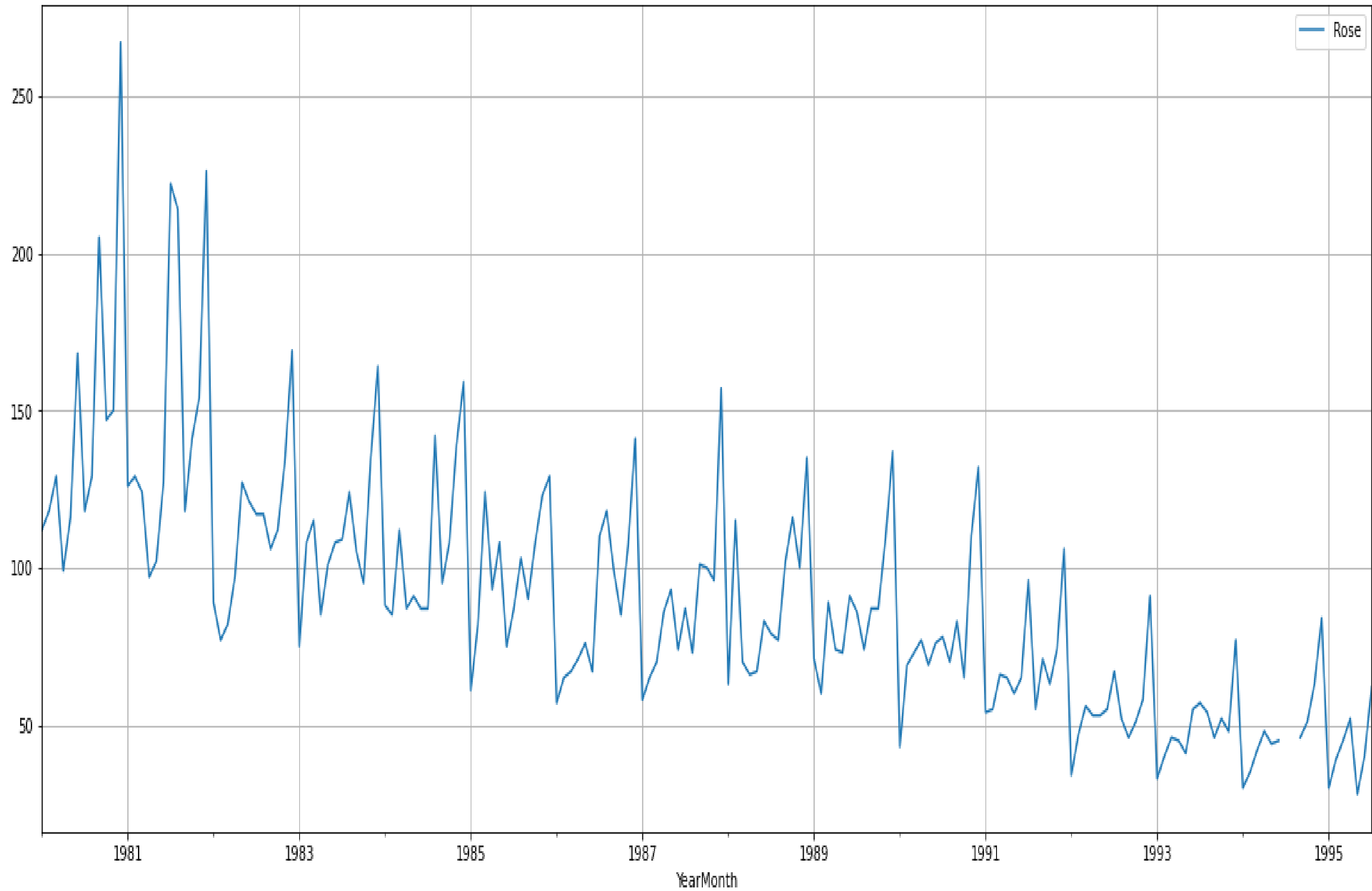
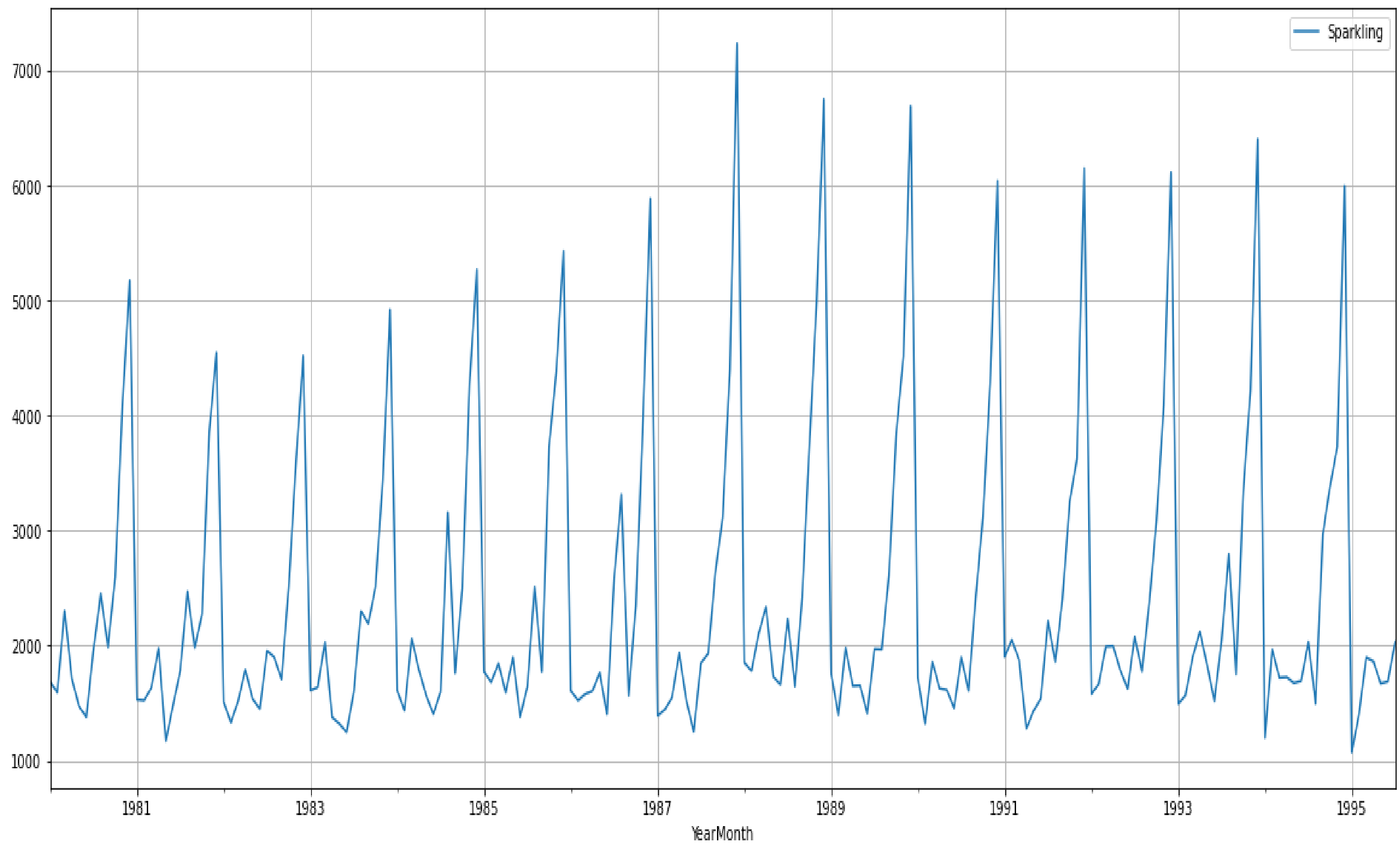
1. **Read the data as an appropriate Time Series data and plot the data.**

Below is the plot for Rose dataset :-



Below is the plot for Sparkling dataset :-



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

Below is the five number summary for the rose data set :-

	count	mean	std	min	25%	50%	75%	max
Rose	185.0	90.394595	39.175344	28.0	63.0	86.0	112.0	267.0

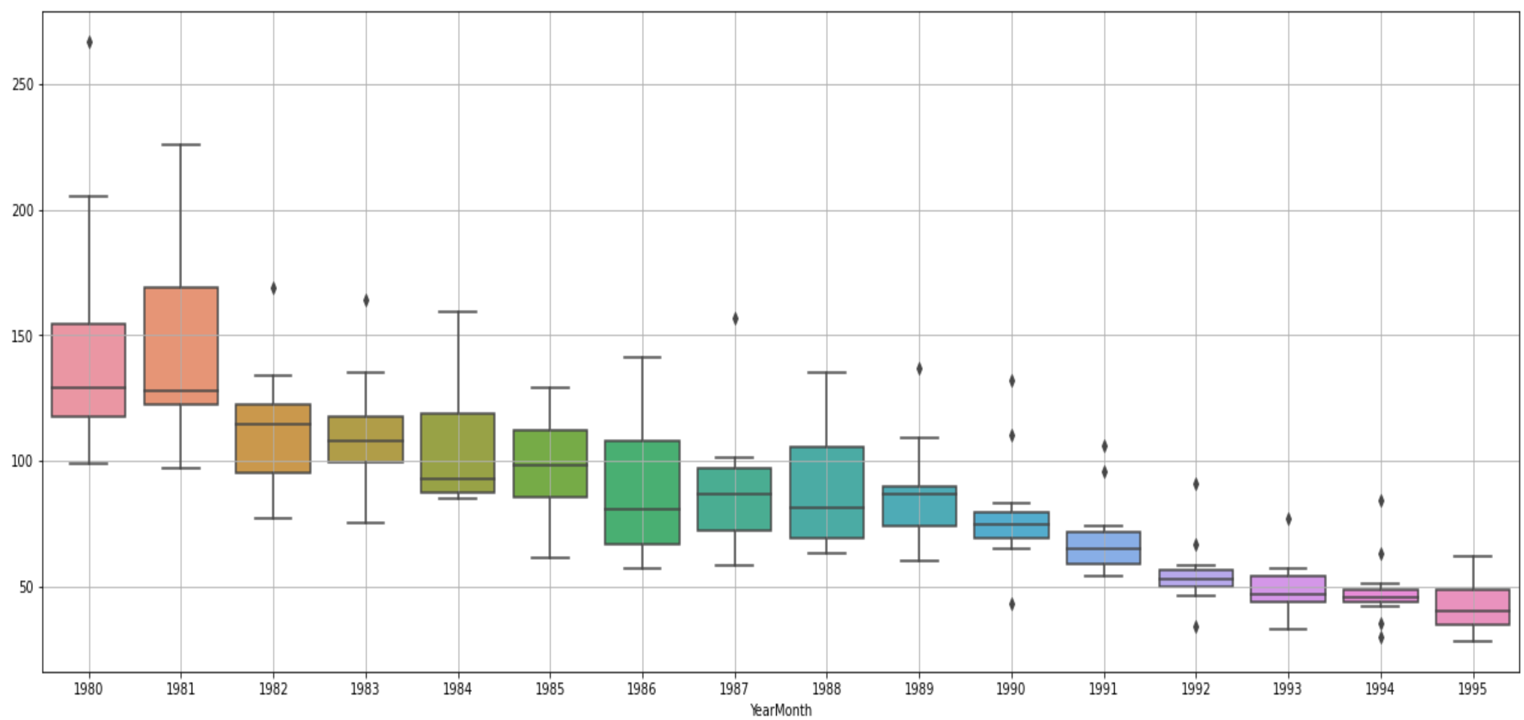
Below is the five number summary for the sparkling data set :-

	count	mean	std	min	25%	50%	75%	max
Sparkling	187.0	2402.417112	1295.11154	1070.0	1605.0	1874.0	2549.0	7242.0

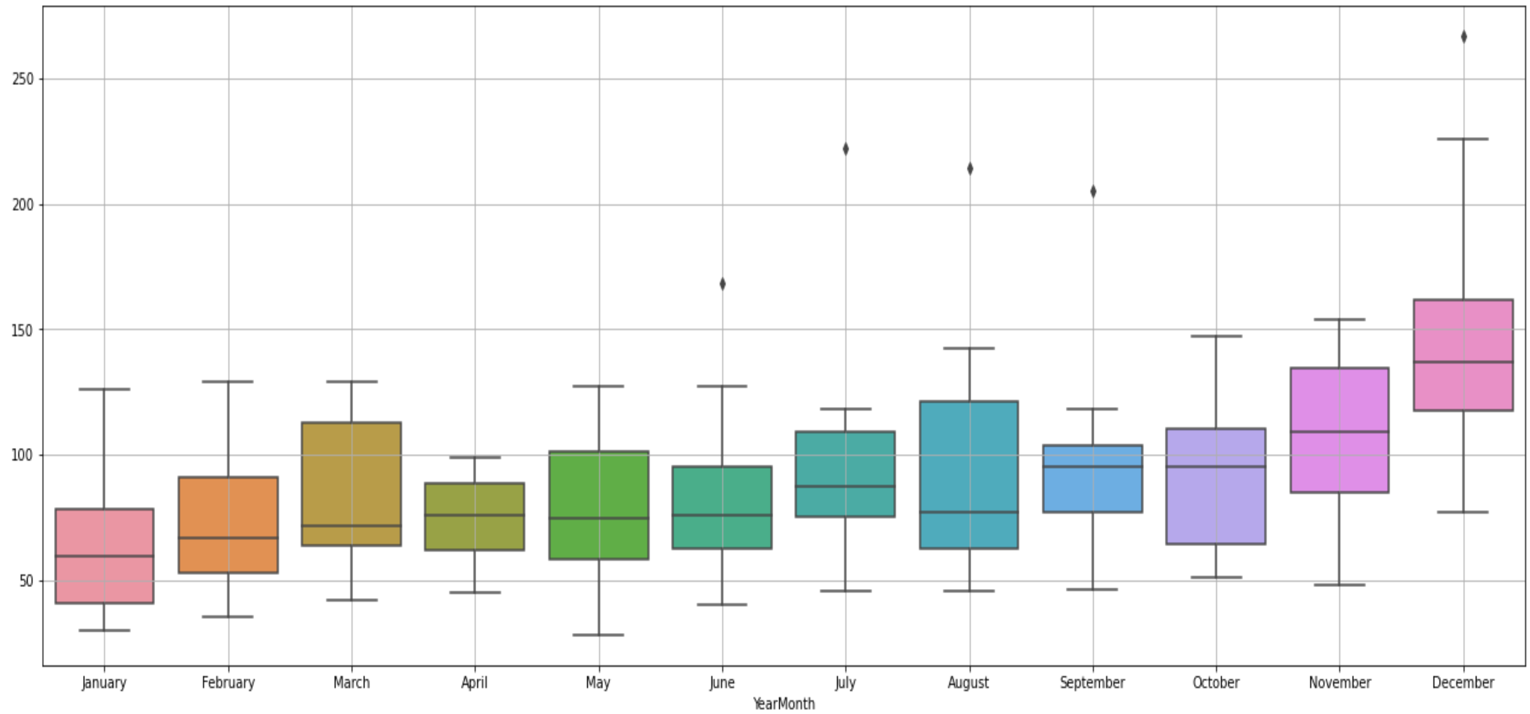
Rose datasets have two months with null information as below based on the null check. Sparkling data set is free of null values.

	Rose
YearMonth	
1994-07-01	NaN
1994-08-01	NaN

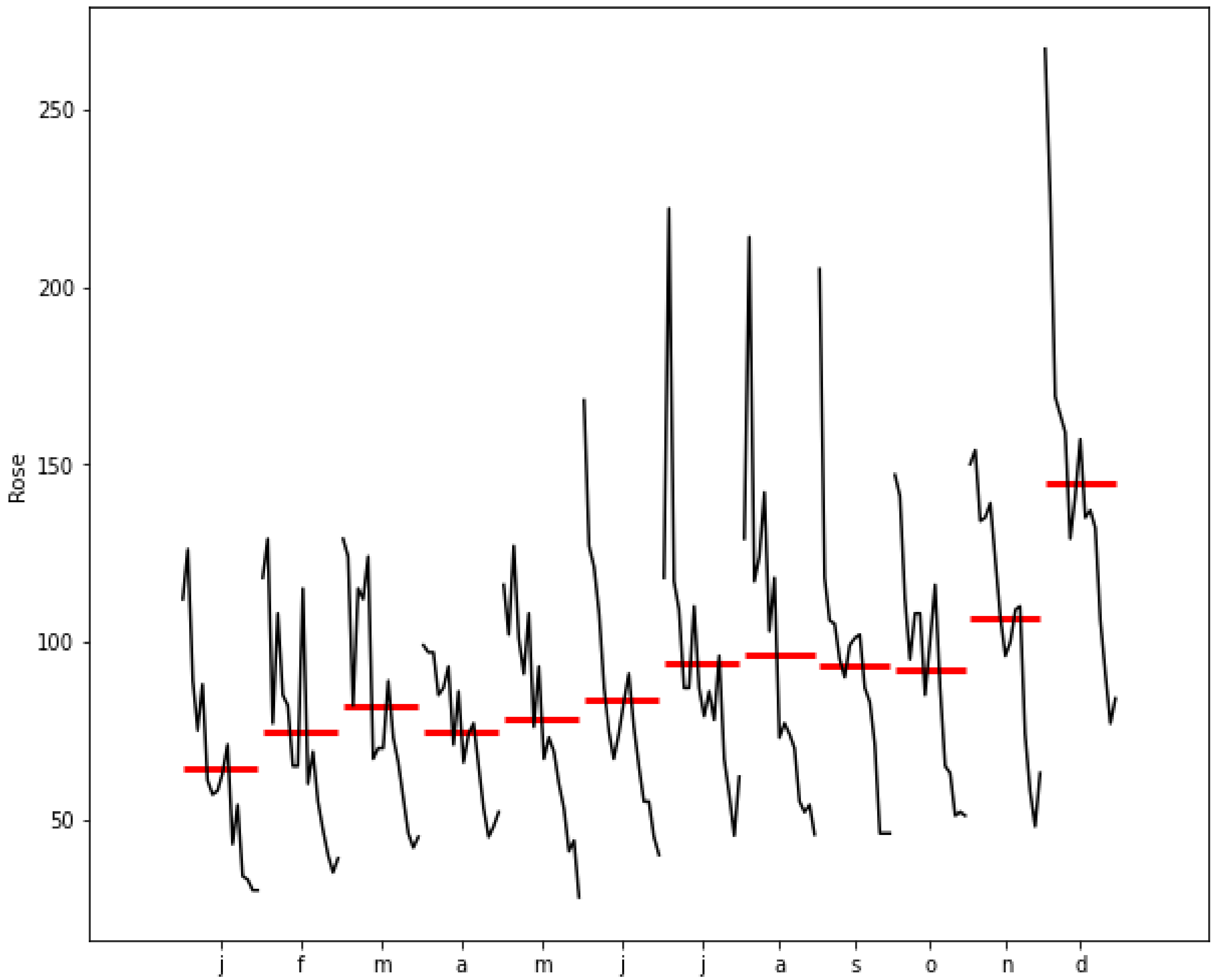
Following is the box plot depicting spread of sales for Rose wine across years for the entire data set. This depicts the presence of trend in the Rose wine sales and there is decreasing trend in the sales for Rose wine across the years. Also depicts that later years has had comparatively more outliers in the sales compared to earlier years.



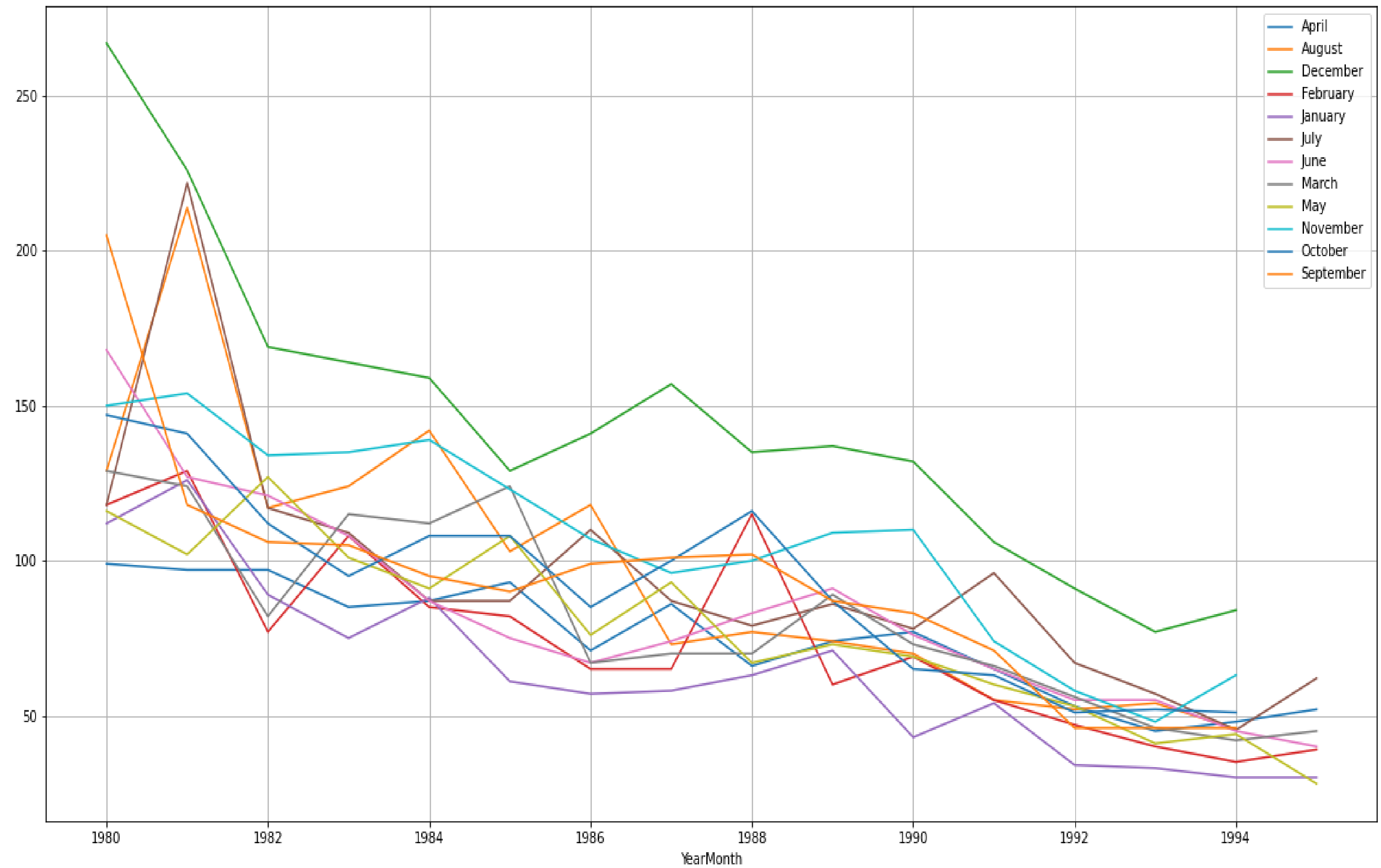
Following is the box plot depicting spread of sales for Rose wine by month across the years for the entire data set. It can be noticed that December has had the highest sales compared to other months. Also very minimal outliers are noticed during the second half of the year generally.



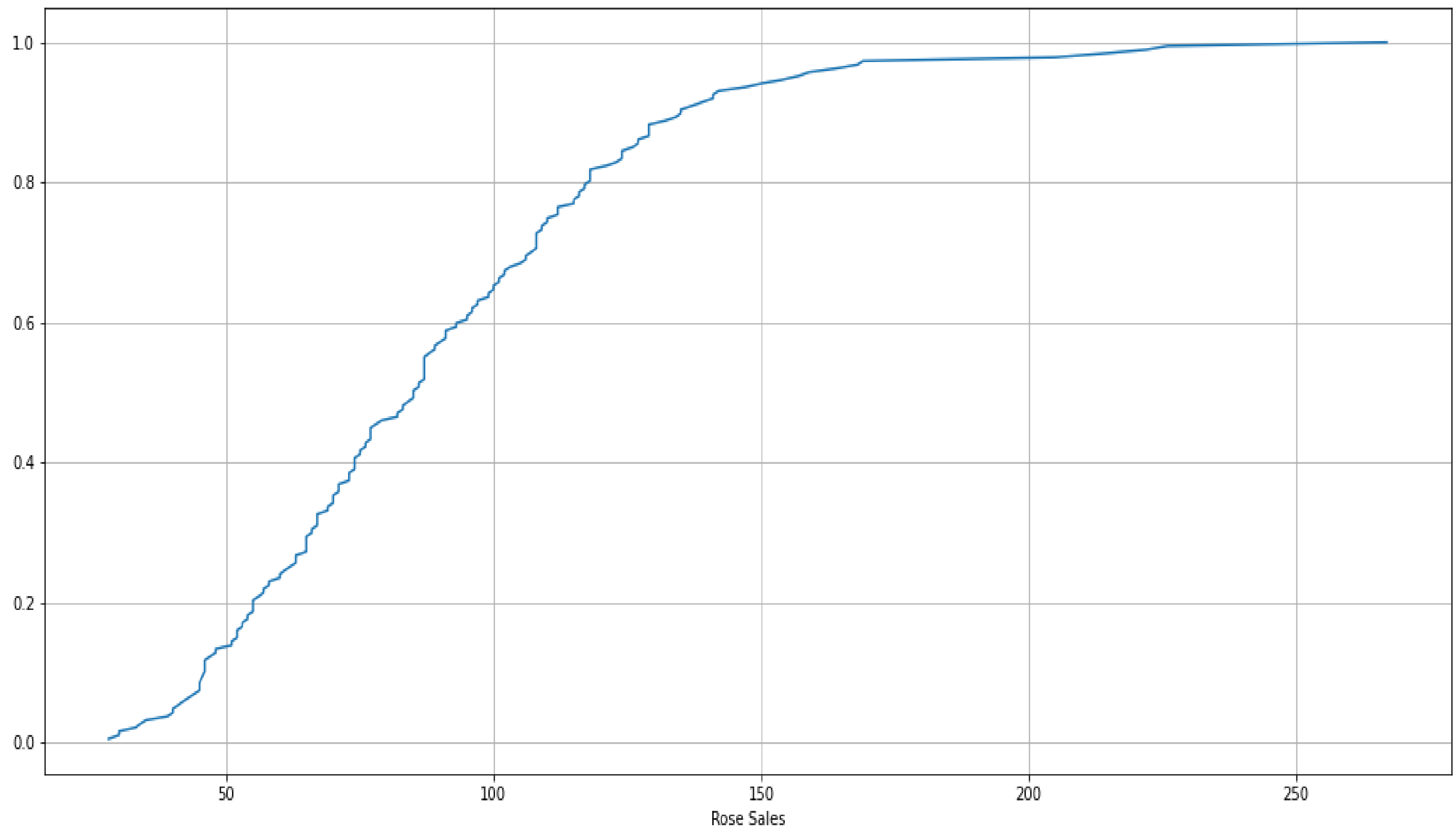
The below plot depicts the spread of Rose wine sales by each month putting all the years together. This also reveals December had a wider range of transactions compared to other months with highest mean sales too.



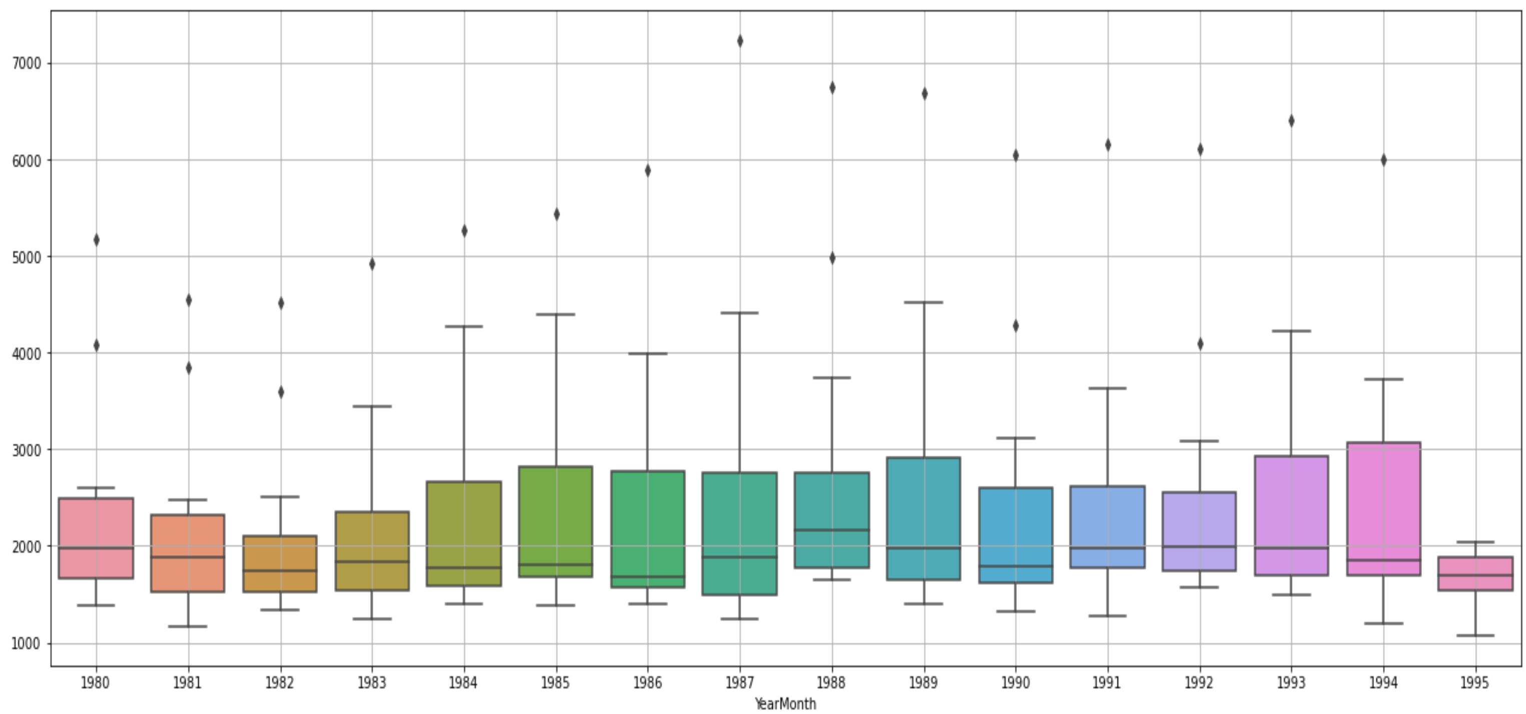
The below plot depicts the trend of monthly sales across years for Rose wine. This depicts that while the Rose wine sales are decreasing across years, the December month has had the peak sales during this period and January has the lowest.



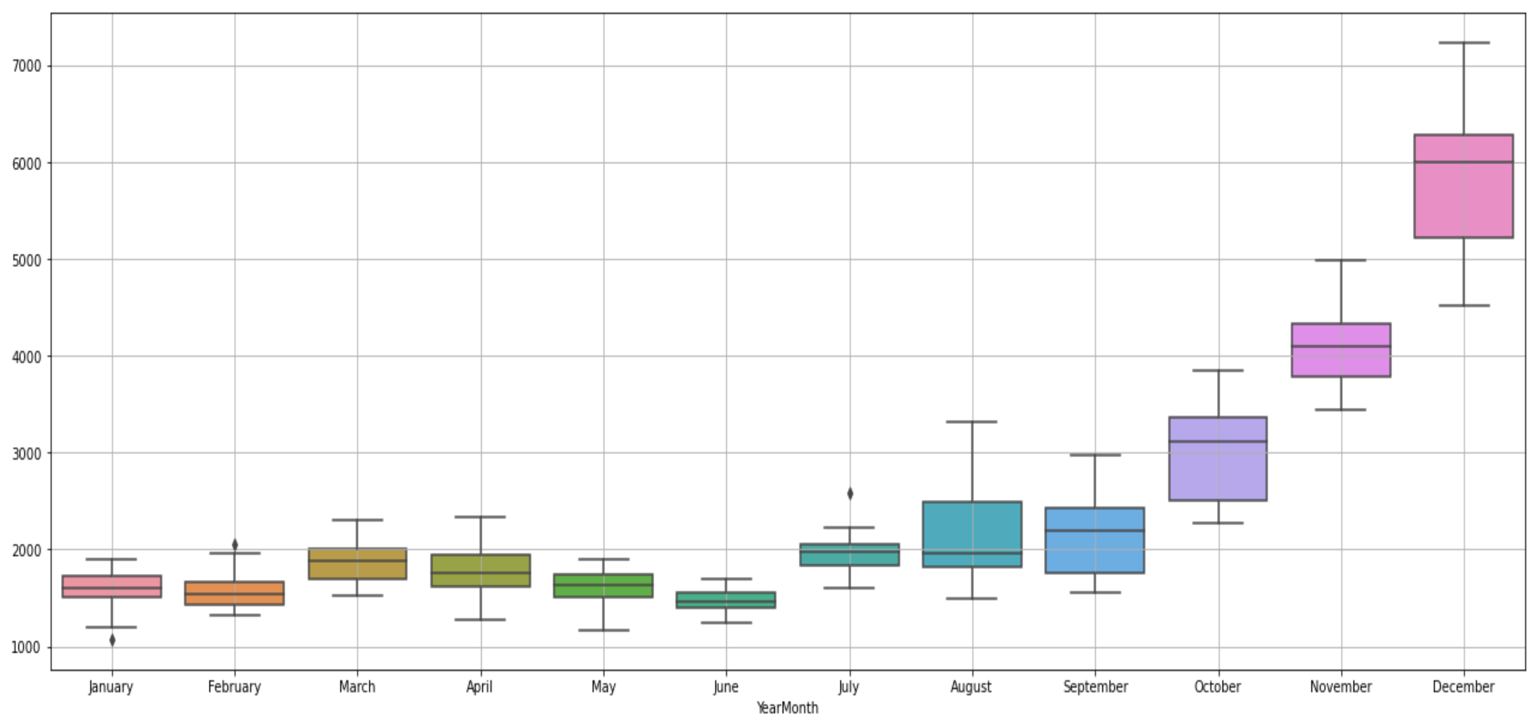
Below plot depicts the empirical cumulative distribution of the sales for Rose wine sales.



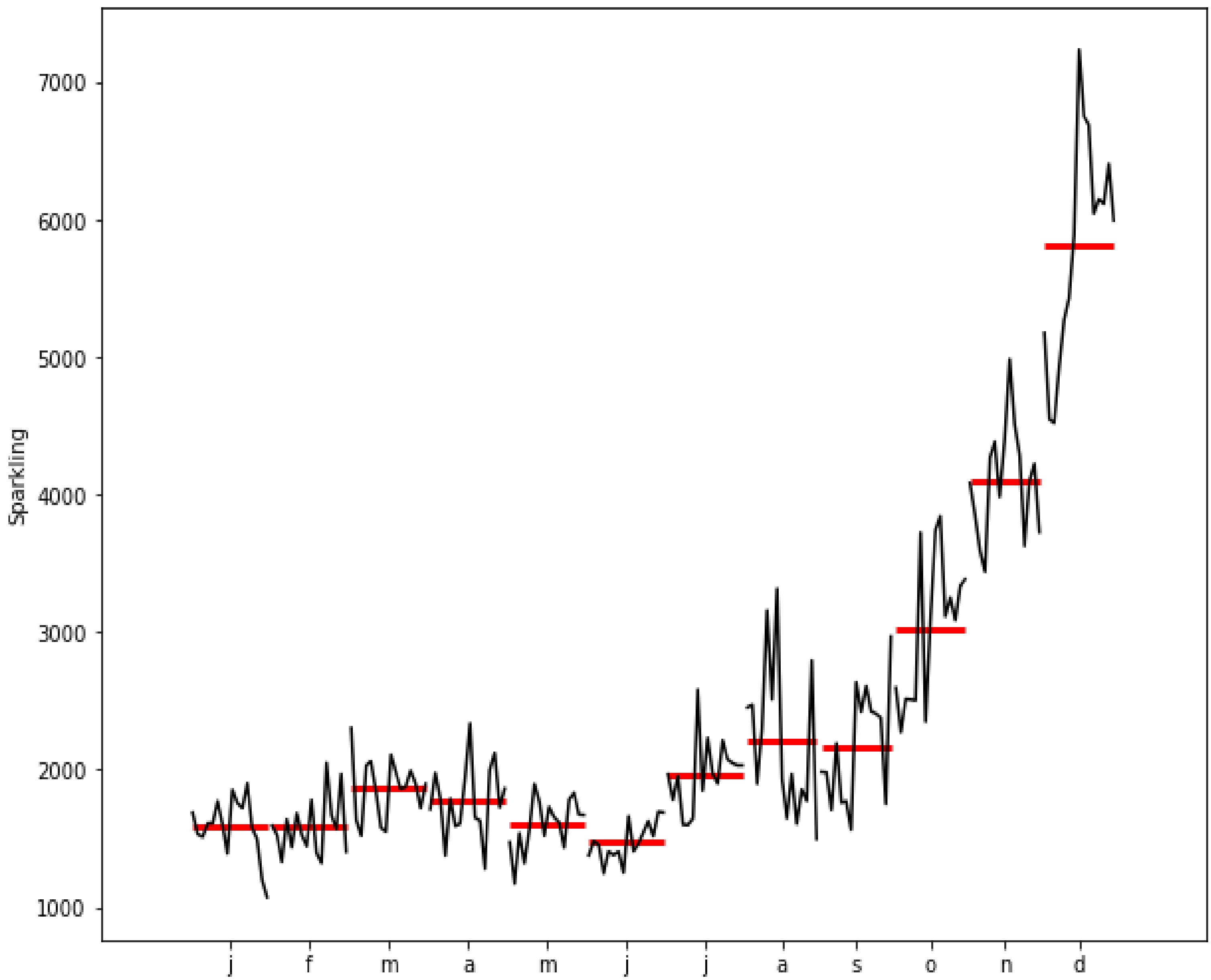
Below plot depicts the pattern of sales across years for the sparkling wine. This depicts that the sales for the sparkling sales across years more or less tends to approximately the same and there isn't a significant trend. However in this case outliers are spread across almost all years except 1995.



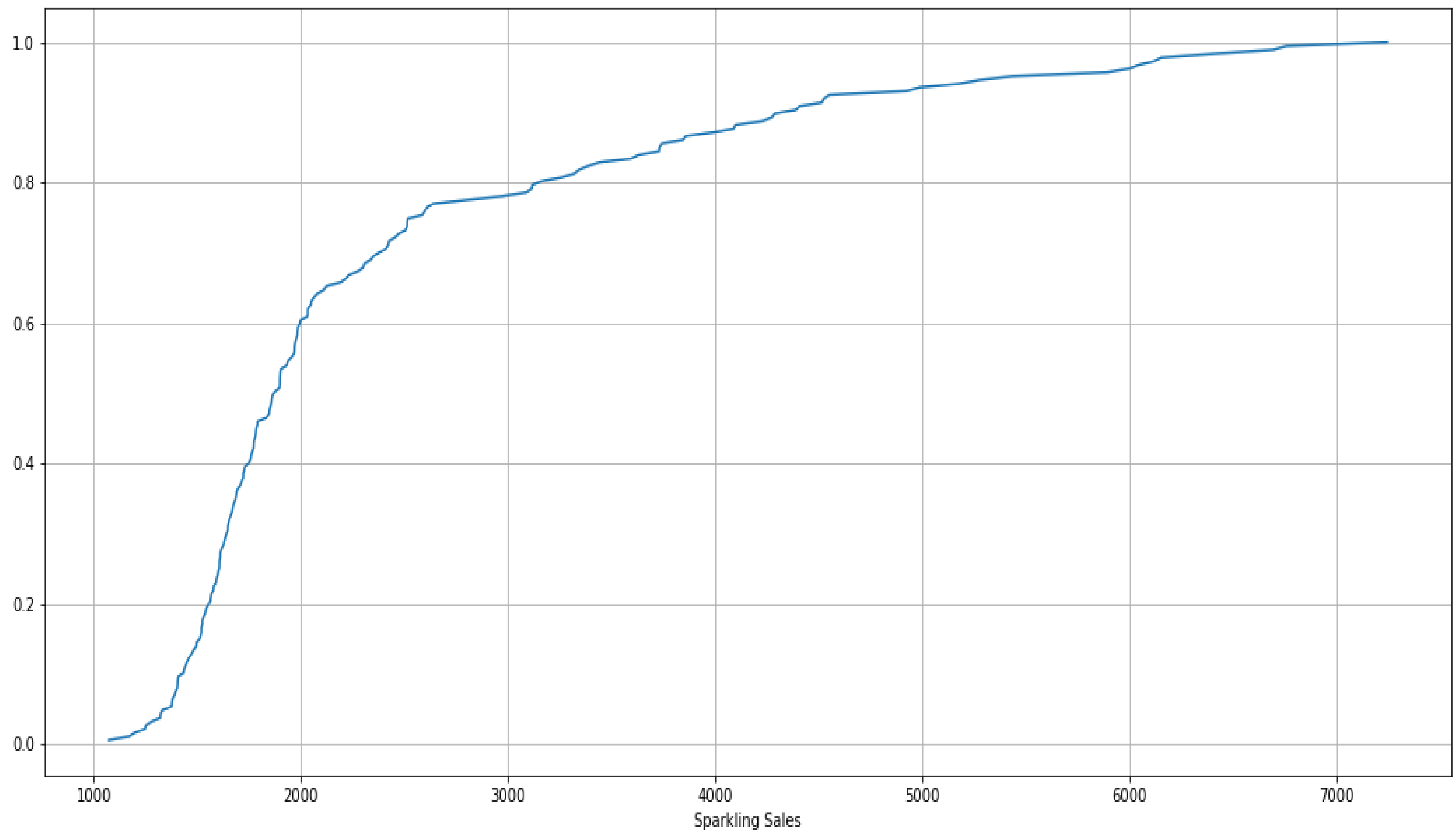
Below plot depicts sales pattern across months depicts an increasing trend towards the later half of the year with December showing highest sales.



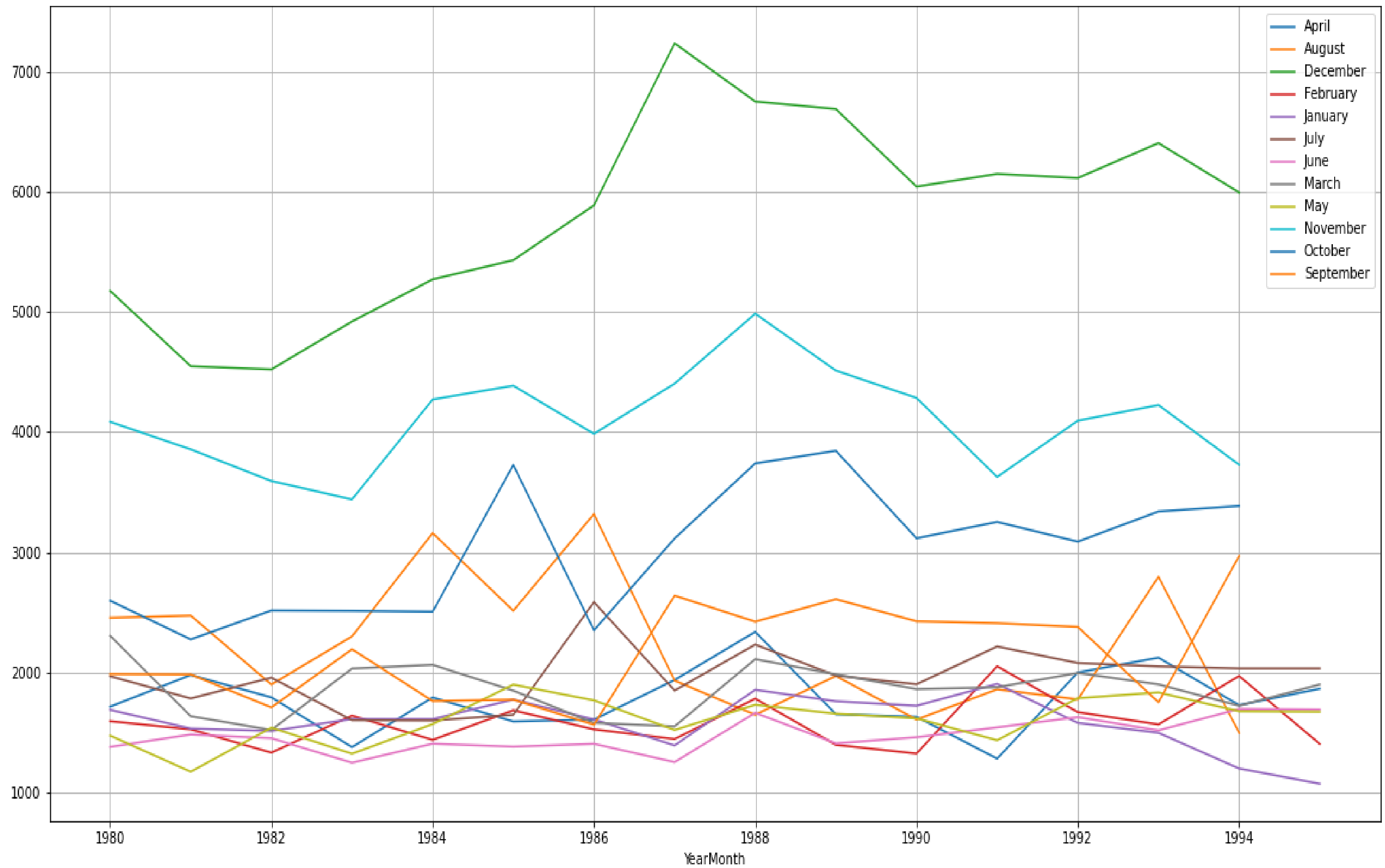
The below plot depicts the spread of sparkling wine sales by each month putting all the years together. Here also its noticed that December has had a wider range of sales comparatively than the other months.



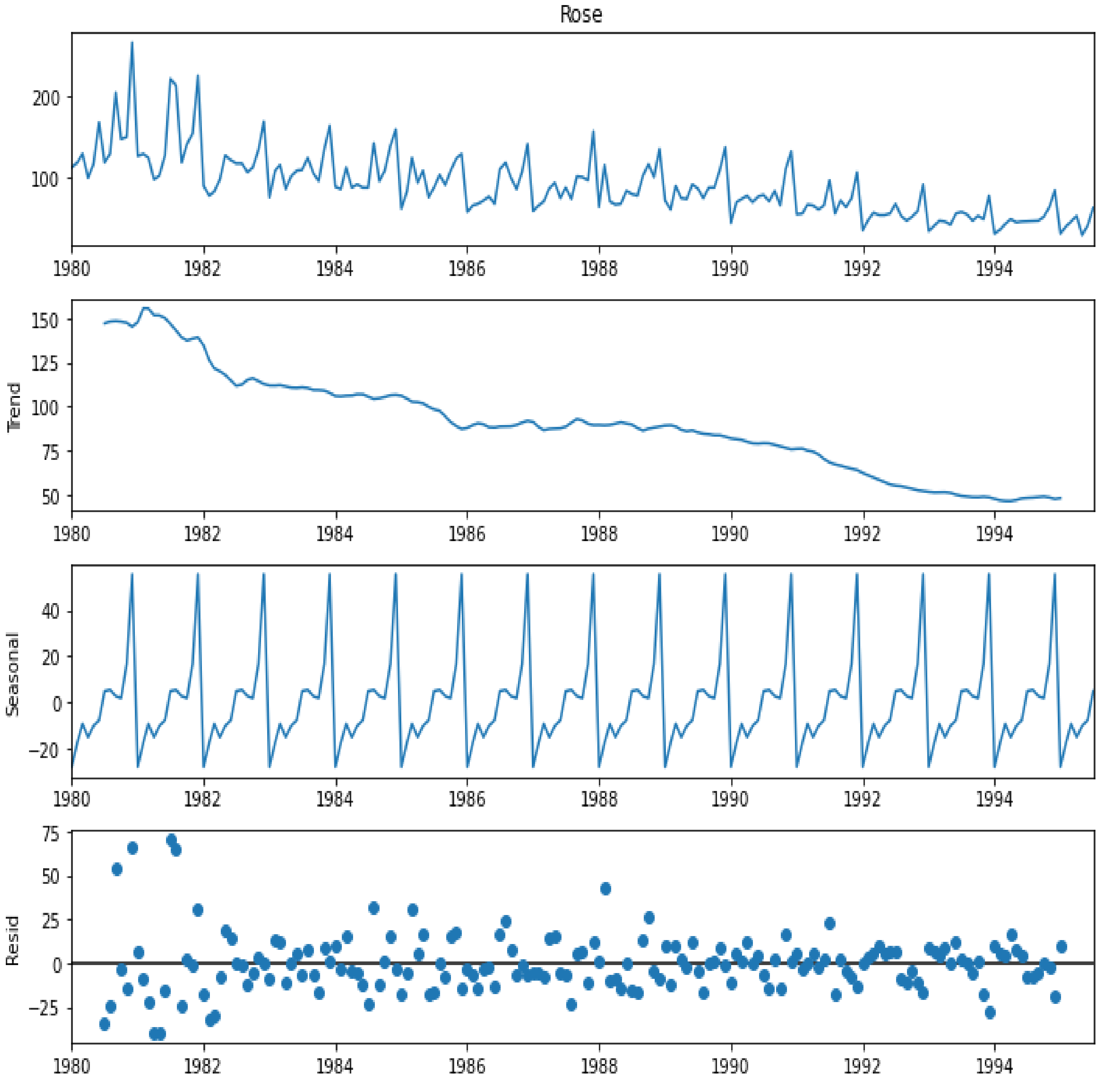
Below depicts the empirical cumulative distribution of sparkling sales :-



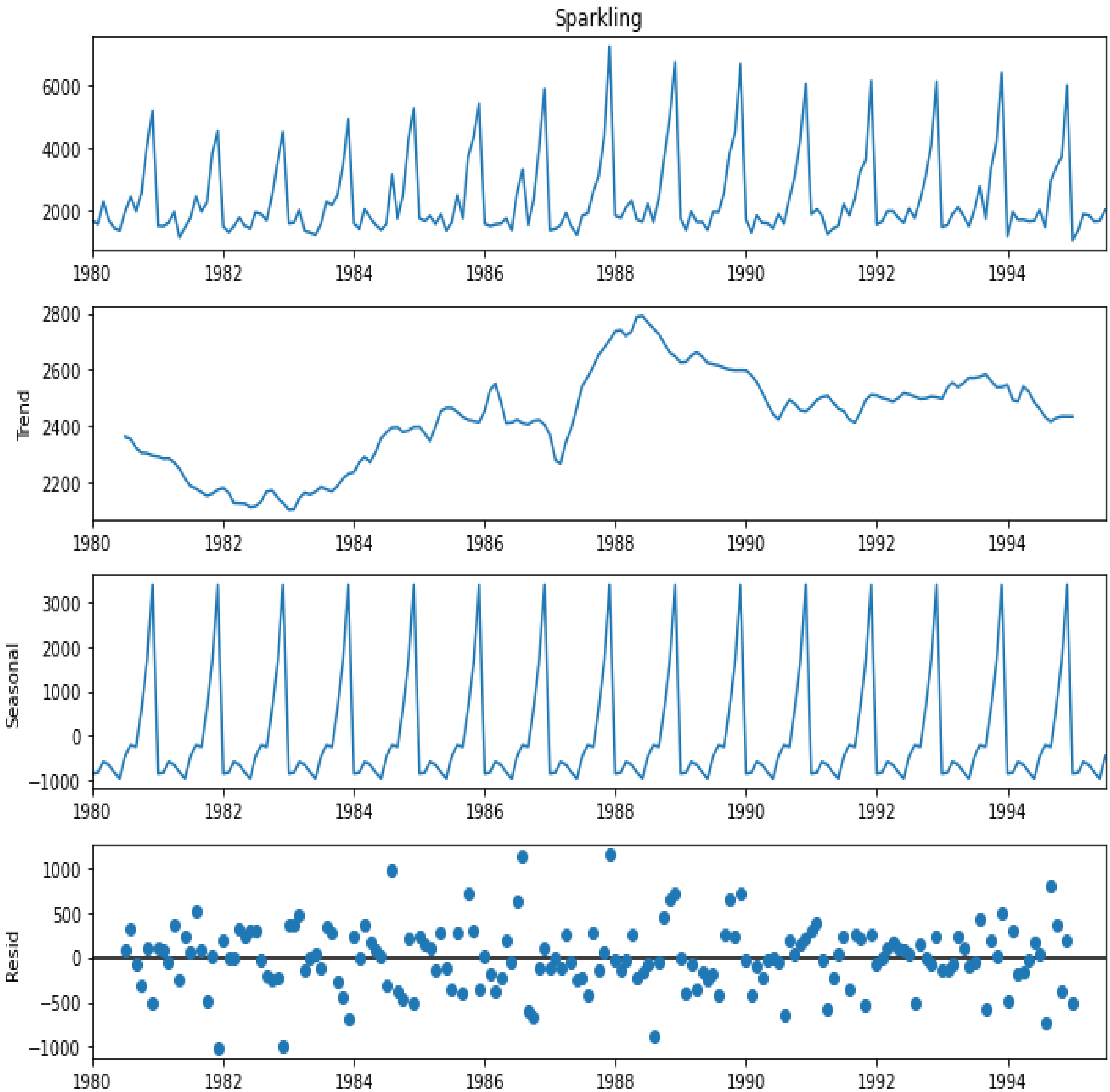
The below plot depicts the trend of monthly sales across years for Sparkling wine. The plot depicts trends across the months with December showing the highest sales across all the years while there are many months cluttering around the lower side of the sales trend such as January, February, July.



Below is the seasonal decomposition of the Rose data set depicting level, trend, seasonality and residual.

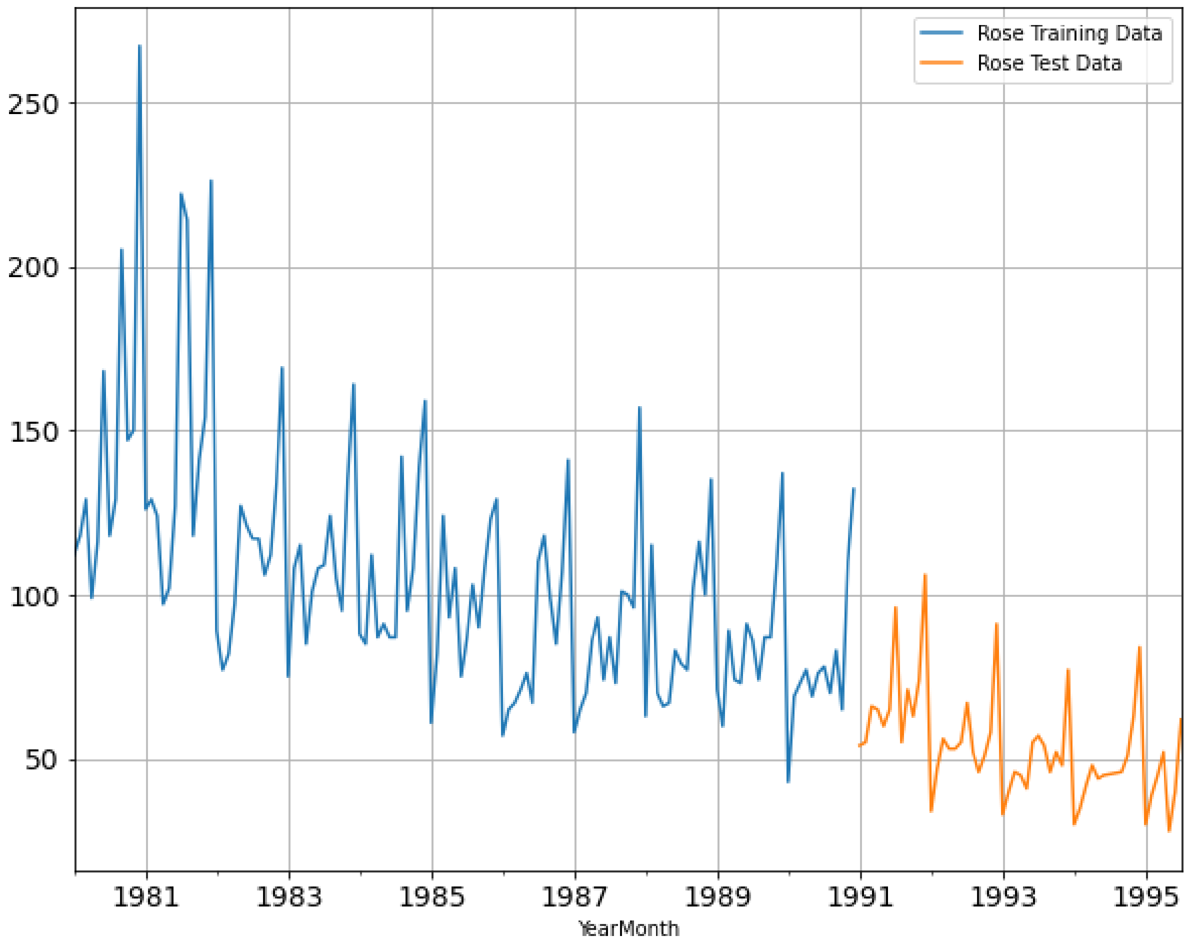


Below is the seasonal decomposition of the sparkling data set depicting level, trend, seasonality and residual.

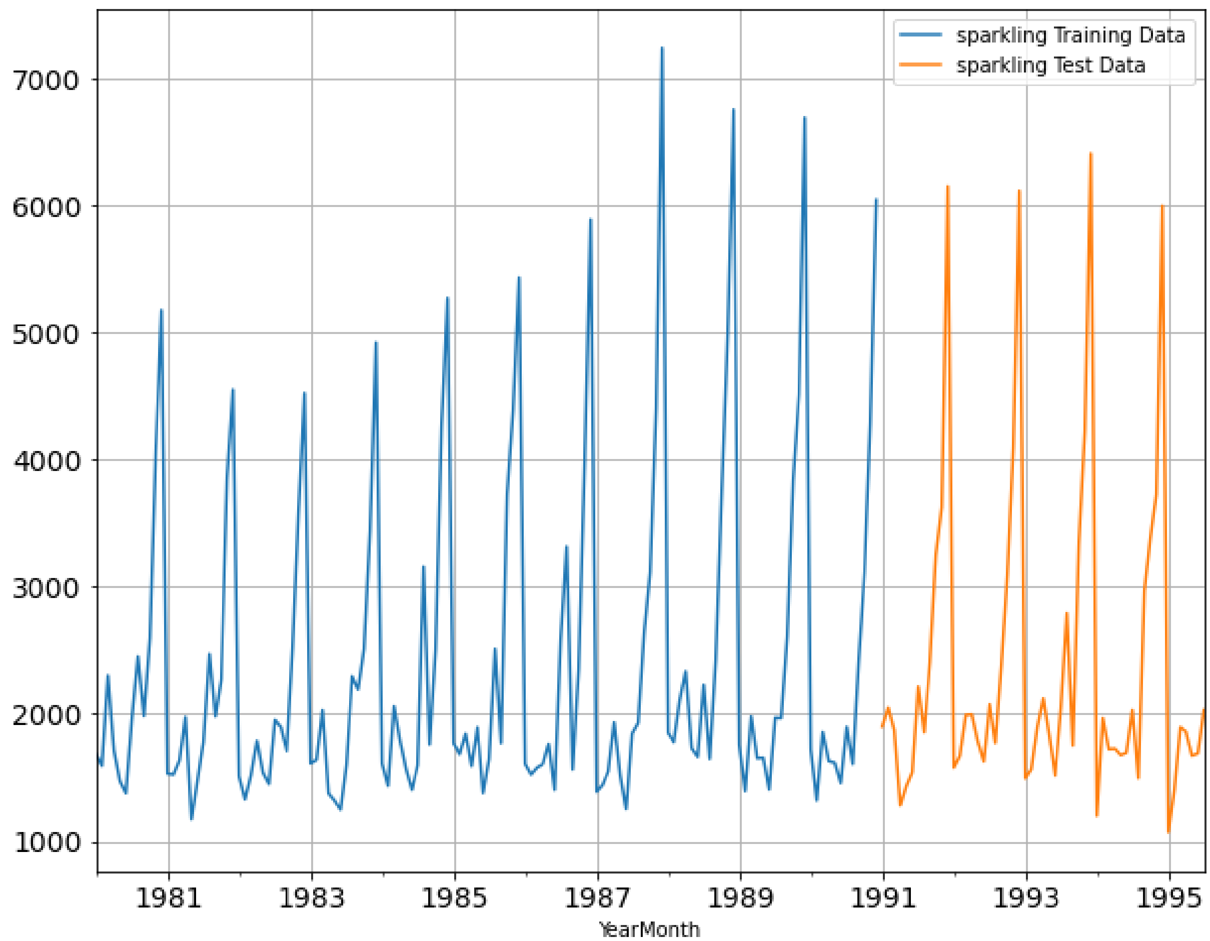


3. Split the data into training and test. The test data should start in 1991.

Please check below for the plot of training and testing data set for the Rose wine after the data prior to 1991 has been split into the training while from 1991 and beyond splits into test data.



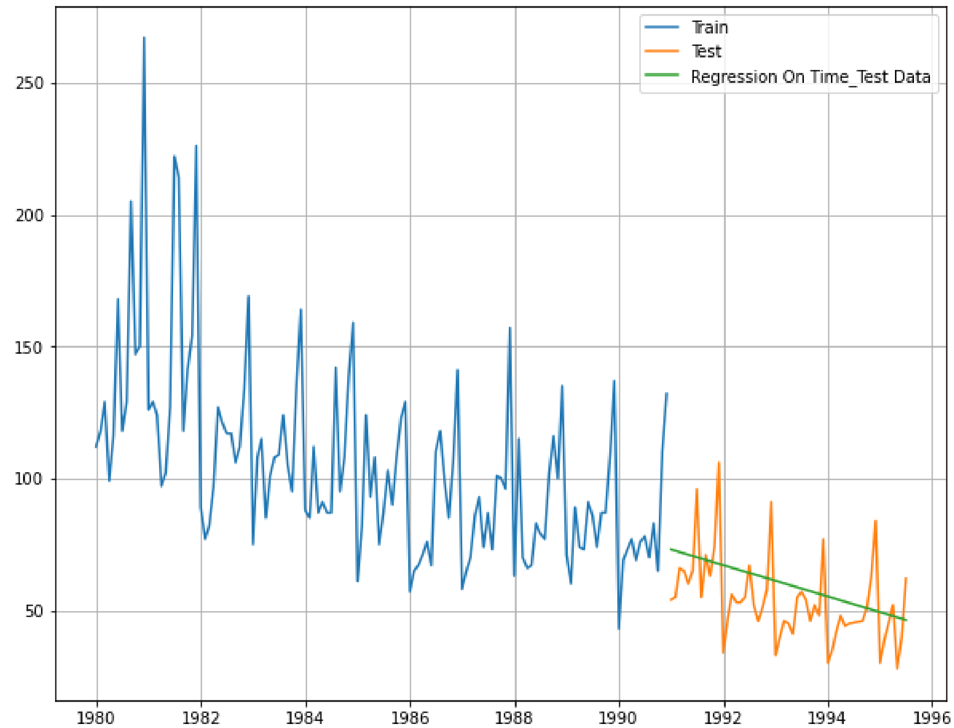
Please check below for the plot of training and testing data set for the Sparkling wine after the data prior to 1991 has been split into the training while from 1991 and beyond splits into test data.



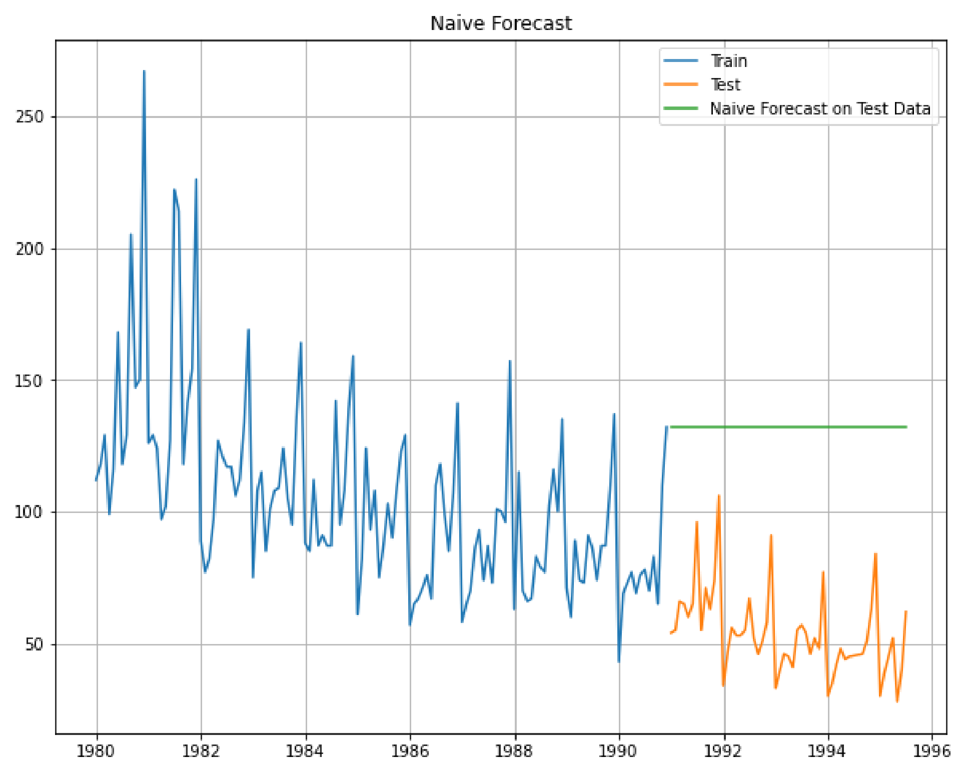
4. **Build various exponential smoothing models on the training data and evaluate the model using RMSE on the test data. Other models such as regression,naïve forecast models, simple average models etc. should also be built on the training data and check the performance on the test data using RMSE.**

MODELS FOR ROSE WINE DATA SET ->

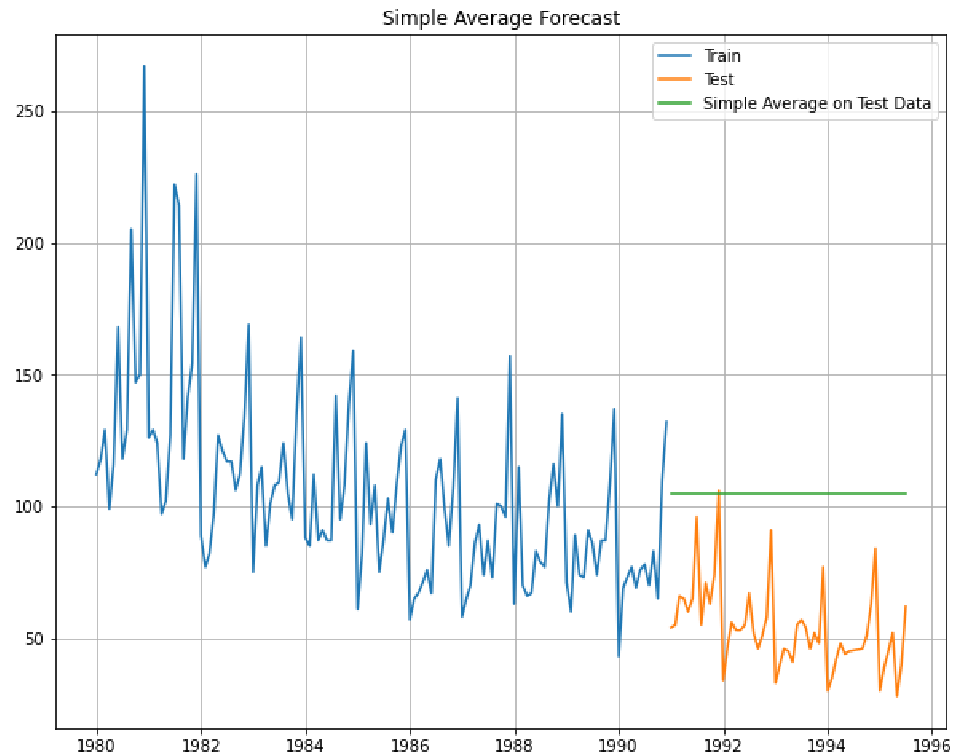
Below plot from Linear Regression model depicts the prediction on the test data overlaps with the trend from the actuals however being smoothened to the straight line with just the trend without any seasonality.



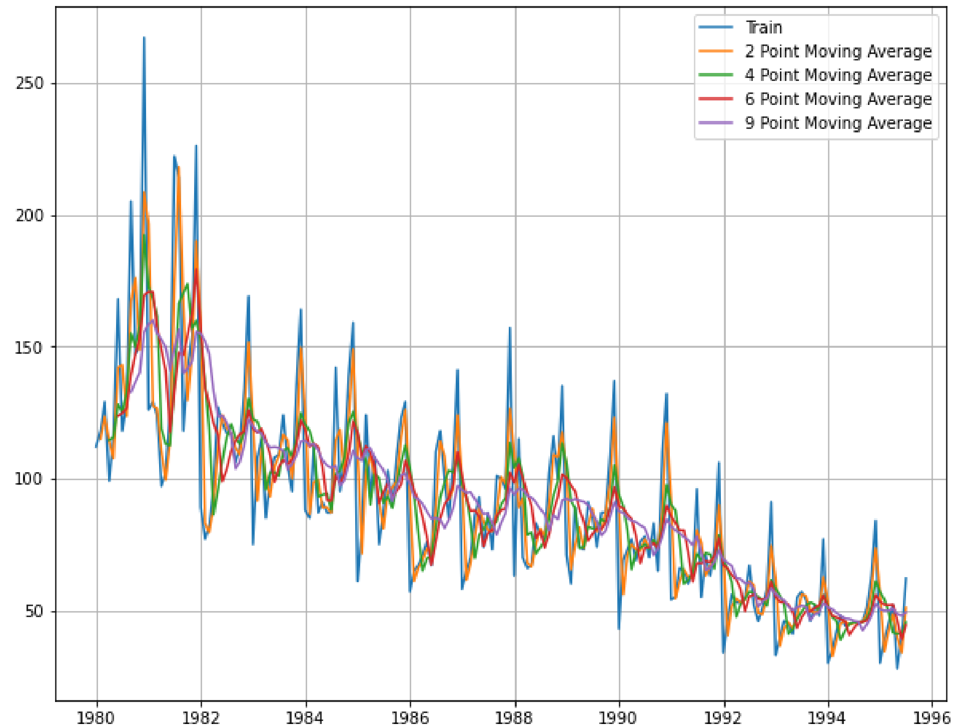
Below plot from Naive model depicts the prediction on the test data being away from the actuals and being constant throughout while having values higher than the originals.



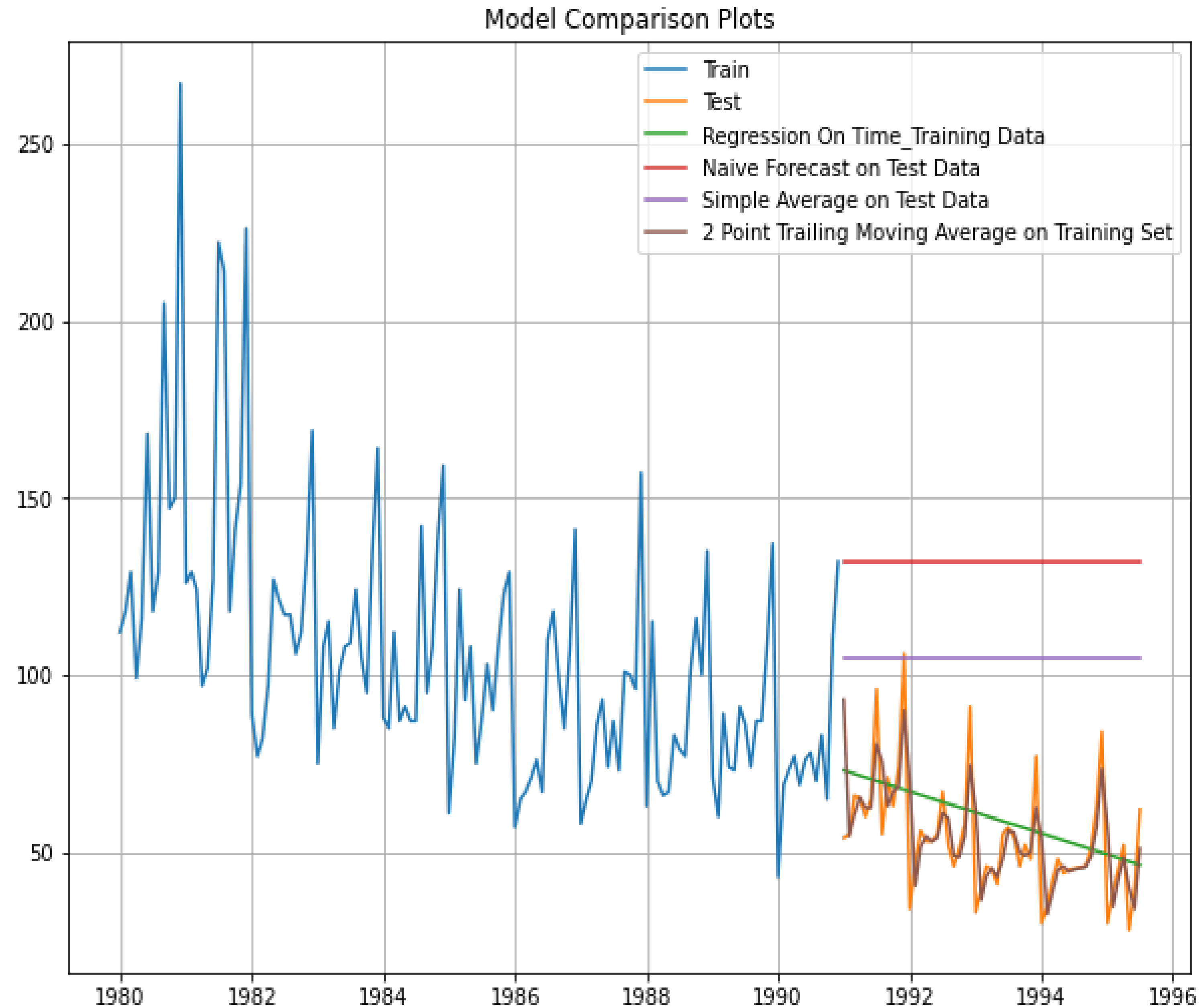
Below plot from simple Average model depicts the prediction on the test data being away from the actuals and being constant throughout while having values higher than the originals.



Plot below depicts the outcome of forecast against the test data for the moving average model with 2 point moving average showing up more closer to the original values however higher point moving average gets smoothened more and more as the points increase.



Below chart provides comparative chart of prediction trend after adopting respective straight forward models against the time series with 2 point moving average model catching up much closer to the trend and the seasonality



We can now move to 3 types of smoothing models across single, double and triple exponential smoothing models.

Exponential smoothing models apply weighted averages of past observations with weights decaying as observations get older. Recent observations have significant weightage. Based on the smoothing models one or more parameters control how weights decay and each of these parameters will have its values ranging from 0 to 1.

Below are the comparative error measures (root mean squared error) across the above models with moving average 2 point being the best of all. However considering the objective of taking the model application to the dataset beyond this to consider exponential smoothing and ARIMA/SARIMA models we are to compare the performance of other models alone for the given data sets for Rose and Sparkling wines towards narrowing down the best performing model among those based on the RMSE values and predict next 12 months of sales for each of the wines accordingly. Below is just a summary of performance by models so far worked upon with the stated observation above.

Model	RMSE
Linear Regression	15.61187
Naive Model	79.71877
Simple Average	53.46057
Moving Average - rolling 2	11.52928
Movinbg Average - rolling 4	14.4514
Moving Average - rolling 6	14.56633
Moving Average - rolling 9	14.72763

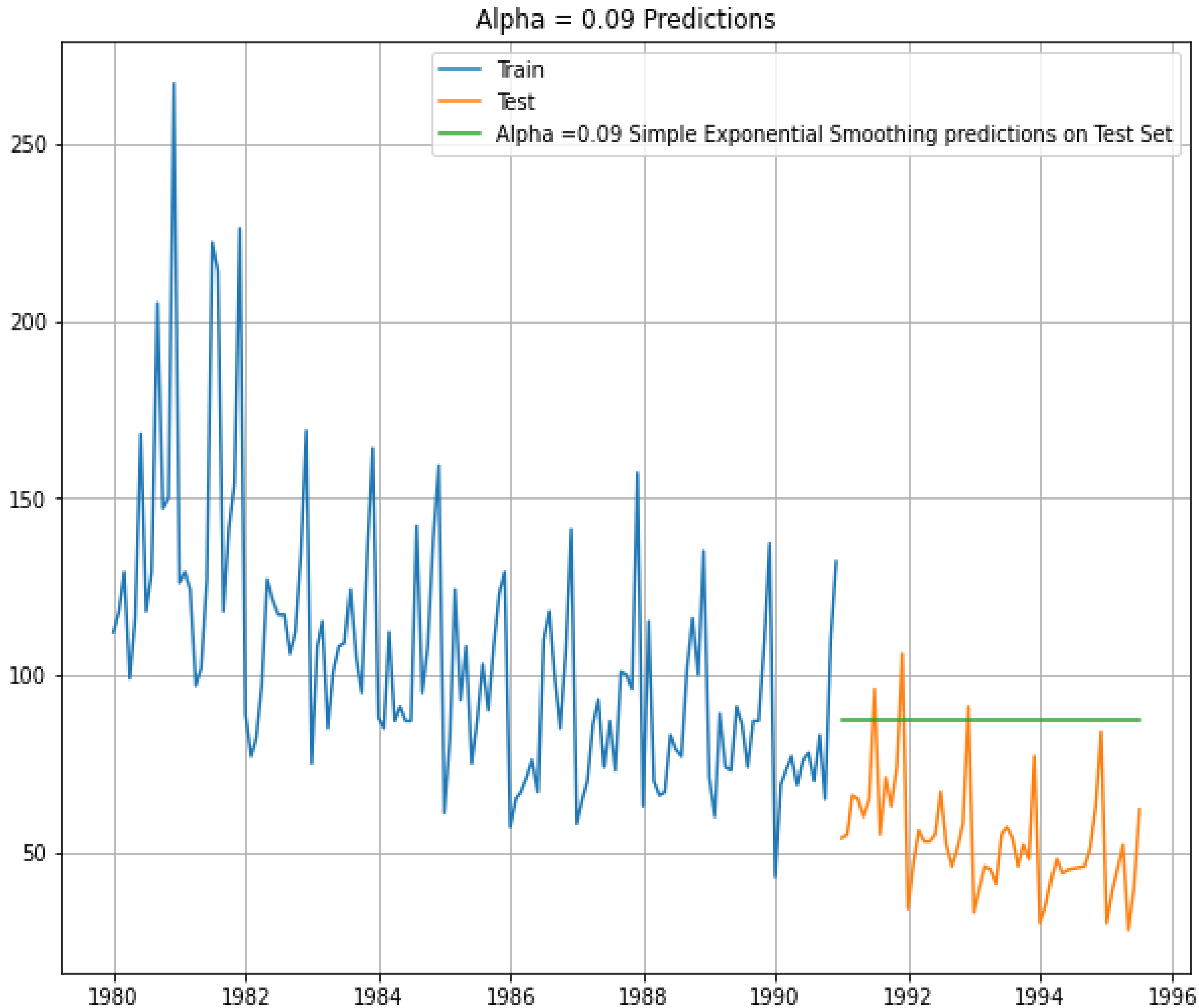
Single exponential smoothing model:

If the time series neither has a noticeable trend or seasonality it is understood to retain only the level and its related parameter that controls the decay of weight across the observations in time series referred to as alpha will range from 0 to 1 with 1 meaning the forecast is closely following the actuals whereas on the converse 0 refers to forecasts are farther from the actual observations with the forecast being more smooth. Please note level refers to the local mean. Alpha smoothens the level.

After auto fitment of a single exponential smoothening model against the training data for Rose wine dataset below are the parameters that could be derived that depicts the smoothening level.

```
{'smoothing_level': 0.09874933517484011,
 'smoothing_trend': nan,
 'smoothing_seasonal': nan,
 'damping_trend': nan,
 'initial_level': 134.38703609891138,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.09 for the single exponential smoothing. The respective RMSE value is 36.79.



Also please note below is the manual fitment done for this SES model across the range of values for the alpha and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha value being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

	RMSE
Alpha:0.3 Single Exponential Smoothing	47.504821
Alpha:0.4 Single Exponential Smoothing	53.767406
Alpha:0.5 Single Exponential Smoothing	59.641786
Alpha:0.6 Single Exponential Smoothing	64.971288
Alpha:0.7 Single Exponential Smoothing	69.698162

Double exponential smoothing model:

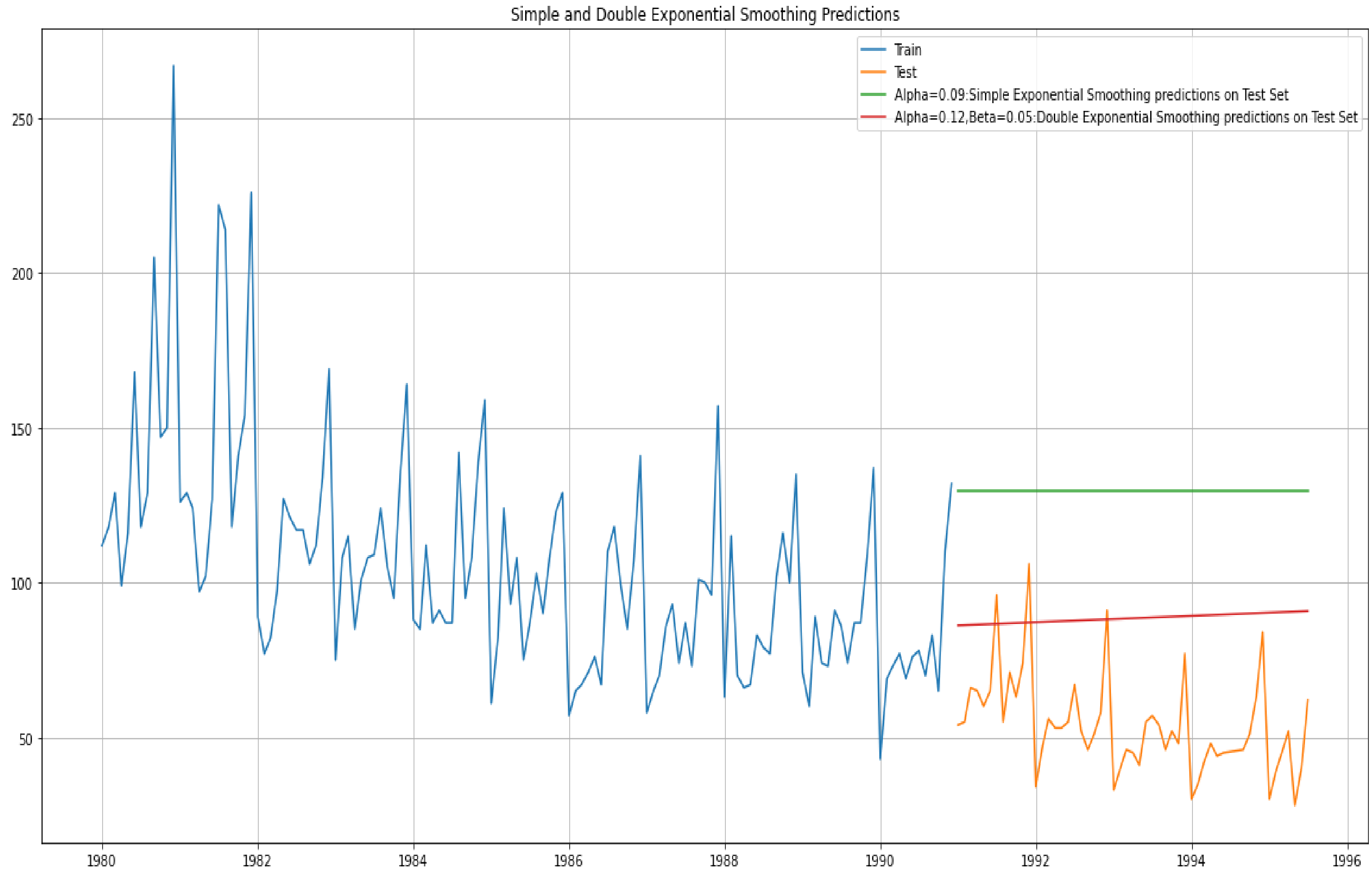
This is a further extension to the single exponential smoothing model and applies to datasets where there is a trend but not seasonality. Hence both level and trend are considered towards weighing the observations from the time series. Apart from the parameter alpha for the level , this introduces the beta parameter for the trend. Beta smoothens the trend.

After auto fitment of double exponential smoothening model against the training data for Rose wine dataset below are the parameters that could be derived that depicts the smoothening level and the trend. Accordingly, the alpha value is 0.12 and the beta value is 0.05. RMSE value for the auto fitted model is 38.28.

```
==Holt model Exponential Smoothing Estimated Parameters ==

{'smoothing_level': 0.12981260063088668, 'smoothing_trend': 0.05376220098709802, 'smoothing_seasona
nan, 'initial_level': 145.73070601479063, 'initial_trend': -0.10069596155782001, 'initial_seasons':
4), 'use_boxcox': False, 'lamda': None, 'remove_bias': False}
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.12, beta value of 0.05 for the double exponential smoothing.



Also please note below is the manual fitment done for this DES model across a range of values for the alpha and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha and gamma value mentioned above being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

	RMSE
Alpha:0.3 Beta:0.3 Double Exponential Smoothing	53.716816
Alpha:0.3 Beta:0.4 Double Exponential Smoothing	57.670101
Alpha:0.3 Beta:0.5 Double Exponential Smoothing	62.159216
Alpha:0.4 Beta:0.3 Double Exponential Smoothing	63.955820
Alpha:0.3 Beta:0.6 Double Exponential Smoothing	66.956973

Triple exponential or Holt Winters model

Apart from level (alpha), trend (beta) this model applies to the data with seasonality and hence introduces a new parameter called gamma. Gamma smoothens the seasonality.

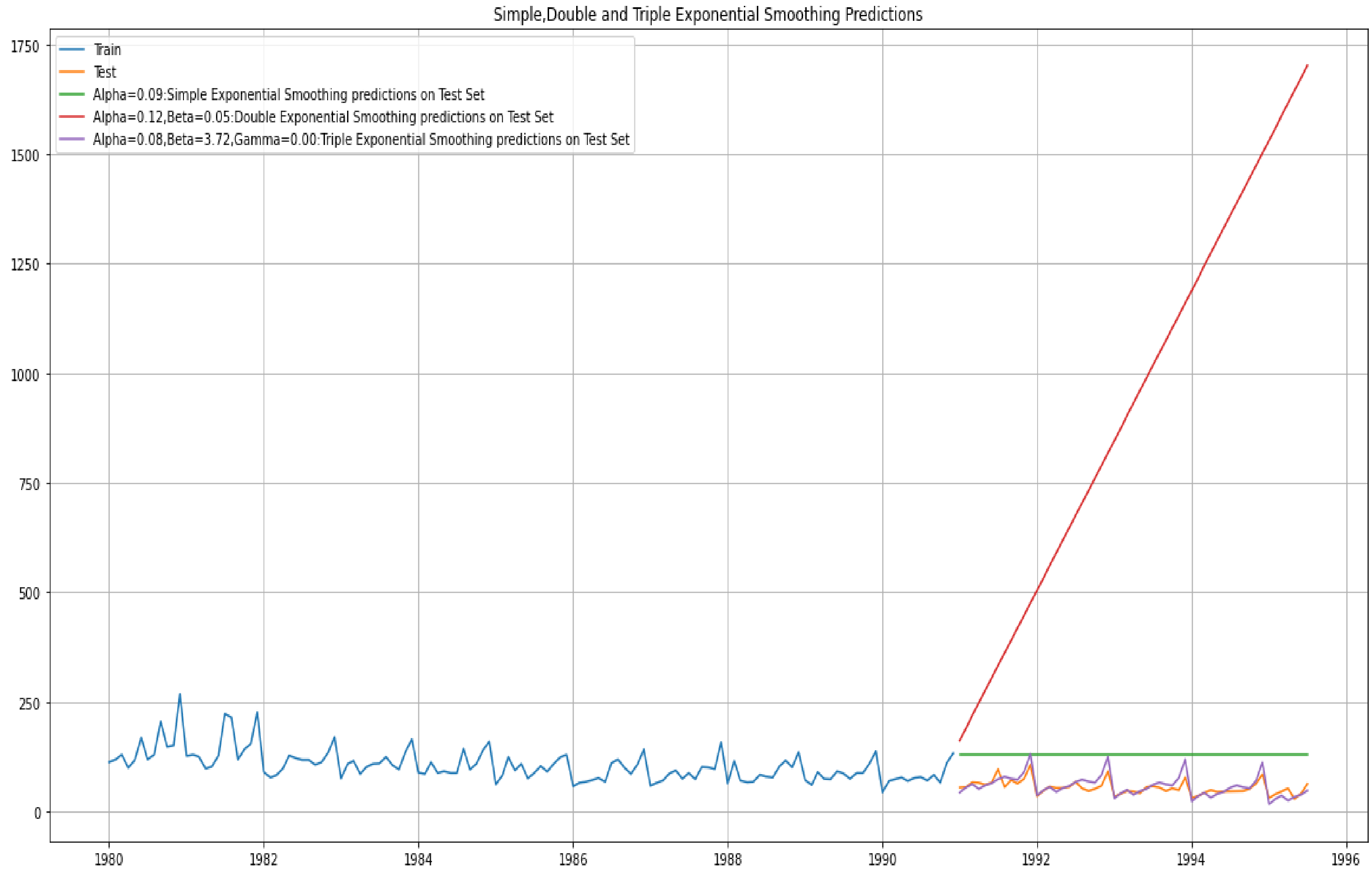
Beta value of 0 refers to insignificant year over year movement with 1 being the converse. A higher value of gamma attributes most of the data fluctuations in the observations across time series to seasonality.

After the auto fitment of triple exponential smoothening model against the training data for Rose wine dataset below are the parameters that could be derived that depicts the smoothening level, trend and the seasonality. Accordingly alpha value is 0.08, beta value is 3.72 and the gamma value is 0.00. RMSE value for the auto fitted model is 14.28.

```
==Holt Winters model Exponential Smoothing Estimated Parameters ==

{'smoothing_level': 0.08836782954933799, 'smoothing_trend': 3.7265369347685534e-06, 'smoothing_sea
379, 'damping_trend': nan, 'initial_level': 146.57689198128827, 'initial_trend': -0.54793320459149
ay([-31.19657397, -18.85433488, -10.86210616, -21.51886836,
       -12.7199789 ,  -7.23811729,   2.66927264,   8.79928342,
         4.85478098,   2.96421129,  21.04754145,  63.34400663]), 'use_boxcox': False, 'lamda': Non
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.08, beta value of 3.72 and the gamma value of 0.00 for the triple exponential smoothing.



Also please note below is the manual fitment done for this TES model across a range of values for the alpha and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha, beta and gamma values mentioned above being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

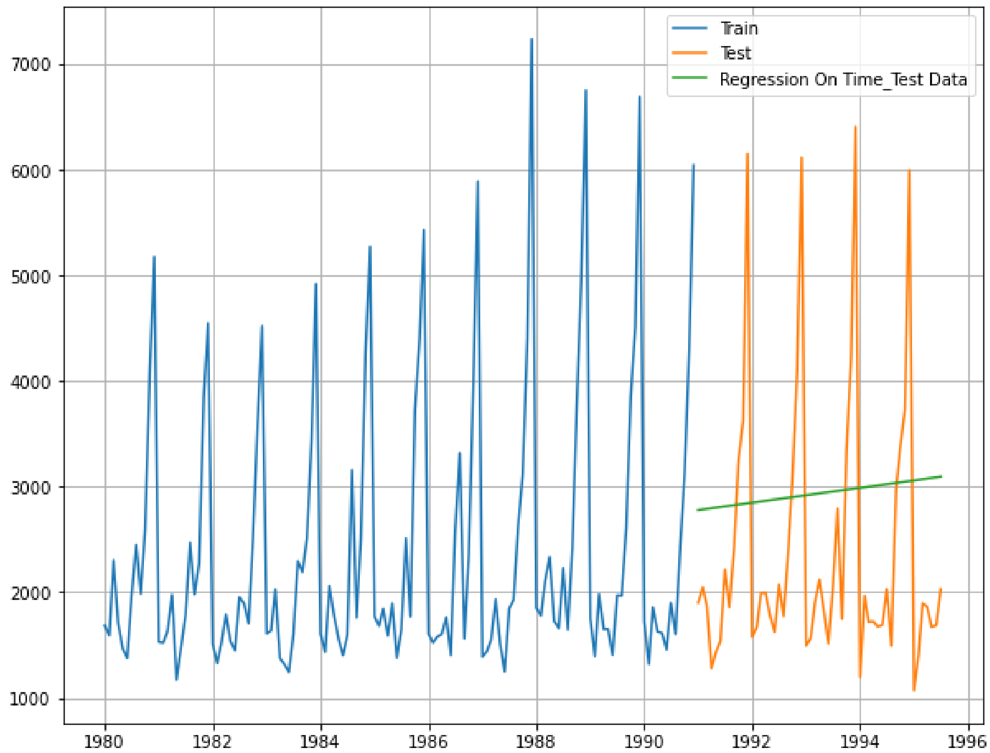
	RMSE
Alpha:0.5 Beta:0.3 Gamma:0.4 Triple Exponential Smoothing	15.761378
Alpha:0.5 Beta:0.5 Gamma:0.5 Triple Exponential Smoothing	15.762185
Alpha:0.9 Beta:0.3 Gamma:0.5 Triple Exponential Smoothing	15.763352
Alpha:0.6 Beta:0.9 Gamma:0.3 Triple Exponential Smoothing	15.767329
Alpha:0.3 Beta:0.9 Gamma:0.4 Triple Exponential Smoothing	15.768134

Below is the summary of RMSE values across all the models run so far and within the scope of models considered for assignment triple exponential model has performed much better with lowest RMSE value. Please note that the moving average model is not considered within the scope of models for arriving at better alternates,

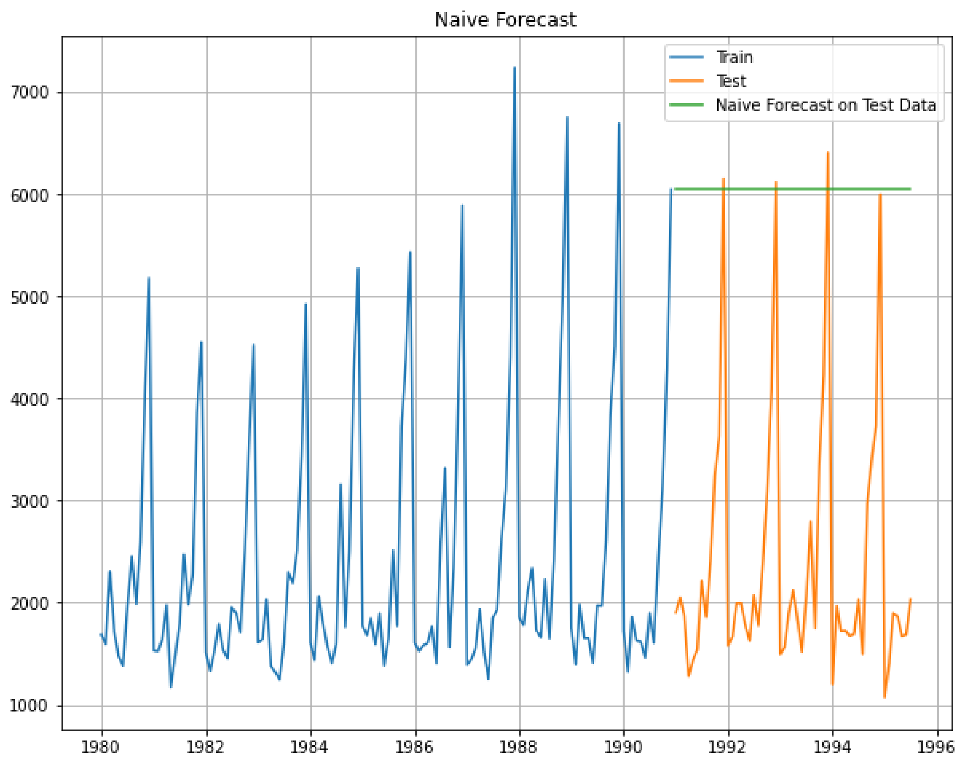
	RMSE
Linear Regression	15.611866
Naive Model	79.718773
Simple Average	53.460570
Moving Average - rolling 2	11.529278
Movinbg Average - rolling 4	14.451403
Moving Average - rolling 6	14.566327
Moving Average - rolling 9	14.727630
Simple Exponential Smoothing, alpha-0.09	36.796228
Double Exponential Smoothing, autofit: alpha-0.12, beta-0.05	38.281548
Triple Exponential Smoothing,alpha-0.08 beta-3.72 gamma=0.00	14.287208

MODELS FOR SPARKLING WINE DATA SET ->

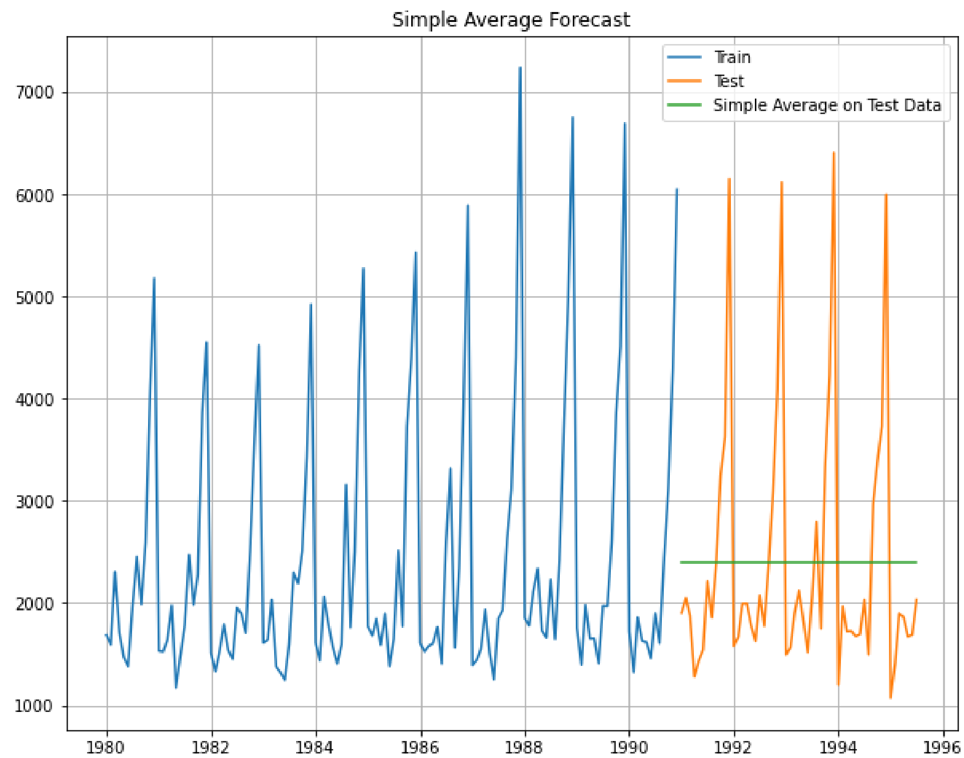
Below plot from Linear Regression model depicts the prediction on the test data overlaps with the trend from the actuals however being smoothened to the straight line with just the trend without any seasonality.



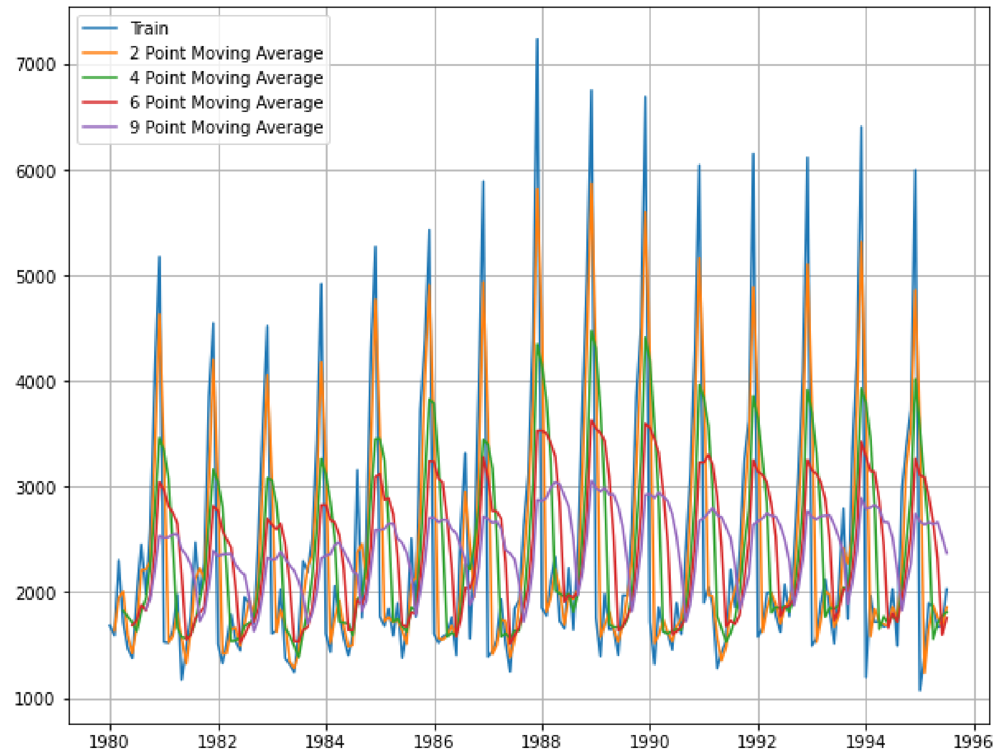
Below plot from Naive model depicts the prediction on the test data overlapping with the peaks of the actuals and being constant throughout.

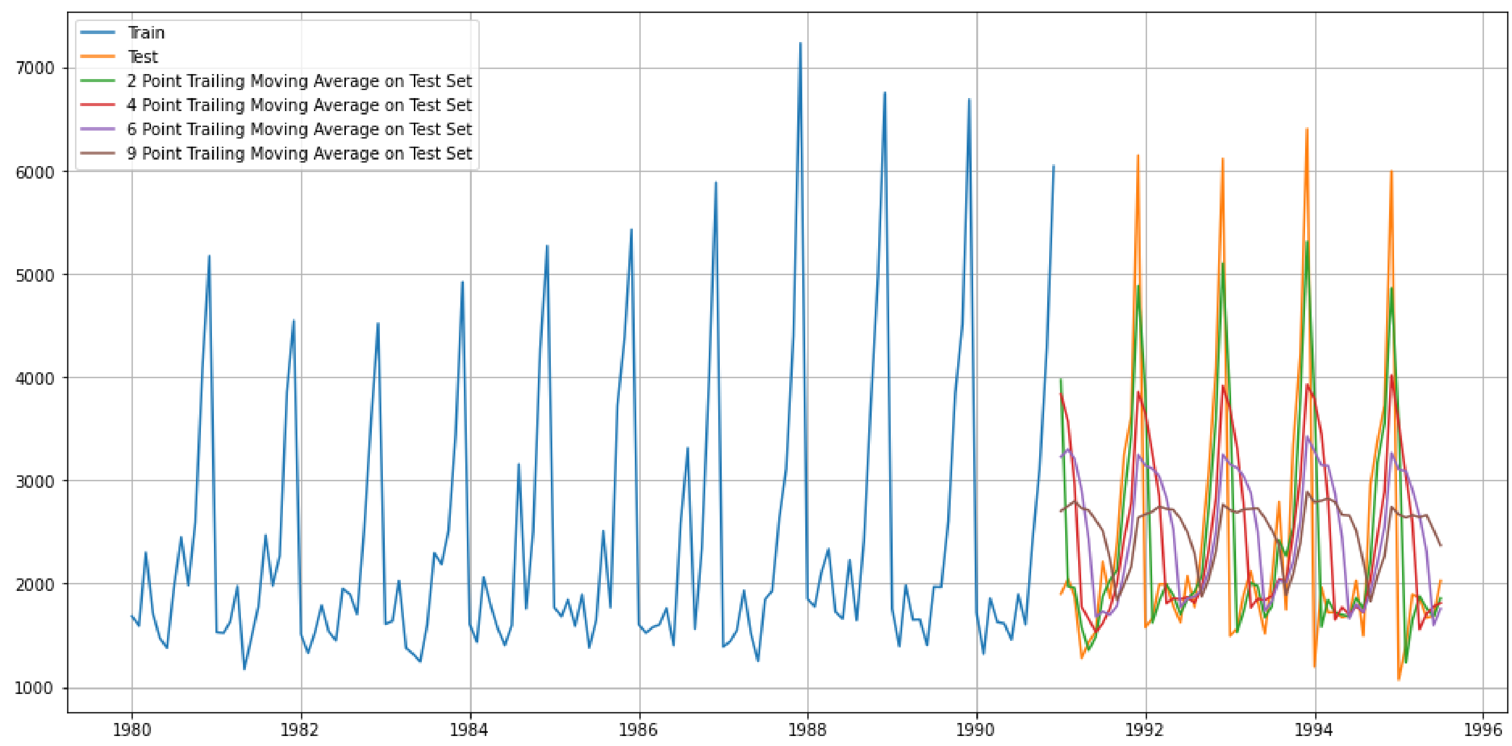


Below plot from simple Average model depicts the prediction on the test data overlapping by dissecting the spikes in the actuals and being constant throughout.

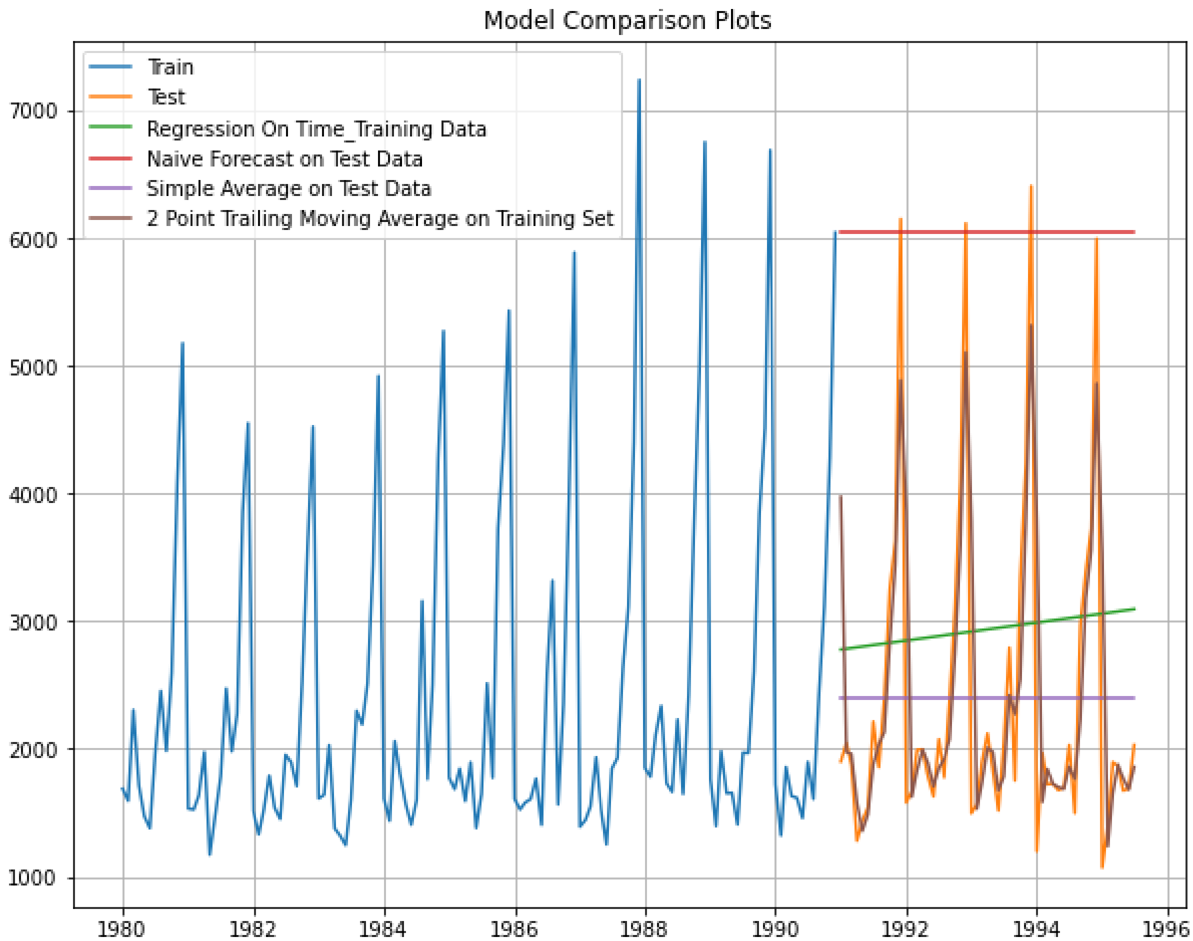


Plot below depicts the outcome of forecast against the test data for the moving average model with 2 point moving average showing up closer to the original values however higher point moving average gets smoothened more and more as the points increase.





Below chart provides comparative chart of prediction trend after adopting respective straight forward models against the time series with 2 point moving average model catching up much closer to the trend and the seasonality

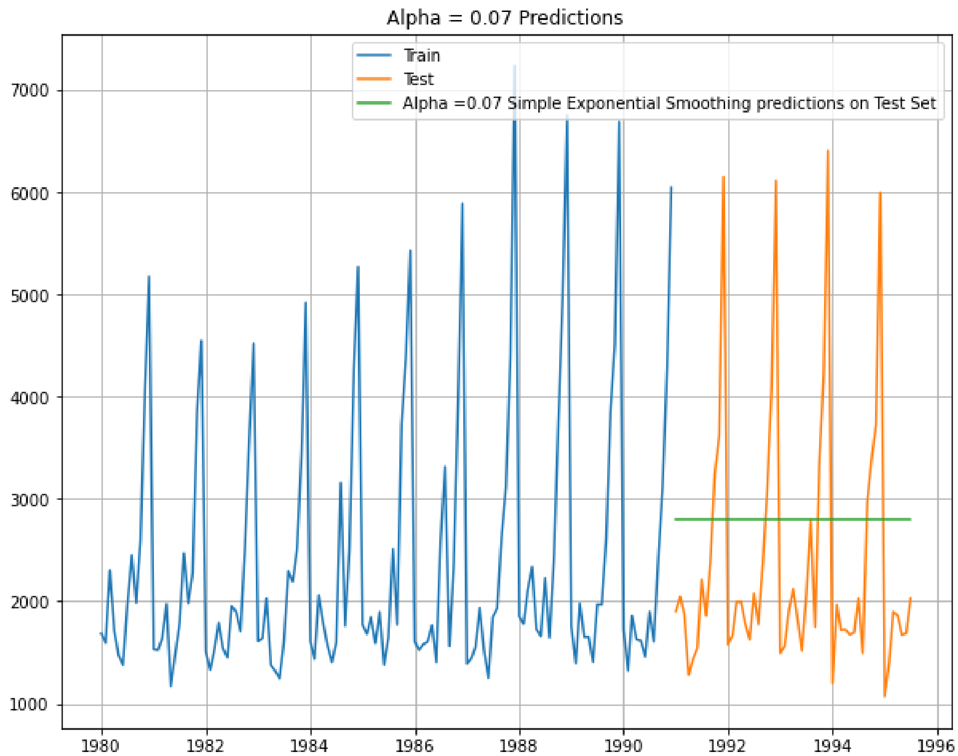


Single exponential smoothing :-

After auto fitment of a single exponential smoothening model against the training data for Sparkling wine dataset below are the parameters that could be derived that depicts the smoothening level. Accordingly the alpha parameter is 0.07 indicating the weightage of observations for the level.

```
{'smoothing_level': 0.07029459943040381,
 'smoothing_trend': nan,
 'smoothing_seasonal': nan,
 'damping_trend': nan,
 'initial_level': 1764.1004162520212,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove bias': False}
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.07 for the single exponential smoothing. The respective RMSE value is 1338.01



Also please note below are the manual fitment done for this SES model across a range of values for the alpha and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha value being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

	RMSE
Alpha:0.3 Single Exponential Smoothing	1935.507132
Alpha:0.4 Single Exponential Smoothing	2311.919615
Alpha:0.5 Single Exponential Smoothing	2666.351413
Alpha:0.6 Single Exponential Smoothing	2979.204388
Alpha:0.7 Single Exponential Smoothing	3249.944092

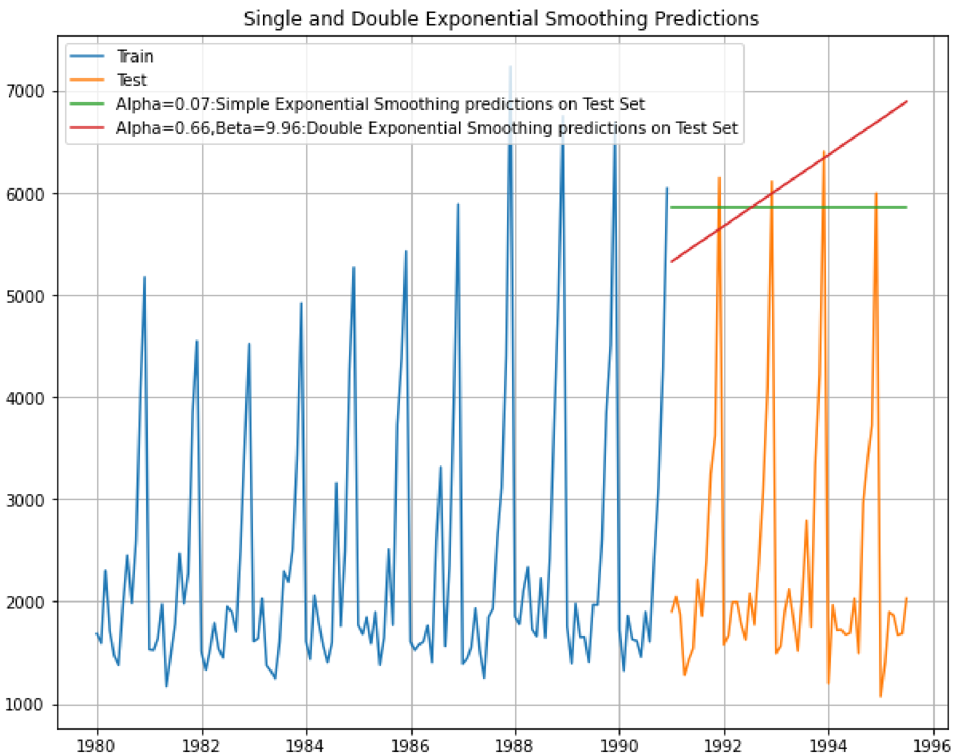
Double exponential smoothing(DES)/ Holt model:

After auto fitment of double exponential smoothening model against the training data for Sparkling wine dataset below are the parameters that could be derived that depicts the smoothening level and the trend. Accordingly, the alpha value is 0.66 and the beta value is 9.96. RMSE value for the auto fitted model is 3949.99.

```
==Holt model Exponential Smoothing Estimated Parameters ==

{'smoothing_level': 0.6638769092832238, 'smoothing_trend': 9.966251357628782e-05, 'smoothing_seaso
d': nan, 'initial_level': 1502.5681711003654, 'initial_trend': 29.020225552837097, 'initial_season
4), 'use_boxcox': False, 'lamda': None, 'remove_bias': False}
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.66 and beta value of 9.95 for the double exponential smoothing. The respective RMSE value is 3949.99.



Also please note below is the manual fitment done for this DES model across a range of parameter values for the alpha and the beta parameter and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha value being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

	RMSE
Alpha:0.3 Beta:0.3 Double Exponential Smoothing	2351.870915
Alpha:0.3 Beta:0.4 Double Exponential Smoothing	2651.137869
Alpha:0.3 Beta:0.5 Double Exponential Smoothing	3051.730134
Alpha:0.4 Beta:0.3 Double Exponential Smoothing	3090.486632
Alpha:0.4 Beta:0.4 Double Exponential Smoothing	3491.182959

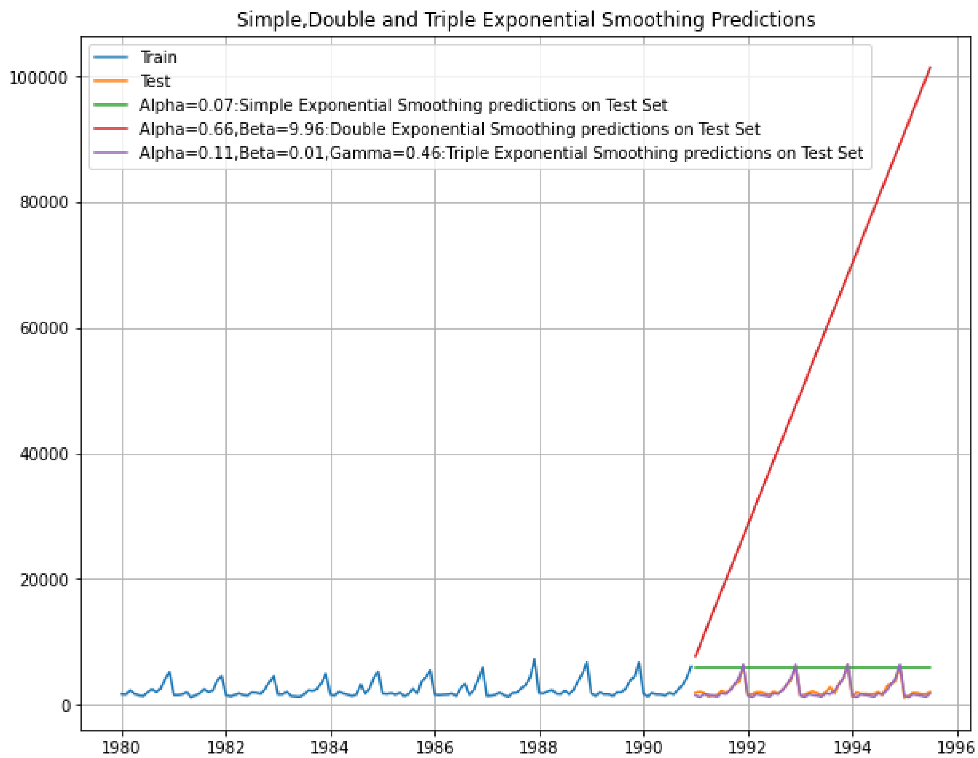
Triple exponential or Holt winters model:

After auto fitment of the triple exponential smoothening model against the training data for Sparkling wine dataset below are the parameters that could be derived that depicts the smoothening level, trend and the seasonality. Accordingly alpha value is 0.11, beta value is 0.01 and the gamma value is 0.46. RMSE value for the auto fitted model is 378.62.

```
==Holt Winters model Exponential Smoothing Estimated Parameters ==

{'smoothing_level': 0.11127217750369374, 'smoothing_trend': 0.012360783181435476, 'smoothing_seasor
'damping_trend': nan, 'initial_level': 2356.5783644431663, 'initial_trend': -0.018472685444676173,
([-636.2336051 , -722.98357701, -398.64355469, -473.43067518,
       -808.42508554, -815.35030576, -384.23066985,   72.99519329,
       -237.44272885,  272.32601496, 1541.37820977, 2590.07759464]), 'use_boxcox': False, 'lamda':
e}
```

Below plot depicts the results of the model on the test data for the auto fitted alpha value of 0.11, beta value of 0.01 and the gamma value of 0.46 for the triple exponential smoothing.



Also please note below is the manual fitment done for this TES model across a range of parameter values for the alpha and the beta parameter and it has been noticed that their RMSE value is much more than the auto fitted models resulting in autofitted alpha value being considered for this model. The below list depicts the top 5 lowest RMSE values among the permutations and combinations across the parameter range.

	RMSE
Alpha:0.8 Beta:0.7 Gamma:0.7 Triple Exponential Smoothing	1275.282558
Alpha:0.5 Beta:0.8 Gamma:0.7 Triple Exponential Smoothing	1275.464720
Alpha:0.3 Beta:0.4 Gamma:0.9 Triple Exponential Smoothing	1276.210498
Alpha:0.3 Beta:1.0 Gamma:0.9 Triple Exponential Smoothing	1276.215193
Alpha:0.6 Beta:0.6 Gamma:0.8 Triple Exponential Smoothing	1278.335339

Based on the above comparison of smoothing models it is evident that triple exponential smoothing, otherwise Holt winters model is able to forecast values much closer to the actuals after considering level, trend and the seasonality parameters based on the auto fitted parameter values depicted above.

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 = 0.05.**

ARIMA model requires the time series to be stationary towards being able to proceed with the model building. Data is defined to be stationary if its mean and variance are constant over a period of time and the correlation between the two time periods depends only on the distance or lag between the two periods.

Hence a formal stationarity (hypothesis) test needs to be applied on the time series data to check whether it follows stationary process for which the hypothesis definition given as below:

Null Hypothesis: Time series is non stationary

Alternate hypothesis: Time series is stationary

Based on the hypothesis done for the Rose Wine time series, it is understood that the p_value for the test supports the null hypothesis and hence the series is not stationary. Please find below the test statistics and the p value for the same.

```
DF test statistic is -1.877
DF test p-value is 0.3431
```

```
Please find below the 5 number summary after applying one level of difference to the data set.
```

	Rose
count	186.000000
mean	-0.268817
std	35.089222
min	-141.000000
25%	-8.000000
50%	5.000000
75%	15.750000
max	117.000000

Accordingly after applying the difference of

Based on the hypothesis done for the Sparkling Wine time series, it is understood that the p_value for the test supports the null hypothesis and hence the series is not stationary. Please find below the test statistics and the p value for the same.

```
DF test statistic is -1.360
DF test p-value is 0.6011
```

Please find below the 5 number summary after applying one of level of difference to the Sparkling data set.

	Sparkling
count	186.000000
mean	1.854839
std	1460.142257
min	-5389.000000
25%	-228.750000
50%	191.000000
75%	693.500000
max	2837.000000

Also during ARIMA model building exercise, differencing parameters could be derived using auto ARIMA to be the required level of differencing to make the series stationary towards optimal AIC.

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.**

ARIMA and SARIMA for Sparkling wine dataset.

Auto correlation function (ACF): ACF of order (p) measures the strength of dependency of current observations on past observations whereas PACF provides correlation value between current and (k) lagged series by removing the influence of all other observations that exist in between. ACF and PACF act together to be considered for identification of order of autoregression.

In general, ARIMA models are defined by 3 parameters

p: No of autoregressive terms
d: No of differencing to stationarize the series
q: No of moving average terms

Parameter p can be utilized towards representing the current value of a variable in the time series as a linear function of its past values through auto regression (AR) process. PACF can be used for identifying the value of p.

Parameter q can be utilized towards representing the current value of the series as a function of past forecast errors through the moving average (MA) model. ACF can be used to identify the value of q.

ARIMA model is an advance version of ARMA model where $d > 0$ indicates that the original series is non-stationary and d differencing is required to make is stationary.

In order to arrive optimal combination of p, d, q to apply to the ARIMA model what we do here is to build auto ARIMA process towards narrowing down the best values for these parameters by comparing AIC value of the ARIMA model output for each p,d,q combination accordingly to narrow down the combination with the lowest AIC score. Based on the range of p and q to iterate through 0, 1 and 2 along with d (differencing parameter for applying stationarity) to iterate for 0 and 1 for various combination of p,d,q across permutations and combinations, we arrived at following AIC scores after applying ARIMA model.

```
ARIMA(0, 1, 0) - AIC:2269.582796371201
ARIMA(0, 1, 1) - AIC:2264.9064368172944
ARIMA(0, 1, 2) - AIC:2232.783097684661
ARIMA(1, 1, 0) - AIC:2268.5280606648653
ARIMA(1, 1, 1) - AIC:2235.013945358969
ARIMA(1, 1, 2) - AIC:2233.5976471190693
ARIMA(2, 1, 0) - AIC:2262.035600095461
ARIMA(2, 1, 1) - AIC:2232.36048987915
ARIMA(2, 1, 2) - AIC:2210.6181252975794
```

Accordingly ARIMA model with the order of (2,1,2) has performed the best with lowest AIC score. Lower the AIC score better the model performance.

Below is the statistical summary of the ARIMA result for the narrowed down order of (2,1,2).

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:           D.Sparkling   No. Observations:                  131
Model:                ARIMA(2, 1, 2)   Log Likelihood               -1099.309
Method:                      css-mle   S.D. of innovations           1012.640
Date:               Sun, 17 Jan 2021   AIC                           2210.618
Time:                       12:29:21   BIC                           2227.869
Sample:                   02-01-1980   HQIC                          2217.628
                        - 12-01-1990
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 5.5855      0.517     10.811      0.000       4.573       6.598
ar.L1.D.Sparkling     1.2699      0.074     17.046      0.000       1.124       1.416
ar.L2.D.Sparkling    -0.5601      0.074     -7.617      0.000      -0.704      -0.416
ma.L1.D.Sparkling    -1.9980      0.042    -47.154      0.000      -2.081      -1.915
ma.L2.D.Sparkling     0.9980      0.042     23.539      0.000       0.915       1.081
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.1335           -0.7074j            1.3361           -0.0888
AR.2            1.1335           +0.7074j            1.3361            0.0888
MA.1            1.0005           +0.0000j            1.0005            0.0000
MA.2            1.0016           +0.0000j            1.0016            0.0000
-----------------------------------------------------------------------------
```

Accordingly based on the predictions applied on the test series based on the above model the resulting RMSE (root mean square error value) is 1374.6492.

Also, now let's check into the SARIMA model.

On top of the ARIMA model, additionally we could apply seasonal adjustments to the SARIMA model.

The most general form of seasonal ARIMA is ,

$ARIMA(p,d,q)*ARIMA(P,D,Q)$[m], where P, D, Q are defined as seasonal AR component, seasonal difference and seasonal MA component respectively. And, 'm' represents the frequency (time interval) at which the data is observed.

In this case we are going to apply 6 and 12 for SARIMA to compare model outcome. We use the same p, d, q ranges as before for ARIMA while retaining P=p and Q=q with D as 0 for the seasonal part.

Accordingly below are the lists of auto SARIMA model outcomes along with its AIC score for m=6.

```
SARIMA(0, 1, 0)x(0, 0, 0, 6)6 - AIC:2251.3597196862966
SARIMA(0, 1, 0)x(0, 0, 1, 6)6 - AIC:2152.3780761716284
SARIMA(0, 1, 0)x(0, 0, 2, 6)6 - AIC:1955.6355536890933
SARIMA(0, 1, 0)x(1, 0, 0, 6)6 - AIC:2164.4097581959904
SARIMA(0, 1, 0)x(1, 0, 1, 6)6 - AIC:2079.559984442563
SARIMA(0, 1, 0)x(1, 0, 2, 6)6 - AIC:1926.9360111185642
SARIMA(0, 1, 0)x(2, 0, 0, 6)6 - AIC:1839.4012986872267
SARIMA(0, 1, 0)x(2, 0, 1, 6)6 - AIC:1841.199361751051
SARIMA(0, 1, 0)x(2, 0, 2, 6)6 - AIC:1810.9177805657487
SARIMA(0, 1, 1)x(0, 0, 0, 6)6 - AIC:2230.1629078505825
SARIMA(0, 1, 1)x(0, 0, 1, 6)6 - AIC:2130.5652859082847
SARIMA(0, 1, 1)x(0, 0, 2, 6)6 - AIC:1918.1876339543767
SARIMA(0, 1, 1)x(1, 0, 0, 6)6 - AIC:2139.573242878454
SARIMA(0, 1, 1)x(1, 0, 1, 6)6 - AIC:2006.5174298135796
SARIMA(0, 1, 1)x(1, 0, 2, 6)6 - AIC:1855.7093274084523
SARIMA(0, 1, 1)x(2, 0, 0, 6)6 - AIC:1798.7885104034895
SARIMA(0, 1, 1)x(2, 0, 1, 6)6 - AIC:1800.77179337265
SARIMA(0, 1, 1)x(2, 0, 2, 6)6 - AIC:1741.7036712072565
SARIMA(0, 1, 2)x(0, 0, 0, 6)6 - AIC:2187.4410101687026
SARIMA(0, 1, 2)x(0, 0, 1, 6)6 - AIC:2087.6843840215897
SARIMA(0, 1, 2)x(0, 0, 2, 6)6 - AIC:1886.1151457125393
SARIMA(0, 1, 2)x(1, 0, 0, 6)6 - AIC:2129.7395689235523
SARIMA(0, 1, 2)x(1, 0, 1, 6)6 - AIC:1988.4215580217822
SARIMA(0, 1, 2)x(1, 0, 2, 6)6 - AIC:1839.6963217060352
SARIMA(0, 1, 2)x(2, 0, 0, 6)6 - AIC:1791.6537079050197
SARIMA(0, 1, 2)x(2, 0, 1, 6)6 - AIC:1793.6190999290054
SARIMA(0, 1, 2)x(2, 0, 2, 6)6 - AIC:1727.8888035990105
SARIMA(1, 1, 0)x(0, 0, 0, 6)6 - AIC:2250.3181267386713
SARIMA(1, 1, 0)x(0, 0, 1, 6)6 - AIC:2151.0782683083426
SARIMA(1, 1, 0)x(0, 0, 2, 6)6 - AIC:1953.3652245477829
SARIMA(1, 1, 0)x(1, 0, 0, 6)6 - AIC:2146.1836648562185
SARIMA(1, 1, 0)x(1, 0, 1, 6)6 - AIC:2073.981368525952
SARIMA(1, 1, 0)x(1, 0, 2, 6)6 - AIC:1917.5889468384437
SARIMA(1, 1, 0)x(2, 0, 0, 6)6 - AIC:1813.2423977989204
SARIMA(1, 1, 0)x(2, 0, 1, 6)6 - AIC:1814.8301602829295
SARIMA(1, 1, 0)x(2, 0, 2, 6)6 - AIC:1791.3715264887628
SARIMA(1, 1, 1)x(0, 0, 0, 6)6 - AIC:2204.9340491545727
SARIMA(1, 1, 1)x(0, 0, 1, 6)6 - AIC:2103.2471520742797
SARIMA(1, 1, 1)x(0, 0, 2, 6)6 - AIC:1906.3976381402158
```

```
SARIMA(1, 1, 1)x(1, 0, 0, 6)6 - AIC:2109.667120973266
SARIMA(1, 1, 1)x(1, 0, 1, 6)6 - AIC:2005.612566393106
SARIMA(1, 1, 1)x(1, 0, 2, 6)6 - AIC:1856.0775241006636
SARIMA(1, 1, 1)x(2, 0, 0, 6)6 - AIC:1776.9417670618593
SARIMA(1, 1, 1)x(2, 0, 1, 6)6 - AIC:1778.8222557528889
SARIMA(1, 1, 1)x(2, 0, 2, 6)6 - AIC:1743.3797826615128
SARIMA(1, 1, 2)x(0, 0, 0, 6)6 - AIC:2188.463345050498
SARIMA(1, 1, 2)x(0, 0, 1, 6)6 - AIC:2089.132092446418
SARIMA(1, 1, 2)x(0, 0, 2, 6)6 - AIC:1908.3347898062104
SARIMA(1, 1, 2)x(1, 0, 0, 6)6 - AIC:2108.5645510270633
SARIMA(1, 1, 2)x(1, 0, 1, 6)6 - AIC:1987.1476984956794
SARIMA(1, 1, 2)x(1, 0, 2, 6)6 - AIC:1838.9472829343013
SARIMA(1, 1, 2)x(2, 0, 0, 6)6 - AIC:1773.4229389294615
SARIMA(1, 1, 2)x(2, 0, 1, 6)6 - AIC:1775.2584010169296
SARIMA(1, 1, 2)x(2, 0, 2, 6)6 - AIC:1730.1038790837822
SARIMA(2, 1, 0)x(0, 0, 0, 6)6 - AIC:2227.302761872421
SARIMA(2, 1, 0)x(0, 0, 1, 6)6 - AIC:2145.3576991201103
SARIMA(2, 1, 0)x(0, 0, 2, 6)6 - AIC:1945.1561426085786
SARIMA(2, 1, 0)x(1, 0, 0, 6)6 - AIC:2124.9071786318195
SARIMA(2, 1, 0)x(1, 0, 1, 6)6 - AIC:2054.170071228054
SARIMA(2, 1, 0)x(1, 0, 2, 6)6 - AIC:1915.633692249958
SARIMA(2, 1, 0)x(2, 0, 0, 6)6 - AIC:1782.735782105787
SARIMA(2, 1, 0)x(2, 0, 1, 6)6 - AIC:1782.359816938853
SARIMA(2, 1, 0)x(2, 0, 2, 6)6 - AIC:1760.342670823393
SARIMA(2, 1, 1)x(0, 0, 0, 6)6 - AIC:2199.8586131454495
SARIMA(2, 1, 1)x(0, 0, 1, 6)6 - AIC:2103.0859058223045
SARIMA(2, 1, 1)x(0, 0, 2, 6)6 - AIC:1903.0416542490439
SARIMA(2, 1, 1)x(1, 0, 0, 6)6 - AIC:2088.133636367894
SARIMA(2, 1, 1)x(1, 0, 1, 6)6 - AIC:1997.3692882582268
SARIMA(2, 1, 1)x(1, 0, 2, 6)6 - AIC:1852.7863840750376
SARIMA(2, 1, 1)x(2, 0, 0, 6)6 - AIC:1794.8112219321938
SARIMA(2, 1, 1)x(2, 0, 1, 6)6 - AIC:1763.1914589558787
SARIMA(2, 1, 1)x(2, 0, 2, 6)6 - AIC:1743.8742069625332
SARIMA(2, 1, 2)x(0, 0, 0, 6)6 - AIC:2176.868114688141
SARIMA(2, 1, 2)x(0, 0, 1, 6)6 - AIC:2068.7780944519573
SARIMA(2, 1, 2)x(0, 0, 2, 6)6 - AIC:1889.7875404654014
SARIMA(2, 1, 2)x(1, 0, 0, 6)6 - AIC:2074.1102217500147
SARIMA(2, 1, 2)x(1, 0, 1, 6)6 - AIC:1955.605896297144
SARIMA(2, 1, 2)x(1, 0, 2, 6)6 - AIC:1826.0433954137
SARIMA(2, 1, 2)x(2, 0, 0, 6)6 - AIC:1763.274775274491
SARIMA(2, 1, 2)x(2, 0, 1, 6)6 - AIC:1760.8267450584606
SARIMA(2, 1, 2)x(2, 0, 2, 6)6 - AIC:1752.2758266821847
```

Accordingly following parameters performed well with lowest AIC score for SARIMA 6

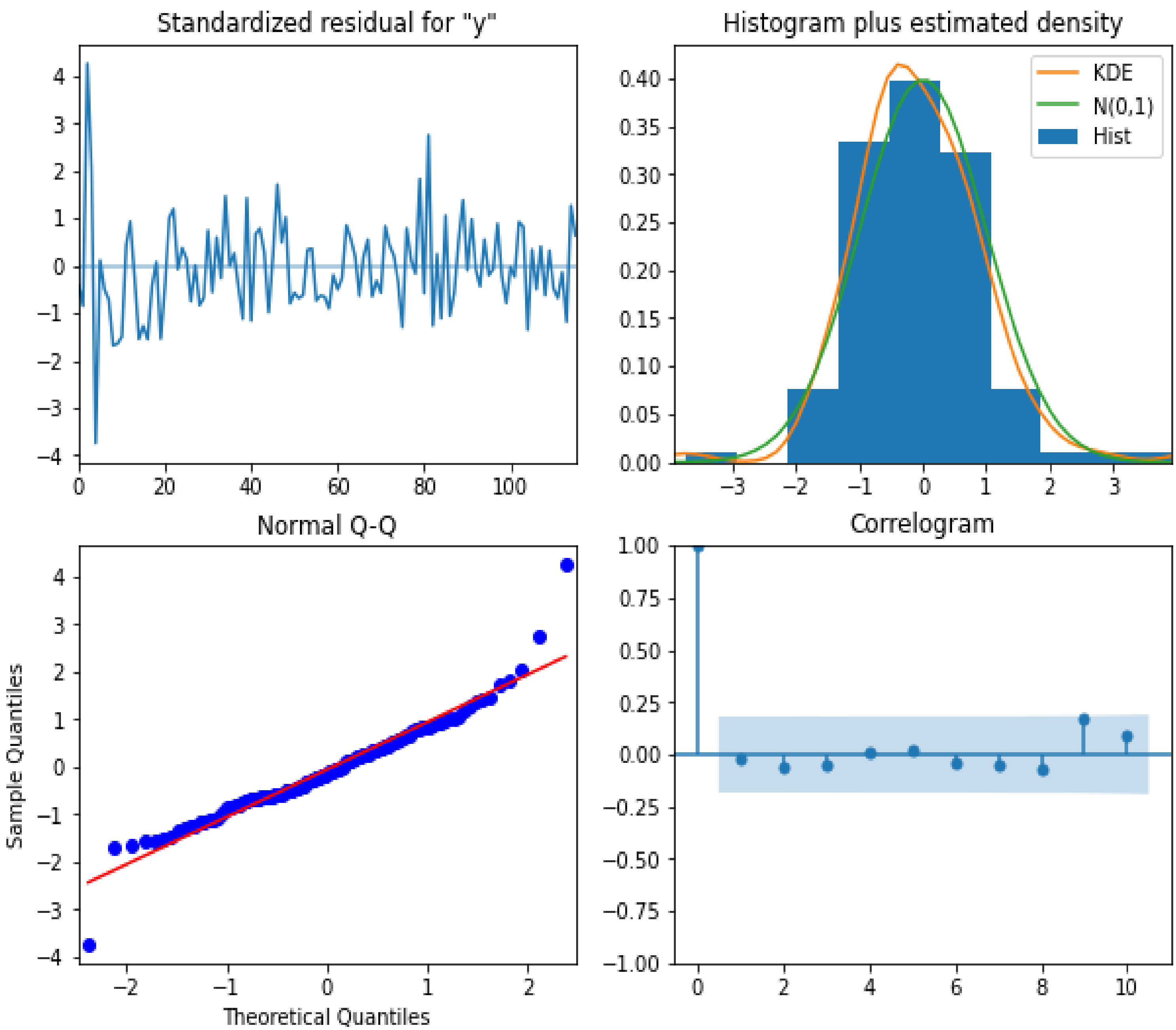
param	seasonal	AIC
(0, 1, 2)	(2, 0, 2, 6)	1727.888804

Please find below the statistical result summary after running the model for the above parameters.

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                  132
Model:             SARIMAX(0, 1, 2)x(2, 0, 2, 6)   Log Likelihood                -856.944
Date:                            Sun, 17 Jan 2021   AIC                           1727.889
Time:                                    12:31:01   BIC                           1747.164
Sample:                                         0   HQIC                          1735.713
                                            - 132
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.7851      0.103     -7.655      0.000      -0.986      -0.584
ma.L2         -0.0975      0.112     -0.870      0.384      -0.317       0.122
ar.S.L6        0.0022      0.026      0.084      0.933      -0.048       0.053
ar.S.L12       1.0396      0.018     58.253      0.000       1.005       1.075
ma.S.L6        0.0428      0.143      0.298      0.766      -0.238       0.324
ma.S.L12      -0.6202      0.090     -6.878      0.000      -0.797      -0.443
sigma2      1.475e+05   1.42e+04     10.371      0.000      1.2e+05    1.75e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                38.96
Prob(Q):                              0.97   Prob(JB):                         0.00
Heteroskedasticity (H):               2.85   Skew:                             0.58
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.59
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Following plot for the residuals on the SARIMA model built based on the above optimized parameter values of (0,1,2) (2,0,2,6) that depicts near normality of the residuals.



Based on the SARIMA model built above below are the predictions for the test data along with its confidence intervals with RMSE value of 601.2547122351654.

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	1375.642794	384.078614	622.862544	2128.423045
1	1116.743965	392.846150	346.779659	1886.708271
2	1667.593098	395.419724	892.584681	2442.601515
3	1528.349292	397.979749	748.323318	2308.375266
4	1372.265429	400.523465	587.253862	2157.276996

Now we retain the same parameters for p,d,q,P,D,Q but run the model for m=12 to apply the 12 month seasonal component. Accordingly the following optimal parameters have been arrived at after the auto SARIMA process.

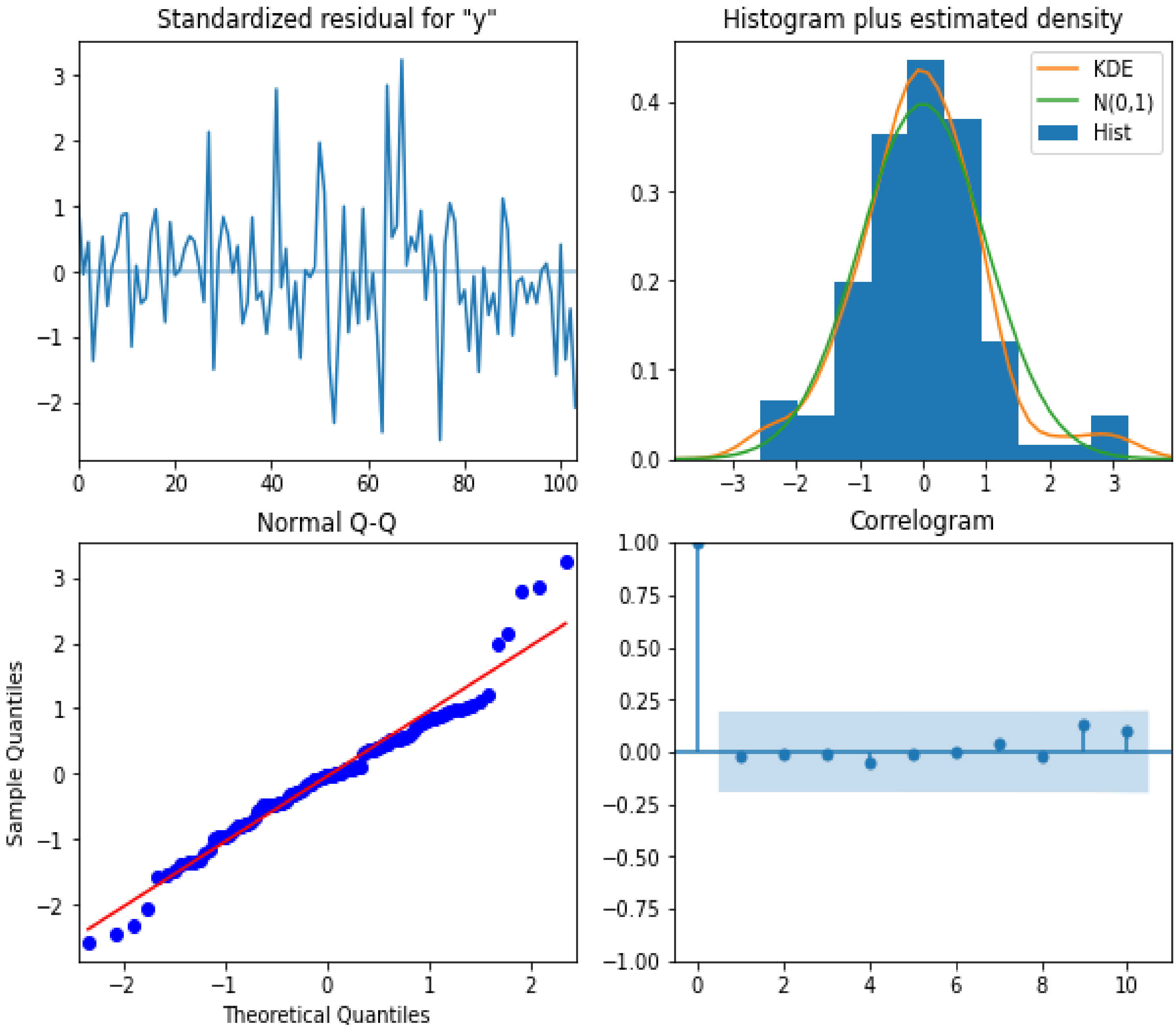
	param	seasonal	AIC
131	(1, 1, 2)	(1, 0, 2, 12)	1555.584247

Please find below the statistical result summary after running the model for the above parameters.

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                  132
Model:             SARIMAX(1, 1, 2)x(1, 0, 2, 12)   Log Likelihood                -770.792
Date:                            Sun, 17 Jan 2021   AIC                           1555.584
Time:                                    12:36:46   BIC                           1574.095
Sample:                                         0   HQIC                          1563.083
                                            - 132
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6281      0.255     -2.463      0.014      -1.128      -0.128
ma.L1         -0.1041      0.225     -0.463      0.643      -0.545       0.337
ma.L2         -0.7276      0.154     -4.734      0.000      -1.029      -0.426
ar.S.L12       1.0439      0.014     72.841      0.000       1.016       1.072
ma.S.L12      -0.5550      0.098     -5.663      0.000      -0.747      -0.363
ma.S.L24      -0.1355      0.120     -1.133      0.257      -0.370       0.099
sigma2      1.506e+05   2.03e+04      7.400      0.000    1.11e+05     1.9e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.04   Jarque-Bera (JB):                11.72
Prob(Q):                              0.84   Prob(JB):                         0.00
Heteroskedasticity (H):               1.47   Skew:                             0.36
Prob(H) (two-sided):                  0.26   Kurtosis:                         4.48
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Following plot for the residuals on the SARIMA model built based on the above optimized parameter values of (1,1,2) (1,0,2,12) that depicts near normality of the residuals.



Based on the SARIMA model built above below are the predictions for the test data along with its confidence intervals with RMSE value of 528.5914475977731.

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	1327.405734	388.344222	566.265045	2088.546423
1	1315.134972	402.007572	527.214610	2103.055335
2	1621.615695	402.001173	833.707874	2409.523516
3	1598.888239	407.238459	800.715527	2397.060951
4	1392.713351	407.968479	593.109826	2192.316876

Below is the comparison of performance across all the models built so far for the Sparkling data set. Based on the model in scope the Triple exponential smoothing / Holt Winters model has performed the best.

	RMSE
Triple Exponential Smoothing	378.626002
Auto SARIMA 12	528.591448
Auto SARIMA 6	601.254712
Moving Average - rolling 2	813.400684
Movinbg Average - rolling 4	1156.589694
Simple Average	1275.081804
Moving Average - rolling 6	1283.927428
Single Exponential Smoothing, alpha-0.07	1338.012144
Moving Average - rolling 9	1346.278315
Auto ARIMA	1374.649208
Linear Regression	1384.558065
Naive Model	3864.279352
Double Exponential Smoothing,Alpha=0.66,Beta=9.96	3949.993290

ARIMA and SARIMA for Rose wine dataset.

Based on the auto ARIMA process below are the parameter values and the respective AIC scores for the Sparkling dataset. We are retaining the p, d, q ranges aligning with what was done for Sparkling dataset.

```
ARIMA(0, 1, 0) - AIC:1335.1526583086775
ARIMA(0, 1, 1) - AIC:1280.7261830464035
ARIMA(0, 1, 2) - AIC:1276.8353726229147
ARIMA(1, 1, 0) - AIC:1319.348310580781
ARIMA(1, 1, 1) - AIC:1277.775749172235
ARIMA(1, 1, 2) - AIC:1277.3592262067277
ARIMA(2, 1, 0) - AIC:1300.6092611745498
ARIMA(2, 1, 1) - AIC:1279.0456894093218
ARIMA(2, 1, 2) - AIC:1279.2986939364814
```

Accordingly, the parameter with the order of (0,1,2) for (p,d,q) has performed better with the least AIC Score of 1276.835 for us to proceed with applying those parameter for the ARIMA model to check the statistical result on the output.

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                 D.Rose   No. Observations:                  131
Model:                 ARIMA(0, 1, 2)   Log Likelihood                -634.418
Method:                       css-mle   S.D. of innovations             30.167
Date:                Sun, 17 Jan 2021   AIC                           1276.835
Time:                        11:53:23   BIC                           1288.336
Sample:                    02-01-1980   HQIC                          1281.509
                         - 12-01-1990
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const           -0.4885      0.085     -5.742      0.000      -0.655      -0.322
ma.L1.D.Rose    -0.7601      0.101     -7.499      0.000      -0.959      -0.561
ma.L2.D.Rose    -0.2398      0.095     -2.518      0.012      -0.427      -0.053
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1            1.0000           +0.0000j            1.0000            0.0000
MA.2           -4.1695           +0.0000j            4.1695            0.5000
-----------------------------------------------------------------------------
```

Based on the above, the following are the predictions on the test time series with the RMSE score of 15.61800957004907.

```
array([83.95205681, 71.47835275, 70.98981208, 70.50127142, 70.01273076,
       69.5241901 , 69.03564944, 68.54710878, 68.05856812, 67.57002746,
       67.0814868 , 66.59294614, 66.10440548, 65.61586481, 65.12732415,
       64.63878349, 64.15024283, 63.66170217, 63.17316151, 62.68462085,
       62.19608019, 61.70753953, 61.21899887, 60.7304582 , 60.24191754,
       59.75337688, 59.26483622, 58.77629556, 58.2877549 , 57.79921424,
       57.31067358, 56.82213292, 56.33359226, 55.8450516 , 55.35651093,
       54.86797027, 54.37942961, 53.89088895, 53.40234829, 52.91380763,
       52.42526697, 51.93672631, 51.44818565, 50.95964499, 50.47110433,
       49.98256366, 49.494023  , 49.00548234, 48.51694168, 48.02840102,
       47.53986036, 47.0513197 , 46.56277904, 46.07423838, 45.58569772])
```

Now let's build the SARIMA model with m = 6 with the same p,d,q,P,D,Q parameter ranges for the auto SARIMA process.

Based on the auto SARIMA outcome below is the optimal parameters narrowed down with the least AIC score to proceed further in building this model.

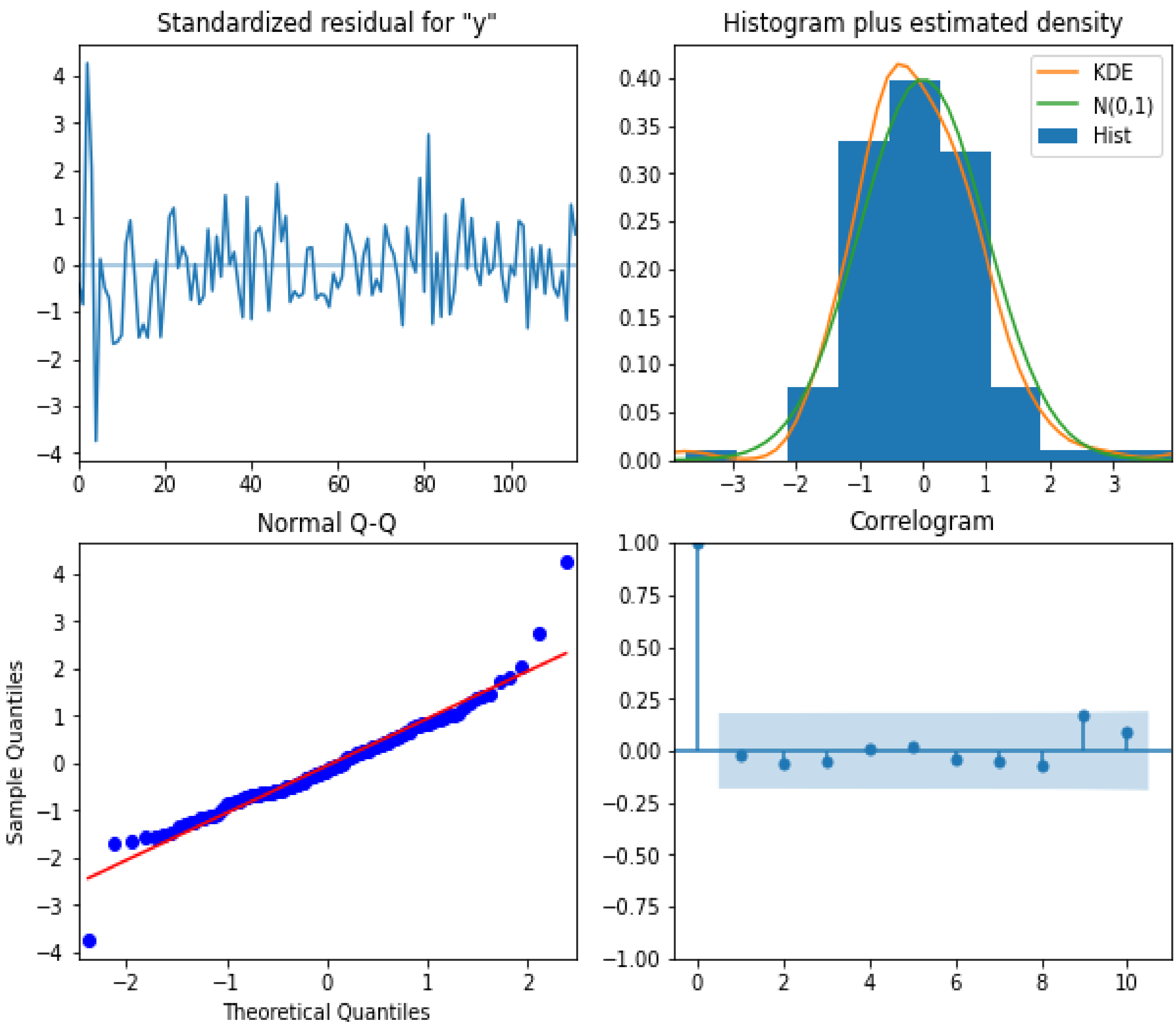
param	seasonal	AIC
(1, 1, 2)	(2, 0, 2, 6)	1041.655817

Below is the statistical summary post the model training.

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                  132
Model:             SARIMAX(1, 1, 2)x(2, 0, 2, 6)   Log Likelihood                -512.828
Date:                            Sun, 17 Jan 2021   AIC                           1041.656
Time:                                    11:55:51   BIC                           1063.685
Sample:                                         0   HQIC                          1050.598
                                            - 132
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.5939      0.149     -3.978      0.000      -0.887      -0.301
ma.L1         -0.1954   1067.034     -0.000      1.000   -2091.544    2091.153
ma.L2         -0.8046    858.586     -0.001      0.999   -1683.603    1681.994
ar.S.L6       -0.0626      0.034     -1.832      0.067      -0.129       0.004
ar.S.L12       0.8451      0.035     23.995      0.000       0.776       0.914
ma.S.L6        0.2226   1067.091      0.000      1.000   -2091.238    2091.683
ma.S.L12      -0.7774    829.526     -0.001      0.999   -1626.618    1625.063
sigma2       335.1984      4.760     70.416      0.000     325.868     344.528
===================================================================================
Ljung-Box (L1) (Q):                   0.07   Jarque-Bera (JB):                56.68
Prob(Q):                              0.78   Prob(JB):                         0.00
Heteroskedasticity (H):               0.47   Skew:                             0.52
Prob(H) (two-sided):                  0.02   Kurtosis:                         6.26
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.03e+21. Standard errors may be unstable.
```

Below plot diagnostics on the residuals depict normality.



Based on the trained model, following are the forecasts on the test series along with the confidence interval with the RMSE score of 26.1352027416264.

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	62.841638	18.848275	25.899698	99.783578
1	67.630850	19.300118	29.803314	105.458386
2	74.746923	19.412680	36.698770	112.795076
3	71.325811	19.475627	33.154284	109.497339
4	76.017740	19.483906	37.829985	114.205495

Likewise below is the model built for SARIMA with m=12.

Optimal parameter post auto SARIMA process is as below:

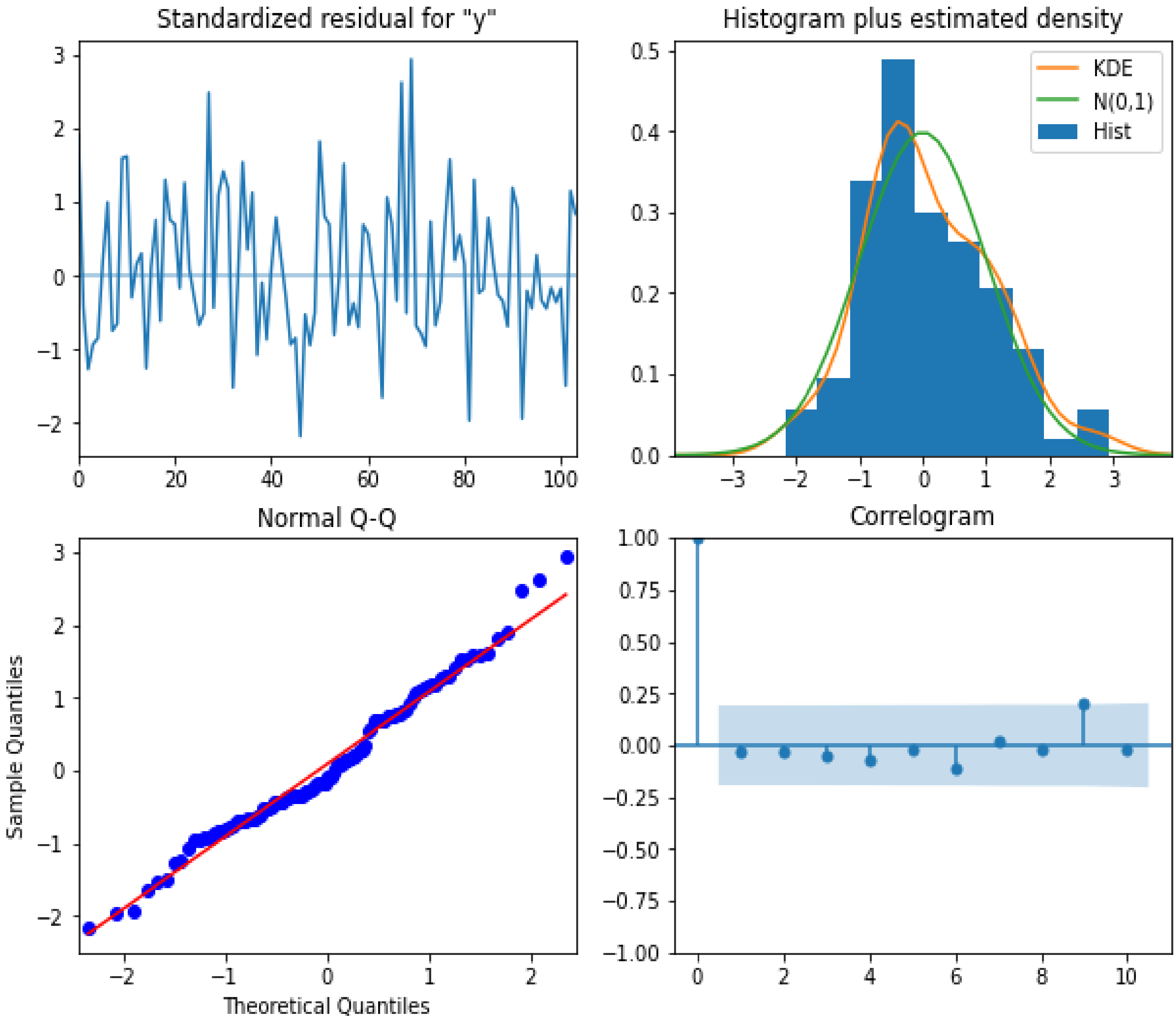
	param	seasonal	AIC
107	(0, 1, 2)	(2, 0, 2, 12)	887.937509

Statistical summary for the above parameters after building the SARIMA model for it is as below.

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                  132
Model:             SARIMAX(0, 1, 2)x(2, 0, 2, 12)   Log Likelihood                -436.969
Date:                            Sun, 17 Jan 2021   AIC                            887.938
Time:                                    11:58:32   BIC                            906.448
Sample:                                         0   HQIC                           895.437
                                            - 132
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.8427    189.601     -0.004      0.996    -372.455     370.769
ma.L2         -0.1573     29.787     -0.005      0.996     -58.539      58.225
ar.S.L12       0.3467      0.079      4.375      0.000       0.191       0.502
ar.S.L24       0.3023      0.076      3.996      0.000       0.154       0.451
ma.S.L12       0.0767      0.133      0.577      0.564      -0.184       0.337
ma.S.L24      -0.0726      0.146     -0.498      0.618      -0.358       0.213
sigma2       251.3136   4.77e+04      0.005      0.996   -9.31e+04    9.37e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):                 2.33
Prob(Q):                              0.75   Prob(JB):                         0.31
Heteroskedasticity (H):               0.88   Skew:                             0.37
Prob(H) (two-sided):                  0.70   Kurtosis:                         3.03
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Below is the plot of residuals depicting normality of the residuals.



Based on the trained model below are the forecasts against the test series with the RMSE score of 26.928361253034.

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	62.867262	15.928500	31.647975	94.086549
1	70.541190	16.147658	38.892361	102.190018
2	77.356410	16.147656	45.707586	109.005234
3	76.208814	16.147656	44.559990	107.857637
4	72.747397	16.147656	41.098574	104.396221

Below is the comparison of performance across all the models built so far for the Rose data set. Based on the model in scope the Triple exponential smoothing model has performed the best not counting moving average approach.

	RMSE
Moving Average - rolling 2	11.529278
Triple Exponential Smoothing,alpha-0.08 beta-3.72 gamma=0.00	14.287208
Movinbg Average - rolling 4	14.451403
Moving Average - rolling 6	14.566327
Moving Average - rolling 9	14.727630
Linear Regression	15.611866
Auto ARIMA	15.618010
Auto SARIMA 6	26.135203
Auto SARIMA 12	26.928361
Simple Exponential Smoothing, alpha-0.09	36.796228
Double Exponential Smoothing, autofit: alpha-0.12, beta-0.05	38.281548
Simple Average	53.460570
Naive Model	79.718773

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.

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.

For Rose data set :-

Below is the comparison of performance across all the models built so far for the Rose data set. Based on the model in scope the Triple exponential smoothing model has performed the best not counting moving average approach.

	RMSE
Moving Average - rolling 2	11.529278
Triple Exponential Smoothing,alpha-0.08 beta-3.72 gamma=0.00	14.287208
Movinbg Average - rolling 4	14.451403
Moving Average - rolling 6	14.566327
Moving Average - rolling 9	14.727630
Linear Regression	15.611866
Auto ARIMA	15.618010
Auto SARIMA 6	26.135203
Auto SARIMA 12	26.928361
Simple Exponential Smoothing, alpha-0.09	36.796228
Double Exponential Smoothing, autofit: alpha-0.12, beta-0.05	38.281548
Simple Average	53.460570
Naive Model	79.718773

Below is the comparison of performance across all the models built so far for the Sparkling data set. Based on the model in scope the Triple exponential smoothing / Holt Winters model has performed the best.

	RMSE
Triple Exponential Smoothing	378.626002
Auto SARIMA 12	528.591448
Auto SARIMA 6	601.254712
Moving Average - rolling 2	813.400684
Movinbg Average - rolling 4	1156.589694
Simple Average	1275.081804
Moving Average - rolling 6	1283.927428
Single Exponential Smoothing, alpha-0.07	1338.012144
Moving Average - rolling 9	1346.278315
Auto ARIMA	1374.649208
Linear Regression	1384.558065
Naive Model	3864.279352
Double Exponential Smoothing,Alpha=0.66,Beta=9.96	3949.993290

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.

With the Triple exponential model being the best across both Rose and Sparkling wine datasets we are going ahead predicting for next 12 months using the full data volume based on the Holt Winters model as below.

For Rose wine data set below are the predictions of sales for next 12 months along with the respective confidence factor.

	lower_CI	prediction	upper_ci
1995-08-01	39.514343	50.653396	146.560064
1995-09-01	36.201611	47.340665	143.247333
1995-10-01	35.198081	46.337135	142.243803
1995-11-01	49.862746	61.001799	156.908467
1995-12-01	87.618318	98.757371	194.664039
1996-01-01	3.484192	14.623246	110.529914
1996-02-01	13.819039	24.958092	120.864760
1996-03-01	21.399891	32.538945	128.445613
1996-04-01	14.218845	25.357898	121.264566
1996-05-01	17.604554	28.743607	124.650275
1996-06-01	23.096147	34.235200	130.141869
1996-07-01	33.700390	44.839443	140.746111

For Sparkling wine data set below are the predictions of sales for next 12 months along with the respective confidence factor.

	lower_CI	prediction	upper_ci
1995-08-01	530.527521	1884.017475	7407.526326
1995-09-01	1079.442169	2432.932123	7956.440974
1995-10-01	1909.381577	3262.871531	8786.380382
1995-11-01	2573.024605	3926.514560	9450.023411
1995-12-01	4775.775352	6129.265306	11652.774157
1996-01-01	-94.108589	1259.381365	6782.890216
1996-02-01	248.104462	1601.594416	7125.103267
1996-03-01	491.499478	1844.989432	7368.498283
1996-04-01	470.646470	1824.136424	7347.645275
1996-05-01	316.043270	1669.533225	7193.042076
1996-06-01	257.819200	1611.309154	7134.818005
1996-07-01	649.450102	2002.940056	7526.448907