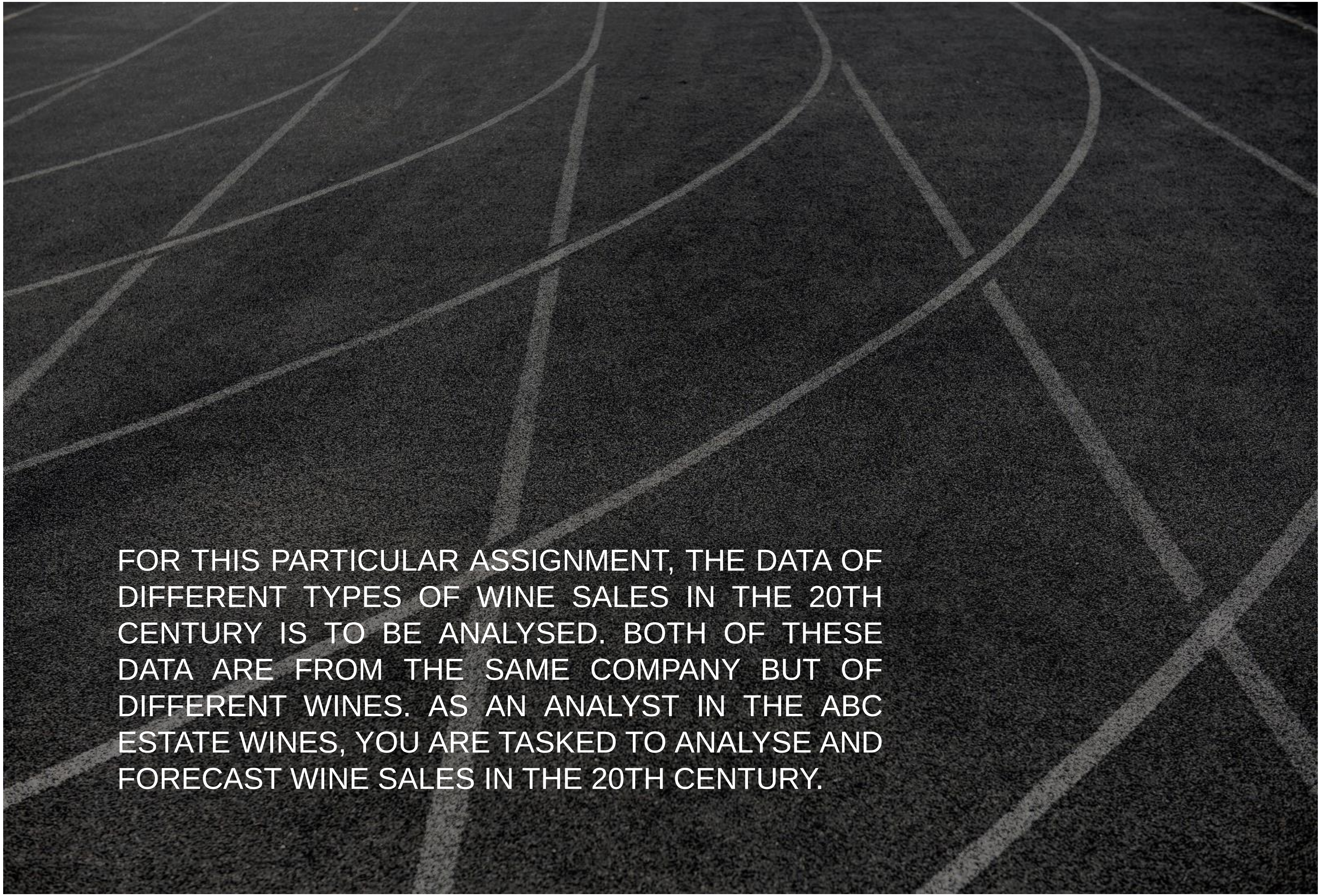
TIME SERIES FORECASTING

Rateesh Upendran

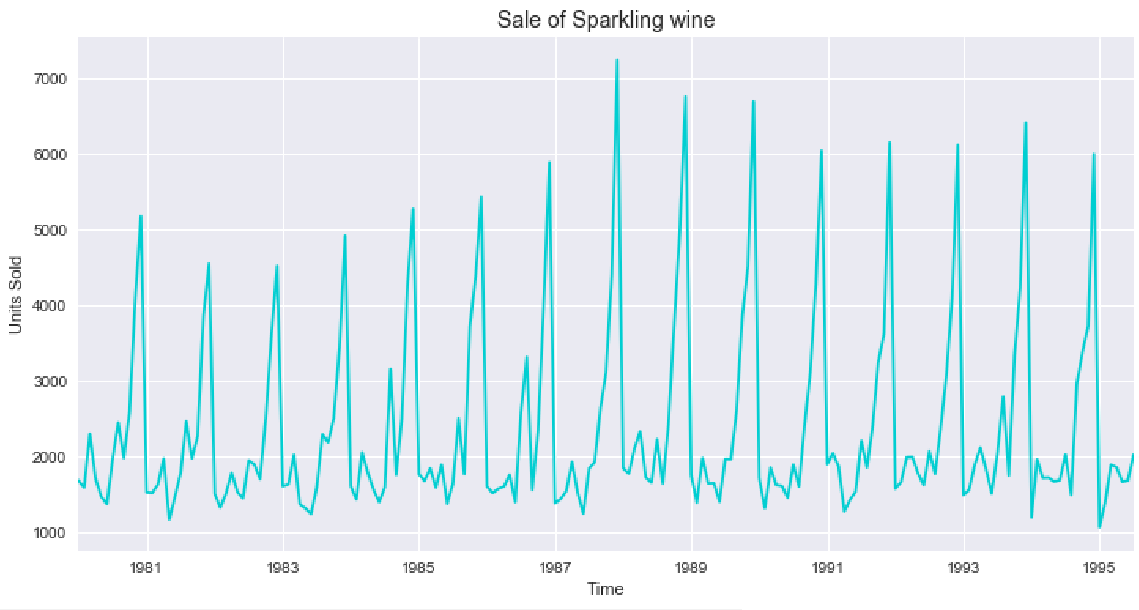
September 2020

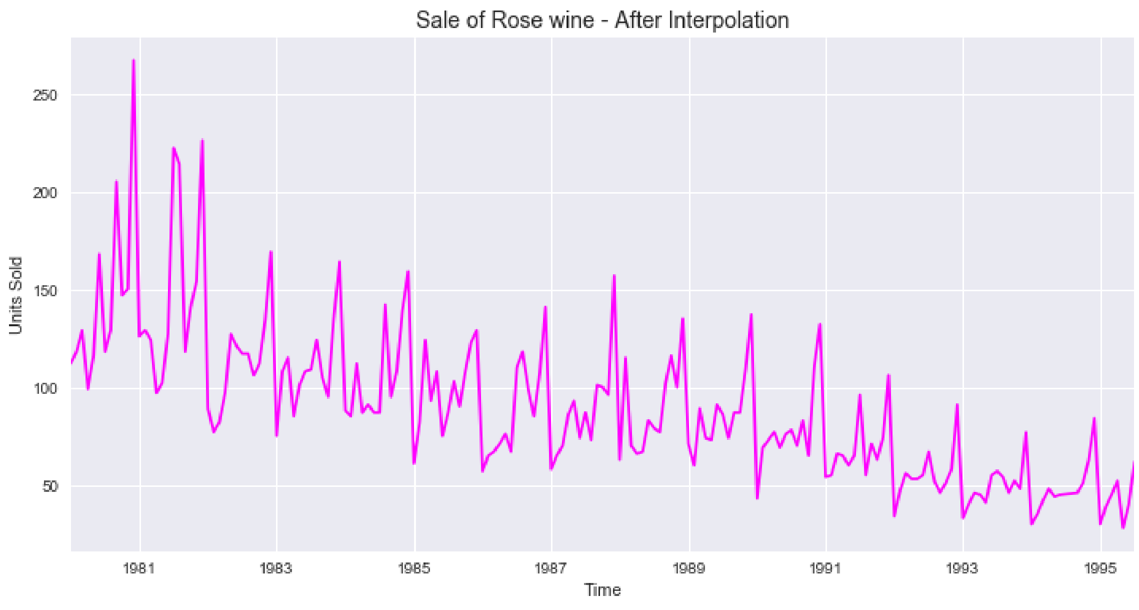


FOR THIS PARTICULAR ASSIGNMENT, THE DATA OF DIFFERENT TYPES OF WINE SALES IN THE 20TH CENTURY IS TO BE ANALYSED. BOTH OF THESE DATA ARE FROM THE SAME COMPANY BUT OF DIFFERENT WINES. AS AN ANALYST IN THE ABC ESTATE WINES, YOU ARE TASKED TO ANALYSE AND FORECAST WINE SALES IN THE 20TH CENTURY.

1. READ & PLOT

- Monthly sales of two type of wines, such as Sparkling and Rose are given, for a period from January, 1980 to July, 1995.
- The given data files are read as is and a date-range has been applied on the data as index
- Both the given datasets of the respective type of wines is combined to a single data frame, for the sake of comparability of the timeseries components and forecast
- The Rose time-series got values missing for two months in 1994, which are imputed using interpolation (linear method)
- Rose data after interpolation for year 1994 is given below as well as the plot
- Both the datasets shows significant seasonality. While sale of Rose shows evident downward trend, Sparkling doesn’t shows any consistent trend but has upward and downward slopes during the time period
- While Sparkling wine has been consistently favoured over the years by customers, the demand for Rose had been fell out-of-favour over the years





Reading data as time-series

```
date = pd.date_range(start='1/1/1980', end='8/1/1995', freq='M')
date
```

```
DatetimeIndex(['1980-01-31', '1980-02-29', '1980-03-31', '1980-04-30',
               '1980-05-31', '1980-06-30', '1980-07-31', '1980-08-31',
               '1980-09-30', '1980-10-31',
               ...
               '1994-10-31', '1994-11-30', '1994-12-31', '1995-01-31',
               '1995-02-28', '1995-03-31', '1995-04-30', '1995-05-31',
               '1995-06-30', '1995-07-31'],
              dtype='datetime64[ns]', length=187, freq='M')
```

Creating the combined Dataframe

```
df = pd.DataFrame({'YearMonth':date,
                   'Sparkling':df_spark.Sparkling,
                   'Rose':df_rose.Rose})
df.set_index('YearMonth',inplace=True)
```

Imputation of missing values

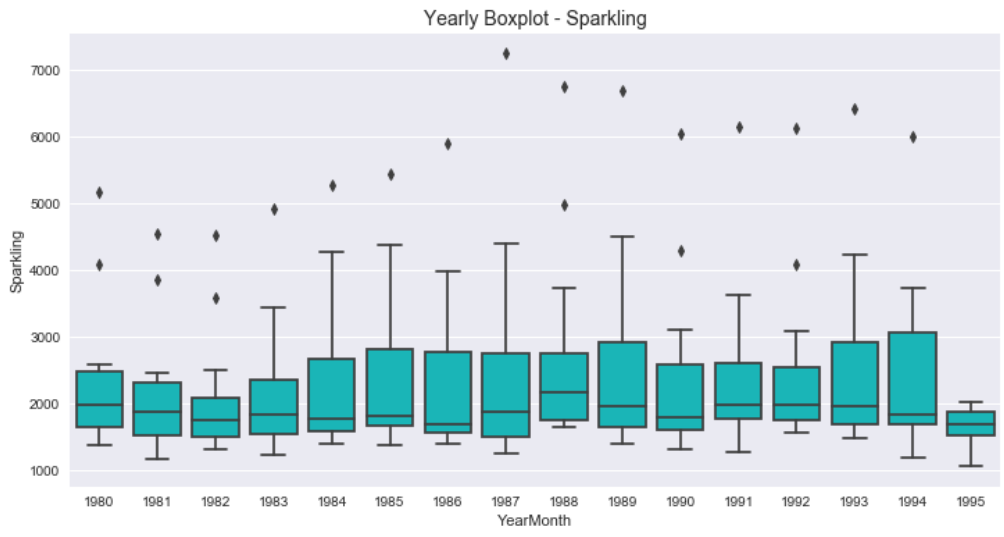
```
df.Rose['1994']
```

```
YearMonth
1994-01-31    30.000000
1994-02-28    35.000000
1994-03-31    42.000000
1994-04-30    48.000000
1994-05-31    44.000000
1994-06-30    45.000000
1994-07-31    45.336957
1994-08-31    45.673913
1994-09-30    46.000000
1994-10-31    51.000000
1994-11-30    63.000000
1994-12-31    84.000000
```

2. EXPLORATORY DATA ANALYSIS

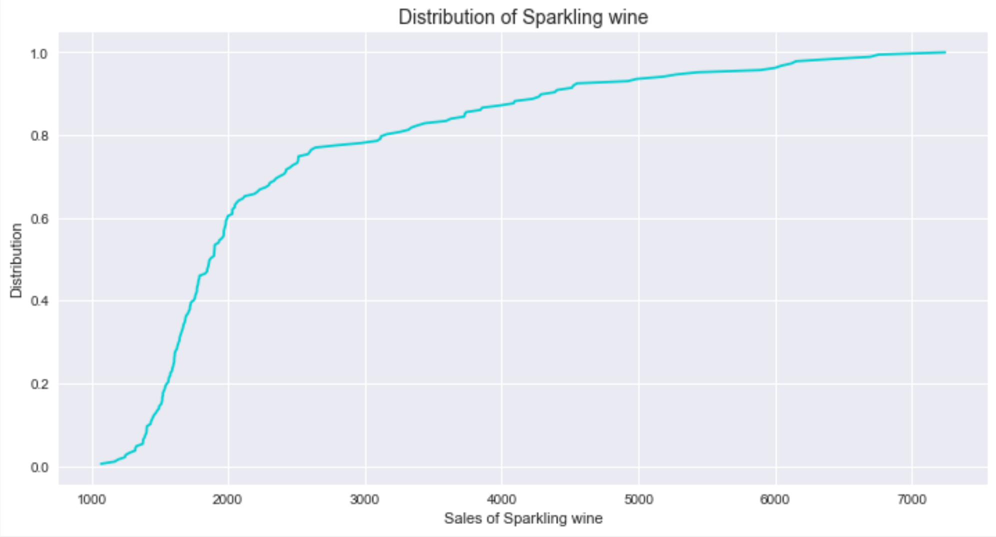
Sparkling

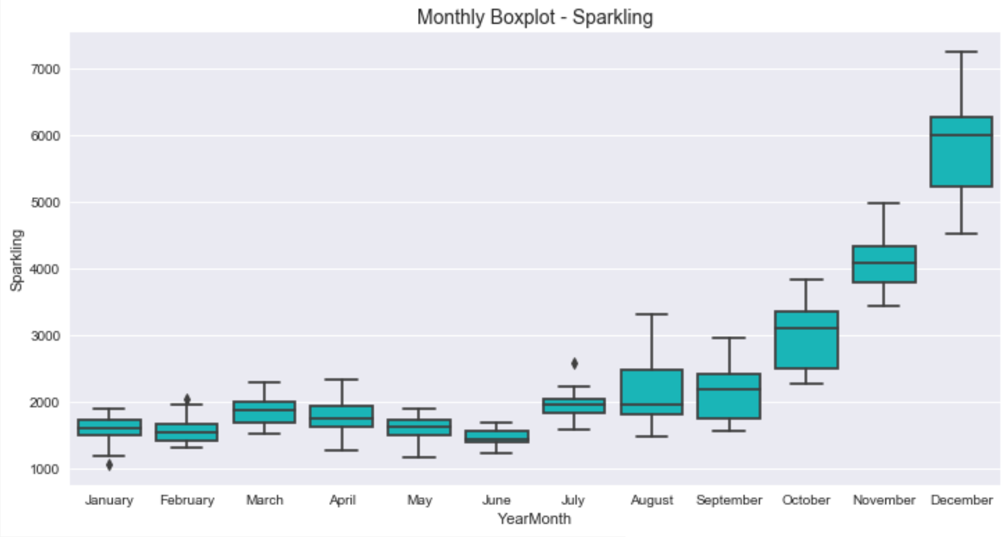
- The descriptive summary of the data shows that on an average 2402 units of Sparkling wines were sold each month on the given period of time. 50% of months sales varied from 1605 units to 2549 units. Maximum sale reported in a month is 7242 units.
- The Empirical CDF plot shows that, in 80% of months, at least 3000 units of Sparkling wine were sold
- The yearly-boxplot, shows that the average sale of Sparkling has been more or less consistent across the period, at or a little below 2000 units.
- The outliers in the yearly-boxplot most probably represent the seasonal sale during the seasonal months
- The monthly-box-plot shows a clear seasonality during the festive seasonal months of October, November and December, which peaks in December. The sale tanks in the month of June.



Descriptive Statistics

	Sparkling	Rose
count	187.000000	185.000000
mean	2402.417112	90.394595
std	1295.111540	39.175344
min	1070.000000	28.000000
25%	1605.000000	63.000000
50%	1874.000000	86.000000
75%	2549.000000	112.000000
max	7242.000000	267.000000

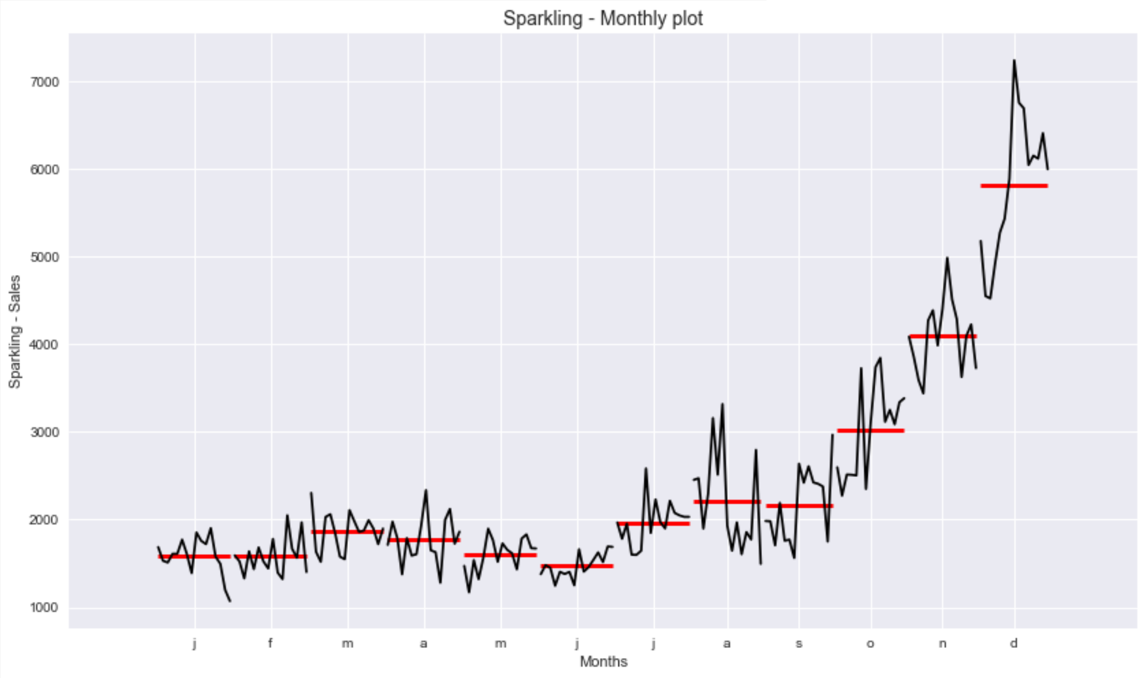


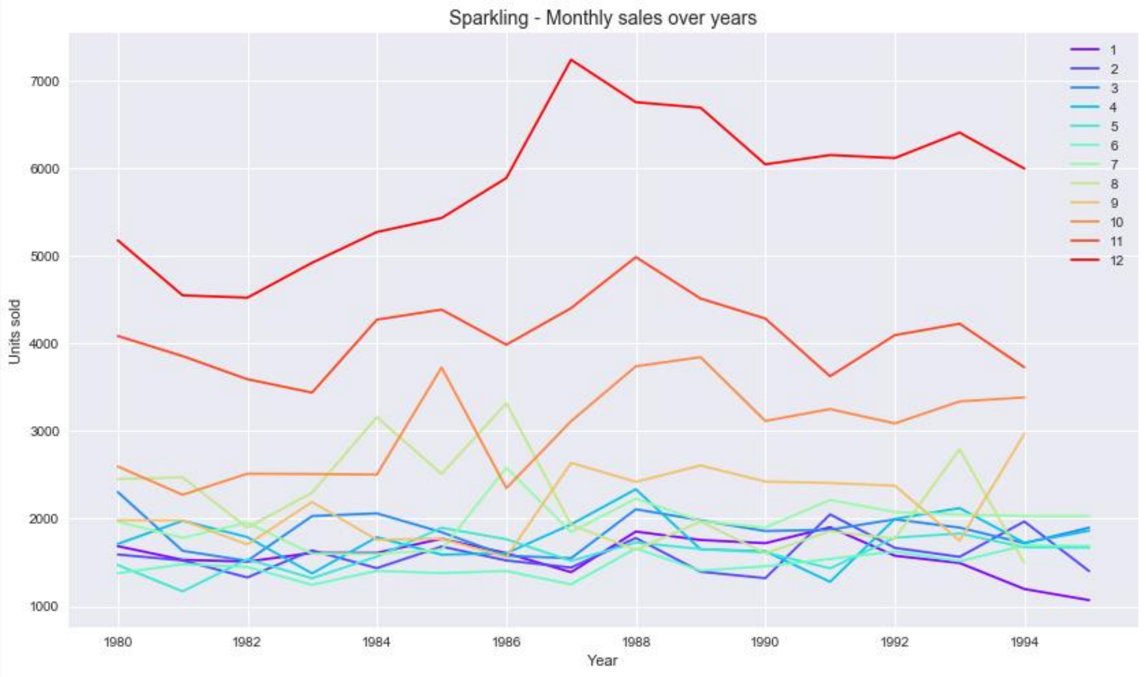


2. EXPLORATORY DATA ANALYSIS

Sparkling

- The monthly plot for Sparkling shows mean and variation of units sold each month over the years. Sale in seasonal months shows a higher variation than in the lean months.
- Sale in December with a mean few points below 6000, varies from 7400 to 4500 units over the years. Whereas sale in November varies from 3500 units to 5000 units and sale in October varies from 2500 to 4000 units
- The lean months from January till September shows more or less a consistent sale around 2000 units



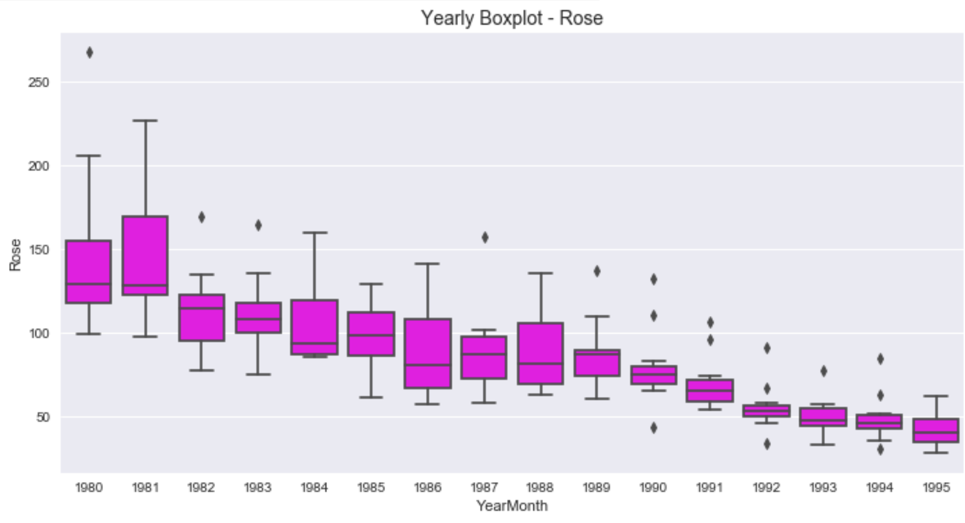


- The plot of monthly sale over the years also shows the seasonality component of the time-series, with October November and December selling exponentially higher volumes
- The highest volume of Sparkling wines were sold in December,1987 and the least of December sale was in 1981. Post 1987 December sales is around an average 6500 units, which was around 5000 in early 80’s
- The seasonal sale since 1990 has been more or less consistent around 6000 units in December, 4000 units in November and 3000 units in October
- Sales for the months from January to July is seen to be consistent across the years, compared to the rest of the months

2. EXPLORATORY DATA ANALYSIS

Rose

- The descriptive summary of the data shows that on an average 90 units of Rose wines were sold each month on the given period of time. 50% of months sales varied from 63 units to 112 units. Maximum sale reported in a month is 267 units and minimum of 28 units
- The Empirical CDF plot shows that, in 80% of months, at least 120 units of Rose wine were sold
- The yearly-boxplot, shows that the average sale of Rose wine moving according to the downward trend in sales over the years. The outliers over upperbound in the yearly-boxplot most probably represent the seasonal sale during the seasonal months
- The monthly-box-plot shows a clear seasonality during the seasonal months of November and December. Though the sale tanks in the month of January, it picks up in the due course of the year.
- Average sale in December is around 140 units, November is around 110 units and October is around 90 units



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	Sparkling	Rose
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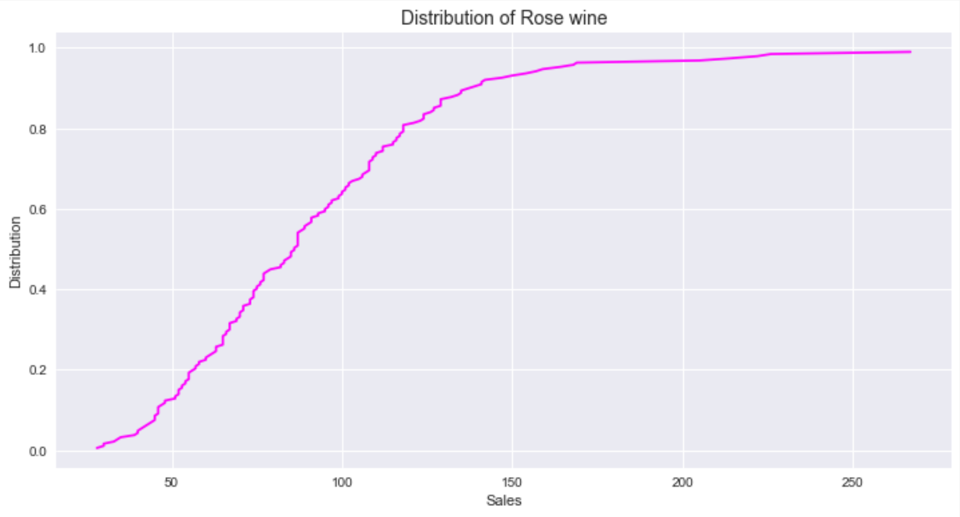
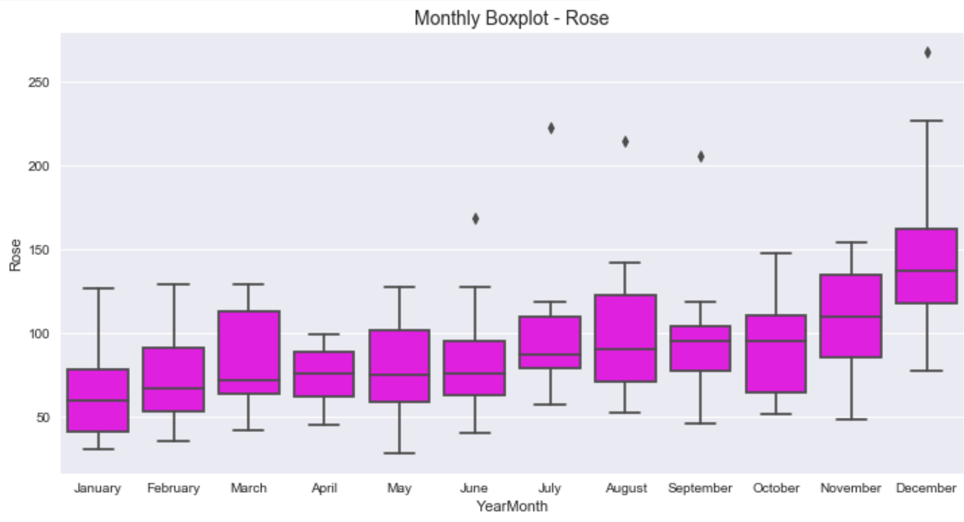
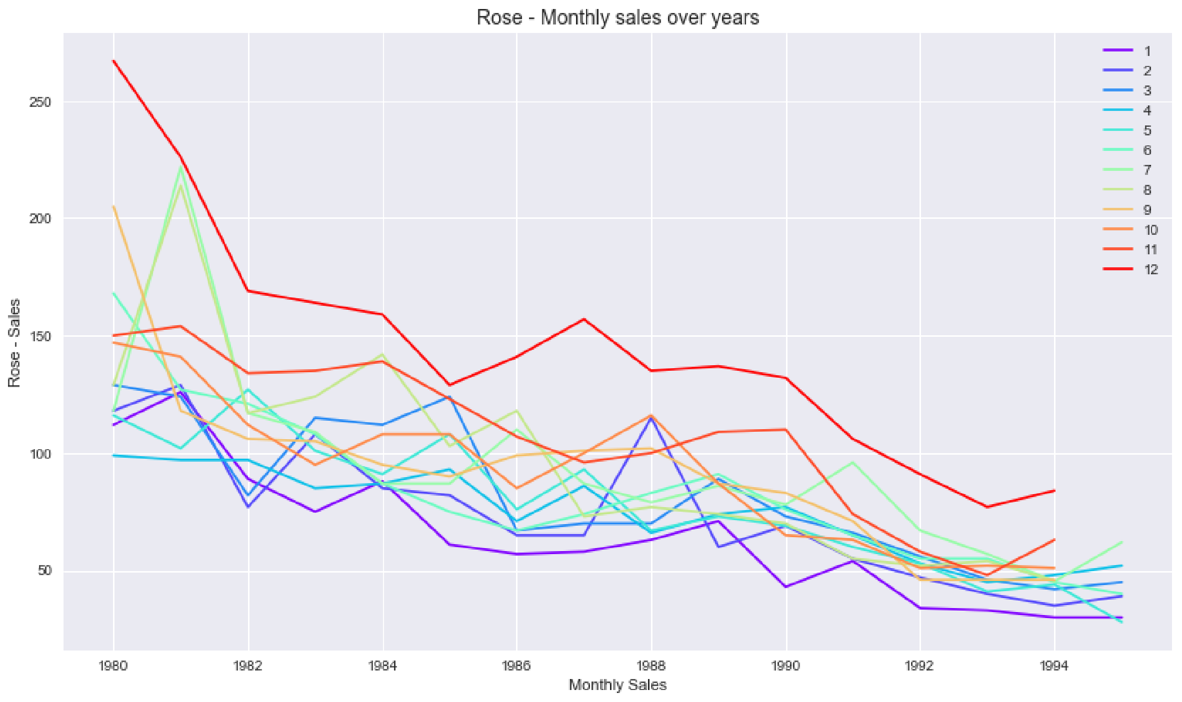


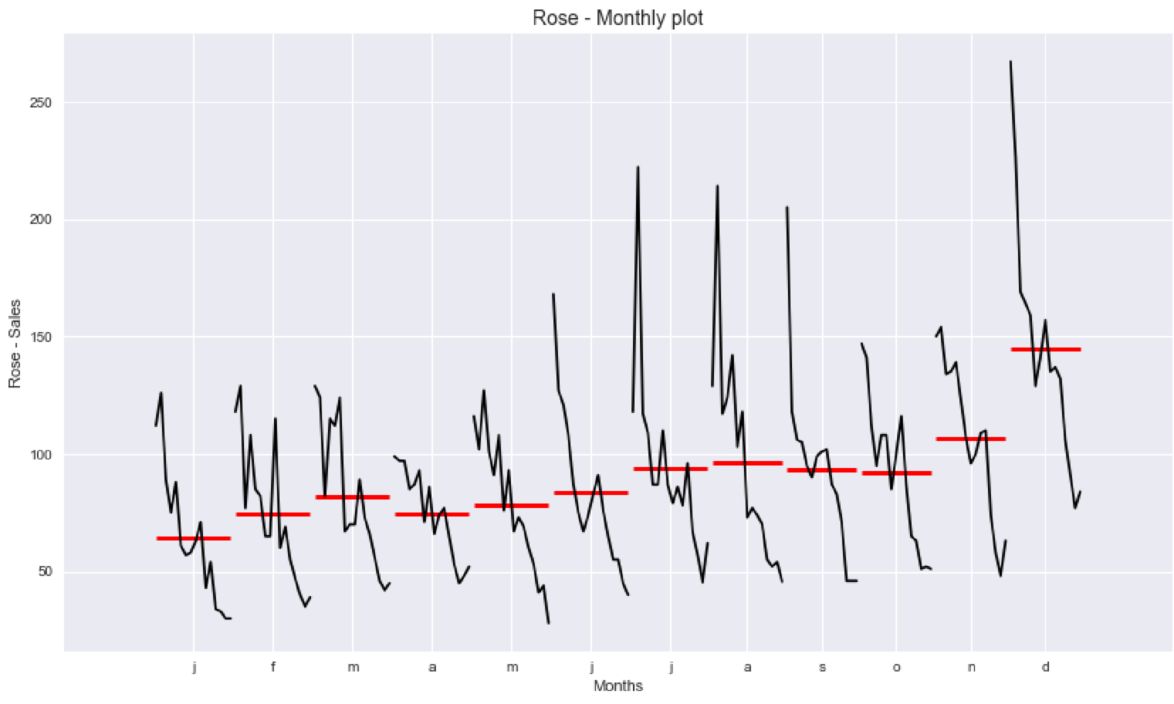


2. EXPLORATORY DATA ANALYSIS

Rose

- The monthly plot for Rose shows mean and variation of units sold each month over the years. Sale in months such as July, August, September and December shows a higher variation than the rest
- Sale in December with a mean few points below 100, varies from 75 to 270 units over the years. Whereas the average sale is less than or closer to 100 units (above 50) for the rest of the year





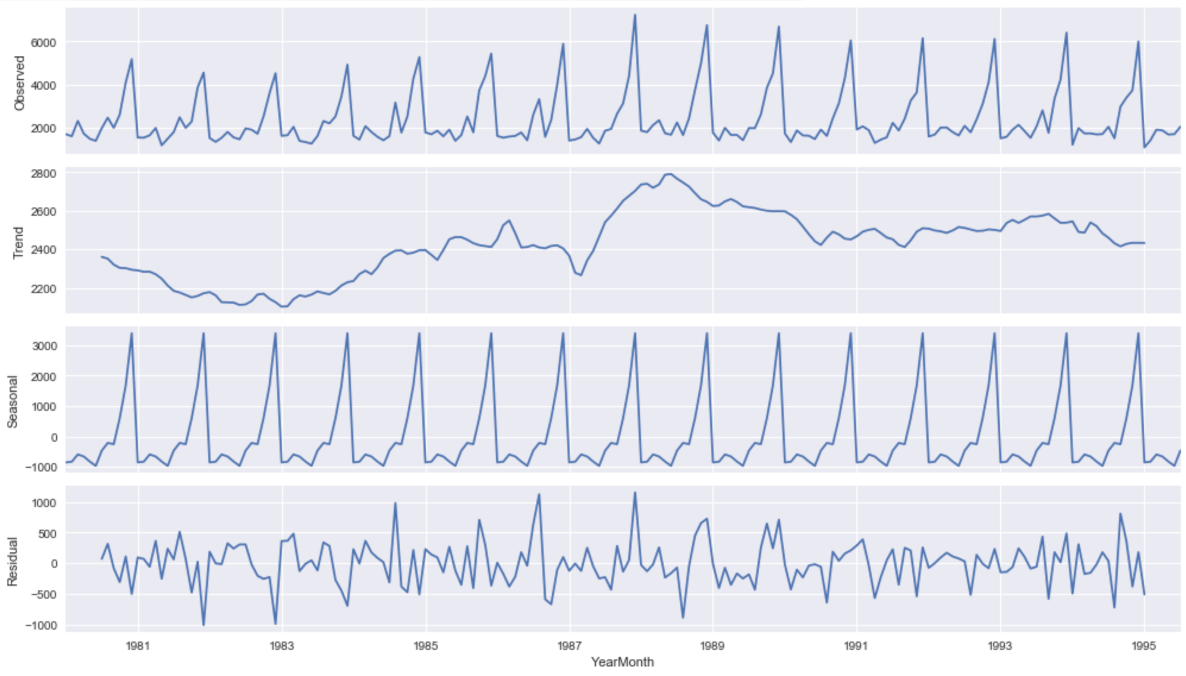
- The plot of monthly sale over the years also shows the seasonality component of the time-series, with November and December selling exponentially higher volumes than other months.
- The highest volume of Rose wines were sold in December,1980 and the least of December sale was in 1993. Though December sale picked after 1983, it consistently dipped after 1987

2. TIME SERIES DECOMPOSITION

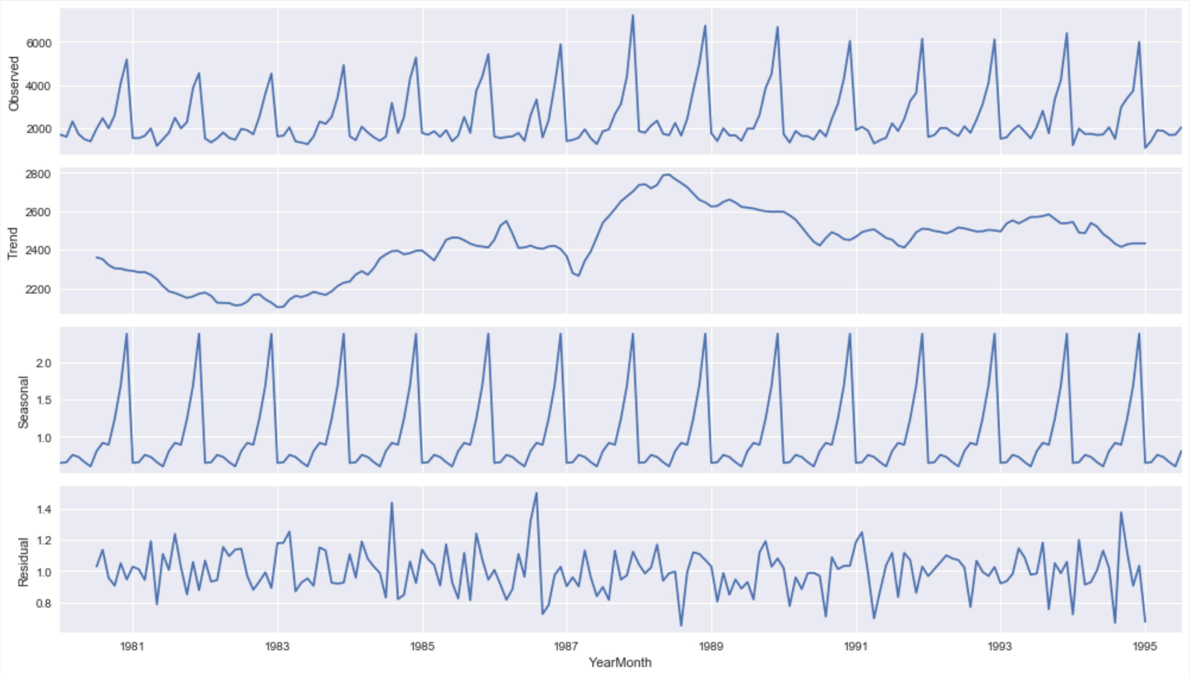
Sparkling

- The decomposition plots of Sparkling wine sales is given here
- As the altitude of the seasonal peaks in the observed plot is changing according to the change in trend, the time-series is assumed to be ‘multiplicative’
- The plot of the trend component does not show a consistent trend, but an intermediary period shows an upward slope which gets consistent on the late half of time-series
- The additive model shows the seasonality with a variance of 3000 units and the multiplicative model shows a variance of 30%

Additive model



Multiplicative model



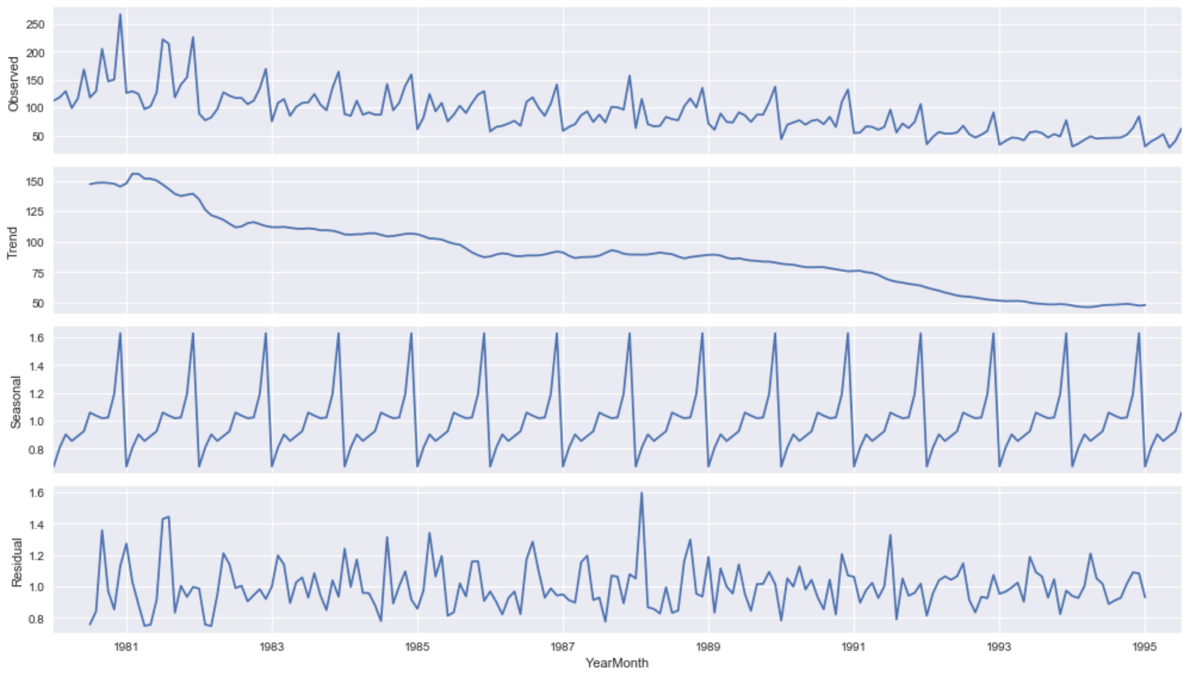
- The residual shows a pattern of high variability across the period of time-series, which is more or less consistent in both additive and multiplicative decompositions
- The additive model shows a mean variance around 0 and the multiplicative model shows a variance around 10%
- If the seasonality and residual components are independent of the trend, then you have an additive series. If the seasonality and residual components are in fact dependent, meaning they fluctuate on trend, then you have a multiplicative series.

2. TIME SERIES DECOMPOSITION

Rose

- The observed plot of the decomposition diagrams shows visible annual seasonality and a downward trend. The early period of the plot shows higher variation than in the later periods
- The trend diagram shows a downward trend overall. Exponential dips can be seen between 1981 and 1983 and later from 1991 to 1993
- Seasonal components are quite visible and consistent in both the observed and seasonal charts of the diagrams. The additive chart shows variance in seasonality from -20 to 50 units and the multiplicative model shows variance of 16%

Multiplicative model



Additive model

- The residuals shows a pattern of high variability across the period of time-series, which is more or less consistent in both additive and multiplicative decompositions
- The variance in residuals shows higher variance in the early period of the series, which explains the higher variance in observed plot at same time period
- The additive model shows a mean variance around 0 and the multiplicative model shows a variance around 15%
- As the seasonality peaks are consistently reducing its altitude in consistent with trend, the series can be treated as multiplicative in model building

3. SPLIT TRAIN & TEST DATA

- The train and test datasets are created with year 1991 as starting year for test data, using index.year property of time series index
- The plots of Sparkling and Rose time-series as train ans test are given here

```
train=df[df.index.year < 1991]
test=df[df.index.year >= 1991]
```

Test data starts from 1991

YearMonth	Sparkling	Rose
1980-01-31	1686	112.0
1980-02-29	1591	118.0
1980-03-31	2304	129.0
1980-04-30	1712	99.0
1980-05-31	1471	116.0

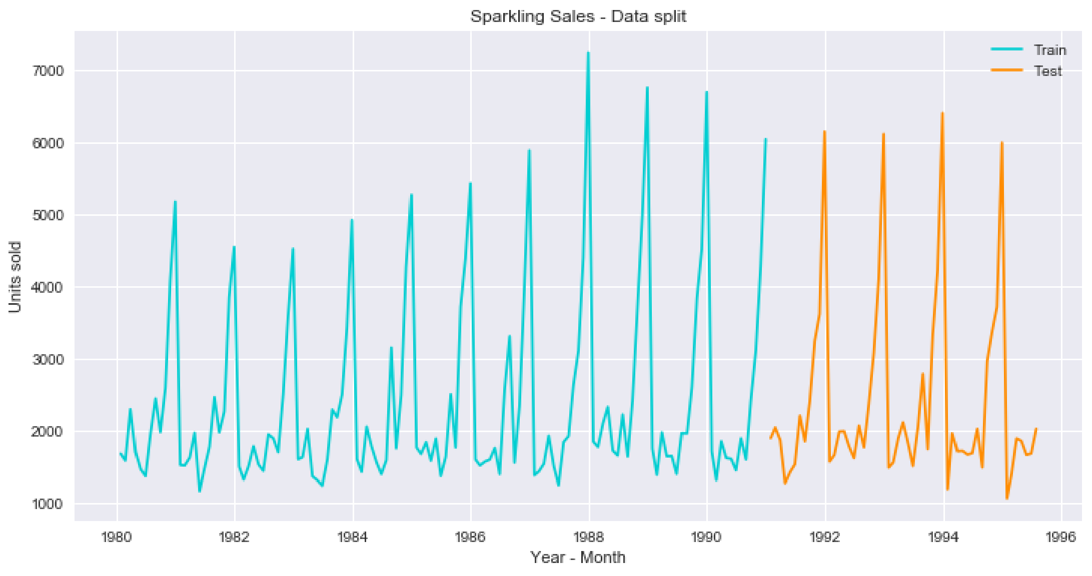
YearMonth	Sparkling	Rose
1990-08-31	1605	70.0
1990-09-30	2424	83.0
1990-10-31	3116	65.0
1990-11-30	4286	110.0
1990-12-31	6047	132.0

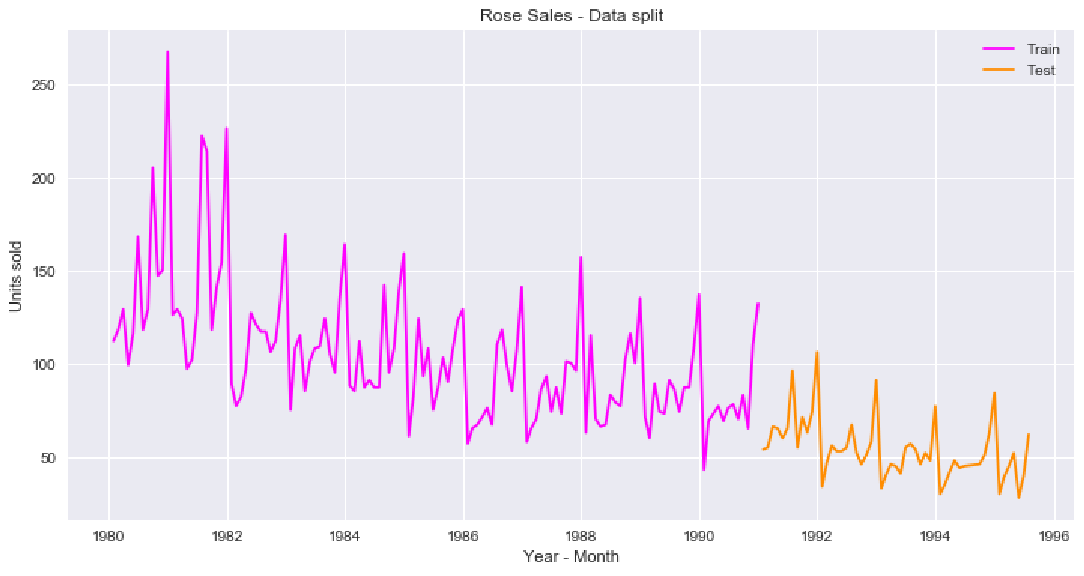
First and last 5 records of train dataset

YearMonth	Sparkling	Rose
1991-01-31	1902	54.0
1991-02-28	2049	55.0
1991-03-31	1874	66.0
1991-04-30	1279	65.0
1991-05-31	1432	60.0

YearMonth	Sparkling	Rose
1995-03-31	1897	45.0
1995-04-30	1862	52.0
1995-05-31	1670	28.0
1995-06-30	1688	40.0
1995-07-31	2031	62.0

First and last 5 records of test dataset

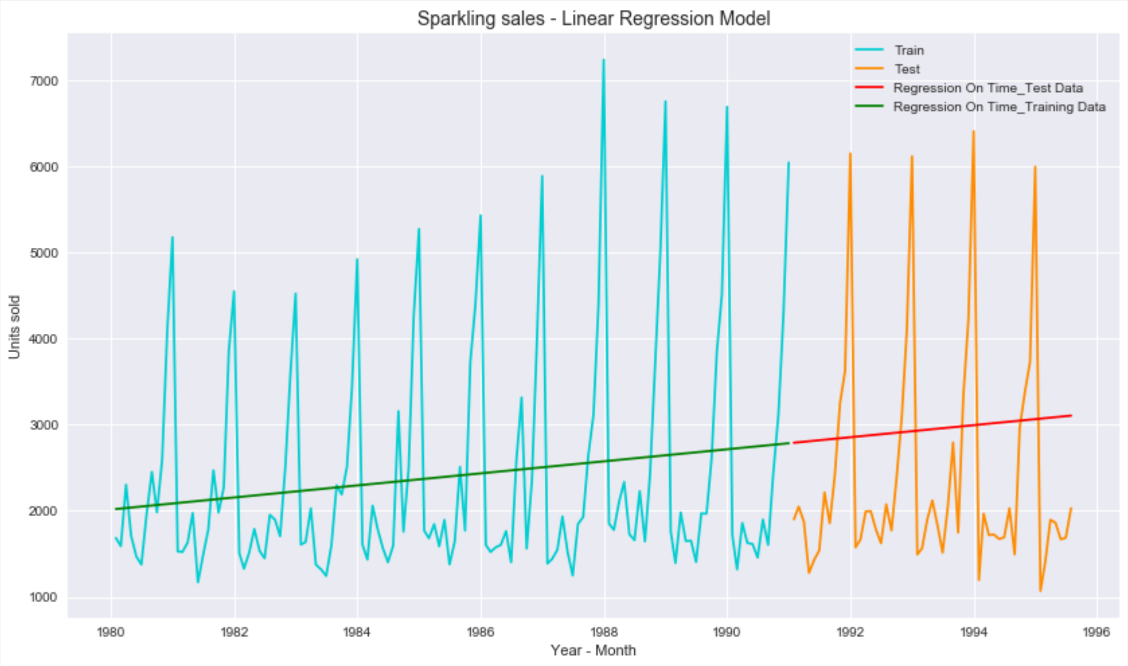




4. LINEAR REGRESSION ON TIME

- To regress the sale of Sparkling and Rose wines, numerical time instance order for both training and test set were generated and the values added to the respective datasets

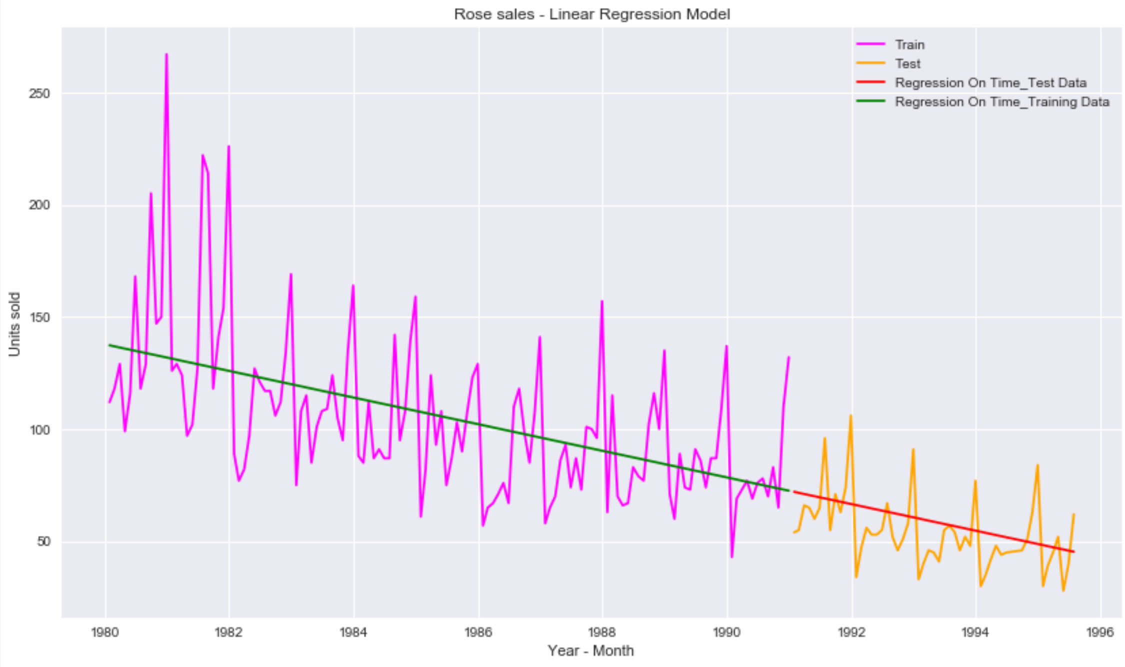
Sparkling



	RMSE	MAPE
Train	1279.32	40.05
Test	1389.16	50.15

- The linear regression plots shows a gradual upward trend in forecast of Sparkling wine, consistent with the observed trend which was not visually apparent
- The RMSE and MAPE values for Train and Test data sets are as above. 50% of forecast is erroneous

Rose



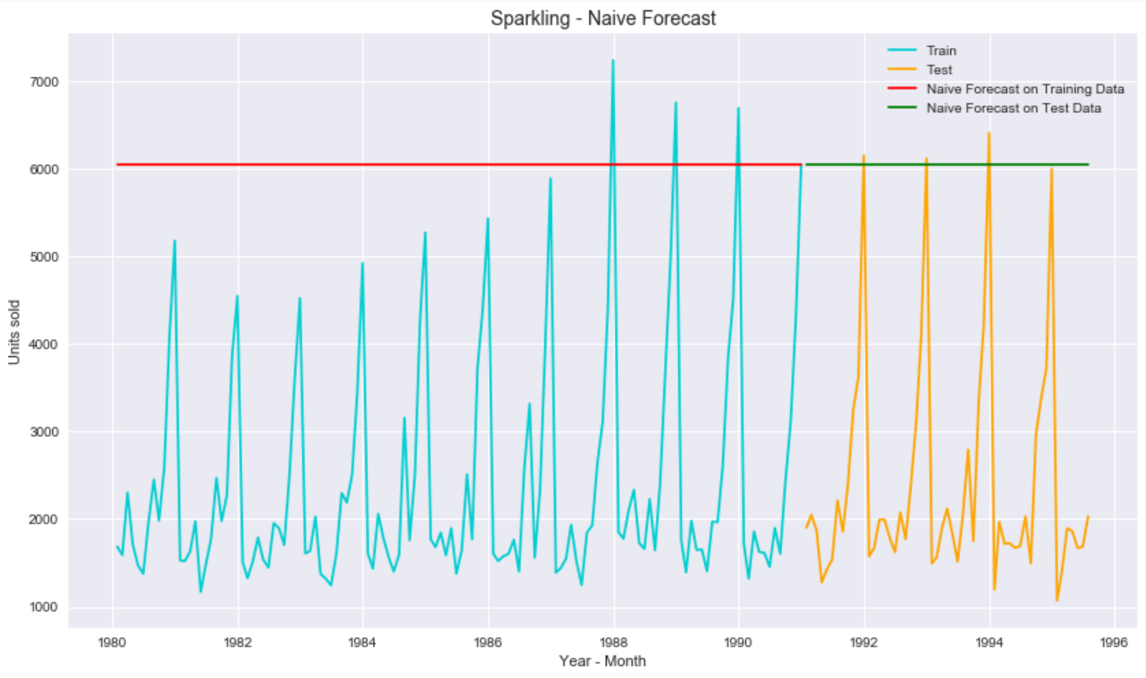
	RMSE	MAPE
Train	30.72	21.22
Test	15.27	22.82

- The linear regression on the Rose dataset shows an apparent downward trend as consistent with the observed time-series
- The RMSE and MAPE of the forecast is given above. The model leaves a 23% error in forecast against test set
- The model has successfully captured the trend of both the series, but does not reflects the seasonality

4. NAÏVE FORECASTING

- In naive model, 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.

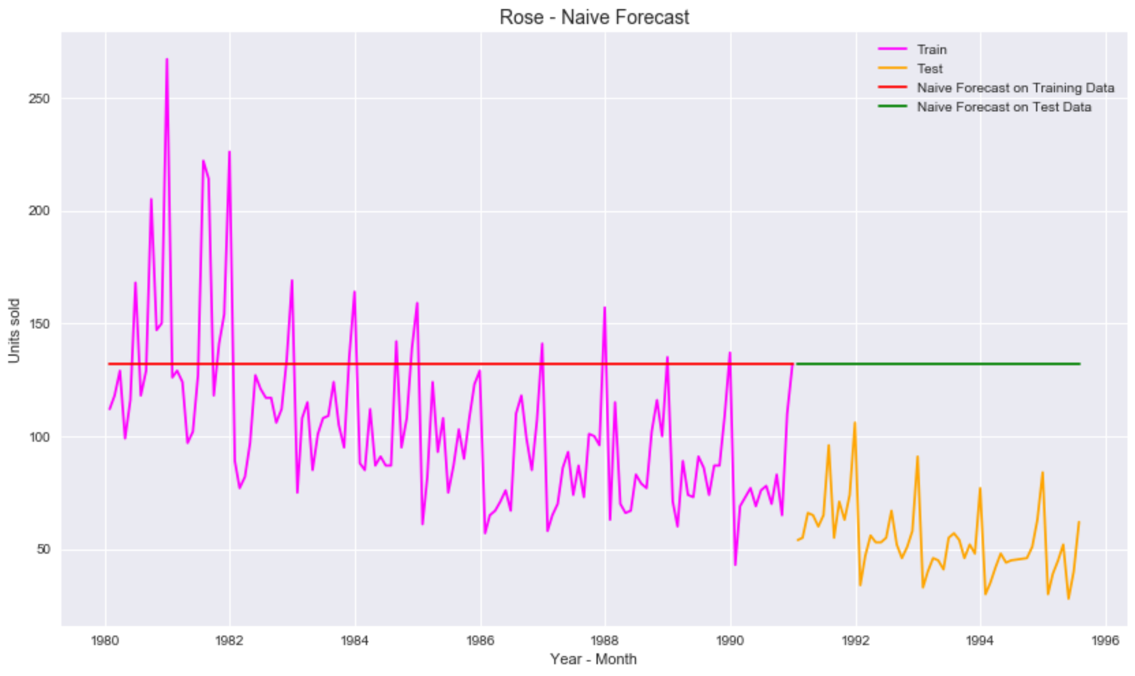
Sparkling



	RMSE	MAPE
Train	3867.70	153.17
Test	3864.28	152.87

- The model has taken the last value from the test set and fitted it on the rest of the train time period and used the same value to forecast the test set
- The performance metrices above shows a very poor fitment and high % of error

Rose



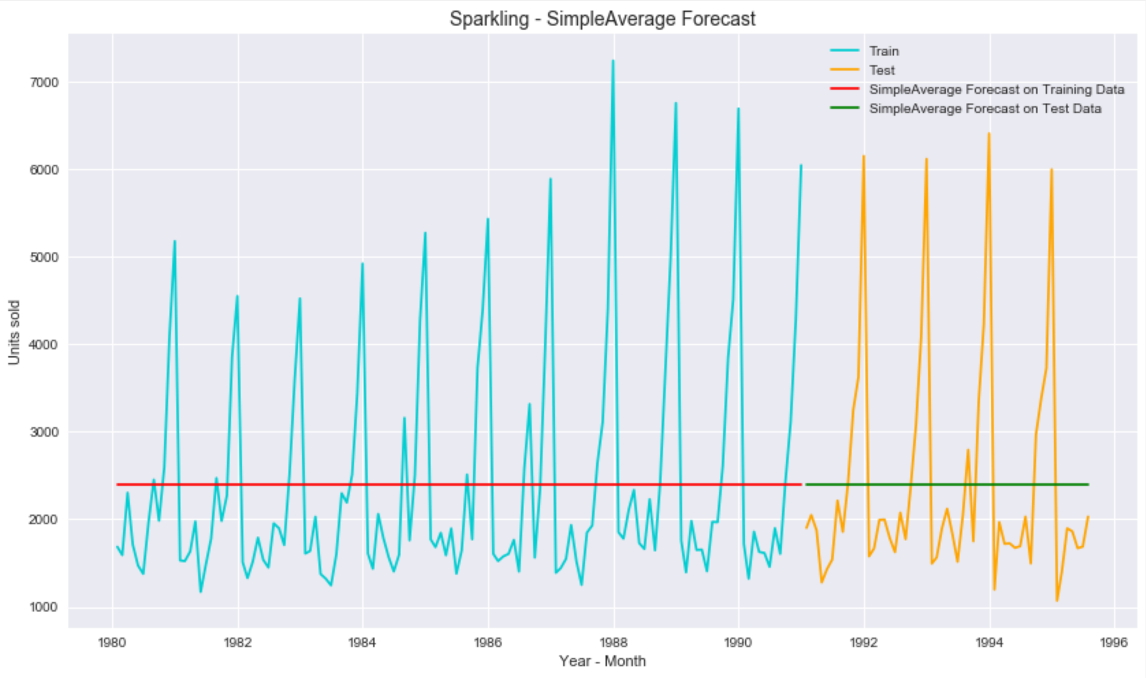
	RMSE	MAPE
Train	45.06	36.38
Test	79.72	145.10

- As Rose data set has a downward trend the percentage of error in train is lesser and is very high in test
- The model does not capture the trend nor seasonality of the given datasets

4. SIMPLE AVERAGE FORECASTING

- In the Simple Average model, the forecast is done using the mean of the time-series variable from the training set

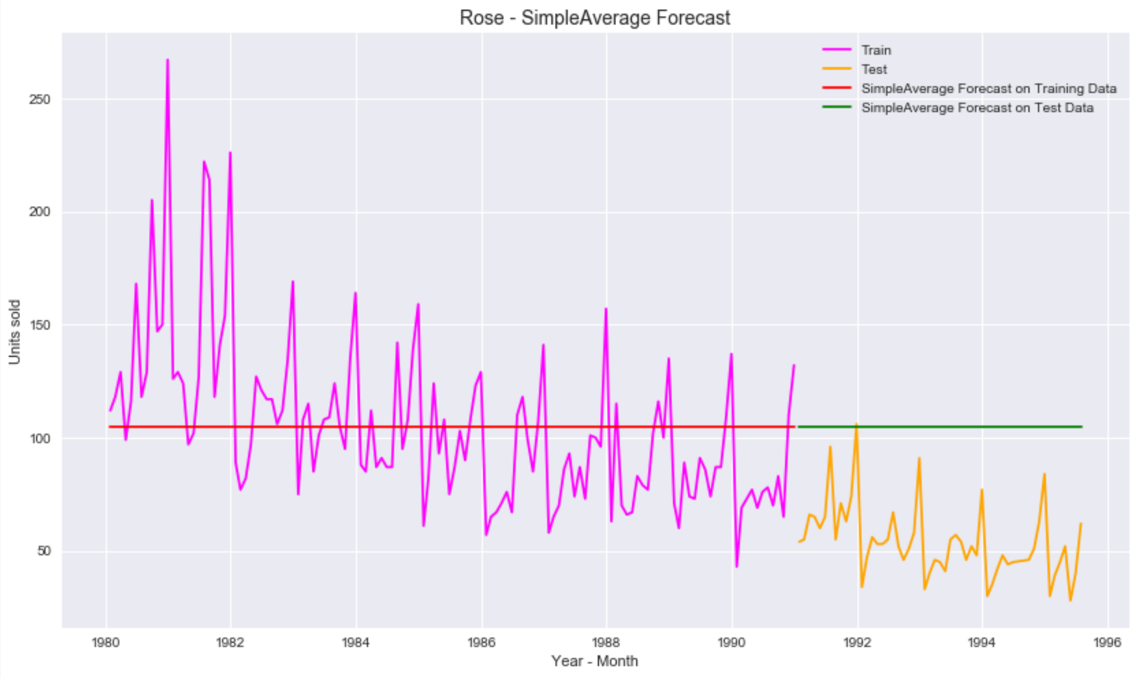
Sparkling



	RMSE	MAPE
Train	1298.48	40.36
Test	1275.08	38.90

- The model is not capable of either forecasting nor able to capture the trend and seasonality present in the dataset
- For Sparkling the RMSE and MAPE is consistent in both test and train datasets

Rose



	RMSE	MAPE
Train	36.03	25.39
Test	53.46	94.93

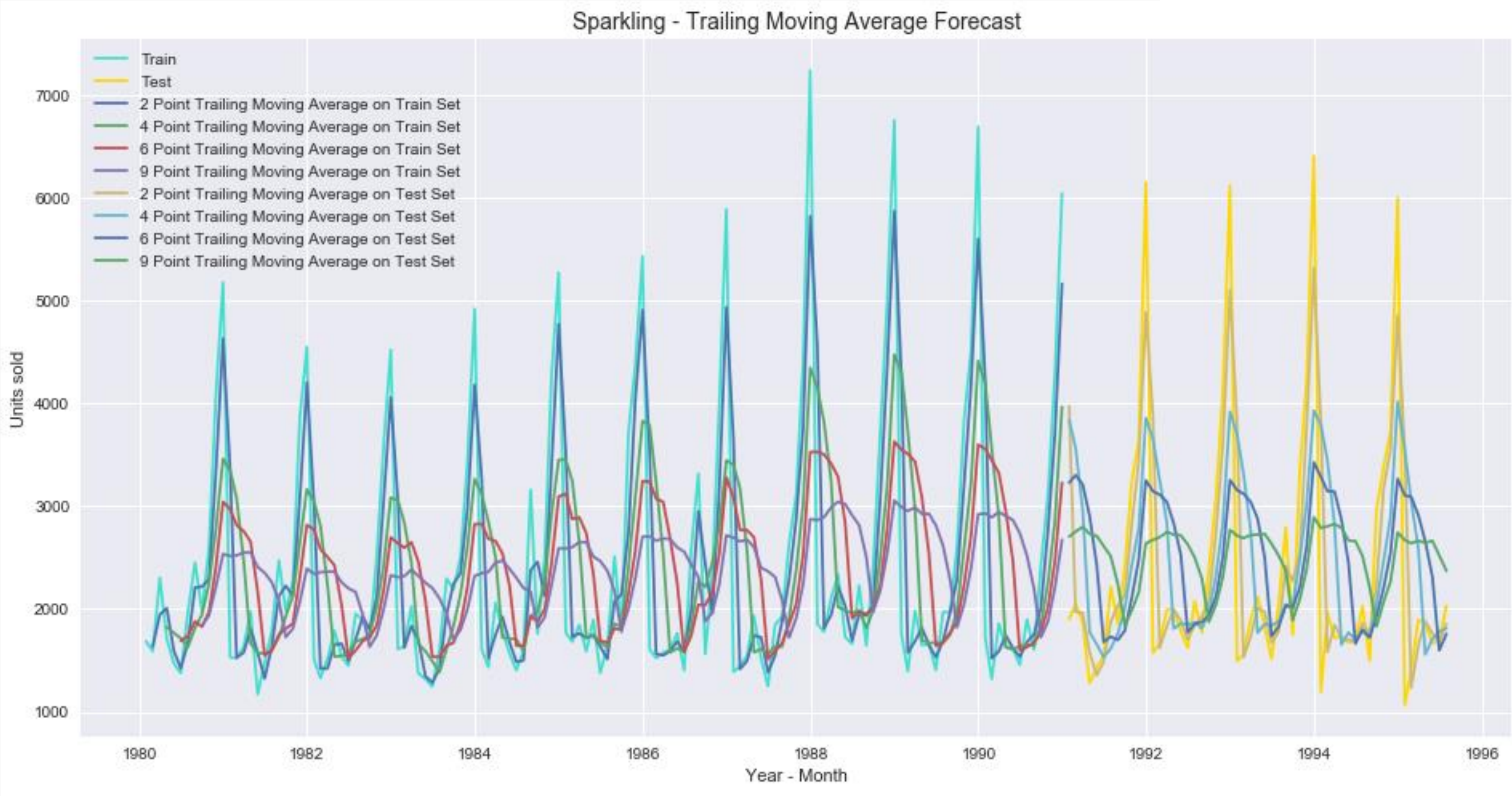
- For Rose dataset, the model forecast is almost 100% error in test data and 25% in train
- Due to the downward trend the performance in train data set is better than the test dataset

4. MOVING AVERAGE

Sparkling

- For the moving average model, we will calculate rolling means (or trailing moving averages) for different intervals. The best interval can be determined by the maximum accuracy (or the minimum error),
- The moving average models are built for trailing 2 points, 4 points, 6 points and 9 points
- For Sparkling dataset the accuracy is found to be higher with the lower rolling point averages
- In moving average forecasts the values can be fitted with a delay of n number of points
- The Root Mean Squared Error and Mean Absolute Percentage Error of the test set are given below
- The best interval of moving average from the model is 2 point

Model	RMSE	MAPE
2 point MA	813.40	19.70
4 point MA	1156.59	35.96
6 point MA	1283.93	43.86
9 point MA	1346.28	46.86

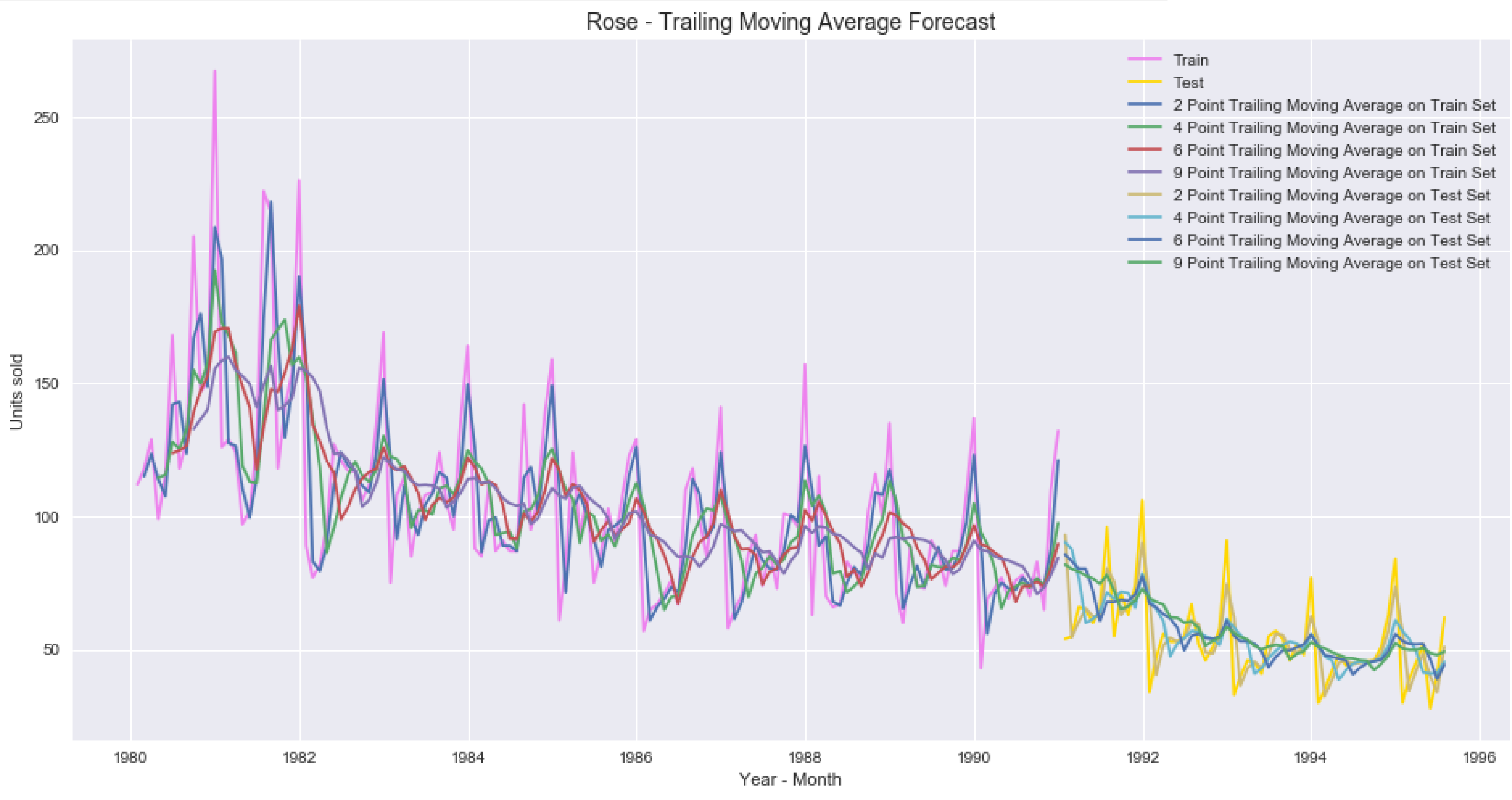


4. TRAILING MOVING AVERAGE

Rose

- For the moving average model, we are going to calculate rolling means (or trailing moving averages) for different intervals.
- The best interval can be determined by the maximum accuracy (or the minimum error),
- The moving average models are built for trailing 2 points, 4 points, 6 points and 9 points
- For Rose dataset the accuracy is found to be higher with the lower rolling point averages
- In moving average forecasts the values can be fitted with a delay of n number of points
- The Root Mean Squared Error and Mean Absolute Percentage Error of the test set are given below
- The best interval of moving average from the model is 2 point

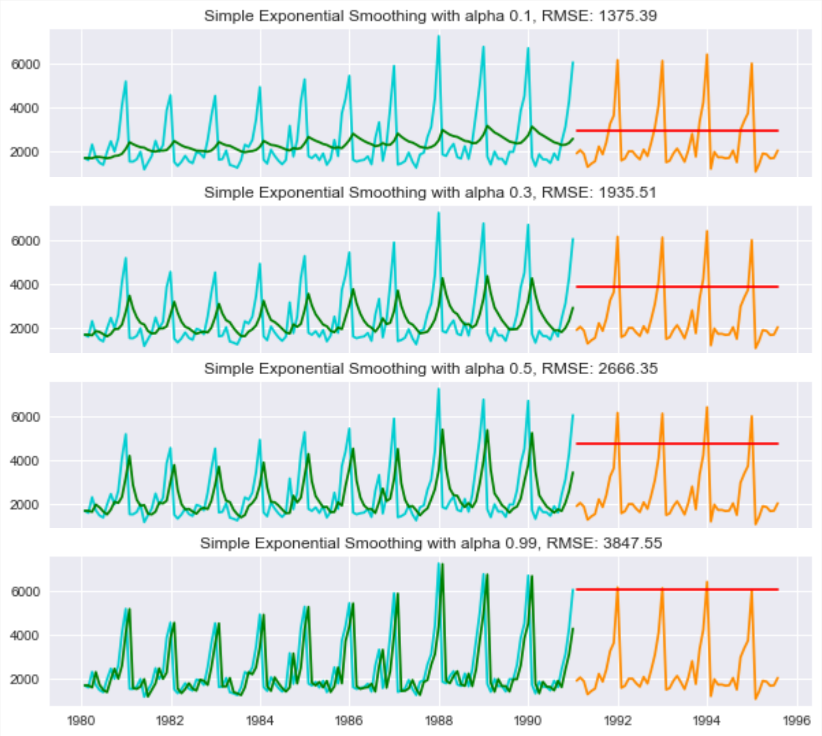
Model	RMSE	MAPE
2 point MA	11.53	13.54
4 point MA	14.45	19.49
6 point MA	14.57	20.82
9 point MA	14.73	21.01

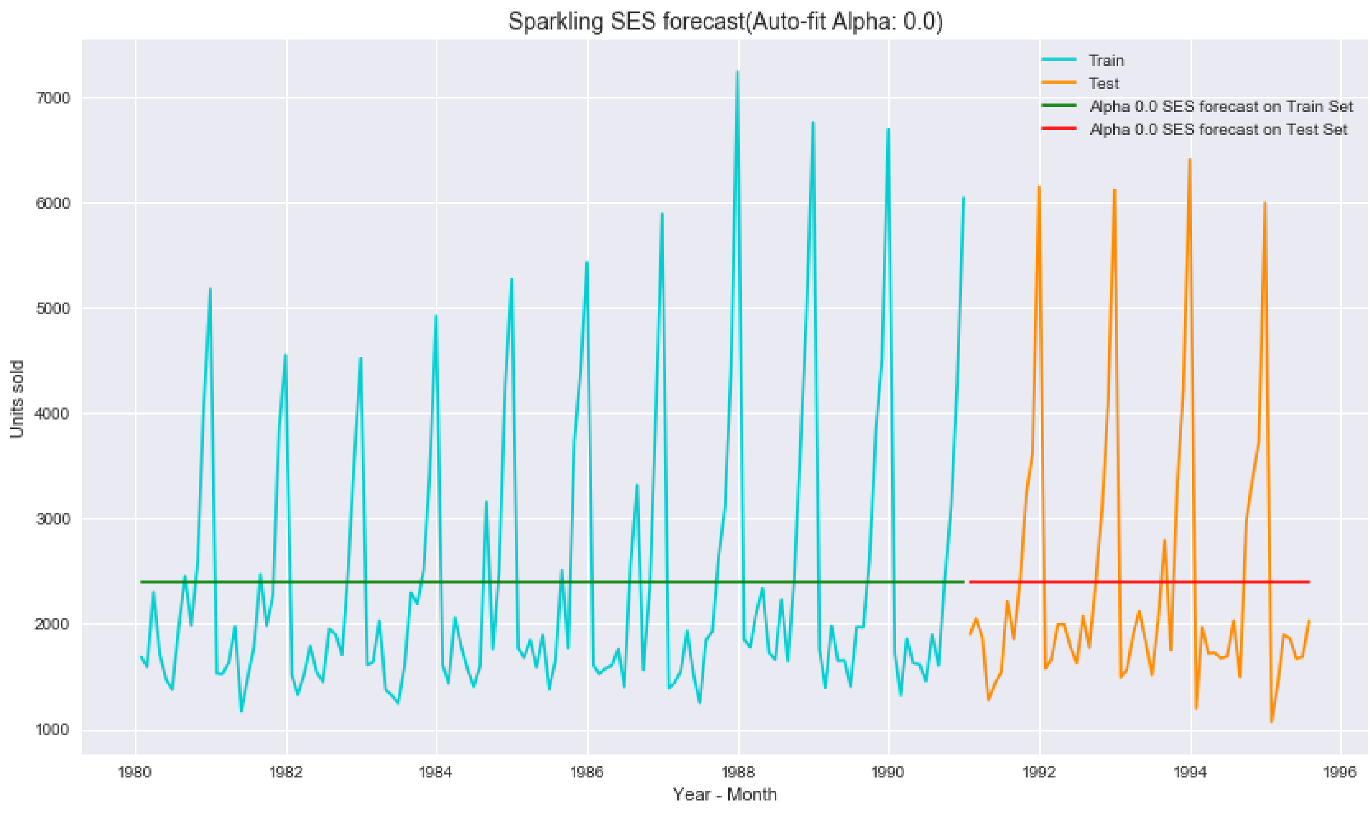


4. SIMPLE EXPONENTIAL SMOOTHING

Sparkling

- Simple Exponential Smoothing is applied if the time-series has neither a trend nor seasonality, which is not the case with the given data
- The forecasting using smoothing levels of alpha between 0 and 1 are as below, where the smoothing levels are passed manually
- For alpha value closer to 1, forecasts follows the actual observation closely and closer to 0, forecasts are farther from actual and line gets smoothened
- For Sparkling, test RMSE is found to be higher for values closer to zero, which is same as in Simple average forecast





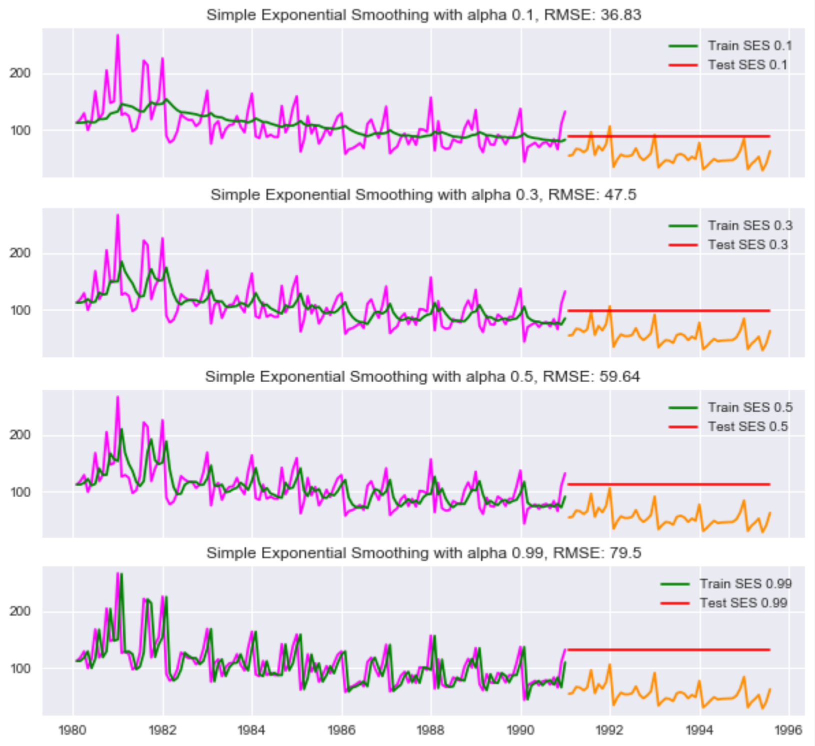
- On the second iteration, the model was ran without passing a value for alpha and used parameters *'optimized=True, use_brute=True'*
- The autofit model picked 0.0 as the smoothing parameter and retuned consistent RMSE values in train and test datasets, which is higher in accuracy than in first iteration
- As the smoothing level is 0.0, we got a completely smoothened out forecast with an initial value 2403.79 applied across the series

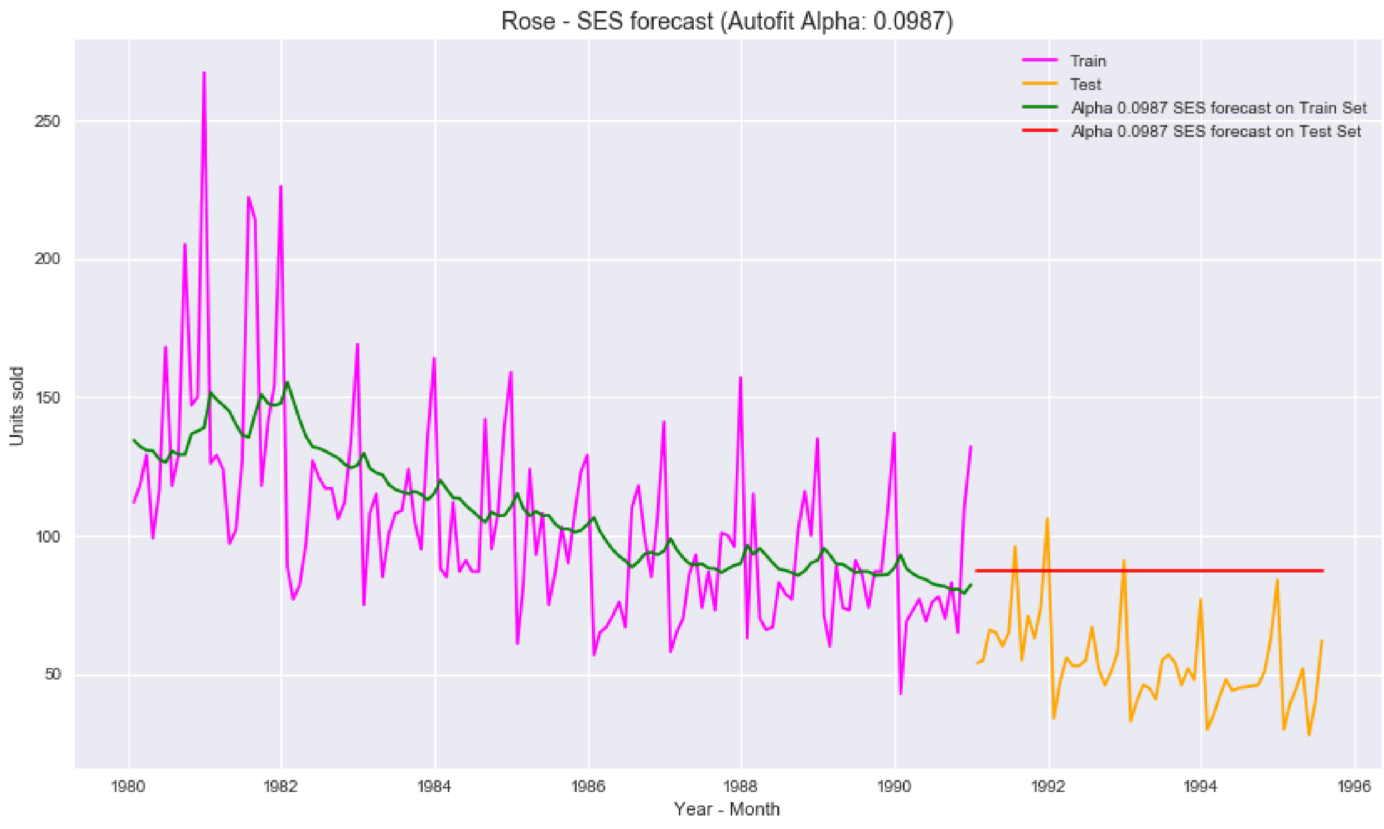
	RMSE	MAPE
Train	1298.48	40.36
Test	1275.08	38.90

4. SINGLE EXPONENTIAL SMOOTHING

Rose

- Simple Exponential Smoothing is usually applied if the time-series has neither a trend nor seasonality, which is not the case with the given data
- The forecasting using smoothing levels or alpha between 0 and 1 are as below, where the values were passed manually
- For alpha value closer to 1, forecasts follows the actual observation closely and closer to 0, forecasts are farther from actual and line gets smoothened
- The test RMSE is found to be higher for values closer to zero





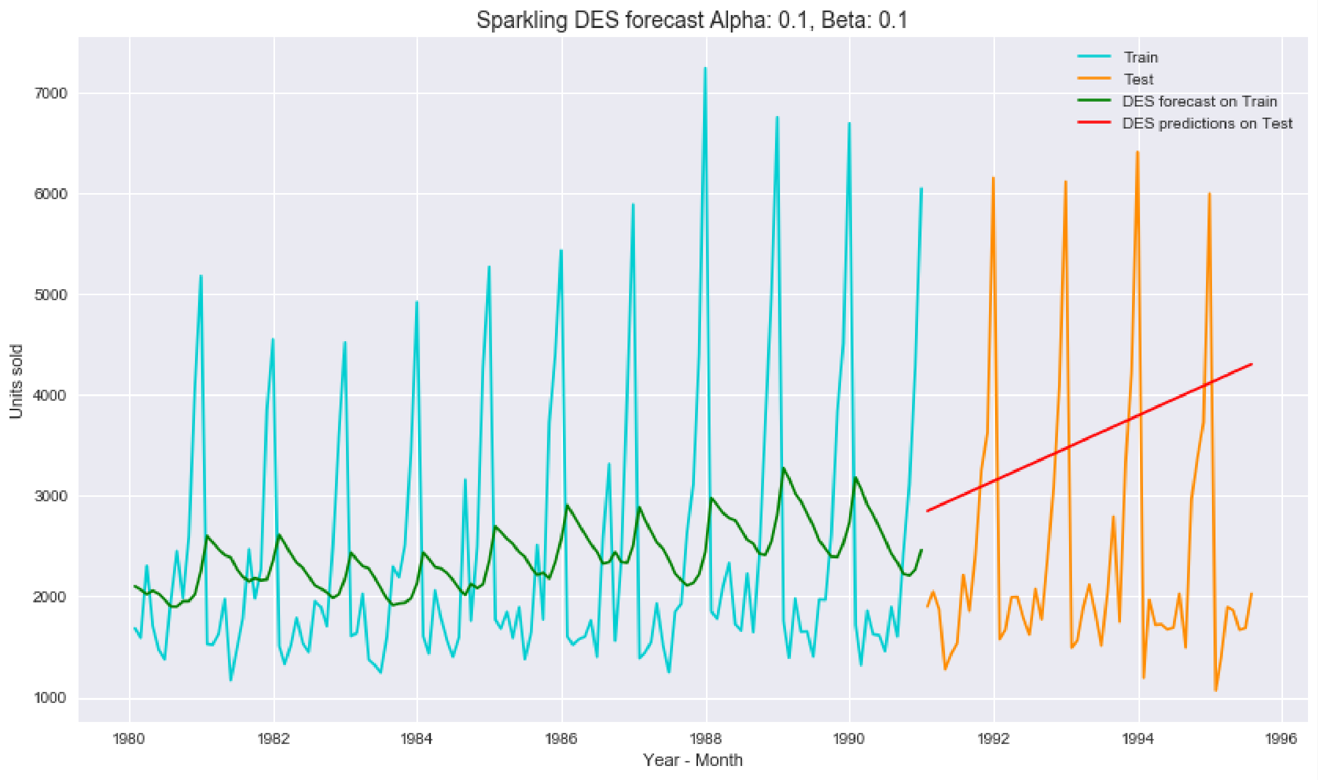
- On the second iteration, the model was ran without passing a value for alpha and used parameters *'optimized=True, use_brute=True'*
- The autofit model picked 0.098 as the smoothing parameter and retuned consistent RMSE values in train and test datasets, which is consistent with alpha 0.1 in first iteration

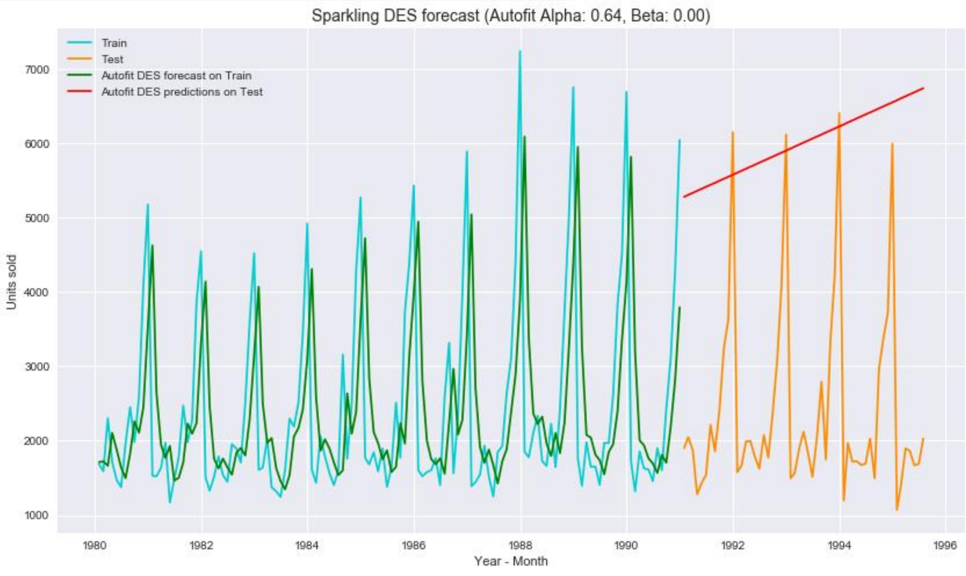
	RMSE	MAPE
Train	31.50	22.73
Test	36.80	63.88

4. DOUBLE EXPONENTIAL SMOOTHING

Sparkling

- The Double Exponential Smoothing models is applicable when data has trend, but no seasonality. Sparkling data contain slight trend component and very significant seasonality
- In first iteration, smoothing level (alpha) and trend (beta) are fitted to the model iteratively from values 0.1 to 1 and the best combination was chosen based on the RMSE and MAPE values, which is as below with alpha 0.1 and beta 0.1
- On the second iteration the model was allowed to chose the optimized values using parameters '*optimized=True, use_brute=True*'





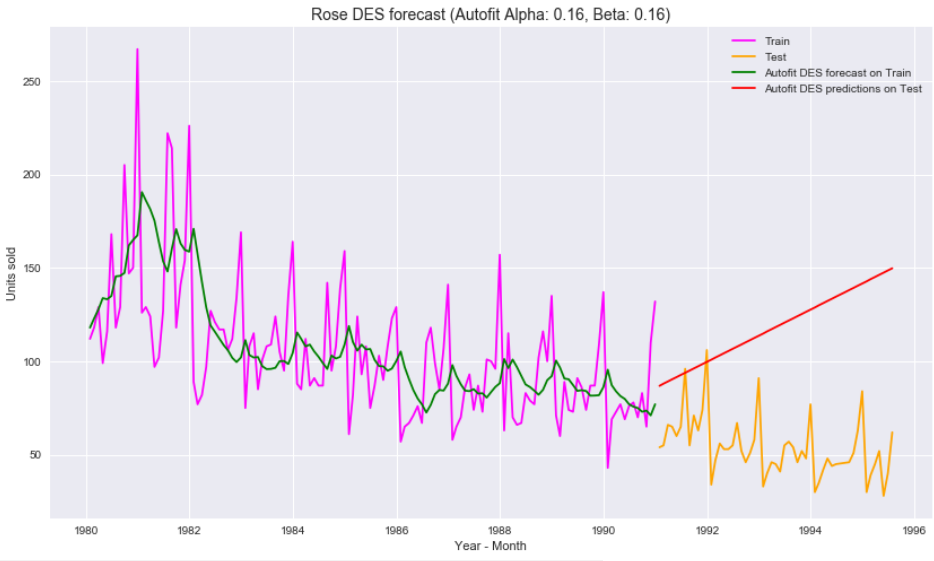
	Alpha	Beta	Train RMSE	Train MAPE	Test RMSE	Test MAPE
0	0.100000	0.1	1363.47000	44.26	1779.4300	67.23
1	0.100000	0.2	1401.76000	45.65	2599.7900	95.44
10	0.200000	0.1	1412.03000	46.62	3611.7700	135.41
100	0.647811	0.0	1337.48427	39.11	3851.1715	152.07

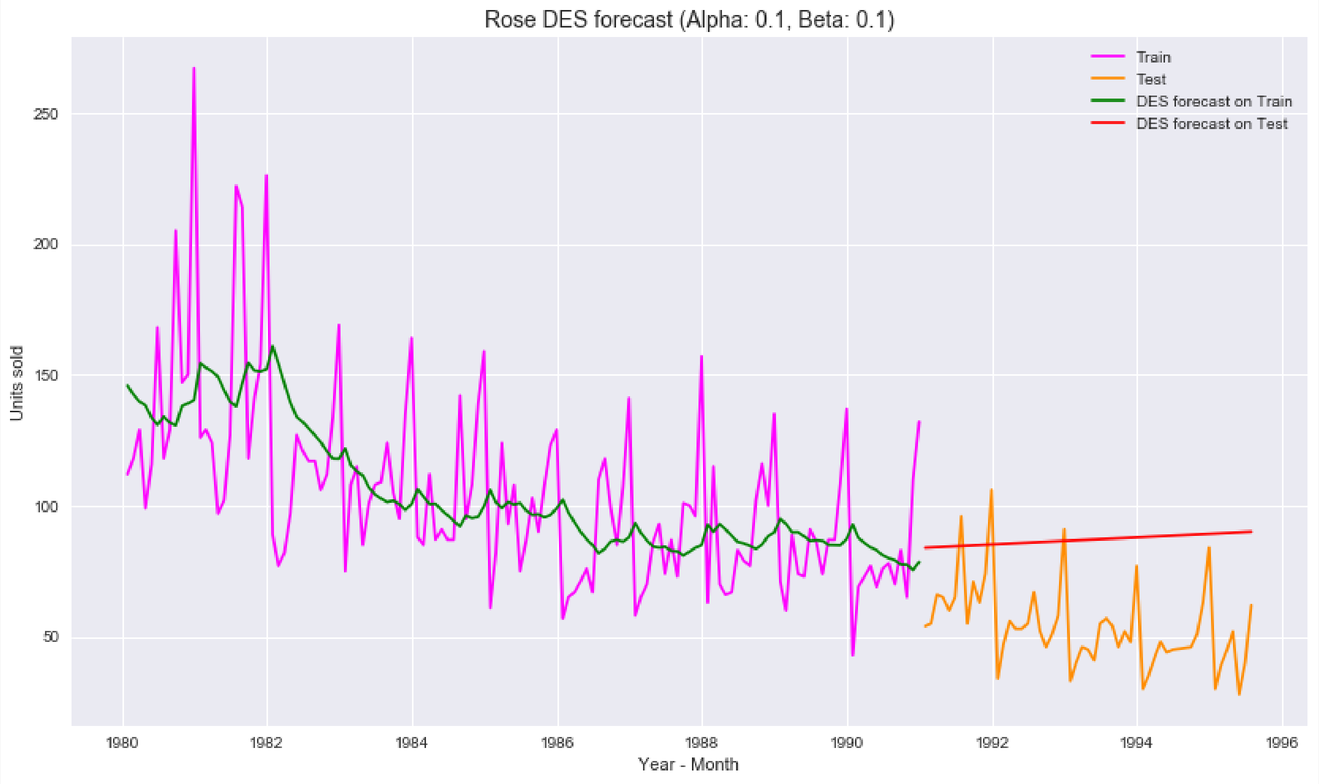
- The autofit model retuned higher accuracy in train dataset, but faired poorly in test, compared with the values in manual iteration
- The model evaluation parameters of top three models from manual iteration and the autofit models are as given above
- The best model chosen as final one is with alpha 0.1 and beta 0.1

4. DOUBLE EXPONENTIAL SMOOTHING

Rose

- The Double Exponential Smoothing models is applicable when data has trend, but no seasonality. Rose data contain significant trend component and seasonality
- In first iteration, smoothing level (alpha) and trend (beta) are fitted to the model iteratively from values 0.1 to 1 and the best combination was chosen based on the RMSE and MAPE values, which is as below with alpha 0.1 and beta 0.1
- On the second iteration the model was allowed to chose the optimized values using parameters '*optimized=True, use_brute=True*'





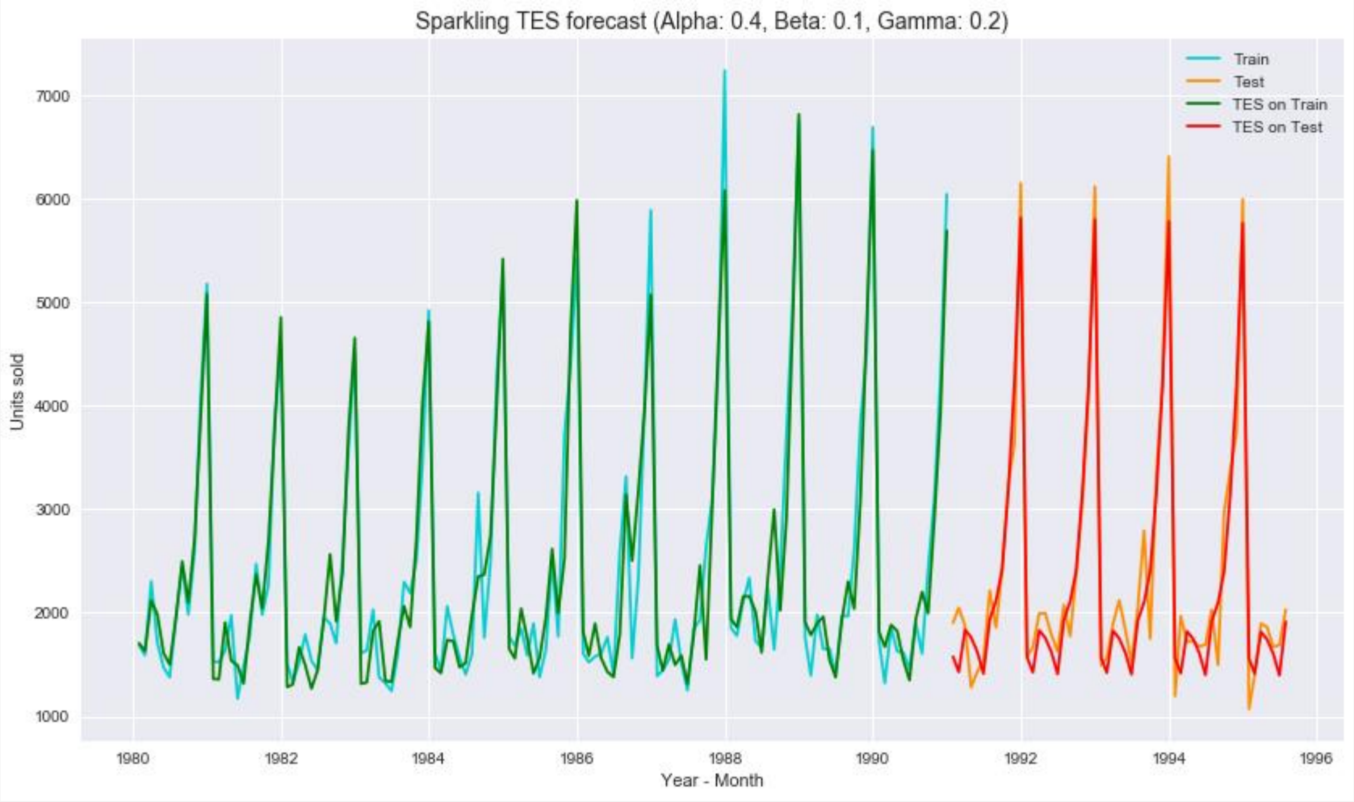
	Alpha	Beta	Train RMSE	Train MAPE	Test RMSE	Test MAPE
0	0.100000	0.100000	32.026565	22.78	37.056912	64.02
1	0.100000	0.200000	33.450729	24.45	48.688399	83.09
10	0.200000	0.100000	32.796403	23.06	65.731352	113.20
100	0.157895	0.157895	33.074575	23.99	70.572197	120.25

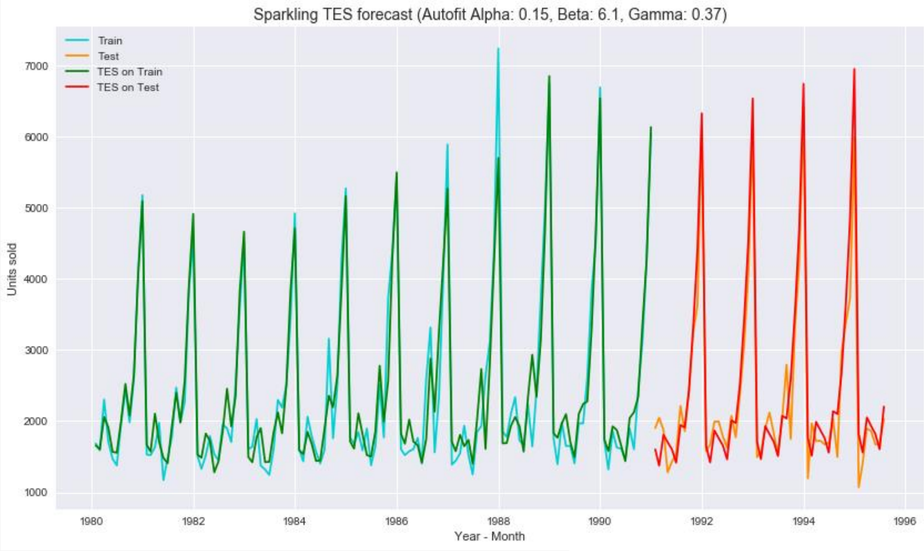
- The autofit model retuned higher accuracy in train dataset, on par with the best models from iteration 1, but faired behind in the test accuracy scores
- The model evaluation parameters of the best models are given as above
- The best model chosen as final one is the one with alpha 0.1 and beta 0.1

4. TRIPLE EXPONENTIAL SMOOTHING

Sparkling

- The Triple Exponential Smoothing models (Holt-Winter's Model) is applicable when data has both trend and seasonality. Sparkling data contain slight trend and significant seasonality
- In first iteration, smoothing level (alpha), trend (beta) and seasonality (gamma) are fitted to the model iteratively from values 0.1 to 1 and the best combination was chosen based on the RMSE and MAPE values, which is as below with alpha 0.4, beta 0.1 and gamma 0.2
- On the second iteration the model was allowed to chose the optimized values using parameters '*optimized=True, use_brute=True*'





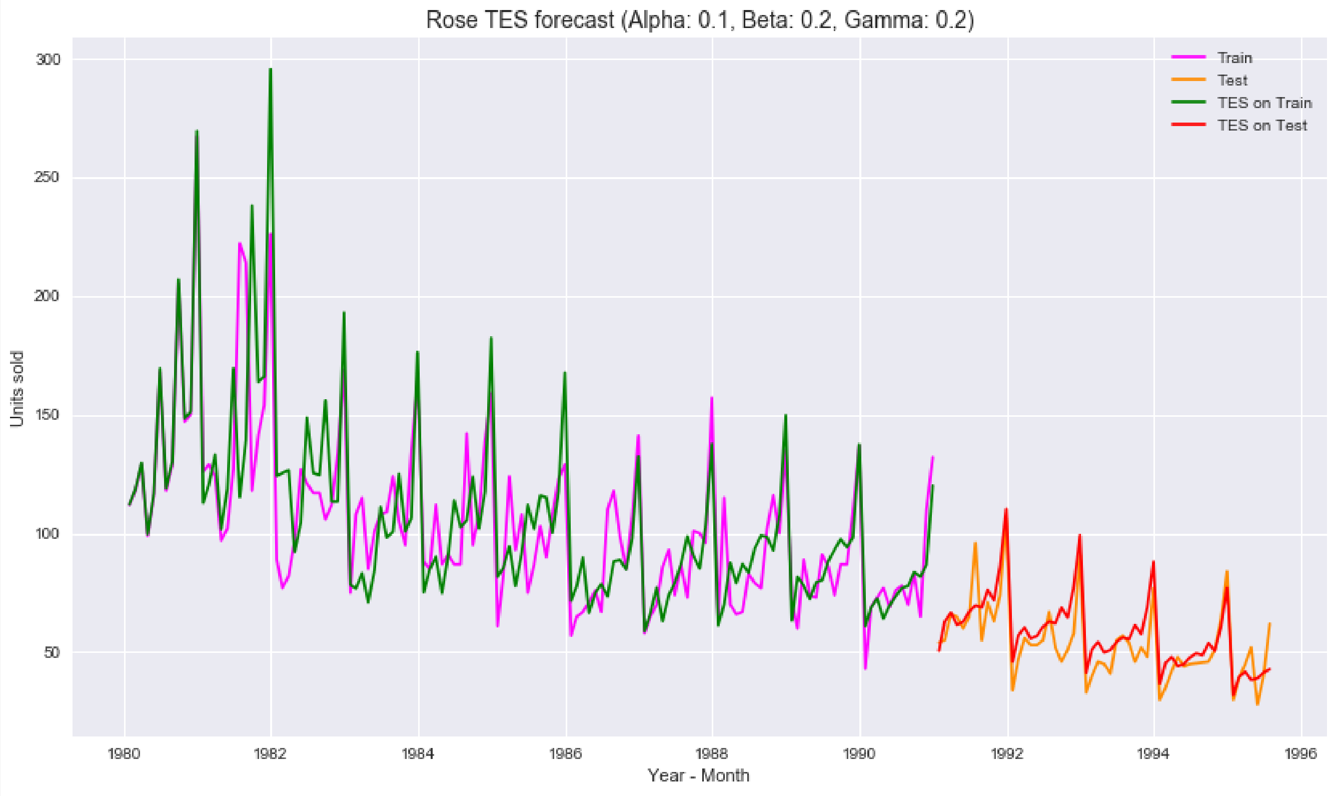
	Alpha	Beta	Gamma	Train RMSE	Train MAPE	Test RMSE	Test MAPE
301	0.4	0.1	0.2	373.281410	11.05	312.211095	10.20
211	0.3	0.2	0.2	377.346884	11.23	315.195004	10.07
300	0.4	0.1	0.1	370.807398	11.06	318.281180	10.00
402	0.5	0.1	0.3	390.181794	11.54	325.690492	9.99
1000	0.15	0.0	0.37	353.379117	10.18	3.842030e+02	11.94

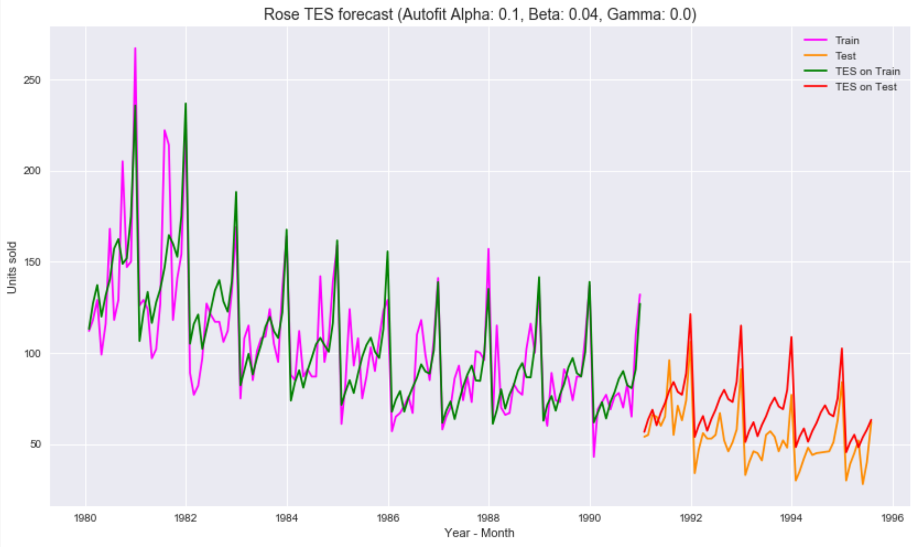
- The autofit model retuned higher accuracy in train dataset, much higher than the values from iteration 1, but faired poorly in accuracy in test
- The model evaluation parameters of the best models are given as above, including one from the autofit iteration
- The best model chosen as final one is the one with alpha 0.4, beta 0.1 and gamma 0.2

4. TRIPLE EXPONENTIAL SMOOTHING

Rose

- The Triple Exponential Smoothing models (Holt-Winter's Model) is applicable when data has both trend and seasonality. Rose data contain both trend and seasonality significantly
- In first iteration, smoothing level (alpha), trend (beta) and seasonality (gamma) are fitted to the model iteratively from values 0.1 to 1 and the best combination was chosen based on the RMSE and MAPE values, which is as below with alpha 0.1, beta 0.2 and gamma 0.2
- On the second iteration the model was allowed to chose the optimized values using parameters '*optimized=True, use_brute=True*'





	Alpha	Beta	Gamma	Train RMSE	Train MAPE	Test RMSE	Test MAPE
11	0.1	0.2	0.2	24.365597	15.36	9.640616	13.96
12	0.1	0.2	0.3	23.969166	15.13	9.935672	14.21
10	0.1	0.2	0.1	25.529854	16.06	9.943512	14.39
142	0.2	0.5	0.3	27.631767	17.87	10.026322	14.34
1000	0.106096	0.048439	0.0	18.578860	13.21	17.369210	28.88

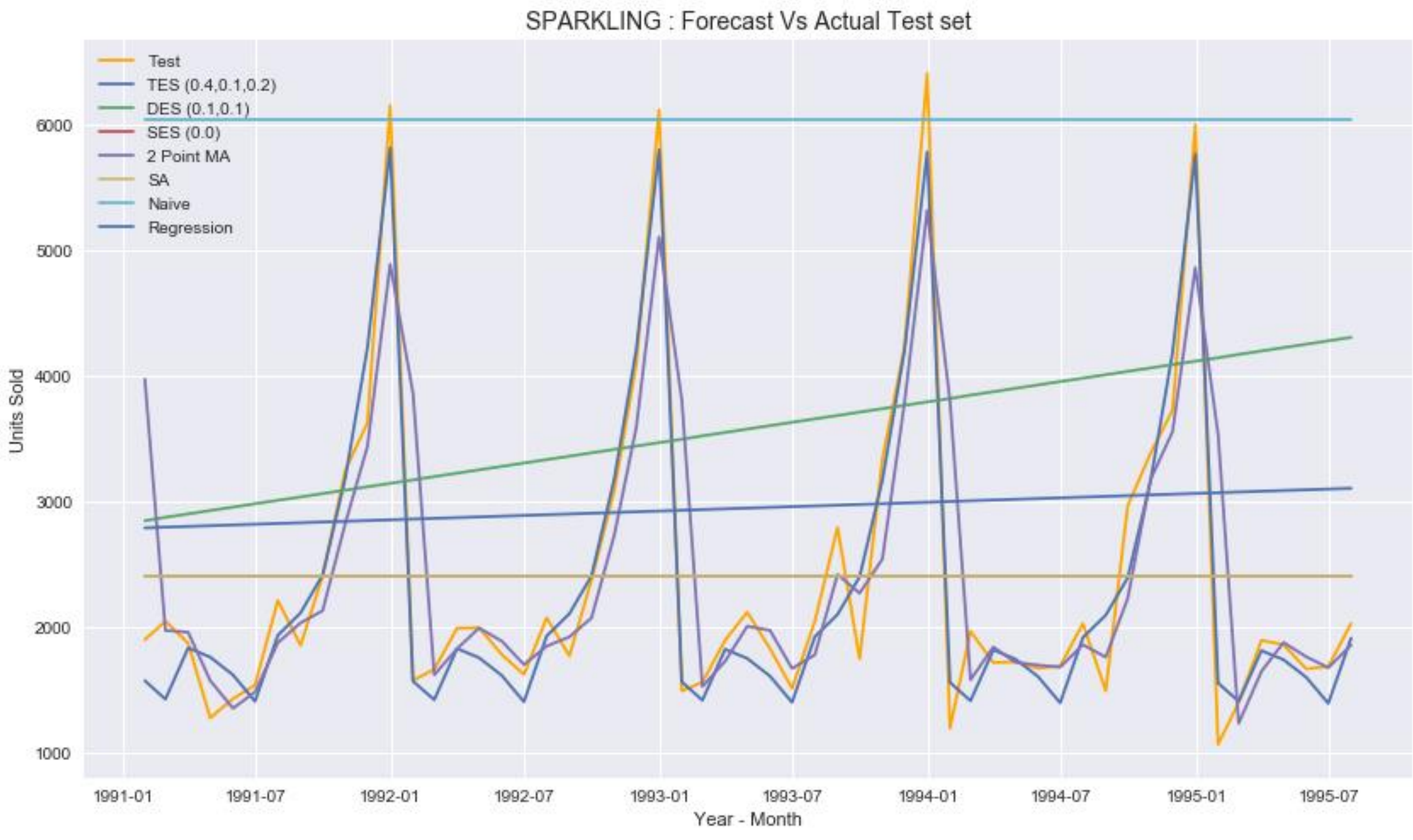
- The autofit model retuned higher accuracy in train dataset, much higher than the values from iteration 1, but faired poorly in accuracy in test
- The model evaluation parameters of the best models are given as above, including one from the autofit iteration
- The best model chosen as final one is the one with alpha 0.1, beta 0.2 and gamma 0.2

4. MODEL COMPARISON

Sparkling

- The accuracy of the time-series forecast models build in the previous sections of this report is as below, sorted by RMSE in test data
- The plot of the forecasts fitted on to the test data is given as well
- From the comparison of accuracy values and the plot it can be inferred that Triple Exponential Smoothing is the best model, which has trend as well as seasonality components fitting well with the test data
- 2 point trailing moving average model is also found to have fit well with a slight lag in test dataset

	Test RMSE	Test MAPE
TES Alpha 0.4, Beta 0.4, Gamma 0.2	312.211095	10.20
TES Alpha 0.15, Beta 0.00, Gamma 0.37	384.203001	11.94
2 point TMA	813.400684	19.70
4 point TMA	1156.589694	35.96
SimpleAverage	1275.081804	38.90
SES Alpha 0.00	1275.081823	38.90
6 point TMA	1283.927428	43.86
9 point TMA	1346.278315	46.86
RegressionOnTime	1389.135175	50.15
DES Alpha 0.1,Beta 0.1	1779.430000	67.23
DES Alpha 0.6,Beta 0.0	3851.171500	152.07
NaiveModel	3864.279352	152.87

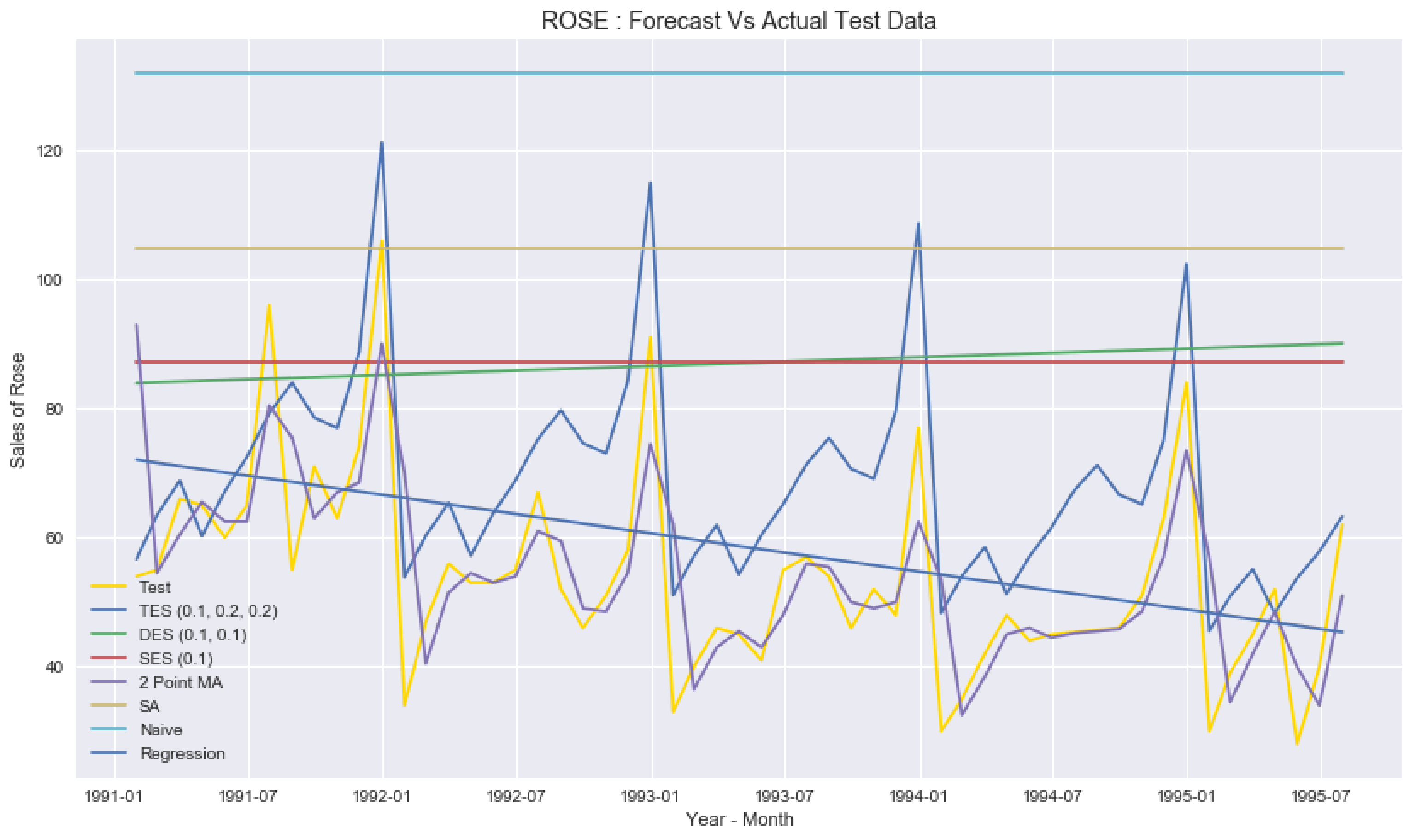


4. MODEL COMPARISON

Rose

- The accuracy of the time-series forecast models build in the previous sections of this report is as below, sorted by RMSE in test data
- The plot of the forecasts fitted on to the test data is given as well
- From the comparison of accuracy values and the plot it can be inferred that Triple Exponential Smoothing is the best model, which has trend as well as seasonality components fitting well with the test data
- 2 point trailing moving average model is also found to have fit well with a slight lag in test dataset

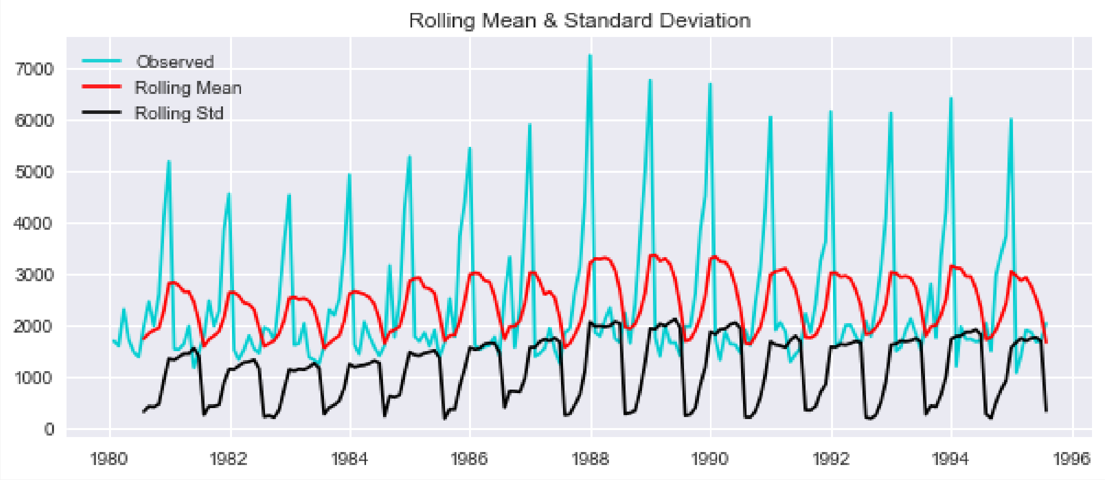
	Test RMSE	Test MAPE
TES Alpha 0.1, Beta 0.2, Gamma 0.2	9.640616	13.96
2 point TMA	11.529278	13.54
4 point TMA	14.451364	19.49
6 point TMA	14.566269	20.82
9 point TMA	14.727594	21.01
RegressionOnTime	15.268885	22.82
TES Alpha 0.11, Beta 0.05, Gamma 0.00	17.369210	28.88
SES Alpha 0.01	36.796019	63.88
DES Alpha 0.10, Beta 0.10	37.056912	64.02
SimpleAverage	53.460350	94.93
DES Alpha 0.16, Beta 0.16	70.572197	120.25
NaiveModel	79.718559	145.10



5. CHECK STATIONARITY OF DATA

Sparkling

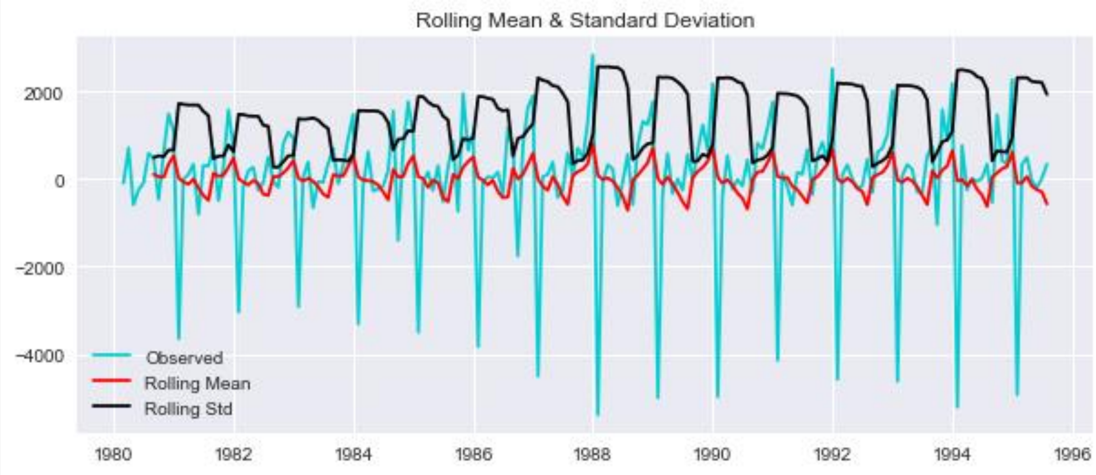
- Augmented Dickey Fuller test is the statistical test to check the stationarity of a time series. The test determine the presence of unit root in the series to understand if the series is stationary or not
- **Null Hypothesis**: The series has a unit root, that is series is non-stationary
- **Alternate Hypothesis**: The series has no unit root, that is series is stationary
- If we fail to reject the null hypothesis, it can say that the series is non-stationary and if we accept the null hypothesis, it can say that the series is stationary
- The ADF test on the original Sparkling series retuned the below values, where p-value is greater than alpha .05 so we fail to reject the null hypothesis.



Results of Dickey-Fuller Test:	
Test Statistic	-1.360497
p-value	0.601061
#Lags Used	11.000000
Number of Observations Used	175.000000
Critical Value (1%)	-3.468280
Critical Value (5%)	-2.878202
Critical Value (10%)	-2.575653

<u>ADF on original series</u>

- P-Value > alpha .05
- Test statistic > Critical values
- Fail to reject the null hypothesis
- The series is non-stationary



<u>ADF on differenced series</u>

- P-Value < alpha .05
- Test statistic < Critical values
- Reject the null hypothesis
- The series is stationary

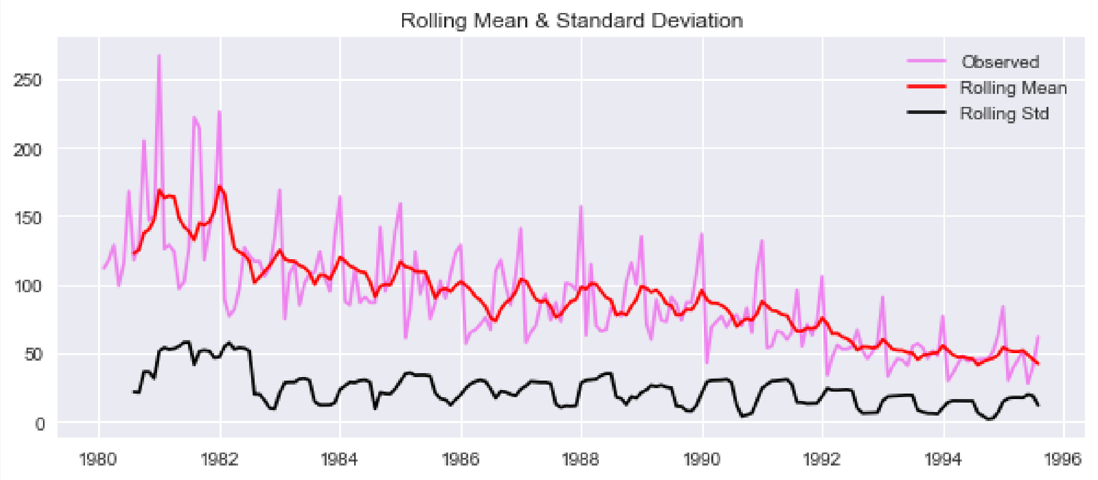
Results of Dickey-Fuller Test:	
Test Statistic	-45.050301
p-value	0.000000
#Lags Used	10.000000
Number of Observations Used	175.000000
Critical Value (1%)	-3.468280
Critical Value (5%)	-2.878202
Critical Value (10%)	-2.575653

- Differencing of order one is applied on the Sparkling series as above and tested for stationarity. At an order of differencing 1, the series is found to be stationary as above
- The rolling mean and standard deviation is also plotted to understand the component of seasonality and to ascertain if its multiplicative or additive in character
- The altitude of rolling mean and std dev is seen changing according to change in slope, which indicates multiplicity
- The ADF test is also done in this exercise with logarithmic transformation of the train data and differencing of seasonal order (12), to understand if removing the multiplicity of the seasonal component will have an impact on the accuracy of model

5. CHECK STATIONARITY OF DATA

Rose

- Augmented Dickey Fuller test is the statistical test to check the stationarity of a time series. The test determine the presence of unit root in the series to understand if the series is stationary or not
- **Null Hypothesis**: The series has a unit root, that is series is non-stationary
- **Alternate Hypothesis**: The series has no unit root, that is series is stationary
- If we fail to reject the null hypothesis, it can say that the series is non-stationary and if we accept the null hypothesis, it can say that the series is stationary
- The ADF test on the original Rose series retuned the below values, where p-value is greater than alpha .05 so we fail to reject the null hypothesis.

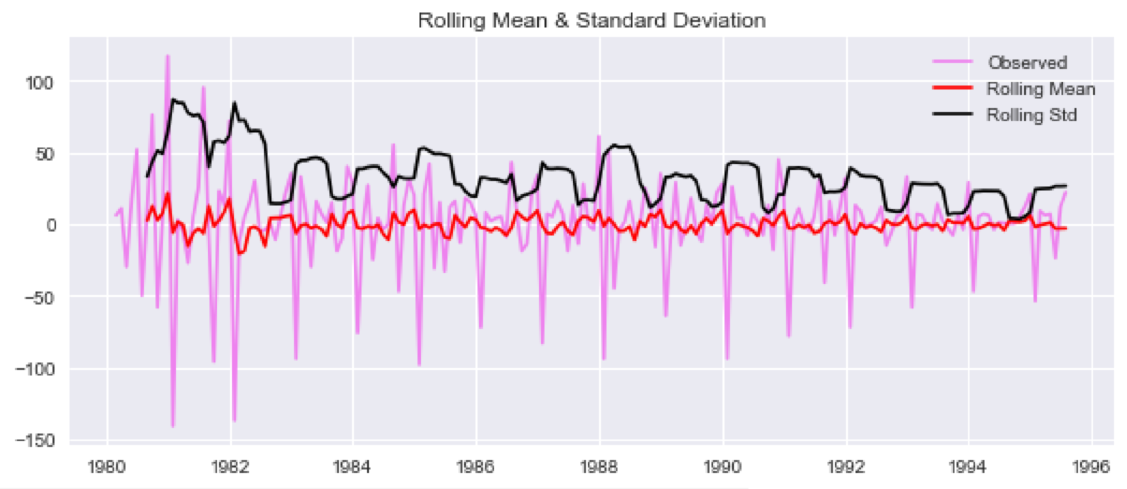


Results of Dickey-Fuller Test:

Test Statistic	-1.876719
p-value	0.343091
#Lags Used	13.000000
Number of Observations Used	173.000000
Critical Value (1%)	-3.468726
Critical Value (5%)	-2.878396
Critical Value (10%)	-2.575756

<u>ADF on original series</u>

- P-Value > alpha .05
- Test statistic > Critical values
- Fail to reject the null hypothesis
- The series is non-stationary



<u>ADF on differenced series</u>

- P-Value < alpha .05
- Test statistic < Critical values
- Reject the null hypothesis
- The series is stationary

Results of Dickey-Fuller Test:

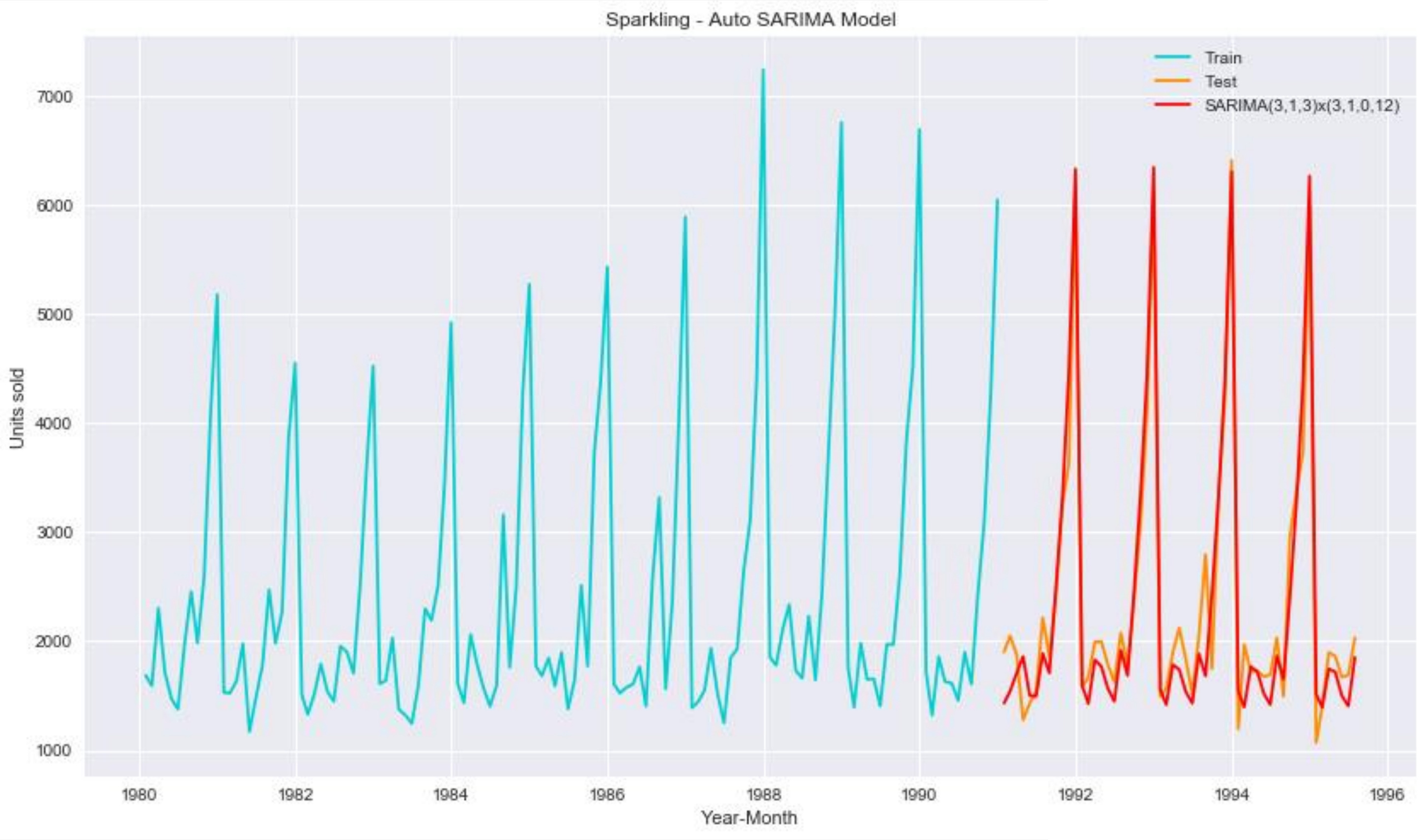
Test Statistic	-8.044395e+00
p-value	1.810868e-12
#Lags Used	1.200000e+01
Number of Observations Used	1.730000e+02
Critical Value (1%)	-3.468726e+00
Critical Value (5%)	-2.878396e+00
Critical Value (10%)	-2.575756e+00

- Differencing of order one is applied on the Sparkling series as above and tested for stationarity
- At an order of differencing 1, the series is found to be stationary as above
- The rolling mean and standard deviation is also plotted to understand the component of seasonality and to ascertain if its multiplicative or additive in character
- The plot of rolling mean and standard deviation indicates that the seasonality is multiplicative as the altitude of plot varies with respect to trend
- The ADF test is also done in this exercise with logarithmic transformation of the train data and differencing of seasonal order (12), to understand if removing the multiplicity of the seasonal component will have an impact on the accuracy of model

6. AUTO SARIMA

Sparkling

- As the Sparkling series of data contain seasonality component we will be building SARIMA model, rather than ARIMA
- Two iterations of automated SARIMA models were attempted in this exercise, one with original data and another with log transformation of the data, as an element of multiplicity in seasonality is suspected
- The model built with original data is found to be higher in accuracy scores of RMSE and MAPE, which is selected as the final model
- The optimal parameters for (p, d, q)x(P, D, Q) were selected in accordance with the lowest Akaike Information Criteria (AIC) values
- The top three models with lowest AIC values are as given. As per the AIC criteria, the optimum values for final SARIMA model selected is (3, 1, 3)x(3, 1, 0, 12)
- The diagnostics plot of the model was derived and the standardized residuals are found to follow a mean of zero, and the histogram shows the residuals follow a normal distribution
- The Normal Q-Q plot also shows that the quantiles come from a normal distribution as the points forms roughly a straight line
- The correlogram shows the autocorrelation of the residuals and there are no significant lags above the confidence index
- The RMSE and MAPE values of the automated SARIMA models built are given here
- The diagnostics plot of the selected model is given in the next slide



	param	seasonal	AIC
252	(3, 1, 3)	(3, 1, 0, 12)	1213.282561
253	(3, 1, 3)	(3, 1, 1, 12)	1215.213337
220	(3, 1, 1)	(3, 1, 0, 12)	1215.898777

	Test RMSE	Test MAPE
Auto SARIMA(3,1,3)x(3,1,0,12)	331.614531	10.33
Auto SARIMA(0,1,1)x(1,0,1,12)-Log10	336.800722	11.19

6. AUTO SARIMA

Sparkling

- From the below model summary it can be inferred that AR(1), MA(1), MA(3), MA(2) terms has the highest absolute weightage.
- From the p-values it can be inferred that terms AR(1), AR(2), MA(1), MA(2), MA(3) and seasonal AR(1) are significant terms, as their values are below 0.05

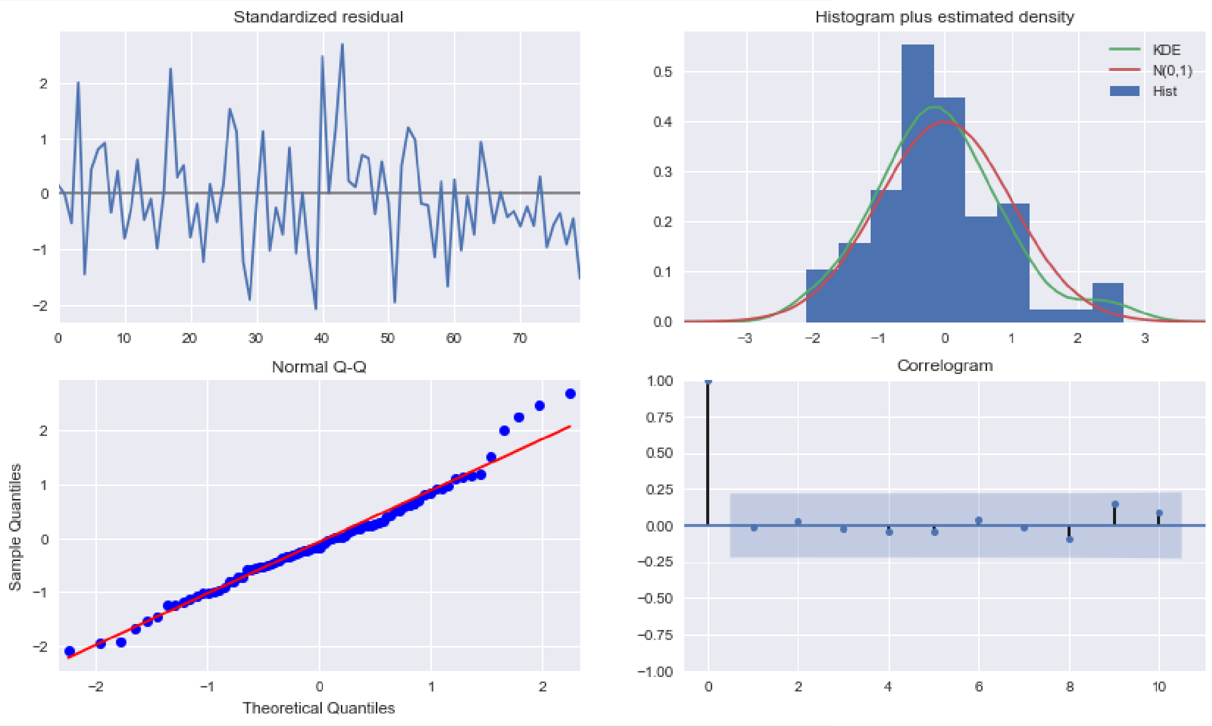
Model Summary – SARIMA (3, 1, 3)x(3, 1, 0, 12)

Dep. Variable:	y	No. Observations:	132
Model:	SARIMAX(3, 1, 3)x(3, 1, 0, 12)	Log Likelihood	-596.641
Date:	Sun, 13 Sep 2020	AIC	1213.283
Time:	19:55:24	BIC	1237.103
Sample:	0 - 132	HQIC	1222.833
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.6142	0.176	-9.177	0.000	-1.959	-1.269
ar.L2	-0.6124	0.299	-2.048	0.041	-1.198	-0.026
ar.L3	0.0860	0.161	0.536	0.592	-0.229	0.401
ma.L1	0.9853	0.465	2.117	0.034	0.073	1.898
ma.L2	-0.8739	0.166	-5.268	0.000	-1.199	-0.549
ma.L3	-0.9464	0.483	-1.960	0.050	-1.893	-0.000
ar.S.L12	-0.4521	0.142	-3.193	0.001	-0.730	-0.175
ar.S.L24	-0.2345	0.144	-1.625	0.104	-0.517	0.048
ar.S.L36	-0.1007	0.122	-0.828	0.408	-0.339	0.138
sigma2	1.839e+05	8.86e+04	2.076	0.038	1.03e+04	3.57e+05

Ljung-Box (Q):	23.21	Jarque-Bera (JB):	4.06
Prob(Q):	0.98	Prob(JB):	0.13
Heteroskedasticity (H):	0.73	Skew:	0.48
Prob(H) (two-sided):	0.42	Kurtosis:	3.54

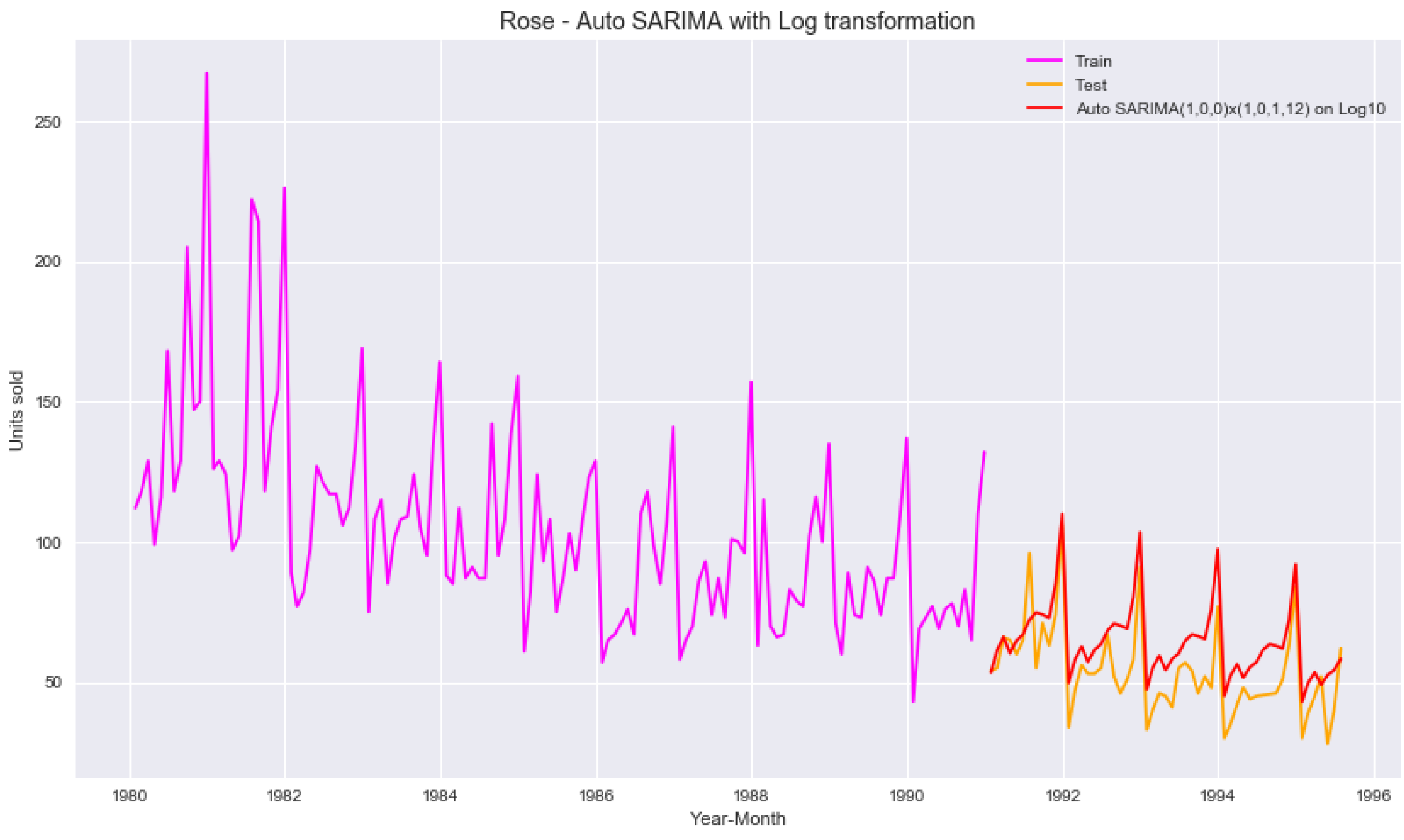
Diagnostics plot – SARIMA (3, 1, 3)x(3, 1, 0, 12)



6. AUTO SARIMA

Rose

- As the Rose series of data contain seasonality component we will be building SARIMA model, rather than ARIMA
- Two iterations of automated SARIMA models were attempted in this exercise, one with original data and another with log transformation of the data, as the seasonality got apparent multiplicity
- The model built with log transformed data is found to be higher in accuracy scores of RMSE and MAPE, which is selected as the final model
- To handle multiplicity of seasonality, the data was log transformed to make it additive
- The optimal parameters for (p, d, q)x(P, D, Q) were selected in accordance with the lowest Akaike Information Criteria (AIC) values
- The top three models with lowest AIC values are as given here and the final selected one is (1, 0, 0)x(1, 0, 1, 12)
- The diagnostics plot of the model was derived and the standardized residuals are found to follow a mean of zero, and the histogram shows the residuals follow a normal distribution
- The Normal Q-Q plot also shows that the quantiles come from a normal distribution as the points forms roughly a straight line
- The correlogram shows the autocorrelation of the residuals and there are no points significant above the confidence index
- The RMSE and MAPE values of the automated SARIMA models built are given here
- The diagnostics plot of the selected model is given in the next slide



	param	seasonal	AIC
31	(1, 0, 0)	(1, 0, 1, 12)	-257.620760
4	(0, 0, 0)	(1, 0, 1, 12)	-256.170282
40	(1, 0, 1)	(1, 0, 1, 12)	-255.482062

	Test RMSE	Test MAPE
Auto SARIMA(3,1,1)x(3,1,1,12)	16.823618	25.48
Auto SARIMA(1,0,0)x(1,0,1,12)-Log10	13.595882	21.93

6. AUTO SARIMA

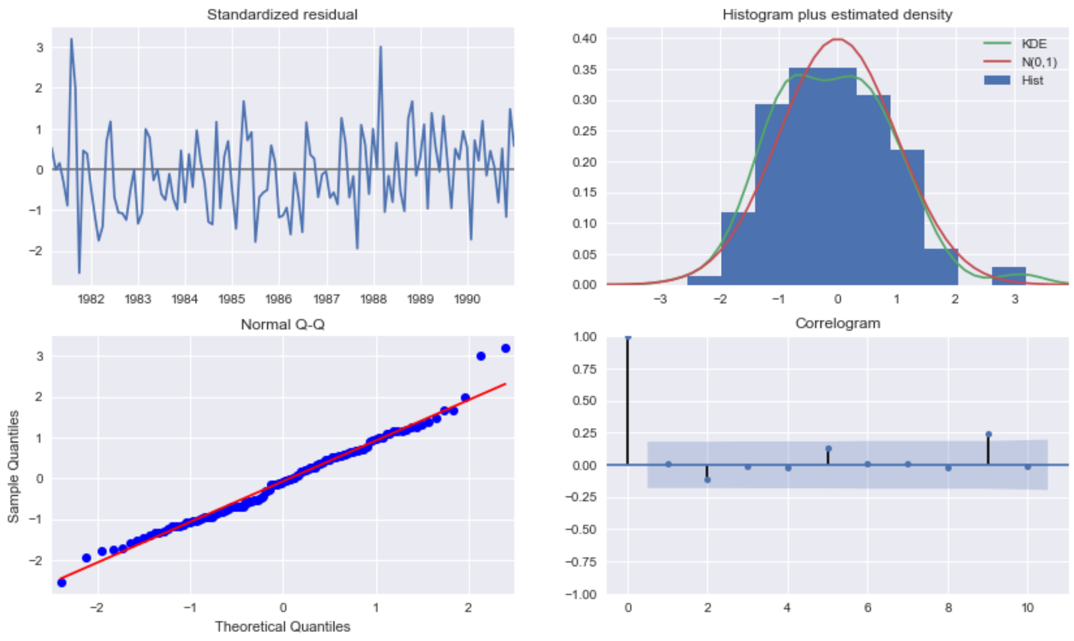
Rose

- From the below model summary it can be inferred that seasonal AR(2) term has the highest weightage, followed by seasonal MA(2)
- From the p-values it can be inferred that all the AR and MA terms are significant as the values are below .05

Model Summary – SARIMA (1, 0, 0)x(1, 0, 1, 12)

```
==========================================================================================
Dep. Variable:                               Rose   No. Observations:                  132
Model:             SARIMAX(1, 0, 0)x(1, 0, 1, 12)   Log Likelihood                 132.810
Date:                            Sun, 13 Sep 2020   AIC                           -257.621
Time:                                    20:24:09   BIC                           -246.504
Sample:                                01-31-1980   HQIC                          -253.107
                                     - 12-31-1990
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.1689      0.078      2.179      0.029       0.017       0.321
ar.S.L12       0.9872      0.001    751.658      0.000       0.985       0.990
ma.S.L12      -0.9411      0.351     -2.684      0.007      -1.628      -0.254
sigma2         0.0052      0.002      2.885      0.004       0.002       0.009
===================================================================================
Ljung-Box (Q):                       24.28   Jarque-Bera (JB):                 4.00
Prob(Q):                              0.98   Prob(JB):                         0.14
Heteroskedasticity (H):               0.86   Skew:                             0.40
Prob(H) (two-sided):                  0.64   Kurtosis:                         3.40
===================================================================================
```

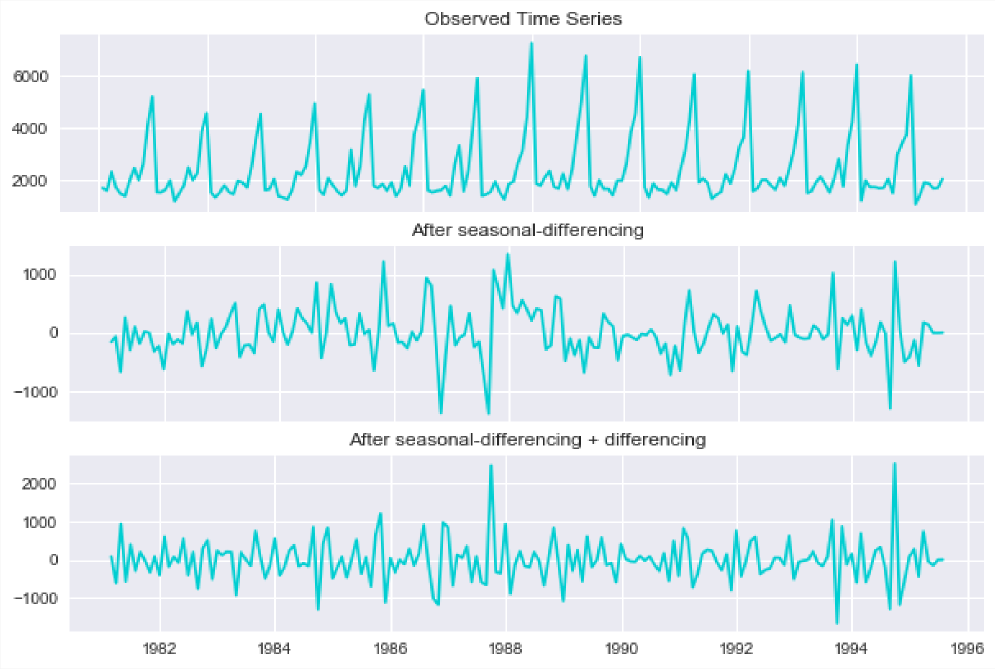
Diagnostics plot – SARIMA (1, 0, 0)x(1, 0, 1, 12)



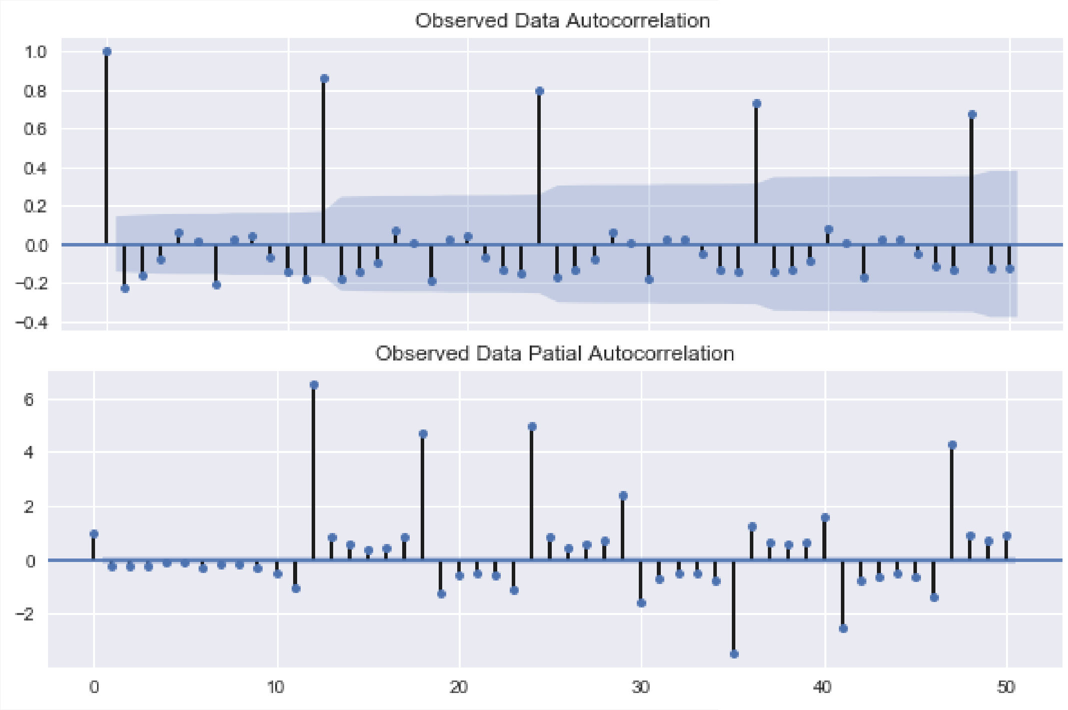
7. MANUAL SARIMA

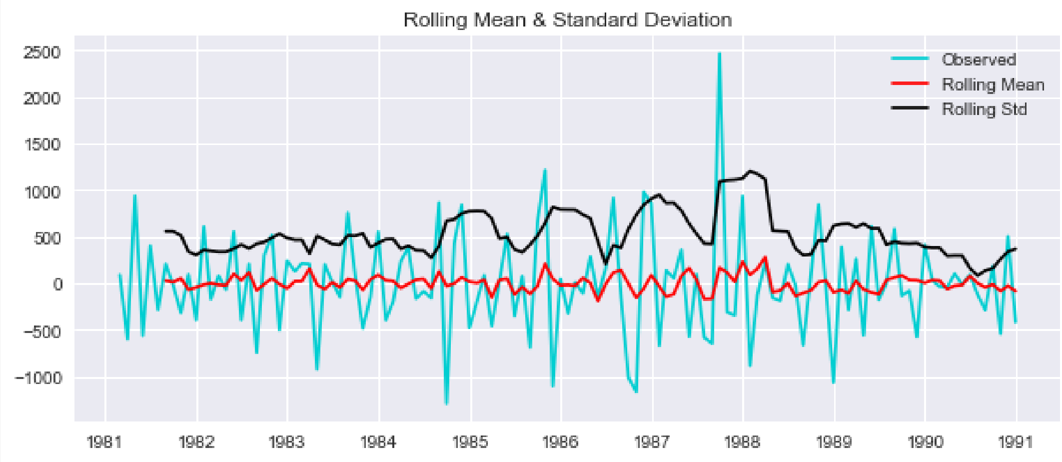
Sparkling

- From the ACF plot of the observed/ train data, it can be inferred that at seasonal interval of 12, the plot is not quickly tapering off. So a seasonal differencing of 12 has to be taken
- From the plots below an apparent slight trend is still existing after differencing of seasonal order of 12. With a further differencing of order one, no trend is present



- An ADF test need to be done to check the stationarity after the above differencing. With a p-value below alpha 0.05 and test statistic below critical values, it can be confirmed that the data is stationary
- ACF and PACF plots of the seasonal-differenced + one order differenced data is created to find the values for (p,d,q)x(P,D,Q), continued on next slide…



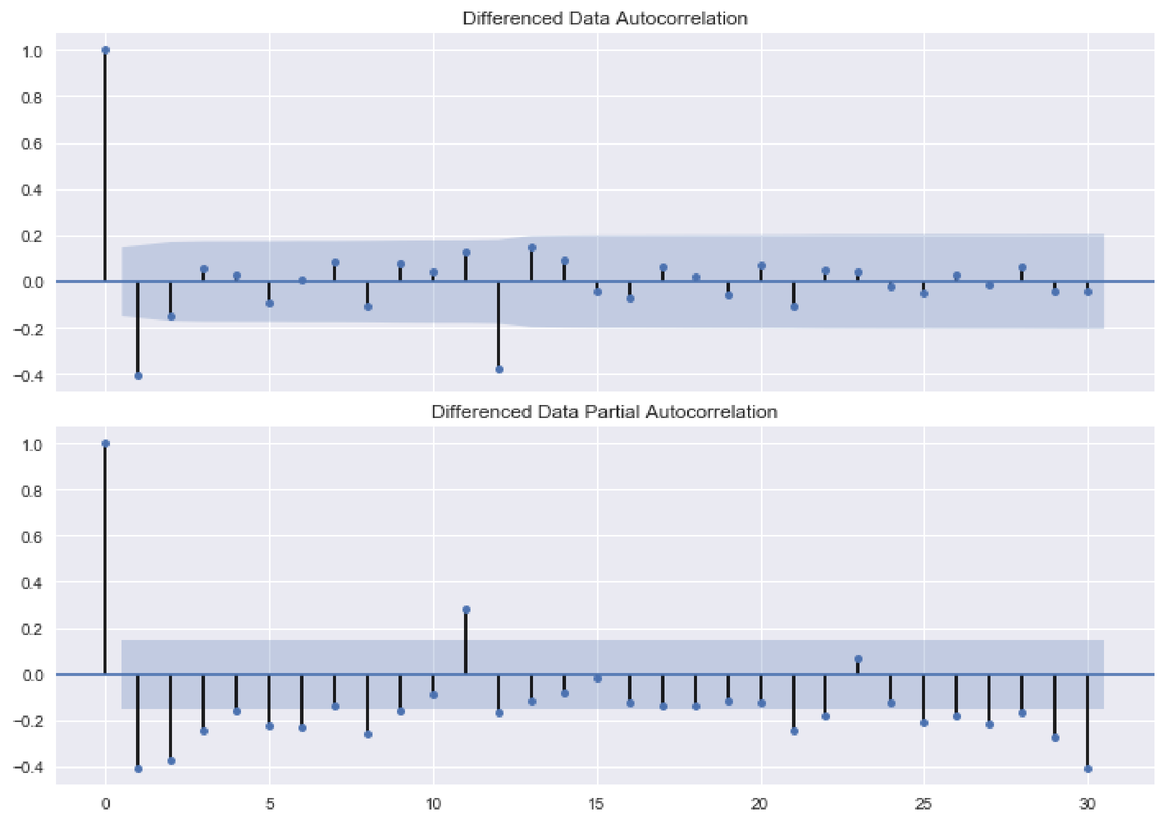



```
Results of Dickey-Fuller Test:
Test Statistic                 -3.342905
p-value                         0.013066
#Lags Used                     10.000000
Number of Observations Used   108.000000
Critical Value (1%)            -3.492401
Critical Value (5%)            -2.888697
Critical Value (10%)           -2.581255
```

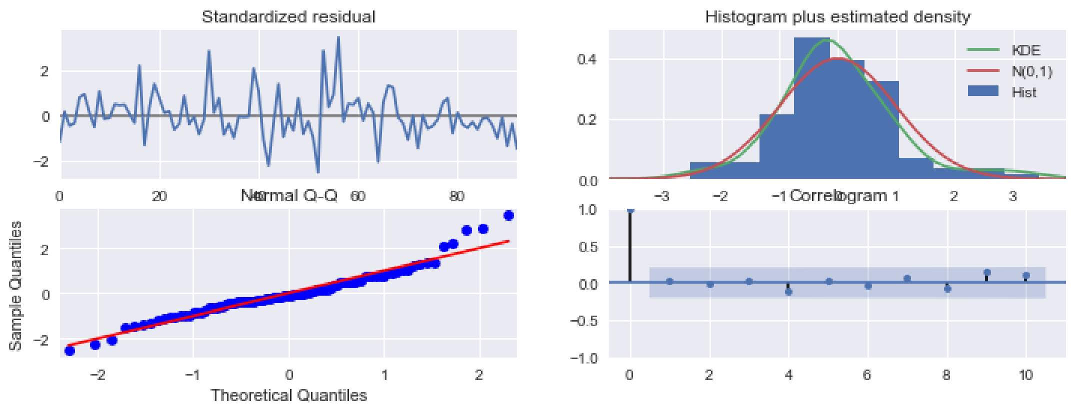
7. MANUAL SARIMA

Sparkling

- Here we have taken alpha = 0.05 and seasonal period as 12
- From the PACF plot it can be seen that till 3rd lag its significant before cut-off, so AR term ‘p = 3’ is chosen. At seasonal lag of 12, it almost cuts off, so seasonal AR ‘P = 1’
- From ACF plot it can be seen that lag 1 is significant before it cuts off, so MA term ‘q = 1’ is selected and at seasonal lag of 12, a significant lag is apparent, so kept seasonal MA term ‘Q = 1’ initially



- The seasonal MA term ‘Q’ was later optimized to 2, by validating model performance, as the data might be under-differenced
- The final selected terms for SARIMA model is (3, 1, 1)x(0, 1, 2, 12)
- The diagnostic plot for the model is as below, which clearly shows a normal distribution of residuals, where more values are around zero
- The Normal Q-Q plot also shows that the quantiles come from a normal distribution as the points forms roughly a straight line
- The correlogram shows the autocorrelation of the residuals and there are no points significant above the confidence index

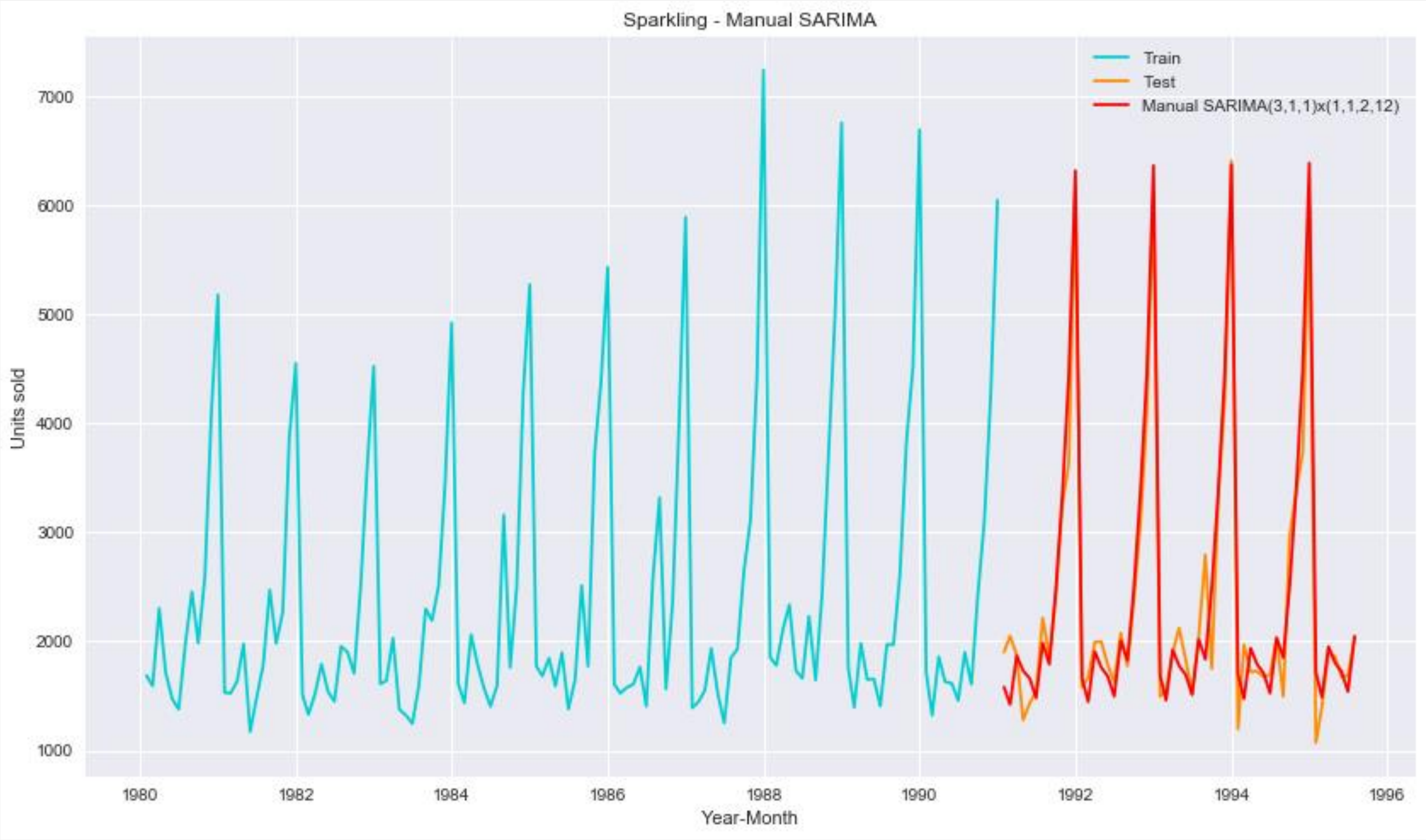


- Please refer the next slide for the forecast plotted against the test data. The performance of the model is as follows

	RMSE	MAPE
Test	324.108	9.48

7. MANUAL SARIMA

Sparkling



	coef	std err	z	P>|z|
ar.L1	0.2229	0.130	1.713	0.087
ar.L2	-0.0798	0.131	-0.607	0.544
ar.L3	0.0921	0.122	0.756	0.450
ma.L1	-1.0241	0.094	-10.925	0.000
ar.S.L12	-0.1992	0.866	-0.230	0.818
ma.S.L12	-0.2109	0.881	-0.239	0.811
ma.S.L24	-0.1299	0.381	-0.341	0.733

- The model summary indicates that that only MA(1) term used in the model is significant in terms of p-values
- From the multiple iterations of SARIMA models, below is the comparison of the models in terms of its accuracy attributes of RMSE and MAPE

SARIMA Model comparison

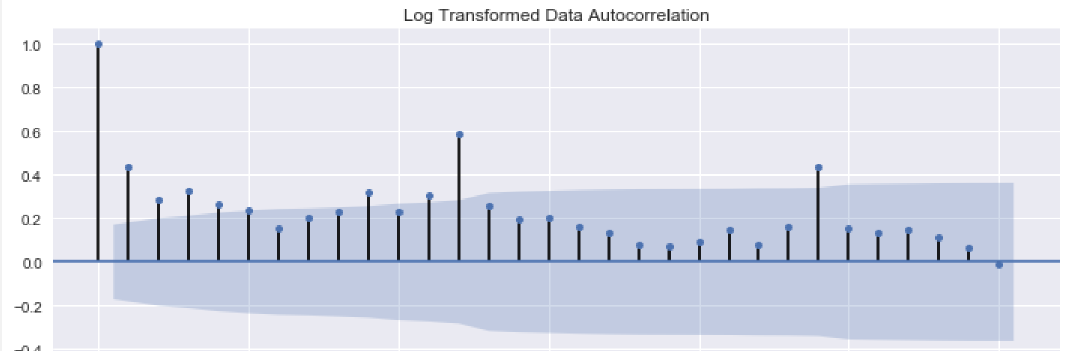
	Test RMSE	Test MAPE
Auto SARIMA(3,1,3)x(3,1,0,12)	331.614531	10.33
Auto SARIMA(0,1,1)x(1,0,1,12)-Log10	336.800722	11.19
Manual SARIMA(3,1,1)x(1,1,2,12)	324.108003	9.48

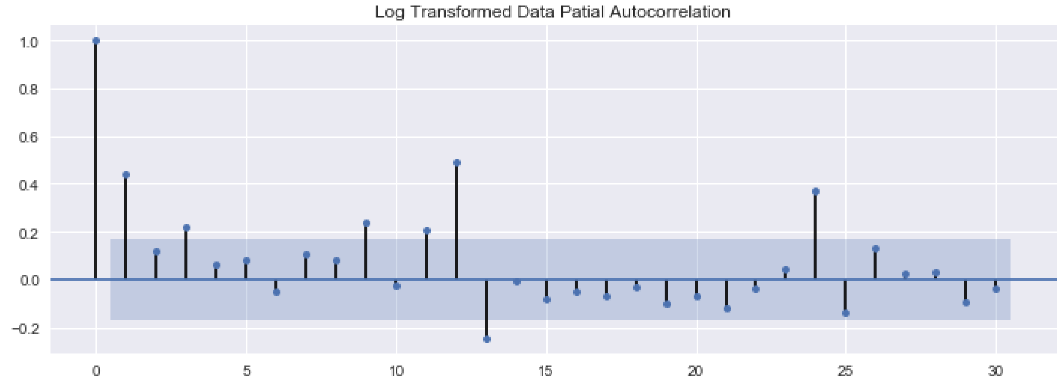
7. MANUAL SARIMA

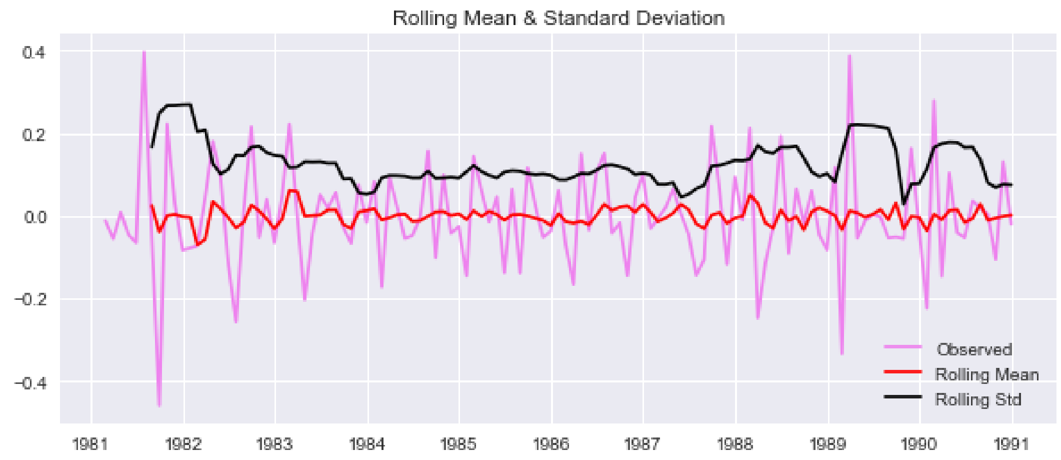
Rose

- Log transformation of the data is done to handle multiplicity of seasonality
- From the ACF plot of the log transformed data, it can be seen that at seasonal interval of 12, the plot is not quickly tapering off. So we need to take a seasonal differencing of 12
- From the plots below it can be seen that a slight trend is still existing after differencing of seasonal order of 12. With a further differencing of order one, no trend is present

- Have done an ADF test to check the stationarity after the above differencing. With a p-value below alpha 0.05 and test statistic below critical values, it can be confirmed that the data is stationary
- ACF and PACF plots of the seasonal-differenced + one order differenced data is created to find the values for (p,d,q)x(P,D,Q), continued on next slide…





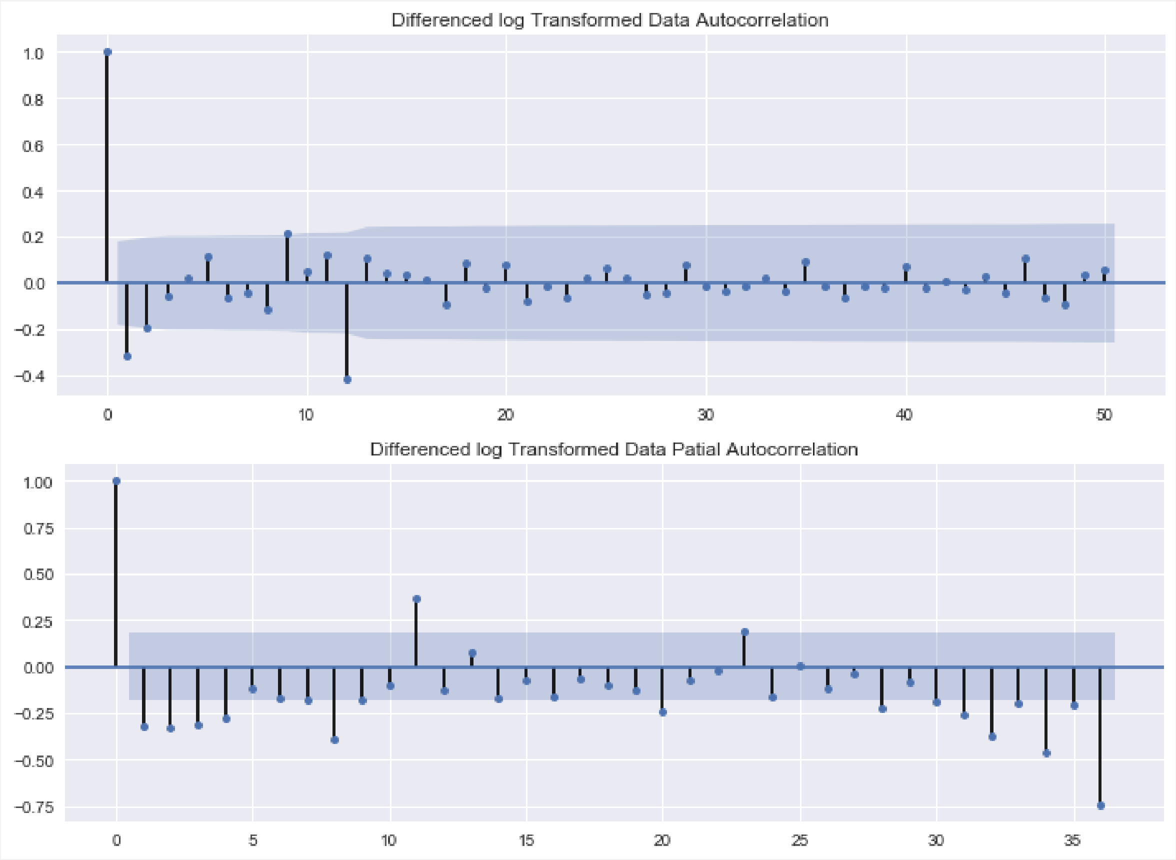


Test Statistic	-3.910109
p-value	0.001962
#Lags Used	11.000000
Number of Observations Used	107.000000
Critical Value (1%)	-3.492996
Critical Value (5%)	-2.888955
Critical Value (10%)	-2.581393

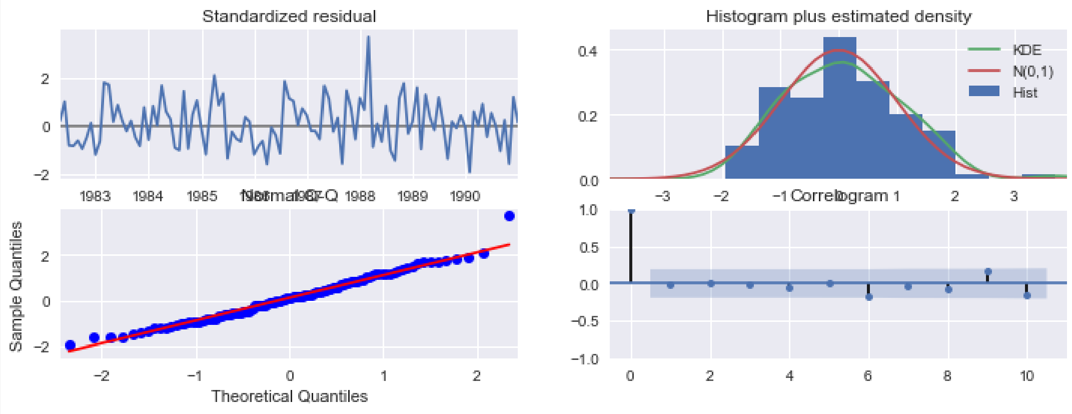
7. MANUAL SARIMA

Rose

- Here we have taken alpha = 0.05 and seasonal period as 12
- From the PACF plot it can be seen that till lag 4 is significant before cut-off, so AR term ‘p = 4’ is chosen. At seasonal lag of 12, it cuts off, so keep seasonal AR ‘P = 0’
- From ACF plot, lag 1 and 2 are significant before it cuts off, so lets keep MA term ‘q = 1’ and at seasonal lag of 12, a significant lag is apparent, so lets keep ‘Q = 1’



- The final selected terms for SARIMA model is (4, 1, 1)x(0, 1, 1, 12), as inferred from the ACF and PACF plots
- The diagnostic plot for the model is as below, which clearly shows a normal distribution of residuals, where more values are around zero
- The Normal Q-Q plot also shows that the quantiles come from a normal distribution as the points forms roughly a straight line
- The correlogram shows the autocorrelation of the residuals and there are no points significant above the confidence index



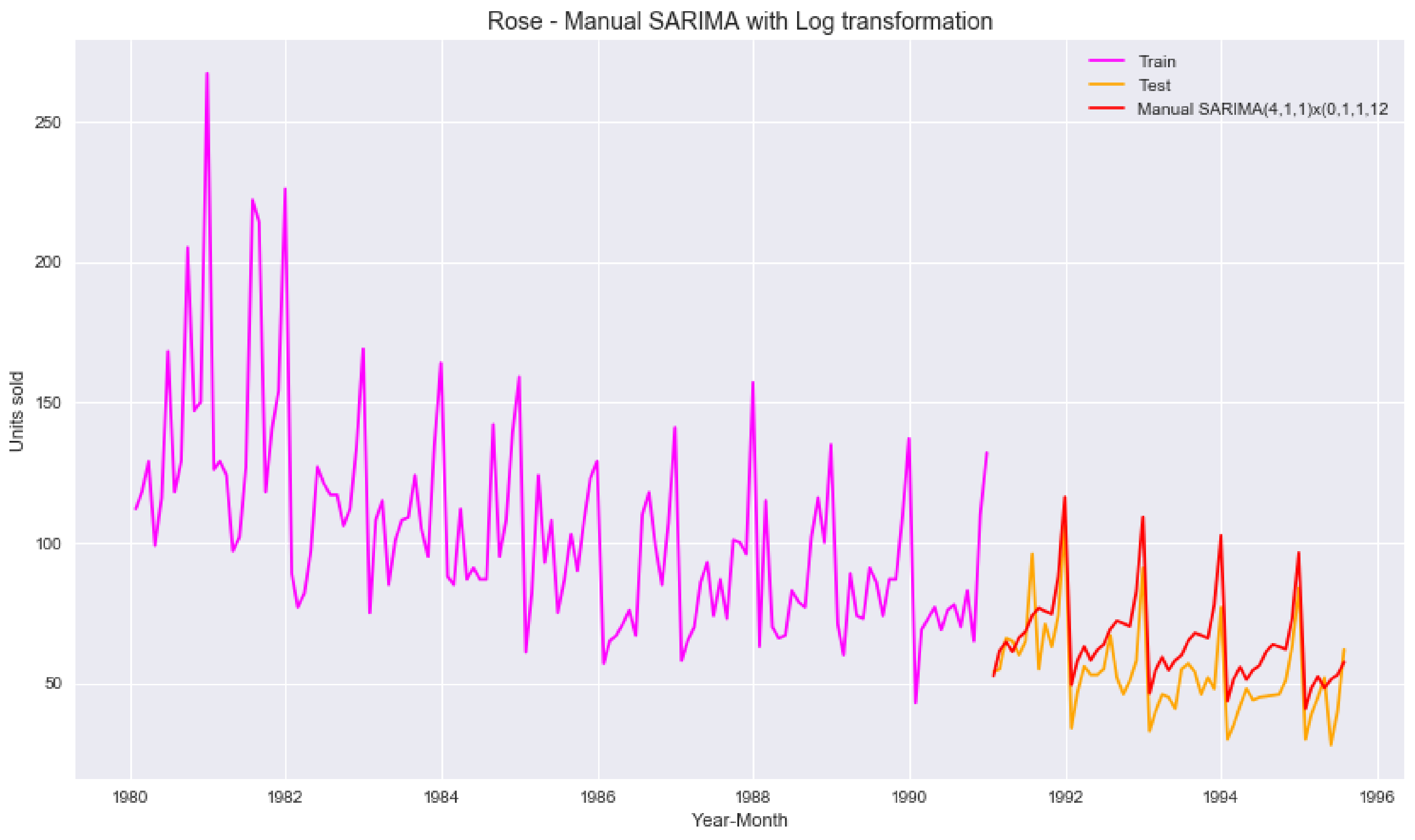
- Please refer the next slide for the forecast plotted against the test data. The performance of the model is as follows

	RMSE	MAPE
Test	14.176	23.10

7. MANUAL SARIMA

Rose

- Below is the plot of forecasts fitted with the test data



Model Summary SARIMA(4, 1, 1)x(0, 1, 1, 12)

	coef	std err	z	P>|z|
ar.L1	-0.0013	0.118	-0.011	0.991
ar.L2	-0.1553	0.126	-1.230	0.219
ar.L3	-0.1600	0.113	-1.422	0.155
ar.L4	-0.1504	0.121	-1.242	0.214
ma.L1	-0.8434	0.074	-11.399	0.000
ma.S.L12	-0.9963	6.071	-0.164	0.870

- The model summary indicates that that none of the terms used in the model are significant in terms of p-values
- From the multiple iterations of SARIMA models, below is the comparison of the models in terms of its accuracy attributes of RMSE and MAPE

SARIMA Model Comparison

	Test RMSE	Test MAPE
Auto SARIMA(3,1,1)x(3,1,1,12)	16.823618	25.48
Auto SARIMA(1,0,0)x(1,0,1,12)-Log10	13.595882	21.93
Manual SARIMA(4,1,2)x(0,1,1,12)	16.823618	25.48
Manual SARIMA(4,1,1)x(0,1,1,12)-Log10	14.176381	23.10

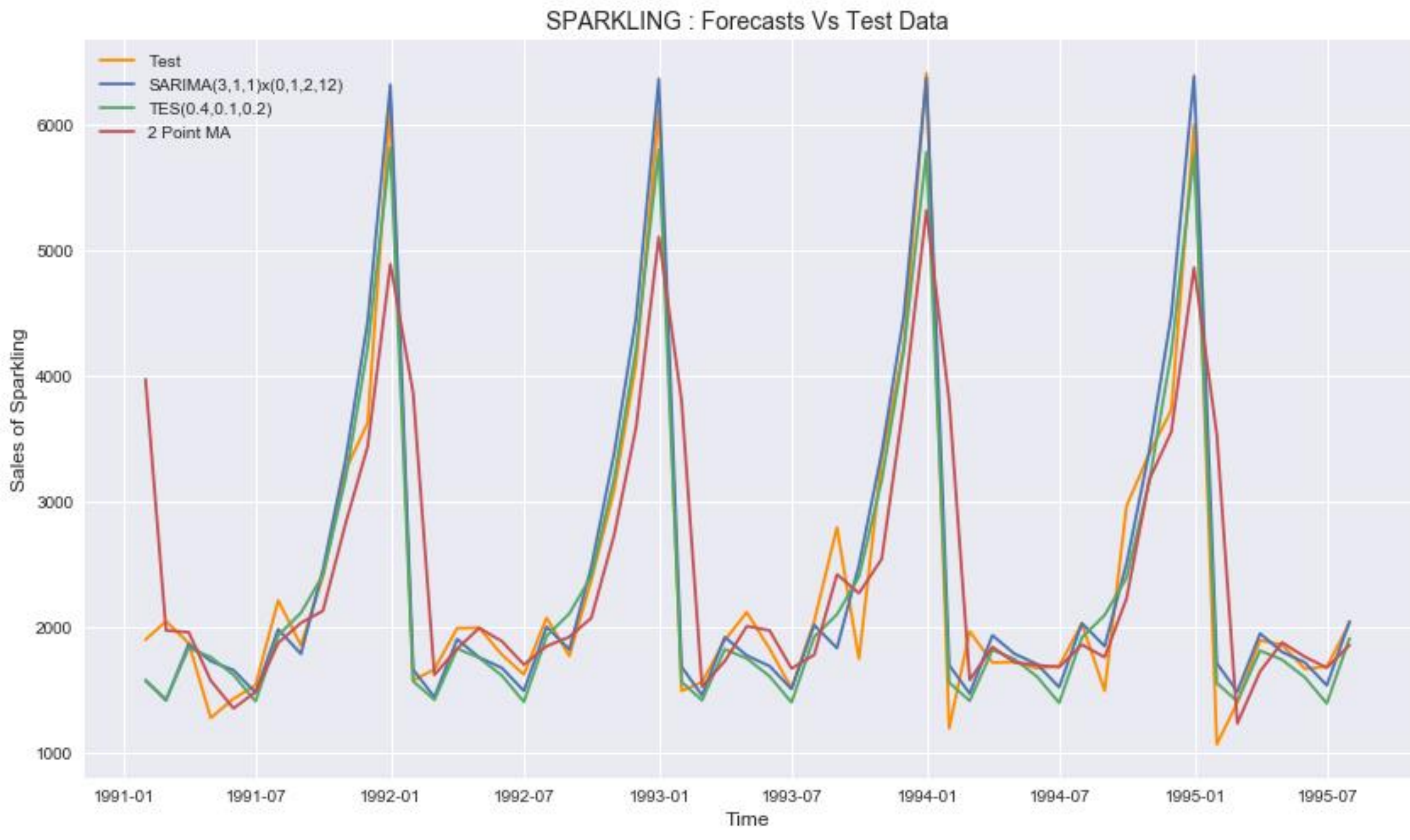
8. MODEL COMPARISON

Sparkling

- The overall comparison of all the time-series forecast models are listed below in accordance with increasing RMSE against test data or in the order of decreasing accuracy
- Triple Exponential Smoothing is found to be the best model, followed by SARIMA

Sparkling - Overall Model Comparison

	Test RMSE	Test MAPE
TES Alpha 0.4, Beta 0.4, Gamma 0.2	312.211095	10.20
Manual SARIMA(3,1,1)x(1,1,2,12)	324.108003	9.48
Auto SARIMA(3,1,3)x(3,1,0,12)	331.614531	10.33
Auto SARIMA(0,1,1)x(1,0,1,12)-Log10	336.800722	11.19
TES Alpha 0.15, Beta 0.00, Gamma 0.37	384.203001	11.94
2 point TMA	813.400684	19.70
4 point TMA	1156.589694	35.96
SimpleAverage	1275.081804	38.90
SES Alpha 0.00	1275.081823	38.90
6 point TMA	1283.927428	43.86
9 point TMA	1346.278315	46.86
RegressionOnTime	1389.135175	50.15
DES Alpha 0.1,Beta 0.1	1779.430000	67.23
DES Alpha 0.6,Beta 0.0	3851.171500	152.07
NaiveModel	3864.279352	152.87



- The best of SARIMA, Triple Exponential Smoothing and Moving Average models are plotted above against the test data
- The SARIMA and Triple Exponential Smoothing are found to be comparable in terms of performance and fitment with the test data

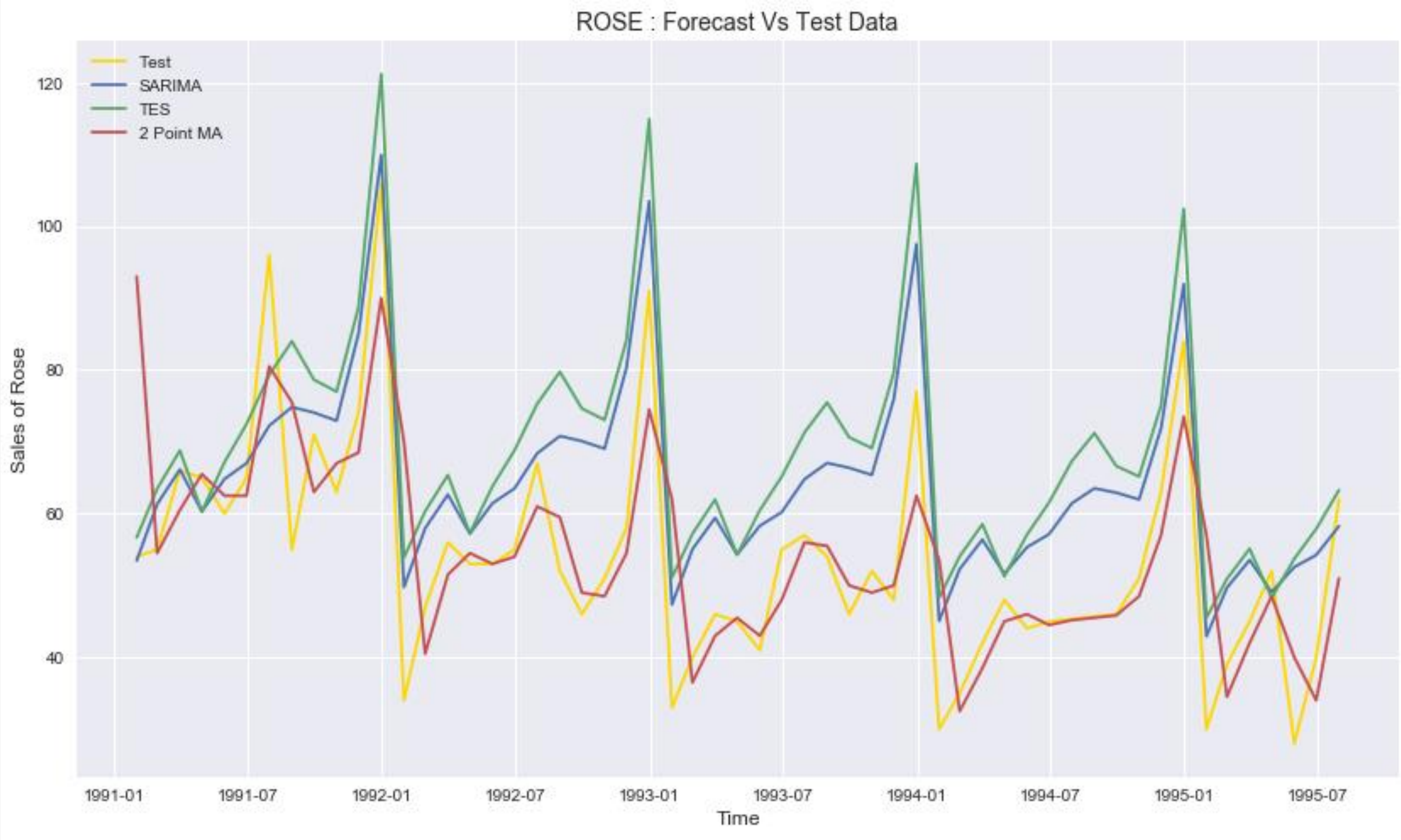
8. MODEL COMPARISON

Rose

- The overall comparison of all the time-series forecast models are listed below in accordance with increasing RMSE against test data or in the order of decreasing accuracy
- Triple Exponential Smoothing is found to be the best model, followed by 2 point Moving Average

Rose - Overall Model Comparison

	Test RMSE	Test MAPE
TES Alpha 0.1, Beta 0.2, Gamma 0.2	9.640616	13.96
2 point TMA	11.529278	13.54
Auto SARIMA(1,0,0)x(1,0,1,12)-Log10	13.595882	21.93
Manual SARIMA(4,1,1)x(0,1,1,12)-Log10	14.176381	23.10
4 point TMA	14.451364	19.49
6 point TMA	14.566269	20.82
9 point TMA	14.727594	21.01
RegressionOnTime	15.268885	22.82
Manual SARIMA(4,1,2)x(0,1,1,12)	15.377144	22.16
Auto SARIMA(3,1,1)x(3,1,1,12)	16.823618	25.48
TES Alpha 0.11, Beta 0.05, Gamma 0.00	17.369210	28.88
SES Alpha 0.01	36.796019	63.88
DES Alpha 0.10, Beta 0.10	37.056912	64.02
SimpleAverage	53.460350	94.93
DES Alpha 0.16, Beta 0.16	70.572197	120.25
NaiveModel	79.718559	145.10

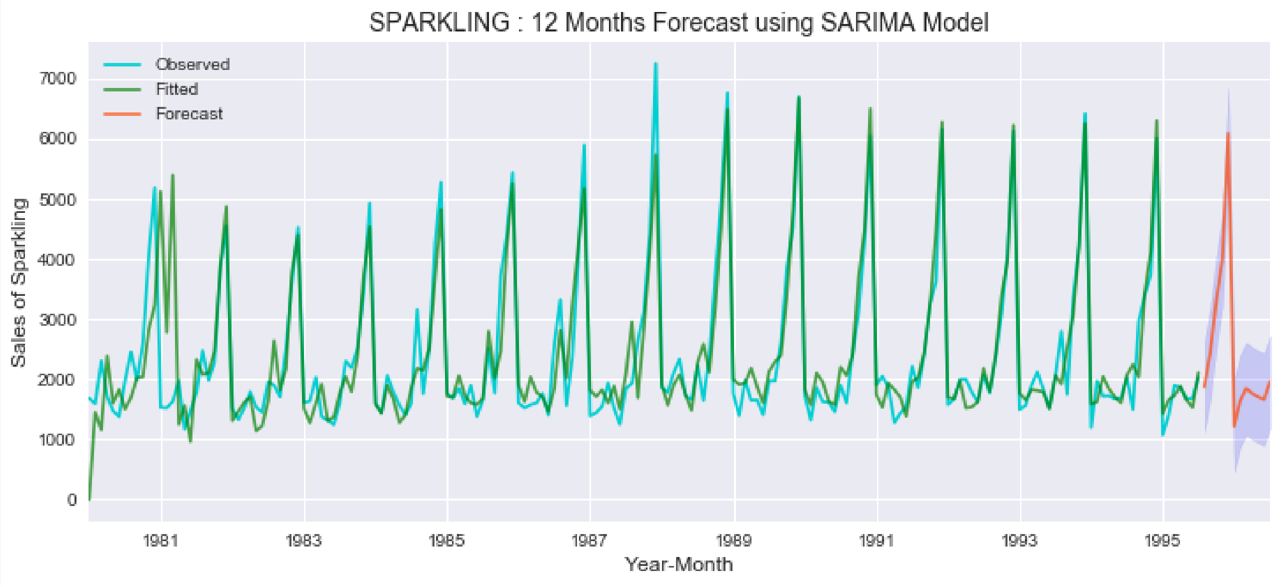


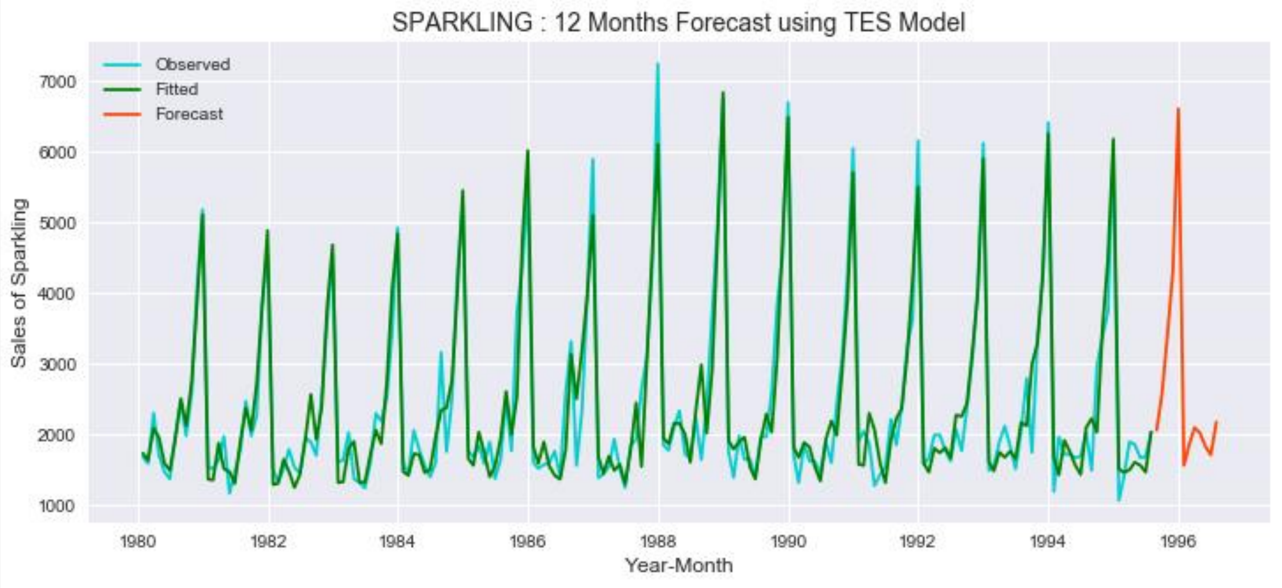
- The best of SARIMA, Triple Exponential Smoothing and Moving Average models are plotted above against the test data
- 2 point trailing moving average is found to be having the best fitment against the test data, through with a lag of 2 and falling short at times
- Both SARIMA and TES forecasts are a bit higher than the actuals at any given point in time

9. PREDICT INTO FUTURE

Sparkling

- Based on the overall model evaluation and comparison, Triple Exponential Smoothing (Holt Winter's) and SARIMA are selected for final prediction into 12 months in future
- TES model *alpha: 0.4, beta: 0.1 and gamma: 0.2 & trend: 'additive', seasonal: 'multiplicative'* is found to be the best model in terms of accuracy scored against the full data
- The model predicts an upward trend and continuation of the seasonal surge in sales in the upcoming 12 months. According to the model the seasonal sale will be more than that of the previous year
- The 12 month prediction of the TES model is as below
- The SARIMA model is built with parameters (3, 1, 3)x(1, 1, 2, 12), is found to be the most optimal SARIMA model





- SARIMA model has reflected the trend and seasonality of the series continuing into the future year as well. The seasonal altitude predicted us more conservative than TES model
- SARIMA model is seen to have better fitment with the most recent observed data and shows high variations in the farthest periods of observations, which explains the high RMSE and MAPE values
- The RMSE and MAPE values of the two models are as below

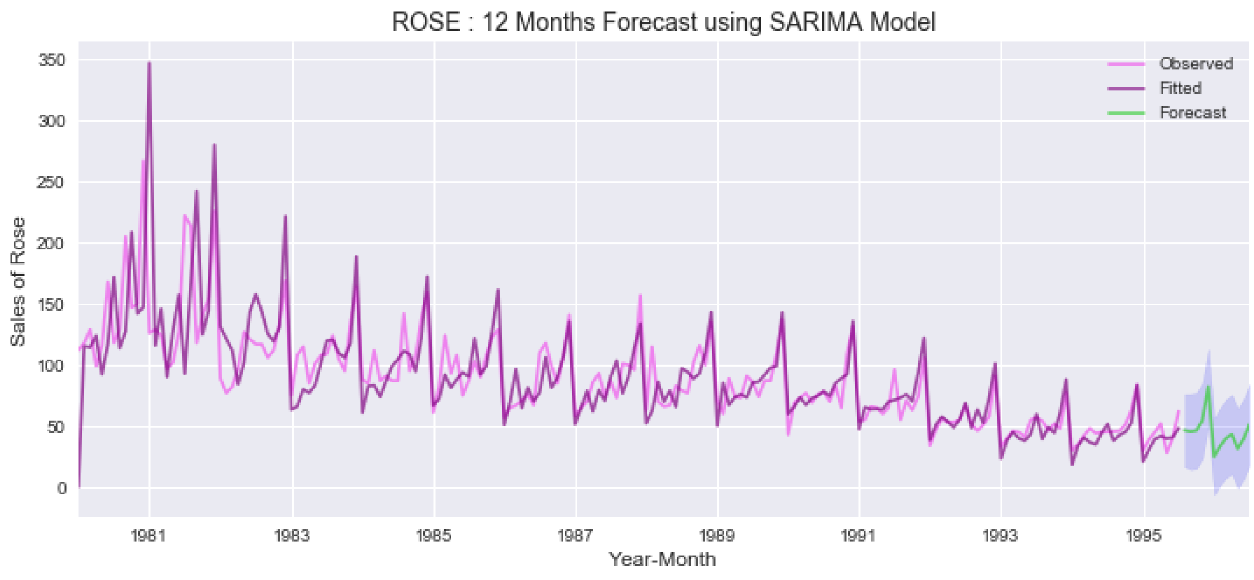
<u>Model evaluation on full data</u>

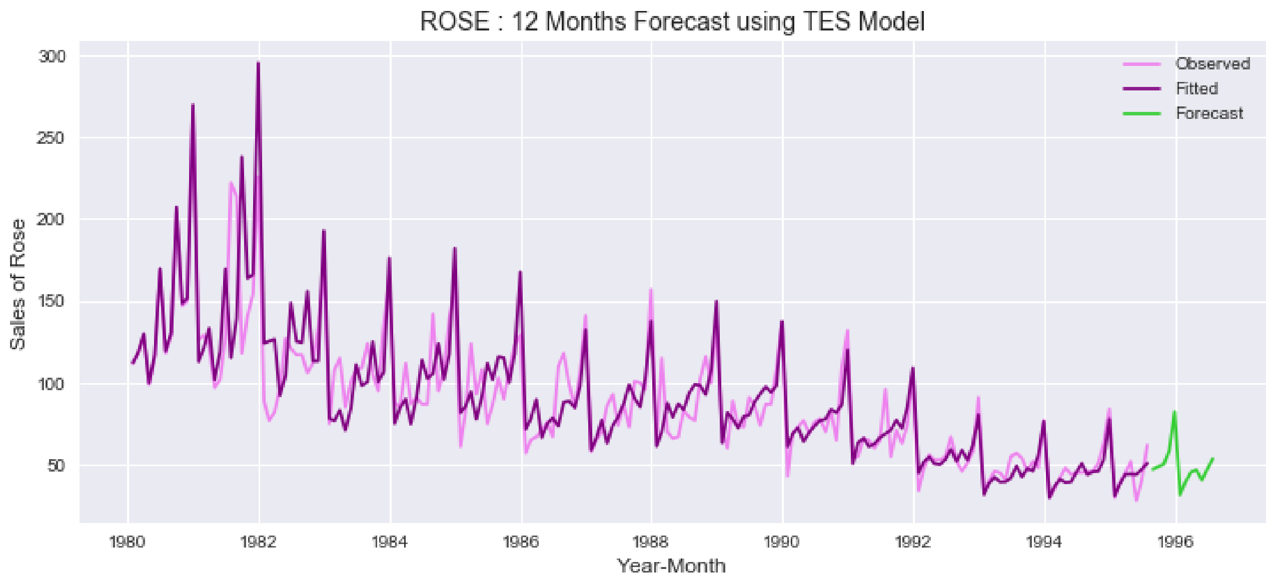
	RMSE	MAPE
TES Forecast	376.821	11.30
SARIMA Forecast	591.238	14.86

9. PREDICT INTO FUTURE

Rose

- Based on the overall model evaluation and comparison, Triple Exponential Smoothing (Holt Winter's) and SARIMA are selected for final prediction into 12 months in future
- TES model *alpha: 0.1, beta: 0.2 and gamma: 0.2 & trend: 'additive', seasonal: 'multiplicative'* is found to be the best model in terms of accuracy scored against the full data
- The model predicts continuation of the trend in sales and seasonality in year end sales. The prediction shows a stabilization of downward trend, as the sales will be almost same as previous observed year
- The 12 month prediction of the TES model is as below
- The SARIMA model is built with parameters (4, 1, 1)x(0, 1, 1, 12), is found to be the most optimal SARIMA model for the complete time-series





- SARIMA model has also reflected the trend and seasonality of the series continuing into the future year as well.
- SARIMA model is seen to have better fitment with the most recent observed data and shows high variations in the farthest periods of observations, which explains the high RMSE and MAPE values
- The RMSE and MAPE values of the two models are as below

Model evaluation on full data

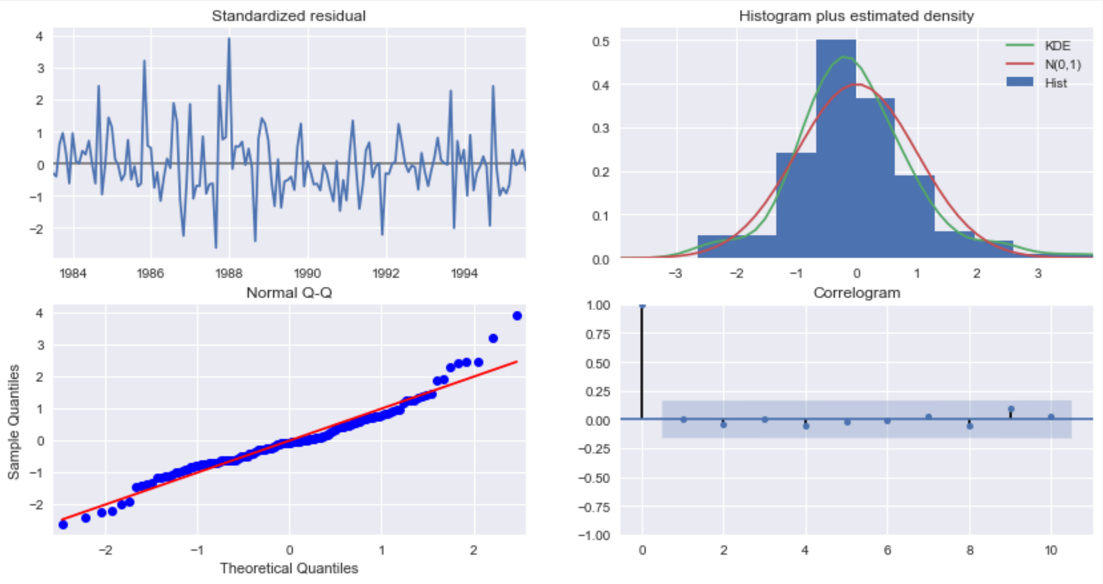
	RMSE	MAPE
TES Forecast	20.881	14.48
SARIMA Forecast	30.676	19.40

10. FINAL MODEL

Sparkling

- The SARIMA model built on the complete Sparkling timeseries is chosen, as prediction provide confidence interval which give better explainabiity and confidence to the forecasts
- The diagnostics plot of the model shows that the residuals follow a normal distribution with most values around mean zero. The residuals also follow a straight line in normal QQ plot
- The model summary also provides valuable insights in the model. From the snapshot of summary below it can be understood that AR(2), MA(3) terms has the highest absolute weightage. The p-values indicates that the terms AR(1), AR(2), MA(1), MA(2) and MA(3) are the most significant terms
- The rest of the p-values got values higher than alpha 0.05, which fails to reject the hull hypothesis that these terms are not significant

Model Diagnostics – SARIMA (3,1,1)x(1,1,2,12)



Model Summary – SARIMA (3,1,1)x(1,1,2,12)

Dep. Variable:	Sparkling	No. Observations:	187
Model:	SARIMAX(3, 1, 3)x(1, 1, 2, 12)	Log Likelihood	-1078.437
Date:	Sun, 13 Sep 2020	AIC	2176.875
Time:	20:24:33	BIC	2206.711
Sample:	01-31-1980	HQIC	2188.998
	- 07-31-1995		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4227	0.086	-4.913	0.000	-0.591	-0.254
ar.L2	-0.9092	0.053	-17.290	0.000	-1.012	-0.806
ar.L3	0.1426	0.087	1.641	0.101	-0.028	0.313
ma.L1	-0.4114	0.078	-5.283	0.000	-0.564	-0.259
ma.L2	0.4623	0.083	5.584	0.000	0.300	0.625
ma.L3	-0.9674	0.104	-9.333	0.000	-1.171	-0.764
ar.S.L12	-0.0701	0.709	-0.099	0.921	-1.459	1.319
ma.S.L12	-0.4550	0.721	-0.631	0.528	-1.868	0.958
ma.S.L24	-0.0811	0.397	-0.205	0.838	-0.858	0.696
sigma2	1.461e+05	1.04e-06	1.4e+11	0.000	1.46e+05	1.46e+05

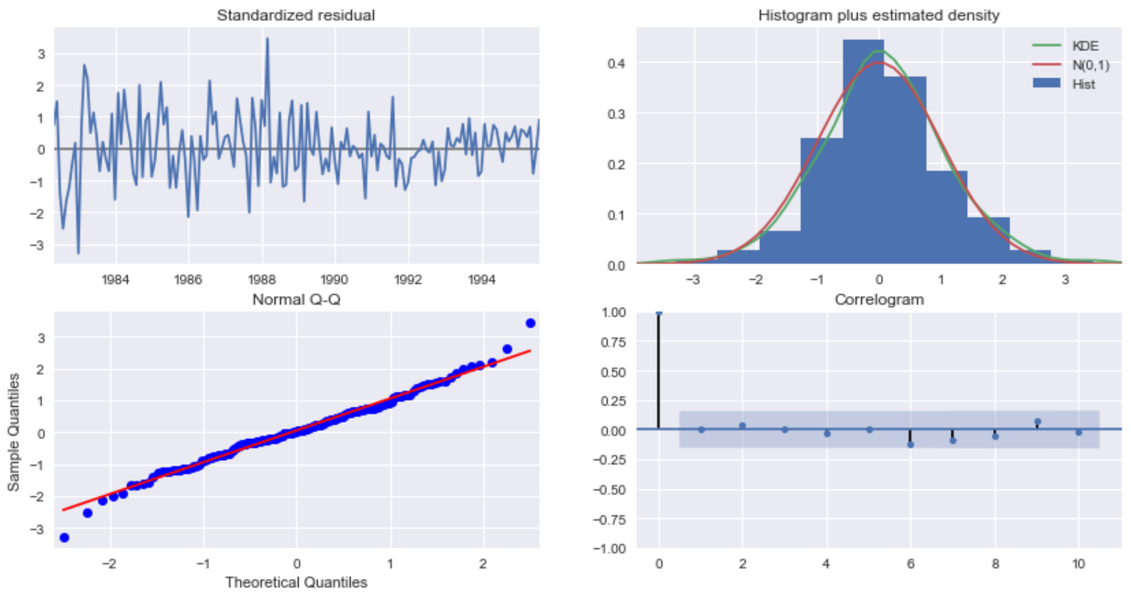
Ljung-Box (Q):	17.11	Jarque-Bera (JB):	35.59
Prob(Q):	1.00	Prob(JB):	0.00
Heteroskedasticity (H):	0.72	Skew:	0.66
Prob(H) (two-sided):	0.26	Kurtosis:	5.03

10. FINAL MODEL

Rose

- The SARIMA model is chosen as the final model for prediction on Rose dataset, as it provide confidence interval and better explainability of the model
- The diagnostics plot of the model shows that the residuals follow a normal distribution with most values around mean zero. The residuals also follow a straight line in normal QQ plot
- The model summary also provides valuable insights in the model. From the snapshot of summary below it can be understood that MA(1) and seasonal MA(1) term has the highest weightage. The p-values indicates that the terms MA(1) and Seasonal MA(1) are the most significant terms
- The rest of the p-values got values higher than alpha 0.05, which fails to reject the hull hypothesis that these terms are not significant
- Prediction on the Rose time-series is on a wider confidence band than sparkling

Model Diagnostics – SARIMA (4,1,1)x(0,1,1,12)



Model Summary – SARIMA (4,1,1)x(0,1,1,12)

```
==============================================================================================
Dep. Variable:                                Rose   No. Observations:                     187
Model:             SARIMAX(4, 1, 1)x(0, 1, 1, 12)   Log Likelihood                   -664.135
Date:                             Sun, 13 Sep 2020   AIC                              1342.270
Time:                                     20:24:35   BIC                              1363.796
Sample:                                 01-31-1980   HQIC                             1351.011
                                      - 07-31-1995
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0914      0.084      1.093      0.274      -0.072       0.255
ar.L2         -0.1077      0.077     -1.393      0.164      -0.259       0.044
ar.L3         -0.1314      0.076     -1.729      0.084      -0.280       0.018
ar.L4         -0.1071      0.078     -1.375      0.169      -0.260       0.046
ma.L1         -0.8270      0.055    -14.901      0.000      -0.936      -0.718
ma.S.L12      -0.5963      0.059    -10.122      0.000      -0.712      -0.481
sigma2       232.4248     24.359      9.542      0.000     184.682     280.168
===================================================================================
Ljung-Box (Q):                       35.39   Jarque-Bera (JB):                 5.30
Prob(Q):                              0.68   Prob(JB):                         0.07
Heteroskedasticity (H):               0.22   Skew:                             0.04
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.89
===================================================================================
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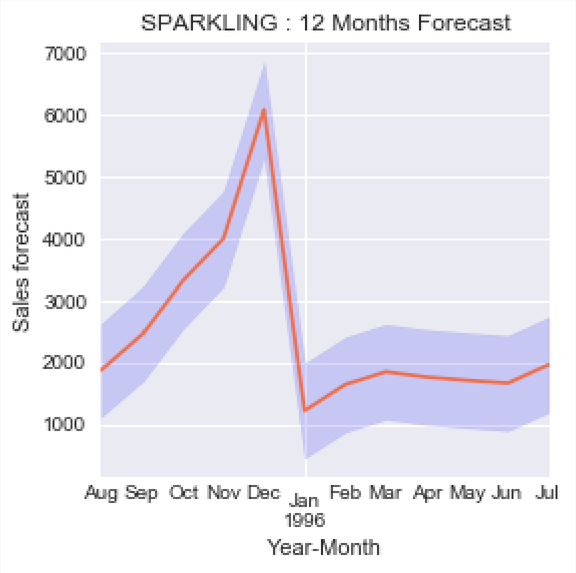
10. RECOMMENDATIONS

Sparkling

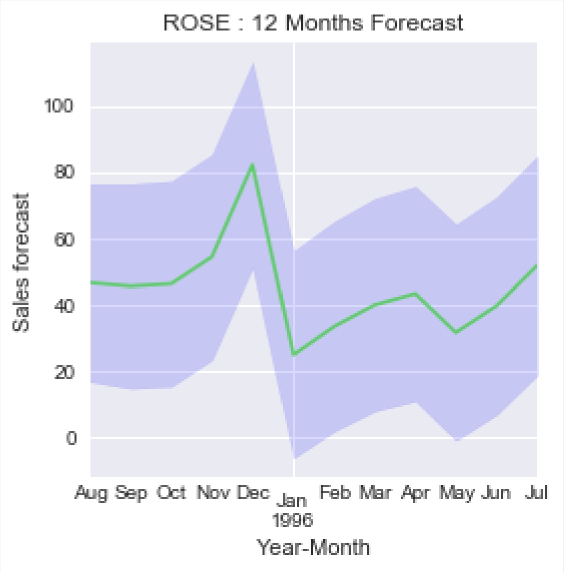


Forecasted Values

	Sparkling
1995-08-31	1873.20
1995-09-30	2445.15
1995-10-31	3312.82
1995-11-30	3994.61
1995-12-31	6084.20
1996-01-31	1216.50
1996-02-29	1640.54
1996-03-31	1847.26
1996-04-30	1762.31
1996-05-31	1708.44
1996-06-30	1663.80
1996-07-31	1961.50

- The model forecasts sale of **29510** units of Sparkling wine in 12 months into future. Which is an average sale of **2459 units per month**
- The seasonal sale in December 1995 will hit a maximum of **6084 units**, before it drops to the lowest sale in January 1996; at **1216 units**.
- The wine company is recommended to ramp up their procurement and production line in accordance with the above forecasts for the **third quarter of 1995** (October, November and December), which is a total of **13,392 units** of sparkling wine is expected to be sold.
- The forecast also indicates that the year-on-year sale of sparkling wine is not showing an upward trend. The winery must adopt innovative marketing skills to improve the sale compared to previous years
- Adding more exogenous variable into the timeseries data can improve forecasts

Rose



Forecasted Values

	ROSE
1995-08-31	46.54
1995-09-30	45.51
1995-10-31	46.23
1995-11-30	54.32
1995-12-31	82.21
1996-01-31	24.81
1996-02-29	33.35
1996-03-31	39.87
1996-04-30	43.23
1996-05-31	31.53
1996-06-30	39.56
1996-07-31	51.70

- The model forecasts sale of **539 units** of Rose wine in 12 months into future. Which is an average sale of **45 units per month**
- The seasonal sale in December 1995 will reach a maximum of **82 units**, before it drops to the lowest sale in January 1996; at **25 units**.
- Unlike Sparkling wine, Rose wine sells very low number of units and the standard deviation is only **14.5**. Which means that higher demand does not impact procurement and production
- Apart from higher sale in November and December months, Rose sales will be above average in the summer months of July and August
- The winery should investigate the low demand for Rose wine in market and make corrective actions in marketing and promotions

THANK YOU