Problem Statement

The dataset consists of monthly totals of international airline passengers from 1995 to 2002. Our main aim is to predict the number of passengers for the next five years using time series forecasting. Prepare a document for each model explaining how many dummy variables you have created and also include the RMSE value for each model.

In [2]:

```
#importing required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [3]:

```
al = pd.read_excel("D:/DataScience/Class/assignment working/Forcasting/Airlines Data.xlsx")
```

In [4]:

```
al.head(13)
```

Out[4]:

	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
5	1995-06-01	135
6	1995-07-01	148
7	1995-08-01	148
8	1995-09-01	136
9	1995-10-01	119
10	1995-11-01	104
11	1995-12-01	118
12	1996-01-01	115

In [5]:

```
al.tail(13)
```

Out[5]:

	Month	Passengers
83	2001-12-01	278
84	2002-01-01	284
85	2002-02-01	277
86	2002-03-01	317
87	2002-04-01	313
88	2002-05-01	318
89	2002-06-01	374
90	2002-07-01	413
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

In [6]:

```
#checking NA values
al.isna().sum()
```

Out[6]:

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

In [7]:

```
#checking Duplicates
al.duplicated
```

Out[7]:

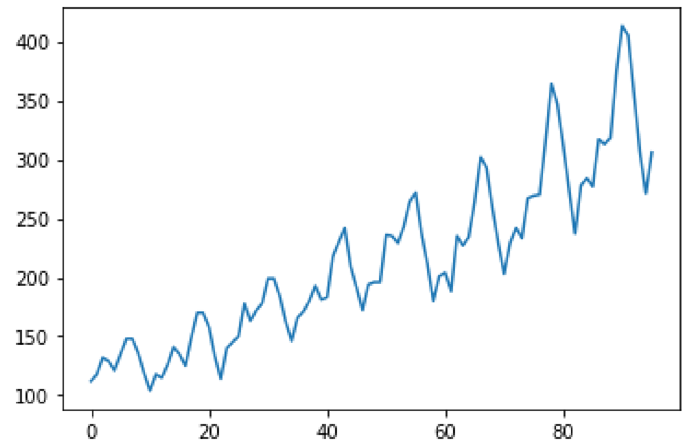
```
<bound method DataFrame.duplicated of         Month  Passengers
0  1995-01-01         112
1  1995-02-01         118
2  1995-03-01         132
```

```
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 x 2 columns]>
```

In [8]:

```
#plotting time series plot
al.Passengers.plot()
plt.show()
```



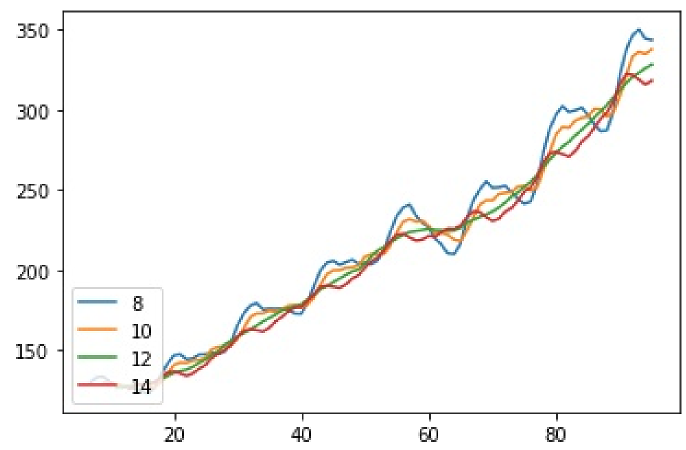
In [ ]:

In [ ]:

In [ ]:

In [9]:

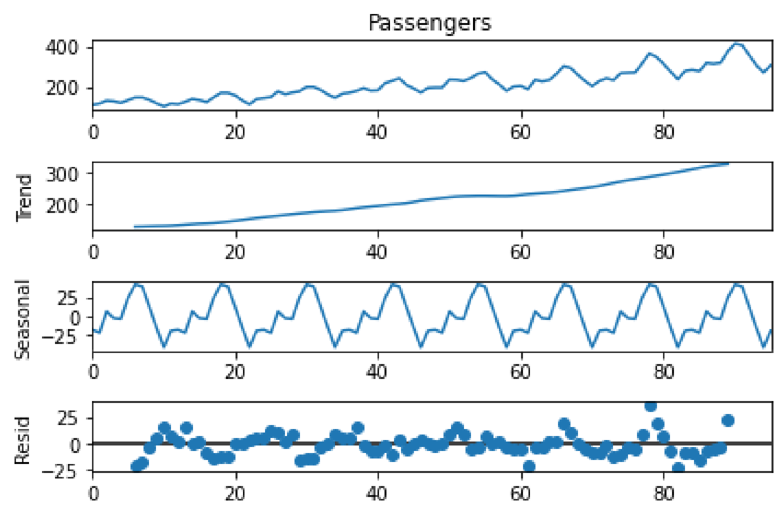
```
# Centering moving average for the time series
for i in range (8,15,2):
    al.Passengers.rolling(i).mean().plot(label=str(i))
plt.legend(loc=3)
plt.show()
```

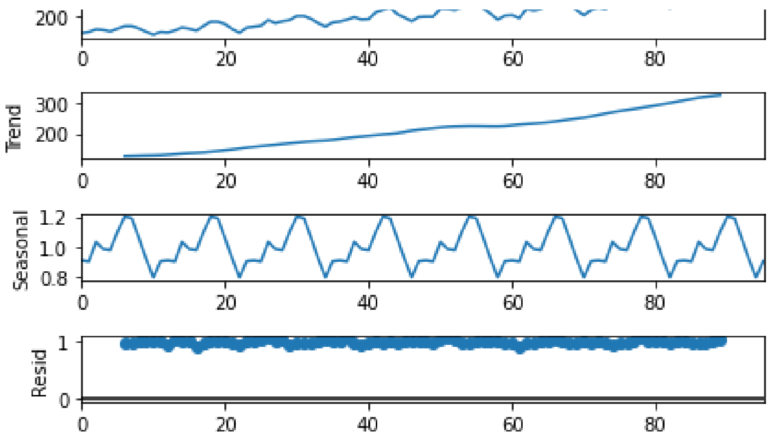


at lag = 12 we are getting good smoothen curve

In [10]:

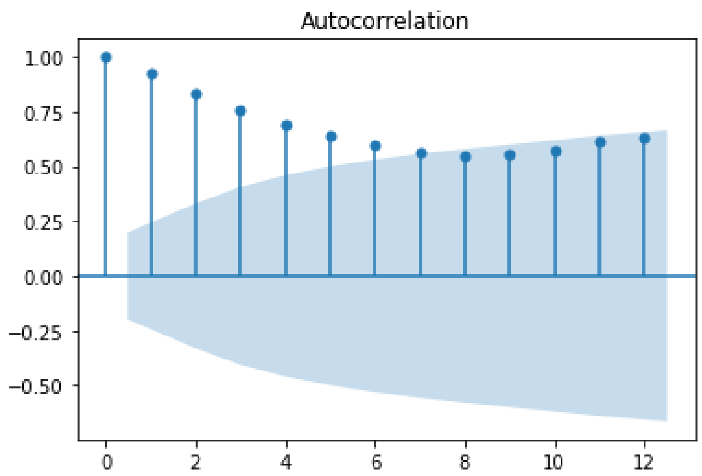
```
# Time series decomposition plot
from statsmodels.tsa.seasonal import seasonal_decompose
decompose_ts_add = seasonal_decompose(al.Passengers, model = "additive", period = 12)
decompose_ts_add.plot()
decompose_ts_mul = seasonal_decompose(al.Passengers, model = "multiplicative", period = 12)
decompose_ts_mul.plot()
plt.show()
```





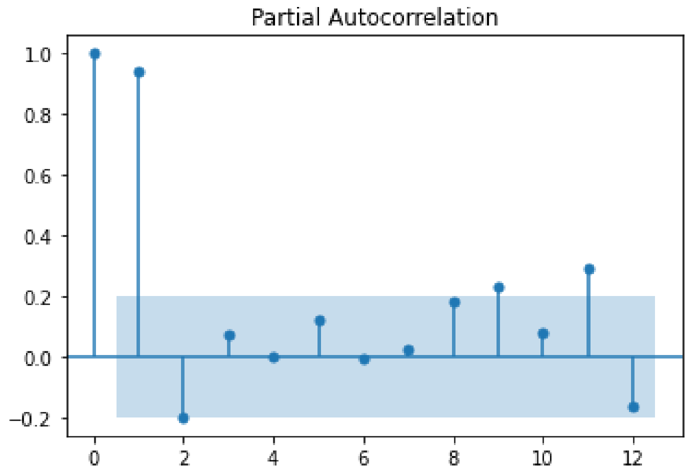
In [11]:

```
# ACF plot on Original data sets
import statsmodels.graphics.tsaplots as tsa_plots
tsa_plots.plot_acf(al.Passengers, lags = 12)
plt.show()
```



In [12]:

```
tsa_plots.plot_pacf(al.Passengers, lags=12)
plt.show()
```



In [13]:

```
#Splitting data into train and test
```

In [14]:

```
Train = al.head(71)
Test=al.tail(24)
```

In [ ]:

```

```

In [15]:

```
# Creating a function to calculate the MAPE value for test data
def MAPE(pred,org):
    temp = np.abs((pred-org)/org)*100
    return np.mean(temp)
```

In [16]:

```
# Simple Exponential Method
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
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)
```

```
C:\Users\theas\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters\model.py:427: FutureWarning: After 0.13 initialization must be handled at model creation
  warnings.warn(
```

Out[16]:

```
20.000366885320275
```

In [17]:

```
# Holt method
from statsmodels.tsa.holtwinters import Holt
hw_model = Holt(Train["Passengers"]).fit(smoothing_level=0.01)
```

```
pred_hw = hw_model.predict(start = Test.index[0], end = Test.index[-1])
MAPE(pred_hw, Test.Passengers)
```

Out[17]:

```
10.718773009471683
```

In [18]:

```
# Holts winter exponential smoothing with additive seasonality and additive trend
from statsmodels.tsa.holtwinters import ExponentialSmoothing
hwe_model_add_add = ExponentialSmoothing(Train["Passengers"], seasonal = "add", trend = "add", seasonal_periods = 12).fit(smoothi
ng_level=0.01)
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[18]:

```
8.15162420154798
```

In [19]:

```
# Holts winter exponential smoothing with multiplicative seasonality and additive trend
hwe_model_mul_add = ExponentialSmoothing(Train["Passengers"], seasonal = "mul", trend = "add", seasonal_periods = 12).fit(smoothi
ng_level=0.01)
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[19]:

```
8.471807943001211
```

final model Holts winter exponential smoothing with additive seasonality and additive trend

In [20]:

```
#preparing new data to store predictions
pred = pd.read_excel("D:/DataScience/Class/assignment working/Forcasting/pred_Airlines Data.xlsx")
```

In [21]:

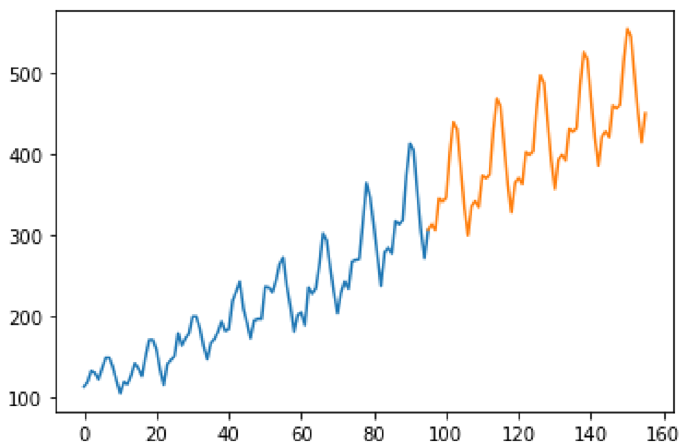
```
final_model = ExponentialSmoothing(al["Passengers"], seasonal = "add", trend = "add", seasonal_periods = 12).fit(smoothing_level=
0.01)
```

In [22]:

```
final_pred = final_model.predict(start = pred.index[0], end = pred.index[-1])
```

In [24]:

```
plt.plot(al.Passengers)
plt.plot(final_pred.iloc[95:])
plt.show()
```



Predicting with Seasonal Arimax model

In [ ]:

In [25]:

```
#adf test to check null hypothesis
#HO- Data is not stationary
#HA- Data is stationary
from statsmodels.tsa.stattools import adfuller
```

In [26]:

```
test = adfuller(al.Passengers)
test
```

Out[26]:

```
(1.3402479596467036,
 0.9968250481137263,
 12,
 83,
 {'1%': -3.5117123057187376,
  '5%': -2.8970475206326833,
  '10%': -2.585712691246915 3},
 626.0084713813505)
```

In [27]:

```
#strong evidence that data is non stationary
#ADFuller test is required for ARIMA only
```

Differencing

In [28]:

```
#making data stationary by removing seasonality and trend
```

In [29]:

```
al["First_Difference"] = al.Passengers - al.Passengers.shift(1)
```

In [30]:

```
al["Seasonal_Difference"] = al.Passengers - al.Passengers.shift(12)
```

In [31]:

```
al.head(20)
```

Out[31]:

	Month	Passengers	First_Difference	Seasonal_Difference
0	1995-01-01	112	NaN	NaN
1	1995-02-01	118	6.0	NaN
2	1995-03-01	132	14.0	NaN
3	1995-04-01	129	-3.0	NaN
4	1995-05-01	121	-8.0	NaN
5	1995-06-01	135	14.0	NaN
6	1995-07-01	148	13.0	NaN
7	1995-08-01	148	0.0	NaN
8	1995-09-01	136	-12.0	NaN
9	1995-10-01	119	-17.0	NaN
10	1995-11-01	104	-15.0	NaN
11	1995-12-01	118	14.0	NaN
12	1996-01-01	115	-3.0	3.0
13	1996-02-01	126	11.0	8.0
14	1996-03-01	141	15.0	9.0
15	1996-04-01	135	-6.0	6.0
16	1996-05-01	125	-10.0	4.0
17	1996-06-01	149	24.0	14.0
18	1996-07-01	170	21.0	22.0
19	1996-08-01	170	0.0	22.0

In [32]:

```
#again Dickey Fuller test to check data is stationary or not
```

In [33]:

```
from statsmodels.tsa.stattools import adfuller
test = adfuller(al.Seasonal_Difference.dropna())
test
```

Out[33]:

```
(-2.690004383862315,
 0.07578397625851786,
 1,
 82,
 {'1%': -3.512738056978279,
  '5%': -2.8974898650628984,
  '10%': -2.585948732897085},
 531.1060746991411)
```

In [34]:

```
al["log_seasonal_diff"]=np.log(al.Seasonal_Difference)
```

```
C:\Users\theas\anaconda3\lib\site-packages\pandas\core\arraylike.py:358: RuntimeWarning: invalid value encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [35]:

```
test = adfuller(al.log_seasonal_diff.dropna())
test
```

Out[35]:

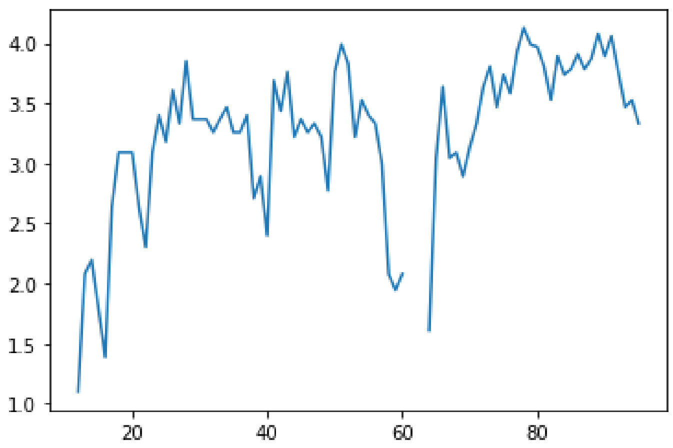
```
(-4.291584015765532,
 0.0004593575293336507,
 0,
 80,
 {'1%': -3.5148692050781247, '5%': -2.8984085156250003, '10%': -2.58643890625},
 60.88061818964134)
```

we can have strong evidence against Null Hypothesis we can reject null hypothesis, the data is stationary

we can have strong evidence against Null Hypothesis,we can reject null hypothesis, the data is stationary

In [36]:

```
al.log_seasonal_diff.plot()
plt.show()
```



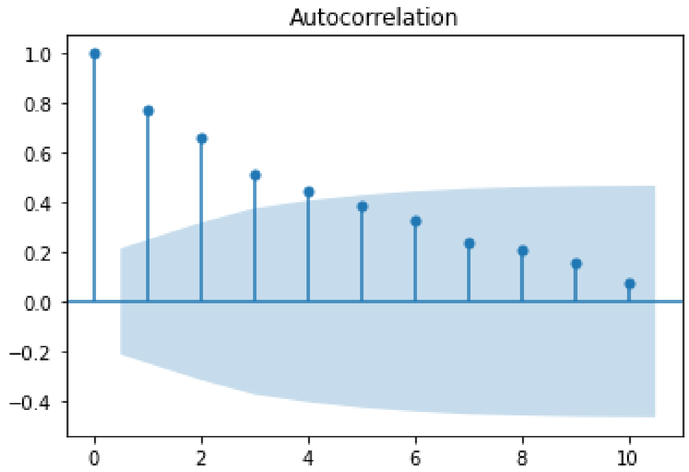
seasonality has been removed succesfully

In [37]:

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf,plot_predict
```

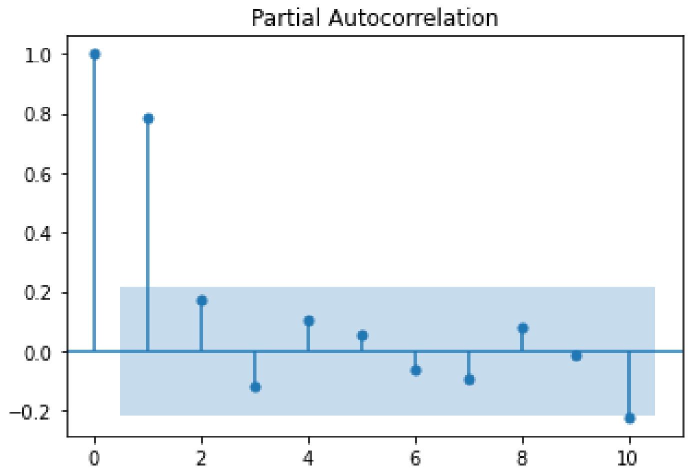
In [38]:

```
plot_acf(al.Seasonal_Difference.dropna(),lags=10)
plt.show()
```



In [39]:

```
plot_pacf(al.Seasonal_Difference.dropna(),lags=10)
plt.show()
```



In [40]:

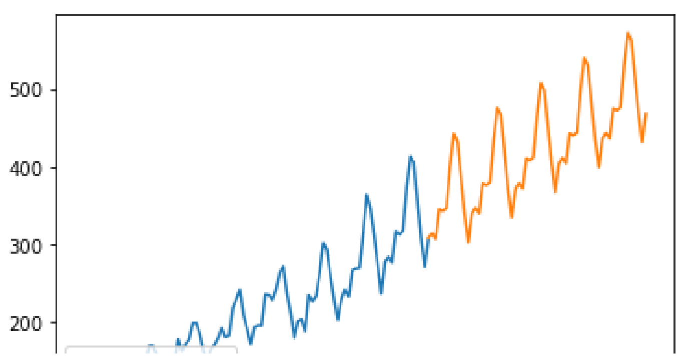
```
import statsmodels.api as sm
```

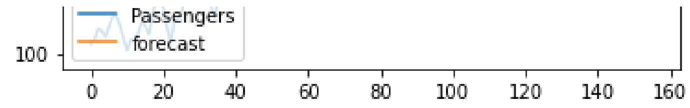
In [41]:

```
model = sm.tsa.statespace.SARIMAX(al["Passengers"],order=(1,1,1),seasonal_order=(1,1,1,12)) #seasonal_order=(p,d,q,m) #m=lag
results=model.fit()
```

In [42]:

```
pred["forecast"] = results.predict(start = pred.index[0], end = pred.index[-1])
al["Passengers"].plot()
plt.legend(loc=3)
pred.forecast.iloc[95:].plot()
plt.legend(loc=3)
plt.show()
```





summary and inference

amongst all the models "Holts winter exponential smoothing with additive seasonality and additive trend" is giving good accuracy

In [ ]:

```

```