DCS 630 Predictive Analytics (DSC630-T302 2231-1)

Bellevue University

8.2 Assignment: Time Series Modeling

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Assignment Instructions:

You will be 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 obsevations 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.

You can use R or Python to complete this assignment. Submit your code and output to the submission link. Make sure to add comments to all of your code and to document your steps, process, and analysis.

Import the Libraries

In [1]:
```
'''
Import the necessary libraries to complete Exercise 8.2.
'''
import numpy as np
import pandas as pd
import seaborn as sns
import scipy.stats
import sklearn
import matplotlib
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import statsmodels.api as sm
from math import sqrt
from statsmodels.tsa.holtwinters import ExponentialSmoothing as HWES
from sklearn import linear_model
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error


import plotly.io as pio
pio.renderers.default = "notebook"
# !pip install Pyppeteer
# !pyppeteer-install

# Ignore warnings throughout the assignment.
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
'''
Check the versions of the packages.
'''
print('numpy version:', np.__version__)
print('pandas version:', pd.__version__)
print('seaborn version:', sns.__version__)
print('matplotlib version:', matplotlib.__version__)
print('sklearn:', sklearn.__version__)
```

```
numpy version: 1.20.3
pandas version: 1.3.4
seaborn version: 0.11.2
matplotlib version: 3.4.3
sklearn: 0.24.2
```

Load the Data

In [3]:
```
'''
Import the dataset.
Note: A copy of the CSV file was placed into the same directory as this notebook.
Utilize pd.read_csv() to read the file as a pandas data frame.
'''
df = pd.read_csv('us_retail_sales.csv')
```

In [4]:
```
'''
Use head() function to display the first 10 rows of data of df.
'''
df.head(10)
```

Out[4]:

	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
5	1997	202371	204286	204990	203399	201699	204675	207014.0	207635.0	208326.0	208078.0	208

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	
6	1998	209666	209552	210832	213633	214639	216337	214841.0	213636.0	215720.0	219483.0	221
7	1999	223997	226250	227417	229037	231235	231903	233948.0	236566.0	237481.0	237553.0	240
8	2000	243436	247133	249825	245831	246201	248160	247176.0	247576.0	251837.0	251221.0	250
9	2001	252654	252704	250328	254763	255218	254022	252997.0	254560.0	249845.0	267999.0	260

In [5]:
```
'''
Understand the shape of the dataset.
'''
print('There are {} rows and {} columns in this dataset.'.format(df.shape[0], df.shape[
```

```
There are 30 rows and 13 columns in this dataset.
```

In [6]:
```
'''
Display the total size of this dataset.
'''
print('This dataset contains {} records.'.format(df.size))
```

```
This dataset contains 390 records.
```

In [7]:
```
'''
Understand if there are any missing values in the dataset.
'''
df.isna().sum().sort_values(ascending = False)
```

Out[7]:
```
JUL     1
AUG     1
SEP     1
OCT     1
NOV     1
DEC     1
YEAR    0
JAN     0
FEB     0
MAR     0
APR     0
MAY     0
JUN     0
dtype: int64
```

In [8]:
```
'''
Understand how many missing values are in the dataset initially.
'''
df.isna().sum().sum()
```

Out[8]:
```
6
```

There are 6 missing values in the dataset. There appears to be one missing value from JUL through DEC.

In [9]:

```
'''
Summarize the findings above with info().
'''
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
```

Prelimnary Data Preparation

In [10]:
```
'''
Reshape the data so that the month and year are combined into one column.
Utilize the melt() function to transpose the MONTH features in combination with the YEA
Remove any extra columns that are not needed for the dataframe.
Code help from DSC 630 Teams post from classmate for Week 8 Discussions.
'''
df = pd.melt(df, id_vars=['YEAR'], var_name=['MONTH'])
df['DATE'] = pd.to_datetime(df['YEAR'].astype(str) + '-' + df['MONTH'].astype(str))
df = df.sort_values(by=['DATE']).drop(columns=['MONTH', 'YEAR']).reset_index(drop=['ind
```

In [11]:
```
'''
Rename the columns as 'sales' and 'date' for convenience for the remainder of the analy
'''
df.columns = ['sales', 'date']
df.head()
```

Out[11]:

	sales	date
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

In [12]:
```
'''
```

```
Show an output of the dataframe at the revised state.
'''
df = df[['date', 'sales']]
df.head()
```

Out[12]:

	date	sales
0	1992-01-01	146925.0
1	1992-02-01	147223.0
2	1992-03-01	146805.0
3	1992-04-01	148032.0
4	1992-05-01	149010.0

In [13]:

```
'''
There are missing data values for several months. Show the missing values present.
'''
df[df.isna().any(axis=1)]
```

Out[13]:

	date	sales
354	2021-07-01	NaN
355	2021-08-01	NaN
356	2021-09-01	NaN
357	2021-10-01	NaN
358	2021-11-01	NaN
359	2021-12-01	NaN

The missing values are from 2021 for months July through December. I explored potentially handling the missing values with interpolation to utilize sales from prior years of the missing values. Tried using linear interpolation and spline interpolation initially to see if there was a difference. Each respective interpolation method returned a value of 550782. After further evaluation, I will remove these records of missing values from the dataset since they are at the tail end of the timeframe.

In [14]:

```
'''
Handle the missing values by removing the missing records from the dataset.
'''
df = df.dropna()
```

In [15]:

```
'''
Convert the 'sales' data to integers.
'''
df['sales'] = df['sales'].astype('int')
```

In [16]:

```
'''
Show there are no additional missing values and all features are integer data types.
```

```
'''
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 354 entries, 0 to 353
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   date    354 non-null    datetime64[ns]
 1   sales   354 non-null    int32         
dtypes: datetime64[ns](1), int32(1)
memory usage: 6.9 KB
```

In [17]:
```
'''
One more check showing there are no additional values missing with the revised data.
'''
df.isna().sum().sum()
```

Out[17]:
```
0
```

In [18]:
```
'''
Set the index for the pandas dataframe using the date column.
'''
df.set_index('date', inplace = True)
```

In [19]:
```
'''
Show the first five rows of the preliminarily cleaned data.
'''
df.head()
```

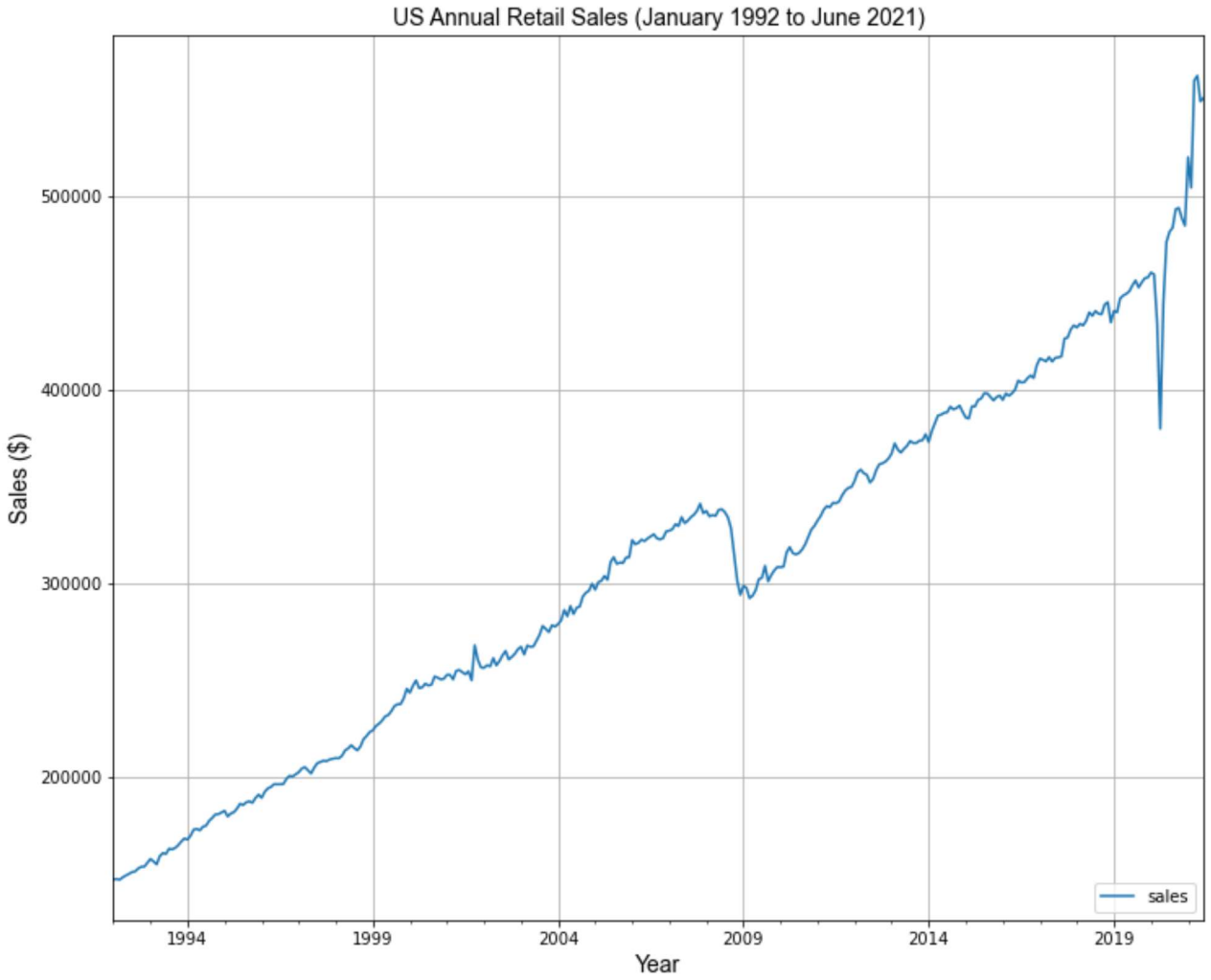
Out[19]:

	sales
date	
1992-01-01	146925
1992-02-01	147223
1992-03-01	146805
1992-04-01	148032
1992-05-01	149010

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

In [20]:
```
'''
Utilize the plot() function to construct a line plot of the US Retail Sales with respec
'''
plt.rcParams["figure.figsize"] = 12, 10
df.plot(grid = 'on')
plt.xlabel("Year", fontsize = 14, family = 'Arial')
plt.ylabel("Sales ($)", fontsize = 14, family = 'Arial')
plt.title('US Annual Retail Sales (January 1992 to June 2021)', family = 'Arial', fonts
```

```
plt.legend(loc = 'lower right')
plt.show()
```

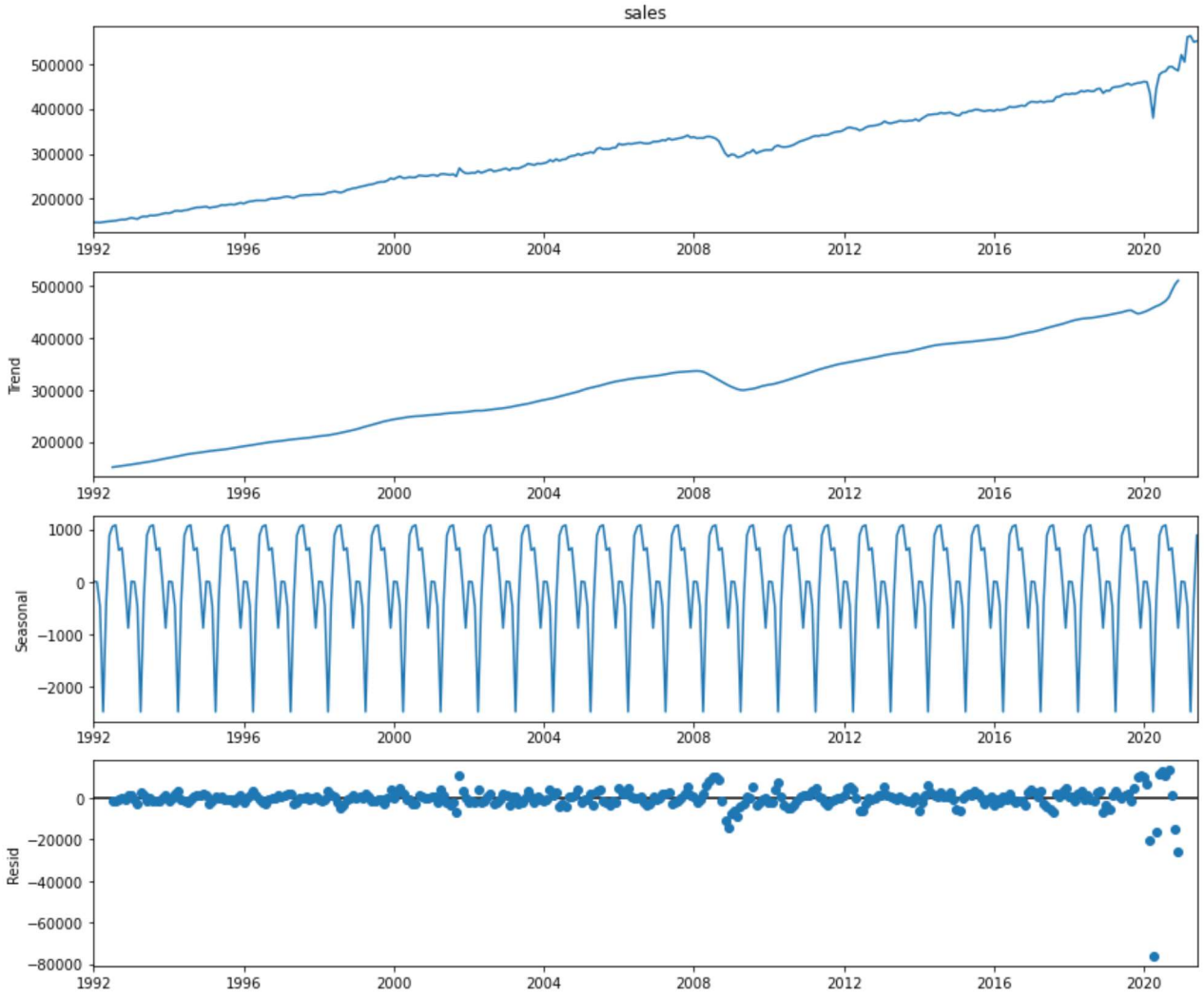


Observations for the line plot of Annual US Retail Sales from 1991 to 2021 are listed below:

- The general sales trend continues to increase from 1991 to 2021.
- There are a few drops in the upward trend around 2008 to 2009 timeframe and in 2020.
- The two drops in retail sales may be attributed to the economic recession in 2008 and the COVID Pandemic in 2020.
- There appears to be a unique seasonal pattern for this retail data. I will decompose the sales data to further analyze this pattern.

In [21]:
```
'''
Use decomposition to figure out observed, trends, seasonal, and residual insights for t
'''
decomposition_additive = sm.tsa.seasonal_decompose(df['sales'], model = 'additive')
```

In [22]:
```
'''
Plot the decomposition of the data that was stored above. (additive)
'''
fig = decomposition_additive.plot()
```

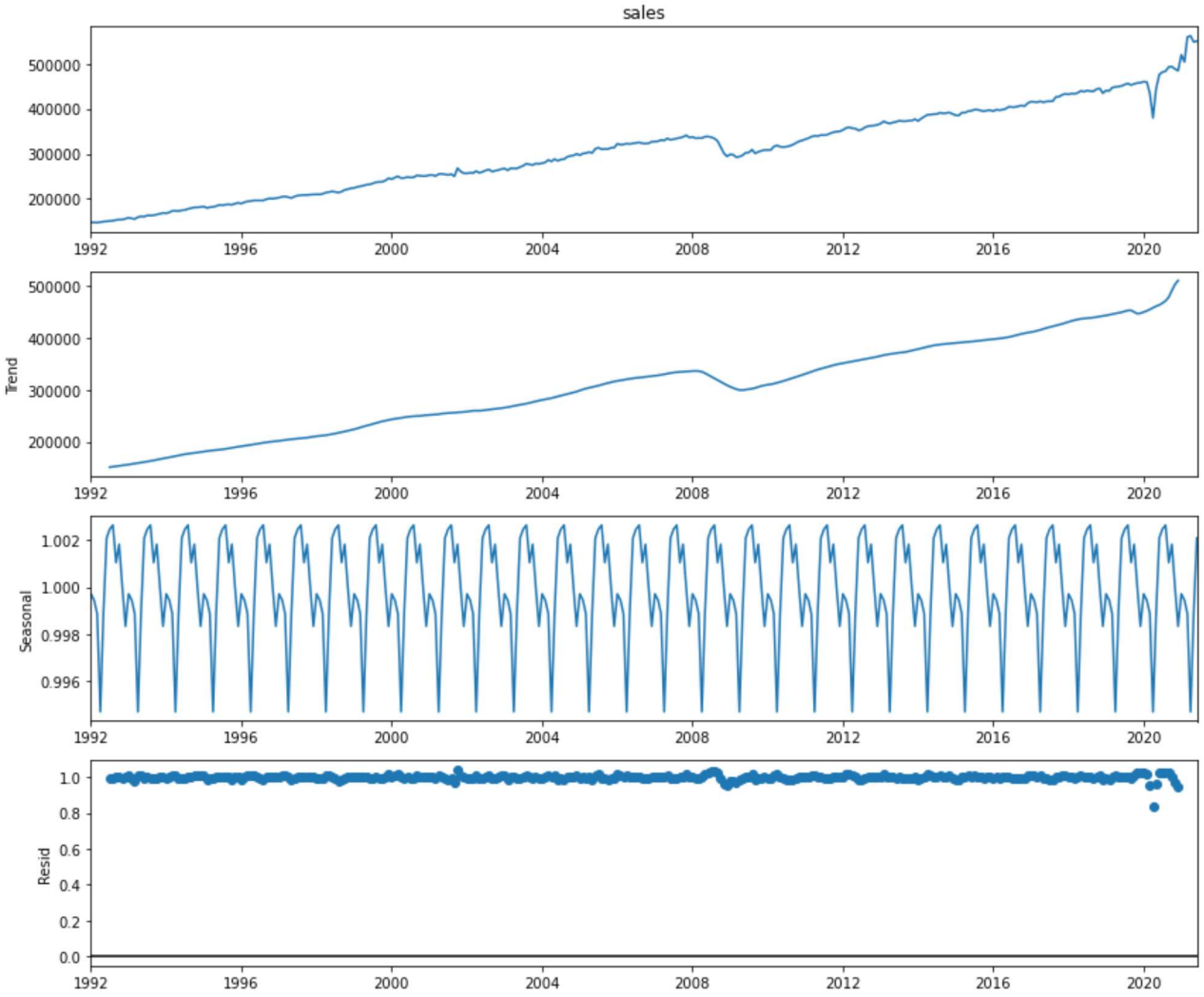


Observations for the additive time series decomposition plots:

- Trend is clearly identified to continually increase with the exceptions of the two aforementioned anamolies.
- Seasonal pattern is easier to visualize after decomposition.
- Residuals are centered about 0 and start to drift further around 2008-2009 and 2019-2021.

In [23]:
```
'''
Use decomposition to figure out observed, trends, seasonal, and residual insights for t
'''
decomposition_multiply = sm.tsa.seasonal_decompose(df['sales'], model = 'multiply')
```

In [24]:
```
'''
Plot the decomposition of the data that was stored above. (multiply)
'''
fig = decomposition_multiply.plot()
```



Observations for the multiply time series decomposition plots:

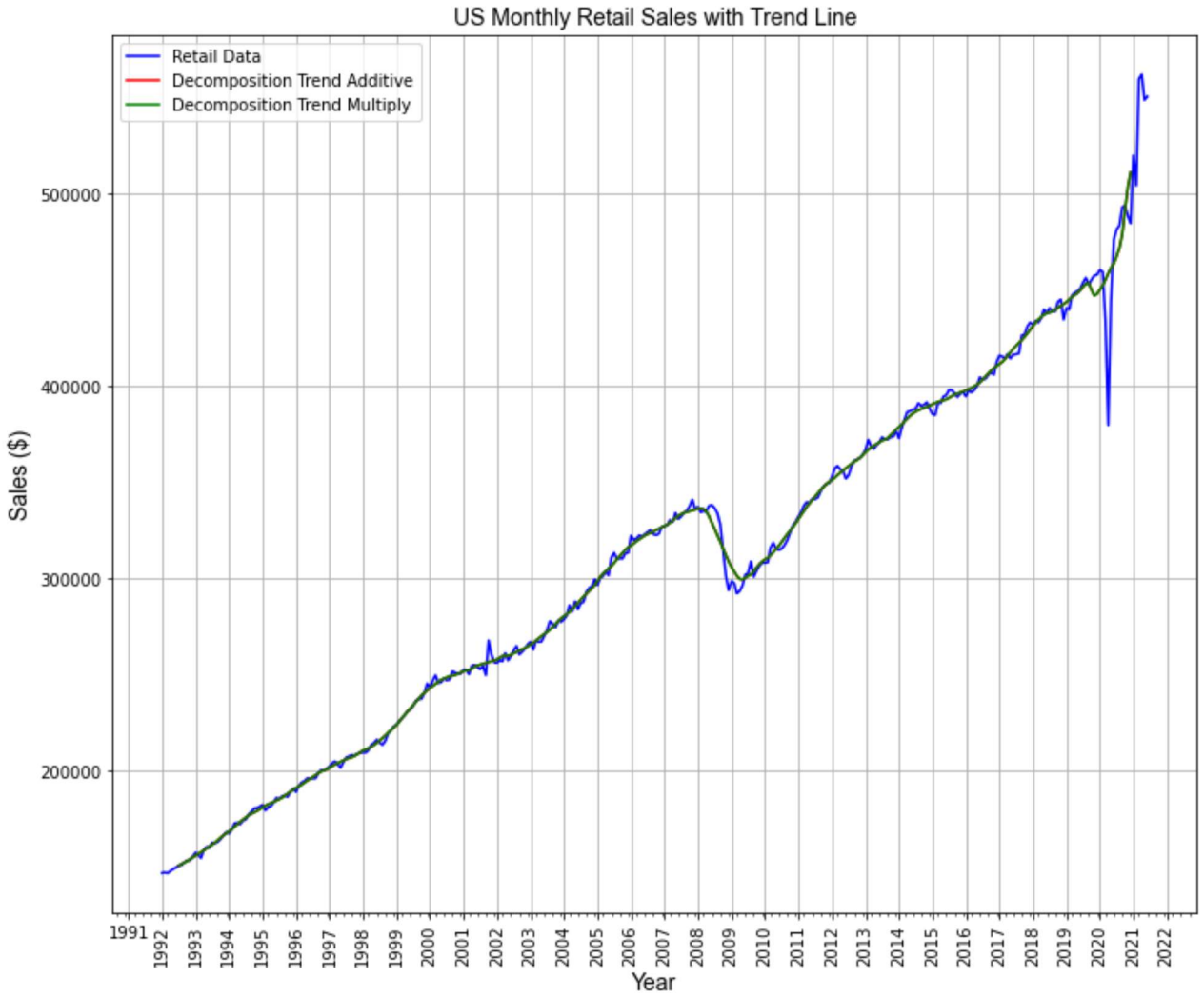
- Similar result for trend as the additive time series decomposition.
- Similar result for the seasonal plot.
- Residuals are centered about 1 and drift around 2008-2009 and 2020.

In [25]:

```
'''
Try creating another plot showing with respect to month over the same timeframe as the
'''
fig, ax = plt.subplots()
ax.grid(True)

year = mdates.YearLocator(month = 1)
month = mdates.MonthLocator(interval = 3)
year_format = mdates.DateFormatter("%Y")
month_format = mdates.DateFormatter("%m")

ax.xaxis.set_minor_locator(month)

ax.xaxis.grid(False, which = "minor")
ax.xaxis.set_major_locator(year)
ax.xaxis.set_major_formatter(year_format)
plt.setp(ax.get_xticklabels(), rotation = 90)
```

```
plt.plot(df.index, df['sales'], c = 'blue', label = 'Retail Data')
plt.plot(decomposition_additive.trend.index, decomposition_additive.trend, c = 'red', l
plt.plot(decomposition_multiply.trend.index, decomposition_multiply.trend, c = 'green',
plt.legend(loc='upper left')
plt.xlabel("Year", fontsize = 14, family = 'Arial')
plt.ylabel("Sales ($)", fontsize = 14, family = 'Arial')
plt.title('US Monthly Retail Sales with Trend Line', family = 'Arial', fontsize = 14)
```

Out[25]: Text(0.5, 1.0, 'US Monthly Retail Sales with Trend Line')



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 [26]:
```
'''
Split the data into training and test data sets.
As specified for the assignment, the training set will be prior to July 2020.
Test data will be from July 2020 through June 2021.
'''
df_train = df.iloc[:-12]
df_test = df.iloc[-12:]
```

3) Use the training set to build a predictive model for the monthly

retail sales.

In [27]:
```
'''
Utilize the training data to build a Holt-Winters Forecast with Exponential Smoothing m
'''
hw_model = HWES(df_train, seasonal_periods=4, trend='mul', seasonal = 'add', freq = 'MS
```

In [28]:
```
'''
Fit the hw model that was just constructed.
'''
fit_model = hw_model.fit(optimized = True, use_brute = True)
```

In [30]:
```
'''
Show the summary of the model.
'''
print(fit_model.summary())
```

```
                       ExponentialSmoothing Model Results
==============================================================================
Dep. Variable:                    sales   No. Observations:                  342
Model:             ExponentialSmoothing   SSE                 12078587621.229
Optimized:                         True   AIC                          5959.922
Trend:                   Multiplicative   BIC                          5990.601
Seasonal:                      Additive   AICC                         5960.587
Seasonal Periods:                     4   Date:                Sun, 23 Oct 2022
Box-Cox:                          False   Time:                        07:59:07
Box-Cox Coeff.:                    None
==============================================================================
                         coeff                 code              optimized
------------------------------------------------------------------------------
smoothing_level            0.8889286                alpha                 True
smoothing_trend            0.0329233                 beta                 True
smoothing_seasonal         0.0246825                gamma                 True
initial_level             2.9923e+05                  l.0                 True
initial_trend              1.0049099                  b.0                 True
initial_seasons.0         -1.5231e+05                  s.0                 True
initial_seasons.1         -1.5201e+05                  s.1                 True
initial_seasons.2         -1.5243e+05                  s.2                 True
initial_seasons.3          -1.512e+05                  s.3                 True
------------------------------------------------------------------------------
```

I chose seasonal_periods = 4, trend = 'mul', and seasonal = 'add' based on the RMSE output later in the analysis. These values provided the lowest RMSE score. In addition, I utilized, the outputs for the seasonal and trend plots above to help drive the decisions.

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

In [34]:
```
'''
Create a forecast for the last year of data.
'''
forecast_sales = fit_model.forecast(steps = 12)
```

In [35]:
```
'''
Convert the predicted values into a DataFrame.
Label the predicted values as 'predicted_sales'.
Convert the predicted values to integer datatypes.
Show the forecasted sales.
'''
forecast_sales_df = pd.DataFrame(forecast_sales)
forecast_sales_df.columns = ['predicted_sales']
forecast_sales_df['predicted_sales'] = forecast_sales_df['predicted_sales'].astype('int
forecast_sales_df
```

Out[35]:

	predicted_sales
2020-07-01	473597
2020-08-01	474333
2020-09-01	479110
2020-10-01	479641
2020-11-01	481087
2020-12-01	481845
2021-01-01	486644
2021-02-01	487197
2021-03-01	488666
2021-04-01	489447
2021-05-01	494268
2021-06-01	494844

In [36]:
```
'''
Add the original_sales values from the last year to the forecast_sales_df.
'''
forecast_sales_df['original_sales'] = df_test
forecast_sales_df
```

Out[36]:

	predicted_sales	original_sales
2020-07-01	473597	481627
2020-08-01	474333	483716
2020-09-01	479110	493327
2020-10-01	479641	493991
2020-11-01	481087	488652
2020-12-01	481845	484782
2021-01-01	486644	520162
2021-02-01	487197	504458
2021-03-01	488666	559871

	predicted_sales	original_sales
2021-04-01	489447	562269
2021-05-01	494268	548987
2021-06-01	494844	550782

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

In [37]:
```
'''
Calcualte RMSE using mean_squared_error() from sklearn.metrics.
'''
rmse = sqrt(mean_squared_error(df_test['sales'],forecast_sales_df['predicted_sales']))
print('RMSE:{}'.format(round(rmse,2)))
```

```
RMSE:10662.93
```

Extra Practice: Plot the predicted values, training data, and test data.

In [38]:
```
fig = plt.figure()
fig.suptitle('Plot of US Retail Sales from 1991 to 2021')
past, = plt.plot(df_train.index, df_train, 'b.-',label = 'Sales History')
future, = plt.plot(df_test.index, df_test, 'r.-', label = 'Actual Sales')
predicted_future, = plt.plot(df_test.index, forecast_sales, 'g.-', label = 'Sales Forec
plt.legend(handles=[past, future, predicted_future])
plt.show()
```

Plot of US Retail Sales from 1991 to 2021