Air Passengers

September 16, 2023

1 Problem Statement

2 Air Passenger

Perform the following tasks:

- Visualize the Air Passenger time series and check for any trend, seasonality or random patterns.
- Stantionarize the series using decomposition or differencing techniques
- Plot ACF/PACF and find (p,q,d) parameters
- Build the Model
- Make Predictions using Final Model

[1]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid',color_codes= True)
matplotlib.rc('xtick',labelsize=40)
matplotlib.rc('ytick',labelsize=40)
import datetime
from datetime import datetime as dt
```

[2]:
```
data =pd.read_csv("AirPassengers.csv")
data.head()
```

[2]:

	Month	#Passengers
0	1949-01	112
1	1949-02	118
2	1949-03	132
3	1949-04	129
4	1949-05	121

[3]:
```
data.shape
```

[3]: (144, 2)

[4]:
```
#lets rename passenger column name
data.rename(columns={'#Passengers':'Passengers'}, inplace =True)
data.head()
```

[4]:
```
     Month  Passengers
0  1949-01         112
1  1949-02         118
2  1949-03         132
3  1949-04         129
4  1949-05         121
```

[5]:
```
# lets check the info of air passenger
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Month       144 non-null    object
 1   Passengers  144 non-null    int64
dtypes: int64(1), object(1)
memory usage: 2.4+ KB
```

[6]:
```
# lets convert the month into date for more accurate  time plot
data["Month"]= pd.to_datetime(data["Month"])
```

[7]:
```
data.head()
```

[7]:
```
       Month  Passengers
0 1949-01-01         112
1 1949-02-01         118
2 1949-03-01         132
3 1949-04-01         129
4 1949-05-01         121
```

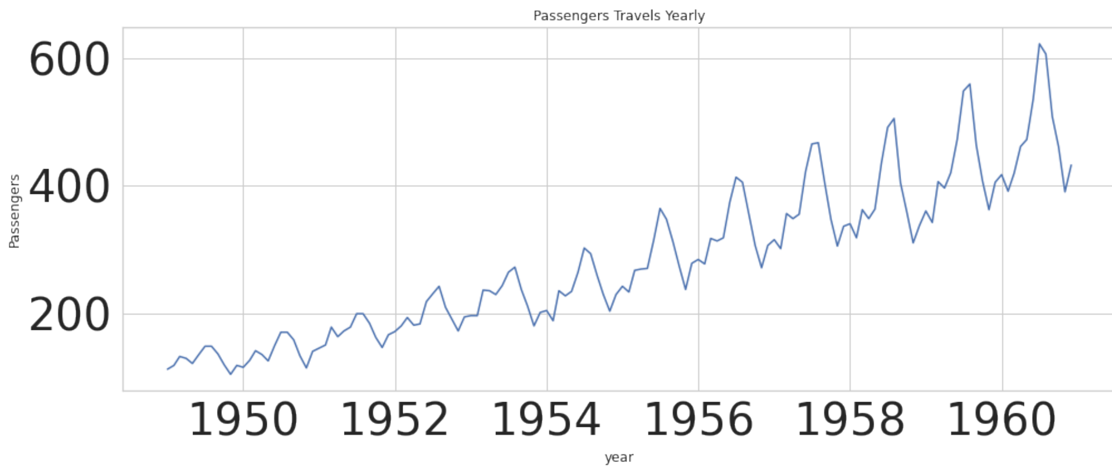
NOTE : date has been taken fixed 1st by default for ploting the time plot and check any zero mean, most freqent variance ,noise happening in the graph.

3 Visualize Air Passenger Data and check for any trend, seasonality and resdual:

[8]:
```
plt.figure(figsize=(16,6))
plt.plot(data['Month'],data['Passengers'])
plt.xlabel("year")
plt.ylabel("Passengers")
```

```
plt.title("Passengers Travels Yearly")
```

[8]: Text(0.5, 1.0, 'Passengers Travels Yearly')



Interpretation : There is a clear increasing trend from 1950 to 1960 * we can also see that there is a consistent increase from 1958 to 1960 hence there can be strong seasonal patterns.

4 Visualize in the form of Stack line Charts

[9]:
```
# lets split the month column in year and month properly for better␣
↪understanding
data['Year']=data['Month'].dt.year
data['month'] =data['Month'].dt.strftime('%b')
data.head()
```

[9]:

	Month	Passengers	Year	month
0	1949-01-01	112	1949	Jan
1	1949-02-01	118	1949	Feb
2	1949-03-01	132	1949	Mar
3	1949-04-01	129	1949	Apr
4	1949-05-01	121	1949	May

[10]:
```
data['month'].unique
```

[10]:
```
<bound method Series.unique of 0      Jan
1      Feb
2      Mar
3      Apr
4      May
      …
```

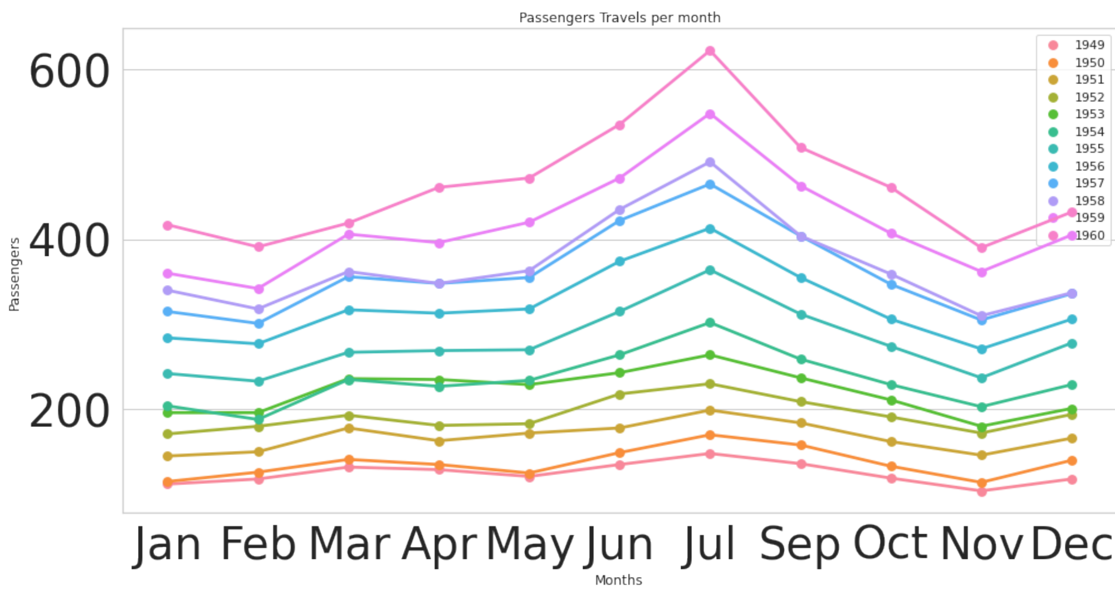
```
139     Aug
140     Sep
141     Oct
142     Nov
143     Dec
Name: month, Length: 144, dtype: object>
```

[11]:

```
# lets visualize:
plt.figure(figsize=(16,8))
sns.pointplot(x='month', y="Passengers",hue='Year',data=data,␣
 ↪order=['Jan','Feb','Mar','Apr','May','Jun','Jul','Sep','Oct','Nov','Dec'])
plt.xlabel('Months')
plt.ylabel('Passengers')
plt.title("Passengers Travels per month")
plt.legend(loc="upper right")
```

[11]:

```
<matplotlib.legend.Legend at 0x7f9680548250>
```

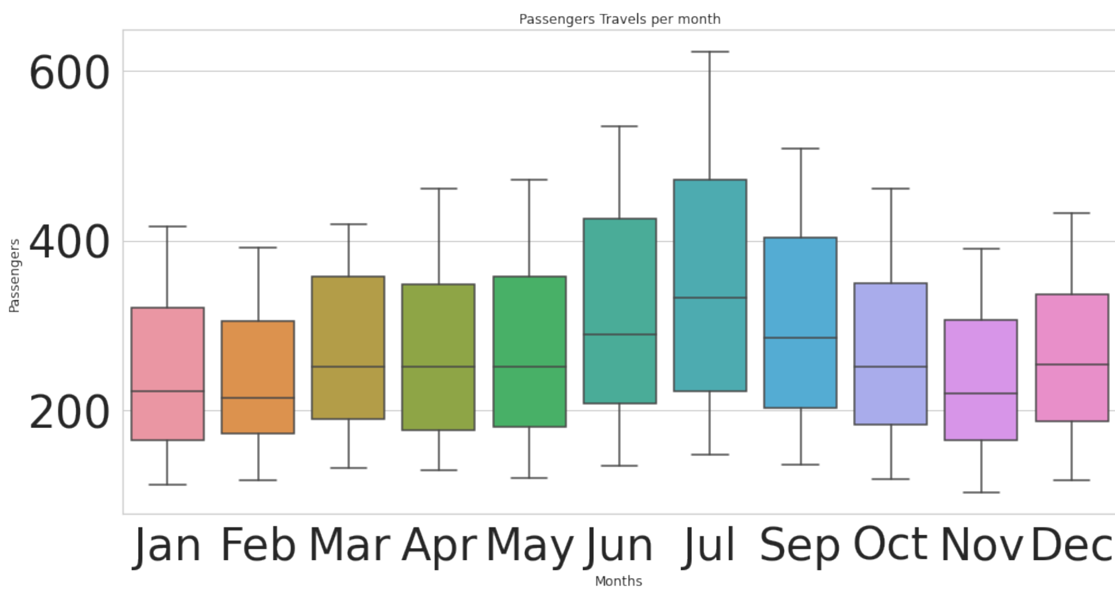


Intrpretation : * There is a large jump in the month july around 600 above paseengers travels in year 1959 to 1960. * However in the same year range there is a drop in the passenger travel in the month of November. * There is a colinearity in year 1958,1956.

5 Visualize the Box Plot:

[12]:
```
plt.figure(figsize=(16,8))
sns.boxplot(x='month', y="Passengers",data=data,␣
 ↪order=['Jan','Feb','Mar','Apr','May','Jun','Jul','Sep','Oct','Nov','Dec']
)
plt.xlabel('Months')
plt.ylabel('Passengers')
plt.title("Passengers Travels per month")
```

[12]:
```
Text(0.5, 1.0, 'Passengers Travels per month')
```

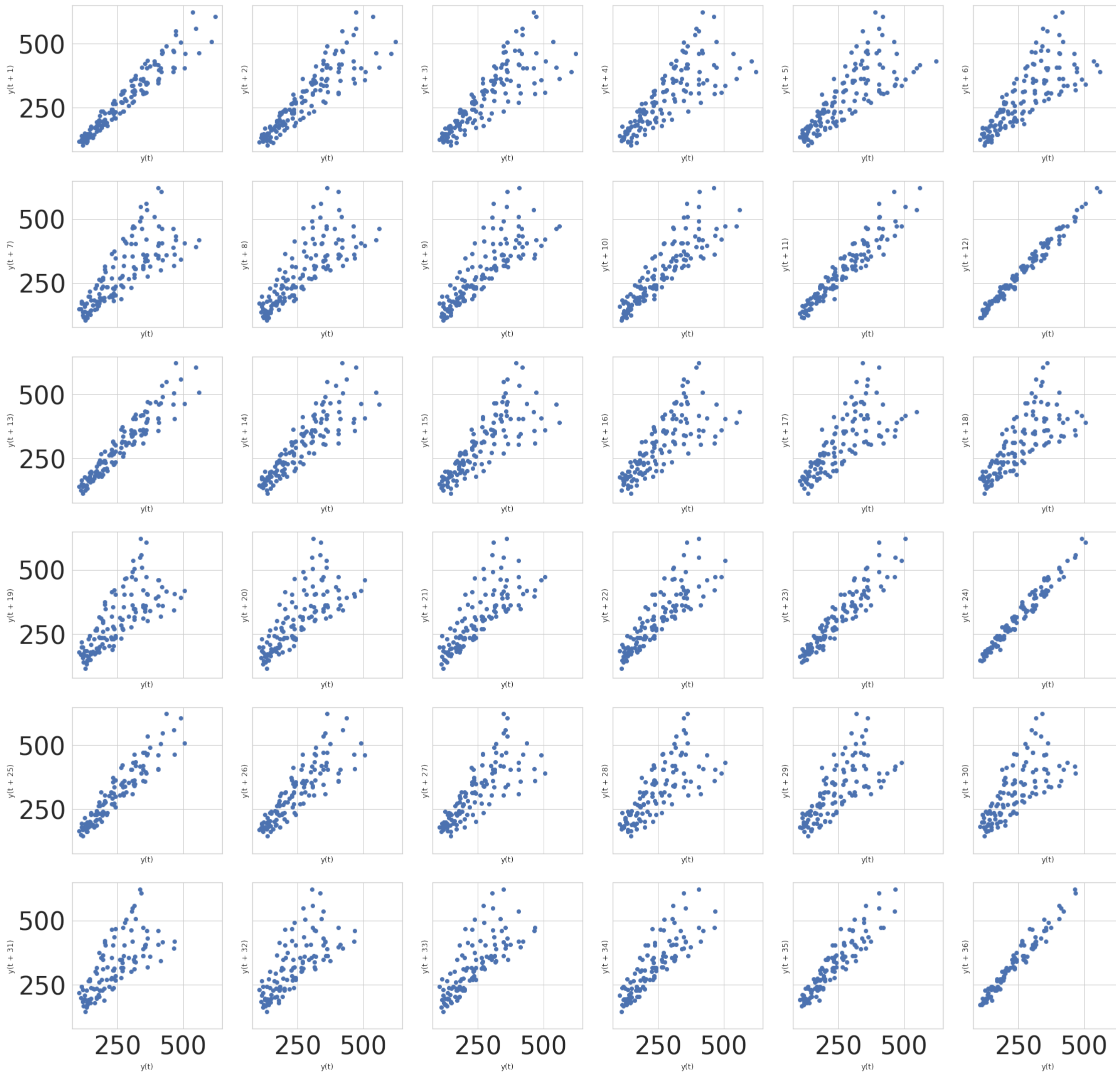


Interpretation : there are fluctuations in the passenger number to travel we can see that in july has a long whiskers whch depicts that there are large number of passengers travels in the month of july.

LagPlot:Lets check the above prediction is made accurate or not by checking the dataset is choosen randomly or not by using Lag Plot

[13]:
```
from pandas.plotting import lag_plot
plot_lags =30
rows=int( plot_lags/5)
cols = int(plot_lags/5)
fig,axes =plt.subplots(rows,cols,sharex=True,sharey=True)
fig.set_figwidth(plot_lags)
fig.set_figheight(plot_lags)
count=1
for i in range(rows):
    for j in range(cols):
```

```
        lag_plot(data['Passengers'], lag =count, ax=axes[i,j])
        count+=1
```

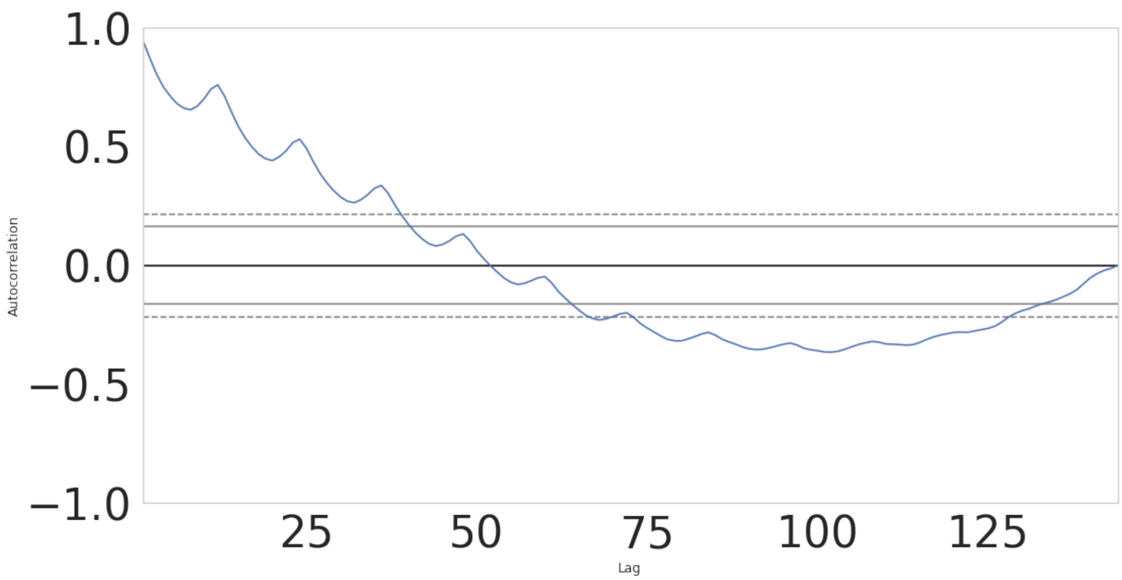


Interpretation : we can see that there is constant patterns in the graph hence data is not random here.

6 Lets check colinearity between the datasets by using Auto Correlation and Partial Auto Correlation fuction:

[14]:
```
from pandas.plotting import autocorrelation_plot
plt.figure(figsize=(16,8))
autocorrelation_plot(data['Passengers'])
```

[14]: <AxesSubplot: xlabel='Lag', ylabel='Autocorrelation'>



Interpretation : there is damp/downward trend which shows a ngative autocorrelation.

7 Decomposition Time Series Data.

Lets create a data frame called a decompose and indulge month and passengers data into it for finding any trends, seasonality or residuals.

[15]:
```
decompose =data[['Month','Passengers']]
decompose.head()
```

[15]:

	Month	Passengers
0	1949-01-01	112
1	1949-02-01	118
2	1949-03-01	132
3	1949-04-01	129
4	1949-05-01	121

[16]:
```
#Lets make the index with dates:
```

[17]:
```
decompose.index=data['Month']
decompose.head()
```

[17]:

	Month	Passengers
Month		
1949-01-01	1949-01-01	112
1949-02-01	1949-02-01	118

```
1949-03-01 1949-03-01         132
1949-04-01 1949-04-01         129
1949-05-01 1949-05-01         121
```

[18]:
```
decompose =decompose[['Passengers']]
decompose.head()
```

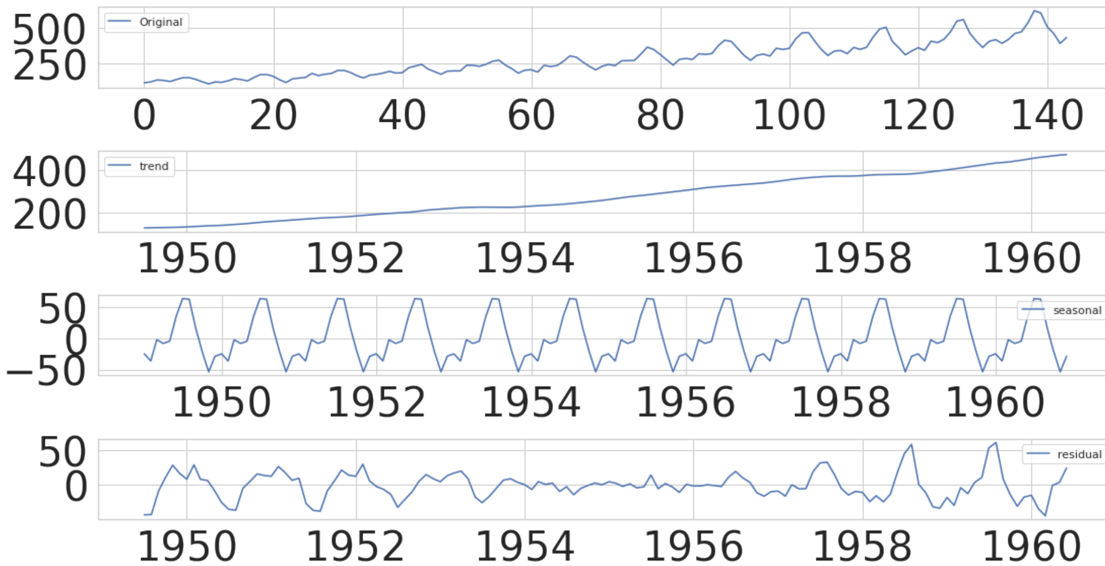
[18]:
```
            Passengers
Month
1949-01-01         112
1949-02-01         118
1949-03-01         132
1949-04-01         129
1949-05-01         121
```

8 Importing Decomposition Model and Ploting the graphs on trends, seasonality and residuals:

[19]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

[20]:
```
decomposition =seasonal_decompose(decompose)
trend =decomposition.trend
seasonal =decomposition.seasonal
residual =decomposition.resid
```

[21]:
```
plt.figure(figsize=(16,8))
plt.subplot(411)
plt.plot(data['Passengers'],label="Original")
plt.legend(loc="best")
plt.subplot(412)
plt.plot(trend,label="trend")
plt.legend(loc="best")
plt.subplot(413)
plt.plot(seasonal,label="seasonal")
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual,label="residual")
plt.legend(loc="best")
plt.tight_layout()
```



Interpretation : * there is a rise in trend graph (linearly) from 1950 to 1960.

9 Standarize the series using differecing techniques:

[22]:
```
import math
from math import pow, sqrt
from sklearn.metrics import mean_squared_error
```

[23]:
```
data.head()
```

[23]:
```
        Month  Passengers  Year month
0 1949-01-01         112  1949   Jan
1 1949-02-01         118  1949   Feb
2 1949-03-01         132  1949   Mar
3 1949-04-01         129  1949   Apr
4 1949-05-01         121  1949   May
```

[24]:
```
# lets split the data set
data.index=data["Month"]
data=data[['Passengers']]
data.head()
```

[24]:
```
            Passengers
Month
1949-01-01         112
1949-02-01         118
1949-03-01         132
```

```
1949-04-01          129
1949-05-01          121
```

[25]:
```
x_train =data[data.index <datetime.datetime(1960,1,1,0,0,0)]
x_test= data[data.index >= datetime.datetime(1960,1,1,0,0,0)]
```

[26]:
```
print("The shape of x train set", x_train.shape)
print("THe Shape of the x test",x_test.shape)
```

```
The shape of x train set (132, 1)
THe Shape of the x test (12, 1)
```

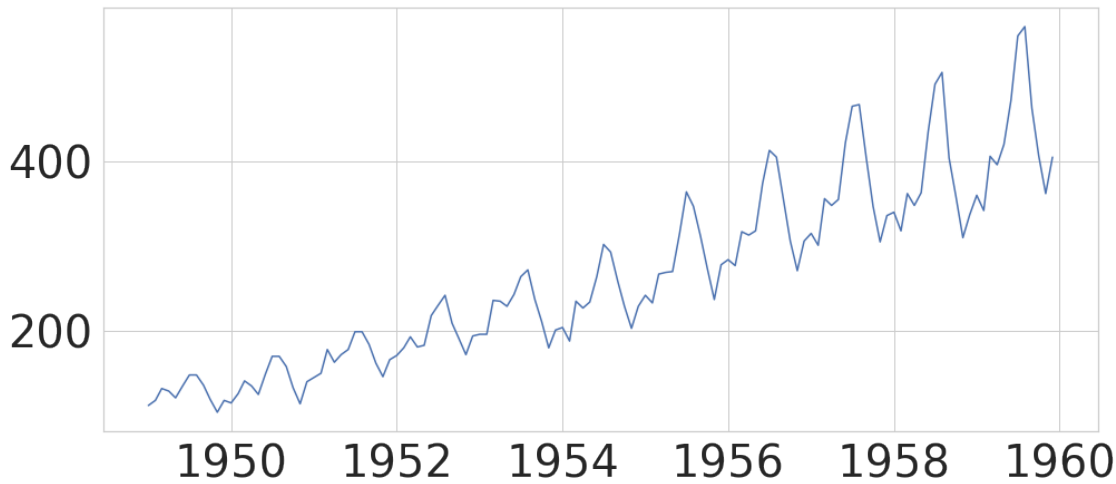
[27]:
```
# lets check the p value by using  Augmented dickey-fuller(ADF) Test:
from statsmodels.tsa.stattools import adfuller
```

[28]:
```
# define the stationary test :
def stationary_test(data):
    dftest =adfuller(data.Passengers, autolag='AIC')
    dfoutput= pd.Series(dftest[0:4],index=['Test Statistic','P value','#Lag␣
 ↪Used','Number of Observations Used'])
    for key, value in dftest[4].items():
        dfoutput['Critical Values(%s)'%key]=value
    print(dfoutput)

    plt.figure(figsize=(16,7))
    plt.plot(data.index,data.Passengers)
    plt.show()
```

[29]:
```
stationary_test(x_train)
```

```
Test Statistic                   0.888027
P value                          0.992932
#Lag Used                       13.000000
Number of Observations Used    118.000000
Critical Values(1%)             -3.487022
Critical Values(5%)             -2.886363
Critical Values(10%)            -2.580009
dtype: float64
```



Interpretation : the p value here is 0.99 hence time series data is not stationary.

[30]:
```
# lets convert into logarithm data:
log_train =x_train
log_train =log_train["Passengers"].apply(lambda x: math.log(x+1))
log_train
```

[30]:
```
Month
1949-01-01    4.727388
1949-02-01    4.779123
1949-03-01    4.890349
1949-04-01    4.867534
1949-05-01    4.804021
                 …
1959-08-01    6.327937
1959-09-01    6.139885
1959-10-01    6.011267
1959-11-01    5.894403
1959-12-01    6.006353
Name: Passengers, Length: 132, dtype: float64
```

[31]:
```
# lets put in dataframe
log_train = pd.DataFrame(log_train)
log_train
```

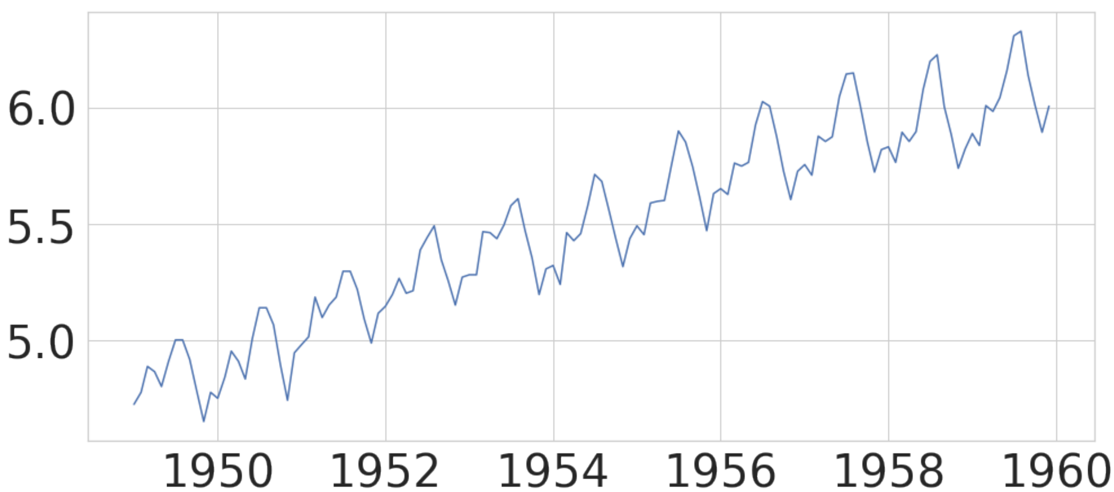
[31]:
```
            Passengers
Month
1949-01-01    4.727388
1949-02-01    4.779123
1949-03-01    4.890349
1949-04-01    4.867534
```

```
1949-05-01    4.804021
…                  …
1959-08-01    6.327937
1959-09-01    6.139885
1959-10-01    6.011267
1959-11-01    5.894403
1959-12-01    6.006353

[132 rows x 1 columns]
```

[32]:
```
# lets check again the p value and the graph using dickey fuller
stationary_test(log_train)
```

```
Test Statistic                  -1.307055
P value                          0.625938
#Lag Used                       13.000000
Number of Observations Used    118.000000
Critical Values(1%)             -3.487022
Critical Values(5%)             -2.886363
Critical Values(10%)            -2.580009
dtype: float64
```

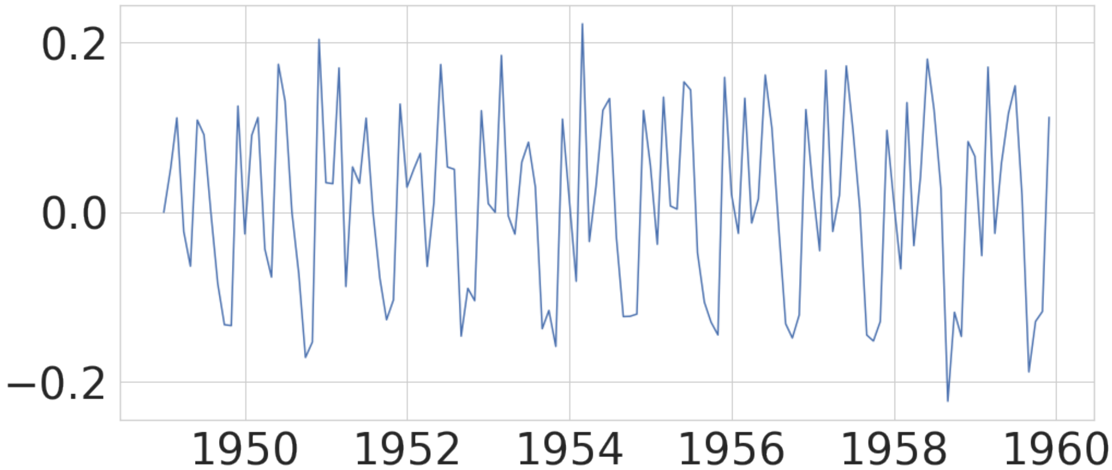


Interperation : Here we can see the p value drops from 0.99 to 0.62, hence data is not stationary * lets use the technique differencing

[33]:
```
first_diff =log_train['Passengers']-log_train['Passengers'].shift(1)
first_diff =first_diff.fillna(0)
first_diff =pd.DataFrame(first_diff)
```

[34]:
```
stationary_test(first_diff)
```

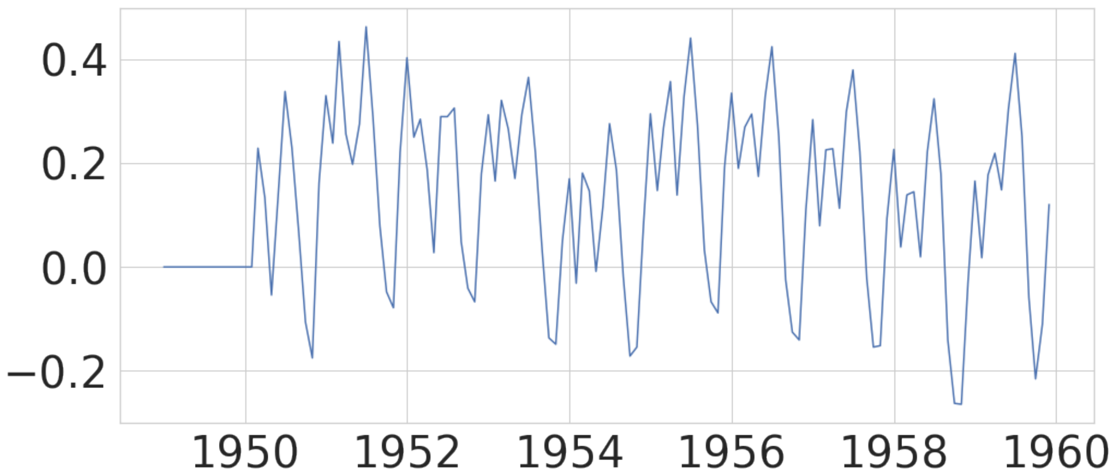
```
Test Statistic                  -3.090415
P value                          0.027271
#Lag Used                       13.000000
Number of Observations Used    118.000000
Critical Values(1%)             -3.487022
Critical Values(5%)             -2.886363
Critical Values(10%)            -2.580009
dtype: float64
```



$Interpretation: $ the P value is less than 0.05 which is 0.027 hence we achieved stationary.

[35]:
```
# check for seasonal differentiating for stationary check
seasonal_diff =log_train['Passengers']-log_train['Passengers'].shift(14)
seasonal_diff= seasonal_diff.fillna(0)
seasonal_diff =pd.DataFrame(seasonal_diff)
stationary_test(seasonal_diff)
```

```
Test Statistic                  -3.144552
P value                          0.023427
#Lag Used                       13.000000
Number of Observations Used    118.000000
Critical Values(1%)             -3.487022
Critical Values(5%)             -2.886363
Critical Values(10%)            -2.580009
dtype: float64
```



Interretation : The p-value is less than 0.05, and we can clearly see that the differencing has led to the stationarity of data.

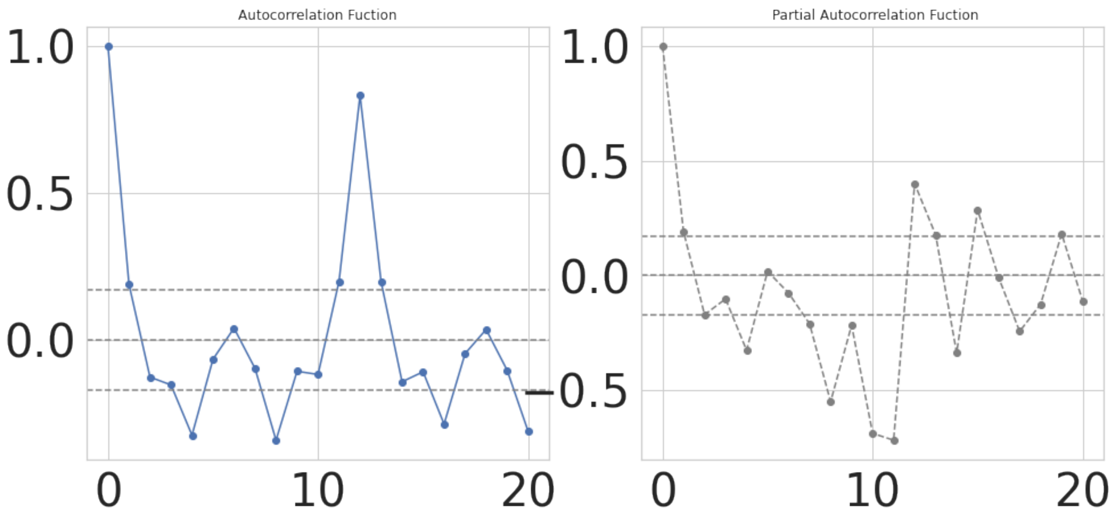
10 ARIMA Model:

[72]:
```
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import acf, pacf
```

[37]:
```
# Lets find ACF and PACF plots for p,q,d values:
#z_score =1.96 as we need confidence level =95%
lag_acf =acf(first_diff, nlags= 20)
lag_pacf =pacf(first_diff,nlags=20)
plt.figure(figsize=(16,7))
# for ACF:
plt.subplot(121)
plt.plot(lag_acf,marker="o")
plt.axhline(y=0, linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(first_diff)),linestyle='--',color='gray')
plt.axhline(y =1.96/np.sqrt(len(first_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Fuction')

# For PACF:
plt.subplot(122)
plt.plot(lag_pacf, marker="o",linestyle='--',color='gray')
plt.axhline(y=0, linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(first_diff)),linestyle='--',color='gray')
plt.axhline(y =1.96/np.sqrt(len(first_diff)),linestyle='--',color='gray')
plt.title(' Partial Autocorrelation Fuction')
```

[37]:
```
Text(0.5, 1.0, ' Partial Autocorrelation Fuction')
```



Interpretation : p value is around 1 and q= 1 as well

[52]:
```
model =ARIMA(log_train, order=(2,2,1),freq ='MS')
result_ARIMA= model.fit()
```

```
/usr/local/lib/python3.10/site-packages/statsmodels/tsa/base/tsa_model.py:471:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/site-packages/statsmodels/base/model.py:604:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[53]:
```
print(result_ARIMA.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:             Passengers   No. Observations:                  132
Model:                 ARIMA(2, 2, 1)   Log Likelihood                 109.160
Date:                Sat, 16 Sep 2023   AIC                           -210.321
Time:                        20:15:12   BIC                           -198.851
Sample:                    01-01-1949   HQIC                          -205.660
                         - 12-01-1959
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.2295      0.109      2.097      0.036       0.015       0.444
ar.L2         -0.1662      0.111     -1.495      0.135      -0.384       0.052
```

```
ma.L1         -0.9999     26.053     -0.038      0.969    -52.064     50.064
sigma2         0.0105      0.274      0.038      0.969     -0.527      0.548
================================================================================
===
Ljung-Box (L1) (Q):                   0.06   Jarque-Bera (JB):
6.33
Prob(Q):                              0.80   Prob(JB):
0.04
Heteroskedasticity (H):               1.23   Skew:
0.20
Prob(H) (two-sided):                  0.50   Kurtosis:
2.00
================================================================================
===

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

[54]:

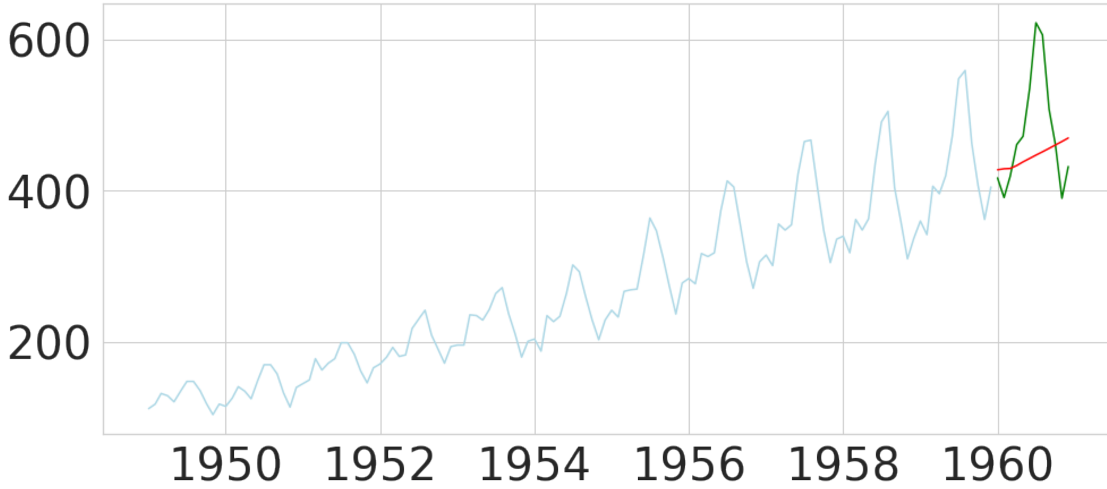
```python
plt.figure(figsize=(16,7))
plt.plot(x_train.index,x_train.values, color="lightblue")
plt.plot(x_test.index,x_test.values,color='green')

pred= pd.DataFrame(result_ARIMA.forecast(len(x_test)))
pred.columns =["Passenger_Travel"]
pred.index= x_test.index

pred["Passenger_Travel"] =pred["Passenger_Travel"].apply(lambda x:math.exp(x)-1)

measure= math.sqrt(mean_squared_error(x_test.values, pred.values))
print(measure)
plt.plot(pred.index,pred.fillna(0).values,color='red')
plt.show()
```

```
79.765307543679
```




```
[58]: pred= pd.DataFrame(result_ARIMA.forecast(len(x_test)))
pred.columns =["Passenger_Travel"]
pred.index= x_test.index
```

```
[59]: pred
```

```
[59]:             Passenger_Travel
Month
1960-01-01          6.060723
1960-02-01          6.063842
1960-03-01          6.064766
1960-04-01          6.073707
1960-05-01          6.084852
1960-06-01          6.095171
1960-07-01          6.104934
1960-08-01          6.114706
1960-09-01          6.124573
1960-10-01          6.134460
1960-11-01          6.144336
1960-12-01          6.154206
```

```
[56]: pred["Passenger_Travel"] =pred["Passenger_Travel"].apply(lambda x:math.exp(x)-1)
```

```
[57]: pred
```

```
[57]:             Passenger_Travel
Month
1960-01-01     5.513025e+185
1960-02-01     2.103067e+186
1960-03-01     3.130800e+186
```

```
1960-04-01     1.494207e+188
1960-05-01     1.941982e+190
1960-06-01     1.847002e+192
1960-07-01     1.435351e+194
1960-08-01     1.169233e+196
1960-09-01     1.038476e+198
1960-10-01     9.732960e+199
1960-11-01     9.493708e+201
1960-12-01     9.664162e+203
```

[55]:
```
measure= math.sqrt(mean_squared_error(x_test.values, pred.values))
print(measure)
```

```
79.765307543679
```

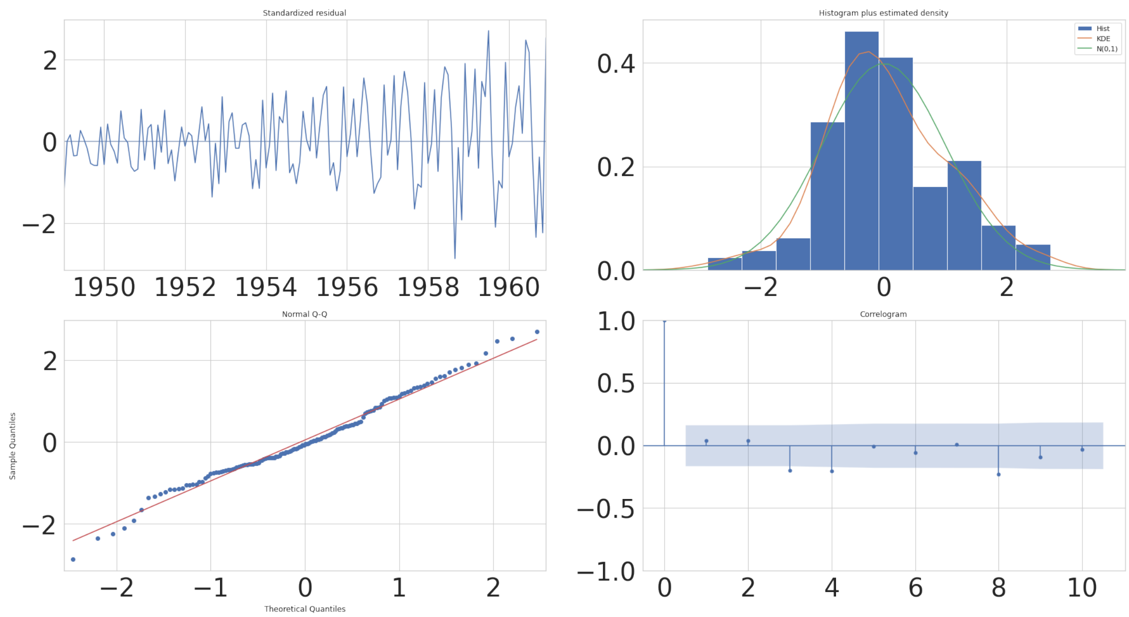
[60]:
```
!pip install pmdarima --quiet
import pmdarima as pm
```

```
DEPRECATION: beakerx-base 2.0.1 has a non-standard dependency specifier
ipywidgets<8pandas,>=7.5.1. pip 23.3 will enforce this behaviour change. A
possible replacement is to upgrade to a newer version of beakerx-base or contact
the author to suggest that they release a version with a conforming dependency
specifiers. Discussion can be found at
https://github.com/pypa/pip/issues/12063
```

[63]:
```
ARIMA_model =pm.auto_arima(data['Passengers'],
                          start_p=1,start_q=1,test='adf', max_p=3,m=1, d= None,
                          seasonal =False,
                          trace=False,
                          error_action= 'warn',
                          suppress_warnings=True,stepwise= True)
```

$NOTE$: * test='adf', # use adftest to find optimal 'd' * max_p=3, max_q=3, # maximum p and q * m=1, # frequency of series (if m==1, seasonal is set to FALSE automatically) * d=None,# let model determine 'd' * seasonal=False, # No Seasonality for standard ARIMA * trace=False, #logs * error_action='warn', #shows errors ('ignore' silences these)

[70]:
```
# lets plot standarized residual ,correlogram,Normal q-q, histogram
ARIMA_model.plot_diagnostics(figsize=(30,16))
plt.show()
```



11 Model Diagnostics

Four plots result from the plot_diagnostics function. The Standardized residual, Histogram plus KDE estimate, Normal q-q, and the correlogram.

We can interpret the model as a good fit based on the following conditions.

12 Standardized residual

There are no obvious patterns in the residuals, with values having a mean of zero and having a uniform variance.

13 Histogram plus KDE estimate

The KDE curve should be very similar to the normal distribution (labeled as N(0,1) in the plot)

14 Normal Q-Q

Most of the data points should lie on the straight line

15 Correlogram (ACF plot)

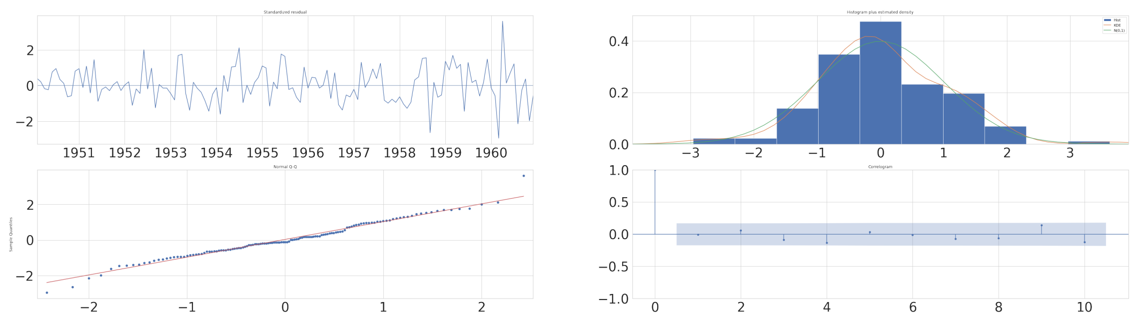
95% of correlations for lag greater than zero should not be significant. The grey area is the confidence band, and if values fall outside of this then they are statistically significant. In our case, there are a few values outside of this area, and therefore we may need to add more predictors to make the model more accurate

16 SARIMA Model

Now let's try the same strategy as we did above, except let's use a SARIMA model so that we can account for seasonality.

[74]:
```
# Seasonal - fit stepwise auto-ARIMA
SARIMA_model = pm.auto_arima(data["Passengers"], start_p=1, start_q=1,
                         test='adf',
                         max_p=3, max_q=3,
                         m=12, #12 is the frequncy of the cycle
                         start_P=0,
                         seasonal=True, #set to seasonal
                         d=None,
                         D=1, #order of the seasonal differencing
                         trace=False,
                         error_action='ignore',
                         suppress_warnings=True,
                         stepwise=True)
```

[77]:
```
SARIMA_model.plot_diagnostics(figsize=(60,16))
plt.show()
```

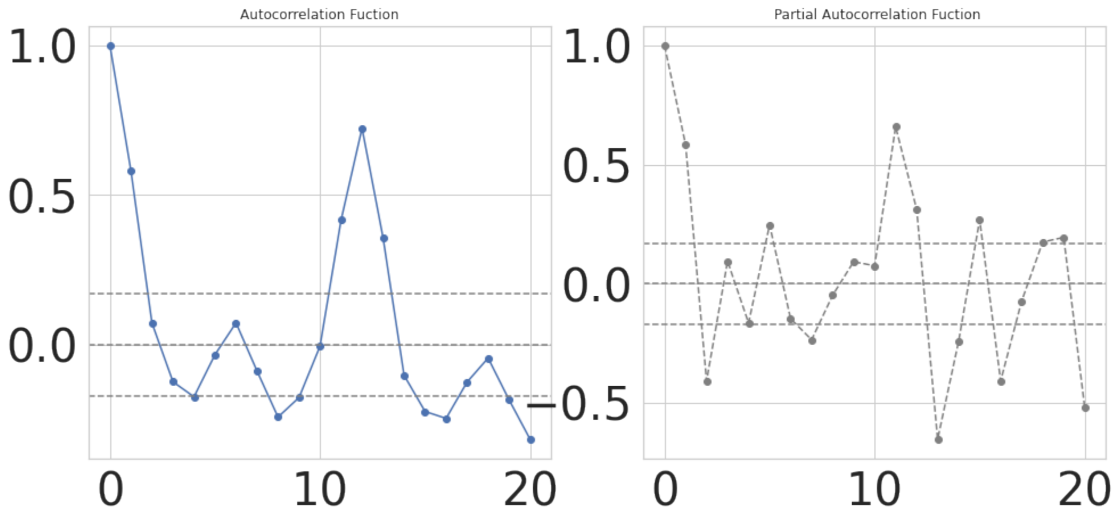


17 Lets Plot ACF and PACF: using seasonal_diff

[78]:
```
lag_acf =acf(seasonal_diff, nlags= 20)
lag_pacf =pacf(seasonal_diff,nlags=20)
plt.figure(figsize=(16,7))
# for ACF:
plt.subplot(121)
plt.plot(lag_acf,marker="o")
plt.axhline(y=0, linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(seasonal_diff)),linestyle='--',color='gray')
plt.axhline(y =1.96/np.sqrt(len(seasonal_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Fuction')
```

```
# For PACF:
plt.subplot(122)
plt.plot(lag_pacf, marker="o",linestyle='--',color='gray')
plt.axhline(y=0, linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(seasonal_diff)),linestyle='--',color='gray')
plt.axhline(y =1.96/np.sqrt(len(seasonal_diff)),linestyle='--',color='gray')
plt.title(' Partial Autocorrelation Fuction')
```

[78]: Text(0.5, 1.0, ' Partial Autocorrelation Fuction')



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