### **Time Series Modeling**

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

```
In [65]:
```

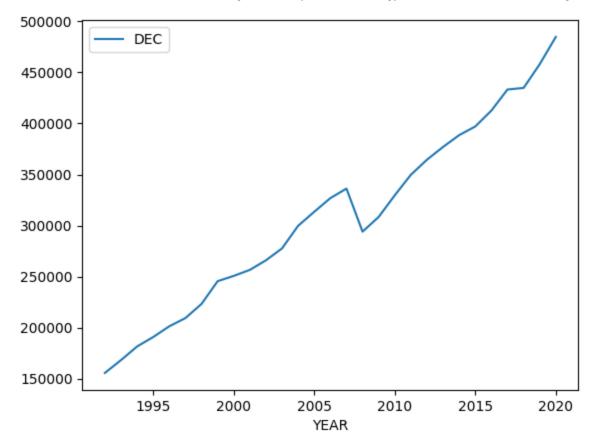
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear\_model import LinearRegression
from datetime import datetime
from sklearn import metrics
from statsmodels.tsa.ar\_model import AutoReg
from numpy import sqrt
from sklearn.metrics import mean\_squared\_error

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

In [46]:

time df.plot('YEAR', 'DEC')

Out[46]:<Axes: xlabel='YEAR'>



Although not pictured to save room, plotting all months by year showed a very similar line shape across all months. An increase from 1995 to 2006–2007, a sharp decline from 2008–2009 and then back to an increase all th way till 2021. We can confrim this with the MELT function below.

Out[50]:		YEAR	MONTH	SALES	Month	DATE
	0	1992	JAN	146925.0	1	1992-01-01
	1	1993	JAN	157555.0	1	1993-01-01
	2	1994	JAN	167518.0	1	1994-01-01
	3	1995	JAN	182413.0	1	1995-01-01
	4	1996	JAN	189135.0	1	1996-01-01

```
In [51]:
    #clean the data up
    time_df_clean = time_df_short[['DATE','SALES']].sort_values('DATE')
    time_df_clean = time_df_clean.dropna()
```

```
time datetime index = pd.DatetimeIndex(time df clean['DATE'].values)
      time_df_clean = time_df_clean.set_index(time_datetime_index)
      time_df_clean.drop('DATE', axis=1, inplace=True)
      time_df_clean
Out[51]:
                     SALES
```

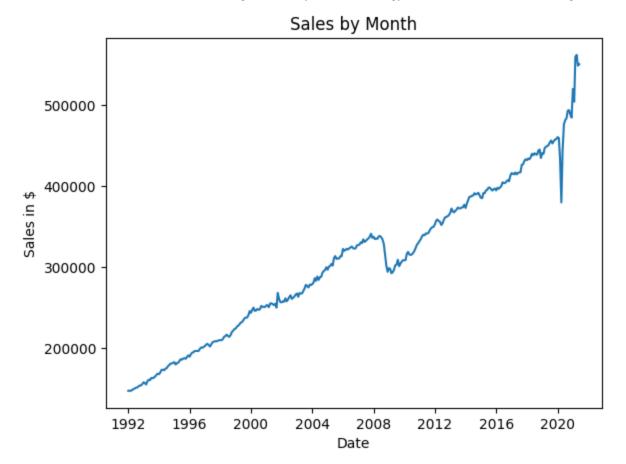
1992-01-01 146925.0 1992-02-01 147223.0 1992-03-01 146805.0 1992-04-01 148032.0 1992-05-01 149010.0 **2021-02-01** 504458.0 2021-03-01 559871.0 **2021-04-01** 562269.0 **2021-05-01** 548987.0

354 rows × 1 columns

**2021-06-01** 550782.0

## In [52]:

```
#plot the new frame to confrim the line trends of the first graph
plt.plot(time_df_clean["SALES"])
plt.title('Sales by Month')
plt.xlabel('Date')
plt.ylabel('Sales in $')
plt.show()
```



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.

```
In [53]:
          train_time_df = time_df_clean[time_df_clean.index < '2020-07-01']
          test_time_df = time_df_clean[time_df_clean.index >= '2020-07-01']
```

In [54]:
 train\_time\_df

Out[54]:		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
	•••	
	2020-02-01	459610.0
	2020-03-01	434281.0
	2020-04-01	379892.0
	2020-05-01	444631.0

#### **SALES**

#### **2020-06-01** 476343.0

342 rows × 1 columns

In [55]:

test\_time\_df

0		
Out[55]:		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
	2020-12-01	484782.0
	2021-01-01	520162.0
	2021-02-01	504458.0
	2021-03-01	559871.0
	2021-04-01	562269.0
	2021-05-01	548987.0

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

In [58]:
 time\_model = AutoReg(train\_time\_df, lags=5).fit()

/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-packages/statsm odels/tsa/base/tsa\_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.

self \_\_init\_dates(dates, freq)

**2021-06-01** 550782.0

In [59]:

print(time\_model.summary())

# AutoReg Model Results

=========	========	=========	=======	=========	=======	========	
Dep. Variab Model: Method: Date: Time: Sample:		SALES AutoReg(5) Conditional MLE Sat, 03 Feb 2024 20:36:22 06-01-1992 - 06-01-2020		Observations: Likelihood of innovation	าร	342 -3375.942 5424.567 6765.884 6792.624 6776.542	
==========	coef	std err	z	======== P> z	[0.025	0.975]	
const	2180.0628	1089 <b>.</b> 933	2.000	0.045	43.833	4316.293	

2/3/24,	8:46	PM

SALES.L1	0.8523	0.055	15.449	0.000	0.744	0.960
SALES.L2	-0.3524	0.080	-4.407	0.000	-0.509	-0.196
SALES.L3	0.3427	0.130	2.629	0.009	0.087	0.598
SALES.L4	0.2459	0.134	1.839	0.066	-0.016	0.508
SALES.L5	-0.0908	0.100	-0.904	0.366	-0.288	0.106
			Roots			

=======	======================================	Imaginary	Modulus	Frequency
AR.1	1.0013	-0.0000j	1.0013	-0.0000
AR.2	0.0573	-1.2351j	1.2364	-0.2426
AR.3	0.0573	+1.2351j	1.2364	0.2426
AR.4	-2.0016	-0.0000j	2.0016	-0.5000
AR.5	3.5941	-0.0000j	3.5941	-0.0000

<sup>4.</sup> Use the model to predict the monthly retail sales on the last year of data.

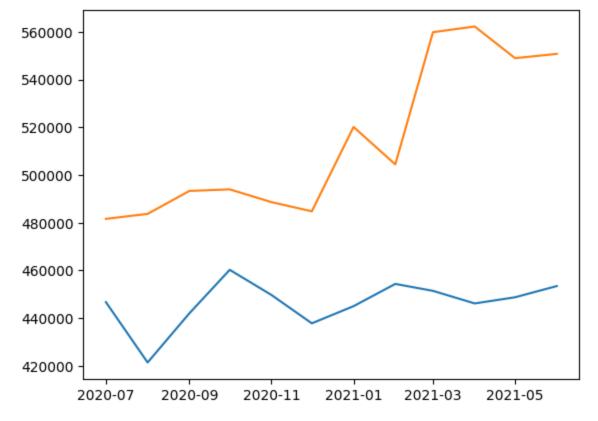
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-packages/statsm odels/tsa/deterministic.py:302: UserWarning: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index with a unit increment support extending. The index is set will contain the position relative to the data length.

fcast\_index = self.\_extend\_index(index, steps, forecast\_index)

In [61]:

plt.plot(time\_pred)
plt.plot(test\_time\_df)

Out[61]:[<matplotlib.lines.Line2D at 0x1200c6690>]



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

```
In [67]:
    rmse = sqrt(mean_squared_error(test_time_df, time_pred))
    print('Test RMSE: %.3f' % rmse)
```

Test RMSE: 73875.521