**Time Series Forecasting with Walmart Case-Study**

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**Summary**

This report provides an in-depth overview of time series analytics, a powerful tool for understanding data patterns and trends over time with a case study on Walmart Sales data. Time series analytics is widely used across various industries, such as finance, retail, healthcare, and manufacturing, to forecast future performance, optimize operations, and inform strategic decision-making. The report covers fundamental concepts, forecasting methods, applications, and case study to illustrate the practical implementation of time series analytics.

The report includes a case study on the Walmart Dataset, where major time series analytics models have been applied to gain insights into sales patterns, seasonal effects, and other factors that influence sales performance. By leveraging these models, Walmart can optimize inventory management, plan promotions, and make informed strategic decisions to drive growth and enhance overall performance. By exploring the basics of time series analytics, common forecasting methods, diverse applications, and real-world case studies, this report aims to equip readers with a comprehensive understanding of time series analytics and its practical implementation in various industries.

**1. Introduction**

1.1 Background

Time series analytics is the process of analyzing and modeling time-ordered data points to identify trends, patterns, and relationships. It plays a crucial role in various industries, such as finance, retail, healthcare, and manufacturing, for uncovering insights and predicting future outcomes. As data continues to grow exponentially and businesses become increasingly data-driven, the importance of time series analytics has become more pronounced. Organizations that can effectively leverage time series analytics gain a competitive advantage by making informed decisions, optimizing operations, and enhancing overall performance.

1.2 Objective

The primary objective of this project is to provide a comprehensive understanding of time series analytics to help businesses and practitioners harness the power of historical data for improved decision-making. By exploring the fundamental concepts, forecasting methods, applications, and case studies, this report aims to equip readers with a solid foundation in time series analytics, enabling them to:

* Grasp the basic components of time series data and the importance of decomposition in analyzing the underlying structure
* Understand the strengths and limitations of common time series forecasting methods, including exponential smoothing, regression, and ARIMA
* Recognize the diverse applications of time series analytics across different industries, such as finance, retail, healthcare, and manufacturing
* Appreciate the practical implementation of time series analytics through real-world case studiy that is Walmart Sales prediction.

**2. Time Series Analytics Basics**

2.1 Components of Time Series

A time series consists of four main components, which, when combined, help to explain the underlying patterns and behavior of the data. Understanding these components is crucial for accurate time series analysis and forecasting. Below is the example for understanding the Temporal data components.

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2.1.1 Trend

Trend represents the overall direction and movement of the data over a long period. It captures the general pattern of growth, decline, or stability in the data. For example, in the context of sales data, an upward trend would indicate increasing sales over time, while a downward trend signifies a decline in sales. Identifying trends helps businesses anticipate future developments and make strategic decisions accordingly.

2.1.2 Seasonality

Seasonality refers to regular fluctuations in the data that typically occur within fixed periods, such as daily, weekly, monthly, or yearly. Seasonal patterns are often related to factors like weather, holidays, and recurring events. For instance, in retail, sales may peak during the holiday season, while in the energy sector, electricity consumption might be higher during summer months due to increased air conditioning usage. Understanding seasonality is essential for businesses to plan and allocate resources effectively.

2.1.3 Cyclical

Cyclical components represent fluctuations in the data that do not follow a fixed pattern and often arise from broader economic cycles or industry-specific factors. These fluctuations can span multiple years and are typically longer than seasonal patterns. Cyclical components may include business cycles, market expansions, and contractions or fluctuations in demand due to external factors. Identifying and understanding cyclical patterns can help businesses prepare for potential downturns or capitalize on growth opportunities.

2.1.4 Irregular

Irregular components, also known as residual or random components, are unpredictable variations in the data that do not follow a discernible pattern. These fluctuations can result from one-off events, such as natural disasters, policy changes, or unexpected market shocks. Since irregular components are challenging to predict, they can introduce uncertainty and noise into time series forecasts. However, understanding the potential impact of irregular components helps businesses from various industry to develop contingency/ emergency planning and respond more effectively to unforeseen events.

2.2 Decomposition

Decomposition is a technique used to separate the different components of a time series to better understand and analyze the underlying structure. By breaking down the time series data into trend, seasonal, and residual components, analysts can more easily identify the primary drivers of the data and develop accurate forecasting models.

There are two main approaches to decomposition: additive and multiplicative. In additive decomposition, the observed data is the sum of the trend, seasonal, and residual components. In contrast, the multiplicative decomposition assumes that the observed data is the product of the three components. The choice between additive and multiplicative decomposition depends on the nature of the data and the presence of any interactions between the components.

Other information sources that drive the market are news articles, tweets and company press releases. It is often observed that stock performs exceptionally well for a brief period when the company declares quarterly profits. In a few other scenarios, tweets put out by prominent people in the industry also greatly influence the stock’s performance momentarily. By extracting historical data on such information, we analyze the correlation between the amount of swing observed in the market and the sentiment of the information.

Using neural networks and deep learning for this task adds to the solution’s complexity, thereby helping us to identify the complex patterns within the time series data from stock markets. However, the more complex the model is, the more difficult it becomes to interpret the model. Thus, enhances the need to explain such models to reduce computer-generated or data inherent biases. To address this issue, we look to introduce explanations for each selected feature and their contributions to making time series forecasts.

**3. Time Series Forecasting Methods**

There are several methods used for time series forecasting, each with its strengths and limitations. In this section, we will explore five common techniques: Naive method, Moving Average, Exponential Smoothing, Regression, and ARIMA.

3.1 Naïve Method

The Naive method is the simplest time series forecasting technique, assuming that the most recent observation is the best predictor of future values. This method can be useful as a baseline model, but it does not account for trends, seasonality, or other patterns in the data. Ex. Sales of April will be equal to sales of the March.

y(n+1) = y(n)

3.2 Moving Average

The Moving Average method calculates the average of a fixed number of past observations to generate a forecast. This approach smooths out short-term fluctuations and noise, making it easier to identify underlying trends. However, the Moving Average method is not well-suited for capturing seasonality or responding quickly to changes in the data. Ex. Sales of April month will be average of the sales of last three months i.e. March, February and January.

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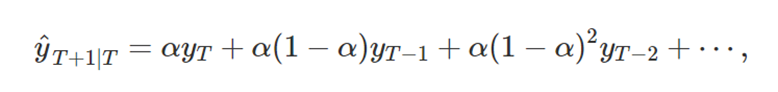
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3.3 Exponential Smoothing

Exponential smoothing is a family of forecasting techniques that applies weighted averages to past observations to make forecasts. The weight assigned to each observation decreases exponentially as it moves further back in time. This method emphasizes the most recent data points, allowing it to capture trends and seasonality in time series data effectively.



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There are three main types of exponential smoothing:

3.3.1. Simple Exponential Smoothing (SES)

Simple Exponential Smoothing is suitable for time series data with no clear trend or seasonality basically random data. It calculates the weighted average of past observations, giving more weight to recent data points. SES produces a forecast by applying a smoothing factor (alpha) between 0 and 1.

Random Data with no trend and no Seasonality

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3.3.2. Holt's Linear Exponential Smoothing

Holt's Linear Exponential Smoothing extends SES to capture trends in the data. It introduces an additional smoothing factor (beta) for the trend component. This method calculates two equations: one for the level (local average) and another for the trend. The forecasts are generated by combining these two components.

Linear Trend with no Seasonality

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3.3.3. Holt-Winters Seasonal Exponential Smoothing

Holt-Winters Seasonal Exponential Smoothing is designed to capture both trend and seasonality in the time series data. It introduces a third smoothing factor (gamma) for the seasonal component. This method calculates three equations: one for the level, one for the trend, and one for the seasonal component. The forecasts are generated by combining all three components.

Linear Trend with Seasonality

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3.4. Regression

Regression is a statistical method used to model the relationship between a dependent variable (e.g., sales) and one or more independent variables (e.g., time, season, or external factors). In the context of time series forecasting, regression can be applied to model trends and other patterns in the data.

3.4.1. Linear Regression

Linear regression is the most basic form of regression, modeling the relationship between the dependent and independent variables using a straight line. It is useful for capturing linear trends in time series data. However, linear regression has limitations in capturing complex patterns, seasonality, and cyclical components. In cases where these factors are present, more advanced regression techniques or other forecasting methods may be more appropriate.

3.4.2. Multiple Regression

Multiple regression is an extension of linear regression, allowing for the inclusion of additional independent variables in the model. This approach can help account for factors such as seasonality, cyclical components, or other external variables that may influence the dependent variable. Multiple regression can improve forecasting accuracy by incorporating more information into the model, but it can also become more complex and computationally intensive as the number of independent variables increases.

3.5 ARIMA

ARIMA (Autoregressive Integrated Moving Average) is a widely used technique for time series forecasting. It models the data as a combination of autoregressive (AR), moving average (MA), and differencing (I) components. One important assumption for ARIMA model is that data should be stationary that is it has constant mean and constant variance. Methods like Augmented Dickey-Fuller Test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test helps to find the stationariness of the temporal data.

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By understanding the strengths and limitations of these forecasting methods, analysts can choose the most appropriate approach for their specific time series data and use case. Combining or adjusting these methods based on the unique characteristics of the data can lead to improved forecasting accuracy and better-informed decision-making.

**4. Case-Study Walmart Data**

Three years data of the 45 stores of the Walmart was selected for analysis and prediction.

EDA: Top 5 stores with highest sales were selected for the analysis. Store number 4, 20, 14, 13 & 2 were selected for the analysis and prediction. Outliers were taken care by replacing them with the mean of the respective column. All the distributions were not normal hence were explored with transforming them to logarithmic, square, square root, etc. Most of the columns were not correlated, The highest correlation was 0.7 between MarkDown1 and MarkDown4.

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Correlation Matrix:

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Log Transformed:

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Square root transformation

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Linear Regression Diagnostics:

Most of the Linear Regression assumptions are violated.

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Model Selection:

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Simple Exponential Smoothing:

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Triple Exponential Smoothing:

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Predicted results are with 80% and 95% significance level.

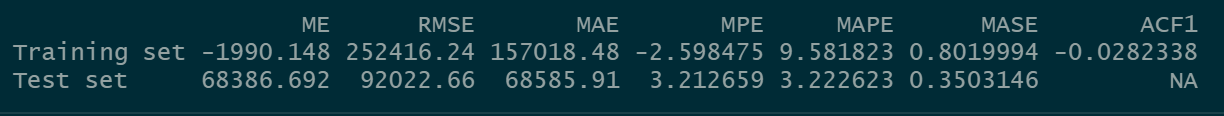
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ARIMA Model

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Accuraccy: RMSE is 92022.66, which means that on average, the forecasted values are off by around $92,022.66 from the actual values. The Mean Absolute Percentage Error(MAPE) is 3.22, which means that on average, the forecasted values are off by around 3.22% from the actual values. The Mean Absolute Scaled Error(MASE) is 0.35, which means that the forecast accuracy is 35% better than a naive forecast that simply uses the previous value as the forecast.

**5. Conclusion**

In conclusion, this project has provided a comprehensive overview of time series analytics, covering the fundamental concepts, various forecasting methods, applications across different industries, and a case study on the Walmart dataset. Through this analysis, we have demonstrated the practical implementation of time series analytics and its potential to drive growth and enhance overall performance.

Among the various forecasting models applied to the Walmart dataset, the ARIMA model emerged as the best performer. The model's accuracy was assessed using the following metrics:

* RMSE (Root Mean Square Error): 92,022.66, indicating that on average, the forecasted values are off by around $92,022.66 from the actual values.
* MAPE (Mean Absolute Percentage Error): 3.22, indicating that on average, the forecasted values are off by around 3.22% from the actual values.
* MASE (Mean Absolute Scaled Error): 0.35, indicating that the forecast accuracy is 35% better than a naive forecast that simply uses the previous value as the forecast.

These results show that the ARIMA model provides a reasonably accurate forecast, making it a valuable tool for predicting sales and informing strategic decision-making at Walmart.

In summary, time series analytics is a powerful tool for understanding data patterns and trends, empowering businesses to make data-driven decisions and improve operational efficiency. By leveraging historical data and selecting the most appropriate forecasting model, organizations can optimize resources, drive growth, and adapt to the rapidly changing market landscape.

**6. References**

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