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GREAT LAKES
INSTITUTE OF MANAGEMENT

TIME SERIES FORECASTING

Group Assignment

(Rose Wine dataset)


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About Us

This section will cover brief introduction about us. We are seasoned professionals with diverse experience.

Rajiv

Am a CA and currently working as **Vice President & Group Head of Internal Audits** for Flipkart, Myntra, PhonePe, e-Kart and Walmart India. Prior to that I have worked in different audit and governance roles in PwC, Coke and Diageo.

Rekha

Overall **20+ years** of corporate and management experience. Currently (from 2018) working as **Strategy Consultant (Independently)** for firms and companies that range from hospitality, manufacturing, and retail industries. Before moving to an independent role was with **KPMG Global Services for 12 years**. Hands-on manager with expertise in accounting systems development, fiscal management. and financial reporting. Proven record of developing and implementing financial and operational controls that improve P&L scenario and competitively position firms.

Nikhil

Overall **13+ years of cross functional experience** in FMCG and Alcobev industry. Working with **Diageo PLC** since 2017, looking after **Data Analytics CoE for Global Audit & Risk department**. Before to that worked with **Coca-Cola for 10 years** and completed stint in operations, supply chain (direct & indirect), Master data maintenance (SAP cross functional role) and Data analytics (Internal Audit).

Lavanya

Working with **Novo Nordisk** as a Manager, having **13 years of techno-functional experience** in SAP Fiori, Embedded Analytics,SCP, ABAP on HANA and also having SAP Consulting experience on UX design strategy, RFP's/Pursuits and solutioning. During this tenure, worked in **various SAP ERP implementation projects spanning across Manufacturing, Healthcare, Retail and FMCG domains**. Prior to this, I have worked with **Accenture, Caterpillar and Wipro**.

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Problem Statement:

For this particular assignment, the data of different types of wine sales in the 20th century is to be analysed. Both of these data are from the same company but of different wines. As an analyst in the ABC Estate Wines, you are tasked to analyse and forecast Wine Sales in the 20th century.

Data set for the Problem: **Rose.csv**

Remarks: All coding performed in Jupyter notebook, named **"Time Series_GA_Grp1_Rose" for Rose**, has been duly attached.

1 Import relevant libraries, read the data as an appropriate Time Series data and plot the data

We imported all necessary libraries before we load the dataset.

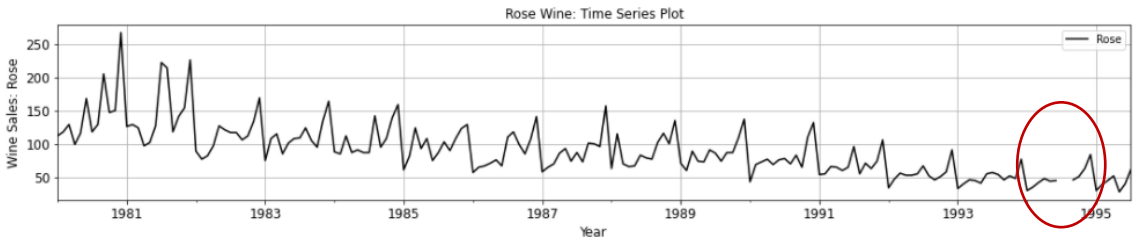
Read the dataset

```
# Load the dataset for "Rose"
df= pd.read_csv('Rose.csv',parse_dates=True,index_col=0)
df.head(2)
```

	Rose
YearMonth	
1980-01-01	112.0
1980-02-01	118.0

Using pandas library we have read the '.csv' file, as a time-stamped file by enabling the parameter 'parse_dates'. Further, time Series in a lot of cases is easier to work if the index is Time stamped. Thus, we are making the zeroth column as index and making 'index_col' is ZERO.

Plot the timeseries



Insights: By looking at the graph, it seems:

- There are **null values** in the data. We will double check the same during EDA.
- There is **promising trend and seasonality** in the data.

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

EDA is performed to understand the data first and try to gather as many insights from it. EDA is a critical process for performing initial investigations on data so as to discover patterns, to spot anomalies and to check assumptions with the help of summary statistics and graphical representations.

Below is the Exploratory Data Analysis for the data sets of our problem statement.

Missing data check

```
df.isnull().sum()
```

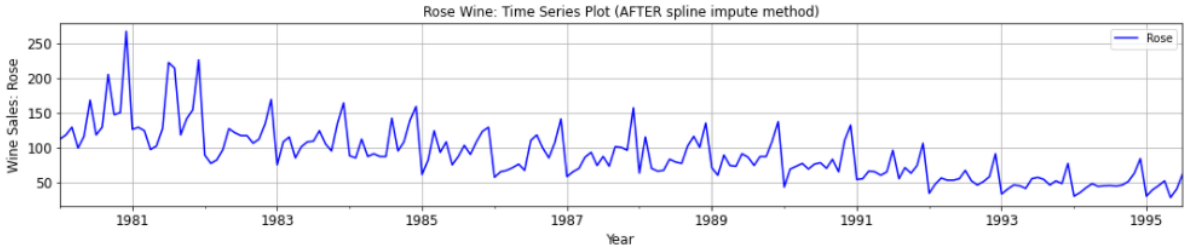
```
Rose    2
dtype: int64
```

Insights: There are **two null values** in the dataset.

Let's impute missing values using "spline" interpolate method.

```
#missing data imputation using "spline" interpolate method
df.interpolate(method = 'spline', order = 2,inplace=True)
```

Plot BEFORE and AFTER plot to check missing values are taken care.




```
df.isnull().sum()
```

```
Rose    0
dtype: int64
```

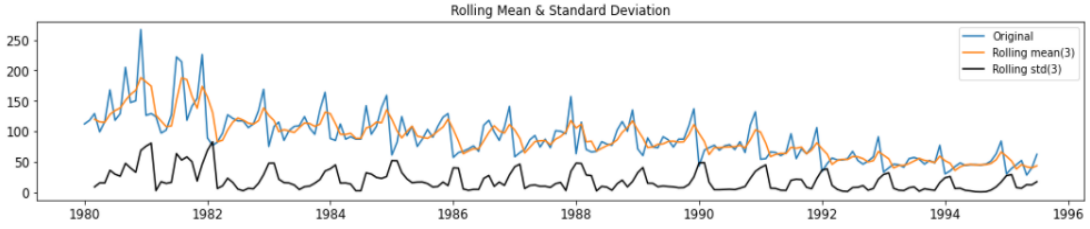
Basic measure of Descriptive Statistics

- We have used '**describe'** function to see the descriptive summary of the dataset.
- Further, we have checked **skewness** of the dataset.
- To check **mean and std deviation** across time we have checked rolling mean and rolling std dev. Using rolling months as 3.

	count	mean	std	min	25%	50%	75%	max
Rose	187.0	89.908354	39.245313	28.0	62.5	85.0	111.0	267.0

```
df.skew()
```

```
Rose    1.266687
dtype: float64
```

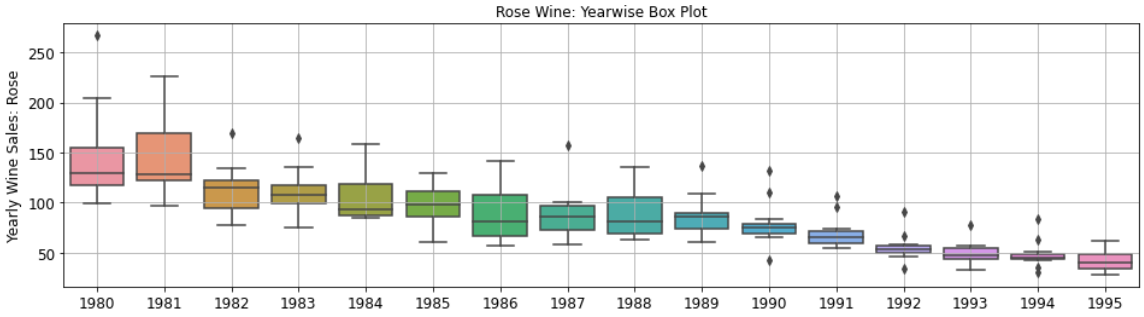


Insights:

- **Mean value is slightly higher than the median value**. It means, **data is skewed**.
- We could see **variation/deviation across the years**.

Plot a year on year boxplot

A boxplot for different years aggregating over different months gives us an indication of the TREND.

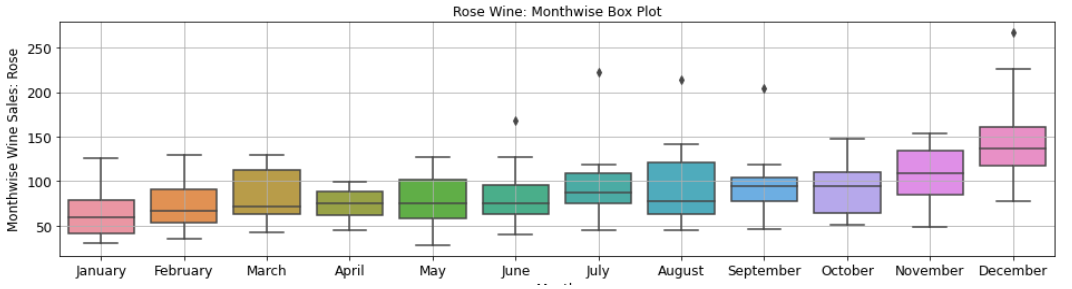


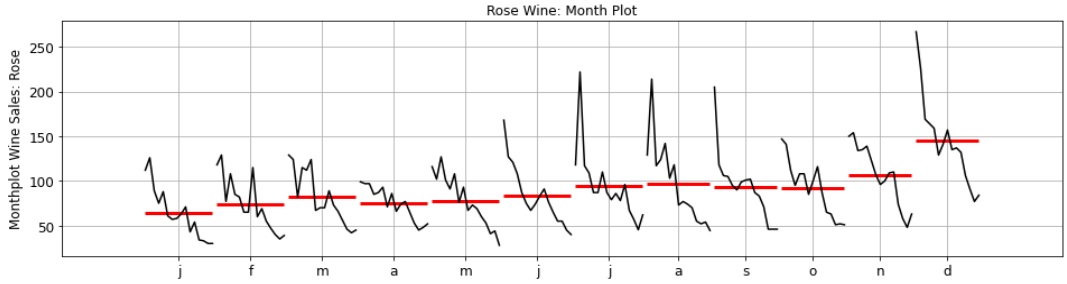
Insights:

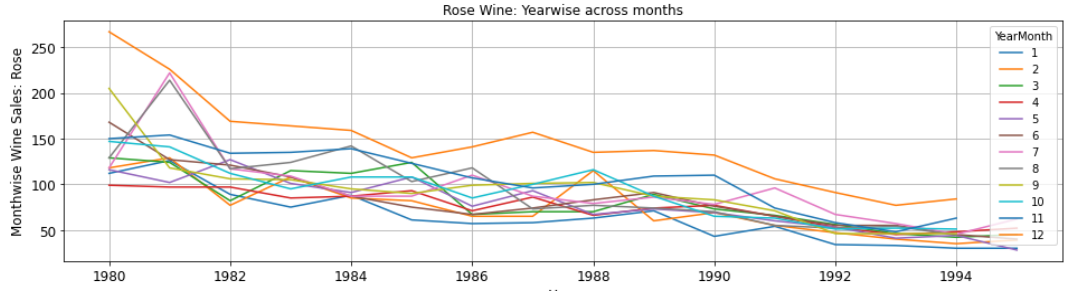
- Trend over years present and in the declining side.
- Median sales value of across the year having decreasing trend. Further, Year 1980 and 1981 are the highest sales years amongst other year.

Month wise plots

A boxplot for different months aggregating over different years, gives us an indication of SEASONALITY. All three plots are the different way of looking at the month wise sales across the years.







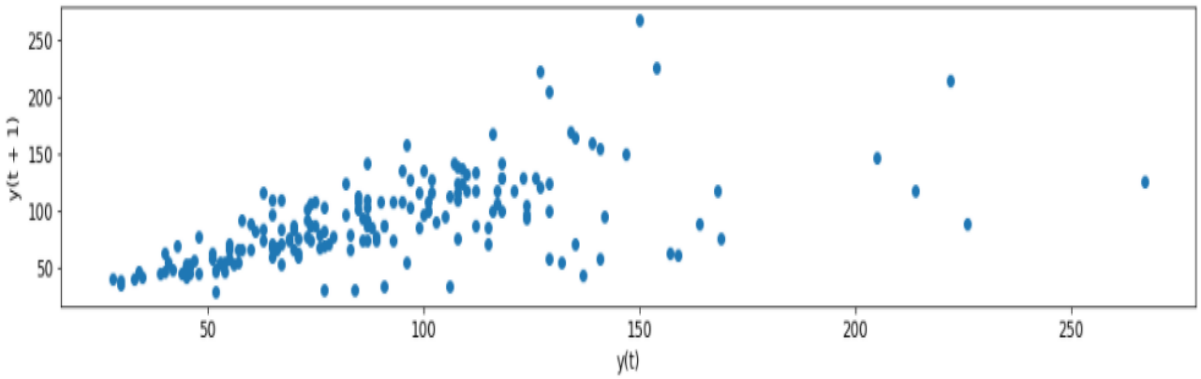
Insights:

- Across the year, median sales is decreasing but if we see the month wise plot it looks like **as month progresses sales is increasing and highest sales across the month is coming from "December"**.
- Further, month plot stats that **there are variations in means sales with the months as well "Jul to Sept and Dec" have this type of trend**.

Lag Plot

If the points cluster along a diagonal line from the bottom-left to the top-right of the plot, it suggests a positive correlation relationship. If the points cluster along a diagonal line from the top-left to the bottom-right, it suggests a negative correlation relationship.

More points tighter in to the diagonal line suggests a stronger relationship and more spread from the line suggests a weaker relationship. A ball in the middle or a spread across the plot suggests weak or no relationship.



Insights:

- Since the points are clustering along a diagonal line from the bottom-left to the top-right of the plot, it suggests a **positive correlation** relationship.
- Besides, points being more spread from the line are suggesting a **weaker relationship** between different periods/months.

Decompose the time series

Time series decomposition involves thinking of a series as a combination of level, trend, seasonality, and noise components.

Decomposition provides a useful abstract model for thinking about time series generally and for better understanding problems during time series analysis and forecasting.

Time Series Components:

A useful abstraction for selecting forecasting methods is to break a time series down into systematic and unsystematic components.

Systematic: Components of the time series that have consistency or recurrence and can be described and modelled.
Non-Systematic: Components of the time series that cannot be directly modelled.

A given time series is thought to consist of three systematic components including level, trend, seasonality, and one non-systematic component called noise.

Component	Description
Level	The average value in the series
Trend	The increasing or decreasing value in the series
Seasonality	The repeating short-term cycle in the series
Noise	The random variation in the series

There are mainly two types of time series decomposition i) Additive and ii) Multiplicative

Additive Decomposition:

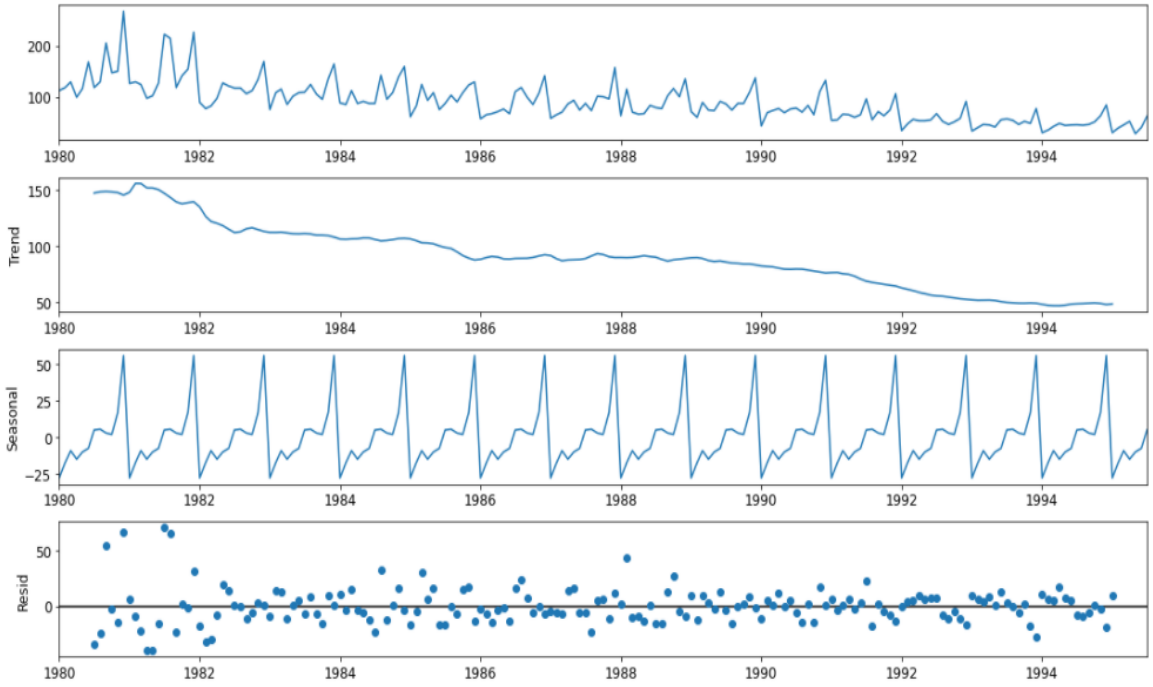
- An additive model suggests that the components are added together.
- An additive model is linear where changes over time are consistently made by the same amount.
- A linear seasonality has the same frequency (width of the cycles) and amplitude (height of the cycles).

Multiplicative Decomposition:

- An additive model suggests that the components are multipled together.
- An additive model is non-linear such as quadratic or exponential.
- Changes increase or decrease over time.
- A non-linear seasonality has an increasing or decreasing frequency (width of the cycles) and / or amplitude (height of the cycles) over time.

Let's decompose the time series and inference the same.

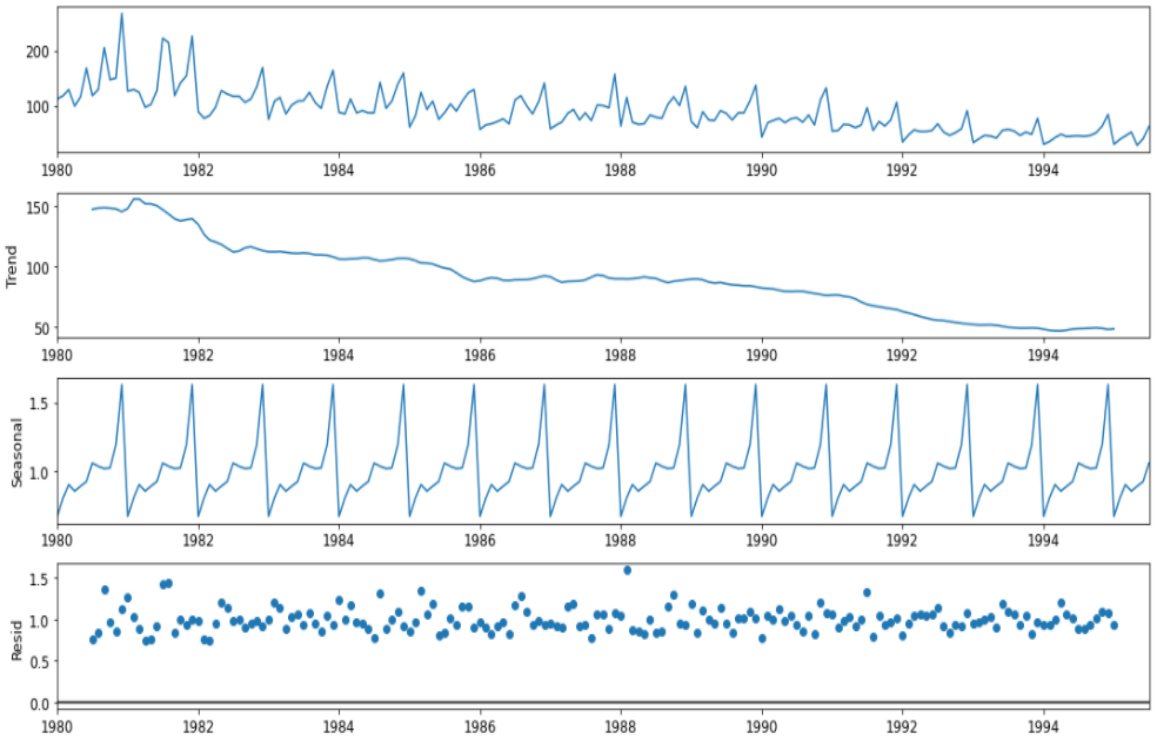
Additive Decomposition:



Insights: In this additive decomposition, we could see that:

- Trend value is moving from 150 to 50. so eventually promising decreasing trend coming out.
- Seasonality, out of mean of 100, around 50 is the seasonality which means, this dataset has the seasonality.
- Residuals, the range of the residual is also around +/- 50 (which leads to noise).

Multiplicative Decomposition:



Insights: In this multiplicative decomposition, we could see that:

- Trend value is moving from 150 to 50. so eventually promising trend coming out.
- Seasonality is as high as 150%, as well.
- Residuals are from 0.5 times to 1.5 times (which leads to noise).

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

Let's split the dataset into train and test. There are total 185 months data available. Mentioned below is the conversion of the same.

- After splitting data into train and test we have 132 months details in train dataset and 55 months details (i.e., from year 1991) in test dataset.
- Further, time series plot also indicate trains and test split.

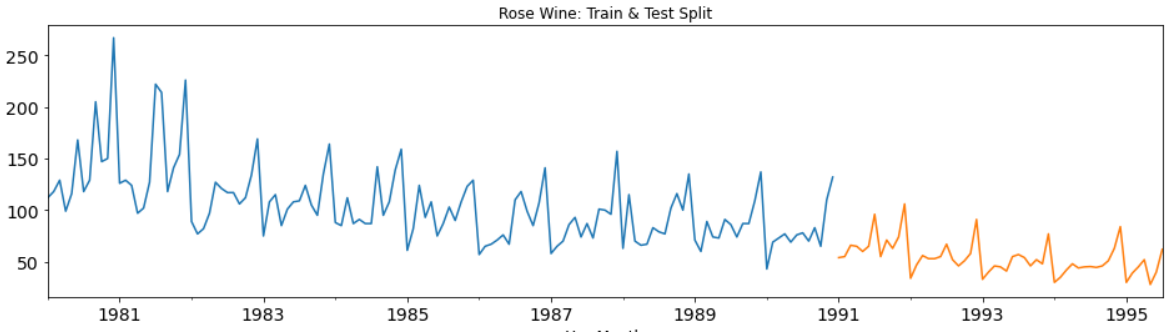
```
train    =   df[df.index<'1991']
test     =   df[df.index>='1991']
```

```
Train Dataset: Rose
                Rose
YearMonth
1980-01-01   112.0
1980-02-01   118.0
                Rose
YearMonth
1990-11-01   110.0
1990-12-01   132.0
```

```
Test Dataset: Rose
                Rose
YearMonth
1991-01-01   54.0
1991-02-01   55.0
                Rose
YearMonth
1995-06-01   40.0
1995-07-01   62.0
```

```
Train Dataset Shape: (132, 1)
```

```
Test Dataset Shape: (55, 1)
```



4 Model Building using various Time series techniques

As a part of this exercise, we have tried to build as many models which we learned during our time series forecasting classes.

The common rule for each model:

- We will build the model and fit the model on train data.
- Predict the values on test data.
- Further, on test data we will be checking the performance using RMSE parameter.

Let's go ahead and build models one by one.

Model1: Regression on Time

For this model, we are going to regress the 'Rose sales' variable against the order of the occurrence(monthly).

Let's follow below steps:

- Create the train and test data copy to use for this model
- Create time variable for train data and test data which would be useful for this model
- Train and test split (x_train, x_test, y_train, y_test) based on times series variable
- Import the linear regression library and fit the model in train data.

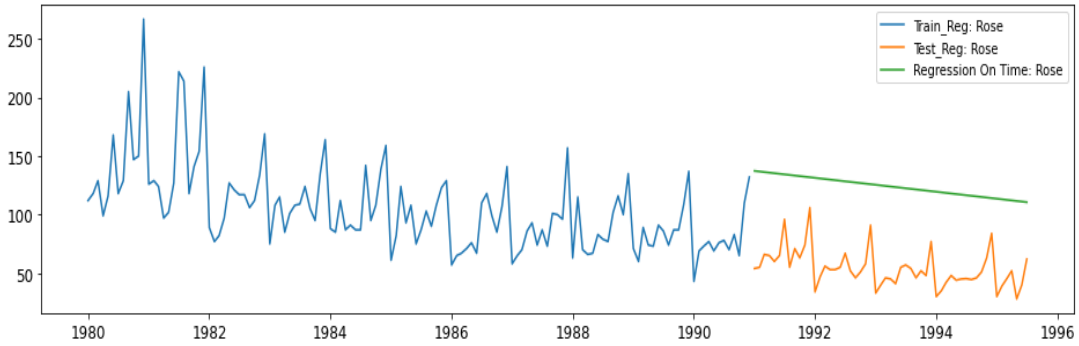
```
# fit the linear regression model
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train_reg, y_train_reg)
```

```
LinearRegression()
```

- Predict the values on test data

```
#predictions on test data
predictions          = model.predict(x_test_reg)
y_test_reg['RegOnTime'] = predictions
```

- Plot the view of train, test data with predictions



- Calculate RMSE value on test data

```
rmse_reg = sqrt(mean_squared_error(test_reg.Rose, y_test_reg.RegOnTime))
rmse_reg = round(rmse_reg, 3)
print("For RegressionOnTime: Rose,  RMSE is %3.3f" %(rmse_reg))
```

```
For RegressionOnTime: Rose,  RMSE is 71.617
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model2: Regression on Time With Seasonal Components

In this model, we are adding seasonal component in regression on time and check the test RMSE value.

Steps:

- Create the train and test data copy to use for this model
- Create **time variable and month seasonality (m1 to m12)** for train data and test data which would be useful for this model. This divides the dataset into m1 to m12 and repeats the pattern.

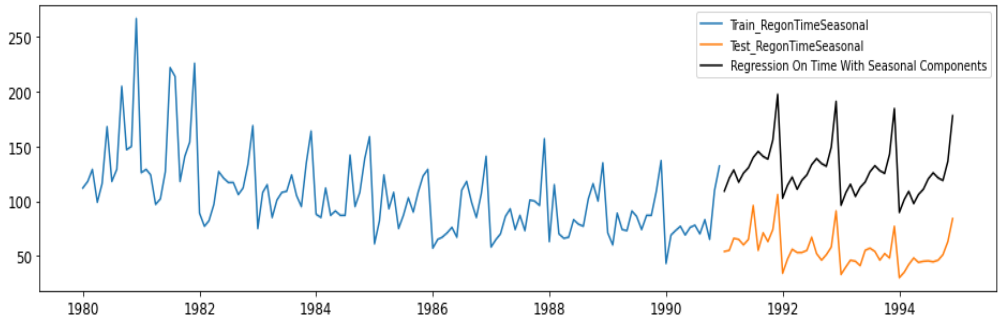
```
# define time and monthseasonality for train data
time = [i+1 for i in range(len(train_ROTS))]
train_ROTS['time'] = time
monthSeasonality = ['m1', 'm2', 'm3', 'm4', 'm5', 'm6', 'm7', 'm8', 'm9', 'm10', 'm11', 'm12'] #defining the 12 months

# define time and monthseasonality for test data
# excluding year which doesn't have full year seasonality incldued
#(i.e. 1995 have only 7 months hence exluding the same from test dataset)
time = [i+1 for i in range(len(test_ROTS)-7)]
test_ROTS = test_ROTS[test_ROTS.index <= '1994-12-01']
test_ROTS['time'] = time
monthSeasonality = ['m1', 'm2', 'm3', 'm4', 'm5', 'm6', 'm7', 'm8', 'm9', 'm10', 'm11', 'm12'] #defining the 12 months
```

- Use “get_dummies” function to convert each m1 to m12 into columns for train and test data
- Train and test split (x_train, x_test, y_train, y_test) based on times series variable

```
x_train_ROTS  = train_ROTSComplete.drop('Rose', axis=1)
x_test_ROTS   = test_ROTSComplete.drop('Rose', axis=1)
y_train_ROTS  = train_ROTSComplete[['Rose']]
y_test_ROTS   = test_ROTSComplete[['Rose']]
```

- Fit the linear regression model in train data.
- Predict the values on test data
- Plot the view of train, test data with predictions



- Calculate RMSE value on test data

```
rmse_ROTS = sqrt(mean_squared_error(test_ROTSComplete.Rose, y_test_ROTS.RegOnTimeSeasonal))
rmse_ROTS = round(rmse_ROTS,3)
print("For RegOnTimeSeasonal,  RMSE is %3.3f" %(rmse_ROTS))
```

```
For RegOnTimeSeasonal,  RMSE is 73.425
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model3: Naive Approach: $\hat{y}\ t{+}1{=}yt$

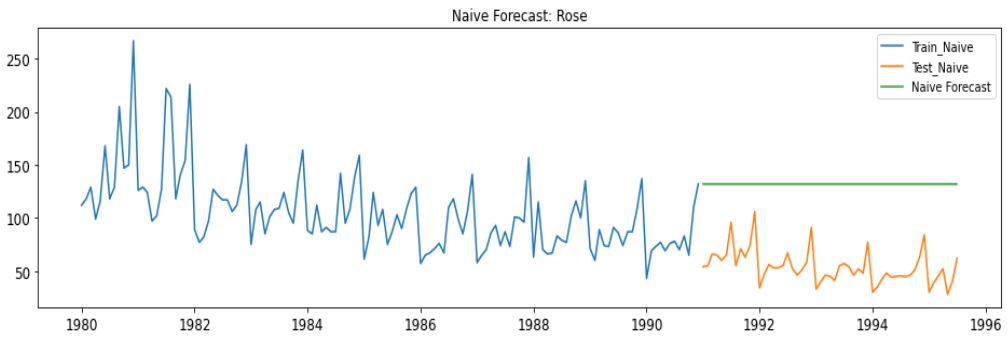
A naive forecast involves using the previous observation directly as the forecast without any change. It is often called the persistence forecast as the prior observation is persisted. This simple approach can be adjusted slightly for seasonal data.

Steps:

- Create the train and test data copy to use for this model
- Create naïve model using previous observation

```
y_hat_s['naive'] = dd_s[len(dd_s)-1]
```

- Plot the view of train, test data with naive



- Calculate RMSE value on test data

```
rmse_Naive = sqrt(mean_squared_error(test.Rose, y_hat_s.naive))
rmse_Naive = round(rmse_Naive, 3)
print("For Naive model,  RMSE is %3.3f" %(rmse_Naive))
```

```
For Naive model,  RMSE is 79.741
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 4: Simple Average

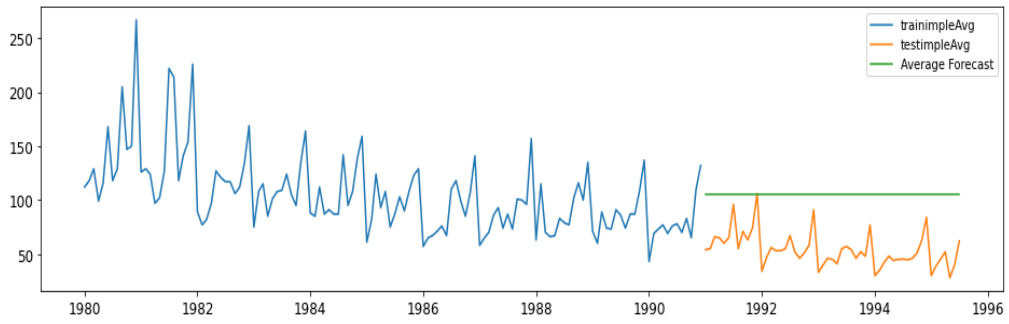
The model is very simple. Average the data by months and calculate the average for the period. Then plot the same so see the variation.

Steps:

- Create the train and test data copy to use for this model
- Create time variable **average mean** for train data and test data which would be useful for this model

```
y_hat_avg_s['avg_forecast'] = train['Rose'].mean()
```

- Plot the view of train, test data with simple mean details



- Calculate RMSE value on test data

```
rmse_SA = sqrt(mean_squared_error(test.Rose, y_hat_avg_s.avg_forecast))
rmse_SA = round(rmse_SA, 3)
print("For Simple Average model,  RMSE is %3.3f" %(rmse_SA))
```

```
For Simple Average model,  RMSE is 53.484
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 5: Moving Average (MA)

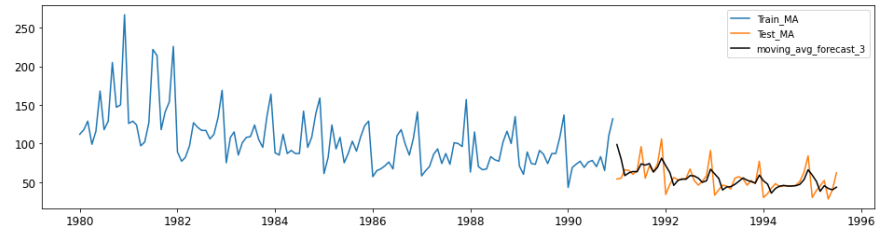
In the method of moving average, successive arithmetic averages are computed from overlapping groups of successive values of a time series. Each group includes all the observations in a given time interval, termed as the period of moving average.

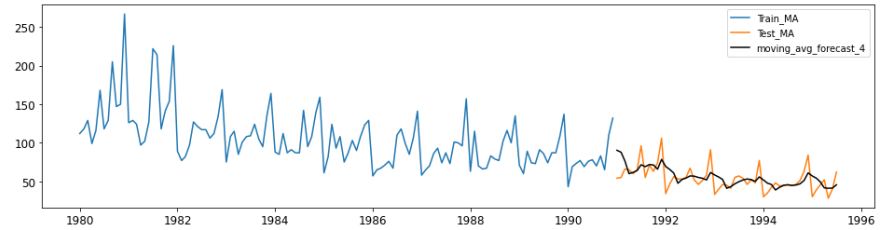
In this dataset we are going to take rolling mean for 3 months, 4 months, 5 months, 6 months, 8 months and 12 months and will see at which rolling mean we are getting better results.

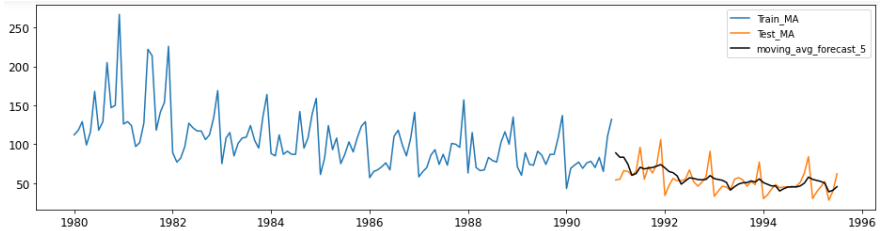
Steps:

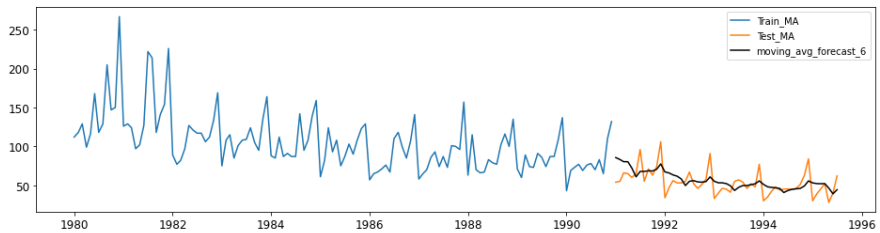
- Create the copy of full dataset to use for this model
- Create moving averages (rolling mean) for said moths as above.
- Create the columns related to same defined moving average months
- Split the dataset into train and test
- Plot the view of train, test data with each rolling means

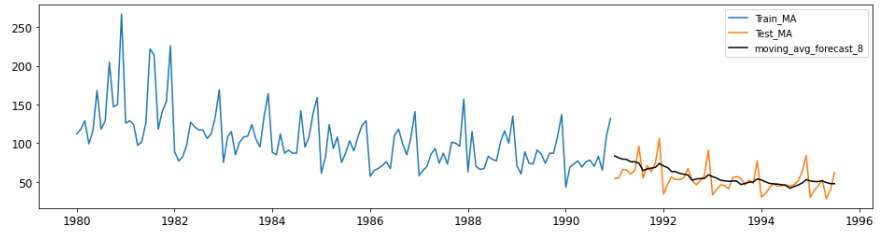
```
# rolling MA details
df_MA['moving_avg_forecast_3']  = df_MA['Rose'].rolling(3).mean()
df_MA['moving_avg_forecast_4']  = df_MA['Rose'].rolling(4).mean()
df_MA['moving_avg_forecast_5']  = df_MA['Rose'].rolling(5).mean()
df_MA['moving_avg_forecast_6']  = df_MA['Rose'].rolling(6).mean()
df_MA['moving_avg_forecast_8']  = df_MA['Rose'].rolling(8).mean()
df_MA['moving_avg_forecast_12'] = df_MA['Rose'].rolling(12).mean()
```

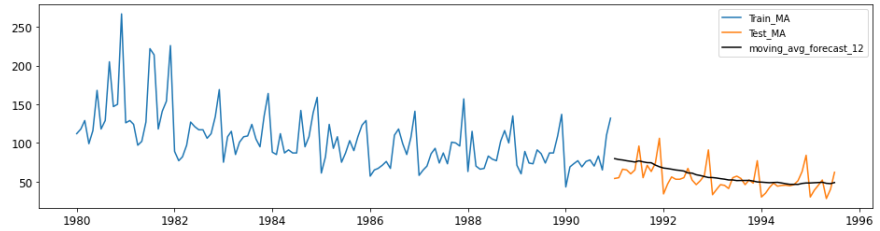












We could see here, as the rolling month increases accuracy is dropping off.

- Calculate RMSE value on test data

```
For Moving Average model, moving_avg_forecast_3  RMSE is 14.129
For Moving Average model, moving_avg_forecast_4  RMSE is 14.457
For Moving Average model, moving_avg_forecast_5  RMSE is 14.481
For Moving Average model, moving_avg_forecast_6  RMSE is 14.572
For Moving Average model, moving_avg_forecast_8  RMSE is 14.803
For Moving Average model, moving_avg_forecast_12  RMSE is 15.239
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 6: Simple Exponential Smoothing (SES)

Single Exponential Smoothing (SES), is a time series forecasting method for univariate data without a trend or seasonality. It requires a single parameter called alpha (a), also called the smoothing factor or smoothing coefficient. This parameter controls the rate at which the influence of the observations at prior time steps decay exponentially. **Alpha is often set to a value between 0 and 1 and considered as Smoothing factor for the level**
A value close to 1 indicates fast learning (that is, only the most recent values influence the forecasts), whereas a value close to 0 indicates slow learning (past observations have a large influence on forecasts).

Let's build the model using below steps:

- Import SimpleExpSmoothing library from statsmodels.tsa.api
- Fit the model using train data using optimised equals to True.

```
model_SES = SimpleExpSmoothing(train['Rose'])
```

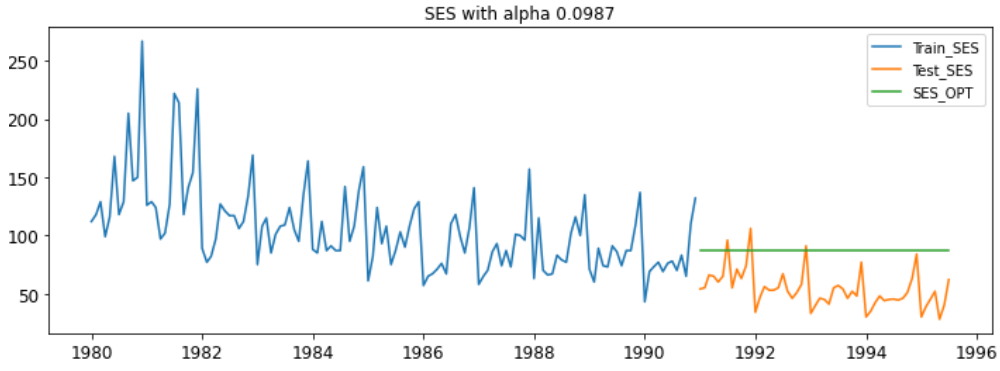
```
model_SES_fit = model_SES.fit(optimized = True)
```

- Print the SES parameter and its initial level

```
== Simple Exponential Smoothing (SES)

Smoothing Level 0.0987
Initial Level 134.387
```

- Create the copy of test dataset before we do prediction
- Do the prediction on test data
- Plot the view of train, test data with predictions



The alpha value is close to 0 indicates slow learning (past observations have a large influence on forecasts).

- Calculate RMSE value on test data

```
rmse_SES = sqrt(mean_squared_error(test['Rose'], y_hat_avg_SES.SES))
rmse_SES = round(rmse_SES, 3)
print("For SES model: For alpha = %1.2f,  RMSE is %3.3f" %(alpha_value,rmse_SES))
```

```
For SES model: For alpha = 0.10,  RMSE is 36.820
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 7: Simple Exponential Smoothing (SES) with least RMSE

Let's build the model using below steps:

- Create table which helps to store alpha and RMSE value
- Create the copy of test dataset for this model
- Create the for loop function using alpha value from 0.01 to 1 and interval is 0.01 and put all the below steps in the loop to get the alpha value which has least RMSE value.
    - Fit the model using train data using optimised equals to True.
    - Do the prediction on test data
    - Calculate RMSE value on test data
    - Store the alpha value and RMSE value and sort the same by least RMSE value

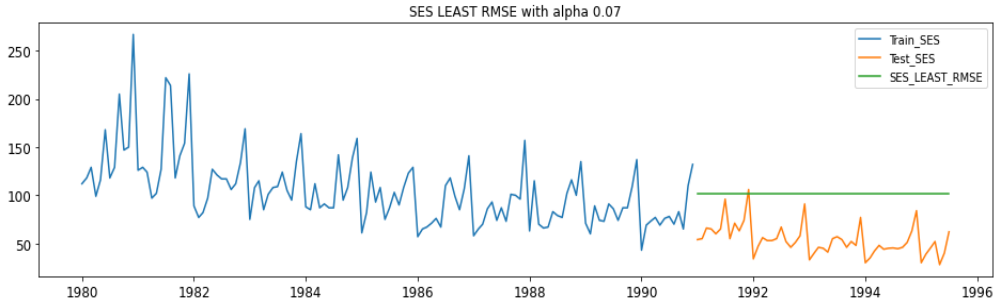
```
SES_least_rmse = resultsDf_model.sort_values(by=['Test RMSE'],ascending=True)
SES_least_rmse.head(2)
```

	Alpha Values	Test RMSE
6	0.07	36.459396
7	0.08	36.486588

```
print("For SES model(least RMSE): For alpha = %3.2f,  RMSE is %3.3f"
    %(SES_least_rmse.iloc[0].values[0],SES_least_rmse.iloc[0].values[1]))
```

```
For SES model(least RMSE): For alpha = 0.07,  RMSE is 36.459
```

- Plot the view of train, test data with predictions



The alpha value is close to 0 indicates slow learning (past observations have a large influence on forecasts).

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 8: Holt's Linear Trend Method (Double Exponential Smoothing)

Double Exponential Smoothing is an extension to Exponential Smoothing that explicitly adds support for trends in the univariate time series. In addition to the **alpha parameter for controlling smoothing factor for the level, an additional smoothing factor is added to control the decay of the influence of the change in trend called beta (b).**

Double Exponential Smoothing with an additive trend is classically referred to as Holt's linear trend model, named for the developer of the method Charles Holt.

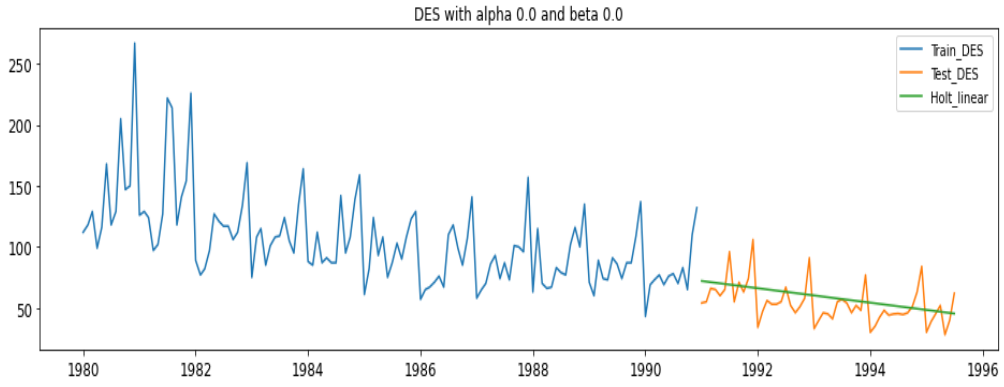
Let's build the model using below steps:

- Import Holt library from statsmodels.tsa.api
- Create the copy of test dataset
- Fit the model using train dataset.
- Do the prediction on test data
- Print the DES parameters and its initial level

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

Smoothing Level 0.0
Smoothing Trend 0.0
Initial Level 137.8155
```

- Plot the view of train, test data with predictions



The alpha and beta value are close to 0 which indicates slow learning (past observations have a large influence on forecasts).

- Calculate RMSE value on test data

```
rmse_DES            =  np.sqrt(mean_squared_error(test['Rose'], y_hat_avg_DES['Holt_linear']))

print("For alpha = %1.2f, For beta = %1.2f,  RMSE is %4.2f"
      %(alpha_DES_value, beta_DES_value, rmse_DES))
```

```
For alpha = 0.00, For beta = 0.00,  RMSE is 15.28
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 9: DES model - Best alpha and beta with least RMSE

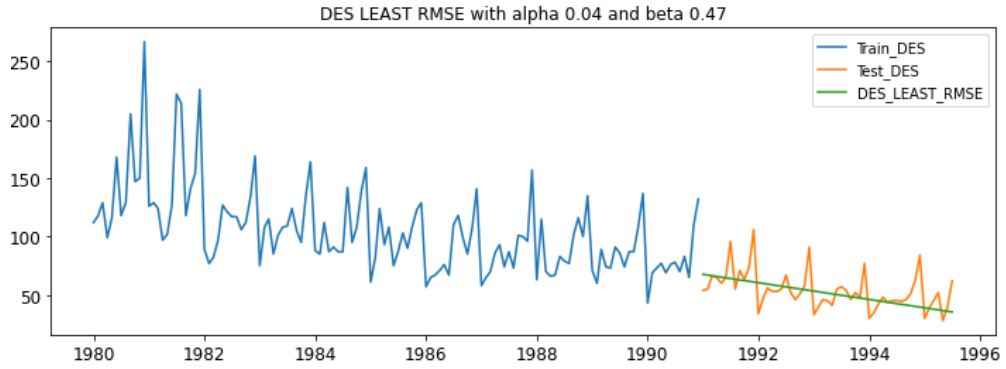
Let's build the model using below steps:

- Create table which helps to store alpha, beta and RMSE value
- Create the for loop function using alpha value from 0.01 to 1 and interval is 0.01 and put all the below steps in the loop to get the alpha value which has least RMSE value.
    - Fit the model using train data using optimised equals to false.
    - Do the prediction on test data
    - Calculate RMSE value on test data
    - Store the alpha, beta and RMSE value and sort the same by least RMSE value

```
DES_least_rmse = resultsDfDES_model.sort_values(by=['Test RMSE'],ascending=True)
DES_least_rmse.head(2)
```

	Alpha Values	Beta Values	Test RMSE
343	0.04	0.47	14.566308
222	0.03	0.25	14.687964

- Plot the view of train, test data with predictions



The alpha and beta values are close 0 which indicates slow learning (past observations have a large influence on forecasts).

- Calculate RMSE value on test data

```
print("For DES model(least RMSE): For alpha = %1.2f, beta = %1.2f, RMSE is %3.2f"
    %(DES_least_rmse.iloc[0].values[0],DES_least_rmse.iloc[0].values[1],DES_least_rmse.iloc[0].values[2]))
```

```
For DES model(least RMSE): For alpha = 0.04, beta = 0.47, RMSE is 14.57
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 10: Holt-Winters Method - Additive seasonality

Triple Exponential Smoothing is an extension of Exponential Smoothing that explicitly adds support for seasonality to the univariate time series. This method is sometimes called Holt-Winters Exponential Smoothing, named for two contributors to the method: Charles Holt and Peter Winters. In addition to **the alpha and beta smoothing factors, a new parameter is added called gamma (g) that controls the influence on the seasonal component**.

As with the trend, the seasonality may be modeled as either an additive or multiplicative process for a linear or exponential change in the seasonality.

Additive Seasonality: Triple Exponential Smoothing with a linear seasonality.
Multiplicative Seasonality: Triple Exponential Smoothing with an exponential seasonality.

In summary, *Being an adaptive method, Holt-Winter's exponential smoothing allows the level, trend and seasonality patterns to change over time*

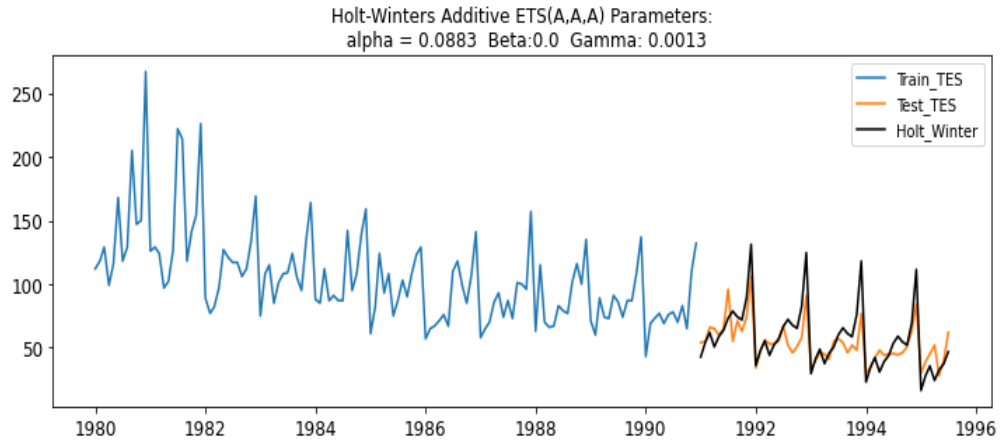
Let's build the model using below steps:

- Import ExponentialSmoothing library from statsmodels.tsa.api
- Create the copy of test dataset for this model
- Fit the model using train dataset using **hyperparameters as "seasonal_periods" = 12, trend = "additive", seasonal = "additive".**
- Do the prediction on test data
- Print the TES parameters and its initial level

```
== Holt-Winters Additive ETS(A,A,A) Parameters ==

Smoothing Level:  0.0883
Smoothing Trend:  0.0
Smoothing Seasonal:  0.0013
Initial Level:  77.0094
Initial Trend:  -0.5495
Initial Seasons:  [ 38.7425  51.0657  58.9921  48.2684  56.9677  62.3791  72.3964  78.5321
  74.5857  72.7823  90.8438 133.1995]
```

- Plot the view of train, test data with predictions



The alpha, beta and gamma value are close to 0 which indicates slow learning (past observations have a large influence on forecasts)

- Calculate RMSE value on test data

```
rmse_TES_a            =  np.sqrt(mean_squared_error(test['Rose'], y_hat_TES_a_avg['Holt_Winter']))

print("For TES(Additive) model: alpha = %1.2f, beta = %1.2f, gamma = %1.2f, RMSE is %3.2f"
      %(alpha_TES_a_value, beta_TES_a_value, gamma_TES_a_value, rmse_TES_a))
```

```
For TES(Additive) model: alpha = 0.09, beta = 0.00, gamma = 0.00, RMSE is 14.30
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 11: Holt-Winters Method - Multiplicative seasonality

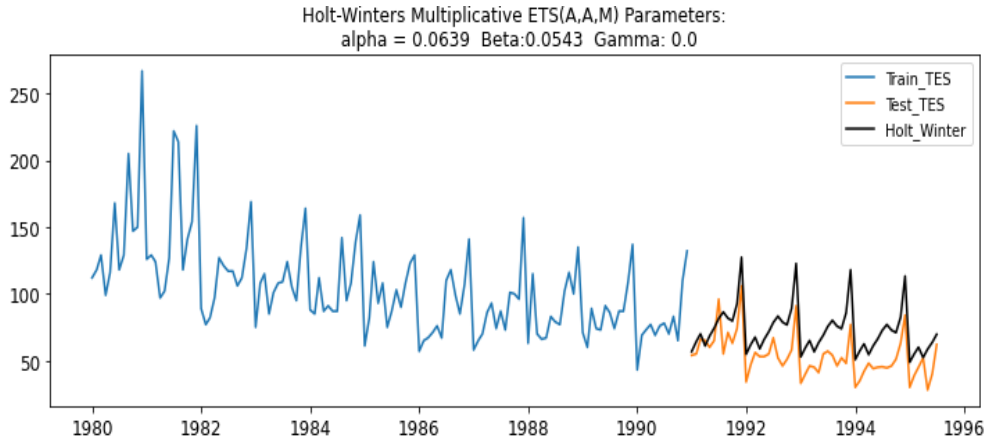
Let's build the model using below steps:

- Create the copy of test dataset for this model
- Fit the model using train dataset using **hyperparameters as "seasonal_periods" = 12, trend = "additive", seasonal = "multiplicative".**
- Do the prediction on test data
- Print the TES parameters and its initial level

```
== Holt-Winters Multiplicative ETS(A,A,M) Parameters ==

Smoothing Level:  0.0639
Smoothing Trend:  0.0543
Smoothing Seasonal:  0.0
Initial Level:  52.7062
Initial Trend:  -0.3295
Initial Seasons:  [2.1403 2.4289 2.6533 2.3193 2.6074 2.8435 3.1251 3.323  3.1538 3.0851
 3.596  4.96  ]
```

- Plot the view of train, test data with predictions



The alpha, beta and gamma value are close 0 which indicates slow learning (past observations have a large influence on forecasts).

- Calculate RMSE value on test data

```
rmse_TES_m              =  np.sqrt(mean_squared_error(test['Rose'], y_hat_TES_m_avg['Holt_Winter']))

print("For TES(Multiplicative) alpha = %1.2f, beta = %1.2f, gamma = %1.2f, RMSE is %3.2f"
      %(alpha_TES_m_value, beta_TES_m_value, gamma_TES_m_value, rmse_TES_m))
```

```
For TES(Multiplicative) alpha = 0.06, beta = 0.05, gamma = 0.00, RMSE is 21.29
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

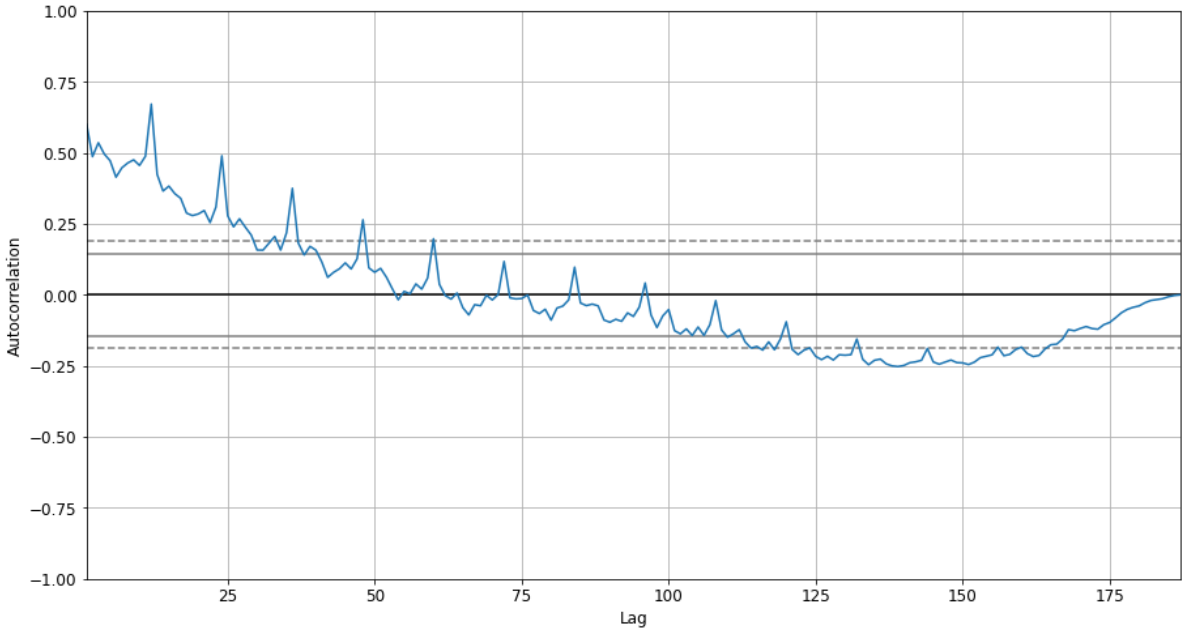
5 Check for the stationarity of the data

A stationary time series is one whose statistical properties **such as mean, variance, autocorrelation, etc. are all constant over time.** Such statistics are useful as descriptors of future behaviour only if the series is stationary. Mentioned below is the hypothesis to test the stationarity.

H0 : Time series is non-stationary and H1 : Time series is stationary
(if p value is less than 0.05 then the series is called stationary).

Note: If the series is non-stationary, stationarise the time series by taking a difference of the time series. Then we can use this particular differenced series to train the models. We do not need to worry about stationarity for the Test Data because we are not building any models on the test Data, we are only evaluating our models over there.

Auto correlation plot helps to see the same.



Insights:
We can quantify the strength and type of relationship between observations and their lags. In statistics, this is called correlation, and when calculated against lag values in time series it is called autocorrelation (self-correlation).

A correlation value calculated between two groups of numbers, such as observations and their lag1 values, results in a number between -1 and 1. The sign of this number indicates a negative or positive correlation respectively. A value close to zero suggests a weak correlation, whereas a value closer to -1 or 1 indicates a strong correlation. Dotted lines are provided that indicate any correlation values above those lines are statistically significant (meaningful).

Using ADF (Augmented Dickey–Fuller) test, we will be able to find out whether the time series is stationary or not. Let's run ADF test on full data and train dataset.

ADF Test (Full data and Train data)

- Import adfuller library from the statsmodels.tsa.stattool
- Run the adfuller test on full dataset and train dataset

```
dftest = adfuller(df,regression='ct')
print('dftest statistic is %3.3f' %dftest[0])
print('dftest p-value is' ,dftest[1])
print('Number of lags used' ,dftest[2])
```

```
dftest statistic is -2.242
dftest p-value is 0.46643710204731414
Number of lags used 13
```

```
dftest = adfuller(train,regression='ct')
print('dftest statistic is %3.3f' %dftest[0])
print('dftest p-value is' ,dftest[1])
print('Number of lags used' ,dftest[2])
```

```
dftest statistic is -1.686
dftest p-value is 0.7569093051047049
Number of lags used 13
```

Both full data and train data p value is more then 0.05. hence, series in non-stationary.

Convert non-stationary to stationary (Full data and Train data)

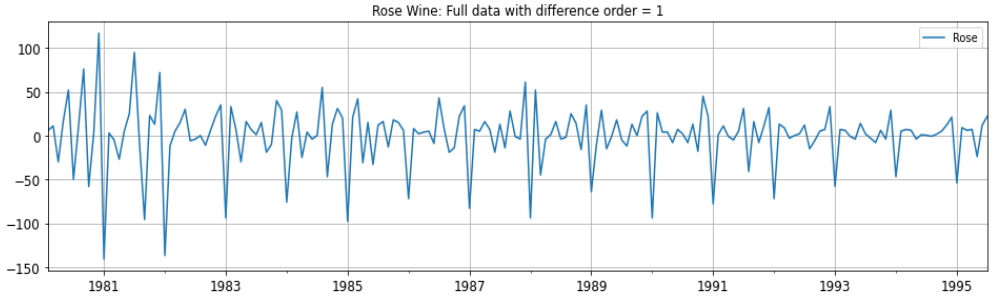
A non-stationary process with a deterministic trend becomes stationary after removing the trend, or detrending. Using differencing method we remove non-stationarity from the dataset.

As such, the process of differencing can be repeated more than once until all temporal dependence has been removed. The number of times that differencing is performed is called the difference order.

Full dataset after difference order (1) and p value less than 0.05 (stationary) series.

```
dftest = adfuller(df.diff(1).dropna(),regression='ct')
print('dftest statistic is %3.3f' %dftest[0])
print('dftest p-value is' ,dftest[1])
print('Number of lags used' ,dftest[2])
```

```
dftest statistic is -8.161
dftest p-value is 3.034192412610866e-11
Number of lags used 12
```



Train dataset after difference order (1) and p value less than 0.05 (stationary) series.

```
dftest = adfuller(train.diff(1).dropna(),regression='ct')
print('dftest statistic is %3.3f' %dftest[0])
print('dftest p-value is' ,dftest[1])
print('Number of lags used' ,dftest[2])
```

```
dftest statistic is -6.804
dftest p-value is 3.8948313567830344e-08
Number of lags used 12
```

6 Build Automated version of ARIMA & SARIMA model with least AIC value

In point5, we have concluded that original series both (full and train) dataset were non-stationary and after doing difference order of (1) we were able to convert series into stationary.

While building ARIMA and SARIMA we will consider this point. Let's build these models.

Model12: Auto ARIMA model – least AIC value

An autoregressive integrated moving average (ARIMA), is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends.

It is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. The model's goal is to predict future securities or financial market moves by examining the differences between values in the series instead of through actual values. An ARIMA model can be understood by outlining each of its components as follows:

Autoregression (AR): refers to a model that shows a changing variable that regresses on its own lagged, or prior, values.
Integrated (I): represents the differencing of raw observations to allow for the time series to become stationary (i.e., data values are replaced by the difference between the data values and the previous values).
Moving average (MA): incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.

ARIMA Parameters: Each component in ARIMA functions as a parameter with a standard notation. For ARIMA models, a standard notation would be ARIMA with p, d, and q, where integer values substitute for the parameters to indicate the type of ARIMA model used. The parameters can be defined as:

p: the number of lag observations in the model; also known as the lag order.
d: the number of times that the raw observations are differenced; also known as the degree of differencing.
q: the size of the moving average window; also known as the order of the moving average.

Auto ARIMA: The module auto.arima fits the best ARIMA model to univariate time series according to either AIC, AIC or BIC value. This function conducts a search over possible model within the order constraints provided.

The Akaike information criterion (AIC) is an estimator of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection.

Let's build the model using below steps:

- Define "p", "q" and "d" value and create a for loop to create the combinations which would be used for the model. We already have "d" value as (1) based on differencing order.
- Create table to store "p", "d" and "q" combination and AIC value
- Import ARIMA library from statsmodels.tsa.arima.model
- Create the for loop within the pdq parameters defined by itertools to get the least AIC value.
    - Fit the model using train data using all the combinations.

- Print the p,d,q combinations with AIC value
- Store these values into table which we have created in step2

```
ARIMA_least_AIC = ARIMA_AIC.sort_values(by='AIC',ascending=True)
ARIMA_least_AIC.head(2)
```

	param	AIC
13	(2, 1, 3)	1274.694995
23	(4, 1, 3)	1278.451412

- Create ARIMA model using order (p,d,q) which has lowest AIC value (here order is (2,1,3)).
- Fit the model on train dataset.
- Print the ARIMA result summary

```
                               SARIMAX Results
==========================================================================================
Dep. Variable:                      Rose   No. Observations:                  132
Model:                 ARIMA(2, 1, 3)   Log Likelihood                -631.347
Date:                Mon, 28 Jun 2021   AIC                           1274.695
Time:                        13:05:37   BIC                           1291.946
Sample:                    01-01-1980   HQIC                          1281.705
                         - 12-01-1990
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -1.6775      0.084    -20.007      0.000      -1.842      -1.513
ar.L2         -0.7283      0.084     -8.685      0.000      -0.893      -0.564
ma.L1          1.0448      0.662      1.579      0.114      -0.252       2.341
ma.L2         -0.7719      0.135     -5.713      0.000      -1.037      -0.507
ma.L3         -0.9047      0.600     -1.507      0.132      -2.082       0.272
sigma2       860.0026    557.970      1.541      0.123    -233.598    1953.603
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                24.40
Prob(Q):                              0.88   Prob(JB):                         0.00
Heteroskedasticity (H):               0.40   Skew:                             0.71
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.57
===================================================================================
```

Here, we could see all p value are less than 0.05 except ma.L1 and ma.L3. further, all the coeff value are making sense towards the model.

- Do the prediction on test data
- Calculate RMSE value on test data

```
ARIMA_RMSE = metrics.mean_squared_error(test['Rose'],predictions,squared=False)

print("AutoARIMA Model(least AIC)(2,1,3):, RMSE is %3.2f"
      %(ARIMA_RMSE))
```

```
AutoARIMA Model(least AIC)(2,1,3):, RMSE is 36.84
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 13: Auto SARIMA model – least AIC value

The seasonal part of an ARIMA model has the same structure as the non-seasonal part: it may have an AR factor, an MA factor, and/or an order of differencing.
In the seasonal part of the model, all of these factors operate across multiples of lag s (the number of periods in a season).
A seasonal ARIMA model is classified as an ARIMA(p,d,q)x(P,D,Q) model,
Where:
P=number of seasonal autoregressive (SAR) terms,
D=number of seasonal differences,
Q=number of seasonal moving average (SMA) terms
S = seasonal terms (here, series is monthly. So, S = 12)

Let's build the model using below steps:

- Define (p, d ,q) (P, D, Q) value and create a for loop to create the combinations which would be used for the model. We already have "d" value as (1) based on differencing order.
- Create table to store (p, d ,q) (P, D, Q) combination and AIC value
- Create the for loop within the pdq and PDQ parameters defined by itertools to get the least AIC value.
    - Fit the model using train data using all the combinations using hypers parameters as order = "pdq combination", seasonal order = "PDQ combination", enforce_stationarity and enforce_invertibility equals to false
    - Print the (p,d,q) and (P,D,Q) combinations with AIC value
    - Store these values into table which we have created in step2

```
SARIMA_AIC.sort_values(by=['AIC']).head(2)
```

	param	seasonal	AIC
71	(0, 1, 3)	(2, 1, 2, 12)	767.224375
143	(1, 1, 3)	(2, 1, 2, 12)	767.559746

- Create SARIMA model using order (p,d,q) (P,D,Q) which has lowest AIC value (here order = (0,1,3) and seasonal order = (2,1,2,12)).
- Fit the model on train dataset.
- Print the SARIMA result summary

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                  132
Model:             SARIMAX(0, 1, 3)x(2, 1, [1, 2], 12)   Log Likelihood                -375.612
Date:                                 Mon, 28 Jun 2021   AIC                            767.224
Time:                                         13:08:32   BIC                            787.311
Sample:                                             0   HQIC                           775.328
                                                  - 132
Covariance Type:                                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.9817      0.190     -5.175      0.000      -1.353      -0.610
ma.L2         -0.0472      0.176     -0.268      0.789      -0.392       0.298
ma.L3         -0.0043      0.131     -0.033      0.974      -0.260       0.252
ar.S.L12       0.0637      0.158      0.405      0.686      -0.245       0.372
ar.S.L24      -0.0502      0.045     -1.110      0.267      -0.139       0.038
ma.S.L12      -0.7987      0.362     -2.203      0.028      -1.509      -0.088
ma.S.L24      -0.0784      0.200     -0.393      0.694      -0.469       0.313
sigma2       178.0501     52.573      3.387      0.001      75.008     281.092
==========================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 5.49
Prob(Q):                              0.94   Prob(JB):                         0.06
Heteroskedasticity (H):               0.93   Skew:                             0.42
Prob(H) (two-sided):                  0.84   Kurtosis:                         3.85
==========================================================================================
```

- Do the prediction on test data
- Calculate RMSE value on test data

```
SARIMA_RMSE = metrics.mean_squared_error(test['Rose'],predictions.predicted_mean,squared=False)

print("AutoSARIMA Model(least AIC)(0,1,3)(2,1,2,12):, RMSE is %3.2f"
      %(SARIMA_RMSE))
```

```
AutoSARIMA Model(least AIC)(0,1,3)(2,1,2,12):, RMSE is 16.67
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

7 Build ARIMA & SARIMA models based on the cut-off points of ACF & PACF

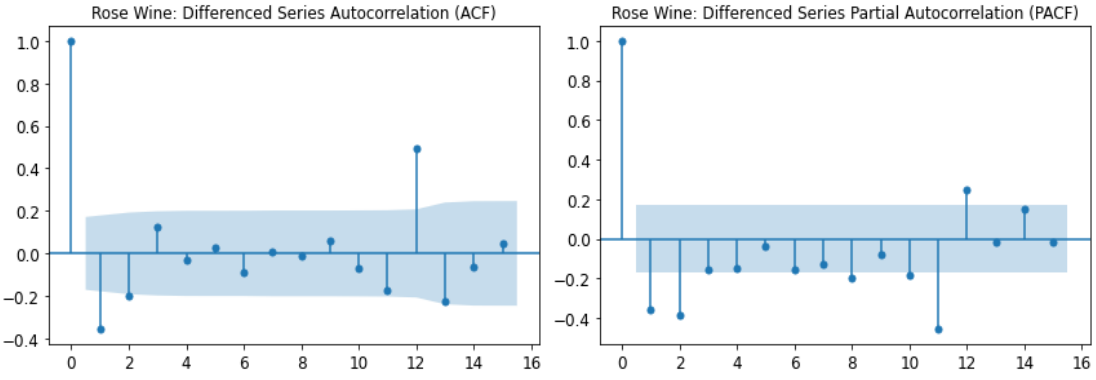
ACF (Auto Correlation function): it is merely a bar chart of the coefficients of correlation between a time series and lags of itself. Auto correlation of different orders gives inside information regarding the time series. ACF make sense only if time series is stationary. Significant auto correlation imply observations of long past influences current observations. ACF represents the q value.
PACF (Partial auto Correlation function): it is a plot of the partial correlation coefficients between the series and lags of itself. PACF represents the p value.

ACF and PACF together to be considered for identification of order of auto regression.

Model 14: Manual ARIMA model – using ACF and PACF value

Let's build the model using below steps:

- First let's plot ACF and PACF at the order difference of (1).



Based on graph, let's evaluate p and q value. Here, we have taken alpha=0.05.

- The Auto-Regressive parameter in an ARIMA model is 'p' which comes from the significant lag before which the PACF plot cuts-off to 0.
- The Moving-Average parameter in an ARIMA model is 'q' which comes from the significant lag before the ACF plot cuts-off to 0.

By looking at the above plots, we will take the value of p and q to be 2. Hence, let's take **ACF(q)(MA) value as 2 and PACF(p)(AR) value as 2**

- Create ARIMA model using order (p,d,q) based on ACF and PACF plot {order = (2,1,2)}.
- Fit the model on train dataset.
- Print the ARIMA result summary

```
                               SARIMAX Results
==========================================================================================
Dep. Variable:                           Rose   No. Observations:                  132
Model:                 ARIMA(2, 1, 2)   Log Likelihood                -635.935
Date:                Mon, 28 Jun 2021   AIC                           1281.871
Time:                        13:08:33   BIC                           1296.247
Sample:                    01-01-1980   HQIC                          1287.712
                         - 12-01-1990
Covariance Type:                  opg
==========================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4540      0.469     -0.969      0.333      -1.372       0.464
ar.L2          0.0001      0.170      0.001      0.999      -0.334       0.334
ma.L1         -0.2541      0.459     -0.554      0.580      -1.154       0.646
ma.L2         -0.5984      0.430     -1.390      0.164      -1.442       0.245
sigma2       952.1601     91.424     10.415      0.000     772.973    1131.347
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                34.16
Prob(Q):                              0.88   Prob(JB):                         0.00
Heteroskedasticity (H):               0.37   Skew:                             0.79
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.94
===================================================================================
```

- Do the prediction on test data
- Calculate RMSE value on test data

```
ARIMA_Manual_RMSE = metrics.mean_squared_error(test['Rose'],predictions,squared=False)

print("ManualARIMA Model(ACF-PACF)(2,1,2):, RMSE is %3.2f"
      %(ARIMA_Manual_RMSE))
```

```
ManualARIMA Model(ACF-PACF)(2,1,2):, RMSE is 36.89
```

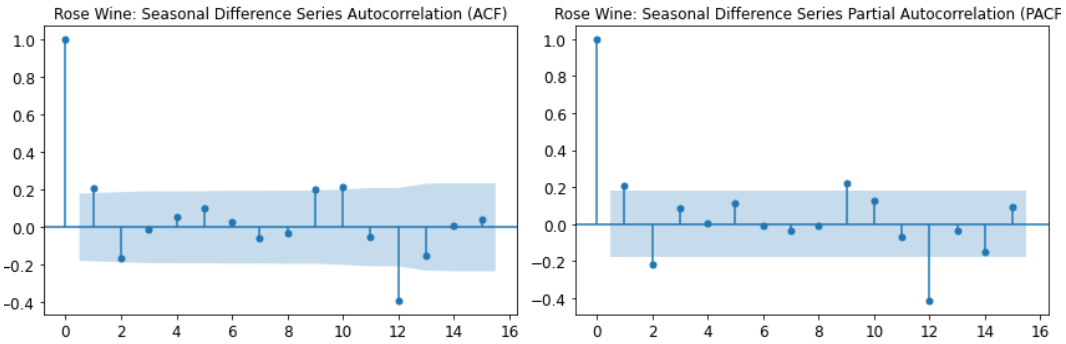
- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

Model 15: Manual SARIMA model – using ACF and PACF value

In SARIMA, we will be incorporating seasonal component for which we need to take seasonal order difference as (12) because this is a monthly time series.

Let's build the model using below steps:

- First let's plot ACF and PACF at the order difference of (12) to get P and Q value. D will be 1 as we will be taking seasonal difference



Based on graph, let's evaluate P and Q value. Here, we have taken alpha=0.05.

- The Auto-Regressive parameter in an ARIMA model is 'P' which comes from the significant seasonal lag before which the seasonal PACF plot cuts-off to 0.

- The Moving-Average parameter in an ARIMA model is 'Q' which comes from the significant seasonal lag before the seasonal ACF plot cuts-off to 0.

By looking at the above plots, we will take the value of P and Q to be 1. Hence, let's take **Seasonal ACF(Q)(MA) value as 1 and Seasonal PACF(P)(AR) value as 1**

- Create SARIMA model using order (p,d,q) (P,D,Q,S) based on seasonal ACF and seasonal PACF plot {order = (2,1,2) and seasonal order = (1,1,1,12)}.
- Fit the model on train dataset.
- Print the SARIMA result summary

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                Rose   No. Observations:                  132
Model:             SARIMAX(2, 1, 2)x(1, 1, [1], 12)   Log Likelihood                -450.847
Date:                              Mon, 28 Jun 2021   AIC                            915.693
Time:                                      13:08:35   BIC                            934.204
Sample:                                  01-01-1980   HQIC                           923.192
                                       - 12-01-1990
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.1034      0.133      8.286      0.000       0.842       1.364
ar.L2         -0.3436      0.109     -3.150      0.002      -0.557      -0.130
ma.L1         -1.8152      0.105    -17.288      0.000      -2.021      -1.609
ma.L2          0.8668      0.093      9.275      0.000       0.684       1.050
ar.S.L12      -0.3877      0.069     -5.625      0.000      -0.523      -0.253
ma.S.L12      -0.0788      0.130     -0.605      0.545      -0.334       0.176
sigma2       338.2792     53.802      6.287      0.000     232.829     443.729
===================================================================================
Ljung-Box (L1) (Q):                   0.25   Jarque-Bera (JB):                 0.03
Prob(Q):                              0.62   Prob(JB):                         0.98
Heteroskedasticity (H):               0.66   Skew:                             0.04
Prob(H) (two-sided):                  0.22   Kurtosis:                         2.97
===================================================================================
```

- Do the prediction on test data
- Calculate RMSE value on test data

```
SARIMA_Manual_RMSE = metrics.mean_squared_error(test['Rose'],predictions,squared=False)

print("ManualSARIMA Model(ACF-PACF)(2,1,2)(1,1,1,12):, RMSE is %3.2f"
      %(SARIMA_Manual_RMSE))
```

```
ManualSARIMA Model(ACF-PACF)(2,1,2)(1,1,1,12):, RMSE is 13.27
```

- Store the test RMSE values in the table. This would help us to compare the models once we build all the models.

8 Build a table with all the models

We have built total of 15 models and mentioned below is table which consist of model name, its corresponding parameters and respective RMSE values (in ascending order).

	Model	WineType	Test_RMSE
0	ManualSARIMA Model(ACF-PACF)(2,1,2)(1,1,1,12)	Rose	13.269988
0	moving_avg_forecast_3	Rose	14.129000
0	TES(Holt_Winter)-Add(L:0.09,T:0.0,S:0.0)	Rose	14.295361
0	moving_avg_forecast_4	Rose	14.457000
0	moving_avg_forecast_5	Rose	14.481000
0	DES(least RMSE)(L:0.04,T:0.47)	Rose	14.566308
0	moving_avg_forecast_6	Rose	14.572000
0	moving_avg_forecast_8	Rose	14.803000
0	moving_avg_forecast_12	Rose	15.239000
0	DES(Holt_linear)(L:0.0,T:0.0)	Rose	15.276707
0	AutoSARIMA Model(least AIC)(0,1,3)(2,1,2,12)	Rose	16.673252
0	TES(Holt_Winter)-Mul(L:0.06,T:0.05,S:0.0)	Rose	21.285869
0	SES(least RMSE)(L:0.07)	Rose	36.459396
0	AutoARIMA Model(least AIC)(2,1,3)	Rose	36.837514
0	ManualARIMA Model(ACF-PACF)(2,1,2)	Rose	36.894783
0	Simple Average	Rose	53.484000
0	RegressionOnTime	Rose	71.617000
0	RegressionOnTimeSeasonal	Rose	73.425000
0	Naive model	Rose	79.741000

Around total of 15 models we have built for "Rose Wine" dataset and the best model which is coming out is

SARIMA Model (ACF and PACF) with parameters (p=2,d=1,q=2)(P=1,D=1,Q=1,F=12) and test RMSE value ~13

Now, we will take this model and forecast 12 months into the future with appropriate confidence intervals to see how the predictions look. We have to build our model on the full data for this.

9 Run the best model on full dataset & predict 12 months into the future with appropriate CI (confidence intervals)

Here, we have both training and full data both were non-stationary hence, nothing to be done in terms of stationarity. Let's run the best model (i.e. Manual SARIMA with order (2,1,2) and seasonal order (1,1,1,12))

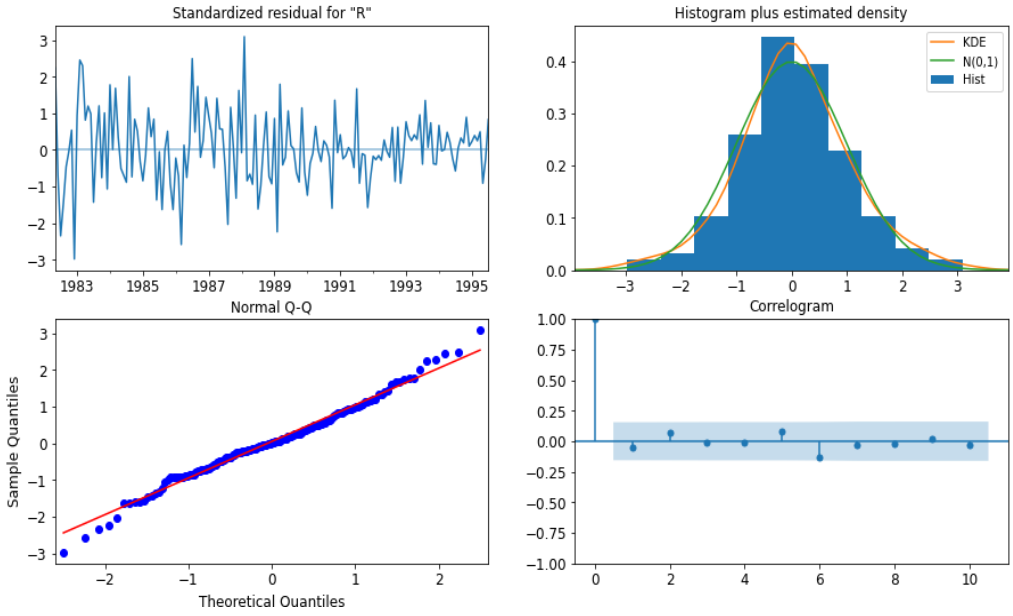
Run best model on full dataset

Let's build the model using below steps:

- Create SARIMA model using order = (2,1,2) and seasonal order = (1,1,1,12).
- Fit the model on **full dataset**.
- Print the SARIMA result summary

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                Rose   No. Observations:                  187
Model:             SARIMAX(2, 1, 2)x(1, 1, [1], 12)   Log Likelihood                -665.357
Date:                              Mon, 28 Jun 2021   AIC                           1344.714
Time:                                      13:08:36   BIC                           1366.197
Sample:                                  01-01-1980   HQIC                          1353.438
                                       - 07-01-1995
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.1076      0.093     11.896      0.000       0.925       1.290
ar.L2         -0.3258      0.080     -4.096      0.000      -0.482      -0.170
ma.L1         -1.8277      0.068    -27.021      0.000      -1.960      -1.695
ma.L2          0.8784      0.060     14.602      0.000       0.760       0.996
ar.S.L12      -0.3825      0.049     -7.748      0.000      -0.479      -0.286
ma.S.L12      -0.0859      0.093     -0.922      0.357      -0.268       0.097
sigma2       251.0878     26.981      9.306      0.000     198.206     303.970
===================================================================================
Ljung-Box (L1) (Q):                   0.38   Jarque-Bera (JB):                 2.95
Prob(Q):                              0.54   Prob(JB):                         0.23
Heteroskedasticity (H):               0.22   Skew:                             0.04
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.66
===================================================================================
```

- Run the plot diagnostic for full dataset on SARIMA result



Predict 12 months into the future with appropriate CI

Let's predict the values using below steps:

- Do the prediction on 12 months after the date at which time series ends. So forecast will be from Aug'1995 to Jul'1996.
- Use summary_frame to get predicted values for next 12 months with confidence interval of 95%

```
prediction_nxt12mnths = results_model_fulldata.get_forecast(steps=12)
```

```
prediction_nxt12mnths.summary_frame(alpha=0.05)
```

Rose	mean	mean_se	mean_ci_lower	mean_ci_upper
1995-08-01	52.903052	15.845750	21.845953	83.960151
1995-09-01	47.575612	16.454674	15.325045	79.826180
1995-10-01	52.335140	16.463905	20.066480	84.603800
1995-11-01	57.442749	16.463936	25.174026	89.711471
1995-12-01	82.696318	16.474391	50.407106	114.985530
1996-01-01	31.828066	16.539195	-0.588161	64.244293
1996-02-01	39.321502	16.689000	6.611664	72.031339
1996-03-01	45.945160	16.921723	12.779193	79.111128
1996-04-01	52.306244	17.216637	18.562256	86.050233
1996-05-01	37.754561	17.550187	3.356827	72.152296
1996-06-01	45.123998	17.903679	10.033431	80.214564
1996-07-01	57.110691	18.264742	21.312454	92.908927

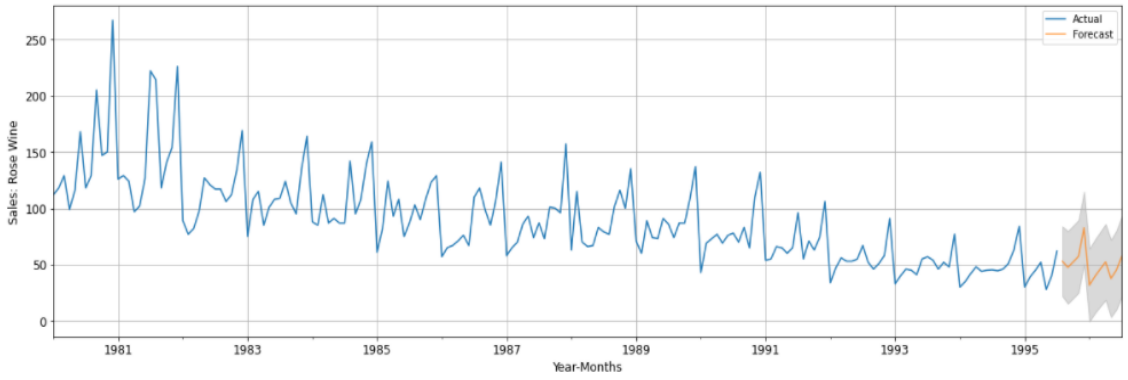
- Calculate RMSE value on full data

```
RMSE_fulldata = metrics.mean_squared_error(df['Rose'],results_model_fulldata.fittedvalues,squared=False)

print("ManualSARIMA Model(ACF-PACF)(2,1,2)(1,1,1,12):, RMSE is %3.2f"
      %(RMSE_fulldata))
```

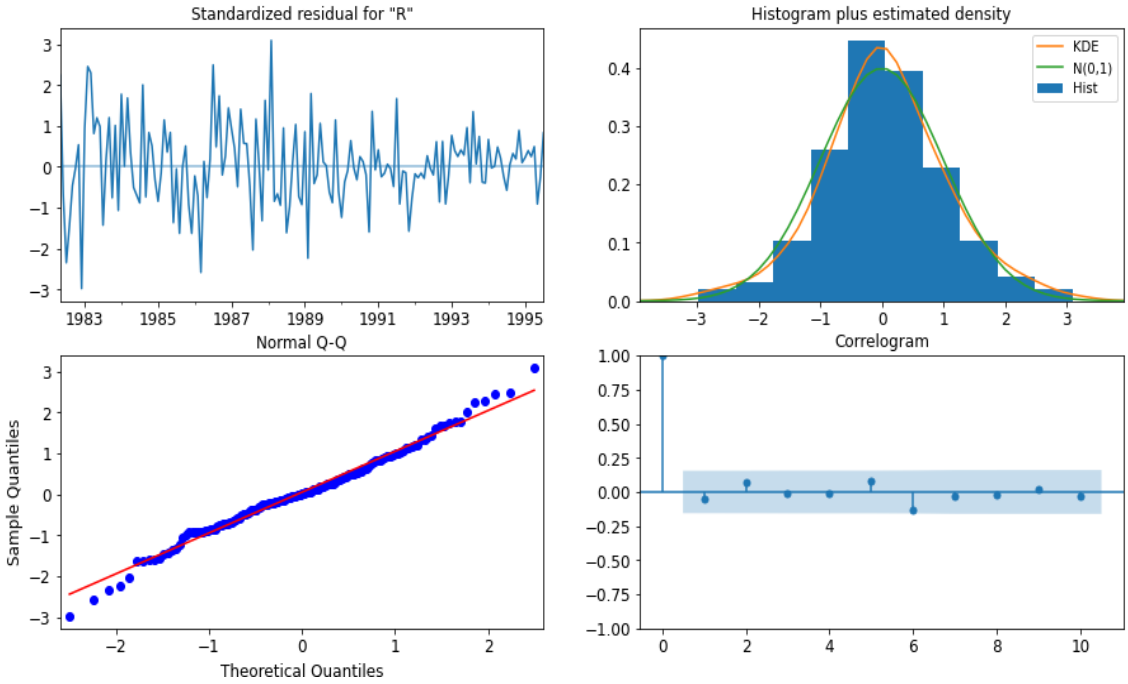
```
ManualSARIMA Model(ACF-PACF)(2,1,2)(1,1,1,12):, RMSE is 38.73
```

- Plot the full dataset with forecast value and confidence interval band.



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

Key Findings



Plot diagnostics summary charts gives promising result and below are point that justifies the same.

- **(Top left chart):** Residual chart says it is ranges between 4 to -2 which is good. The residuals over time don't display any obvious seasonality and appear to be white noise.

- **(Bottom right chart):** This is confirmed by the autocorrelation (i.e. correlogram) plot, which shows that the time series residuals have low correlation with lagged versions of itself. Autocorrelation (correlogram) plot of the residuals doesn't show the unexplained correlation which is left in the data.

- **(Bottom left chart):** QQ (Normality) plot have the linear relationship. Further, it shows that the ordered distribution of residuals (blue dots) follows the linear trend of the samples taken from a standard normal distribution with N(0, 1). Again, this is a strong indication that the residuals are normally distributed.

- **(Top right chart):** Distribution plot is seeming to be normal with mean 0 and std as 1 with in no real outliers.

So, Overall we can conclude that that residuals are random with no information or juice in them and our model produces a satisfactory fit that could help us understand our time series data and forecast future values.

Recommendations

Time series forecasting helps businesses make informed business decisions because it can be based on historical data patterns. It can be used to forecast future conditions and events. mentioned below are four key characteristics which time series forecasting has.

1. **Reliability:** Time series forecasting is most reliable, especially when the data represents a broad time period such as large numbers of observations for longer time periods. Information can be extracted by measuring data at various intervals.

2. **Seasonal patterns:** Data points variances measured can reveal seasonal fluctuation patterns that serve as the basis for forecasts. Such information is of particular importance to markets whose products fluctuate seasonally because it helps them plan for production and delivery requirements.

3. **Trend estimation:** Time series method can also be used to identify trends because data tendencies from it can be useful to managers when measurements show a decrease or an increase in sales for a particular product.

4. **Growth:** Time series method is useful to measure both endogenous and financial growth. Endogenous growth is the development from within an organization's internal human capital that leads to economic growth. For example, the impact of policy variables can be evidenced through time series analysis.

Based on the Rose wine dataset, it is coming out that this timeseries has **declining trend and seasonality (~80% of the sale is coming from last qtr. that is Oct to Dec.) Further, there are certain spikes across the months mainly in Jul to Sep and Dec.**

According to us, mentioned below are the **ways through which we could manage the business seasonality**.

- **Look for ways to diversify:** we can offset seasonality by being as innovative as possible. Whether that means diversifying product lines or by pre-empting what your customers want. Market survey is the best way to understand the business/customer needs.
- **Promotional campaign:** Due to strong presence of seasonality, Company should start stock up the wine from July and ensure the availability for December sales (Christmas and New Year eve) and during non-peak seasons Jan, Feb should run promotions to catch up the sales. Overall, the Rose wine sales are going down over period of time and hence company should promote product more through marketing, promotions, branding, etc.
- **Develop sales, inventory and staffing plans:** Planning inventory and sales at least six months ahead will helps pinpoint where business needs to build in a cash cushion to tide over during quieter periods. Plan everything from stock levels to staff. That way business has the supplies and all material required when demand picks up again. A cash flow forecast can also help with this.
- **Think ahead**: how will this new seasonal business develop? Will it simply become an addition to your current business, or has it got strong enough legs to stand on its own?