TIME SERIES FORECASTING PROJECT

-----ROSE-----

By Giridharan Velmurugan

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Problem Statement

For this assignment the data of different types of wine sales in the 20th century is to be analysed. As an analyst in the ABC Estate Wines, you are tasked to analyse and forecast wines sales in the 20th Century.

Data Dictionary –

1) Year Month: This feature holds the year and month in the format "YYYY-MM"
2) Rose: This is the feature that holds the sales units for the corresponding year month

The record of sales starts from "January of 1980" and ends on "July of 1995". Totalling to 15 years and 7 months of recorded sales.

Read and Plot the Dataframe

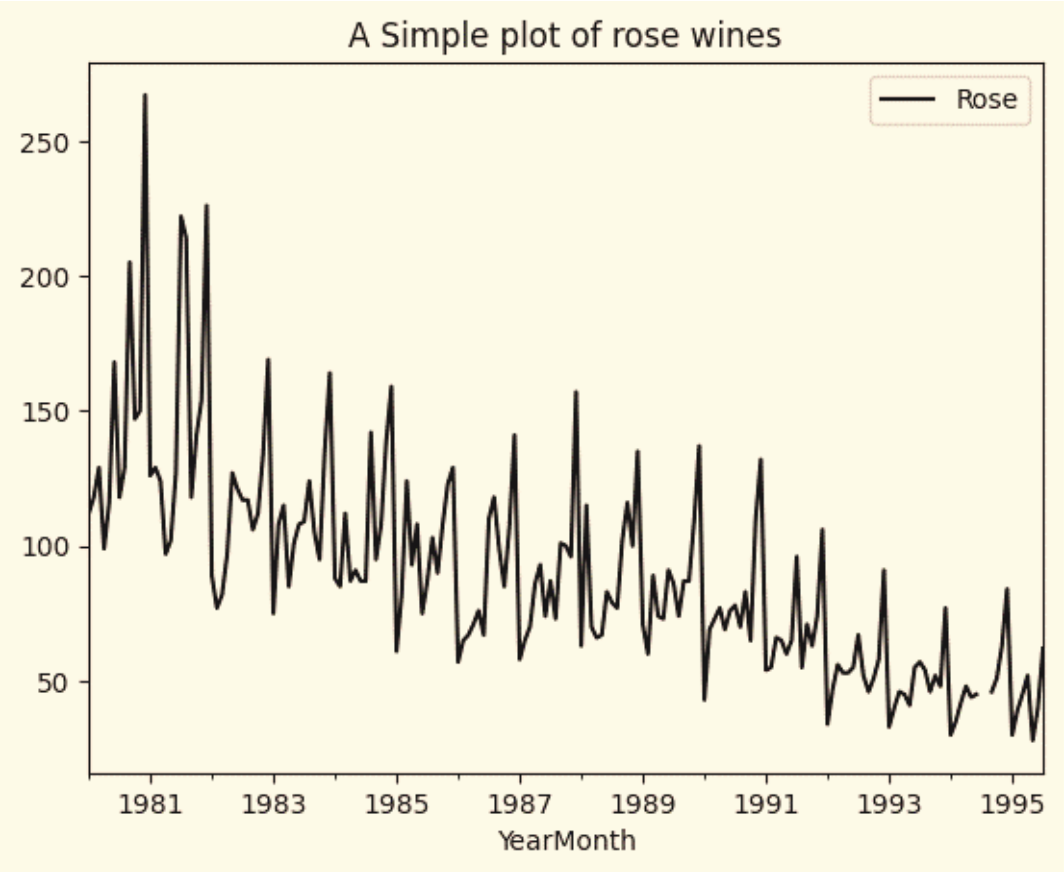
The dataframe has only two features, they are 'YearMonth' and 'Rose' as seen above. The dataframe is read in such a format that the feature 'YearMonth' is converted to a yyyy-mm-dd format and set as the index.

This would reduce the said dataframe from two features to one(which would be sales units 'Rose').

A peek is given in the table below.

YearMonth	Rose
1980-01-01	112
1980-02-01	118
1980-03-01	129
1980-04-01	99
1980-05-01	116

Plot of the dataframe.



From the plot, we can see that there is trend and seasonality. The trend is pointing downwards meaning we are seeing a reduction in sales over the years.

Moreover, we can see a small gap just before the year 1995, this shows that we have some missing or null values within a year.

EDA and Decomposition

The data starts from January of 1980 and goes all the way till July of 1995, totalling 187 months. There are null values in the months of July and August of 1994.

We will be using historical forward fill and backward fill imputation to replace the null values. For July 1994 we will use backwards fill, using 1995 July sales value, for August 1994 we will use forwards fill, using 1993 August sales value.

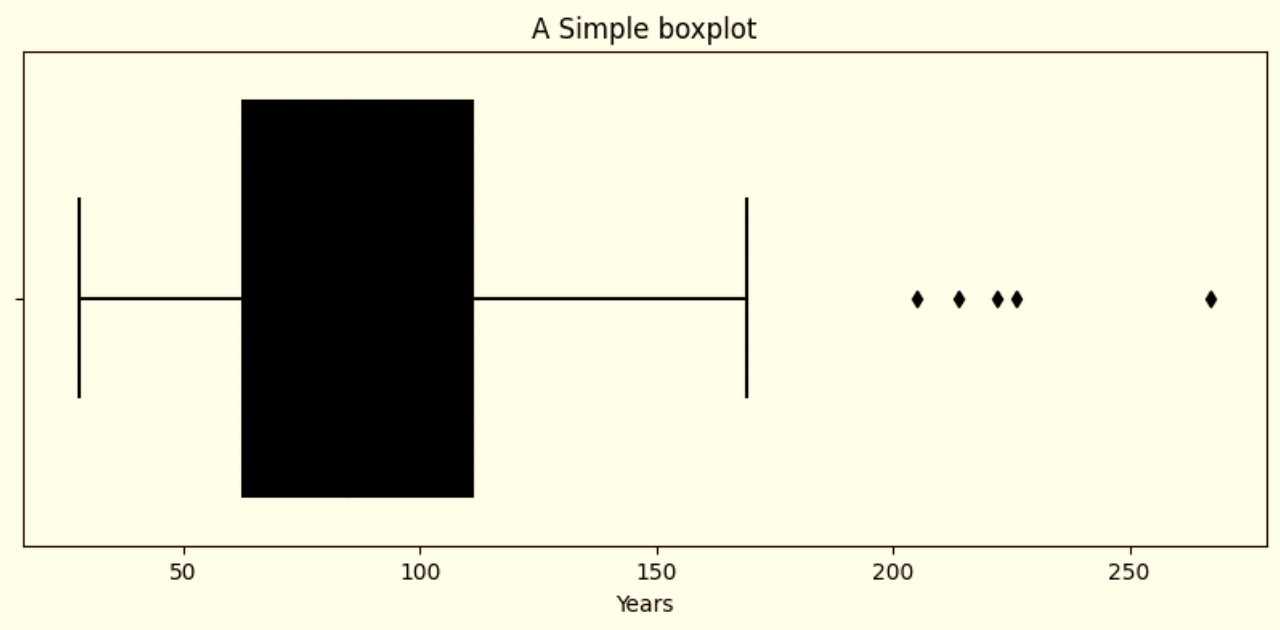
There are some duplicated values, this is nothing to worry as each value is tagged with a different timestamp, making each entry legitimate.

Below is a simple boxplot that is done on the entirety of the dataframe, overall, we do have some outliers, but these can be attributed to the peaks we saw earlier.

The mean sits at around 91 units.

The inter quartile range is between 63 and 111 units.

The minimum units sold in 187 months was 28, and the maximum stands at a staggering 267 units which is of course an outlier.

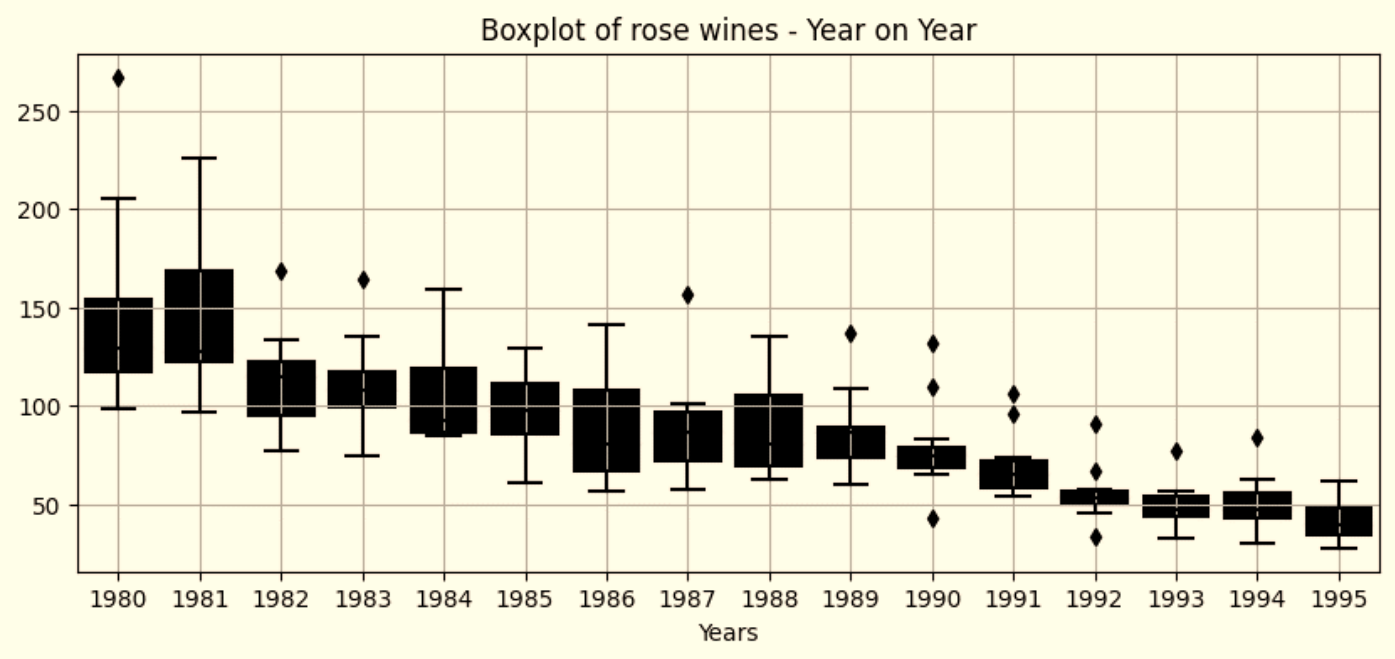


The next plot is also a boxplot, but one that is explained for each year.

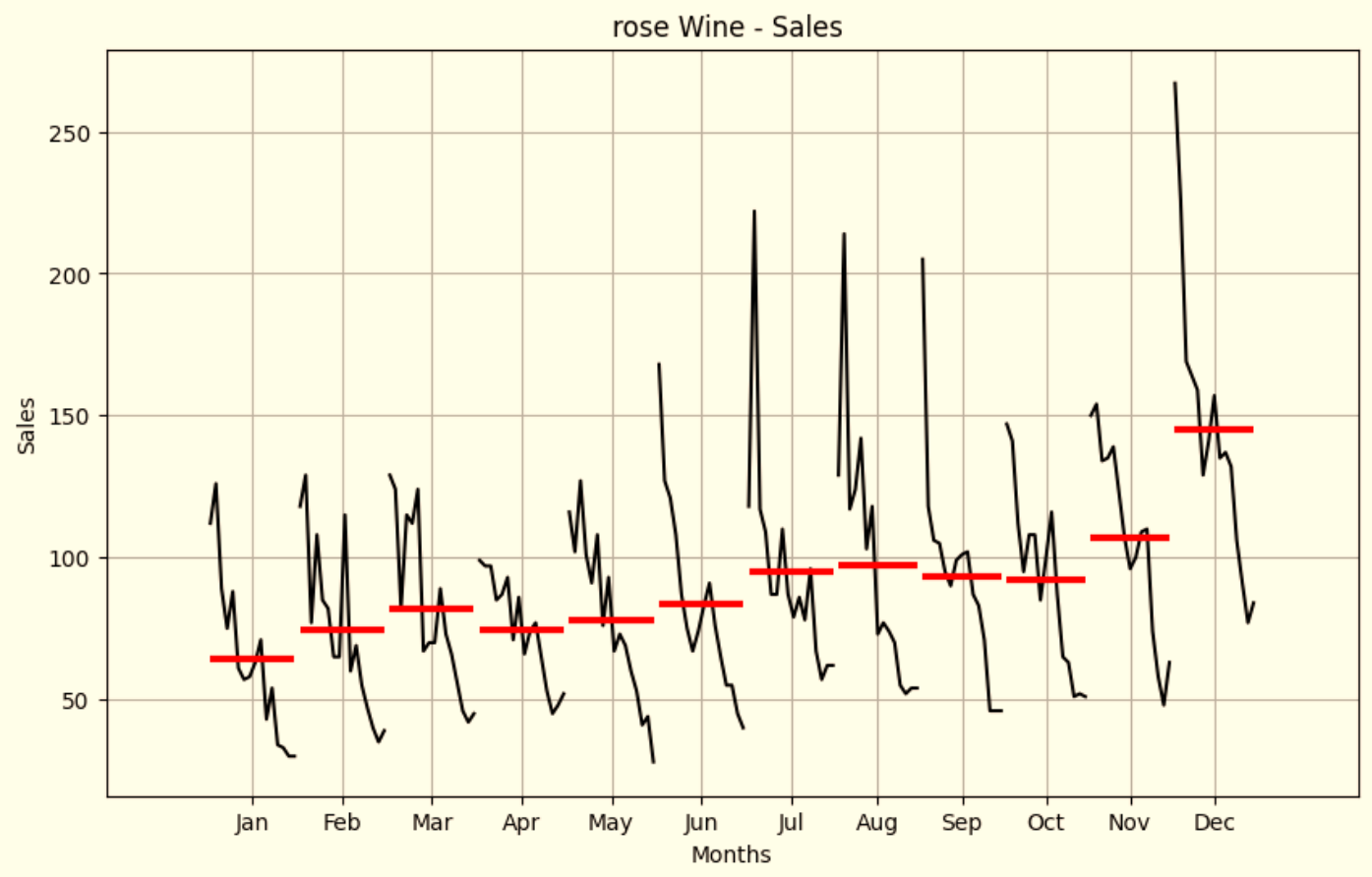
We can see that each year has outliers, and some of them even have two, even at the lower ends. Again, these could be the peaks and troughs that we saw previously.

1995 is an odd year, considering we only have data till July, nonetheless, even then it has the lowest sales average of any year.

Out of 15 years, we have had 4 leaps years. – 1980, 1984, 1988 and 1992.



Next, we see a different plot that shows the variations between months of different years.



This plot shows a lot of information but confirms that as we near holiday season the sales increase drastically. On Average there is approximately, an increase of 127%, between January and December(this is only present within a year), comparing years is a different scenario.

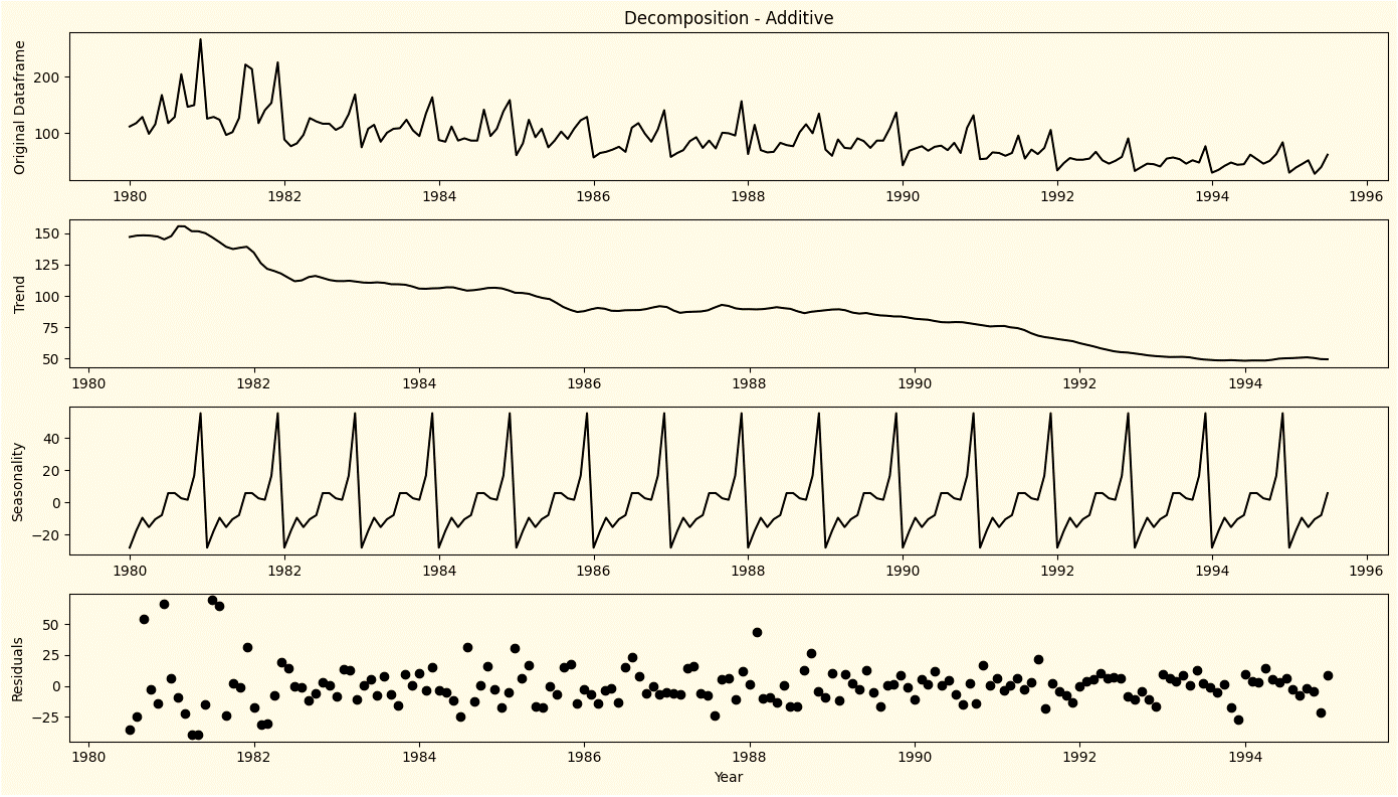
We can see that the months exhibits a lot of variation, this is because of the downward trend accompanied by seasonality from 1980 to 1995.

The month of December shows the most variation at round 190 units, then comes the months of June to September.

Now, let's decompose. Decomposition is the process where we dissect the data into multiple components. It helps us in understanding complex data patterns, improving predictive models, detecting anomalies, and preparing data for further analysis.

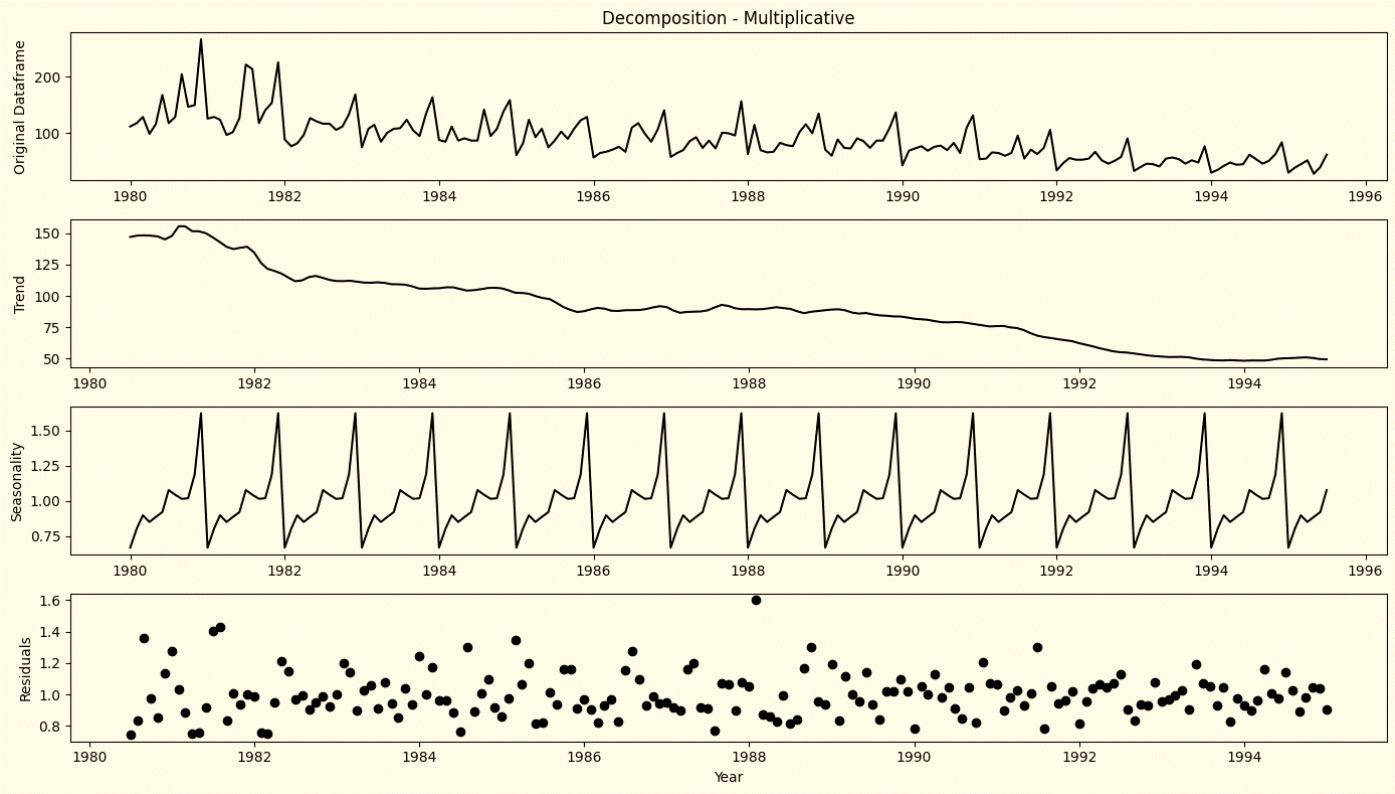
- **Trend: Shows the long-term progression of the data, indicating an increase, decrease, or stability over time.**
- **Seasonality: Reveals patterns that repeat at regular intervals, like daily, weekly, monthly, or yearly patterns.**
- **Residuals: These are what remains after the trend and seasonal components have been removed, often providing insights into irregular factors or noise in the data.**

Below is additive decomposition, where we assume data elements all add up to grow into a good and predictable fit.



As initially said, there is a clear downward trend in the data. Trend is not saturating but rather continuous, importantly there is no massive change over the years, suggesting it to be additive. Seasonality is consistent which raises if info has been captured effectively or not. The residuals are somewhat scattered based on the scales but do form a slight pattern. This means that the additive model is capturing the fit but not to a great extent.

Given below is multiplicative decomposition, where we assume data elements multiply and grow to become a better fit.



Trend is like additive decomposition. Seasonality seems to be better captures in multiplicative decomposition as the variations are in line with trend.

Residuals are closely ranged between 0.8 to 1.6 at the max, if we compare this to additive residuals which range between -35 to +60 we can see that the variation captured by this method is not particularly good either.

Train and Test data

Since we are dealing with a dataframe that is indexed based on Date-Time, we cannot randomize the train and test data split, we must segregate them in an orderly fashion. This is done so that we do not break continuity, furthermore time-series predictions work by predicting a portion of future timelines continuously and not by cherry picking.

Train dataframe to start from January of 1980 and end in December of 1994, totalling 132 months.

Test dataframe to start from January of 1991 totalling to 55 months.

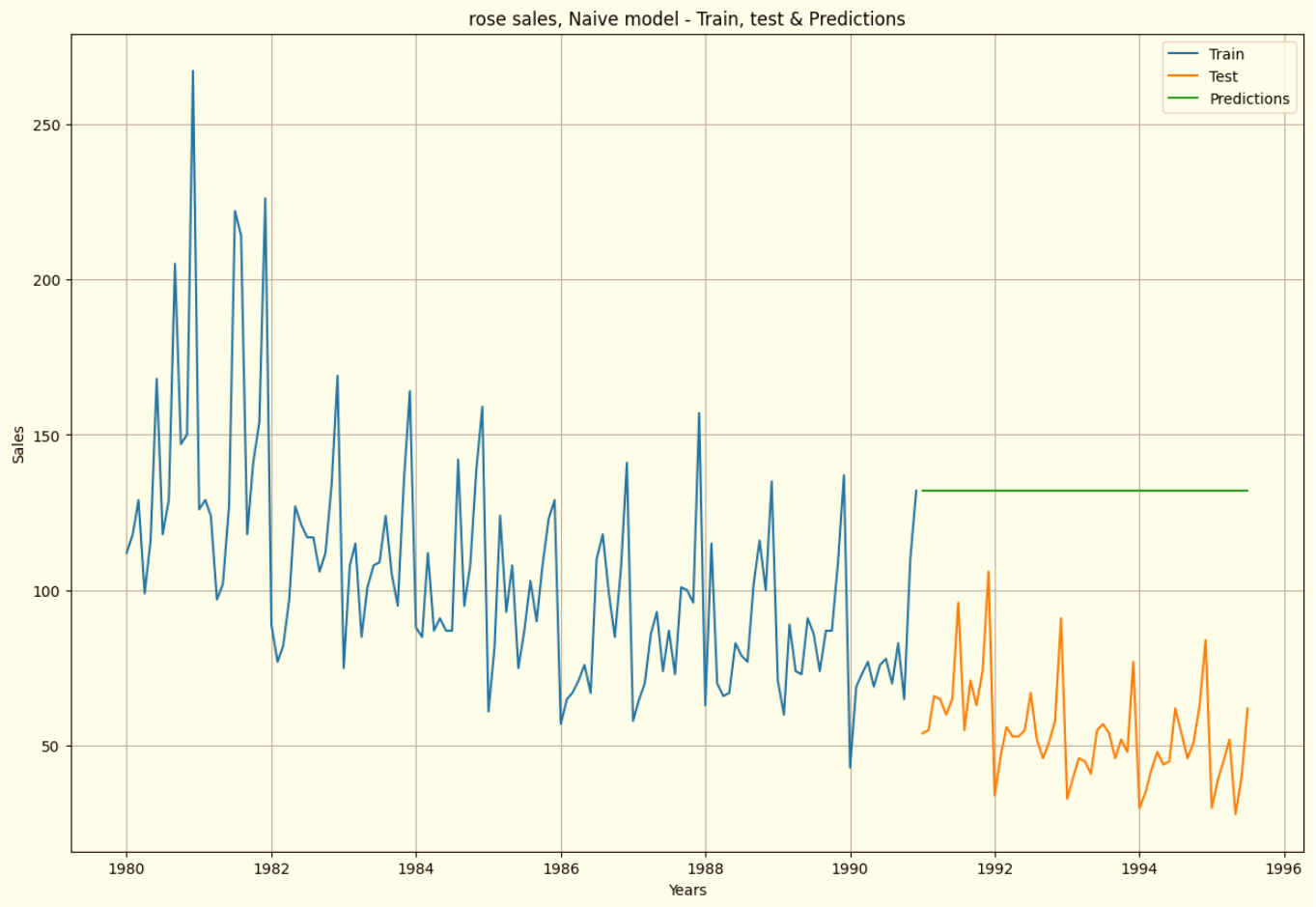
Building Predictive Time-Series Models

Forecast using Naïve method.

Naive forecasting is the simplest form of time series forecasting, based on the assumption that future values will be the same or very similar to the most recent observed value. The primary advantage of naive forecasting is its simplicity. It doesn't require any complex calculations or analysis; it is simply plug and play. We use the most recent month's sales as the prediction for the next month, making it easy to understand and apply.

In our case, we used the sales figure from the last available month(This would be December of 1990) as the forecast for each subsequent month. This method serves as a baseline to assess how much more accurate our sophisticated models are."

While naive forecasting is straightforward, it doesn't account for trends, seasonality, or any other changes in the data over time. Therefore, it's less accurate, especially in volatile markets or with seasonal sales data.



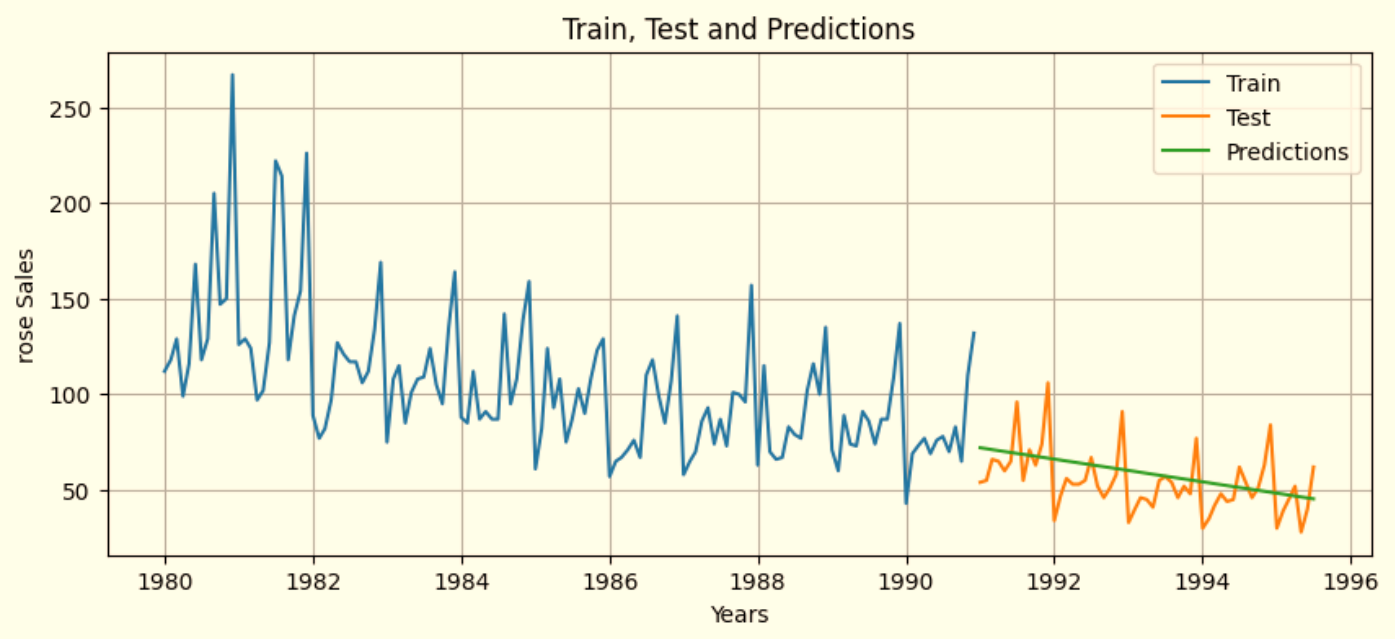
The green line in the plot above is the predictions, visually it is clear that it is not a good fit.

To measure how accurate our predictions are, we use a statistic called the Root Mean Square Error (RMSE). Think of RMSE as a ruler that measures the distance between our predicted sales and what happened. A smaller value means our predictions were closer to reality.

RMSE for naïve forecasting is "79.264", considering the scales we are dealing with here, this is not particularly good. The benchmark has now been set.

Forecast using Regression.

Linear regression helps us draw a line through based on historical sales data to project future sales. It's like connecting the dots in a way that shows where our sales are heading. Generally, regression employs dependent and independent variables(in various combinations). Here the dataframe being a univariate time series, the time index is the major factor.



The above plot shows the train, test, and linear regression predictions. The Green line cutting across the original test values in orange are the predictions and they are somewhat like the average line. Regression has captured the trend mildly and the predictions mirror the same.

The RMSE is 15.306, which is a high value considering the scale of the sales we are dealing with here. Linear regression clearly struggles to capture the seasonality we have in place.

Linear regression, from the looks of it, proves to be a poor and unreliable model, but still performs significantly well in comparison to naïve forecasting.

Forecast using Moving Averages.

The moving averages method calculates the average sales over a set number of past months and uses this average to predict future sales. We analysed our sales using different 'trailing values' – 2, 4, 6, 9, 12, and 15 months. This means we calculated averages over these various time spans. A 2-month trailing value averages the last two months of sales, a 4-month value averages the last four months, and so on.

Using different trailing values allows us to understand how our sales forecasts change when we consider shorter versus longer historical periods.

The table below, shows a small peek of the data for 2 and 4 trailed averages.

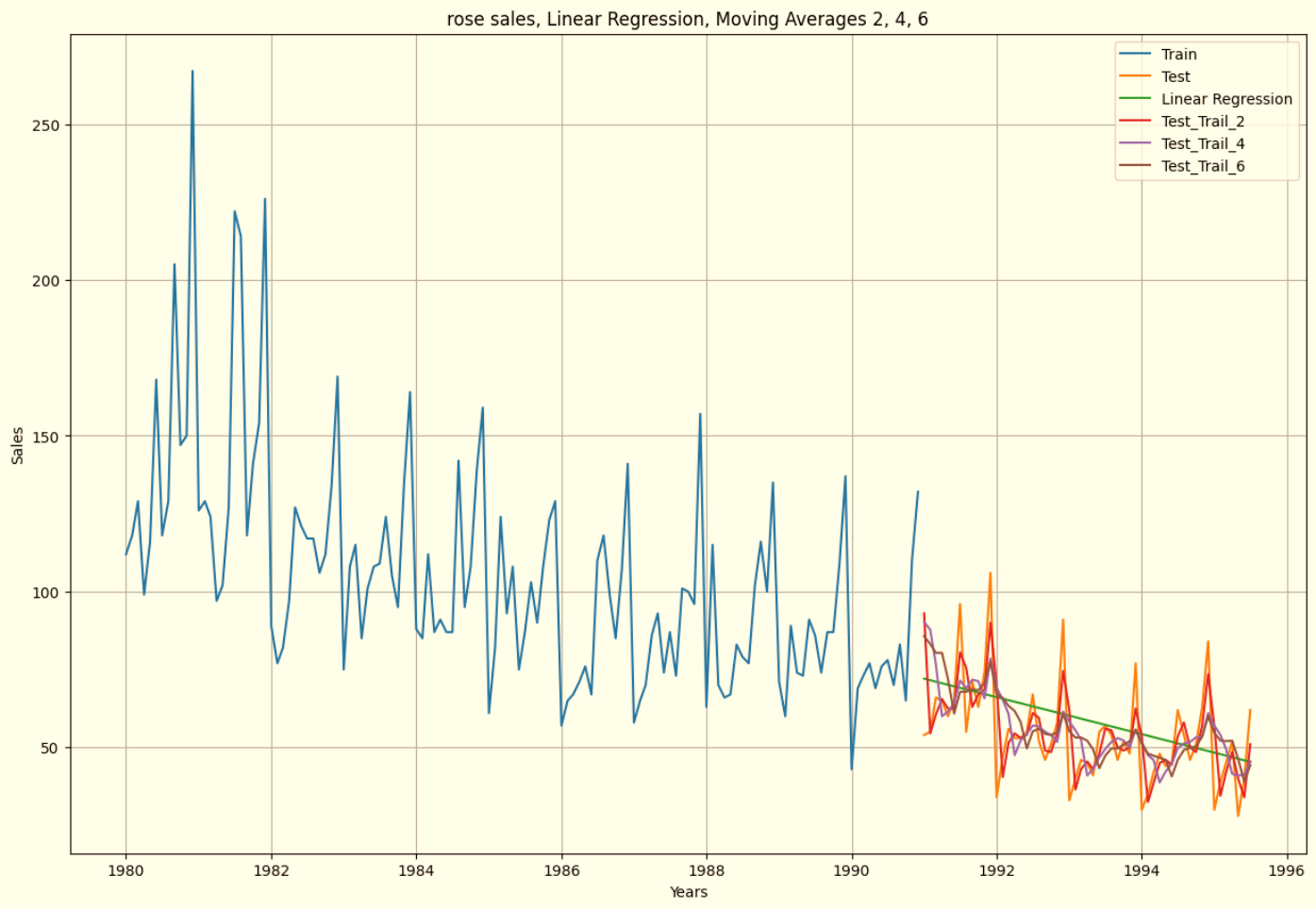
YearMonth	Rose	Sparkling - Trailing by 2	Sparkling - trailing by 4
1/1/1980	112	NaN	NaN
1/2/1980	118	115	NaN
1/3/1980	129	123.5	NaN
1/4/1980	99	114	114.5
1/5/1980	116	107.5	115.5

Let's discuss the RMSE values,

Root mean square error for **trail 2 is 11.611,** Root mean square error for **trail 4 is 14.536,**

Root mean square error for **trail 6 is 14.578,** Root mean square error for **trail 9 is 14.83,**

Root mean square error for **trail 12 is 15.375,** Root mean square error for **trail 15 is 15.287**



The plot shows the train, test, and predictions for trailing 2, 4, 6 along with linear regression. The moving average method seems to perform better than linear regression, particularly the model where the trailing mean is done by 2 values. Rest of the trailing values are very close to linear regression.

The RMSE for trailing average of 2 is the best of the lot, even when comparing Linear regression. Second comes average trailed by 4 values, then 6, 9, 15 and finally 12.

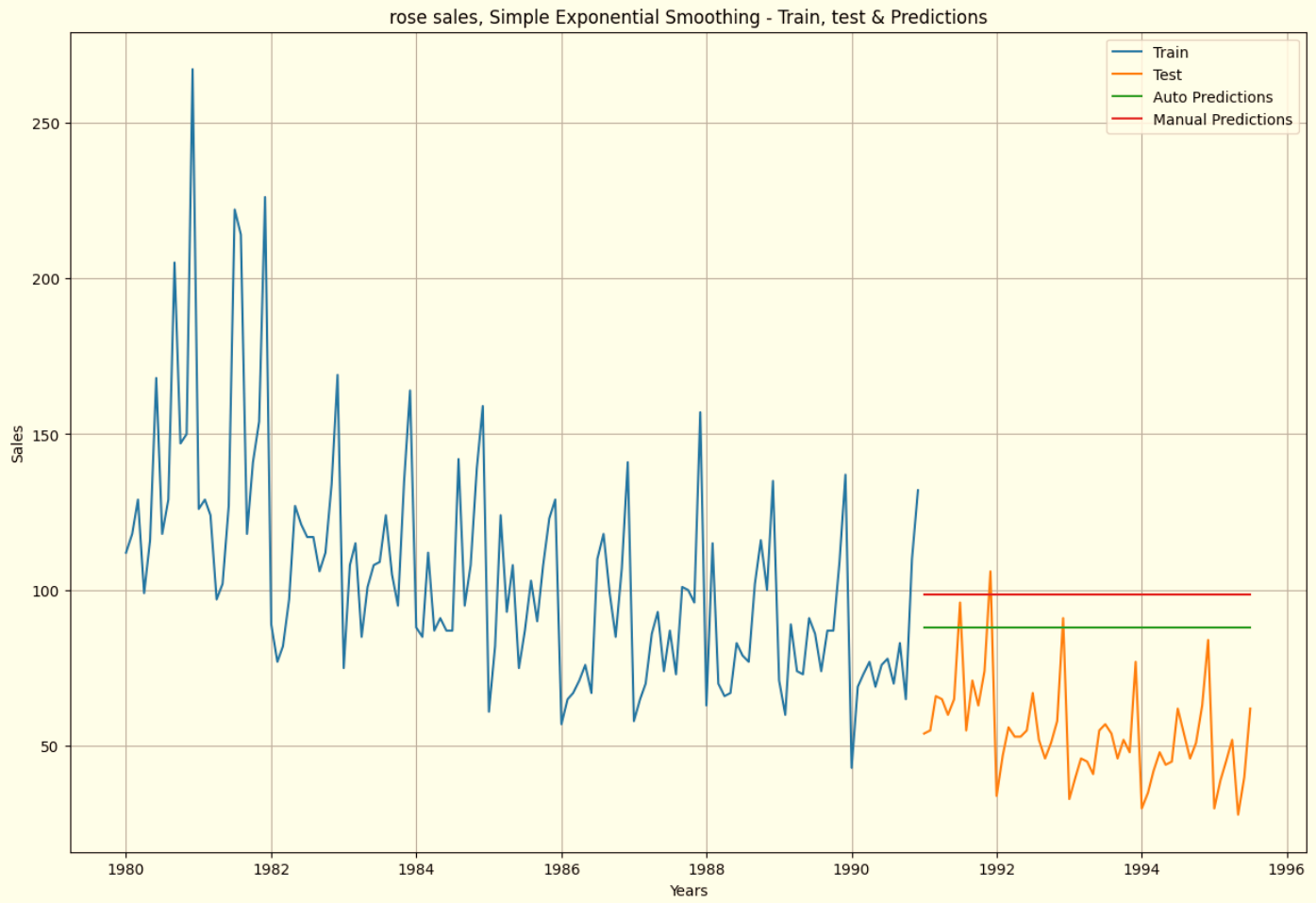
Forecast using Simple Exponential Smoothing.

Simple Exponential Smoothing works by assigning exponentially decreasing weights to past sales data. This means more recent sales data is considered more heavily in predicting future sales.

In SES model, the key parameter we use is known as 'alpha' or the smoothing factor or level parameter. Alpha is a number between 0(lower) and 1(higher) that determines how much weight the model gives to the most recent sales data.

We autofit and let the package decide on the right alpha value initially, in this instance we get it to be around “0.12”. **The RMSE value we got was 37.159.** This is more than twice to linear regression and approximately half of naïve method. Hence this is not adequate and is a poor fit.

Finding the right alpha value is crucial in building a better model and understanding of the data. We tried multiple alpha values ranging from 0.3 to 0.9(in steps of 0.1).



The green and red lines going across are predictions done with alpha as “0.12(autofit)” and “0.3(manual)”, provided in the plot above.

The alpha values we manually tested did not perform any better, they were way of their mark with the least being 0.3, with an **RMSE value of 47.060,** very poor in comparison.

Simple exponential smoothing(SES) has not captured the trend or seasonality of the data provided. The performance of this model is less than moving averages model.

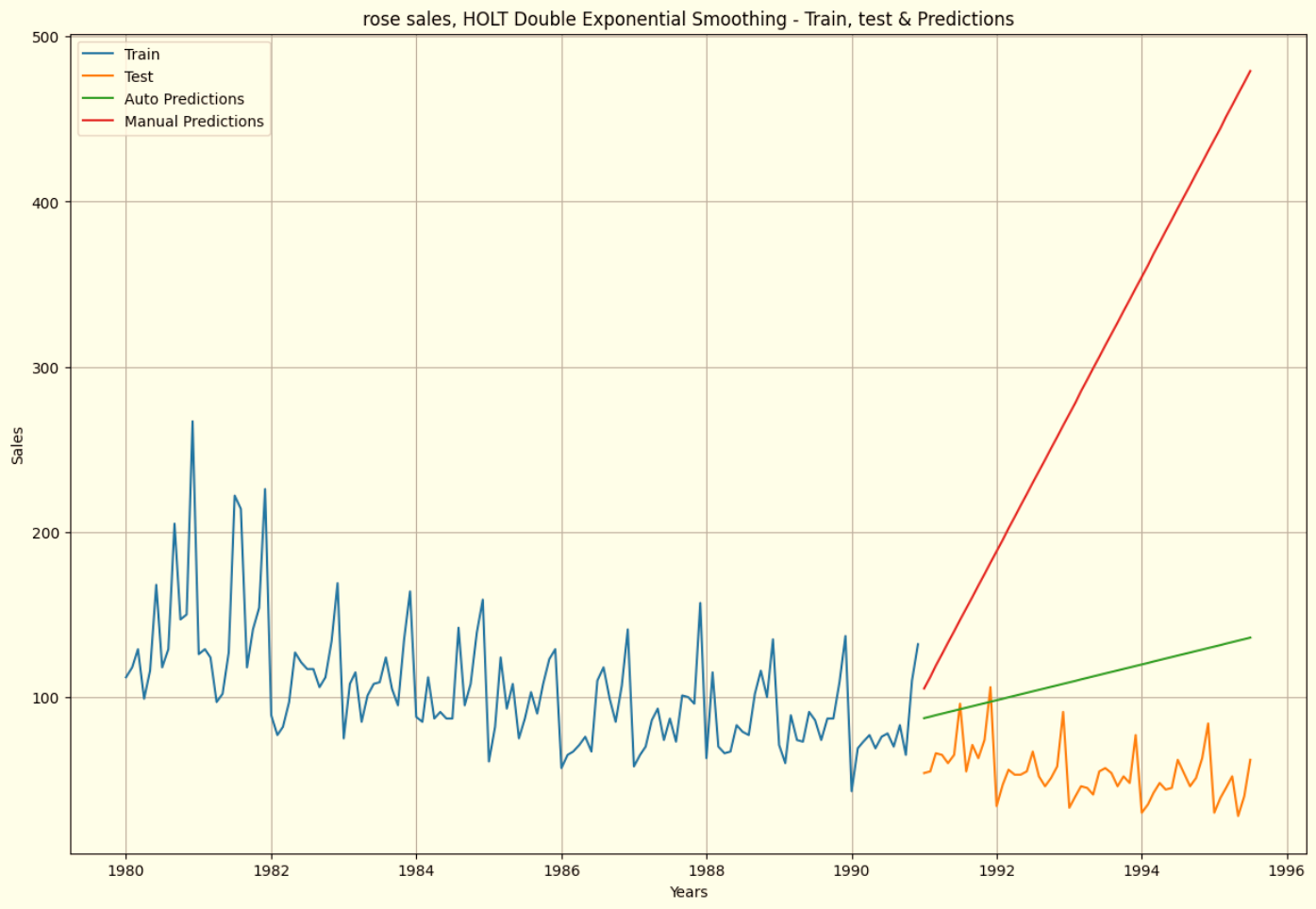
Forecast using Double Exponential Smoothing(Holt's Method).

Double Exponential Smoothing is an extension of Simple Exponential Smoothing, designed to better handle data with trends, without considering seasonality. This method is ideal for data where trends, either increasing or decreasing, are present over time.

Like SES, alpha in Double Exponential Smoothing controls the level smoothing, we have another parameter called beta which controls the trend component. Higher beta value adapts quicker to recent change in trend and vice versa.

We autofit and let the package decide on the right alpha value initially along with the beta value, in this instance we get it alpha to be around "0.16" and beta to be '0.13". **The RMSE value we got was 62.514.** A very poor fit compared to SES.

Finding the right alpha and beta value is crucial in building a better model and understanding of the data. We tried multiple alpha values ranging from 0.3 to 0.9(in steps of 0.1) and likewise for beta too.



The red line in the plot above corresponds to a Manual prediction done with alpha and beta as "0.3"(the best of the manual combinations we tested). Similarly, the green line corresponds to Auto prediction done with as alpha as "0.16" and beta as "0.13".

The manual predictions performed abysmal in comparison. **An RMSE value of "264.975"** was obtained.

Double exponential smoothing(DES) has not captured the trend coherently for the data provided. The performance of this model pales in comparison to moving averages.

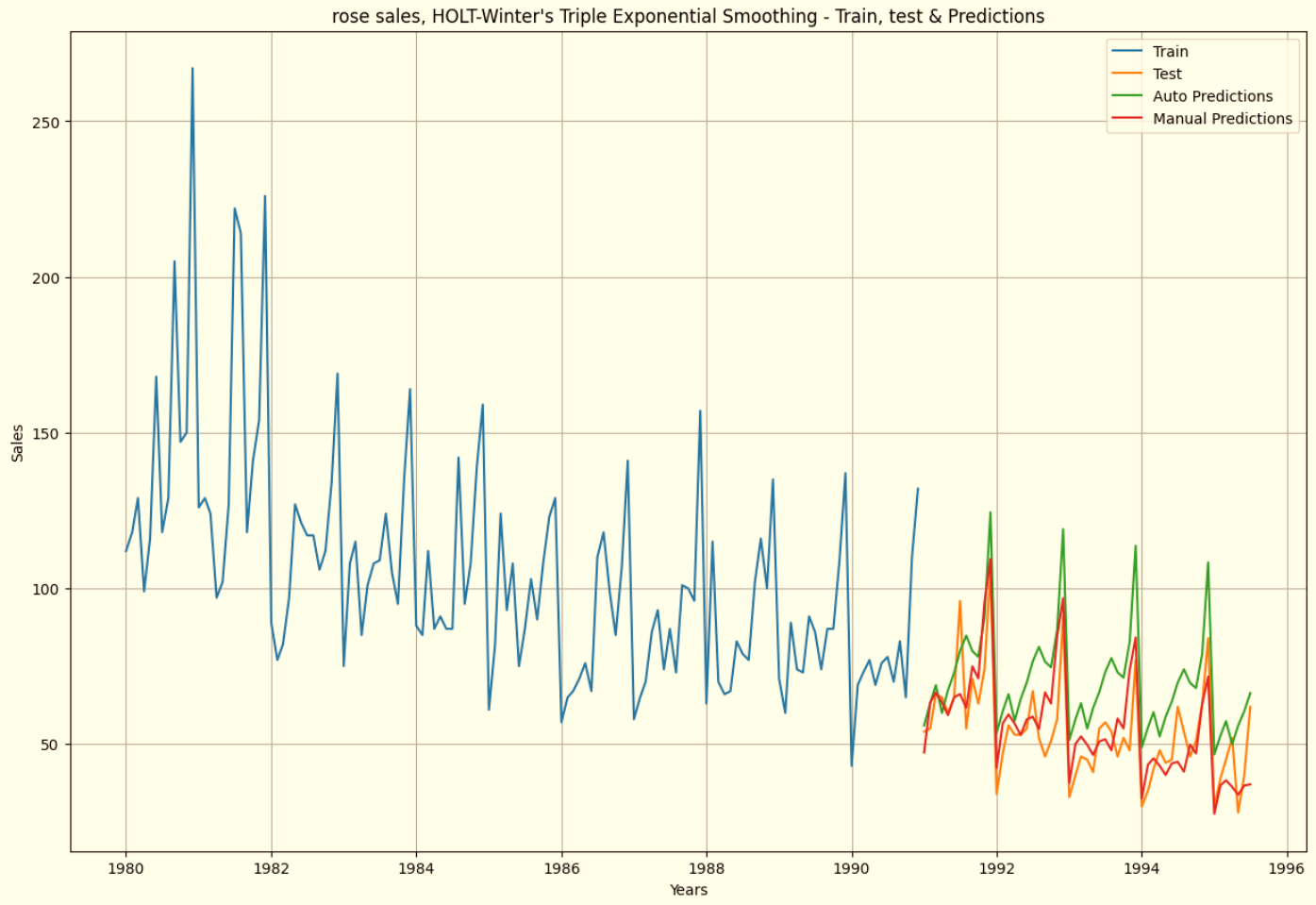
Forecast using Triple Exponential Smoothing(Holt-Winter's Method).

Triple Exponential Smoothing takes it up a notch from DES by adding a seasonal component. It's particularly effective for data where both trend and seasonality are present, like the dataframe that we have with us. Here gamma is used to smooth the seasonality component.

Initially we let the package autofit the parameters, obtained are alpha as "0.07", beta as "0.03" and gamma as "0.0008", The RMSE value we got was 18.661 As expected, TES has performed better than DES or SES, but still is lagging moving averages.

Manual models were created in the same lines as we did for DES, gamma was also set within the same value ranges. The best model from this was where alpha, beta was "0.3" and gamma was "0.4", with an RMSE value of "10.565". Manual predictions performed better than auto fit by a good margin.

The plot below shows the predictions, Manual TES model has performed good to an extent that the curves are very close to the original test values. The green line which portrays auto predictions can be seen to be off the mark, the difference of around 8 RMSE units' effect is seen clearly.



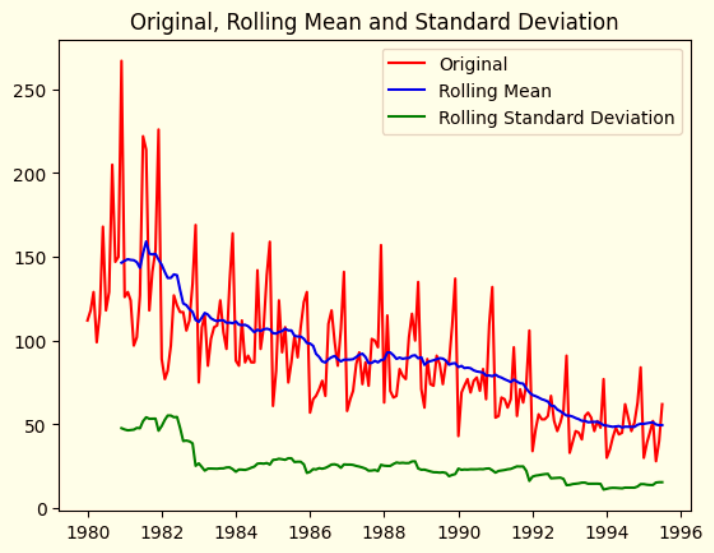
Test of Stationarity

In time series analysis, it's important to know whether our data is “STATIONARY”, meaning that its statistical properties like mean, variance and the like are constant over time. This is important for certain types of forecasting models to work effectively.

We can think of stationarity like levelling the playing field. We might have short term fluctuations here and there, but overall values remain similar.

One simple way to check for stationarity is by visually inspecting the plot of the time series. If the series appears to have a consistent mean and variance, and doesn't portray trend or seasonality, it may be stationary. But visual inspection might not be enough in most real-world scenarios, hence we use a statistical test called Augmented Dickey-Fuller (ADF) test. This test checks if a unit root is present in the series, which is a sign of non-stationarity. In simple terms, it helps us determine if the patterns in our data are influenced by time-based structure.

Below plot on the left shows the mean against the original values along with standard deviation.



Now let’s run Augmented Dickey-Fuller Test on our timeseries(in its unadulterated form) and check for stationarity, below environment is set and conditions are determined.

Null Hypothesis HO : Time Series is non-stationary.
Alternate Hypothesis Ha : Time Series is stationary.

If p-value(significance) < 0.05 then null hypothesis (i.e.) Time Series is non-stationary is rejected else the Time Series is non-stationary is failed to be rejected.

The obtained p-value “0.33” is greater than 0.05, hence we have failed to reject the null hypothesis.

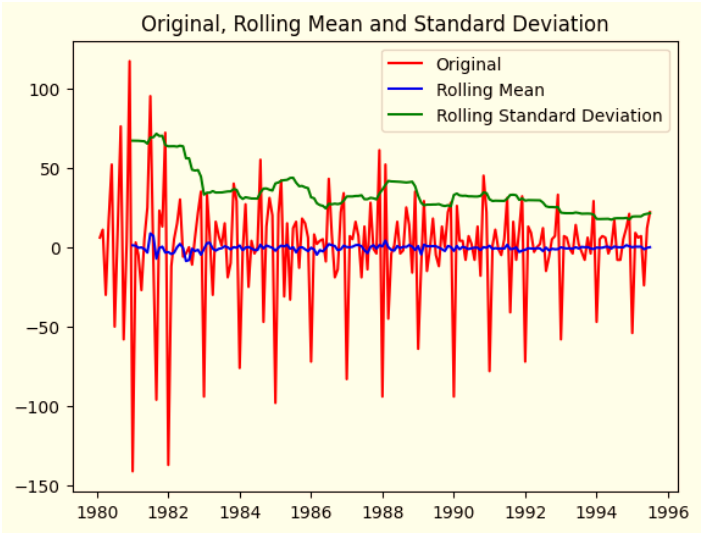
If our data is found to be non-stationary and, it is in our case, we need to transform it to make it stationary. Hence, we will involve differencing. Differencing is not the only method that we can employ there are other ways like employing logarithms transformations.

The plot on the right shows the mean and original values after differencing to the order of 1, now by referencing the scales we can see that the datraframe has achieved stationarity.

Applying Augment Dicky-Fuller test and basing the same conditions, **we get the significance to be “0.000”,** meaning we have successfully rejected the null hypothesis.

The dataframe has achieved stationarity after differencing it by an order of 1.

The above steps that we have done are very crucial to the models that are going to be built. Stationarity helps in setting the ground and providing reliable and robust forecasting methods and ensuring our business strategies are based.



Auto Regressive Integrated Moving Average(ARIMA)

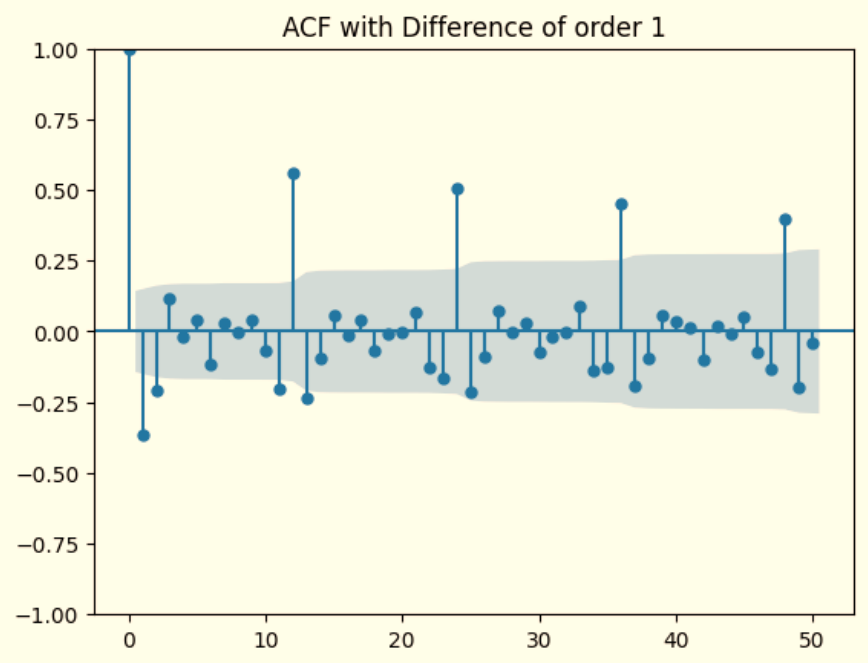
ARIMA is a sophisticated forecasting model that combines three key concepts: Auto Regression (AR), Integration (I), and Moving Averages (MA). AR looks at the relationship of current to be predicted values with its past counterparts, Integration(I) helps in making the series stationary and Moving averages(MA) incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The three concepts of ARIMA model have their unique parameters: (p, d, q). 'p' is the order of the Auto Regressive part, 'd' is the degree of differencing required to make the series stationary, and 'q' is the order of the Moving Average part.

Selecting the right (p, d, q) values is crucial. This is where the Akaike Information Criterion (AIC) comes in. AIC is a tool used to compare different ARIMA models on how well they fit the data. A lower AIC value generally indicates a better model. Our goal is to find the ARIMA model with the lowest AIC value, as it suggests an optimal balance between model fit and complexity.

Before we proceed with model building, we must first uncover what the values of “p” and “q” would be, “d” is already set a ‘1’, courtesy of differentiation. This is where two major plots come in, they are Autocorrelation Function(ACF) and Partial Autocorrelation Function(PACF).

ACF for “q” (MA parameter): The ACF plot helps us identify the optimal value for 'q', the MA (Moving Average) part of our ARIMA model.

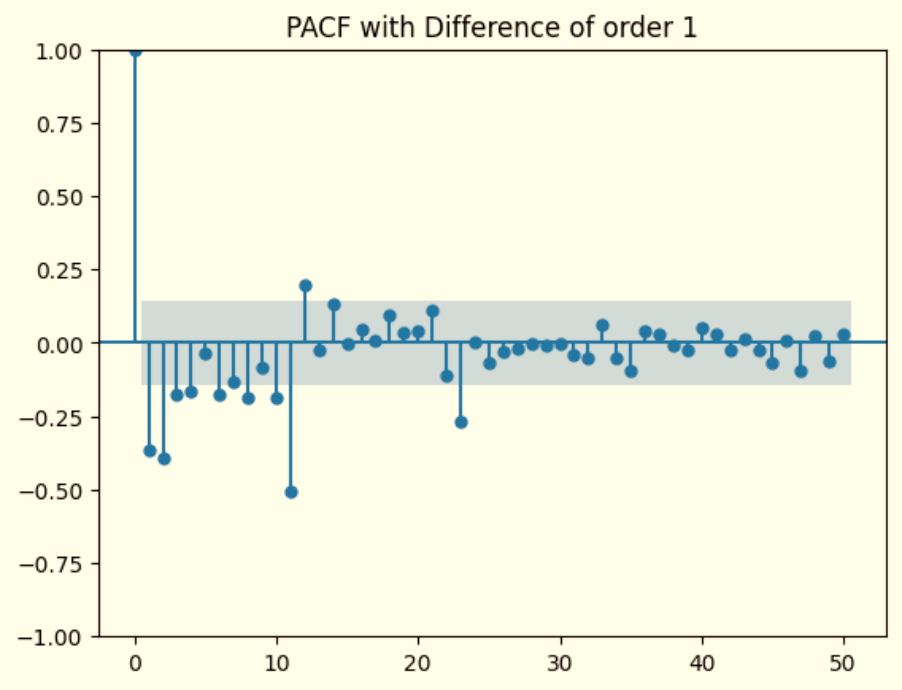


The plot above is used to find the optimal value(s). The shaded region represents the confidence bands, hence if a point(lag value) lies outside the band, then it indicates that it is statistically significant. It also means we can find meaningful relationships between observations at this lag.

Look for the lag where the correlation starts to become insignificant (bars start to fall within the shaded area). This point often suggests a good value for 'q', in this case being ‘3’.

Note that the first point is a value gauged against itself therefore it will always be 1.

PACF for "p" (AR parameter): Similarly, the PACF plot is used to determine 'p', the AR (Auto Regressive) part.



The same guidelines from ACF apply here to, hence 4 would be a good value for 'p' as start.

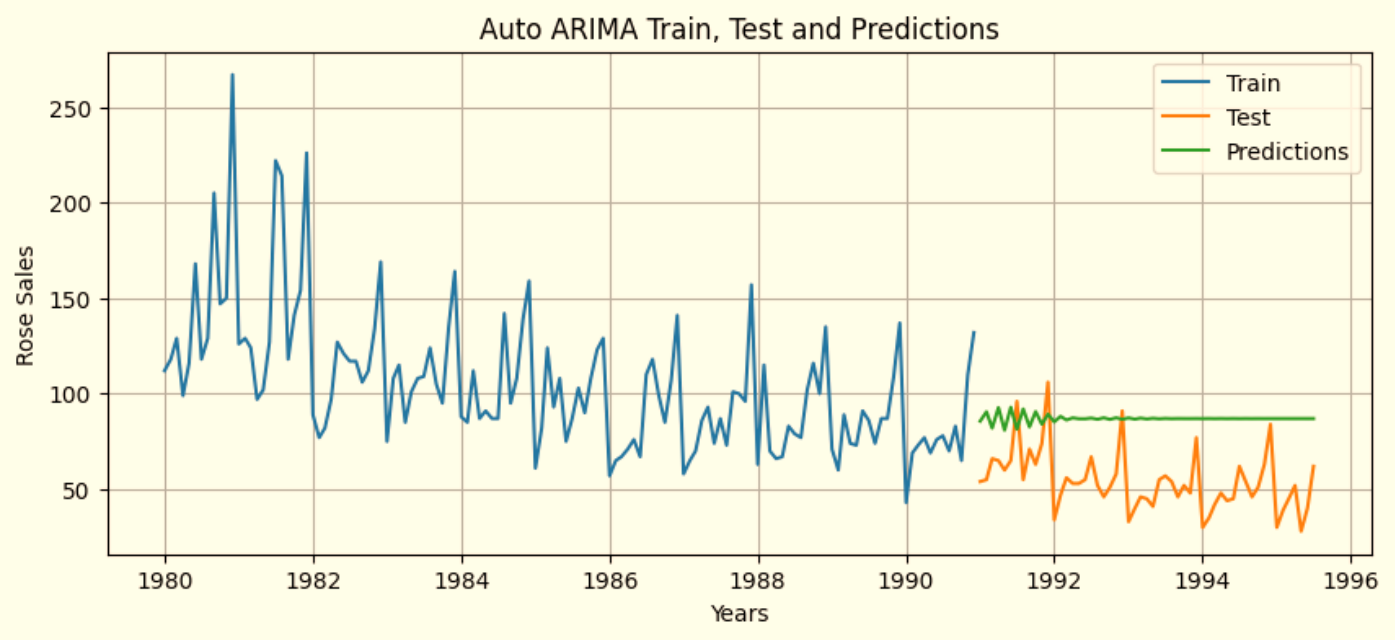
Now let's model ARIMA, instead of choosing one value for p and q we will use this range 0, 1, 2, 3, 4 to test different parameter combinations(insignificant values are also chosen to determine how they perform). 'd' will remain constant at 1.

Please find the top 5 parameter combinations that worked best.

Parameter (p, d, q)	Akaike_Value
(2, 1, 3)	1274.70
(4, 1, 3)	1278.45
(3, 1, 3)	1278.66
(2, 1, 4)	1278.77
(1, 1, 4)	1279.61

From the above table we can see that the best performing one was with parameters "pdq" as (2,1,3). But the runner up had the 'pdq' as (4,1,3), incorporating one of the insignificant values. This is shows that even in some scenarios we can be influenced by trivial values.

We built ARIMA with 'pdq' values as (2, 1, 3). The RMSE value that we obtained was "36.385". ARIMA has produced a model that is average in comparison to the models we have built until now.



The plot above shows the train, test, and predictions. We can see that the performance of ARIMA is not up to par.

Seasonal Auto Regressive Integrated Moving Average(SARIMA)

Seasonal Auto Regressive Integrated Moving Average is an extension of ARIMA model by adding a seasonal component. It's particularly useful for time series data with clear seasonal patterns like the one discussed now.

A SARIMA model is typically denoted as SARIMA(p, d, q)(P, D, Q, s). Here, p, d, q are the non-seasonal ARIMA parameters, and P, D, Q are the seasonal components of the model, with 's' representing the length of the seasonal cycle.

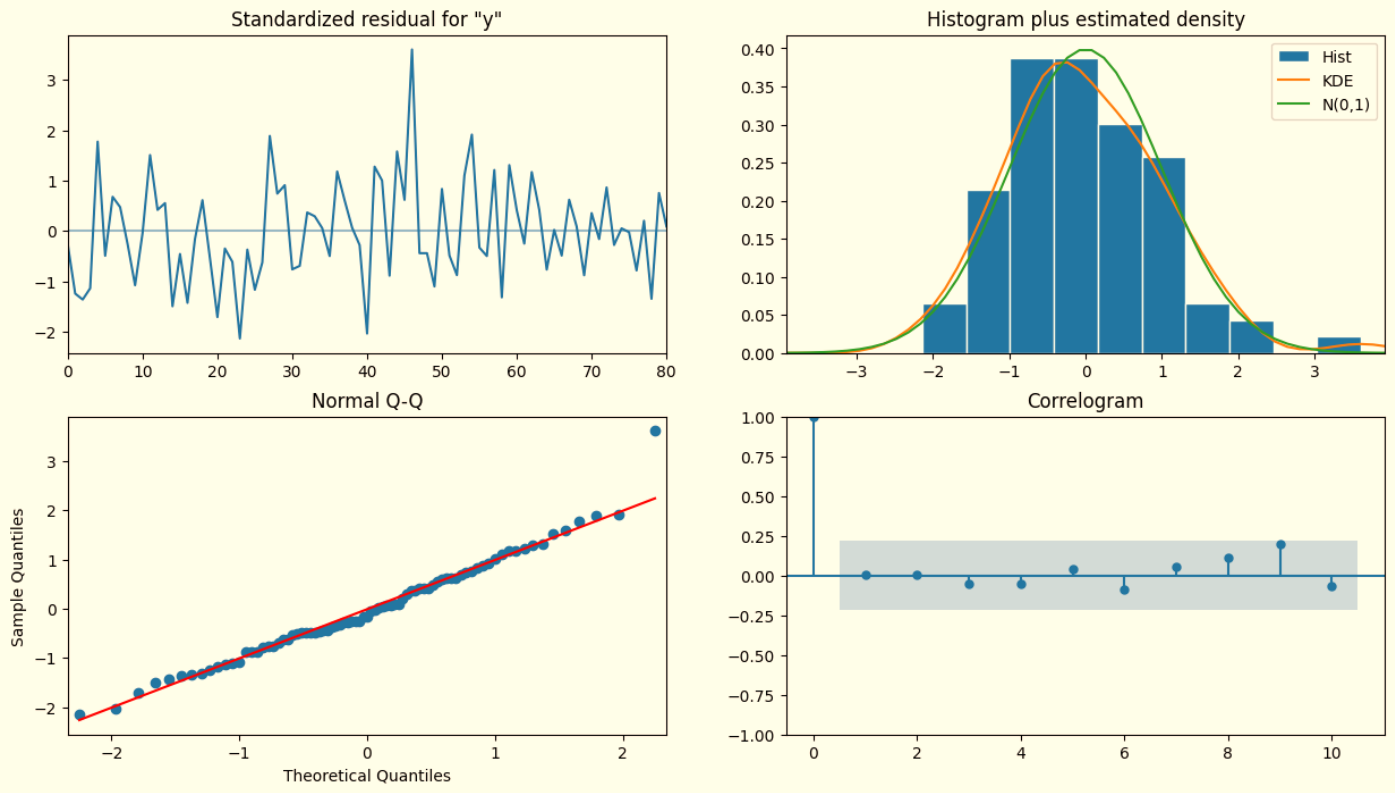
For example, SARIMA(1, 1, 1)(1, 1, 1, 12) would mean a model with one non-seasonal AR term, one differencing, one MA term, and similarly one seasonal AR term, one seasonal differencing, and one seasonal MA term, with a seasonal period of 12 (which could be 12 months in a yearly cycle).

Now let's model SARIMA, we will use the same 'pdq' value range from ARIMA for both non-seasonal and seasonal components, seasonality 's' alone will have the value as '12' which is consistent with our data.

Please find the top 5 parameter combinations that worked best.

Non-Seasonal 'pdq'	Seasonal 'pdq' with 's'	Akaike_Value
(1, 1, 1)	(0, 1, 3, 12)	12
(0, 1, 3)	(0, 1, 3, 12)	14
(2, 1, 2)	(0, 1, 3, 12)	16
(0, 1, 4)	(0, 1, 3, 12)	16
(2, 1, 3)	(0, 1, 3, 12)	18

The RMSE obtained from the top pick parameter combinations above is "16.521", which is better than ARIMA, very close to linear regression but still not good as TES.



Top-Left: Standardized Residual plot shows the residuals of the model over time. You would want to see no direct pattern or trends, which would suggest that the model has captured the time series structure well. The residuals seem to be fluctuating around zero without systematic patterns, which is a good sign.

Top-Right: Histogram plus Estimated Density plot compares the distribution of the standardized residuals to a normal distribution. The blue bars represent the histogram of the standardized residuals, showing the frequency of residual values. The orange line is a kernel density estimate (KDE), which is a smoothed version of the histogram. The green line represents a standard normal distribution. You would want the KDE (orange line) to follow the normal distribution (green line) closely. In our plot there seems to be a slight deviation when they peak, but they are almost following within the same footsteps in other regions. This is implying it is not perfect enough but very close. This indicates that the model has areas where it can be improved.

Bottom-Left: Normal Q-Q plot is used to assess if the residuals are normally distributed. The dots represent the quantiles of the residuals, and the line represents a normal distribution and following that would mean we have a normal distribution at hand. As seen, there is only one point that is deviating clearly, but other than the points follow the line diligently.

Bottom-Right: Correlogram (ACF Plot) shows the autocorrelation of the residuals at different lags. Ideally, you would want to see that the autocorrelations are within the blue shaded area. This would suggest that the model has captured the time series' autocorrelation structure well. In our plot, all the autocorrelation coefficients are within the blue area, which suggests that there's no significant autocorrelation in the residuals.

Summary of built models and performance

Below is a table that shows the performance of all the models that built and predicted. For our dataframe triple exponential smoothing manual approach followed by Moving average trailing by 2 points have taken first and second spots respectively. Spots 3, 4, 5 and 6 all are taken by Moving average method trailing by 4, 6, 9, 15 in order.

We have considered Naïve method to be our benchmark, considering the performance characteristics, **TES manual approach is relatively 86.7% better than naïve method.**

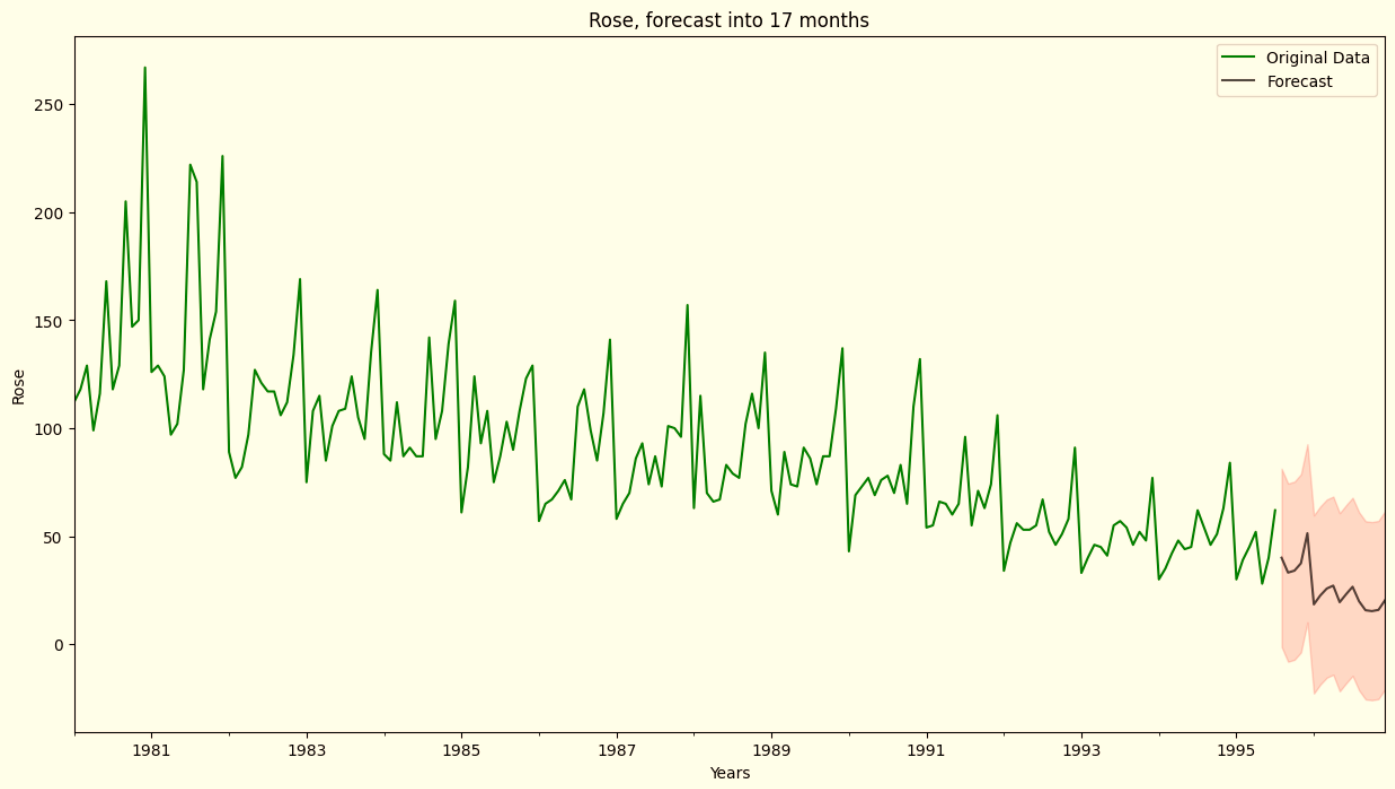
Model	Root Mean Square Error
Triple Exponential Smoothing(Manual) where alpha, beta are 0.3 and gamma is 0.4	10.565
Moving Average Trailing by 2 points	11.611
Moving Average Trailing by 4 points	14.536
Moving Average Trailing by 6 points	14.578
Moving Average Trailing by 9 points	14.830
Moving Average Trailing by 15 points	15.287
Linear Regression	15.306
Moving Average Trailing by 12 points	15.375
SARIMA with "pdq" as (1, 1, 1) and "PDQs" as (0, 1, 3, 12)	16.521
Triple Exponential Smoothing(Auto-fit) where alpha, beta and gamma are 0.07, 0.03, 0.0008	18.661
ARIMA with "pdq" as (2, 1, 3)	36.386
Simple Exponential Smoothing(Auto-fit) with Alpha as 0.12	37.159
Simple Exponential Smoothing(Manual) with Alpha as 0.3	47.060
Double Exponential Smoothing(Auto-fit) where Alpha is 0.16 and beta as 0.13	62.514
Naive_Model	79.264
Double_Exponential_Smoothing_Alpha_0.3_Beta_0.3 Double Exponential Smoothing(Manual) where Alpha and beta are 0.3.	264.975

The worst model was Double exponential smoothing manual approach that has a whopping 234.3% performance degrade to our benchmark.

Forecast - 17 month's

The best model we have is Triple exponential smoothing where alpha, beta is "0.3" and gamma as "0.4". Now we will use this model to forecast 17 months from 1995 August to 1996 December.

The below plot shows the forecasts(the black line), since these are predictions there can be some errors, hence the shaded region around the forecast are the confidence bands set at 95% confidence.



The downward trend has been perfectly captured and we can see that in the forecasts. The confidence intervals are broad and occupy a significant part of the plot space. This fundamentally implies we have a much variability in the values predicted over the accepted confidence bands.

The forecast also suggests that we might see a new all-time low in sales, in the latter part of 1996.

Process Summary and business insight's

We have been tasked with forecasting sales of wine and the dataframe was provided for use.

Plotting the dataframe showed us hints of strong trend and seasonality. Decomposing the dataframe confirmed the same. We encountered two instances where the data was filled with null values(empty), the same was dealt by using historical imputation. We segregated the data into train and test.

After completing pre-processing of data, it was used to build time series forecasting models. The benchmark model was set by using the naïve method, we used Linear regression, moving averages trailing by various values, Exponential smoothing techniques(simple, double, and triple).

The data was also used to build complex models like Autoregressive integrated moving averages(ARIMA) and Seasonal Autoregressive integrated moving averages(SARIMA).

To make ARIMA and SARIMA a reality we had to perform "test of stationarity" to see if the dataframe has constant mean and variations throughout. Augmented Dicky-fuller test was used to achieve stationarity.

ARIMA and SARIMA were built upon multiple combinations of 'pdq', but we kept seasonality as '12' since we had strong evidence to support the claim. Akaike Information criterion(AIC) was used to gauge the parameter combinations and get the best of the lot.

Comparing the performance of the model throughout was done with the help of Root mean square error(RMSE). The lower RMSE value the better the model performed.

Triple exponential smoothing with a huge performance difference over other models took the top spot on the podium. Thereby becoming the best performing model.

Business insights.

- **The forecasts suggest that we are going to see lower sales in the coming months, hence we must take steps to curb production as to reduce losses.**
- **The sales of Rose wine will not see an increase compared to previous years, even in time of holiday season we could struggle quite a bit.**
- **The initial months(from January to June) could be the most hurting time, it might be a very rough road with no foreseeable improvement.**
- **Forecast suggests that we can see a new all-time sales low in the latter part of 1996.**
- **We need to revert and think of our strategy, the share in the market could reduce drastically, we must take necessary measures to turn this around.**
- **Analysing what worked in the years 1980, 1981 and 1982 could provide us with some information that could be of good use now.**