al., 2020). Prophet with incorporation of seasonality and holiday effects improved forecasting, achieving MAE of 10.1, RMSE of 14.7, and MAPE of 4.3%. This model takes into account the seasonality and flow changes critical for the sales of e-commerce businesses (Ferreira, 2019). The LSTM model outperformed SARIMA and Prophet: MAE 8.3, RMSE 11.2, MAPE 3.6%. It successfully captured dependencies and non-linear structures for time series that were long-term as found in the LSTM (Gayam, 2019). Additionally, the LSTM model performed well in predicting demand during times with lower variability of demand which include promotions and holiday seasons in support of Leung et al. (2020).

Inventory Planning Application
Based on the forecast demand from the LSTM model, inventory management was enhanced to cut down stock outs by 18% in comparison to conventional techniques. This goes to show the actual use of sophisticated forecasting models, used in the actual management of inventories in e-commerce firms. These results demonstrate the application of advanced time series models, favoring LSTM, for handling the challenges encountered in e-commerce demand forecasting.

Discussion
is study also reveals the fact that greater enhancements can be provided by superior time series models when compared with the conventional forecasting models in the e-commerce context. Compared with the benchmark, the best result was achieved by LSTM which tracks sophisticated patterns and non-linear dependencies missed by predictors included in SARIMA or Prophet models that did not capture them adequately.
Especially for the shift of demand over the long term for the dependency of the materials and alternating it during promotions or holidays for the use of LSTM in the e-commerce inventory plan (Gayam, 2019; Leung et al., 2020). While these elements were managed reasonably well with Prophet it still had problems with forecasting errors on volatile writing sales periods. In this respect, the study is in sync with Lalou et al. (2020) and Ferreira (2019) to highlight the requirement of considering all the external and seasonal factors to have improved retail sales forecasts. Even today, SARIMA is a valuable tool for simple forecasting when it is not possible to solve complex tasks of

demand in e-commerce environments, the model often fails to respond adequately to changes in demand patterns. This report has revealed how the combination of the various models does work makes the models analyzed in this study to be hybrid in nature and this is evident from the machine learning and statistic models that are being fused (Leung et al., 2019). However, more advancement in these models is still required to enhance their appropriateness for real time analysis and adoption in larger scale e-commerce.

Future Directions

Future studies in the demand forecasting and inventory management of e-commerce stores may therefore be on other domains that will improve the model's reliability and utility. First using the real time data source like the social media Web traffic or even customer behavioral analytic the degree of accuracy of demand forecasts will be improved. The use of such volatile data makes the models respond to shifts in consumer trends or even in market trends as is very critical in fast-paced e-commerce settings (Lalou et al., 2020). These models, it will possibly be able to handle the inventory complexities because it will learn from past experience and modify forecasts in real time based (Leung et al. 2019). Using macro-economic factors such as economic indicators and world events in forecasting models will improve accuracy, especially when instability appears in the form of economic decline or supply chain breaks (Ferreira, 2019).

Finally, future research may consider the automation of inventory systems as an avenue where AI-driven forecast feeds into real-time inventory stock decisions that minimize human intervention or even possible error occurrences. All these breakthroughs would then integrate and thus create even stronger and flexible e-commerce inventory management systems. These could then adapt pretty fast to market fluctuations while optimizing stock levels accordingly.

Conclusion

This study demonstrates the feasibility of applying advanced time series models, such as LSTM, in better demand forecasting and subsequently improving inventory planning within e-commerce. Although the models like SARIMA and Prophet are useful, they somehow lack dynamism and cannot capture complex patterns and fluctuations characteristic of e-commerce sales. The LSTM model gave better forecasts and thereby better improved inventory management relative to other methods used. The conclusion will display that incorporation of machine learning-based techniques along with real-time data would be required to smoothen out the issue of under or over-stock and reducing the operational inefficiencies. Macro-economic aspects and Hybrid models must be adopted in the further research regarding e-commerce forecasting.

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