Air Passenger Traffic Forecasting using Time Series

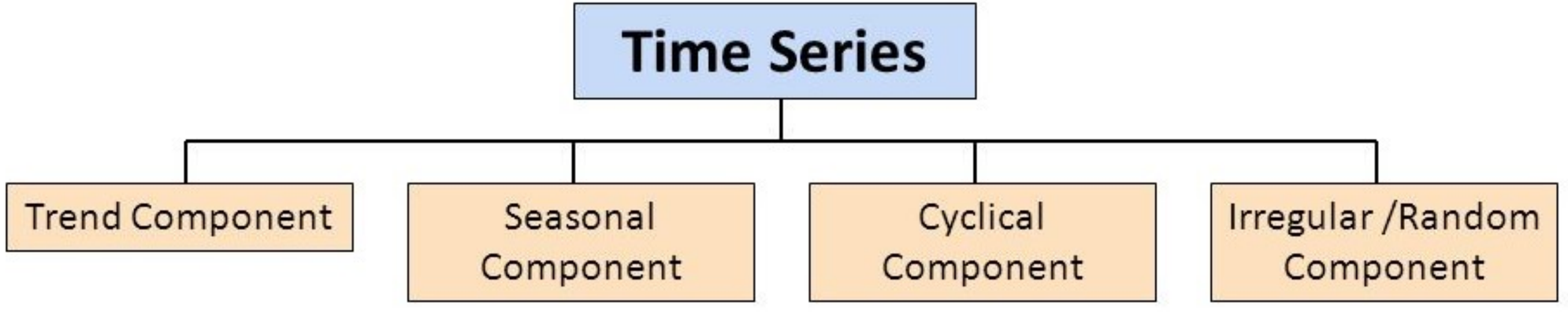
What is Time Series

A Time Series is a series of data points indexed (or listed or graphed) in time order.

The four components of Time Series are:

1. Trend, which describe the movement along the term;
2. Seasonal variations, which represent seasonal changes;
3. Cyclical fluctuations, which correspond to periodical but not seasonal variations;
4. Irregular variations, which are other nonrandom sources of variations of series.

Time-Series Components



Aim

In this project we are collecting the yearly data of the passenger number of the aeroplane and later predict the future year passenger number. In this project we forecaset the number of global air passenger journeys to increase at an average rate of 4.0% each year over the next 20 years. The number of global air passenger journeys is expected to increase at an average rate of 5.3% each year over the next 5 years.

Getting Started

Import Libraries

In [88]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt #plt.show()
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

Get the Data

In [54]:
```
#Data loading
data = pd.read_csv("AirPassengers.csv")
data.head()
```

Out[54]:

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

EDA

In [55]:
```
data.shape #to check the no.of rows and columns
```

Out[55]:
```
(144, 2)
```

In [56]:
```
data.describe()
```

Out[56]:

	#Passengers
count	144.000000
mean	280.298611
std	119.966317
min	104.000000
25%	180.000000
50%	265.500000
75%	360.500000
max	622.000000

In [57]:
```
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
```

In [58]:
```
#changing Month Feature to DateTime Format
data['Month'] = pd.to_datetime(data['Month'])
```

In [59]:
```
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    datetime64[ns]
 1   #Passengers  144 non-null    int64         
dtypes: datetime64[ns](1), int64(1)
memory usage: 2.4 KB
```

In [60]:
```
#In Time series, date column should always be set as Index
data = data.set_index(['Month'])
data.head()
```

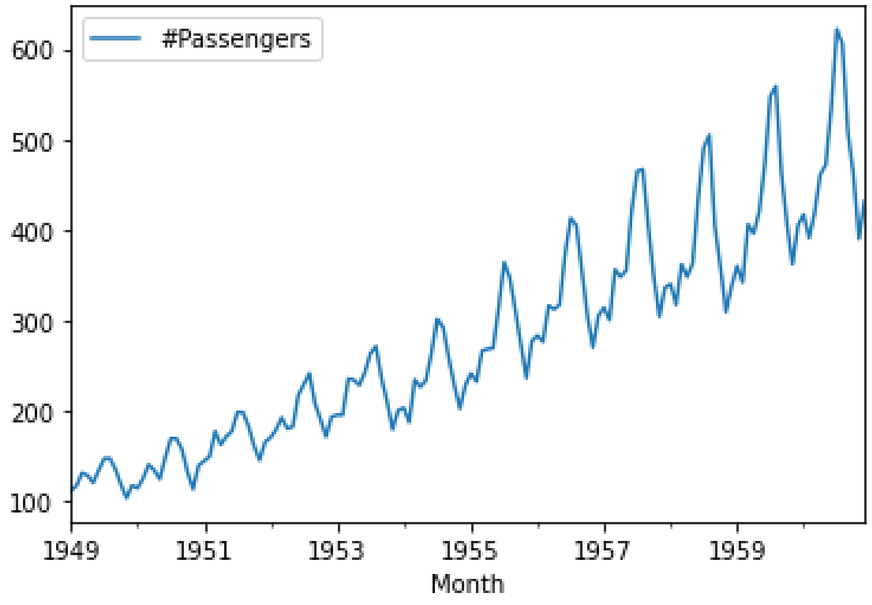
Out[60]:

Month	#Passengers
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121

In [61]:
```
data.shape
```

Out[61]:
```
(144, 1)
```

In [78]:
```
#Month vs Passengers plot
data.plot()
plt.show()
```



In the above plot, upward trend and seasonality is clearly visible.

Data Stationary Tests before Transformation

Lets check if the data is stationary or not

1. Adfuller Test

In [63]:
```
#f- format while print statement is used

from statsmodels.tsa.stattools import adfuller

#ADF Test - if the p-value < 0.05 - Data is stationary
result = adfuller(data)
print(f'ADF Statistic,{result[0]}') #some default value based upon the critial values
print(f'p-value={result[1]}')
print(f'n_lags,{result[2]}') #previous no.of observations used for prediction

# print(f'Result: The series is {"not " if result[1]>0.05 else ""}stationary')
```

```
if(result[1]>0.05):
    print("The series is not stationary")
else:
    print("series is stationary")
```

```
ADF Statistic,0.8153688792060502
p-value=0.991880243437641
n_lags,13
The series is not stationary
```

2. KPSS Test (*optional*)

In [64]:
```
# # KPSS test - if p<0.05 - data is not stationary
# from statsmodels.tsa.stattools import kpss
# def kpss_test(series, **kw):
#     statistic, p_value, n_lags, critical_values = kpss(series, **kw)
#     # Format Output
#     print(f'KPSS Statistic: {statistic}')
#     print(f'p-value: {p_value}')
#     print(f'num lags: {n_lags}')
#     print('Critial Values:')
#     for key, value in critical_values.items():
#         print(f'   {key} : {value}')
#     print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

# kpss_test(data)
```

Test Conclusion After performing stationary tests, we conclude data is not stationary. So, it becomes important to station our data before we can analyze it further

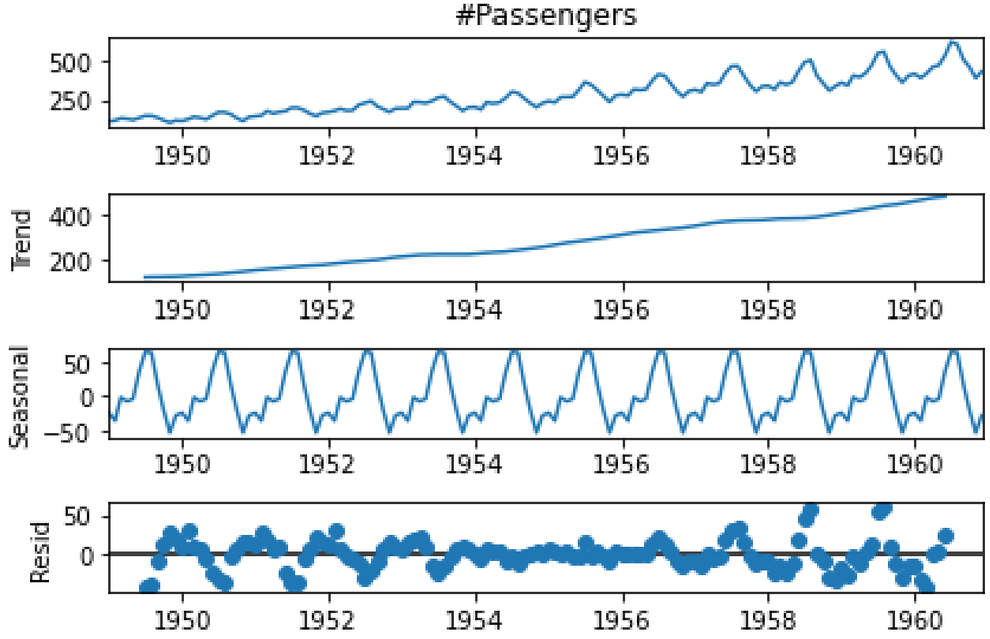
Visualization

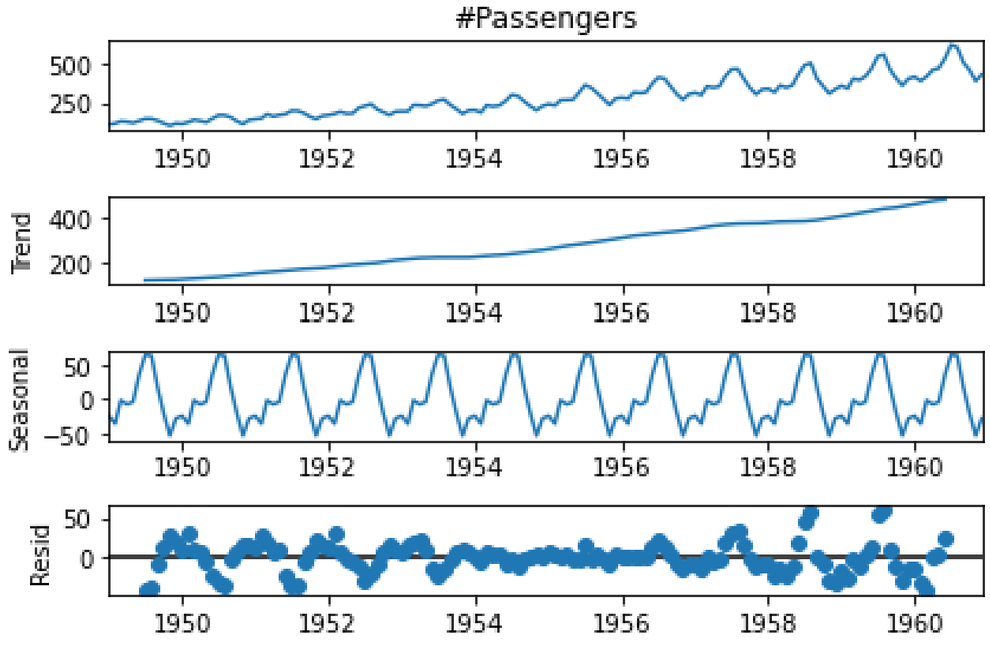
Seasonal decompose - it plots the trend, Seasonal, Residual sepreately

In [65]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

decomposition = seasonal_decompose(data['#Passengers'])
decomposition.plot()
```

Out[65]:



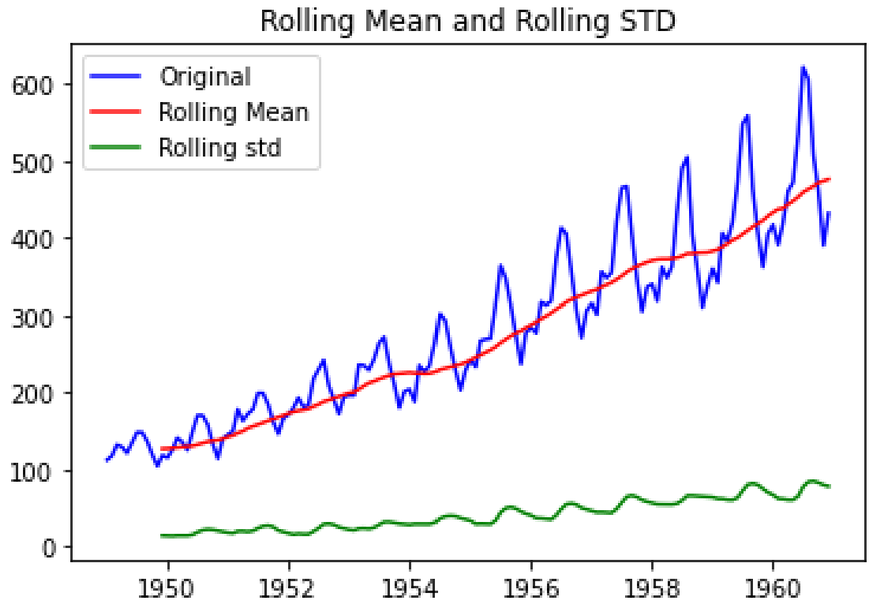


Rolling Statistics

Rolling is a very useful operation for time series data. Rolling means creating a rolling window with a specified size and perform calculations on the data in this window which, of course, rolls through the data.

In [66]:
```
#Rolling stats - to plot the mean and STD
rolling_mean_data= data.rolling(window=12).mean()
rolling_std_data= data.rolling(window=12).std()
```

In [68]:
```
#Lets plot the rolling mean and rolling std
plt.plot(data,color='blue',label='Original')
plt.plot(rolling_mean_data,color='red',label='Rolling Mean')
plt.plot(rolling_std_data,color='green',label='Rolling std')
plt.legend(loc='best')
plt.title('Rolling Mean and Rolling STD')
plt.show()
```



From the above graph, we see that rolling mean itself has a trend component even though rolling standard deviation is fairly constant with time. For our time series to be stationary, we need to ensure that both the rolling statistics ie: mean & std. dev. remain time invariant or constant with time. Thus the curves for both of them have to be parallel to the x-axis, which in our case is not so.

Transformations

In [69]:
```
#applying log transformation on our data
first_log = np.log(data)
```

In [70]:
```
#dropping null values
first_log = first_log.dropna()
```

In [71]:
```
first_log
```

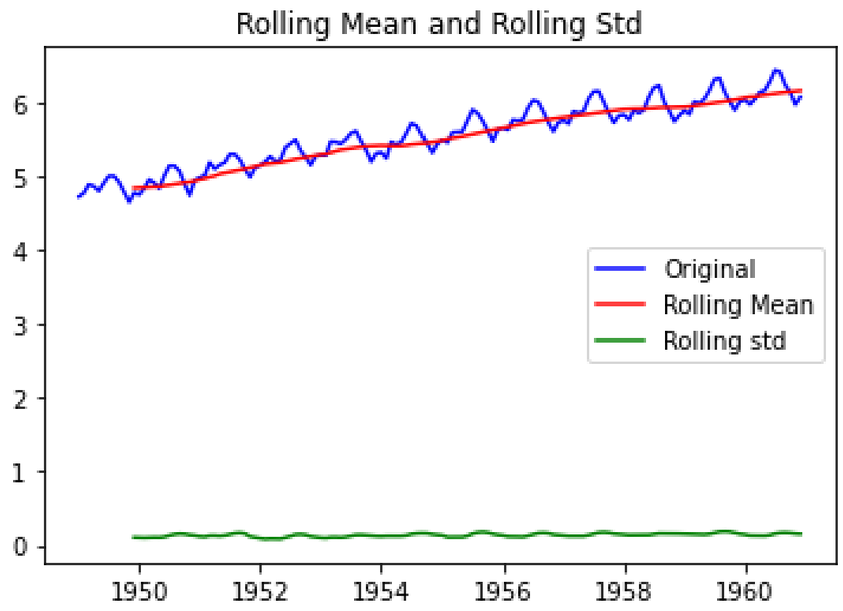
Out[71]:

Month	#Passengers
1949-01-01	4.718499
1949-02-01	4.770685
1949-03-01	4.882802
1949-04-01	4.859812
1949-05-01	4.795791
...	...
1960-08-01	6.406880
1960-09-01	6.230481
1960-10-01	6.133398
1960-11-01	5.966147
1960-12-01	6.068426

144 rows × 1 columns

In [72]:
```
#Rolling stats - mean and std of log transformed data
mean_log=first_log.rolling(window=12).mean()
std_log=first_log.rolling(window=12).std()
```

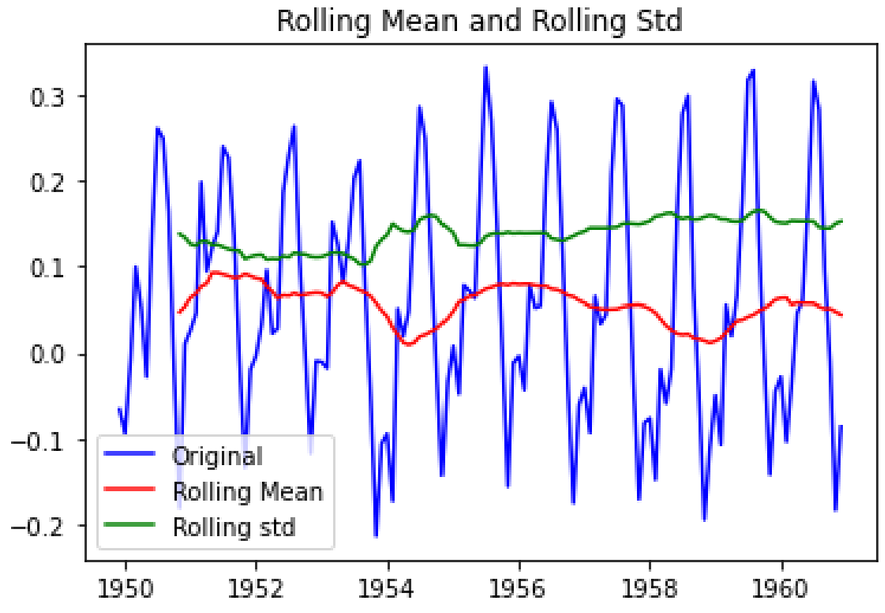
In [75]:
```
#Lets plot the rolling mean and rolling std of log transformed data
plt.plot(first_log,color='blue',label='Original')
plt.plot(mean_log,color='red',label='Rolling Mean')
plt.plot(std_log,color='green',label='Rolling std')
plt.legend(loc='best')
plt.title('Rolling Mean and Rolling Std')
plt.show()
```



In [76]:
```
#Taking best data i.e., between log_data and mean_log data
new_data = first_log - mean_log
new_data = new_data.dropna()
```

In [77]:
```
#Rolling stats - to plot the mean and std
mean_log=new_data.rolling(window=12).mean()
std_log=new_data.rolling(window=12).std()

#Lets plot the rolling mean and rolling std
plt.plot(new_data,color='blue',label='Original')
plt.plot(mean_log,color='red',label='Rolling Mean')
plt.plot(std_log,color='green',label='Rolling std')
plt.legend(loc='best')
plt.title('Rolling Mean and Rolling Std')
plt.show()
```



Data Stationary Test after Transformation

Lets check if the data is stationary or not

In [22]:
```
#To check the data is stationary or not
#Ad fuller
#f- format while print statement is used

from statsmodels.tsa.stattools import adfuller

#ADF Test - if the p-value < 0.05 - Data is stationary
result = adfuller(new_data)
print(f'ADF Statistic,{result[0]}') #some default value based upon the critial values
print(f'p-value={result[1]}')
print(f'n_lags,{result[2]}') #previous no.of observations used for prediction

#print(f'Result: The series is {"not " if result[1]>0.05 else ""}stationary')

if(result[1]>0.05):
    print("The series is not stationary")
```

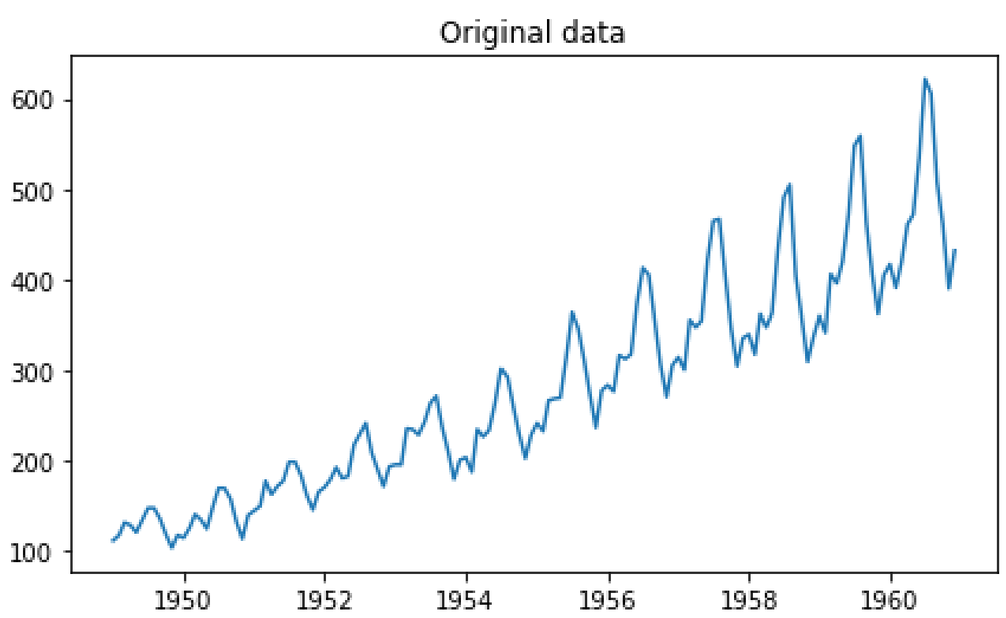
```
else:
    print("series is stationary")
```

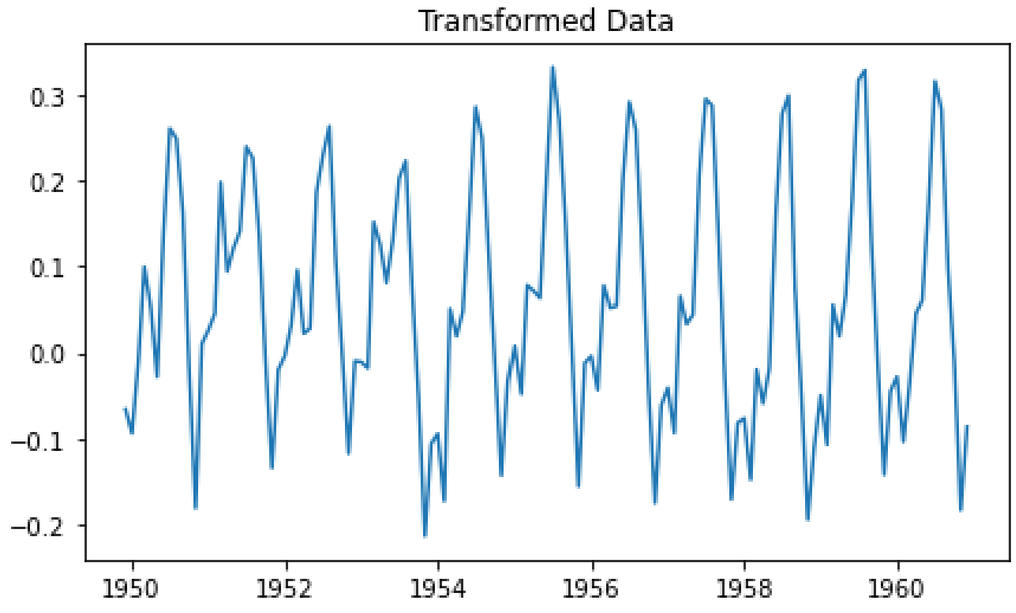
```
ADF Statistic,-3.1629079913008784
p-value=0.022234630001242536
n_lags,13
series is stationary
```

Finally, our data is stationary

Original Data vs Transformed Data

In [80]:
```
fig= plt.subplots(figsize=(7,4))
plt.plot(data);
plt.title('Original data');
fig= plt.subplots(figsize=(7,4))
plt.plot(new_data)
plt.title('Transformed Data');
```





Model Building

ARIMA

Auto Regressive Integrated Moving Average ARIMA is a method for forecasting or predicting future outcomes based on a historical time series.

ARIMA models use differencing to convert a non-stationary time series into a stationary one, and then predict future values from historical data.

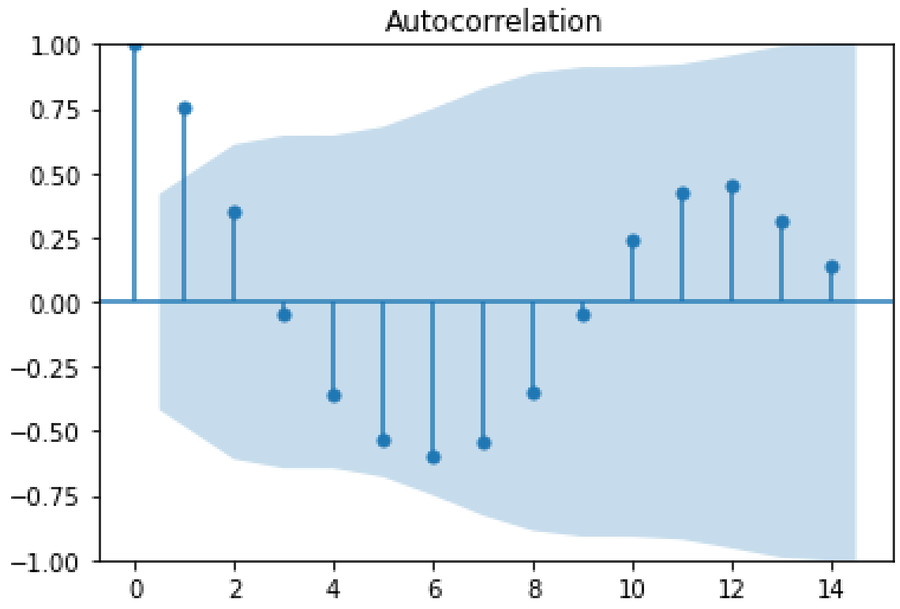
These models use “auto” correlations and moving averages over residual errors in the data to forecast future values.

An ARIMA model has three component functions: AR (p), the number of lag observations or autoregressive terms in the model; I (d), the difference in the nonseasonal observations; and MA (q), the size of the moving average window.

- p - Partial Autocorrelation Function (PACF)
- d - Differencing
- q - Autocorrelation Function (ACF)

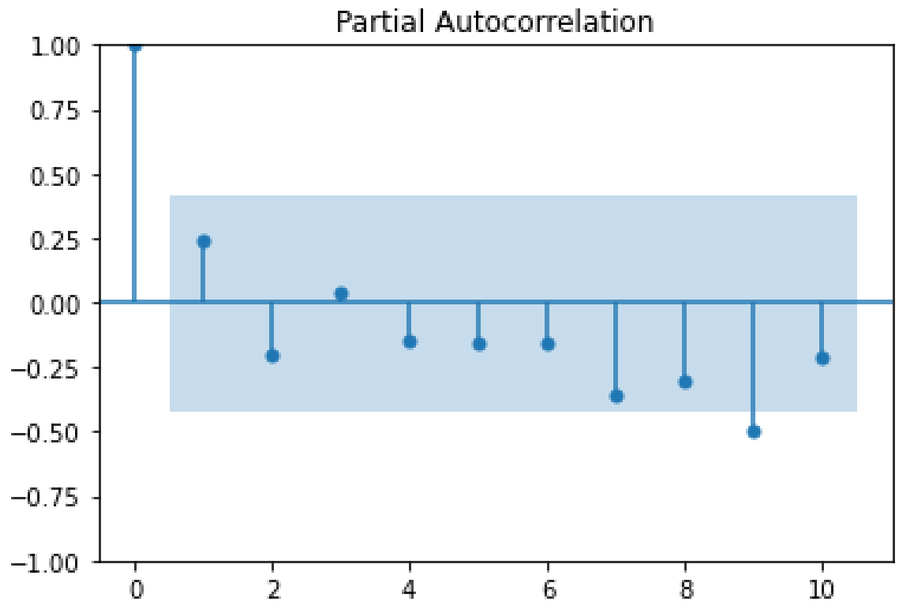
In [83]:
```
from statsmodels.tsa.stattools import acf
from statsmodels.graphics.tsaplots import plot_acf
```

In [84]:
```
acf_plot=acf(new_data.dropna()) #Gradual decrease and previuous point to that - q(2)
plot_acf(acf_plot);
```



In [89]:
```
from statsmodels.tsa.stattools import pacf
from statsmodels.graphics.tsaplots import plot_pacf
```

In [90]:
```
pacf_plot=pacf(new_data.dropna()) #the data point or lag where there is a sudden shut-off - p(1)
plot_pacf(pacf_plot,lags=10);
```

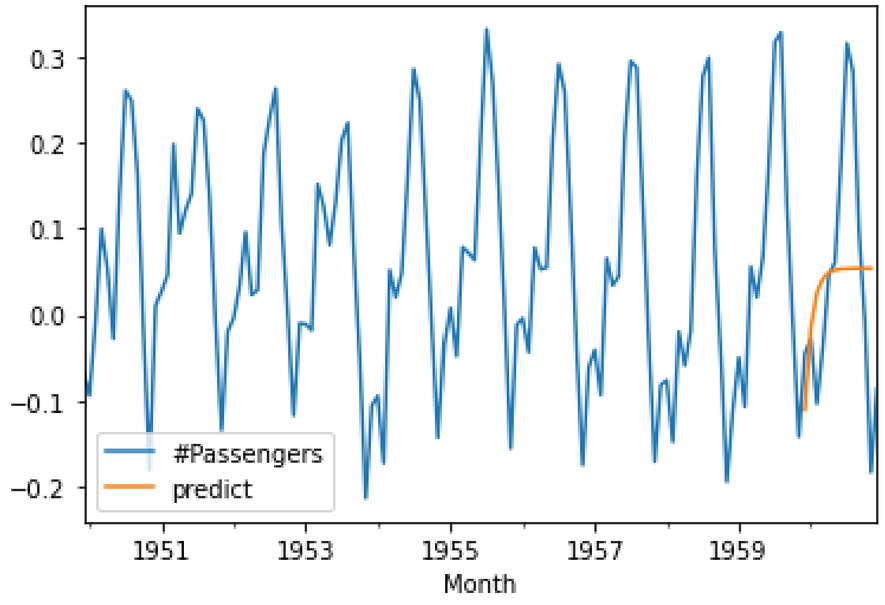


In [91]:
```
#Train Test Split
train=new_data.iloc[:120]['#Passengers']
test=new_data.iloc[121:]['#Passengers']
```

In [92]:
```
from statsmodels.tsa.arima.model import ARIMA
```

In [93]:
```
model = ARIMA(train,order=(1,1,2))
model_fit=model.fit()
```

In [96]:
```
new_data['predict']=model_fit.predict(start=len(train),end=len(train)+len(test)-1)
new_data[['#Passengers','predict']].plot();
```



Auto ARIMA

For Checking best parameters for ARIMA

In [115…

```
import pmdarima as pm

model = pm.auto_arima(new_data['#Passengers'],
                      m=12, seasonal=True,
                     start_p=0, start_q=0, max_order=4, test='adf',error_action='ignore',
                          suppress_warnings=True,
                     stepwise=True, trace=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,0,0)(1,0,1)[12] intercept   : AIC=-414.583, Time=0.33 sec
 ARIMA(0,0,0)(0,0,0)[12] intercept   : AIC=-152.169, Time=0.04 sec
 ARIMA(1,0,0)(1,0,0)[12] intercept   : AIC=inf, Time=0.33 sec
 ARIMA(0,0,1)(0,0,1)[12] intercept   : AIC=-312.940, Time=0.16 sec
 ARIMA(0,0,0)(0,0,0)[12]             : AIC=-133.698, Time=0.04 sec
 ARIMA(0,0,0)(0,0,1)[12] intercept   : AIC=-236.028, Time=0.14 sec
 ARIMA(0,0,0)(1,0,0)[12] intercept   : AIC=inf, Time=0.26 sec
 ARIMA(0,0,0)(2,0,1)[12] intercept   : AIC=-413.734, Time=0.58 sec
 ARIMA(0,0,0)(1,0,2)[12] intercept   : AIC=-413.957, Time=0.65 sec
 ARIMA(0,0,0)(0,0,2)[12] intercept   : AIC=inf, Time=0.25 sec
 ARIMA(0,0,0)(2,0,0)[12] intercept   : AIC=inf, Time=0.49 sec
 ARIMA(0,0,0)(2,0,2)[12] intercept   : AIC=-410.565, Time=0.59 sec
 ARIMA(1,0,0)(1,0,1)[12] intercept   : AIC=-476.233, Time=0.63 sec
 ARIMA(1,0,0)(0,0,1)[12] intercept   : AIC=-324.579, Time=0.18 sec
 ARIMA(1,0,0)(2,0,1)[12] intercept   : AIC=-474.262, Time=0.77 sec
 ARIMA(1,0,0)(1,0,2)[12] intercept   : AIC=-472.307, Time=0.69 sec
 ARIMA(1,0,0)(0,0,0)[12] intercept   : AIC=-233.989, Time=0.04 sec
 ARIMA(1,0,0)(0,0,2)[12] intercept   : AIC=-370.389, Time=0.39 sec
 ARIMA(1,0,0)(2,0,0)[12] intercept   : AIC=inf, Time=0.74 sec
 ARIMA(1,0,0)(2,0,2)[12] intercept   : AIC=-470.833, Time=1.02 sec
 ARIMA(2,0,0)(1,0,1)[12] intercept   : AIC=-476.009, Time=0.39 sec
 ARIMA(1,0,1)(1,0,1)[12] intercept   : AIC=-474.207, Time=0.55 sec
 ARIMA(0,0,1)(1,0,1)[12] intercept   : AIC=-453.826, Time=0.39 sec
 ARIMA(2,0,1)(1,0,1)[12] intercept   : AIC=-471.228, Time=0.60 sec
 ARIMA(1,0,0)(1,0,1)[12]             : AIC=-477.715, Time=0.27 sec
 ARIMA(1,0,0)(0,0,1)[12]             : AIC=-325.215, Time=0.18 sec
 ARIMA(1,0,0)(1,0,0)[12]             : AIC=inf, Time=0.13 sec
 ARIMA(1,0,0)(2,0,1)[12]             : AIC=-475.762, Time=0.66 sec
 ARIMA(1,0,0)(1,0,2)[12]             : AIC=-475.763, Time=0.57 sec
 ARIMA(1,0,0)(0,0,0)[12]             : AIC=-232.914, Time=0.05 sec
 ARIMA(1,0,0)(0,0,2)[12]             : AIC=-370.161, Time=0.24 sec
 ARIMA(1,0,0)(2,0,0)[12]             : AIC=inf, Time=0.39 sec
 ARIMA(1,0,0)(2,0,2)[12]             : AIC=-473.765, Time=0.68 sec
 ARIMA(0,0,0)(1,0,1)[12]             : AIC=-414.129, Time=0.09 sec
 ARIMA(2,0,0)(1,0,1)[12]             : AIC=-477.678, Time=0.32 sec
 ARIMA(1,0,1)(1,0,1)[12]             : AIC=-477.150, Time=0.42 sec
 ARIMA(0,0,1)(1,0,1)[12]             : AIC=-454.088, Time=0.20 sec
 ARIMA(2,0,1)(1,0,1)[12]             : AIC=-476.201, Time=0.46 sec
```

```
Best model:  ARIMA(1,0,0)(1,0,1)[12]
Total fit time: 14.956 seconds
```

SARIMAX

Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors, or SARIMAX, is an extension of the ARIMA class of models.

SARIMAX is used on data sets that have seasonal cycles. The difference between ARIMA and SARIMAX is the seasonality and exogenous factors (seasonality and regular ARIMA don't mix well).

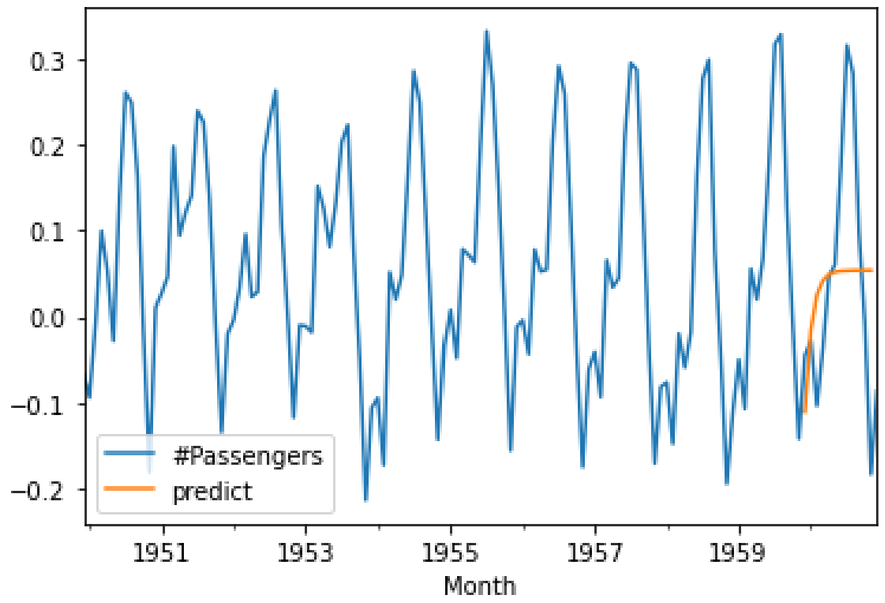
Overall, ARIMA is a very decent type of models. However, the problem with this vanilla version is that it cannot handle seasonality — a big weakness. Comes SARIMA — the predecessor of SARIMAX. One shorthand notation for SARIMA models is:

$$\text{SARIMA}\ (p,d,q) \times (P,D,Q,S)$$

In [100…
```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [101…
```
model=SARIMAX(train,order=(1,1,2),seasonal_order=(1,1,2,12))
model=model.fit();
```

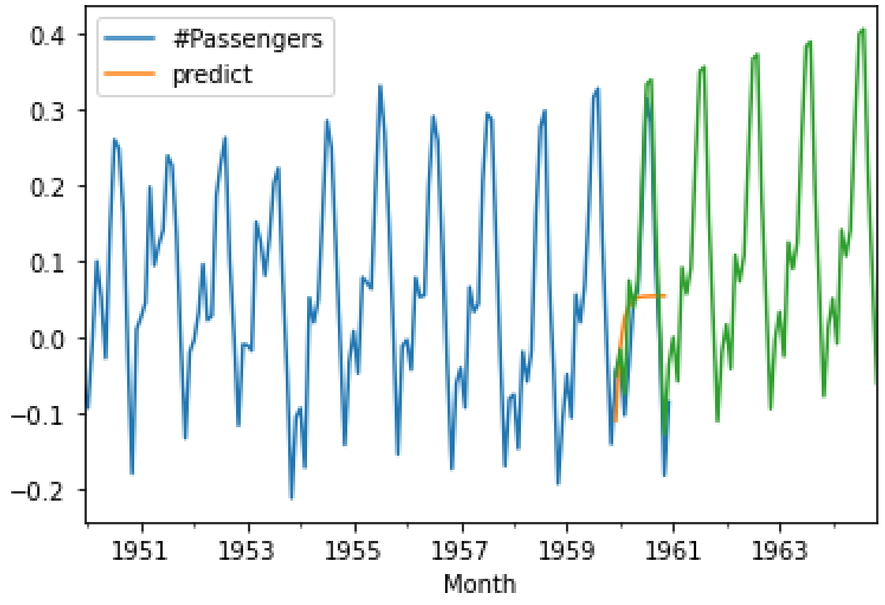
In [107…
```
predict =model.predict(start=len(train), end=len(train)+len(test)-1)
new_data[['#Passengers','predict']].plot();
```



Forecasting: for predicting furture

In [108…

```
#for predicting furture
forecast = model.forecast(steps=60)
new_data.plot()
forecast.plot();
```



Conclusion

Training has been done with an ARIMA model. Techniques like moving average and differencing were used to convert the available time series into a stationary time series. ACF and PACF was plotted and the appropriate values of p, d and q for ARIMA were found. The final forecasting shows increase in passengers in coming 5 Years.