Holiday Forecasting: A Machine Learning Approach to Forecast Shipment Volume for a Leading Fashion Retailer

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Abstract

This study provides an approach to predict estimated number of packages for various origin destination combinations during holiday season. The motivation for this study is that retailers need accurate demand forecasts for tactical and operational planning within the business. Having the ability to plan reliably for these special days during holiday season can give visibility to third party logistics partners about the right amount of shipments being shipped to customers. In collaboration with a leading fashion retailer, we researched and developed a methodology that could capture these unusual holiday shipment volume peaks using machine learning algorithms, then estimate the number of packages for various origin destination combinations.

Introduction

Generating accurate forecasts can be a challenging endeavor, but even more so during holidays, where chaotic demand spikes occur. Forecasting the volume of holiday shipments would help the retailers give more visibility to their logistics partners to plan last mile operations efficiently. Efficient capacity planning has been the core of last mile supply chain which leads to better negotiation for rates with partners and help in operational planning.

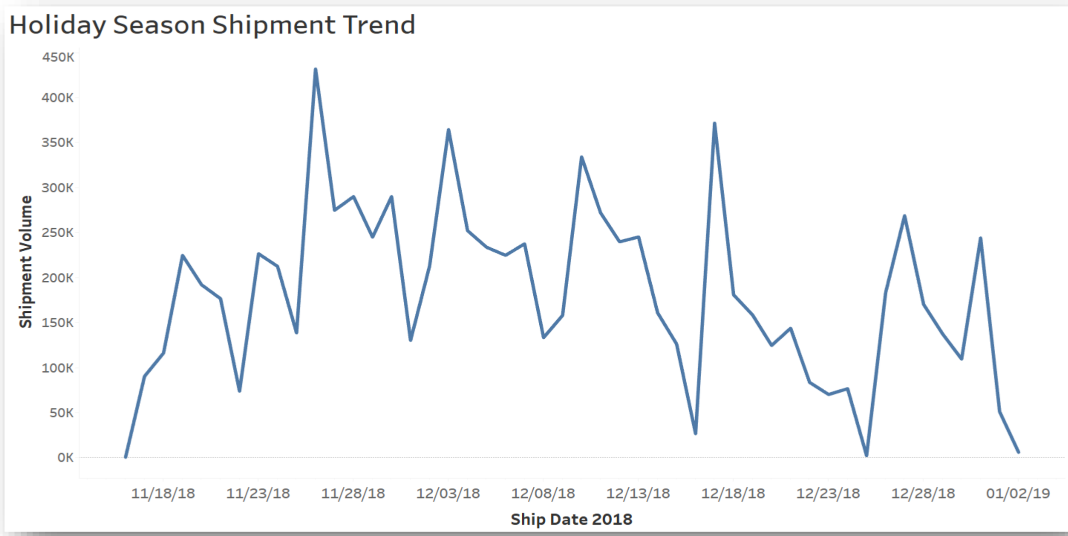

Figure 1

Literature Review

We looked through various approaches which have already been studied to generate reliable and scalable forecasts.

Author, Year	Study	Motivation for research
(Brown 2018)	Forecasting Time-Series data with Prophet	To gain an understanding of applications of Prophet
(Fischer and Krauss 2018)	Deep learning with LSTM networks for financial market predictions	To gain insights into the prediction capabilities of LSTM.
(Karlsson 2013)	A review of unsupervised feature learning and deep learning for time-series	To gain an understanding of applications of deep learning in time series forecasting
(Toshniwal and Joshi 2005)	Using Cumulative Weighted Slopes for Clustering Time Series Data	To study a new approach for clustering time series data

Methodology

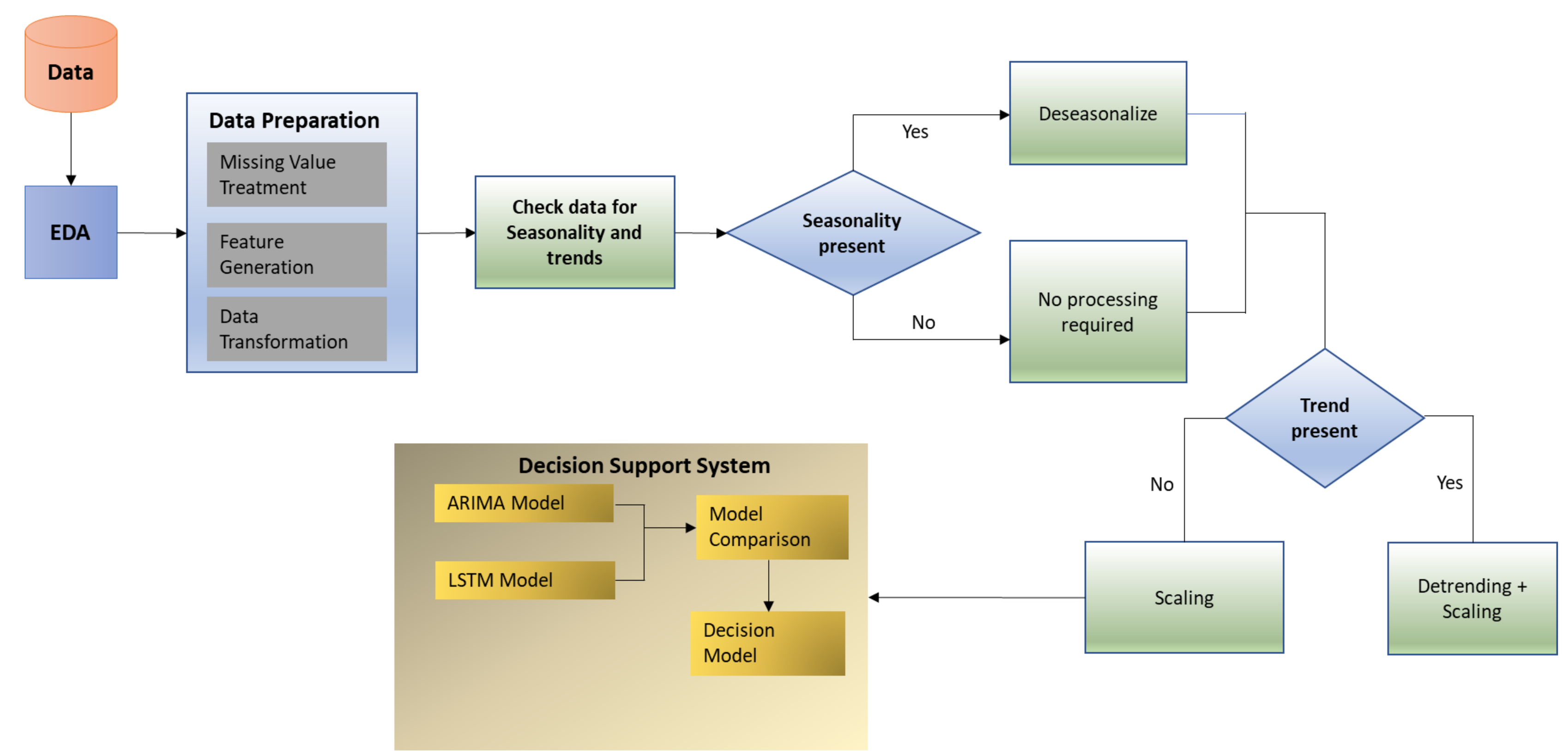

Figure 2

Data:
Three years shipment level data of a leading Online retailer at Fulfilment center and zip-code level. Additional factors like weight were provided along with the shipping zone of the customer and service mode of the delivery

Data-cleaning:

- Removed observations with missing values in Zone & Zip-code
- Shipments with '0' weight are considered in <1 pound weight bucket
- Formulated 204 distinct combinations of Fulfilment Centre and Zone
- Three years of data were merged to consecutive intervals where each year had 6 weeks of shipping information

SARIMA Model
SARIMA also known as Seasonal ARIMA was fitted to time series data of volume of shipments for various Fulfilment Centre - Shipping Zone combinations and was used to forecast shipments for 2019. Seasonality factor was taken as 42 days. Exogenous factors like spikes on certain days were taken into account while building the time series model. Additive model was used as there was no correlation between trends and seasonality. (p,d,q) leading to the lowest AIC was obtained through grid search methodology.

LSTM Model
Long/Short-term memory network is a type of recurrent neural network, specifically designed to learn long term dependencies. The current model works on Many-In-Many-Out mechanism, that is it predicts multiple forecast outputs using multiple inputs (lag variables).

Descaling: The output of the LSTM network is inverse transformed to obtain the original range of values.

Adding back the seasonality and trend: We add back the seasonal and trend components to the forecast output from the model.

Statistical performance measures: The performance of both the models SARIMA and LSTM was judged over MAPE (Mean Absolute Percentage Error) across all time series models.

Results

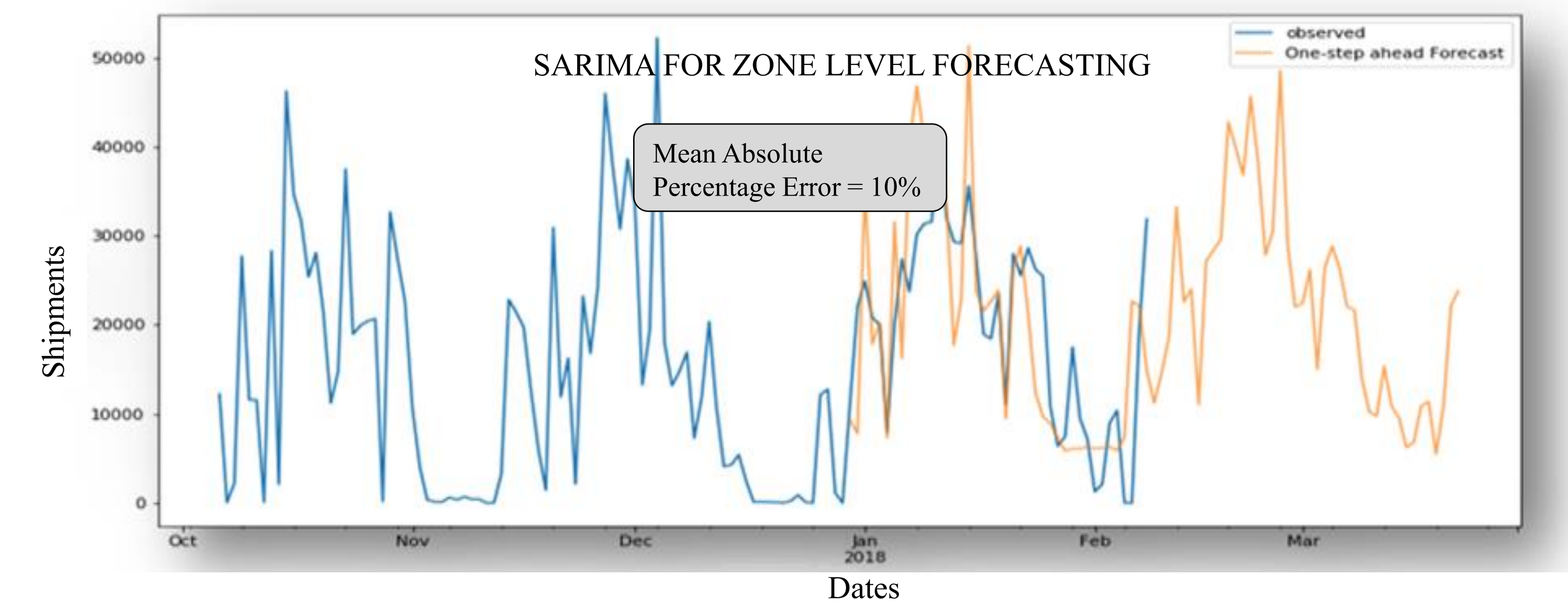

Figure 3

Seasonal ARIMA was modelled for multiple univariate time series corresponding to different FC–Zone combinations and the weekly MAPE was found to be between 10% and 40% for the top 25 combinations which contributed to 96% of shipment volume.

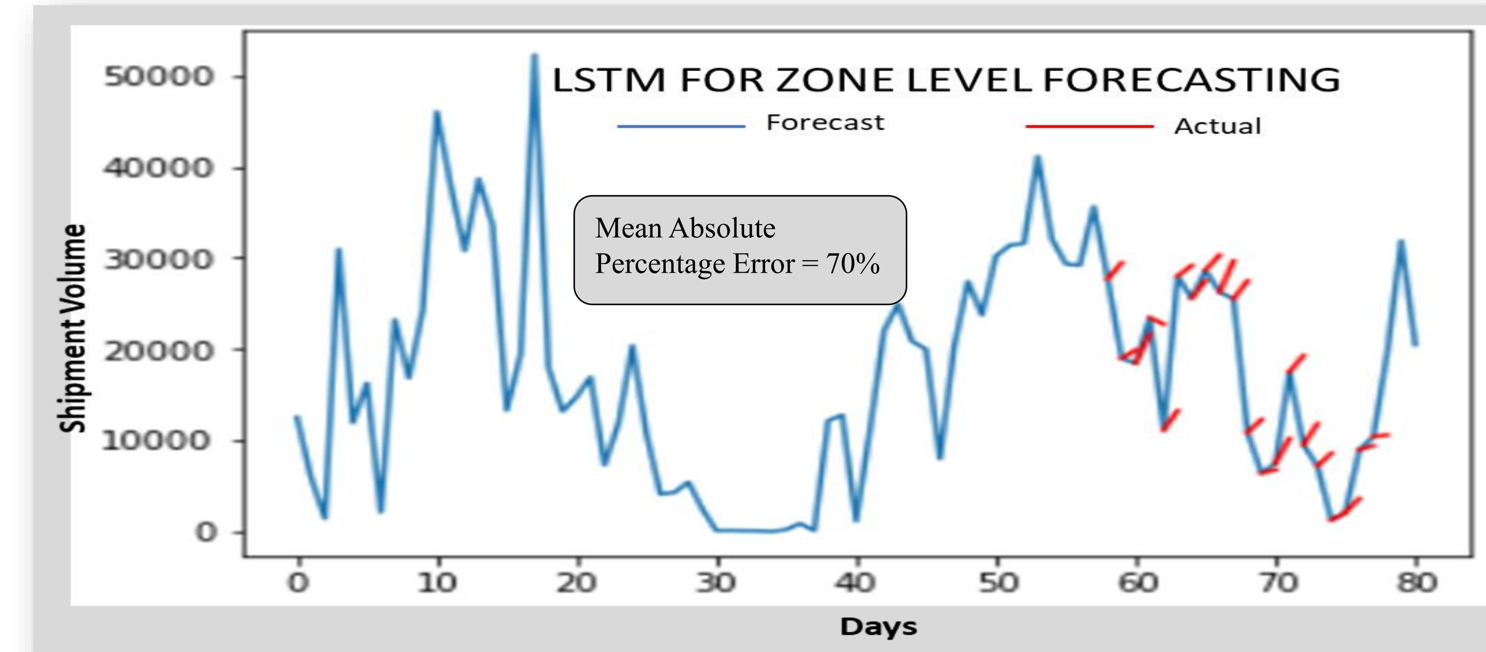

Figure 4

LSTM was similarly modelled for multiple univariate time series corresponding to different FC–Zone combinations and the weekly MAPE was found to be 70%. Hence SARIMA performed better than LSTM.

Conclusion

Holiday Planning is the core of operational performance in most industries and thus an efficient forecast can help organizations. It was observed that SARIMA is one such model that performed better (lower MAPE) than LSTM and aggregating shipments at weekly level provided better accuracy than that at daily level. However, with more data points in each time series the LSTM and SARIMA will train better and the accuracy of forecasts will be enhanced. Also incorporating more years of data would have enabled these models to give a much better accuracy.

Acknowledgments

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