Botts_Rodriguez_Final

November 18, 2023

[108]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from scipy import stats
from sklearn.metrics import mean_squared_error
from math import sqrt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
import pmdarima as pm
```

[109]:
```
import warnings
warnings.filterwarnings("ignore")
```

[110]:
```
df = pd.read_csv('sales_data.csv')
```

0.1 Data Cleaning

0.1.1 Feature Reduction

[112]:
```
# remove id columns
df = df.drop(columns=['Order ID', 'Product_ean', 'catégorie', 'Purchase␣
↪Address'])
```

0.1.2 Check for Missing Values

[114]:
```
#check for missing values in the entire dataframe
df.isnull().sum()
```

[114]:
```
Order Date          0
Product             0
Quantity Ordered    0
Price Each          0
Cost price          0
turnover            0
```

```
margin               0
dtype: int64
```

0.1.3 Reformat Data types

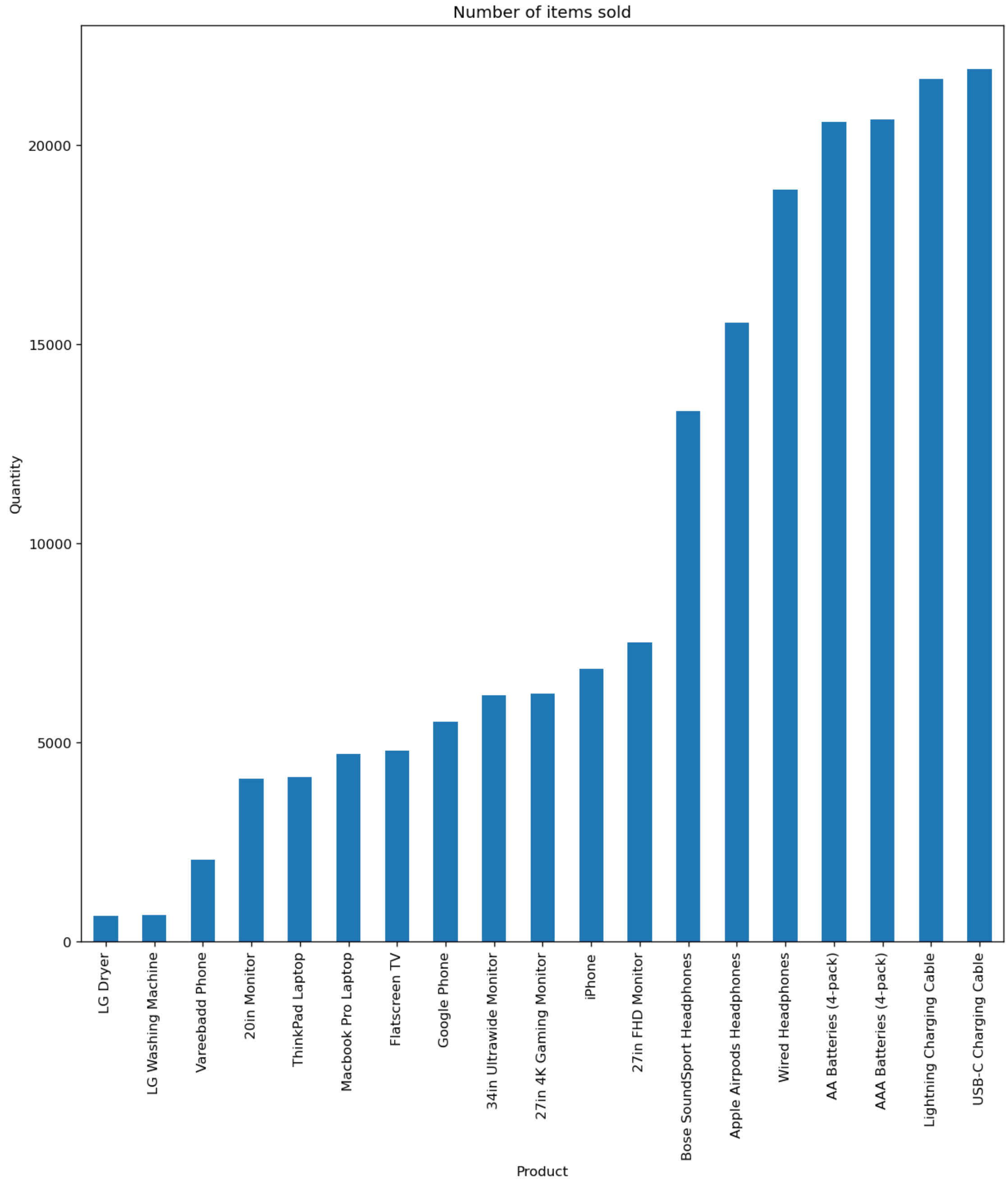
[116]:
```python
# Covert 'Order Date' to datetime format
df['Order Date'] = pd.to_datetime(df['Order Date'])
```

0.2 Exploratory Analysis

[118]:
```python
# Compare the number of items sold by product
items_sold = df['Product'].groupby(df['Product']).count().sort_values()
```

[120]:
```python
items_sold.plot(kind='bar')
plt.ylabel('Quantity')
plt.title('Number of items sold')
```

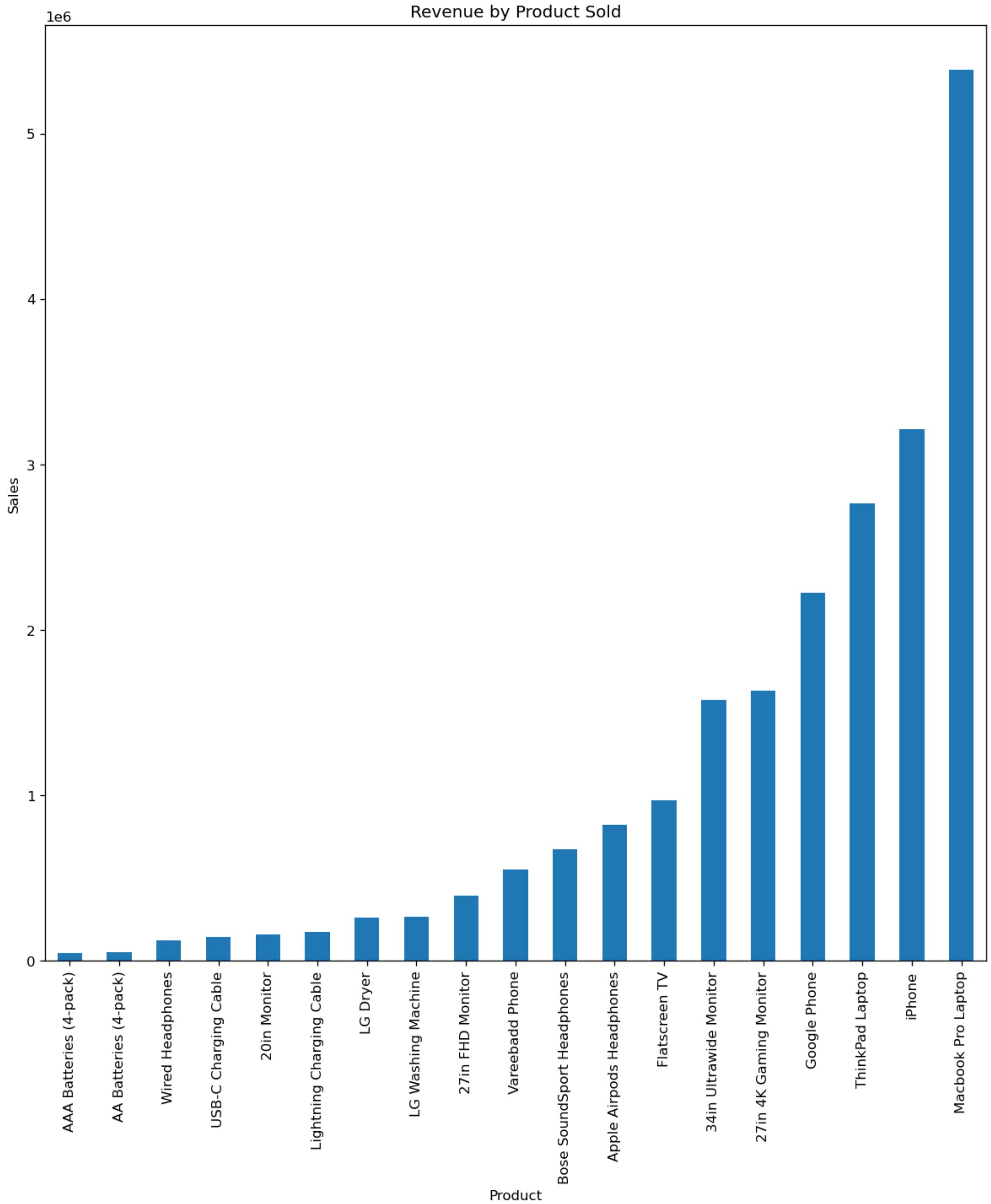
[120]:
```
Text(0.5, 1.0, 'Number of items sold')
```



[121]:
```
# Compare the revenue generated by product
sum_sold = df['margin'].groupby(df['Product']).sum().sort_values()
```

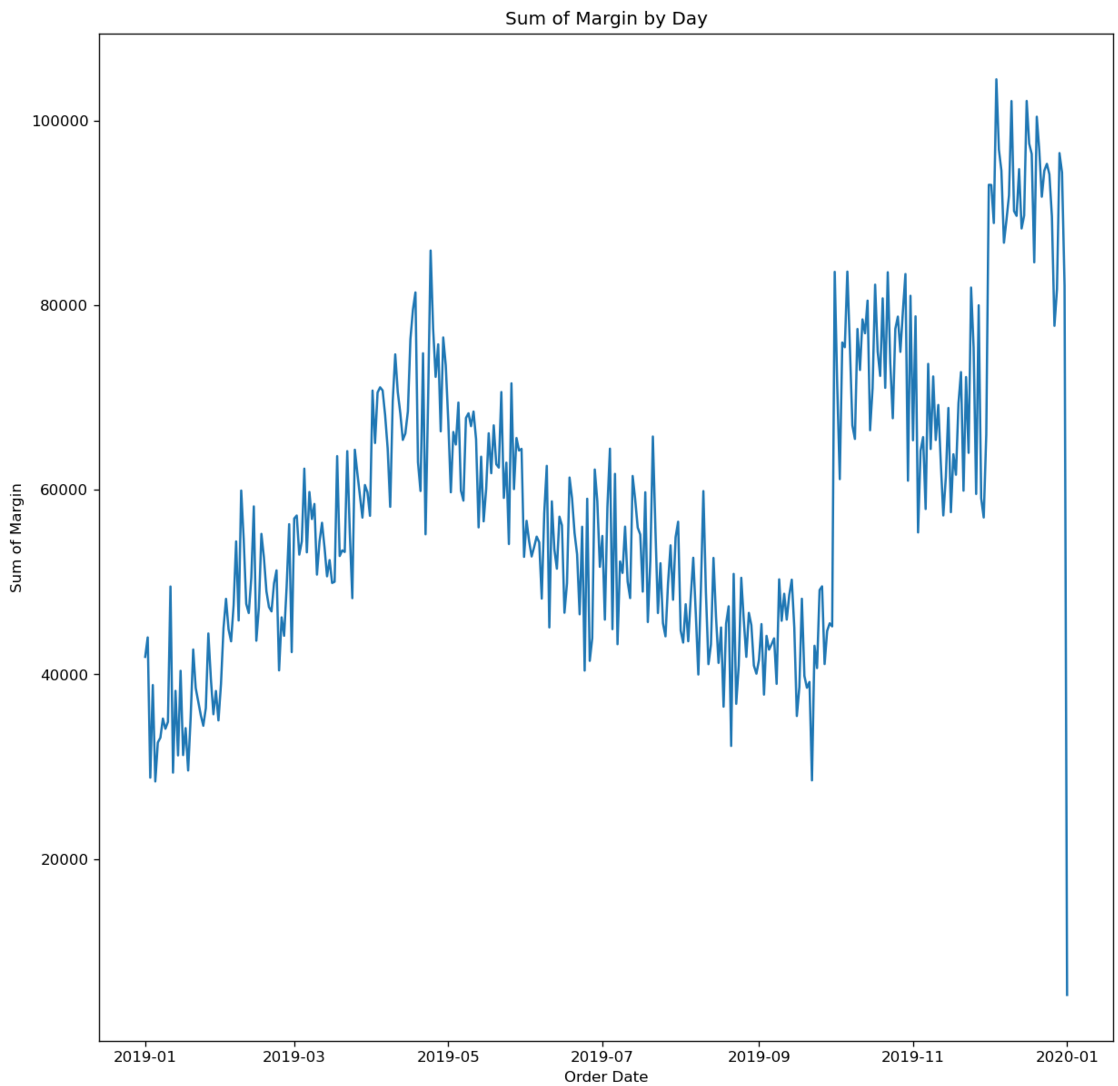
[123]:
```
sum_sold.plot(kind='bar')
plt.ylabel('Sales')
plt.title('Revenue by Product Sold')
```

[123]: Text(0.5, 1.0, 'Revenue by Product Sold')



[124]:
```
# calcuate the profit margins generate by date
daily_margin = df.groupby(df['Order Date'].dt.date)['margin'].sum().
 ↪reset_index()
```

```
plt.plot(daily_margin['Order Date'], daily_margin['margin'])

# Adding labels and title to the graph
plt.xlabel('Order Date')
plt.ylabel('Sum of Margin')
plt.title('Sum of Margin by Day')

# Displaying the graph
plt.show()
```



[ ]:
```
# Assuming the dataset is stored in a pandas DataFrame called 'df'
df['Order Date'] = pd.to_datetime(df['Order Date'])
```

```
# Grouping the data by product and day, and calculating the sum of the 'margin'␣
↪column
product_margin = df.groupby(['Product', df['Order Date'].dt.date])['margin'].
↪sum().reset_index()

# Creating a graph for each product
for product in df['Product'].unique():
    product_data = product_margin[product_margin['Product'] == product]
    plt.plot(product_data['Order Date'], product_data['margin'])
    plt.xlabel('Order Date')
    plt.ylabel('Sum of Margin')
    plt.title(f'Sum of Margin for {product}')
    plt.show()
```

0.3 Explore the Target Feature, Profit Margin

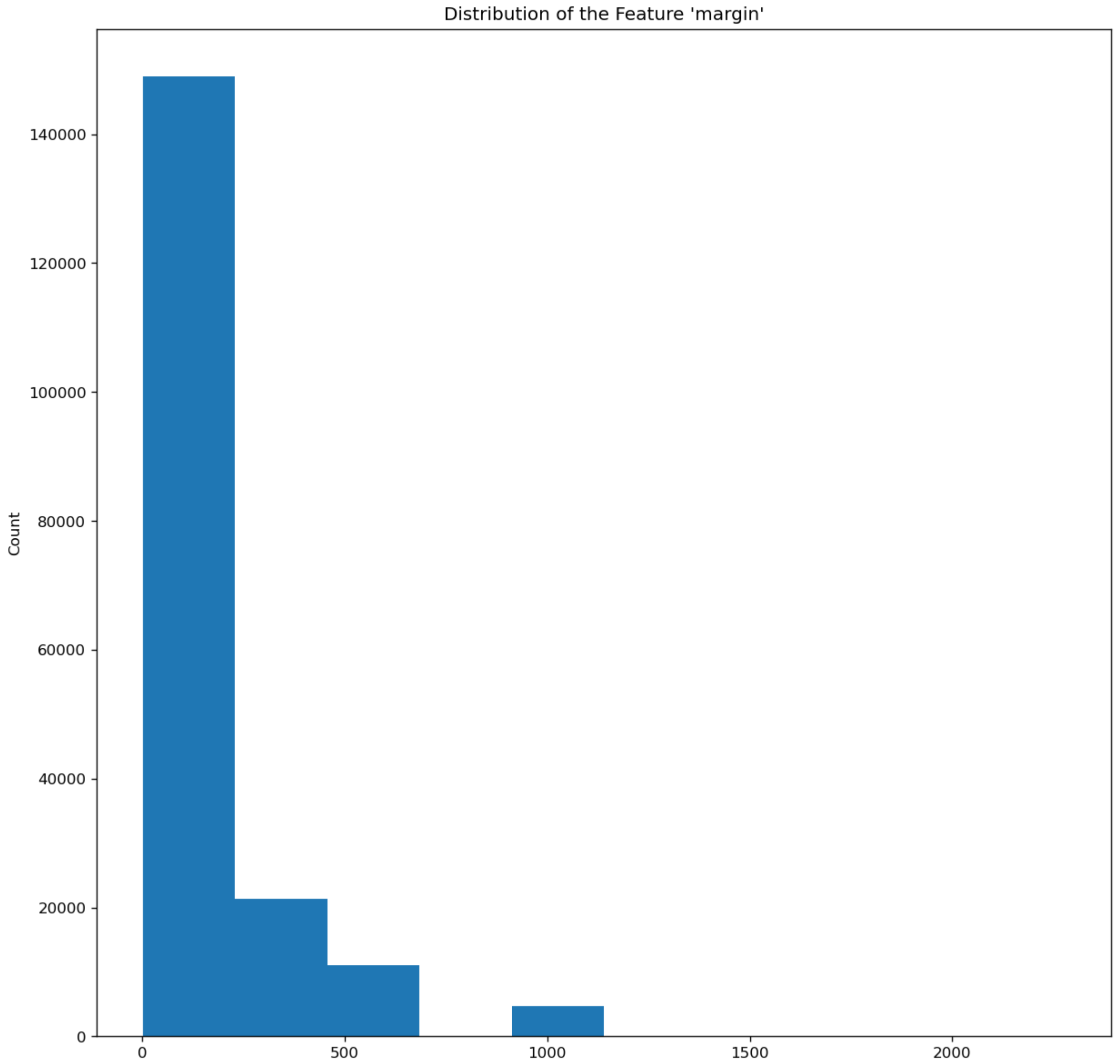
[126]:
```
df['margin'].describe()
```

[126]:
```
count    185950.000000
mean        115.289422
std         225.227190
min           1.495000
25%           5.975000
50%           7.475000
75%          52.500000
max        2278.000000
Name: margin, dtype: float64
```

0.3.1 Check the Distribution of the Target Feature

[127]:
```
#plot the distribution of the target variable
plt.hist(df['margin'])
plt.title("Distribution of the Feature 'margin'")
plt.ylabel("Count")
```

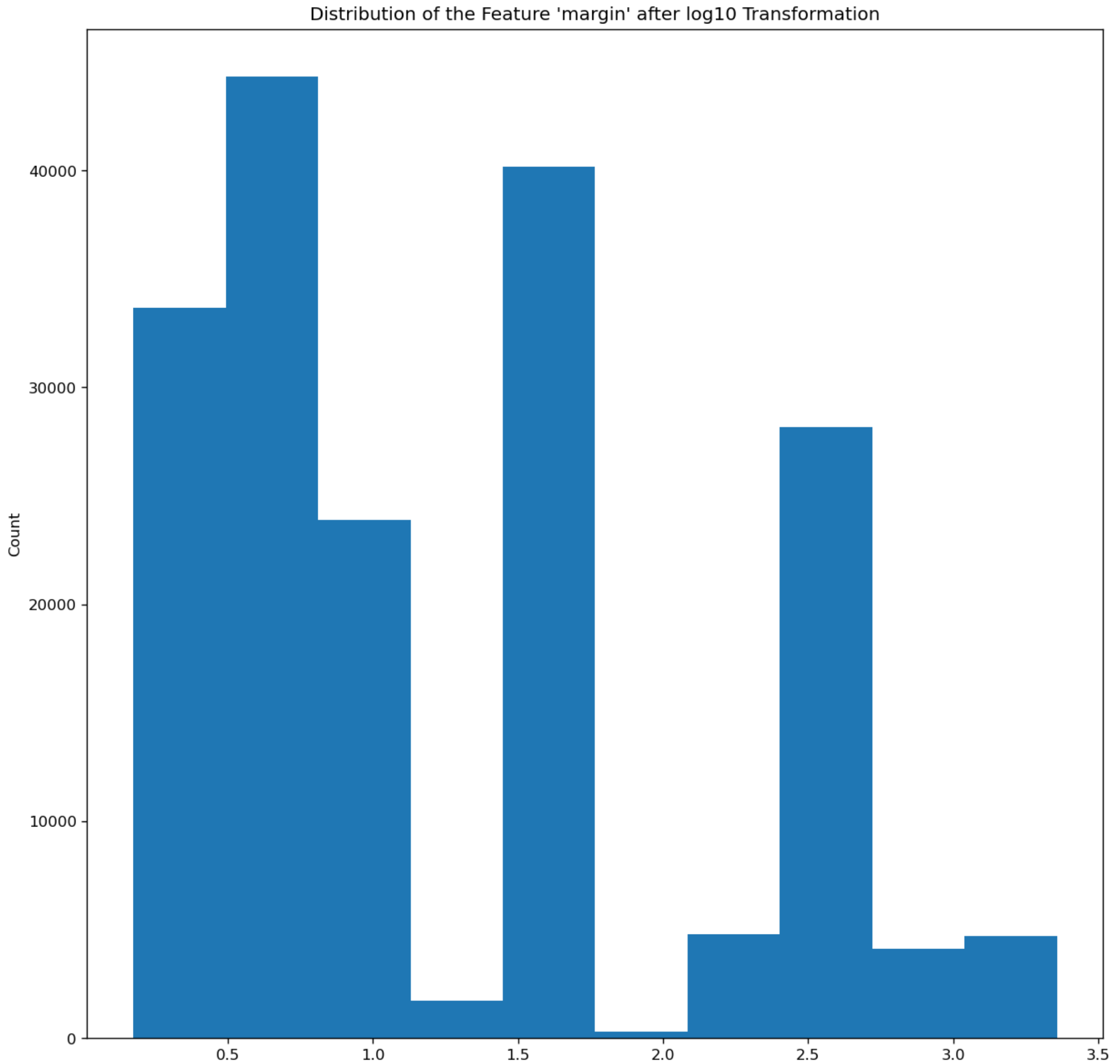
[127]:
```
Text(0, 0.5, 'Count')
```



The histogram of profit margin shows a strong positive skew.

[128]:
```
#use a log 10 transformation to correct the positive skew in the feature␣
↪'margin'
log_margin = np.log10(df['margin'])

plt.hist(log_margin)
plt.title("Distribution of the Feature 'margin' after log10 Transformation")
plt.ylabel("Count")
```

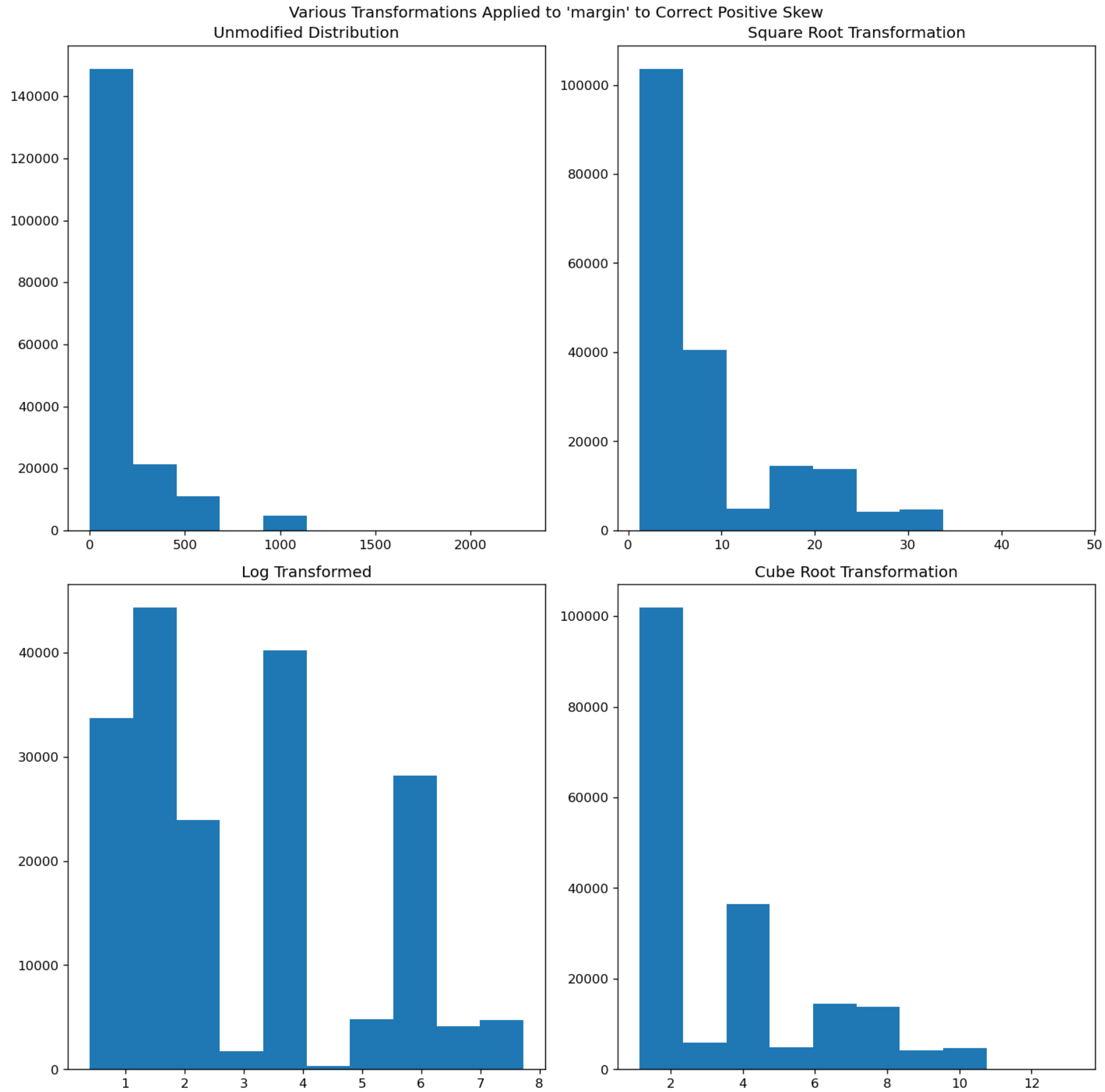
[128]: Text(0, 0.5, 'Count')



When a log 10 transformation is applied to the target variable, a multimodal distribition emerges. It should be evaluated if other transformations can generate a more normal distribution.

[129]:
```
# Compare the effectiveness of various transformations for correcting the␣
↪positive skew

fig, axs = plt.subplots(2, 2)
fig.suptitle("Various Transformations Applied to 'margin' to Correct Positive␣
↪Skew")
axs[0, 0].hist(df['margin'])
axs[0, 0].set_title("Unmodified Distribution")
axs[1, 0].hist(np.log(df['margin']))
axs[1, 0].set_title("Log Transformed")
axs[0, 1].hist(np.sqrt(df['margin']))
```

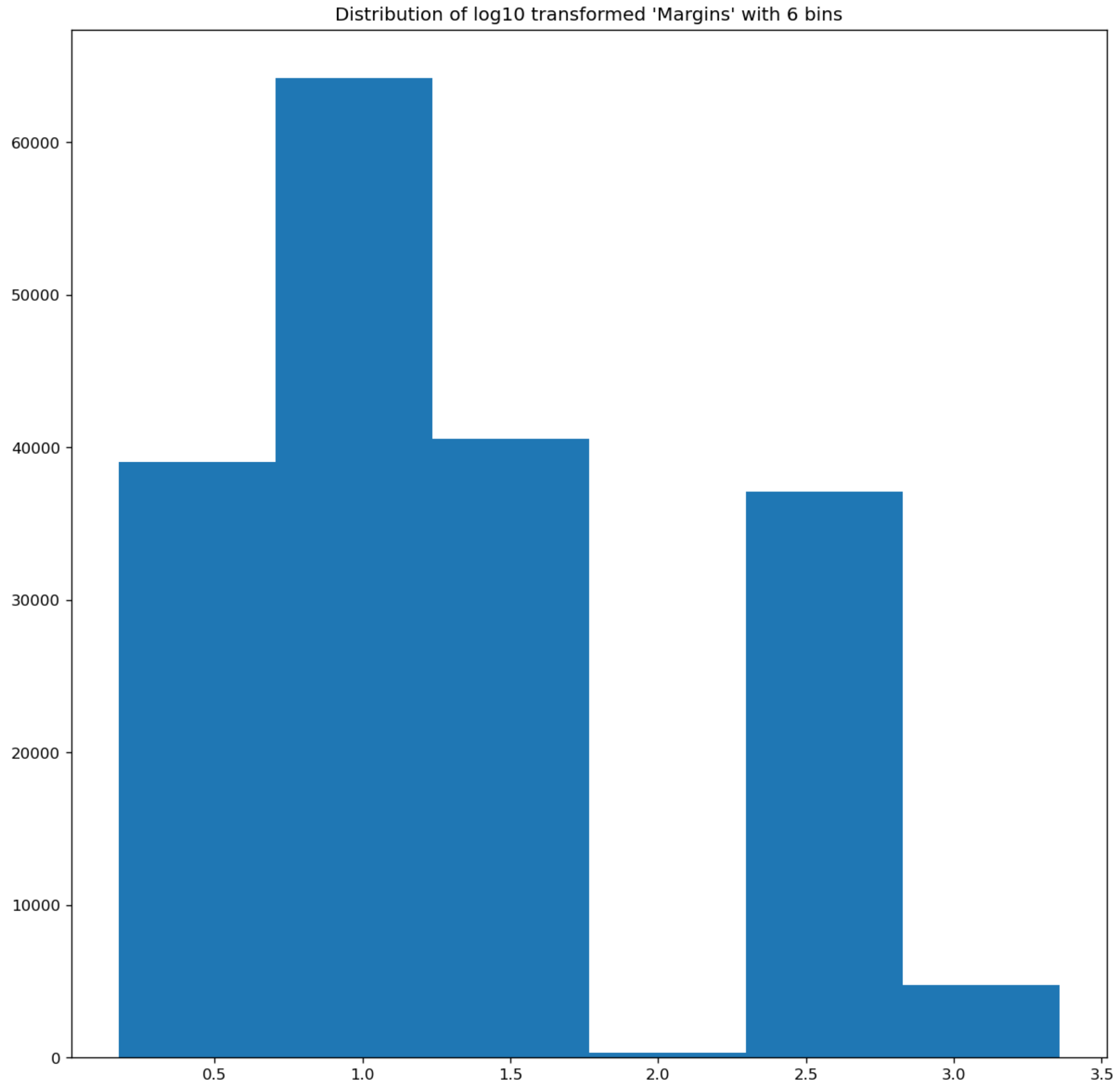
```
axs[0, 1].set_title("Square Root Transformation")
axs[1, 1].hist(np.cbrt(df['margin']))
axs[1, 1].set_title("Cube Root Transformation")
fig.tight_layout()
```



A log10 transformation is the most effective at correcting the postive skew.

[130]:
```
# Bin the data to correct the multimodal distribution
plt.hist(np.log10(df['margin']), bins=6)
plt.title("Distribution of log10 transformed 'Margins' with 6 bins")
```

[130]:
```
Text(0.5, 1.0, "Distribution of log10 transformed 'Margins' with 6 bins")
```



Binning the data into 6 bins reduces the effect of the multimodal distribution and the targer variable more closely approaches a normal distribution.

[131]:
```
# create an object for the binned datas
margin_binned = pd.qcut(log_margin, q=6)
margin_binned.head()
```

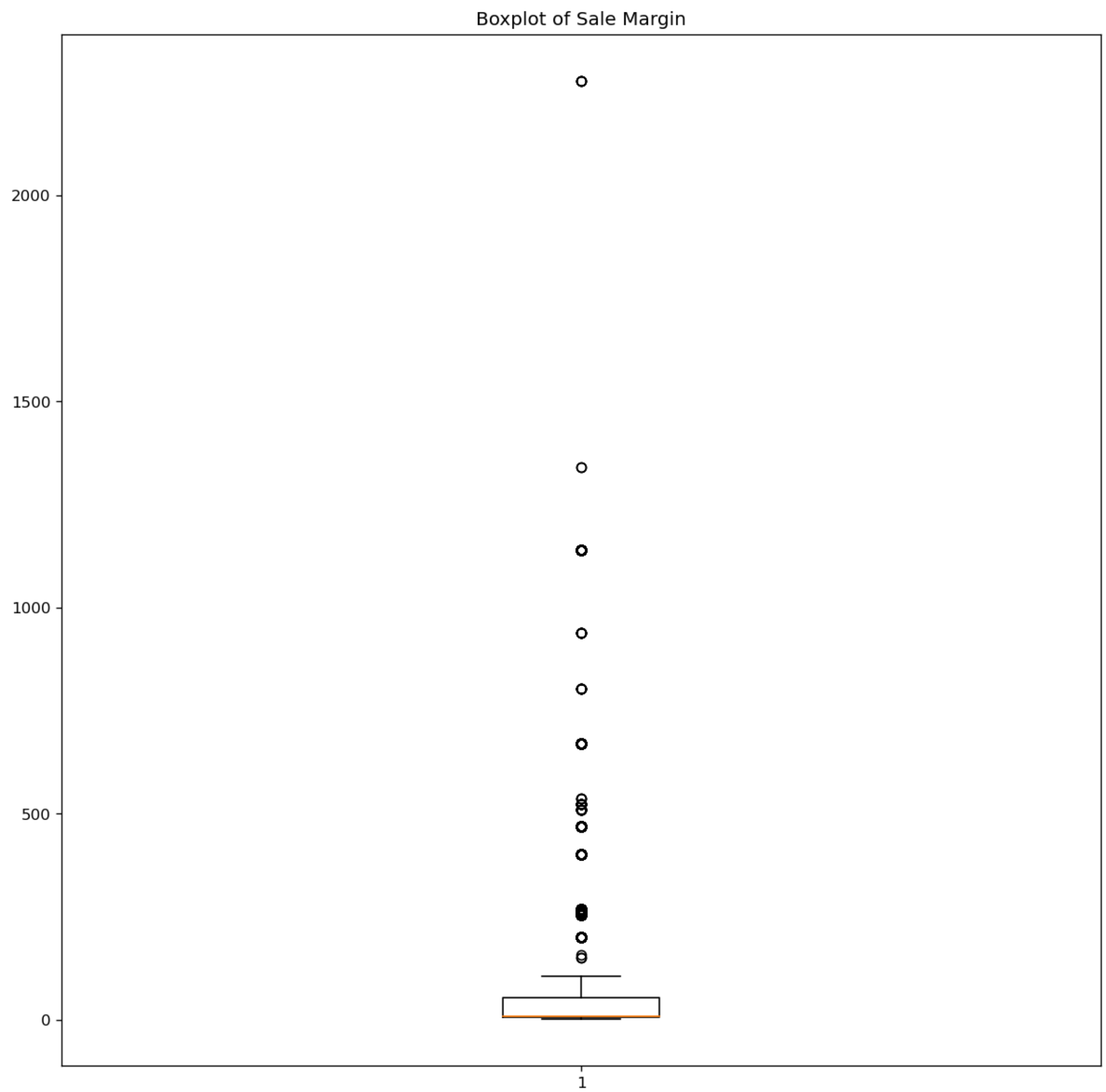
[131]:
```
0    (2.406, 3.358]
1    (0.778, 0.874]
2     (0.874, 1.72]
3     (0.874, 1.72]
4    (0.476, 0.778]
Name: margin, dtype: category
Categories (6, interval[float64, right]): [(0.174, 0.476] < (0.476, 0.778] <
```

```
(0.778, 0.874] < (0.874, 1.72] < (1.72, 2.406] < (2.406, 3.358]]
```

0.3.2 Check for Outliers in the Target Feature

[132]:
```
plt.boxplot(df['margin'])
plt.title("Boxplot of Sale Margin")
```

[132]:
```
Text(0.5, 1.0, 'Boxplot of Sale Margin')
```



As expected in a feature with strong positive skew, the boxplot suggests a high number of outliers.

[133]:
```
# calculate the upper and lower thresholds for outliers using IQR methodology
upper = np.percentile(df['margin'], 75) + 1.5*stats.iqr(df['margin'])
```

```
lower = np.percentile(df['margin'], 25) - 1.5*stats.iqr(df['margin'])

print(upper)
print(lower)
```

```
122.2875
-63.81249999999999
```

The upper threshold for identifying outliers is 122.2875, which is slightly above the mean. This is not surprising based on the strong skew shown in the histogram. The lower threshold is negative. This threshold will be ignored becuase there are no negative values of 'margin'.

[134]:
```
# create a dataframe of the outliers to investigate why there is such a large␣
 ↪number of instance that are flagged as outliers
outliers = df[df['margin']>upper]

outliers.head()
```

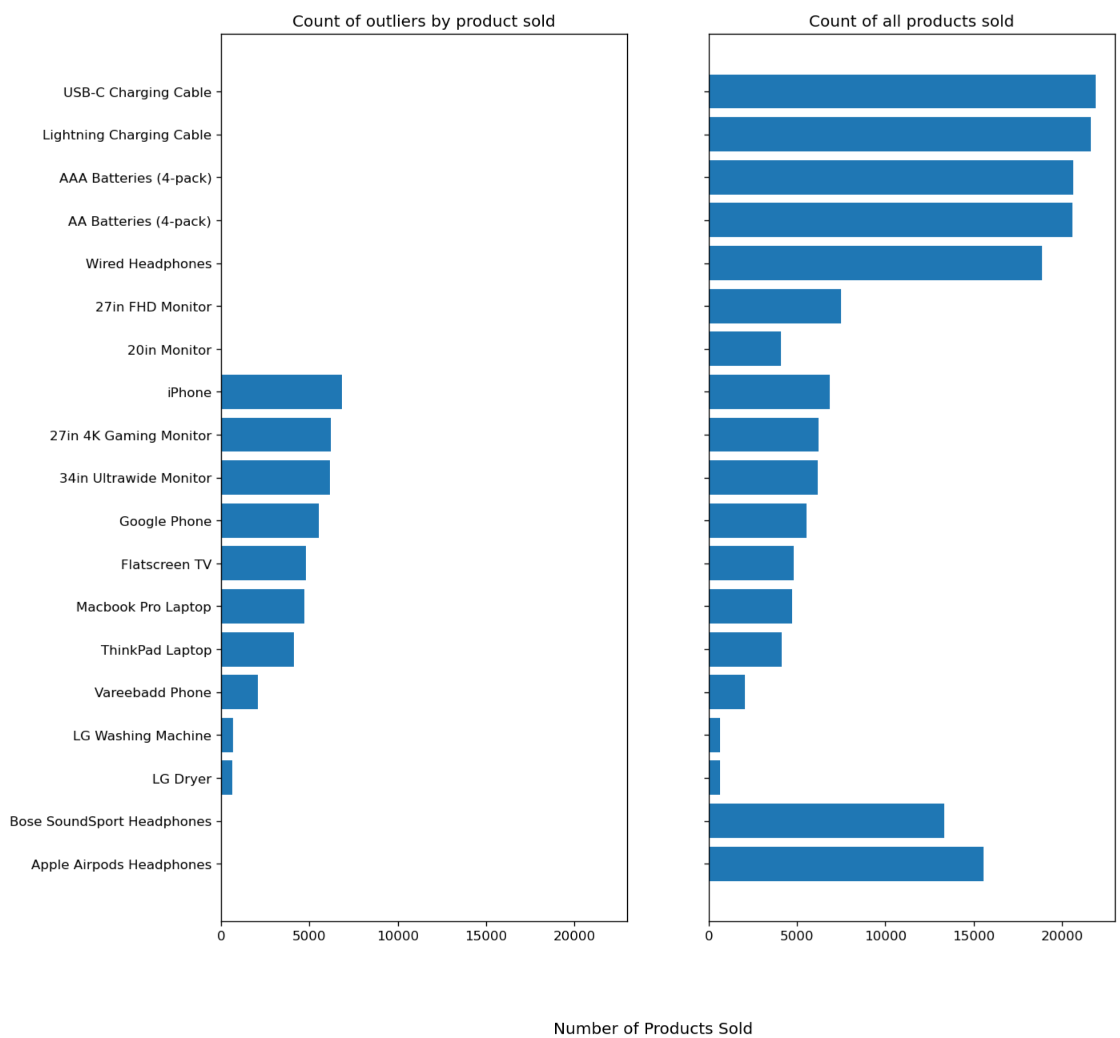
[134]:
```
            Order Date                 Product  Quantity Ordered  Price Each  \
0  2019-01-22 21:25:00                  iPhone                 1      700.00
6  2019-01-26 12:16:00  27in 4K Gaming Monitor                 1      389.99
11 2019-01-31 10:12:00      Macbook Pro Laptop                 1     1700.00
14 2019-01-03 21:54:00           Flatscreen TV                 1      300.00
16 2019-01-10 11:20:00         Vareebadd Phone                 1      400.00

    Cost price  turnover     margin
0     231.0000    700.00   469.0000
6     128.6967    389.99   261.2933
11    561.0000   1700.00  1139.0000
14     99.0000    300.00   201.0000
16    132.0000    400.00   268.0000
```

[136]:
```
# count the number of products sold in sales that were flagged as outliers
outliers_sold = outliers['Product'].groupby(outliers['Product']).count().
 ↪sort_values(ascending=True)
outliers_sold
```

[136]:
```
Product
Apple Airpods Headphones         1
Bose SoundSport Headphones       2
LG Dryer                       646
LG Washing Machine             666
Vareebadd Phone               2065
ThinkPad Laptop               4128
Macbook Pro Laptop            4724
Flatscreen TV                 4800
Google Phone                  5525
34in Ultrawide Monitor        6181
```

```
27in 4K Gaming Monitor        6230
iPhone                        6842
Name: Product, dtype: int64
```

[137]:
```python
# plot the products that were identified as outliers next to all products sold
fig, (ax1, ax2) = plt.subplots(1, 2, sharex=True, sharey=True)
fig.supxlabel('Number of Products Sold')

ax1.barh(outliers_sold.index, outliers_sold)
ax1.set_title("Count of outliers by product sold")
ax2.barh(items_sold.index, items_sold)
ax2.set_title("Count of all products sold")

plt.show()
```



In the bar graph above, it appears that the presence of outliers in item profit margin is associated with the specific product being sold.

[138]:
```
# determine if all sales for specific items are considered outliers
for x in outliers_sold.index:
    if outliers_sold[x] == items_sold[x]:
        print("True", x)
    else:
        print("False", x)
```

```
False Apple Airpods Headphones
False Bose SoundSport Headphones
True LG Dryer
True LG Washing Machine
True Vareebadd Phone
True ThinkPad Laptop
True Macbook Pro Laptop
True Flatscreen TV
True Google Phone
True 34in Ultrawide Monitor
True 27in 4K Gaming Monitor
True iPhone
```

All products in the outliers dataframe except two were exclusively outliers. The two exceptions (Apple Airpods and Bose SoundSport Headphones) are likely to contain authentic outliers. The other products were likely flagged as outliers because their profit margin is signifcantly higher than other products. It may be best to separate out these products and treat them as a separate dataset.

[139]:
```
#confirm the data accuaracy of the three inconsistent observations in the␣
 ↪outlier dataframe
outliers[(outliers['Product']== 'Apple Airpods Headphones') |␣
 ↪(outliers['Product']=='Bose SoundSport Headphones')]
```

[139]:
```
                 Order Date                     Product  Quantity Ordered  \
74751   2019-06-03 20:37:00  Bose SoundSport Headphones                 3
96771   2019-07-29 19:51:00  Bose SoundSport Headphones                 3
175842  2019-12-31 21:37:00    Apple Airpods Headphones                 3

        Price Each  Cost price  turnover   margin
74751        99.99      49.995    299.97  149.985
96771        99.99      49.995    299.97  149.985
175842      150.00      97.500    450.00  157.500
```

[140]:
```
# view these product details in the original dataframe
df[(df['Product']== 'Apple Airpods Headphones') | (df['Product']=='Bose␣
 ↪SoundSport Headphones')]
```

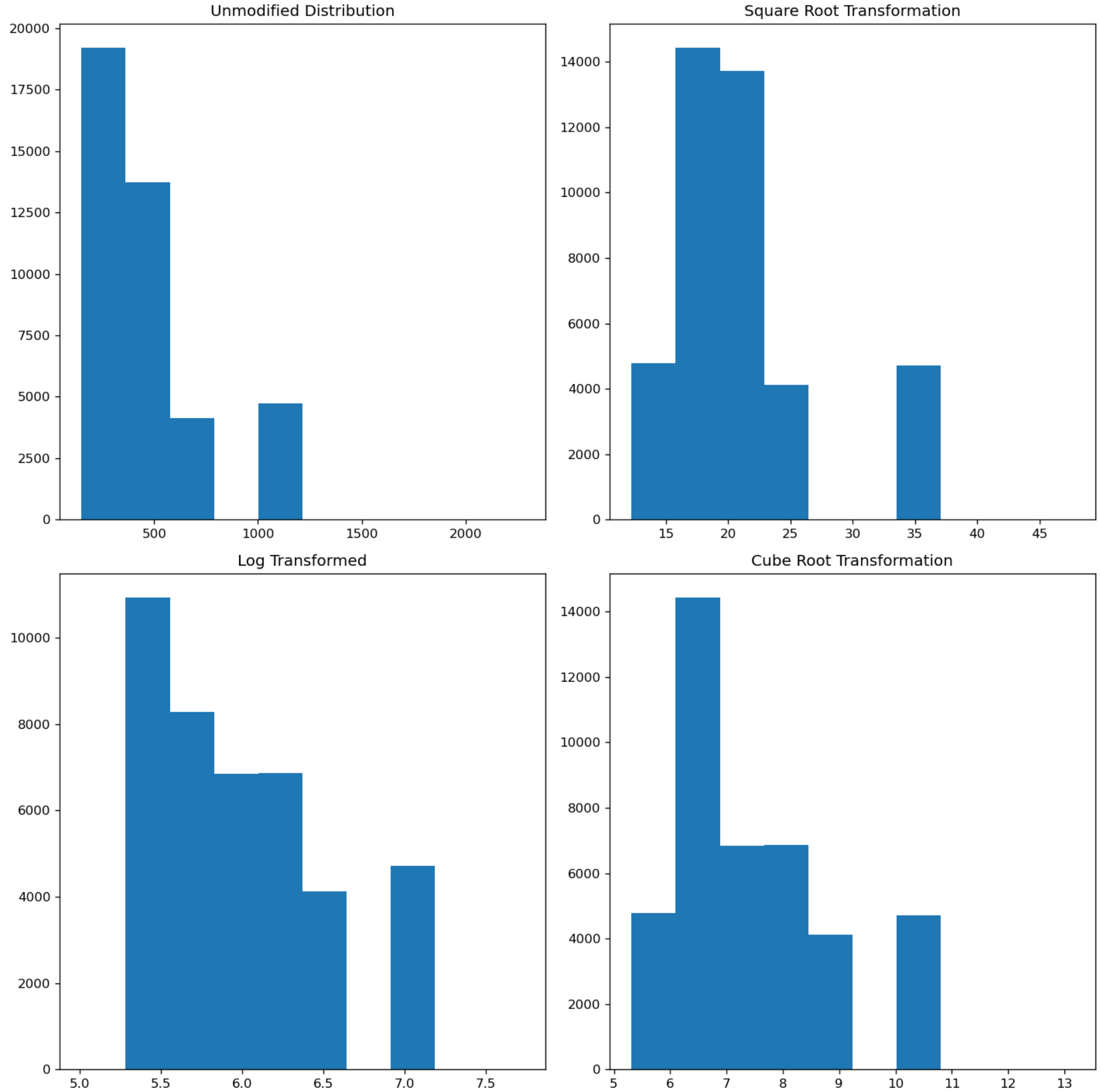
[140]:
```
                 Order Date                     Product  Quantity Ordered  \
8       2019-01-01 10:30:00  Bose SoundSport Headphones                 1
9       2019-01-22 21:20:00    Apple Airpods Headphones                 1
```

```
10     2019-01-07 11:29:00    Apple Airpods Headphones                1
17     2019-01-24 08:13:00    Apple Airpods Headphones                1
23     2019-01-12 18:51:00    Apple Airpods Headphones                1
…                    …                          …                …
185929 2019-12-18 08:29:00    Apple Airpods Headphones                1
185935 2019-12-26 23:17:00    Apple Airpods Headphones                1
185939 2019-12-16 17:41:00    Apple Airpods Headphones                1
185941 2019-12-31 19:07:00  Bose SoundSport Headphones                1
185949 2019-12-21 21:45:00  Bose SoundSport Headphones                1

        Price Each  Cost price  turnover  margin
8            99.99      49.995     99.99  49.995
9           150.00      97.500    150.00  52.500
10          150.00      97.500    150.00  52.500
17          150.00      97.500    150.00  52.500
23          150.00      97.500    150.00  52.500
…             …          …       …     …
185929      150.00      97.500    150.00  52.500
185935      150.00      97.500    150.00  52.500
185939      150.00      97.500    150.00  52.500
185941       99.99      49.995     99.99  49.995
185949       99.99      49.995     99.99  49.995

[28874 rows x 7 columns]
```

The cost of goods and the price sold is matches in both datasets. These instances were flagged as outliers because the number of items purchased pushed the margin of the sale above the upper outlier threshold. These values should not be removed.

0.4 Check the distribution of 'margin' in the separated datasets

[141]:
```python
# View the distribution of margins in the outlier dataset
fig, axs = plt.subplots(2, 2)
axs[0, 0].hist(outliers['margin'])
axs[0, 0].set_title("Unmodified Distribution")
axs[1, 0].hist(np.log(outliers['margin']))
axs[1, 0].set_title("Log Transformed")
axs[0, 1].hist(np.sqrt(outliers['margin']))
axs[0, 1].set_title("Square Root Transformation")
axs[1, 1].hist(np.cbrt(outliers['margin']))
axs[1, 1].set_title("Cube Root Transformation")
fig.tight_layout()
```



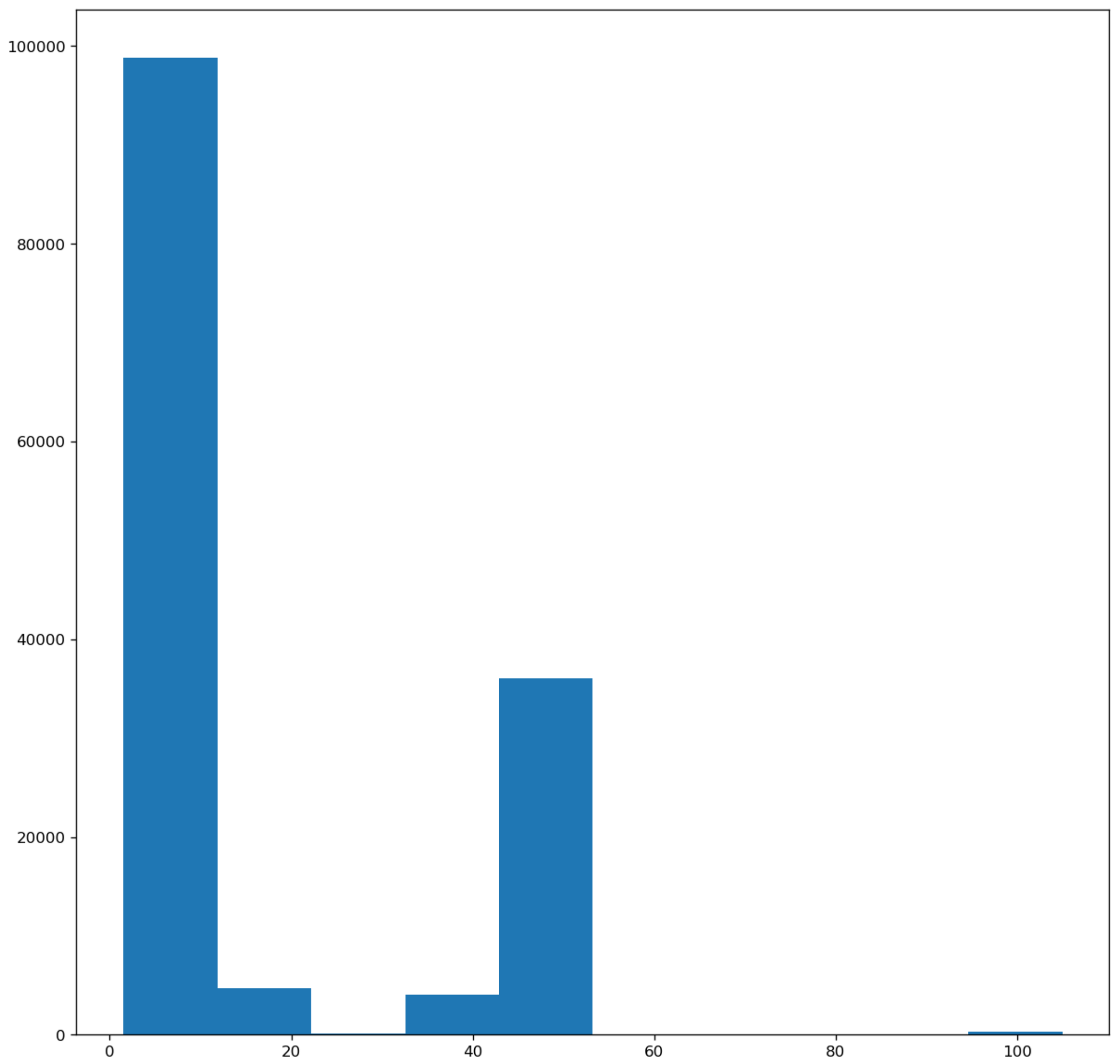
[142]:
```
# create a dataframe of all observations not in the outliers data
df2 = df[~df.index.isin(outliers.index)]

df2.head()
```

[142]:
```
           Order Date                     Product  Quantity Ordered  Price Each  \
1 2019-01-28 14:15:00  Lightning Charging Cable                 1       14.95
2 2019-01-17 13:33:00          Wired Headphones                 2       11.99
3 2019-01-05 20:33:00          27in FHD Monitor                 1      149.99
4 2019-01-25 11:59:00          Wired Headphones                 1       11.99
5 2019-01-29 20:22:00    AAA Batteries (4-pack)                 1        2.99

   Cost price  turnover   margin
```

```
1      7.4750     14.95   7.4750
2      5.9950     23.98  11.9900
3     97.4935    149.99  52.4965
4      5.9950     11.99   5.9950
5      1.4950      2.99   1.4950
```

[143]:
```python
# plot the distribution of 'margin' of the original dataset with outliers␣
 ↪removed
# low margin items
plt.hist(df2['margin'])
```

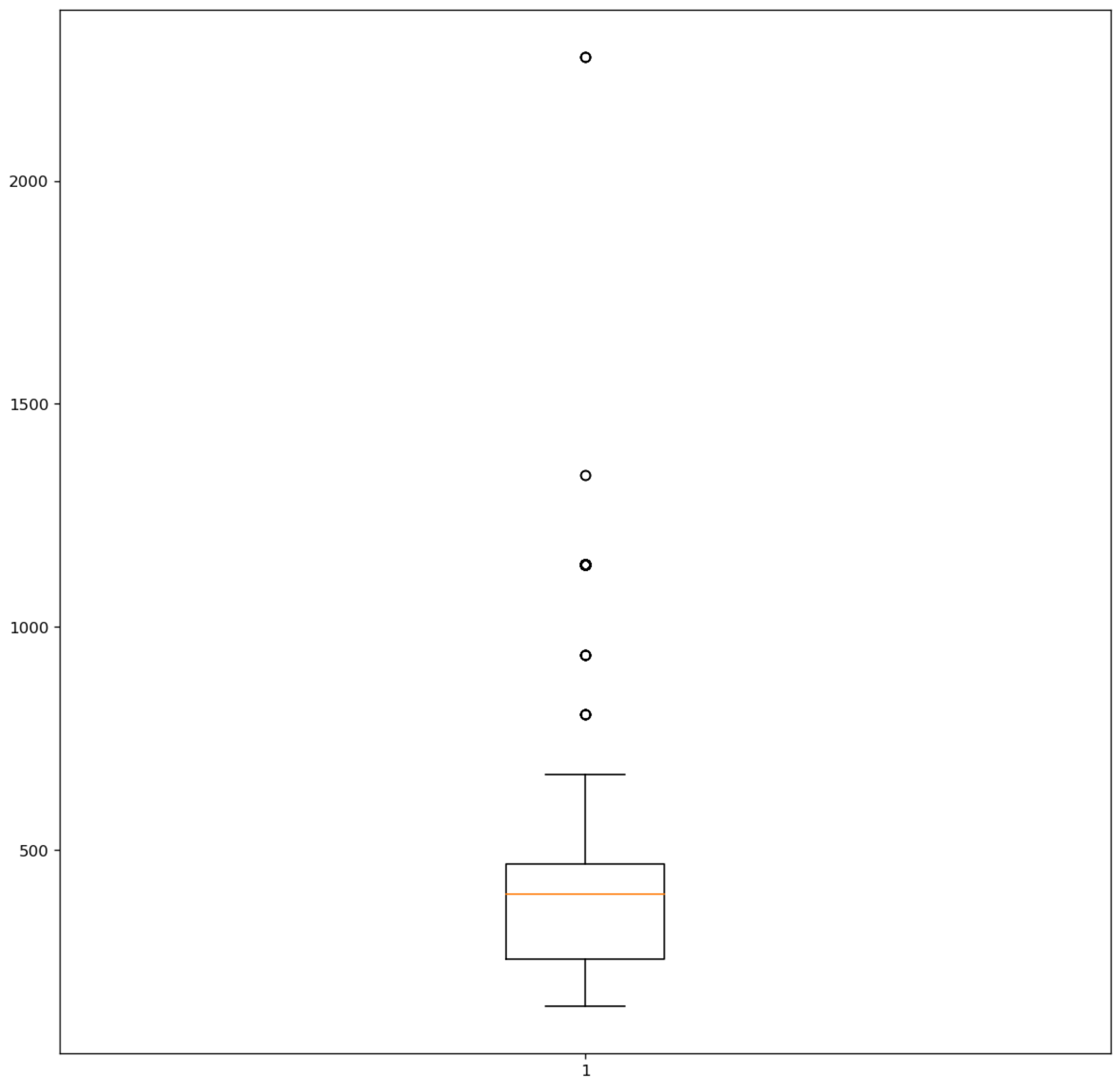
[143]:
```
(array([9.8798e+04, 4.7320e+03, 1.3000e+02, 4.0740e+03, 3.6097e+04,
        0.0000e+00, 0.0000e+00, 2.8000e+01, 0.0000e+00, 2.8100e+02]),
 array([  1.495 ,  11.8455,  22.196 ,  32.5465,  42.897 ,  53.2475,
         63.598 ,  73.9485,  84.299 ,  94.6495, 105.    ]),
 <BarContainer object of 10 artists>)
```



Without the outliers included in the dataset, 'margins' has a bimodal distribution.

[144]:
```
# check for outliers in outlier df
plt.boxplot(outliers['margin'])
```

[144]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x151cde6b0>,
  <matplotlib.lines.Line2D at 0x151cdf0d0>],
 'caps': [<matplotlib.lines.Line2D at 0x151cdeda0>,
  <matplotlib.lines.Line2D at 0x151cdf430>],
 'boxes': [<matplotlib.lines.Line2D at 0x151cde170>],
 'medians': [<matplotlib.lines.Line2D at 0x151cdda50>],
 'fliers': [<matplotlib.lines.Line2D at 0x151cdc310>],
 'means': []}
```



[145]:
```
# calculate outlier thresholds for the outlier df using IQR
upper2 = np.percentile(outliers['margin'], 75) + 1.5*stats.
 ↪iqr(outliers['margin'])
lower2 = np.percentile(outliers['margin'], 25) - 1.5*stats.
 ↪iqr(outliers['margin'])

print(upper2)
print(lower2)
```

```
790.61005
-67.01675
```

[146]:
```
# create a new dataframe of outliers
outliers2 = outliers[outliers['margin']>upper2]

outliers2.head()
```

[146]:
```
              Order Date             Product  Quantity Ordered  Price Each  \
11  2019-01-31 10:12:00  Macbook Pro Laptop                 1      1700.0
55  2019-01-19 08:17:00  Macbook Pro Laptop                 1      1700.0
82  2019-01-13 23:51:00  Macbook Pro Laptop                 1      1700.0
128 2019-01-17 21:00:00  Macbook Pro Laptop                 1      1700.0
155 2019-01-10 12:59:00  Macbook Pro Laptop                 1      1700.0

     Cost price  turnover  margin
11        561.0    1700.0  1139.0
55        561.0    1700.0  1139.0
82        561.0    1700.0  1139.0
128       561.0    1700.0  1139.0
155       561.0    1700.0  1139.0
```

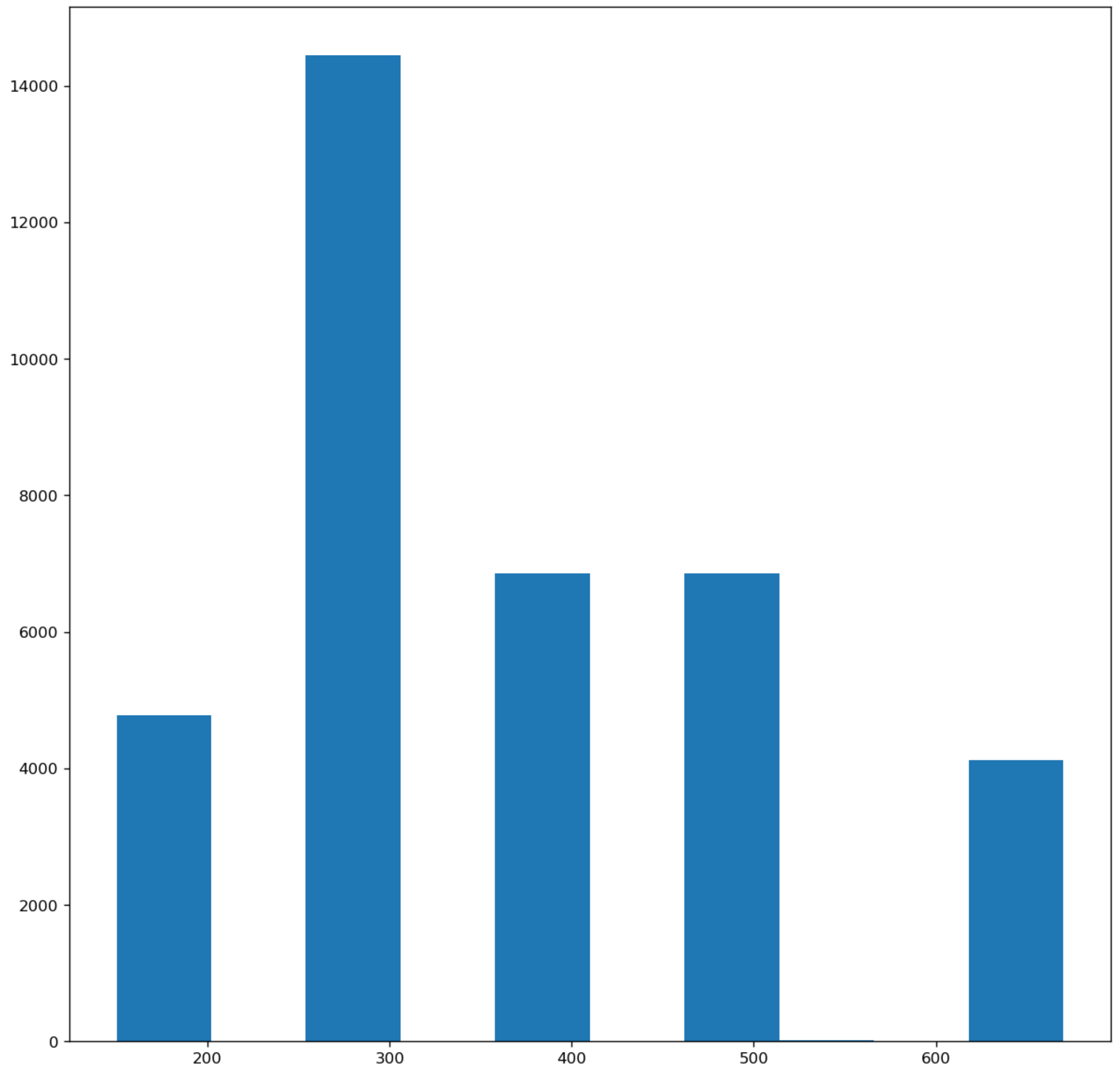
[147]:
```
# count the number of products sold in sales that were flagged as outliers
outliers2_sold = outliers2['Product'].groupby(outliers2['Product']).count().
 ↪sort_values(ascending=True)
outliers2_sold
```

[147]:
```
Product
ThinkPad Laptop          2
Google Phone             7
iPhone                   7
Macbook Pro Laptop    4724
Name: Product, dtype: int64
```

[148]:
```
#eliminate MacBooks from the original outlier list
# high margin
outliers3 = outliers[~outliers.index.isin(outliers2.index)]
```

[149]:
```
#high margin items except macbooks
plt.hist((outliers3['margin']))
```

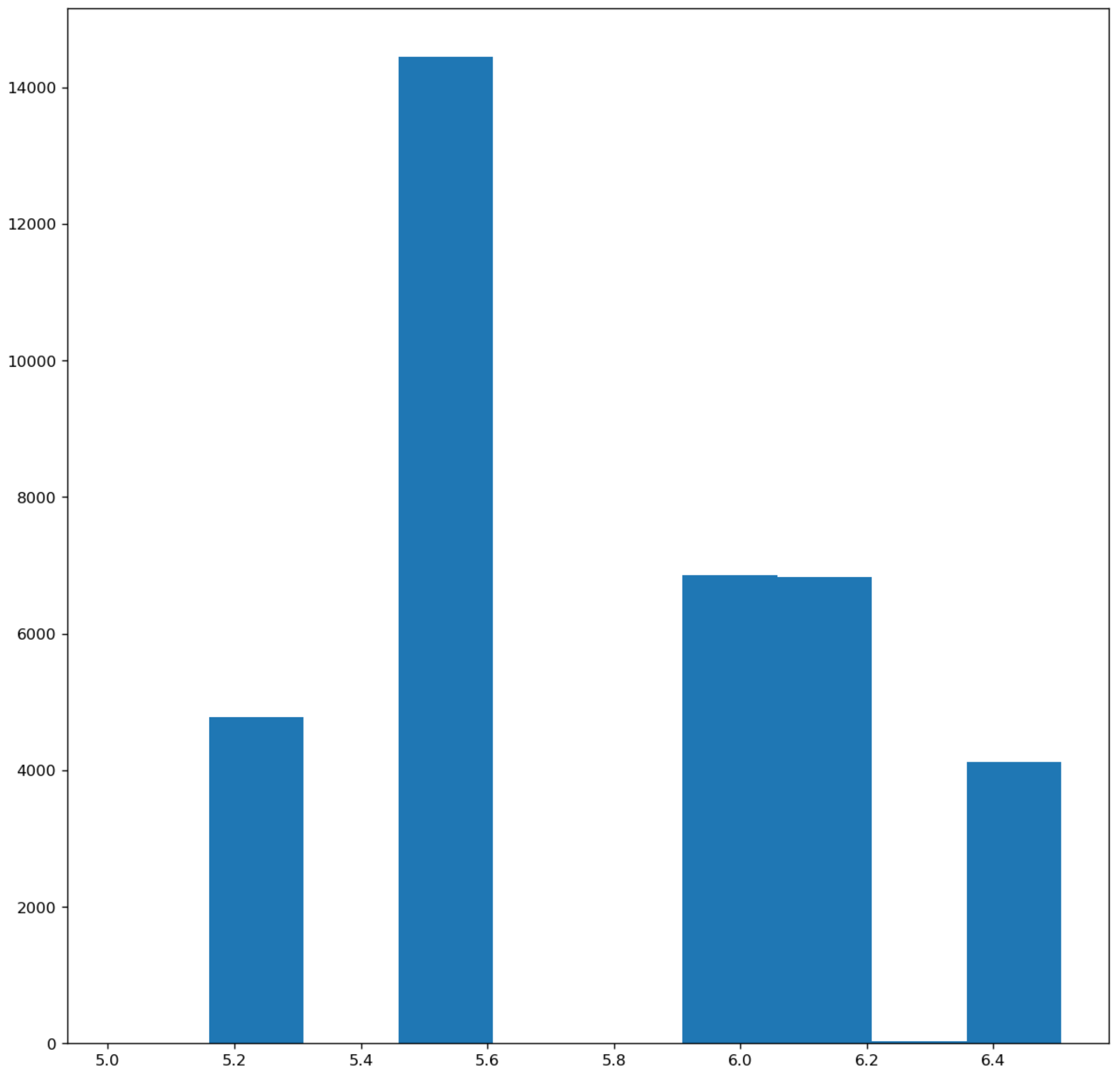
[149]:
```
(array([ 4784.,     0., 14441.,     0.,  6849.,     0.,  6853.,    17.,
            0.,  4126.]),
 array([149.985  , 201.98583, 253.98666, 305.98749, 357.98832, 409.98915,
        461.98998, 513.99081, 565.99164, 617.99247, 669.9933 ]),
 <BarContainer object of 10 artists>)
```



The distribution of 'margin' for the outlier df is almost normal after removing macbooks. This suggest that the original dataset should be divided into three datasets.

[150]:
```
# apply log transformation to target feature
plt.hist(np.log(outliers3['margin']))
```

[150]:
```
(array([3.0000e+00, 4.7810e+03, 0.0000e+00, 1.4441e+04, 0.0000e+00,
        0.0000e+00, 6.8490e+03, 6.8350e+03, 3.5000e+01, 4.1260e+03]),
 array([5.01053529, 5.16020853, 5.30988177, 5.45955502, 5.60922826,
        5.7589015 , 5.90857474, 6.05824799, 6.20792123, 6.35759447,
        6.50726771]),
 <BarContainer object of 10 artists>)
```



0.5 Build a model for the Very High Margin data subset

0.5.1 Prep the series

[159]:
```
# group the sales into daily sum
mcb = outliers2.groupby(df['Order Date'].dt.date)['margin'].sum()
```

[159]:

```
Order Date
2019-01-01    10251.0
2019-01-02    10251.0
2019-01-03     4556.0
2019-01-04    11390.0
2019-01-05     4556.0
                …
2019-12-28    18224.0
2019-12-29    25862.0
2019-12-30    22780.0
2019-12-31    17085.0
2020-01-01     1139.0
Name: margin, Length: 366, dtype: float64
```

[160]:

```
# drop the last row becuase it appears to be only half a day of data
mcb = mcb.drop(mcb.index[365])
```

[161]:

```
# take the log of the data to remove the positive skew
mcb = np.log(mcb)
```

0.6 Check the stationarity

[162]:

```
# Utilize adf to test for stationarity
result = adfuller(mcb.dropna())
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
```

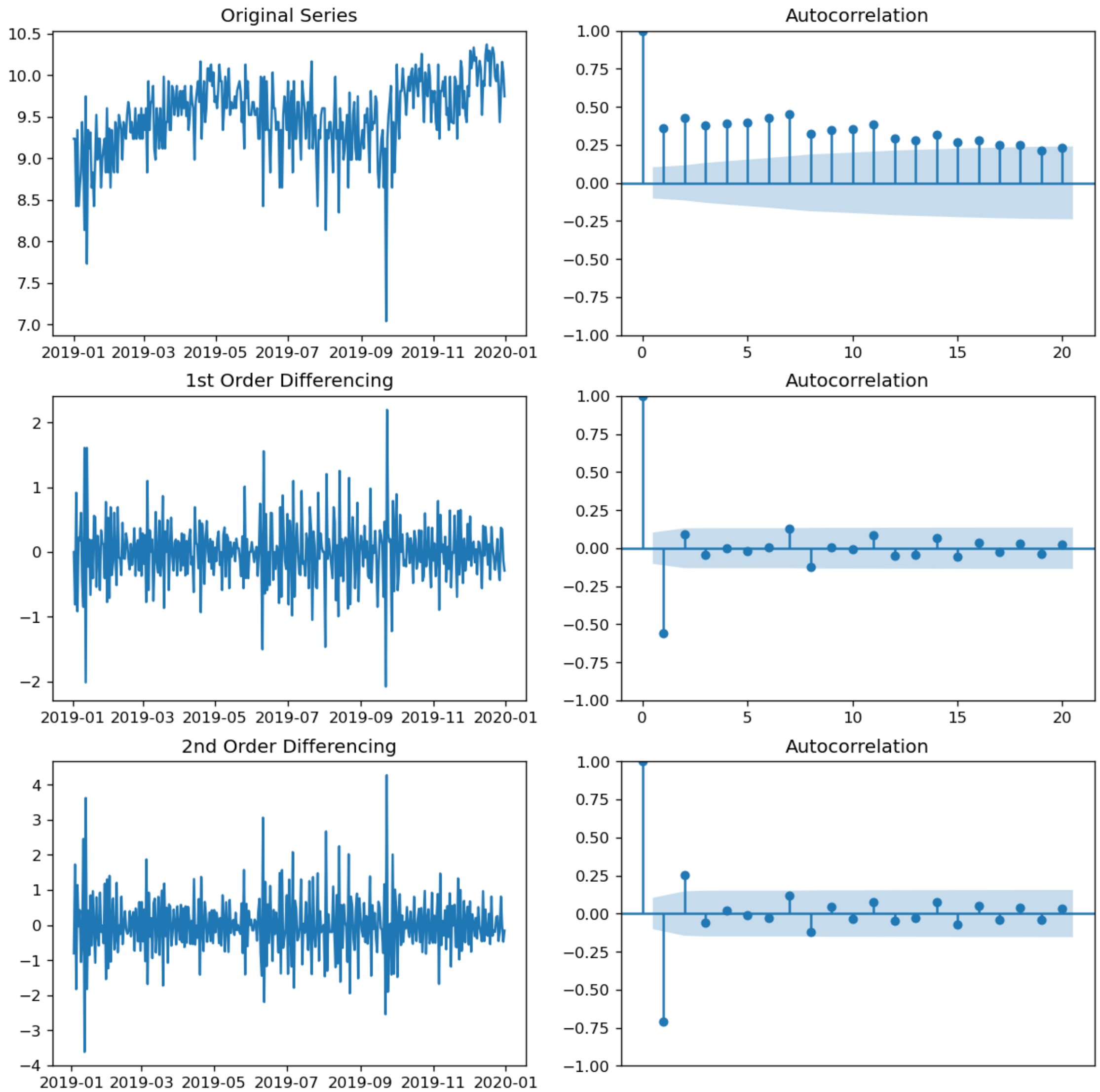
```
ADF Statistic: -2.698054
p-value: 0.074376
```

The p-value is > .05, so the data is not stationary. It will need to be differenced

[163]:

```
# Create a chart to check for stationality and view ACF

plt.rcParams.update({'figure.figsize':(12,12), 'figure.dpi':120})

# Original Series
fig, axes = plt.subplots(3, 2)
axes[0, 0].plot(mcb); axes[0, 0].set_title('Original Series')
plot_acf(mcb, ax=axes[0, 1], lags=20)

# 1st Differencing
axes[1, 0].plot(mcb.diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(mcb.diff().dropna(), ax=axes[1, 1], lags=20)

# 2nd Differencing
axes[2, 0].plot(mcb.diff().diff()); axes[2, 0].set_title('2nd Order␣
 ↪Differencing')
```

```
plot_acf(mcb.diff().diff().dropna(), ax=axes[2, 1], lags=20)

plt.xticks([])
plt.show()
```



0.7 Determine optimal p, d, q orders

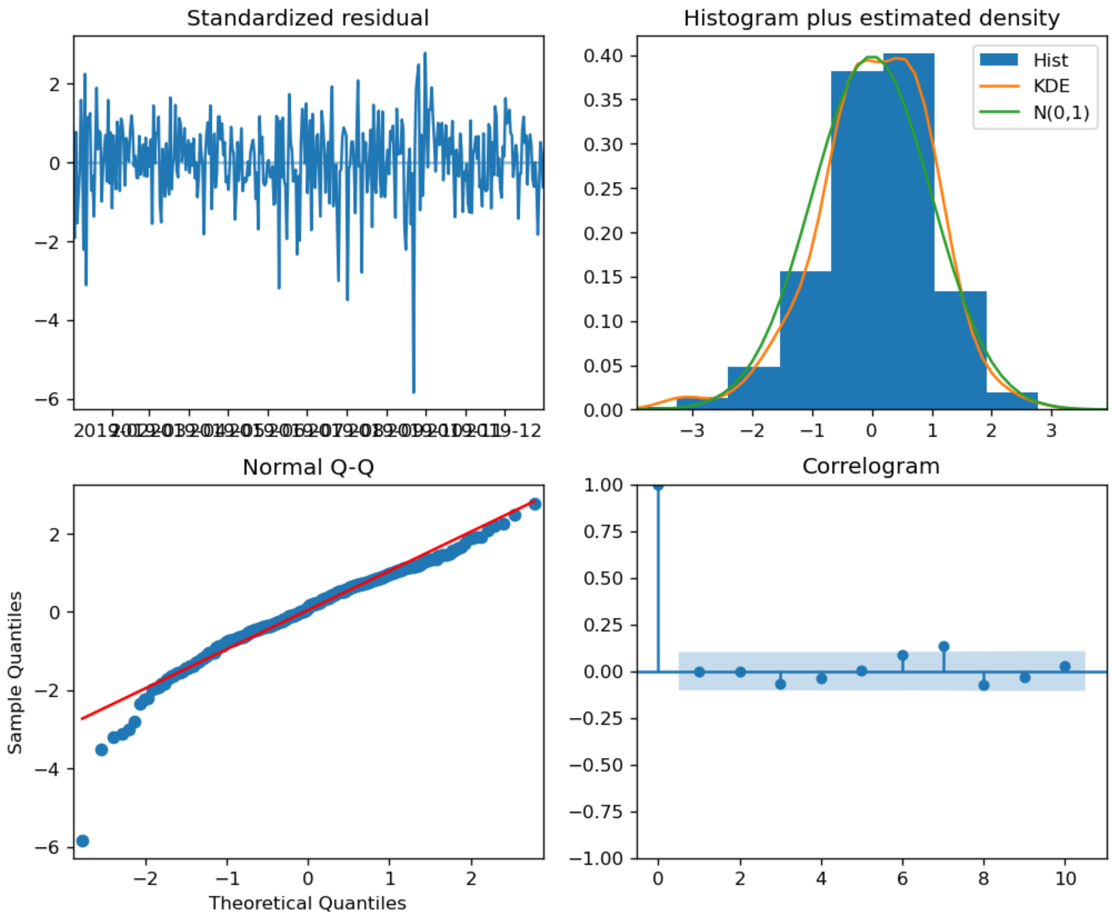
[164]:
```
# use autoarima to determine the optimal orders
aamodel = pm.auto_arima(mcb, start_p=1, start_q=1,
                        test='adf',         # use adftest to find optimal 'd'
                        max_p=5, max_q=5, # maximum p and q
                        m=1,                # frequency of series
                        d=None,             # let model determine 'd'
```

```
                                 seasonal=False,   # No Seasonality
                                 start_P=0,
                                 D=0,
                                 trace=True,
                                 error_action='ignore',
                                 suppress_warnings=True,
                                 stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=300.146, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=543.169, Time=0.04 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=410.171, Time=0.03 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=302.760, Time=0.05 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=541.171, Time=0.03 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=302.137, Time=0.11 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=300.606, Time=0.12 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=300.065, Time=0.07 sec
 ARIMA(0,1,3)(0,0,0)[0] intercept   : AIC=302.003, Time=0.08 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=304.059, Time=0.07 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=299.307, Time=0.02 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=302.302, Time=0.01 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=299.380, Time=0.05 sec
 ARIMA(0,1,3)(0,0,0)[0]             : AIC=301.193, Time=0.02 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=299.431, Time=0.02 sec
 ARIMA(1,1,3)(0,0,0)[0]             : AIC=303.307, Time=0.02 sec

Best model:  ARIMA(0,1,2)(0,0,0)[0]
Total fit time: 0.850 seconds
```

[165]:

```
# Plot model diagnostics
aamodel.plot_diagnostics(figsize=(10,8))
plt.show()
```



(Top left) Data is stationary. (Top right) Data has a fairly uniform distribution with a zero mean. (Bottom left) Data does not appear highly skewed. (Bottom right) residual errors are not autocorrelated. Based on these results, the model using auto arima's recommended orders appears fit to forecast.

0.7.1 Fit ARIMA model to very high margin dataset

[166]:
```
# model very high margin items
X = mcb
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()

# walk-forward validation
for t in range(len(test)):
    model = ARIMA(history, order=(0,1,2))
    model_fit = model.fit()
```

```
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test[t]
    history.append(obs)

# calculate rmse
rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE:', rmse)
```

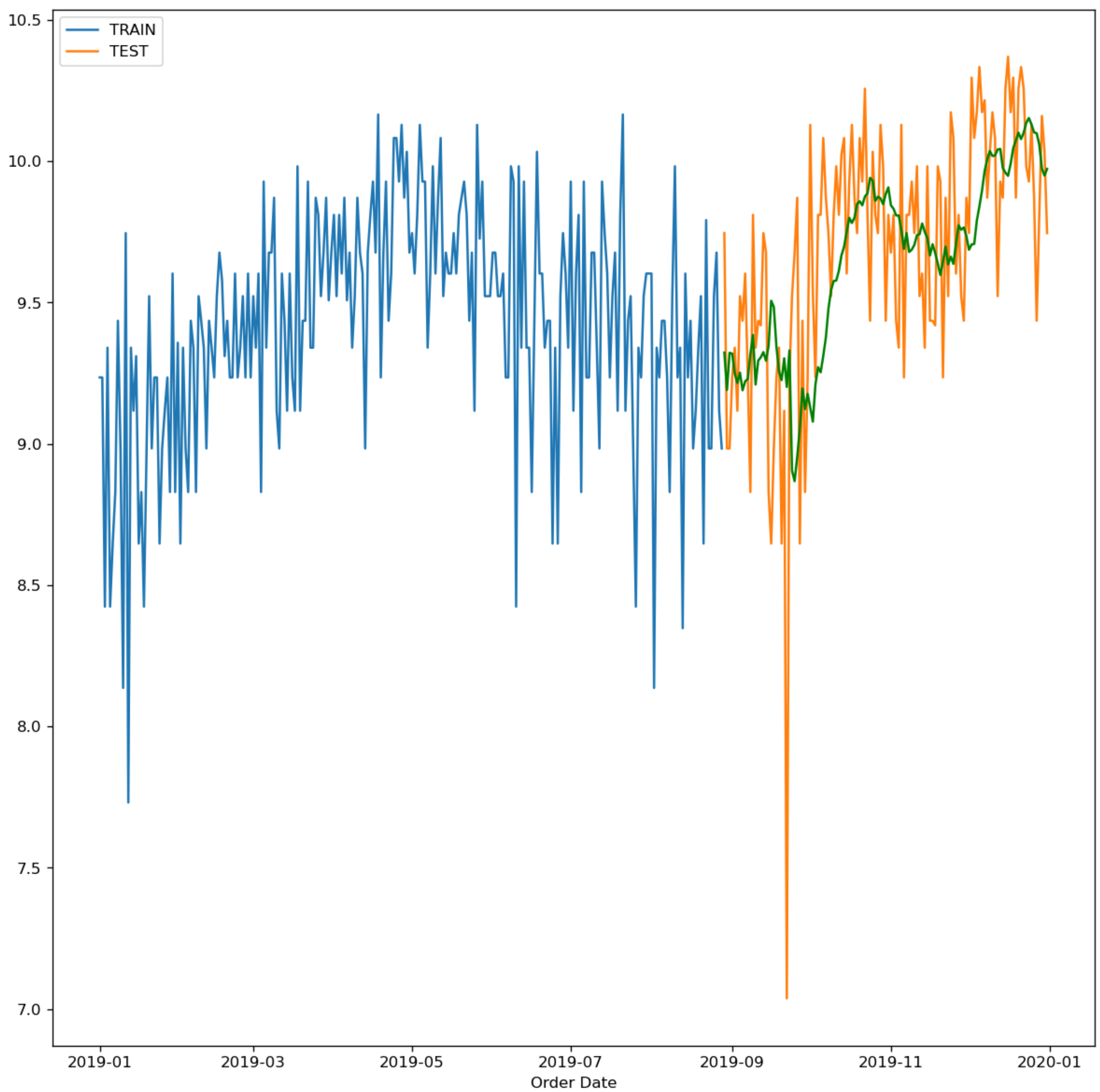
```
Test RMSE: 0.3924200075701837
```

[167]:
```
model_fit.summary()
```

[167]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  364
Model:                 ARIMA(0, 1, 2)   Log Likelihood                -146.555
Date:                Wed, 15 Nov 2023   AIC                            299.111
Time:                        18:15:51   BIC                            310.794
Sample:                             0   HQIC                           303.755
                                - 364
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.9802      0.051    -19.302      0.000      -1.080      -0.881
ma.L2          0.1170      0.046      2.536      0.011       0.027       0.207
sigma2         0.1307      0.006     21.227      0.000       0.119       0.143
================================================================================
===
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
245.91
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               1.41   Skew:
-0.97
Prob(H) (two-sided):                  0.06   Kurtosis:
6.54
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
"""
```

```
[168]: # plot predicted values against test values
train.plot(legend=True, label='TRAIN')
test.plot(legend=True, label='TEST')
plt.plot(X[size:len(X)].index, predictions, color='green')
```

```
[168]: [<matplotlib.lines.Line2D at 0x156195300>]
```



Predicted values do not reach the same extreme values as the measured values from the test set. The steep drop of sales in October is of particular concern becuase the prediction is much more mild than actual recorded sales.

```
[169]: # generate a 30 day forcast from the model
```

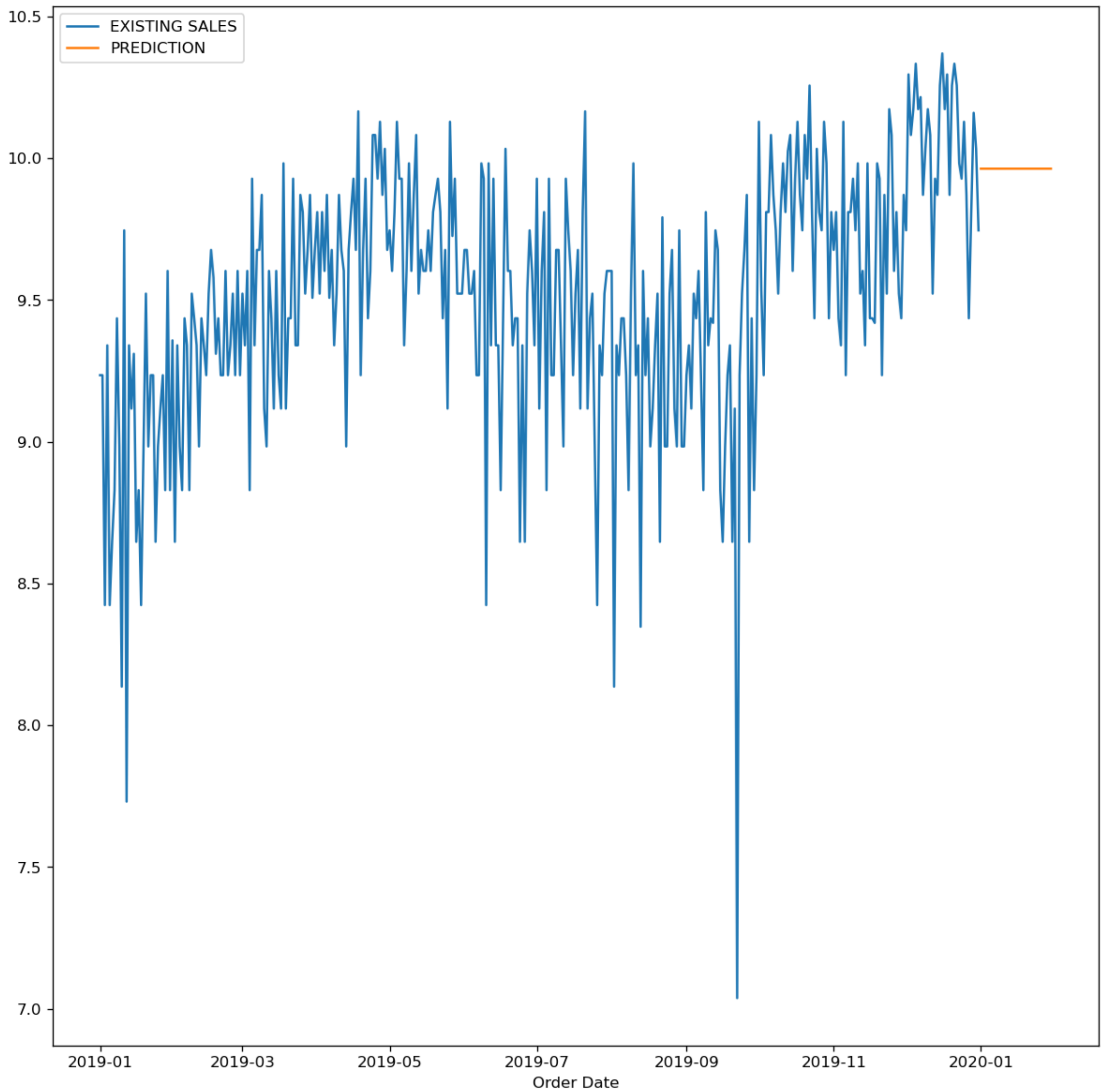
```
X = mcb
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in X]
predictions = list()

# walk-forward validation
for t in range(30):
    model = ARIMA(history, order=(0,1,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    history.append(yhat)

#create an index for the predictions list
dates2 = pd.date_range(start='1/1/2020', periods = 30)
```

[170]:
```
#check predicted sales values for the next 10 days
predictions[:10]
```

[170]:
```
[9.963499235523276,
 9.96350139178531,
 9.963503330871845,
 9.96350496198486,
 9.963506418365345,
 9.963507670070129,
 9.963508766674087,
 9.963509705794307,
 9.963510547653243,
 9.963511260319999]
```

[171]:
```
#plot the original sales numbers and the 30 day forecast
mcb.plot(legend=True, label='EXISTING SALES')
plt.plot(dates2, predictions, label='PREDICTION')
plt.legend()
```

[171]:
```
<matplotlib.legend.Legend at 0x1561df6a0>
```



The model forcast shows a fairly linear sales pattern for the next 30 days. Sales numbers are near the peak of sales for the year, so the company should be optomistic about the sales of these items.

0.8 Build a model for the Low Margin data subset

0.8.1 Prep the data

[172]:
```
# group the sales into daily sum
lm = df2.groupby(df['Order Date'].dt.date)['margin'].sum()

# drop the last date because it appears to be only a half day of data
lm = lm.drop(lm.index[365])

# log transform the series to adjust for positive skew
```

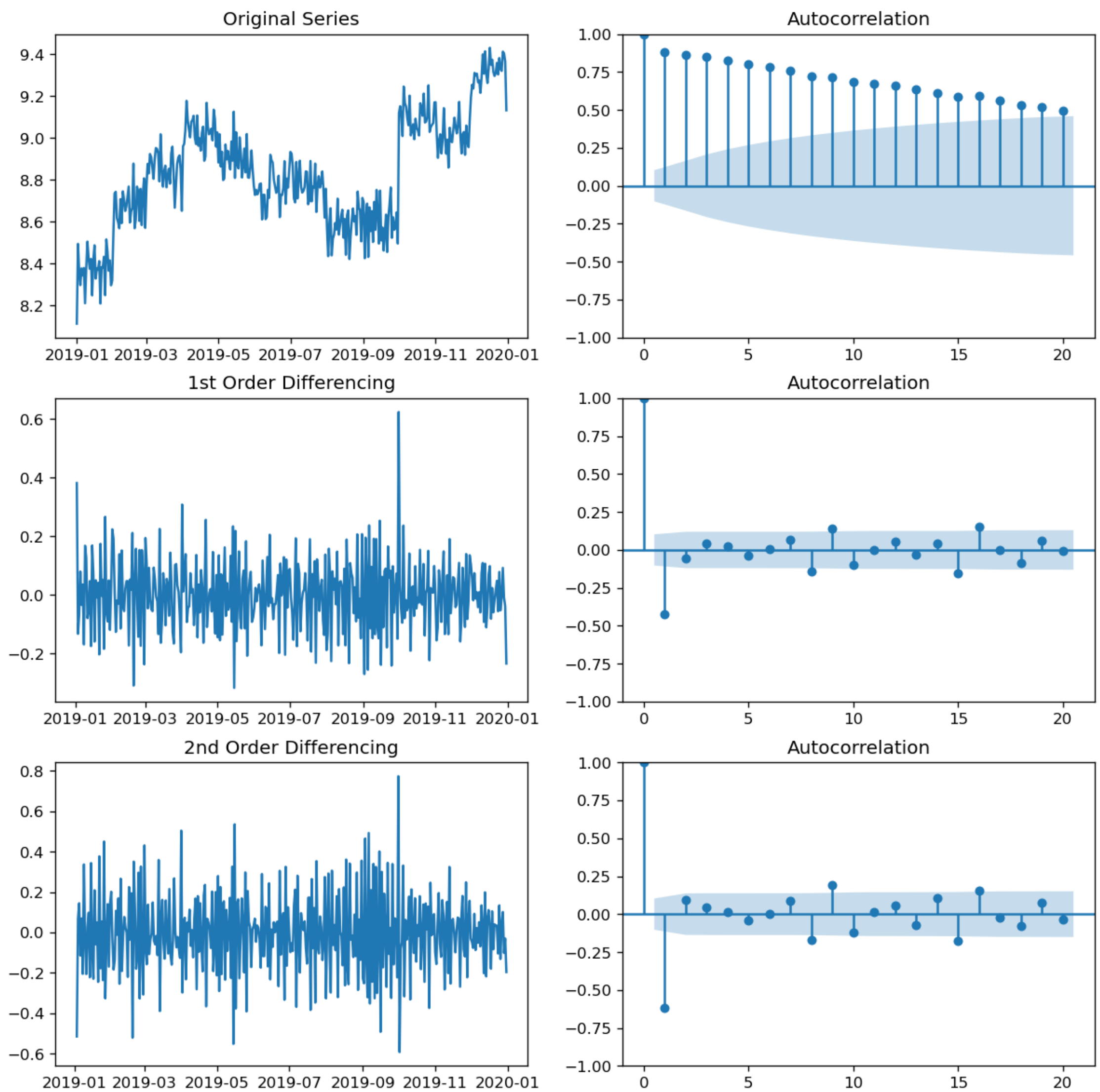
```
lm = np.log(lm)
```

0.8.2 Check for stationarity

[173]:
```
# Utilize adf to test for stationarity
result = adfuller(lm.dropna())
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
```

```
ADF Statistic: -1.952079
p-value: 0.307972
```

[174]:
```
# Original Series
fig, axes = plt.subplots(3, 2)
axes[0, 0].plot(lm); axes[0, 0].set_title('Original Series')
plot_acf(lm, ax=axes[0, 1], lags=20)

# 1st Differencing
axes[1, 0].plot(lm.diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(lm.diff().dropna(), ax=axes[1, 1], lags=20)

# 2nd Differencing
axes[2, 0].plot(lm.diff().diff()); axes[2, 0].set_title('2nd Order␣
↪Differencing')
plot_acf(lm.diff().diff().dropna(), ax=axes[2, 1], lags=20)

plt.show()
```



0.8.3 Determine optimal ARIMA orders for low margin dataset

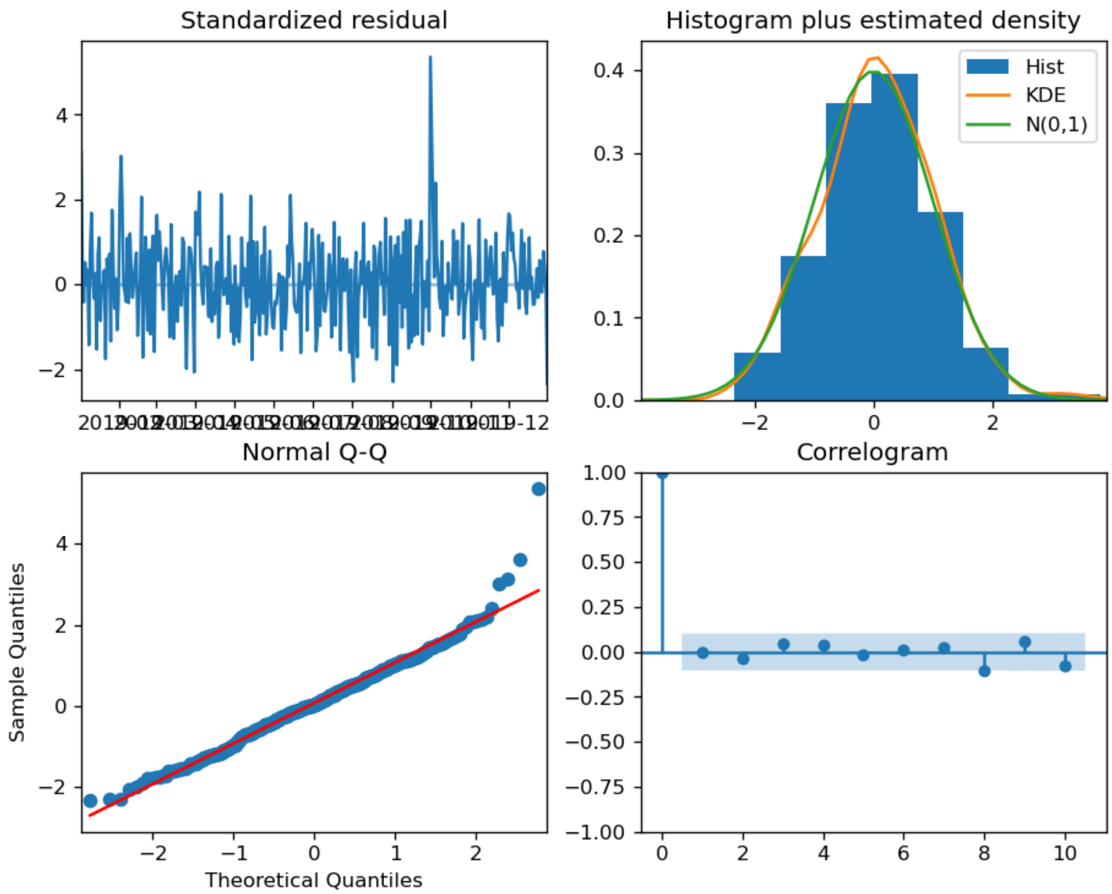
[175]:
```
# use autoarima to determine the optimal orders
aamodel = pm.auto_arima(lm, start_p=1, start_q=1,
                        test='adf',        # use adftest to find optimal 'd'
                        max_p=5, max_q=5, # maximum p and q
                        m=1,               # frequency of series
                        d=None,            # let model determine 'd'
                        seasonal=False,    # No Seasonality
                        start_P=0,
                        D=0,
                        trace=True,
                        error_action='ignore',
```

```
                         suppress_warnings=True,
                         stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-612.620, Time=0.16 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-499.557, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-571.639, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-614.608, Time=0.03 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-501.362, Time=0.01 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=-612.622, Time=0.04 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=-613.424, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=-614.847, Time=0.04 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=-612.884, Time=0.03 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=-612.893, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=-573.189, Time=0.01 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=-610.949, Time=0.03 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0]
Total fit time: 0.585 seconds
```

[176]:

```
# plot the residual plots of the model
aamodel.plot_diagnostics(figsize=(9,7))
plt.show()
```



(Top left) Data is stationary. (Top right) Data has a fairly uniform distribution with a zero mean. (Bottom left) Data does not appear highly skewed. (Bottom right) residual errors are not autocorrelated. Based on these results, the model using auto arima's recommended orders appears fit to forecast.

0.8.4 Fit ARIMA model for low margin dataset

[177]:
```
# model low margin items
X = lm
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()

# walk-forward validation
for t in range(len(test)):
    model = ARIMA(history, order=(0,1,1))
    model_fit = model.fit()
    output = model_fit.forecast()
```

```
    yhat = output[0]
    predictions.append(yhat)
    obs = test[t]
    history.append(obs)

# calculate rmse
rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE:', rmse)
```

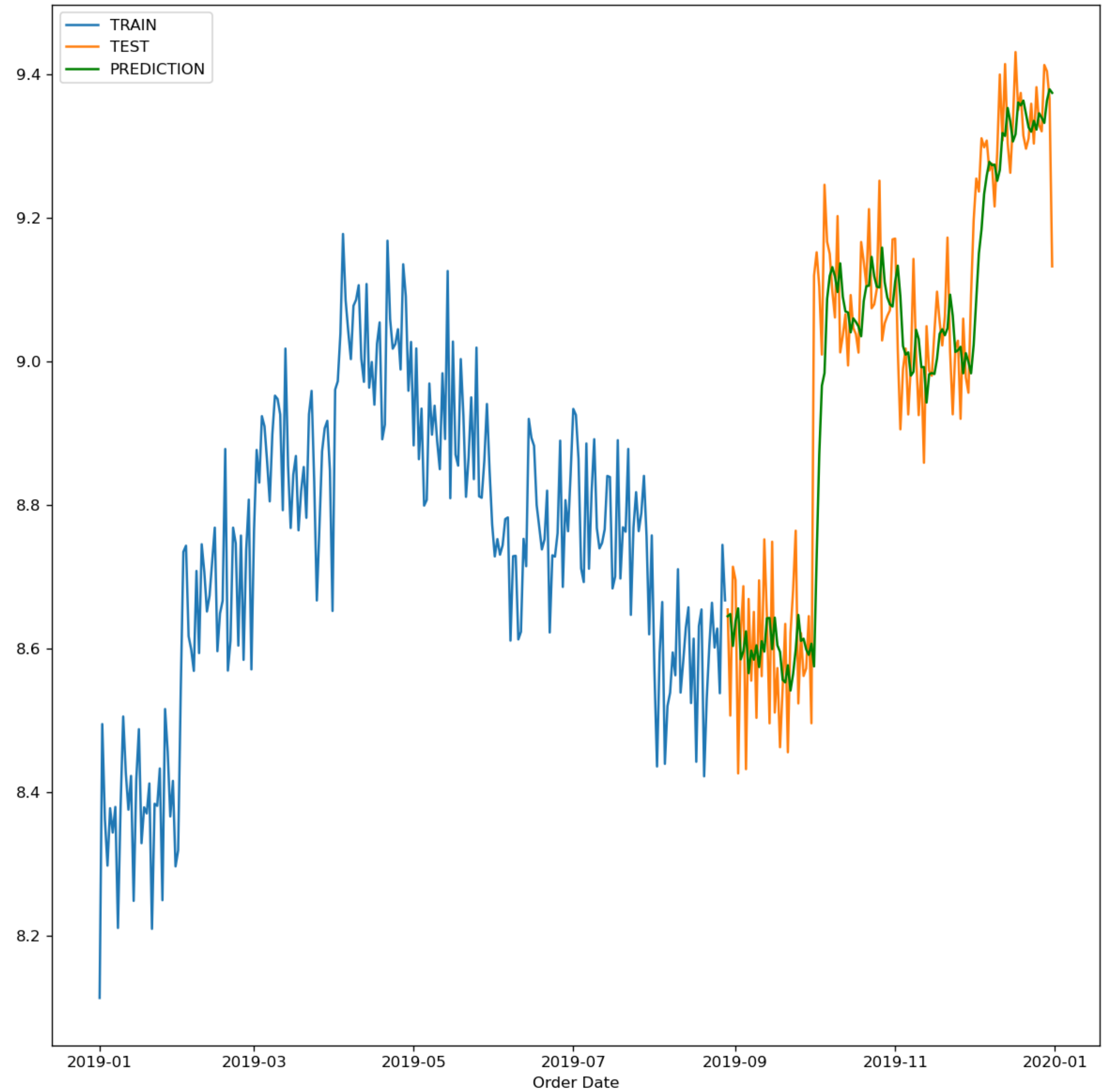
```
Test RMSE: 0.11186035495796498
```

[178]:
```
#print model summary statistics
model_fit.summary()
```

[178]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  364
Model:                 ARIMA(0, 1, 1)   Log Likelihood                 310.823
Date:                Wed, 15 Nov 2023   AIC                           -617.646
Time:                        18:15:55   BIC                           -609.857
Sample:                             0   HQIC                          -614.550
                                - 364
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.6143      0.033    -18.784      0.000      -0.678      -0.550
sigma2         0.0105      0.001     19.327      0.000       0.009       0.012
================================================================================
===
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
79.34
Prob(Q):                              0.95   Prob(JB):
0.00
Heteroskedasticity (H):               1.08   Skew:
0.55
Prob(H) (two-sided):                  0.69   Kurtosis:
5.01
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
"""
```

[179]:
```
# plot predicted values against test values
train.plot(legend=True, label='TRAIN')
test.plot(legend=True, label='TEST')
plt.plot(X[size:len(X)].index, predictions, color='green', label='PREDICTION')
plt.legend()
```

[179]: <matplotlib.legend.Legend at 0x151ae5480>



Predicted values do not reach the same extreme values as the measured values from the test set, but follow do follow the pattern of the revenue closely. Predicted values capture the steep climbs in revenue, but do not capture the drop towards the end of the time series. This drop might be predicted if there were more data available for training.

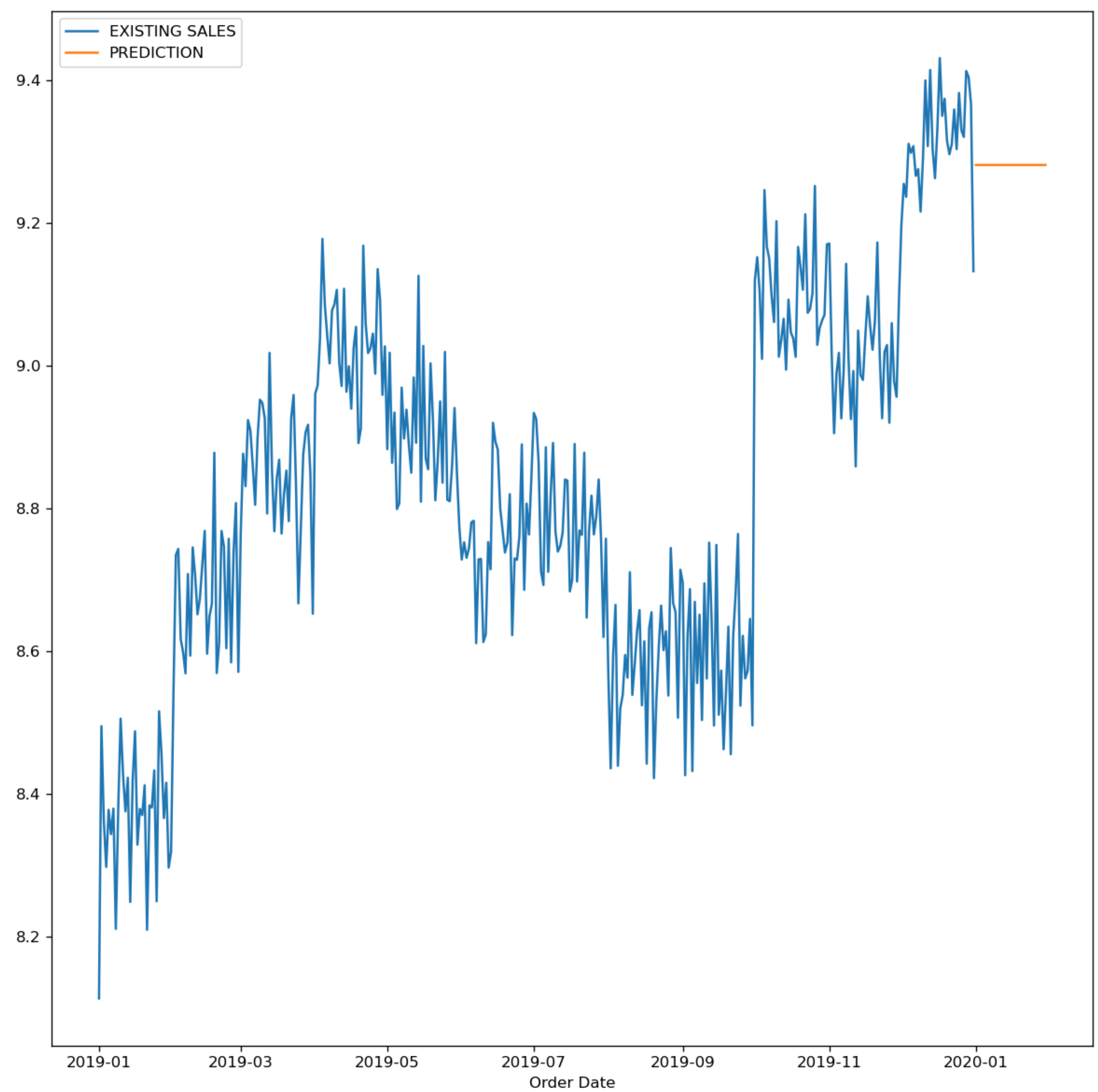
[180]:
```
# generate a 30 day forcast
X = lm
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in X]
predictions = list()

# walk-forward validation
for t in range(30):
    model = ARIMA(history, order=(0,1,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    history.append(yhat)

#create an index for the predictions list
dates2 = pd.date_range(start='1/1/2020', periods = 30)
```

[181]:
```
#check predicted sales values for the next 10 days
predictions[:10]
```

[181]:
```
[9.281137177491111,
 9.281135379734023,
 9.281136972662182,
 9.281137080778457,
 9.281137517926634,
 9.281137408864451,
 9.28113735053827,
 9.281137350925286,
 9.281137339187675,
 9.281137446228614]
```

[182]:
```
# plot predicted sales
lm.plot(legend=True, label='EXISTING SALES')
plt.plot(dates2, predictions, label='PREDICTION')
plt.legend()
```

[182]:
```
<matplotlib.legend.Legend at 0x155a40790>
```



The model forcast shows a fairly linear sales pattern for the next 30 days. Items in this subset appear to have a monthly sales pattern. The model predicts sales in the next month to be above average for this dataset, but below the peak sales for this year.

0.9 Build a model for the High Margin data subset

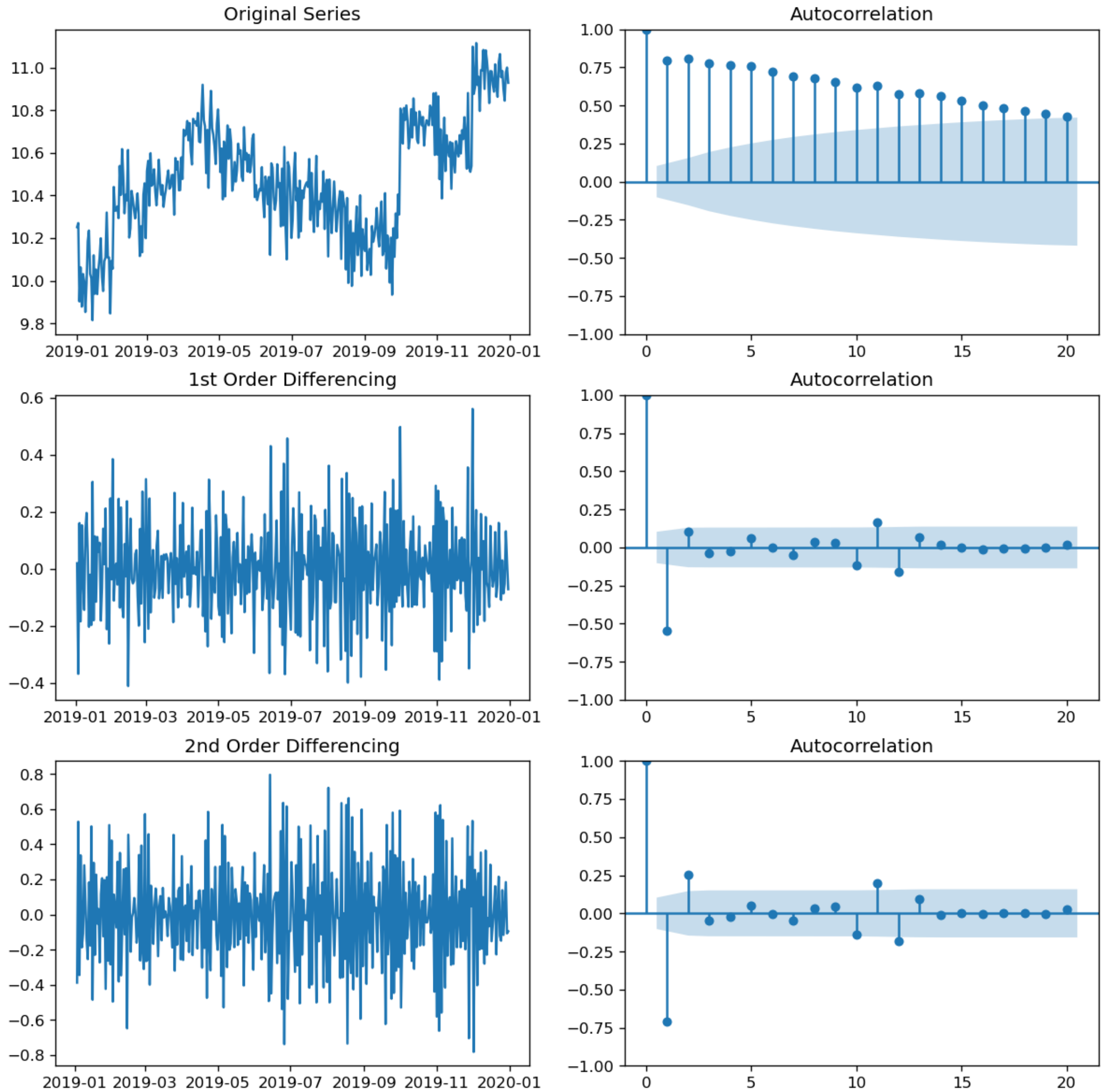
[183]:
```
# group the sales into daily sum
hm = outliers3.groupby(df['Order Date'].dt.date)['margin'].sum()

# drop the last row because it appears to be only a half day of data
hm = hm.drop(hm.index[365])

# log transform the series to adjust for positive skew
```

```
hm = np.log(hm)
```

[184]:
```
# use adf to test for stationarity
result = adfuller(hm.dropna())
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
```

```
ADF Statistic: -1.876697
p-value: 0.343102
```

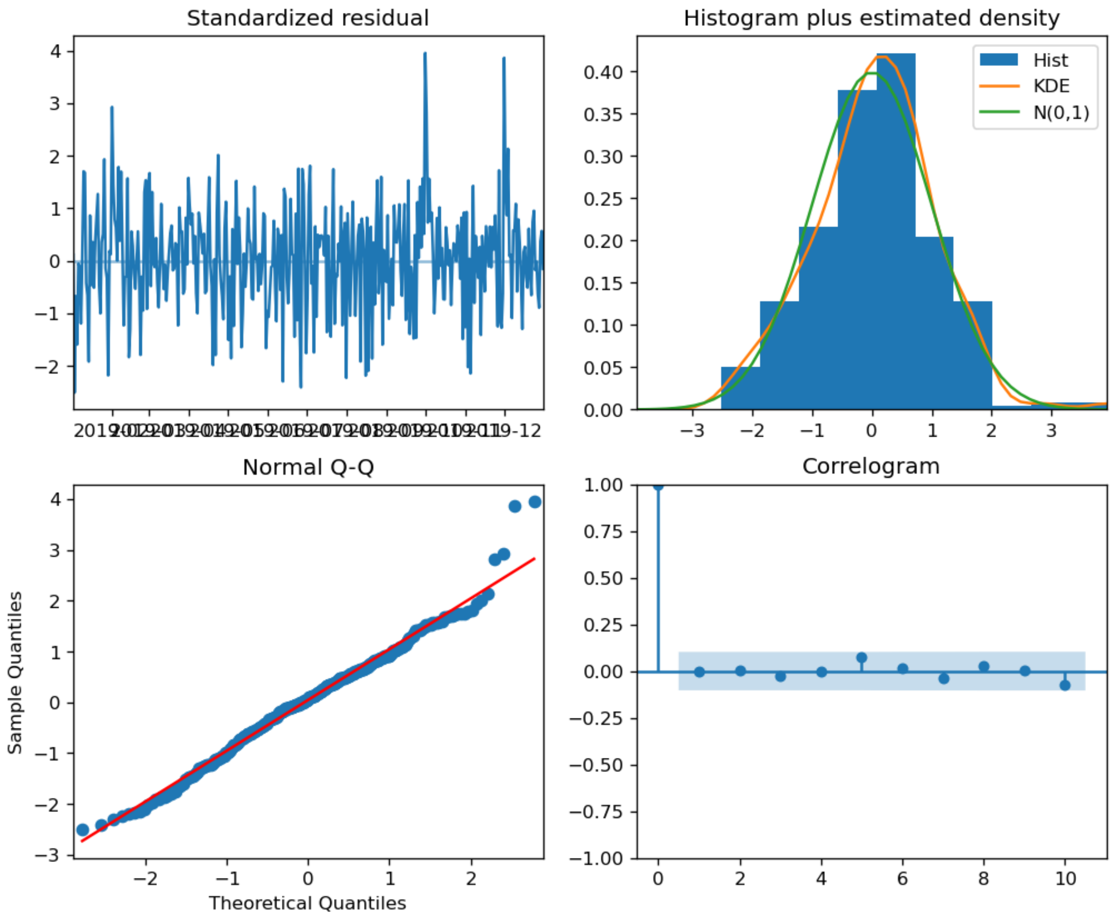
[185]:
```
# use a plot and ACF to confirm stationarity results
# Original Series
fig, axes = plt.subplots(3, 2)
axes[0, 0].plot(hm); axes[0, 0].set_title('Original Series')
plot_acf(hm, ax=axes[0, 1], lags=20)

# 1st Differencing
axes[1, 0].plot(hm.diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(hm.diff().dropna(), ax=axes[1, 1], lags=20)

# 2nd Differencing
axes[2, 0].plot(hm.diff().diff()); axes[2, 0].set_title('2nd Order␣
 ↪Differencing')
plot_acf(hm.diff().diff().dropna(), ax=axes[2, 1], lags=20)

plt.show()
```



[186]:
```
# use autoarima to determine the optimal orders
aamodel = pm.auto_arima(hm, start_p=1, start_q=1,
                        test='adf',        # use adftest to find optimal 'd'
                        max_p=5, max_q=5, # maximum p and q
                        m=1,               # frequency of series
                        d=None,            # let model determine 'd'
                        seasonal=False,    # No Seasonality
                        start_P=0,
                        D=0,
                        trace=True,
                        error_action='ignore',
                        suppress_warnings=True,
                        stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-428.860, Time=0.06 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-255.452, Time=0.03 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-381.000, Time=0.04 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-426.525, Time=0.08 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-257.408, Time=0.03 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=-426.896, Time=0.09 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=-426.921, Time=0.10 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=-428.714, Time=0.09 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=-407.562, Time=0.04 sec
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=-424.896, Time=0.12 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=-429.838, Time=0.03 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=-427.267, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=-382.843, Time=0.02 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=-427.858, Time=0.05 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=-427.874, Time=0.03 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=-429.719, Time=0.05 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=-409.238, Time=0.02 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=-425.885, Time=0.09 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 0.995 seconds
```

[187]:
```
aamodel.plot_diagnostics(figsize=(10,8))
plt.show()
```



(Top left) Data is stationary. (Top right) Data has a fairly uniform distribution with a zero mean. (Bottom left) Data does not appear highly skewed. (Bottom right) residual errors are not autocorrelated. Based on these results, the model using auto arima's recommended orders appears fit to forecast.

0.9.1 Fit an ARIMA model for High Margin dataset

[188]:
```
# model high margin items
X = hm
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()

# walk-forward validation
for t in range(len(test)):
    model = ARIMA(history, order=(1,1,1))
    model_fit = model.fit()
```

```
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test[t]
    history.append(obs)

print('predicted=%f, expected=%f' % (yhat, obs))

# evaluate forecasts
rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE: %.3f' % rmse)
```

```
predicted=10.949863, expected=10.929179
Test RMSE: 0.136
```

[189]:

```
# print summary statistics for the model
model_fit.summary()
```

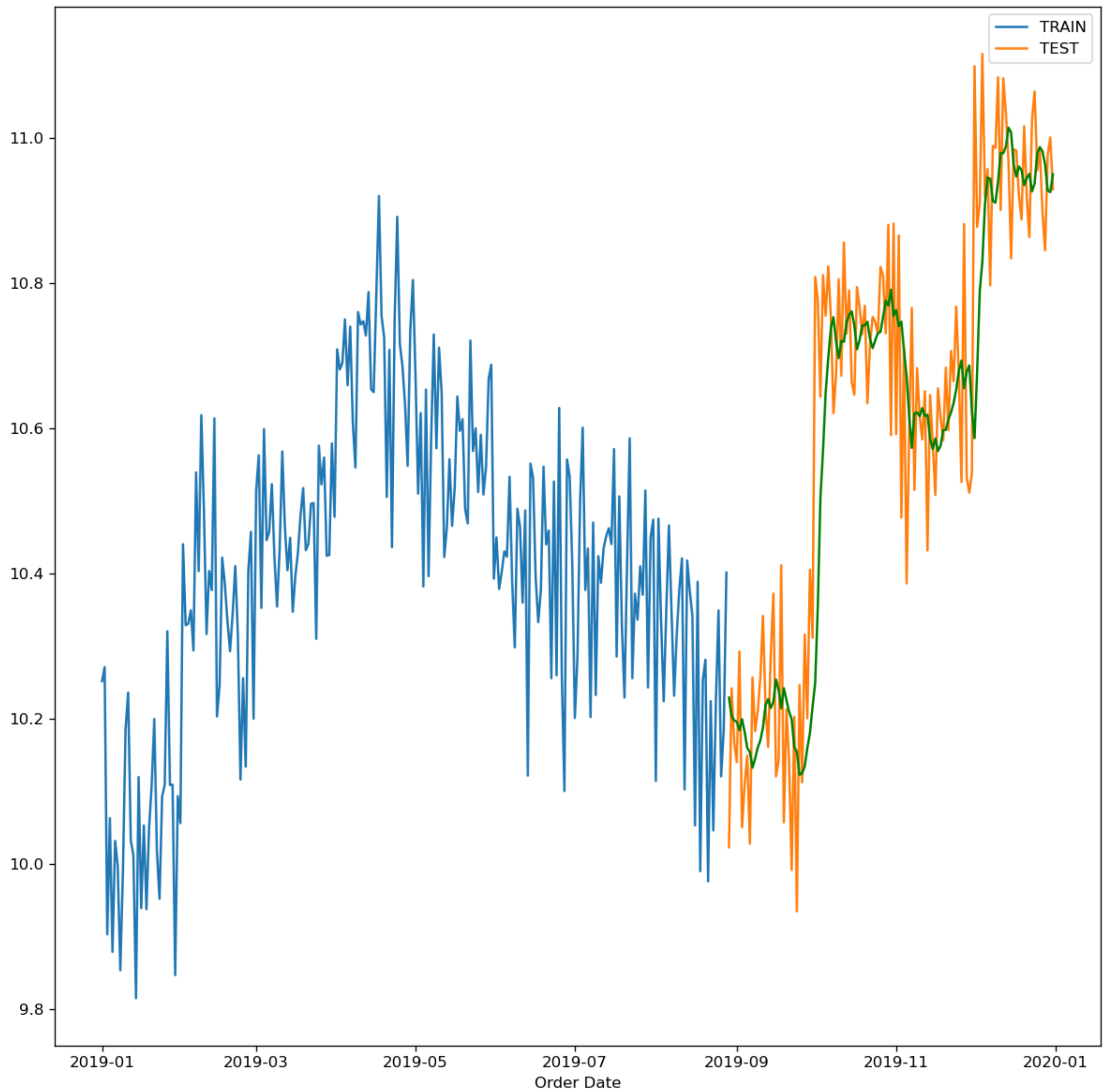
[189]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  364
Model:                 ARIMA(1, 1, 1)   Log Likelihood                 216.832
Date:                Wed, 15 Nov 2023   AIC                           -427.664
Time:                        18:16:01   BIC                           -415.981
Sample:                             0   HQIC                          -423.020
                                - 364
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1554      0.065     -2.394      0.017      -0.283      -0.028
ma.L1         -0.6262      0.050    -12.539      0.000      -0.724      -0.528
sigma2         0.0177      0.001     15.613      0.000       0.015       0.020
================================================================================
===
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
8.69
Prob(Q):                              0.99   Prob(JB):
0.01
Heteroskedasticity (H):               1.04   Skew:
0.11
Prob(H) (two-sided):                  0.84   Kurtosis:
3.72
================================================================================
===
```

```
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
"""
```

[190]:
```
# plot predicted values against test set
train.plot(legend=True, label='TRAIN')
test.plot(legend=True, label='TEST')
plt.plot(X[size:len(X)].index, predictions, color='green')
```

[190]:
```
[<matplotlib.lines.Line2D at 0x150f8c3d0>]
```



Predicted values do not reach the same extreme values as the measured values from the test set, but follow do follow the pattern of the revenue closely.

[191]:

```
# generate a 30 day forcast with the model
X = hm
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in X]
predictions = list()

# walk-forward validation
for t in range(30):
    model = ARIMA(history, order=(1,1,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    history.append(yhat)

#create an index for the predictions list
dates2 = pd.date_range(start='1/1/2020', periods = 30)
```

[192]:

```
#check predicted sales values for the next 10 days
predictions[:10]
```

[192]:

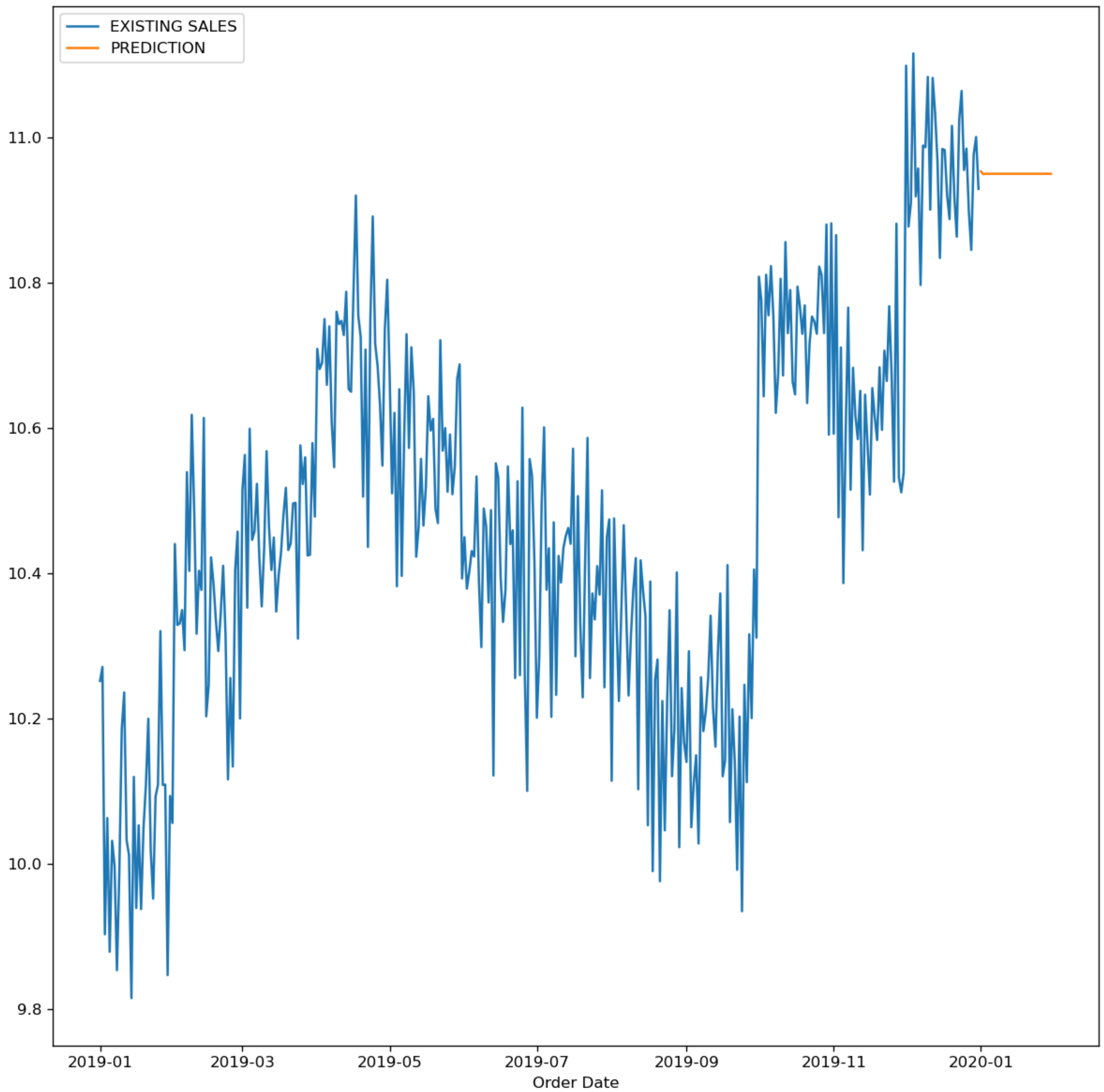
```
[10.953255159075395,
 10.949508635684774,
 10.950091607229503,
 10.950000891010498,
 10.950014983309863,
 10.950012790241706,
 10.950013127757698,
 10.950013074981388,
 10.950013083189914,
 10.950013081369175]
```

[193]:

```
# plot forcasted values with historical sales numbers
hm.plot(legend=True, label='EXISTING SALES')
plt.plot(dates2, predictions, label='PREDICTION')
plt.legend()
```

[193]:

```
<matplotlib.legend.Legend at 0x1511cb280>
```



Predicted sales are fairly linear over the next 30 days. Our model suggests that sales in this category peaked last month and will experience a slight decline in next 30 days.