Exercise 8.2 - Time Series Modeling

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:

1. Plot the data with proper labeling and make some observations on the graph.
2. 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.
3. Use the training set to build a predictive model for the monthly retail sales.
4. Use the model to predict the monthly retail sales on the last year of data.
5. Report the RMSE of the model predictions on the test set.

In [1]:

```
## import the required packages

import pandas as pd
import numpy as nm
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from datetime import datetime
```

In [2]:

```
## import the retail sales data into dataframe

sales_df = pd.read_csv('us_retail_sales.csv')
sales_df.head()
```

Out[2]:

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	
0	1992	146925	147223	146805	148032	149010	149800	150761.0	151067.0	152588.0	153521.0	153
1	1993	157555	156266	154752	158979	160605	160127	162816.0	162506.0	163258.0	164685.0	166
2	1994	167518	169649	172766	173106	172329	174241	174781.0	177295.0	178787.0	180561.0	180
3	1995	182413	179488	181013	181686	183536	186081	185431.0	186806.0	187366.0	186565.0	189
4	1996	189135	192266	194029	194744	196205	196136	196187.0	196218.0	198859.0	200509.0	200

Understanding the data

In [3]:

```
sales_df.shape
```

Out[3]: (30, 13)

In [4]:

```
sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 30 entries, 0 to 29
Data columns (total 13 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   YEAR    30 non-null     int64  
 1   JAN     30 non-null     int64  
 2   FEB     30 non-null     int64  
 3   MAR     30 non-null     int64  
 4   APR     30 non-null     int64  
 5   MAY     30 non-null     int64  
 6   JUN     30 non-null     int64  
 7   JUL     29 non-null     float64
 8   AUG     29 non-null     float64
 9   SEP     29 non-null     float64
 10  OCT     29 non-null     float64
 11  NOV     29 non-null     float64
 12  DEC     29 non-null     float64
dtypes: float64(6), int64(7)
memory usage: 3.2 KB
```

Creating a one dimensional data set of the sales data set with Year being the ID, Month being the variable and the sales being the value

In [5]:

```
sales_data = pd.melt(sales_df, id_vars=["YEAR"], var_name="Month", value_name="Sales")
sales_data
```

Out[5]:

	YEAR	Month	Sales
0	1992	JAN	146925.0
1	1993	JAN	157555.0
2	1994	JAN	167518.0
3	1995	JAN	182413.0
4	1996	JAN	189135.0
...	...	...	...
355	2017	DEC	433282.0
356	2018	DEC	434803.0
357	2019	DEC	458055.0
358	2020	DEC	484782.0
359	2021	DEC	NaN

360 rows × 3 columns

Replacing the month names with numbers

In [6]:

```
sales_data["Month"].replace({'JAN': 1, 'FEB': 2, 'MAR': 3, 'APR': 4, 'MAY': 5, 'JUN': 6
                'SEP': 9, 'OCT': 10, 'NOV': 11, 'DEC': 12}, inplace=True)
sales_data
```

Out[6]:

	YEAR	Month	Sales

	YEAR	Month	Sales
0	1992	1	146925.0
1	1993	1	157555.0
2	1994	1	167518.0
3	1995	1	182413.0
4	1996	1	189135.0
...	...	...	...
355	2017	12	433282.0
356	2018	12	434803.0
357	2019	12	458055.0
358	2020	12	484782.0
359	2021	12	NaN

360 rows × 3 columns

creating a new field Date based on the Year and Month fields and assigning the first day of that month.

In [7]:

```
sales_data['DATE'] = pd.to_datetime(sales_data[['YEAR', 'Month']].assign(DAY=1))
sales_data
```

Out[7]:

	YEAR	Month	Sales	DATE
0	1992	1	146925.0	1992-01-01
1	1993	1	157555.0	1993-01-01
2	1994	1	167518.0	1994-01-01
3	1995	1	182413.0	1995-01-01
4	1996	1	189135.0	1996-01-01
...	...	...	...	...
355	2017	12	433282.0	2017-12-01
356	2018	12	434803.0	2018-12-01
357	2019	12	458055.0	2019-12-01
358	2020	12	484782.0	2020-12-01
359	2021	12	NaN	2021-12-01

360 rows × 4 columns

Sorting the dataset on date and resetting the index values

In [8]:

```
sales_data = sales_data.sort_values(by=['DATE'])
```

```
sales_data
```

Out[8]:

	YEAR	Month	Sales	DATE
0	1992	1	146925.0	1992-01-01
30	1992	2	147223.0	1992-02-01
60	1992	3	146805.0	1992-03-01
90	1992	4	148032.0	1992-04-01
120	1992	5	149010.0	1992-05-01
...	...	...	...	...
239	2021	8	NaN	2021-08-01
269	2021	9	NaN	2021-09-01
299	2021	10	NaN	2021-10-01
329	2021	11	NaN	2021-11-01
359	2021	12	NaN	2021-12-01

360 rows × 4 columns

In [9]:

```
sales_data = sales_data.reset_index(drop=True)
sales_data
```

Out[9]:

	YEAR	Month	Sales	DATE
0	1992	1	146925.0	1992-01-01
1	1992	2	147223.0	1992-02-01
2	1992	3	146805.0	1992-03-01
3	1992	4	148032.0	1992-04-01
4	1992	5	149010.0	1992-05-01
...	...	...	...	...
355	2021	8	NaN	2021-08-01
356	2021	9	NaN	2021-09-01
357	2021	10	NaN	2021-10-01
358	2021	11	NaN	2021-11-01
359	2021	12	NaN	2021-12-01

360 rows × 4 columns

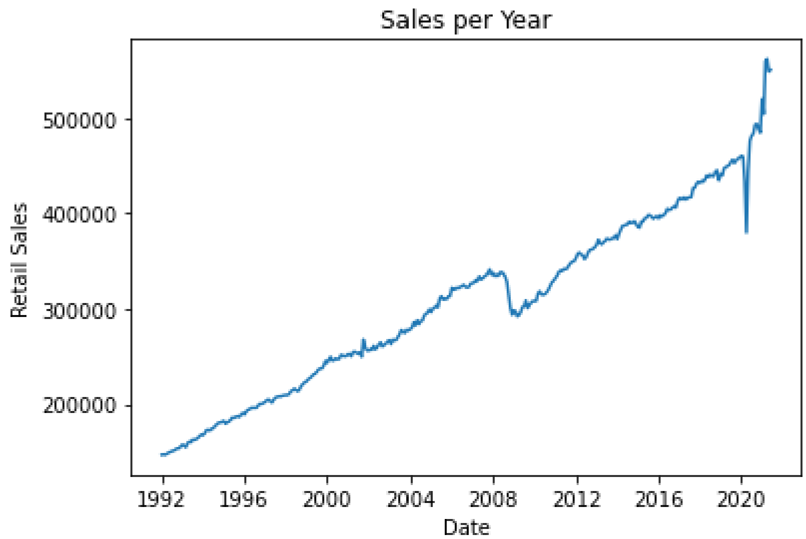
In [10]:

```
## Plotting the dataset - date vs retail sales

x = sales_data.DATE
y = sales_data.Sales
```

```
plt.plot(x, y)
plt.xlabel("Date")
plt.ylabel("Retail Sales")
plt.title("Sales per Year")
```

Out[10]: Text(0.5, 1.0, 'Sales per Year')



We can see there was a slump in the retail sales during the 2008-2009 recession. but it slowly picked up until the 2020 pandemic early that year which again saw a steep fall for a brief period of time.

In [11]:

```
## Dropping all the nulls in the dataset

sales_data.dropna(inplace=True)
sales_data
```

Out[11]:

	YEAR	Month	Sales	DATE
0	1992	1	146925.0	1992-01-01
1	1992	2	147223.0	1992-02-01
2	1992	3	146805.0	1992-03-01
3	1992	4	148032.0	1992-04-01
4	1992	5	149010.0	1992-05-01
...	...	...	...	...
349	2021	2	504458.0	2021-02-01
350	2021	3	559871.0	2021-03-01
351	2021	4	562269.0	2021-04-01
352	2021	5	548987.0	2021-05-01
353	2021	6	550782.0	2021-06-01

354 rows × 4 columns

In [12]:

```python
## adding a new feature OrdDate which is the integer conversion of the date value for t

sales_data['OrdDate'] = pd.to_datetime(sales_data['DATE'])
sales_data['OrdDate'] = sales_data['OrdDate'].map(datetime.toordinal)
```

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.

Sales is the target value to be predicted.

In [13]:

```python
## splitting data into train and test sets

train_df = sales_data[sales_data['DATE'] < '2020-07-01']
test_df = sales_data[sales_data['DATE'] >= '2020-07-01']
```

In [14]:

```python
X_train = train_df[['OrdDate']]
y_train = train_df[["Sales"]]
X_test = test_df[['OrdDate']]
y_test = test_df[["Sales"]]
```

In [15]:

```python
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12 entries, 342 to 353
Data columns (total 1 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   OrdDate   12 non-null     int64
dtypes: int64(1)
memory usage: 192.0 bytes
```

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

Building a prediction model using Linear Regression model

In [16]:

```python
## Linear regression modeling
# Create a model
model = LinearRegression()

# Fit the model to the training set
model.fit(X_train, y_train)
```

Out[16]:

```
LinearRegression()
```

In [17]:

```python
## predicting the sales values on the test set

test_predictions = model.predict((X_test))
test_predictions
```

Out[17]:

```
array([[449450.188174  ],
```

```
       [450339.37662852],
       [451228.56508304],
       [452089.07003903],
       [452978.25849355],
       [453838.76344953],
       [454727.95190405],
       [455617.14035857],
       [456420.2783175 ],
       [457309.46677202],
       [458169.971728  ],
       [459059.16018252]])
```

In [18]:

```
y_test = y_test.reset_index(drop=True)
y_test
```

Out[18]:

	Sales
0	481627.0
1	483716.0
2	493327.0
3	493991.0
4	488652.0
5	484782.0
6	520162.0
7	504458.0
8	559871.0
9	562269.0
10	548987.0
11	550782.0

In [19]:

```
## converting the prediction result array to dataframe

pred_test = pd.DataFrame(test_predictions, columns=['pred_sales'])
pred_test
```

Out[19]:

	pred_sales
0	449450.188174
1	450339.376629
2	451228.565083
3	452089.070039
4	452978.258494
5	453838.763450
6	454727.951904
7	455617.140359

	pred_sales
8	456420.278317
9	457309.466772
10	458169.971728
11	459059.160183

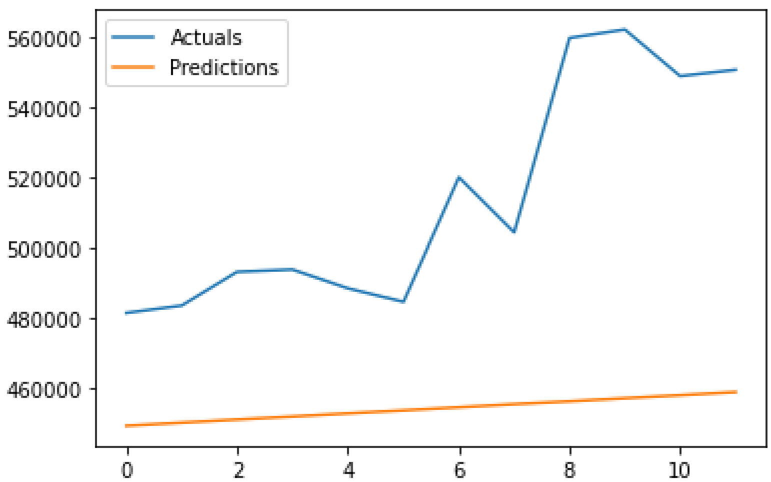
In [20]:

```
## plotting the actuals and predicted values.

plt.plot(y_test, label = 'Actuals')
plt.plot(test_predictions, label = 'Predictions')
plt.legend()
```

Out[20]:

```
<matplotlib.legend.Legend at 0x1fd511bcf10>
```



In [21]:

```
print('Test RMSE:', metrics.mean_squared_error(y_test, test_predictions, squared=False))
```

```
Test RMSE: 66429.10224838056
```

From the Actuals and Predictions plot and RMSE score, we can see the predicted values are way off the actuals. This could be because the actuals had a spike during the mid of 2020, during the pandemic.