Chitramoy_Mukherjee-DSC630-Week-08-Assignment 1

May 5, 2024

DSC-630-T302 Chitramoy Mukherjee Date : 05/01/2024 Week8 - Exercise 8.2 - Time Series Modeling

You will be using the dataset us_retail_sales.csv for this assignment. This data gives the total monthly retail sales in the US from January 1992 until June 2021. With this dataset, complete the following steps:

```
* Plot the data with proper labeling and make some observations on the graph.
* Split this data into a training and test set. Use the last year of data (July 2020 -
June 2021) of data as your
  test set and the rest as your training set.
* Use the training set to build a predictive model for the monthly retail sal
* Use the model to predict the monthly retail sales on the last year of data.
* Report the RMSE of the model predictions on the test set.
```

You can use R or Python to complete this assignment. Submit your code and output to the submission link. Make sure to add comments to all of your code and to document your steps, process, and analysis.

[9]:
```
# import libraries
import pandas as pd
import numpy as np
from numpy import sqrt
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.ar_model import AutoReg
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from sklearn import metrics
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.stattools import adfuller
from tqdm import tqdm_notebook
from itertools import product
%matplotlib inline
```

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

[10]:
```
# Load the dataset
df = pd.read_csv('C:
↪\\Users\\Chitramoy\\Desktop\\MS-DSC\\DSC-630\\Week-8\\us_retail_sales.csv')

# Preview the dataframe
df.head(5)
```

[10]:
```
   YEAR     JAN     FEB     MAR     APR     MAY     JUN       JUL       AUG  \
0  1992  146925  147223  146805  148032  149010  149800  150761.0  151067.0
1  1993  157555  156266  154752  158979  160605  160127  162816.0  162506.0
2  1994  167518  169649  172766  173106  172329  174241  174781.0  177295.0
3  1995  182413  179488  181013  181686  183536  186081  185431.0  186806.0
4  1996  189135  192266  194029  194744  196205  196136  196187.0  196218.0

        SEP       OCT       NOV       DEC
0  152588.0  153521.0  153583.0  155614.0
1  163258.0  164685.0  166594.0  168161.0
2  178787.0  180561.0  180703.0  181524.0
3  187366.0  186565.0  189055.0  190774.0
4  198859.0  200509.0  200174.0  201284.0
```

[11]:
```
#expand the dataframe
df_2 = pd.melt(df, id_vars=['YEAR'], var_name="MONTH", value_name="SALES")
#convert months to numerical value
df_2['Month'] = df_2['MONTH'].map({'JAN': 1, 'FEB': 2, 'MAR': 3, 'APR': 4,'MAY':
↪5,'JUN':6,'JUL':7,'AUG':8,'SEP':9,'OCT':10,'NOV':11,'DEC':12})
#create year-month-date conversion
df_2['DATE']=pd.to_datetime(df_2[['YEAR','Month']].assign(DAY=1))
# create dataframe with only needed columns
df_new = df_2[['DATE','SALES']].sort_values('DATE')
df_new = df_new.dropna()
# preview new dataframe
df_new.head(10)
```

[11]:
```
          DATE     SALES
0   1992-01-01  146925.0
30  1992-02-01  147223.0
60  1992-03-01  146805.0
90  1992-04-01  148032.0
120 1992-05-01  149010.0
150 1992-06-01  149800.0
180 1992-07-01  150761.0
210 1992-08-01  151067.0
240 1992-09-01  152588.0
270 1992-10-01  153521.0
```

[12]:
```python
# Check the shape of the dataframe. 354 records and 2 columns
df_new.shape
```

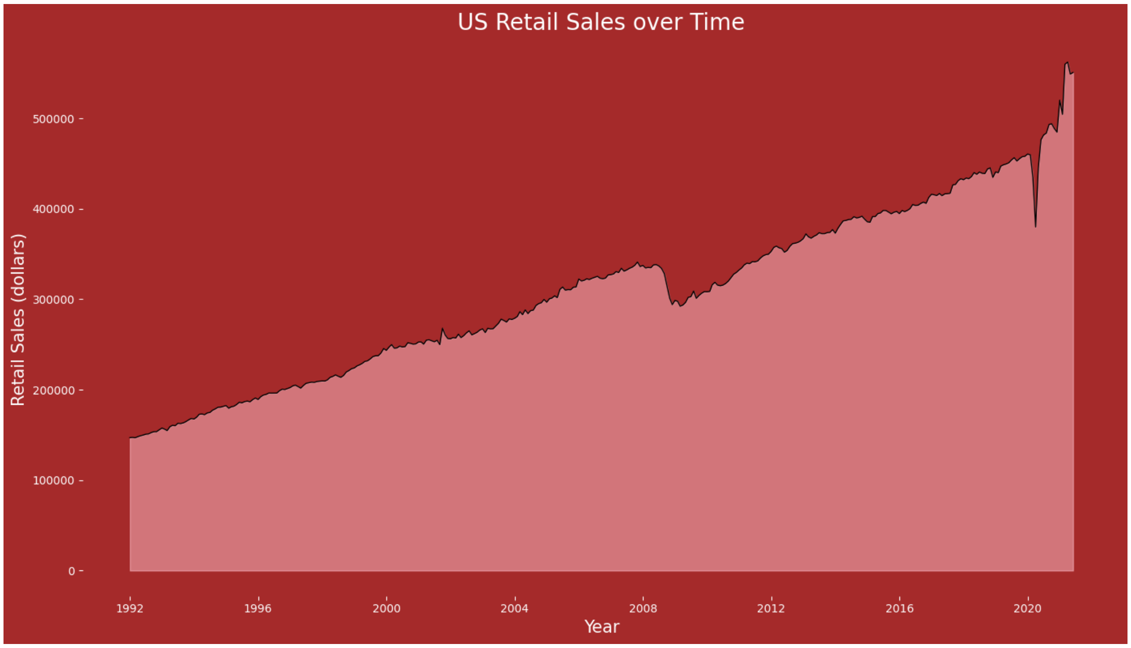
[12]: (354, 2)

[14]:
```python
# Checking the dtypes of the variables
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 354 entries, 0 to 179
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   DATE    354 non-null    datetime64[ns]
 1   SALES   354 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 8.3 KB
```

0.1 Plot the data with proper labeling and make some observations on the graph.

[15]:
```python
#create an area chart to show Sales vs Date
fig = plt.figure(figsize=(14,8), facecolor='brown')
plt.plot(df_new['DATE'], df_new['SALES'], linewidth=1, color='black')
plt.fill_between(df_new['DATE'], df_new['SALES'], color='pink', alpha=0.5)
plt.box(False)
plt.title('US Retail Sales over Time', fontsize=20, color='white')
plt.xlabel('Year', color='white', fontsize=15)
plt.ylabel('Retail Sales (dollars) ', color='white', fontsize=15)
plt.tick_params(axis='x', colors='white')
plt.tick_params(axis='y', colors='white')
plt.tight_layout()
plt.show()
```



Clearly, the time series is not stationary, as its mean is not constant through time, and we see an increasing variance in the data, a sign of heteroscedasticity. The graph depicts a steady increase in retail revenue each year with an exception of 2008 and 2020. During the years of 2007 to 2009, the economy was entering a downturn due to the great recession due to lax lending in the mortgage housing market. In the year of 2020, the Covid-19 Pandemic slowed spending for many due to being in various lockdown situations. Definitely have upward sales trend.

[16]:
```
#set the date as the index
df_new.set_index("DATE",inplace=True)
```

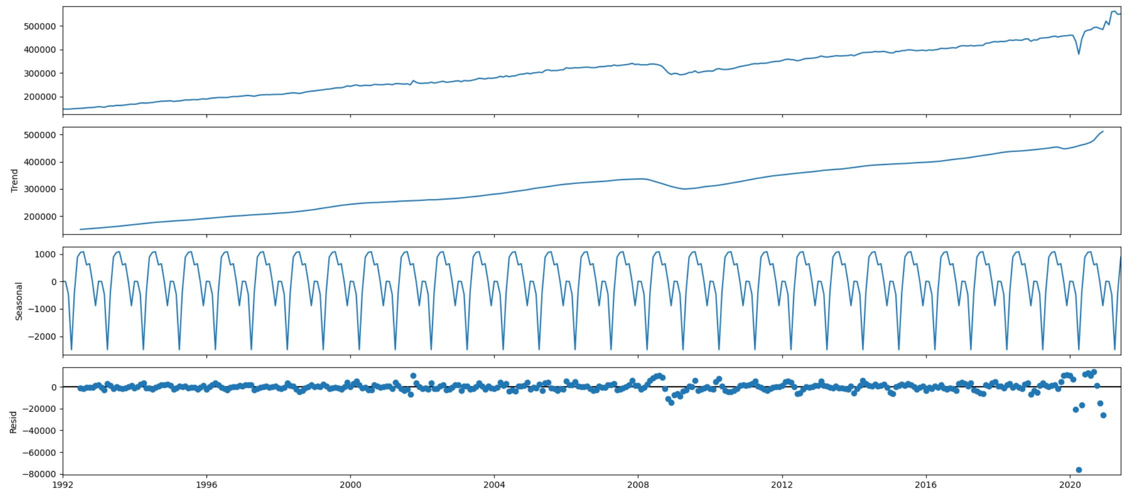
[17]:
```
df_new.tail()
#### Analyzing the chart, I can observe that the time-series has seasonality␣
↪pattern. There is an upward trend over the years as well.
```

[17]:

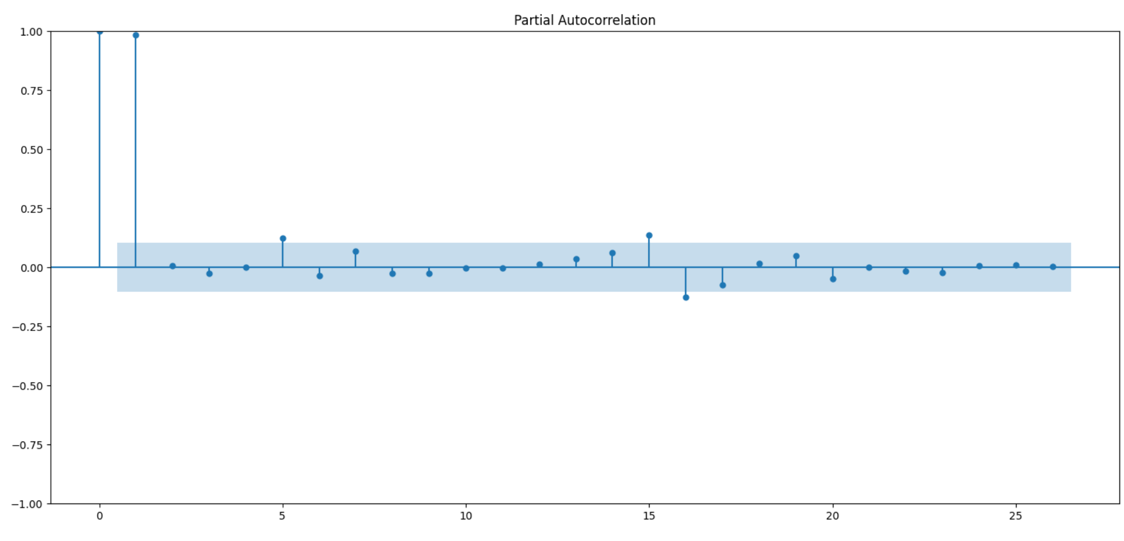
DATE	SALES
2021-02-01	504458.0
2021-03-01	559871.0
2021-04-01	562269.0
2021-05-01	548987.0
2021-06-01	550782.0

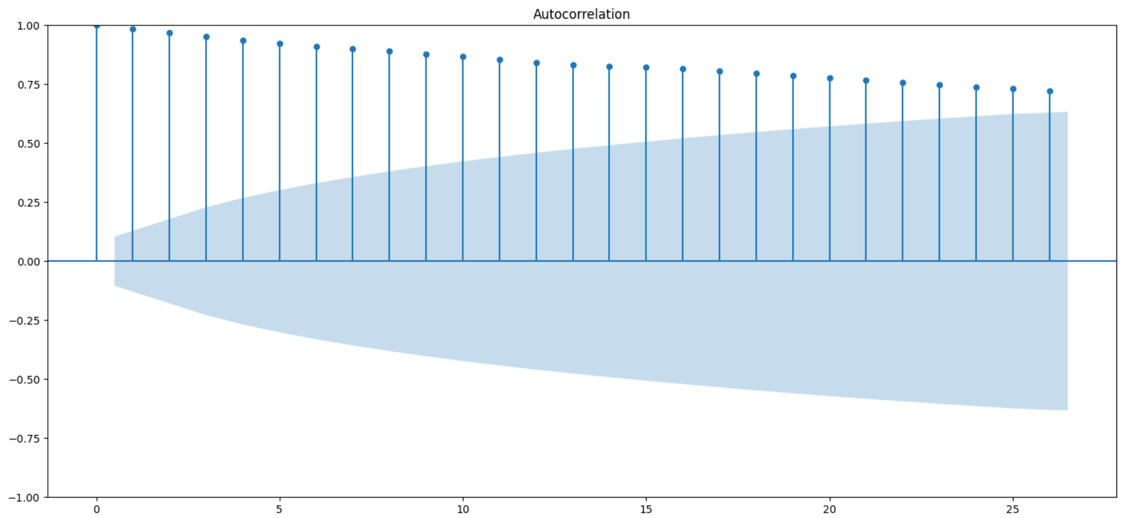
[18]:
```
from pylab import rcParams
rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(df_new, model='additive')
fig = decomposition.plot()
plt.show()
```

```
# Using the "sm.tsa.seasonal_decompose" command from the pylab library I can␣
↪decompose the time-series into three distinct components: trend,
# seasonality, and noise. I can see upward sales trend over the year and also␣
↪seasonality effect yearly by looking at the plot above.
```



[19]:
```
# To make sure, let's plot the PACF and ACF:
plot_pacf(df_new['SALES']);
plot_acf(df_new['SALES']);
```





[20]:
```
# Again, no information can be deduced from those plots. I can further test for␣
↪stationarity with the Augmented
# Dickey-Fuller test:
ad_fuller_result = adfuller(df_new['SALES'])
print(f'ADF Statistic: {ad_fuller_result[0]}')
print(f'p-value: {ad_fuller_result[1]}')
```

```
ADF Statistic: 1.4490526692726289
p-value: 0.9973259755033455
```

[21]:
```
# Now, let's take the differencinng in an effort to make it stationary:
data = df_new.copy()
data['Sales First Differencing'] = data['SALES'] - data['SALES'].shift(1)
data['Seasonal First Differencing'] = data['SALES'] - data['SALES'].shift(12)
data.head()
```

[21]:

DATE	SALES	Sales First Differencing	Seasonal First Differencing
1992-01-01	146925.0	NaN	NaN
1992-02-01	147223.0	298.0	NaN
1992-03-01	146805.0	-418.0	NaN
1992-04-01	148032.0	1227.0	NaN
1992-05-01	149010.0	978.0	NaN

[22]:
```
# Dickey-Fuller test:
ad_fuller_result = adfuller(data['Seasonal First Differencing'].dropna())
print(f'ADF Statistic: {ad_fuller_result[0]}')
print(f'p-value: {ad_fuller_result[1]}')
```

```
ADF Statistic: -2.2393804106097703
p-value: 0.1922642410718154
```

[23]:
```python
# Dickey-Fuller test:
ad_fuller_result = adfuller(data['Sales First Differencing'].dropna())
print(f'ADF Statistic: {ad_fuller_result[0]}')
print(f'p-value: {ad_fuller_result[1]}')
```

```
ADF Statistic: -2.7280371246391555
p-value: 0.06931100597169161
```

0.1.1 Split this data into a training and test set. Use the last year of data (July 2020 – June 2021) of data as your test set and the rest as your training set.

[24]:
```python
# build the train, test set
train, test = df_new[df_new.index < '2020-07-01'], df_new[df_new.index >=
↪'2020-07-01']
train.head()
```

[24]:

DATE	SALES
1992-01-01	146925.0
1992-02-01	147223.0
1992-03-01	146805.0
1992-04-01	148032.0
1992-05-01	149010.0

[19]:
```python
test.head()
```

[19]:

DATE	SALES
2020-07-01	481627.0
2020-08-01	483716.0
2020-09-01	493327.0
2020-10-01	493991.0
2020-11-01	488652.0

0.1.2 Use the training set to build a predictive model for the monthly retail sales.

[25]:
```python
#Instantiate and fit the AR model with training data
ar_model = AutoReg(train, lags=3).fit()

#print summary
print(ar_model.summary())
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                  SALES   No. Observations:                  342
Model:                     AutoReg(3)   Log Likelihood               -3396.835
Method:               Conditional MLE   S.D. of innovations           5438.308
Date:                Sun, 05 May 2024   AIC                           6803.670
```

```
Time:                        17:12:27   BIC                           6822.800
Sample:                    04-01-1992   HQIC                          6811.293
                         - 06-01-2020
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       2087.5148   1076.084      1.940      0.052     -21.572    4196.601
SALES.L1       0.8672      0.054     15.942      0.000       0.761       0.974
SALES.L2      -0.3893      0.076     -5.129      0.000      -0.538      -0.241
SALES.L3       0.5199      0.069      7.526      0.000       0.385       0.655
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0013           -0.0000j            1.0013           -0.0000
AR.2           -0.1263           -1.3802j            1.3860           -0.2645
AR.3           -0.1263           +1.3802j            1.3860            0.2645
-----------------------------------------------------------------------------
```

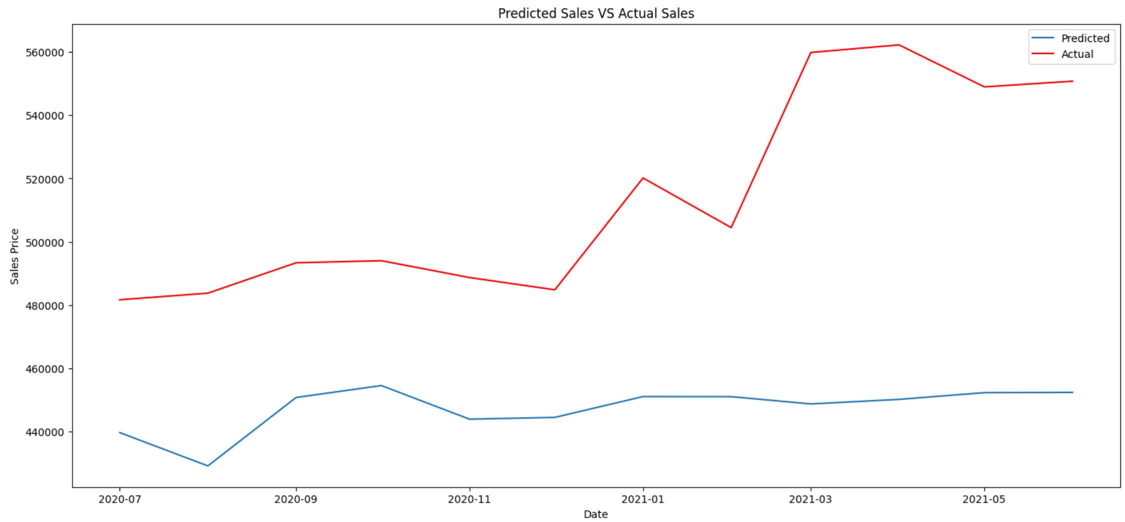
0.1.3 Use the model to predict the monthly retail sales on the last year of data.

[26]:

```
# Make the predictions
pred = ar_model.predict(start=len(train), end=(len(df_new)-1), dynamic=False)
# Plot the prediction vs test data
from matplotlib import pyplot
pyplot.plot(pred, label='Predicted')
pyplot.plot(test, color='red', label='Actual')
plt.title("Predicted Sales VS Actual Sales")
plt.xlabel("Date")
plt.ylabel("Sales Price")
plt.legend()
```

[26]:

```
<matplotlib.legend.Legend at 0x2364e293a40>
```



0.1.4 Report the RMSE of the model predictions on the test set.

[27]:
```
# Find the square root of the mean of test sales value minus the predict test␣
↪sales values
rmse = sqrt(mean_squared_error(test, pred))
print('Test RMSE is %.3f' % rmse)
```

```
Test RMSE is 72691.589
```

Summary The unusual high RMSE value signifies that the autoregressive model is not optimal for this exercise. The important value is an indication of how close the predictions are to the actual values. Lower values of RMSE indicate a better fit. RMSE is a worthy measure of how accurately the model predicts the response. It can be the most important criterion for fit if the main purpose of the model is prediction. An explanation for the gap in prediction and actual could be that there was an unusual spike in sales during the period of prediction time frame.

0.1.5 Moving Average Model

[28]:
```
df_new['lag1'] = df_new['SALES'].shift(1)
```

[29]:
```
df_new['Resid'] = df_new['SALES'] - df_new['lag1']
```

[30]:
```
df_new.reset_index(inplace=True)
```

[31]:
```
df_new.head()
```

[31]:

	DATE	SALES	lag1	Resid
0	1992-01-01	146925.0	NaN	NaN
1	1992-02-01	147223.0	146925.0	298.0
2	1992-03-01	146805.0	147223.0	-418.0

```
3 1992-04-01  148032.0  146805.0  1227.0
4 1992-05-01  149010.0  148032.0   978.0
```

[32]:
```
train, test = df_new.Resid[df_new.DATE < '2020-07-01'], df_new.Resid[df_new.
 ↪DATE >= '2020-07-01']
train
```

[32]:
```
0          NaN
1        298.0
2       -418.0
3       1227.0
4        978.0
        …
337     -976.0
338   -25329.0
339   -54389.0
340    64739.0
341    31712.0
Name: Resid, Length: 342, dtype: float64
```

[34]:
```
#Instantiate and fit the AR model with training data
ar_model = AutoReg(train.iloc[1:], lags=3).fit()
```

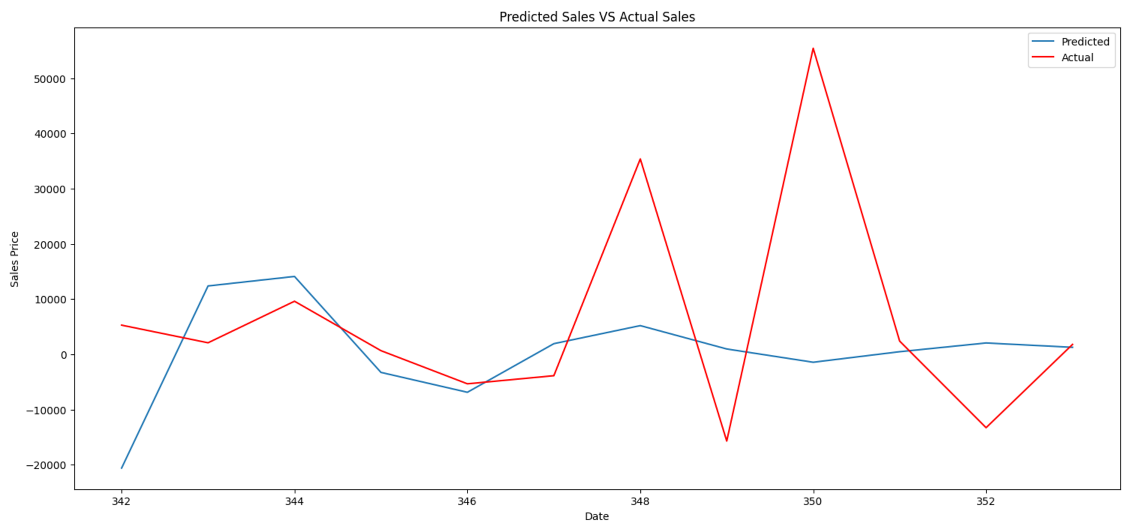
[35]:
```
#print summary
print(ar_model.summary())
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                  Resid   No. Observations:                  341
Model:                     AutoReg(3)   Log Likelihood               -3386.071
Method:               Conditional MLE   S.D. of innovations           5426.349
Date:                Sun, 05 May 2024   AIC                           6782.141
Time:                        17:13:04   BIC                           6801.256
Sample:                             3   HQIC                          6789.759
                                  341
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       1577.0546    314.705      5.011      0.000     960.244    2193.865
Resid.L1      -0.1476      0.055     -2.680      0.007      -0.256      -0.040
Resid.L2      -0.4918      0.071     -6.975      0.000      -0.630      -0.354
Resid.L3      -0.1612      0.095     -1.699      0.089      -0.347       0.025
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            0.1417          -1.3566j            1.3639           -0.2334
AR.2            0.1417          +1.3566j            1.3639            0.2334
```

```
AR.3            -3.3338           -0.0000j            3.3338            -0.5000
-----------------------------------------------------------------------------
```

[151]:

```
# Make the predictions
pred = ar_model.predict(start=len(train), end=(len(df_new)-1), dynamic=False)
# Plot the prediction vs test data
from matplotlib import pyplot
pyplot.plot(pred, label='Predicted')
pyplot.plot(test, color='red', label='Actual')
plt.title("Predicted Sales VS Actual Sales")
plt.xlabel("Date")
plt.ylabel("Sales Price")
plt.legend()
plt.show()
```



[36]:

```
# Find the square root of the mean of test sales value minus the predict test␣
↪sales values
rmse = sqrt(mean_squared_error(test, pred))
print('Test RMSE is %.3f' % rmse)
```

```
Test RMSE is 441541.556
```

Summary With Moving Average Model, RMSE errors are reduced significantly. Since I used reseduals to predict future sales get some advantages.

0.1.6 ARIMA model :

[37]:

```
df_arima = df_new.copy()
df_arima.head()
```

[37]:
```
         DATE     SALES      lag1   Resid
0 1992-01-01  146925.0       NaN     NaN
1 1992-02-01  147223.0  146925.0   298.0
2 1992-03-01  146805.0  147223.0  -418.0
3 1992-04-01  148032.0  146805.0  1227.0
4 1992-05-01  149010.0  148032.0   978.0
```

[38]:
```python
### Testing For Stationarity
from statsmodels.tsa.stattools import adfuller
```

[39]:
```python
test_result=adfuller(df_arima['SALES'])
```

[40]:
```python
def adfuller_test(sales):
    result=adfuller(sales)
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of␣
↪Observations Used']
    for value,label in zip(result,labels):
        print(label+' : '+str(value) )
    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis(Ho), reject the␣
↪null hypothesis. Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit␣
↪root, indicating it is non-stationary ")
```

[41]:
```python
adfuller_test(df_arima['SALES'])
```

```
ADF Test Statistic : 1.4490526692726289
p-value : 0.9973259755033455
#Lags Used : 12
Number of Observations Used : 341
weak evidence against null hypothesis, time series has a unit root, indicating
it is non-stationary
```

[43]:
```python
# Differencinng
df_arima['Sales First Difference'] = df_arima['SALES'] - df_arima['SALES'].
↪shift(1)
```

[44]:
```python
df_arima['Seasonal First Difference']=df_arima['SALES']-df_arima['SALES'].
↪shift(12)
```

[45]:
```python
df_arima.head(13)
```

[45]:
```
         DATE     SALES      lag1   Resid  Sales First Difference  \
0  1992-01-01  146925.0       NaN     NaN                     NaN
1  1992-02-01  147223.0  146925.0   298.0                   298.0
2  1992-03-01  146805.0  147223.0  -418.0                  -418.0
3  1992-04-01  148032.0  146805.0  1227.0                  1227.0
```

```
4   1992-05-01  149010.0  148032.0   978.0                    978.0
5   1992-06-01  149800.0  149010.0   790.0                    790.0
6   1992-07-01  150761.0  149800.0   961.0                    961.0
7   1992-08-01  151067.0  150761.0   306.0                    306.0
8   1992-09-01  152588.0  151067.0  1521.0                   1521.0
9   1992-10-01  153521.0  152588.0   933.0                    933.0
10  1992-11-01  153583.0  153521.0    62.0                     62.0
11  1992-12-01  155614.0  153583.0  2031.0                   2031.0
12  1993-01-01  157555.0  155614.0  1941.0                   1941.0

    Seasonal First Difference
0                         NaN
1                         NaN
2                         NaN
3                         NaN
4                         NaN
5                         NaN
6                         NaN
7                         NaN
8                         NaN
9                         NaN
10                        NaN
11                        NaN
12                    10630.0
```

[165]:

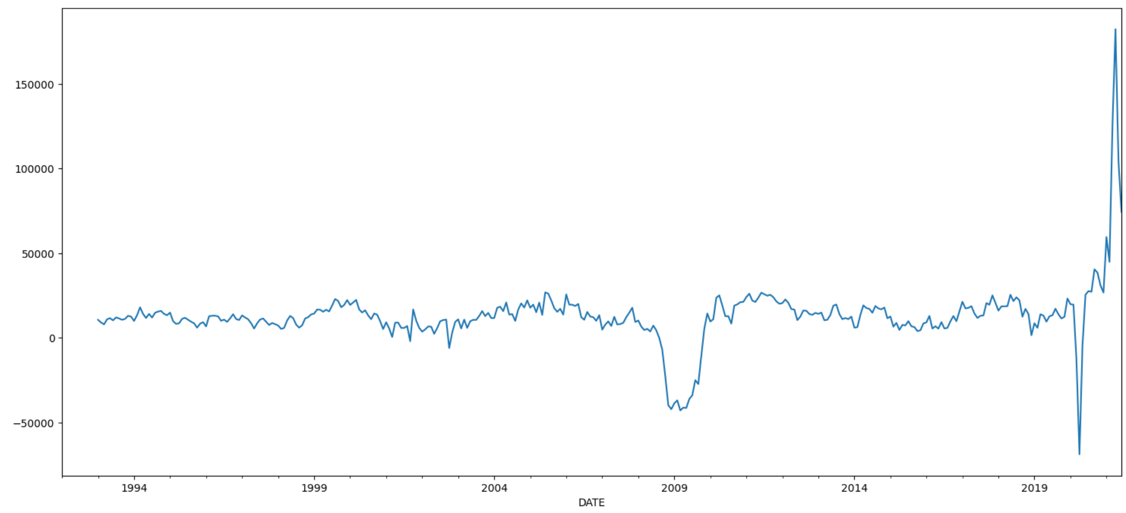
```
## Again test dickey fuller test
adfuller_test(df_arima['Seasonal First Difference'].dropna())
```

```
ADF Test Statistic : -2.2393804106097703
p-value : 0.1922642410718154
#Lags Used : 16
Number of Observations Used : 325
weak evidence against null hypothesis, time series has a unit root, indicating
it is non-stationary
```

[46]:

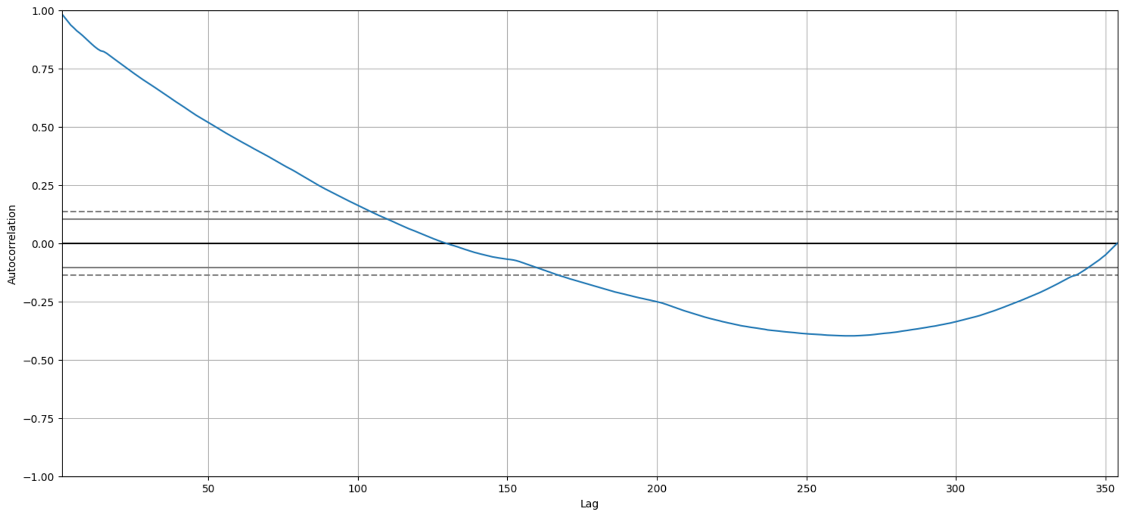
```
df_arima.set_index("DATE")['Seasonal First Difference'].plot()
```

[46]: <Axes: xlabel='DATE'>




```
[46]: # Auto correlation Plot
      from pandas.plotting import autocorrelation_plot
      autocorrelation_plot(df_arima['SALES'])
```

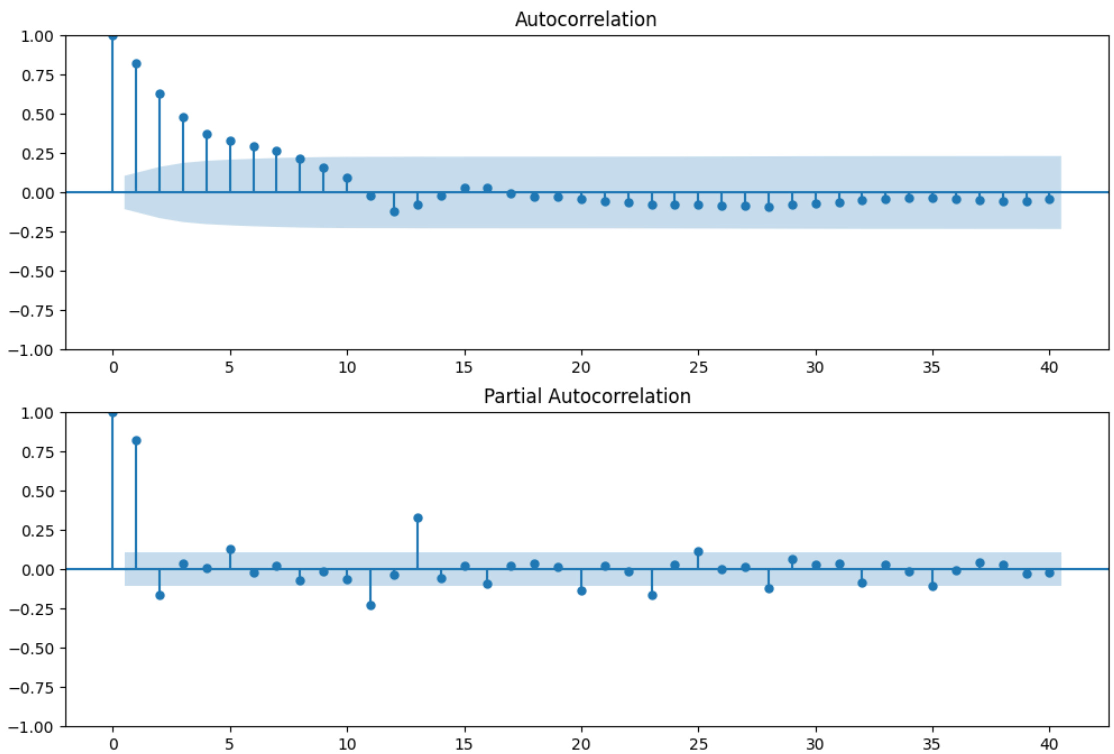
[46]: <Axes: xlabel='Lag', ylabel='Autocorrelation'>




```
[47]: from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

```
[48]: fig = plt.figure(figsize=(12,8))
      ax1 = fig.add_subplot(211)
      fig = sm.graphics.tsa.plot_acf(df_arima['Seasonal First Difference'].iloc[13:
       ↪],lags=40,ax=ax1)
```

```
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_arima['Seasonal First Difference'].iloc[13:
    ],lags=40,ax=ax2)
```



[49]:
```
# For non-seasonal data
#p=8, d=1, q=0 or 1
from statsmodels.tsa.arima.model import ARIMA
```

[50]:
```
df_arima = df_arima.set_index("DATE")
```

[57]:
```
train, test = df_arima[df_arima.index < '2020-07-01'], df_arima[df_arima.index
    >= '2020-07-01']
```

[52]:
```
model=ARIMA(train['SALES'],order=(8,1,1))
model_fit=model.fit()
```

[58]:
```
model_fit.summary()
```

[58]:

Dep. Variable:	SALES	**No. Observations:**	342
Model:	ARIMA(8, 1, 1)	**Log Likelihood**	-3436.232
Date:	Sun, 05 May 2024	**AIC**	6892.464
Time:	17:14:44	**BIC**	6930.782
Sample:	01-01-1992 - 06-01-2020	**HQIC**	6907.730
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
ar.L1	0.9662	0.019	49.870	0.000	0.928	1.004
ar.L2	-0.0954	0.018	-5.198	0.000	-0.131	-0.059
ar.L3	0.0867	0.044	1.961	0.050	4.2e-05	0.173
ar.L4	0.0405	0.186	0.218	0.828	-0.324	0.405
ar.L5	-0.0080	0.238	-0.034	0.973	-0.474	0.458
ar.L6	0.0244	0.145	0.169	0.866	-0.259	0.308
ar.L7	-0.0067	0.115	-0.059	0.953	-0.233	0.219
ar.L8	-0.0077	0.087	-0.088	0.930	-0.179	0.164
ma.L1	-0.9991	0.028	-36.223	0.000	-1.053	-0.945
sigma2	3.089e+07	1.79e-08	1.73e+15	0.000	3.09e+07	3.09e+07

Ljung-Box (L1) (Q):	0.17	**Jarque-Bera (JB):**	49619.23
Prob(Q):	0.68	**Prob(JB):**	0.00
Heteroskedasticity (H):	14.81	**Skew:**	0.28
Prob(H) (two-sided):	0.00	**Kurtosis:**	62.09

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.69e+30. Standard errors may be unstable.

[54]:

```
test
```

[54]:

```
                SALES      lag1    Resid  Sales First Difference  \
DATE
2020-07-01  481627.0  476343.0   5284.0                  5284.0
2020-08-01  483716.0  481627.0   2089.0                  2089.0
2020-09-01  493327.0  483716.0   9611.0                  9611.0
2020-10-01  493991.0  493327.0    664.0                   664.0
2020-11-01  488652.0  493991.0  -5339.0                 -5339.0
2020-12-01  484782.0  488652.0  -3870.0                 -3870.0
2021-01-01  520162.0  484782.0  35380.0                 35380.0
2021-02-01  504458.0  520162.0 -15704.0                -15704.0
2021-03-01  559871.0  504458.0  55413.0                 55413.0
2021-04-01  562269.0  559871.0   2398.0                  2398.0
2021-05-01  548987.0  562269.0 -13282.0                -13282.0
2021-06-01  550782.0  548987.0   1795.0                  1795.0

            Seasonal First Difference
DATE
```

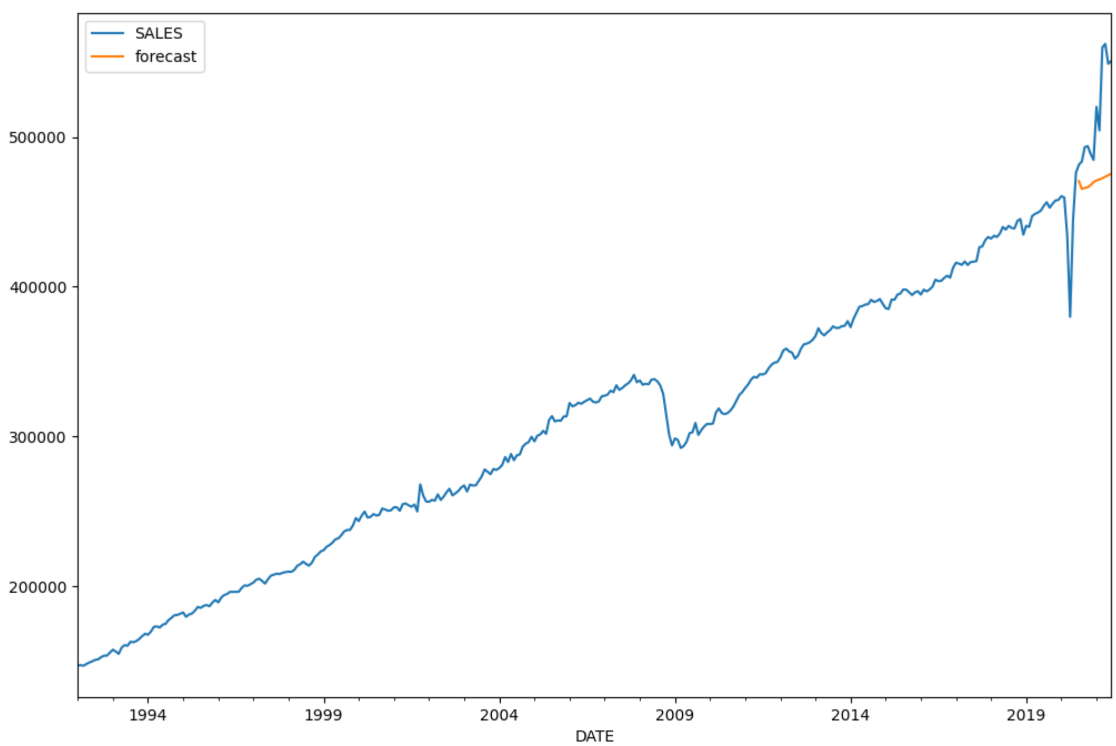
```
2020-07-01                          27615.0
2020-08-01                          27216.0
2020-09-01                          40478.0
2020-10-01                          38505.0
2020-11-01                          30994.0
2020-12-01                          26727.0
2021-01-01                          59576.0
2021-02-01                          44848.0
2021-03-01                         125590.0
2021-04-01                         182377.0
2021-05-01                         104356.0
2021-06-01                          74439.0
```

[59]:

```
df_arima['forecast']=model_fit.
 ↪predict(start='2020-07-01',end='2021-06-01',dynamic=True)
df_arima[['SALES','forecast']].plot(figsize=(12,8))
```

[59]:

```
<Axes: xlabel='DATE'>
```



[60]:

```
df_arima.tail(12)
```

[60]:

```
                    SALES      lag1    Resid  Sales First Difference  \
DATE
```

```
2020-07-01  481627.0  476343.0   5284.0                        5284.0
2020-08-01  483716.0  481627.0   2089.0                        2089.0
2020-09-01  493327.0  483716.0   9611.0                        9611.0
2020-10-01  493991.0  493327.0    664.0                         664.0
2020-11-01  488652.0  493991.0  -5339.0                       -5339.0
2020-12-01  484782.0  488652.0  -3870.0                       -3870.0
2021-01-01  520162.0  484782.0  35380.0                       35380.0
2021-02-01  504458.0  520162.0 -15704.0                      -15704.0
2021-03-01  559871.0  504458.0  55413.0                       55413.0
2021-04-01  562269.0  559871.0   2398.0                        2398.0
2021-05-01  548987.0  562269.0 -13282.0                      -13282.0
2021-06-01  550782.0  548987.0   1795.0                        1795.0

            Seasonal First Difference       forecast
DATE
2020-07-01                    27615.0  470465.117037
2020-08-01                    27216.0  465331.907771
2020-09-01                    40478.0  466105.147904
2020-10-01                    38505.0  466443.805832
2020-11-01                    30994.0  467904.230481
2020-12-01                    26727.0  469946.603227
2021-01-01                    59576.0  471026.856631
2021-02-01                    44848.0  471680.073761
2021-03-01                   125590.0  472540.337572
2021-04-01                   182377.0  473516.319557
2021-05-01                   104356.0  474488.665292
2021-06-01                    74439.0  475464.865171
```

Conclusion : The unusual high RMSE value signifies that the autoregressive model is not optimal for this exercise. The important value is an indication of how close the predictions are to the actual values. Lower values of RMSE indicate a better fit. RMSE is a worthy measure of how accurately the model predicts the response. It can be the most important criterion for fit if the main purpose of the model is prediction. An explanation for the gap in prediction and actual could be that there was an unusual spike in sales during the period of prediction time frame. With Moving Average Model, RMSE errors are reduced significantly. Since I used reseduals to predict future sales get some advantages. ARIMA model doesn't consider seasanility causing the prediction is not good but SARIMA model can predict the sales more accurately because of the season consideration but the SARIMA model code execusion didn't gave any output because of that I couldn't compared the SARIMA output with other model output.

model=sm.tsa.statespace.SARIMAX(train.SALES,order=(8, 1, 1),seasonal_order=(8,1,1,12)) results=model.fit() df_arima['forecast']=results.predict(start='2020-07-01',end='2021-06-01',dynamic=True) df_arima[['SALES','forecast']].plot(figsize=(12,8))