DSC 680 Applied Data Science (T301-2237-1)

Bellevue University

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Project 1 - Sales Forecasting and Late Delivery Prediction

1) Business Case

In today's world, a supplier that understands their customers' needs and can provide the material (or service) in a timely fashion becomes invaluable. Customers tend to retain suppliers with high performance and this project will focus on two main aspects. The first objective is to develop a model for sales forecasting based on historical data. A foundational understanding of customer demand can help suppliers better manage their own internal supply chain and processes. The second focus is to determine a method for predicting late deliveries. This allows the supplier to correct ongoing issues with late deliveries or communicate with customers early in the process. The relationships between customers and suppliers within a system often get compared to a stream. One supplier may report to a particular customer, then that customer serves as a supplier for an alternate customer downstream and so on... Organizations can relay these strategies to their suppliers "upstream" to continue to meet customer expectations. The research questions associated with this project are outlined below:

Objective 1: Prediction of Future Sales

- Which categories had the highest sales ?
- Which customers bought the most ?
- Are there any variables strongly correlated with sales?
- Which model provides the best accuracy for forecasting sales?

Objective 2: Prediction of Late Deliveries

- Which categories had the highest number of late deliveries ?
- Does a particular product tend to be late ?
- Do customers in a particular geographic area tend to receive late shipments?
- Are there any variables strongly correlated with late deliveries?
- Which model provides the best accuracy for predicting late deliveries?

Data Set Source

The dataset used for this analysis can be found through the link below:

DataCo SMART SUPPLY CHAIN FOR BIG DATA

Import Necessary Libraries

In [168…

```
'''
Import the necessary libraries for the analysis.
'''
import csv
import numpy as np
import pandas as pd
import operator
from collections import OrderedDict
from pathlib import Path
import pickle

## matplotlib and seaborn imports
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
import plotly.express as px

## scipy imports
import scipy.stats
from scipy import stats
from scipy.stats import shapiro
from scipy.stats import pointbiserialr

## sklearn imports
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression, LinearRegression, Lasso
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, BaggingCl
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score, accuracy_sc
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

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
```

2) Data Understanding

Start by overviewing the data set, univariate analysis, and multivariate analysis.

Data Set Overview

In [3]:
```
'''
Utilize the open() function from csv to understand type of encoding for data.
'''
data = open('DataCoSupplyChainDataset.csv', 'r')
data
```

Out[3]:
```
<_io.TextIOWrapper name='DataCoSupplyChainDataset.csv' mode='r' encoding='cp1252'>
```

In [4]:
```
'''
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.
Use head() function to display the first 10 rows of data of df.
'''
df = pd.read_csv('DataCoSupplyChainDataset.csv', encoding = 'cp1252', parse_dates = ['orde
                                                                                    'shipp

df.head(10)
```

Out[4]:

	Type	Days for shipping (real)	Days for shipment (scheduled)	Benefit per order	Sales per customer	Delivery Status	Late_delivery_risk	Category Id	Category Name	Cust
0	DEBIT	3	4	91.250000	314.640015	Advance shipping	0	73	Sporting Goods	C
1	TRANSFER	5	4	-249.089996	311.359985	Late delivery	1	73	Sporting Goods	C
2	CASH	4	4	-247.779999	309.720001	Shipping on time	0	73	Sporting Goods	Sa
3	DEBIT	3	4	22.860001	304.809998	Advance shipping	0	73	Sporting Goods	Ar
4	PAYMENT	2	4	134.210007	298.250000	Advance shipping	0	73	Sporting Goods	C
5	TRANSFER	6	4	18.580000	294.980011	Shipping canceled	0	73	Sporting Goods	Tonav
6	DEBIT	2	1	95.180000	288.420013	Late delivery	1	73	Sporting Goods	C
7	TRANSFER	2	1	68.430000	285.140015	Late delivery	1	73	Sporting Goods	
8	CASH	3	2	133.720001	278.589996	Late delivery	1	73	Sporting Goods	C
9	CASH	2	1	132.149994	275.309998	Late delivery	1	73	Sporting Goods	San R

10 rows × 53 columns

In [5]:
```
'''
Understand the shape of the dataset.
```

```
Display the total size of this dataset.
'''
print('There are {} rows and {} columns in this dataset.'.format(df.shape[0], df.shape[1]))
print('This dataset contains {} records.'.format(df.size))
```

```
There are 180519 rows and 53 columns in this dataset.
This dataset contains 9567507 records.
```

In [6]:

```
'''
Find the type of data within each column initially.
'''
df.dtypes
```

Out[6]:

```
Type                                     object
Days for shipping (real)                  int64
Days for shipment (scheduled)             int64
Benefit per order                       float64
Sales per customer                      float64
Delivery Status                          object
Late_delivery_risk                        int64
Category Id                               int64
Category Name                            object
Customer City                            object
Customer Country                         object
Customer Email                           object
Customer Fname                           object
Customer Id                               int64
Customer Lname                           object
Customer Password                        object
Customer Segment                         object
Customer State                           object
Customer Street                          object
Customer Zipcode                        float64
Department Id                             int64
Department Name                          object
Latitude                                float64
Longitude                               float64
Market                                   object
Order City                               object
Order Country                            object
Order Customer Id                         int64
order date (DateOrders)          datetime64[ns]
Order Id                                  int64
Order Item Cardprod Id                    int64
Order Item Discount                     float64
Order Item Discount Rate                float64
Order Item Id                             int64
Order Item Product Price                float64
Order Item Profit Ratio                 float64
Order Item Quantity                       int64
Sales                                   float64
Order Item Total                        float64
Order Profit Per Order                  float64
Order Region                             object
Order State                              object
Order Status                             object
Order Zipcode                           float64
Product Card Id                           int64
Product Category Id                       int64
Product Description                     float64
Product Image                            object
Product Name                             object
Product Price                           float64
Product Status                            int64
shipping date (DateOrders)       datetime64[ns]
```

```
Shipping Mode                                  object
dtype: object
```

In [7]:

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

Out[7]:

```
Product Description              180519
Order Zipcode                    155679
Customer Lname                        8
Customer Zipcode                      3
Type                                  0
Order Profit Per Order                0
Order Item Cardprod Id                0
Order Item Discount                   0
Order Item Discount Rate              0
Order Item Id                         0
Order Item Product Price              0
Order Item Profit Ratio               0
Order Item Quantity                   0
Sales                                 0
Order Item Total                      0
Order Region                          0
order date (DateOrders)               0
Order State                           0
Order Status                          0
Product Card Id                       0
Product Category Id                   0
Product Image                         0
Product Name                          0
Product Price                         0
Product Status                        0
shipping date (DateOrders)            0
Order Id                              0
Order Country                         0
Order Customer Id                     0
Customer Fname                        0
Days for shipment (scheduled)         0
Benefit per order                     0
Sales per customer                    0
Delivery Status                       0
Late_delivery_risk                    0
Category Id                           0
Category Name                         0
Customer City                         0
Customer Country                      0
Customer Email                        0
Customer Id                           0
Days for shipping (real)              0
Customer Password                     0
Customer Segment                      0
Customer State                        0
Customer Street                       0
Department Id                         0
Department Name                       0
Latitude                              0
Longitude                             0
Market                                0
Order City                            0
Shipping Mode                         0
dtype: int64
```

In [8]:

```
'''
```

```
Understand how many missing values are in the dataset initially.
'''
missing_values = df.isna().sum().sum()
print('This dataset contains {} total missing values.'.format(missing_values))
```

```
This dataset contains 336209 total missing values.
```

In [9]:
```
'''
Reduce the columns that have no data or will not be relevant for sales or late delivery.
'''
drop_list = ['Product Description', 'Order Zipcode', 'Customer Lname', 'Customer Zipcode', 'Ca
             'Customer Fname', 'Customer Email', 'Customer Password', 'Product Status', 'Ca
             'Order Id', 'Order Item Cardprod Id', 'Product Card Id', 'Product Category Id'
             'Longitude', 'Latitude', 'Order Customer Id']
df.drop(drop_list, axis = 1, inplace = True)
```

In [10]:
```
print("These are the {} columns that were removed initially from the data set:".format(len
print(*drop_list, sep = ", ")
```

```
These are the 19 columns that were removed initially from the data set:
Product Description, Order Zipcode, Customer Lname, Customer Zipcode, Product Image, Custo
mer Fname, Customer Email, Customer Password, Product Status, Category Id, Department Id,
Order Id, Order Item Cardprod Id, Product Card Id, Product Category Id, Order Item Discoun
t Rate, Longitude, Latitude, Order Customer Id
```

The columns listed above were removed from the data. The reasoning behind removing the columns initially stems from either majority of missing values within the feature, the feature was irrelevant to the objectives, or there was another feature that provided better clarity for the variable. In addition, the customer first and last name will be removed and the Customer Id will be considered for the remainder of the analysis. Although this data set is public, it is good practice for data privacy. Other variables may be removed later in the analyis, but will be included up through this point.

In [11]:
```
'''
Understand how many missing values are in the dataset after removing irrelevant columns.
'''
missing_values = df.isna().sum().sum()
print('This dataset contains {} total missing values after features have been removed.'.fo
```

```
This dataset contains 0 total missing values after features have been removed.
```

In [12]:
```
'''
Understand the shape of the revised data set.
Display the total size of this data set.
'''
print('There are {} rows and {} columns in this dataset.'.format(df.shape[0], df.shape[1])
print('This dataset contains {} records.'.format(df.size))
```

```
There are 180519 rows and 34 columns in this dataset.
This dataset contains 6137646 records.
```

In [13]:
```
'''
Further understand unique values within the features.
'''
df['Type'].unique()
```

Out[13]:
```
array(['DEBIT', 'TRANSFER', 'CASH', 'PAYMENT'], dtype=object)
```

In [14]:
```
'''
```

```
Further understand unique values within the features.
'''
df['Days for shipping (real)'].unique()
```

Out[14]:
```
array([3, 5, 4, 2, 6, 0, 1], dtype=int64)
```

In [15]:
```
'''
Further understand unique values within the features.
'''
df['Days for shipment (scheduled)'].unique()
```

Out[15]:
```
array([4, 1, 2, 0], dtype=int64)
```

In [16]:
```
'''
Further understand unique values within the features.
'''
df['Delivery Status'].unique()
```

Out[16]:
```
array(['Advance shipping', 'Late delivery', 'Shipping on time',
       'Shipping canceled'], dtype=object)
```

In [17]:
```
'''
Further understand unique values within the features.
'''
df['Late_delivery_risk'].unique()
```

Out[17]:
```
array([0, 1], dtype=int64)
```

In [18]:
```
'''
Further understand unique values within the features.
'''
df['Category Name'].unique()
```

Out[18]:
```
array(['Sporting Goods', 'Cleats', 'Shop By Sport', "Women's Apparel",
       'Electronics', 'Boxing & MMA', 'Cardio Equipment', 'Trade-In',
       "Kids' Golf Clubs", 'Hunting & Shooting', 'Baseball & Softball',
       "Men's Footwear", 'Camping & Hiking', 'Consumer Electronics',
       'Cameras ', 'Computers', 'Basketball', 'Soccer', "Girls' Apparel",
       'Accessories', "Women's Clothing", 'Crafts', "Men's Clothing",
       'Tennis & Racquet', 'Fitness Accessories', 'As Seen on  TV!',
       'Golf Balls', 'Strength Training', "Children's Clothing",
       'Lacrosse', 'Baby ', 'Fishing', 'Books ', 'DVDs', 'CDs ', 'Garden',
       'Hockey', 'Pet Supplies', 'Health and Beauty', 'Music',
       'Video Games', 'Golf Gloves', 'Golf Bags & Carts', 'Golf Shoes',
       'Golf Apparel', "Women's Golf Clubs", "Men's Golf Clubs", 'Toys',
       'Water Sports', 'Indoor/Outdoor Games'], dtype=object)
```

In [19]:
```
'''
Further understand unique values within the features.
'''
print("Number of unique product categories: {}".format(len(df['Category Name'].unique())))
```

```
Number of unique product categories: 50
```

In [20]:
```
'''
Further understand unique values within the features.
'''
df['Customer City'].unique()
```

```
Out[20]: array(['Caguas', 'San Jose', 'Los Angeles', 'Tonawanda', 'Miami',
       'San Ramon', 'Freeport', 'Salinas', 'Peabody', 'Canovanas',
       'Paramount', 'Mount Prospect', 'Long Beach', 'Rancho Cordova',
       'Billings', 'Wilkes Barre', 'Roseville', 'Bellflower', 'Wheaton',
       'Detroit', 'Dallas', 'Carlisle', 'Newark', 'Panorama City',
       'Atlanta', 'Fremont', 'Rochester', 'Bayamon', 'Guayama',
       'Juana Diaz', 'Fort Washington', 'Bakersfield', 'Corona',
       'Cincinnati', 'Germantown', 'Carrollton', 'Houston', 'Ewa Beach',
       'Lakewood', 'Rome', 'Vista', 'Fort Worth', 'Fond Du Lac',
       'Philadelphia', 'Ontario', 'Oviedo', 'Buffalo', 'Honolulu',
       'Oceanside', 'North Tonawanda', 'Clovis', 'Jamaica',
       'Granite City', 'Medford', 'Pomona', 'Tempe', 'Santa Ana', 'York',
       'Aurora', 'Simi Valley', 'Silver Spring', 'Saint Paul',
       'San Antonio', 'Bronx', 'Greenville', 'Morristown', 'San Diego',
       'Oxnard', 'Albuquerque', 'Amarillo', 'Lutz', 'Bend',
       'East Brunswick', 'Lancaster', 'Hampton', 'New York',
       'Porterville', 'Portland', 'Strongsville', 'El Paso', 'Del Rio',
       'Bountiful', 'Kent', 'Chicago', 'Plymouth', 'Far Rockaway',
       'Garden Grove', 'Placentia', 'Mentor', 'Santa Clara', 'Union',
       'Westminster', 'Pompano Beach', 'Azusa', 'Fort Lauderdale',
       'Princeton', 'Perth Amboy', 'Loveland', 'Virginia Beach',
       'Louisville', 'Lockport', 'Staten Island', 'Tucson', 'Cleveland',
       'Webster', 'Stockton', 'Martinsburg', 'Cumberland', 'Pekin',
       'Tallahassee', 'Jacksonville', 'Woonsocket', 'Lithonia',
       'Oak Lawn', 'Alhambra', 'New Haven', 'Phoenix', 'Kenner',
       'Washington', 'Holland', 'Morrisville', 'Memphis', 'Federal Way',
       'West Covina', 'Ventura', 'Valrico', 'Kaneohe', 'Brooklyn', 'Lodi',
       'Murfreesboro', 'Carlsbad', 'Hamilton', 'Hayward', 'Bridgeton',
       'Bay Shore', 'Palatine', 'Smyrna', 'Van Nuys', 'Opa Locka',
       'Edison', 'Baytown', 'Sylmar', 'Burnsville', 'Huntington Station',
       'Sunnyvale', 'Sugar Land', 'Brighton', 'Bismarck', 'Gaithersburg',
       'Lilburn', 'Provo', 'Columbia', 'Marietta', 'Rio Grande', 'Denver',
       'Taylor', 'Saint Charles', 'Cupertino', 'Springfield',
       'Mission Viejo', 'Roswell', 'Ypsilanti', 'Peoria', 'Clementon',
       'Antioch', 'Salt Lake City', 'Granada Hills', 'Hempstead',
       'Astoria', 'Gilroy', 'Lenoir', 'Columbus', 'Albany', 'Humacao',
       'Lindenhurst', 'Elyria', 'Riverside', 'Carson', 'Mesa', 'San Juan',
       'Vega Baja', 'Mayaguez', 'Arecibo', 'San Sebastian', 'Eugene',
       'Algonquin', 'Indianapolis', 'Buena Park', 'Catonsville',
       'Jersey City', 'Lombard', 'New Bedford', 'Newburgh', 'Lansdale',
       'Baltimore', 'Fullerton', 'Sacramento', 'Greensboro', 'Roseburg',
       'Modesto', 'Encinitas', 'Watsonville', 'Meridian', 'Endicott',
       'Katy', 'Visalia', 'Lompoc', 'Ogden', 'Raleigh',
       'Hacienda Heights', 'Union City', 'Hollywood', 'Bolingbrook',
       'West Lafayette', 'Woodbridge', 'Weslaco', 'Bell Gardens',
       'La Mirada', 'North Bergen', 'Madison', 'South San Francisco',
       'North Las Vegas', 'Methuen', 'Costa Mesa', 'Glen Burnie',
       'Fairfield', 'Winnetka', 'Mcallen', 'Joliet', 'Brownsville',
       'Pawtucket', 'Colorado Springs', 'Quincy', 'Pittsfield', 'Chino',
       'Marion', 'North Hills', 'Salina', 'Hyattsville',
       'North Richland Hills', 'Spring Valley', 'Lawrence', 'Milpitas',
       'Rowland Heights', 'Gardena', 'Cicero', 'Asheboro', 'La Crosse',
       'Florissant', 'Canyon Country', 'Ithaca', 'Allentown', 'Escondido',
       'Martinez', 'Troy', 'Arlington', 'Davis', 'Chandler', 'Elgin',
       'Palmdale', 'Massapequa', 'Pittsburg', 'West New York', 'Orlando',
       'Hanover', 'Glendale', 'Enfield', 'Baldwin Park', 'Chino Hills',
       'Toms River', 'Wyandotte', 'Mililani', 'Harvey', 'Mechanicsburg',
       'Opelousas', 'Kailua', 'Norfolk', 'Elmhurst', 'Chillicothe',
       'Canoga Park', 'Jackson', 'Moreno Valley', 'New Orleans',
       'San Benito', 'New Castle', 'Bloomfield', 'Cypress', 'Marrero',
       'Grand Prairie', 'Greeley', 'Littleton', 'Longmont', 'Chesapeake',
       'Englewood', 'Arlington Heights', 'Tampa', 'Irvington',
       'Forest Hills', 'Dearborn', 'Compton', 'Garland', 'Waipahu',
       'Carmichael', 'Tustin', 'Anaheim', 'Canton', 'Stafford',
       'South Richmond Hill', 'Middletown', 'West Orange', 'Daly City',
       'Powder Springs', 'Parkville', 'Hialeah', 'Beloit', 'Aguadilla',
```

```
       'Carolina', 'Yauco', 'Saint Peters', 'Augusta', 'Chapel Hill',
       'East Lansing', 'Stamford', 'Diamond Bar', 'Milwaukee',
       'Lawrenceville', 'Manchester', 'La Puente', 'Victorville',
       'Richmond', 'Eagle Pass', 'Fontana', 'Ballwin', 'New Braunfels',
       'Las Vegas', 'Goose Creek', 'Pharr', 'Yonkers', 'El Monte',
       'Reynoldsburg', 'Hamtramck', 'Medina', 'Highland', 'Jonesboro',
       'Elk Grove', 'Montebello', 'San Francisco', 'Glenview',
       'Rock Hill', 'Austin', 'Scottsdale', 'Santa Cruz', 'Oregon City',
       'Annandale', 'Plano', 'Piscataway', 'El Cajon', 'Hilliard',
       'Orange Park', 'Decatur', 'San Pablo', 'Douglasville', 'Henderson',
       'College Station', 'Round Rock', 'Mesquite', 'Broken Arrow',
       'Redmond', 'Findlay', 'La Habra', 'Laguna Hills', 'San Bernardino',
       'Apex', 'South El Monte', 'Irving', 'Blacksburg',
       'Dorchester Center', 'Potomac', 'Winter Park', 'Stone Mountain',
       'Goleta', 'Hagerstown', 'Alameda', 'Saint Louis', 'Pico Rivera',
       'Chula Vista', 'Hollister', 'North Hollywood', 'New Brunswick',
       'Beaverton', 'Chicago Heights', 'Hesperia', 'Cary', 'Sanford',
       'Laredo', 'Westland', 'Stockbridge', 'Carol Stream', 'Wichita',
       'Olathe', 'Flushing', 'Lynwood', 'Revere', 'Westerville',
       'Cordova', 'Hanford', 'Rialto', 'Mchenry', 'Mission', 'Salem',
       'Duluth', 'Danbury', 'Frankfort', 'Upland', 'Rosemead',
       'Mount Pleasant', 'Lake Forest', 'West Chester', 'Woodside',
       'Norcross', 'Fresno', 'Zanesville', 'Painesville', 'Lynnwood',
       'Massillon', 'Crystal Lake', 'Rego Park', 'Ann Arbor', 'Wyoming',
       'La Mesa', 'Edinburg', 'Howell', 'Michigan City', 'Sheboygan',
       'Moline', 'Yuma', 'Campbell', 'Charlotte', 'Oakland', 'San Marcos',
       'Walnut', 'Harlingen', 'Rio Rancho', 'Nashville', 'Annapolis',
       'Laguna Niguel', 'Santee', 'West Jordan', 'Hickory', 'Manati',
       'Trujillo Alto', 'Ponce', 'Toa Alta', 'Irwin', 'South Ozone Park',
       'Ridgewood', 'Bowling Green', 'Richardson', 'Sun Valley',
       'Huntington Beach', 'Fargo', 'Waukegan', 'Highland Park',
       'Cerritos', 'Lewisville', 'Alpharetta', 'New Albany', 'Denton',
       'Temecula', 'Tinley Park', 'Dundalk', 'Crown Point', 'Lawton',
       'Fayetteville', 'Milford', 'Bartlett', 'Reno', 'Passaic', 'Reseda',
       'Levittown', 'Wayne', 'Metairie', 'Wheeling', 'Hawthorne', 'Napa',
       'Berwyn', 'Fountain Valley', 'Las Cruces', 'Apopka', 'Folsom',
       'El Centro', 'Jackson Heights', 'Pacoima', 'Hendersonville',
       'Clearfield', 'Seattle', 'Saginaw', 'Conway', 'Sandusky',
       'San Pedro', 'Grove City', 'Knoxville', 'Huntington Park',
       'Greensburg', 'Poway', 'O Fallon', 'Chambersburg', 'Normal',
       'Lynn', 'Bensalem', 'Bristol', 'Williamsport', 'Longview',
       'Norwalk', 'Bayonne', 'Tulare', 'National City', 'Dayton', 'Tracy',
       'Summerville', 'Merced', 'Brockton', 'Vallejo', 'West Haven',
       'Pasadena', 'South Gate', 'Warren', 'Clarksville', 'Muskegon',
       'Brandon', 'Rancho Cucamonga', 'Santa Maria', 'Doylestown',
       'Colton', 'Indio', 'Plainfield', 'Bellingham', 'Spring',
       'Livermore', 'Santa Fe', 'Palo Alto', 'Henrico', 'Des Plaines',
       'Birmingham', 'Broomfield', 'Guaynabo', 'Cayey', 'Citrus Heights',
       'Spokane', 'Dubuque', 'Madera', 'Everett', 'Brentwood',
       'Morganton', 'Vacaville', 'Malden', 'Gwynn Oak', 'Toa Baja',
       'Taunton', 'Freehold', 'Sumner', 'Wilmington', 'CA'], dtype=object)
```

In [21]:

```
'''
Further understand unique values within the features.
'''
df['Customer Country'].unique()
```

Out[21]:

```
array(['Puerto Rico', 'EE. UU.'], dtype=object)
```

In [22]:

```
'''
United States is in Estados Unidos (Spanish). Switch value to United States in data frame.
'''
df['Customer Country'] = df['Customer Country'].replace({'EE. UU.': 'United States'})
```

In [23]:
```
'''
Further understand unique values within the features.
'''
df['Customer Id'].unique()
```

Out[23]:
```
array([20755, 19492, 19491, ..., 18579, 16244,  2677], dtype=int64)
```

In [24]:
```
'''
Further understand unique values within the features.
'''
print("Number of customers: {}".format(len(df['Customer Id'].unique())))
```

```
Number of customers: 20652
```

In [25]:
```
'''
Further understand unique values within the features.
'''
df['Customer Segment'].unique()
```

Out[25]:
```
array(['Consumer', 'Home Office', 'Corporate'], dtype=object)
```

In [26]:
```
'''
Further understand unique values within the features.
'''
df['Customer State'].unique()
```

Out[26]:
```
array(['PR', 'CA', 'NY', 'FL', 'MA', 'IL', 'MT', 'PA', 'MI', 'TX', 'DE',
       'GA', 'MD', 'OH', 'HI', 'NJ', 'WI', 'AZ', 'CO', 'MN', 'NC', 'NM',
       'OR', 'SC', 'VA', 'UT', 'WA', 'KY', 'WV', 'RI', 'CT', 'LA', 'TN',
       'DC', 'ND', 'MO', 'IN', 'ID', 'NV', 'KS', 'AR', 'OK', 'AL', 'IA',
       '95758', '91732'], dtype=object)
```

In [27]:
```
'''
Further understand unique values within the features.
'''
df['Department Name'].unique()
```

Out[27]:
```
array(['Fitness', 'Apparel', 'Golf', 'Footwear', 'Outdoors', 'Fan Shop',
       'Technology', 'Book Shop', 'Discs Shop', 'Pet Shop',
       'Health and Beauty '], dtype=object)
```

In [28]:
```
'''
Further understand unique values within the features.
'''
print("Number of departments: {}".format(len(df['Department Name'].unique())))
```

```
Number of departments: 11
```

In [29]:
```
'''
Further understand unique values within the features.
'''
df['Market'].unique()
```

Out[29]:
```
array(['Pacific Asia', 'USCA', 'Africa', 'Europe', 'LATAM'], dtype=object)
```

In [30]:
```
'''
Further understand unique values within the features.
```

```
'''
df['Order City'].unique()
```

Out[30]:
```
array(['Bekasi', 'Bikaner', 'Townsville', ..., 'Tongling', 'Liuyang',
       'Nashua'], dtype=object)
```

In [31]:
```
'''
Further understand unique values within the features.
'''
df['Order Country'].unique()
```

Out[31]:
```
array(['Indonesia', 'India', 'Australia', 'China', 'Japón',
       'Corea del Sur', 'Singapur', 'Turquía', 'Mongolia',
       'Estados Unidos', 'Nigeria', 'República Democrática del Congo',
       'Senegal', 'Marruecos', 'Alemania', 'Francia', 'Países Bajos',
       'Reino Unido', 'Guatemala', 'El Salvador', 'Panamá',
       'República Dominicana', 'Venezuela', 'Colombia', 'Honduras',
       'Brasil', 'México', 'Uruguay', 'Argentina', 'Cuba', 'Perú',
       'Nicaragua', 'Ecuador', 'Angola', 'Sudán', 'Somalia',
       'Costa de Marfil', 'Egipto', 'Italia', 'España', 'Suecia',
       'Austria', 'Canada', 'Madagascar', 'Argelia', 'Liberia', 'Zambia',
       'Níger', 'SudAfrica', 'Mozambique', 'Tanzania', 'Ruanda', 'Israel',
       'Nueva Zelanda', 'Bangladés', 'Tailandia', 'Irak', 'Arabia Saudí',
       'Filipinas', 'Kazajistán', 'Irán', 'Myanmar (Birmania)',
       'Uzbekistán', 'Benín', 'Camerún', 'Kenia', 'Togo', 'Ucrania',
       'Polonia', 'Portugal', 'Rumania', 'Trinidad y Tobago',
       'Afganistán', 'Pakistán', 'Vietnam', 'Malasia', 'Finlandia',
       'Rusia', 'Irlanda', 'Noruega', 'Eslovaquia', 'Bélgica', 'Bolivia',
       'Chile', 'Jamaica', 'Yemen', 'Ghana', 'Guinea', 'Etiopía',
       'Bulgaria', 'Kirguistán', 'Georgia', 'Nepal',
       'Emiratos Árabes Unidos', 'Camboya', 'Uganda', 'Lesoto',
       'Lituania', 'Suiza', 'Hungría', 'Dinamarca', 'Haití',
       'Bielorrusia', 'Croacia', 'Laos', 'Baréin', 'Macedonia',
       'República Checa', 'Sri Lanka', 'Zimbabue', 'Eritrea',
       'Burkina Faso', 'Costa Rica', 'Libia', 'Barbados', 'Tayikistán',
       'Siria', 'Guadalupe', 'Papúa Nueva Guinea', 'Azerbaiyán',
       'Turkmenistán', 'Paraguay', 'Jordania', 'Hong Kong', 'Martinica',
       'Moldavia', 'Qatar', 'Mali', 'Albania', 'República del Congo',
       'Bosnia y Herzegovina', 'Omán', 'Túnez', 'Sierra Leona', 'Yibuti',
       'Burundi', 'Montenegro', 'Gabón', 'Sudán del Sur', 'Luxemburgo',
       'Namibia', 'Mauritania', 'Grecia', 'Suazilandia', 'Guyana',
       'Guayana Francesa', 'República Centroafricana', 'Taiwán',
       'Estonia', 'Líbano', 'Chipre', 'Guinea-Bissau', 'Surinam',
       'Belice', 'Eslovenia', 'República de Gambia', 'Botsuana',
       'Armenia', 'Guinea Ecuatorial', 'Kuwait', 'Bután', 'Chad',
       'Serbia', 'Sáhara Occidental'], dtype=object)
```

In [32]:
```
'''
Further understand unique values within the features.
'''
print("Number of countries for orders: {}".format(len(df['Order Country'].unique())))
```

```
Number of countries for orders: 164
```

In [33]:
```
'''
United States is in Estados Unidos (Spanish). Switch value to United States in data frame.
'''
df['Order Country'] = df['Order Country'].replace({'Estados Unidos': 'United States'})
```

In [34]:
```
'''
Further understand unique values within the features.
```

```
'''
df['Order Item Id'].unique()
```

Out[34]:
```
array([180517, 179254, 179253, ...,  65129,  65126,  65113], dtype=int64)
```

In [35]:
```
'''
Further understand unique values within the features.
'''
print("Number of orders: {}".format(len(df['Order Item Id'].unique())))
```

```
Number of orders: 180519
```

In [36]:
```
'''
Further understand unique values within the features.
'''
df['Order Region'].unique()
```

Out[36]:
```
array(['Southeast Asia', 'South Asia', 'Oceania', 'Eastern Asia',
       'West Asia', 'West of USA ', 'US Center ', 'West Africa',
       'Central Africa', 'North Africa', 'Western Europe',
       'Northern Europe', 'Central America', 'Caribbean', 'South America',
       'East Africa', 'Southern Europe', 'East of USA', 'Canada',
       'Southern Africa', 'Central Asia', 'Eastern Europe',
       'South of  USA '], dtype=object)
```

In [37]:
```
'''
Further understand unique values within the features.
'''
df['Order State'].unique()
```

Out[37]:
```
array(['Java Occidental', 'Rajastán', 'Queensland', ...,
       'Bistrita-Nasaud', 'Tottori', 'Khorezm'], dtype=object)
```

In [38]:
```
'''
Further understand unique values within the features.
'''
df['Order Status'].unique()
```

Out[38]:
```
array(['COMPLETE', 'PENDING', 'CLOSED', 'PENDING_PAYMENT', 'CANCELED',
       'PROCESSING', 'SUSPECTED_FRAUD', 'ON_HOLD', 'PAYMENT_REVIEW'],
      dtype=object)
```

In [39]:
```
df['Product Name'].unique()
```

Out[39]:
```
array(['Smart watch ', 'Perfect Fitness Perfect Rip Deck',
       "Under Armour Girls' Toddler Spine Surge Runni",
       "Nike Men's Dri-FIT Victory Golf Polo",
       "Under Armour Men's Compression EV SL Slide",
       "Under Armour Women's Micro G Skulpt Running S",
       "Nike Men's Free 5.0+ Running Shoe",
       "Glove It Women's Mod Oval 3-Zip Carry All Gol",
       'Bridgestone e6 Straight Distance NFL San Dieg',
       "Columbia Men's PFG Anchor Tough T-Shirt",
       'Titleist Pro V1x Golf Balls',
       'Bridgestone e6 Straight Distance NFL Tennesse',
       'Polar FT4 Heart Rate Monitor', 'ENO Atlas Hammock Straps',
       "adidas Men's F10 Messi TRX FG Soccer Cleat",
       "Brooks Women's Ghost 6 Running Shoe",
       "Nike Men's CJ Elite 2 TD Football Cleat",
       "Diamondback Women's Serene Classic Comfort Bi",
       'Industrial consumer electronics', 'Web Camera', 'Dell Laptop',
```

```
'SOLE E25 Elliptical', 'Elevation Training Mask 2.0',
"adidas Men's Germany Black Crest Away Tee",
'Team Golf Pittsburgh Steelers Putter Grip',
'Glove It Urban Brick Golf Towel',
'Team Golf Texas Longhorns Putter Grip',
"Nike Men's Deutschland Weltmeister Winners Bl",
'Team Golf St. Louis Cardinals Putter Grip', 'Summer dresses',
'Porcelain crafts', "Men's gala suit",
'Team Golf Tennessee Volunteers Putter Grip',
'Team Golf San Francisco Giants Putter Grip',
'Glove It Imperial Golf Towel', "Nike Men's Comfort 2 Slide",
'Under Armour Hustle Storm Medium Duffle Bag',
"Under Armour Kids' Mercenary Slide",
"Under Armour Women's Ignite PIP VI Slide",
"Nike Men's Free TR 5.0 TB Training Shoe",
'adidas Youth Germany Black/Red Away Match Soc',
"TYR Boys' Team Digi Jammer",
"Glove It Women's Imperial Golf Glove",
'Titleist Pro V1x High Numbers Golf Balls',
'Bridgestone e6 Straight Distance NFL Carolina',
"Under Armour Women's Ignite Slide",
'Titleist Pro V1x High Numbers Personalized Go',
'GoPro HERO3+ Black Edition Camera', 'Total Gym 1400',
"Children's heaters", 'Team Golf New England Patriots Putter Grip',
"adidas Kids' F5 Messi FG Soccer Cleat",
"Nike Women's Tempo Shorts",
"Glove It Women's Mod Oval Golf Glove",
'Titleist Pro V1 High Numbers Personalized Gol',
"Under Armour Men's Tech II T-Shirt", 'Baby sweater',
'Mio ALPHA Heart Rate Monitor/Sport Watch',
'Field & Stream Sportsman 16 Gun Fire Safe', 'Sports Books ',
"Diamondback Boys' Insight 24 Performance Hybr",
'Polar Loop Activity Tracker', 'Garmin Forerunner 910XT GPS Watch',
'DVDs ', 'CDs of rock',
"Nike Kids' Grade School KD VI Basketball Shoe",
"Nike Women's Free 5.0 TR FIT PRT 4 Training S",
"Hirzl Women's Soffft Flex Golf Glove",
"The North Face Women's Recon Backpack", 'Lawn mower',
'Nike Dri-FIT Crew Sock 6 Pack',
"Nike Women's Legend V-Neck T-Shirt",
'Garmin Approach S4 Golf GPS Watch',
'insta-bed Neverflat Air Mattress',
"Nike Men's Kobe IX Elite Low Basketball Shoe",
'Adult dog supplies', 'First aid kit',
'Garmin Approach S3 Golf GPS Watch', 'Rock music',
'Fighting video games',
'Fitbit The One Wireless Activity & Sleep Trac',
'Stiga Master Series ST3100 Competition Indoor',
"Diamondback Girls' Clarity 24 Hybrid Bike 201",
'adidas Brazuca 2014 Official Match Ball',
'GolfBuddy VT3 GPS Watch',
'Bushnell Pro X7 Jolt Slope Rangefinder',
'Yakima DoubleDown Ace Hitch Mount 4-Bike Rack',
"Nike Men's Fingertrap Max Training Shoe",
'Bowflex SelectTech 1090 Dumbbells', 'SOLE E35 Elliptical',
"Hirzl Women's Hybrid Golf Glove", "Hirzl Men's Hybrid Golf Glove",
'TaylorMade 2014 Purelite Stand Bag', 'Bag Boy Beverage Holder',
'Bag Boy M330 Push Cart', 'Clicgear 8.0 Shoe Brush',
'Titleist Small Wheeled Travel Cover', 'Clicgear Rovic Cooler Bag',
'Titleist Club Glove Travel Cover', 'Ogio Race Golf Shoes',
"LIJA Women's Argyle Golf Polo",
"LIJA Women's Eyelet Sleeveless Golf Polo",
"LIJA Women's Button Golf Dress",
"LIJA Women's Mid-Length Panel Golf Shorts",
"TaylorMade Women's RBZ SL Rescue",
"Cleveland Golf Women's 588 RTX CB Satin Chrom",
```

```
       "Top Flite Women's 2014 XL Hybrid",
       'MDGolf Pittsburgh Penguins Putter',
       'TaylorMade White Smoke IN-12 Putter',
       'Cleveland Golf Collegiate My Custom Wedge 588',
       "Merrell Men's All Out Flash Trail Running Sho",
       "Merrell Women's Grassbow Sport Waterproof Hik",
       "Merrell Women's Siren Mid Waterproof Hiking B",
       "Merrell Women's Grassbow Sport Hiking Shoe", 'Toys ',
       'Pelican Sunstream 100 Kayak', 'Pelican Maverick 100X Kayak',
       "O'Brien Men's Neoprene Life Vest"], dtype=object)
```

In [40]:

```
'''
Further understand unique values within the features.
'''
print("Number of unique products: {}".format(len(df['Product Name'].unique())))
```

```
Number of unique products: 118
```

In [41]:

```
'''
Further understand unique values within the features.
'''
df['Shipping Mode'].unique()
```

Out[41]:

```
array(['Standard Class', 'First Class', 'Second Class', 'Same Day'],
      dtype=object)
```

Highlights for Data Set Overview:

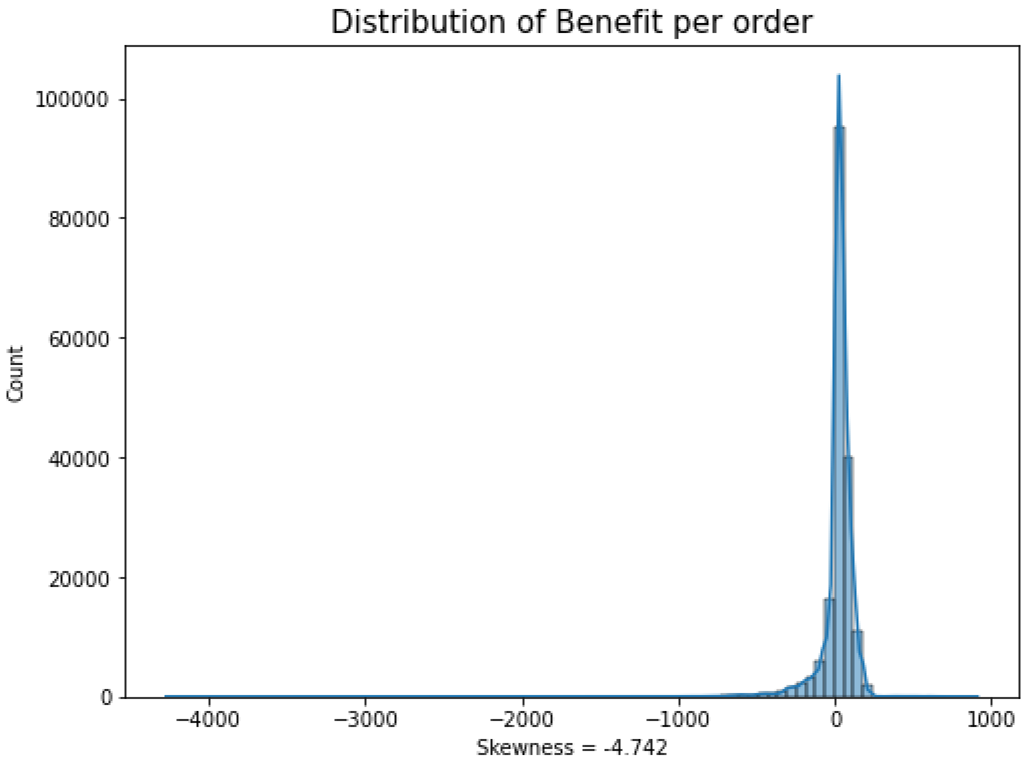
- The data set consisted of 53 features and 180519 rows initially (9567507 records).
- There were 16 columns removed for either majority missing data, duplicate feature information, or irrelevant to the objectives.
- No missing data observed in the data set after the 16 columns were removed.
- Order Date and Ship Date were converted to DateTime data types.
- Orders come from 164 different Countries.
- Customer Countries are only 2 (United States and Puerto Rico)
- The data set originally had the United States as EE. US. or Estados Unidos. This was converted to United States in both cases.
- There were 20652 unique Customer ID's.
- There were 180519 Orders included in this data (row length).
- There were 11 unique departments with 118 different products sold and 50 different product categories.
- Recommend potentially creating another feature such as Difference (in Days) Between Ship and Order Dates.

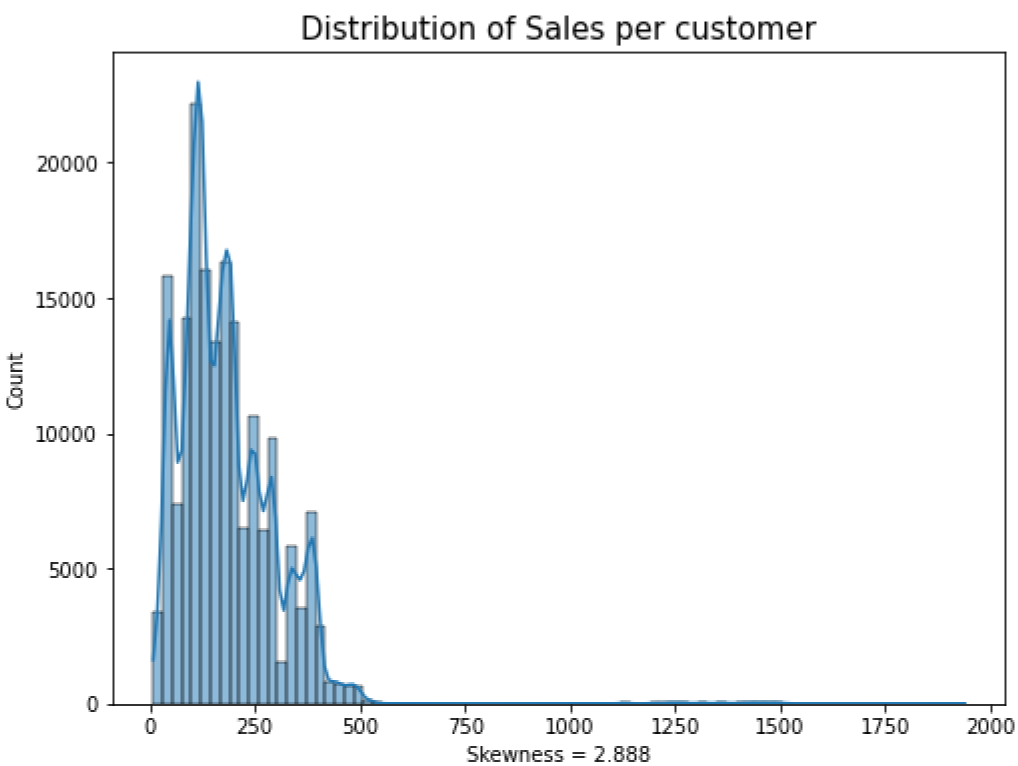
Univariate Analysis

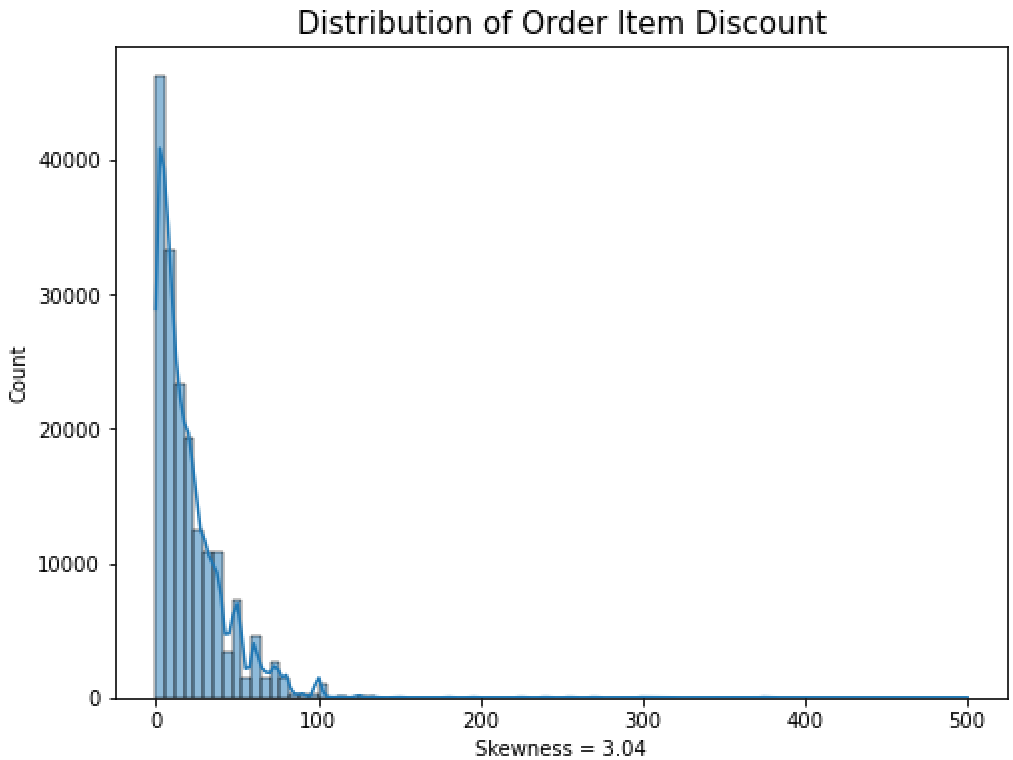
In [42]:

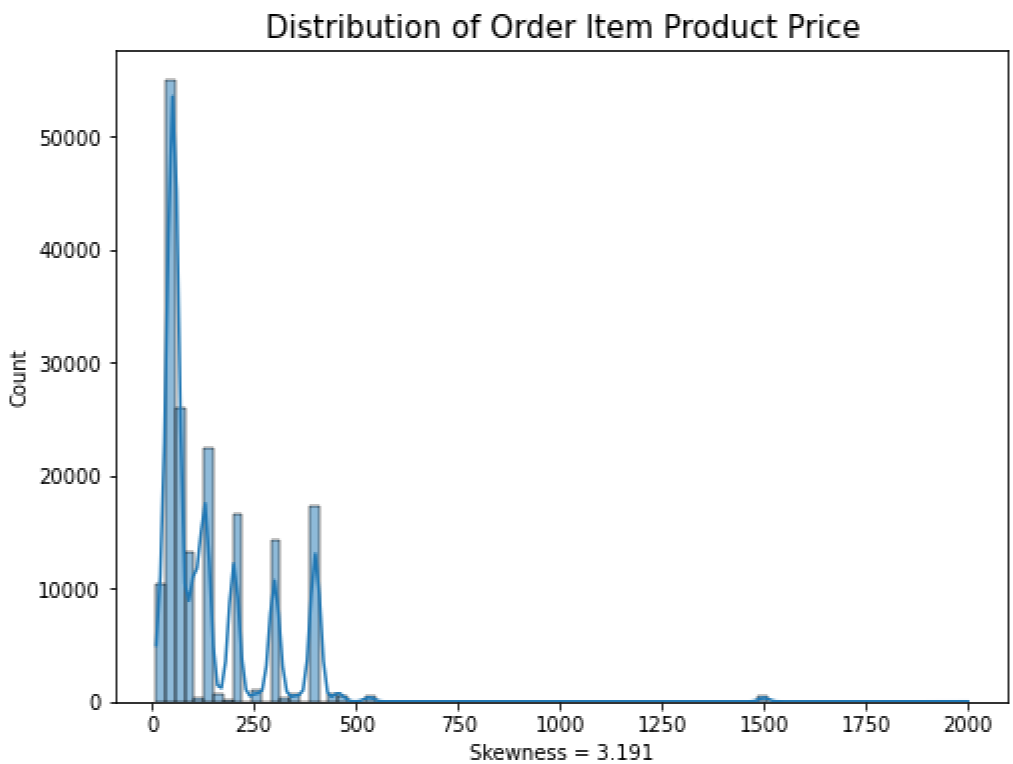
```
'''
Understand the distribution for the continuous numeric features within the dataset.
The code below will loop through each feature and illustrate how the feature is distribute
The skewness value will also be included below the chart.
'''
cont_columns = df[['Benefit per order', 'Sales per customer', 'Order Item Discount',
                   'Order Item Product Price', 'Order Item Profit Ratio','Sales', 'Orde
                   'Order Profit Per Order', 'Product Price']]

for col in cont_columns:
    plt.figure(figsize=(8,6))
    sns.histplot(x =df[col], kde = True, multiple = 'stack', bins = 85)
```

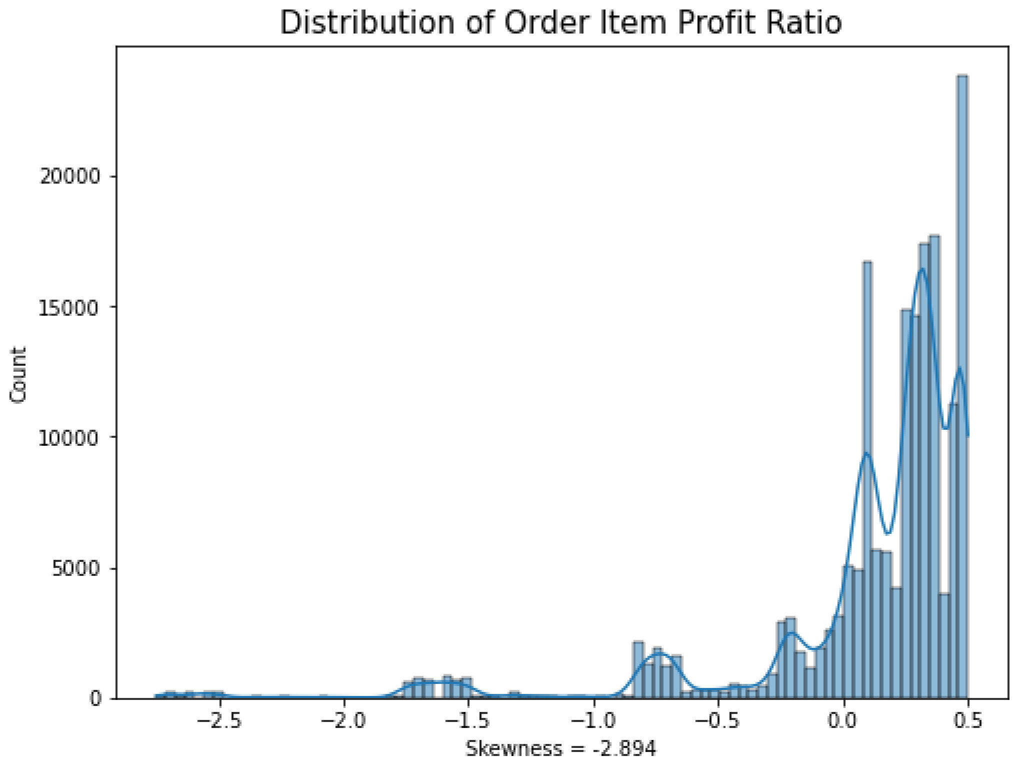
```
    plt.title("Distribution of {}".format(col), fontsize=15)
    plt.xlabel(f"Skewness = {round(df[col].skew(),3)}", fontsize=10)
    plt.xticks(fontsize=10)
    plt.yticks(fontsize=10)
    plt.show()
```

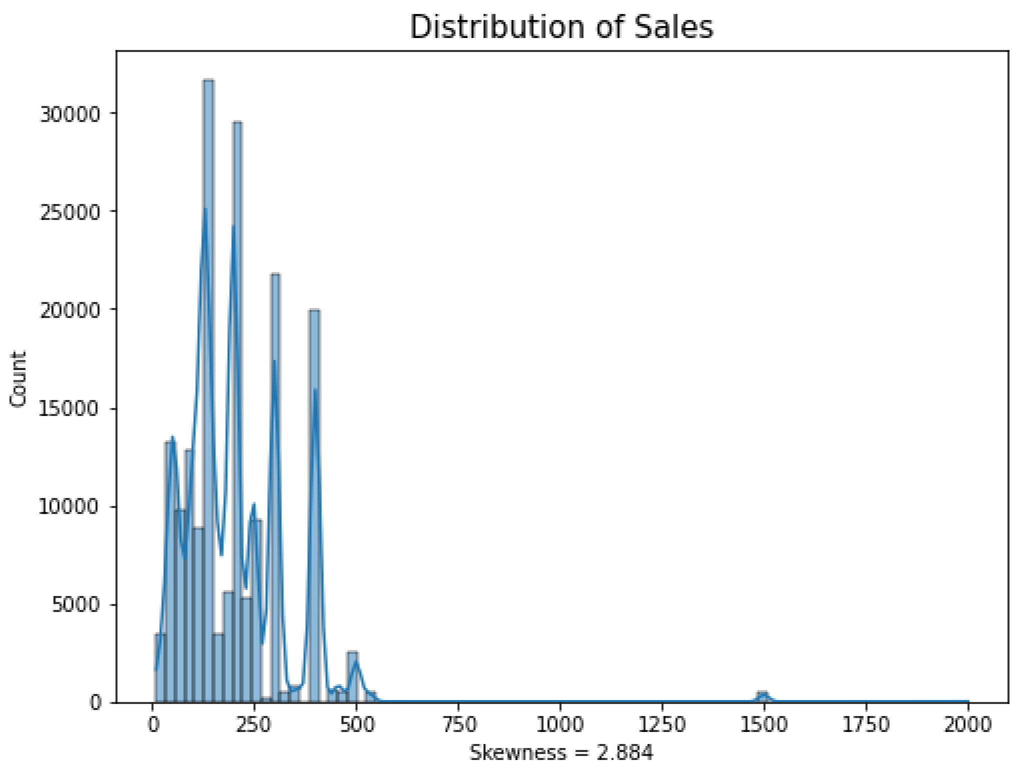


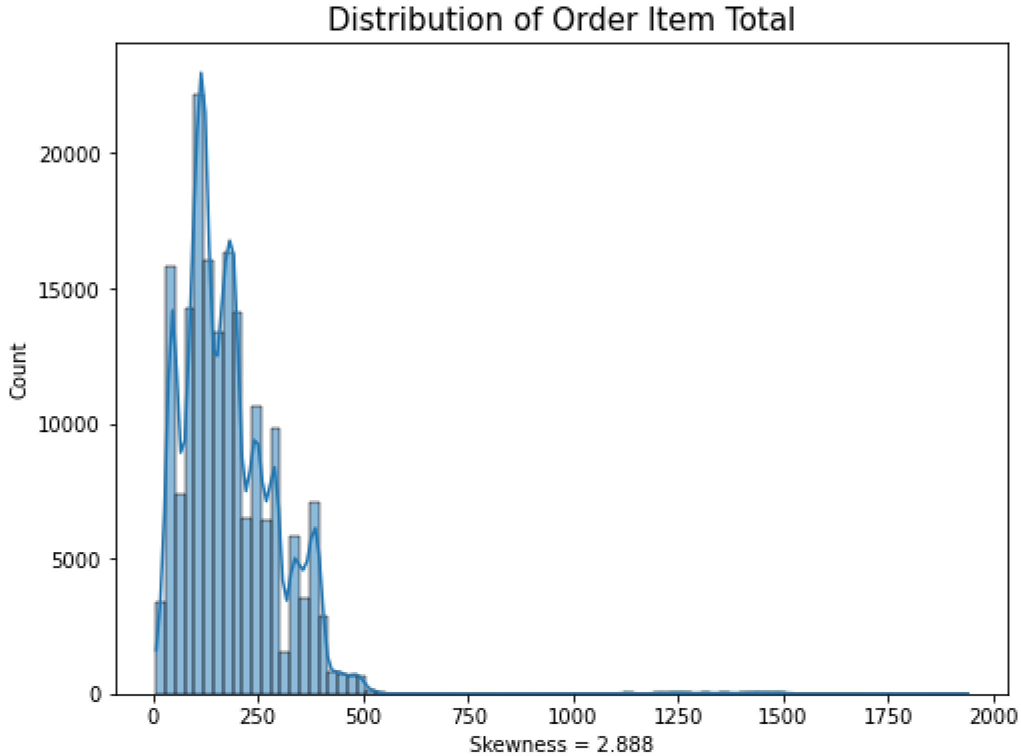


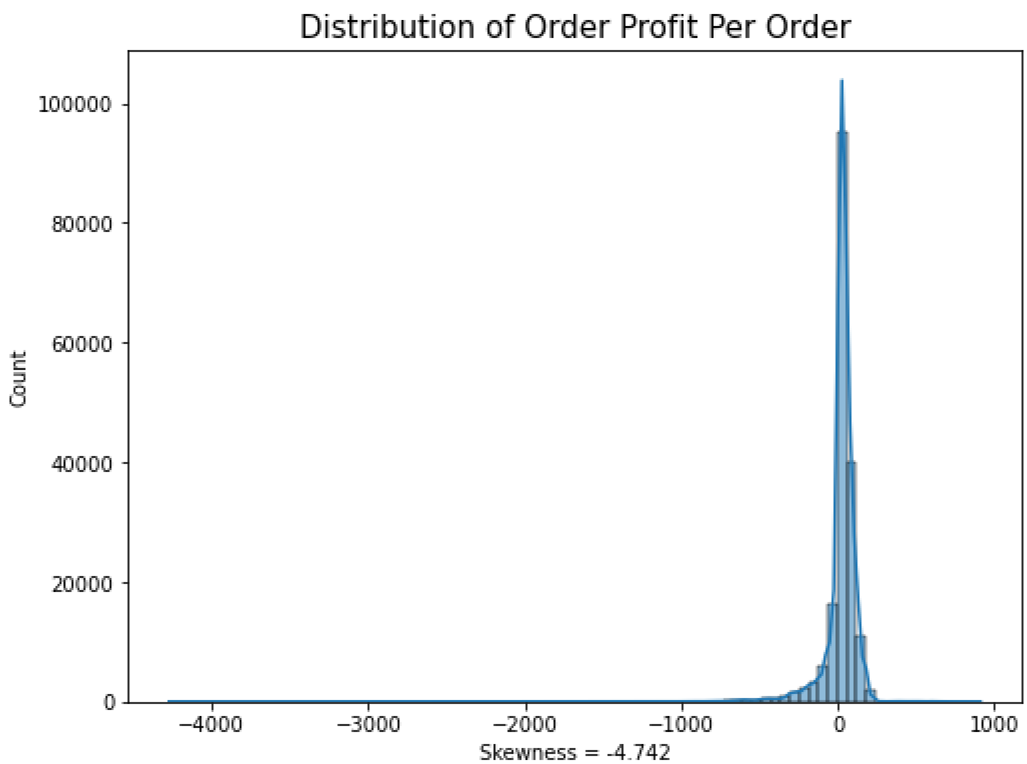

Distribution of Order Item Discount
Count
40000
30000
20000
10000
0
0
100
200
300
400
500
Skewness = 3.04

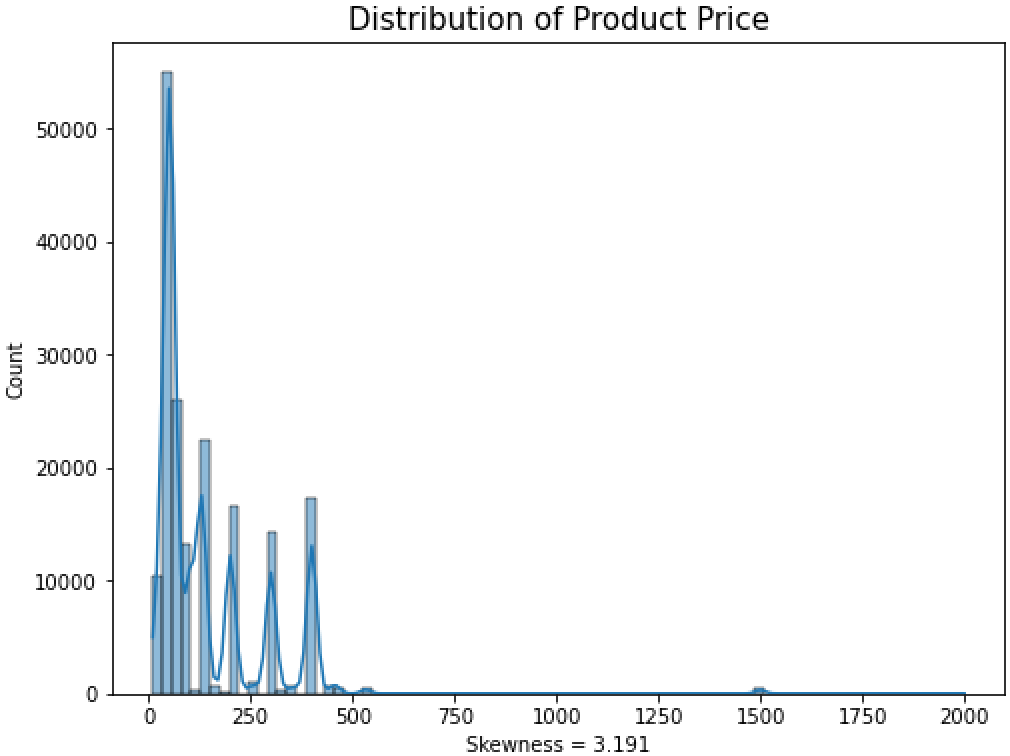

Distribution of Order Item Product Price
Count
50000
40000
30000
20000
10000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 3.191


Distribution of Order Item Profit Ratio
Count
20000
15000
10000
5000
0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
Skewness = -2.894


Distribution of Sales
Count
30000
25000
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 2.884

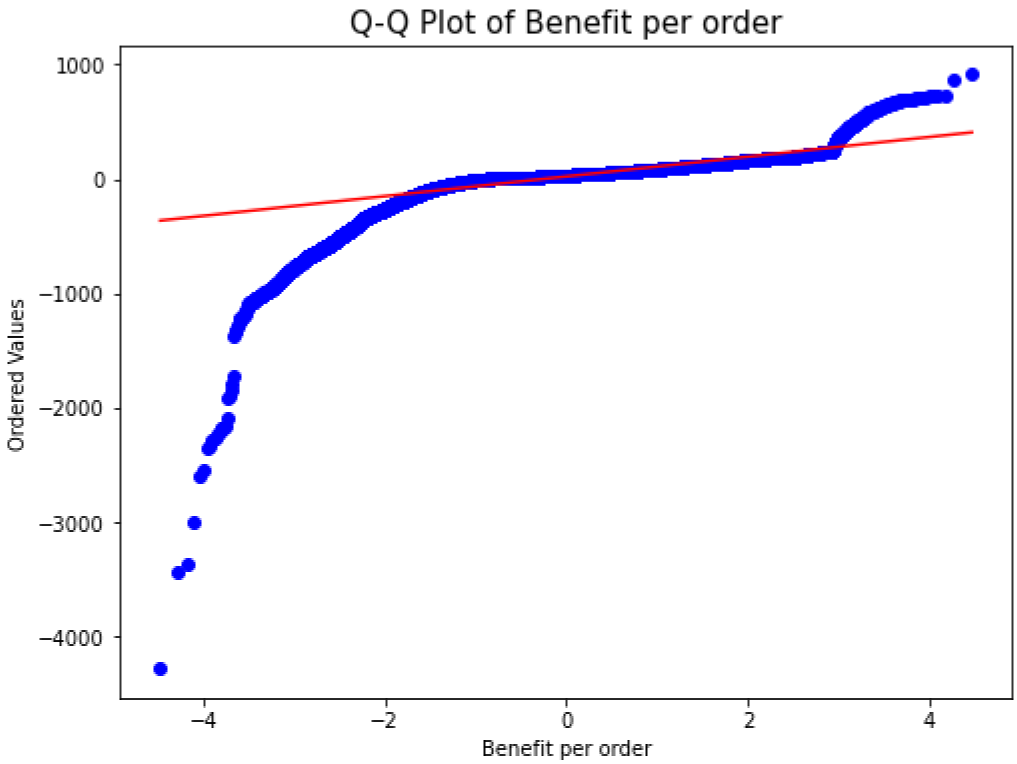

Distribution of Order Item Total
Count
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 2.888


Distribution of Order Profit Per Order
Count
100000
80000
60000
40000
20000
0
−4000
−3000
−2000
−1000
0
1000
Skewness = -4.742

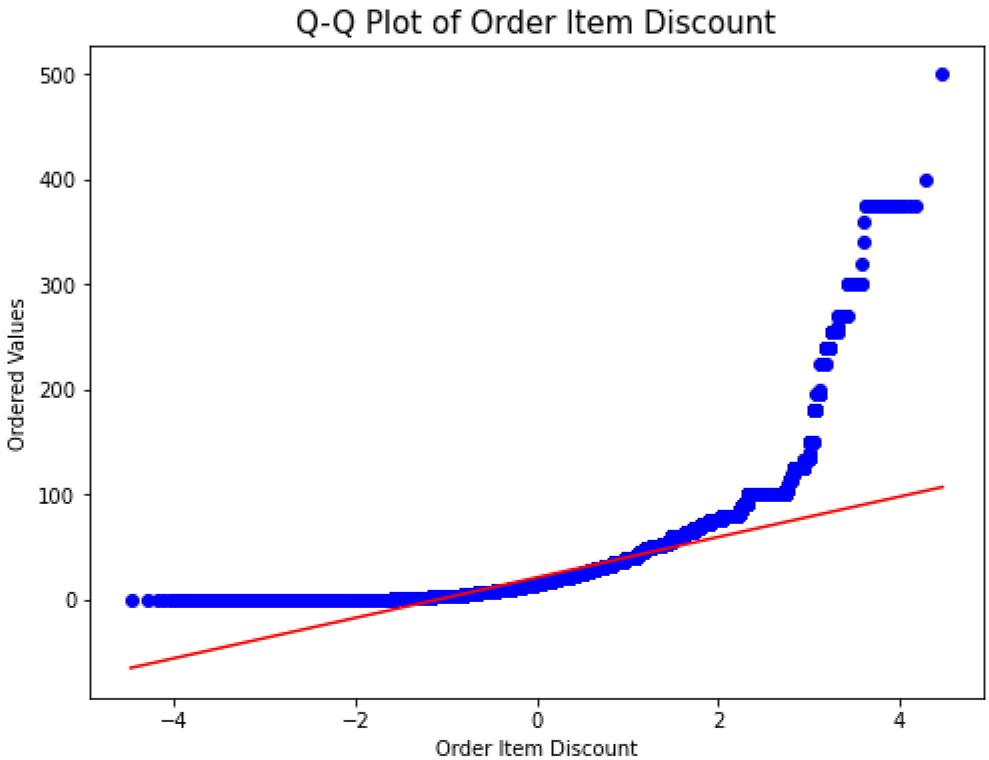


In [43]:

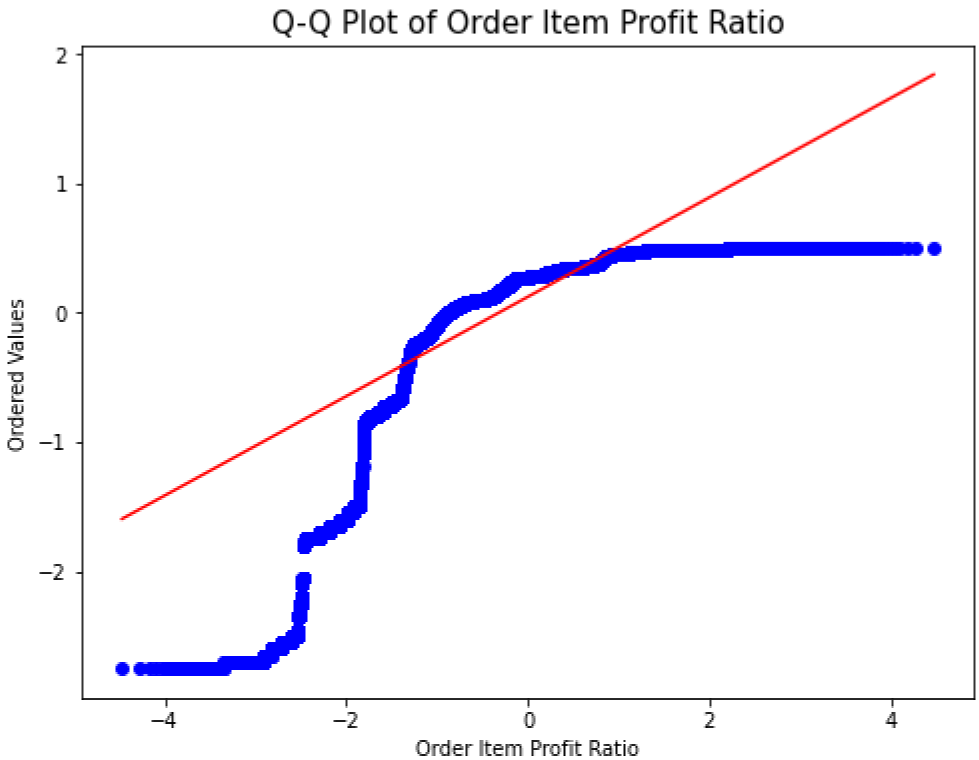
```
'''
Understand whether the continuous numeric features within the dataset are normally distrib
The code below will loop through each feature and illustrate how the feature is distribute
'''
cont_columns = df[['Benefit per order', 'Sales per customer', 'Order Item Discount',
                   'Order Item Product Price', 'Order Item Profit Ratio','Sales', 'Orde
                   'Order Profit Per Order', 'Product Price']]

for col in cont_columns:
    plt.figure(figsize=(8,6))
    fig = stats.probplot(df[col], plot = sns.mpl.pyplot)
    plt.title("Q-Q Plot of {}".format(col), fontsize=15)
    plt.xlabel("{}".format(col), fontsize=10)
    plt.xticks(fontsize=10)
    plt.yticks(fontsize=10)
    plt.show()
```

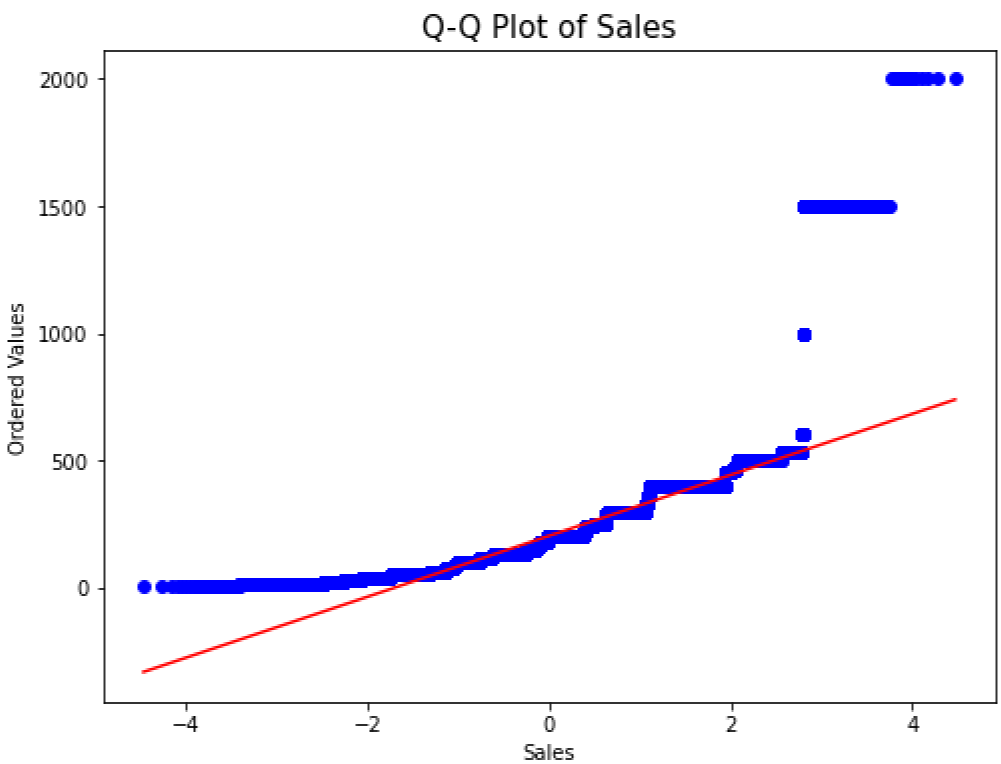

Q-Q Plot of Benefit per order
1000
0
−1000
−2000
−3000
−4000
Ordered Values
−4
−2
0
2
4
Benefit per order


Q-Q Plot of Sales per customer
2000
1500
1000
500
0
Ordered Values
−4
−2
0
2
4
Sales per customer

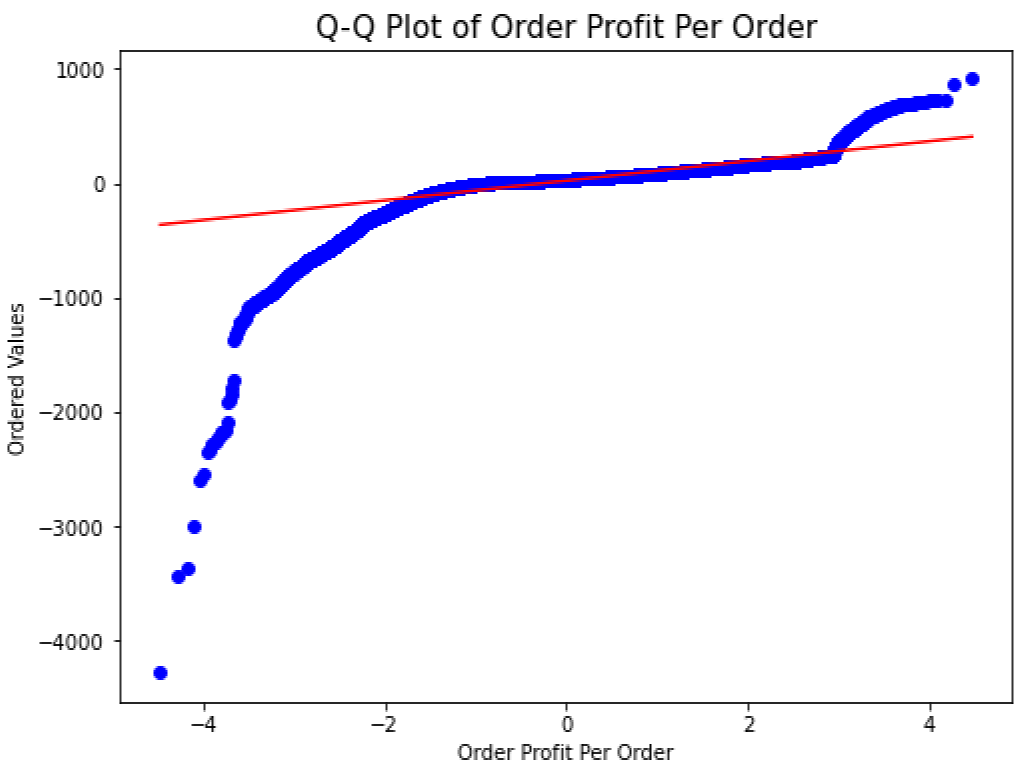

Q-Q Plot of Order Item Discount
Ordered Values
Order Item Discount
500
400
300
200
100
0
−4
−2
0
2
4

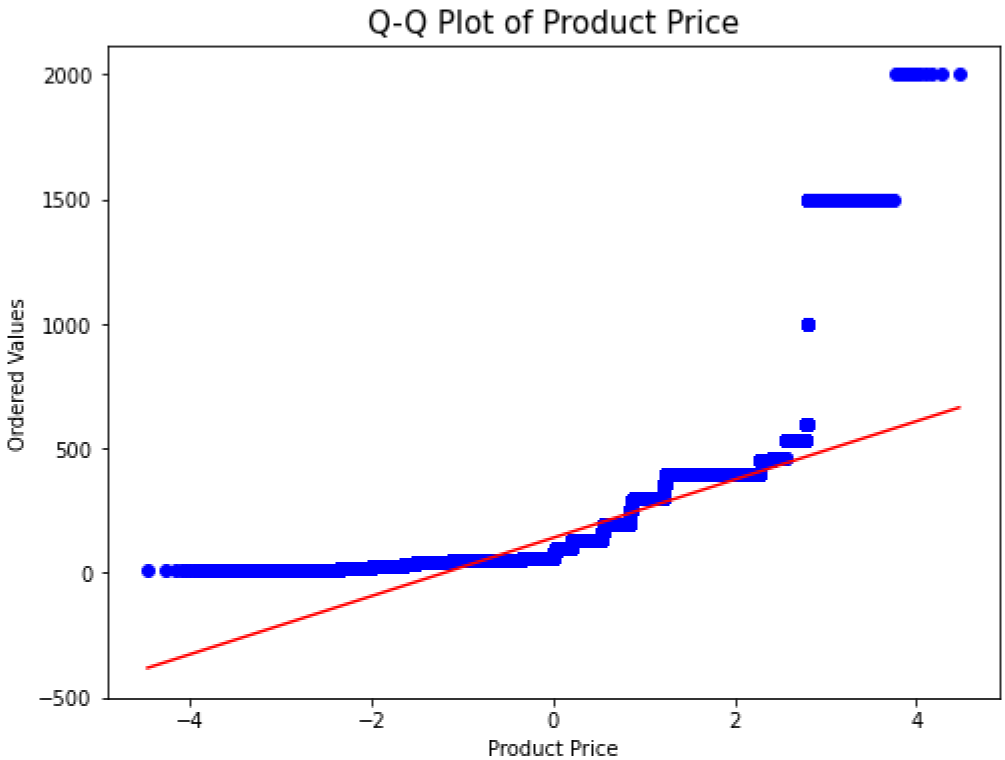

Q-Q Plot of Order Item Product Price
Ordered Values
Order Item Product Price
2000
1500
1000
500
0
−500
−4
−2
0
2
4


Q-Q Plot of Order Item Profit Ratio
Ordered Values
Order Item Profit Ratio
2
1
0
−1
−2
−4
−2
0
2
4

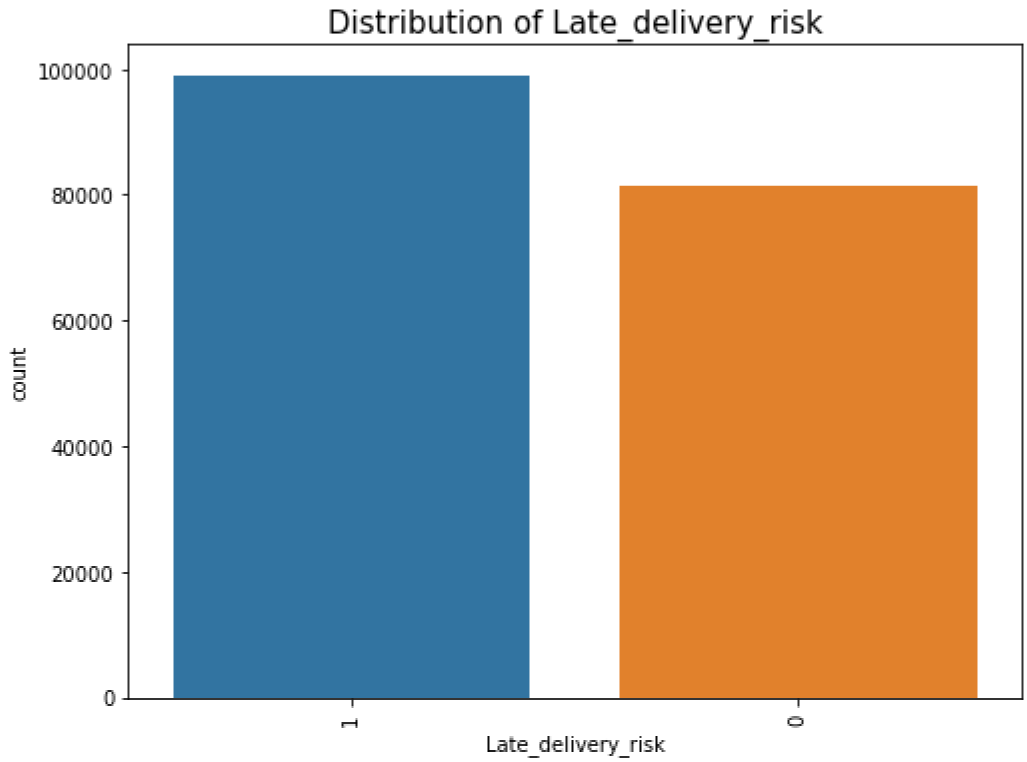

Q-Q Plot of Sales
Ordered Values
Sales
2000
1500
1000
500
0
−4
−2
0
2
4

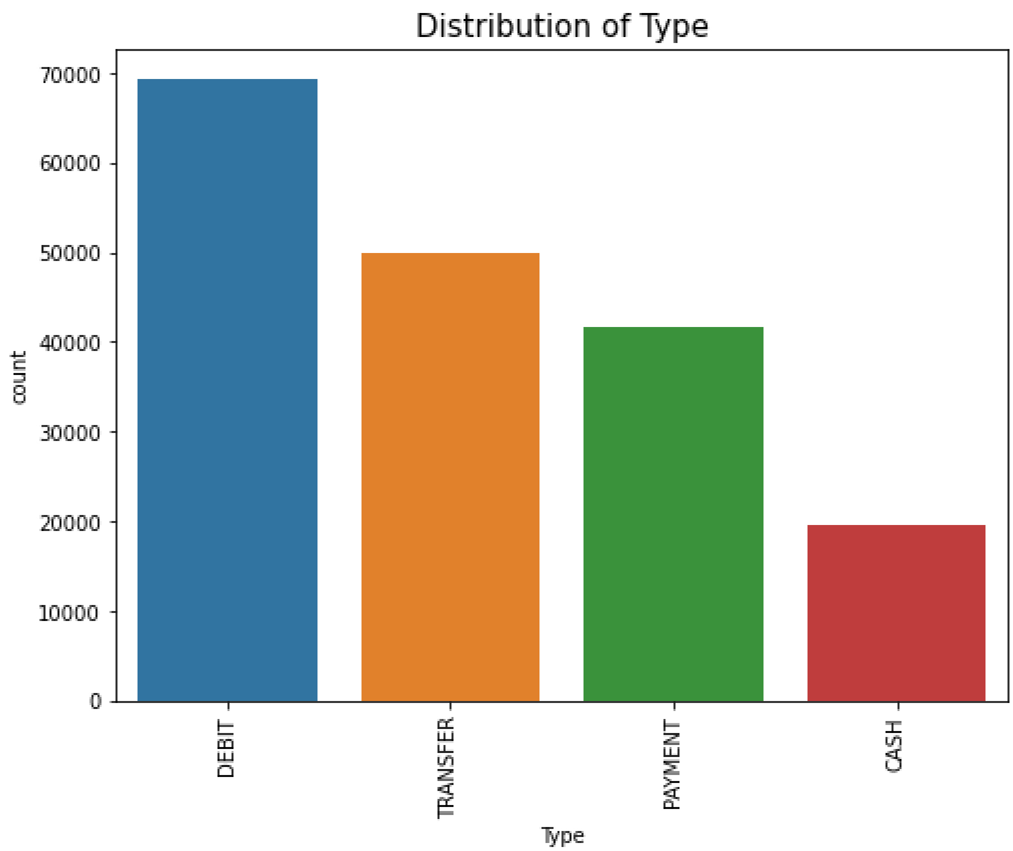

Q-Q Plot of Order Item Total
Ordered Values
Order Item Total
2000
1500
1000
500
0
−4
−2
0
2
4

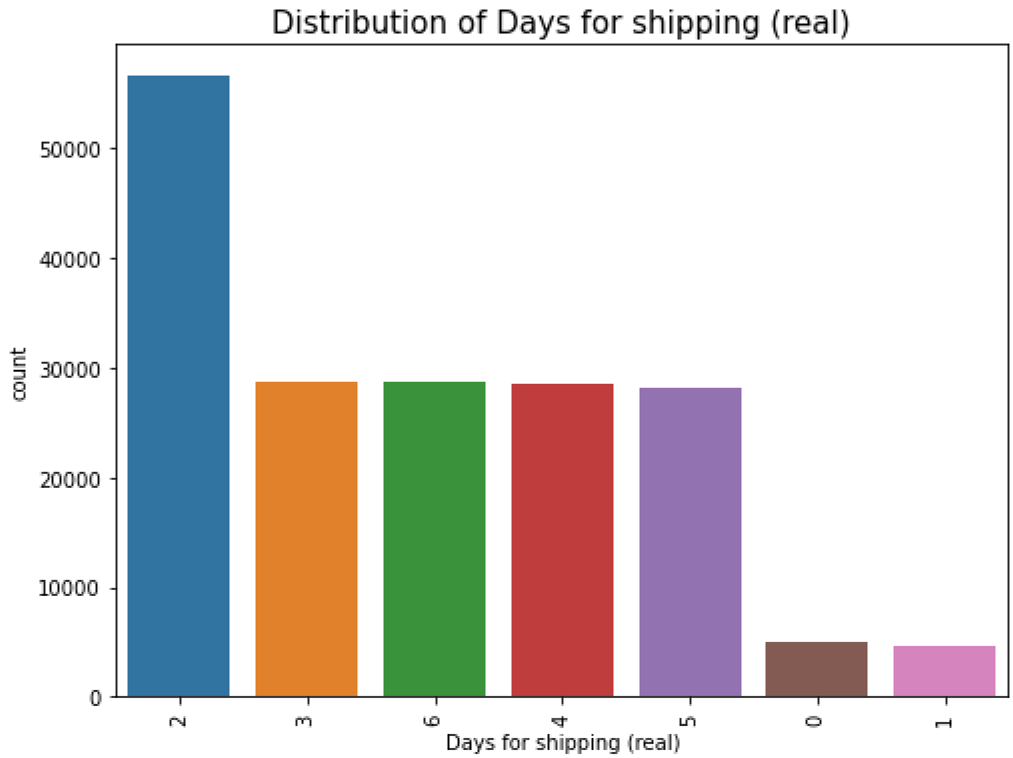

Q-Q Plot of Order Profit Per Order
Ordered Values
Order Profit Per Order
1000
0
−1000
−2000
−3000
−4000
−4
−2
0
2
4

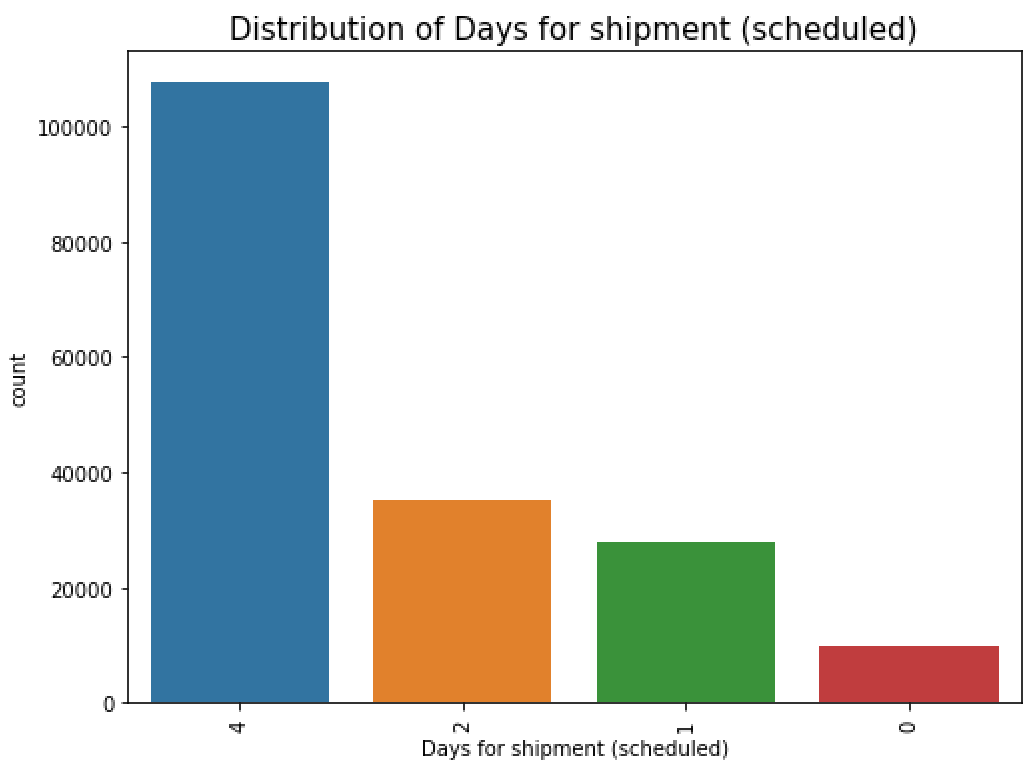


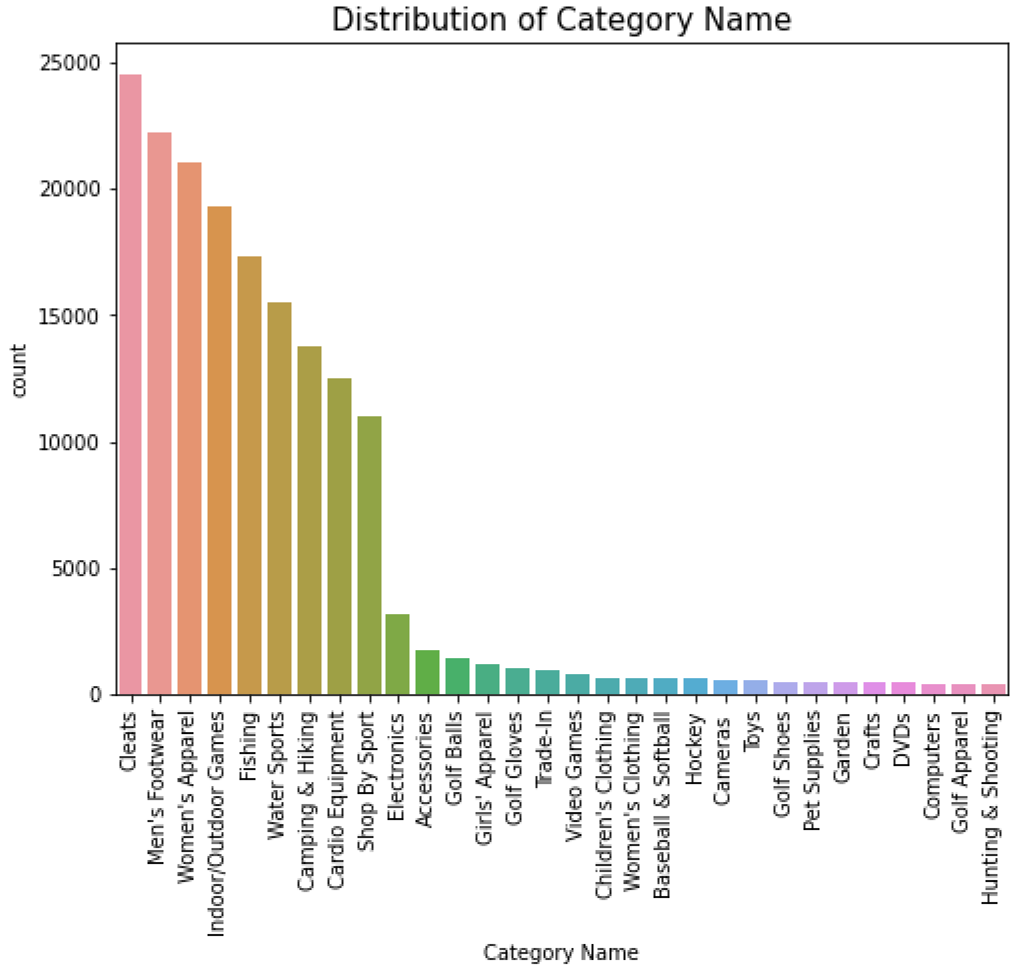
In [44]:
```
'''
Understand the balance of the categorical and discrete features with a countplot.
Late Delivery Risk is 1 (Late Delivery) and 0 (Not Late Delivery).
The code below will loop through each feature and illustrate the count of unique items wit
Useful for understanding balance within the data.
'''
cat_disc_columns = df[['Late_delivery_risk', 'Type', 'Days for shipping (real)', 'Days for
                       'Category Name','Customer City', 'Customer Country',
                       'Customer Id', 'Customer Segment', 'Customer State', 'Department Nar
                       'Market', 'Order City', 'Order Country', 'Order Item Id', 'Order Ite
                       'Order Region', 'Order State', 'Order Status', 'Shipping Mode']]

for col in cat_disc_columns:
    plt.figure(figsize=(8,6))
    sns.countplot(x=df[col], order = df[col].value_counts().iloc[:30].index)
    plt.title("Distribution of {}".format(col), fontsize=15)
    plt.xticks(fontsize=10, rotation = 90)
    plt.yticks(fontsize=10)
    plt.show()
```

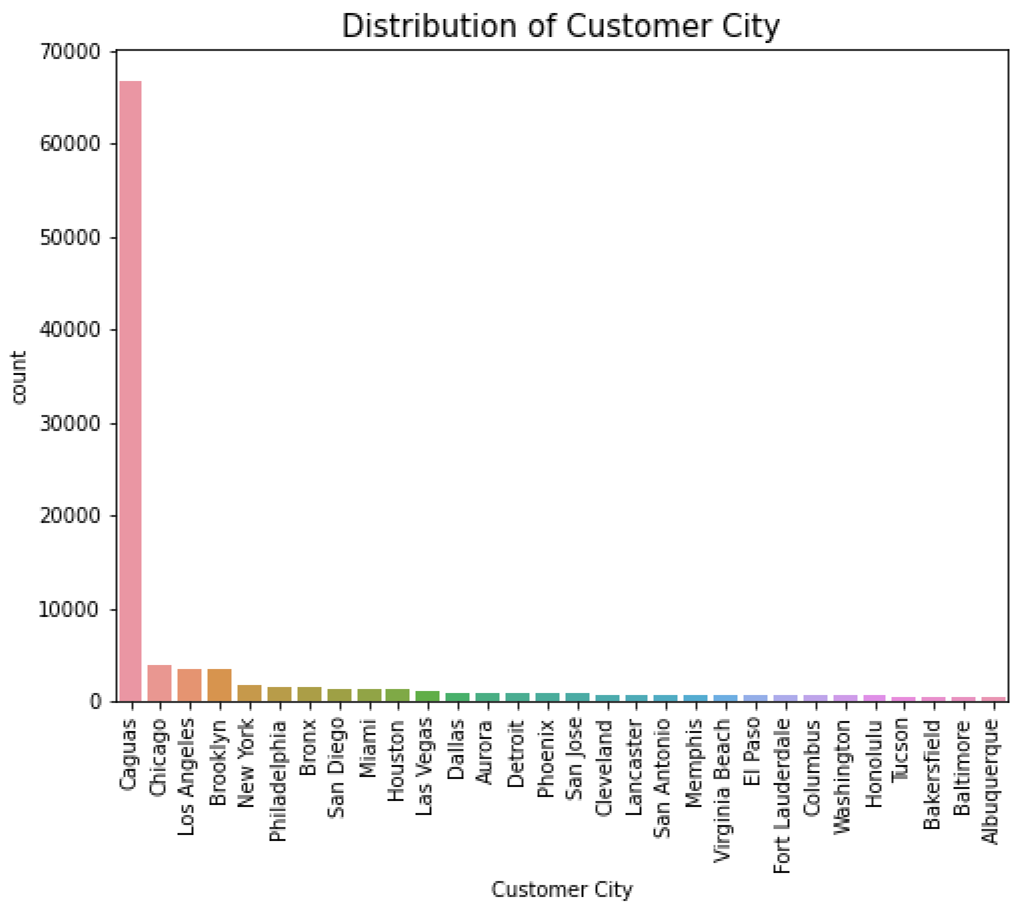

Distribution of Late_delivery_risk
count
100000
80000
60000
40000
20000
0
1
0
Late_delivery_risk

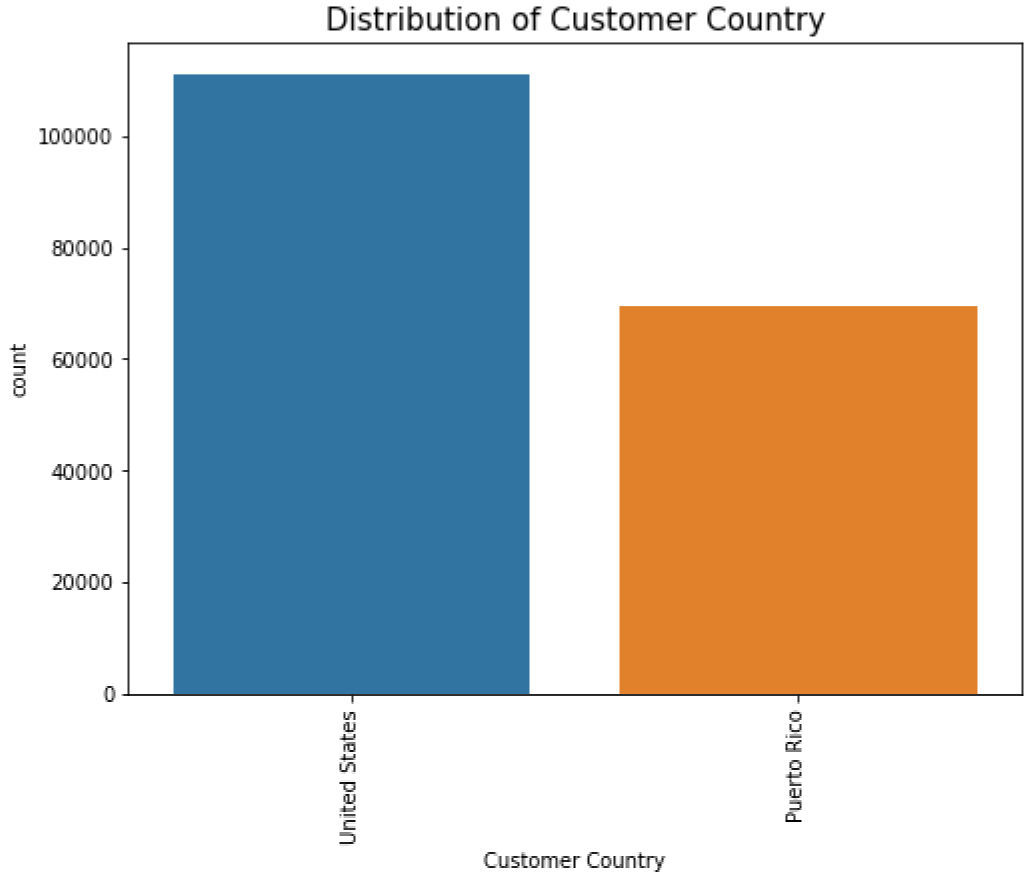

Distribution of Type
count
70000
60000
50000
40000
30000
20000
10000
0
DEBIT
TRANSFER
PAYMENT
CASH
Type

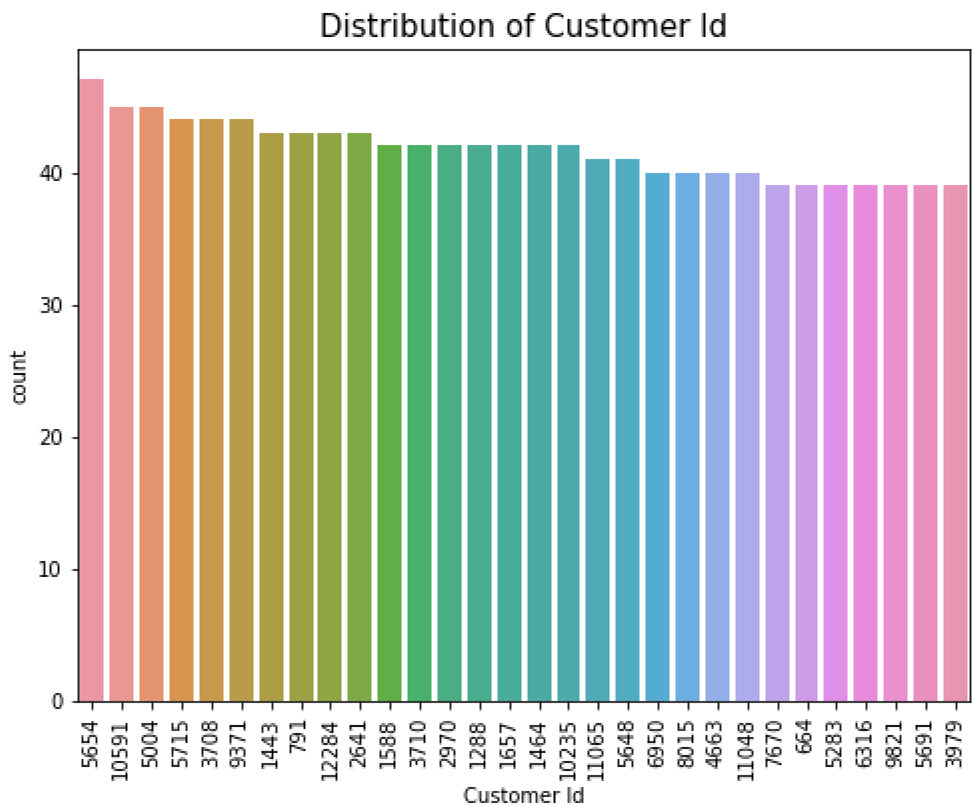

Distribution of Days for shipping (real)
count
50000
40000
30000
20000
10000
0
2
3
6
4
5
0
1
Days for shipping (real)

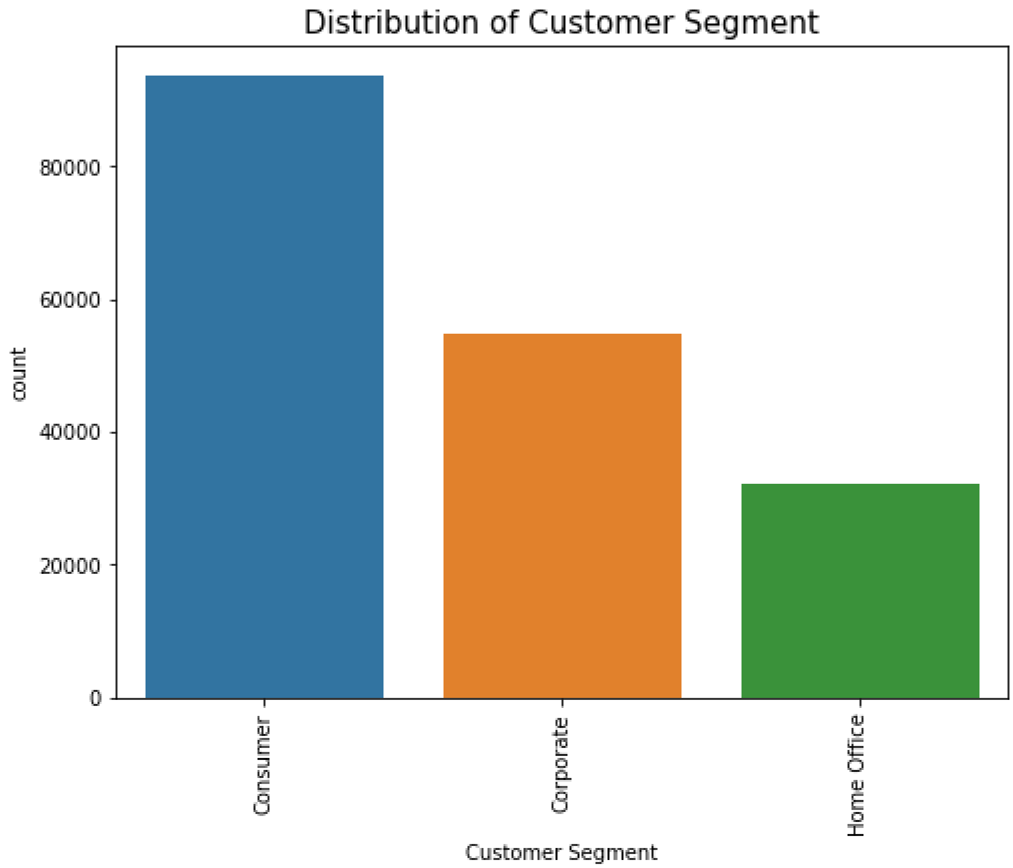

Distribution of Days for shipment (scheduled)
count
100000
80000
60000
40000
20000
0
4
2
1
0
Days for shipment (scheduled)

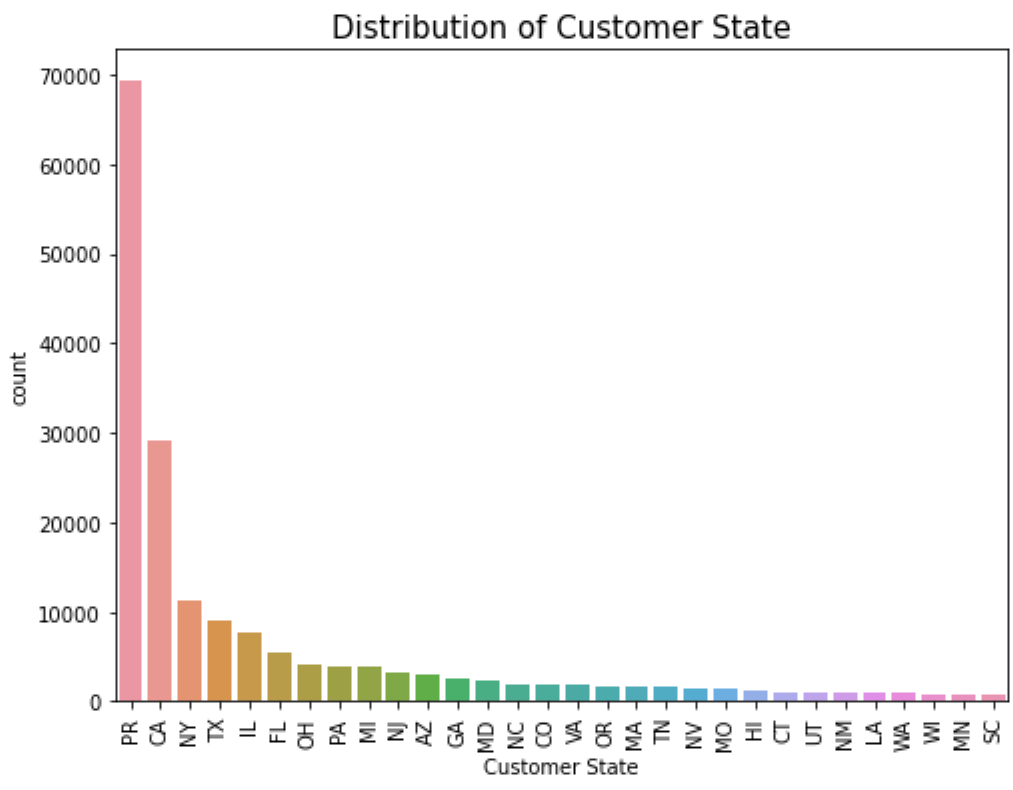

Distribution of Category Name
count
Category Name
25000
20000
15000
10000
5000
0
Cleats
Men's Footwear
Women's Apparel
Indoor/Outdoor Games
Fishing
Water Sports
Camping & Hiking
Cardio Equipment
Shop By Sport
Electronics
Accessories
Golf Balls
Girls' Apparel
Golf Gloves
Trade-In
Video Games
Children's Clothing
Women's Clothing
Baseball & Softball
Hockey
Cameras
Toys
Golf Shoes
Pet Supplies
Garden
Crafts
DVDs
Computers
Golf Apparel
Hunting & Shooting

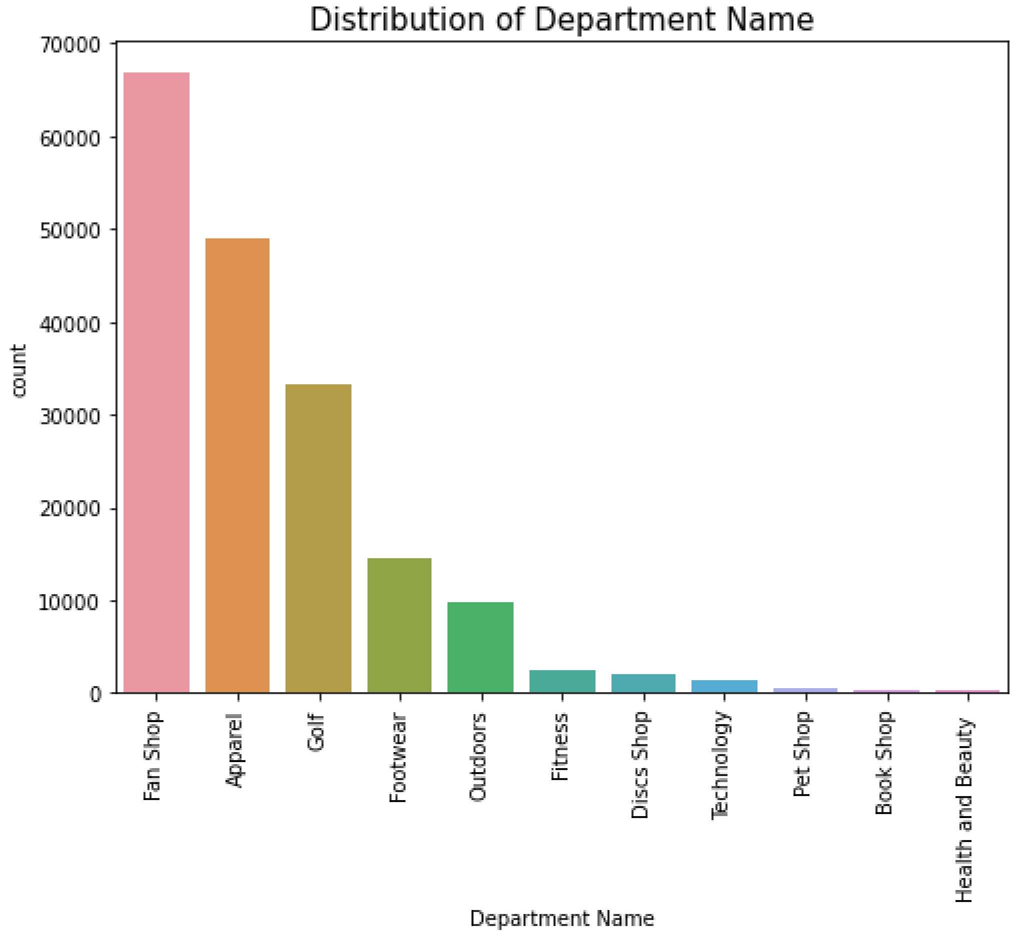

Distribution of Customer City
count
Customer City
70000
60000
50000
40000
30000
20000
10000
0
Caguas
Chicago
Los Angeles
Brooklyn
New York
Philadelphia
Bronx
San Diego
Miami
Houston
Las Vegas
Dallas
Aurora
Detroit
Phoenix
San Jose
Cleveland
Lancaster
San Antonio
Memphis
Virginia Beach
El Paso
Fort Lauderdale
Columbus
Washington
Honolulu
Tucson
Bakersfield
Baltimore
Albuquerque

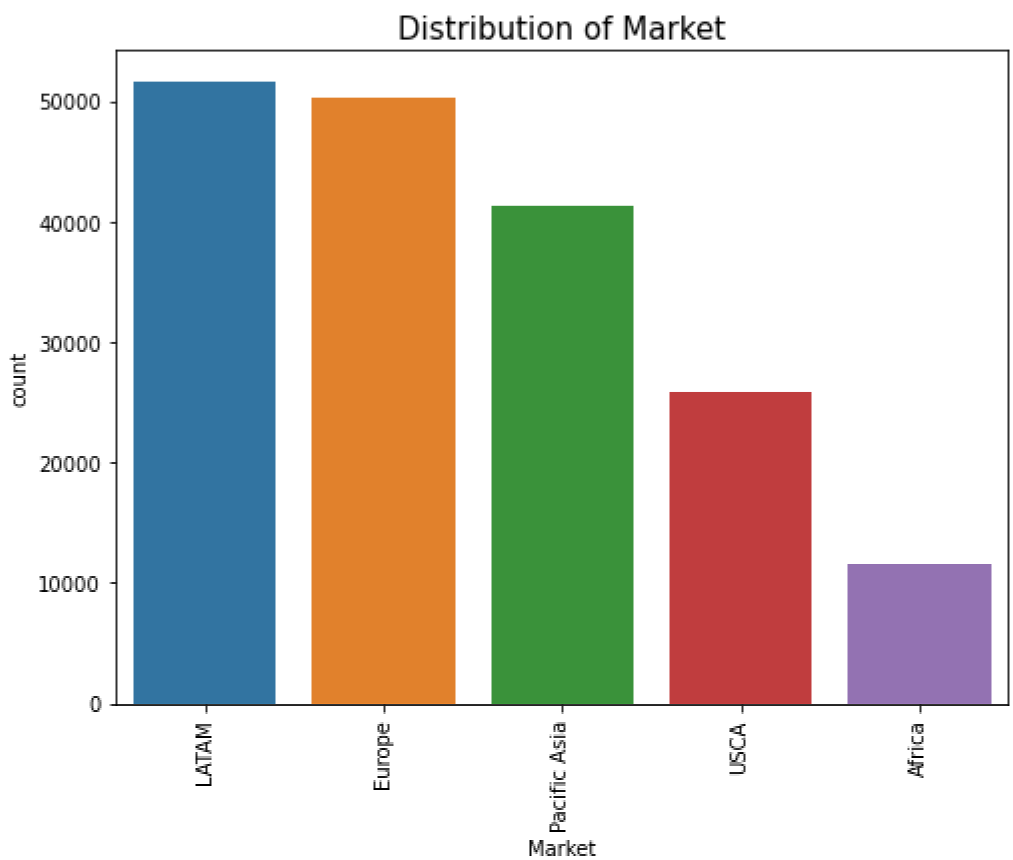

Distribution of Customer Country
count
100000
80000
60000
40000
20000
0
United States
Puerto Rico
Customer Country

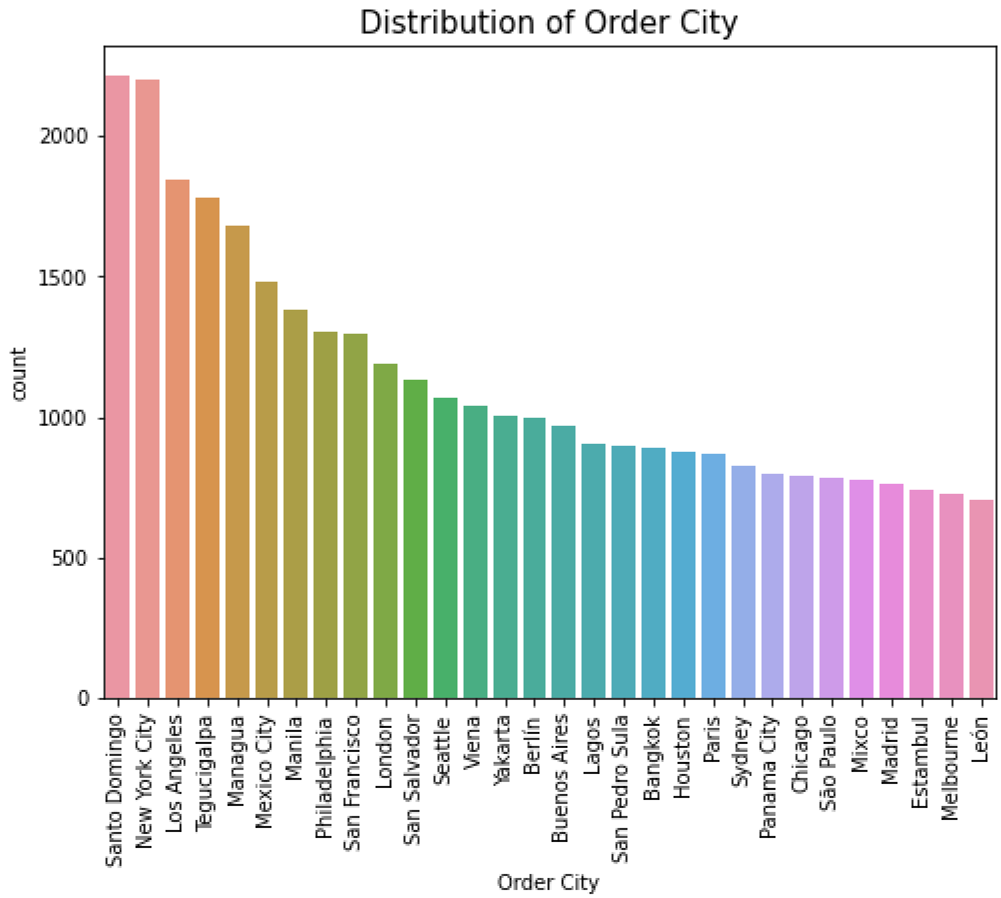

Distribution of Customer Id
count
40
30
20
10
0
5654
10591
5004
5715
3708
9371
1443
791
12284
2641
1588
3710
2970
1288
1657
1464
10235
11065
5648
6950
8015
4663
11048
7670
664
5283
6316
9821
5691
3979
Customer Id


Distribution of Customer Segment
count
80000
60000
40000
20000
0
Consumer
Corporate
Home Office
Customer Segment

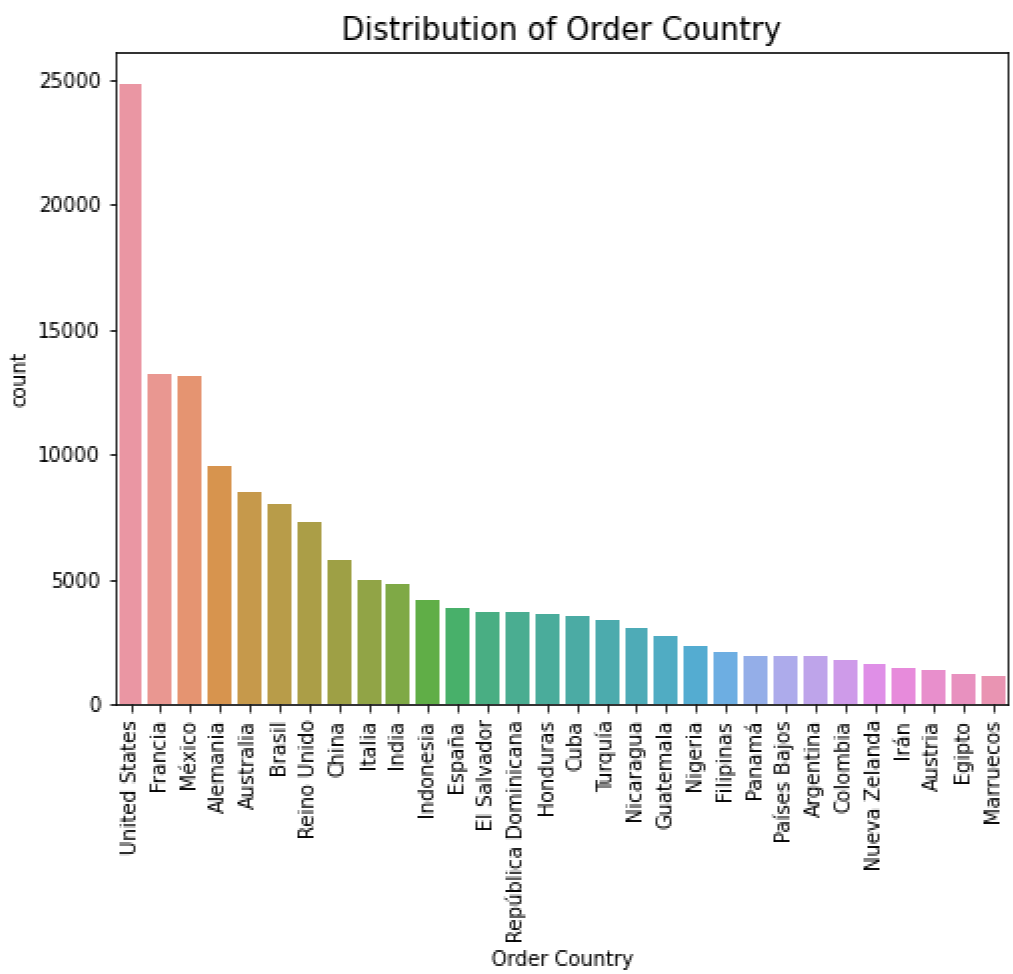

Distribution of Customer State
count
70000
60000
50000
40000
30000
20000
10000
0
PR
CA
NY
TX
IL
FL
OH
PA
MI
NJ
AZ
GA
MD
NC
CO
VA
OR
MA
TN
NV
MO
HI
CT
UT
NM
LA
WA
WI
MN
SC
Customer State


Distribution of Department Name
count
Department Name
Fan Shop
Apparel
Golf
Footwear
Outdoors
Fitness
Discs Shop
Technology
Pet Shop
Book Shop
Health and Beauty

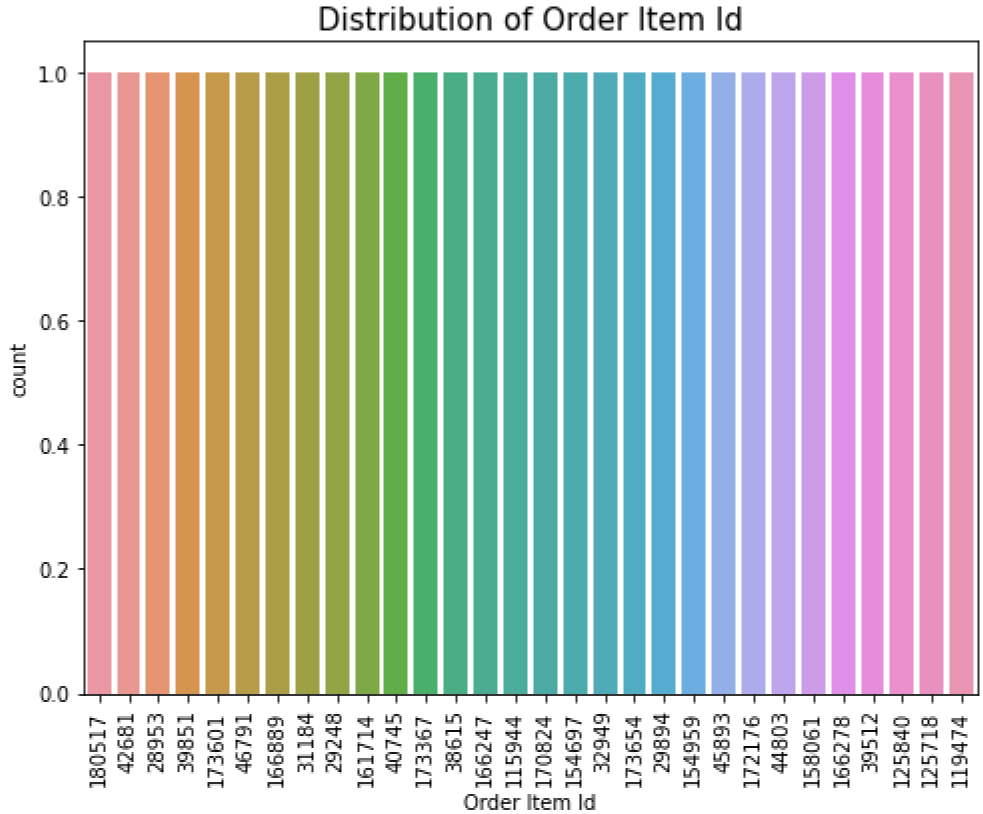

Distribution of Market
count
Market
LATAM
Europe
Pacific Asia
USCA
Africa



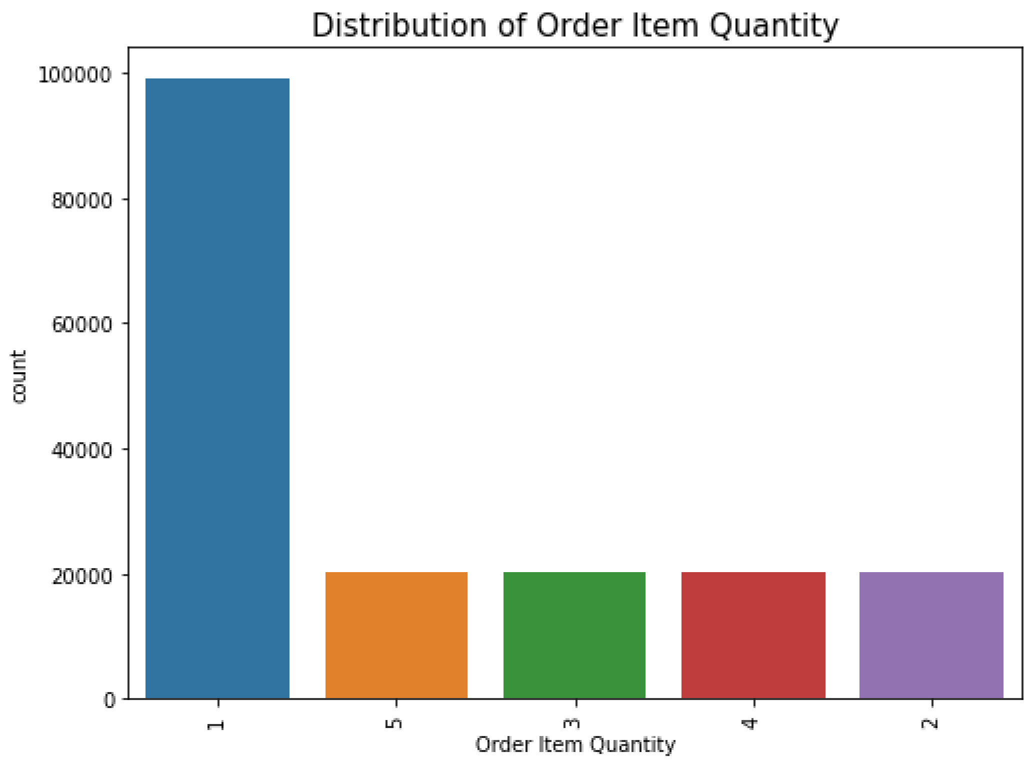
Distribution of Order City
count
0
500
1000
1500
2000
Santo Domingo
New York City
Los Angeles
Tegucigalpa
Managua
Mexico City
Manila
Philadelphia
San Francisco
London
San Salvador
Seattle
Viena
Yakarta
Berlín
Buenos Aires
Lagos
San Pedro Sula
Bangkok
Houston
Paris
Sydney
Panama City
Chicago
São Paulo
Mixco
Madrid
Estambul
Melbourne
León
Order City



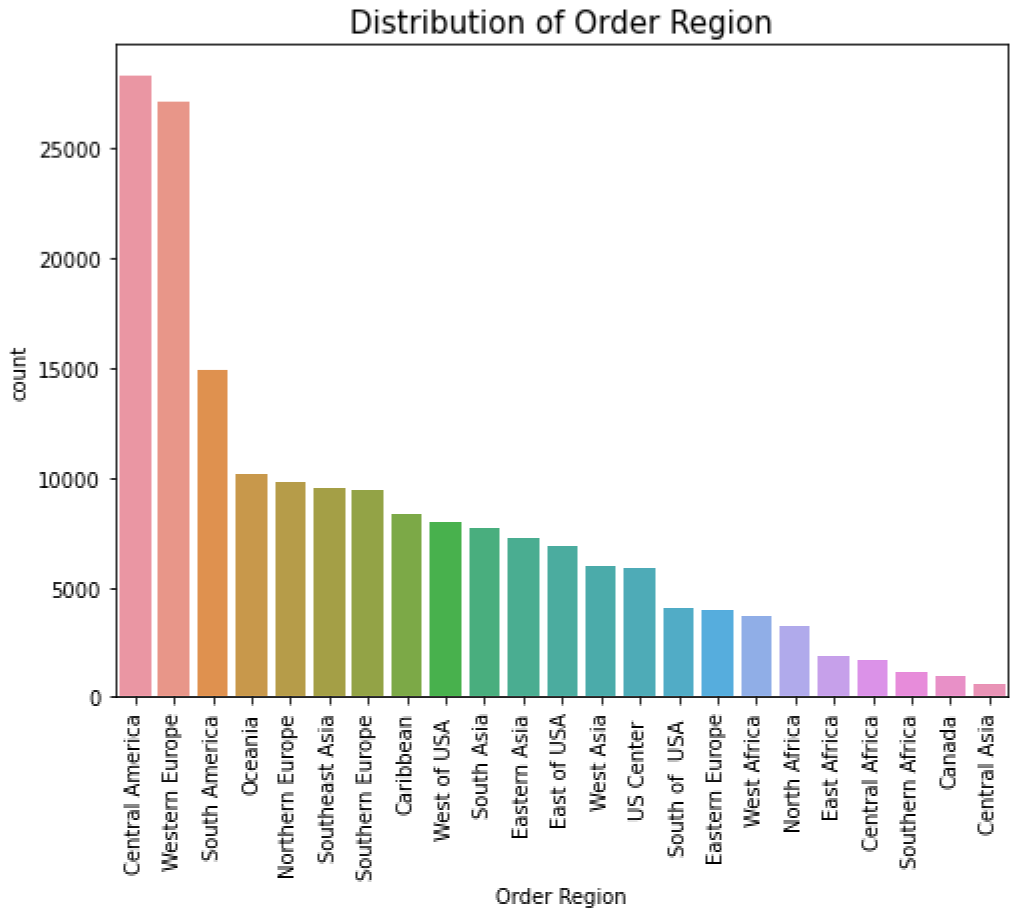
Distribution of Order Country
count
0
5000
10000
15000
20000
25000
United States
Francia
México
Alemania
Australia
Brasil
Reino Unido
China
Italia
India
Indonesia
España
El Salvador
República Dominicana
Honduras
Cuba
Turquía
Nicaragua
Guatemala
Nigeria
Filipinas
Panamá
Países Bajos
Argentina
Colombia
Nueva Zelanda
Irán
Austria
Egipto
Marruecos
Order Country

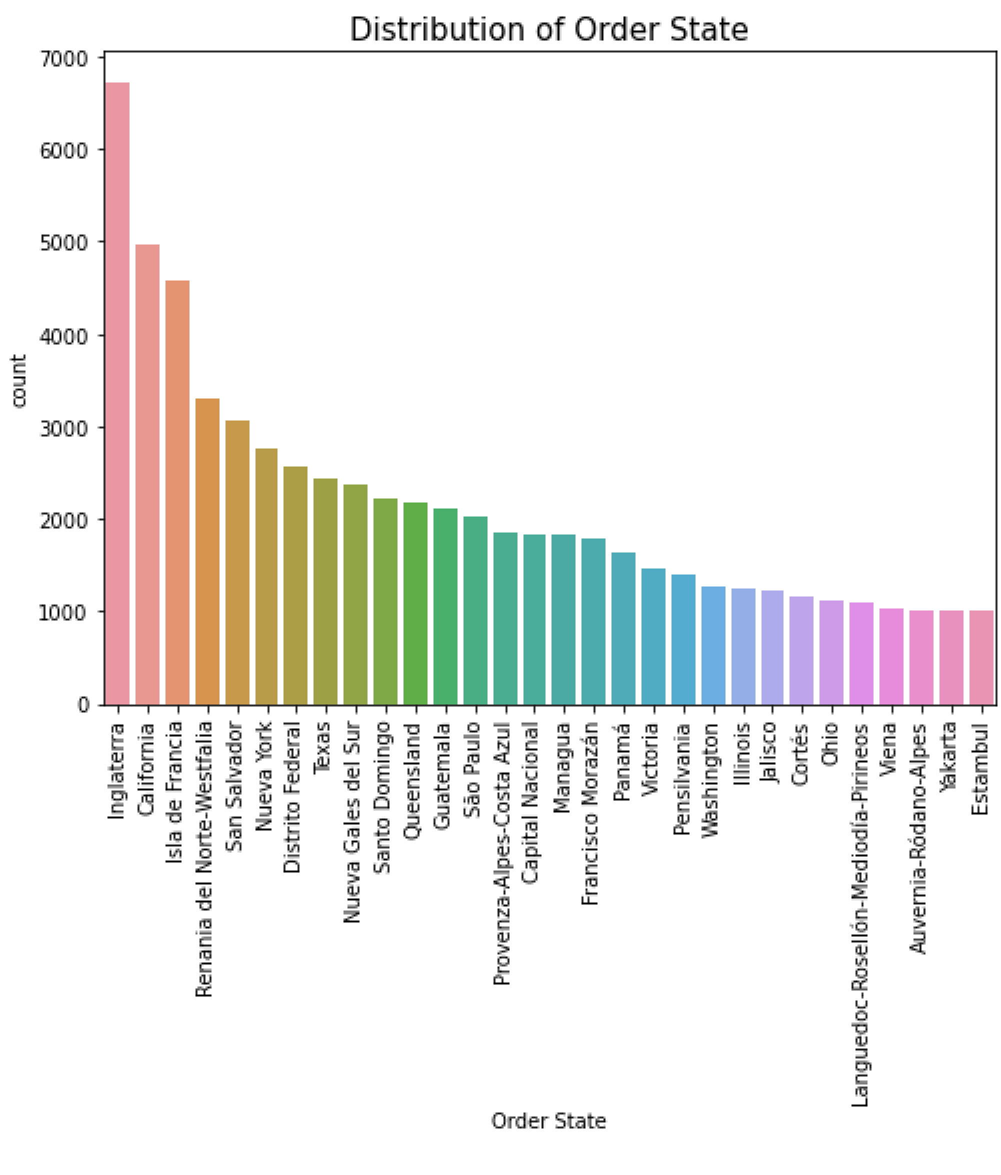


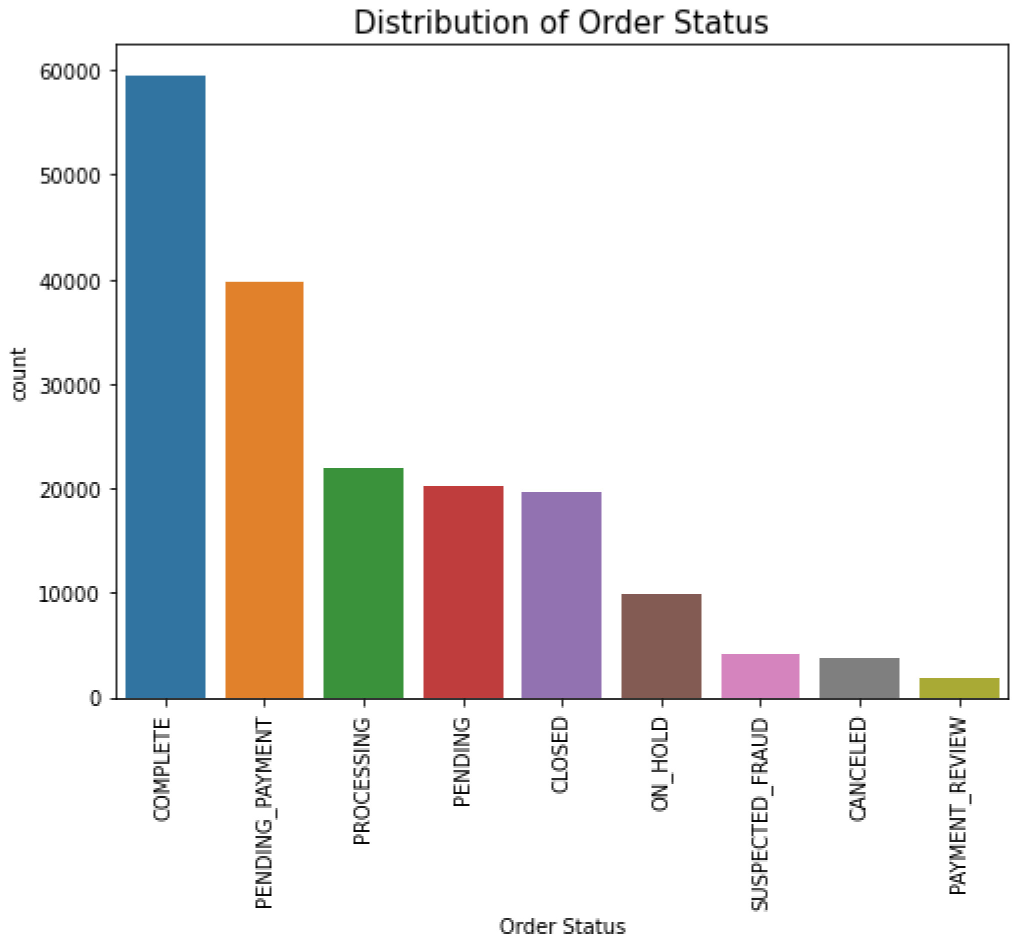
Distribution of Order Item Id
count
1.0
0.8
0.6
0.4
0.2
0.0
180517
42681
28953
39851
173601
46791
166889
31184
29248
161714
40745
173367
38615
166247
115944
170824
154697
32949
173654
29894
154959
45893
172176
44803
158061
166278
39512
125840
125718
119474
Order Item Id



Distribution of Order Item Quantity
count
100000
80000
60000
40000
20000
0
1
5
3
4
2
Order Item Quantity


Distribution of Order Region
count
0
5000
10000
15000
20000
25000
Central America
Western Europe
South America
Oceania
Northern Europe
Southeast Asia
Southern Europe
Caribbean
West of USA
South Asia
Eastern Asia
East of USA
West Asia
US Center
South of USA
Eastern Europe
West Africa
North Africa
East Africa
Central Africa
Southern Africa
Canada
Central Asia
Order Region


Distribution of Order State
count
0
1000
2000
3000
4000
5000
6000
7000
Inglaterra
California
Isla de Francia
Renania del Norte-Westfalia
San Salvador
Nueva York
Distrito Federal
Texas
Nueva Gales del Sur
Santo Domingo
Queensland
Guatemala
São Paulo
Provenza-Alpes-Costa Azul
Capital Nacional
Managua
Francisco Morazán
Panamá
Victoria
Pensilvania
Washington
Illinois
Jalisco
Cortés
Ohio
Languedoc-Rosellón-Mediodía-Pirineos
Viena
Auvernia-Ródano-Alpes
Yakarta
Estambul
Order State



Highlights for Univariate Analysis:

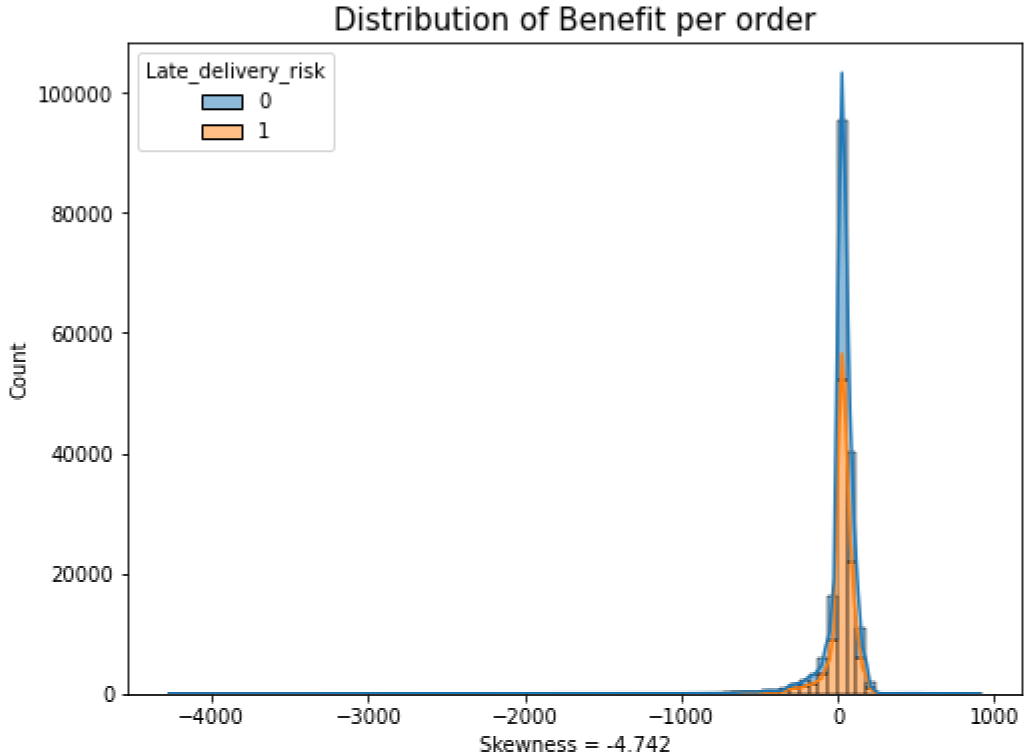
- Continuous, numerical, features within the data tend to have a skew and appear non-normal based on the Q-Q Plots.

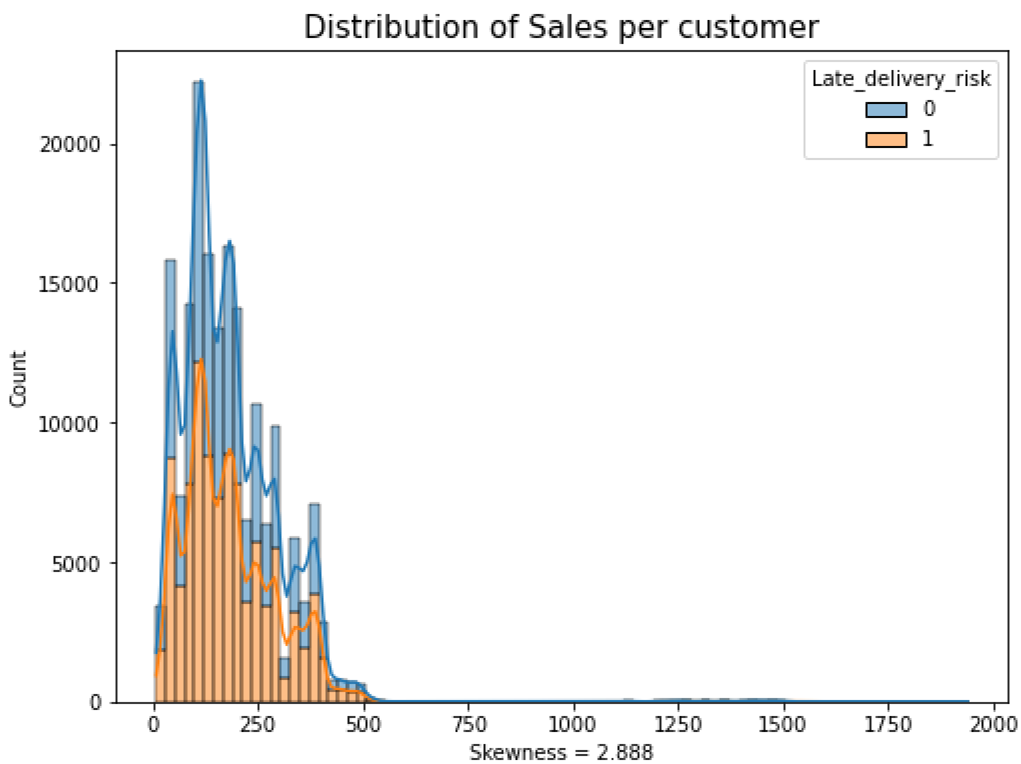
- Most customers spend less than $500, but there are some that spend between $1000-$1500.
- The company is not making profit on roughly half of its orders.
- Product price feature is similarly distributed as Order Item Product Price.
- Balance for late deliveries within the data set appears sufficient to continue with the analysis.
- Most transaction types are debit, transfers, and payments. Least is cash transactions.
- It most often takes 2 days to ship items, although it can also vary up to 6 days.
- Most orders have 4 days scheduled for shipments.
- Most orders are for cleats, Men's Footwear, Women's Apparel, Indoor/Outdoor Games, Fishing, Water Sports, Camping and Hiking, and Cardio Equipiment.
- Customers tend to be Consumers, Corporate, and Home Office (in that order).
- Most orders are from the Fan Shop, Apparel, Golf, Footwear, or Outdoors.
- Most orders only include 1 item.
- Most orders have been complete, however there are a lot of pending payment, processing, and pending orders.
- Most orders are shipped Standard Class.

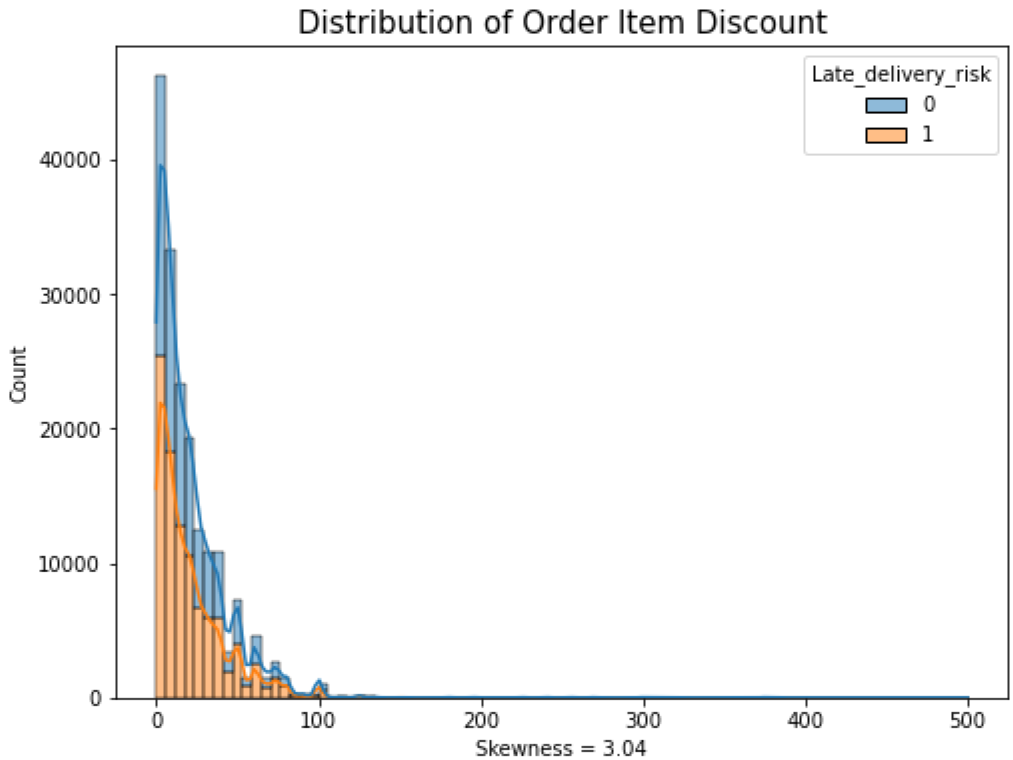
Multivariate Analysis

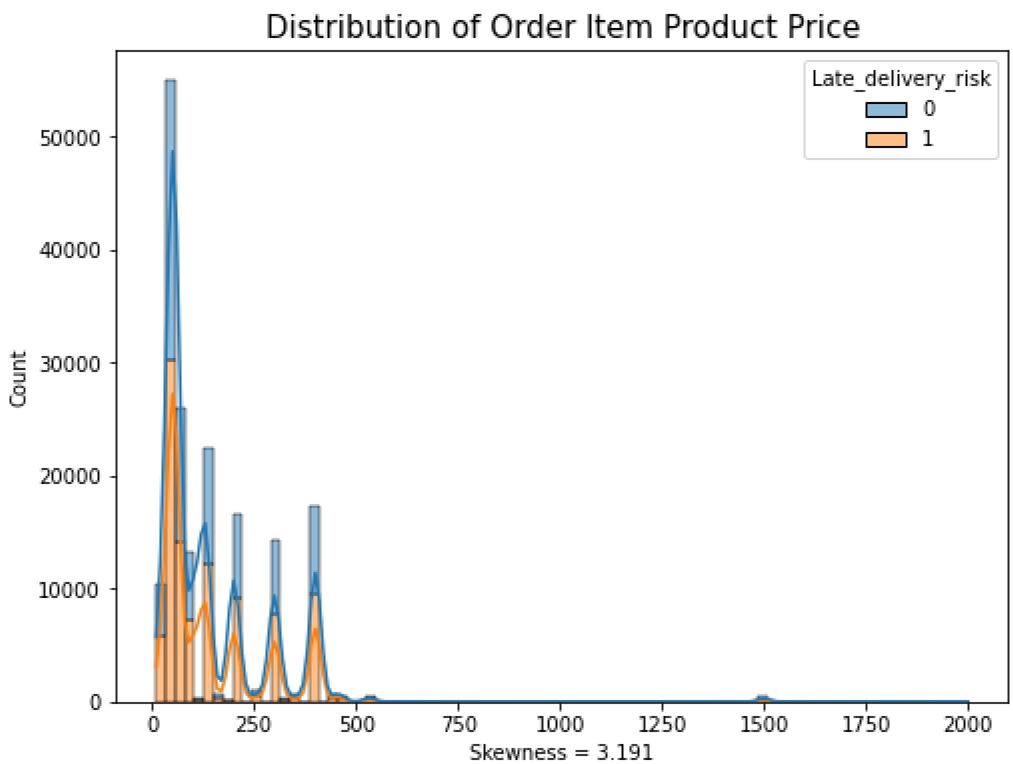
The Late_delivery_risk will be grouped within the previous charts to see if there are any obvious findings.

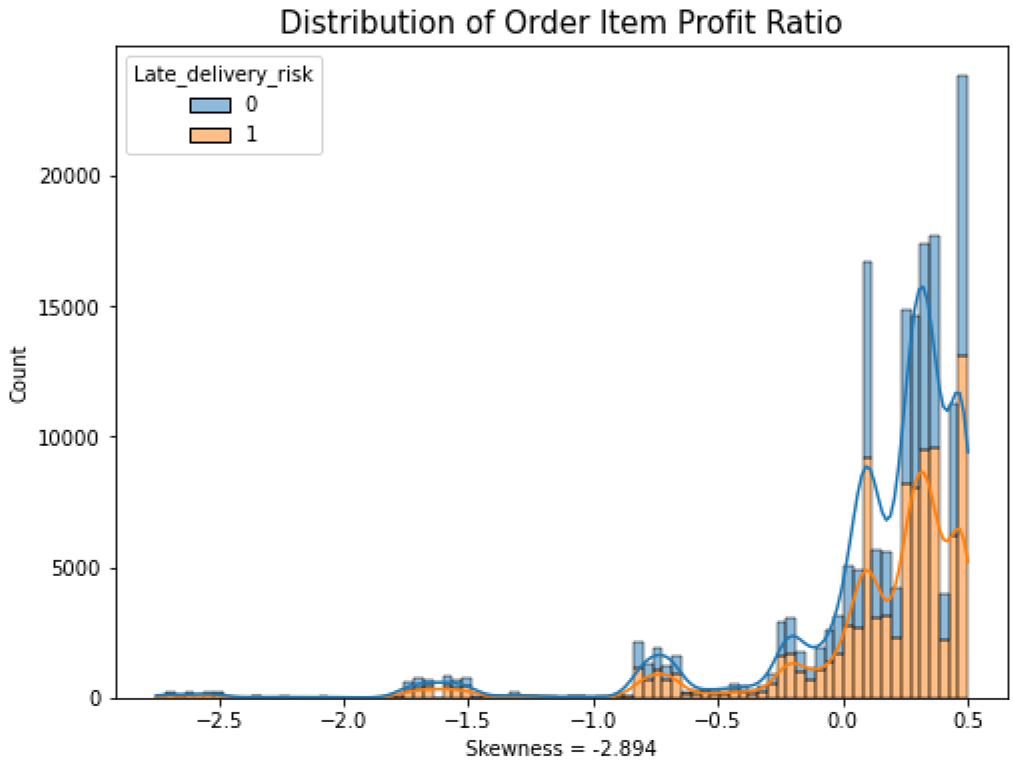
In [45]:
```
'''
Understand the distribution for the continuous numeric features within the dataset.
The code below will loop through each feature and illustrate how the feature is distribute
The skewness value will also be included below the chart.
'''
cont_columns = df[['Benefit per order', 'Sales per customer', 'Order Item Discount',
                      'Order Item Product Price', 'Order Item Profit Ratio','Sales', 'Orde
                      'Order Profit Per Order', 'Product Price']]

for col in cont_columns:
    plt.figure(figsize=(8,6))
    sns.histplot(x =df[col], hue = df['Late_delivery_risk'], kde = True, multiple = 'stack
    plt.title("Distribution of {}".format(col), fontsize=15)
    plt.xlabel(f"Skewness = {round(df[col].skew(),3)}", fontsize=10)
    plt.xticks(fontsize=10)
    plt.yticks(fontsize=10)
    plt.show()
```

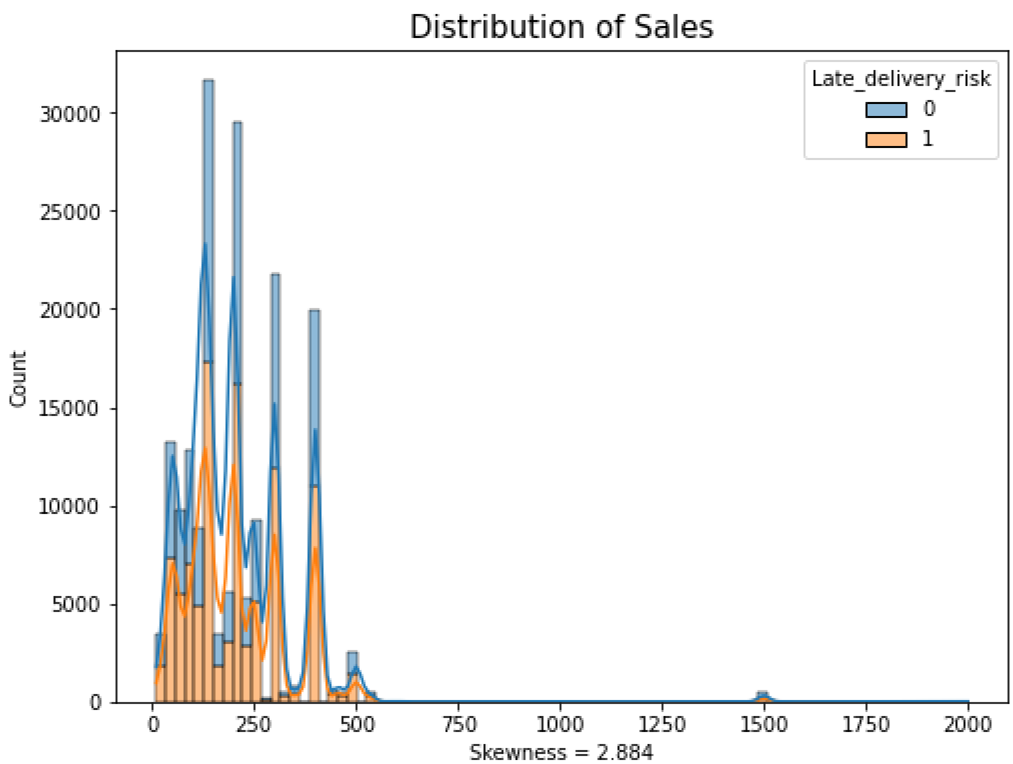

Distribution of Benefit per order
Late_delivery_risk
0
1
Count
100000
80000
60000
40000
20000
0
−4000
−3000
−2000
−1000
0
1000
Skewness = -4.742

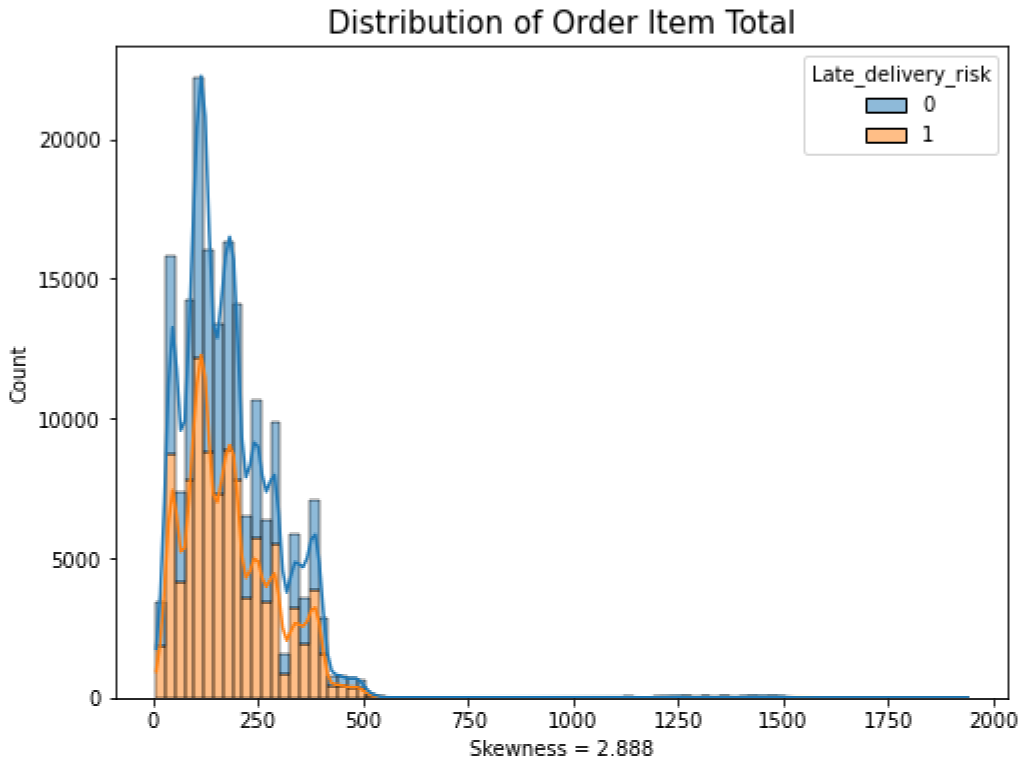

Distribution of Sales per customer
Late_delivery_risk
0
1
Count
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 2.888

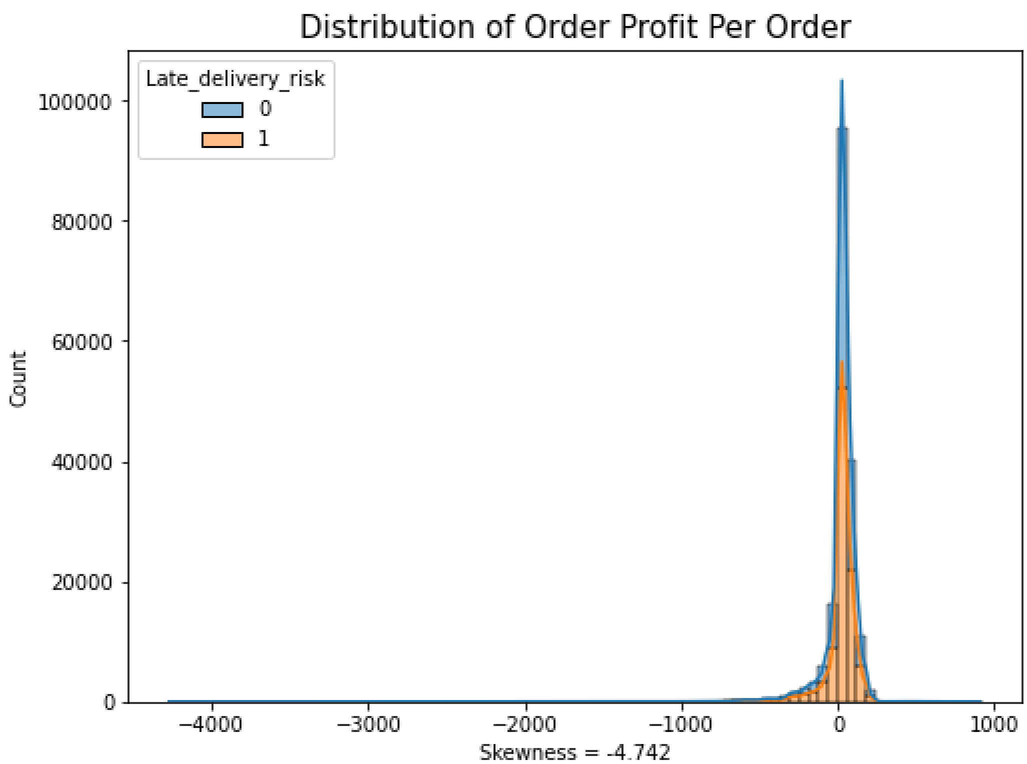

Distribution of Order Item Discount
Late_delivery_risk
0
1
40000
30000
20000
10000
0
Count
0
100
200
300
400
500
Skewness = 3.04

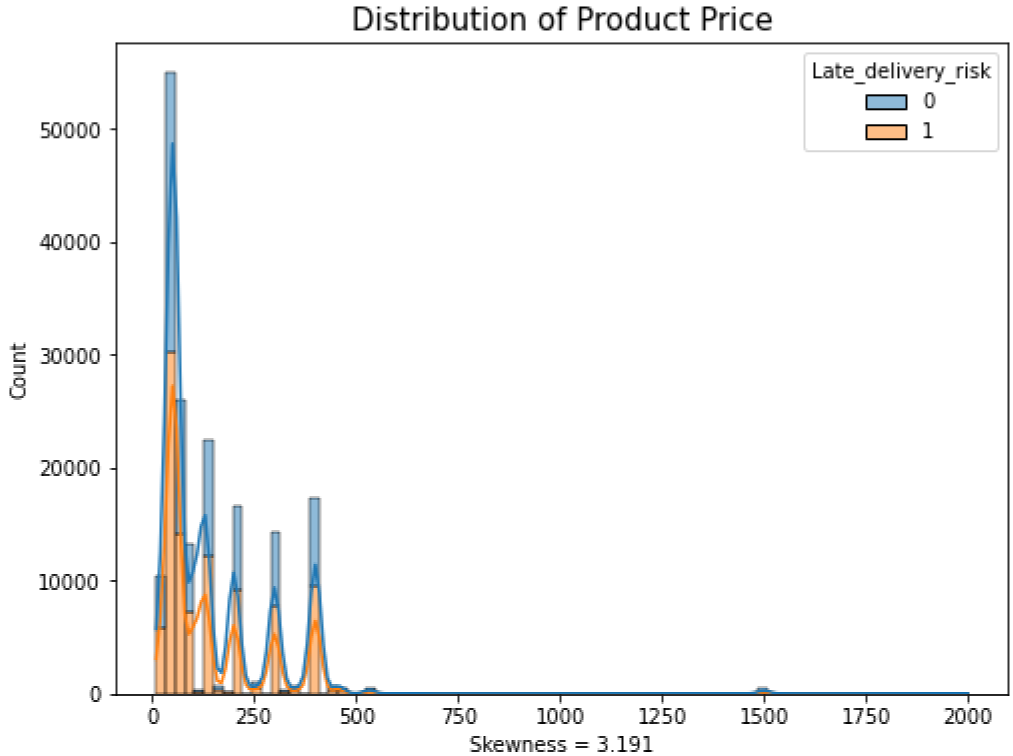

Distribution of Order Item Product Price
Late_delivery_risk
0
1
50000
40000
30000
20000
10000
0
Count
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 3.191


Distribution of Order Item Profit Ratio
Late_delivery_risk
0
1
Count
20000
15000
10000
5000
0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
Skewness = -2.894


Distribution of Sales
Late_delivery_risk
0
1
Count
30000
25000
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 2.884

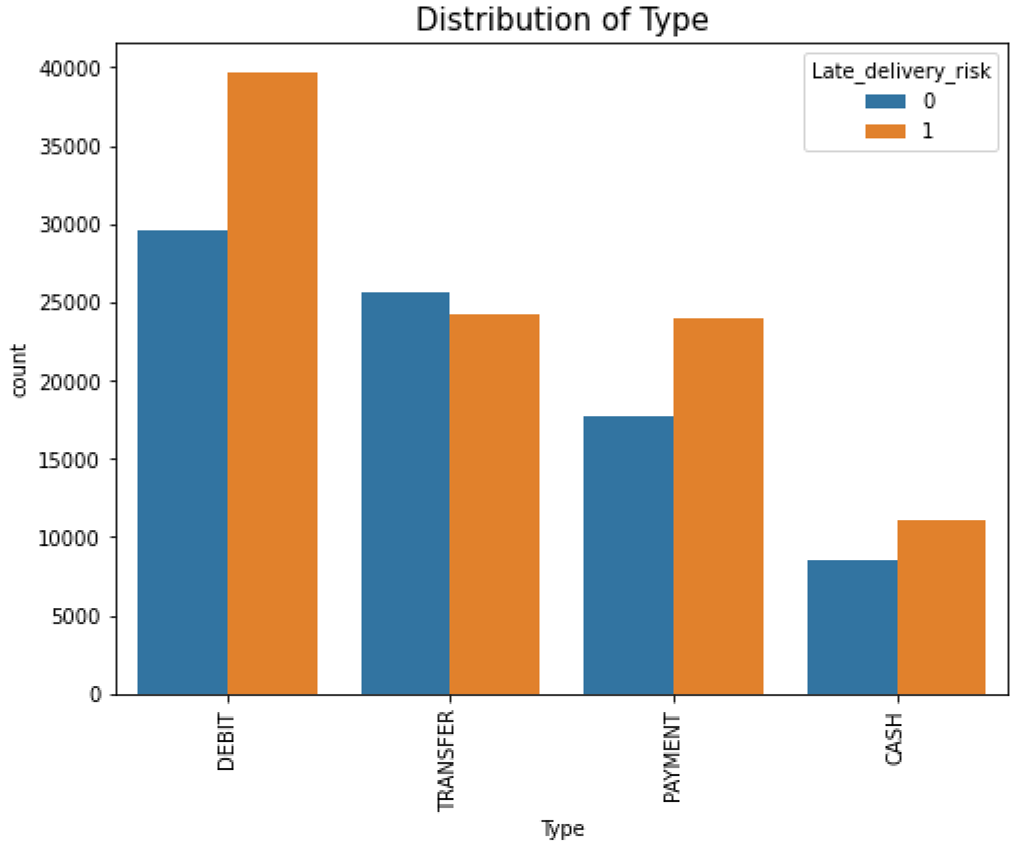

Distribution of Order Item Total
Late_delivery_risk
0
1
Count
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
Skewness = 2.888

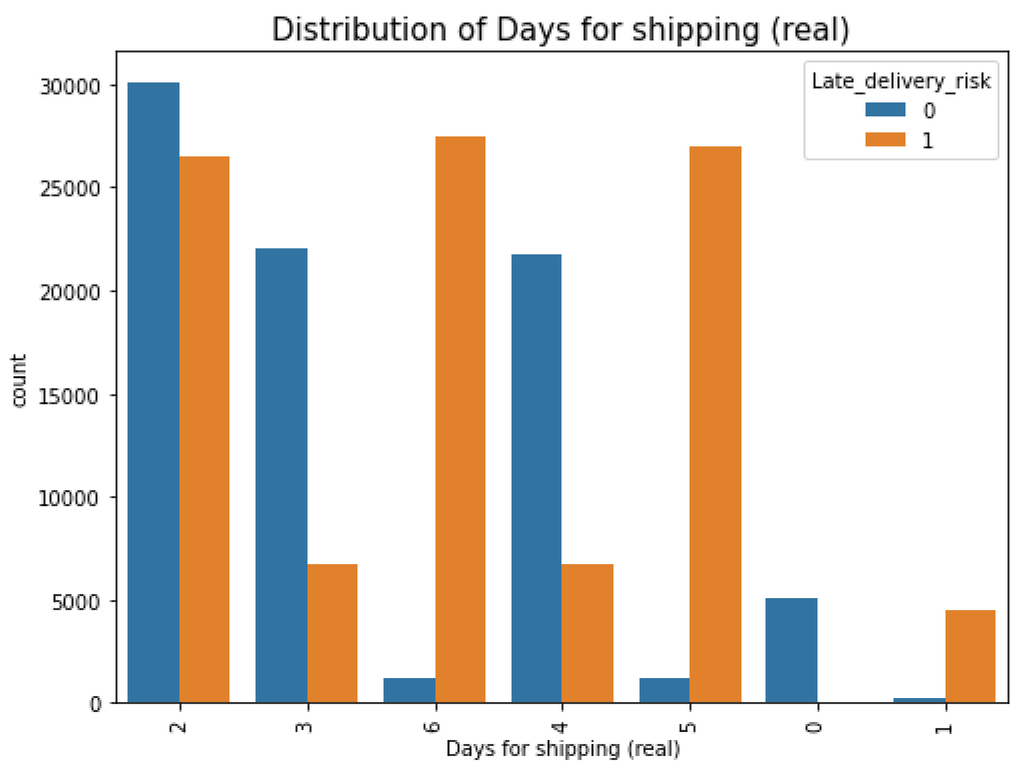

Distribution of Order Profit Per Order
Late_delivery_risk
0
1
Count
100000
80000
60000
40000
20000
0
−4000
−3000
−2000
−1000
0
1000
Skewness = -4.742

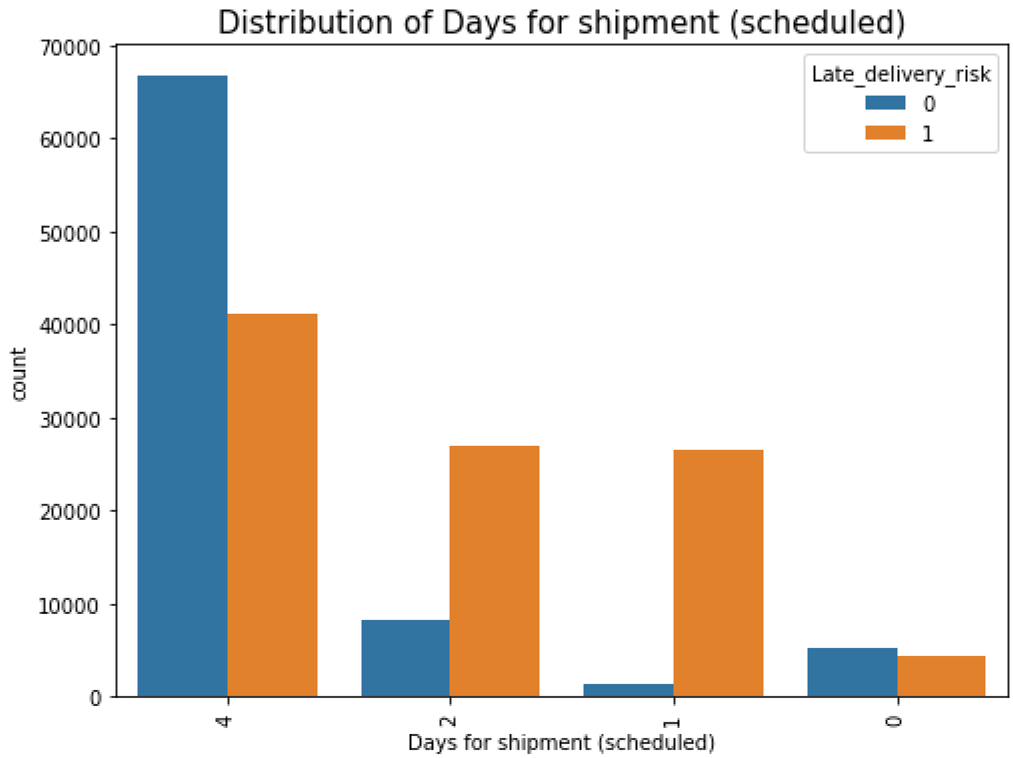


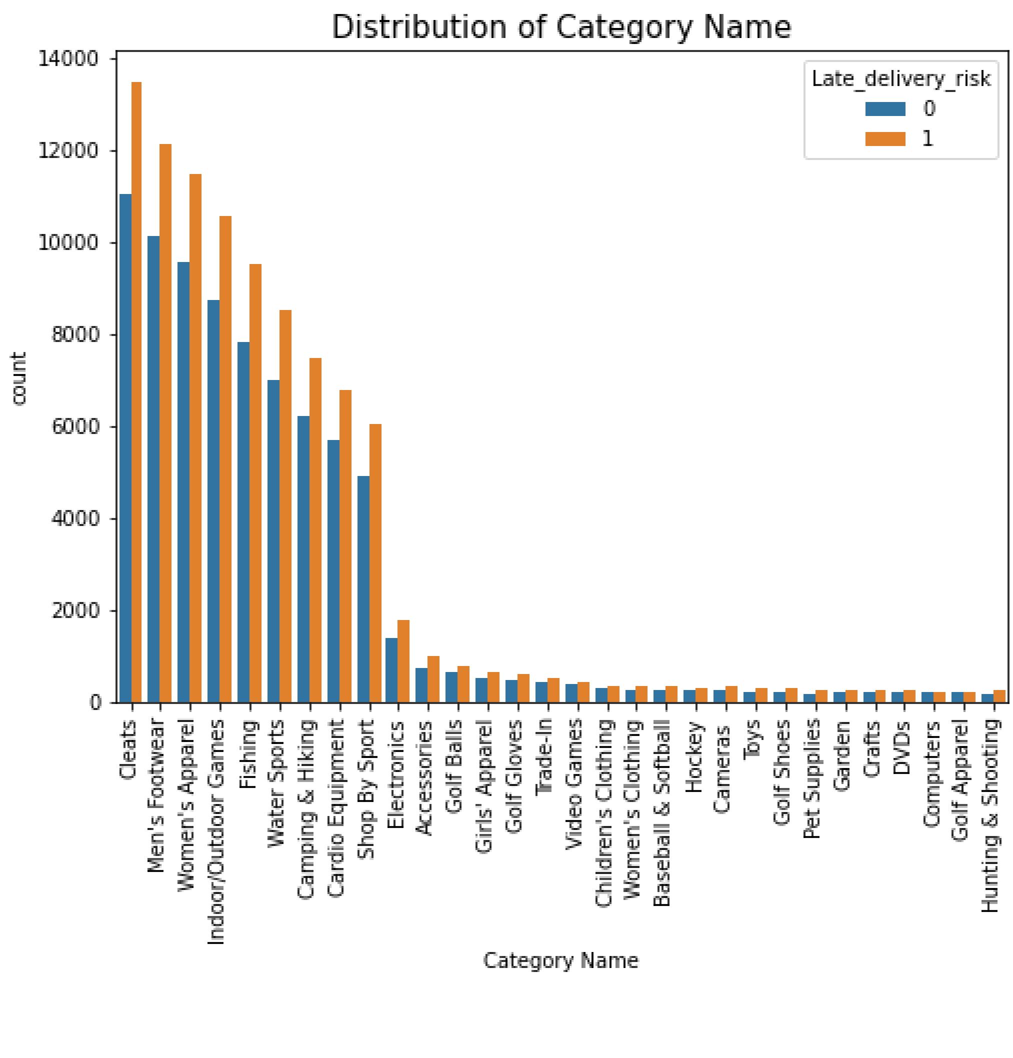
In [46]:

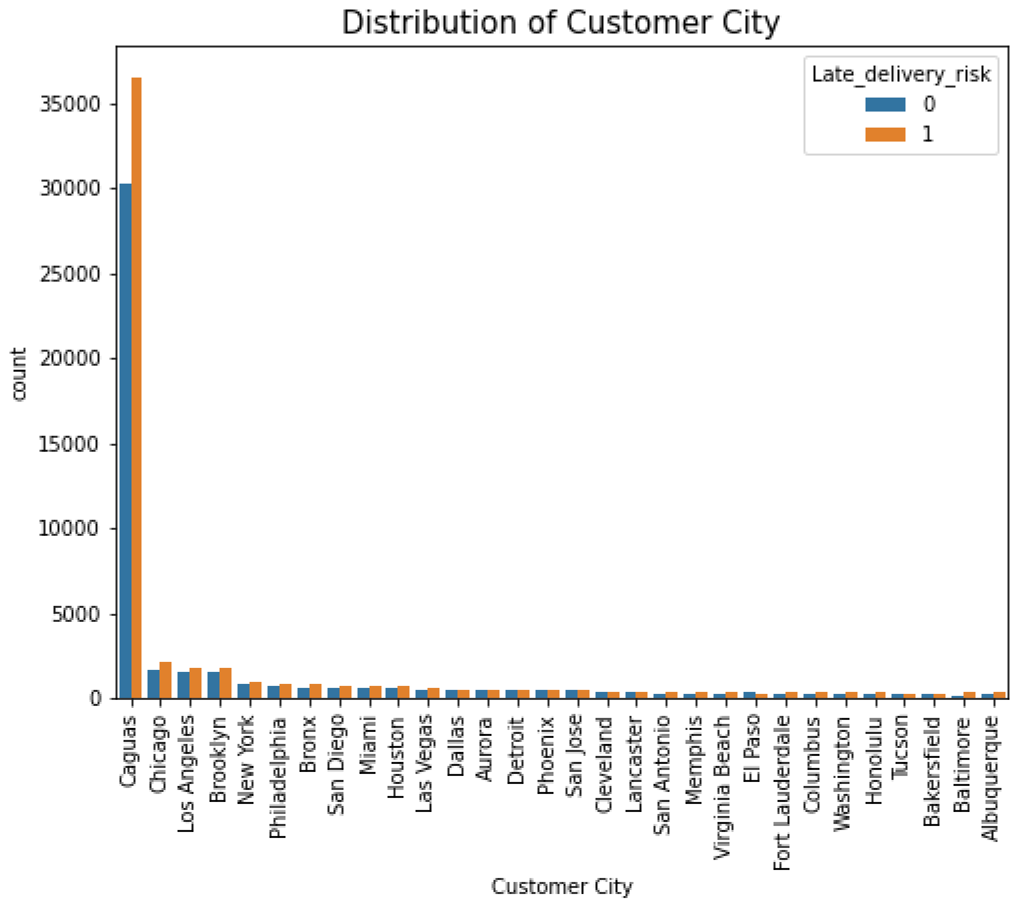
```
'''
Understand the balance of the categorical and discrete features with a countplot.
The code below will loop through each feature and illustrate the count of unique items wit
Useful for understanding balance within the data.
'''
cat_disc_columns = df[['Type', 'Days for shipping (real)', 'Days for shipment (scheduled)'
                        'Category Name','Customer City', 'Customer Country',
                        'Customer Id', 'Customer Segment', 'Customer State', 'Department Nar
                        'Market', 'Order City', 'Order Country', 'Order Item Id', 'Order Ite
                        'Order Region', 'Order State', 'Order Status', 'Shipping Mode']]

for col in cat_disc_columns:
    plt.figure(figsize=(8,6))
    sns.countplot(x=df[col], order = df[col].value_counts().iloc[:30].index, hue = df['Lat
    plt.title("Distribution of {}".format(col), fontsize=15)
    plt.xticks(fontsize=10, rotation = 90)
    plt.yticks(fontsize=10)
    plt.show()
```


Distribution of Type
Late_delivery_risk
0
1
count
40000
35000
30000
25000
20000
15000
10000
5000
0
DEBIT
TRANSFER
PAYMENT
CASH
Type

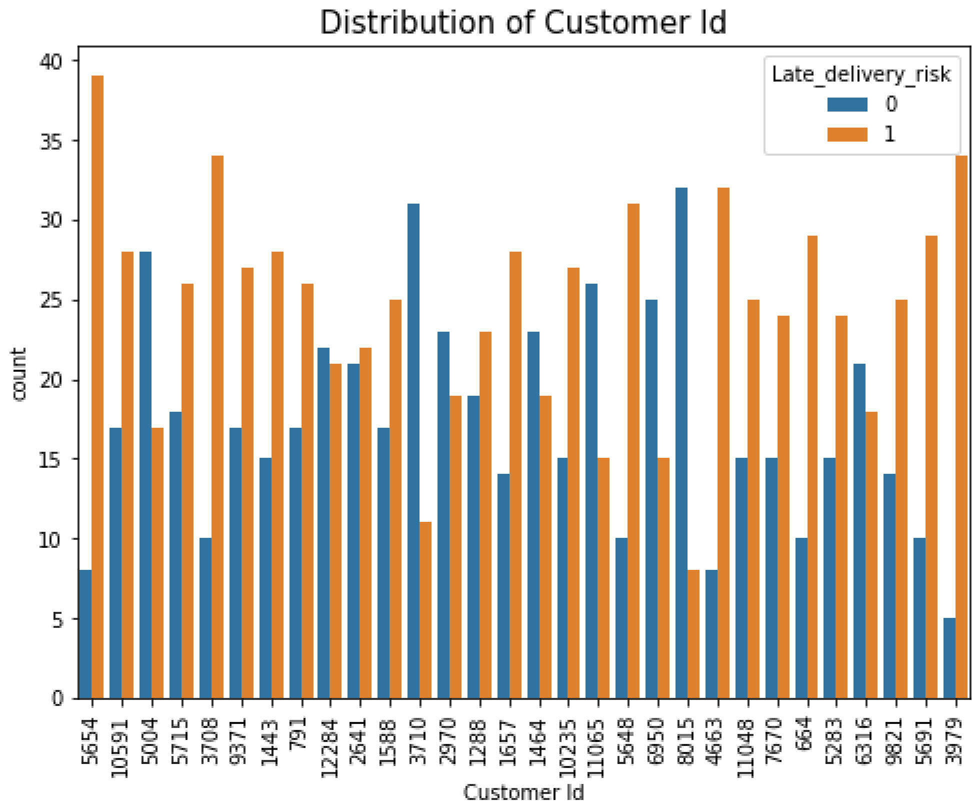

Distribution of Days for shipping (real)
Late_delivery_risk
0
1
count
30000
25000
20000
15000
10000
5000
0
2
3
6
4
5
0
1
Days for shipping (real)


Distribution of Days for shipment (scheduled)
Late_delivery_risk
0
1
count
70000
60000
50000
40000
30000
20000
10000
0
4
2
1
0
Days for shipment (scheduled)

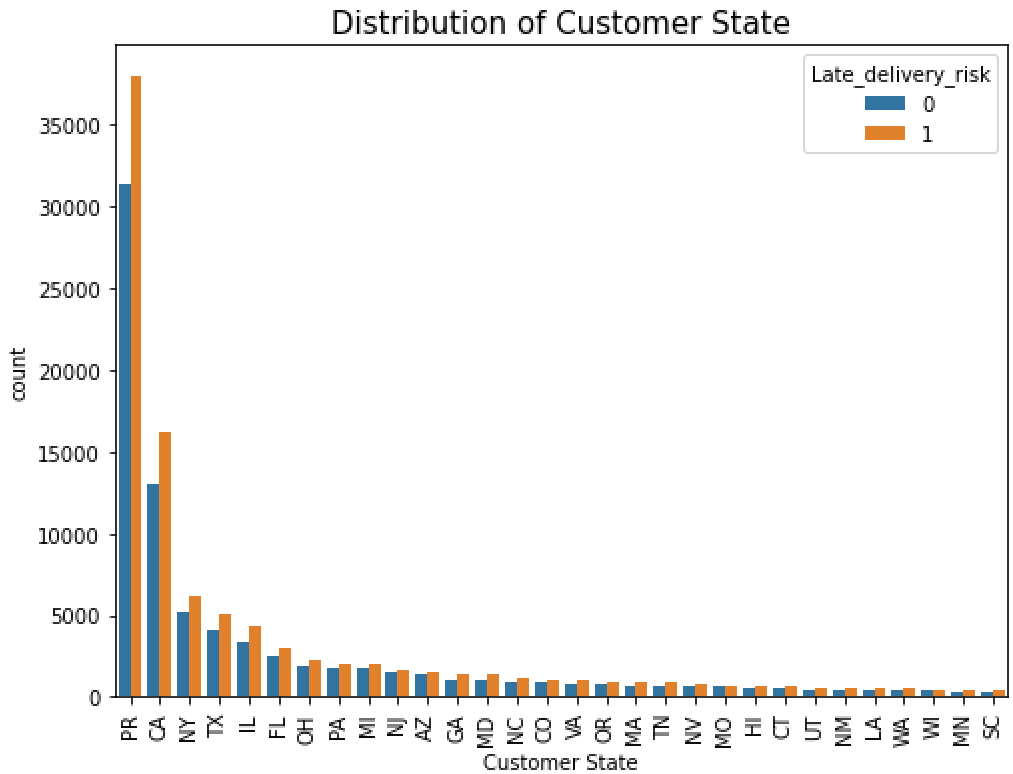

Distribution of Category Name
Late_delivery_risk
0
1
count
14000
12000
10000
8000
6000
4000
2000
0
Cleats
Men's Footwear
Women's Apparel
Indoor/Outdoor Games
Fishing
Water Sports
Camping & Hiking
Cardio Equipment
Shop By Sport
Electronics
Accessories
Golf Balls
Girls' Apparel
Golf Gloves
Trade-In
Video Games
Children's Clothing
Women's Clothing
Baseball & Softball
Hockey
Cameras
Toys
Golf Shoes
Pet Supplies
Garden
Crafts
DVDs
Computers
Golf Apparel
Hunting & Shooting
Category Name

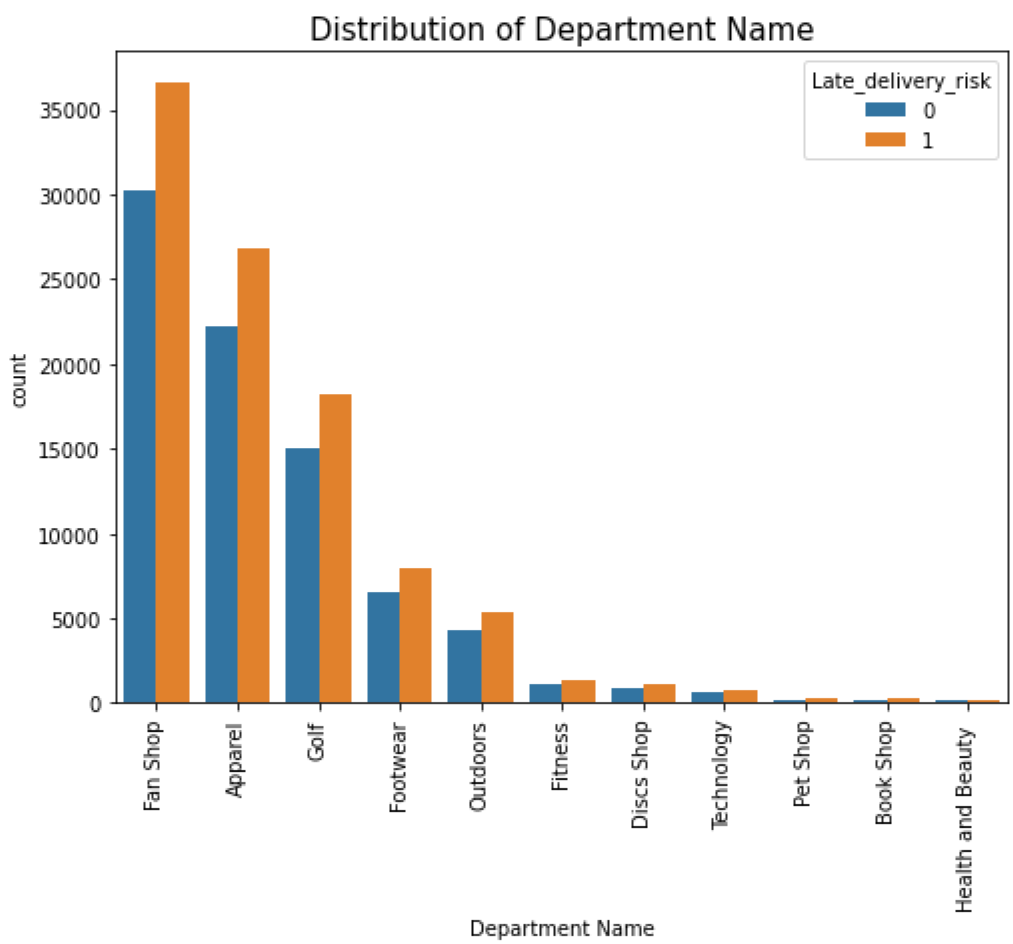

Distribution of Customer City
Late_delivery_risk
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
Caguas
Chicago
Los Angeles
Brooklyn
New York
Philadelphia
Bronx
San Diego
Miami
Houston
Las Vegas
Dallas
Aurora
Detroit
Phoenix
San Jose
Cleveland
Lancaster
San Antonio
Memphis
Virginia Beach
El Paso
Fort Lauderdale
Columbus
Washington
Honolulu
Tucson
Bakersfield
Baltimore
Albuquerque
Customer City

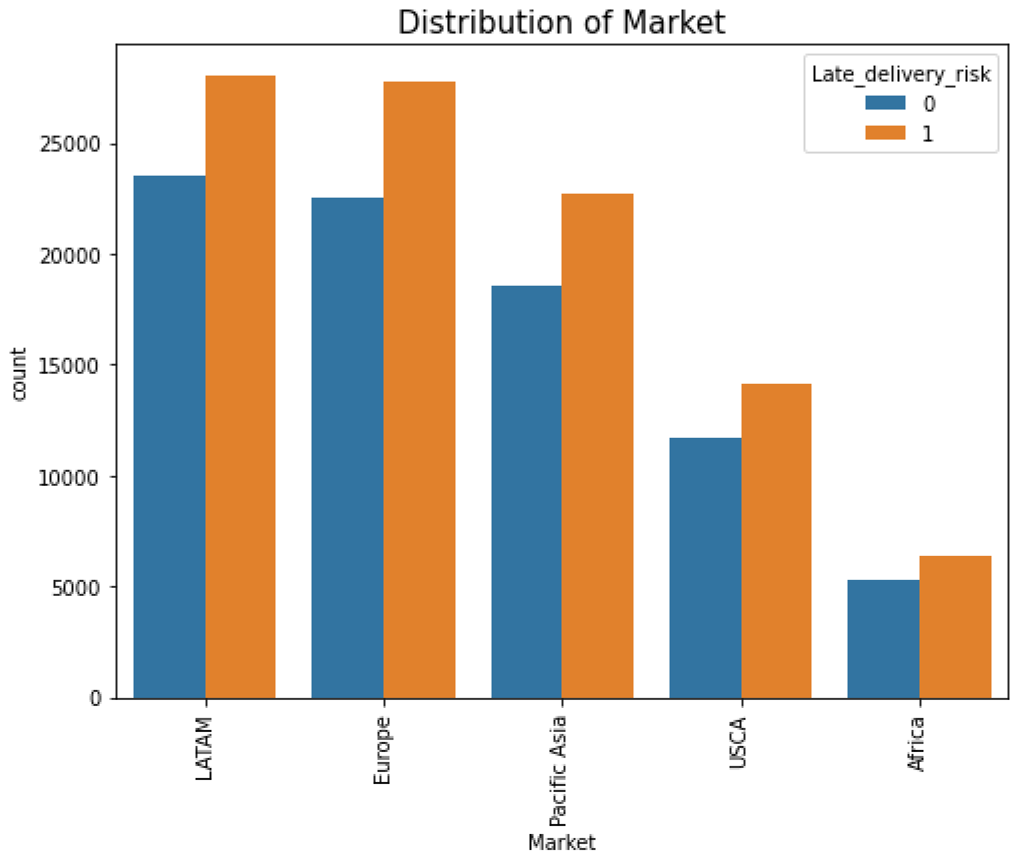

Distribution of Customer Country
Late_delivery_risk
0
1
count
60000
50000
40000
30000
20000
10000
0
United States
Puerto Rico
Customer Country

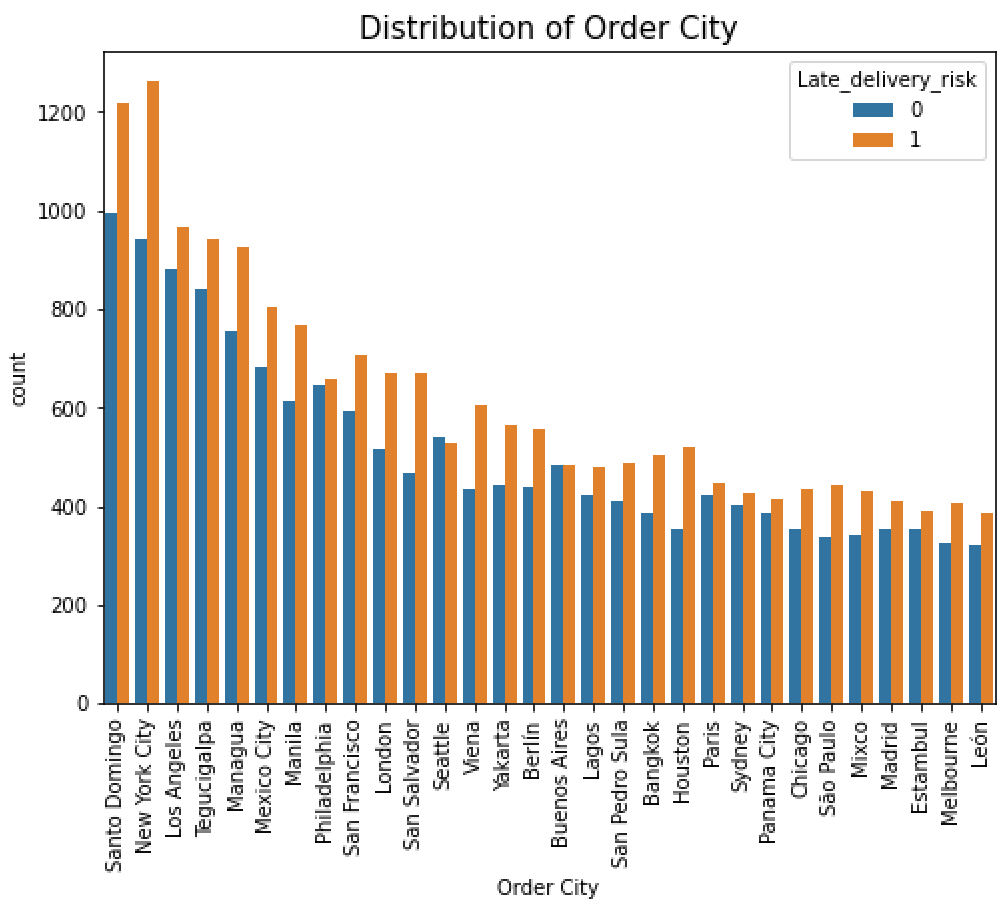

Distribution of Customer Id
Late_delivery_risk
0
1
count
Customer Id
5654
10591
5004
5715
3708
9371
1443
791
12284
2641
1588
3710
2970
1288
1657
1464
10235
11065
5648
6950
8015
4663
11048
7670
664
5283
6316
9821
5691
3979

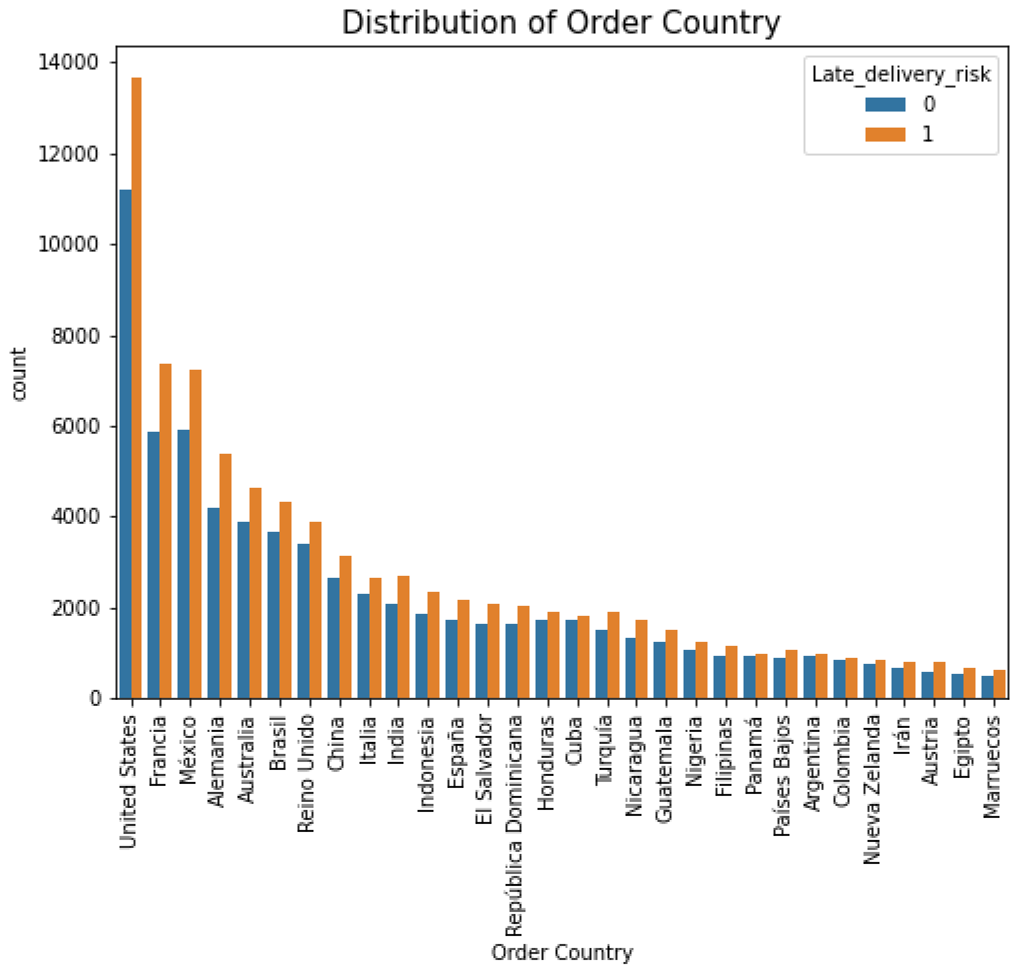

Distribution of Customer Segment
Late_delivery_risk
0
1
count
Customer Segment
Consumer
Corporate
Home Office

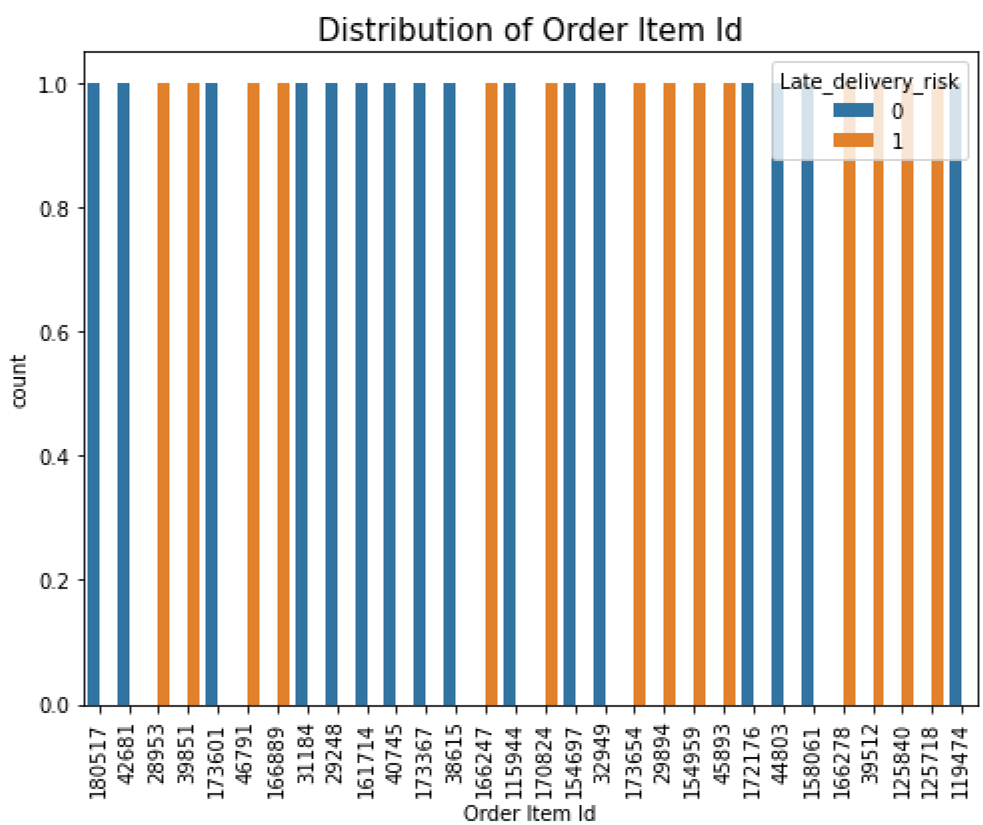

Distribution of Customer State
Late_delivery_risk
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
PR
CA
NY
TX
IL
FL
OH
PA
MI
NJ
AZ
GA
MD
NC
CO
VA
OR
MA
TN
NV
MO
HI
CT
UT
NM
LA
WA
WI
MN
SC
Customer State

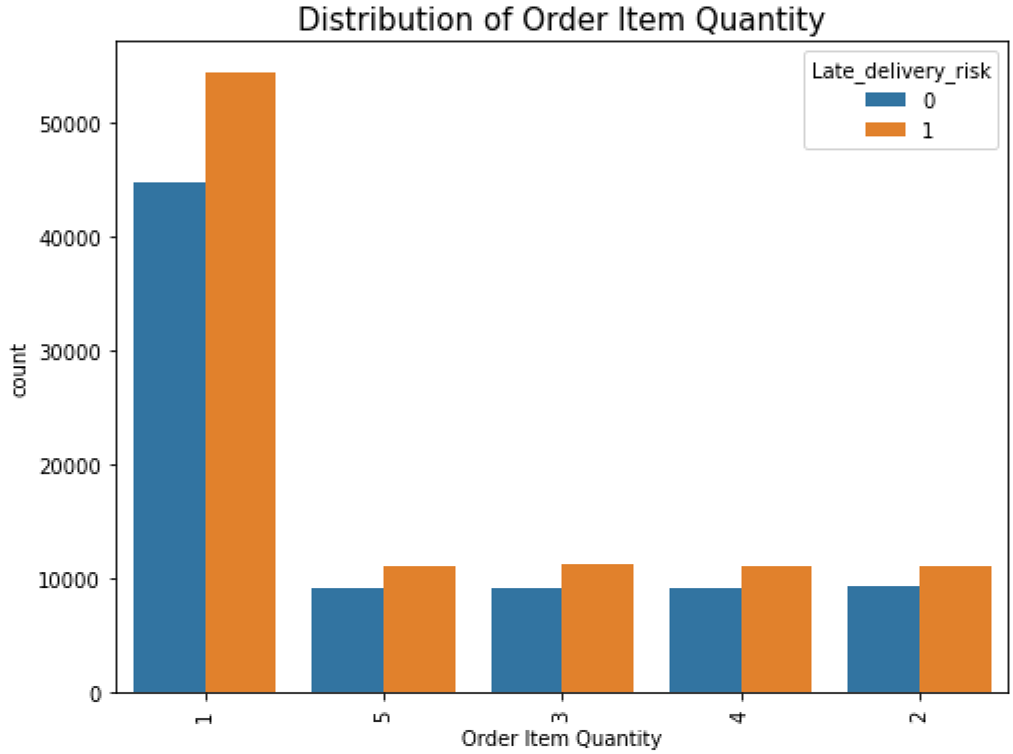

Distribution of Department Name
Late_delivery_risk
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
Fan Shop
Apparel
Golf
Footwear
Outdoors
Fitness
Discs Shop
Technology
Pet Shop
Book Shop
Health and Beauty
Department Name

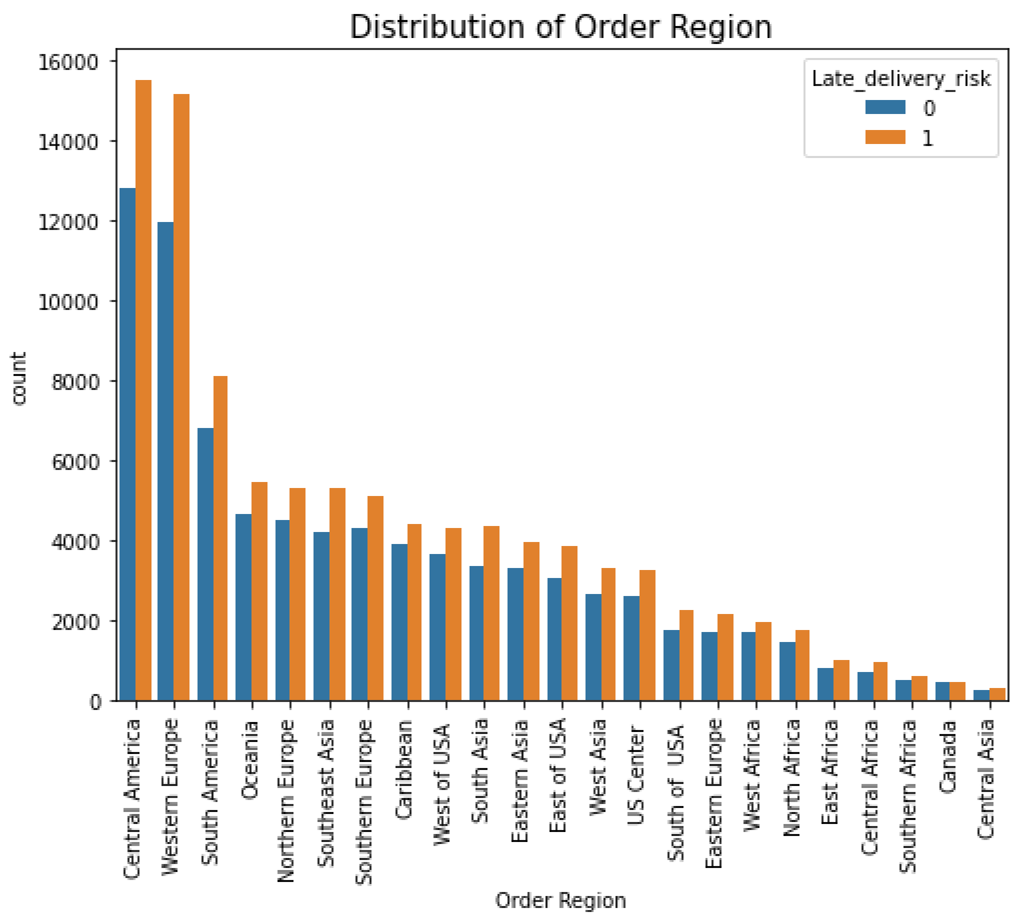

Distribution of Market
Late_delivery_risk
0
1
count
0
5000
10000
15000
20000
25000
LATAM
Europe
Pacific Asia
USCA
Africa
Market

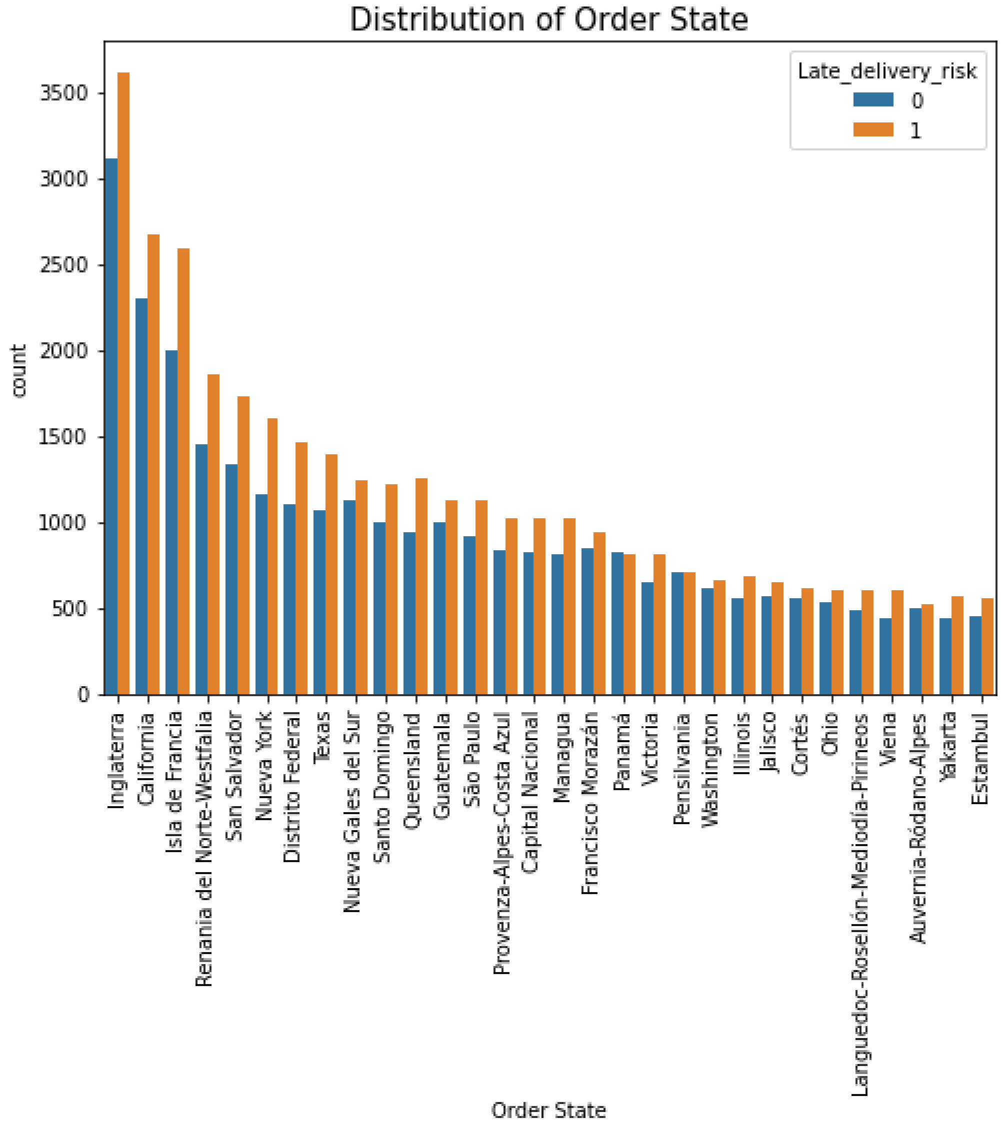

Distribution of Order City
Late_delivery_risk
0
1
count
0
200
400
600
800
1000
1200
Santo Domingo
New York City
Los Angeles
Tegucigalpa
Managua
Mexico City
Manila
Philadelphia
San Francisco
London
San Salvador
Seattle
Viena
Yakarta
Berlín
Buenos Aires
Lagos
San Pedro Sula
Bangkok
Houston
Paris
Sydney
Panama City
Chicago
São Paulo
Mixco
Madrid
Estambul
Melbourne
León
Order City

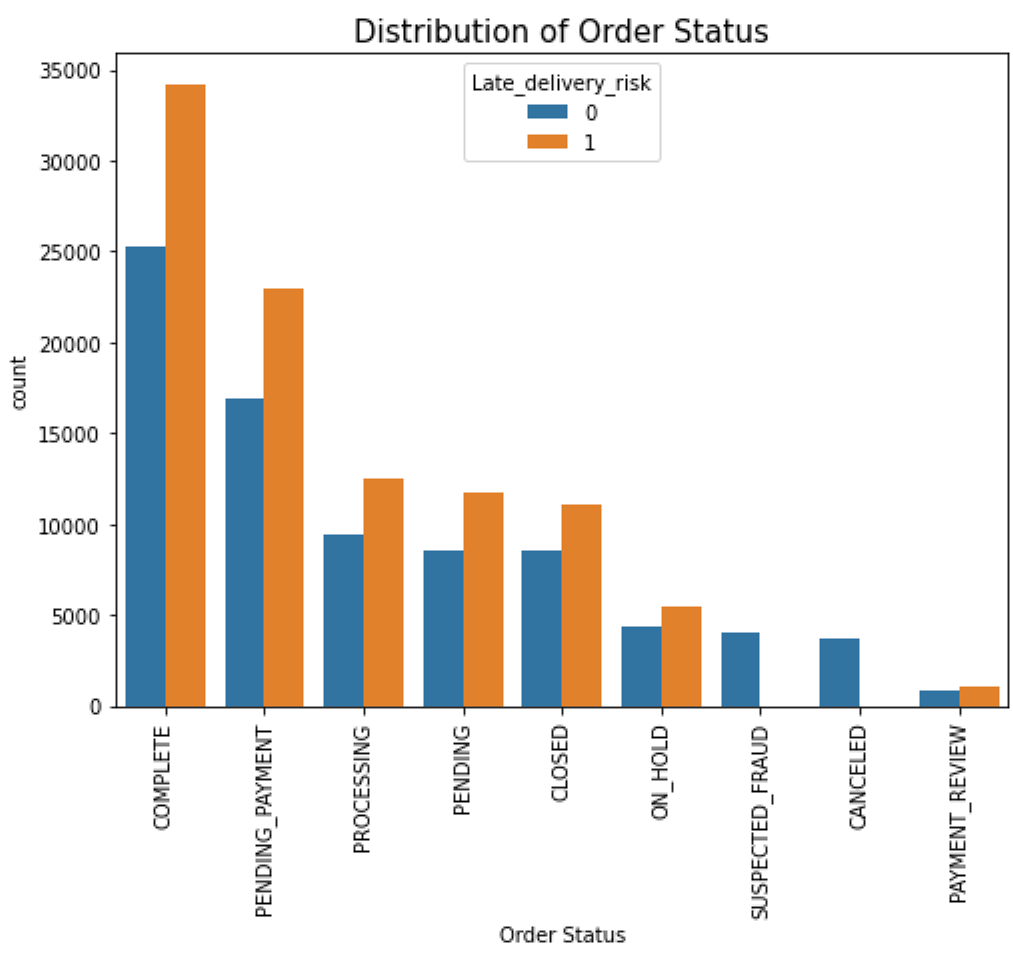

Distribution of Order Country
Late_delivery_risk
0
1
count
14000
12000
10000
8000
6000
4000
2000
0
United States
Francia
México
Alemania
Australia
Brasil
Reino Unido
China
Italia
India
Indonesia
España
El Salvador
República Dominicana
Honduras
Cuba
Turquía
Nicaragua
Guatemala
Nigeria
Filipinas
Panamá
Países Bajos
Argentina
Colombia
Nueva Zelanda
Irán
Austria
Egipto
Marruecos
Order Country


Distribution of Order Item Id
Late_delivery_risk
0
1
count
1.0
0.8
0.6
0.4
0.2
0.0
180517
42681
28953
39851
173601
46791
166889
31184
29248
161714
40745
173367
38615
166247
115944
170824
154697
32949
173654
29894
154959
45893
172176
44803
158061
166278
39512
125840
125718
119474
Order Item Id


Distribution of Order Item Quantity
Late_delivery_risk
0
1
count
0
10000
20000
30000
40000
50000
1
5
3
4
2
Order Item Quantity


Distribution of Order Region
Late_delivery_risk
0
1
count
0
2000
4000
6000
8000
10000
12000
14000
16000
Central America
Western Europe
South America
Oceania
Northern Europe
Southeast Asia
Southern Europe
Caribbean
West of USA
South Asia
Eastern Asia
East of USA
West Asia
US Center
South of USA
Eastern Europe
West Africa
North Africa
East Africa
Central Africa
Southern Africa
Canada
Central Asia
Order Region


Distribution of Order State
Late_delivery_risk
0
1
count
3500
3000
2500
2000
1500
1000
500
0
Inglaterra
California
Isla de Francia
Renania del Norte-Westfalia
San Salvador
Nueva York
Distrito Federal
Texas
Nueva Gales del Sur
Santo Domingo
Queensland
Guatemala
São Paulo
Provenza-Alpes-Costa Azul
Capital Nacional
Managua
Francisco Morazán
Panamá
Victoria
Pensilvania
Washington
Illinois
Jalisco
Cortés
Ohio
Languedoc-Rosellón-Mediodía-Pirineos
Viena
Auvernia-Ródano-Alpes
Yakarta
Estambul
Order State

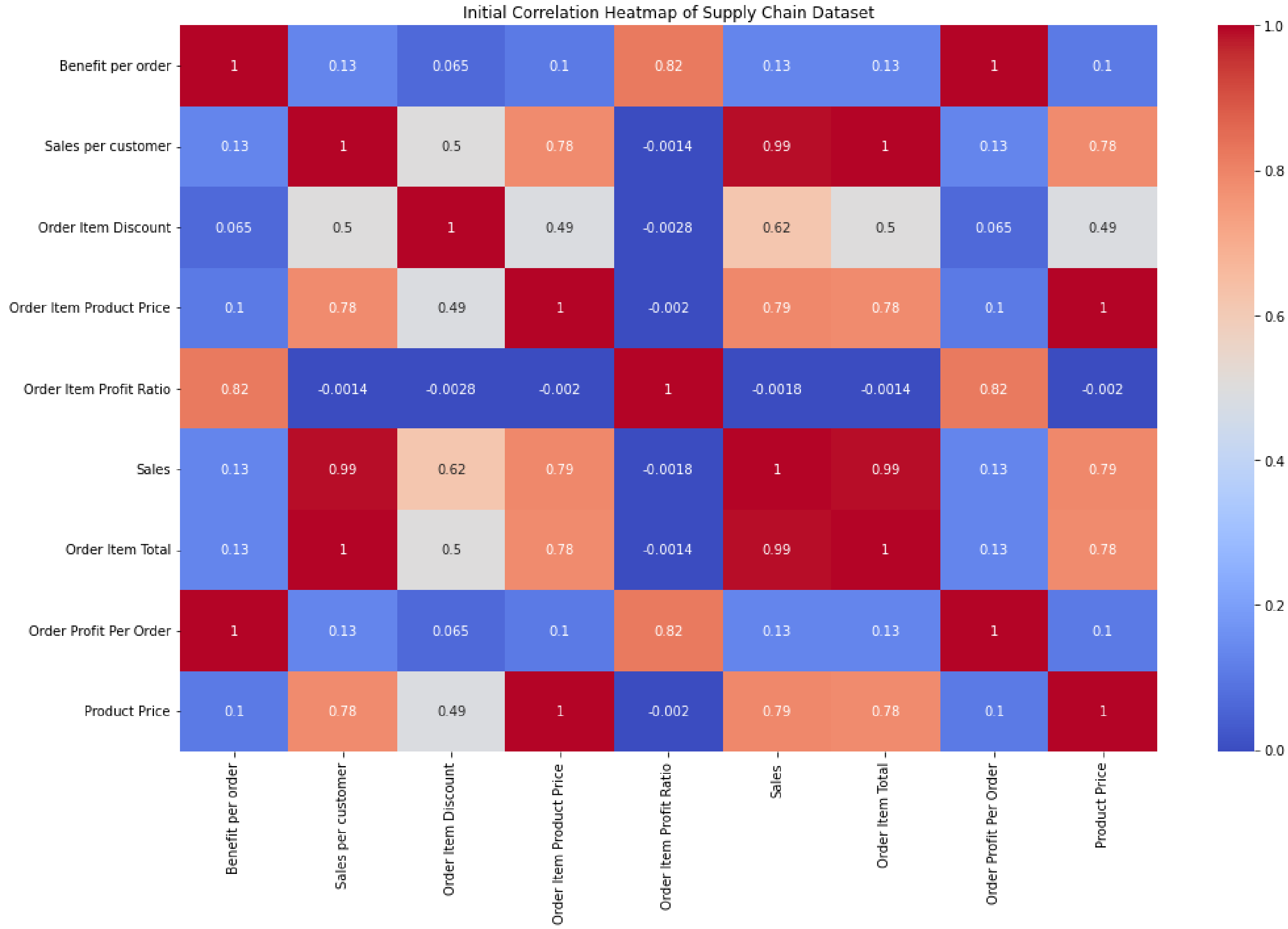

Distribution of Order Status
Late_delivery_risk
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
COMPLETE
PENDING_PAYMENT
PROCESSING
PENDING
CLOSED
ON_HOLD
SUSPECTED_FRAUD
CANCELED
PAYMENT_REVIEW
Order Status

In [47]:

```
'''
Display a correlation heatmap for sales. Utilize sns.heatmap() to generate the figure.
'''
# Calculate the correlation coefficient with corr().
correlation_number = cont_columns.corr()

# Create the heatmap for the correlation coefficients calculated above.
fig, ax = plt.subplots(1, 1, figsize=(15,10), tight_layout = True)
sns.heatmap(correlation_number, annot = True, cmap = 'coolwarm')
plt.title('Initial Correlation Heatmap of Supply Chain Dataset')
```

Out[47]:

```
Text(0.5, 1.0, 'Initial Correlation Heatmap of Supply Chain Dataset')
```



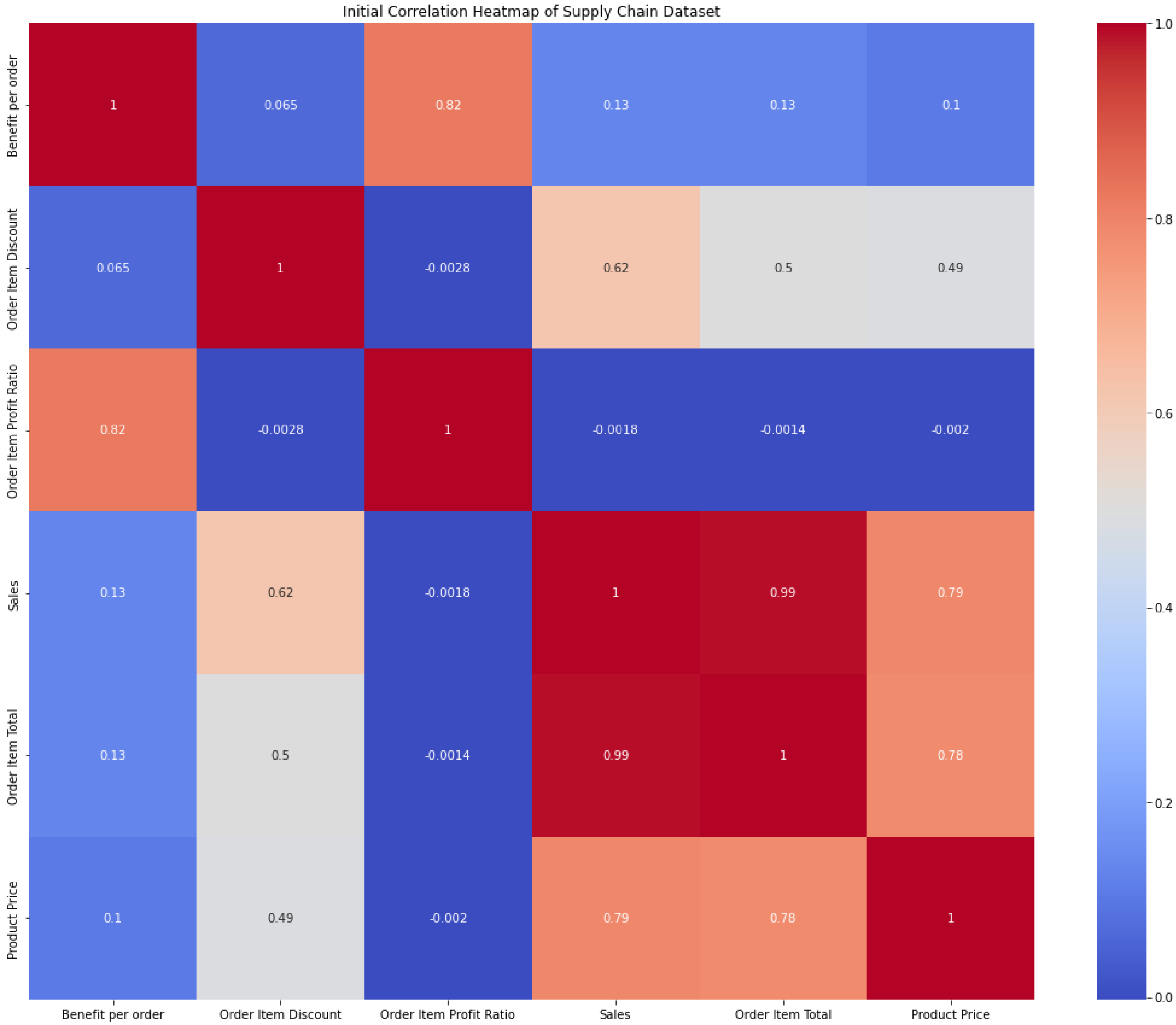
Multicollinearity is present for Benefit per order and Order profit per order, Sales per Customer and Order Item Total, Sales per Customer and Sales, Order Item Product Price and Product Price, Order Item Profit Ratio and Benefit per Order.

In [48]:

```
'''
Display a correlation heatmap for sales. Utilize sns.heatmap() to generate the figure.
'''
revised_cont_df = cont_columns[['Benefit per order', 'Order Item Discount',
                               'Order Item Profit Ratio','Sales', 'Order Item Total', 'Pr

## Calculate the correlation coefficient with corr().
correlation_number = revised_cont_df.corr()

## Create the heatmap for the correlation coefficients calculated above.
fig, ax = plt.subplots(1, 1, figsize=(15,12), tight_layout = True)
sns.heatmap(correlation_number, annot = True, cmap = 'coolwarm')
plt.title('Initial Correlation Heatmap of Supply Chain Dataset')
```

Out[48]:

```
Text(0.5, 1.0, 'Initial Correlation Heatmap of Supply Chain Dataset')
```



In [49]:

```
'''
Check pointbiserial correlations for late delivery.
'''
# Calculate the correlation coefficient for features with potability.
correlation_number_pb1 = pointbiserialr(df['Late_delivery_risk'],df['Days for shipping (re
correlation_number_pb2 = pointbiserialr(df['Late_delivery_risk'],df['Days for shipment (sc
correlation_number_pb3 = pointbiserialr(df['Late_delivery_risk'],df['Benefit per order'])
correlation_number_pb4 = pointbiserialr(df['Late_delivery_risk'],df['Sales per customer'])
correlation_number_pb5 = pointbiserialr(df['Late_delivery_risk'],df['Order Item Discount']
correlation_number_pb6 = pointbiserialr(df['Late_delivery_risk'],df['Order Item Product Pr
correlation_number_pb7 = pointbiserialr(df['Late_delivery_risk'],df['Order Item Quantity']
correlation_number_pb8 = pointbiserialr(df['Late_delivery_risk'],df['Sales'])
correlation_number_pb9 = pointbiserialr(df['Late_delivery_risk'],df['Order Item Total'])
correlation_number_pb10 = pointbiserialr(df['Late_delivery_risk'],df['Order Profit Per Ord
correlation_number_pb11 = pointbiserialr(df['Late_delivery_risk'],df['Product Price'])

# Create a dictionary of the pointbiserial correlation values.
pb_corr_dict = {'shipping_real_corr':correlation_number_pb1, 'shipping_sched_corr':correla
                'benefits_per_order_corr':correlation_number_pb3, 'sales_per_customer_corr
                'order_item_discount_corr':correlation_number_pb5, 'order_item_prod_price_
                'order_item_quantity_corr':correlation_number_pb7, 'sales_corr':correlatio
                'order_item_total_corr':correlation_number_pb9, 'order_profit_per_order_co
                'product_price':correlation_number_pb11}
pb_corr_dict
```

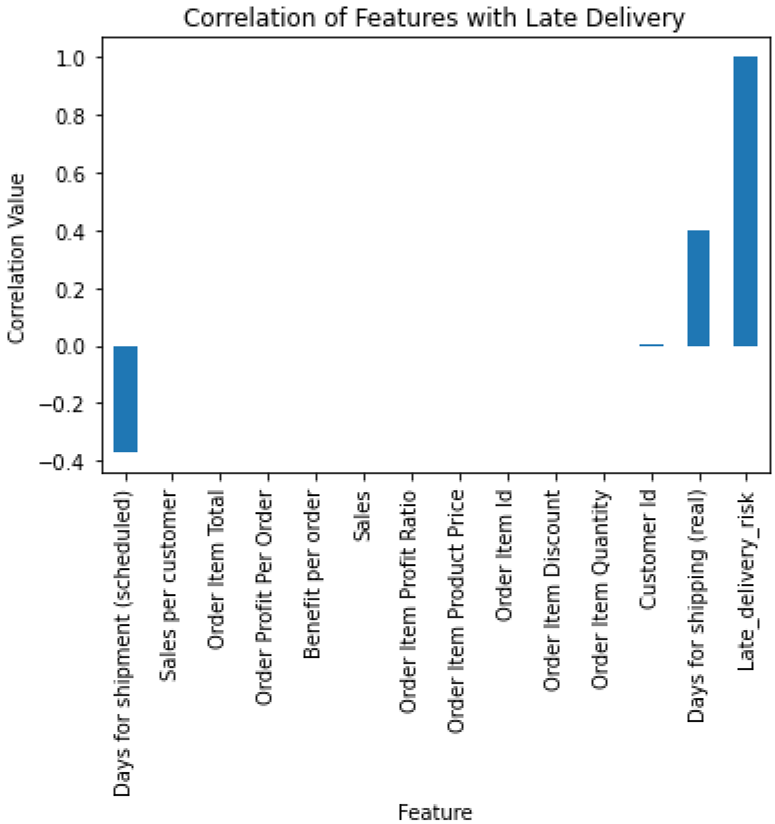
```
Out[49]: {'shipping_real_corr': PointbiserialrResult(correlation=0.4014149301112235, pvalue=0.0),
 'shipping_sched_corr': PointbiserialrResult(correlation=-0.36935177196333274, pvalue=0.
0),
 'benefits_per_order_corr': PointbiserialrResult(correlation=-0.003726996128802091, pvalue
=0.11330685388058316),
 'sales_per_customer_corr': PointbiserialrResult(correlation=-0.003791261522631677, pvalue
=0.10722159451928712),
 'order_item_discount_corr': PointbiserialrResult(correlation=-0.0007499082512339258, pval
ue=0.7500182399255557),
 'order_item_prod_price_corr': PointbiserialrResult(correlation=-0.0021752490565457114, pv
alue=0.3553799904919728),
 'order_item_quantity_corr': PointbiserialrResult(correlation=-0.00013923280125809182, pva
lue=0.9528277237121991),
 'sales_corr': PointbiserialrResult(correlation=-0.0035643605069127257, pvalue=0.129923664
74644568),
 'order_item_total_corr': PointbiserialrResult(correlation=-0.003791261522631677, pvalue=
0.10722159451928712),
 'order_profit_per_order_corr': PointbiserialrResult(correlation=-0.003726996128802091, pv
alue=0.11330685388058316),
 'product_price': PointbiserialrResult(correlation=-0.0021752490565457114, pvalue=0.355379
9904919728)}
```

```
In [50]: '''
Sort the dictionary by correlation value.
'''
sorted_dict = sorted(pb_corr_dict.items(), key = operator.itemgetter(1))
sorted_dict
```

```
Out[50]: [('shipping_sched_corr',
  PointbiserialrResult(correlation=-0.36935177196333274, pvalue=0.0)),
 ('sales_per_customer_corr',
  PointbiserialrResult(correlation=-0.003791261522631677, pvalue=0.10722159451928712)),
 ('order_item_total_corr',
  PointbiserialrResult(correlation=-0.003791261522631677, pvalue=0.10722159451928712)),
 ('benefits_per_order_corr',
  PointbiserialrResult(correlation=-0.003726996128802091, pvalue=0.11330685388058316)),
 ('order_profit_per_order_corr',
  PointbiserialrResult(correlation=-0.003726996128802091, pvalue=0.11330685388058316)),
 ('sales_corr',
  PointbiserialrResult(correlation=-0.0035643605069127257, pvalue=0.12992366474644568)),
 ('order_item_prod_price_corr',
  PointbiserialrResult(correlation=-0.0021752490565457114, pvalue=0.3553799904919728)),
 ('product_price',
  PointbiserialrResult(correlation=-0.0021752490565457114, pvalue=0.3553799904919728)),
 ('order_item_discount_corr',
  PointbiserialrResult(correlation=-0.0007499082512339258, pvalue=0.7500182399255557)),
 ('order_item_quantity_corr',
  PointbiserialrResult(correlation=-0.00013923280125809182, pvalue=0.9528277237121991)),
 ('shipping_real_corr',
  PointbiserialrResult(correlation=0.4014149301112235, pvalue=0.0))]
```

```
In [51]: '''
Create a visual to show which features are most correlated with Late Delivery.
'''
df.corr()['Late_delivery_risk'][:-1].sort_values().plot(kind='bar')
plt.xlabel("Feature")
plt.ylabel("Correlation Value")
plt.title("Correlation of Features with Late Delivery")
```

```
Out[51]: Text(0.5, 1.0, 'Correlation of Features with Late Delivery')
```



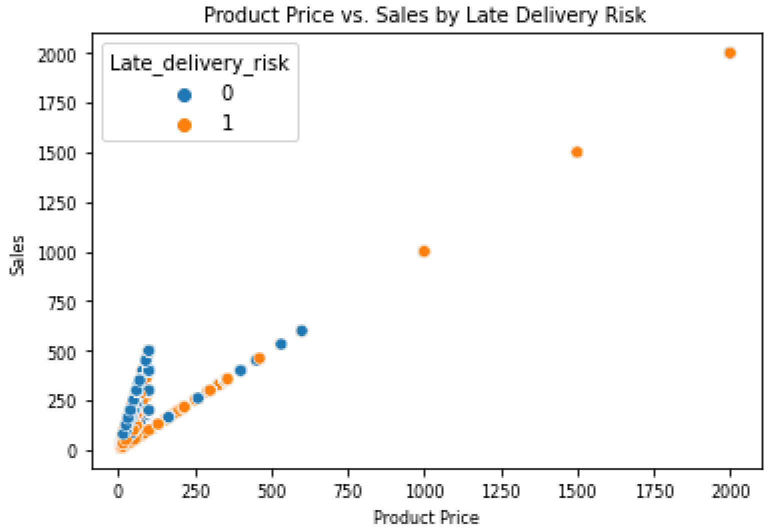
Highlights for Multivariate Analysis:

- Sales have a strong direct correlation with Product Price, Discount, and Order Item Total.
- Multicollinearity is present within the features of the data set.
- Days for shipment (scheduled) has a strong inverse correlation with Late Delivery.
- Days for shipping (real) has a strong direct correlation with Late Delivery.
- Late Delivery appears to be a systematic issue evident in on-time and late-deliveries for all categories.
- It may be beneficial to understand ratio of Late Delivery Risk for different categories during feature engineering.

More Exploratory Data Analysis (EDA)

Interested in further evaluating variable relationships, time trends, and geographical trends in this section.

In [52]:
```
'''
Generate scatter plot showing relationship between Product Price and Sales.
'''
sns.scatterplot(x='Product Price', y='Sales', data=df, hue = df['Late_delivery_risk'])
plt.title("Product Price vs. Sales by Late Delivery Risk", fontsize=10)
plt.xlabel("Product Price", fontsize=8)
plt.ylabel("Sales", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```



In [53]:

```
'''
Generate scatter plot showing relationship between Product Price and Benefit per Order.
'''
sns.scatterplot(x='Product Price', y='Benefit per order', data=df, hue = df['Late_delivery
plt.title("Product Price vs. Benefit per Order by Late Delivery Risk", fontsize=10)
plt.xlabel("Product Price", fontsize=8)
plt.ylabel("Benefit per Order", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```

In [54]:

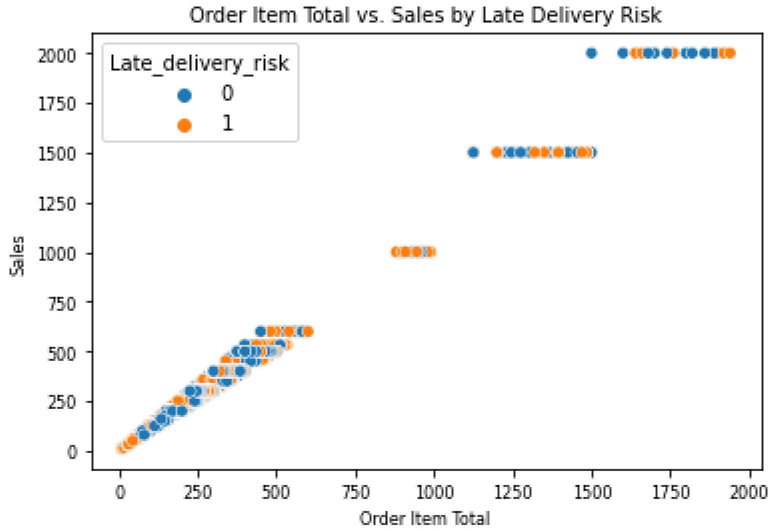
```
'''
Generate scatter plot showing relationship between Discount Value and Sales.
'''
sns.scatterplot(x='Order Item Discount', y='Sales', data=df, hue = df['Late_delivery_risk'
plt.title("Discount vs. Sales by Late Delivery Risk", fontsize=10)
plt.xlabel("Discount", fontsize=8)
plt.ylabel("Sales", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```

In [55]:

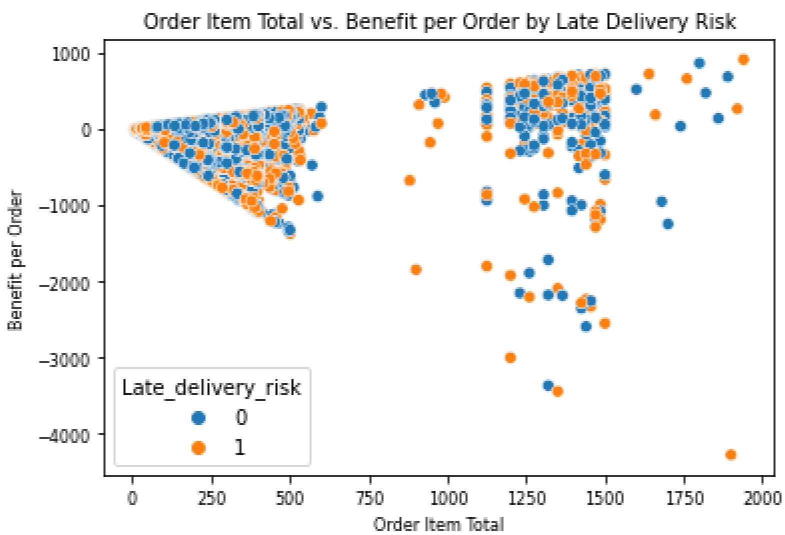
```
'''
Generate scatter plot showing relationship between Discount value and Benefit per order.
'''
sns.scatterplot(x='Order Item Discount', y='Benefit per order', data=df, hue = df['Late_de
plt.title("Discount vs. Benefit per Order by Late Delivery Risk", fontsize=10)
plt.xlabel("Discount", fontsize=8)
plt.ylabel("Benefit per Order", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```

In [56]:

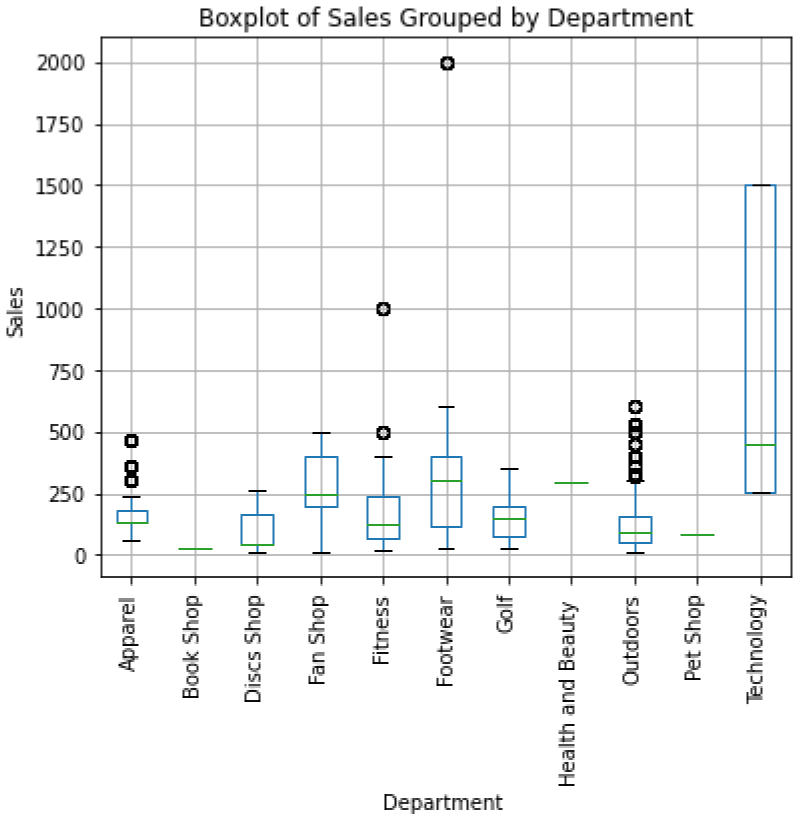
```
'''
Generate scatter plot showing relationship between Order Item Total and Sales.
'''
sns.scatterplot(x='Order Item Total', y='Sales', data=df, hue = df['Late_delivery_risk'])
plt.title("Order Item Total vs. Sales by Late Delivery Risk", fontsize=10)
plt.xlabel("Order Item Total", fontsize=8)
plt.ylabel("Sales", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```



In [57]:
```
'''
Generate scatter plot showing relationship between Order Item Total and Benefit per Order.
'''
sns.scatterplot(x='Order Item Total', y='Benefit per order', data=df, hue = df['Late_deliv
plt.title("Order Item Total vs. Benefit per Order by Late Delivery Risk", fontsize=10)
plt.xlabel("Order Item Total", fontsize=8)
plt.ylabel("Benefit per Order", fontsize=8)
plt.suptitle('')
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.show()
```

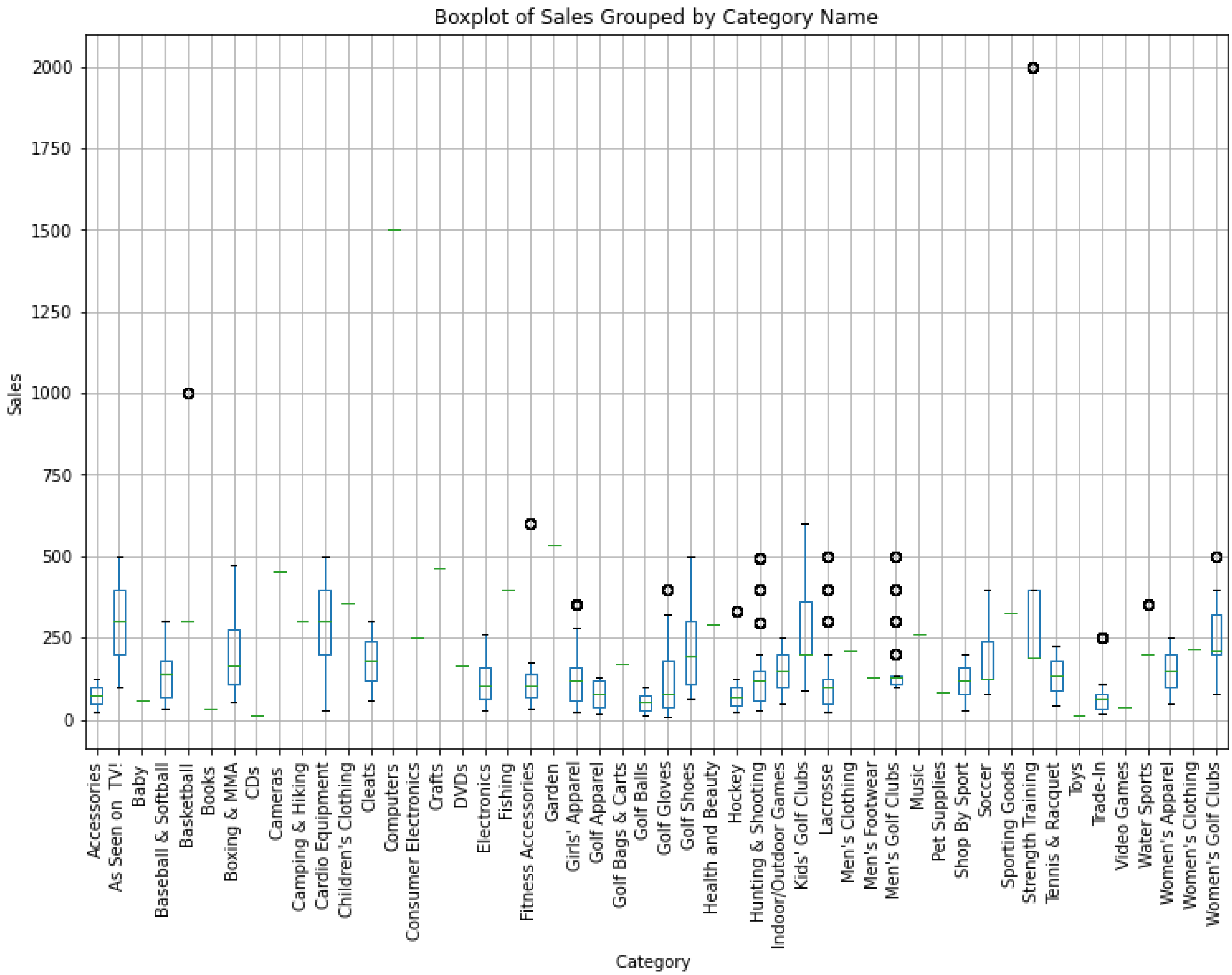


In [58]:
```
'''
Generate boxplot showing Sale grouped by Department.
'''
df.boxplot(column = 'Sales', by = 'Department Name', figsize=(6,5))
plt.title("Boxplot of Sales Grouped by Department", fontsize=12)
plt.xlabel("Department ", fontsize=10)
plt.ylabel("Sales", fontsize=10)
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [59]:

```
'''
Generate boxplot of Sales grouped by Category Name.
'''
df.boxplot(column = 'Sales', by = 'Category Name', figsize=(12,8))
plt.title("Boxplot of Sales Grouped by Category Name", fontsize=12)
plt.xlabel("Category ", fontsize=10)
plt.ylabel("Sales", fontsize=10)
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [60]:

```
'''
Group Customer Id by Benefit per order to provide insights into order profits (high).
'''
group_by_customer_sales = df.groupby(['Customer Id'])['Benefit per order'].mean().sort_val
group_by_customer_sales[:10]
```

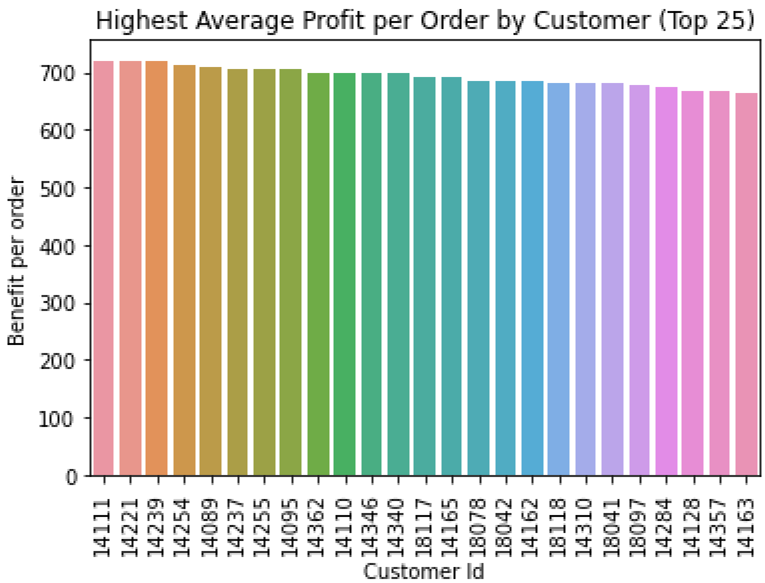
Out[60]:

```
Customer Id
14111    720.299988
14221    720.000000
14239    720.000000
14254    712.950012
14089    708.750000
14237    705.599976
14255    705.599976
14095    705.000000
14362    698.400024
14110    698.400024
Name: Benefit per order, dtype: float64
```

In [61]:

```
'''
Generate bar chart showing average profits by customer. (high)
'''
sns.barplot(x='Customer Id', y='Benefit per order', data = df,
            order = group_by_customer_sales.iloc[:25].index)
plt.title('Highest Average Profit per Order by Customer (Top 25)')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
```

```
plt.yticks(fontsize=10)
plt.show()
```



In [62]:

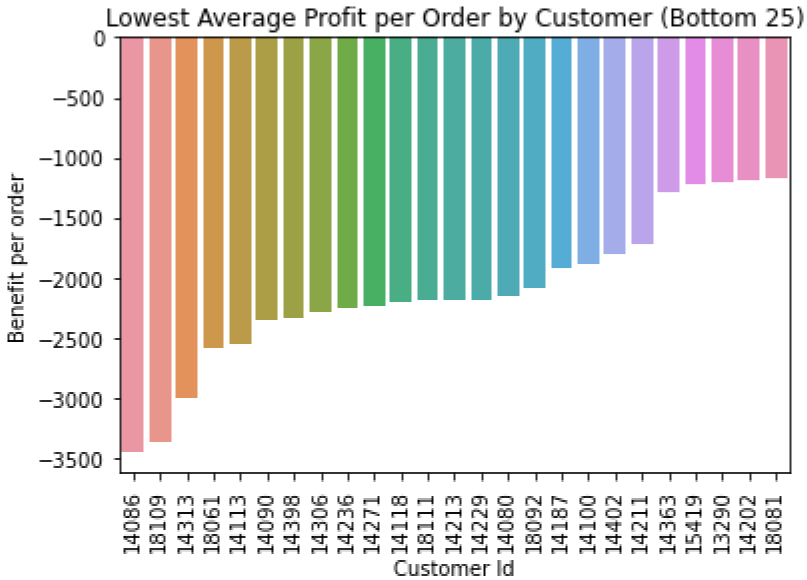
```
'''
Group Customer Id by Benefit per order to provide insights into order profits (low).
'''
group_by_customer_sales1 = df.groupby(['Customer Id'])['Benefit per order'].mean().sort_va
group_by_customer_sales1[:10]
```

Out[62]:

```
Customer Id
14086   -3442.50
18109   -3366.00
14313   -3000.00
18061   -2592.00
14113   -2550.00
14090   -2351.25
14398   -2328.00
14306   -2280.00
14236   -2255.25
14271   -2232.00
Name: Benefit per order, dtype: float64
```

In [63]:

```
'''
Generate bar chart showing average profits by customer (low).
'''
sns.barplot(x='Customer Id', y='Benefit per order', data = df,
            order = group_by_customer_sales1.iloc[:25].index)
plt.title('Lowest Average Profit per Order by Customer (Bottom 25)')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [64]:

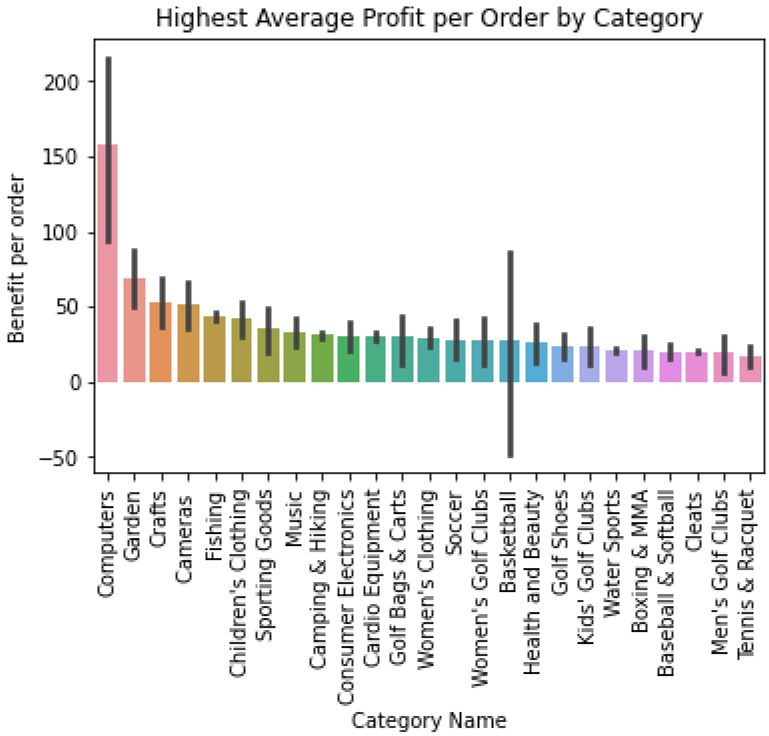
```
'''
Group Category Name by Benefit per order to provide insights into order profits (high).
'''
group_by_category_sales = df.groupby(['Category Name'])['Benefit per order'].mean().sort_v
group_by_category_sales[:10]
```

Out[64]:

```
Category Name
Computers                 157.594593
Garden                     69.097128
Crafts                     52.750351
Cameras                    51.165203
Fishing                    43.649106
Children's Clothing        41.684202
Sporting Goods             35.066135
Music                      33.263410
Camping & Hiking           31.135230
Consumer Electronics       30.680742
Name: Benefit per order, dtype: float64
```

In [65]:

```
'''
Generate bar chart showing average profits by category (high).
'''
sns.barplot(x='Category Name', y='Benefit per order', data = df,
            order = group_by_category_sales.iloc[:25].index)
plt.title('Highest Average Profit per Order by Category')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [66]:

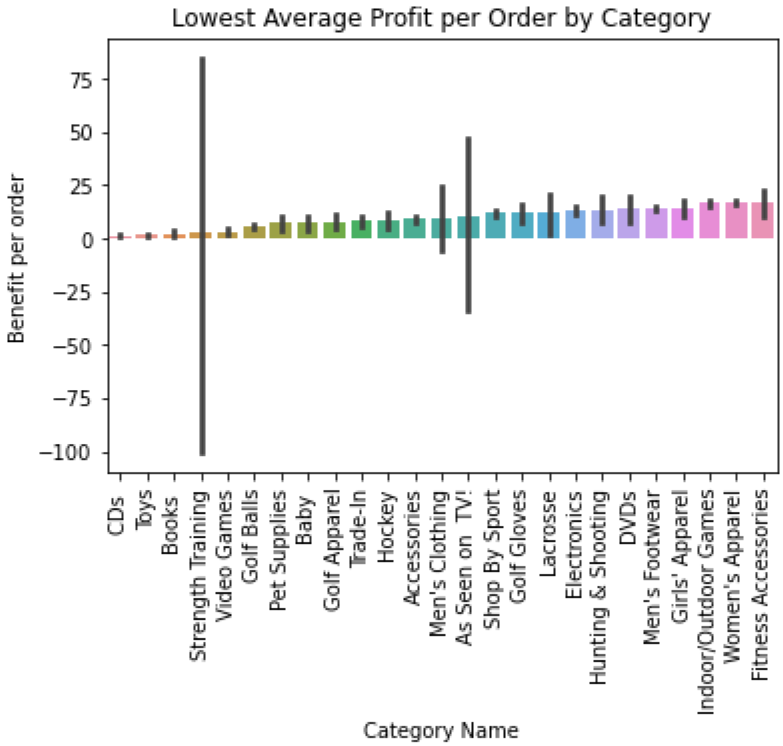
```
'''
Group Category Name by Benefit per order to provide insights into order profits (low).
'''
group_by_category_sales1 = df.groupby(['Category Name'])['Benefit per order'].mean().sort_
group_by_category_sales1[:10]
```

Out[66]:

```
Category Name
CDs                     1.416421
Toys                    1.702665
Books                   2.180272
Strength Training       2.993785
Video Games             3.242864
Golf Balls              5.656047
Pet Supplies            7.295244
Baby                    7.367295
Golf Apparel            7.928141
Trade-In                8.126663
Name: Benefit per order, dtype: float64
```

In [67]:

```
'''
Generate bar chart showing average profits by category (low).
'''
sns.barplot(x='Category Name', y='Benefit per order', data = df,
            order = group_by_category_sales1.iloc[:25].index)
plt.title('Lowest Average Profit per Order by Category')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [68]:

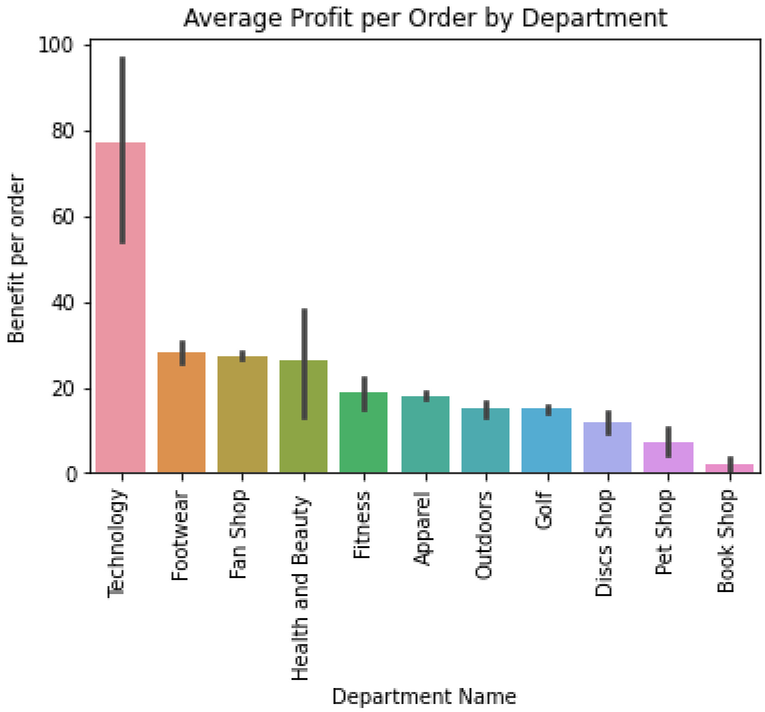
```
'''
Group Deparment Name by Benefit per order to provide insights into order profits.
'''
group_by_department_sales = df.groupby(['Department Name'])['Benefit per order'].mean().sc
group_by_department_sales
```

Out[68]:

```
Department Name
Technology          77.249154
Footwear            28.242513
Fan Shop            27.432366
Health and Beauty   26.225497
Fitness             18.772917
Apparel             17.998345
Outdoors            14.996021
Golf                14.976627
Discs Shop          11.941323
Pet Shop             7.295244
Book Shop            2.180272
Name: Benefit per order, dtype: float64
```

In [69]:

```
'''
Generate bar chart showing average profits by department.
'''
sns.barplot(x='Department Name', y='Benefit per order', data = df,
            order = group_by_department_sales.index)
plt.title('Average Profit per Order by Department')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [70]:

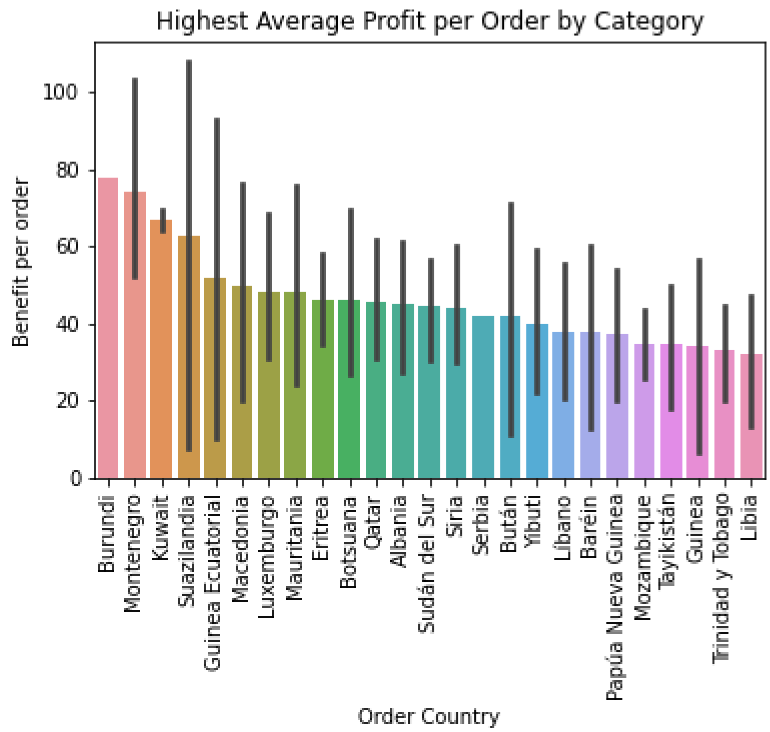
```
'''
Group Order Country by Benefit per order to provide insights into order profits (high).
'''
group_by_order_country_sales= df.groupby(['Order Country'])['Benefit per order'].mean().sc
group_by_order_country_sales[:10]
```

Out[70]:

```
Order Country
Burundi              77.750000
Montenegro           74.347272
Kuwait               66.915001
Suazilandia          62.492001
Guinea Ecuatorial    51.680001
Macedonia            49.575001
Luxemburgo           48.313000
Mauritania           48.156191
Eritrea              46.240000
Botsuana             46.174616
Name: Benefit per order, dtype: float64
```

In [71]:

```
'''
Generate bar chart showing average profits by country (high).
'''
sns.barplot(x='Order Country', y='Benefit per order', data = df,
            order = group_by_order_country_sales.iloc[:25].index)
plt.title('Highest Average Profit per Order by Category')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [72]:

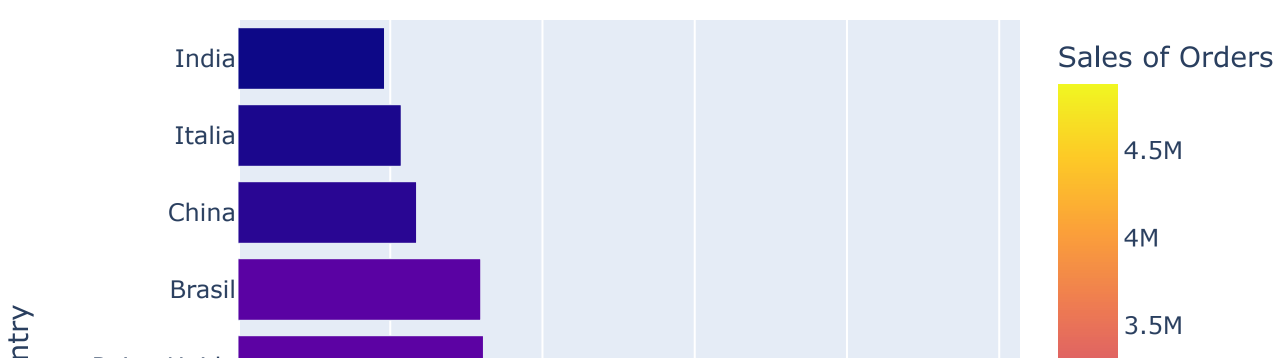
```
'''
Group Order Country by Benefit per order to provide insights into order profits (low).
'''
group_by_order_country_sales1 = df.groupby(['Order Country'])['Benefit per order'].mean().
group_by_order_country_sales1[:10]
```

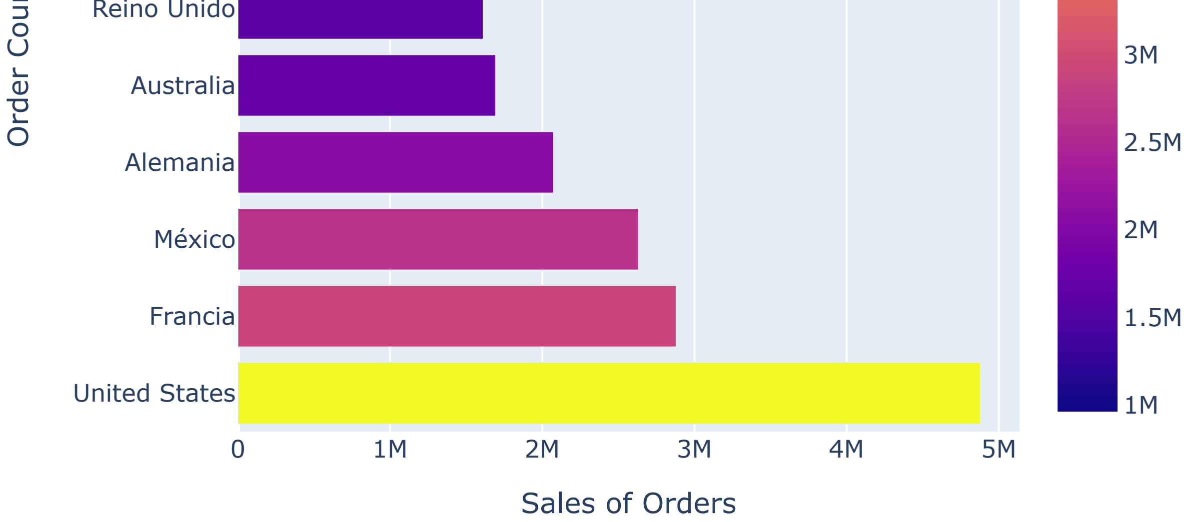
Out[72]:

```
Order Country
Chad                      -90.903331
República de Gambia       -53.166000
Guinea-Bissau             -51.740000
Taiwán                    -47.397932
Guayana Francesa          -25.764445
Belice                    -17.565385
Sáhara Occidental          -8.760000
Bosnia y Herzegovina       -7.275112
Ruanda                     -3.837443
Mongolia                   -3.623164
Name: Benefit per order, dtype: float64
```

In [73]:

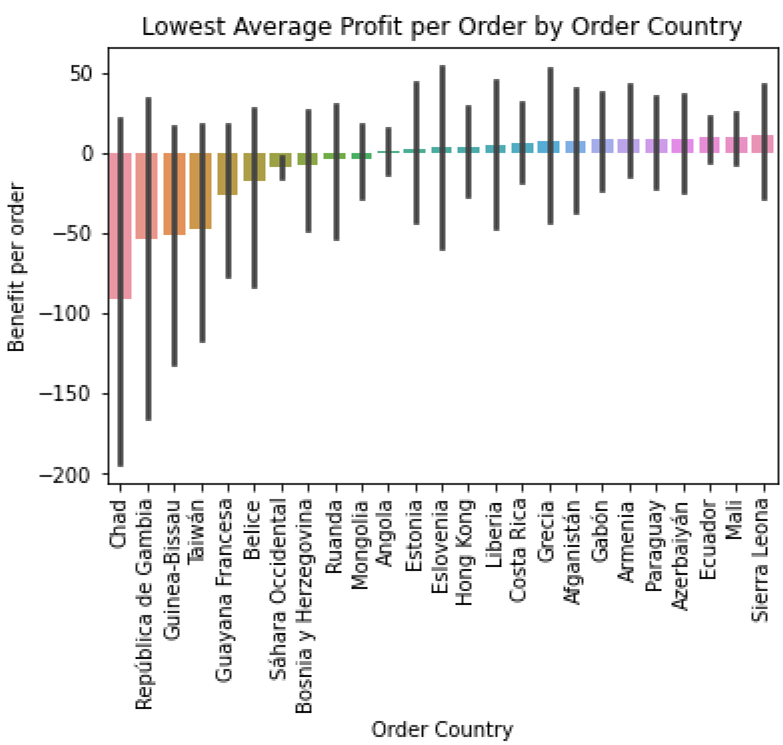
```
'''
Show Top 10 Sales by Country.
'''
df_sales_country=df.groupby([ 'Order Country'])['Sales'].sum().reset_index(name='Sales of
px.bar(df_sales_country.head(10), x='Sales of Orders',y = 'Order Country',color ='Sales of
```





In [74]:

```
'''
Generate bar chart showing average profits by Order Country (low).
'''
sns.barplot(x='Order Country', y='Benefit per order', data = df,
            order = group_by_order_country_sales1.iloc[:25].index)
plt.title('Lowest Average Profit per Order by Order Country')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [75]:

```
'''
Group Order Region by Benefit per order to provide insights into order profits (high).
'''
group_by_order_region_sales = df.groupby(['Order Region'])['Benefit per order'].mean().so
group_by_order_region_sales[:10]
```

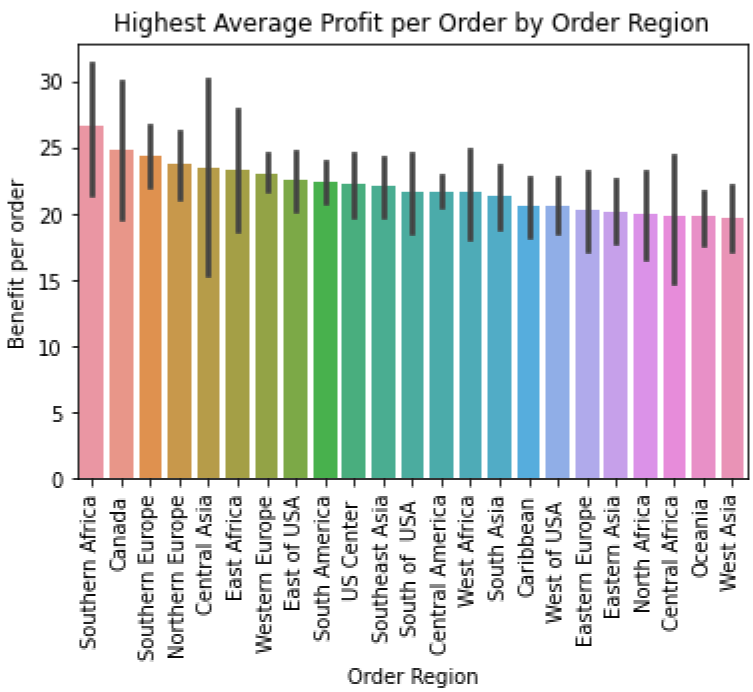
Out[75]:

```
Order Region
Southern Africa     26.643086
```

```
Canada               24.922534
Southern Europe      24.475584
Northern Europe      23.840952
Central Asia         23.590018
East Africa          23.308709
Western Europe       23.071529
East of USA          22.597730
South America        22.440870
US Center            22.268427
Name: Benefit per order, dtype: float64
```

In [76]:

```
'''
Generate bar chart showing average profits by Order Country (high).
'''
sns.barplot(x='Order Region', y='Benefit per order', data = df,
            order = group_by_order_region_sales.iloc[:25].index)
plt.title('Highest Average Profit per Order by Order Region')
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```

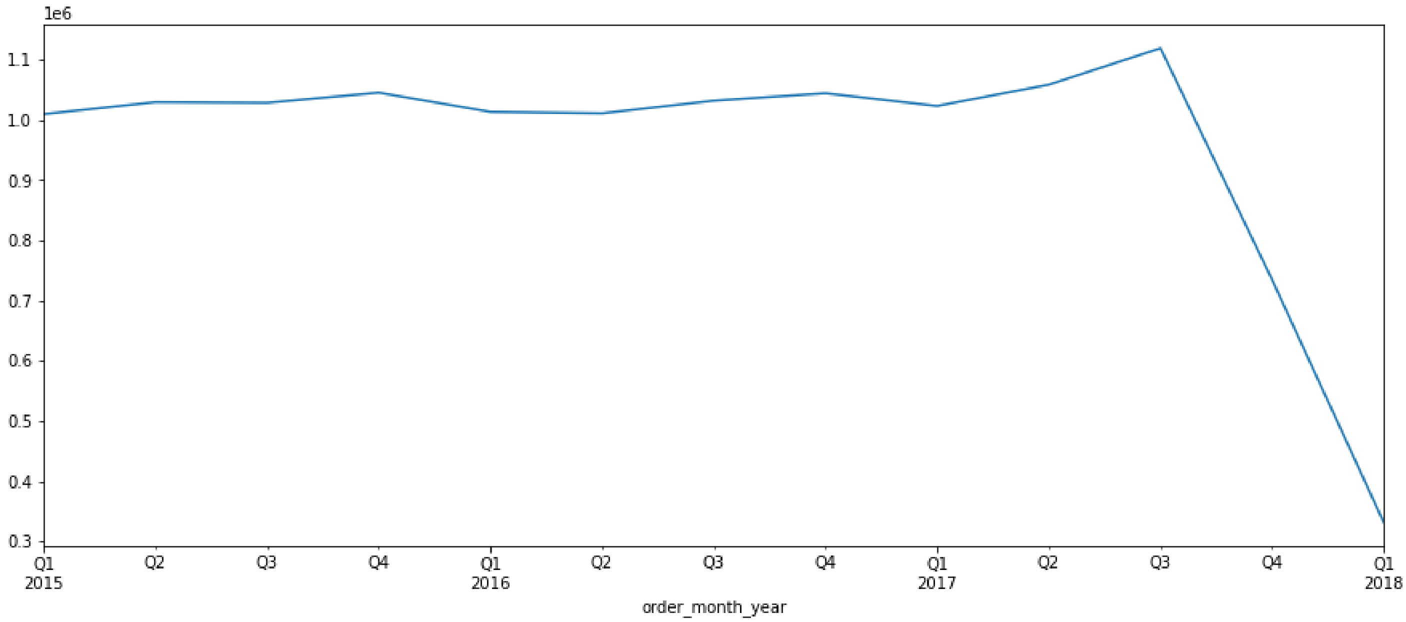


In [77]:

```
'''
Create variables for the order year, month, week day, hour and month/year.
'''
df['order_year']= pd.DatetimeIndex(df['order date (DateOrders)']).year
df['order_month'] = pd.DatetimeIndex(df['order date (DateOrders)']).month
df['order_week_day'] = pd.DatetimeIndex(df['order date (DateOrders)']).weekday
df['order_hour'] = pd.DatetimeIndex(df['order date (DateOrders)']).hour
df['order_month_year'] = pd.to_datetime(df['order date (DateOrders)']).dt.to_period('M')
```

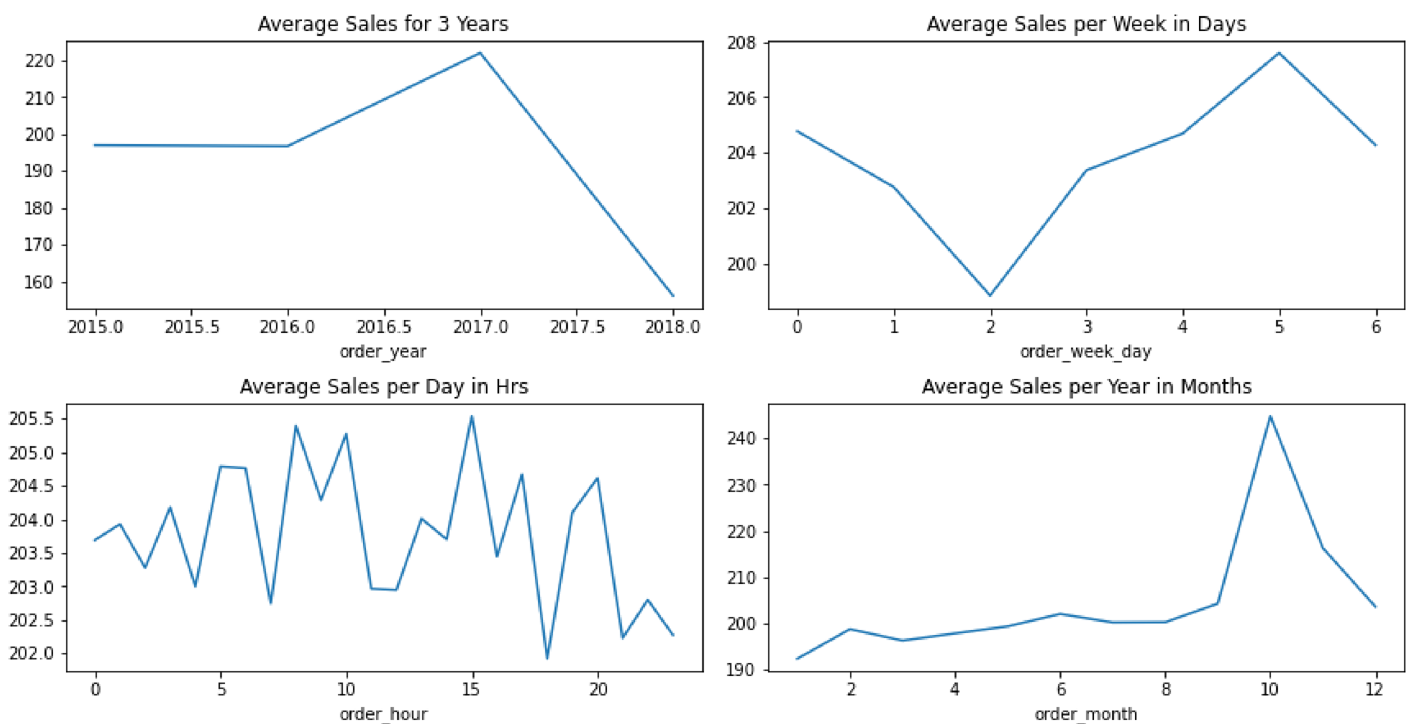
In [78]:

```
'''
Plot the Sales based on order Quarter/Year.
'''
quarter= df.groupby('order_month_year')
quarter_sales=quarter['Sales'].sum().resample('Q').mean().plot(figsize=(15,6))
```



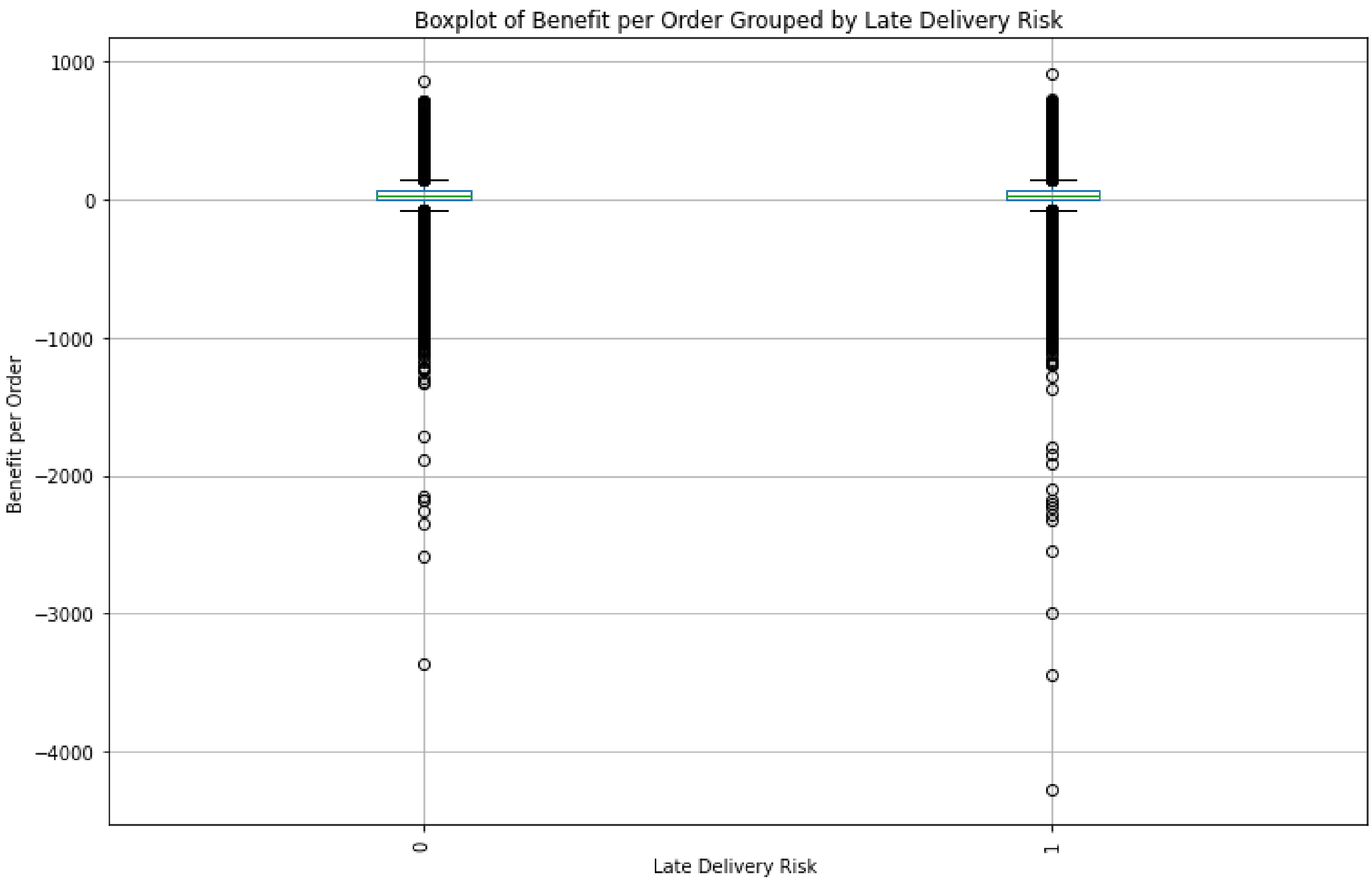
In [79]:

```
'''
Determine if Sales are trending differently across years, week days, time of the day, or c
'''
plt.figure(figsize=(10,12))
plt.subplot(4, 2, 1)
quarter= df.groupby('order_year')
quarter['Sales'].mean().plot(figsize=(12,12),title='Average Sales for 3 Years')
plt.subplot(4, 2, 2)
days=df.groupby("order_week_day")
days['Sales'].mean().plot(figsize=(12,12),title='Average Sales per Week in Days')
plt.subplot(4, 2, 3)
hours=df.groupby("order_hour")
hours['Sales'].mean().plot(figsize=(12,12),title='Average Sales per Day in Hrs')
plt.subplot(4, 2, 4)
month_v=df.groupby("order_month")
month_v['Sales'].mean().plot(figsize=(12,12),title='Average Sales per Year in Months')
plt.tight_layout()
plt.show()
```



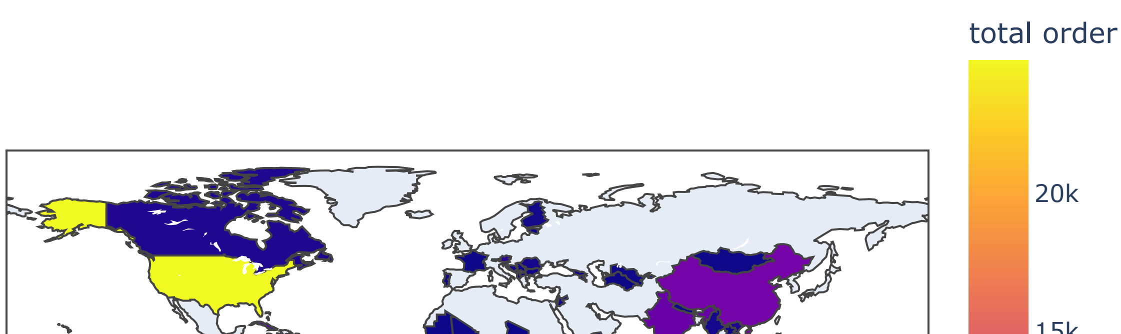
In [80]:

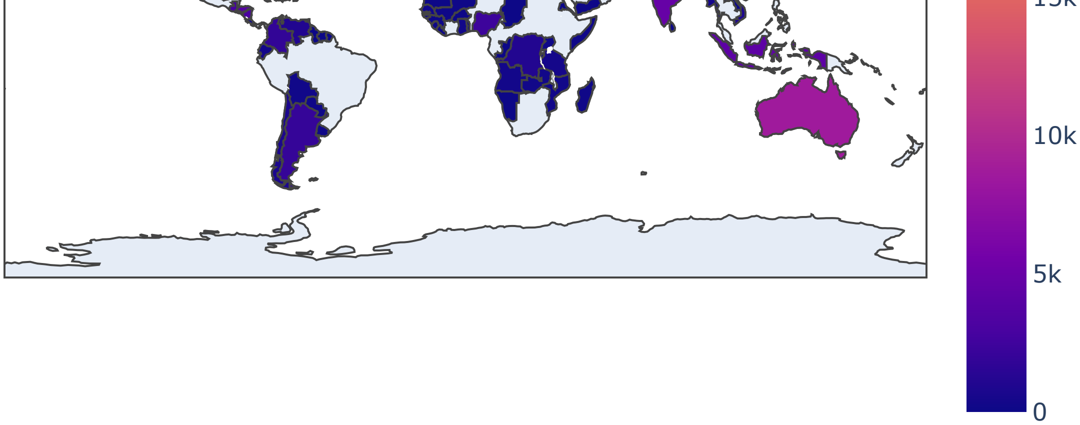
```
'''
Generate a boxplot of Benefit per Order by Late Delivery Risk.
'''
df.boxplot(column = 'Benefit per order', by = 'Late_delivery_risk', figsize=(12,8))
plt.title("Boxplot of Benefit per Order Grouped by Late Delivery Risk", fontsize=12)
plt.xlabel("Late Delivery Risk ", fontsize=10)
plt.ylabel("Benefit per Order", fontsize=10)
plt.suptitle('')
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [81]:

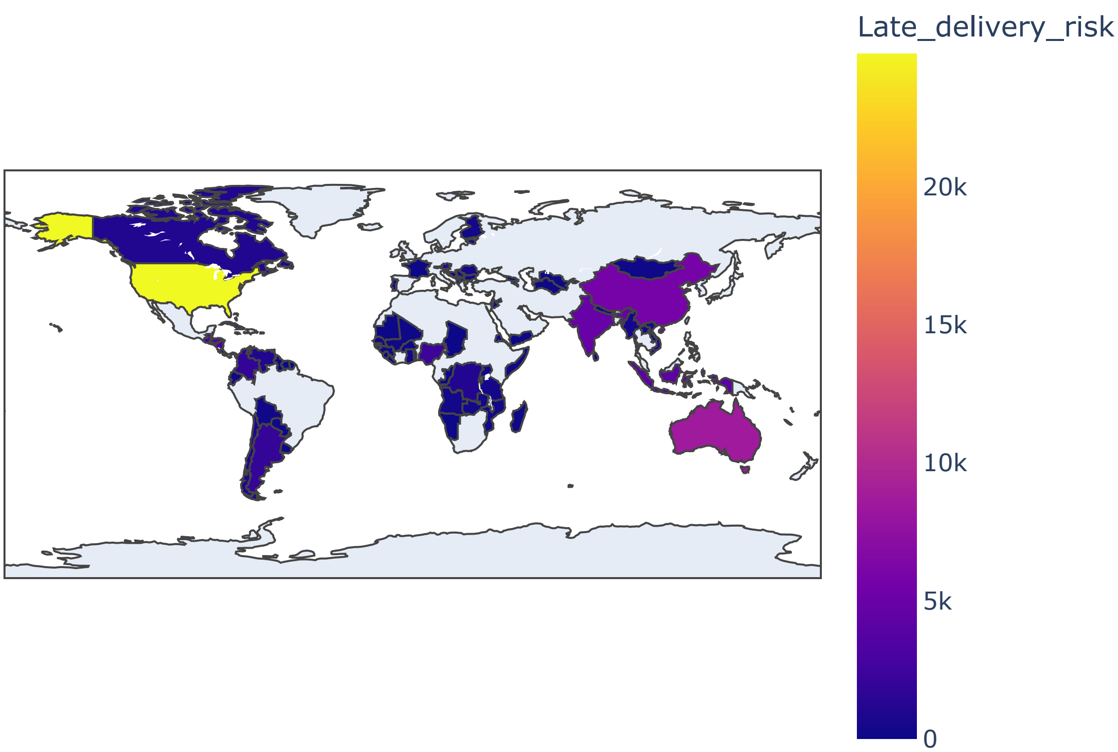
```
'''
Show geographic locations of order countries.
'''
geo_df = df.groupby(['Order Country'])['Benefit per order'].count().reset_index(name='tota

fig = px.choropleth(geo_df ,  locationmode='country names', locations='Order Country',
                    color='total order',hover_name='Order Country')
fig.show()
```





In [82]:

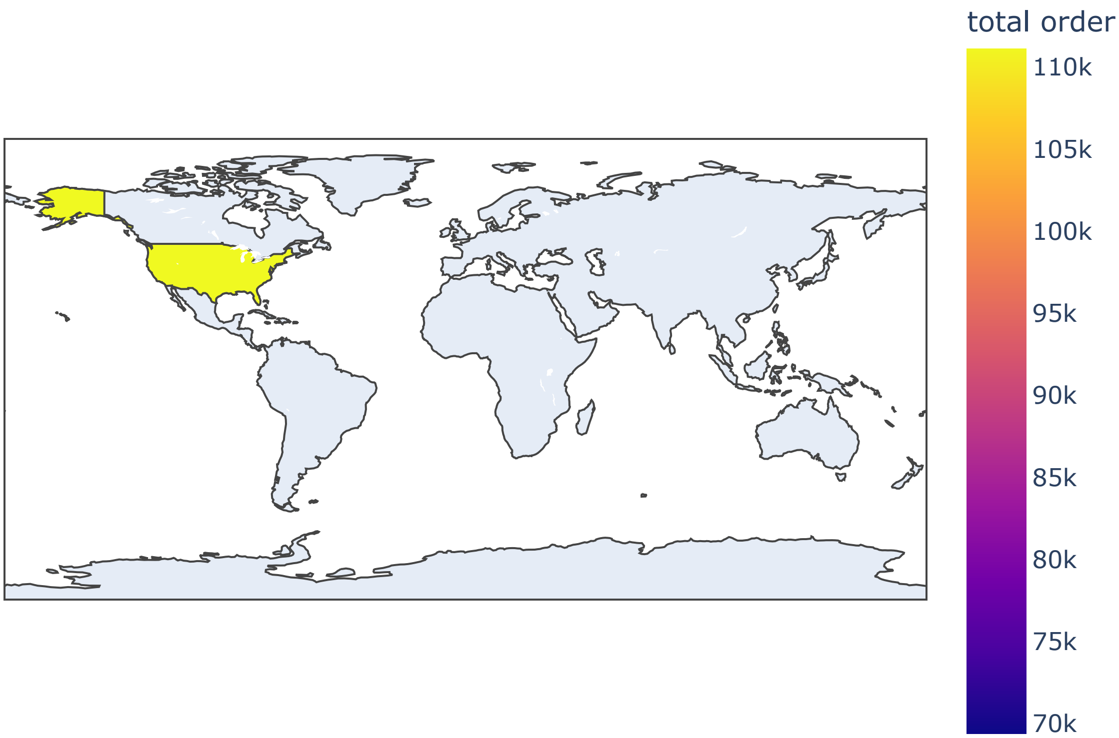
```
'''
Show geographic locations of order countriesby Late Delivery Risk.
'''
geo_df = df.groupby(['Order Country'])['Late_delivery_risk'].count().reset_index(name='Lat

fig = px.choropleth(geo_df ,  locationmode='country names', locations='Order Country',
                    color='Late_delivery_risk',hover_name='Order Country')
fig.show()
```



In [83]:

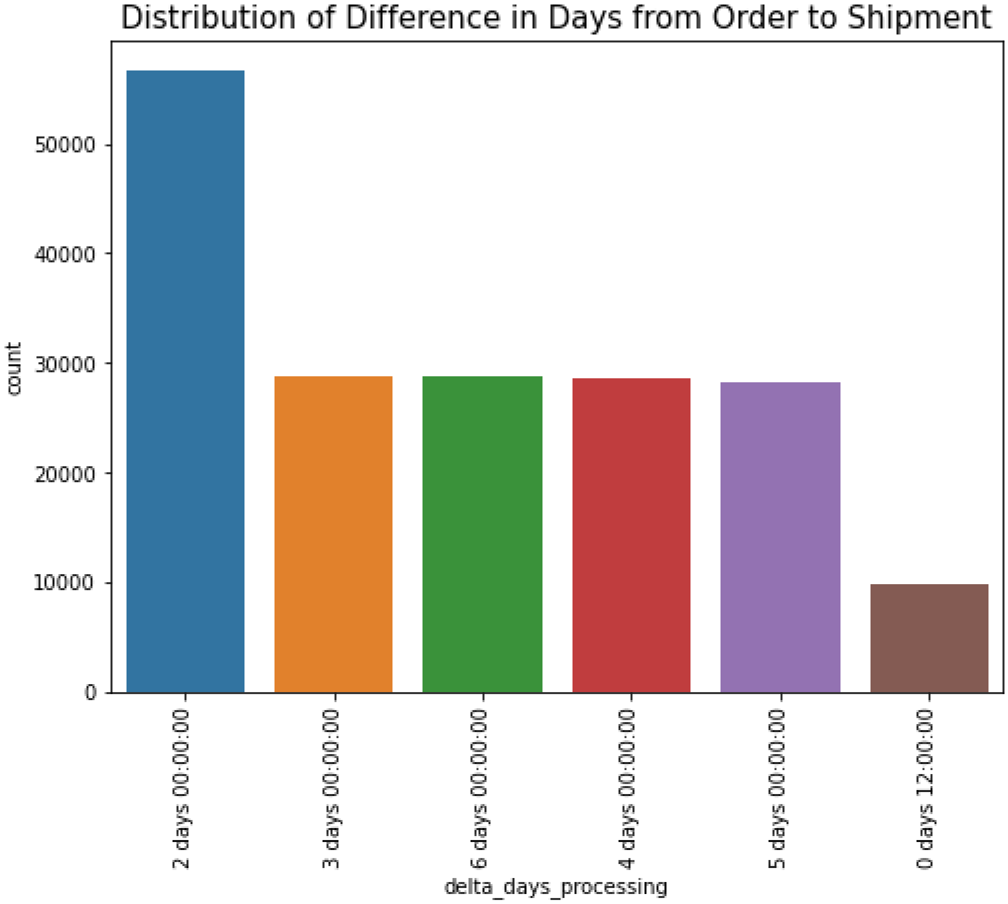
```
'''
```

```
Show geographic locations of customer countries.
'''
geo_df2 = df.groupby(['Customer Country'])['Benefit per order'].count().reset_index(name='

fig = px.choropleth(geo_df2 ,  locationmode='country names', locations='Customer Country',
                    color='total order',hover_name='Customer Country')
fig.show()
```



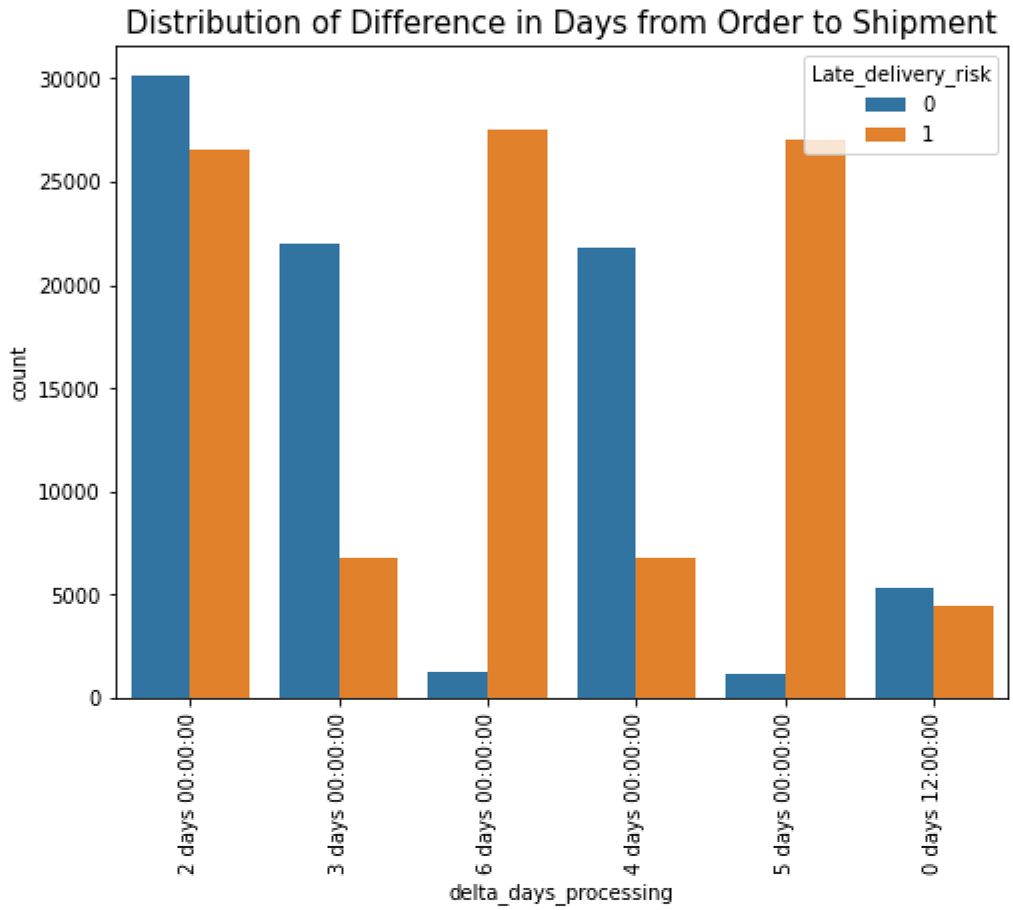
In [84]:
```
'''
Try creating a feature for difference in days from shipping date from order date.
'''
df['delta_days_processing'] = df['shipping date (DateOrders)'] - df['order date (DateOrder
```

In [85]:
```
'''
Show count of delta in days from order placement to shipment.
'''
plt.figure(figsize=(8,6))
sns.countplot(x=df['delta_days_processing'], order = df['delta_days_processing'].value_cou
plt.title("Distribution of Difference in Days from Order to Shipment", fontsize=15)
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [86]:

```
'''
Show count of delta in days from order placement to shipment with late delivery breakdown.
'''
plt.figure(figsize=(8,6))
sns.countplot(x=df['delta_days_processing'], order = df['delta_days_processing'].value_cou
plt.title("Distribution of Difference in Days from Order to Shipment", fontsize=15)
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```

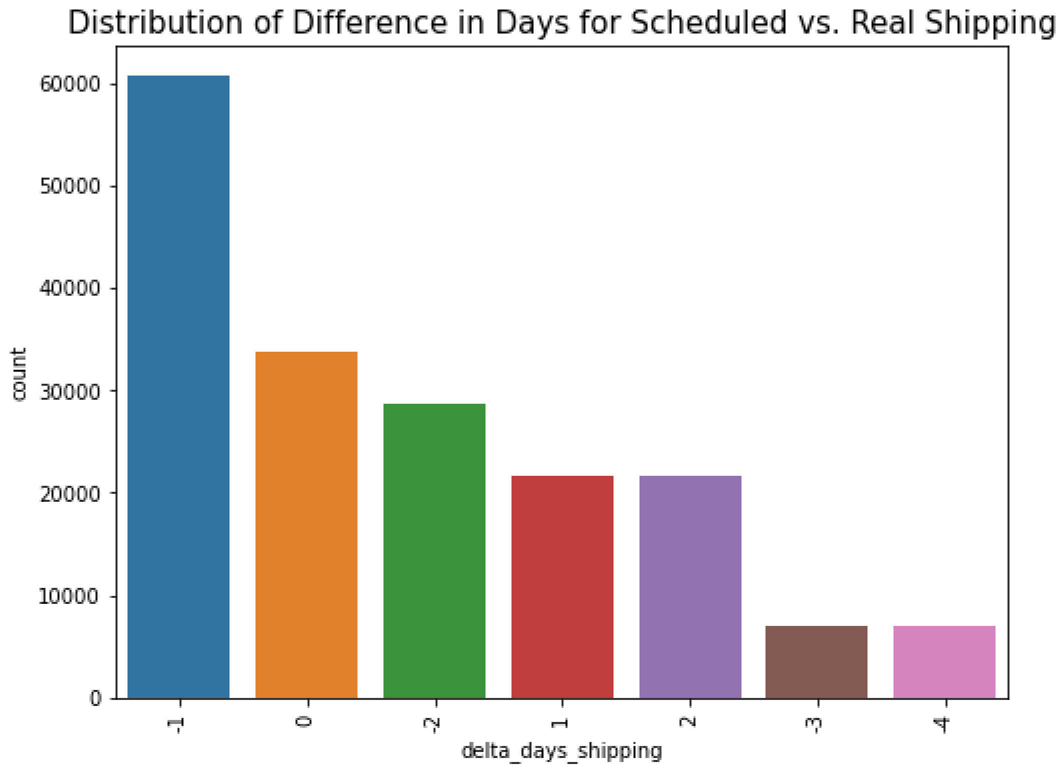


In [87]:

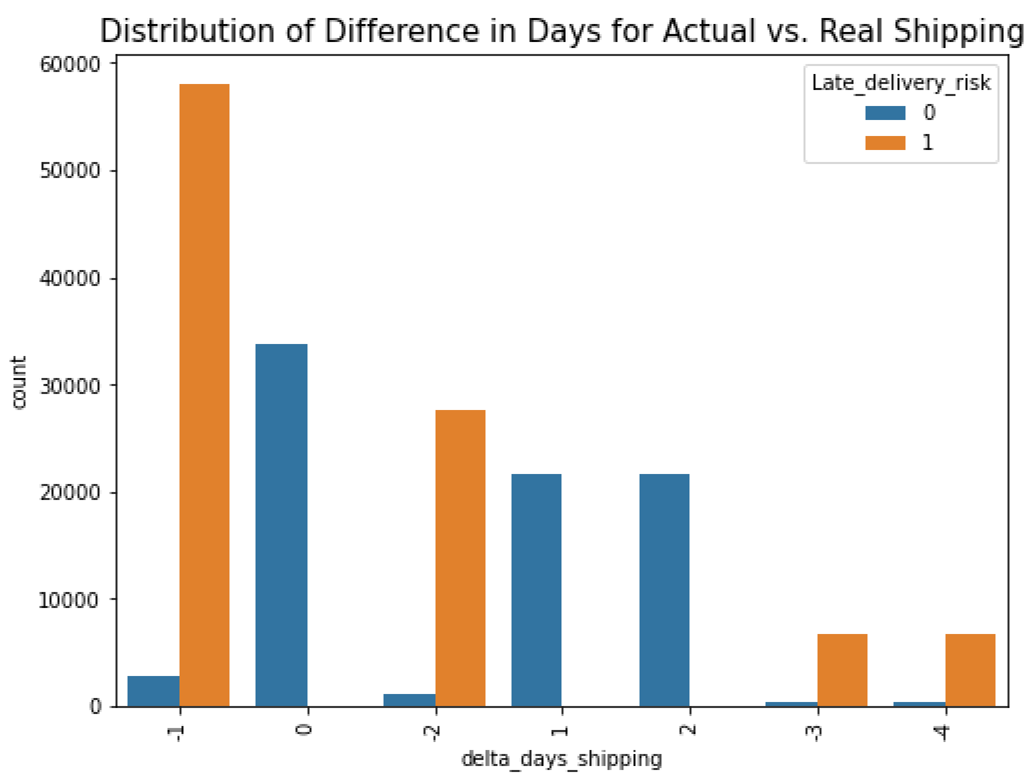
```
'''
Try creating a feature for difference in days actual vs scheduled shipping days.
'''
df['delta_days_shipping'] = df['Days for shipment (scheduled)'] - df['Days for shipping (r
```

In [88]:

```
'''
Show count of delta in days from scheduled vs. actual shipping days.
'''
plt.figure(figsize=(8,6))
sns.countplot(x=df['delta_days_shipping'], order = df['delta_days_shipping'].value_counts
plt.title("Distribution of Difference in Days for Scheduled vs. Real Shipping", fontsize=1
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```

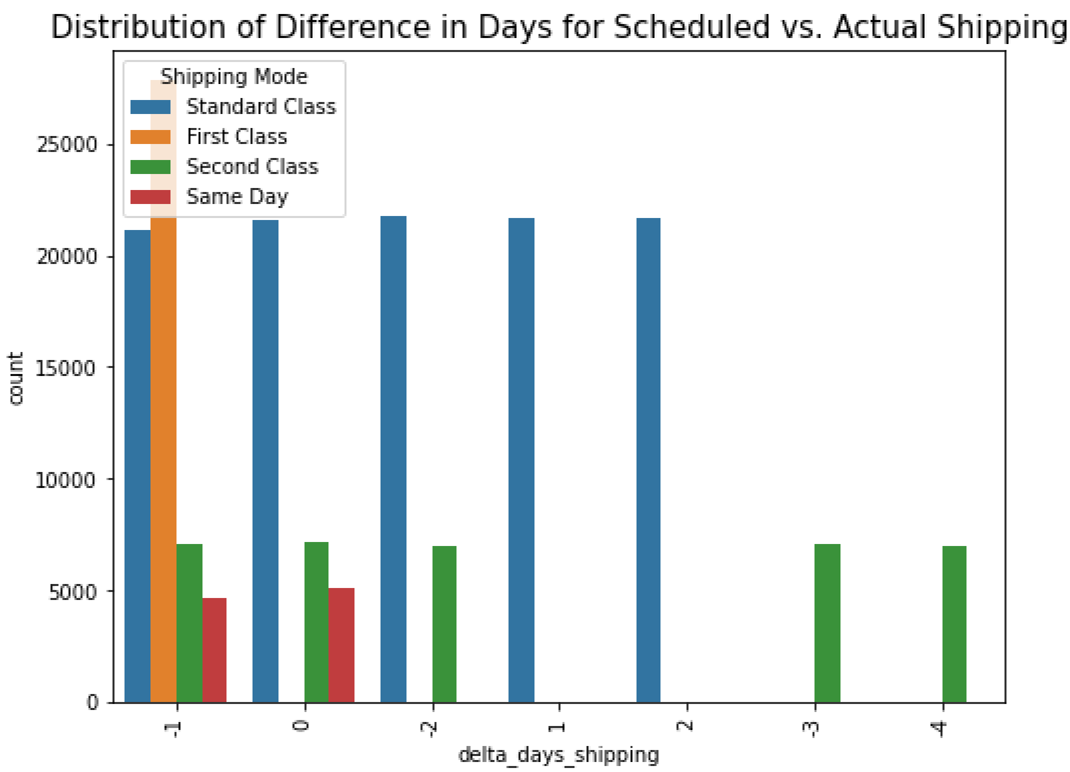


In [89]:
```
'''
Show count of delta in days from scheduled vs. actual shipping days with Late Delivery Bre
'''
plt.figure(figsize=(8,6))
sns.countplot(x=df['delta_days_shipping'], order = df['delta_days_shipping'].value_counts
plt.title("Distribution of Difference in Days for Actual vs. Real Shipping", fontsize=15)
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```



In [90]:
```
'''
Show Shipping Mode by difference in days from scheduled vs. actual shipping time.
'''
```

```
plt.figure(figsize=(8,6))
sns.countplot(x=df['delta_days_shipping'], order = df['delta_days_shipping'].value_counts
plt.title("Distribution of Difference in Days for Scheduled vs. Actual Shipping", fontsize
plt.xticks(fontsize=10, rotation = 90)
plt.yticks(fontsize=10)
plt.show()
```

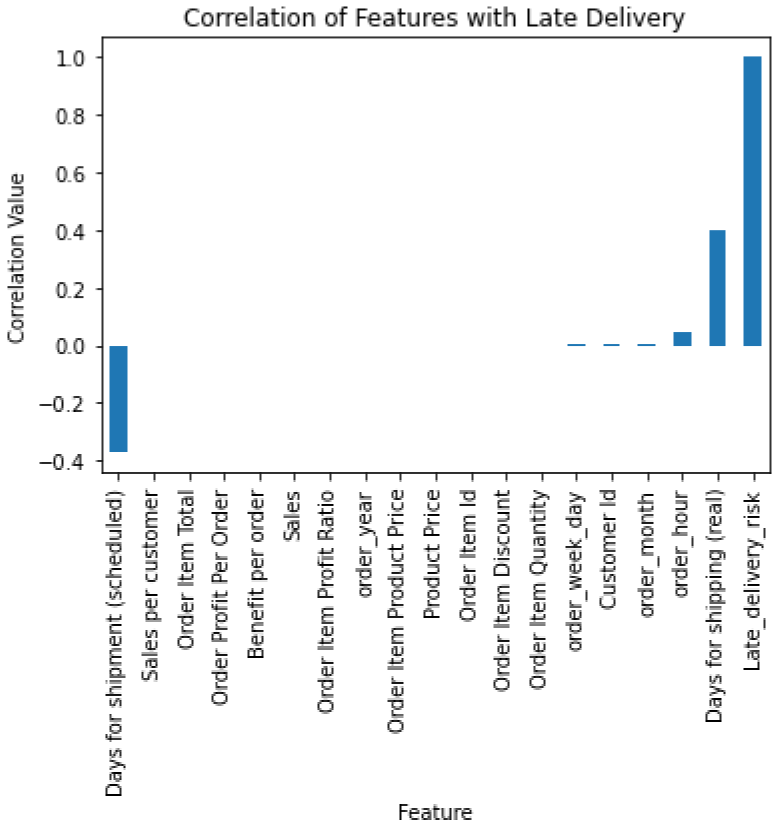


In [91]:

```
'''
Create a visual to show which features are most correlated with Late Delivery.
'''
df.corr()['Late_delivery_risk'][:-1].sort_values().plot(kind='bar')
plt.xlabel("Feature")
plt.ylabel("Correlation Value")
plt.title("Correlation of Features with Late Delivery")
```

Out[91]:

```
Text(0.5, 1.0, 'Correlation of Features with Late Delivery')
```



Highlights for More Exploratory Data Analysis (EDA):

- Most sales came from the technology department during this timeframe (2015-2018).
- Technology had the most average profit per order compared to other departments. (around $77.25) Computers had the most average profit per order compared to other categories. (around $158.00)
- The Book Shop department had the lowest average profit per order. (around $2.18) CD's where the lowest average profit per order compared to other categories. (around $1.41)
- Average sales went up from 2015-2017, but then declined from 2017-2018.
- Most orders are coming in from the United States, but orders are coming in from around the world.
- Late delivieries does not appear to be impacting profits per order.
- Feature was generated for delta days for processing which was calculated from the difference in days when the order was placed and when the order was shipped. Most late deliveries are present when it takes 5 or 6 days of processing.
- Feature was generated for the delta days between scheduled vs. actual shipping days. It is most often taking an extra day to ship than scheduled resulting in a lot of late deliveries.
- All shipping modes are used for the orders that took a day extra to deliver. Only Standard and Second Class shipping modes were used for orders that took longer than an extra day to be delivered. Orders arriving early where only shipped Standard.
- Days for shipment (scheduled) and ship_hour are indirectly correlated with late delivery risk.
- Days for shipping (real) and order hour are the strongest direct correlations with late delivery risk.

3) Data Preparation

This section focuses on the data preparation steps prior to training/testing a predictive model. After consideration of removal of outliers outside of the IQR (+/- 1.5sigma), it was decided to leave all remaining records in the data set for training and testing. Sales will have some outliers that may need to be considered periodically, so this will reflect closer to expected results for future sales. However, the suspected fraud and pending orders will be removed prior to feeding the data into the model.

In [92]:

```
'''
Review the current data set shape.
'''
df.shape
```

Out[92]:

```
(180519, 41)
```

In [93]:

```
'''
Overview the existing df.
'''
df.head()
```

Out[93]:

	Type	Days for shipping (real)	Days for shipment (scheduled)	Benefit per order	Sales per customer	Delivery Status	Late_delivery_risk	Category Name	Customer City	Cust Co
0	DEBIT	3	4	91.250000	314.640015	Advance shipping	0	Sporting Goods	Caguas	P
1	TRANSFER	5	4	-249.089996	311.359985	Late delivery	1	Sporting Goods	Caguas	P
2	CASH	4	4	-247.779999	309.720001	Shipping on time	0	Sporting Goods	San Jose	U
3	DEBIT	3	4	22.860001	304.809998	Advance shipping	0	Sporting Goods	Los Angeles	U
4	PAYMENT	2	4	134.210007	298.250000	Advance shipping	0	Sporting Goods	Caguas	P

5 rows × 41 columns

In [94]:

```
'''
Show the existing columns currently in the data set.
'''
df.columns
```

Out[94]:

```
Index(['Type', 'Days for shipping (real)', 'Days for shipment (scheduled)',
       'Benefit per order', 'Sales per customer', 'Delivery Status',
       'Late_delivery_risk', 'Category Name', 'Customer City',
       'Customer Country', 'Customer Id', 'Customer Segment', 'Customer State',
       'Customer Street', 'Department Name', 'Market', 'Order City',
       'Order Country', 'order date (DateOrders)', 'Order Item Discount',
       'Order Item Id', 'Order Item Product Price', 'Order Item Profit Ratio',
       'Order Item Quantity', 'Sales', 'Order Item Total',
       'Order Profit Per Order', 'Order Region', 'Order State', 'Order Status',
       'Product Name', 'Product Price', 'shipping date (DateOrders)',
       'Shipping Mode', 'order_year', 'order_month', 'order_week_day',
       'order_hour', 'order_month_year', 'delta_days_processing',
       'delta_days_shipping'],
      dtype='object')
```

In [95]:

```
'''
Removal of Suspected Fraud Orders data.
'''
df = df.loc[df['Order Status'] != 'SUSPECTED_FRAUD']
```

In [96]:

```
'''
Removal of Pending Orders data.
```

```
'''
df = df.loc[df['Order Status'] != 'PENDING']
```

Revisited the data understanding previously performed and found no major shifts or differences. I will keep the removal of the SUSPECTED_FRAUD and PENDING Order Status data at this step in the analysis.

In [97]:

```
'''
Review the current data set shape after removing Suspected Fraud and Pending Orders.
'''
df.shape
```

Out[97]:

```
(156230, 41)
```

Preparation for Sales Prediction

In [98]:

```
'''
Create df_sales
'''
df_sales = df[['Benefit per order', 'Order Item Discount',
                                 'Order Item Profit Ratio','Sales', 'Product Price']]
```

In [99]:

```
df_sales.shape
```

Out[99]:

```
(156230, 5)
```

In [100…

```
df_sales.head()
```

Out[100…

	Benefit per order	Order Item Discount	Order Item Profit Ratio	Sales	Product Price
0	91.250000	13.110000	0.29	327.75	327.75
2	-247.779999	18.030001	-0.80	327.75	327.75
3	22.860001	22.940001	0.08	327.75	327.75
4	134.210007	29.500000	0.45	327.75	327.75
5	18.580000	32.779999	0.06	327.75	327.75

In [101…

```
'''
Prior to performing any additional data preparation tasks, the data will be split into
a training and test set. Start by defining the features and target variables as X and y, r
The target variable will be price and the remaining columns will be the initial features.
'''
X = df_sales.drop('Sales', axis = 1)
y = df_sales['Sales']
```

In [102…

```
'''
Utilize the train_test_split() function to split data into a training and test data set.
I'll be splitting the entire data set into 80% Training and 20% Test.
'''
X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.2, random_state =
```

In [103…

```
'''
Understand/Verify the shape of the training and test data sets just created.
```

```
'''
print("The X_train shape is {} rows and {} columns.".format(X_train.shape[0],X_train.shape
print("The y_train shape is {} rows.".format(y_train.shape[0]))
print("The X_test shape is {} rows and {} columns.".format(X_test.shape[0],X_test.shape[1]
print("The y_test shape is {} rows.".format(y_test.shape[0]))
```

```
The X_train shape is 124984 rows and 4 columns.
The y_train shape is 124984 rows.
The X_test shape is 31246 rows and 4 columns.
The y_test shape is 31246 rows.
```

In [104…

```
'''
View the first 5 rows of the x_sales_train data set.
'''
X_train.head()
```

Out[104…

	Benefit per order	Order Item Discount	Order Item Profit Ratio	Product Price
112272	-326.119995	32.490002	-1.50	49.980000
9387	9.170000	14.400000	0.06	31.990000
65293	37.439999	5.200000	0.30	129.990005
178848	26.959999	16.990000	0.33	49.980000
138222	-240.110001	40.000000	-0.67	399.980011

In [105…

```
'''
View the first 5 rows of the x_sales_test data set. These should match.
'''
X_test.head()
```

Out[105…

	Benefit per order	Order Item Discount	Order Item Profit Ratio	Product Price
65453	12.180000	6.5	0.28	50.000000
83096	80.919998	51.0	0.33	299.980011
175916	7.950000	9.6	0.11	39.990002
7264	-138.520004	11.0	-0.73	99.989998
25351	0.000000	0.0	0.00	24.990000

Preparation for Late Delivery Prediction

In [106…

```
'''
Create df_late_Delivery
'''
df_ld = df[['Late_delivery_risk', 'Days for shipping (real)',
            'Days for shipment (scheduled)','Order Region',
            'Department Name', 'Category Name']]
```

In [107…

```
'''
Split the data into training and test set, where Late Delivery is the target.
'''
X_ld = df_ld.drop('Late_delivery_risk', axis = 1)
y_ld = df_ld['Late_delivery_risk']
```

In [108…

```
'''
Utilize the train_test_split() function to split data into a training and test data set.
I'll be splitting the entire data set into 80% Training and 20% Test.
'''
X_train_ld, X_test_ld, y_train_ld, y_test_ld = train_test_split(X_ld,y_ld, test_size = 0.3
```

In [109…

```
'''
Understand/Verify the shape of the training and test data sets just created.
'''
print("The X_train_ld shape is {} rows and {} columns.".format(X_train_ld.shape[0],X_trair
print("The y_train_ld shape is {} rows.".format(y_train_ld.shape[0]))
print("The X_test_ld shape is {} rows and {} columns.".format(X_test_ld.shape[0],X_test_lc
print("The y_test_ld shape is {} rows.".format(y_test_ld.shape[0]))
```

```
The X_train_ld shape is 109361 rows and 5 columns.
The y_train_ld shape is 109361 rows.
The X_test_ld shape is 46869 rows and 5 columns.
The y_test_ld shape is 46869 rows.
```

In [110…

```
'''
Create Dummy Variables for the categorical columns with first dummy variable dropped to pr
'''
X_train_ld = pd.get_dummies(X_train_ld, drop_first = True)
X_test_ld = pd.get_dummies(X_test_ld, drop_first = True)
```

In [111…

```
'''
Understand/Verify the shape of the training and test data sets just created.
'''
print("The X_train_ld shape is {} rows and {} columns.".format(X_train_ld.shape[0],X_trair
print("The X_test_ld shape is {} rows and {} columns.".format(X_test_ld.shape[0],X_test_lc
```

```
The X_train_ld shape is 109361 rows and 83 columns.
The X_test_ld shape is 46869 rows and 83 columns.
```

In [112…

```
'''
View the first 5 rows of the X_train data set.
'''
X_train_ld.head()
```

Out[112…

	Days for shipping (real)	Days for shipment (scheduled)	Order Region_Caribbean	Order Region_Central Africa	Order Region_Central America	Order Region_Central Asia	Order Region_East Africa	Regi
126098	4	2	0	0	0	0	0	
35718	2	1	0	0	0	0	0	
5064	4	4	0	0	0	0	0	
73390	4	4	0	0	0	0	0	
31830	4	4	0	0	1	0	0	

5 rows × 83 columns

In [113…

```
'''
View the first 5 rows of the X_test data set.These should match without any issues.
'''
X_test_ld.head()
```

Out[113…

	Days for shipping (real)	Days for shipment (scheduled)	Order Region_Caribbean	Order Region_Central Africa	Order Region_Central America	Order Region_Central Asia	Order Region_East Africa	Regi
65453	6	2	0	0	0	0	0	
83096	4	4	0	0	0	0	0	
175916	2	1	0	0	0	0	0	
7264	6	2	0	0	0	0	0	
25351	2	1	0	0	0	0	0	

5 rows × 83 columns

Highlights for Data Preparation:

- Removed records with Order Status equal to SUSPTECTED FRAUD and PENDING.
- Used Train, Test method to split data into 80% Training and 20% Testing subsets for Sales Models.
- Prepared df_sales for Sales Forecasting Models.
- Used Train, Test method to split data into 70% Training and 30% Testing subsets for Sales Models
- Prepared df_ld for Late Delivery Prediction Models.

4) Predictive Modeling

Predictive Model for Sales Forecasting - Linear Regression

In [114…

```
'''
Create a Linear Regression Model.
Fit the model to the training data sets (without PCA or Variance Threshold Performed)
Create predictions to validate the model performance on "unseen data".
Create predictions to validate the model performance on trained data.
'''
model_lr = LinearRegression()
model_lr.fit(X_train, y_train)
model_lr_prediction = model_lr.predict(X_test)
model_lr_prediction_train = model_lr.predict(X_train)
```

In [115…

```
'''
Calculate the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Erro
and R2 Score for the model on the train and test data.
'''
lr_mae = mean_absolute_error(y_test, model_lr_prediction)
lr_mse = mean_squared_error(y_test, model_lr_prediction)
lr_rmse = np.sqrt(lr_mse)
lr_r2 = r2_score(y_test, model_lr_prediction)
lr_r2_train = r2_score(y_train, model_lr_prediction_train)
print("MAE of the Linear Regression Model is:", round(lr_mae,4))
print("MSE of the Linear Regression Model is:", round(lr_mse,4))
print("RMSE of the Linear Regression Model is:", round(lr_rmse,4))
print("R2 Score of the Linear Regression Model on Test Data is:", round(lr_r2,4))
print("R2 Score of the Linear Regression Model on Train Data is:", round(lr_r2_train,4))
```

```
MAE of the Linear Regression Model is: 54.9142
MSE of the Linear Regression Model is: 5237.4988
RMSE of the Linear Regression Model is: 72.3706
R2 Score of the Linear Regression Model on Test Data is: 0.6983
R2 Score of the Linear Regression Model on Train Data is: 0.7047
```

Predictive Model for Sales Forecasting - Lasso Regression

In [116…

```
'''
Create a Lasso Regression Model.
Fit the model to the training data sets (without PCA or Variance Threshold Performed)
Create predictions to validate the model performance on "unseen data".
Create predictions to validate the model performance on trained data.
'''
model_lasso = Lasso()
model_lasso.fit(X_train, y_train)
model_lasso_prediction = model_lasso.predict(X_test)
model_lasso_prediction_train = model_lasso.predict(X_train)
```

In [117…

```
'''
Calculate the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error
and R2 Score for the model on the train and test data.
'''
lasso_mae = mean_absolute_error(y_test, model_lasso_prediction)
lasso_mse = mean_squared_error(y_test, model_lasso_prediction)
lasso_rmse = np.sqrt(lasso_mse)
lasso_r2 = r2_score(y_test, model_lasso_prediction)
lasso_r2_train = r2_score(y_train, model_lasso_prediction_train)
print("MAE of the Lasso Regression Model is:", round(lasso_mae,4))
print("MSE of the Lasso Regression Model is:", round(lasso_mse,4))
print("RMSE of the Lasso Regression Model is:", round(lasso_rmse,4))
print("R2 Score of the Lasso Regression Model on Test Data is:", round(lasso_r2,4))
print("R2 Score of the Lasso Regression Model on Train Data is:", round(lasso_r2_train,4))
```

```
MAE of the Lasso Regression Model is: 55.2038
MSE of the Lasso Regression Model is: 5235.6336
RMSE of the Lasso Regression Model is: 72.3577
R2 Score of the Lasso Regression Model on Test Data is: 0.6984
R2 Score of the Lasso Regression Model on Train Data is: 0.7039
```

Predictive Model for Sales Forecasting - Decision Tree

In [118…

```
'''
Create a Decision Tree Model.
Fit the model to the training data sets (without PCA or Variance Threshold Performed)
Create predictions to validate the model performance on "unseen data".
Create predictions to validate the model performance on trained data.
'''
model_dt = DecisionTreeRegressor()
model_dt.fit(X_train, y_train)
model_dt_prediction = model_dt.predict(X_test)
model_dt_prediction_train = model_dt.predict(X_train)
```

In [119…

```
'''
Calculate the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error
and R2 Score for the model on the train and test data.
'''
dt_mae = mean_absolute_error(y_test, model_dt_prediction)
dt_mse = mean_squared_error(y_test, model_dt_prediction)
dt_rmse = np.sqrt(dt_mse)
dt_r2 = r2_score(y_test, model_dt_prediction)
dt_r2_train = r2_score(y_train, model_dt_prediction_train)
print("MAE of the Decision Tree Model is:", round(dt_mae,4))
print("MSE of the Decision Tree Model is:", round(dt_mse,4))
print("RMSE of the Decision Tree Model is:", round(dt_rmse,4))
```

```
print("R2 Score of the Decision Tree Model on Test Data is:", round(dt_r2,4))
print("R2 Score of the Decision Tree Model on Train Data is:", round(dt_r2_train,4))
```

```
MAE of the Decision Tree Model is: 1.2707
MSE of the Decision Tree Model is: 95.6173
RMSE of the Decision Tree Model is: 9.7784
R2 Score of the Decision Tree Model on Test Data is: 0.9945
R2 Score of the Decision Tree Model on Train Data is: 0.9995
```

Predictive Model for Sales Forecasting - Random Forest Regressor

In [120…

```
'''
Create a Random Forest Model.
Fit the model to the training data sets (without PCA or Variance Threshold Performed)
Create predictions to validate the model performance on "unseen data".
Create predictions to validate the model performance on trained data.
'''
model_rf = RandomForestRegressor()
model_rf.fit(X_train, y_train)
model_rf_prediction = model_rf.predict(X_test)
model_rf_prediction_train = model_rf.predict(X_train)
```

In [121…

```
'''
Calculate the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Erro
and R2 Score for the model on the train and test data.
'''
rf_mae = mean_absolute_error(y_test, model_rf_prediction)
rf_mse = mean_squared_error(y_test, model_rf_prediction)
rf_rmse = np.sqrt(rf_mse)
rf_r2 = r2_score(y_test, model_rf_prediction)
rf_r2_train = r2_score(y_train, model_rf_prediction_train)
print("MAE of the Random Forest Model is:", round(rf_mae,4))
print("MSE of the Random Forest Model is:", round(rf_mse,4))
print("RMSE of the Random Forest Model is:", round(rf_rmse,4))
print("R2 Score of the Random Forest Model on Test Data is:", round(rf_r2,4))
print("R2 Score of the Random Forest Model on Train Data is:", round(rf_r2_train,4))
```

```
MAE of the Random Forest Model is: 1.2942
MSE of the Random Forest Model is: 57.0259
RMSE of the Random Forest Model is: 7.5515
R2 Score of the Random Forest Model on Test Data is: 0.9967
R2 Score of the Random Forest Model on Train Data is: 0.9992
```

Predictive Modeling for Late Deliveries - Logistic Regression

In [122…

```
'''
Setup the Logistic Regression Classifier.
Setting the class_weight to balanced.
'''
lr = LogisticRegression(solver = 'liblinear', multi_class='ovr', class_weight = 'balanced'
```

In [123…

```
'''
Fit the Logistic Regression Classifier on the training dataset.
'''
lr_classifier = lr.fit(X_train_ld, y_train_ld)
lr_classifier
```

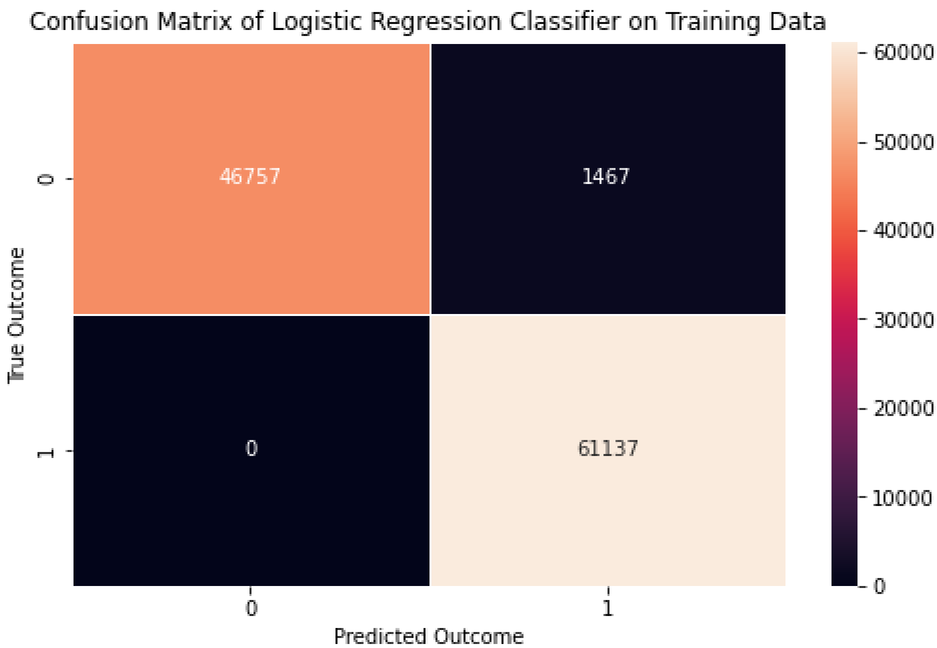
Out[123…

```
LogisticRegression(class_weight='balanced', multi_class='ovr',
                   solver='liblinear')
```

In [124…
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_lr_train = lr.predict(X_train_ld)
```

In [125…
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the training d
'''
cm_lr_train = confusion_matrix(y_train_ld, y_predictions_lr_train)
```

In [126…
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_lr_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Logistic Regression Classifier on Training Data')
plt.show()
```



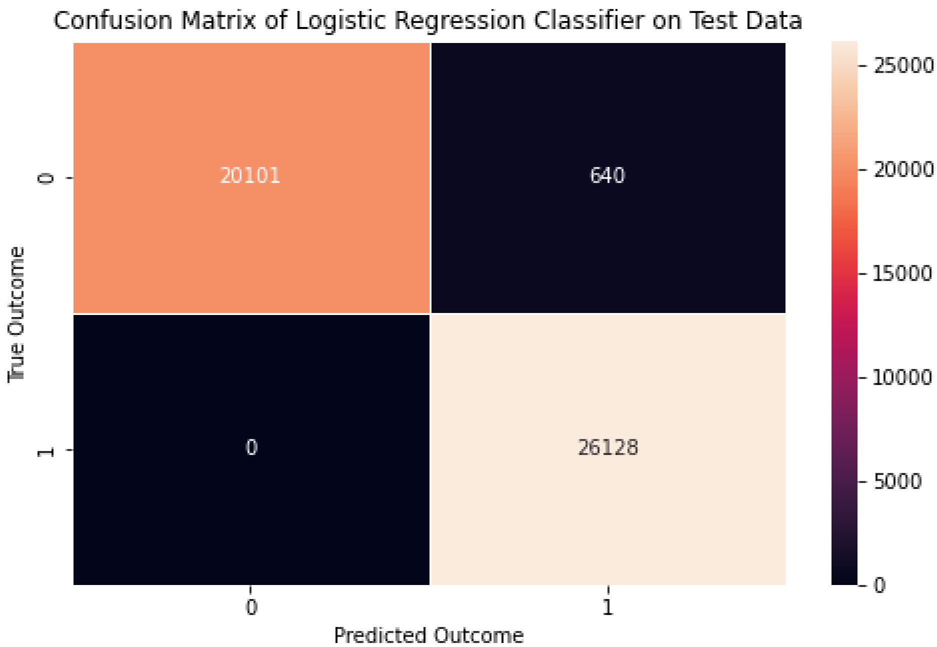
In [127…
```
'''
Obtain the y_prediction probabilities for each record in the test dataset.
'''
y_predictions_lr_test = lr.predict(X_test_ld)
```

In [128…
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the test datas
'''
cm_lr_test = confusion_matrix(y_test_ld, y_predictions_lr_test)
```

In [129…
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the test datas
'''
cm_lr_test = confusion_matrix(y_test_ld, y_predictions_lr_test)
```

In [130…
```
'''
```

```
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_lr_test, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Logistic Regression Classifier on Test Data')
plt.show()
```



In [131…

```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test_ld, y_predictions_lr_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     20741
           1       0.98      1.00      0.99     26128

    accuracy                           0.99     46869
   macro avg       0.99      0.98      0.99     46869
weighted avg       0.99      0.99      0.99     46869
```

In [132…

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_lr_train = accuracy_score(y_train_ld, y_predictions_lr_train)
accuracy_lr_test = accuracy_score(y_test_ld, y_predictions_lr_test)
precision_lr = precision_score(y_test_ld, y_predictions_lr_test)
recall_lr = recall_score(y_test_ld, y_predictions_lr_test)
f1_lr = f1_score(y_test_ld, y_predictions_lr_test)
print("Accuracy of Logistic Regression Model on training data is:{}".format(accuracy_lr_tr
print("Accuracy of Logistic Regression Model on testing data is:{}".format(accuracy_lr_tes
print("Precision of Logistic Regression Model on testing data is:{}".format(precision_lr))
print("Recall of Logistic Regression Model on testing data is:{}".format(recall_lr))
print("F1 Score of Logistic Regression Model on testing data is:{}".format(f1_lr))
```

```
Accuracy of Logistic Regression Model on training data is:0.986585711542506
Accuracy of Logistic Regression Model on testing data is:0.9863449188162752
Precision of Logistic Regression Model on testing data is:0.9760908547519426
```

Recall of Logistic Regression Model on testing data is:1.0
F1 Score of Logistic Regression Model on testing data is:0.9879007864488808

Predictive Modeling for Late Deliveries - Decision Tree Classifier

In [133…

```
'''
Standardize the X_train and X_test datasets for the remainder of the models being evaluate
'''
sc = StandardScaler()
X_train_ld = sc.fit_transform(X_train_ld)
X_test_ld = sc.transform(X_test_ld)
```

In [134…

```
'''
Create the Decision Tree Classifier.
'''
dt = DecisionTreeClassifier()
```

In [135…

```
'''
Fit the Decision Tree Classifier on the training dataset.
'''
decision_tree_classifier = dt.fit(X_train_ld, y_train_ld )
decision_tree_classifier
```

Out[135…

```
DecisionTreeClassifier()
```

In [136…

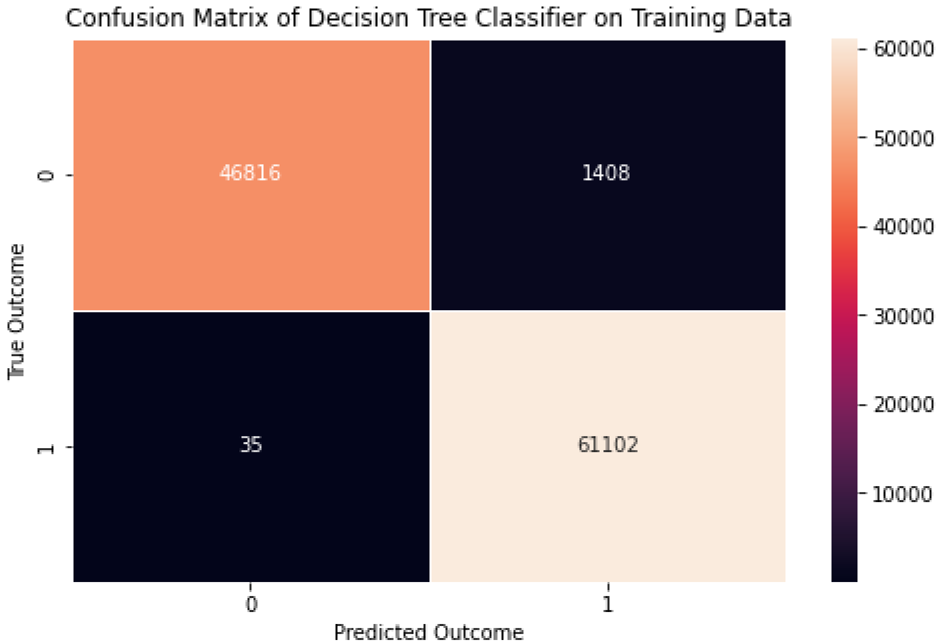
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_dt_train = dt.predict(X_train_ld)
```

In [137…

```
'''
Generate a Confusion Matrix for the Decision Tree Classifier based on the training dataset
'''
cm_dt_train = confusion_matrix(y_train_ld, y_predictions_dt_train)
```

In [138…

```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_dt_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Decision Tree Classifier on Training Data')
plt.show()
```

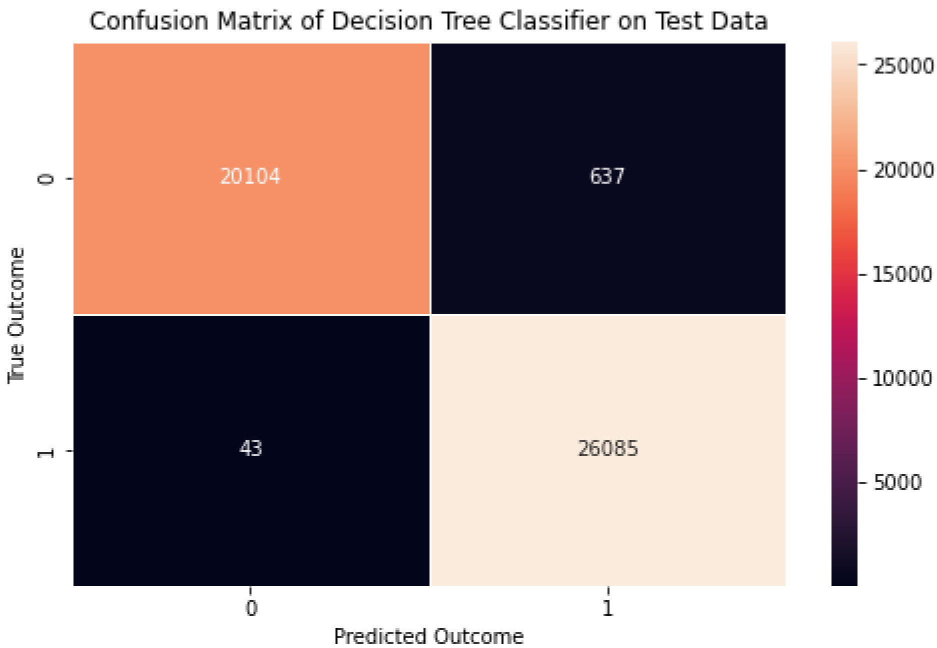


In [139…
```
'''
Obtain the y_predictions for the decision tree classifier.
'''
y_predictions_dt_test = dt.predict(X_test_ld)
```

In [140…
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_dt = confusion_matrix(y_test_ld, y_predictions_dt_test)
cm_dt
```

Out[140…
```
array([[20104,   637],
       [   43, 26085]], dtype=int64)
```

In [141…
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_dt, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Decision Tree Classifier on Test Data')
plt.show()
```



In [142…

```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test_ld ,y_predictions_dt_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     20741
           1       0.98      1.00      0.99     26128

    accuracy                           0.99     46869
   macro avg       0.99      0.98      0.99     46869
weighted avg       0.99      0.99      0.99     46869
```

In [143…

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_dt_train = accuracy_score(y_train_ld, y_predictions_dt_train)
accuracy_dt_test = accuracy_score(y_test_ld, y_predictions_dt_test)
precision_dt = precision_score(y_test_ld, y_predictions_dt_test)
recall_dt = recall_score(y_test_ld, y_predictions_dt_test)
f1_dt = f1_score(y_test_ld, y_predictions_dt_test)
print("Accuracy of Decision Tree Model on training data is:{}".format(accuracy_dt_train))
print("Accuracy of Decision Tree Model on testing data is:{}".format(accuracy_dt_test))
print("Precision of Decision Tree Model on testing data is:{}".format(precision_dt))
print("Recall of Decision Tree Model on testing data is:{}".format(recall_dt))
print("F1 Score of Decision Tree Model on testing data is:{}".format(f1_dt))
```

```
Accuracy of Decision Tree Model on training data is:0.9868051682043874
Accuracy of Decision Tree Model on testing data is:0.9854914762422924
Precision of Decision Tree Model on testing data is:0.9761619639248559
Recall of Decision Tree Model on testing data is:0.9983542559706062
F1 Score of Decision Tree Model on testing data is:0.9871333964049195
```

Predictive Modeling for Late Deliveries - Random Forest Classifier

In [144…

```
'''
Create the Random Forest Classifier.
Select number of estimators based on error reduction plot for this model.
```

```
'''
rf = RandomForestClassifier(n_estimators = 21)
```

In [145…

```
'''
Fit the Random Forest Classifier on the training dataset.
'''
random_forest_classifier = rf.fit(X_train_ld, y_train_ld)
random_forest_classifier
```

Out[145…

```
RandomForestClassifier(n_estimators=21)
```

In [146…

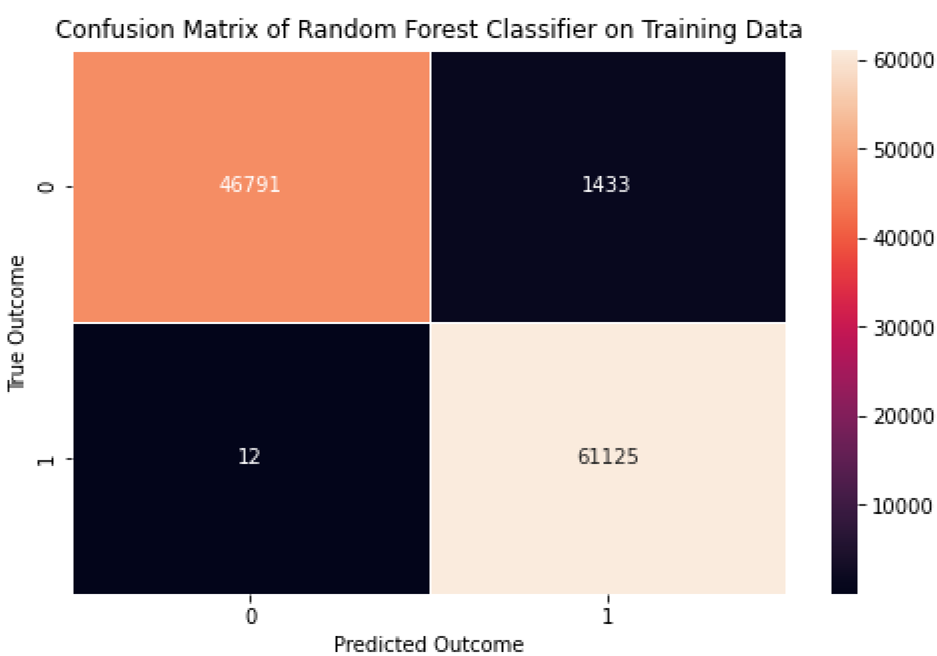
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_rf_train = rf.predict(X_train_ld)
```

In [147…

```
'''
Generate a Confusion Matrix for the Random Forest Classifier based on the training dataset
'''
cm_rf_train = confusion_matrix(y_train_ld, y_predictions_rf_train)
```

In [148…

```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_rf_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Random Forest Classifier on Training Data')
plt.show()
```



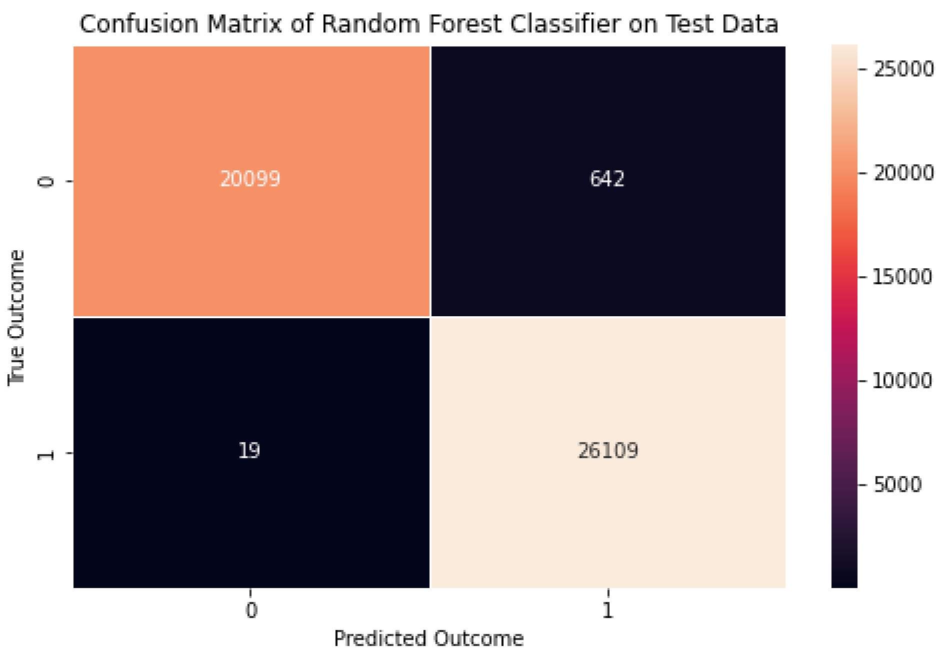
In [149…

```
'''
Obtain the y_predictions for the Random Forest classifier.
'''
y_predictions_rf_test = rf.predict(X_test_ld)
```

In [150…
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_rf = confusion_matrix(y_test_ld, y_predictions_rf_test)
cm_rf
```

Out[150…
```
array([[20099,   642],
       [   19, 26109]], dtype=int64)
```

In [151…
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_rf, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Random Forest Classifier on Test Data')
plt.show()
```

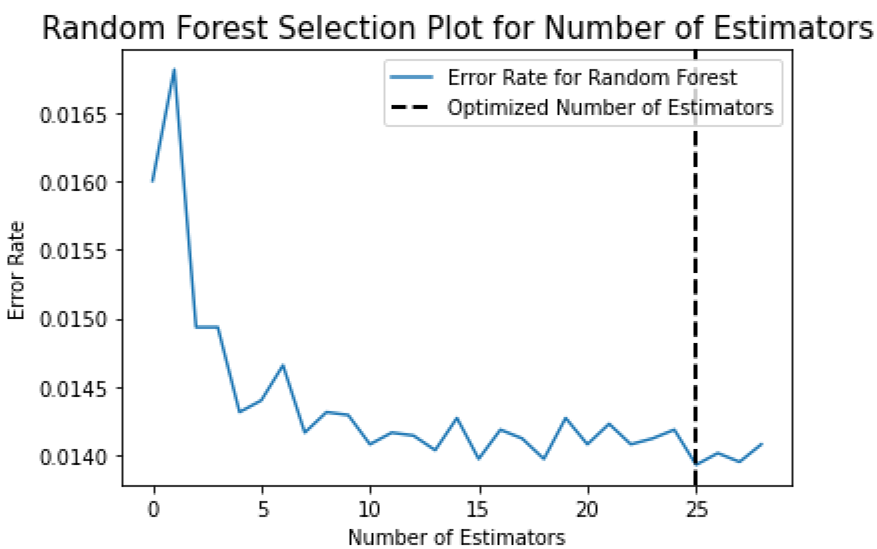


In [152…
```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test_ld, y_predictions_rf_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     20741
           1       0.98      1.00      0.99     26128

    accuracy                           0.99     46869
   macro avg       0.99      0.98      0.99     46869
weighted avg       0.99      0.99      0.99     46869
```

In [153…
```
'''
Choose an optimal number of estimators for Random Forest by plotting the error rate for th
'''
# Create an empty list for error rate.
error_rate_rf = []

# Create a for loop to get error rates appended to the error_rate list.
```

```
for i in np.arange(1, 30):

    new_model = RandomForestClassifier(n_estimators = i)

    new_model.fit(X_train_ld, y_train_ld)

    new_predictions = new_model.predict(X_test_ld)

    error_rate_rf.append(np.mean(new_predictions != y_test_ld))

# Create the plot to assist with selecting a K value for the KNN classifier.
plt.plot(error_rate_rf, label = 'Error Rate for Random Forest')
plt.title("Random Forest Selection Plot for Number of Estimators", fontsize=15)
plt.xlabel("Number of Estimators", fontsize=10)
plt.ylabel("Error Rate", fontsize=10)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.axvline(x=pd.Series(error_rate_rf).idxmin(), linewidth = 2, color = 'k', linestyle = '
            label = 'Optimized Number of Estimators')
plt.legend(loc = 'upper right')
plt.show()
```



In [154…

```
'''
Show the optimum number of estimators on the plot above.
'''
print('Optimum number of estimators for Random Forest:{}'.format(pd.Series(error_rate_rf).
```

Optimum number of estimators for Random Forest:25

In [155…

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_rf_train = accuracy_score(y_train_ld, y_predictions_rf_train)
accuracy_rf_test = accuracy_score(y_test_ld, y_predictions_rf_test)
precision_rf = precision_score(y_test_ld, y_predictions_rf_test)
recall_rf = recall_score(y_test_ld, y_predictions_rf_test)
f1_rf = f1_score(y_test_ld, y_predictions_rf_test)
print("Accuracy of Random Forest Model on training data is:{}".format(accuracy_rf_train))
print("Accuracy of Random Forest Model on testing data is:{}".format(accuracy_rf_test))
print("Precision of Random Forest Model on testing data is:{}".format(precision_rf))
print("Recall of Random Forest Model on testing data is:{}".format(recall_rf))
print("F1 Score of Random Forest Model on testing data is:{}".format(f1_rf))
```

Accuracy of Random Forest Model on training data is:0.9867868801492305

```
Accuracy of Random Forest Model on testing data is:0.9858968614649342
Precision of Random Forest Model on testing data is:0.9760008971627229
Recall of Random Forest Model on testing data is:0.9992728107777097
F1 Score of Random Forest Model on testing data is:0.9874997636112633
```

Highlights for Predictive Modeling:

- Sales Forecasting had 4 models trained and tested: Linear Regression, Lasso Regression, Decision Tree Regressor, and Random Forest Regressor.
- Late Delivery prediction had 3 models trained and tested: Logistic Regression, Decision Tree Classifier, Random Forest Classifier.

5) Evaluation

Sales Forecasting Evaluation

In [156…

```
'''
Create a dictionary summarizing the evaluation criteria for the four models.
'''
summary_data_sales = OrderedDict([('MAE', [lr_mae, lasso_mae, dt_mae, rf_mae]),
                          ('MSE', [lr_mse, lasso_mse, dt_mse, rf_mse]),
                          ('RMSE', [lr_rmse, lasso_rmse, dt_rmse, rf_rmse]),
                          ('R2_Score_Train', [lr_r2_train, lasso_r2_train, dt_r2_train, r
                          ('R2_Score_Test', [lr_r2, lasso_r2, dt_r2, rf_r2]),
                          ('Model', ['LinearRegression','Lasso', 'DecisionTree','RandomFo
```

In [159…

```
'''
Display the summary evaluation metrics for the four models in a pandas dataframe.
'''
summary_df_sales = pd.DataFrame(summary_data_sales, index = summary_data_sales['Model'])
```

In [160…

```
'''
Sort the values based on the highest R-Squared Score on the test data.
'''
summary_df_sales.sort_values(by = "R2_Score_Test", ascending = False)
```

Out[160…

	MAE	MSE	RMSE	R2_Score_Train	R2_Score_Test	Model
RandomForest	1.294214	57.025861	7.551547	0.999179	0.996715	RandomForest
DecisionTree	1.270657	95.617256	9.778408	0.999530	0.994493	DecisionTree
Lasso	55.203839	5235.633555	72.357678	0.703851	0.698444	Lasso
LinearRegression	54.914229	5237.498800	72.370566	0.704701	0.698337	LinearRegression

Late Delivery Prediction Evaluation

In [161…

```
'''
Create a dictionary summarizing the evaluation criteria for the models.
'''
summary_data_ld = OrderedDict([('Model', ['Logistic_Regression', 'Decision_Tree','Random_F
                          ('Model_Accuracy_Test',[accuracy_lr_test, accuracy_dt_test, acc
                           ('Model_Accuracy_Training',[accuracy_lr_train, accuracy_dt_tra
                          ('Model_Precision_Score',[precision_lr, precision_dt, precision
                          ('Model_Recall_Score',[recall_lr,recall_dt,recall_rf]),
                          ('Model_F1_Score', [f1_lr,f1_dt, f1_rf]),])
```

In [162…

```
'''
Display the summary evaluation metrics for the six models in a pandas dataframe.
Sort the Models based on accuracy for each model from the test dataset.
'''
summary_df_ld = pd.DataFrame(summary_data_ld, index = summary_data_ld['Model'])
display(summary_df_ld.sort_values(by = 'Model_Accuracy_Test', ascending = False))
```

	Model	Model_Accuracy_Test	Model_Accuracy_Training	Model_Precision_Score	Model_
Logistic_Regression	Logistic_Regression	0.986345	0.986586	0.976091	
Random_Forest	Random_Forest	0.985897	0.986787	0.976001	
Decision_Tree	Decision_Tree	0.985491	0.986805	0.976162	

In [163…

```
'''
Create a list of the models stored in a tuple along with the name.
'''
models = []
models.append(('Logistic_Regression', lr))
models.append(('Decision_Tree', dt))
models.append(('Random_Forest', rf))
```

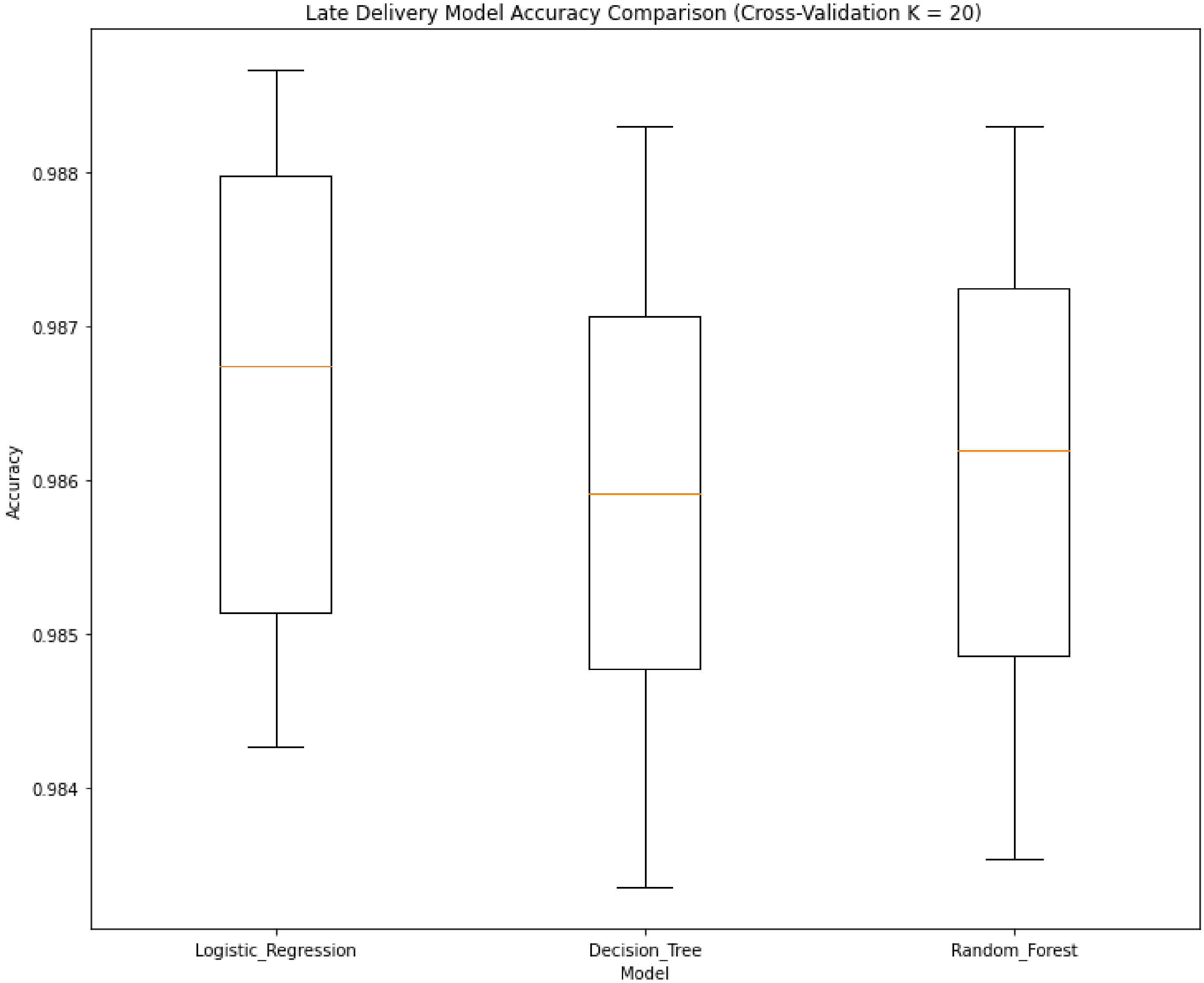
In [164…

```
'''
Check the models on 20 splits using kfold cross-validation.
'''
cv_results = []
names = []

for name,model in models:
    kfold = StratifiedKFold(n_splits = 20)
    results = cross_val_score(model, X_train_ld, y_train_ld, cv = kfold, scoring = 'accura
    cv_results.append(results)
    names.append(name)
    print('Model Type:{}, Average Accuracy Score: {}, Standard Deviation: {}'.format(name,
                                                                                    rour
                                                                                    rour
```

```
Model Type:Logistic_Regression, Average Accuracy Score: 0.9866, Standard Deviation: 0.0015
Model Type:Decision_Tree, Average Accuracy Score: 0.9858, Standard Deviation: 0.0014
Model Type:Random_Forest, Average Accuracy Score: 0.9861, Standard Deviation: 0.0014
```

In [165…

```
'''
Plot the model performance to show which models perform
the most accurate along with which models have the most variation in accuracy.
'''
plt.figure(figsize = (12,10))
plt.boxplot(cv_results, labels = names)
plt.title("Late Delivery Model Accuracy Comparison (Cross-Validation K = 20)")
plt.xlabel("Model")
plt.ylabel("Accuracy")
plt.show()
```



Highlights for Evaluation:

- Random Forest Regressor is best method for Sales Forecasting. (99.7% R2 score on test data)
- Logistic Regression Classifier is best method for Late Delivery Prediction. (98.7% Accuracy after 20 k-folds cross-validation)

6) Deployment Recommendation

The Random Forest Regressor for prediction of sales and the Logistic Regression Classifier for late delivery prediction appear ready for deployment. Prior to releasing the models, a few recommendations need to be made. First, recommend consulting technical experts within the supply chain group to confirm/discuss the findings. In addition, the data utilized in this analysis was from 2015-2018. I recommend utilizing more up-to-date data for training and testing. Lastly, I would recommend trying some alternative models for each case study to see if there are any additional improvements to the current model performance. Additional actions from this analysis include looking into the decline in sales from 2017-2018, investigating high profit orders from customers, and adjusting the scheduled delivery days currently used (or improve the lead time for days between orders processed and orders shipped).

Create Results Directory

In [172…

```
results_dir = Path('C:/Users/jkmey/Documents/Github/DSC680_Course_Assignments/DSC_680_Appl
```

```
results_dir.mkdir(parents=True, exist_ok = True)
```

In [173…

```
'''
Save the Random Forest Model.
'''
rf_result_model_file = results_dir.joinpath('Sales_Forecasting_Model_RF.h5')
pickle.dump(model_rf, open(rf_result_model_file, 'wb'))
```

In [176…

```
'''
Save the Logistic Regression Model.
'''
lr_result_model_file = results_dir.joinpath('Late_Delivery_Model_RF.h5')
pickle.dump(lr_classifier, open(lr_result_model_file, 'wb'))
```