Sales Forcasting Project

Objective:

Perform EDA and Predict the sales of the next 7 days from the last date of the Training dataset.

Dataset:

Superstore Sales Dataset from https://www.kaggle.com/rohitsahoo/sales-forecasting

Loading Phase

In [1]:

```
# Load required packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
# load in dataset

url = '~/Documents/GitHub/Sales_Prediction/train.csv'

data = pd.read_csv(url)

data.head()
```

Out[2]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	
0	1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	H
1	2	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	H
2	3	CA-2017-138688	12/06/2017	16/06/2017	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	
3	4	US-2016-108966	11/10/2016	18/10/2016	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	La
4	5	US-2016-108966	11/10/2016	18/10/2016	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	La

Exploratory Data Analysis

In [3]:

```
# summarize dataset

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9800 entries, 0 to 9799
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Row ID         9800 non-null   int64  
 1   Order ID       9800 non-null   object 
 2   Order Date     9800 non-null   object 
 3   Ship Date      9800 non-null   object 
 4   Ship Mode      9800 non-null   object 
 5   Customer ID    9800 non-null   object 
 6   Customer Name  9800 non-null   object 
 7   Segment        9800 non-null   object 
 8   Country        9800 non-null   object 
 9   City           9800 non-null   object 
 10  State          9800 non-null   object 
 11  Postal Code    9789 non-null   float64
 12  Region         9800 non-null   object 
 13  Product ID     9800 non-null   object 
 14  Category       9800 non-null   object 
 15  Sub-Category   9800 non-null   object 
 16  Product Name   9800 non-null   object 
 17  Sales          9800 non-null   float64
dtypes: float64(2), int64(1), object(15)
memory usage: 1.3+ MB
```

In [4]:

```
# remove Row ID

data.drop('Row ID', axis = 1, inplace = True)
```

In [5]:

```
# convert dates to datetime

data['Order Date'] = pd.to_datetime(data['Order Date'], format = '%d/%m/%Y')
data['Ship Date'] = pd.to_datetime(data['Ship Date'], format = '%d/%m/%Y')

print(data['Order Date'].dtypes, data['Ship Date'].dtypes)
```

```
datetime64[ns] datetime64[ns]
```

In [6]:

```
# drop NA in postal codes and convert to integer

data = data.dropna()

data['Postal Code'] = data['Postal Code'].astype('int64')
```

In [7]:

```
data['Postal Code'].dtype
```

Out[7]:

```
dtype('int64')
```

In [8]:

```
# add in new features from dates

data['Order Year'] = data['Order Date'].dt.year
data['Order Month'] = data['Order Date'].dt.month
data['Order Day'] = data['Order Date'].dt.day
data['Order Week_day'] = data['Order Date'].dt.weekday

data['Ship Year'] = data['Ship Date'].dt.year
data['Ship Month'] = data['Ship Date'].dt.month
data['Ship Day'] = data['Ship Date'].dt.day
data['Ship Week_day'] = data['Ship Date'].dt.weekday

data['Ship Delay'] = pd.Series(delta.days for delta in (data['Ship Date'] - d
```

In [9]:

```
data.head()
```

Out[9]:

	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	S
0	CA-2017-152156	2017-11-08	2017-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	Kent
1	CA-2017-152156	2017-11-08	2017-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	Kent
2	CA-2017-138688	2017-06-12	2017-06-16	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Los Angeles	Califo
3	US-2016-108966	2016-10-11	2016-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	Flo
4	US-2016-108966	2016-10-11	2016-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	Flo

5 rows × 26 columns

In [10]:

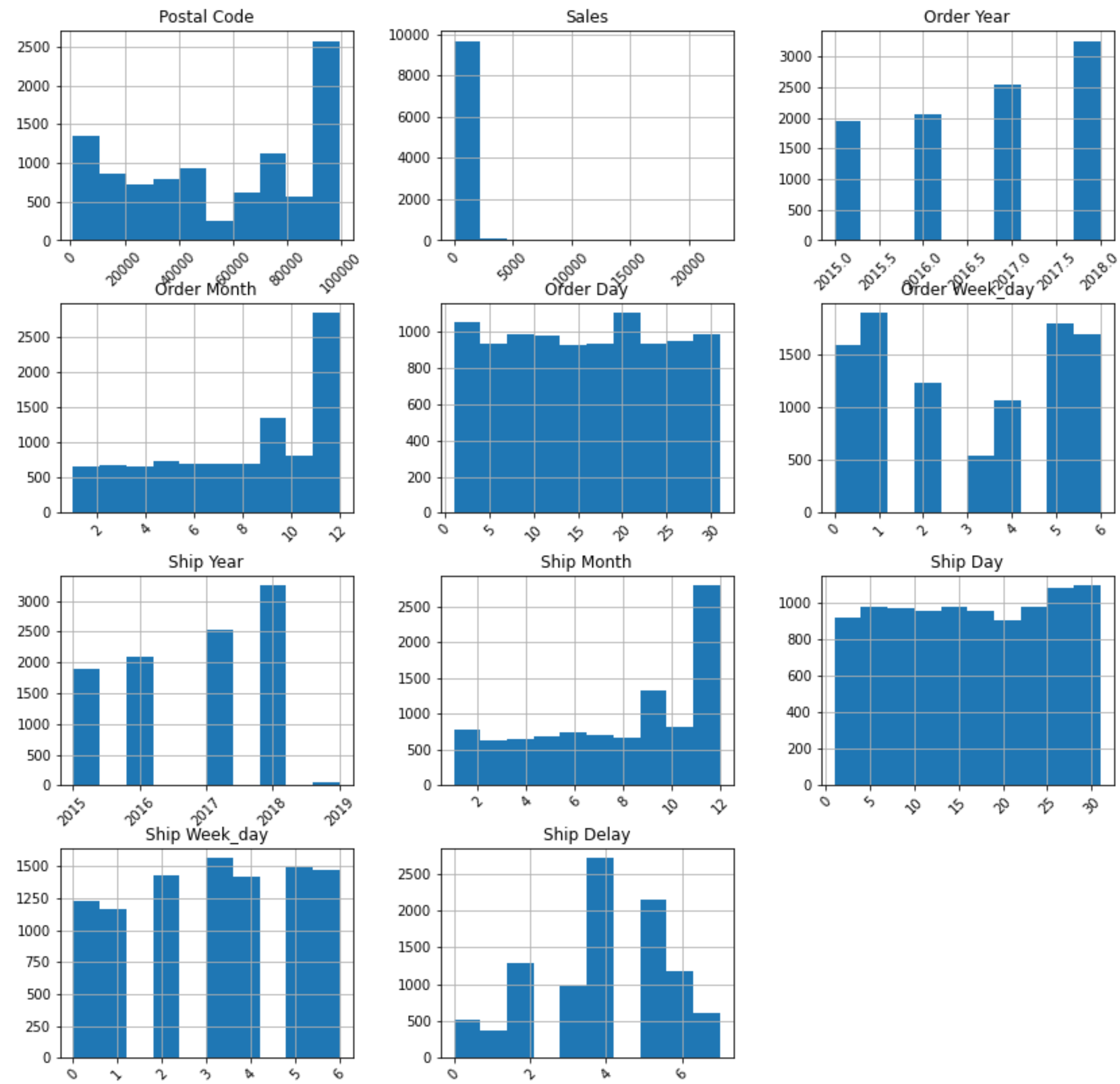
```
# exploration function
def explore(df):
    print("Shape: ", df.shape, "/n")
    print(df.dtypes, "/n")
    print(df.head(), "/n")
    # numeric data statistics
    print(df.describe())
    df.hist(figsize=(14,14), xrot=45)
    plt.show()
    # categorical data statistics
    print(df.describe(include = 'object'))
    for column in df.select_dtypes(include = 'object'):
        if df[column].nunique() < 10:
            sns.countplot(y = column, data = df).figure.savefig('plots/{}_dis
            plt.show()
```

In [11]:

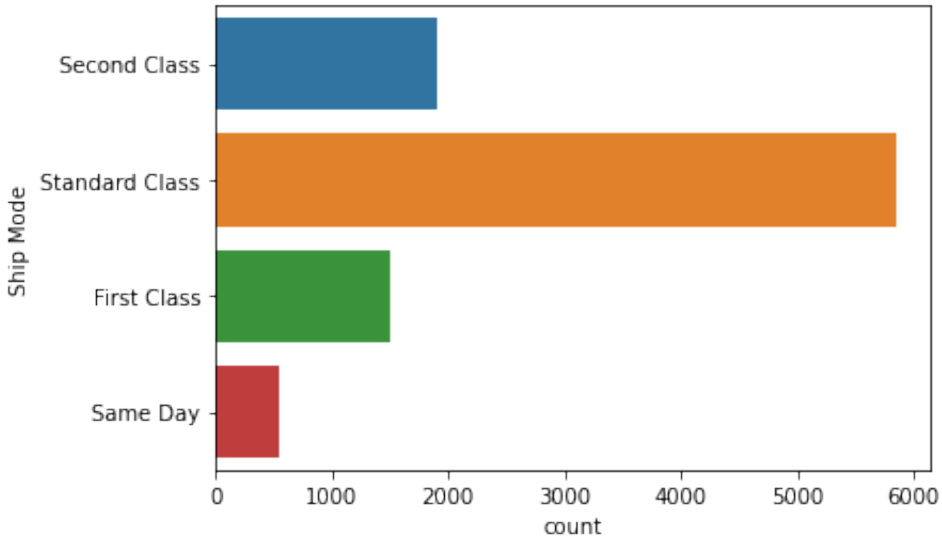
```
explore(data)
```

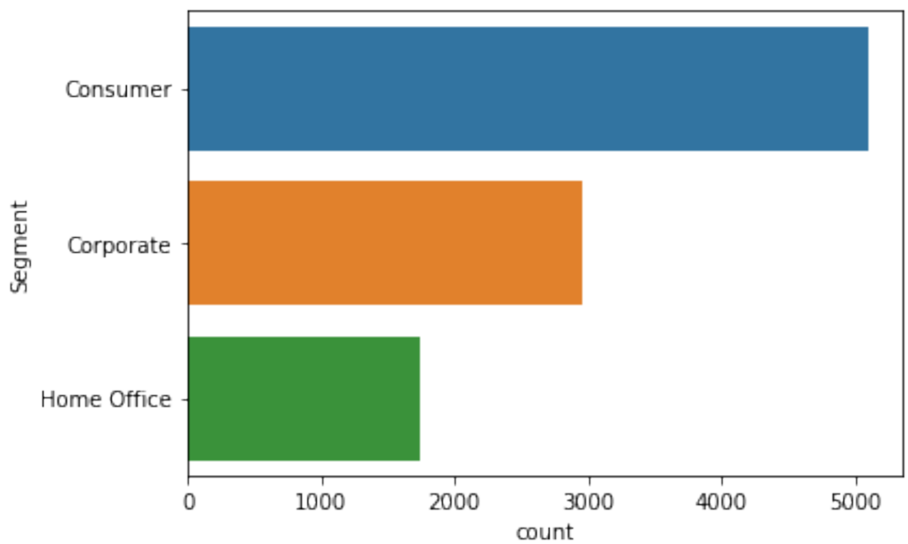
```
Shape:  (9789, 26) /n
Order ID                  object
Order Date        datetime64[ns]
Ship Date         datetime64[ns]
Ship Mode                 object
Customer ID               object
Customer Name             object
Segment                   object
Country                   object
City                      object
State                     object
Postal Code                int64
Region                    object
Product ID                object
Category                  object
Sub-Category              object
Product Name              object
Sales                    float64
Order Year                 int64
Order Month                int64
Order Day                  int64
Order Week_day             int64
Ship Year                  int64
Ship Month                 int64
Ship Day                   int64
Ship Week_day              int64
Ship Delay               float64
dtype: object /n
         Order ID Order Date  Ship Date       Ship Mode Customer ID  \
0  CA-2017-152156 2017-11-08 2017-11-11    Second Class    CG-12520
1  CA-2017-152156 2017-11-08 2017-11-11    Second Class    CG-12520
2  CA-2017-138688 2017-06-12 2017-06-16    Second Class    DV-13045
3  US-2016-108966 2016-10-11 2016-10-18  Standard Class    SO-20335
4  US-2016-108966 2016-10-11 2016-10-18  Standard Class    SO-20335
```

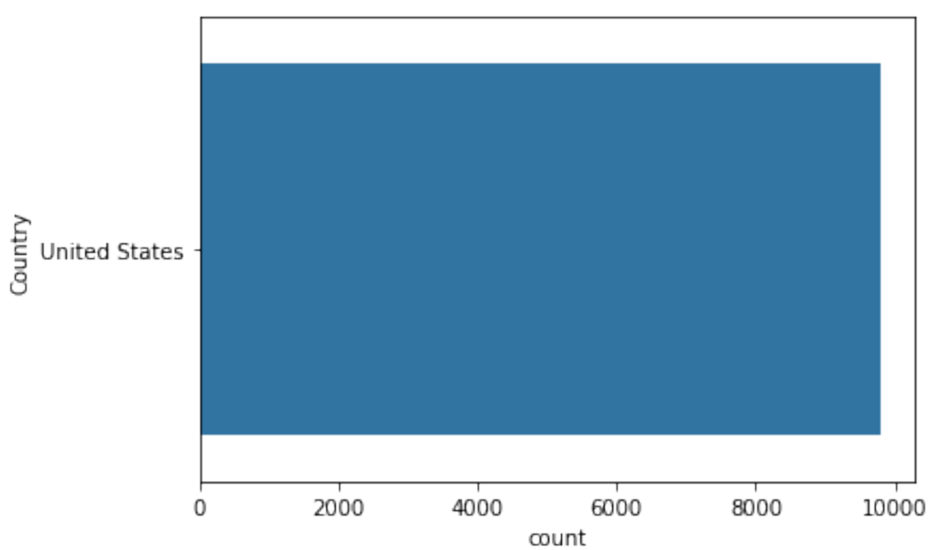
```
     Customer Name    Segment        Country             City       State  \
0      Claire Gute   Consumer  United States        Henderson    Kentucky   
1      Claire Gute   Consumer  United States        Henderson    Kentucky   
2  Darrin Van Huff  Corporate  United States      Los Angeles  California   
3   Sean O'Donnell   Consumer  United States  Fort Lauderdale     Florida   
4   Sean O'Donnell   Consumer  United States  Fort Lauderdale     Florida   

   ...     Sales Order Year Order Month Order Day Order Week_day Ship Year  \
0  ...  261.9600       2017          11         8              2      2017   
1  ...  731.9400       2017          11         8              2      2017   
2  ...   14.6200       2017           6        12              0      2017   
3  ...  957.5775       2016          10        11              1      2016   
4  ...   22.3680       2016          10        11              1      2016   

   Ship Month  Ship Day  Ship Week_day  Ship Delay  
0          11        11              5         3.0  
1          11        11              5         3.0  
2           6        16              4         4.0  
3          10        18              1         7.0  
4          10        18              1         7.0  

[5 rows x 26 columns] /n
        Postal Code         Sales   Order Year  Order Month    Order Day  \
count   9789.000000   9789.000000  9789.000000  9789.000000  9789.000000   
mean   55273.322403    230.116193  2016.723567     7.822658    15.486771   
std    32041.223413    625.302079     1.124184     3.277864     8.755461   
min     1040.000000      0.444000  2015.000000     1.000000     1.000000   
25%    23223.000000     17.248000  2016.000000     5.000000     8.000000   
50%    58103.000000     54.384000  2017.000000     9.000000    16.000000   
75%    90008.000000    210.392000  2018.000000    11.000000    23.000000   
max    99301.000000  22638.480000  2018.000000    12.000000    31.000000   

       Order Week_day    Ship Year   Ship Month     Ship Day  Ship Week_day  \
count     9789.000000  9789.000000  9789.000000  9789.000000    9789.000000   
mean         2.994790  2016.738788     7.756359    15.891817       3.138829   
std          2.180615     1.127048     3.334105     8.805848       1.962572   
min          0.000000  2015.000000     1.000000     1.000000       0.000000   
25%          1.000000  2016.000000     5.000000     8.000000       2.000000   
50%          3.000000  2017.000000     9.000000    16.000000       3.000000   
75%          5.000000  2018.000000    11.000000    24.000000       5.000000   
max          6.000000  2019.000000    12.000000    31.000000       6.000000   

        Ship Delay  
count  9778.000000  
mean      3.961955  
std       1.750578  
min       0.000000  
25%       3.000000  
50%       4.000000  
75%       5.000000  
max       7.000000  
```

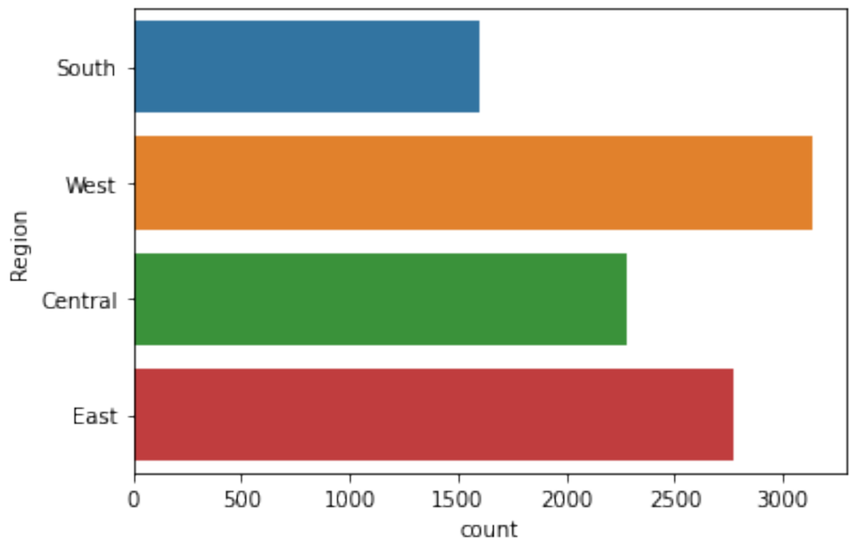


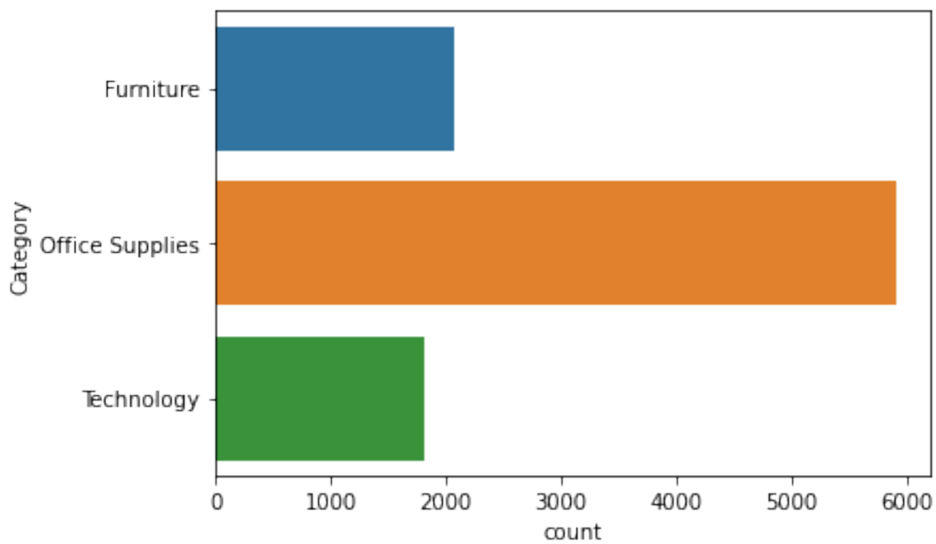

```
              Order ID       Ship Mode Customer ID  Customer Name   Segment  \
count             9789            9789        9789           9789      9789
unique            4916               4         793            793         3
top     CA-2018-100111  Standard Class    WB-21850  William Brown  Consumer
freq                14            5849          35             35      5096

              Country           City       State Region       Product ID  \
count            9789           9789        9789   9789             9789
unique              1            529          48      4             1860
top     United States  New York City  California   West  OFF-PA-10001970
freq             9789            891        1946   3140               18

               Category Sub-Category      Product Name
count              9789         9789              9789
unique                3           17              1848
top     Office Supplies      Binders  Staple envelope
freq               5903         1492                47
```


Second Class
Standard Class
First Class
Same Day
Ship Mode
0
1000
2000
3000
4000
5000
6000
count


Consumer
Corporate
Home Office
Segment
0
1000
2000
3000
4000
5000
count


United States
Country
0
2000
4000
6000
8000
10000
count





In [12]:

```
# create a dictionay for counting each occurance of delay
delay = {}

for x in data['Ship Delay']:
    if x in delay:
        delay[x] += 1
    else:
        delay[x] = 1

print('Ship Delay Counts:')

for key in sorted(delay): # sorts keys for delay dictionary
    if key <= data['Ship Delay'].max(): # eliminates printing nan values
        print(key, ': ', delay[key])
```

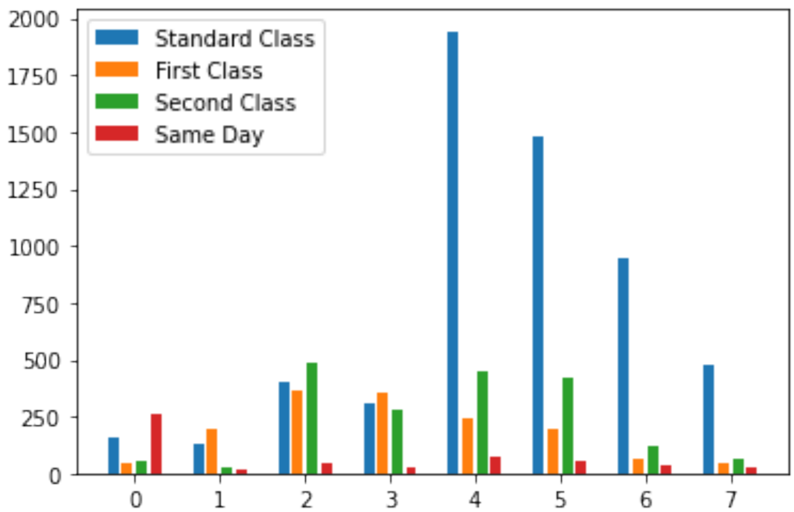
```
Ship Delay Counts:
0.0 :  514
1.0 :  362
2.0 :  1291
3.0 :  975
4.0 :  2708
5.0 :  2144
6.0 :  1169
7.0 :  615
```

In [13]:

```
# apply counter column to data and groupby
data['COUNTER'] = 1
group_data = data.groupby(['Ship Delay', 'Ship Mode'])['COUNTER'].sum().reset_

print(group_data)
```

```
    Ship Delay       Ship Mode  COUNTER
0          0.0     First Class       41
1          0.0        Same Day      265
2          0.0    Second Class       50
3          0.0  Standard Class      158
4          1.0     First Class      193
5          1.0        Same Day       19
6          1.0    Second Class       24
7          1.0  Standard Class      126
8          2.0     First Class      367
9          2.0        Same Day       45
10         2.0    Second Class      482
11         2.0  Standard Class      397
12         3.0     First Class      358
13         3.0        Same Day       25
14         3.0    Second Class      282
15         3.0  Standard Class      310
16         4.0     First Class      240
17         4.0        Same Day       72
18         4.0    Second Class      453
19         4.0  Standard Class     1943
20         5.0     First Class      191
21         5.0        Same Day       53
22         5.0    Second Class      420
23         5.0  Standard Class     1480
24         6.0     First Class       65
25         6.0        Same Day       34
26         6.0    Second Class      123
27         6.0  Standard Class      947
28         7.0     First Class       46
29         7.0        Same Day       25
30         7.0    Second Class       63
31         7.0  Standard Class      481
```

In [14]:
```
# create bar chart of shipping delay counts grouped by shipping method
fig, ax = plt.subplots()

ax.bar(x = group_data[group_data['Ship Mode'] == 'Standard Class']['Ship Dela
ax.bar(x = group_data[group_data['Ship Mode'] == 'First Class']['Ship Delay']
ax.bar(x = group_data[group_data['Ship Mode'] == 'Second Class']['Ship Delay'
ax.bar(x = group_data[group_data['Ship Mode'] == 'Same Day']['Ship Delay'] +

plt.legend()
plt.show()
```



In [15]:
```
# remove customer ID and name from data
data = data.drop(columns = ['Customer ID', 'Customer Name'])
```

In [16]:
```
data.columns
```

Out[16]:
```
Index(['Order ID', 'Order Date', 'Ship Date', 'Ship Mode', 'Segment',
       'Country', 'City', 'State', 'Postal Code', 'Region', 'Product ID',
       'Category', 'Sub-Category', 'Product Name', 'Sales', 'Order Year',
       'Order Month', 'Order Day', 'Order Week_day', 'Ship Year', 'Ship Month'
,
       'Ship Day', 'Ship Week_day', 'Ship Delay', 'COUNTER'],
      dtype='object')
```

In [17]:
```
data['Country'].unique()
```

Out[17]:
```
array(['United States'], dtype=object)
```

Since everything is listed within the United States, we can reduce features to zipcode only to identify locations

In [18]:
```
data = data.drop(columns = ['Country', 'City', 'State', 'COUNTER'])

data.columns
```

Out[18]:
```
Index(['Order ID', 'Order Date', 'Ship Date', 'Ship Mode', 'Segment',
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Sales', 'Order Year', 'Order Month', 'Order Day',
       'Order Week_day', 'Ship Year', 'Ship Month', 'Ship Day',
       'Ship Week_day', 'Ship Delay'],
      dtype='object')
```

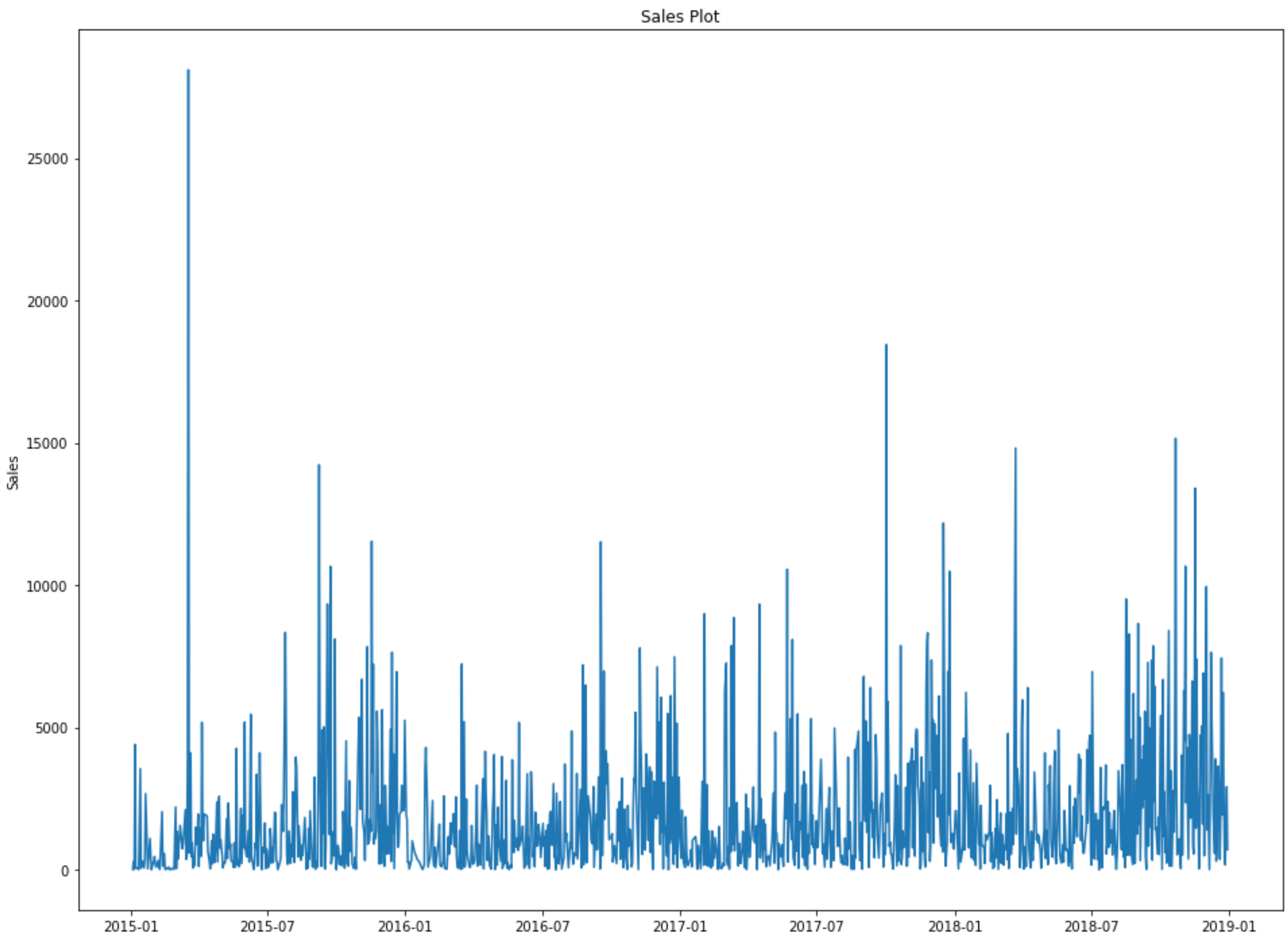
Plot sales over time

In [19]:
```
# groupby order date and sum sales
sales_data = data.groupby('Order Date')['Sales'].sum().reset_index()

sales_data.head()
```

Out[19]:

	Order Date	Sales
0	2015-01-03	16.448
1	2015-01-04	288.060
2	2015-01-05	19.536
3	2015-01-06	4407.100
4	2015-01-07	87.158

In [20]:
```
# plot sales data

fig, ax = plt.subplots(figsize = (16,12))

ax.plot(sales_data['Order Date'], sales_data['Sales'])
ax.set_title('Sales Plot')
ax.set(ylabel = 'Sales')
fig.savefig("plots/sales.png")
```

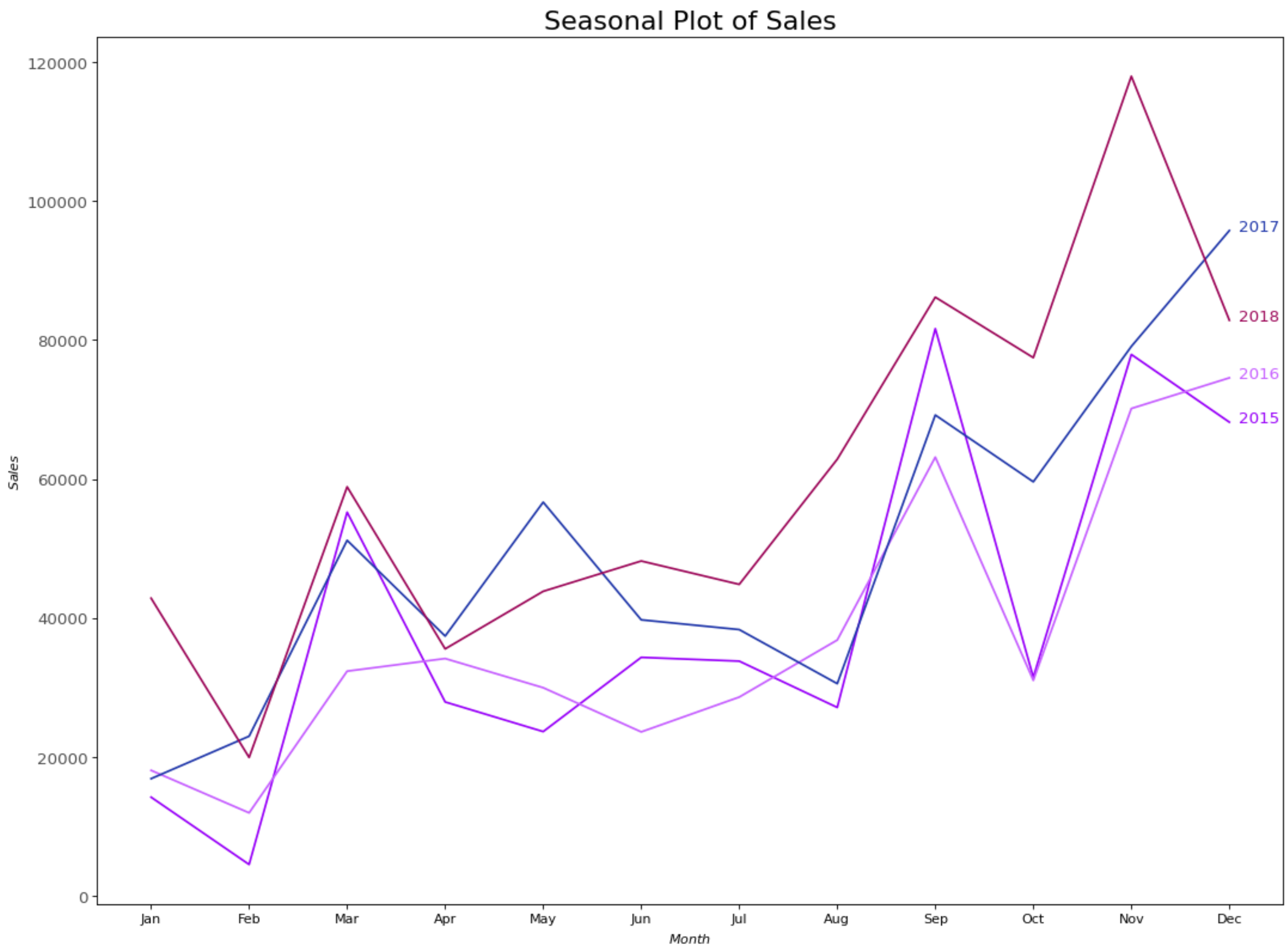


Look for seasonal trends

In [21]:

```
import matplotlib as mpl

# prepare data
sales_data['year'] = [d.year for d in sales_data['Order Date']]
sales_data['month'] = [d.strftime('%b') for d in sales_data['Order Date']]
sales_data['month'] = pd.Categorical(sales_data['month'], ['Jan', 'Feb', 'Mar



# remove order date
sales = sales_data.drop(columns = ['Order Date'])

# group sales_data by month and year to identify trends
sales = sales.groupby(['month', 'year'])['Sales'].sum().reset_index()

years = sales['year'].unique()

# colors
np.random.seed(100)
mycolors = np.random.choice(list(mpl.colors.XKCD_COLORS.keys()), len(years),
```

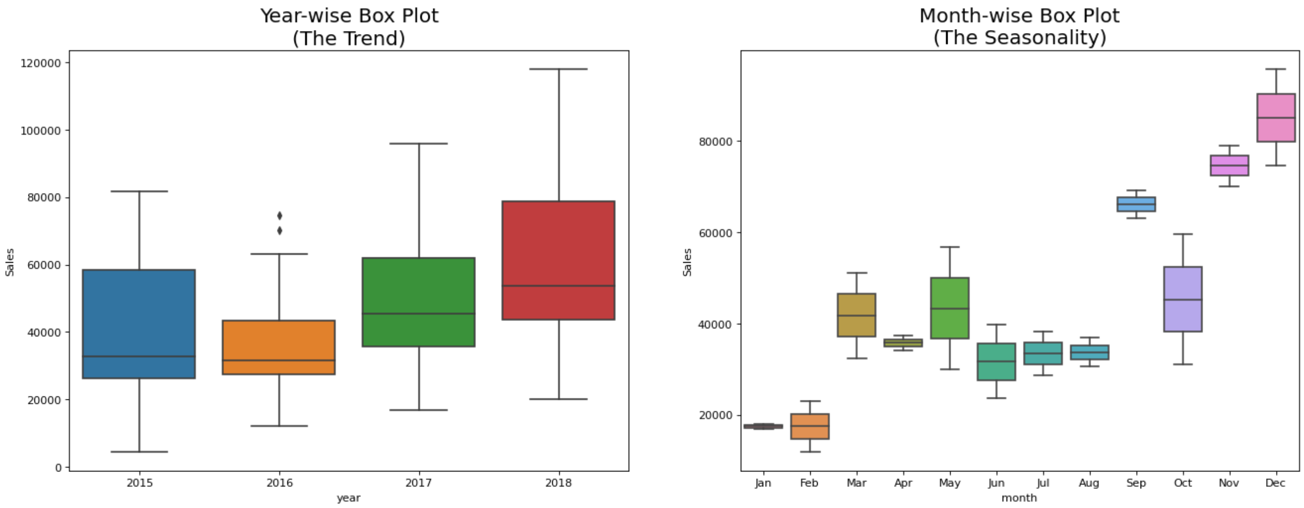
In [22]:
```
# seasonal plot
plt.figure(figsize = (16, 12), dpi = 80)
for i, y in enumerate(years):
        plt.plot('month', 'Sales', data = sales.loc[sales.year == y, :], colo
        plt.text(sales.loc[sales.year == y, :].shape[0]-.9, sales.loc[sales.y

# Decoration
plt.gca().set(ylabel = '$Sales$', xlabel = '$Month$')
plt.yticks(fontsize = 12, alpha = .7)
plt.title("Seasonal Plot of Sales", fontsize = 20)
plt.savefig("plots/seasons.png")
```



Identifying general trend and seasonality with box plots

In [23]:

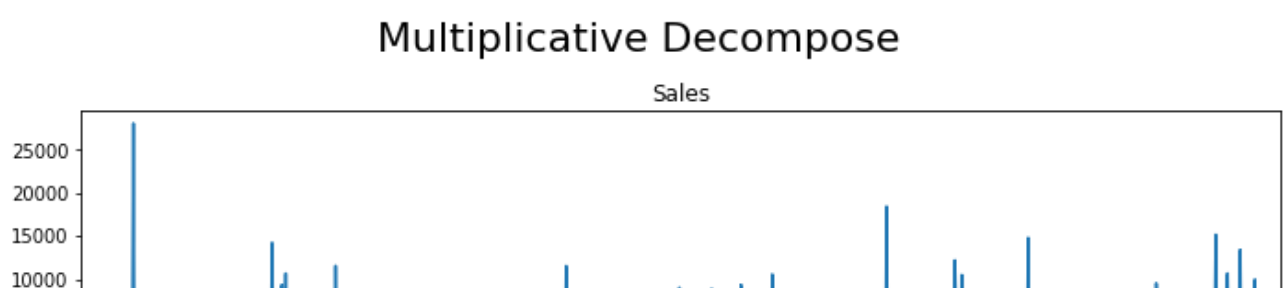
```
# Draw Plot
fig, axes = plt.subplots(1, 2, figsize = (20,7), dpi= 80)
sns.boxplot(x = 'year', y = 'Sales', data = sales, ax = axes[0])
sns.boxplot(x = 'month', y = 'Sales', data = sales.loc[~sales.year.isin([2015

# Set Title
axes[0].set_title('Year-wise Box Plot\n(The Trend)', fontsize = 18);
axes[1].set_title('Month-wise Box Plot\n(The Seasonality)', fontsize = 18)
plt.savefig("plots/trend_seasons.png")
```

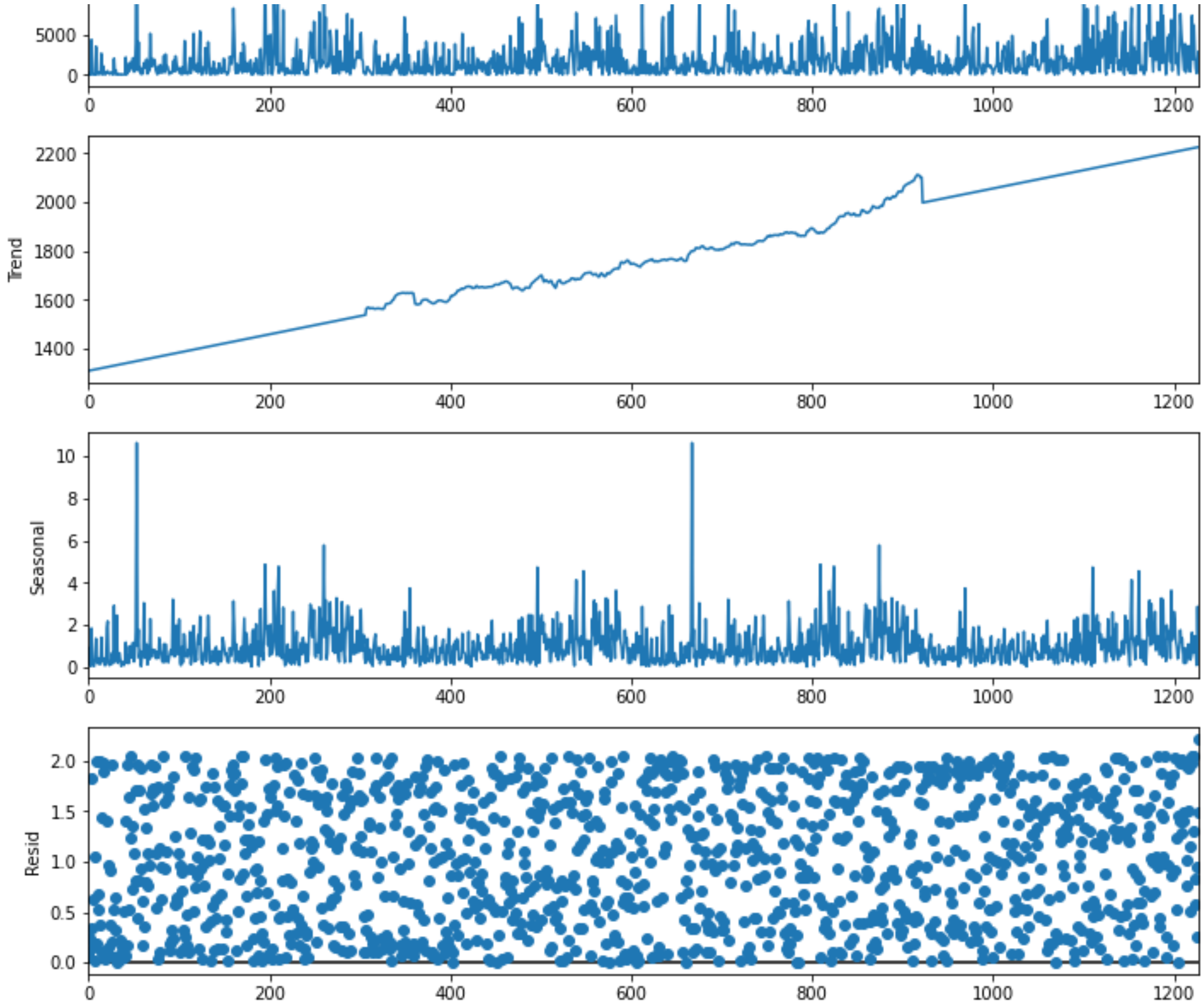


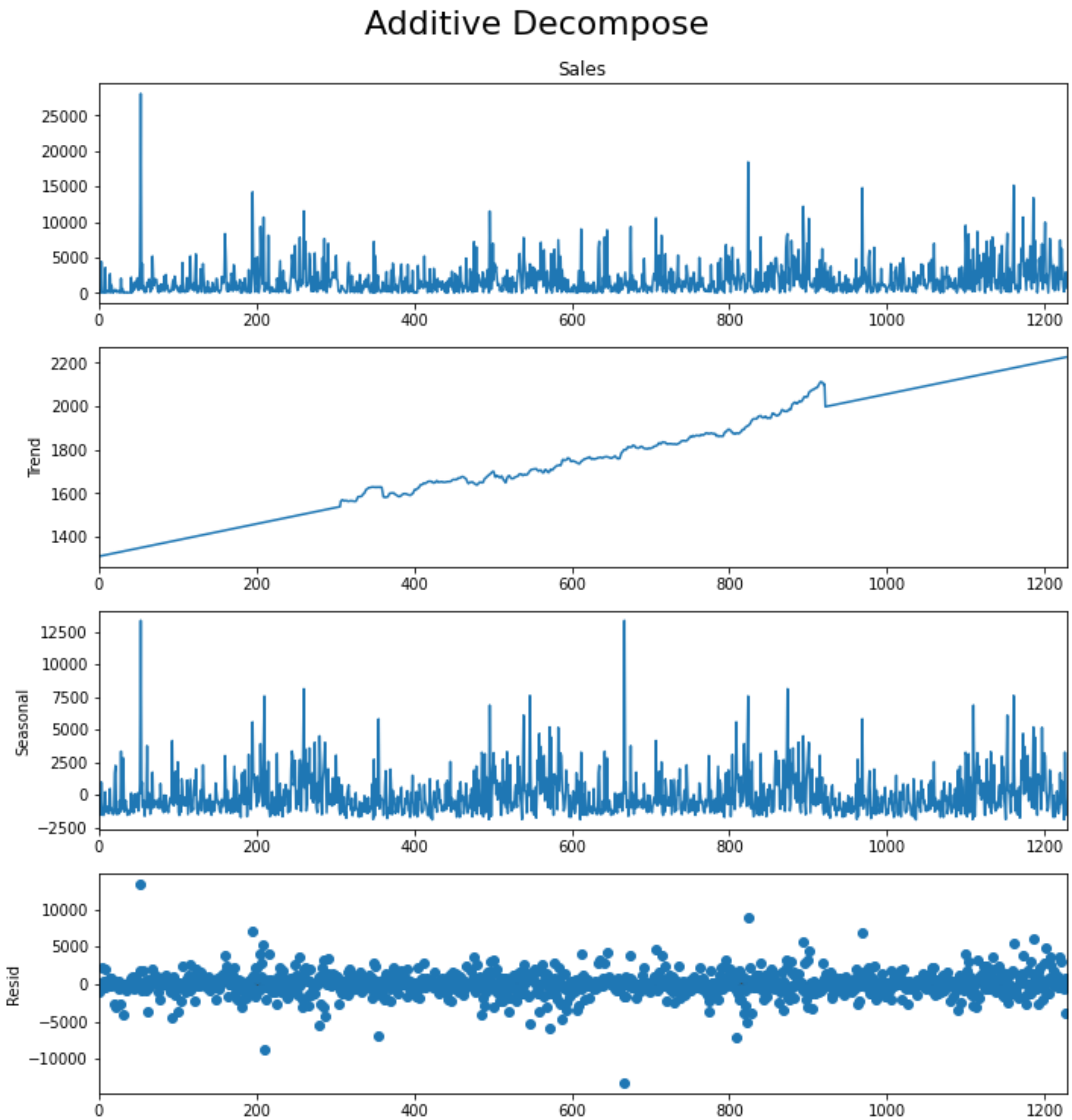
Classical decomposition of series

In [24]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse

# Multiplicative Decomposition
result_mul = seasonal_decompose(sales_data['Sales'], model = 'multiplicative'

# Additive Decomposition
result_add = seasonal_decompose(sales_data['Sales'], model = 'additive', extr

# Plot
plt.rcParams.update({'figure.figsize': (10, 10)})
result_mul.plot().suptitle('Multiplicative Decompose', fontsize = 22, y = 1.0
result_add.plot().suptitle('Additive Decompose', fontsize = 22, y = 1.03)
plt.savefig("plots/decomp.png")
```

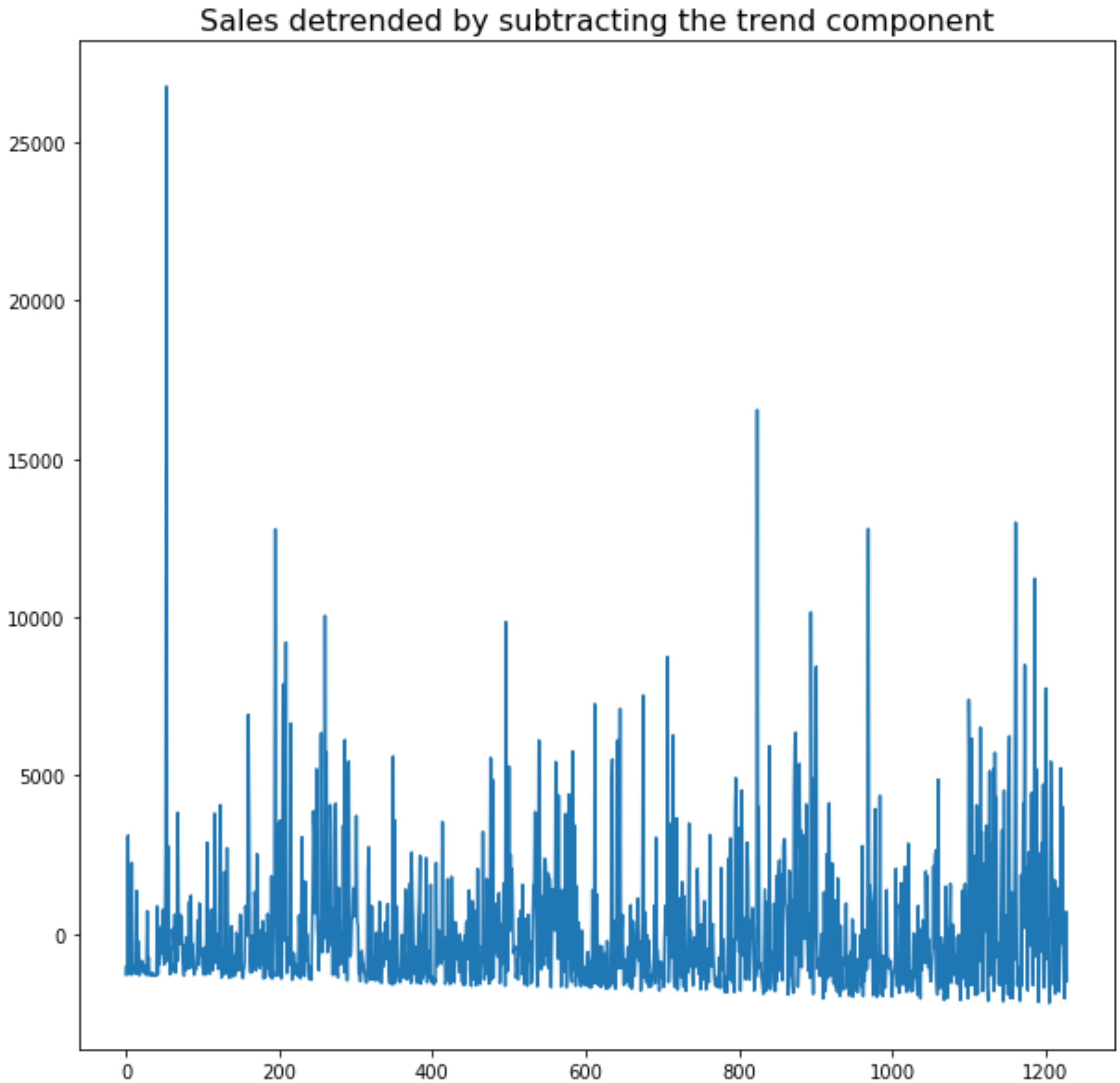



5000
0
0
200
400
600
800
1000
1200
Trend
2200
2000
1800
1600
1400
Seasonal
10
8
6
4
2
Resid
2.0
1.5
1.0
0.5
0.0



In [25]:

```
detrended = sales_data.Sales.values - result_add.trend
plt.plot(detrended)
plt.title('Sales detrended by subtracting the trend component', fontsize = 16
plt.savefig("plots/detrended.png")
```



Testing for stationary series

In [26]:

```
from statsmodels.tsa.stattools import adfuller

# ADF Test
result = adfuller(sales_data.Sales.values, autolag = 'AIC')
print(f'ADF Statistic: {result[0]}')
print(f'p-value: {result[1]}')
for key, value in result[4].items():
    print('Critial Values:')
    print(f'   {key}, {value}')
```

```
ADF Statistic: -5.712554167940101
p-value: 7.243309858005893e-07
Critial Values:
   1%, -3.4357480073434905
Critial Values:
   5%, -2.863923702481129
Critial Values:
   10%, -2.568039121778048
```

p-value is less than 0.05 and therfore the null hypothesis that series is non-stationary is rejected.

Split data into train and test sets

In [27]:

```
import math

train_data = sales_data[:math.ceil(0.75 * len(sales_data))]

test_data = sales_data[math.ceil(0.75 * len(sales_data)):]
```

In [28]:

```
print("75% sales_data: ", math.ceil(0.75 * len(sales_data)))
print("train_data: ", len(train_data))
print("25% sales_data: ", math.floor(0.25 * len(sales_data)))
print("test_data: ", len(test_data))
```

```
75% sales_data:  922
train_data:  922
25% sales_data:  307
test_data:  307
```

Baseline using last value to predict next

In [29]:

```
# determine MSE of baseline model using Naive Method

summation = 0
n = len(test_data)
for i in range (0, n):
    if i == 0:
        diff = test_data['Sales'].iloc[i] - train_data['Sales'].iloc[-1]
        squared_difference = diff**2
        summation = summation + squared_difference
    else:
        diff = test_data['Sales'].iloc[i] - test_data['Sales'].iloc[i-1]
        squared_difference = diff**2
        summation = summation + squared_difference
MSE = summation/n
print("The Mean Square Error for the Baseline Model is: " , MSE)
print("The Mean Error for the Baseline Model is: " , np.sqrt(MSE))
```

```
The Mean Square Error for the Baseline Model is:  10683301.207483001
The Mean Error for the Baseline Model is:  3268.531965192172
```

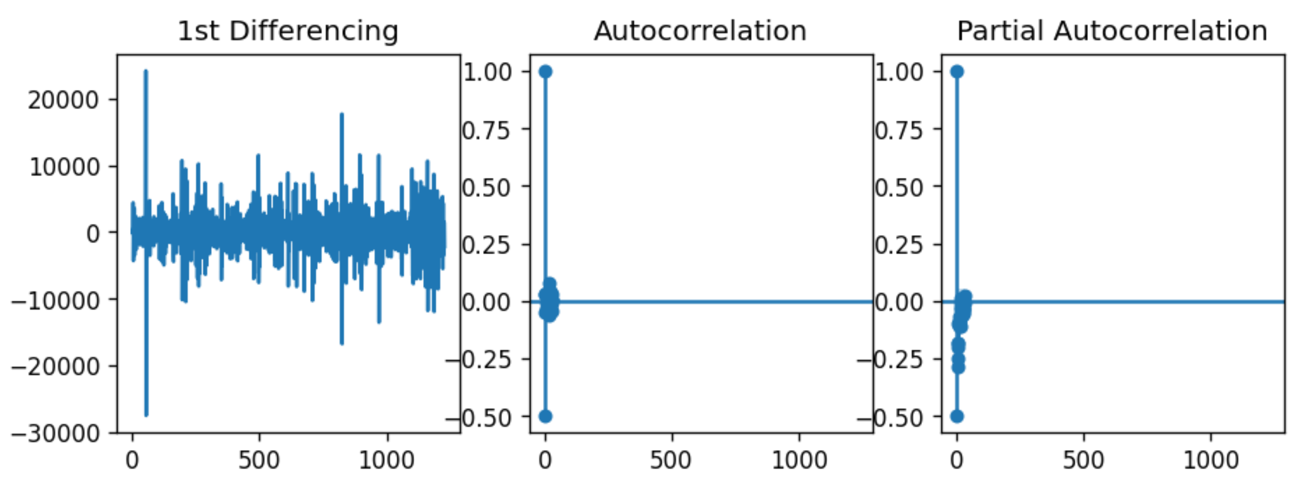
Build ARIMA model

In [30]:
```
sales_data = sales_data.drop(columns = ['year', 'month'])

sales_data.head()
```

Out[30]:

	Order Date	Sales
0	2015-01-03	16.448
1	2015-01-04	288.060
2	2015-01-05	19.536
3	2015-01-06	4407.100
4	2015-01-07	87.158

In [31]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# PACF plot of 1st differenced series
plt.rcParams.update({'figure.figsize': (9,3), 'figure.dpi': 120})

fig, axes = plt.subplots(1, 3, sharex = True)
axes[0].plot(sales_data.Sales.diff()); axes[0].set_title('1st Differencing')
plot_acf(sales_data.Sales.diff().dropna(), ax = axes[1])
plot_pacf(sales_data.Sales.diff().dropna(), ax = axes[2])

plt.savefig('plots/acf_pacf.png')
```



In [32]:
```
sales_data = sales_data.set_index('Order Date')
```

In [33]:
```
sales_data.index = pd.DatetimeIndex(sales_data.index).to_period('D')

sales_data = sales_data.squeeze()

print(type(sales_data))

sales_data.head()
```

```
<class 'pandas.core.series.Series'>
```

Out[33]:
```
Order Date
2015-01-03      16.448
2015-01-04     288.060
2015-01-05      19.536
2015-01-06    4407.100
2015-01-07      87.158
Freq: D, Name: Sales, dtype: float64
```

In [34]:
```
train_data = train_data.drop(columns = ['year', 'month'])
train_data = train_data.set_index('Order Date').to_period('D').squeeze()

test_data = test_data.drop(columns = ['year', 'month'])
test_data = test_data.set_index('Order Date').to_period('D').squeeze()
```

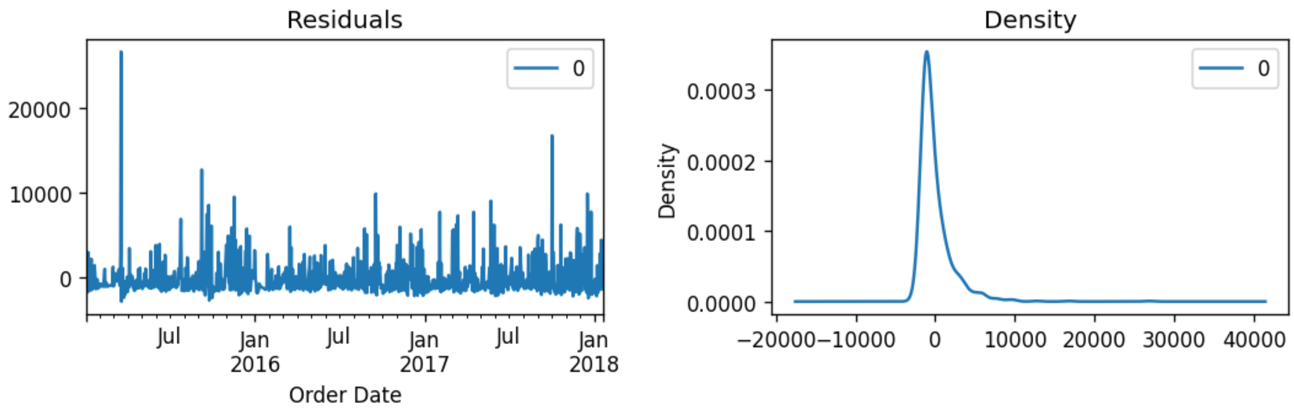
In [35]:
```
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.arima.model import ARIMAResults

model = ARIMA(train_data, order = (5, 0, 2))
model_fit = model.fit()
print(model_fit.summary())
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/
statsmodels/tsa/statespace/sarimax.py:966: UserWarning: Non-stationary startin
g autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/
statsmodels/tsa/statespace/sarimax.py:978: UserWarning: Non-invertible startin
g MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Sales   No. Observations:                  922
Model:                 ARIMA(5, 0, 2)   Log Likelihood               -8397.249
Date:                Sun, 30 May 2021   AIC                          16812.499
Time:                        21:06:53   BIC                          16855.937
Sample:                    01-03-2015   HQIC                         16829.073
                         - 01-21-2018
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       1692.8989    220.768      7.668      0.000    1260.201    2125.597
ar.L1          0.1462      1.174      0.125      0.901      -2.154       2.446
ar.L2          0.7947      1.150      0.691      0.489      -1.458       3.048
ar.L3         -0.0546      0.046     -1.197      0.231      -0.144       0.035
ar.L4         -0.0139      0.060     -0.230      0.818      -0.132       0.104
ar.L5          0.0360      0.046      0.778      0.437      -0.055       0.127
ma.L1         -0.0740      1.174     -0.063      0.950      -2.374       2.226
ma.L2         -0.7358      1.069     -0.688      0.491      -2.832       1.360
sigma2      4.809e+06    9.47e+04     50.789      0.000    4.62e+06    4.99e+06
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                383
81.79
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               0.86   Skew:
3.95
Prob(H) (two-sided):                  0.19   Kurtosis:
33.61
==============================================================================
=====

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

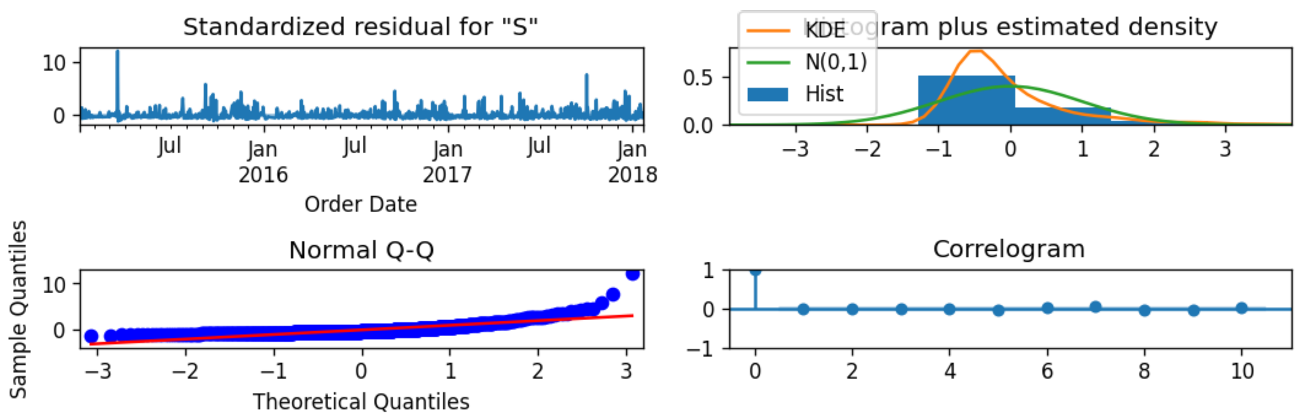
In [36]:

```
# Plot residual errors
residuals = pd.DataFrame(model_fit.resid)
fig, ax = plt.subplots(1, 2)
residuals.plot(title = "Residuals", ax = ax[0])
residuals.plot(kind = 'kde', title = 'Density', ax = ax[1])
plt.tight_layout()
plt.savefig("plots/residual_errors.png")
```



In [37]:

```
# Actual vs Fitted
model_fit.plot_diagnostics()
plt.tight_layout()
plt.savefig("plots/model_diagnostics.png")
```



Predictions

In [39]:

```
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

model_2 = ARIMA(train_data, order = (5, 0, 2))
fitted = model_2.fit()

# Forecast
fc = fitted.forecast()
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/
statsmodels/tsa/statespace/sarimax.py:966: UserWarning: Non-stationary startin
g autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/
statsmodels/tsa/statespace/sarimax.py:978: UserWarning: Non-invertible startin
g MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

In [40]:
```
print(fc)
```

```
2017-07-13    1993.767287
Freq: D, dtype: float64
```

In [41]:
```
pred = fitted.forecast(steps = 307)
```

In [42]:
```
# determine MSE of ARIMA model

summation = 0
n = len(test_data)
for i in range (0, n):
    diff = test_data.iloc[i] - pred[i]
    squared_difference = diff**2
    summation = summation + squared_difference
MSE = summation/n
print("The Mean Square Error for the Baseline Model is: " , MSE)
print("The Mean Error for the Baseline Model is: " , np.sqrt(MSE))
```

```
The Mean Square Error for the Baseline Model is:  6187505.5137038315
The Mean Error for the Baseline Model is:  2487.4697010624736
```

The ARIMA model is better than baseline

In [43]:
```
pred_7 = fitted.forecast(steps = 314) # 307 points in test data plus the next

print(pred_7[307:])
```

```
2018-05-16    1692.898967
2018-05-17    1692.898965
2018-05-18    1692.898963
2018-05-19    1692.898961
2018-05-20    1692.898959
2018-05-21    1692.898958
2018-05-22    1692.898956
Freq: D, Name: predicted_mean, dtype: float64
```

In [44]:
```
print('Training data average: ', train_data.mean())
```

```
Training data average:  1692.8989528199565
```

What is happening here is the ARIMA model is using a value very close to the average of the training data to predict the next 7 days past our test data. lets see what a baseline looks like just for the training data.

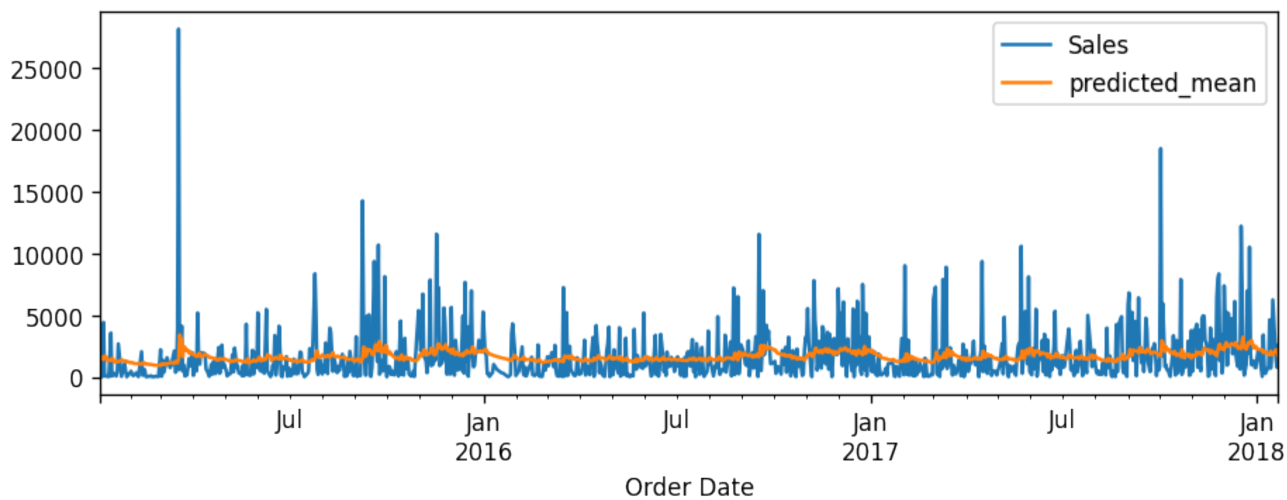
In [58]:
```
preds = fitted.predict(steps = 307)
```

In [60]:
```
preds.tail()
```

Out[60]:
```
Order Date
2018-01-15    1924.096573
2018-01-16    1772.863293
2018-01-19    2206.484688
2018-01-20    2128.863541
2018-01-21    1727.633928
Freq: D, Name: predicted_mean, dtype: float64
```

In [76]:
```
train_data.plot(legend = True)
preds.plot(legend = True)
```

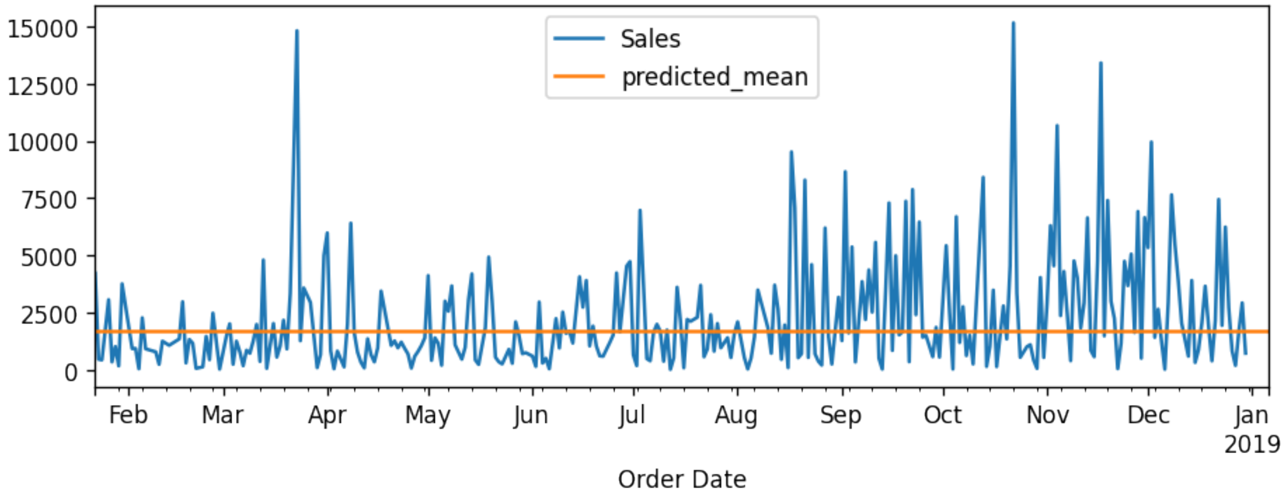
Out[76]:
```
<AxesSubplot:xlabel='Order Date'>
```



In [73]:
```
forcasts = fitted.predict(start = '2018-01-22', end = '2019-01-06')
```

In [75]:
```
test_data.plot(legend = True)
forcasts.plot(legend = True)
```

Out[75]: <AxesSubplot:xlabel='Order Date'>



In [ ]: