Forecasting (Airlines_Data)

Forecast the Airlines Passengers data set. Prepare a document for each model explaining how many dummy variables you have created and RMSE value for each model. Finally which model you will use for Forecasting

1. Import Libs

In [6]:

```
import pandas as pd
import numpy as np
from numpy import sqrt
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
from datetime import datetime,time
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.holtwinters import SimpleExpSmoothing # SES
from statsmodels.tsa.holtwinters import Holt # Holts Exponential Smoothing
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import matplotlib
from pandas import DataFrame
from pandas import Grouper
from numpy import log
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima_model import ARIMA
from pylab import rcParams
from sklearn.metrics import mean_squared_error
from pandas.plotting import lag_plot
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.holtwinters import Holt
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import statsmodels.graphics.tsaplots as tsa_plots
import statsmodels.tsa.statespace as tm_models
import itertools
import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [7]:

```
df = pd.read_excel('Airlines+Data.xlsx')
df
```

Out[7]:

	Month	Passengers
0	1995-01-01	112
1	1995-02-01	118
2	1995-03-01	132
3	1995-04-01	129
4	1995-05-01	121
...	...	...
91	2002-08-01	405
92	2002-09-01	355
93	2002-10-01	306
94	2002-11-01	271
95	2002-12-01	306

96 rows × 2 columns

3. EDA

In [8]:

```
df.isna().sum()
```

Out[8]:

```
Month         0
Passengers    0
dtype: int64
```

In [9]:

```
df.dtypes
```

Out[9]:

```
Month         datetime64[ns]
Passengers             int64
dtype: object
```

In [10]:

```
df.describe()
```

Out[10]:

	Passengers
count	96.000000
mean	213.708333
std	71.918216
min	104.000000
25%	156.000000
50%	200.000000
75%	264.750000
max	413.000000

converte Month column to index

In [11]:

```
df.set_index('Month',inplace=True)
```

In [12]:

```
df
```

Out[12]:

	Passengers
Month	
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121
...	...
2002-08-01	405
2002-09-01	355
2002-10-01	306
2002-11-01	271
2002-12-01	306

96 rows × 1 columns

In [13]:

```
df.index.year
```

Out[13]:

```
Int64Index([1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 199
5,
            1995, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 199
6,
            1996, 1996, 1997, 1997, 1997, 1997, 1997, 1997, 1997, 1997, 199
7,
            1997, 1997, 1997, 1998, 1998, 1998, 1998, 1998, 1998, 1998, 199
8,
            1998, 1998, 1998, 1998, 1999, 1999, 1999, 1999, 1999, 1999, 199
9,
            1999, 1999, 1999, 1999, 1999, 2000, 2000, 2000, 2000, 2000, 200
0,
            2000, 2000, 2000, 2000, 2000, 2000, 2001, 2001, 2001, 2001, 200
1,
            2001, 2001, 2001, 2001, 2001, 2001, 2001, 2002, 2002, 2002, 200
2,
            2002, 2002, 2002, 2002, 2002, 2002, 2002, 2002],
           dtype='int64', name='Month')
```

In [15]:

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

Out[15]:

```
Passengers    0
dtype: int64
```

found the 16 duplicated rows

In [16]:

```
df[df.duplicated()].shape
```

Out[16]:

```
(16, 1)
```

In [17]:

```
df[df.duplicated()]
```

Out[17]:

	Passengers
Month	
1995-08-01	148
1995-12-01	118
1996-04-01	135
1996-08-01	170
1997-06-01	178
1997-08-01	199
1998-11-01	172
1999-02-01	196
1999-11-01	180
2000-03-01	235
2000-06-01	264
2000-10-01	229
2000-12-01	229
2001-01-01	242
2001-11-01	237
2002-12-01	306

removed the duplicated

In [18]:

```
df.drop_duplicates(inplace=True)
```

In [19]:

```
df
```

Out[19]:

	Passengers
Month	
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121
...	...
2002-07-01	413
2002-08-01	405
2002-09-01	355
2002-10-01	306
2002-11-01	271

80 rows × 1 columns

In [20]:

```
DF = df.copy()
```

In [21]:

```
DF
```

Out[21]:

Month	Passengers
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121
...	...
2002-07-01	413
2002-08-01	405
2002-09-01	355
2002-10-01	306
2002-11-01	271

80 rows × 1 columns

In [22]:

```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 80 entries, 1995-01-01 to 2002-11-01
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Passengers  80 non-null     int64
dtypes: int64(1)
memory usage: 1.2 KB
```

In [23]:

```
DF.ndim
```

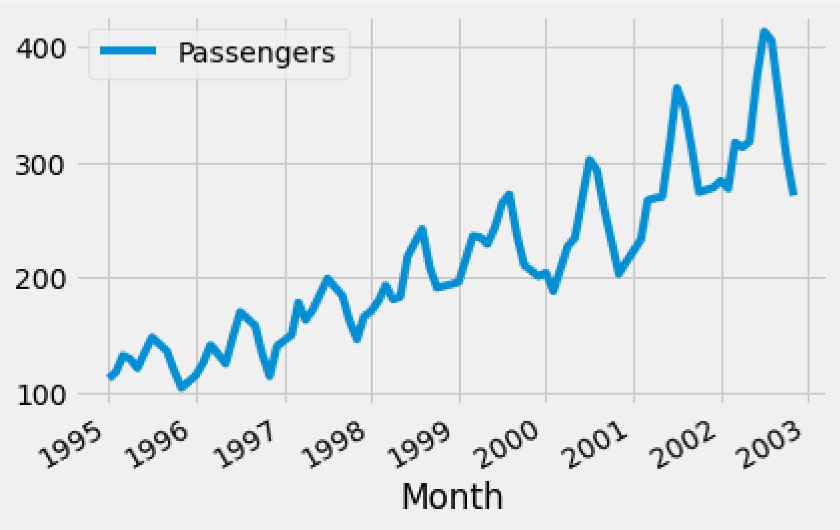
Out[23]:

2

4. Visulization

In [24]:

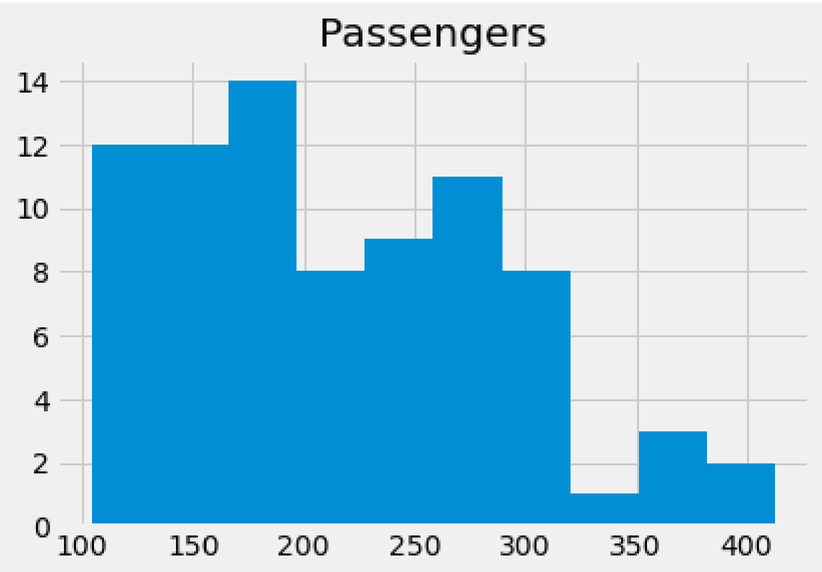
```
DF.plot()
plt.show()
```



here we can say that the trend is upward and the sessionality is multiplicative

In [25]:

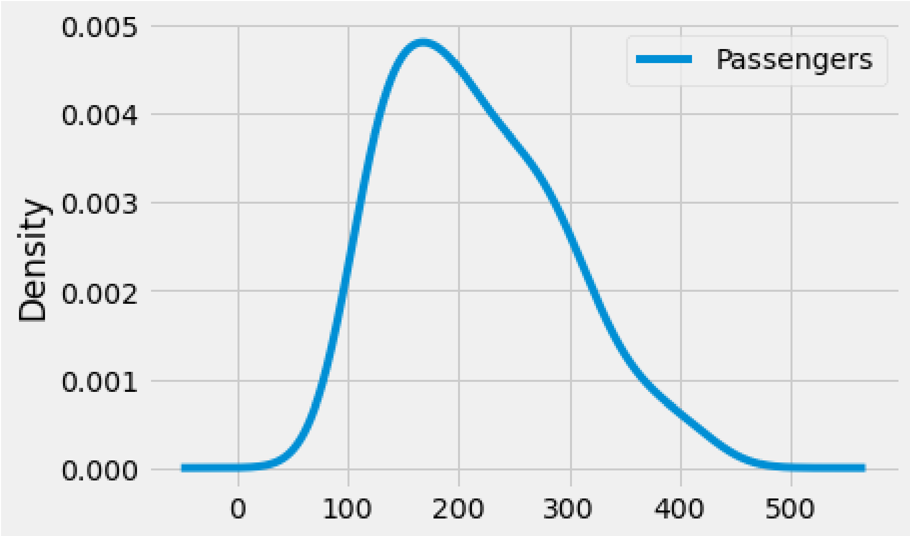
```
DF.hist()
plt.show()
```



density plot

In [26]:

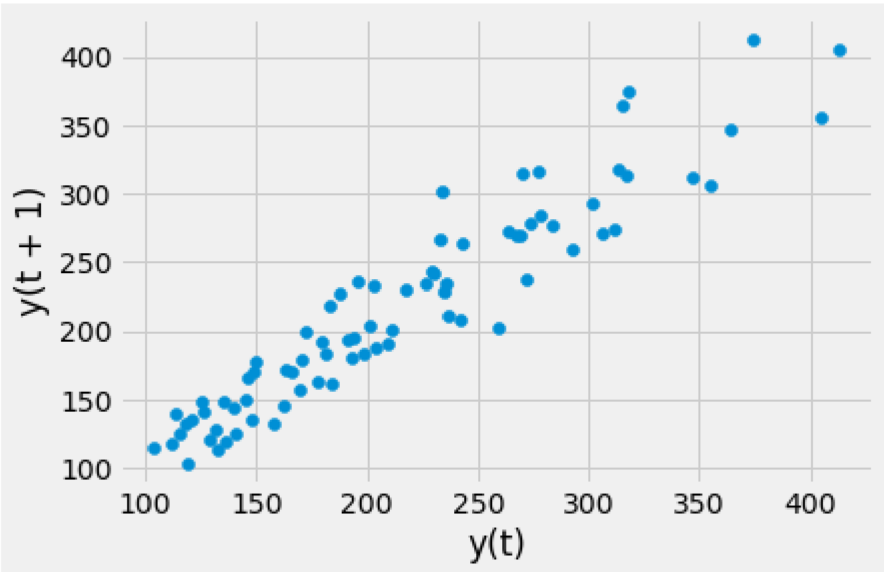
```
DF.plot(kind='kde')
plt.show()
```



Lag_plot

In [27]:

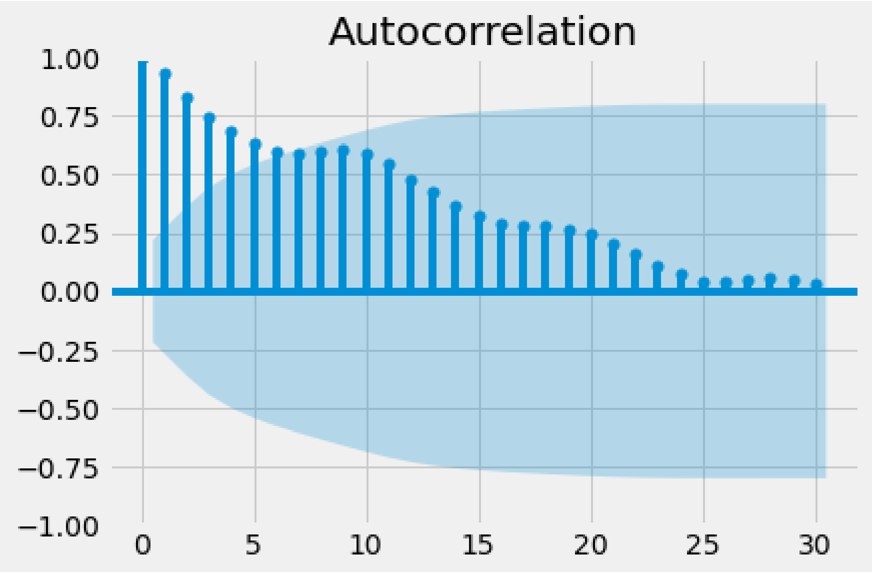
```
lag_plot(DF)
plt.show()
```



Autocorrelation Plot

In [28]:

```
plot_acf(DF,lags=30)
plt.show()
```



UpSampling

In [29]:

```
upsampled = DF.resample('M').mean()
print(upsampled.head(32))
```

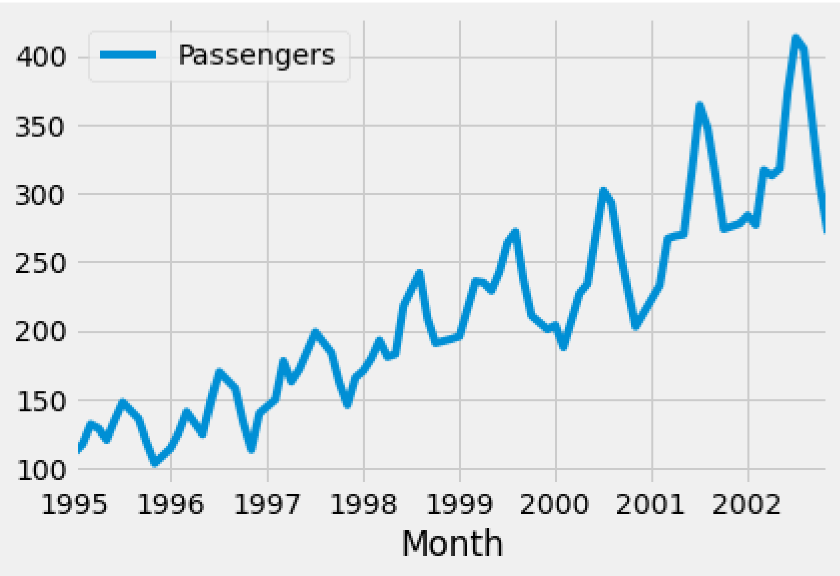
```
            Passengers
Month
1995-01-31       112.0
1995-02-28       118.0
1995-03-31       132.0
1995-04-30       129.0
1995-05-31       121.0
1995-06-30       135.0
1995-07-31       148.0
1995-08-31         NaN
1995-09-30       136.0
1995-10-31       119.0
1995-11-30       104.0
1995-12-31         NaN
1996-01-31       115.0
1996-02-29       126.0
1996-03-31       141.0
1996-04-30         NaN
1996-05-31       125.0
1996-06-30       149.0
1996-07-31       170.0
1996-08-31         NaN
1996-09-30       158.0
1996-10-31       133.0
1996-11-30       114.0
1996-12-31       140.0
1997-01-31       145.0
1997-02-28       150.0
1997-03-31       178.0
1997-04-30       163.0
1997-05-31       172.0
1997-06-30         NaN
1997-07-31       199.0
1997-08-31         NaN
```

interplation is done for nan values

In [30]:

```
interpolated = upsampled.interpolate(method='linear')
print(interpolated.head(15))
interpolated.plot()
plt.show()
```

```
            Passengers
Month
1995-01-31       112.0
1995-02-28       118.0
1995-03-31       132.0
1995-04-30       129.0
1995-05-31       121.0
1995-06-30       135.0
1995-07-31       148.0
1995-08-31       142.0
1995-09-30       136.0
1995-10-31       119.0
1995-11-30       104.0
1995-12-31       109.5
1996-01-31       115.0
1996-02-29       126.0
1996-03-31       141.0
```



In [31]:

```
interpolated
```

Out[31]:

	Passengers
Month	
1995-01-31	112.0
1995-02-28	118.0
1995-03-31	132.0
1995-04-30	129.0
1995-05-31	121.0
...	...
2002-07-31	413.0
2002-08-31	405.0
2002-09-30	355.0
2002-10-31	306.0
2002-11-30	271.0

95 rows × 1 columns

5. Tranformations

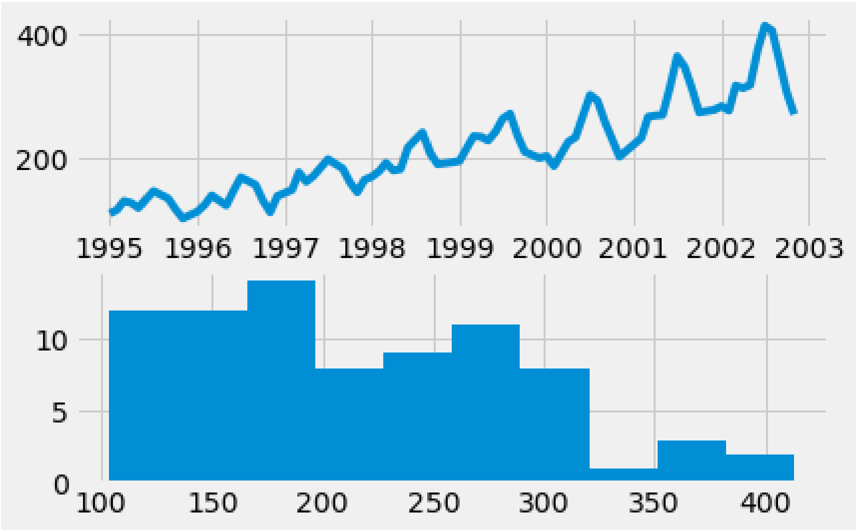
Square Root Transformation

In [33]:

```
dataframe = DataFrame(DF.values)
dataframe.columns = ['Passengers']
dataframe['Passengers'] = sqrt(dataframe['Passengers'])
```

In [34]:

```
# line plot
plt.subplot(211)
plt.plot(DF['Passengers'])
# histogram
plt.subplot(212)
plt.hist(DF['Passengers'])
plt.show()
```



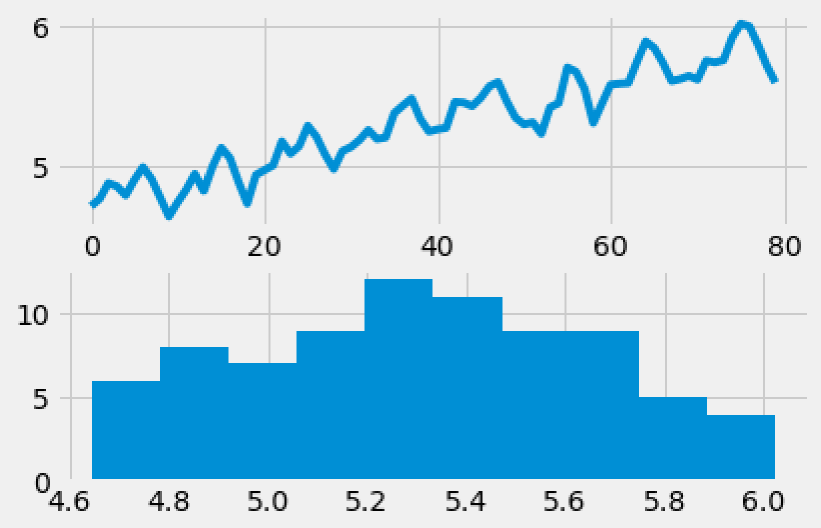
Log Transform

In [35]:

```
dataframe = DataFrame(DF.values)
dataframe.columns = ['Passengers']
dataframe['Passengers'] = log(dataframe['Passengers'])
```

In [36]:

```
plt.subplot(211)
plt.plot(dataframe['Passengers'])
plt.subplot(212)
plt.hist(dataframe['Passengers'])
plt.show()
```



Moving Average

In [37]:

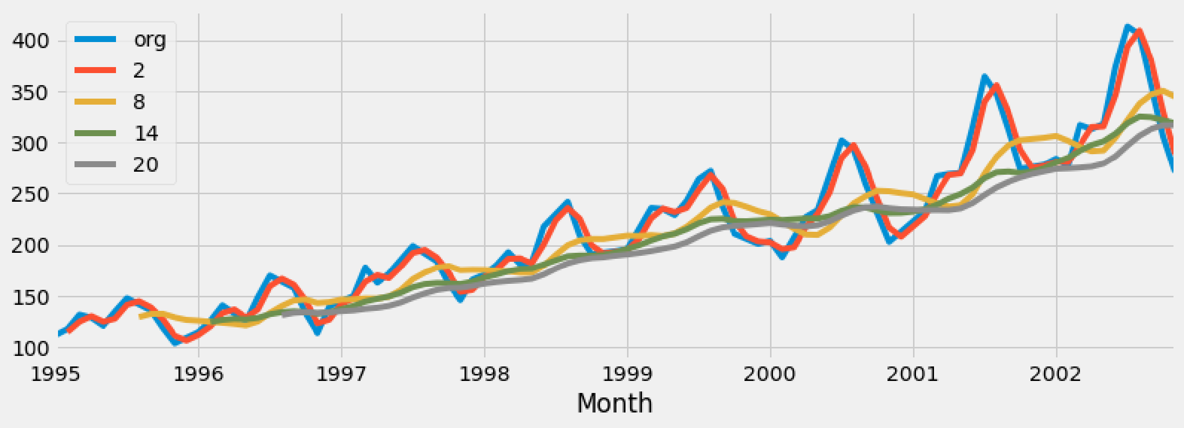
```
Train = interpolated.head(81)
Test = interpolated.tail(14)
```

In [38]:

```
plt.figure(figsize=(12,4))
interpolated.Passengers.plot(label="org")
for i in range(2,24,6):
    interpolated["Passengers"].rolling(i).mean().plot(label=str(i))
plt.legend(loc='best')
```

Out[38]:

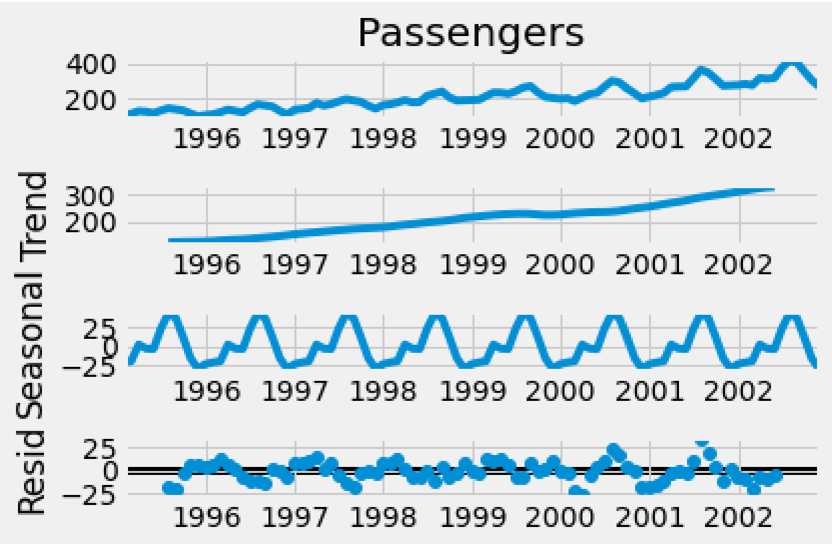
```
<matplotlib.legend.Legend at 0x258002c4f10>
```



Time series decomposition plot

In [40]:

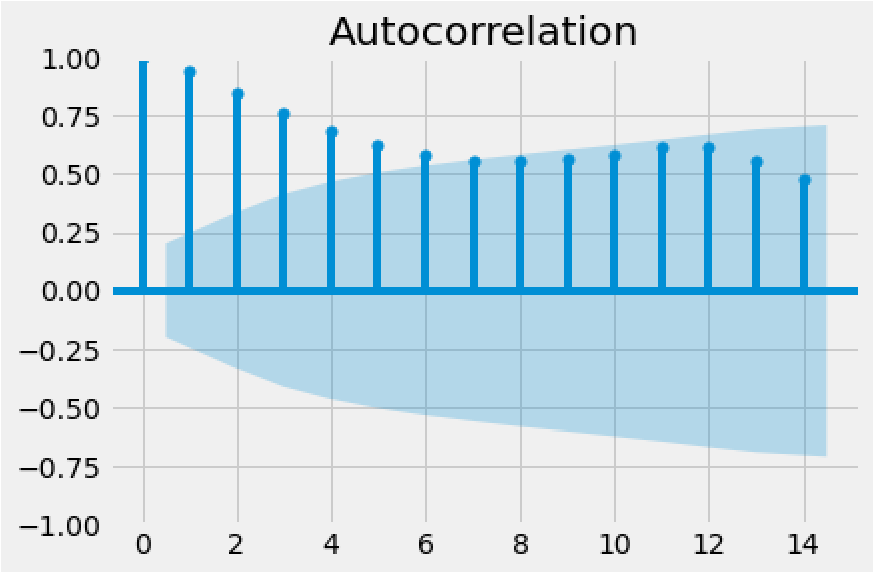
```
decompose_ts_add = seasonal_decompose(interpolated.Passengers,period=12)
decompose_ts_add.plot()
plt.show()
```

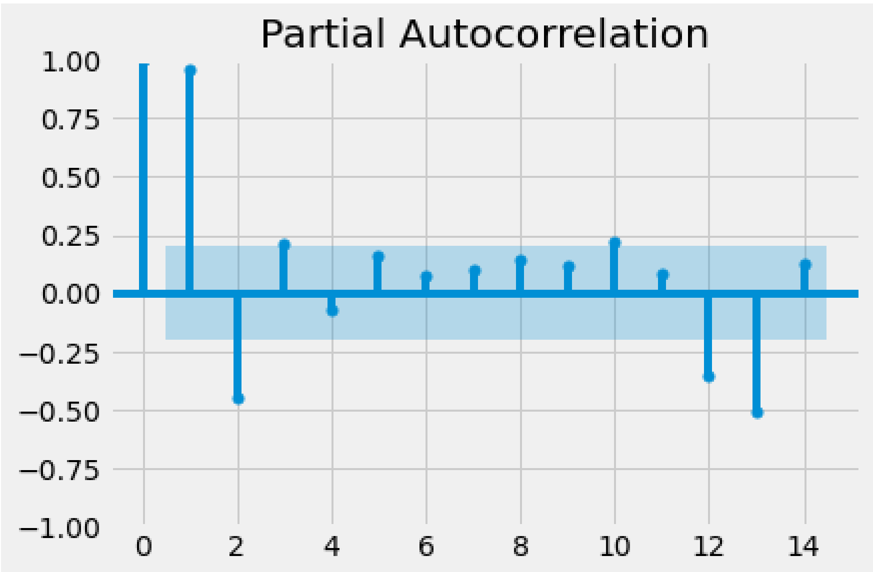


ACF plots and PACF plots

In [41]:

```
tsa_plots.plot_acf(interpolated.Passengers,lags=14)
tsa_plots.plot_pacf(interpolated.Passengers,lags=14)
plt.show()
```





Evaluation Metric MAPE

In [42]:

```
def MAPE(pred,org):
    temp = np.abs((pred-org)/org)*100
    return np.mean(temp)
```

Simple Exponential Method

In [43]:

```
ses_model = SimpleExpSmoothing(Train["Passengers"]).fit(smoothing_level=0.2)
pred_ses = ses_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_ses,Test.Passengers)
```

Out[43]:

```
11.18163872245304
```

Holt method

In [44]:

```
hw_model = Holt(Train["Passengers"]).fit(smoothing_level=0.1, smoothing_slope=0.2)
pred_hw = hw_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hw,Test.Passengers)
```

Out[44]:

```
12.424434303922729
```

Holts winter exponential smoothing with additive seasonality and additive trend

In [45]:

```
hwe_model_add_add = ExponentialSmoothing(Train["Passengers"],seasonal="add",trend="add",sea
pred_hwe_add_add = hwe_model_add_add.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hwe_add_add,Test.Passengers)
```

Out[45]:

```
3.513732035746134
```

Holts winter exponential smoothing with multiplicative seasonality and additive trend

In [46]:

```
hwe_model_mul_add = ExponentialSmoothing(Train["Passengers"],seasonal="mul",trend="add",sea
pred_hwe_mul_add = hwe_model_mul_add.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hwe_mul_add,Test.Passengers)
```

Out[46]:

```
3.233263960121953
```

In [47]:

```
rmse_hwe_mul_add = sqrt(mean_squared_error(pred_hwe_mul_add,Test.Passengers))
rmse_hwe_mul_add
```

Out[47]:

```
12.632692127672167
```

Final Model by combining train and test

In [48]:

```
hwe_model_add_add = ExponentialSmoothing(interpolated["Passengers"],seasonal="add",trend="a
```

Forecasting for next 10 time periods

In [49]:

```
hwe_model_add_add.forecast(10)
```

Out[49]:

```
2002-12-31    276.693521
2003-01-31    285.590883
2003-02-28    287.549296
2003-03-31    293.403027
2003-04-30    294.184750
2003-05-31    293.895109
2003-06-30    290.210198
2003-07-31    288.263328
2003-08-31    290.144521
2003-09-30    289.689357
Freq: M, dtype: float64
```

In [51]:

```
interpolated
```

Out[51]:

	Passengers
Month	
1995-01-31	112.0
1995-02-28	118.0
1995-03-31	132.0
1995-04-30	129.0
1995-05-31	121.0
...	...
2002-07-31	413.0
2002-08-31	405.0
2002-09-30	355.0
2002-10-31	306.0
2002-11-30	271.0

95 rows × 1 columns

In [52]:

```
interpolated.reset_index(inplace=True)
```

In [53]:

```
interpolated['t'] = 1
```

In [54]:

```
interpolated
```

Out[54]:

	Month	Passengers	t
0	1995-01-31	112.0	1
1	1995-02-28	118.0	1
2	1995-03-31	132.0	1
3	1995-04-30	129.0	1
4	1995-05-31	121.0	1
...	...	...	...
90	2002-07-31	413.0	1
91	2002-08-31	405.0	1
92	2002-09-30	355.0	1
93	2002-10-31	306.0	1
94	2002-11-30	271.0	1

95 rows × 3 columns

In [55]:

```
for i,row in interpolated.iterrows():
  interpolated['t'].iloc[i] = i+1
```

In [56]:

```
interpolated
```

Out[56]:

	Month	Passengers	t
0	1995-01-31	112.0	1
1	1995-02-28	118.0	2
2	1995-03-31	132.0	3
3	1995-04-30	129.0	4
4	1995-05-31	121.0	5
...	...	...	...
90	2002-07-31	413.0	91
91	2002-08-31	405.0	92
92	2002-09-30	355.0	93
93	2002-10-31	306.0	94
94	2002-11-30	271.0	95

95 rows × 3 columns

inserted t_sq column with values

In [57]:

```
interpolated['t_sq'] = (interpolated['t'])**2
```

In [58]:

```
interpolated
```

Out[58]:

	Month	Passengers	t	t_sq
0	1995-01-31	112.0	1	1
1	1995-02-28	118.0	2	4
2	1995-03-31	132.0	3	9
3	1995-04-30	129.0	4	16
4	1995-05-31	121.0	5	25
...	...	...	...	...
90	2002-07-31	413.0	91	8281
91	2002-08-31	405.0	92	8464
92	2002-09-30	355.0	93	8649
93	2002-10-31	306.0	94	8836
94	2002-11-30	271.0	95	9025

95 rows × 4 columns

In [59]:

```
interpolated["month"] = interpolated.Month.dt.strftime("%b") # month extraction
interpolated["year"] = interpolated.Month.dt.strftime("%Y") # Year extraction
```

In [60]:

```
interpolated
```

Out[60]:

	Month	Passengers	t	t_sq	month	year
0	1995-01-31	112.0	1	1	Jan	1995
1	1995-02-28	118.0	2	4	Feb	1995
2	1995-03-31	132.0	3	9	Mar	1995
3	1995-04-30	129.0	4	16	Apr	1995
4	1995-05-31	121.0	5	25	May	1995
...	...	...	...	...	...	...
90	2002-07-31	413.0	91	8281	Jul	2002
91	2002-08-31	405.0	92	8464	Aug	2002
92	2002-09-30	355.0	93	8649	Sep	2002
93	2002-10-31	306.0	94	8836	Oct	2002
94	2002-11-30	271.0	95	9025	Nov	2002

95 rows × 6 columns

In [61]:

```
months = pd.get_dummies(interpolated['month'])
```

In [62]:

```
months
```

Out[62]:

	Apr	Aug	Dec	Feb	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep
0	0	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
90	0	0	0	0	0	1	0	0	0	0	0	0
91	0	1	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	1
93	0	0	0	0	0	0	0	0	0	0	1	0
94	0	0	0	0	0	0	0	0	0	1	0	0

95 rows × 12 columns

In [63]:

```
months = months[['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']]
```

In [64]:

```
Airlines = pd.concat([interpolated,months],axis=1)
```

In [65]:

```
Airlines.head()
```

Out[65]:

	Month	Passengers	t	t_sq	month	year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
0	1995-01-31	112.0	1	1	Jan	1995	1	0	0	0	0	0	0	0	0
1	1995-02-28	118.0	2	4	Feb	1995	0	1	0	0	0	0	0	0	0
2	1995-03-31	132.0	3	9	Mar	1995	0	0	1	0	0	0	0	0	0
3	1995-04-30	129.0	4	16	Apr	1995	0	0	0	1	0	0	0	0	0
4	1995-05-31	121.0	5	25	May	1995	0	0	0	0	1	0	0	0	0

In [66]:

```
Airlines['log_passengers'] = np.log(Airlines['Passengers'])
```

In [67]:

```
Airlines
```

Out[67]:

	Month	Passengers	t	t_sq	month	year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Se
0	1995-01-31	112.0	1	1	Jan	1995	1	0	0	0	0	0	0	0	
1	1995-02-28	118.0	2	4	Feb	1995	0	1	0	0	0	0	0	0	
2	1995-03-31	132.0	3	9	Mar	1995	0	0	1	0	0	0	0	0	
3	1995-04-30	129.0	4	16	Apr	1995	0	0	0	1	0	0	0	0	
4	1995-05-31	121.0	5	25	May	1995	0	0	0	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
90	2002-07-31	413.0	91	8281	Jul	2002	0	0	0	0	0	0	1	0	
91	2002-08-31	405.0	92	8464	Aug	2002	0	0	0	0	0	0	0	1	
92	2002-09-30	355.0	93	8649	Sep	2002	0	0	0	0	0	0	0	0	
93	2002-10-31	306.0	94	8836	Oct	2002	0	0	0	0	0	0	0	0	
94	2002-11-30	271.0	95	9025	Nov	2002	0	0	0	0	0	0	0	0	

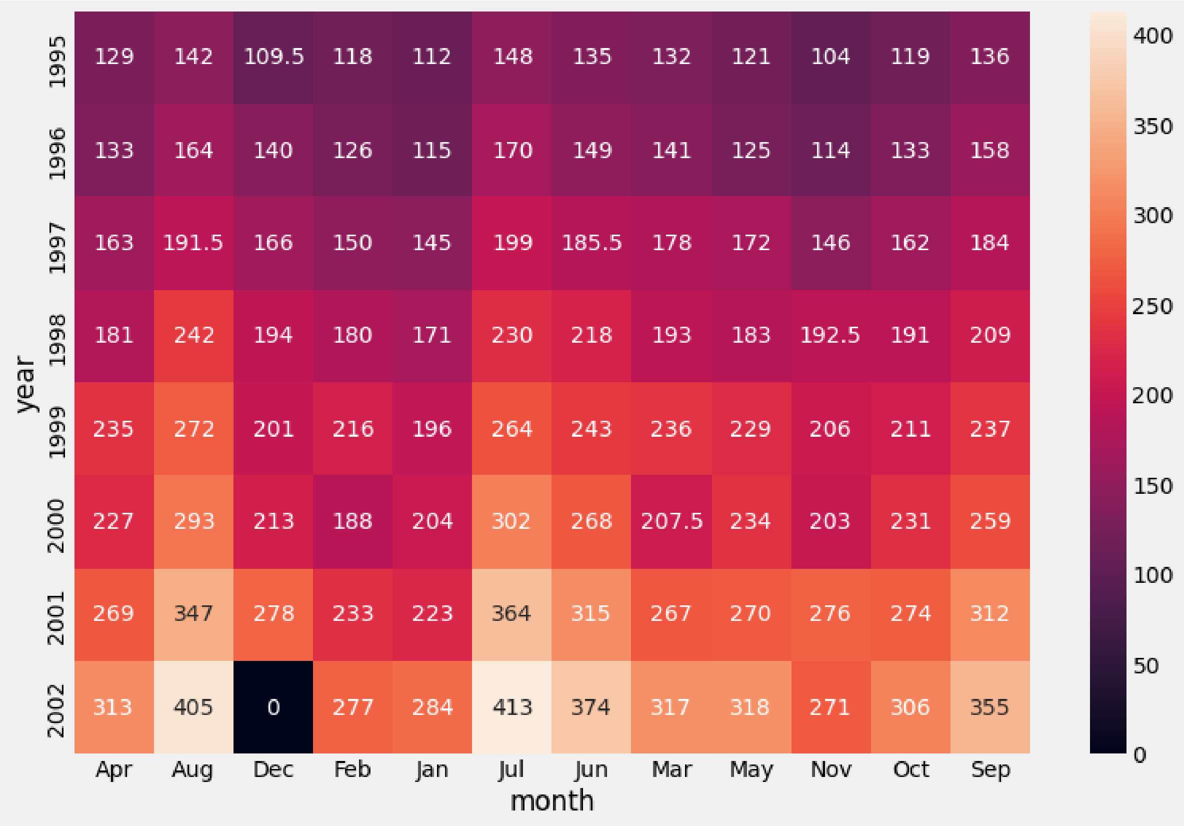
95 rows × 19 columns

In [68]:

```
plt.figure(figsize=(12,8))
heatmap_y_month = pd.pivot_table(data=Airlines,values="Passengers",index="year",columns="mo
sns.heatmap(heatmap_y_month,annot=True,fmt="g")
```

Out[68]:

```
<AxesSubplot:xlabel='month', ylabel='year'>
```

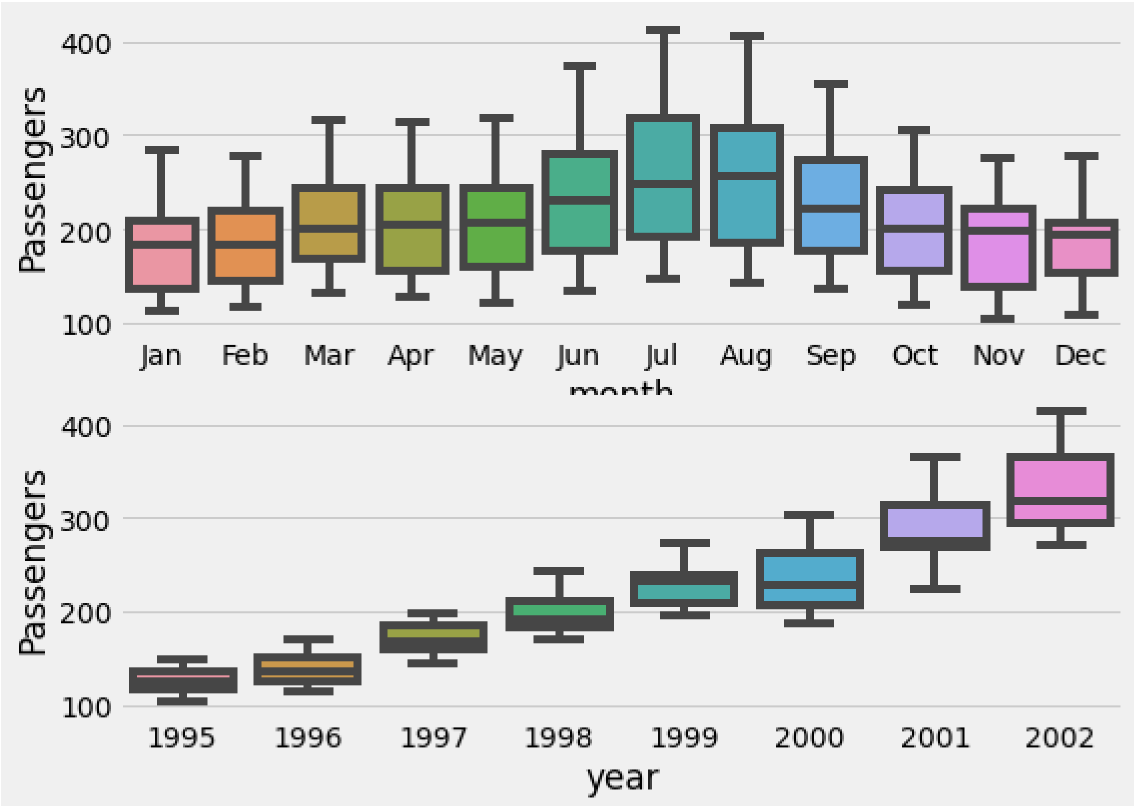


In [70]:

```
plt.figure(figsize=(8,6))
plt.subplot(211)
sns.boxplot(x="month",y="Passengers",data= Airlines)
plt.subplot(212)
sns.boxplot(x="year",y="Passengers",data=Airlines)
```

Out[70]:

```
<AxesSubplot:xlabel='year', ylabel='Passengers'>
```

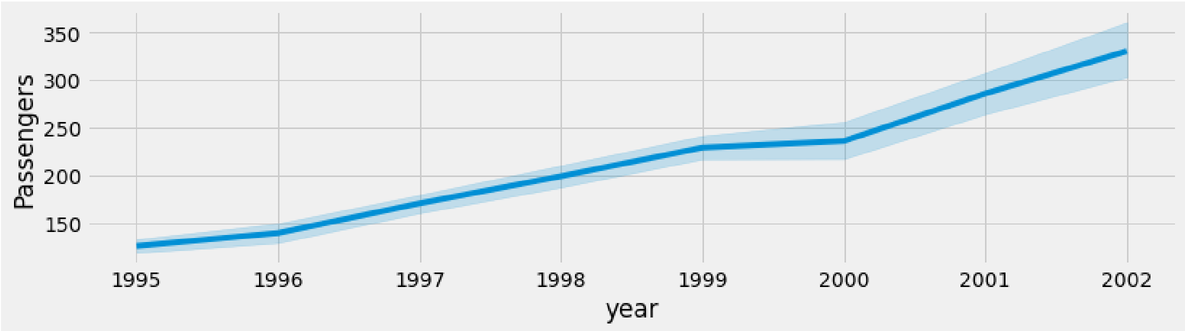


In [71]:

```
plt.figure(figsize=(12,3))
sns.lineplot(x="year",y="Passengers",data=Airlines)
```

Out[71]:

<AxesSubplot:xlabel='year', ylabel='Passengers'>



6. Comparing Multiple Models

In [72]:

```
Train = Airlines.head(81)
Test = Airlines.tail(14)
```

Linear Model

In [73]:

```
linear_model = smf.ols('Passengers~t',data=Train).fit()
pred_linear =  pd.Series(linear_model.predict(pd.DataFrame(Test['t'])))
rmse_linear = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(pred_linear))**2))
rmse_linear
```

Out[73]:

47.87107195088723

Exponential Model

In [74]:

```
Exp = smf.ols('log_passengers~t',data=Train).fit()
pred_Exp = pd.Series(Exp.predict(pd.DataFrame(Test['t'])))
rmse_Exp = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(np.exp(pred_Exp)))**2))
rmse_Exp
```

Out[74]:

42.37179623821827

Quadratic Model

In [75]:

```
Quad = smf.ols('Passengers~t+t_sq',data=Train).fit()
pred_Quad = pd.Series(Quad.predict(Test[["t","t_sq"]]))
rmse_Quad = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(pred_Quad))**2))
rmse_Quad
```

Out[75]:

42.709870425152

Additive seasonality

In [76]:

```
add_sea = smf.ols('Passengers~Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data=Train).fit(
pred_add_sea = pd.Series(add_sea.predict(Test[['Jan','Feb','Mar','Apr','May','Jun','Jul','A
rmse_add_sea = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(pred_add_sea))**2))
rmse_add_sea
```

Out[76]:

130.55762388601403

Additive Seasonality Quadratic

In [77]:

```
add_sea_Quad = smf.ols('Passengers~t+t_sq+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data
pred_add_sea_quad = pd.Series(add_sea_Quad.predict(Test[['Jan','Feb','Mar','Apr','May','Jun
rmse_add_sea_quad = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(pred_add_sea_qua
rmse_add_sea_quad
```

Out[77]:

26.7853719115231

Multiplicative Seasonality

In [78]:

```
Mul_sea = smf.ols('log_passengers~Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data = Train
pred_Mult_sea = pd.Series(Mul_sea.predict(Test))
rmse_Mult_sea = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(np.exp(pred_Mult_sea
rmse_Mult_sea
```

Out[78]:

137.28596175917107

Multiplicative Additive Seasonality

In [79]:

```
Mul_Add_sea = smf.ols('log_passengers~t+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data =
pred_Mult_add_sea = pd.Series(Mul_Add_sea.predict(Test))
rmse_Mult_add_sea = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(np.exp(pred_Mult
rmse_Mult_add_sea
```

Out[79]:

```
13.188070730263902
```

Compareing the results

In [80]:

```
data = {"MODEL":pd.Series(["rmse_linear","rmse_Exp","rmse_Quad","rmse_add_sea","rmse_add_se
table_rmse=pd.DataFrame(data)
table_rmse.sort_values(['RMSE_Values'])
```

Out[80]:

	MODEL	RMSE_Values
6	rmse_Mult_add_sea	13.188071
4	rmse_add_sea_quad	26.785372
1	rmse_Exp	42.371796
2	rmse_Quad	42.709870
0	rmse_linear	47.871072
3	rmse_add_sea	130.557624
5	rmse_Mult_sea	137.285962

In [ ]: