In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.graphics.tsaplots import plot_acf
from pylab import rcParams
from math import sqrt
from sklearn.metrics import mean_squared_error
```

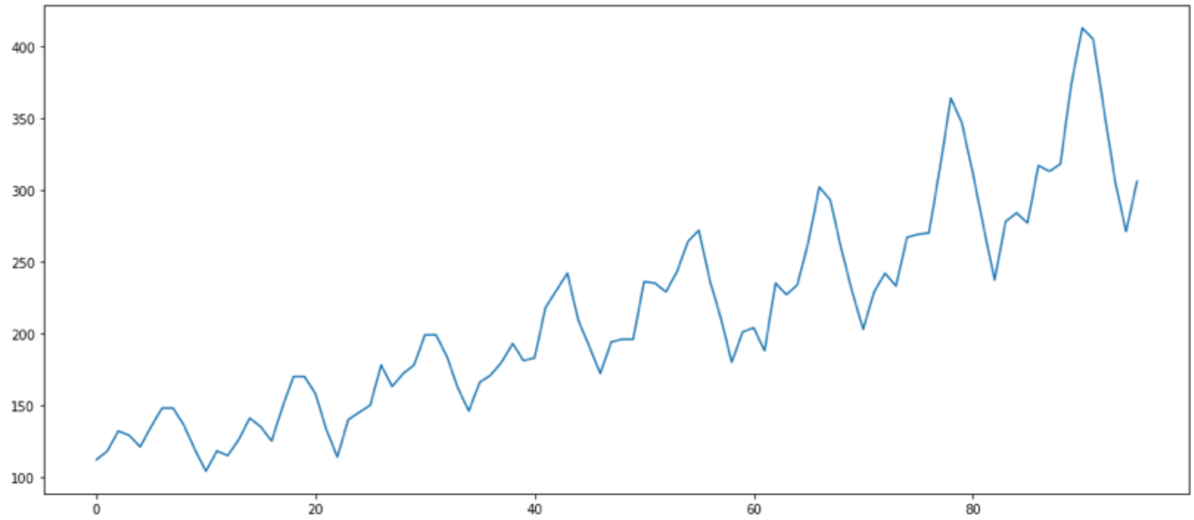
In [2]:
```
airlines_data = pd.read_excel("Airlines+Data.xlsx")
airlines_data
```

Out[2]:

| | 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

In [3]:
```
airlines_data['Passengers'].plot(figsize=(16,7));
```




# The data has a trend and is not stationary.

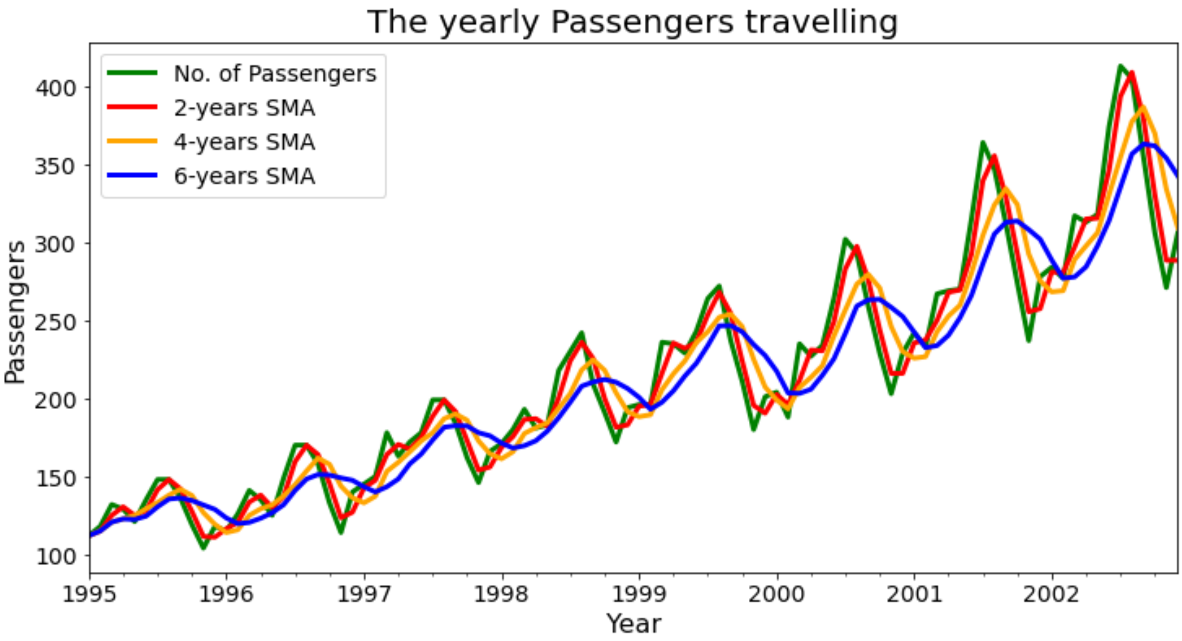
In [4]:
```
airlines_data = airlines_data.set_index('Month')

airlines_data['SMA_2'] = airlines_data['Passengers'].rolling(2, min_
airlines_data['SMA_4'] = airlines_data['Passengers'].rolling(4, min_
airlines_data['SMA_6'] = airlines_data['Passengers'].rolling(6, min_
```

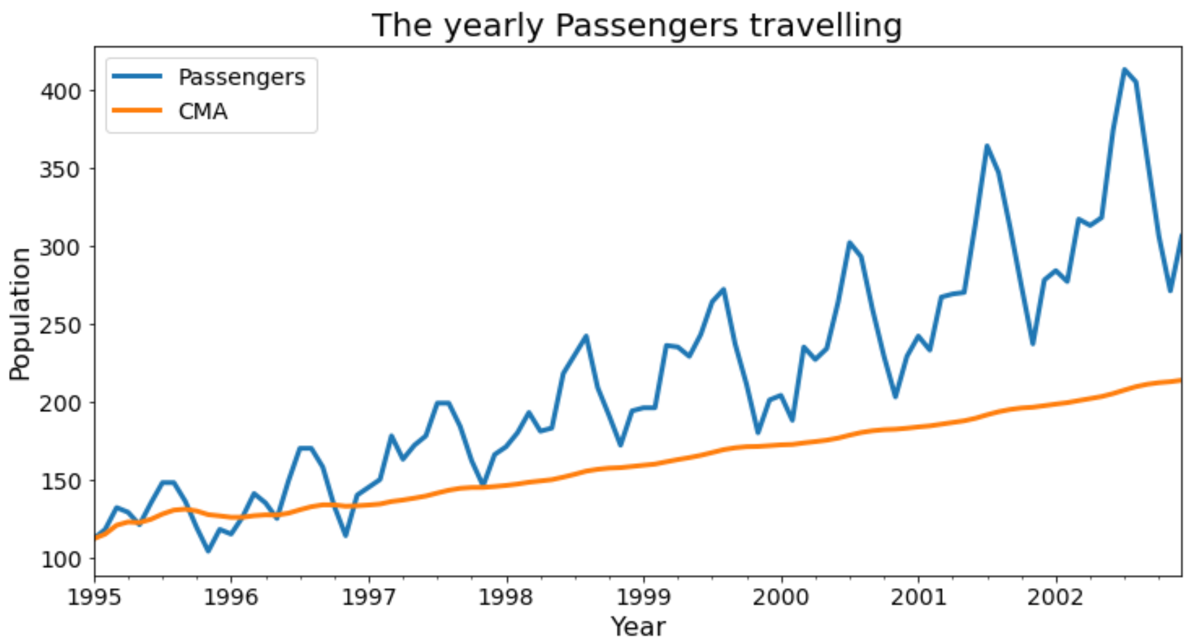
In [5]:

```
colors = ['green', 'red', 'orange','blue']

airlines_data.plot(color=colors, linewidth=3, figsize=(12,6))
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(labels =['No. of Passengers', '2-years SMA', '4-years SM
plt.title('The yearly Passengers travelling', fontsize=20)
plt.xlabel('Year', fontsize=16)
plt.ylabel('Passengers', fontsize=16);
```



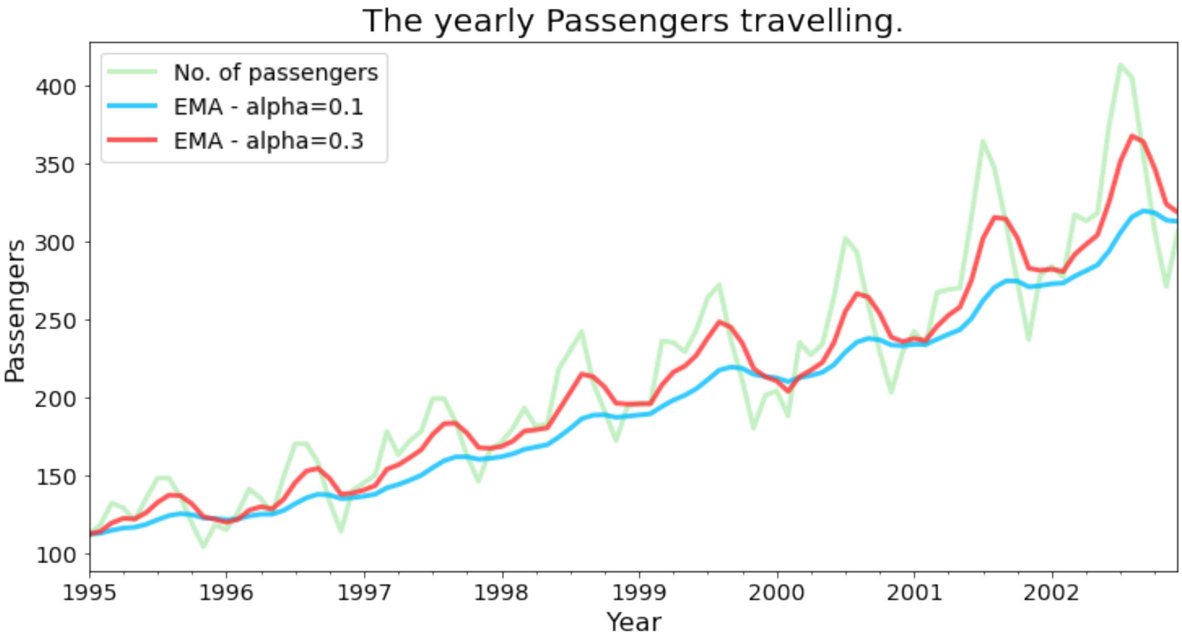
In [6]:
```
airlines_data['CMA'] = airlines_data['Passengers'].expanding().mean
airlines_data[['Passengers', 'CMA']].plot( linewidth=3, figsize=(12
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(labels =['Passengers', 'CMA'], fontsize=14)
plt.title('The yearly Passengers travelling', fontsize=20)
plt.xlabel('Year', fontsize=16)
plt.ylabel('Population', fontsize=16);
```



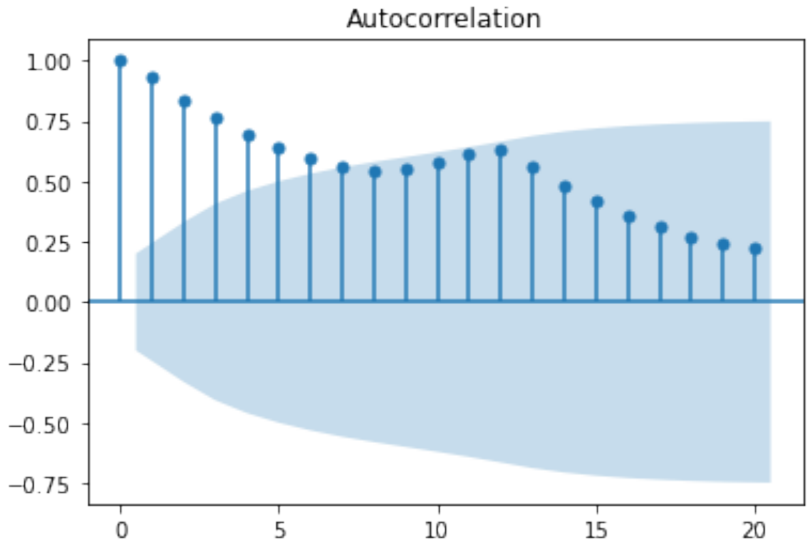

In [7]:
```
'] = airlines_data['Passengers'].ewm(alpha=0.1,adjust=False).mean()
'] = airlines_data['Passengers'].ewm(alpha=0.3,adjust=False).mean()
```

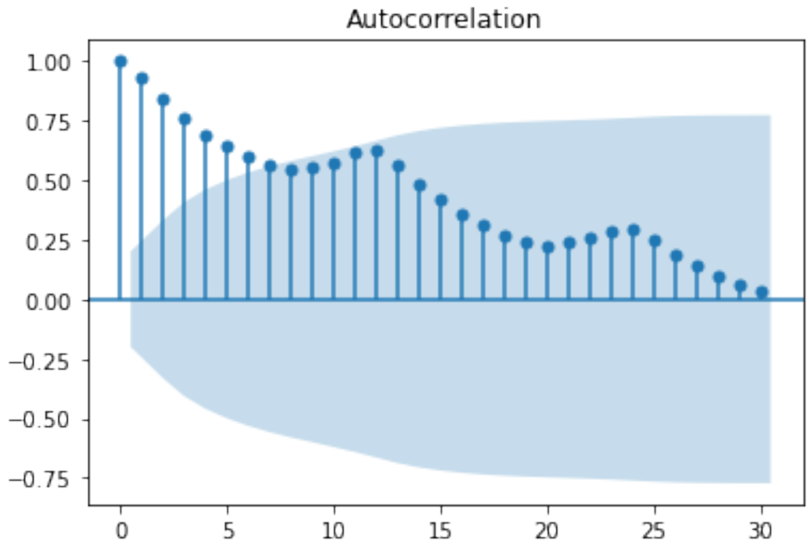
In [8]:
```
colors = ['#B4EEB4', '#00BFFF', '#FF3030']
airlines_data[['Passengers', 'Ema_0.1', 'Ema_0.3']].plot(color=colo
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(labels=['No. of passengers', 'EMA - alpha=0.1', 'EMA - a
plt.title('The yearly Passengers travelling.', fontsize=20)
plt.xlabel('Year', fontsize=16)
plt.ylabel('Passengers', fontsize=16)
```

Out[8]:
```
Text(0, 0.5, 'Passengers')
```

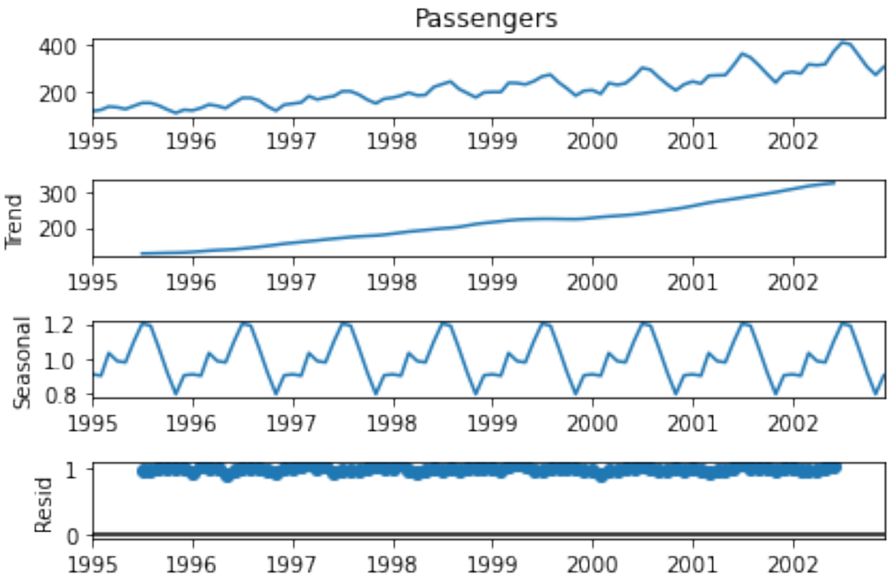


In [9]:
```
plot_acf(airlines_data['Passengers'])
plt.show()
plot_acf(airlines_data['Passengers'],lags=30)
plt.show()
```



In [10]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
ts_mul = seasonal_decompose(airlines_data.Passengers,model="multipl
fig = ts_mul.plot()
plt.show();
```




# Building Arima Model

In [11]:
```
X = airlines_data['Passengers']
size = int(len(X)*0.75)
size
```

Out[11]: 72

In [12]:
```
train , test = X.iloc[0:size],X.iloc[size:len(X)]
```

In [13]:
```
from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(train, order=(5,1,0)).fit(disp=0)
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/arima_m
odel.py:472: FutureWarning:
statsmodels.tsa.arima_model.ARMA and statsmodels.tsa.arima_model.A
RIMA have
been deprecated in favor of statsmodels.tsa.arima.model.ARIMA (not
e the .
between arima and model) and
statsmodels.tsa.SARIMAX. These will be removed after the 0.12 rele
ase.

statsmodels.tsa.arima.model.ARIMA makes use of the statespace fram
ework and
is both well tested and maintained.

To silence this warning and continue using ARMA and ARIMA until th
ey are
removed, use:

import warnings
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARM
A',
                        FutureWarning)
warnings.filterwarnings('ignore', 'statsmodels.tsa.arima_model.ARI
MA',
                        FutureWarning)

  warnings.warn(ARIMA_DEPRECATION_WARN, FutureWarning)
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/ts
a_model.py:524: ValueWarning: No frequency information was provide
d, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/ts
a_model.py:524: ValueWarning: No frequency information was provide
d, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
```

In [14]:
```
print(model.summary())
```

```
                             ARIMA Model Results
==================================================================
============
Dep. Variable:          D.Passengers   No. Observations:
71
Model:                ARIMA(5, 1, 0)   Log Likelihood
-304.792
Method:                      css-mle   S.D. of innovations
17.647
Date:               Thu, 05 Jan 2023   AIC
623.584
Time:                       23:41:41   BIC
```

```
639.423
Sample:                    02-01-1995   HQIC
629.883
                         - 12-01-2000
==================================================================
====================
                           coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------
--------------------
const                    1.8781      1.462      1.285      0.199
-0.987       4.743
ar.L1.D.Passengers       0.1440      0.119      1.213      0.225
-0.089       0.377
ar.L2.D.Passengers      -0.1976      0.119     -1.659      0.097
-0.431       0.036
ar.L3.D.Passengers      -0.1353      0.120     -1.129      0.259
-0.370       0.100
ar.L4.D.Passengers      -0.2453      0.120     -2.047      0.041
-0.480      -0.010
ar.L5.D.Passengers      -0.0263      0.124     -0.213      0.831
-0.268       0.216
                                    Roots
==================================================================
===========
                  Real          Imaginary           Modulus
Frequency
------------------------------------------------------------------
-----------
AR.1            0.8020           -0.9654j            1.2551
-0.1397
AR.2            0.8020           +0.9654j            1.2551
0.1397
AR.3           -1.0374           -1.2843j            1.6509
-0.3581
AR.4           -1.0374           +1.2843j            1.6509
0.3581
AR.5           -8.8496           -0.0000j            8.8496
-0.5000
------------------------------------------------------------------
-----------
```

In [15]:
```python
history = [x for x in train]
history[-1]
```

Out[15]:
```
229
```

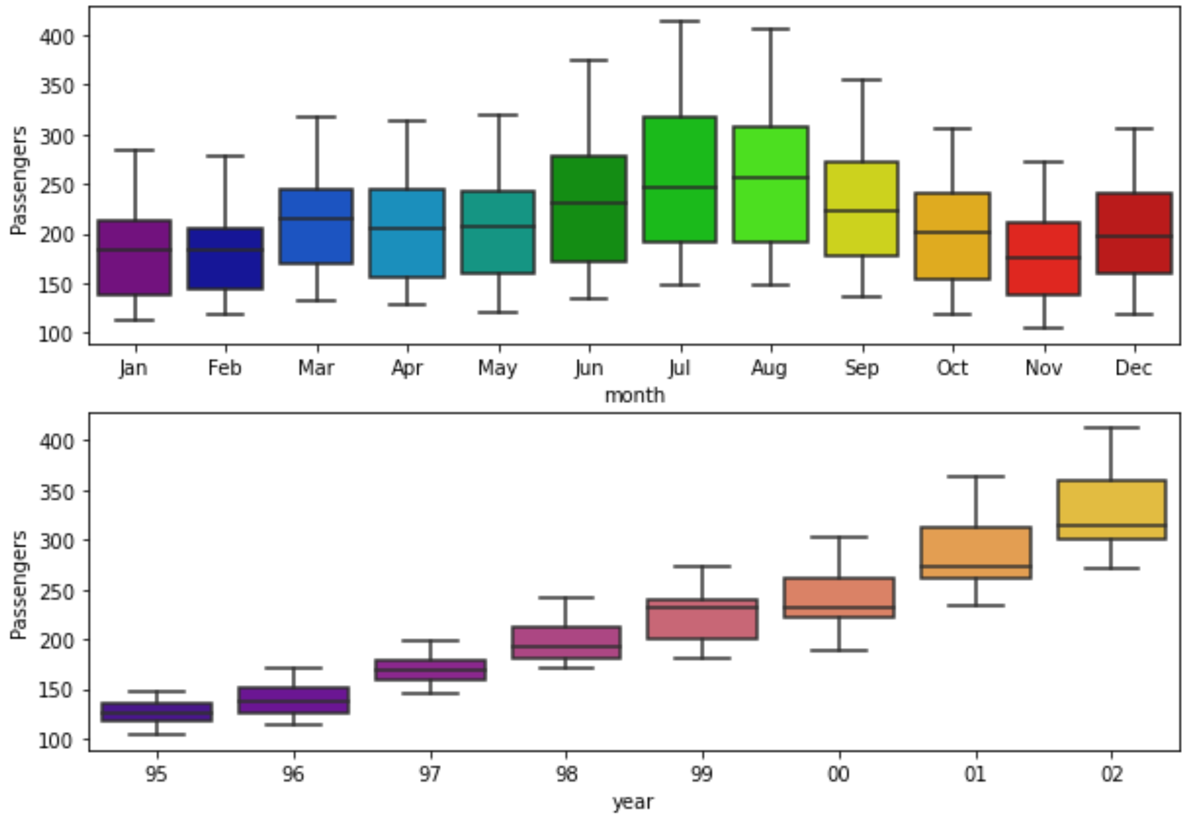
In [16]:
```
history = [x for x in train]
predictions = list()
for i in range(len(test)):
    yhat = history[-1]
    predictions.append(yhat)
# observation
    obs = test[i]
    history.append(obs)
    print('>Predicted=%.3f, Expected=%.3f' % (yhat, obs))
# report performance
rmse = sqrt(mean_squared_error(test, predictions))
print('RMSE: %.3f' % rmse)
```

```
>Predicted=229.000, Expected=242.000
>Predicted=242.000, Expected=233.000
>Predicted=233.000, Expected=267.000
>Predicted=267.000, Expected=269.000
>Predicted=269.000, Expected=270.000
>Predicted=270.000, Expected=315.000
>Predicted=315.000, Expected=364.000
>Predicted=364.000, Expected=347.000
>Predicted=347.000, Expected=312.000
>Predicted=312.000, Expected=274.000
>Predicted=274.000, Expected=237.000
>Predicted=237.000, Expected=278.000
>Predicted=278.000, Expected=284.000
>Predicted=284.000, Expected=277.000
>Predicted=277.000, Expected=317.000
>Predicted=317.000, Expected=313.000
>Predicted=313.000, Expected=318.000
>Predicted=318.000, Expected=374.000
>Predicted=374.000, Expected=413.000
>Predicted=413.000, Expected=405.000
>Predicted=405.000, Expected=355.000
>Predicted=355.000, Expected=306.000
>Predicted=306.000, Expected=271.000
>Predicted=271.000, Expected=306.000
RMSE: 32.687
```

# Building and comparing multiple models

In [17]:
```
final_df = pd.read_excel("Airlines+Data.xlsx")
final_df['Date'] = pd.to_datetime(final_df.Month,format="%b-%y")
final_df['month'] = final_df.Date.dt.strftime("%b") #month extracti
final_df['year'] = final_df.Date.dt.strftime("%y")
```

In [18]:
```
plt.figure(figsize=(10,7))
plt.subplot(211)
sns.boxplot(x="month",y="Passengers",data=final_df,palette='nipy_sp
plt.subplot(212)
sns.boxplot(x="year",y="Passengers",data=final_df,palette='plasma')
```




In [19]:
```
final_df = pd.get_dummies(final_df, columns = ['month'])
```

In [20]:
```
from typing_extensions import final
t= np.arange(1,97)
final_df['t']= t
final_df['t_square']= (t *t)
log_Passengers=np.log(final_df['Passengers'])
final_df['log_Passengers'] =log_Passengers
final_df
```

Out[20]:

| | Month | Passengers | Date | year | month_Apr | month_Aug | month_Dec | month_Feb | mor |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1995-01-01 | 112 | 1995-01-01 | 95 | 0 | 0 | 0 | 0 | |
| **1** | 1995-02-01 | 118 | 1995-02-01 | 95 | 0 | 0 | 0 | 1 | |
| **2** | 1995-03-01 | 132 | 1995-03-01 | 95 | 0 | 0 | 0 | 0 | |
| **3** | 1995-04-01 | 129 | 1995-04-01 | 95 | 1 | 0 | 0 | 0 | |
| **4** | 1995-05-01 | 121 | 1995-05-01 | 95 | 0 | 0 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **91** | 2002-08-01 | 405 | 2002-08-01 | 02 | 0 | 1 | 0 | 0 | |
| **92** | 2002-09-01 | 355 | 2002-09-01 | 02 | 0 | 0 | 0 | 0 | |
| **93** | 2002-10-01 | 306 | 2002-10-01 | 02 | 0 | 0 | 0 | 0 | |
| **94** | 2002-11-01 | 271 | 2002-11-01 | 02 | 0 | 0 | 0 | 0 | |
| **95** | 2002-12-01 | 306 | 2002-12-01 | 02 | 0 | 0 | 1 | 0 | |

96 rows × 19 columns

In [21]:
```
Train, Test = np.split(final_df, [int(.75 *len(final_df))])
```

In [22]:
```
#Linear Model
import statsmodels.formula.api as smf

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.arra
rmse_linear
```

Out[22]: 51.6677929956463

In [23]:
```
#Exponential

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['log_Passengers'])-np.arr
rmse_Exp
```

Out[23]: 297.3698089836234

In [24]:
```
#Quadratic

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

Out[24]: 51.990736401554834

In [25]:
```
#Additive seasonality

add_sea = smf.ols('Passengers~month_Jan+month_Feb+month_Mar+month_A
pred_add_sea = pd.Series(add_sea.predict(Test[['month_Jan','month_F
rmse_add_sea = np.sqrt(np.mean((np.array(Test['Passengers'])-np.arr
rmse_add_sea
```

Out[25]: 127.26451565320338

In [26]:
```
#Additive Seasonality Quadratic

add_sea_Quad = smf.ols('Passengers~t+t_square+month_Jan+month_Feb+m
pred_add_sea_quad = pd.Series(add_sea_Quad.predict(Test[['t','t_squ
rmse_add_sea_quad = np.sqrt(np.mean((np.array(Test['Passengers'])-n
rmse_add_sea_quad
```

Out[26]: 35.24160848593321

In [27]:
```
##Multiplicative Seasonality
Mul_sea = smf.ols('log_Passengers~month_Jan+month_Feb+month_Mar+mon
pred_Mult_sea = pd.Series(Mul_sea.predict(Test[['month_Jan','month_
rmse_Mult_sea = np.sqrt(np.mean((np.array(Test['log_Passengers'])-n
rmse_Mult_sea
```

Out[27]: 173.46096019630764

In [28]:
```
#Multiplicative Additive Seasonality

Mul_Add_sea = smf.ols('log_Passengers~t+month_Jan+month_Feb+month_M
pred_Mult_add_sea = pd.Series(Mul_Add_sea.predict(Test[['t','month_
rmse_Mult_add_sea = np.sqrt(np.mean((np.array(Test['log_Passengers'
rmse_Mult_add_sea
```

Out[28]: 303.3646933542646

In [29]:
```
#Compare the results

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

Out[29]:

| | MODEL | RMSE_Values |
|---|---|---|
| **4** | rmse_add_sea_quad | 35.241608 |
| **0** | rmse_linear | 51.667793 |
| **2** | rmse_Quad | 51.990736 |
| **3** | rmse_add_sea | 127.264516 |
| **5** | rmse_Mult_sea | 173.460960 |
| **1** | rmse_Exp | 297.369809 |
| **6** | rmse_Mult_add_sea | 303.364693 |

In [30]:
```
model_final = smf.ols('Passengers~t+t_square+month_Jan+month_Feb+mo
pred_new  = pd.Series(model_final.predict(Test))
pred_new
```

Out[30]:
```
72    242.330988
73    244.902987
74    271.141653
75    263.713651
76    262.785650
77    283.357649
78    304.429648
79    306.334980
80    282.906979
81    259.978978
82    239.050977
83    260.622976
84    267.321927
85    269.914497
86    296.173733
87    288.766303
88    287.858873
89    308.451443
90    329.544013
91    331.469917
92    308.062487
93    285.155057
94    264.247627
95    285.840197
dtype: float64
```

In [31]:
```
predict_data= pd.DataFrame()
predict_data["forecasted_passengers"] = pd.Series(pred_new)
```

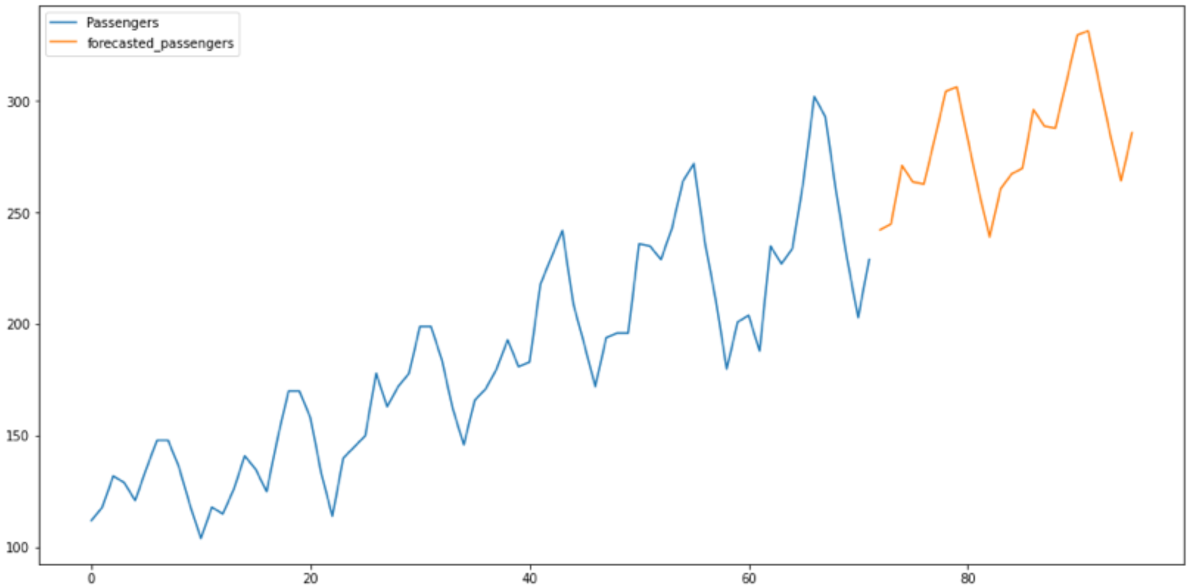
In [32]:
```
visualize = pd.concat([Train,predict_data])
visualize
```

Out[32]:

| | Month | Passengers | Date | year | month_Apr | month_Aug | month_Dec | month_Feb | moı |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1995-01-01 | 112.0 | 1995-01-01 | 95 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **1** | 1995-02-01 | 118.0 | 1995-02-01 | 95 | 0.0 | 0.0 | 0.0 | 1.0 | |
| **2** | 1995-03-01 | 132.0 | 1995-03-01 | 95 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **3** | 1995-04-01 | 129.0 | 1995-04-01 | 95 | 1.0 | 0.0 | 0.0 | 0.0 | |
| **4** | 1995-05-01 | 121.0 | 1995-05-01 | 95 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **91** | NaT | NaN | NaT | NaN | NaN | NaN | NaN | NaN | |
| **92** | NaT | NaN | NaT | NaN | NaN | NaN | NaN | NaN | |
| **93** | NaT | NaN | NaT | NaN | NaN | NaN | NaN | NaN | |
| **94** | NaT | NaN | NaT | NaN | NaN | NaN | NaN | NaN | |
| **95** | NaT | NaN | NaT | NaN | NaN | NaN | NaN | NaN | |

96 rows × 20 columns

In [33]:
```
visualize[['Passengers','forecasted_passengers']].reset_index(drop=
```




In [ ]: