Campbell, Julie_630_Week8

October 18, 2023

1 Week 8: Time Series Modeling

[1]:
```
# Load libraries
import pandas as pd
import numpy as np
import datetime
from statsmodels.tsa.holtwinters import ExponentialSmoothing
# Graphs
import matplotlib.pyplot as plt
import seaborn as sns
# Warnings
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
# Read csv file
sales = pd.read_csv('data/us_retail_sales.csv')
```

[4]:
```
sales.shape
```

[4]:
```
(30, 13)
```

[5]:
```
sales.head()
```

[5]:
```
   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
```

1.1 Prep

[3]:
```
# Melt month columns into rows
sales_melt = pd.melt(sales, id_vars =['YEAR'])
```

[4]:
```
# Create date from year and month
sales_melt['date'] = pd.to_datetime(sales_melt['YEAR'].astype(str) +␣
↪sales_melt['variable'], format='%Y%b')
# Drop year and month
sales_melt = sales_melt.drop(['YEAR', 'variable'], axis=1)
```

[5]:
```
# Sort date
sales_melt = sales_melt.sort_values('date')
```

[6]:
```
# Set index to date
sales_melt = sales_melt.set_index('date')
```

[7]:
```
# Rename value to sales
sales_melt.rename(columns={'value': 'sales'}, inplace=True)
```

[8]:
```
# Find null values
sales_melt.isna().sum()
```

[8]:
```
sales    6
dtype: int64
```

[9]:
```
# Drop null records
sales_melt.dropna(inplace= True, how='any')
```

[154]:
```
# Describe sales
sales_melt.describe()
```

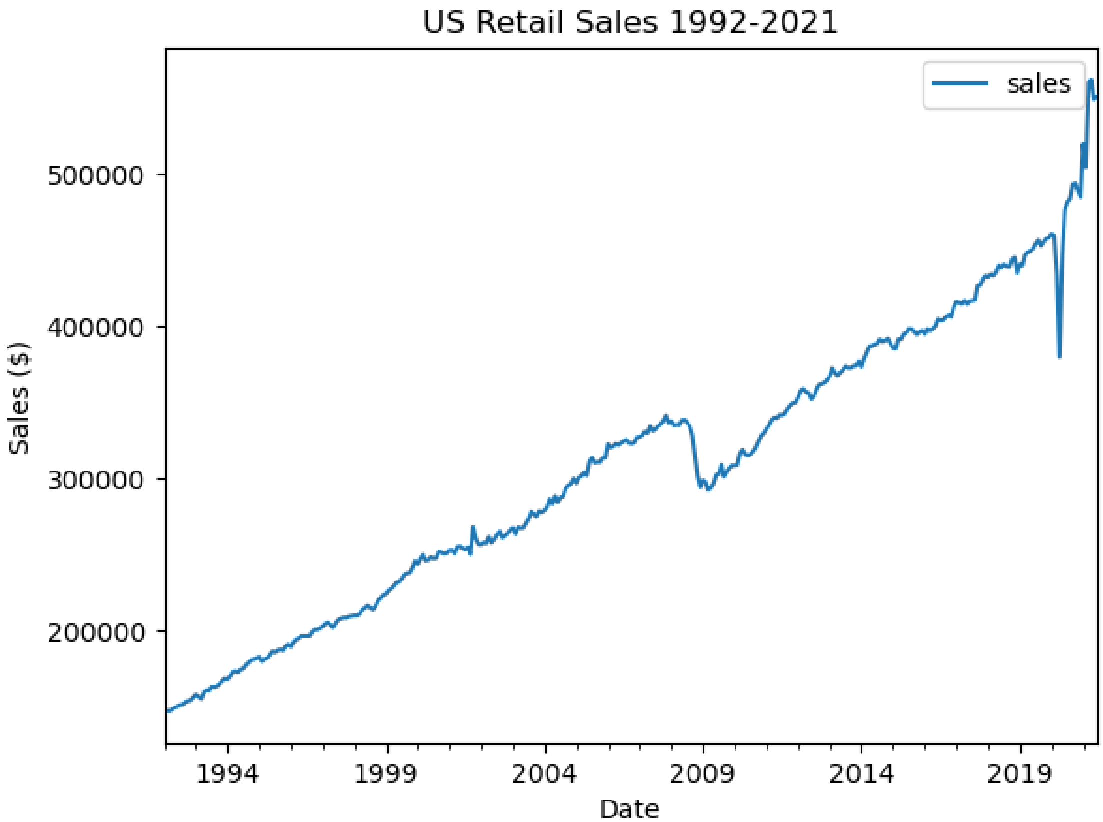
[154]:

	sales
count	354.000000
mean	307006.573446
std	94335.828235
min	146805.000000
25%	231402.000000
50%	309534.500000
75%	378193.750000
max	562269.000000

1.2 Plot

[156]:
```
# Plot true retail sales
sales_melt.plot()
plt.title("US Retail Sales 1992-2021")
plt.xlabel("Date")
```

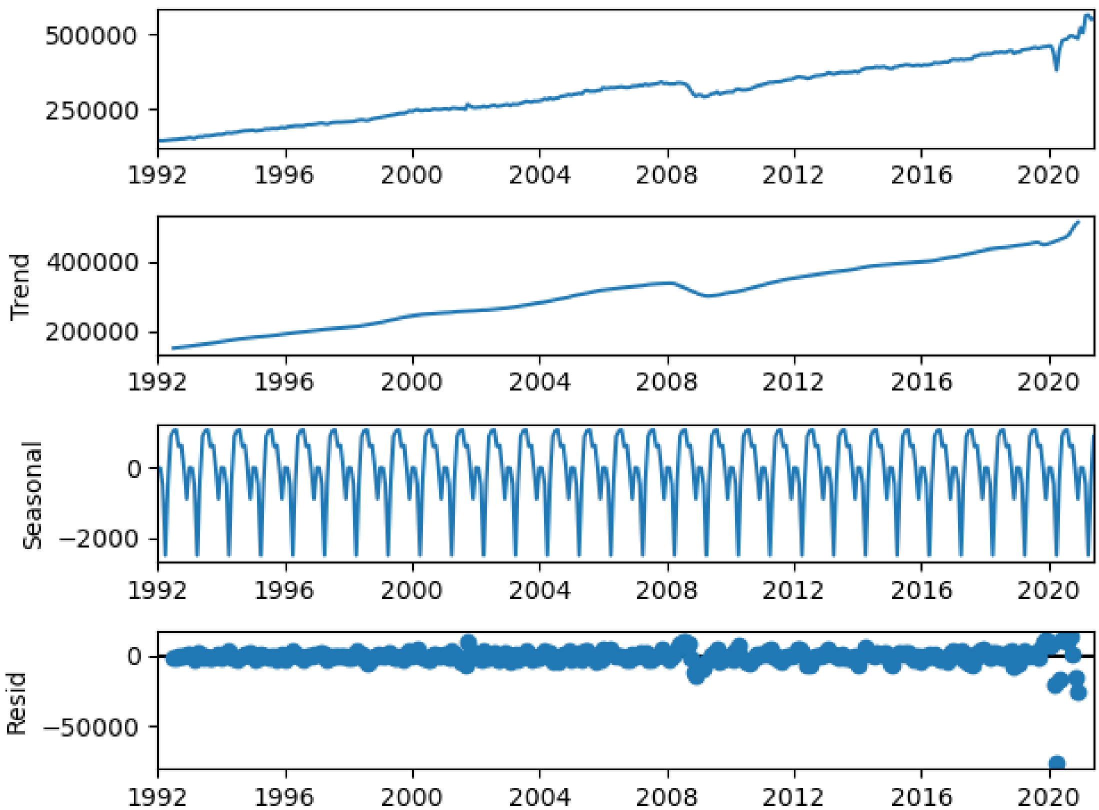
```
plt.ylabel("Sales ($)")
plt.show()
```

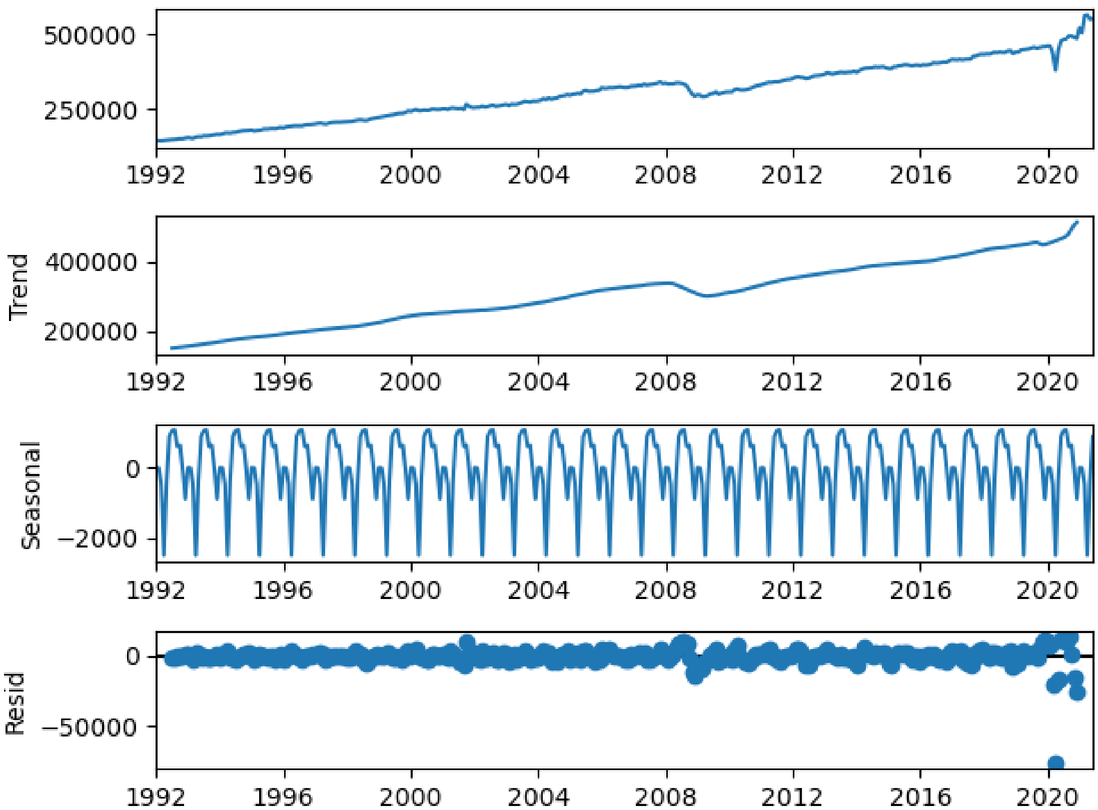


Based on the line plot above, it appears that sales steadily increase until 2020. There appears to be a huge dip and later a much larger spike that historically found.

[198]:
```
# Find seasonality
decompose_data = seasonal_decompose(sales_melt, model="additive")
decompose_data.plot()
```

[198]:


500000
250000
1992
1996
2000
2004
2008
2012
2016
2020
Trend
400000
200000
Seasonal
0
−2000
Resid
0
−50000



1.3 Split

[11]:
```
# Split train/test
train = sales_melt.loc[:'2020-6']
test = sales_melt.loc['2020-07':]
```

1.4 Build

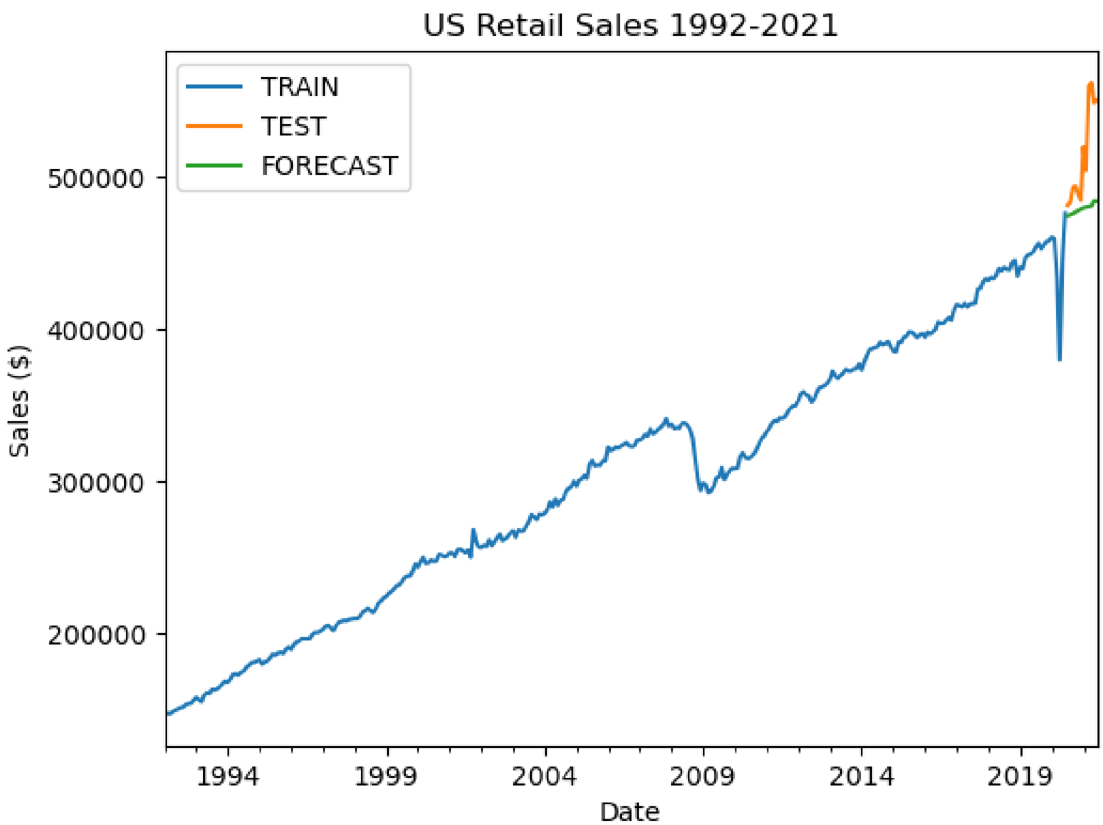
[12]:
```
# Use Holt Winter's Method for time series
fitted_model =␣
↪ExponentialSmoothing(train['sales'],trend='add',seasonal='add',seasonal_periods=12).
↪fit()
```

1.5 Predict

[13]:
```
# Forecast 12 months
forecast = fitted_model.forecast(12)
```

[14]:
```
# Plot true sales vs forecast
train['sales'].plot(legend=True,label='TRAIN')
test['sales'].plot(legend=True,label='TEST')
```

```
forecast.plot(legend=True,label='FORECAST')
plt.title("US Retail Sales 1992-2021")
plt.xlabel("Date")
plt.ylabel("Sales ($)")
plt.show()
```



1.6 RMSE

[15]:
```
#import necessary libraries
from sklearn.metrics import mean_squared_error
from math import sqrt
```

[16]:
```
#calculate RMSE
sqrt(mean_squared_error(test['sales'], forecast))
```

[16]: 45156.97171858642

1.7 Summary

Utilizing the Holt Winter's method, a forecast was made from July 2020 to June 2021. The actual values are greater compared to the forecast values by the RMSE of 45157. This could happen because the past training data was consistent up until the forecasted point where there appears to be a spike.