Business Report

SMDM Project Business Report DSBA

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***PGP-DSBA Online***

***JULY’ 21 Batch***

***Date: 20-02-2022***

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# Problem - 1

*Summary*

The data is gathered from ABC Estate wines, for Sparkling wine sales data from this ABC Estate wine company. An analyst for the company needs to analyze the wine sales in the 19th century and forecast the wine sales for the 20th century.

*Introduction*

The purpose of this exercise is to explore the dataset and make the analyze the wine sales in the 19th Century, based on the sales data we need to forecast for the wine sales data for next 12 months.

*Sample of the dataset:*

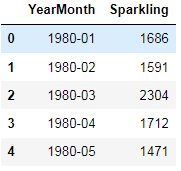


Fig 1.1 Dataset Sample

*Exploratory Data Analysis*

*Let us check the types of variables in the data frame.*



Fig- 1.2. Datatypes of the variable

There are total 187 rows and 2 columns in the dataset. 1 columns are object and 1 columns are int64

*Check for missing values in the dataset:*

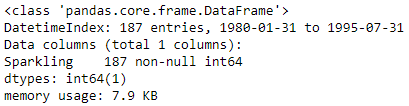


Fig- 1.3. Check null values

**1. Analysis.** **Read the data as an appropriate Time Series data and plot the data.**

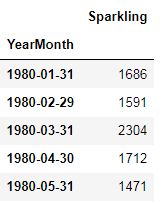


Fig- 1.4. Initialising Date as index Column

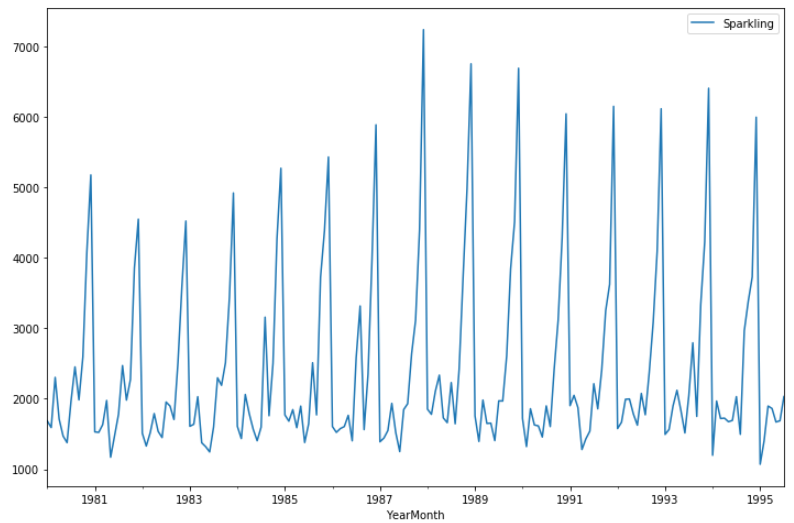


Fig – 1.5 Plotting Sparkling wine data

The sparkling wine sales data has been plotted against the year of sales.

### 2. Perform appropriate Exploratory Data Analysis to understand the data and also perform decomposition.

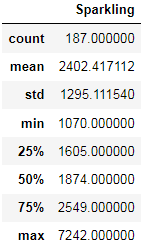


Fig – 1.6 Sparkling wine sales data spread.

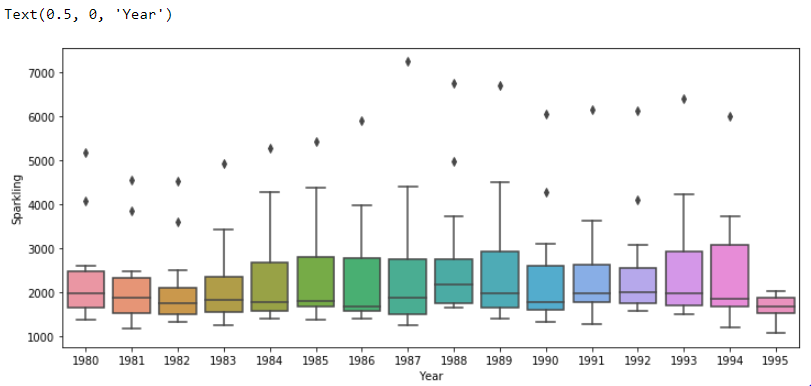


Fig – 1.7 Sparkling wine sales across years

From the above chart (boxplot), there are outliers present in the data and we can observe that there was good sales record for sparkling wine from 1980-1994 and wine sales has been decreased in the year 1995.

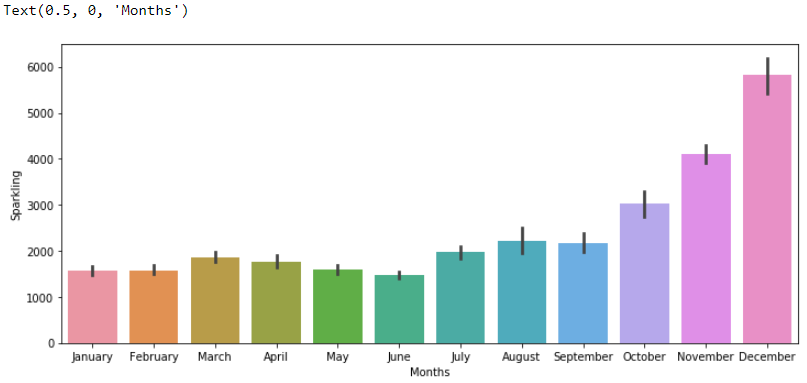


Fig – 1.8 Sparkling wine sales across months

From the above chart (boxplot), the December month has highest number of sparkling wine sales when compared with other months.

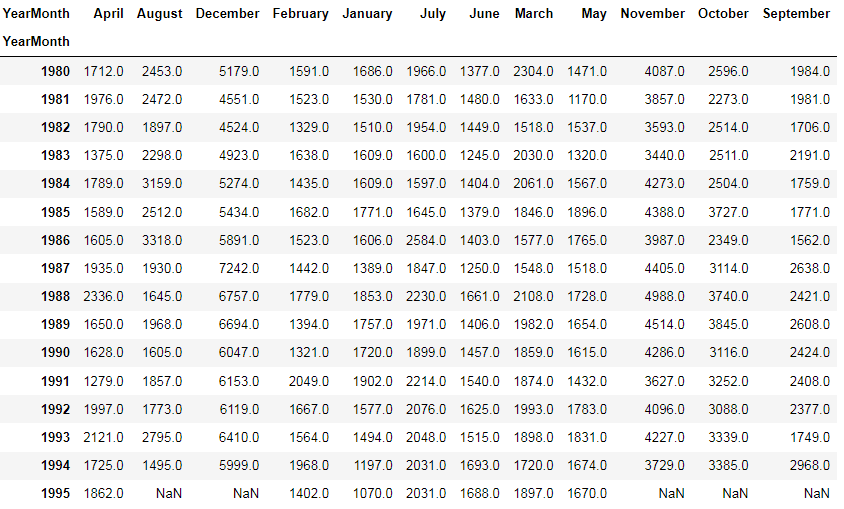


Fig – 1.9 Monthwise wine sales across years

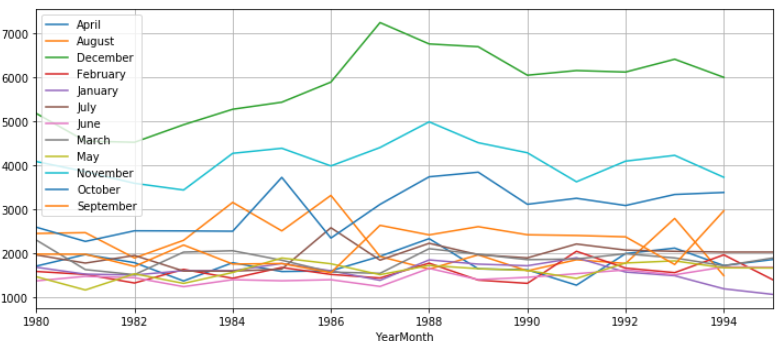


Fig – 1.10 Monthwise wine sales across years

***Additive Model:***

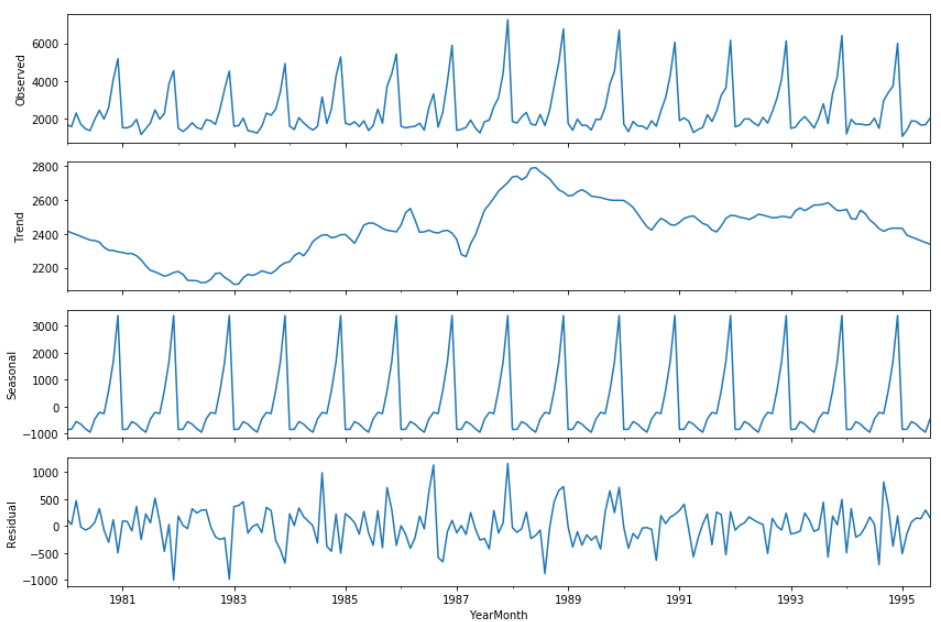


Fig – 1.11 Decompose data form the original dataset for sparkling wines (Additive model)



Fig – 1.12 Trend, Seasonality and residual values after decomposing the original data for sparkling wines (Additive model)

***Multiplicative Model:***

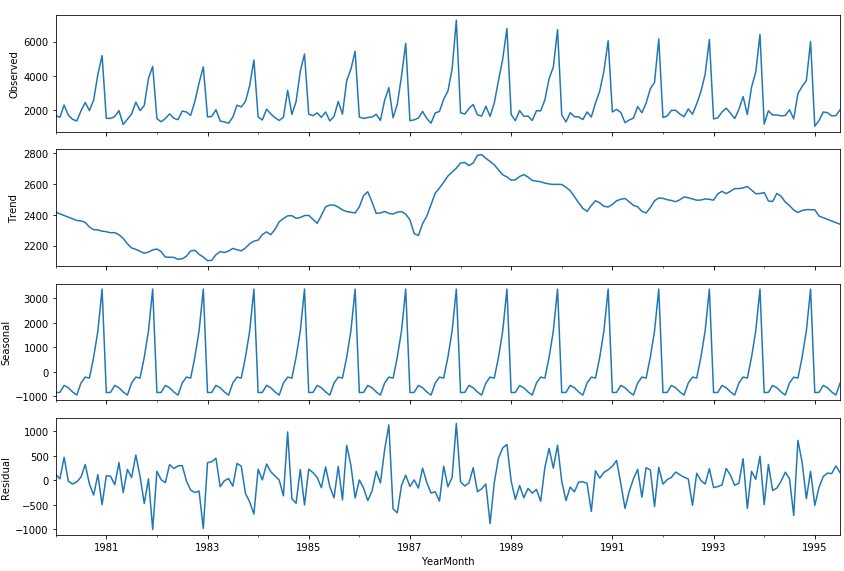


Fig – 1.13 Decompose data form the original dataset for sparkling wines (Multiplicative model)



Fig – 1.14 Trend, Seasonality and residual values after decomposing the original data for sparkling wines (Multiplicative model)

### 3. Split the data into training and test. The test data should start in 1991

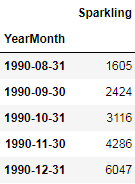


Fig – 1.15 Last 5 values for Training data

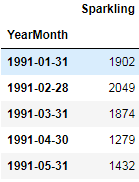


Fig – 1.16 First 5 values for testing data

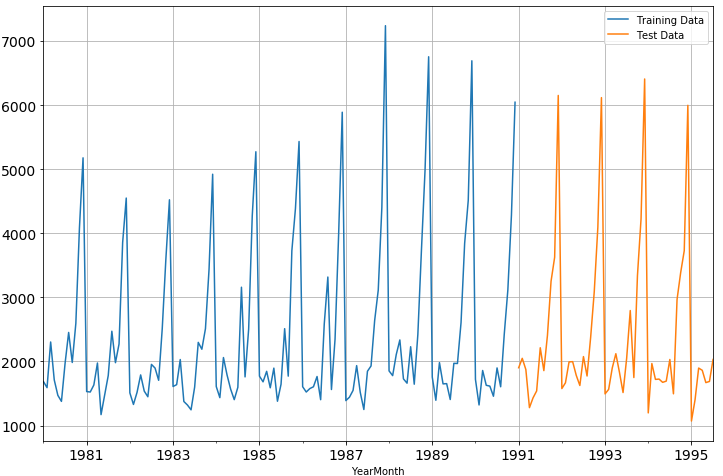


Fig – 1.17 Plotting Training and test dataset for sparkling wines

### 4. Build all the exponential smoothing models on the training data and evaluate the model using RMSE on the test data. Other additional models such as regression, naïve forecast models, simple average models, moving average models should also be built on the training data and check the performance on the test data using RMSE.

### *Model 1: Linear Regression:*

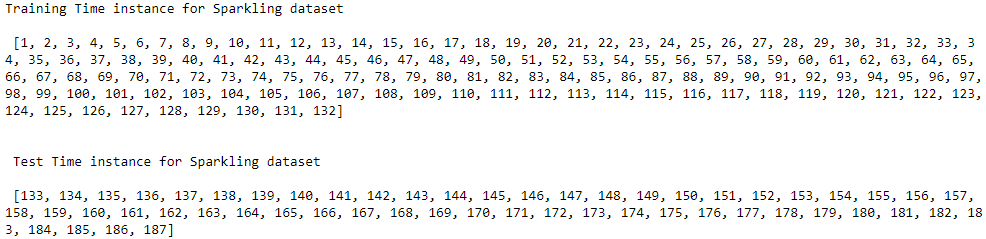


Fig – 1.18 Generating numerical time instance for both training and test dataset for sparkling wines

We see that we have successfully the generated the numerical time instance order for both the training and test set. Now we will add these values in the training and test set.



Fig – 1.19 Initializing Linear Regression method

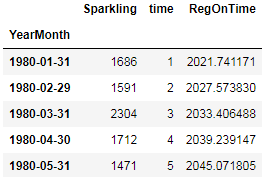


Fig – 1.20 Predicting for training dataset

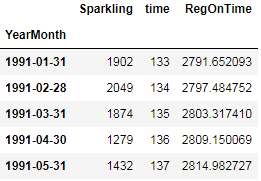


Fig – 1.21 Predicting for test dataset

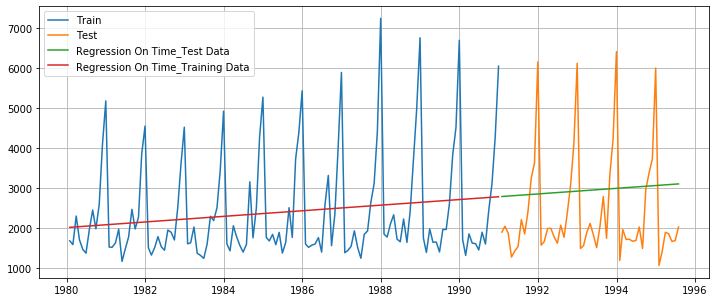


Fig – 1.22 Ploting original and predicted train and test datas using linear regression



Fig – 1.23 RMSE and MAPE value Training data



Fig – 1.24 RMSE and MAPE value Test data



Fig – 1.25 Loading RMSE and MAPE value Test data into dataframe

### *Model - 2: Naive Approach:* (ŷ𝑡+1 = yt)

#### For this particular naive model, we say that the prediction for tomorrow is the same as today and the prediction for day after tomorrow is tomorrow and since the prediction of tomorrow is same as today,therefore the prediction for day after tomorrow is also today.

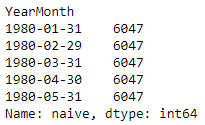


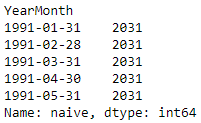
Fig – 1.26 Predicting values for training data using naïve approach  


Fig – 1.27 Predicting values for test data using naïve approach

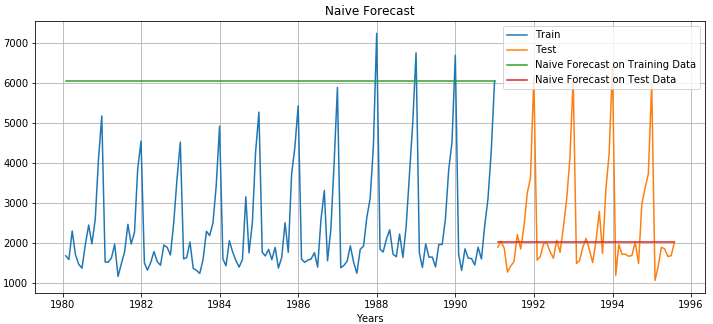


Fig – 1.28 Plotting the predicted values for train and test data using naïve approach



Fig – 1.29 RMSE and MAPE value Training data



Fig – 1.30 RMSE and MAPE value Test data

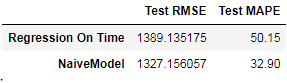


Fig – 1.31 Loading RMSE and MAPE value Test data into dataframe

***Model – 3 Simple Average:***

For this particular simple average method, we will forecast by using the average of the training values

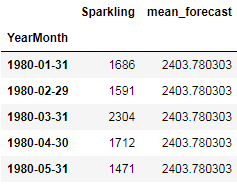


Fig – 1.32 Taking mean of sparkling wine sales training data

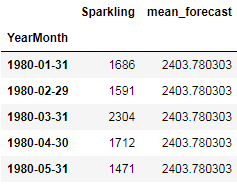


Fig – 1.33 Taking mean of sparkling wine sales test data

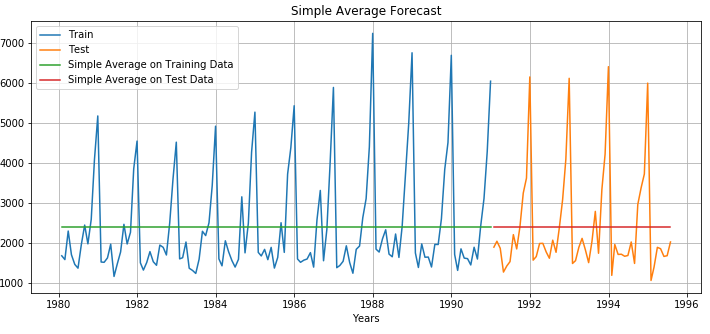


Fig – 1.34 Plotting the Simple Average data, train and test data



Fig – 1.35 RMSE and MAPE value Training data



Fig – 1.36 RMSE and MAPE value Test data

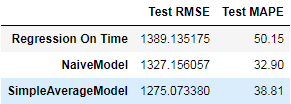


Fig – 1.37 Loading RMSE and MAPE value Test data into dataframe

***Model – 4 Moving Average(MA):***

For the moving average model, we are going to calculate rolling means (or moving averages) for different intervals. The best interval can be determined by the maximum accuracy (or the minimum error) over here.

For Moving Average, we are going to average over the entire data.

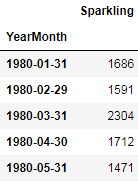


Fig – 1.38 training data

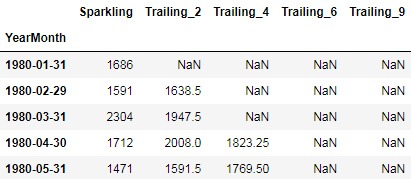


Fig – 1.39 Making data from training data for moving average

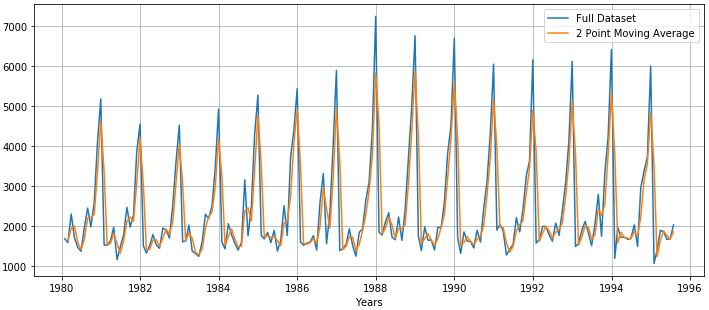


Fig – 1.40 Plotting Moving average data for rolling 2 point

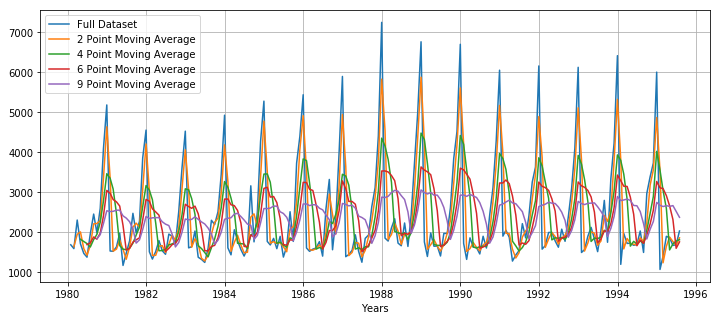


Fig – 1.41 Plotting Moving average data for rolling 2,4,6,9 point

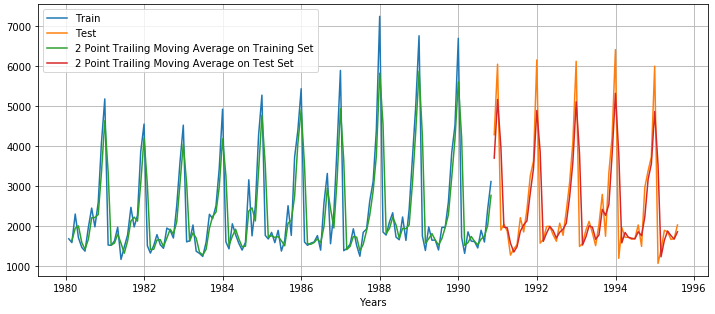


Fig – 1.42 Plotting Moving average data for rolling 2 point for training and test data

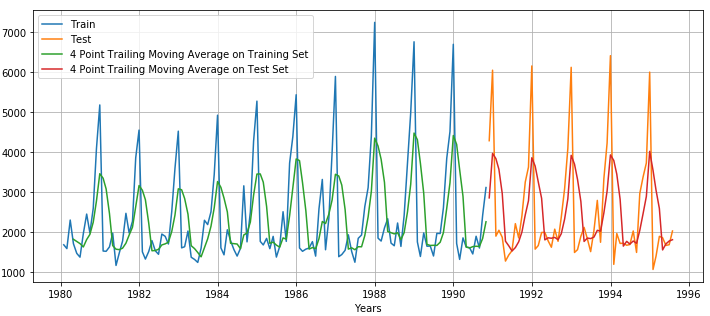


Fig – 1.43 Plotting Moving average data for rolling 4 point for training and test data

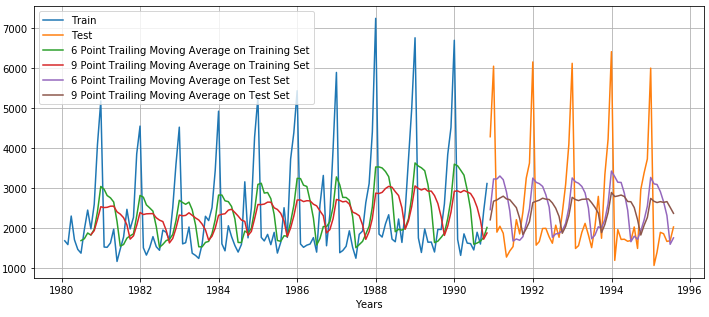


Fig – 1.44 Plotting Moving average data for rolling 6,9 point for training and test data

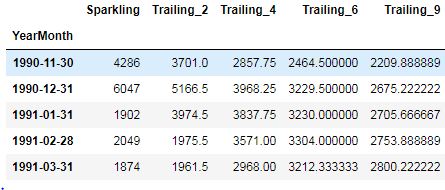


Fig – 1.45 load Moving average data for rolling 2,4,6,9 into the dataframe

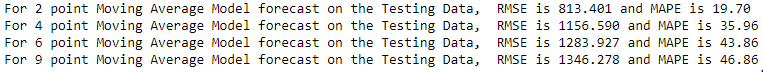


Fig – 1.46 RMSE and MAPE Moving average data for rolling 2,4,6,9

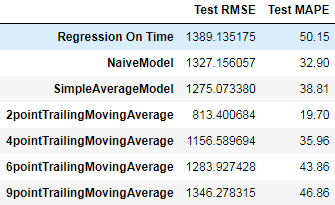


Fig – 1.47 Loading MA data for rolling 2,4,6,9 of RMSE and MAPE value Test data into dataframe

***Model – 5 Simple Exponential Smoothing:***

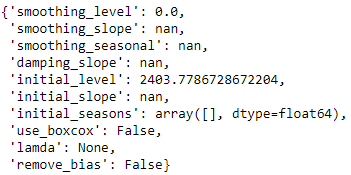
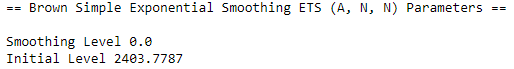


Fig – 1.48 Intializing the Simple Exponential Smoothing



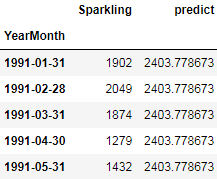


Fig – 1.49 predicting values for the Simple Exponential Smoothing

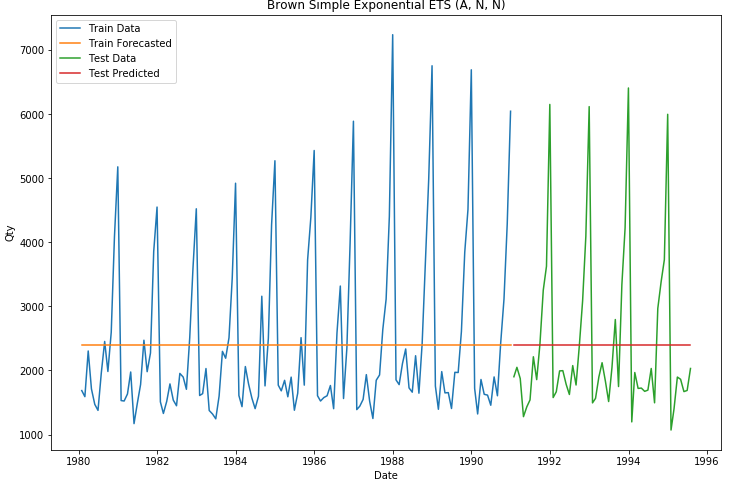


Fig – 1.50 Plotting predicted values for the Simple Exponential Smoothing



Fig – 1.51 RMSE and MAPE value for the training data using Simple Exponential Smoothing



Fig – 1.52 RMSE and MAPE value for the test data using Simple Exponential Smoothing

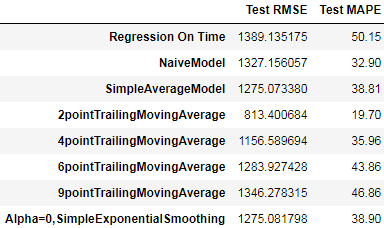


Fig – 1.53 RMSE and MAPE value for the test data using Simple Exponential Smoothing

Setting different alpha values.

Remember, the higher the alpha value more weightage is given to the more recent observation. That means, what happened recently will happen again. We will run a loop with different alpha values to understand which particular value works best for alpha on the test set.

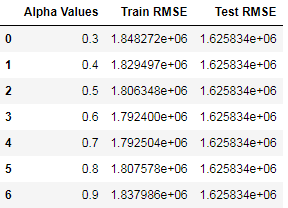


Fig – 1.54 RMSE and MAPE value for different Alpha value using Simple Exponential Smoothing

### *Model 6: Double Exponential Smoothing (Holt's Model):*

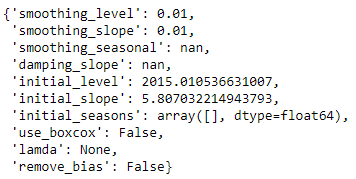


Fig – 1.55 Initializing the Double Exponential Smoothing

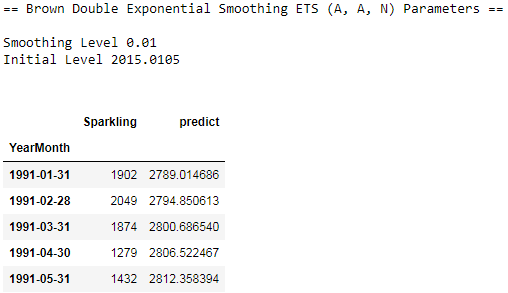


Fig – 1.56 Predicting the values using Double Exponential Smoothing



Fig – 1.57 RMSE and MAPE for training data



Fig – 1.58 RMSE and MAPE for test data

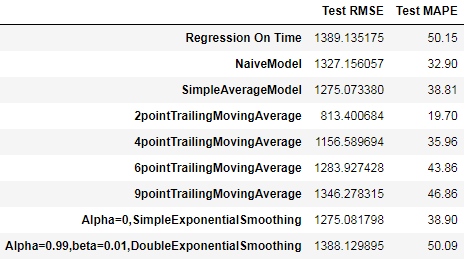


Fig – 1.59 RMSE and MAPE for test data into the dataframe

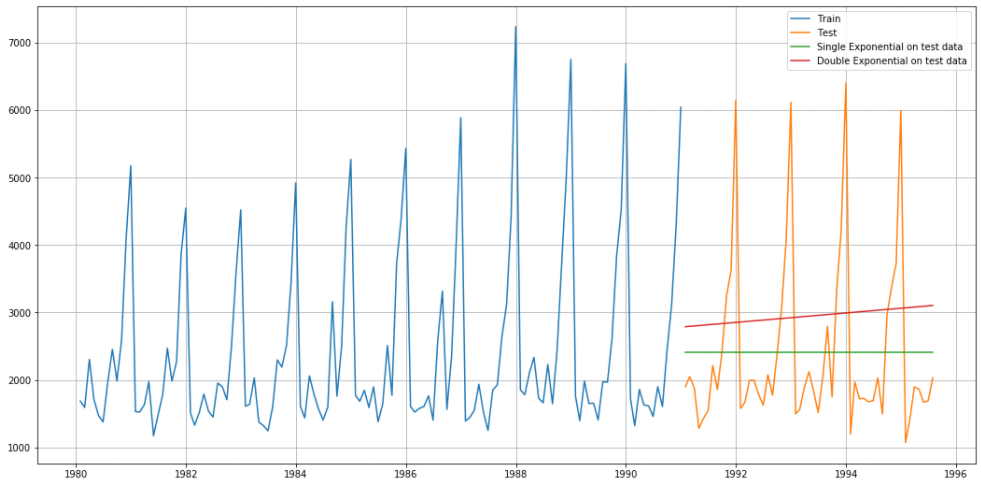


Fig – 1.60 plotting DES predicted output

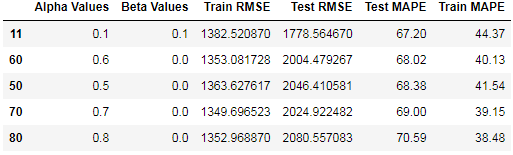


Fig – 1.61 Finding RMSE and MAPE for different Alpha and beta values

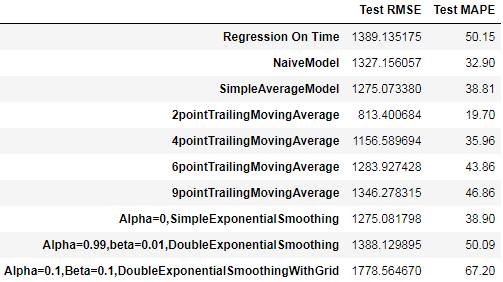


Fig 1.62 Finding the least RMSE and MAPE value from the different ALPHA and BETA values

### *Model 7: Triple Exponential Smoothing (Holt - Winter's Model)*

Three parameters , 𝛽 and 𝛾 are estimated in this model. Level, Trend and Seasonality are accounted for in this model.

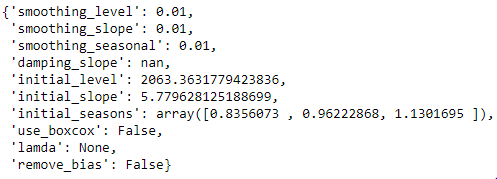


Fig 1.63 Initializing the TES

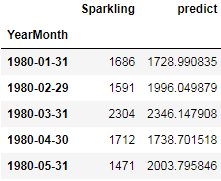


Fig 1.64 Predicting the values from training data

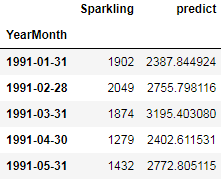


Fig 1.65 Predicting the values from test data

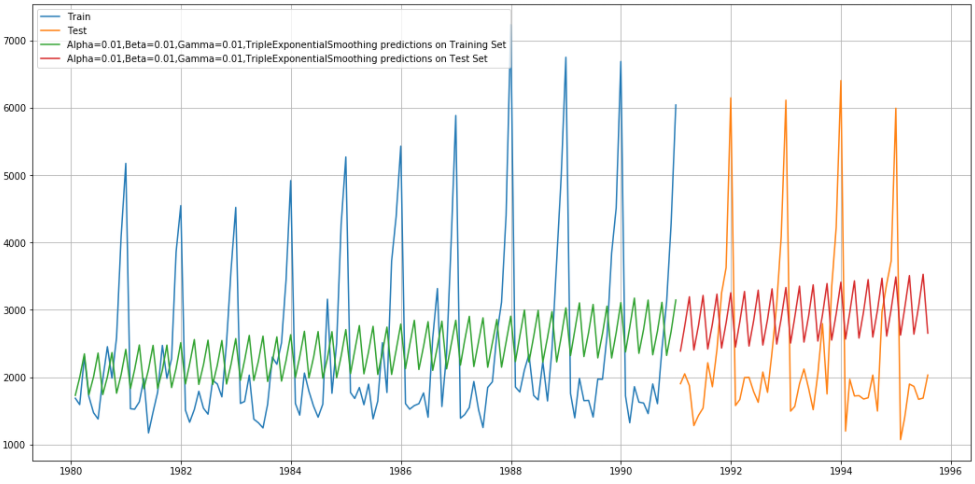


Fig 1.66 Plotting predicted train and test values



Fig 1.67 RMSE and MAPE values from train data



Fig 1.68 RMSE and MAPE values from test data

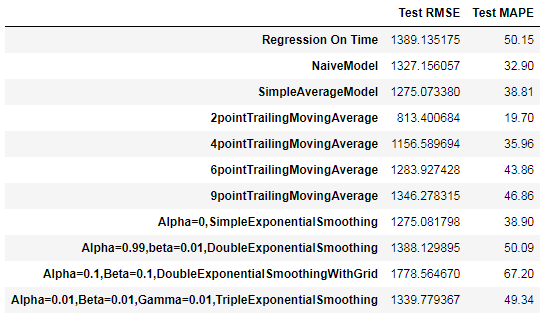


Fig 1.69 RMSE and MAPE for test data into the dataframe

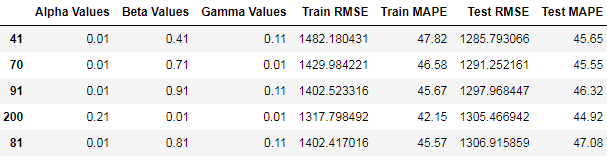


Fig 1.70 RMSE and MAPE for different alpha, beta, and gamma values into the dataframe

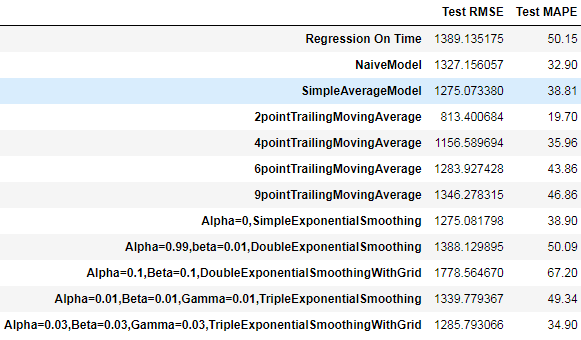


Fig 1.71 Finding least RMSE and MAPE for different alpha, beta, and gamma values and loading into the dataframe

### 5. Check for the stationarity of the data on which the model is being built on using appropriate statistical tests and also mention the hypothesis for the statistical test. If the data is found to be non-stationary, take appropriate steps to make it stationary. Check the new data for stationarity and comment.

***Note:*** Stationarity should be checked at alpha(𝛼) = 0.05.

###### **Null Hypothesis:** p-value > 𝛼 (alpha value) - then the data is not stationary

###### **Alternate Hypothesis:** p-value < 𝛼 (alpha value) - then the data is having stationarity

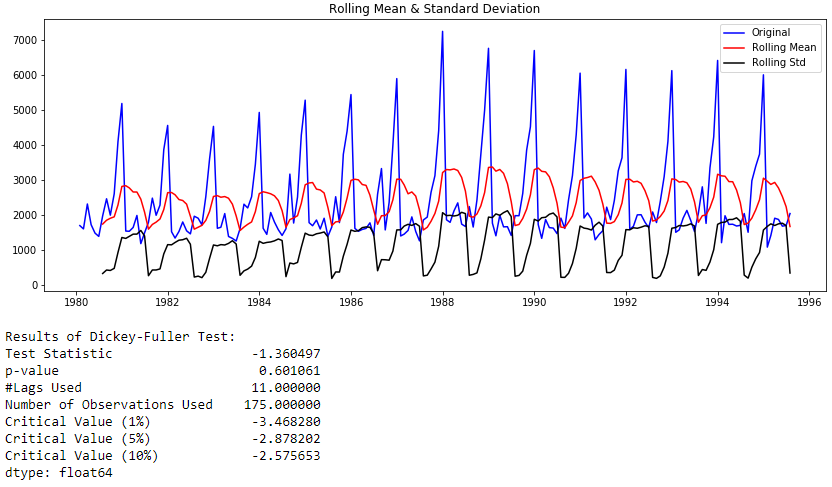


Fig 1.72 Finding the p-value and plotting Rolling mean and standard deviation with original data.

The p-value is greater than the alpha value so the data is not stationarity and alternate hypothesis is rejected. To find the stationarity we need to take the 1st difference and plotting the graph and finding the p-value.

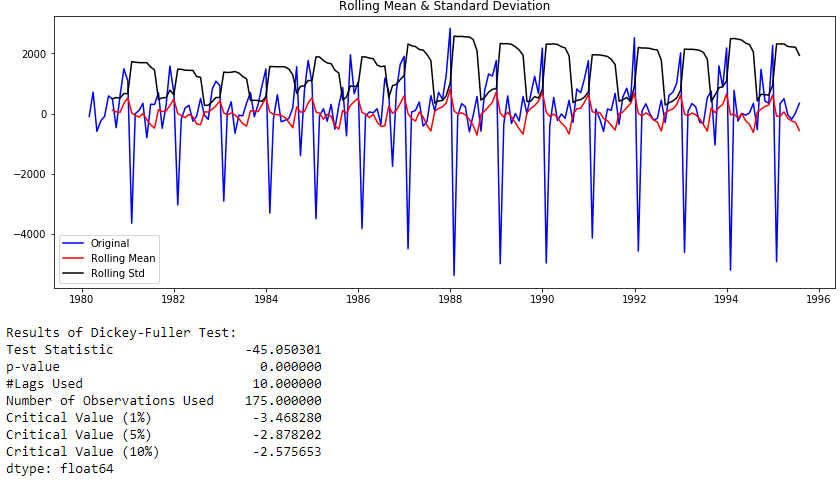


Fig 1.73 Finding the p-value and plotting Rolling mean and standard deviation with original data after taking 1st difference data.

Now p-value is less than alpha value. Therefore null hypothesis is rejected.

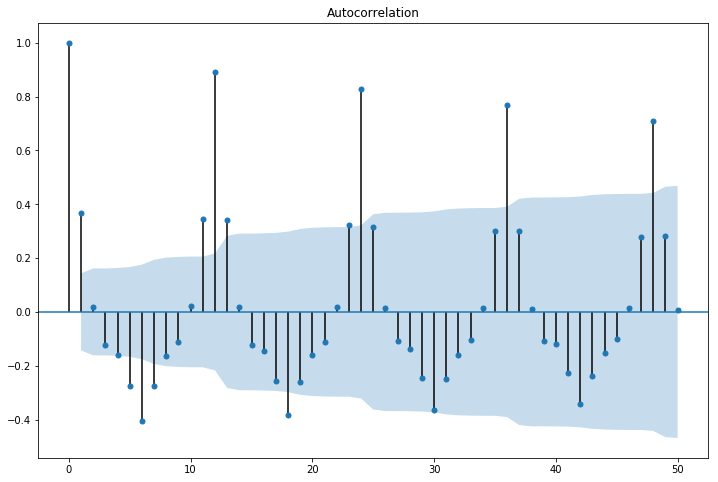


Fig 1.74 ACF plot for original data

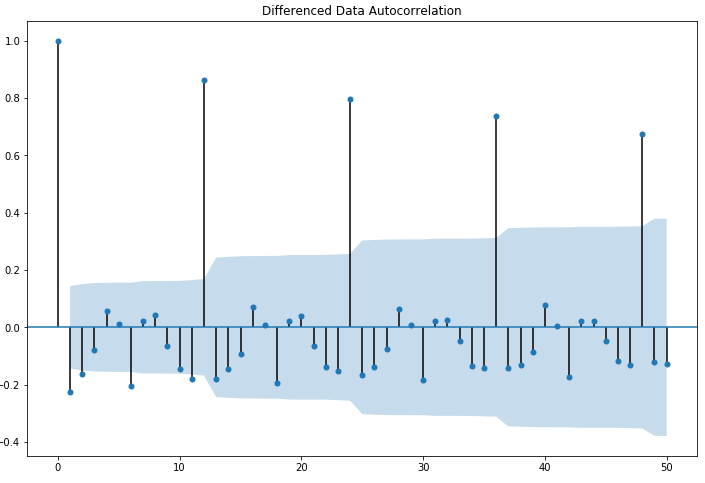


Fig 1.75 ACF plot for 1st difference data

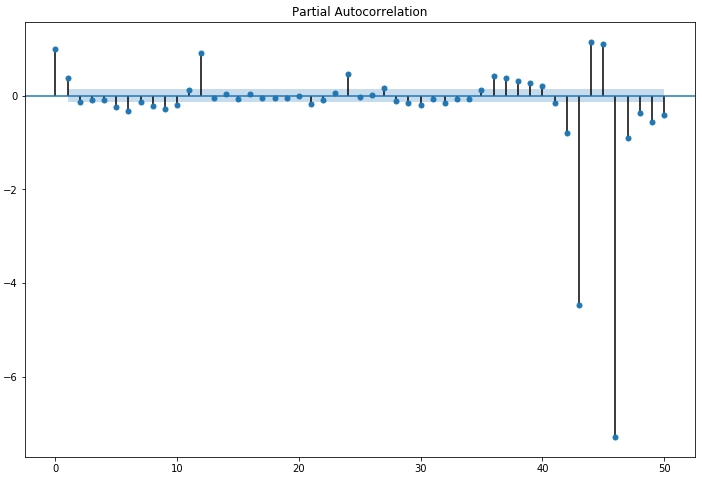


Fig 1.76 PACF plot for original data

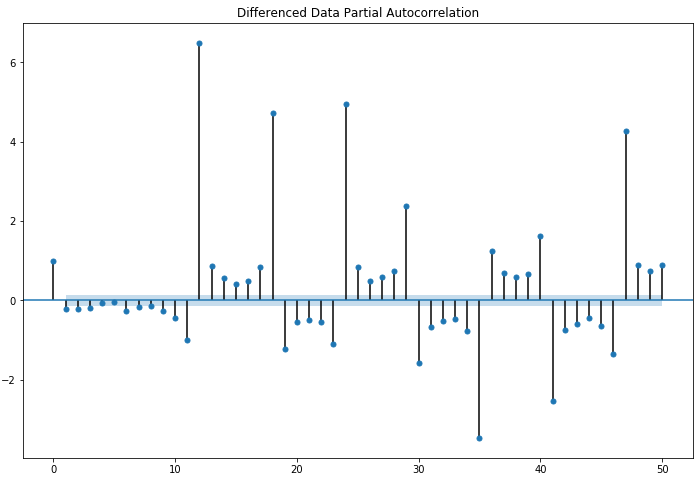


Fig 1.77 PACF plot for 1st difference data

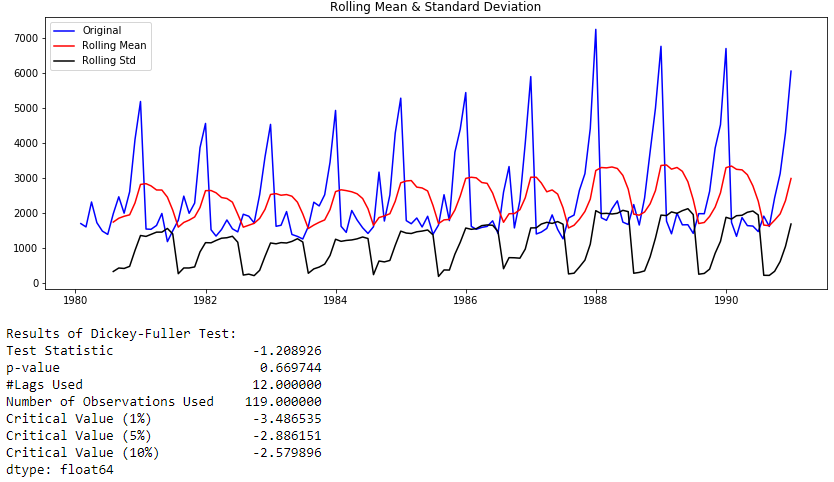


Fig 1.78 Finding stationarity and p-value for train data

The p-value is greater than the alpha value so the data is not stationarity and alternate hypothesis is rejected. To find the stationarity we need to take the 1st difference and plotting the graph and finding the p-value.

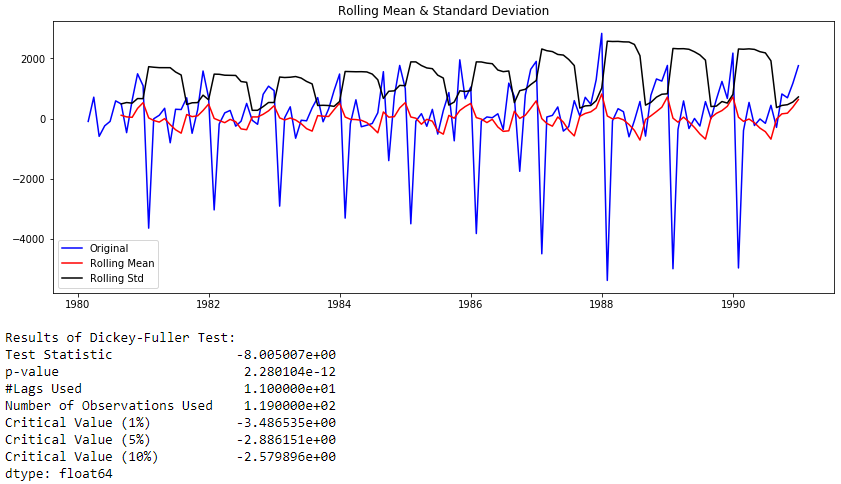


Fig 1.79 Finding stationarity and p-value for train data after taking 1st difference

### 6. Build an automated version of the ARIMA/SARIMA model in which the parameters are selected using the lowest Akaike Information Criteria (AIC) on the training data and evaluate this model on the test data using RMSE.

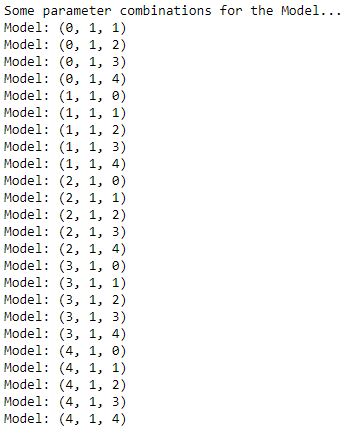


Fig 1.80 Finding combination for the model

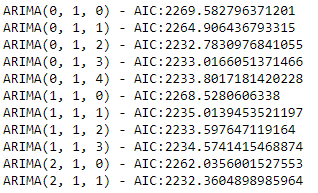


Fig 1.81 Sample AIC value for ARIMA Model

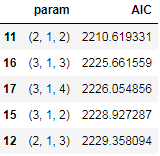


Fig 1.82 Sorting least AIC value for ARIMA Model

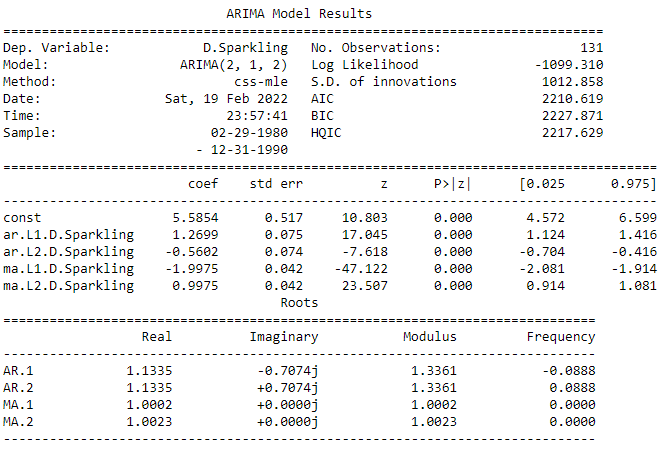


Fig 1.83 Summary report for ARIMA Model



Fig 1.84 RMSE and MAPE for ARIMA Model

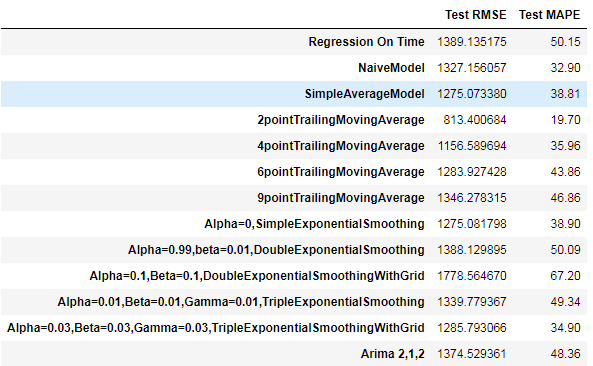


Fig 1.85 RMSE and MAPE for ARIMA Model into the dataframe

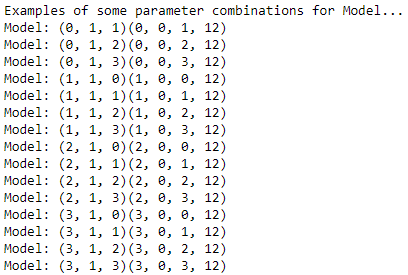


Fig 1.86 combination parameters for SARIMA Model

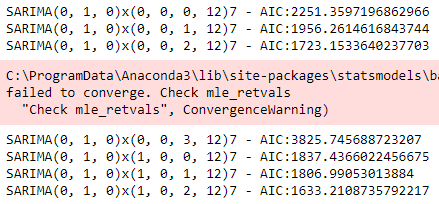


Fig 1.87 Sample AIC for SARIMA Model



Fig 1.88 Sample AIC for SARIMA Model

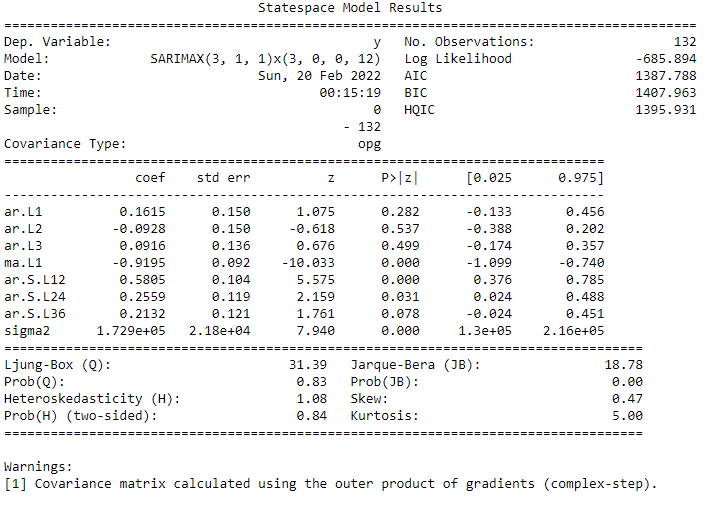


Fig 1.89 Summary report for SARIMA Model

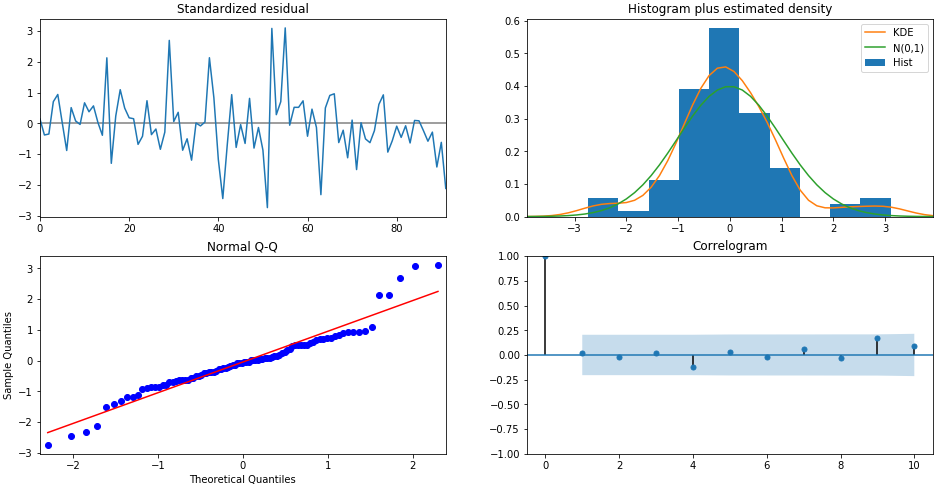


Fig 1.90 plotting diagnostic for SARIMA Model

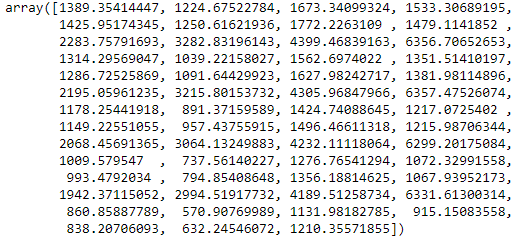


Fig 1.91 Predicting values for testing data



Fig 1.92 RMSE and MAPE SARIMA Model

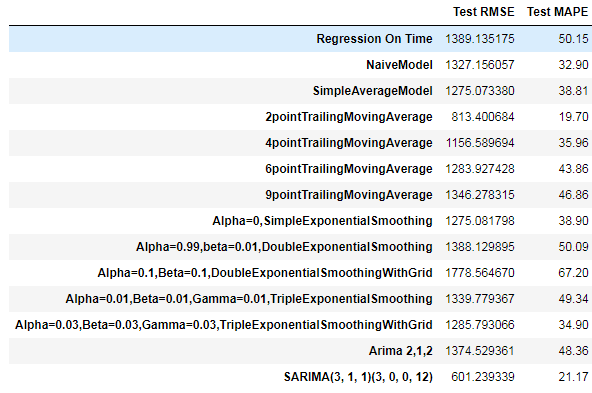


Fig 1.93 Loading RMSE and MAPE SARIMA Model into dataframe

### 7. Build ARIMA/SARIMA models based on the cut-off points of ACF and PACF on the training data and evaluate this model on the test data using RMSE.

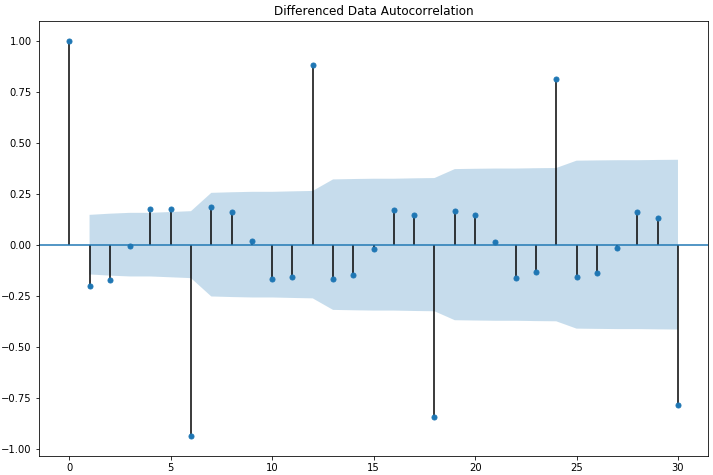


Fig 1.94 Plotting 2nd Difference after taking cut-off points in ACF plot

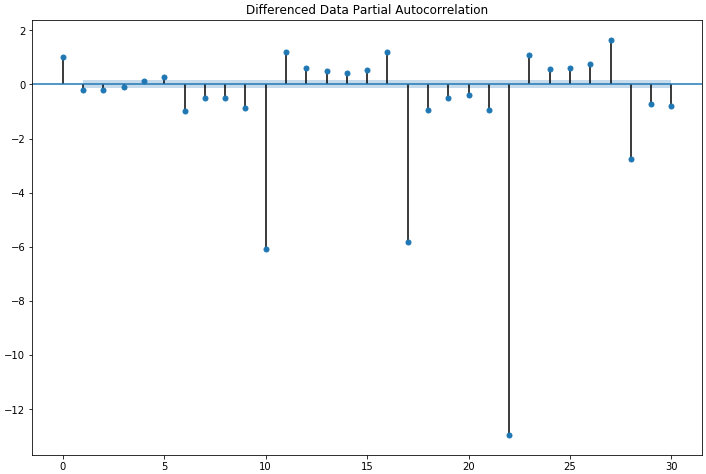


Fig 1.95 Plotting 2nd Difference after taking cut-off points in PACF plot

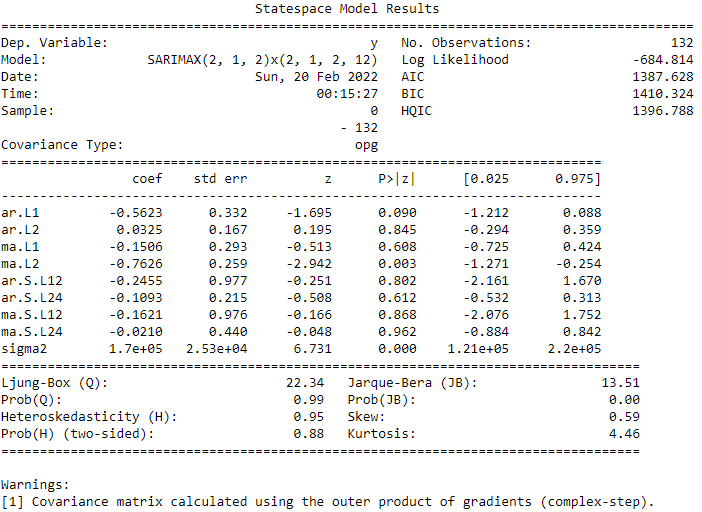


Fig 1.96 Cut-off point summary report for SARIMA model

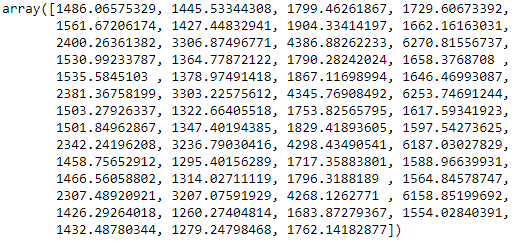


Fig 1.97 predicting values for SARIMA model after taking cutoff points



Fig 1.98 RMSE and MAPE value for cutoff point SARIMA model

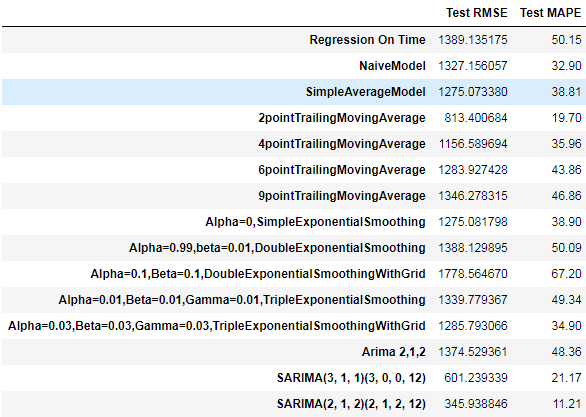


Fig 1.99 Cut-off point for SARIMA model RMSE and MAPE into Dataframe

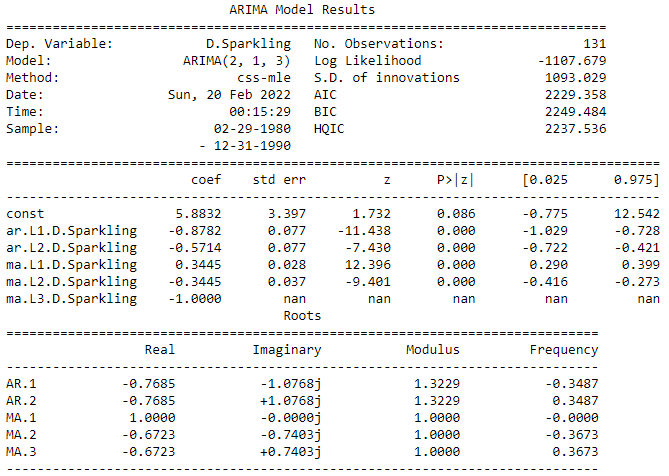


Fig 1.100 Cut-off point for ARIMA model summary report



Fig 1.101 Cut-off point for ARIMA model RMSE and MAPE value

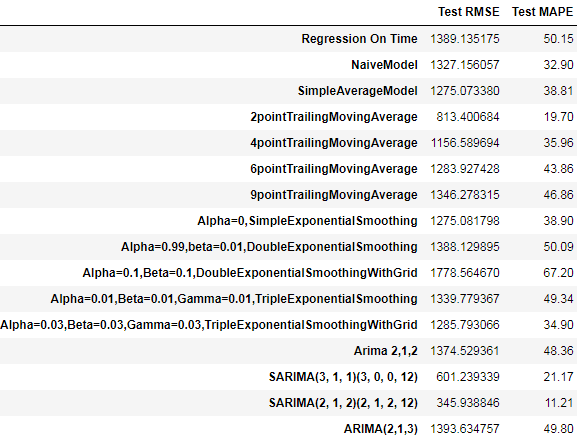


Fig 1.102 Cut-off point for ARIMA model RMSE and MAPE into Dataframe

### 8. Build a table (create a data frame) with all the models built along with their corresponding parameters and the respective RMSE values on the test data.

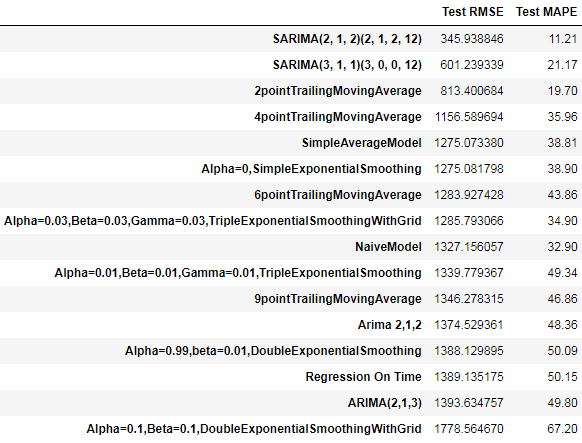


Fig 1.103 Sorting the RMSE value and finding best model

**9. Based on the model-building exercise, build the most optimum model(s) on the complete data and predict 12 months into the future with appropriate confidence intervals/bands.**

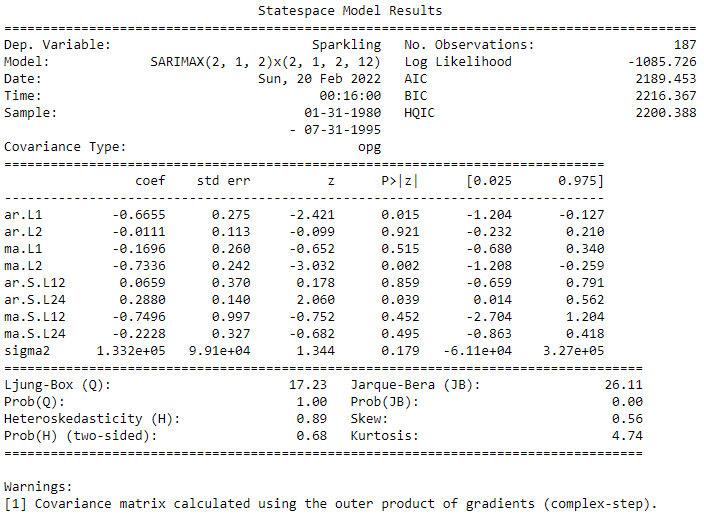


Fig 1.104 Summary report for SARIMA model

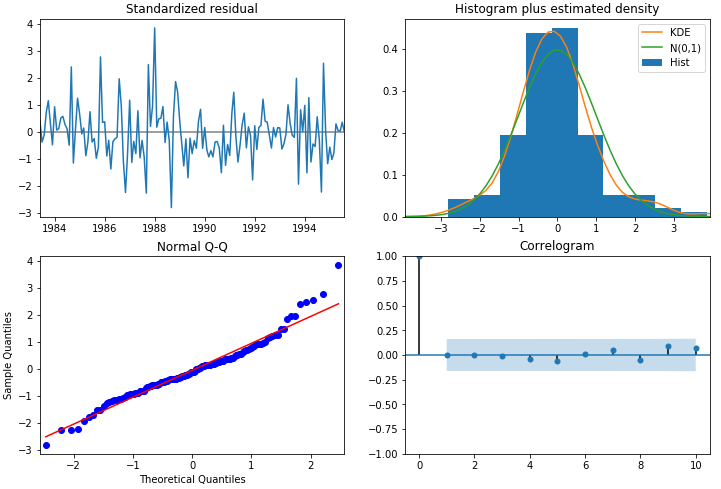


Fig 1.105 plotting diagnostic report for SARIMA model

***Predicting the values for the next 12 months in future***

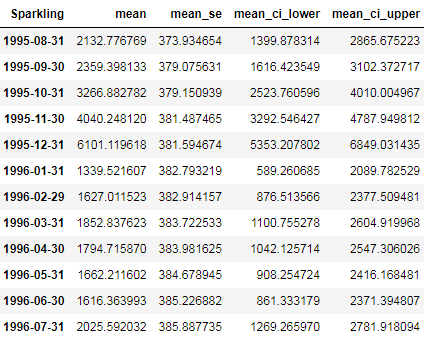


Fig 1.106 Predicting the values



Fig 1.107 RMSE value for future data.

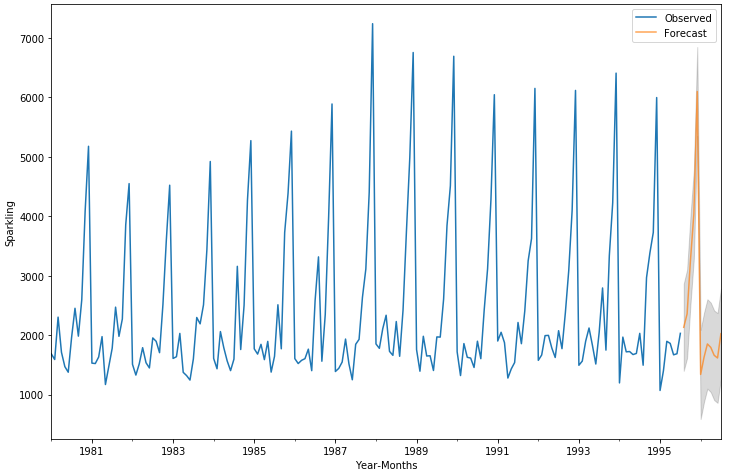


Fig 1.108 Plotting the future data in graph.

### 10. Comment on the model thus built and report your findings and suggest the measures that the company should be taking for future sales.

SARIMA Model is performing best in this case giving us the least error.

Looking at the bar plot, we can see that on December months the sales are highest. We can use these insights to increase our sales further.

We can introduce certain offers in November, December months to attract more customers.

Year 1988 has the highest sales recorded till data. We can go back to find out the reasons to which pushed the sales so much. Looking at the prediction, we can say that the sales figure will be more or less same as that of previous year. Hence some important measures have to be taken to increase the trend. As the trend has been more or less constant throughout the years.