DCS 630

Week 8

Assignment 8

Name: Aniruddha Joshi

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In [ ]:
```
#Defining Libraries required for import
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import sklearn as sk
import textblob as tb
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.stem import PorterStemmer
import operator
import unicodedata
import sys
import re
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import roc_auc_score, confusion_matrix, roc_curve, auc
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
import geopandas as gpd
from geopy.geocoders import Nominatim
```

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
from sklearn.metrics import confusion_matrix, roc_curve, auc, mean_squared_error, r2_score, classification_report
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.metrics import confusion_matrix
from sklearn.inspection import DecisionBoundaryDisplay
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.cm as cm
import warnings
import plotly.express as px
import plotly.io as pio

from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_predict
```

In [ ]:

```python
# Initial settings
pio.renderers.default = "notebook"
warnings.filterwarnings("ignore", category=UserWarning)
```

Questions:

-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 sales.

-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.

In [ ]:
```
#Load the dataset as a Pandas data frame.

us_retail_sales_df = pd.read_csv('us_retail_sales.csv')
```

In [ ]:
```
# Set the index column and parse dates
us_retail_sales_df = us_retail_sales_df.set_index('YEAR')
#us_retail_sales_df.index = pd.to_datetime(us_retail_sales_df.index, format='%Y')

print(us_retail_sales_df)
```

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG
1992	146925	147223	146805	148032	149010	149800	150761.0	151067.0
1993	157555	156266	154752	158979	160605	160127	162816.0	162506.0
1994	167518	169649	172766	173106	172329	174241	174781.0	177295.0
1995	182413	179488	181013	181686	183536	186081	185431.0	186806.0
1996	189135	192266	194029	194744	196205	196136	196187.0	196218.0
1997	202371	204286	204990	203399	201699	204675	207014.0	207635.0
1998	209666	209552	210832	213633	214639	216337	214841.0	213636.0
1999	223997	226250	227417	229037	231235	231903	233948.0	236566.0
2000	243436	247133	249825	245831	246201	248160	247176.0	247576.0
2001	252654	252704	250328	254763	255218	254022	252997.0	254560.0
2002	256307	257670	257059	261333	257573	259786	262769.0	265043.0
2003	267230	263188	267820	267197	267362	270396	273352.0	277965.0
2004	278913	280932	286209	282952	288252	284133	287358.0	287941.0
2005	296696	300557	301308	303760	301776	310989	313520.0	310046.0
2006	322348	320171	320869	322561	321794	323184	324204.0	325324.0
2007	327181	327953	330579	329560	334202	331076	332342.0	334169.0
2008	337412	334584	335193	334843	337947	338311	336771.0	334045.0
2009	298673	297631	292300	293614	296501	302169	302802.0	309023.0
2010	308299	308628	316003	318707	315604	314925	315632.0	317408.0
2011	332357	334710	338007	339884	339303	341600	341373.0	342288.0
2012	352862	357379	358719	356849	356018	352043	353891.0	358450.0
2013	367009	372291	369081	367514	369493	371041	373554.0	372489.0
2014	373033	378581	382601	386689	387100	388106	388359.0	391305.0
2015	385648	385157	391420	391356	394718	395464	398193.0	398105.0
2016	394749	398105	396911	398190	400143	404756	403730.0	403968.0
2017	416081	415503	414620	416889	414540	416505	416744.0	417179.0
2018	432148	434106	433232	435610	439996	438191	440703.0	439278.0
2019	440751	439996	447167	448709	449552	450927	454012.0	456500.0
2020	460586	459610	434281	379892	444631	476343	481627.0	483716.0
2021	520162	504458	559871	562269	548987	550782	NaN	NaN

\

YEAR	SEP	OCT	NOV	DEC
1992	152588.0	153521.0	153583.0	155614.0
1993	163258.0	164685.0	166594.0	168161.0
1994	178787.0	180561.0	180703.0	181524.0
1995	187366.0	186565.0	189055.0	190774.0
1996	198859.0	200509.0	200174.0	201284.0
1997	208326.0	208078.0	208936.0	209363.0
1998	215720.0	219483.0	221134.0	223179.0

```
1999  237481.0  237553.0  240544.0  245485.0
2000  251837.0  251221.0  250331.0  250658.0
2001  249845.0  267999.0  260514.0  256549.0
2002  260626.0  261953.0  263568.0  265930.0
2003  276430.0  274764.0  278298.0  277612.0
2004  293139.0  295115.0  296177.0  299763.0
2005  310673.0  310479.0  313303.0  313473.0
2006  323236.0  322678.0  323343.0  326849.0
2007  335442.0  337530.0  341133.0  336189.0
2008  328343.0  314830.0  301332.0  294025.0
2009  301033.0  304154.0  306675.0  308413.0
2010  320080.0  323900.0  327745.0  329627.0
2011  345496.0  347924.0  349304.0  349744.0
2012  361470.0  361991.0  362876.0  364488.0
2013  372505.0  373663.0  373914.0  377032.0
2014  389860.0  390506.0  391805.0  388569.0
2015  396248.0  394503.0  396240.0  397052.0
2016  405958.0  407395.0  406061.0  412610.0
2017  426501.0  426933.0  431158.0  433282.0
2018  438985.0  444038.0  445242.0  434803.0
2019  452849.0  455486.0  457658.0  458055.0
2020  493327.0  493991.0  488652.0  484782.0
2021       NaN       NaN       NaN       NaN
```

Convert the data to time series dataframe

In [ ]:

```python
# Melt the DataFrame
df_melted = us_retail_sales_df.melt(ignore_index=False, var_name='month', value_name='data')

#copy the year in temp column
df_melted['temp'] = df_melted.index # df_melted['month'] # df_melted.index.to_period('M').astype(str)
#remove indexing
df_melted= df_melted.reset_index(drop=True)
#Concatinate the year and month dataframe
df_melted['year-month'] = pd.to_datetime(df_melted['temp'].astype(str) + '-' +  df_melted['month'])

#sort based on year-month
df_melted=df_melted.sort_values(by='year-month')

#drop unwated temp/column
df_melted=df_melted.drop(columns=['temp','month'])
```

```
#remove last empty readings
df_melted = df_melted.dropna()

#Check the data
df_melted.head(5)
```

Out[ ]:

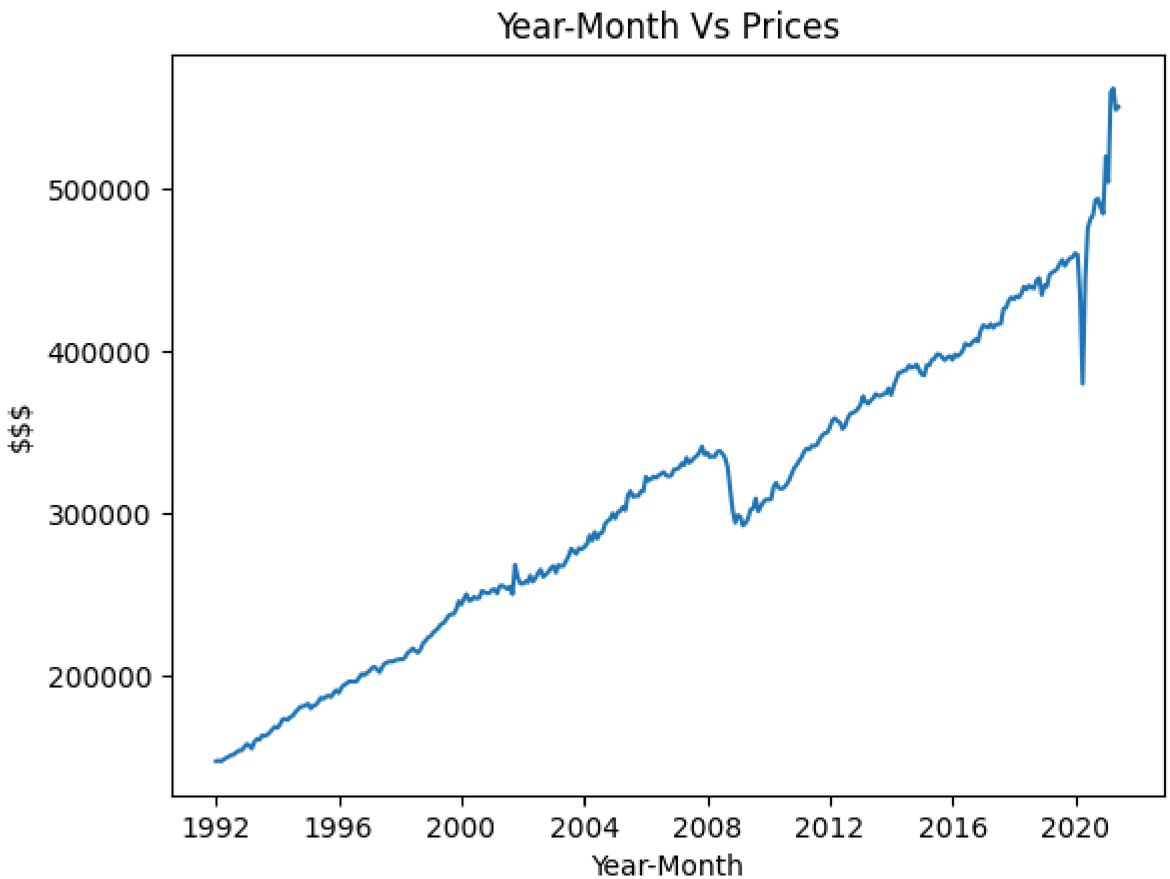
	data	year-month
0	146925.0	1992-01-01
30	147223.0	1992-02-01
60	146805.0	1992-03-01
90	148032.0	1992-04-01
120	149010.0	1992-05-01

In [ ]:

```
#Plot the data
plt.plot(df_melted['year-month'],df_melted['data'])
# Labels
plt.xlabel('Year-Month')
plt.ylabel('$$$')
plt.title('Year-Month Vs Prices')
```

Out[ ]:

```
Text(0.5, 1.0, 'Year-Month Vs Prices')
```



Comments

The graph shows the relationship between Month-year Vs Retail prices.

There increase is prices looks linear however data shows significant dips in 2008 and in 2020/2021. Those dips seem to be related to economic downturn during housing market crash and Covid pandemic.

In [ ]:

```
#print the shape of the data
df_melted.shape
```

Out[ ]:

```
(354, 2)
```

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

In [ ]:

```
# Split the training and testing data
length= df_melted.shape[0]
#Get all records except the last 12 records for training data
training_data_df=df_melted[:length-12]

#For test data, get the last 12 rcods

test_data_df =df_melted[length-12:]

#check the test data from July 2020 - June 2021
test_data_df
```

Out[ ]:

	data	year-month
208	481627.0	2020-07-01
238	483716.0	2020-08-01
268	493327.0	2020-09-01
298	493991.0	2020-10-01
328	488652.0	2020-11-01
358	484782.0	2020-12-01
29	520162.0	2021-01-01
59	504458.0	2021-02-01
89	559871.0	2021-03-01
119	562269.0	2021-04-01
149	548987.0	2021-05-01
179	550782.0	2021-06-01

In [ ]:

```
#reset index. Remove indexing to simply graphs
training_data_df=training_data_df.reset_index(drop=True)
```

```
training_data_df
```

Out[ ]:

	data	year-month
0	146925.0	1992-01-01
1	147223.0	1992-02-01
2	146805.0	1992-03-01
3	148032.0	1992-04-01
4	149010.0	1992-05-01
...	...	...
337	459610.0	2020-02-01
338	434281.0	2020-03-01
339	379892.0	2020-04-01
340	444631.0	2020-05-01
341	476343.0	2020-06-01

342 rows × 2 columns

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

In [ ]:

```
model = ARIMA(training_data_df['data'], order=(25,3,2))  #
model_fit = model.fit()

#p= 25 values form the past samples
#d=3 The model will perform differencing once to remove any trend in the data before making predictions.
#q=2 The model will use a moving average of one past forecast error to adjust its current prediction.
```

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

In [ ]:

```
forecast = model_fit.forecast(steps=12)  # Predict the next 12 months
print(forecast)
```

```
342    494390.324842
343    498867.052808
344    499269.687155
345    495309.450565
346    493222.256002
347    492469.333657
348    490889.369419
349    491947.288901
350    493657.088468
351    498557.218956
352    502469.223689
353    504055.217288
Name: predicted_mean, dtype: float64
```

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

In [ ]:

```
# 2. Calculate RMSE
rmse = np.sqrt(mean_squared_error(test_data_df['data'], forecast))
print("RMSE:", rmse)
```

```
RMSE: 34537.01721395114
```

In [ ]:

```
test_data_df['data']
```

Out[ ]:

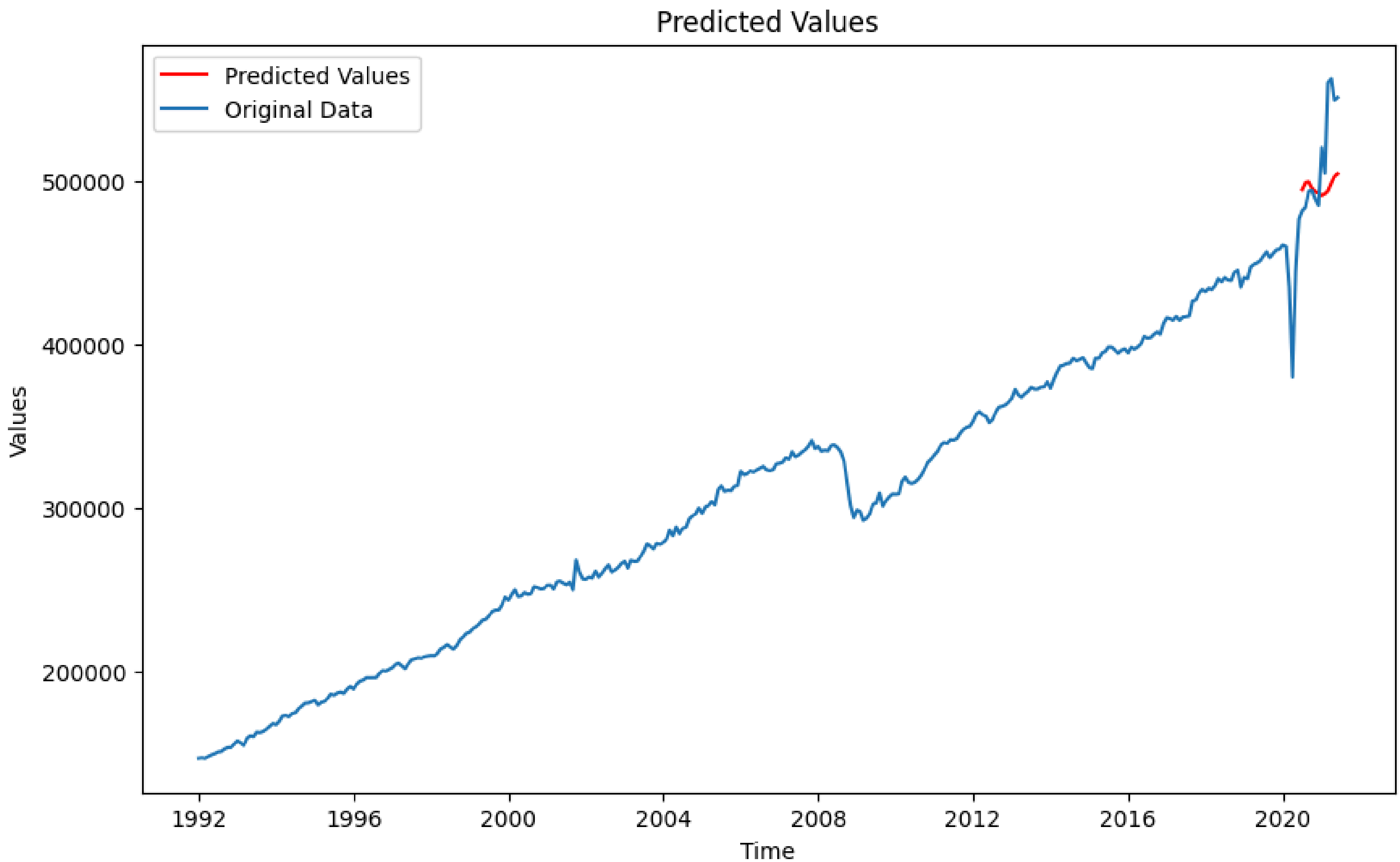
```
208    481627.0
238    483716.0
268    493327.0
298    493991.0
328    488652.0
358    484782.0
29     520162.0
59     504458.0
89     559871.0
119    562269.0
149    548987.0
179    550782.0
Name: data, dtype: float64
```

In [ ]:

```
#plot the graph
plt.figure(figsize=(10, 6))
plt.plot(test_data_df['year-month'],forecast, color='red', label='Predicted Values')
```

```
# Optional: Add the original data for comparison
plt.plot(df_melted['year-month'],df_melted['data'], label='Original Data')

plt.xlabel('Time')
plt.ylabel('Values')
plt.title('Predicted Values')
plt.legend()
plt.show()
```



Second attempt with different tuning parameters

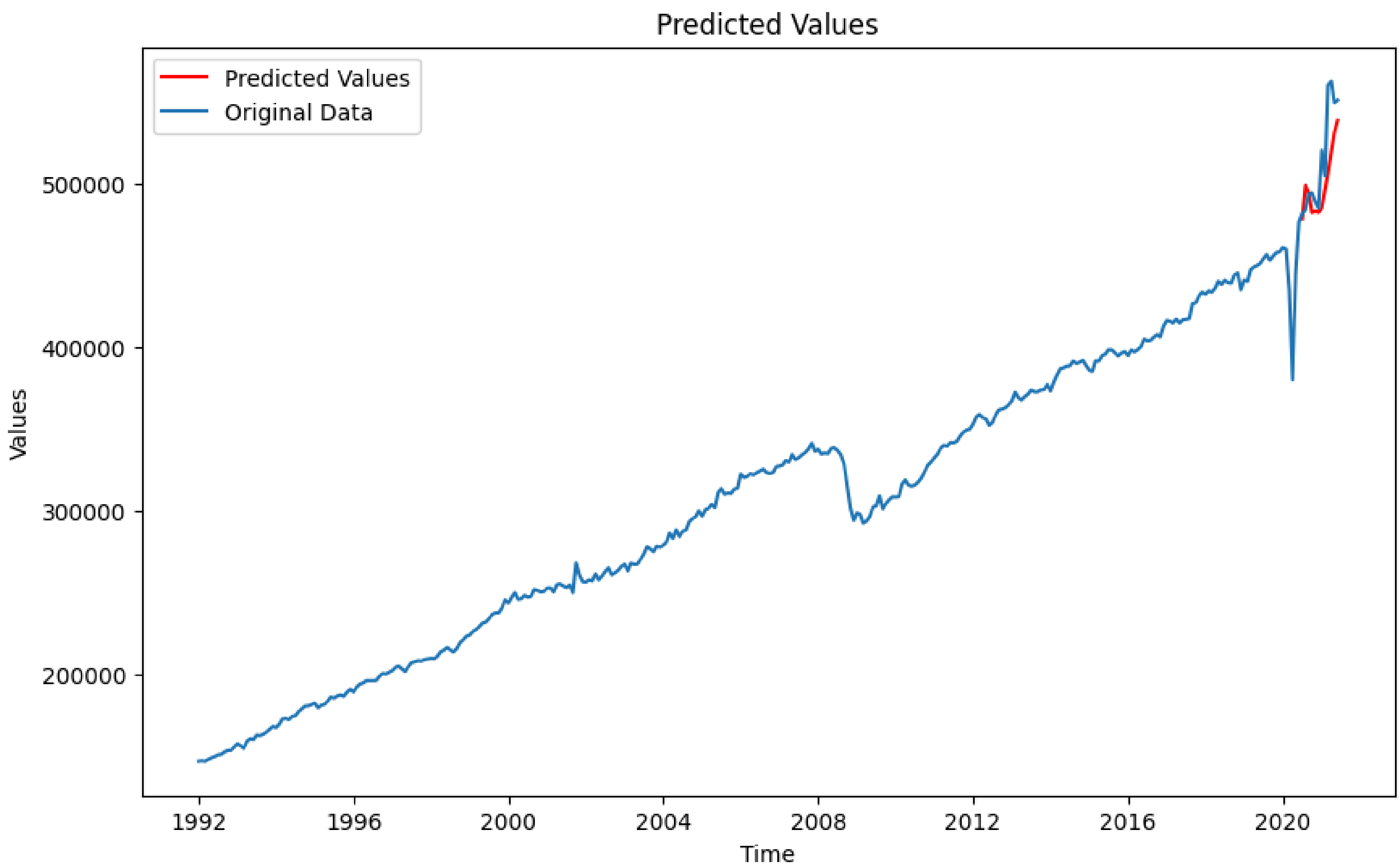
In [ ]:
```
model = ARIMA(training_data_df['data'], order=(25,5,5))  #
model_fit = model.fit()
forecast = model_fit.forecast(steps=12)  # Predict the next 12 months
print(forecast)
#p= 25 values form the past samples
#d=3 The model will perform differencing once to remove any trend in the data before making predictions.
#q=2 The model will use a moving average of one past forecast error to adjust its current prediction.
```

```
342    478145.336108
343    498849.497570
344    493957.334594
345    482138.391856
346    483013.348582
347    482294.354315
348    484493.621067
349    495669.837746
350    506116.692604
351    519111.682882
352    531110.088538
353    538252.708994
Name: predicted_mean, dtype: float64
```

In [ ]:
```
#plot the graph
plt.figure(figsize=(10, 6))
plt.plot(test_data_df['year-month'],forecast, color='red', label='Predicted Values')

# Optional: Add the original data for comparison
plt.plot(df_melted['year-month'],df_melted['data'], label='Original Data')

plt.xlabel('Time')
plt.ylabel('Values')
plt.title('Predicted Values')
plt.legend()
plt.show()
```



In [ ]:
```
# 2. Calculate RMSE
rmse = np.sqrt(mean_squared_error(test_data_df['data'], forecast))
print("RMSE:", rmse)
```

```
RMSE: 24149.05256437495
```

Conslusion:

By using time series libraries like ARIMA, we can predict the value for the extended periods based on past performance.

However, the model needs to be tuned appropriately. In this experiment, we used ARIMA model to predict the future timeseries values.