Time Series Analysis and its Forecasting methods

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Abstract –
The most significant challenges that analysts face in a variety of fields, from finance and economics to manage production operations, to the analysis of political and social policy sessions, to examining the effects of people and the policy decisions they make on the environment, are related to the time-oriented data analysis and forecasting future values of a time series. Therefore, there is a sizable group of individuals in a range of professions, such as economics, finance, science, engineering, and statistics, who need to comprehend the fundamental idea of time series and forecasting.In this paper we will be discussing about time series , it's components, and various kinds of forecasting techniques .

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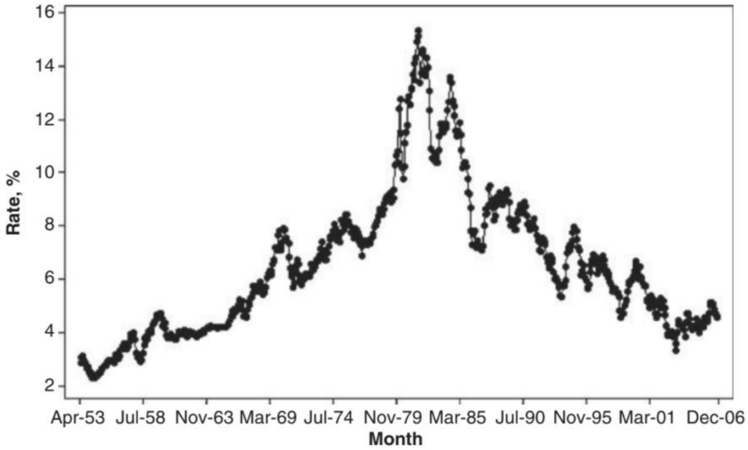
1. Introduction

A forecast is an estimation of certain future quantities or occasions. An important issue in many disciplines, including business and industry, government, economics, environmental sciences, medicine, and social sciences, is forecasting. The use of time series data is a common solution to predicting issues [1]. A time series is a collection of observations made in a specified sequence or over a specific period of time.



The figure shows market yield on US treasury securities at 10-year constant rate fro-mApril 1953 to December 2006.
Image source : Introduction to time series analysis and forecasting[1]

The term "time series plot" refers to this diagram. In most time series and forecasting applications, the rate variable is obtained at uniformly spaced time intervals. Any re-porting period may be utilized, however many corporate applications of forecasting use data that is collected daily, weekly, monthly, quarterly, or yearly. The information can also be instantaneous, like the viscosity of a chemical product at the time it is measured, cumulative, like the total sales for a given month, or statistical, like the activity of a variable over time. **Short-term, medium-term,** and **long-term forecasting** issues are the three main categories.Short-term when the data is measured days, weeks, months etc. Medium-term when the data is measured nearly in every 1 or 2 years and Long-term when it is measured beyond the extent of many years.

2. Components of Time Series

Since we already know that the forecasting problems are mainly classified into short-term, medium-term, and long-term and these are the terms that are derived from the time series analysis of how the data is collected. So, these terms can be decomposed into four components which are:

- Trend
- Seasonal
- Cyclic
- Irregular/ Random

2.1 **<u>Trend component:</u>**General tendency of data increase or decrease during the long period of time . It is a long-term fluctuation. Trend can be upward or downward.

<u>Example-</u> Population of India during the several years.(upward trend)
Infant mortality rate during the various years.(downward trend)

2.2 **<u>Seasonal component :</u>**Seasonal variation is a variation in time series within one year and have the same or almost same pattern every year after year.

Seasonal variation could be caused from :

2.2.1Natural causes : Weather conditions and climatic changes plays an important role.

<u>Example</u> -sale of umbrella during rainy season ,sale of electric fans during summers.

2.2.2 Manmade conventions : Variations that occur due to the customs made by the society.

<u>Example-</u>sale of jewellery during wedding season and sale of crackers during Diwali.

2.3 **Cyclic component :**Cyclical variations in time series are recurrent upward and downward movements in a time series but the period of cycle is more than one year. The complete period is called cycle. The cyclical movements are sometimes called 'Business Cycle'.

The four phase cycle is comprises of the phases of prosperity, recession, depression, and recovery.

2.4 **Irregular/Random component:**The fluctuations are completely and purely random, unpredictable and due to irregular circumstances which is beyond human control and are sometimes part of the system.

<u>Example -</u> war, floods, epidemic, earthquakes etc.

3. Types of forecasting

These are only a handful of the many scenarios in which projections are required to make informed decisions[1] . Despite the great range of issue scenarios that necessitate forecasting, there are only two sorts of forecasting techniques: qualitative and quantitative [1].

The nature of qualitative forecasting approaches is typically subjective, requiring expert opinion. When there is little or no past evidence on which to build a prognosis, qualitative forecasts are frequently used.

A good example is the launch of a new product for which there is no prior history. In this case, the corporation may rely on the subjective estimates of sales and marketing professionals throughout the new product launch phase of the product life cycle. Marketing tests, surveys of potential buyers, and experience with the sales performance of other items are all used in some qualitative forecasting methodologies (both their own and those of competitors). Despite the fact that some data analysis may be undertaken, the forecast is based on subjective assessment. The Delphi Method is perhaps the most formal and well-known qualitative forecasting technique.

Historical data and a forecasting model are formally used in "**Quantitative forecasting**" approaches. The model expresses a statistical relationship between the variable's past and present values and explains data patterns directly. Having followed that, the model is employed to predict future data patterns. Distinct varieties of forecasting models are generally in use. The three most common types of models are regression, smoothing, and general time series models.
Regression models are based on relationships between the studied variable and one or more relevant predictor variables. Considering that the predictor variables are thought to provide an explanation for the factors causing or guiding the observed values of the relevant variable,regression models are sometimes referred to as causal forecasting models. For instance, data on home purchases could be used as a predictor variable to forecast furniture sales. Most regression models are formalised using the least squares method.

Smoothing models typically forecast the variable of interest using a simple function of previous observations. Although these procedures have a formal statistical basis, they are frequently employed and justified heuristically since they are simple to use and yield satisfying results.
General time series models use the statistical features of historical data to establish a formal model, and then use least squares to estimate the unknown parameters of that model.

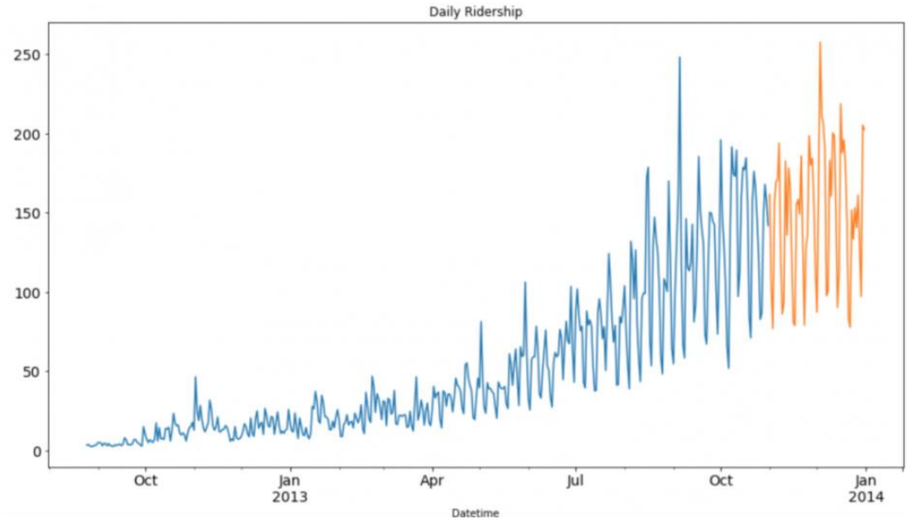
4. Forecasting Process

A process is a collection of linked activities that convert one or more inputs into one or more outputs. Forecasting is no exception to the rule that all job activities are carried out through processes. The following are the steps in the forecasting process:

1. Define the problem
2. Gather data
3. Examine the data
4. Choosing and fitting models
5. Validation of the model
6. Model deployment forecasting
7. Keep an eye on the forecasting model's performance.

- ### Data Processing

Suppose we are given 2 years of data(2012-2014) at ***hourly level*** with the number of commuters travelling and we need to estimate the number of commuters for future[13].



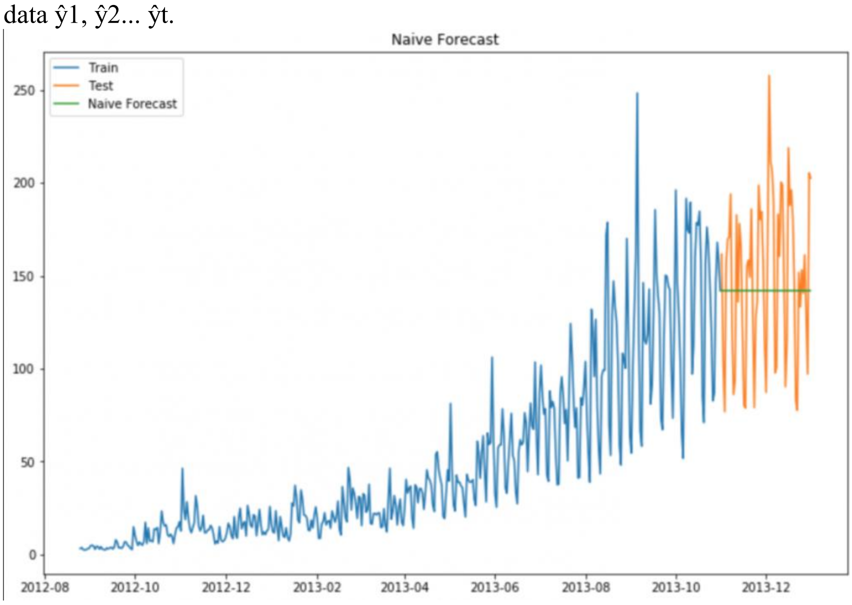
The graph above shows the variation of test and train dataset with time.
We can use the following time series models to forecast the same.

5. Methods of forecasting –

5.1 Naïve method - The value from the preceding day can be obtained when predicting the following day using simple methods, and it is predicted that the value will hold unchanged [4]. This prediction method, known as the naïve method, is based on the presumption that the following expected point will be equal to the preceding observed point, i.e.

$$\hat{\mathbf{Y}}_{t+1} = \hat{\mathbf{y}}_t$$

where $\hat{\mathbf{Y}}_{t+1}$ is a short-hand for the estimate of $\hat{\mathbf{Y}}_{t+1}$ based on the data ŷ1, ŷ2... ŷt.

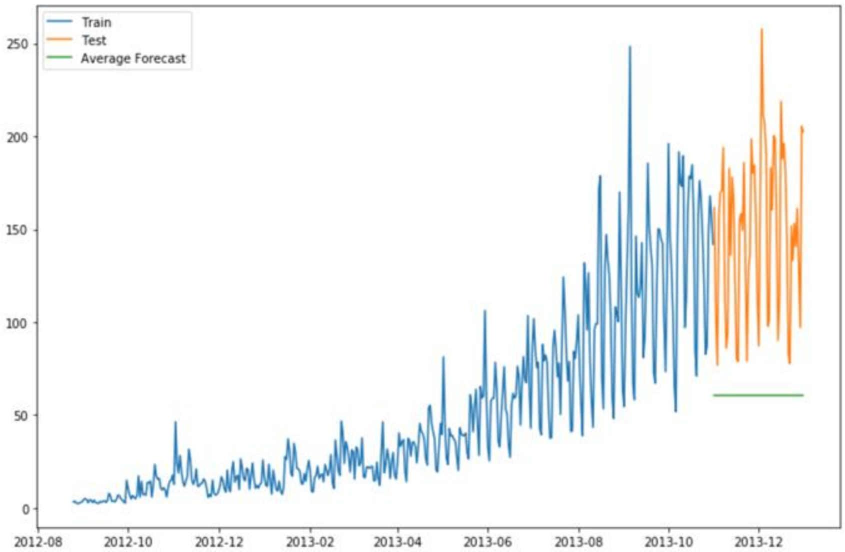


We can infer from the graph that, Naive method isn't suited for datasets with high variability. It is best suited for stable datasets. We can still improve our score by adopting different techniques.

5.2 Simple Average method -In some instances, the data's numbers randomly fluctuate in amplitude with small upticks and downticks, but the average value is maintained. The average value for each time period hasn't changed, despite the dataset's overall minor change [5]. In this instance, we can forecast the number of the following day, which is comparable to the typical of the previous few days. The term "simple averaging technique" refers to a prediction method where the expected value is projected to be equal to the average of all previously observed points. For a period of t + 1, we take all previously recorded values of order n, M(n), calculate the average, and utilise it as the next value, i.e.

$$M\ \hat{y}_{t+1} = 1/n(\sum \hat{y}_t)$$

where n is the number of observations used in calculation and time period t + 1 is the forecast for all future time periods .



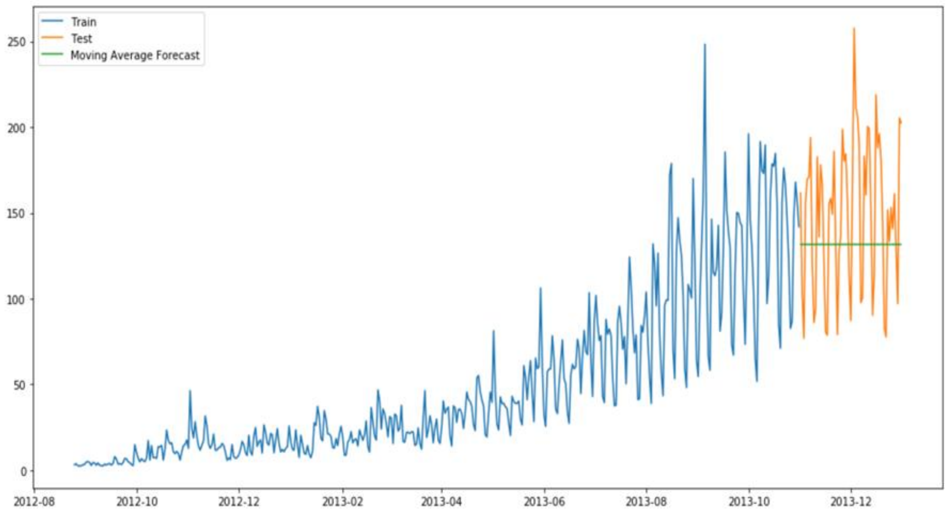
We can see that this model didn't improve our score. Hence we can infer that this method works best when the average at each time period remains constant.

5.3 Moving Average Method - In numerous multiple times, we are given a dataset, in which the quantity of passing increased/decreased pointedly some timeframes back. So as to utilize the past average technique, we need to utilize the mean of all the past information. [6]

Such anticipating strategy which utilizes gap of timeframe for ascertaining the normal is called Moving Average method.

Utilizing a basic moving normal form, we estimate the following significance(s) in a period arrangement dependent on the normal of a set limited numeral p of the past qualities. Subsequently, for all i > p

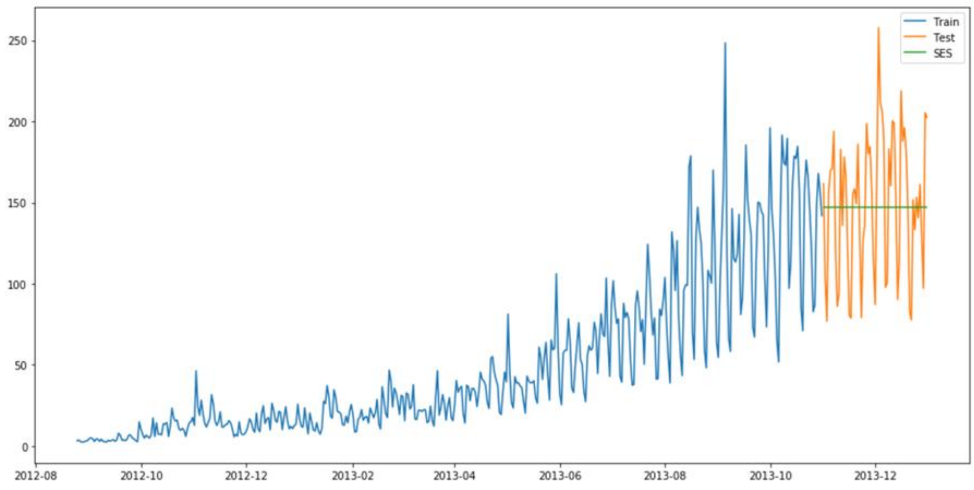
$$\hat{Y}_i = \frac{1}{p}(Y_{i-1} + Y_{i-1} + Y_{i-1} \cdots\cdots + Y_{i-p})$$



For this dataset, it is clear that the Naive approach performs better than Average and Moving Average. The Simple Exponential Smoothing method will now be examined, and its performance will be assessed.

5.4 Simple Exponential Smoothing Method –Time series data can be smoothed using the exponential smoothing rule [7]. In order to assign weights that decrease exponentially over time, exponential functions are used, just as in the basic moving average approach, which weights previous observations equally. The smallest loads are associated with the most prepared recognition, and forecasts are resolved using weighted midpoints, where loads fall exponentially as observations start from further in the past:

$$\hat{Y}_{T+1/T} = \alpha y_T + \alpha\,(1-\alpha)\,y_{T-1} + \alpha\,(1-\alpha)^2 y_{T-2} + \ldots\ldots$$



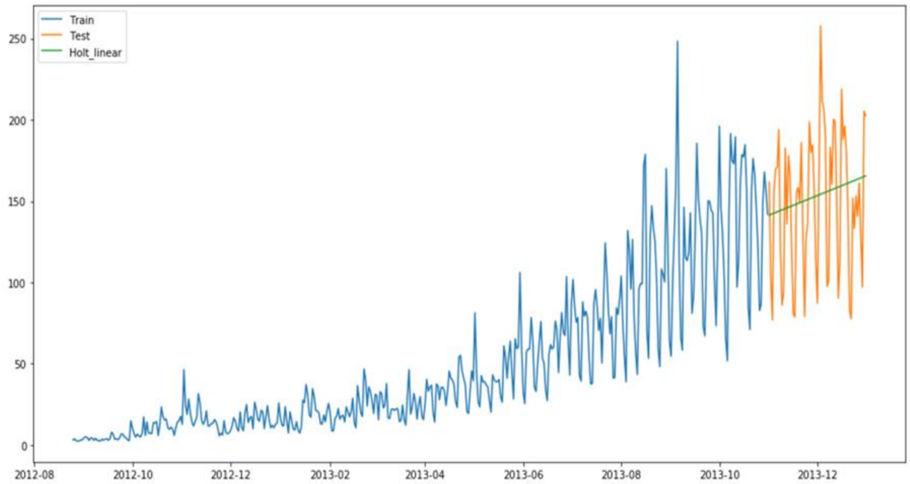
We can see that implementing Simple exponential model generates a better model till now.

5.5 Holt's Linear Trend Method -Holt (1957) extended simple exponential smoothing to allow the forecasting of data with a trend. This method involves a forecast equation and two smoothing equations (one for the level and one for the trend). Each Time plan dataset can be broken down into its segments which are Trend, Irregularity and Residual.

For estimating the information with pattern we need three conditions: level, pattern and consolidation of level and pattern to find normal forecast ŷ.[8]

Forecast :$\mathbf{\hat{y}_{t+h|t}=\ell_t+hb_t}$
Level :$\mathbf{\ell_t=\alpha y_t+(1-\alpha)(\ell_{t-1}+b_{t-1})}$
Trend :$\mathbf{bt=\beta^*(\ell t-\ell t-1)+(1-\beta^*)bt-1}$

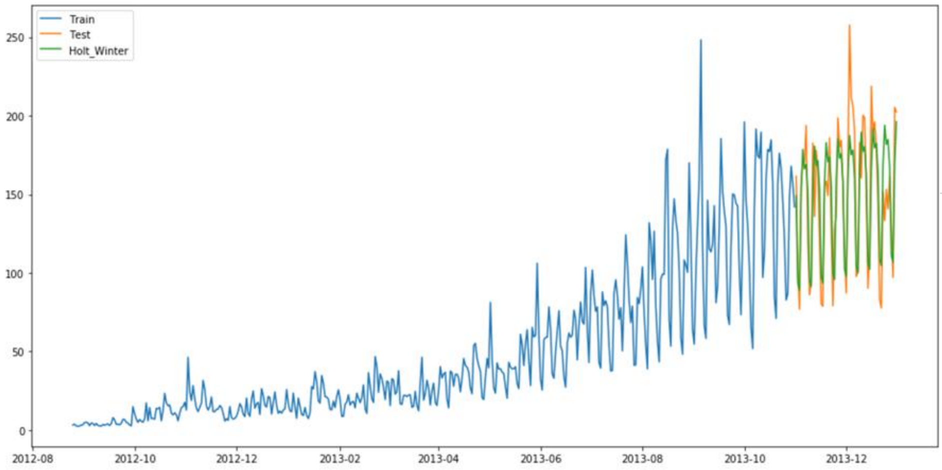
where ℓt denotes an estimate of the level of the series at time t, btdenotes an estimate of the trend (slope) of the series at time t, α is the smoothing parameter for the level, $0\leq\alpha\leq1$, and β^* is the smoothing parameter for the trend, $0\leq\beta^*\leq1$



We can see that this method maps the trend accurately and hence provides a better solution when compared with above models

5.6 Holt's Winter Method - The Holt winter technique usually involves exponential smoothing to the sporadic segments that defy level and pattern [9]. Holt makes use of the irregularity factor in his winter strategy. For the level lt, pattern bt, and the occasional segment denoted by st with smoothing parameters,, and, the Holt-Winters occasional strategy includes the conjecture condition.

Level (L_t) :$\mathbf{\alpha\ (y_t - S_{t-s}) + (1 - \alpha)\ (L_{t-1} + B_{t-1})}$
Trend (b_t) :$\mathbf{\beta\ (L_t - L_{t-1}) + (1 - \beta)\ b_{t-1}}$
Seasonal (S_t) :$\mathbf{\gamma\ (y_t - L_t) + (1 - \gamma)\ S_{t-s}}$
Forecast (F_{t+k}) : $\mathbf{L_t + kb_t + S_{t+k-s}}$
Where; s is the length of the seasonal period
$0 \leq \alpha \leq 1, 0 \leq \beta \leq 1$ and $0 \leq \gamma \leq 1$.



We can see from the graph that mapping correct trend and seasonality provides a far better solution.

5.7 Auto Regressive Integrated Moving Average (ARIMA)-A common and widely used statistical technique for time-series forecasting is the Auto Regressive Integrated Moving Average (ARIMA) model[12]. It belongs to a class of statistical methods that accurately captures the typical temporal dependencies that are specific to time series data. In order to get significant insights and numerous information qualities, ARIMA incorporates procedures for timing analysis. Future values that are dependent on the most recent observed values are predicted by ARIMA using models.

The Moving Average (MA), Auto Regressive (AR), and Integrated (I) are the three parts of ARIMA that will now be dissected (MA).

The AR in [AR]IMA: Auto Regressive

As you might have anticipated, the autoregressive (AR) regression model is based on the idea of autocorrelation, in which the dependent variable depends on its own past values (eg. rainfall today may depend on rainfall yesterday, and so on). The general formula is:
The **p** here is called the lag order which indicates the number of prior lag observations we include in the model

$$Y_t = \beta_1 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p}$$

The I in AR[I]MA: Integrated

Recall our explanation on stationarity. The integrated part of ARIMA attempts to convert the non-stationarity nature of the time-series data to something a little bit more stationary. How can we do that? By performing prediction on the **difference (d)** between any two pair of observation rather than directly on the data itself.

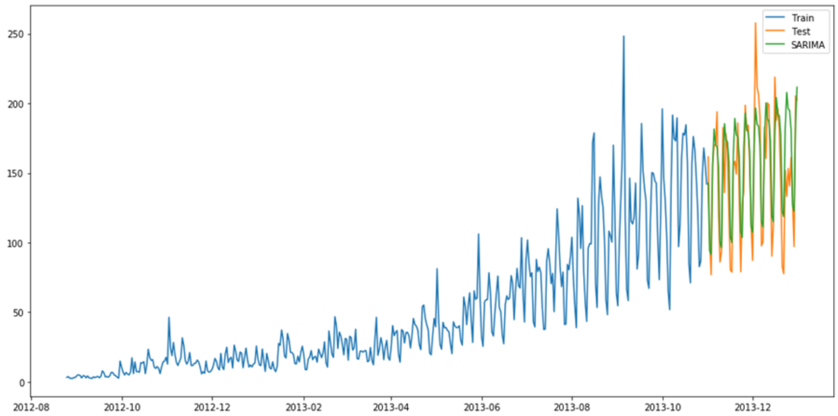
$$Z_t = Y_{t+1} - Y_t \quad \ldots d = 1$$
$$Q_t = Z_{t+1} - Z_t \quad \ldots d = 2$$

The MA in ARI[MA]: Moving Average

Now the final piece of ARIMA is the MA or Moving Average. It attempts to reduce the noise in our time series data by performing some sort of aggregation operation to your past observations in terms of residual error ε

$$Y_t = \beta_2 + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \ldots + \omega_q \varepsilon_{t-q} + \varepsilon_t$$

The ε terms represent the residual errors from the aggregation function and **q** here is another hyperparameter that is identical to **p.** But instead of identifying the time window (**p**) to the time series data itself, **q** specifies the time window for the moving average's residual error.



We can see that it shows similar results as Holt's winters method.

6. Conclusion

Forecasting is significant because it is a crucial input into many different forms of planning and decision-making processes, and it may be applied to a wide range of topics.To understand seasonality, trends, cyclicality, and randomness in sales and distribution as well as other features, time series analysis is one of the most vital aspects of data analytics for any large firm. These elements help enterprises in making well-informed decisions, which are essential to their success.Different time series forecasting models discussed in paper , we can derive that Naïve method generates better results when compared to Average and Moving average method , and as we go further down the each model gives better result than the former one. So, it will be safe to say that either ARIMA or Holt's winters method should be used while forecasting to generate better results.

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