Forecasting SKU Demand using Time Series Models

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BACHELOR OF TECHNOLOGY

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by

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DECLARATION

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/-data/fact/source in my submission to the best of my knowledge. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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This is to certify that the report titled **FORECASTING SKU DEMAND USING TIME SERIES MODELS**, submitted by **Mr. Swapnil Sharma**, to the Indian Institute of Technology, Tirupati, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the project work done by him under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Place: Tirupati
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ABSTRACT

KEYWORDS: Time Series modelling, SKU Demand Forecasting, Time Series Regression, ARMA, AR, MA, ARIMA

In the dynamic landscape of modern business, accurate demand forecasting for Stock Keeping Units (SKUs) has become paramount for effective inventory management and overall operational efficiency. This report delves into the pivotal role of SKU demand forecasting, elucidating its significance in the context of contemporary business operations and shedding light on the intricate complications associated with the forecasting process.The first phase of our project concentrates on leveraging time series models, namely Auto-regressive (AR), Moving Average (MA), and their combination, Auto-regressive Moving Average (ARMA), to enhance the accuracy of SKU demand forecasting. Time series models have proven to be robust tools in capturing the temporal patterns inherent in SKU demand data. However, the forecasting process is not without its challenges, and this report meticulously outlines the complexities involved.To address these challenges and elevate the performance of the time series models, we employ sophisticated diagnostic tools such as Partial Auto-correlation Function (PACF) and Auto-correlation Function (ACF) plots. These tools play a crucial role in identifying and mitigating the impact of auto-correlation, enabling a more refined and precise forecasting model.By providing a comprehensive understanding of the importance of SKU demand forecasting in the broader business context and elucidating the intricacies of time series modeling with AR, MA, and ARMA, this report aims to contribute valuable insights for businesses seeking to optimize their inventory management processes and improve overall supply chain efficiency.

TABLE OF CONTENTS

ABBREVIATIONS

SKU	Stock Keeping Unit
AR	Auto Regressor
MA	Moving Average
ARIMA	Auto-regressive Integrated Moving Average
ARMA	Auto-regressive Moving Average
PACF	Partial Auto-correlation Function
ACF	Auto-correlation Function
ML	Machine Learning
DL	Deep Learning
RNN	Recurrent Neural Networks
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MSE	Mean Square Error

CHAPTER 1

Introduction

1.1 Objectives and Scope

A SKU or Stock Keeping Unit is the unique manufacturer code assigned by the the seller to every type of product it sells. A SKU demand forecasting helps you to optimize inventory levels, improve customer service, improve supply chain efficiency, promotional planning, risk mitigation and lastly competitive advantage by data driven decision making. However, SKU sales can get affected by the factors like promotions, holidays, stock out, store closures, seasonality, market trends, change in price, promotions etc. We can use two different types of models to do the time series analysis that are Time Series Models and Machine Learning Models. Various literature are there that have focused on both of the two. Time series models can be prepared without any extra variable. Time series models can find out the seasonality, market trends and patterns on its own. But for machine learning models you have to provide them with such variables that can affect the sales of SKU. Some of the below points are the objectives of this project in Phase 1.

1. **Scope of Time Series Forecasting:**
   (a) Investigate and analyze the extensive scope of Time Series Forecasting in the context of business operations.

   (b) Explore how Time Series Models can effectively incorporate and account for intricate patterns and external factors such as store closures, holidays, stockouts, advertising campaigns, pricing fluctuations, and sales trends.

2. **Performance of Time Series Modelling:**
   (a) Assess the capabilities of Time Series Models, including Auto-regressive (AR), Moving Average (MA), and their combination (ARMA), in generating accurate and reliable forecasts.

   (b) Explore the suitability of Time Series Models in capturing temporal dependencies and trends within historical data, leading to improved forecasting precision.

3. **Role of PACF and ACF in Model Enhancement:**

(a) Investigate the utilization of diagnostic tools such as Partial Auto-correlation Function (PACF) and Auto-correlation Function (ACF) in evaluating and refining Time Series Models.

(b) Explore how PACF and ACF plots can identify and address issues related to auto-correlation, thereby contributing to the optimization of model performance.

By achieving these objectives, the project aims to provide valuable insights and contribute to the advancement of Time Series Forecasting methodologies, particularly within the dynamic landscape of business operations.

CHAPTER 2

Literature Review

The literature survey presented here encapsulates key findings from diverse research efforts aimed at advancing SKU retail sales forecasting methodologies within distinct industry frameworks. In oneAndrade et al. (2022) study focusing on the grocery sector, the authors delve into the complexities of sales forecasting by integrating factors such as public holidays and item perishability. Employing the XG Boost machine learning algorithm, this research underscores the significance of advanced techniques in addressing the intricate challenges posed by perishable goods. Shifting the focus to computer productsElalem et al. (2023) characterized by short life cycles, another study adopts a hybrid approach, combining traditional time series models like ARIMAX with cutting-edge Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs). This hybrid modeling strategy recognizes the need for adaptability when forecasting sales for products with transient life spans. In a third research effort Taghiyeb et al. (2023), the emphasis is placed on the forecasting of SKU sales, particularly considering the impact of promotions and holidays. Employing a diverse set of machine learning algorithms, including Gradient Boosting, Random Forest, and XG Boost, alongside Artificial Neural Networks (ANNs), this study provides a holistic exploration of forecasting techniques. The inclusion of comparative analyses underscores the importance of accounting for promotional dynamics and holidays, while the integration of ANNs reflects a commitment to capturing intricate patterns in sales data. Collectively, these studies contribute to a nuanced understanding of SKU retail sales forecasting, showcasing the evolving landscape of methodologies tailored to industry-specific challenges.

Extending the literature survey to encompass an additional study, a research effortSeyedan et al. (2023) within the online retail industry has been investigated. This paper places emphasis on the multifaceted dynamics of online retail sales forecasting by integrating factors such as prices, discounts, and past demand. Moreover, the study delves into the critical aspect of safety stock prediction in conjunction with demand forecasting. Employing a sophisticated arsenal of machine learning and neural network methodologies, including Artificial Neural Networks (ANNs), Long Short-Term Memory networks

(LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), the research underscores the need for comprehensive modeling approaches in the online retail landscape. By exploring the interplay between pricing strategies, promotional discounts, and historical demand patterns, this study contributes to a nuanced understanding of the intricate dynamics inherent in online retail sales forecasting.

Through the comprehensive literature survey, several common variables emerge as pivotal elements in SKU forecasting, each playing a distinctive role in enhancing the accuracy and robustness of predictive models. Holidays, as highlighted in multiple studies, consistently prove to be a significant factor influencing SKU forecasting. The temporal disruptions introduced by holidays impact consumer behavior and purchasing patterns, necessitating the incorporation of these events into forecasting models. The literature underscores the importance of understanding how holidays can cause fluctuations in demand, enabling more precise predictions during such periods. PromotionsKourentzes et al. (2016) emerge as another crucial variable influencing SKU forecasting, as evidenced by the examined research efforts. Promotional activities introduce unique demand patterns, often characterized by sudden spikes or fluctuations. Accurate forecasting demands the incorporation of promotion-related variables, allowing models to adapt to the irregularities introduced by marketing campaigns and special events. Stock outs, observed across various studies, present a substantial challenge in SKU forecasting. Instances where products go out of stock can lead to missed sales opportunities and customer dissatisfaction. Literature emphasizes the necessity of accounting for stock out events, employing strategies such as safety stock prediction, to mitigate the impact on forecasting accuracy and maintain optimal inventory levels. Weekends, identified as a recurring variable in the literature, introduce temporal considerations into SKU forecasting. Consumer behavior often exhibits variations between weekdays and weekends, and models need to adapt to these patterns. The literature survey underscores the significance of incorporating day-of-week effects to capture the fluctuations associated with weekends, ensuring more precise predictions and effective inventory management.

CHAPTER 3

Time Series Modelling

3.1 Preliminaries

3.1.1 PACF

PACF stands for Partial Auto-Correlation Function. The PACF is a statistical tool used to tell the correlation between y_t and its lag in time series analysis, after accounting the effects of other lags in between. The PACF at lag k is the correlation between the series and its own lag k values, by taking influence of all the lags from 1 to $k1$ in account. It helps to identify the direct relationship between the current observation and its k_{th} lag. It helps you to find the order of AR model. The mathematical representation of PACF is :

$$\phi_{kk} = \frac{\rho_{t,t-k} - (\sum_{i=1}^{k-1} \phi_{k-1,i})\rho_{t-i,t-k}}{\sqrt{(1-\sum_{i=1}^{k-1} \phi_{k-1,i}^2)(1-\sum_{i=1}^{k-1} \phi_{k-1,i}^2)}} \tag{3.1}$$

where $\rho_{t,t-k}$ is the auto-covariance or ACF value between the time series values at time t and $t-k$, and $\phi_{k-1,i}$ represents the PACF at lags 1 through $k-1$.

3.1.2 ACF

ACF stands for the auto-correlation function and it tells you the value of correlation between the current data point y_t and the lagged data point y_{t-k}. k is the lag. ACF helps you to find the order of an MA model. The mathematical formulation of ACF can be written as:

$$\rho_k = \frac{\mathrm{Cov}(y_t, y_{t-k})}{\sqrt{\mathrm{Var}(y_t) \cdot \mathrm{Var}(y_{t-k})}} \tag{3.2}$$

where the all notations are same as mentioned above. (ρ_k) is the the ACF at lag k.

3.2 AR, MA, ARMA and ARIMA

3.2.1 Auto Regressor (AR) model

In Auto-regressor model the output variable depends on its own past values.The variable y_t is the linear combination of the past p data points and here p represent the order of the AR model or the number of significant lags:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \ldots + \alpha_p y_{t-p} + \varepsilon_t + c \tag{3.3}$$

$$\text{or} \qquad y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t + c \tag{3.4}$$

where ε_t is the noise, error or residual. (α_i) are the coefficients that need to be determined. Auto-regressive models can be flexible in handling the different types of time series patterns. To get the values of the coefficient there are various methods like Ordinary Least Squares, Maximum Likelihood Estimation, Gradient Descent and other types of the Gradient Descent algorithms for example Stochastic Batch Gradient Descent Algorithm.

3.2.2 Moving Average (MA) model

In MA model the output variable y_t can be written as the linear combination of the independent error at time t and previously time points.

$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \tag{3.5}$$

$$\text{or} \qquad y_t = \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t + \mu \tag{3.6}$$

Here, y_t is the time series at time t. μ is the mean of the time series. (ε_{t-i}) are the independent error or residuals that are not correlated to each other,(θ_q) are the coefficients of MA model. q is the order of the MA model.

3.2.3 Auto-regressive Moving Average (ARMA) model

The Auto-regressive Moving Average (ARMA) model is a mixture of AR and MA model. The output variable y_t can be written as the linear combination of AR and MA terms i.e the previous data points and independent errors or residuals.
The general form of an ARMA(p, q) model is given by:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \ldots + \theta_q \varepsilon_{t-q} + \alpha_p y_{t-p} \quad (3.7)$$

$$\text{or} \qquad y_t = \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t + c. \quad (3.8)$$

where all notations depicts the same as the AR and MA model. c is the only new term that is a constant.

3.2.4 Auto-regressive Integrated Moving Average (ARIMA) model

The ARIMA (Auto-regressive Integrated Moving Average) model is indeed an extension of the ARMA (Auto-regressive Moving Average) model, and it includes an additional component for differencing, often denoted as d, which stands for the order of differencing. The notation for an ARIMA model is often denoted as ARIMA(p, d, q), where:

$$(1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p)(1 - B)^d y_t = (1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q)\varepsilon_t \quad (3.9)$$

$$\text{or} \qquad (1 - \sum_{i=1}^{p} \alpha_i B^i)(1 - B)^d y_t = (1 + \sum_{j=1}^{q} \theta_j B^j)\varepsilon_t \quad (3.10)$$

where, all parametes as have same notations as mentioned in the AR, AR, ARMA and ARIMA. Instead B which is the back shift operator :

$$By_t = y_{t-1} \quad (3.11)$$

and d is the differencing order.

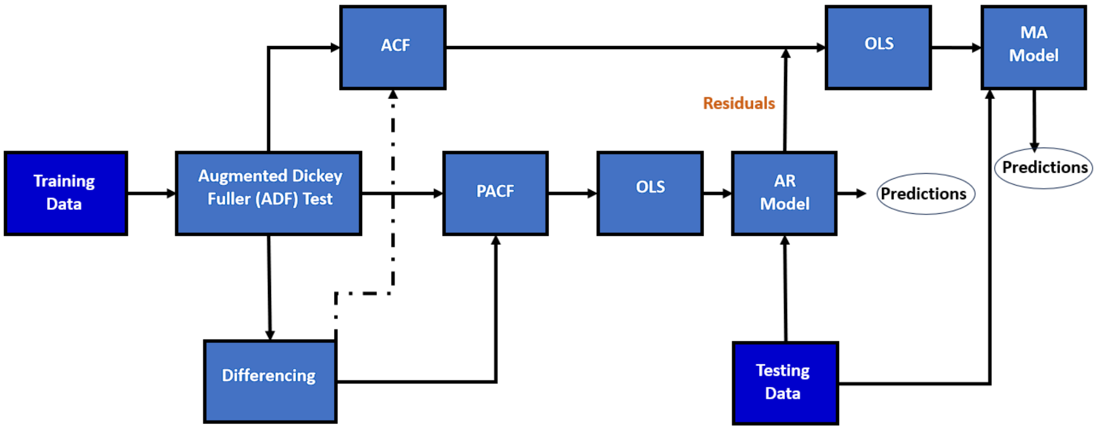

Figure 3.1: Flow diagram of methodology.

3.3 Methodology

Now, let's talk about the methodology. Firstly, we have checked whether the time series that we want to forecast is stationary or not. In the context of time series analysis, a time series is considered stationary if its statistical properties, such as mean and variance, remain constant over time. On the other hand, a non-stationary time series is one whose statistical properties change over time. We have done this using Augmented Dickey-Fuller (ADF) test. The null hypothesis of the ADF test is that the time series possesses a unit root (i.e., it is non-stationary). The alternative hypothesis is that the time series is stationary. The test statistic is compared to critical values to make a decision regarding the null hypothesis. After that we have created the PACF plots. PACF helps you to find the order and the significant lags u should consider while creating the model. We have considered the most significant lags based on 5% significance. We have chosen only the two most significant lags so to avoid the overfitting. We have got the parameters of the AR or coefficients of y_t using the method of ordinary least squares (OLS). After predicting the forecast we move towards the MA model. In MA model the most important step is to get the previous errors in the forecast. We got the values of residuals from the AR model and before that we should get the significant lags from ACF by passing the original time series. After getting the significant lags we got the coefficient of MA model using the OLS method. Please refer [Figure 3.1] for clear understanding.

CHAPTER 4

Results and Discussions

4.1 Case Study

4.1.1 Description of Dataset

The dataset is taken from the Kaggle University of Nicosia & Kaggle (2020) and is the classic M5 forecasting dataset of Walmart stores. The datasets contains the 1914 days of SKU data as the training set and the 28 days of the data for the evaluation. Dataset focuses on the 10 stores of the three states. The states are Texas, California and Wisconsin. Texas contains of 3 stores, Wisconsin 3 stores and California 4 stores. In total there are total 3049 SKUs. These SKUs are divided into three categories Hobbies, Household and Foods. And each category is also divide into subcategories. There are 2 sub categories in Hobbies, 2 in Households and 3 in Foods. Please refer the image for clear information.[Figure 4.1].

4.1.2 Time Series Models for SKU Demand Forecasting

The models we considered for forecasting are AR, MA and ARMA. The order of the AR model is 2 where I got the first two significant lags that are t-16 and t-25. The respective model can be written as.

$$y_t = \alpha_1 y_{t-16} + \alpha_2 y_{t-25} + b \tag{4.1}$$

Now, coming to the MA model the order is 1 and here the most significant lag is t-25. The model will look like.

$$y_t = \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-25} + \mu \tag{4.2}$$

And for the final ARMA model we have considered the orders of (2,1) means including the same lags and errors from AR and MA respectively. Therefore, the model will look

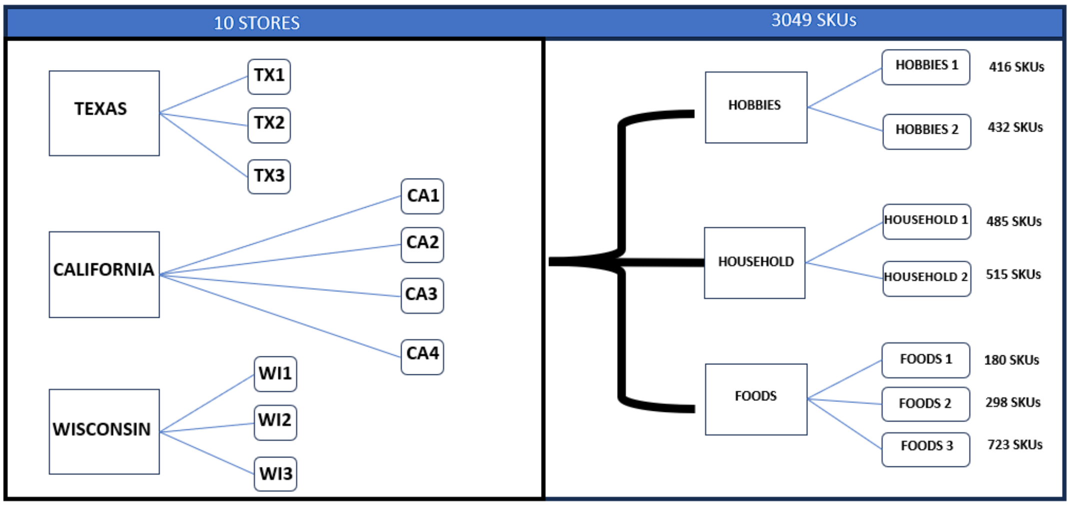

Figure 4.1: Flow diagram of dataset

like:

$$y_t = \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-25} + \alpha_1 y_{t-16} + \alpha_2 y_{t-25} + c \tag{4.3}$$

here, c is the constant term.

4.2 Results

The table of the performance of the respective time series models on the training set is created. Forecasting is done on the store id = "CA_2" and category id = "HOBBIES_1_001".[Table 4.2]

Same has been done for the testing set.[Table 4.1].

From the ACF and PACF we got the significant lags to be t-16 i.e. of 16 days and t-25 i.e. of 25 days[Figure 4.3]. For MA model errors to be considered at t-25 [Figure 4.2].

Table 4.1: Performance Table of testing

Model Name	RMSE	MSE	MAE
AR	0.845	0.714	0.7477
MA	0.084	0.007	0.064
ARMA	0.0865	0.007	0.066

4.2.1 Performance Plots of AR model on each of the sets.

1. **On training set:** Please refer to the [Figure 4.4] for plots of actual values vs the predicted values on training set computed from the AR model.

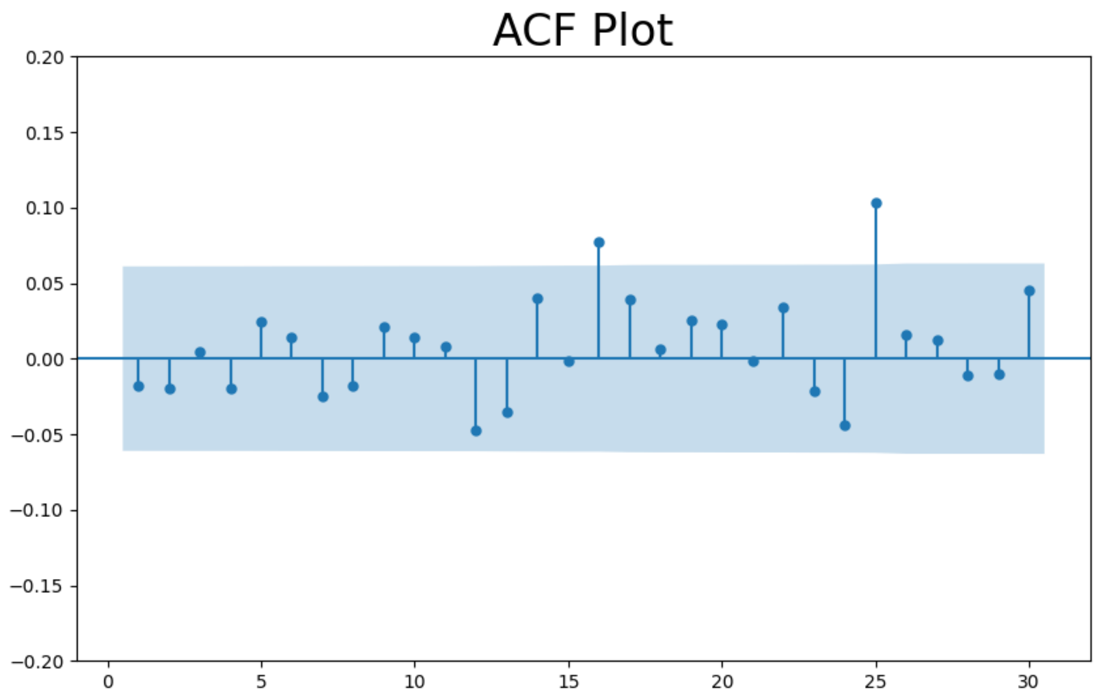

Figure 4.2: ACF Plot for max lags 30

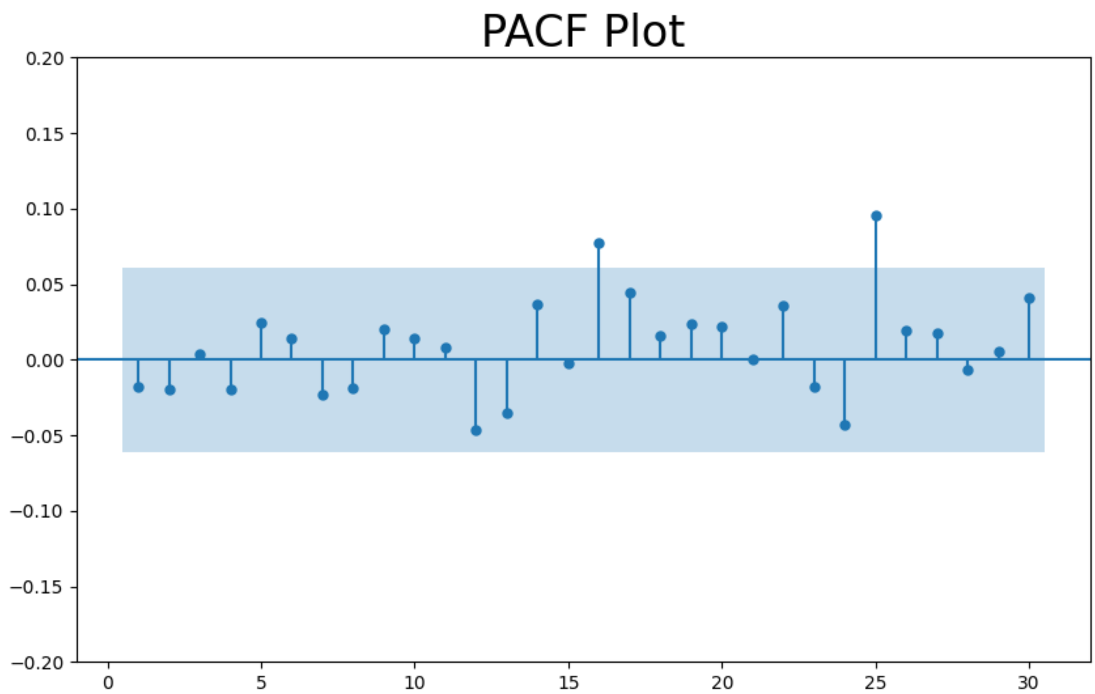

Figure 4.3: PACF Plot for max lags 30

Table 4.2: Performance Table of training

Model Name	RMSE	MSE	MAE
AR	0.835	0.6975	0.665
MA	0.066	0.004	0.052
ARMA	0.065	0.004	0.052

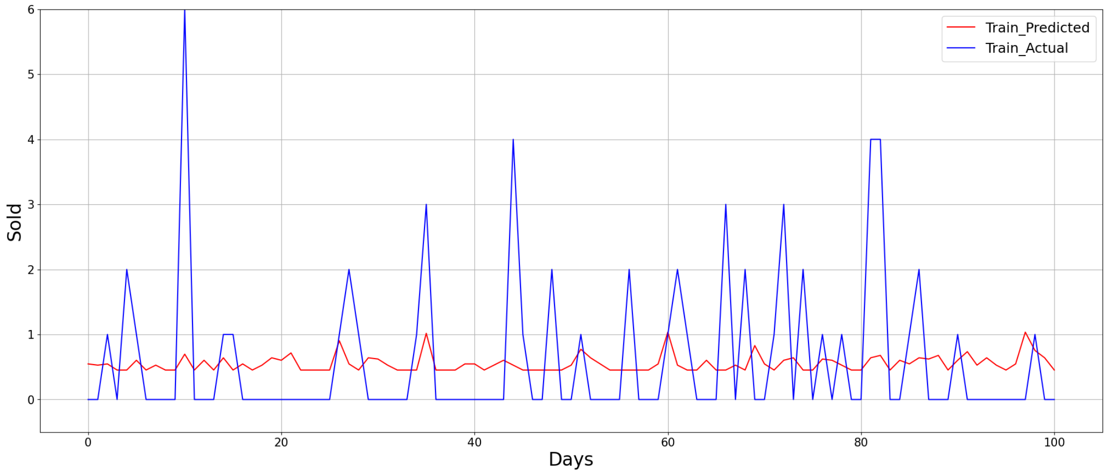

Figure 4.4: Actual vs predicted on training set of AR.

2. **On testing set:** Please refer to the [Figure 4.5] for plots of actual values vs the predicted values on the testing set computed from the AR model.

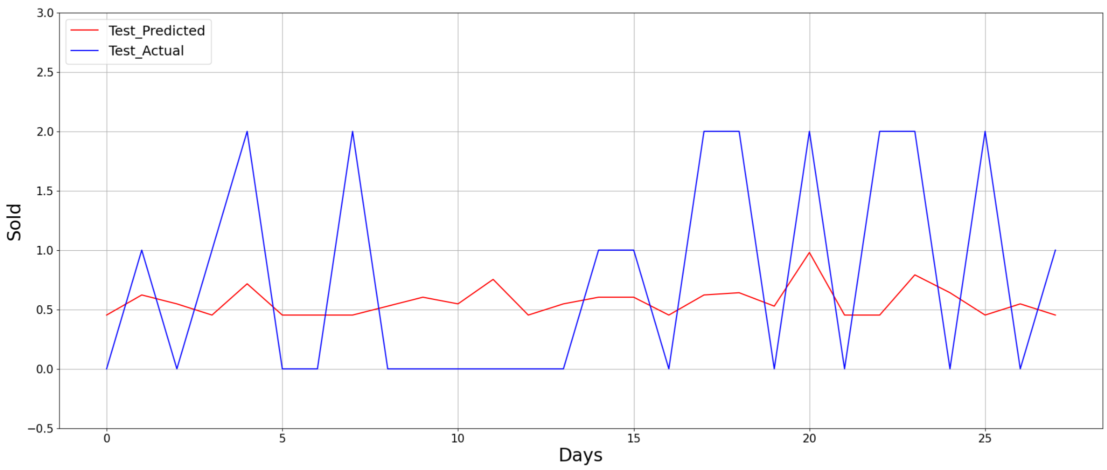

Figure 4.5: Actual VS Predicted on testing set of AR.

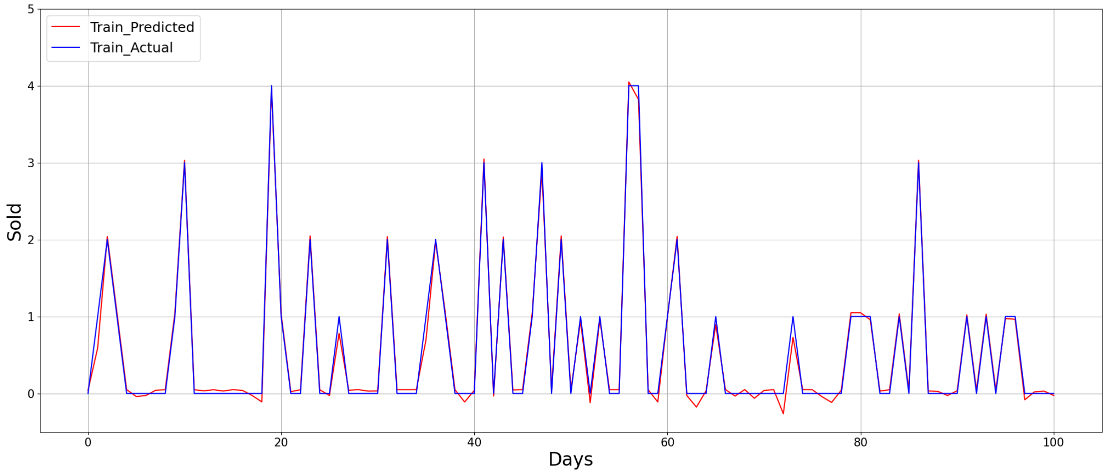

Figure 4.6: Actual vs predicted on training set of MA.

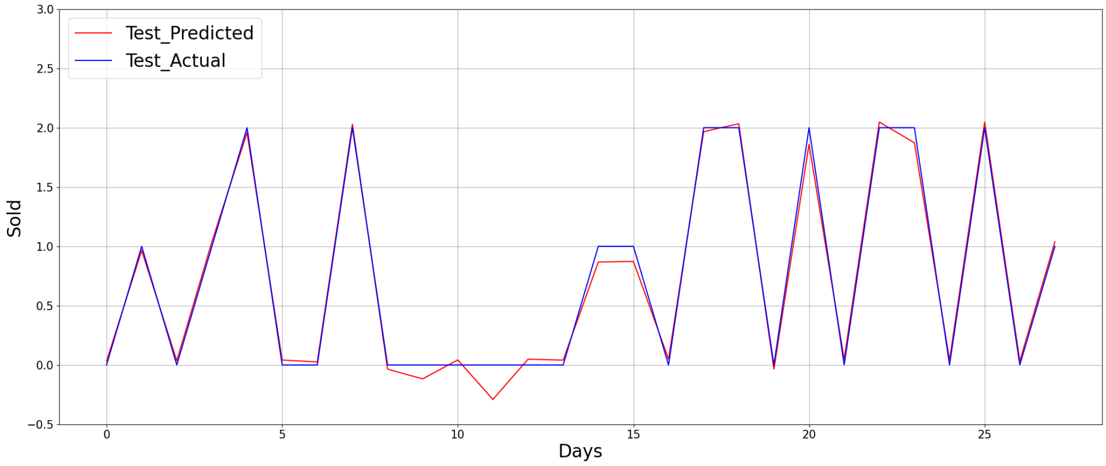

Figure 4.7: Actual vs predicted on testing set of MA.

4.2.2 Performance Plots of MA model on each of the sets.

1. **On training set:** Please refer to the [Figure 4.6] for the plots of the actual values vs the predicted values on training set computed from MA model.

2. **On testing set:** Please refer to the [Figure 4.7] for the plots of the actual values vs the predicted values on testing set computed from MA model.

4.2.3 Performance Plots of ARMA model on each of the sets.

1. **On training set:** Please refer to [Figure 4.8] for the plots of the actual values vs the predicted values of the training set computed from ARMA model.

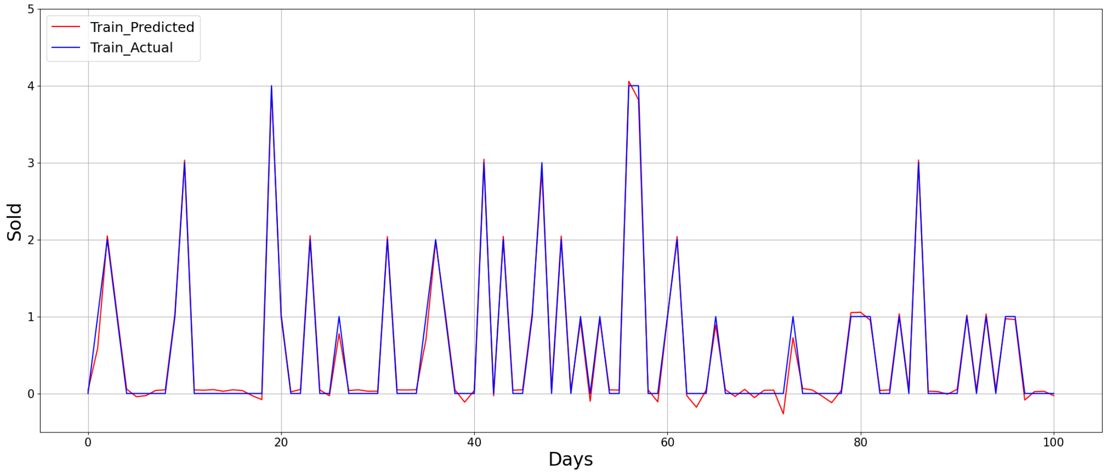

Figure 4.8: Actual vs predicted on training set of ARMA

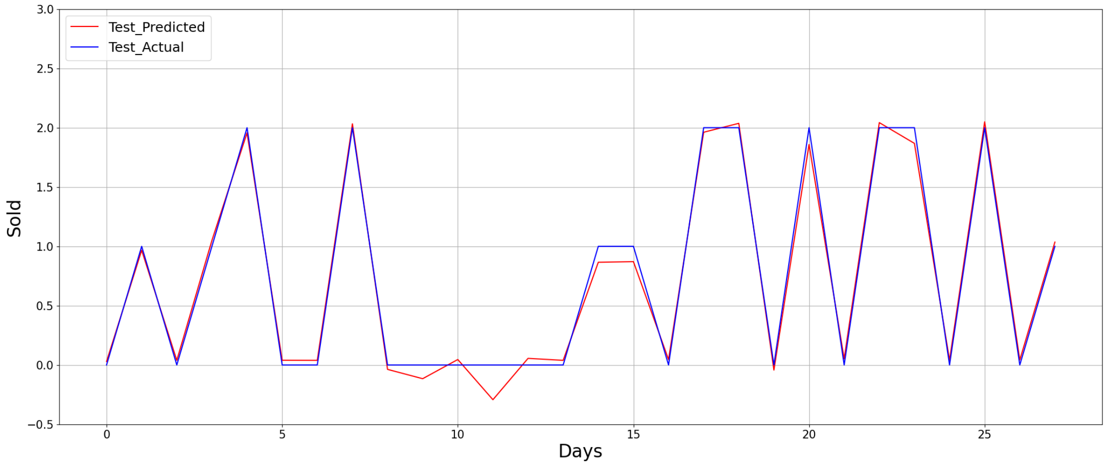

Figure 4.9: Actual vs predicted on testing set of ARMA

2. **On testing set:** Please refer to the [Figure 4.9] for the plots of the actual values vs the predicted values of the testing set computed from ARMA model.

4.3 Discussions

There were the other significant lags having greater than 5% but we have considered the two most significant. Using more number of lags may result in overfitting. We have tried to implement the ARMA(2,1) model also but the results were almost same as MA(1).

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion

In the course of this project, various time series models, including Auto-Regressive (AR), Moving Average (MA), and Auto-Regressive Moving Average (ARMA) models, were applied to the dataset for analysis. The primary objective was to assess their efficacy in extracting essential information from the data. Upon experimentation, it was observed that the Auto-Regressive (AR) model, with an order of 2, did not perform adequately on the dataset. It struggled to capture crucial patterns and trends within the data. However, by considering the errors of the AR model and constructing a Moving Average (MA) model with the order 1, the performance significantly improved. The MA model demonstrated its capability to extract vital information from the dataset. Notably, as the time series was found to be stationary, there was no imperative need to develop an Auto-Regressive Integrated Moving Average (ARIMA) model. Nevertheless, the ARMA model, with consistent orders for AR(2)and MA(1), have the same performance as MA(1) and also the RMSE, MSE and MAE of both models doesn't have much difference.

In conclusion, the MA model emerged as the most suitable choice, successfully addressing various factors, including stockouts, changes in pricing, store closures, and the evolution of pricing and sales trends.

5.2 Future work

The current study opens avenues for further exploration and refinement of time series analysis methodologies. The following areas of future work are identified to enhance the scope and depth of the research:

1. **Start working on the real-industry based dataset:** To broaden the applicability and robustness of the models developed, future efforts will involve working with

real-industry based dataset that would be shared by the Theta Direct Pvt. Ltd.

2. **Using the Advanced Machine Learning Techniques**: The current study focused on traditional time series models, namely AR, MA, and ARMA. Next would be to use the advanced machine learning techniques.

3. **Optimization and Fine-Tuning:** Continuous refinement of the models will be pursued through optimization and fine-tuning. This involves adjusting hyper-parameters, exploring different lag orders, and implementing feature engineering techniques to achieve better model performance.

CHAPTER 6

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