Brian_Reppeto_DSC630_Week_8

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0.0.1 DSC 630 Week :

Activity 8.2

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0.0.2 import libraries

[75]:
```
# import libraries

import pandas as pd
import numpy as np
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
```

[93]:
```
# load the dataset

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

Preview the First 15 Rows

[77]:
```
# head the data

df.head(15)
```

[77]:

	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	
5	1997	202371	204286	204990	203399	201699	204675	207014.0	207635.0	
6	1998	209666	209552	210832	213633	214639	216337	214841.0	213636.0	
7	1999	223997	226250	227417	229037	231235	231903	233948.0	236566.0	
8	2000	243436	247133	249825	245831	246201	248160	247176.0	247576.0	
9	2001	252654	252704	250328	254763	255218	254022	252997.0	254560.0	
10	2002	256307	257670	257059	261333	257573	259786	262769.0	265043.0	
11	2003	267230	263188	267820	267197	267362	270396	273352.0	277965.0	

```
12  2004  278913  280932  286209  282952  288252  284133  287358.0  287941.0
13  2005  296696  300557  301308  303760  301776  310989  313520.0  310046.0
14  2006  322348  320171  320869  322561  321794  323184  324204.0  325324.0

         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
5   208326.0  208078.0  208936.0  209363.0
6   215720.0  219483.0  221134.0  223179.0
7   237481.0  237553.0  240544.0  245485.0
8   251837.0  251221.0  250331.0  250658.0
9   249845.0  267999.0  260514.0  256549.0
10  260626.0  261953.0  263568.0  265930.0
11  276430.0  274764.0  278298.0  277612.0
12  293139.0  295115.0  296177.0  299763.0
13  310673.0  310479.0  313303.0  313473.0
14  323236.0  322678.0  323343.0  326849.0
```

Check for missing values in the dataset by summing the null values for each column

[78]:
```python
# check for nulls

df.isnull().sum()
```

[78]:
```
YEAR    0
JAN     0
FEB     0
MAR     0
APR     0
MAY     0
JUN     0
JUL     1
AUG     1
SEP     1
OCT     1
NOV     1
DEC     1
dtype: int64
```

Fill Missing Values

[79]:
```python
# fill missing values with mean

df.fillna(df.mean(), inplace=True)
```

[80]:
```python
# recheck for missing values after filling with mean

df.isnull().sum()
```

[80]:
```
YEAR    0
JAN     0
FEB     0
MAR     0
APR     0
MAY     0
JUN     0
JUL     0
AUG     0
SEP     0
OCT     0
NOV     0
DEC     0
dtype: int64
```

Transform the dataframe where each year has multiple month columns into a long format where each row represents one month of sales for a particular year

[81]:
```python
# reshape the data into long format

df_long = df.melt(id_vars=['YEAR'], var_name='Month', value_name='Sales')
df_long['Date'] = pd.to_datetime(df_long['YEAR'].astype(str) +␣
 ↪df_long['Month'], format='%Y%b')
df_long = df_long.sort_values('Date')
```

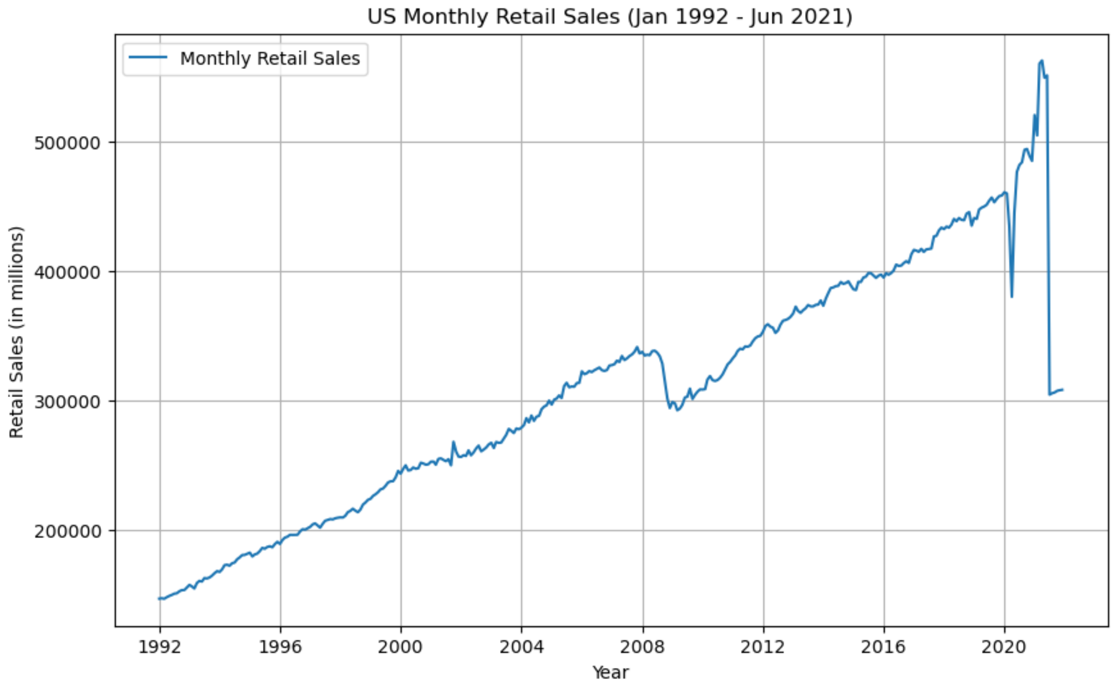
Set the 'Date' column as the index of the df, and convert the index into a period index with a monthly frequency

[82]:
```python
# set the dat column as the index and define frequency as monthly

df_long.set_index('Date', inplace=True)
df_long.index = df_long.index.to_period('M')
```

[91]:
```python
# plot the data

plt.figure(figsize=(10, 6))
plt.plot(df_long.index.to_timestamp(), df_long['Sales'], label='Monthly Retail␣
 ↪Sales')
plt.xlabel('Year')
plt.ylabel('Retail Sales (in millions)')
plt.title('US Monthly Retail Sales (Jan 1992 - Jun 2021)')
plt.grid(True)
plt.legend()
plt.show()
```



The graph shows a general upward trend in monthly retail sales in the US from January 1992 to June 2021. There are noticeable peaks, which typically occur towards the end of each year. The spikes are likely due to holiday spending late in the year. The trend was stable until the 2008 financial crisis, after which there is a slight dip, followed by anoother recovery. Another notable change occurs in 2020, likely due to the COVID-19 pandemic, where sales initially dip sharply and then recover.

Split the dataset into a training set and a test set. The training set will be used to build the predictive model, while the test set will be used to evaluate the accuracy of the model's predictions. The copy method ensures that the original df remains unchanged

[84]:
```
# split the data into training (up to June 2020) and test set (July 2020 - June
↪2021)

train_data = df_long[df_long.index < '2020-07'].copy()
test_data = df_long[(df_long.index >= '2020-07') & (df_long.index <=
↪'2021-06')].copy()
```

0.0.3 Create a model to predict future sales by recognizing patterns in past data, like seasonal changes and overall trends

[86]:
```
# build a predictive model using holt winters
```

```
hw_model = ExponentialSmoothing(train_data['Sales'], seasonal='add',
    trend='add', seasonal_periods=12, use_boxcox=True).fit(optimized=True,
    remove_bias=True)
```

[87]:
```
# predict the monthly retail sales for the last year

hw_predictions = hw_model.forecast(steps=len(test_data))
```

[88]:
```
# report the RMSE of the model predictions on the test set

hw_rmse = np.sqrt(mean_squared_error(test_sales, hw_predictions))
print(f"Holt-Winters RMSE: {hw_rmse}")
```

```
Holt-Winters RMSE: 45306.78927223505
```