GLOBAL SUPERSTORE DATASET SALES ANALYSIS

By Student ID: 202410472

1. Task 1

Import required Python Libraries

In [ ]:
```
# pip install packages
import sys
!{sys.executable} -m pip install word2number
!{sys.executable} -m pip install geopandas
!{sys.executable} -m pip install adjustText

# import libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import socket
import requests
import geopandas as gpd

from matplotlib import ticker as mtick
from tabulate import tabulate
from scipy.stats import chi2_contingency
from word2number import w2n
from adjustText import adjust_text

# Letting pandas to show max columns
pd.set_option('display.max_columns', None)

# Set the style for seaborn plots
sns.set_theme(style="whitegrid")
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: word2number in c:\users\nares\appdata\roaming\pytho
n\python311\site-packages (1.1)
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: geopandas in c:\users\nares\appdata\roaming\python
\python311\site-packages (0.14.3)
Requirement already satisfied: fiona>=1.8.21 in c:\users\nares\appdata\roaming\pyt
hon\python311\site-packages (from geopandas) (1.9.6)
Requirement already satisfied: packaging in c:\programdata\anaconda3\lib\site-pack
ages (from geopandas) (23.1)
Requirement already satisfied: pandas>=1.4.0 in c:\programdata\anaconda3\lib\site-
packages (from geopandas) (2.0.3)
Requirement already satisfied: pyproj>=3.3.0 in c:\users\nares\appdata\roaming\pyt
hon\python311\site-packages (from geopandas) (3.6.1)
Requirement already satisfied: shapely>=1.8.0 in c:\users\nares\appdata\roaming\py
thon\python311\site-packages (from geopandas) (2.0.4)
Requirement already satisfied: attrs>=19.2.0 in c:\programdata\anaconda3\lib\site-
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Requirement already satisfied: certifi in c:\programdata\anaconda3\lib\site-packag
es (from fiona>=1.8.21->geopandas) (2024.2.2)
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kages (from fiona>=1.8.21->geopandas) (8.0.4)
Requirement already satisfied: click-plugins>=1.0 in c:\users\nares\appdata\roamin
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Requirement already satisfied: cligj>=0.5 in c:\users\nares\appdata\roaming\python
\python311\site-packages (from fiona>=1.8.21->geopandas) (0.7.2)
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site-packages
(from fiona>=1.8.21->geopandas) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\programdata\anaconda3
\lib\site-packages (from pandas>=1.4.0->geopandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\programdata\anaconda3\lib\site-p
ackages (from pandas>=1.4.0->geopandas) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\programdata\anaconda3\lib\site
-packages (from pandas>=1.4.0->geopandas) (2023.3)
Requirement already satisfied: numpy>=1.21.0 in c:\programdata\anaconda3\lib\site-
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ges (from click~=8.0->fiona>=1.8.21->geopandas) (0.4.6)
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: adjustText in c:\users\nares\appdata\roaming\python
\python311\site-packages (1.1.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-packages
(from adjustText) (1.24.3)
Requirement already satisfied: matplotlib in c:\programdata\anaconda3\lib\site-pac
kages (from adjustText) (3.7.2)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-packages
(from adjustText) (1.11.1)
Requirement already satisfied: contourpy>=1.0.1 in c:\programdata\anaconda3\lib\si
te-packages (from matplotlib->adjustText) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3\lib\site-p
ackages (from matplotlib->adjustText) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\programdata\anaconda3\lib\s
ite-packages (from matplotlib->adjustText) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anaconda3\lib\s
ite-packages (from matplotlib->adjustText) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\programdata\anaconda3\lib\sit
e-packages (from matplotlib->adjustText) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3\lib\site-
packages (from matplotlib->adjustText) (10.0.1)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in c:\programdata\anaconda3\l
ib\site-packages (from matplotlib->adjustText) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\programdata\anaconda3\li
b\site-packages (from matplotlib->adjustText) (2.8.2)
```

```
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-packa
ges (from python-dateutil>=2.7->matplotlib->adjustText) (1.16.0)
```

Load first 10 records

In [ ]:

```
# Reading CSV file and assigning into a dataframe ss_data
global_super_store_df_org = pd.read_csv('sample-superstore 2023 T3.csv')

# Copy the dataframe before processing
global_super_store_df = global_super_store_df_org.copy()

# Get the first 1000 records only for the EDA
global_super_store_df = global_super_store_df.head(n=1000)

# Set the head to 10 to retrieve the first 10 records
first_10_rows = global_super_store_df.head(n=10)
print(tabulate(first_10_rows, headers='keys', tablefmt='pretty', stralign ='right',
```

Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	State	Postal Code	Region	Product ID	Category	Sub-Category	Product Name	Sales	Quantity	Discount	Profit
7773	CA-2016-108196	25/11/2016	12/02/2016	Standard Class	CS-12505	Cindy Stewart	Consumer	United States	Lancaster	Ohio	43130	Est	TEC-MA-10000418	Technology	Machines	Cubify CubeX 3D Printer Double Head Print	4499.985	5	0.7	-6599.978
684	US-2017-168116	11/04/2017	11/04/2017	Same Day	GT-14635	Grant Thornton	Corporate	United States	Burlington	North Carolina	"27217"	South	TEC-MA-10004125	Technology	Machines	Cubify CubeX 3D Printer Triple Head Print	7999.98	4	0.5	-3839.9904
9775	CA-2014-169019	26/07/2014	30/07/2014	Standard Class	LF-17185	Luke Foster	Consumer	United States	San Antonio	Texas	78207	Central	OFF-BI-10004995	Office Supplies	Binders	GBC DocuBind P400 Electric Binding System	2177.584	8	0.8	-3701.8928
3012	CA-2017-134845	17/04/2017	24/04/2017	Standard Class	SR-20425	Sharelle Roach	Home Office	United States	Louisville	Colorado	80027	West	TEC-MA-10000822	Technology	Machines	Lexmark MX611dhe Monochrome Laser Printer	2549.985	5	0.7	-3399.98
4992	US-2017-122714	12/07/2017	13/12/2017	Standard Class	HG-14965	Henry Goldwyn	Corporate	United States	Chicago	Illinois	60653	Central	OFF-BI-10001120	Office Supplies	Binders	Ibico EPK-21 Electric Binding System	1889.99	5	0.8	-2929.4845
3152	CA-2015-147830	15/12/2015	18/12/2015	First Class	NF-18385	Natalie Fritzler	Consumer	United States	Newark	Ohio	43055	East	TEC-MA-10000418	Technology	Machines	Cubify CubeX 3D Printer Double Head Print	1799.994	Two	0.7	"-2639.9912"
5311	CA-2017-131254	19/11/2017	21/11/2017	First Class	NC-18415	Nathan Cano	Consumer	United States	Houston	Texas	77095	Central	OFF-BI-10003527	Office Supplies	Binders	Fellowes PB500 Electric Punch Plastic Comb Binding Machine with Manual Bind	1525.188	6	0.8	-2287.782
9640	CA-2015-116638	28/01/2015	nan	Second Class	JH-15985	Joseph Holt	Consumer	United States	Concord	North Carolina	28027	South	FUR-TA-10000198	Frnture	Tables	Chromcraft Bull-Nose Wood Oval Conference Tables & Bases	4297.644	Thirteen	0.4	nan
1200	CA-2016-130946	04/08/2016	04/12/2016	Standard Class	ZC-21910	Zuschuss Carroll	Consumer	United States	Houston	Texas	77041	Central	OFF-BI-10004995	Office Supplies	Binders	GBC DocuBind P400 Electric Binding System	1088.792	4	0.8	-1850.9464
2698	CA-2014-145317	18/03/2014	23/03/2014	Standard Class	SM-20320	Sean Miller	Home Office	nan	Jacksonville	Florida	32216	Southh	TEC-MA-10002412	Technology	Machines	Cisco TelePresence System EX90 Videoconferencing Unit	22638.48	6	0.5	-1811.0784

```
+--------+---------------+------------+------------+---------------+------------
-+-----------------+-------------+--------------+-------------+---------------
+-------------+---------+----------------+-----------------+-------------+------
-------------------------------------------------------------------------+----------
+----------+----------+--------------+
```

Understanding of the dataset

Information of descriptive statistics

Using info() and describe() function to get the descriptive statistics

In [ ]:
```
# Get the metadata information about the dataset
# Grouping data types by category
numerical_columns = global_super_store_df.select_dtypes(include=['int64', 'float64'
categorical_columns = global_super_store_df.select_dtypes(include=['object']).colum
datetime_columns = global_super_store_df.select_dtypes(include=['datetime64']).colu

# Define a table width and print the header row with a dotted line
table_width = 250
print("-" * table_width)

# Print each row of the table with content and a dash line
content_list = [f"We are working with a {global_super_store_df.shape} sized dataset
                    f"Numercial columns: {', '.join(numerical_columns)}",
                    f"Categorical columns: {', '.join(categorical_columns)}",
                    f"Date Time columns: {', '.join(datetime_columns)}"]

for content_row in content_list:
    print("| {:<246} |".format(content_row))
    print("-" * table_width)

# Print the table
print(tabulate(global_super_store_df.describe(), headers='keys', tablefmt='pretty',
```

```
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----
| We are working with a (1000, 21) sized dataset.
|
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----
| Numercial columns: Row ID, Sales, Discount
|
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----
| Categorical columns: Order ID, Order Date, Ship Date, Ship Mode, Customer ID, Cu
stomer Name, Segment, Country, City, State, Postal Code, Region, Product ID, Categ
ory, Sub-Category, Product Name, Quantity, Profit
|
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----
| Date Time columns:
|
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----
+-------------------+--------------------+----------------------+
|            Row ID |              Sales |             Discount |
+-------------------+--------------------+----------------------+
|            1000.0 |              999.0 |                999.0 |
|          5033.065 | 415.95479939939935 |  0.4533433433433433 |
| 2955.719828481633 |  940.7397657620787 | 0.22030138136310903 |
|               4.0 |              8.652 |                 0.15 |
|            2435.0 |            73.8495 |                  0.2 |
|            5014.0 |            218.352 |                  0.4 |
|           7727.75 |            475.779 |                  0.7 |
|            9963.0 |           22638.48 |                  0.8 |
+-------------------+--------------------+----------------------+
```

In [ ]:
```
# Print metatype information about the dataset
print(global_super_store_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         1000 non-null   int64
 1   Order ID       999 non-null    object
 2   Order Date     998 non-null    object
 3   Ship Date      997 non-null    object
 4   Ship Mode      997 non-null    object
 5   Customer ID    1000 non-null   object
 6   Customer Name  997 non-null    object
 7   Segment        997 non-null    object
 8   Country        996 non-null    object
 9   City           999 non-null    object
 10  State          998 non-null    object
 11  Postal Code    998 non-null    object
 12  Region         999 non-null    object
 13  Product ID     998 non-null    object
 14  Category       999 non-null    object
 15  Sub-Category   996 non-null    object
 16  Product Name   997 non-null    object
 17  Sales          999 non-null    float64
 18  Quantity       995 non-null    object
 19  Discount       999 non-null    float64
 20  Profit         989 non-null    object
dtypes: float64(2), int64(1), object(18)
memory usage: 164.2+ KB
None
```

Missing Data Analysis

In [ ]:

```python
# Count the number of missing values in each column
missing_values_per_column = global_super_store_df.isna().sum()

# Convert the Series to a DataFrame for tabulation
missing_values_df = missing_values_per_column.to_frame().reset_index()
missing_values_df.columns = ['Column', 'Missing Values']

# Print the tabulated missing values per column
print("Number of missing values per column:\n")
print(tabulate(missing_values_df, headers='keys', tablefmt='pretty', stralign ='rig

# Count the total number of missing values across all columns
total_missing_values = missing_values_per_column.sum()

# Print the total number of missing values
print("\nTotal number of missing values:", total_missing_values)
```

```
Number of missing values per column:

+---------------+----------------+
|        Column | Missing Values |
+---------------+----------------+
|        Row ID |              0 |
|      Order ID |              1 |
|    Order Date |              2 |
|     Ship Date |              3 |
|     Ship Mode |              3 |
|   Customer ID |              0 |
| Customer Name |              3 |
|       Segment |              3 |
|       Country |              4 |
|          City |              1 |
|         State |              2 |
|   Postal Code |              2 |
|        Region |              1 |
|    Product ID |              2 |
|      Category |              1 |
|  Sub-Category |              4 |
|  Product Name |              3 |
|         Sales |              1 |
|      Quantity |              5 |
|      Discount |              1 |
|        Profit |             11 |
+---------------+----------------+

Total number of missing values: 53
```

The primary key of these records are a system-generated, and denoted as column: *RowID*

The datatypes of the dataset are following:

- int64(1)
- float64(2)
- object(18)

A few records of *Quantity* and *Profit* columns has the datatype of object, but it must be float64, thus needs to be cleansed or transformed.

Ship Date and *Order Date* columns are represented as strings, those needs to be converted as datetime.

Once cleansed, the descriptive statistics can be applied to the numerial columns, and they are Sales, Quantity, Discount and Profit/Loss.

Histograms based on categorical features

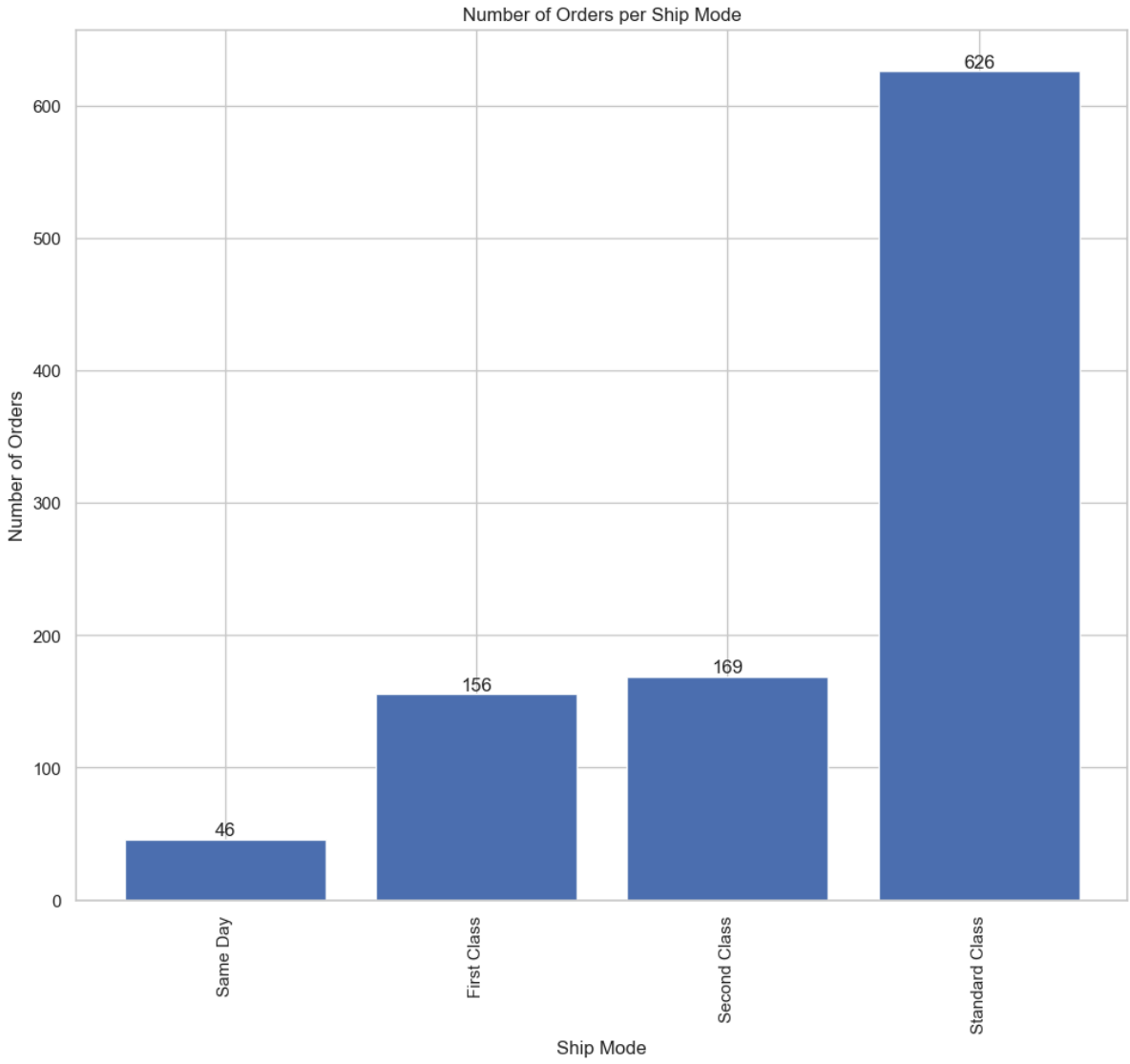
Function to generate a histogram plot for the given dataset.

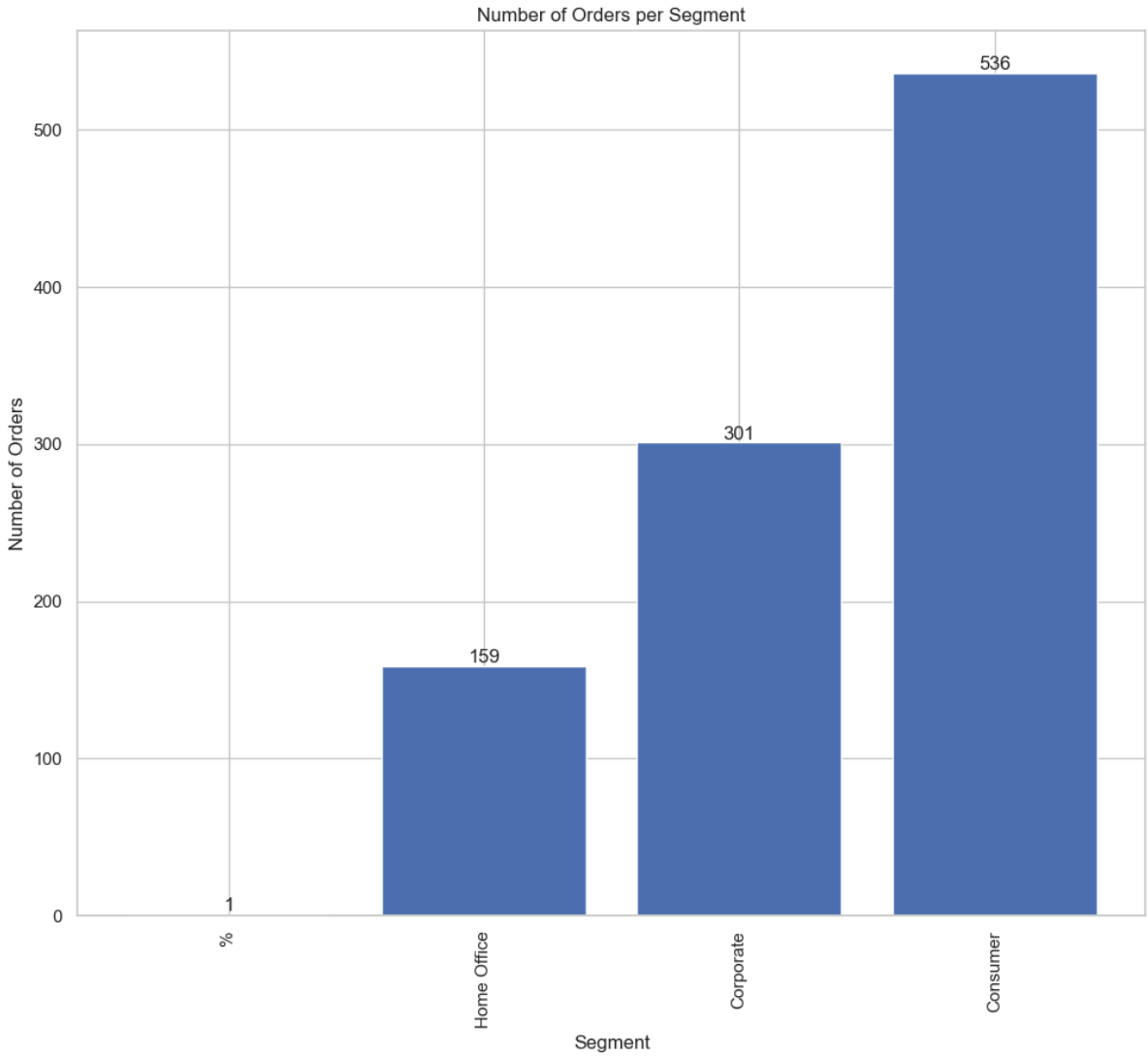
In [ ]:
```
def plot_histogram(data, xlabel, ylabel, title):
    """
    plot_histogram generates a histogram plot for the given dataset.
    Parameters:
      data: Dataset for the histogram plot (pandas Series or any iterable).
      xlabel: Label for the x-axis.
      ylabel: Label for the y-axis.
      title: Title of the plot.
```

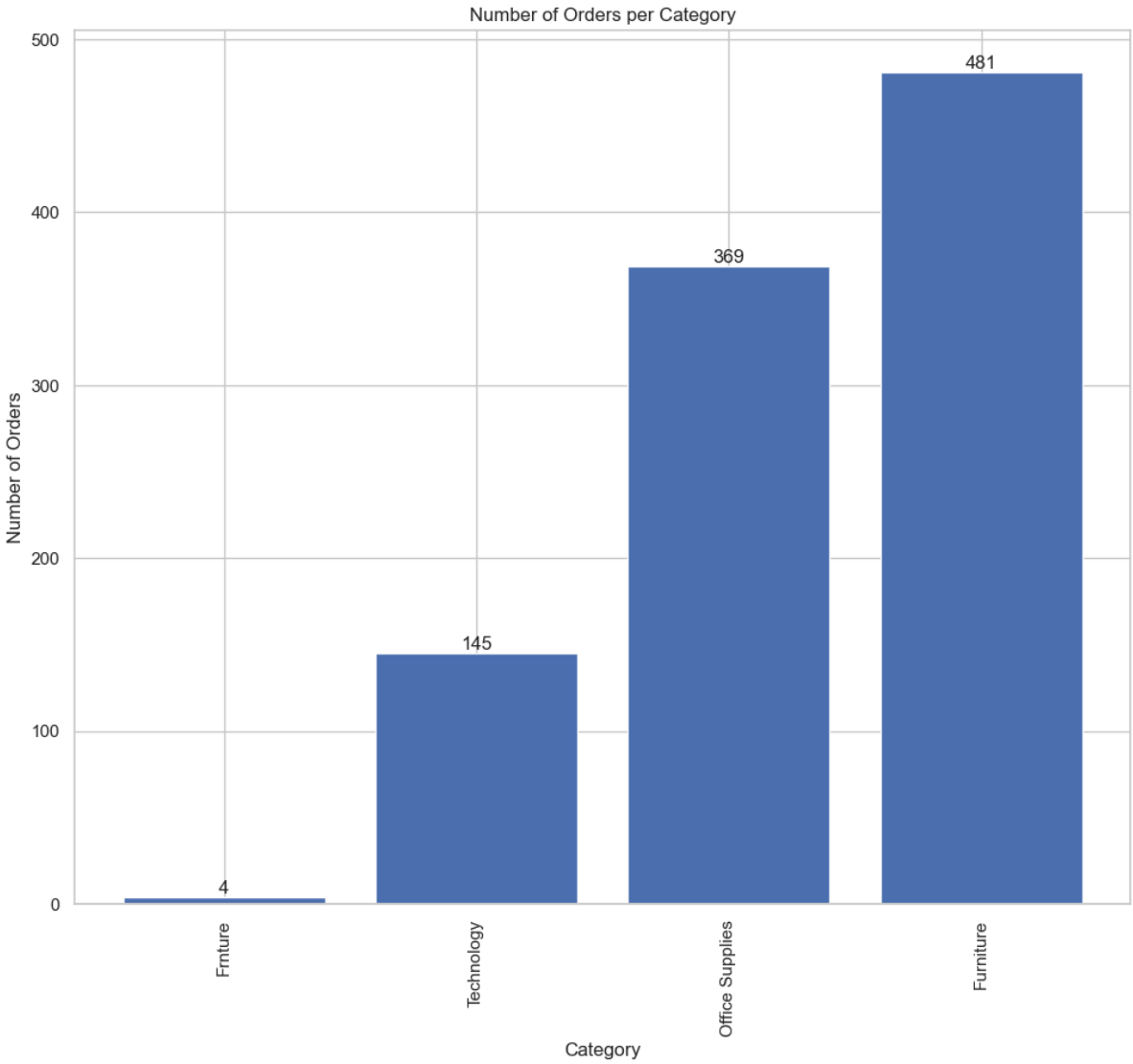
```
    Returns:
      None
    """

    plt.figure(figsize=(12, 10))

    bars = plt.bar(data.index, data)

    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.xticks(rotation=90)

    for bar in bars:
        height = bar.get_height()
        plt.text(bar.get_x() + bar.get_width() / 2, height, height, ha='center', va
    plt.show()
```

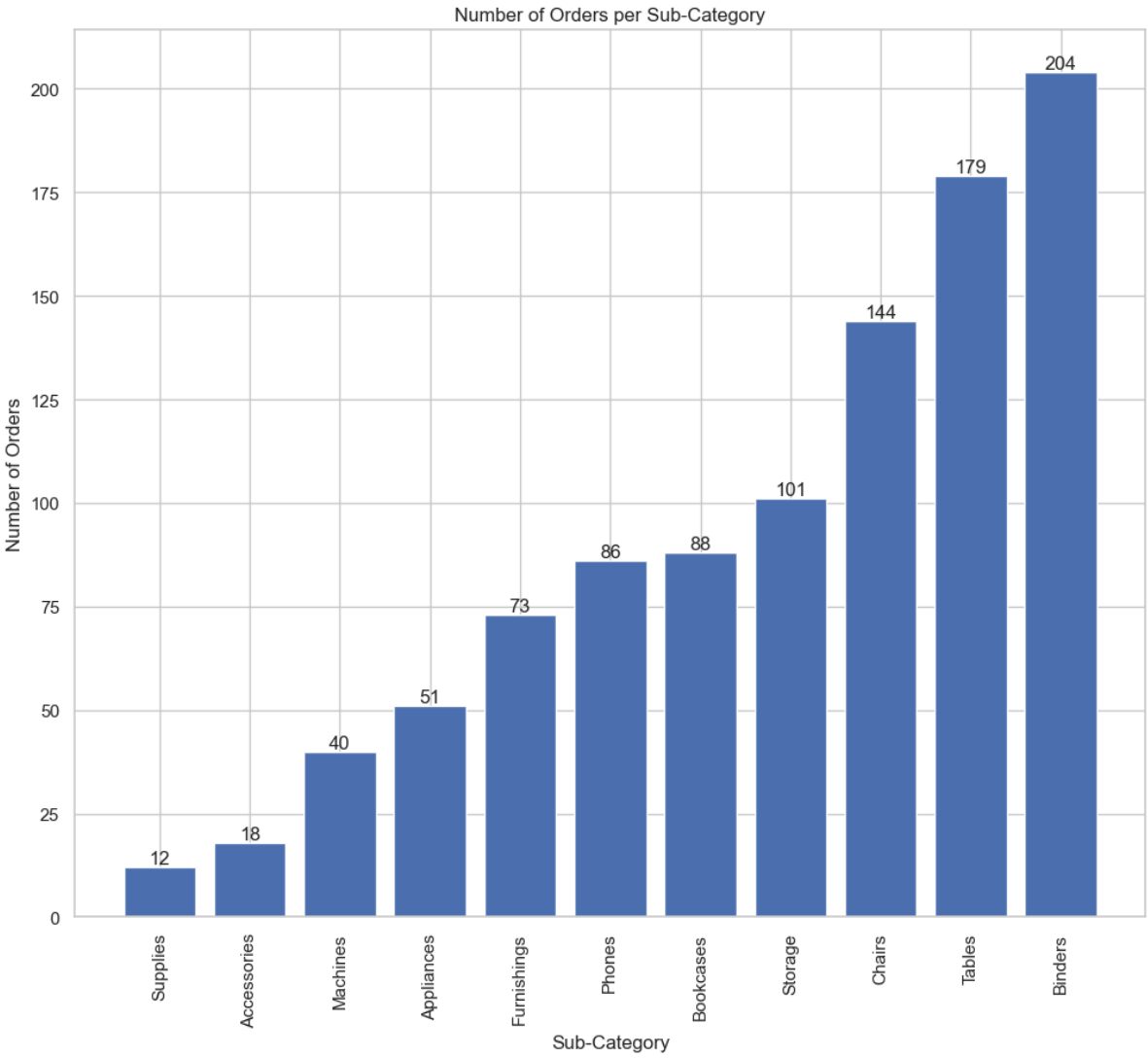
In [ ]:

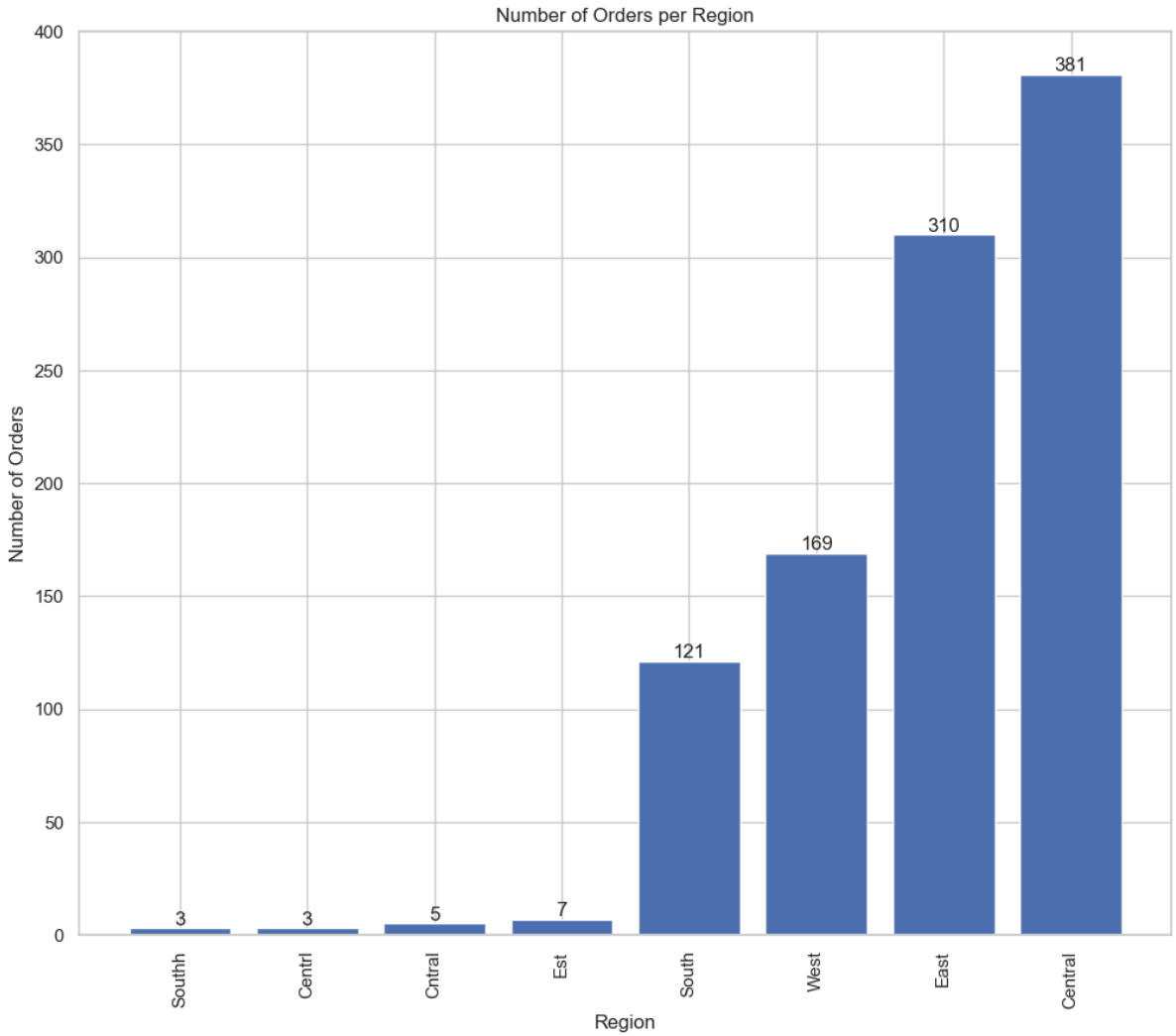
```
# Histogram for 'Ship Mode'
orders_per_segment = global_super_store_df['Ship Mode'].value_counts(ascending=True
plot_histogram(orders_per_segment, 'Ship Mode', 'Number of Orders', 'Number of Orde

# Histogram for 'Segment'
orders_per_segment = global_super_store_df['Segment'].value_counts(ascending=True)
plot_histogram(orders_per_segment, 'Segment', 'Number of Orders', 'Number of Orders

# Histogram for 'Category'
orders_per_category = global_super_store_df['Category'].value_counts(ascending=True
plot_histogram(orders_per_category, 'Category', 'Number of Orders', 'Number of Orde

# Histogram for 'Sub-Category'
orders_per_sub_category = global_super_store_df['Sub-Category'].value_counts(ascend
plot_histogram(orders_per_sub_category, 'Sub-Category', 'Number of Orders', 'Number

# Histogram for 'Region'
orders_per_sub_category = global_super_store_df['Region'].value_counts(ascending=Tr
plot_histogram(orders_per_sub_category, 'Region', 'Number of Orders', 'Number of Or

# Histogram for 'State'
orders_per_sub_category = global_super_store_df['State'].value_counts(ascending=Tru
plot_histogram(orders_per_sub_category, 'State', 'Number of Orders', 'Number of Orc
```

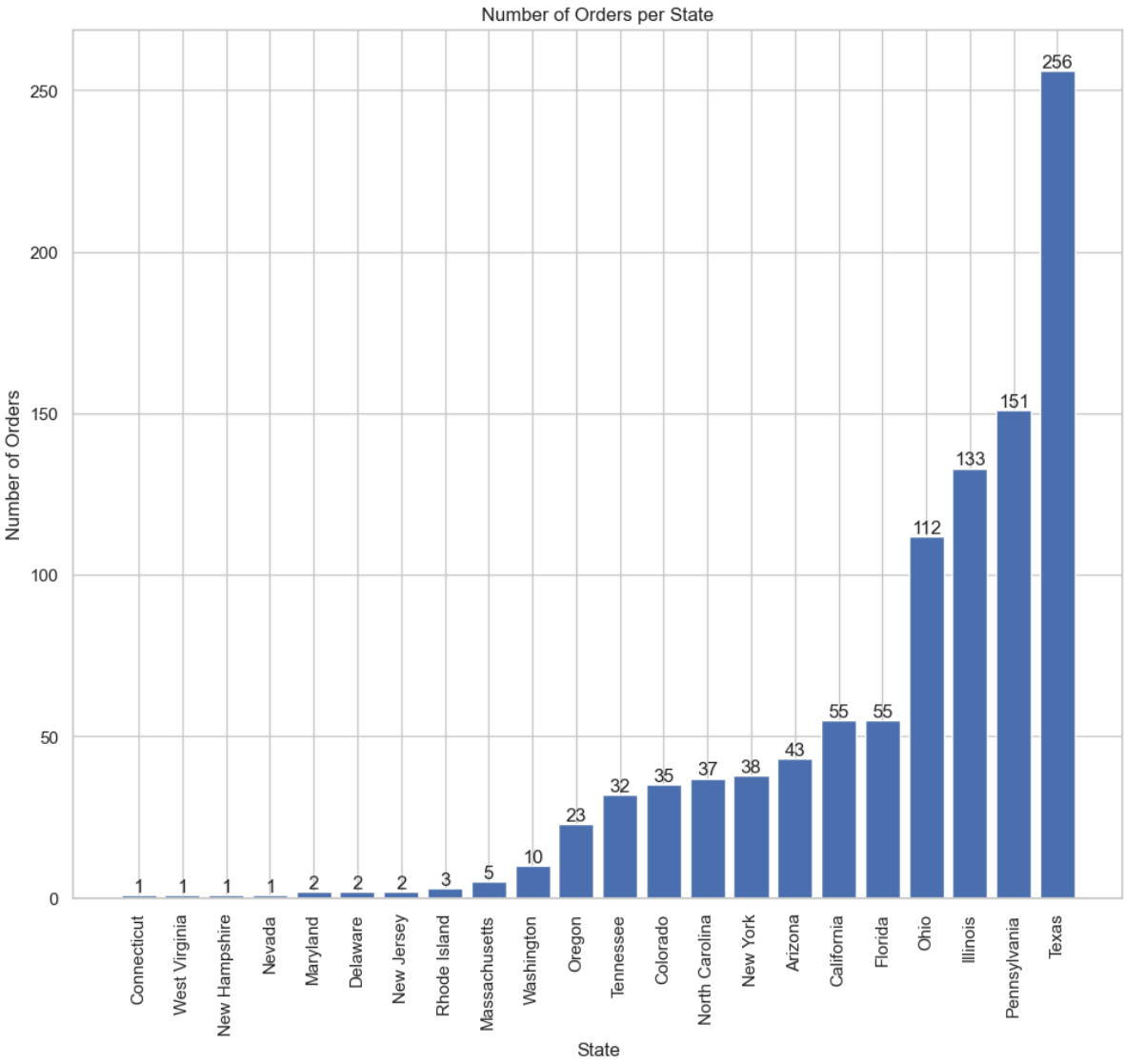

Number of Orders per Ship Mode
Number of Orders
0
100
200
300
400
500
600
46
156
169
626
Same Day
First Class
Second Class
Standard Class
Ship Mode


Number of Orders per Segment
Number of Orders
0
100
200
300
400
500
1
159
301
536
%
Home Office
Corporate
Consumer
Segment


Number of Orders per Category
Number of Orders
500
400
300
200
100
0
4
145
369
481
Frniture
Technology
Office Supplies
Furniture
Category


Number of Orders per Sub-Category
Number of Orders
0
25
50
75
100
125
150
175
200
12
18
40
51
73
86
88
101
144
179
204
Supplies
Accessories
Machines
Appliances
Furnishings
Phones
Bookcases
Storage
Chairs
Tables
Binders
Sub-Category


Number of Orders per Region
Number of Orders
Region
400
350
300
250
200
150
100
50
0
3
3
5
7
121
169
310
381
Southh
Centrl
Cntral
Est
South
West
East
Central



The `plot_histogram()` function can be run after the data cleansing.

2. Task 2

Handling missing values in the dataset

Helper functions

Function to convert alphabetic values in a DataFrame column to numbers and update the DataFrame.

In [ ]:
```
def convert_alphabetic_to_float(df, numerical_feature):
    """
    Convert alphabetic values in a DataFrame column to numbers and update the DataF

    Parameters:
        df (pandas.DataFrame): The DataFrame containing the column to be processed.
        numerical_feature (str): The name of the column containing the values to be

    Returns:
        None. The function modifies the input DataFrame in place.
    """
```

```
    # Create alphabetic filter using regex
    alphabetic_filter = df[numerical_feature].str.contains(r'^[a-zA-Z]+$', na=False
    alphabetic_filtered_df = df.loc[alphabetic_filter]

    # Convert alphabetic values to numbers using w2n.word_to_num library
    alphabetic_filtered_df.loc[:, numerical_feature] = alphabetic_filtered_df[numer

    # Update the original DataFrame with the filtered results
    df.update(alphabetic_filtered_df)

    # Convert the column to float
    df[numerical_feature] = df[numerical_feature].astype(float)
```

Function to check if the machine is connected to internet, so its used in `get_city_from_postal_code` and `get_state_from_postal_code` functions respectively.

In [ ]:
```
def is_internet_connected():
    """
    Check if the machine is connected to the internet by attempting to connect to G
    The function is used to conect to post code API to retrieve City and State
    Returns:
        bool: True if the machine is connected to the internet, False otherwise.
    """
    try:
        # Attempt to connect to Google's DNS server
        socket.create_connection(("8.8.8.8", 53), timeout=3)
        return True
    except OSError:
        pass
    return False
```

Function to retrieve the city name from postal code using zippopotam API.

In [ ]:
```
def get_city_from_postal_code(postal_code):
    """
    get_city_from_postal_code retrieves the city name from postal code using zippop
    Parameters:
        postal_code: Postal code for the city.
    Returns:
        str or None: City name corresponding to the given postal code, or None if p
    """
    if not is_internet_connected():
        return None

    if postal_code == '':
        return None

    url = f"http://api.zippopotam.us/us/{postal_code}"
    response = requests.get(url)
    if response.status_code == 200:
        data = response.json()
        city = data['places'][0]['place name']
        return city
    else:
        return None
```

Function to retrieve the state name from postal code using zippopotam API.

In [ ]:
```
def get_state_from_postal_code(postal_code):
    """
```

```
    get_state_from_postal_code retrieves the state name from postal code using zipp
    Parameters:
        postal_code: Postal code for the state.
    Returns:
        str or None: State name corresponding to the given postal code, or None if
    """

    if not is_internet_connected():
        return None

    if postal_code == '':
        return None

    url = f"http://api.zippopotam.us/us/{postal_code}"
    response = requests.get(url)
    if response.status_code == 200:
        data = response.json()
        state = data['places'][0]['state']
        return state
    else:
        return None
```

Function to format a date string to the format 'yyyy-mm-dd'.

In [ ]:
```
def format_date_in_yyyymmdd(date_str):
    """
    Formats a date string to the format 'yyyy-mm-dd'.

    Parameters:
    - date_str (str or pd.NA): A string representing a date.

    Returns:
    - str or pd.NA: The standardized date string in 'yyyy-mm-dd' format, or pd.NA i
    """
    if pd.notna(date_str) and date_str.strip():  # Check if date is not blank or Na
        try:
            # Attempt to parse as yyyy-mm-dd with dayfirst=False
            return pd.to_datetime(date_str, dayfirst=False, errors='coerce').strfti
        except ValueError:
            # If parsing fails, attempt to parse as dd-mm-yyyy
            return pd.to_datetime(date_str, format='%d-%m-%Y', errors='coerce').str
    else:
        return date_str  # Return the original blank or NaN value
```

Dropping unwanted columns

In [ ]:
```
# Columns to drop
columns_to_drop = ['Row ID', 'Order ID', 'Customer ID', 'Product ID', 'Product Name

# Row ID is not needed for the analysis, hence dropping the column
global_super_store_df.drop(columns=columns_to_drop, inplace=True)
```

Replacing faulty values

In [ ]:
```
# Removing "?" from Quantity column
global_super_store_df['Quantity'] = global_super_store_df['Quantity'].str.replace('

# Removing """ from profit column
global_super_store_df['Profit'] = global_super_store_df['Profit'].str.replace('"',

# Removing """ from Postal Code column
```

```
global_super_store_df['Postal Code'] = global_super_store_df['Postal Code'].str.rep

# Make all records as Country = United States
global_super_store_df['Country'] = 'United States'

# Correcting spelling mistakes on Category column
global_super_store_df['Category'] = global_super_store_df['Category'].replace('Frnt

# Datafix on Category based on subcategories
# Apply the condition element-wise
condition = (global_super_store_df['Category'] == 'NO_CATEGORY') & \
            (global_super_store_df['Sub-Category'].isin(['Binders', 'Storage']))

# Update 'Category' where the condition is True
global_super_store_df.loc[condition, 'Category'] = 'Office Supplies'

# Update empty and wrong records on Segment Column
global_super_store_df['Segment'] = global_super_store_df['Segment'].replace('%', 'N

# Cleanse the Regions
central_regions_to_replace = ['Centrl', 'Cntral']
east_regions_to_replace = ['Est']
south_regions_to_replace = ['Southh']

global_super_store_df['Region'] = global_super_store_df['Region'].replace(central_r
global_super_store_df['Region'] = global_super_store_df['Region'].replace(east_regi
global_super_store_df['Region'] = global_super_store_df['Region'].replace(south_reg

# Cleanse the Order Date column
global_super_store_df['Order Date'] = global_super_store_df['Order Date'].str.repla

# Cleanse the Customer Name column
global_super_store_df['Customer Name'] = global_super_store_df['Customer Name'].str
```

Filling empty values with default values

In [ ]:

```
# Filling values on empty Customer Name records
global_super_store_df['Customer Name'] = global_super_store_df['Customer Name'].fil

# Assuming zero values for NaN on Profit
global_super_store_df['Profit'] = global_super_store_df['Profit'].fillna(0.00)

# Filling values on empty Category and Sub-Category records
global_super_store_df['Category'] = global_super_store_df['Category'].fillna('NO_CA
global_super_store_df['Sub-Category'] = global_super_store_df['Sub-Category'].fillr

# Filling Quantity as 1 as sold quantity cannot be zero
global_super_store_df['Quantity'] = global_super_store_df['Quantity'].fillna(1.00)

# Filling Discount as 0
global_super_store_df['Discount'] = global_super_store_df['Discount'].fillna(0.00)

# Filling Sales as 0
global_super_store_df['Sales'] = global_super_store_df['Sales'].fillna(0.00)

# Filling values on empty Ship Mode records
global_super_store_df['Ship Mode'] = global_super_store_df['Ship Mode'].fillna('NO_

# Filling values on empty Postal Code records
global_super_store_df['Postal Code'] = global_super_store_df['Postal Code'].fillna(

# Filling values on empty Region records
global_super_store_df['Region'] = global_super_store_df['Region'].fillna('NO_REGION
```

```
# Filling values on empty Segment records
global_super_store_df['Segment'] = global_super_store_df['Segment'].fillna('NO_SEGM
```

Applying helper functions to fill the data

In [ ]:
```
# Filter the empty state rows
state_filtered_na = global_super_store_df.loc[pd.isna(global_super_store_df['State'
state_filtered_na

# Apply the function to fill the missing value via API
global_super_store_df.loc[pd.isna(global_super_store_df['State']), 'State'] = state
```

In [ ]:
```
# Filter the empty city rows
city_filtered_na = global_super_store_df.loc[pd.isna(global_super_store_df['City'])
city_filtered_na

# Apply the function to fill the missing value via API
global_super_store_df.loc[pd.isna(global_super_store_df['City']), 'City'] = city_fi
```

In [ ]:
```
# Call the function to convert the the Quantity and Profit columns which has alphab
convert_alphabetic_to_float(global_super_store_df, 'Quantity')
convert_alphabetic_to_float(global_super_store_df, 'Profit')
```

Order Date / Ship Date fixes

In [ ]:
```
# Get the all the records out of that filter to fix
date_fix_condition = (~global_super_store_df['Ship Date'].isna()) & \
                            (~global_super_store_df['Order Date'].isna())

# Standardize Order Date column
global_super_store_df.loc[date_fix_condition, 'Order Date'] = global_super_store_df

# Standardize Ship Date column
global_super_store_df.loc[date_fix_condition, 'Ship Date'] = global_super_store_df.

# Swap Order Date and Ship Date if necessary
for index, row in global_super_store_df.iterrows():
    order_date = pd.to_datetime(row['Order Date'], errors='coerce')  # Coerce error
    ship_date = pd.to_datetime(row['Ship Date'], errors='coerce')  # Coerce errors

    if not pd.isna(order_date) and not pd.isna(ship_date) and order_date > ship_dat
        global_super_store_df.at[index, 'Order Date'], global_super_store_df.at[inc
```

```
C:\Users\nares\AppData\Local\Temp\ipykernel_20456\991193335.py:14: UserWarning: Pa
rsing dates in %d/%m/%Y format when dayfirst=False (the default) was specified. Pa
ss `dayfirst=True` or specify a format to silence this warning.
  return pd.to_datetime(date_str, dayfirst=False, errors='coerce').strftime('%Y-%m
-%d')
C:\Users\nares\AppData\Local\Temp\ipykernel_20456\991193335.py:14: UserWarning: Pa
rsing dates in %d/%m/%Y format when dayfirst=False (the default) was specified. Pa
ss `dayfirst=True` or specify a format to silence this warning.
  return pd.to_datetime(date_str, dayfirst=False, errors='coerce').strftime('%Y-%m
-%d')
C:\Users\nares\AppData\Local\Temp\ipykernel_20456\171948261.py:13: UserWarning: Pa
rsing dates in %d/%m/%Y format when dayfirst=False (the default) was specified. Pa
ss `dayfirst=True` or specify a format to silence this warning.
  order_date = pd.to_datetime(row['Order Date'], errors='coerce')  # Coerce errors
to NaT for comparison
```

In [ ]:
```
# Convert columns to datetime64 dtype
global_super_store_df['Order Date'] = pd.to_datetime(global_super_store_df['Order D
global_super_store_df['Ship Date'] = pd.to_datetime(global_super_store_df['Ship Dat

# Filling 01/01/1970 date as a NO_DATA_DATE date
global_super_store_df['Order Date'] = global_super_store_df['Order Date'].fillna('1
global_super_store_df['Ship Date'] = global_super_store_df['Ship Date'].fillna('197
```

New columns to Analyze

After cleansing the data, the following columns have been added to perform EDA and visualizations.

Column Name	Data Type	Description
Loss	float64	Negative losss will be marked as loss
Shipment Days	float64	Calculate the days between Order Date and Shipped Date
Order Year	int32	Extracted year from Order Date to plot the sales/loss trends
Ship Year	int32	Extracted year from Ship Date to plot the sales/loss trends
Gender	object	Experimenting to guess the gender of the customer to perform gender analysis

In [ ]:
```
# New column Shipment Days
global_super_store_df['Shipment Days'] = (global_super_store_df['Ship Date'] - glob

# New columns: Order Year and Ship Year. extract year from 'Order Date' and 'Ship D
global_super_store_df['Order Year'] = pd.DatetimeIndex(global_super_store_df['Order
global_super_store_df['Ship Year'] = pd.DatetimeIndex(global_super_store_df['Ship D

# Fill NaN values with 0 (assuming missing years should be represented as 0)
global_super_store_df[['Order Year', 'Ship Year']] = global_super_store_df[['Order

# Convert year columns to integer dtype
global_super_store_df[['Order Year', 'Ship Year']] = global_super_store_df[['Order

# New column 'Loss' where loss is negative
global_super_store_df['Loss'] = global_super_store_df['Profit'].apply(lambda x: -x
```

Removing the filler values

Function to filter the Dataframe to apply the filler values.

In [ ]:
```
def filter_out_filler_values_count(df, column, filler_value):
    """
    Filters out rows from the DataFrame where the value in the specified column mat

    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.
        column (str): The name of the column to filter on.
        filler_value: The value to match in the specified column for filtering.

    Returns:
        int: The count of filtered values.
    """
```

```
    filtered_count = len(df[df[column] == filler_value])
    return filtered_count
```

Function to drop the rows based on a filler value.

In [ ]:
```
def remove_filler_values_on_df(df, key_column, key_value):
    """
    Filters out rows from the DataFrame where the value in the key column matches t

    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.
        key_column (str): The name of the column to filter on.
        key_value: The value to match in the key column for filtering.

    Returns:
        None
    """
    # Filter out rows matching the condition
    df.drop(df[df[key_column] == key_value].index, inplace=True)
```

In [ ]:
```
# Define the dictionary of column names and filler values
filter_filler_values_dict = {
    'Category': 'NO_CATEGORY',
    'Sub-Category': 'NO_SUB_CATEGORY',
    'Segment': 'NO_SEGMENT',
    'Ship Mode': 'NO_SHIP_MODE',
    'Customer Name': 'NO_CUSTOMER_NAME',
    'Postal Code': 'NO_POSTAL_CODE',
    'Region': 'NO_REGION',
    'Order Date': '1970/01/01',
    'Ship Date': '1970/01/01'
}
```

In [ ]:
```
# Initialize a list to store the filtered count results
filter_count_results = []

# Iterate over the dictionary filter_filler_values_dict items and apply the filteri
for column, filler_value in filter_filler_values_dict.items():
    filtered_count = filter_out_filler_values_count(global_super_store_df, column,
    filter_count_results.append([column, filler_value, filtered_count])

# Print the results as a table
print(tabulate(filter_count_results, headers=['Column', 'Filler Value', 'Filtered C
```

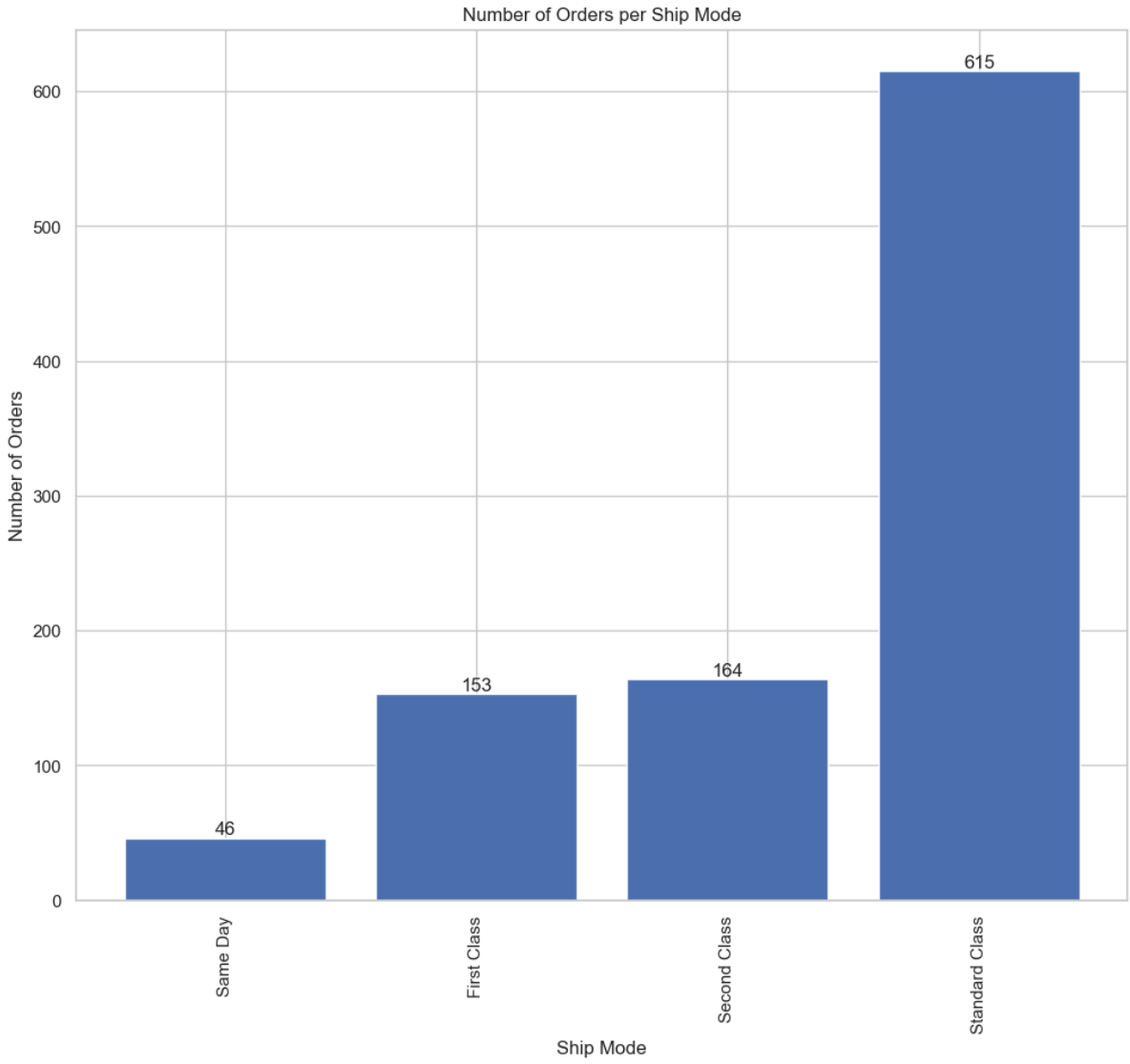
```
+--------------+-----------------+----------------+
|       Column |    Filler Value | Filtered Count |
+--------------+-----------------+----------------+
|     Category |     NO_CATEGORY |              1 |
| Sub-Category | NO_SUB_CATEGORY |              4 |
|      Segment |      NO_SEGMENT |              4 |
|    Ship Mode |    NO_SHIP_MODE |              3 |
|Customer Name|NO_CUSTOMER_NAME |              3 |
|  Postal Code |  NO_POSTAL_CODE |              2 |
|       Region |       NO_REGION |              1 |
|   Order Date |      1970/01/01 |              3 |
|    Ship Date |      1970/01/01 |              3 |
+--------------+-----------------+----------------+
```

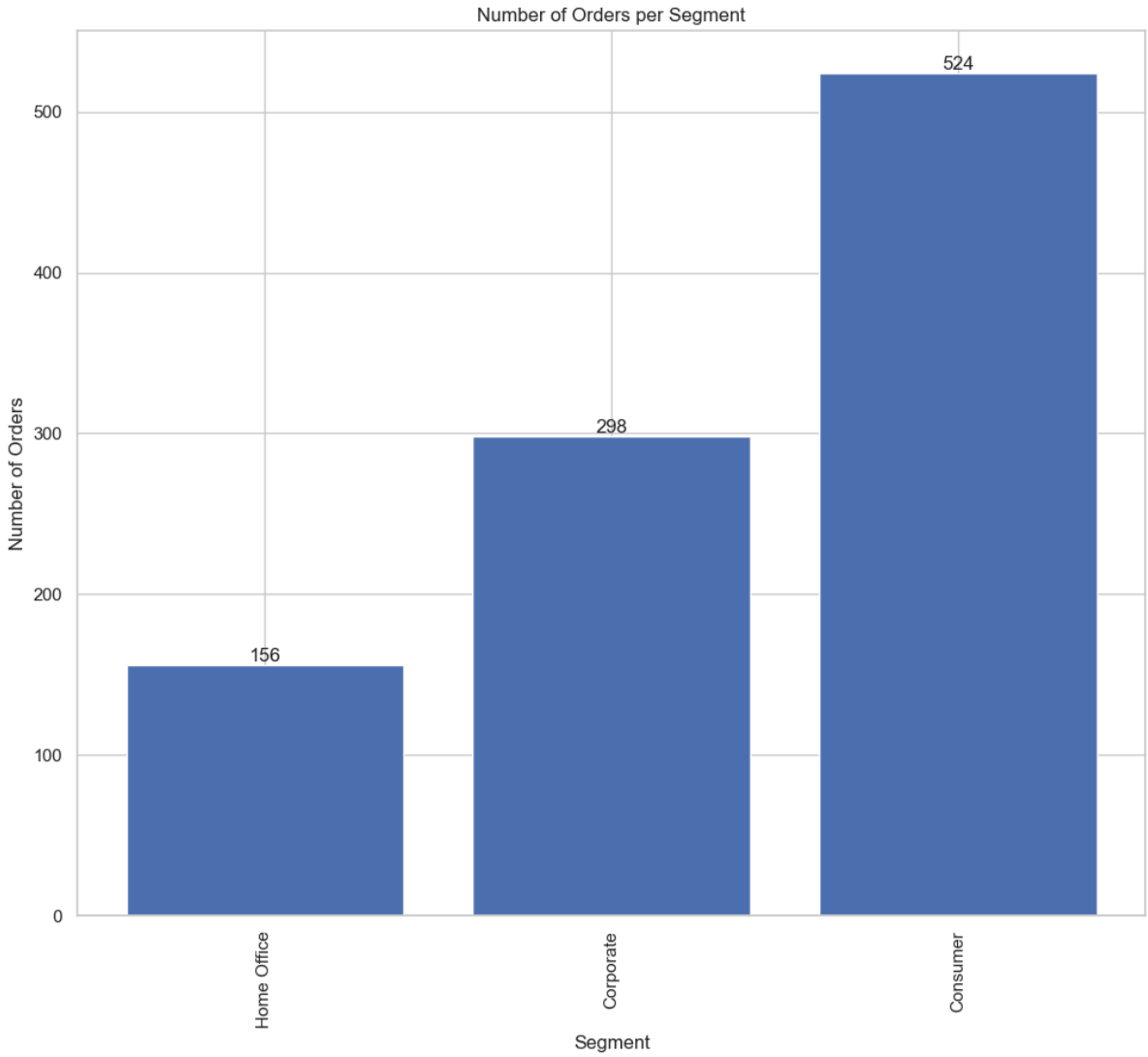
The filler values are pretty small when compared to the dataset (1000 rows). These records are removed from the `global_super_store_df` dataframe.

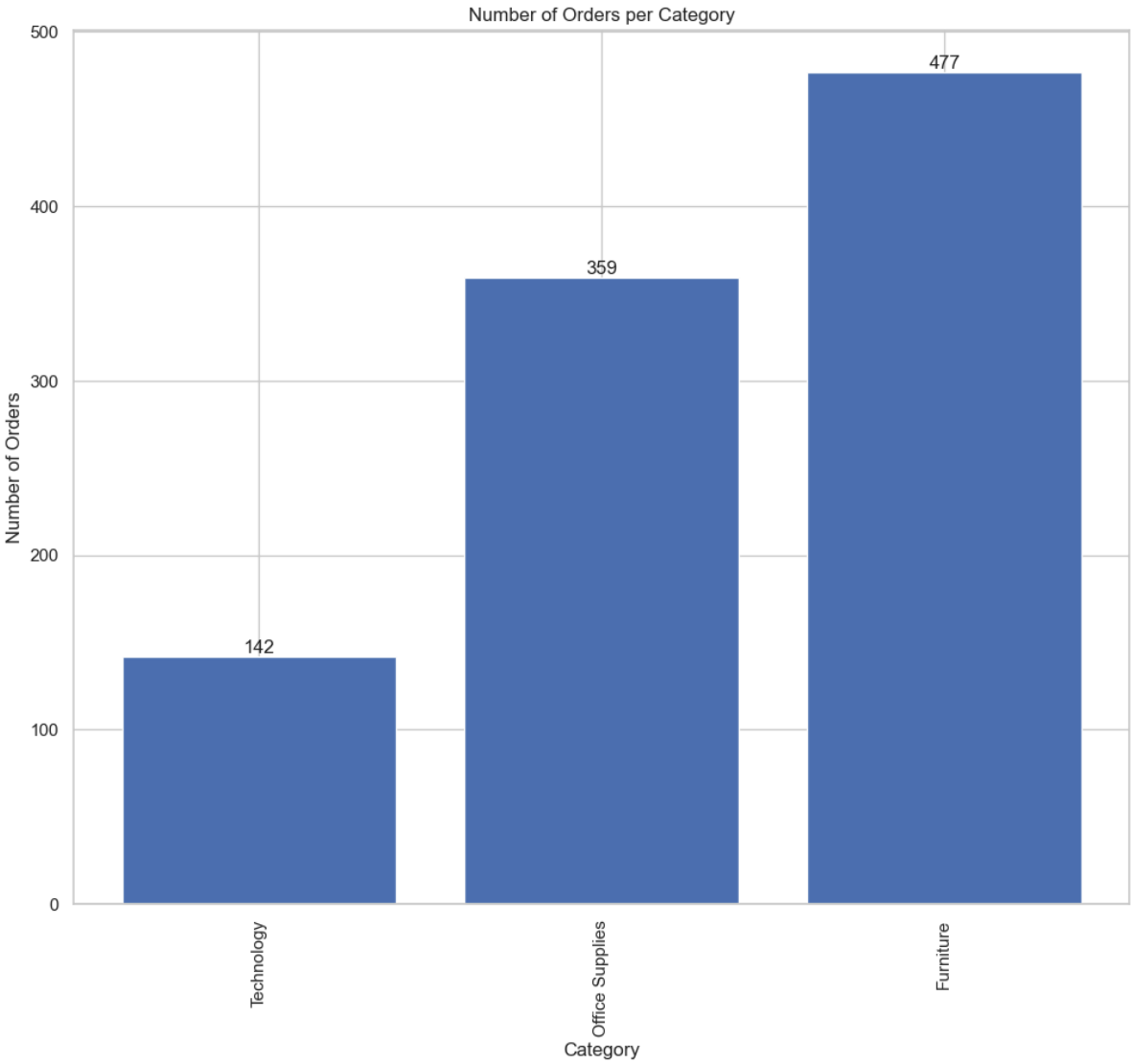
In [ ]:
```
# Iterate over the dictionary items and apply the filtering
for column, filler_value in filter_filler_values_dict.items():
    remove_filler_values_on_df(global_super_store_df, column, filler_value)
```

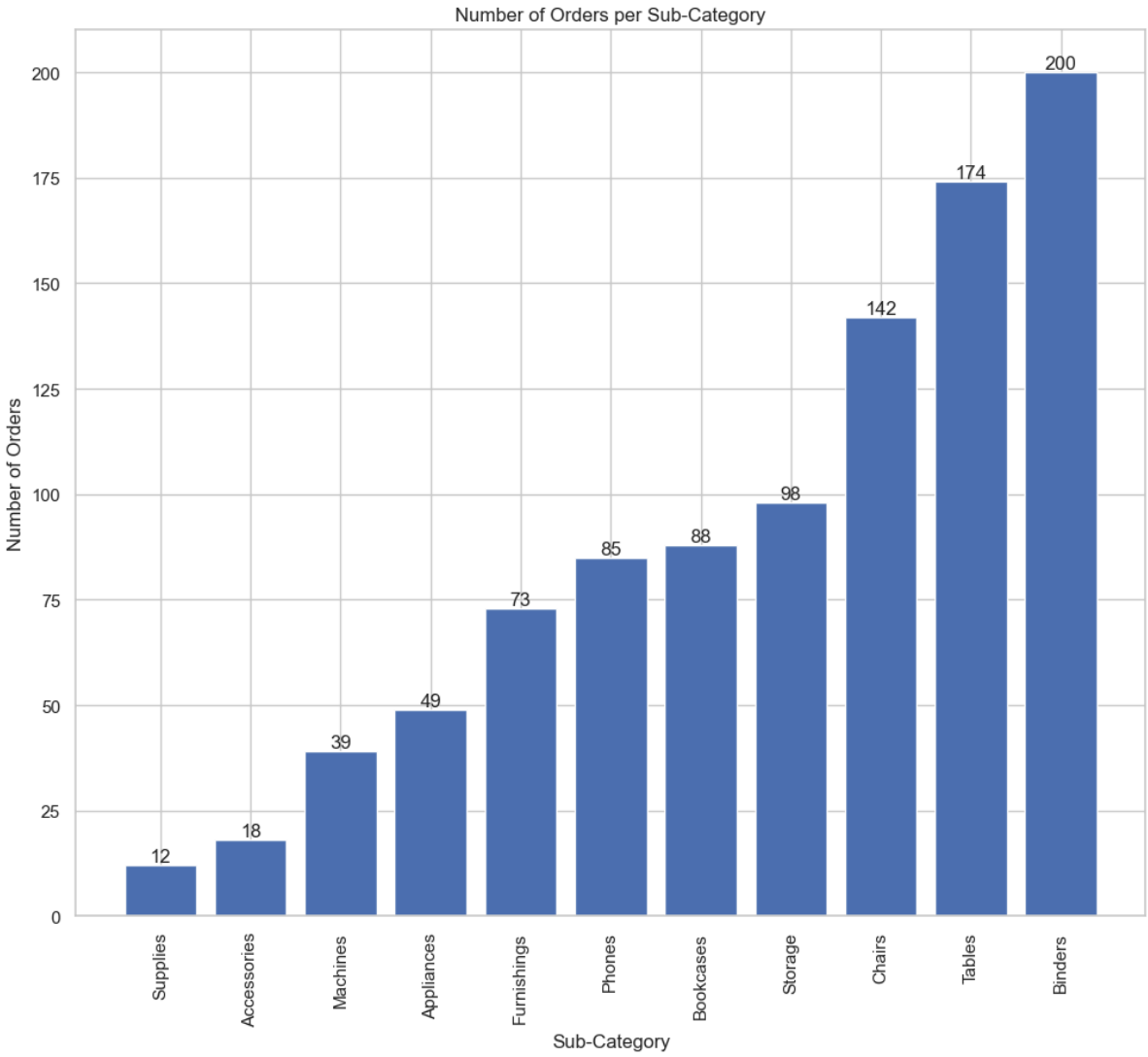
Plotting histograms after cleansing data

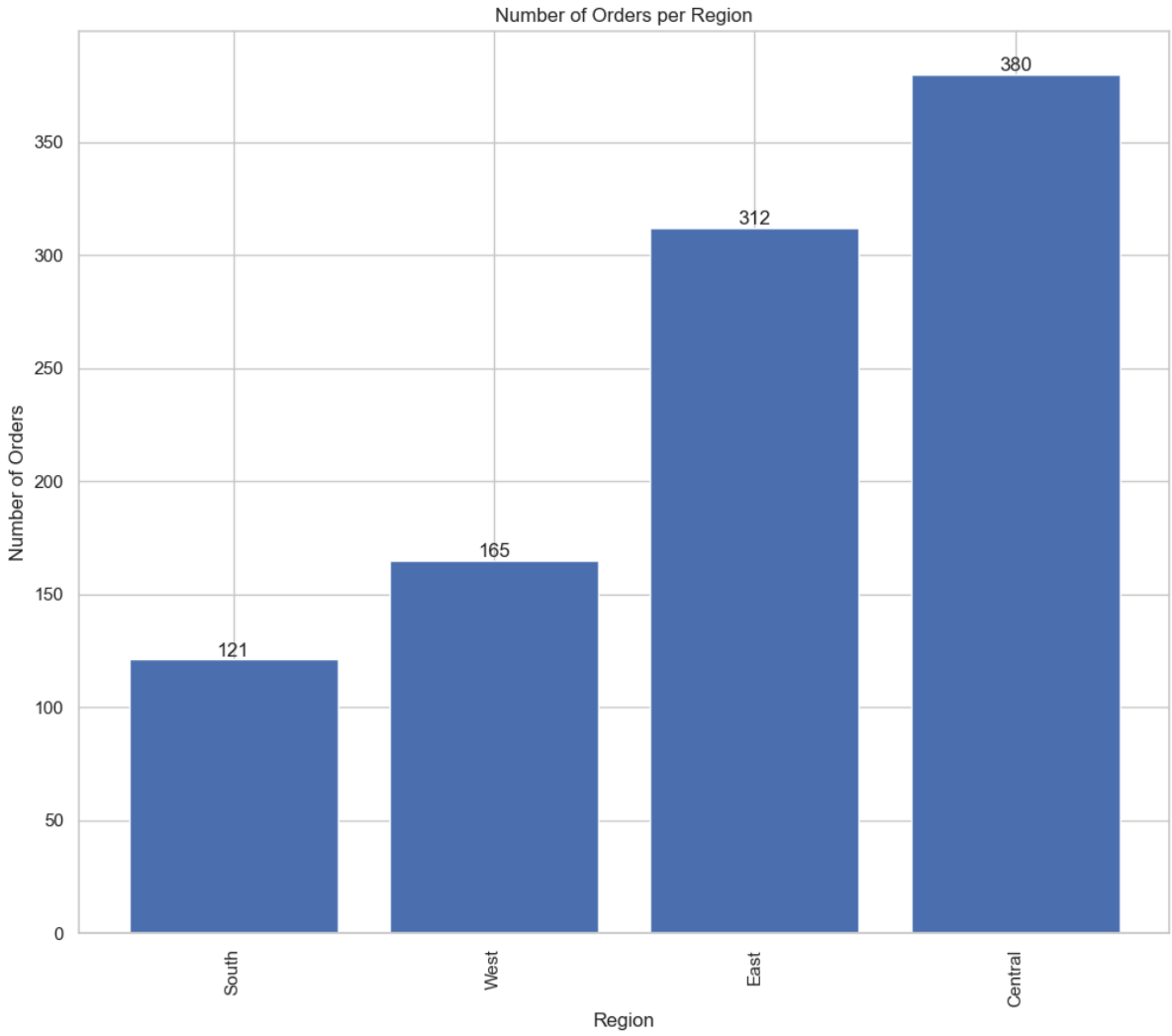
In [ ]:
```
# Histogram for 'Ship Mode'
orders_per_segment = global_super_store_df['Ship Mode'].value_counts(ascending=True
plot_histogram(orders_per_segment, 'Ship Mode', 'Number of Orders', 'Number of Orde

# Histogram for 'Segment'
orders_per_segment = global_super_store_df['Segment'].value_counts(ascending=True)
plot_histogram(orders_per_segment, 'Segment', 'Number of Orders', 'Number of Orders

# Histogram for 'Category'
orders_per_category = global_super_store_df['Category'].value_counts(ascending=True
plot_histogram(orders_per_category, 'Category', 'Number of Orders', 'Number of Orde

# Histogram for 'Sub-Category'
orders_per_sub_category = global_super_store_df['Sub-Category'].value_counts(ascend
plot_histogram(orders_per_sub_category, 'Sub-Category', 'Number of Orders', 'Number

# Histogram for 'Region'
orders_per_sub_category = global_super_store_df['Region'].value_counts(ascending=Tr
plot_histogram(orders_per_sub_category, 'Region', 'Number of Orders', 'Number of Or

# Histogram for 'State'
orders_per_sub_category = global_super_store_df['State'].value_counts(ascending=Tru
plot_histogram(orders_per_sub_category, 'State', 'Number of Orders', 'Number of Orc
```

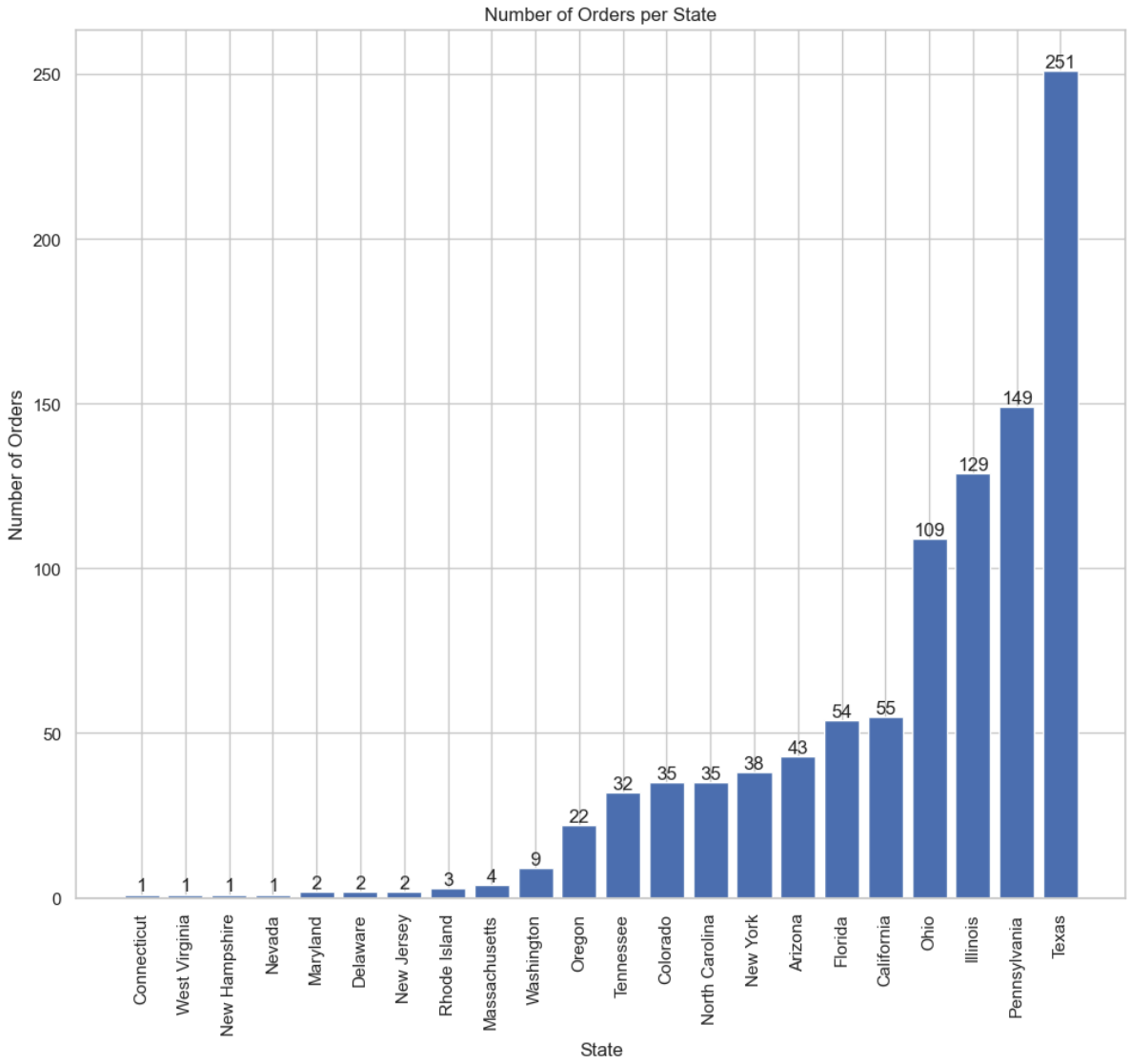

Number of Orders per Ship Mode
Number of Orders
0
100
200
300
400
500
600
46
153
164
615
Same Day
First Class
Second Class
Standard Class
Ship Mode


Number of Orders per Segment
Number of Orders
0
100
200
300
400
500
156
298
524
Home Office
Corporate
Consumer
Segment


Number of Orders per Category
500
400
300
200
100
0
Number of Orders
142
359
477
Technology
Office Supplies
Furniture
Category


Number of Orders per Sub-Category
Number of Orders
0
25
50
75
100
125
150
175
200
12
18
39
49
73
85
88
98
142
174
200
Supplies
Accessories
Machines
Appliances
Furnishings
Phones
Bookcases
Storage
Chairs
Tables
Binders
Sub-Category


Number of Orders per Region
Number of Orders
0
50
100
150
200
250
300
350
121
165
312
380
South
West
East
Central
Region



Descriptive statistics

In [ ]:
```
# Descriptive Statistics
descriptive_stats = global_super_store_df.describe().round(2)

# Generate descriptive statistics
print(tabulate(descriptive_stats, headers='keys', tablefmt='pretty', stralign ='rig
```

```
+-------+-------------------------------+-------------------------------+---------
-+----------+----------+----------+--------------+-----------+-----------+------
---+
|       |                    Order Date |                     Ship Date |    Sales
| Quantity | Discount |   Profit | Shipment Days | Order Year | Ship Year |    Los
s |
+-------+-------------------------------+-------------------------------+---------
-+----------+----------+----------+--------------+-----------+-----------+------
---+
| count |                           978 |                           978 |    978.0
|    978.0 |    978.0 |    978.0 |         978.0 |      978.0 |     978.0 |   978.
0 |
|  mean | 2016-04-29 21:22:27.239263744 | 2016-05-03 21:15:05.521472512 |    409.2
|     4.24 |     0.45 |  -142.19 |          3.99 |    2015.73 |   2015.74 |  142.1
9 |
|   min |           2014-01-07 00:00:00 |           2014-01-12 00:00:00 |      0.0
|      1.0 |      0.0 | -6599.98 |           0.0 |     2014.0 |    2014.0 |     0.
0 |
|   25% |           2015-04-26 00:00:00 |           2015-05-02 00:00:00 |    72.88
|      3.0 |      0.2 |  -120.51 |           3.0 |     2015.0 |    2015.0 |   26.9
5 |
|   50% |           2016-06-14 00:00:00 |           2016-06-19 00:00:00 |   215.57
|      4.0 |      0.4 |   -52.08 |           4.0 |     2016.0 |    2016.0 |   52.0
8 |
|   75% |           2017-05-12 00:00:00 |           2017-05-15 00:00:00 |   462.83
|      6.0 |      0.7 |   -26.95 |           5.0 |     2017.0 |    2017.0 |  120.5
1 |
|   max |           2017-12-29 00:00:00 |           2018-01-02 00:00:00 | 22638.48
|     14.0 |      0.8 |      0.0 |           7.0 |     2017.0 |    2018.0 | 6599.9
8 |
|   std |                           nan |                           nan |   939.86
|     2.27 |     0.22 |    368.8 |           1.7 |       1.13 |      1.13 |   368.
8 |
+-------+-------------------------------+-------------------------------+---------
-+----------+----------+----------+--------------+-----------+-----------+------
---+
```

In [ ]:
```
# Calculate the number of missing values for each column
missing_values = global_super_store_df.isnull().sum().to_frame(name='Missing Value

# Display the missing values using tabulate
print(tabulate(missing_values, headers='keys', tablefmt='pretty', stralign='right',
```

```
+---------------+---------------------+
|               | Missing Value Count |
+---------------+---------------------+
|    Order Date |                   0 |
|     Ship Date |                   0 |
|     Ship Mode |                   0 |
| Customer Name |                   0 |
|       Segment |                   0 |
|       Country |                   0 |
|          City |                   0 |
|         State |                   0 |
|   Postal Code |                   0 |
|        Region |                   0 |
|      Category |                   0 |
|  Sub-Category |                   0 |
|         Sales |                   0 |
|      Quantity |                   0 |
|      Discount |                   0 |
|        Profit |                   0 |
| Shipment Days |                   0 |
|    Order Year |                   0 |
|     Ship Year |                   0 |
|          Loss |                   0 |
+---------------+---------------------+
```

Grouping of data

Helper Functions

Function to print total sales/loss by feature in a tabulate format.

In [ ]:
```python
def print_sales_loss_by_feature(df, sales_loss_feature, category_column):
    """
    print_sales_loss_by_feature, prints total sales/loss by feature in a tabulate f

    Parameters:
    - df (DataFrame): The DataFrame containing the sales data.
    - sales_column (str): The name of the column containing sales data.
    - sales_category_column (str): The name of the column to group by.

    Returns:
    - None
    """
    # Group total sales by category
    sales_category = df.groupby(category_column)[sales_loss_feature].sum().round(4)

    # Convert the grouped DataFrame to a list of lists
    sales_category_list = sales_category.values.tolist()

    # Print the table using tabulate
    print(tabulate(sales_category_list, headers=[category_column, f'Total {sales_lo
```

Grouping Sales/Losses based on Categories

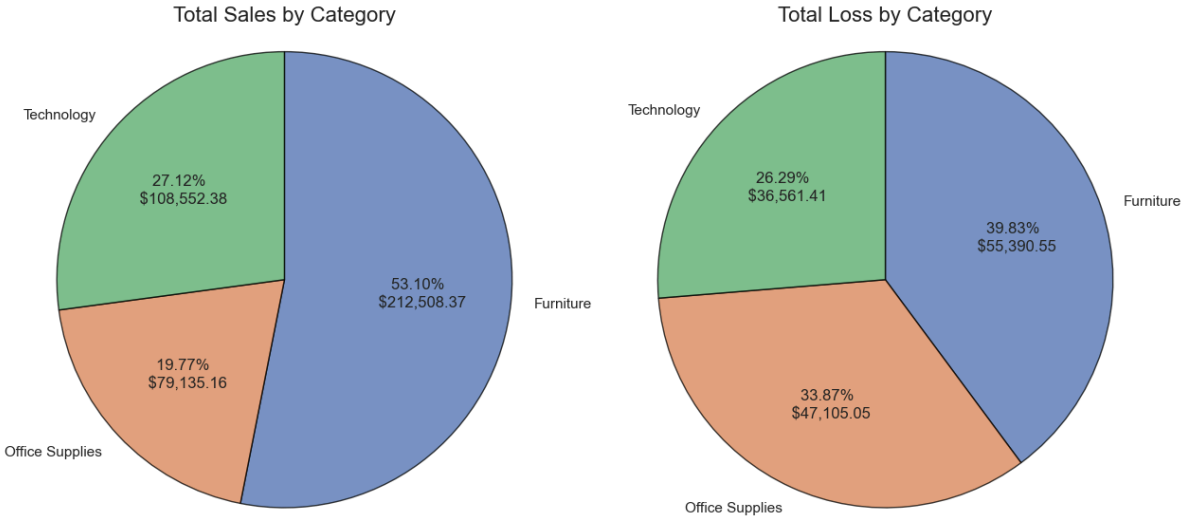
In [ ]:
```python
# group total sales by category from the highest sale.
print_sales_loss_by_feature(global_super_store_df.round(2), 'Sales', 'Category')
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[3], line 2
      1 # group total sales by category from the highest sale.
----> 2 print_sales_loss_by_feature(global_super_store_df.round(2), 'Sales', 'Cate
gory')

NameError: name 'global_super_store_df' is not defined
```

In [ ]:
```
# group total loss by category from the highest sale.
print_sales_loss_by_feature(global_super_store_df.round(2), 'Loss', 'Category')
```

```
+-----------------+------------+
|        Category | Total Loss |
+-----------------+------------+
|       Furniture |   55390.63 |
| Office Supplies |   47105.15 |
|      Technology |   36561.47 |
+-----------------+------------+
```

In [ ]:
```
# group total sales by category, only considering sales
sales_category = global_super_store_df.groupby('Category')['Sales'].sum()

# group total loss by category, only considering losses
loss_category = global_super_store_df.groupby('Category')['Loss'].sum()

# figure size
plt.figure(figsize=(15,10));

# left total sales pie chart
plt.subplot(1,2,1); # 1 row, 2 columns, the 1st plot.
plt.pie(sales_category.values, labels=sales_category.index, startangle=90, counterc
        autopct=lambda p:f'{p:,.2f}% \n ${p * np.sum(sales_category.values) / 100 :
        wedgeprops={'linewidth': 1, 'edgecolor':'black', 'alpha':0.75});
plt.axis('square');
plt.title('Total Sales by Category',  fontdict={'fontsize':16});

# right total loss pie chart
plt.subplot(1,2,2); # 1 row, 2 columns, the 2nd plot
plt.pie(loss_category.values, labels=loss_category.index, startangle=90, counterclo
        autopct=lambda p:f'{p:,.2f}% \n ${p * np.sum(loss_category.values) / 100 :,
        wedgeprops={'linewidth': 1, 'edgecolor':'black', 'alpha':0.75});
plt.axis('square');
plt.title('Total Loss by Category', fontdict={'fontsize':16});
```



> *Total Sales on Categories*

1. Furniture at ~53%
2. Technology at ~27%
3. Office Supplies at ~20%

> *Total Losses on Categories*

1. Furniture at ~39%
2. Office Supplies at ~34%
3. Technology at ~26%

Grouping Sales/Losses based on Sub-Categories

In [ ]:
```
# group total sales by sub-category from the highest sale.
print_sales_loss_by_feature(global_super_store_df.round(2), 'Sales', 'Sub-Category'
```

```
+--------------+-------------+
| Sub-Category | Total Sales |
+--------------+-------------+
|       Tables |    92530.18 |
|     Machines |    71632.22 |
|       Chairs |    67562.95 |
|    Bookcases |    42565.94 |
|      Storage |    32034.07 |
|       Phones |    31868.86 |
|      Binders |     30556.3 |
|     Supplies |    13741.19 |
|  Furnishings |     9849.24 |
|  Accessories |     5051.31 |
|   Appliances |     2803.53 |
+--------------+-------------+
```

In [ ]:
```
# group total loss by sub-category from the highest loss.
print_sales_loss_by_feature(global_super_store_df.round(2), 'Loss', 'Sub-Category')
```

```
+--------------+------------+
| Sub-Category | Total Loss |
+--------------+------------+
|      Binders |   31432.34 |
|     Machines |   29296.35 |
|       Tables |   29176.51 |
|    Bookcases |    11454.5 |
|       Chairs |     8989.0 |
|   Appliances |    7101.94 |
|       Phones |    6676.66 |
|  Furnishings |    5770.62 |
|      Storage |    5659.41 |
|     Supplies |    2911.46 |
|  Accessories |     588.46 |
+--------------+------------+
```

In [ ]:
```
#Grouping the data on category and it's respective sub-categories. Calculating the
sales_per_cat_subcat = global_super_store_df.groupby(['Category', 'Sub-Category'],
sales_per_cat_subcat['Loss %'] = (sales_per_cat_subcat['Loss'] / sales_per_cat_subc

#Sorting the dataframe based on loss margin
sales_per_cat_subcat = sales_per_cat_subcat.sort_values(by=['Loss %'], ascending=Fa
print(tabulate(sales_per_cat_subcat.round(2), headers='keys', tablefmt='pretty', st
```

```
+-----------------+--------------+----------+----------+--------+
|        Category | Sub-Category |    Sales |     Loss | Loss % |
+-----------------+--------------+----------+----------+--------+
| Office Supplies |   Appliances |  2803.57 |   7101.9 | 253.32 |
| Office Supplies |      Binders | 30556.33 | 31432.29 | 102.87 |
|       Furniture |  Furnishings |  9849.27 |  5770.65 |  58.59 |
|      Technology |     Machines | 71632.26 | 29296.32 |   40.9 |
|       Furniture |       Tables |  92530.2 | 29176.48 |  31.53 |
|       Furniture |    Bookcases | 42565.96 | 11454.45 |  26.91 |
| Office Supplies |     Supplies | 13741.18 |  2911.46 |  21.19 |
|      Technology |       Phones | 31868.83 |  6676.65 |  20.95 |
| Office Supplies |      Storage | 32034.07 |   5659.4 |  17.67 |
|       Furniture |       Chairs | 67562.94 |  8988.98 |   13.3 |
|      Technology |  Accessories |  5051.29 |   588.45 |  11.65 |
+-----------------+--------------+----------+----------+--------+
```

Grouping Sales/Losses based on Region

In [ ]:
```
# group total sales by regions from the highest sale.
sales_by_segment = global_super_store_df.groupby(['Region'], as_index=False)[['Sale
sales_by_segment['Sales %'] = (sales_by_segment['Sales'] / global_super_store_df['S
sales_by_segment['Loss %'] = (sales_by_segment['Loss'] / sales_by_segment['Sales'])

# Convert numerical values to strings with commas for thousands separators and roun
for numerical_column in sales_by_segment.select_dtypes(include=['int64', 'float64']
    sales_by_segment[numerical_column] = sales_by_segment[numerical_column].apply(l

# List of total sales by states
print(tabulate(sales_by_segment.round(2), headers='keys', tablefmt='pretty', strali
```

```
+---------+------------+-----------+---------+--------+
|  Region |      Sales |      Loss | Sales % | Loss % |
+---------+------------+-----------+---------+--------+
|    East | 141,134.00 | 46,631.09 |   35.27 |  33.04 |
| Central | 118,801.87 | 49,218.54 |   29.69 |  41.43 |
|   South |  78,709.87 | 21,888.28 |   19.67 |  27.81 |
|    West |  61,550.17 | 21,319.12 |   15.38 |  34.64 |
+---------+------------+-----------+---------+--------+
```

Grouping Sales/Losses based on States

In [ ]:
```
# group total sales by states from the highest sale.
sales_by_states = global_super_store_df.groupby(['State'], as_index=False)[['Sales'
sales_by_states['Sales %'] = (sales_by_states['Sales'] / global_super_store_df['Sal
sales_by_states['Loss %'] = (sales_by_states['Loss'] / sales_by_states['Sales']) *

# Convert numerical values to strings with commas for thousands separators and roun
for numerical_column in sales_by_states.select_dtypes(include=['int64', 'float64'])
    sales_by_states[numerical_column] = sales_by_states[numerical_column].apply(lam

# List of total sales by states
print(tabulate(sales_by_states.round(2), headers='keys', tablefmt='pretty', stralig
```

State	Sales	Loss	Sales %	Loss %
Texas	89,052.53	31,205.35	22.25	35.04
Pennsylvania	67,815.33	19,998.49	16.95	29.49
Ohio	42,400.36	20,619.95	10.59	48.63
Florida	40,932.20	7,925.21	10.23	19.36
Illinois	29,749.34	18,013.19	7.43	60.55
California	27,976.97	3,326.36	6.99	11.89
New York	23,198.86	4,953.83	5.80	21.35
North Carolina	21,728.61	8,132.08	5.43	37.43
Tennessee	16,049.06	5,830.98	4.01	36.33
Arizona	12,751.76	6,351.07	3.19	49.81
Colorado	11,722.51	8,691.70	2.93	74.15
Oregon	5,521.03	2,514.96	1.38	45.55
Washington	2,903.54	325.45	0.73	11.21
Massachusetts	2,575.26	436.25	0.64	16.94
Rhode Island	1,517.50	216.41	0.38	14.26
New Hampshire	1,053.16	105.32	0.26	10.00
Maryland	789.80	71.12	0.20	9.00
Nevada	674.35	109.58	0.17	16.25
West Virginia	673.34	76.95	0.17	11.43
Delaware	510.28	85.90	0.13	16.83
New Jersey	418.29	51.29	0.10	12.26
Connecticut	181.80	15.58	0.05	8.57

State made the highest sales %: Texas \ **State made the lowest sales %:** Connecticut

Grouping Sales/Losses based on Segment

In [ ]:
```
# group total sales by segments from the highest sale.
sales_by_segment = global_super_store_df.groupby(['Segment'], as_index=False)[['Sal
sales_by_segment['Sales %'] = (sales_by_segment['Sales'] / global_super_store_df['S
sales_by_segment['Loss %'] = (sales_by_segment['Loss'] / sales_by_segment['Sales'])

# Convert numerical values to strings with commas for thousands separators and roun
for numerical_column in sales_by_segment.select_dtypes(include=['int64', 'float64']
    sales_by_segment[numerical_column] = sales_by_segment[numerical_column].apply(l

# List of total sales by states
print(tabulate(sales_by_segment.round(2), headers='keys', tablefmt='pretty', strali
```

Segment	Sales	Loss	Sales %	Loss %
Consumer	205,634.12	72,978.65	51.38	35.49
Corporate	118,826.11	42,474.37	29.69	35.74
Home Office	75,735.68	23,604.01	18.92	31.17

Consumer Segment has 50% of Sales share, followed by **Corporate** and **Home Office**.

Grouping Sales/Losses based on Shipping Mode

In [ ]:
```
# group total sales by segments from the highest sale.
sales_by_ship_mode = global_super_store_df.groupby(['Ship Mode'], as_index=False)[[
sales_by_ship_mode['Sales %'] = (sales_by_ship_mode['Sales'] / global_super_store_d
sales_by_ship_mode['Loss %'] = (sales_by_ship_mode['Loss'] / sales_by_ship_mode['Sa

# Convert numerical values to strings with commas for thousands separators and roun
for numerical_column in sales_by_segment.select_dtypes(include=['int64', 'float64']
```

```
    sales_by_ship_mode[numerical_column] = sales_by_ship_mode[numerical_column].app

# List of total sales by states
print(tabulate(sales_by_ship_mode.round(2), headers='keys', tablefmt='pretty', stra
```

```
+----------------+-----------+----------+---------+--------+
|      Ship Mode |     Sales |     Loss | Sales % | Loss % |
+----------------+-----------+----------+---------+--------+
| Standard Class | 257698.95 | 88887.64 |   64.39 |  34.49 |
|   Second Class |  67310.74 |  20253.2 |   16.82 |  30.09 |
|    First Class |  49908.08 | 21371.32 |   12.47 |  42.82 |
|       Same Day |  25278.13 |  8544.86 |    6.32 |   33.8 |
+----------------+-----------+----------+---------+--------+
```

Standard shipping method is preferred as the sales percentage is nearly 64%, followed by **Second Class** and **First Class**. **Same Day** is not an economical option, so only preferred by 6% of the orders.

In [ ]:
```
# Filter the filler date 01/01/1970 - the default NO_DATA date
global_super_store_df_date_filtered = global_super_store_df[(global_super_store_df[
grouped_data = global_super_store_df_date_filtered.round(3).reset_index().values.to

print(tabulate(grouped_data, headers=['Ship Mode', 'Average Shipped in Days'], tabl
```

```
+----------------+-------------------------+
|      Ship Mode | Average Shipped in Days |
+----------------+-------------------------+
|    First Class |                   2.163 |
|       Same Day |                   0.022 |
|   Second Class |                   3.262 |
| Standard Class |                   4.943 |
+----------------+-------------------------+
```

- **Standard Class** shipping method takes ~5 days to ship from the order date.
- **First Class** and **Second Class** are between 2-3 days.
- **Same Day** is as promised, the orders are shipped with a day.

In conclusion, **Second Class** ship mode is the best value for money, being economical than **First Class** and faster than **Standard Class**.

Univariate analysis and visualisation

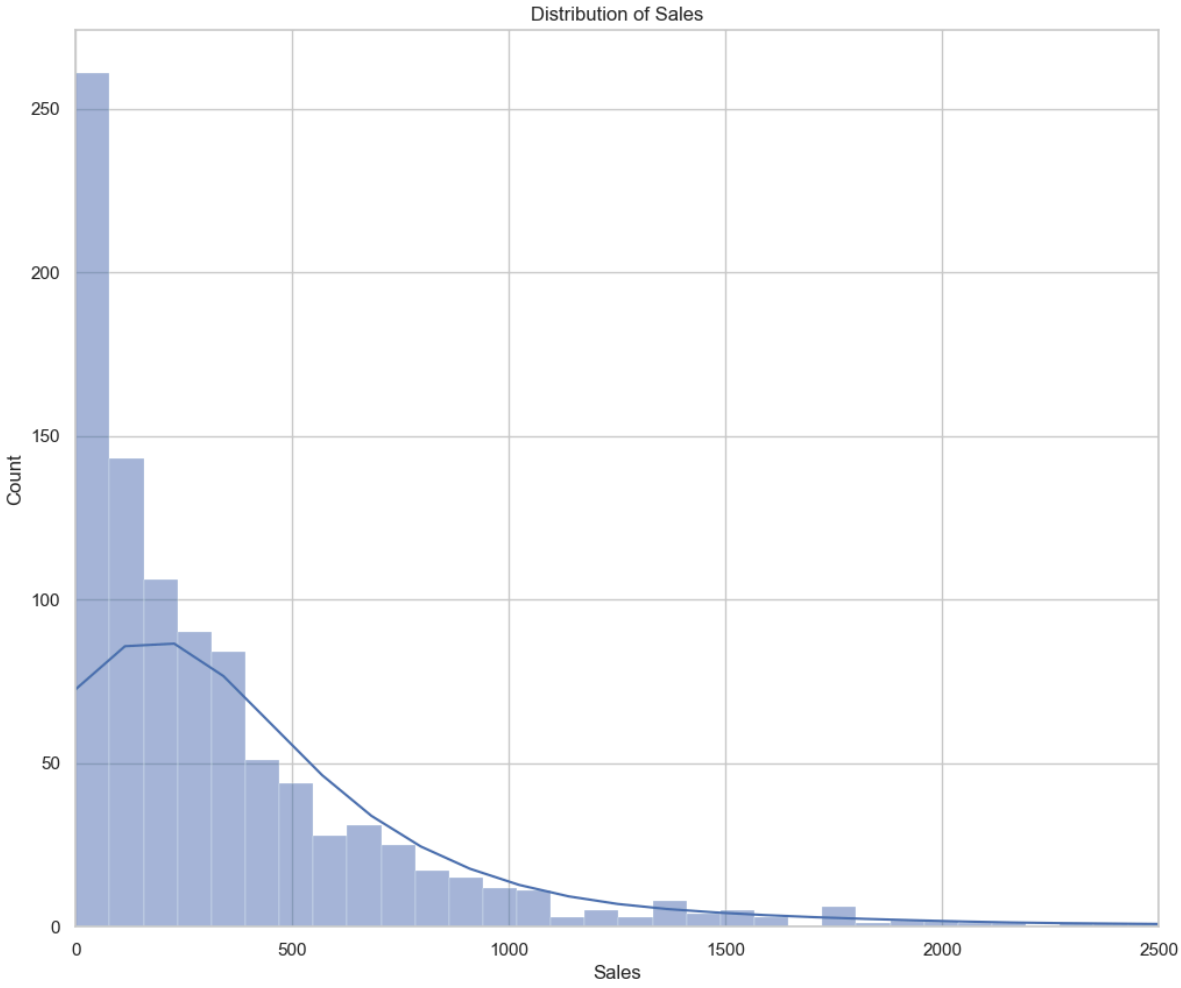
Histograms

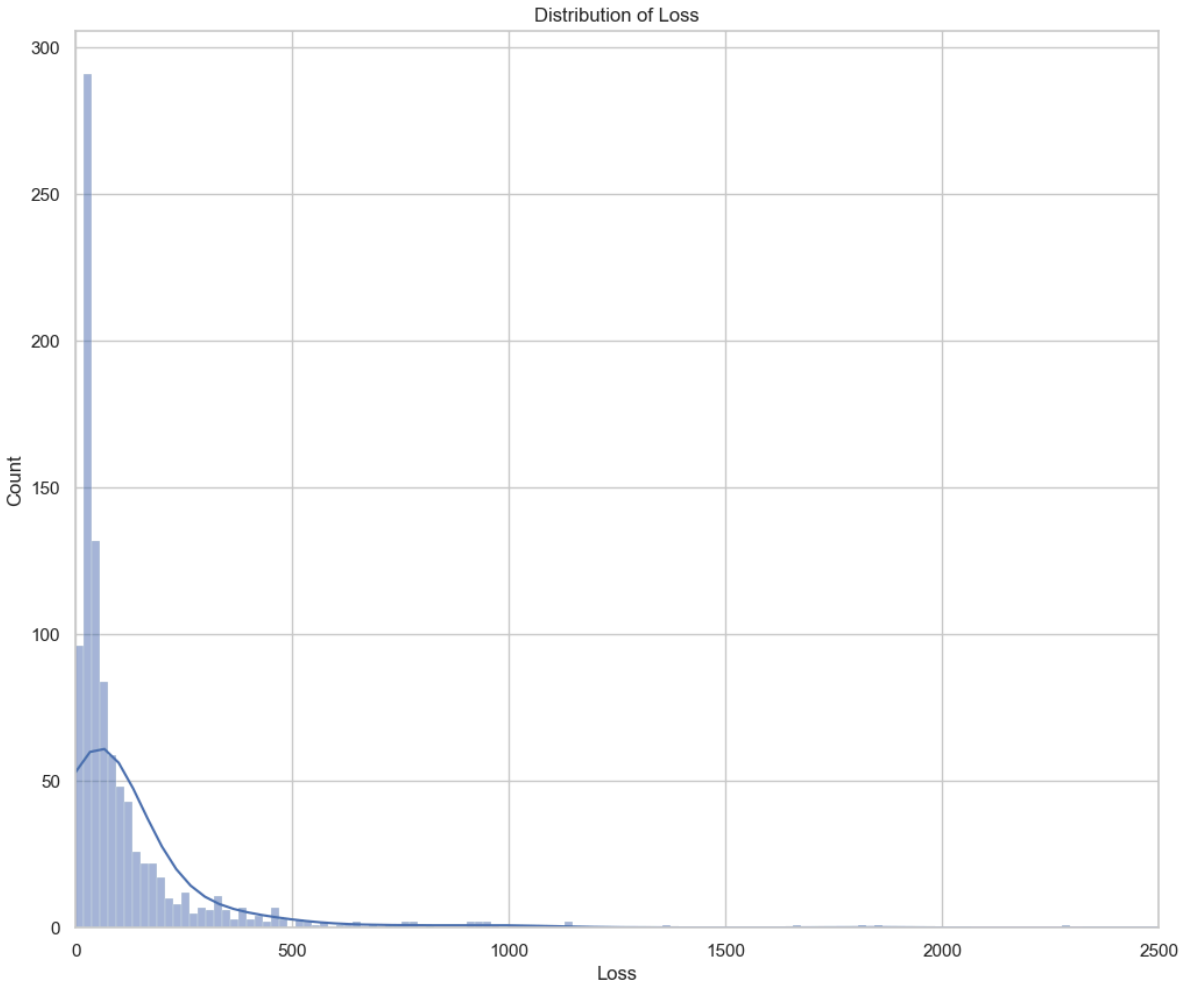
Function to plot the histogram with density plot for a specified column in the DataFrame

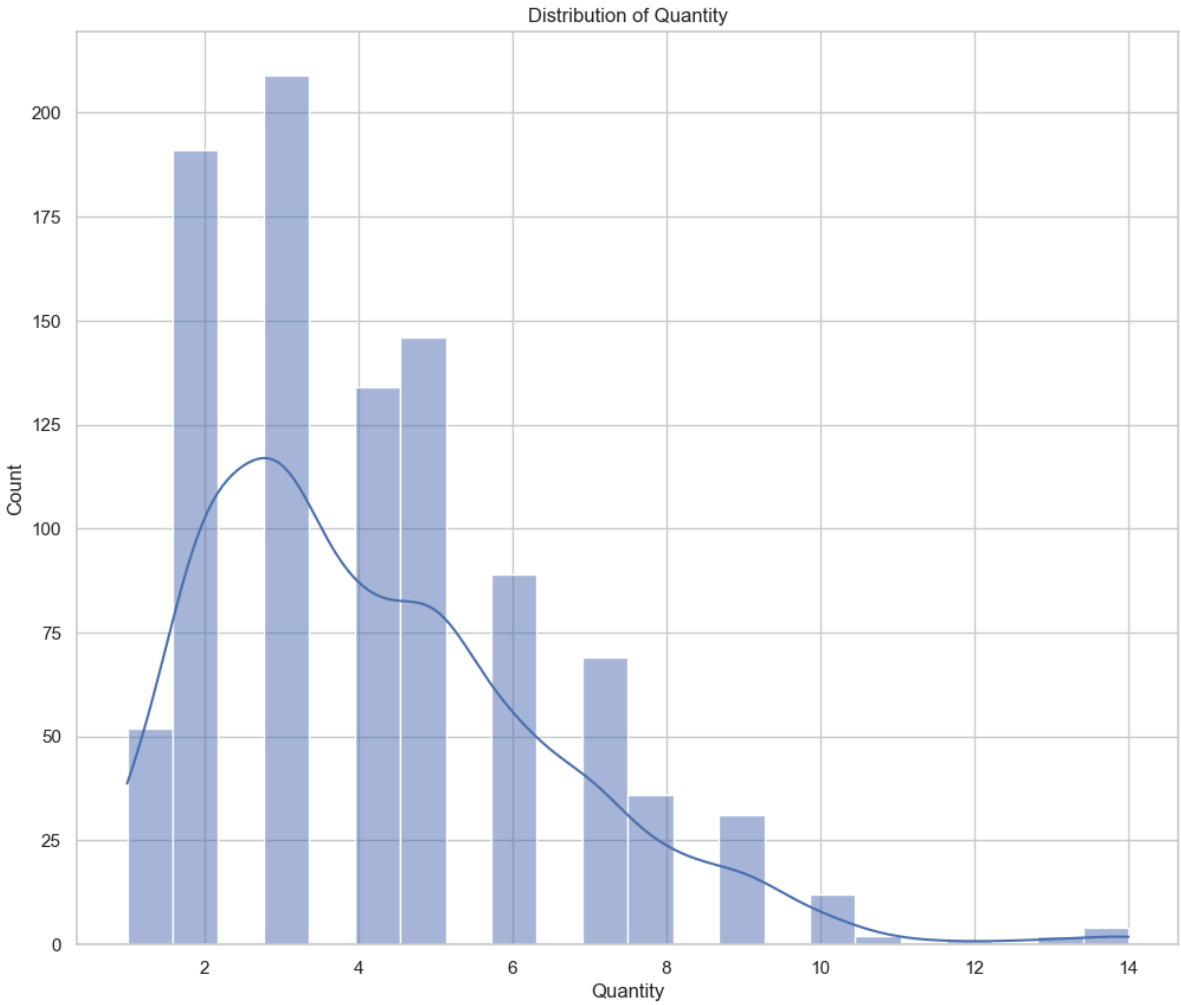
In [ ]:
```
def plot_histogram_density(df, column, xlim=None):
    """
    Plot histogram with density plot for a specified column in the DataFrame.

    Parameters:
    df (DataFrame): Input DataFrame.
    column (str): Name of the column to plot.
    xlim (tuple): Tuple containing the lower and upper limits of the x-axis.

    Returns:
    None
    """
    # Create subplots for each column
```

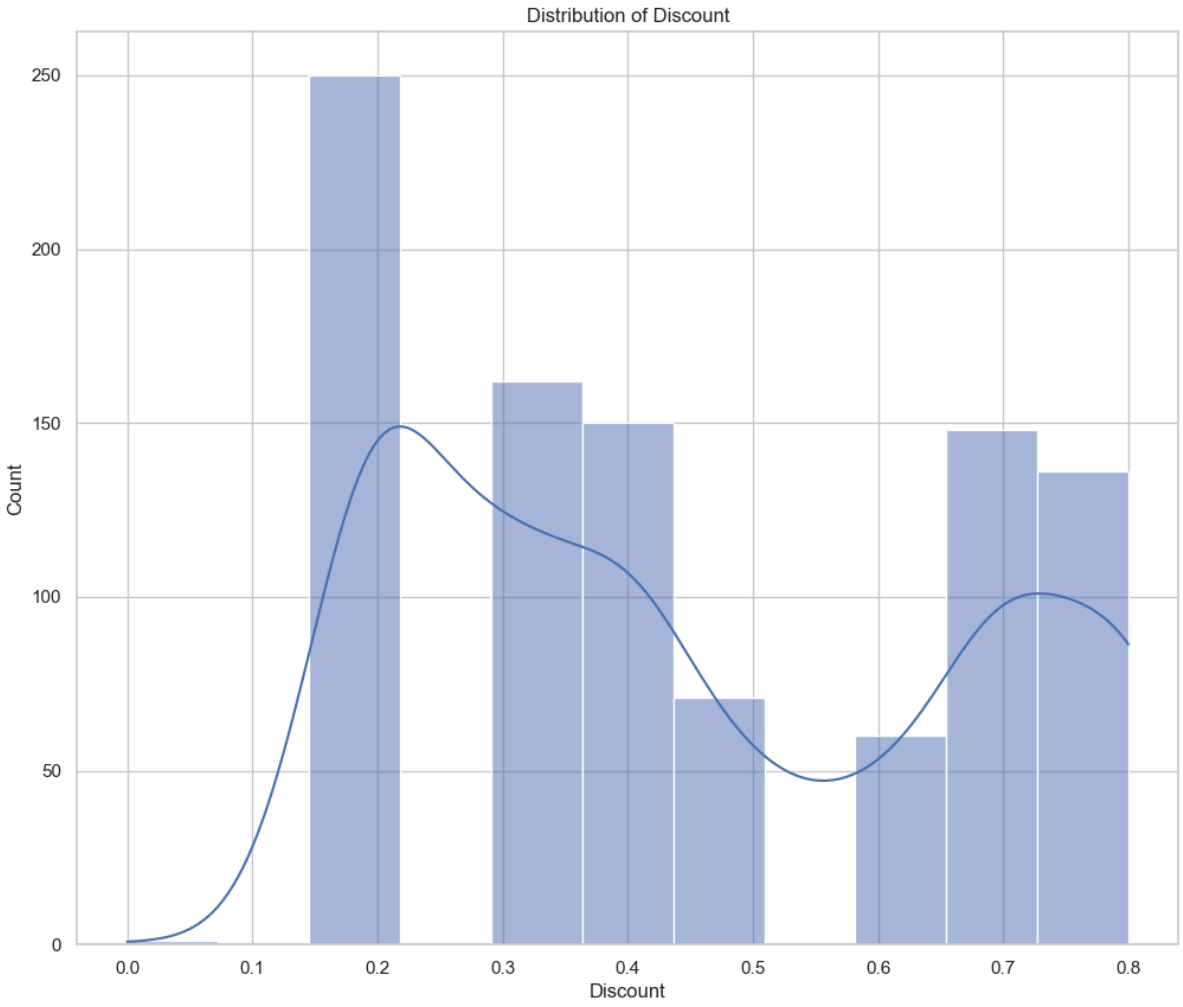
```
    fig, ax = plt.subplots(figsize=(12, 10))

    # Plot histogram with density plot
    sns.histplot(df[column], kde=True, ax=ax)
    ax.set_title(f'Distribution of {column}')

    # Set x-axis limits if specified
    if xlim:
        plt.xlim(xlim)

    # Show the plot
    plt.show()
```

In [ ]:
```
plot_histogram_density(global_super_store_df, 'Sales', xlim=(0, 2500))
plot_histogram_density(global_super_store_df, 'Loss', xlim=(0, 2500))
plot_histogram_density(global_super_store_df, 'Quantity')
plot_histogram_density(global_super_store_df, 'Discount')
```




Distribution of Loss
Count
Loss
0
50
100
150
200
250
300
0
500
1000
1500
2000
2500

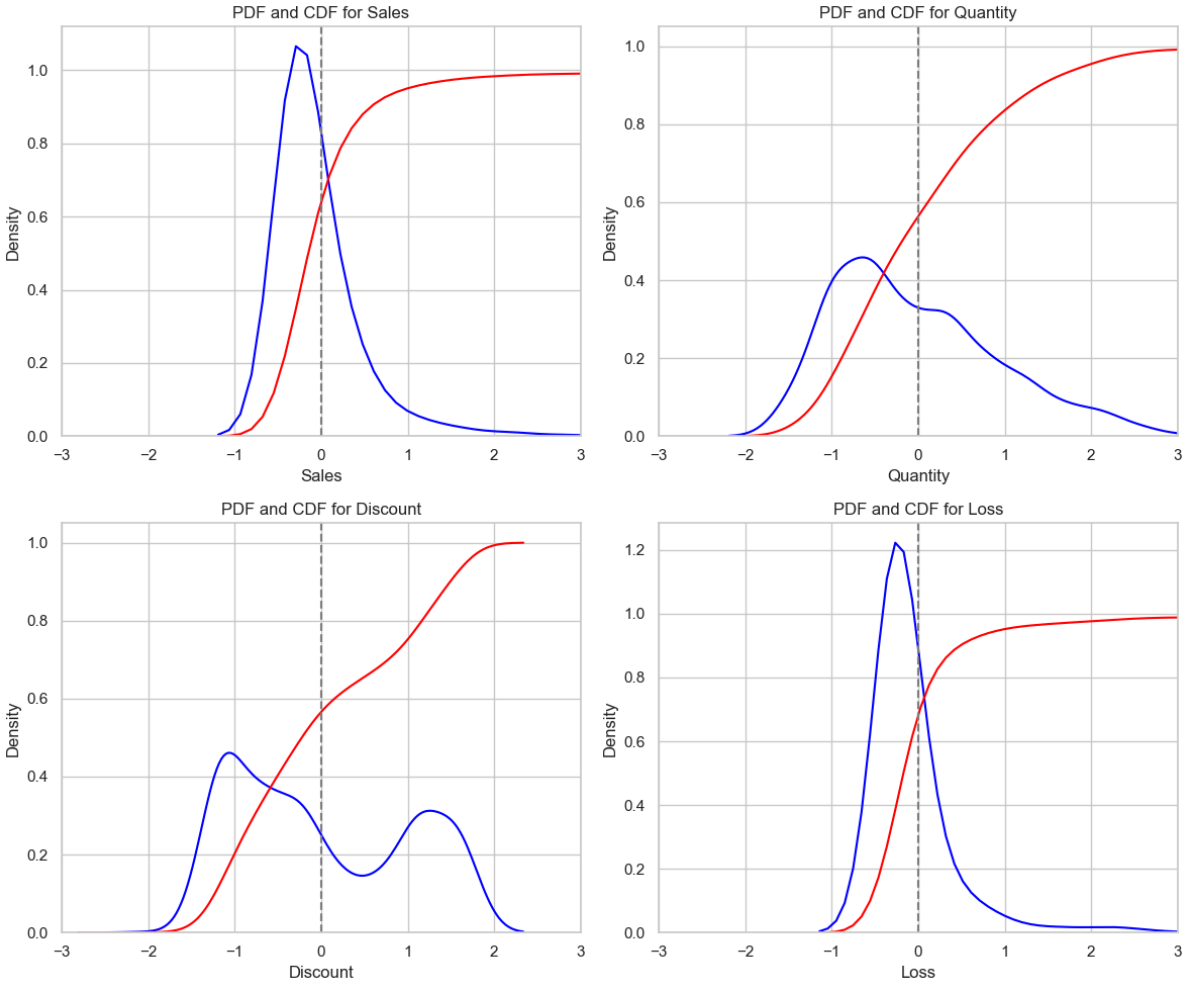

Distribution of Quantity
Count
Quantity
0
25
50
75
100
125
150
175
200
2
4
6
8
10
12
14



Probability Density Function / Cumulative Density Function

In [ ]:
```
# Normalize all columns in the DataFrame
numerical_columns = global_super_store_df.select_dtypes(include=['int64', 'float64'
normalized_df = (global_super_store_df[numerical_columns] - global_super_store_df[r

# Create subplots for each column
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

# Plot PDF and CDF for Sales
sns.kdeplot(normalized_df['Sales'], cumulative=False, ax=axes[0, 0], color='blue',
sns.kdeplot(normalized_df['Sales'], cumulative=True, ax=axes[0, 0], color='red', la
axes[0, 0].set_title('PDF and CDF for Sales')
axes[0, 0].axvline(x=0, linestyle='--', color='gray')  # Add a dotted line at x = 0
axes[0, 0].set_xlim(-3, 3)  # Set custom x-axis limits

# Plot PDF and CDF for Quantity
sns.kdeplot(normalized_df['Quantity'], cumulative=False, ax=axes[0, 1], color='blue
sns.kdeplot(normalized_df['Quantity'], cumulative=True, ax=axes[0, 1], color='red',
axes[0, 1].set_title('PDF and CDF for Quantity')
axes[0, 1].axvline(x=0, linestyle='--', color='gray')  # Add a dotted line at x = 0
axes[0, 1].set_xlim(-3, 3)  # Set custom x-axis limits

# Plot PDF and CDF for Discount
sns.kdeplot(normalized_df['Discount'], cumulative=False, ax=axes[1, 0], color='blue
sns.kdeplot(normalized_df['Discount'], cumulative=True, ax=axes[1, 0], color='red',
axes[1, 0].set_title('PDF and CDF for Discount')
axes[1, 0].axvline(x=0, linestyle='--', color='gray')  # Add a dotted line at x = 0
axes[1, 0].set_xlim(-3, 3)  # Set custom x-axis limits

# Plot PDF and CDF for Loss
```

```
sns.kdeplot(normalized_df['Loss'], cumulative=False, ax=axes[1, 1], color='blue', l
sns.kdeplot(normalized_df['Loss'], cumulative=True, ax=axes[1, 1], color='red', lab
axes[1, 1].set_title('PDF and CDF for Loss')
axes[1, 1].axvline(x=0, linestyle='--', color='gray')  # Add a dotted line at x = 0
axes[1, 1].set_xlim(-3, 3)  # Set custom x-axis limits

# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```



In [ ]:
```
# Calculate skewness for each column
skewness = normalized_df[['Sales', 'Loss', 'Quantity', 'Discount']].skew()

print(tabulate(skewness.to_frame().round(4), headers=['Numercial Features', 'Skewne
```

```
+--------------------+----------+
| Numercial Features | Skewness |
+--------------------+----------+
|              Sales |  15.2478 |
|               Loss |   9.6722 |
|           Quantity |   1.0036 |
|           Discount |    0.331 |
+--------------------+----------+
```

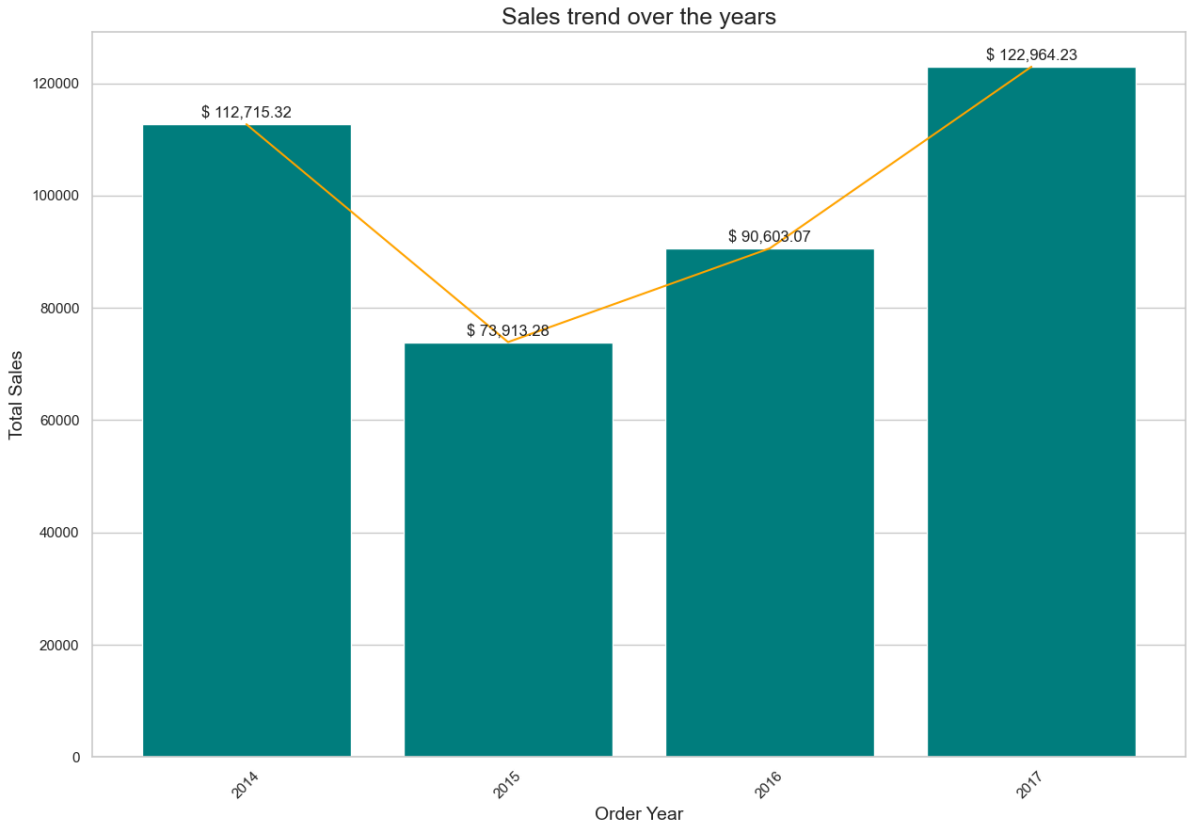
Trends

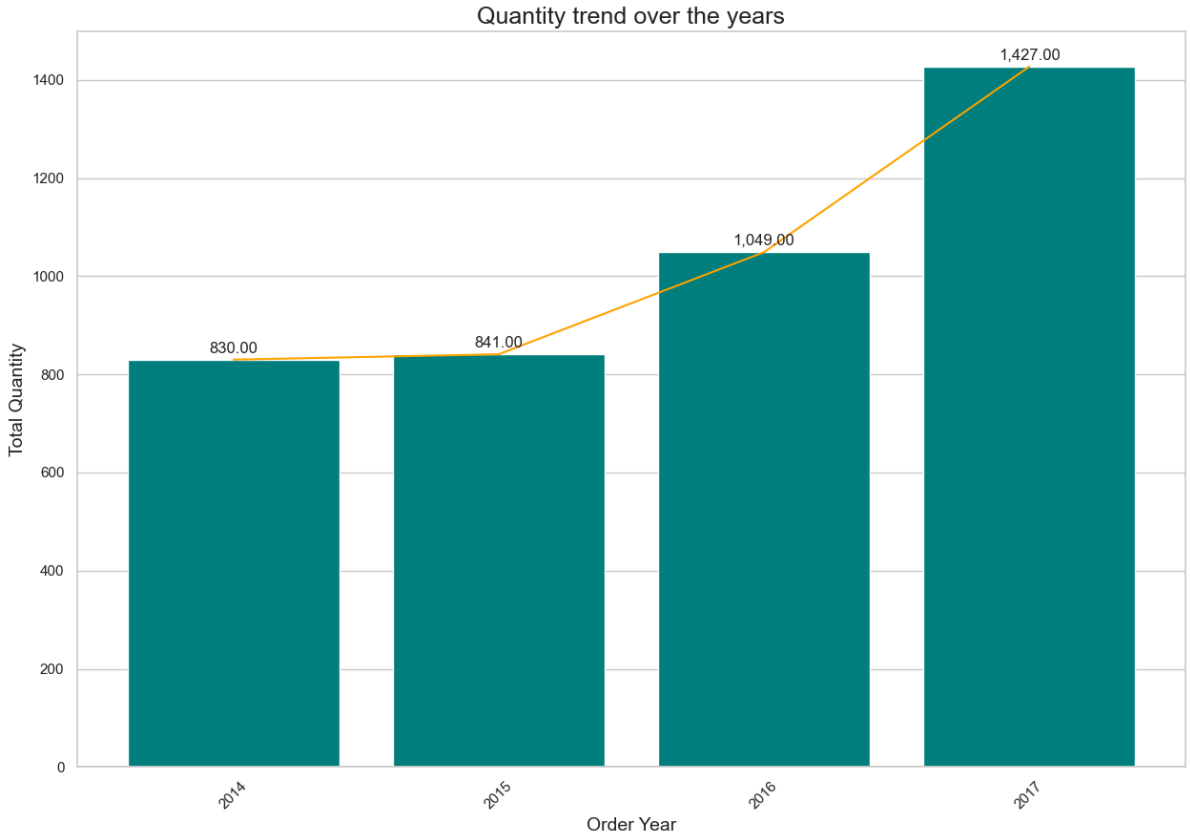
Function to generate a trend plot for a specified column in a DataFrame, showing the total value of the column over the years.

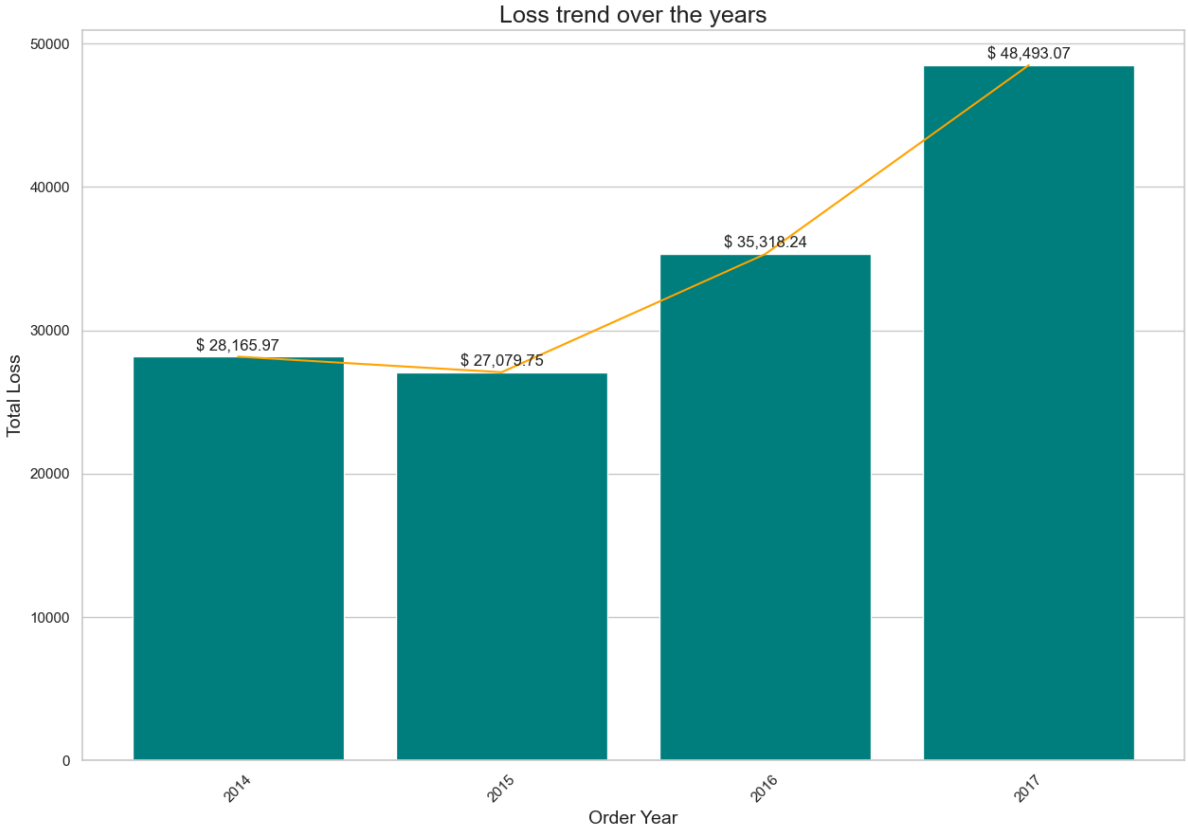
In [ ]:
```
def plot_trend(df, numerical_column, display_dollar_sign=False):
    """
    Generates a trend plot for a specified column in a DataFrame, showing the total

    Parameters:
    - df (DataFrame): The DataFrame containing the data.
    - numerical_column (str): The name of the column for which the trend plot is to
    - display_dollar_sign (bool): Whether to display y-axis values with a dollar si

    Returns:
    None
    """

    # Group by 'Order Year' and calculate the sum of the specified column
    trend_data = df.groupby(['Order Year'])[numerical_column].sum()

    # Create the plot
    fig, ax = plt.subplots(figsize=(15,10))

    # Plot the bar plot
    bars = ax.bar(x=trend_data.index, height=trend_data.values, color='teal')

    # Annotate each bar with its value
    for bar in bars:
        height = bar.get_height()
        if display_dollar_sign:
            ax.annotate('$ {:,.2f}'.format(height),
                        xy=(bar.get_x() + bar.get_width() / 2, height),
                        xytext=(0, 3),  # 3 points vertical offset
                        textcoords="offset points",
                        ha='center', va='bottom')
        else:
            ax.annotate('{:,.2f}'.format(height),
                        xy=(bar.get_x() + bar.get_width() / 2, height),
                        xytext=(0, 3),  # 3 points vertical offset
                        textcoords="offset points",
                        ha='center', va='bottom')

    # Plot the line plot
    ax.plot(trend_data.index, trend_data.values, color='orange')

    # Turn off scientific notation for y-axis
    ax.yaxis.get_major_formatter().set_scientific(False)

    # Set title and labels
    plt.title(f'{numerical_column} trend over the years', fontsize=18)
    plt.ylabel(f'Total {numerical_column}', fontsize=14)
    plt.xlabel('Order Year', fontsize=14)

    # Convert 'Order Year' column to a list of integers
    years = trend_data.index.tolist()

    # Set x-ticks to only include specific years
    plt.xticks(years, rotation=45)

    # Add gridlines
    plt.grid(axis='x')

    # Show the plot
    plt.show()
```

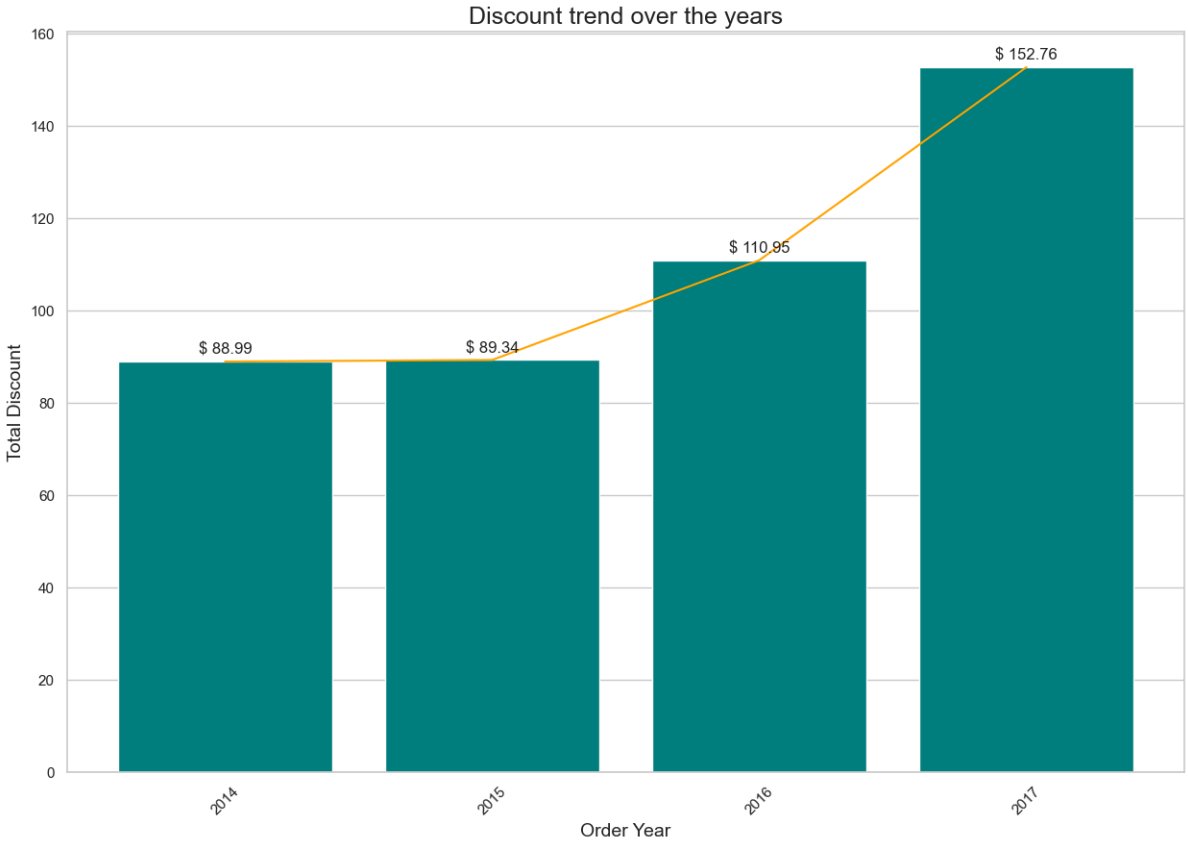
In [ ]:
```
# Call the function for sales
plot_trend(global_super_store_df, 'Sales', display_dollar_sign=True)
```

```
# Call the function for quantities
plot_trend(global_super_store_df, 'Quantity', display_dollar_sign=False)

# Call the function for loss
plot_trend(global_super_store_df, 'Loss', display_dollar_sign=True)

# Call the function for discounts
plot_trend(global_super_store_df, 'Discount', display_dollar_sign=True)
```









Outlier Treatment

Interquartile Range (IQR) Method

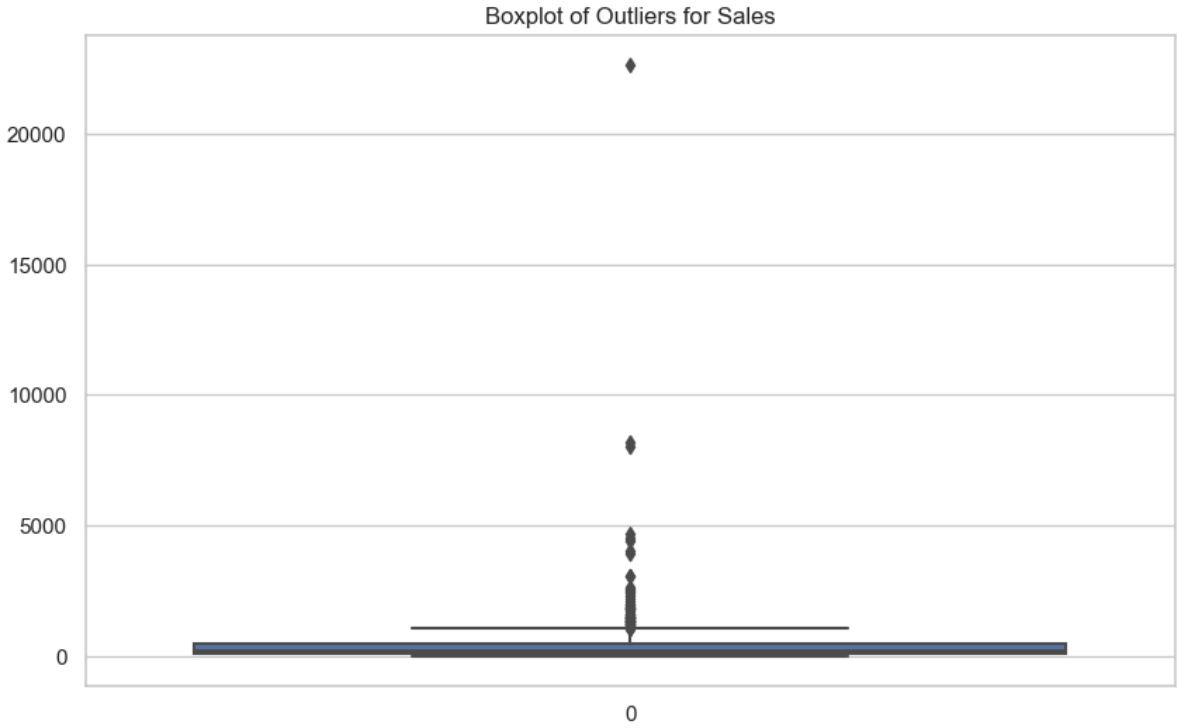
Function to calculate IQR and plot a boxplot.

In [ ]:
```
def detect_plot_outliers_iqr(df, numerical_feature):
    """
    Plots a boxplot for the specified numerical feature and identifies outliers bas
```

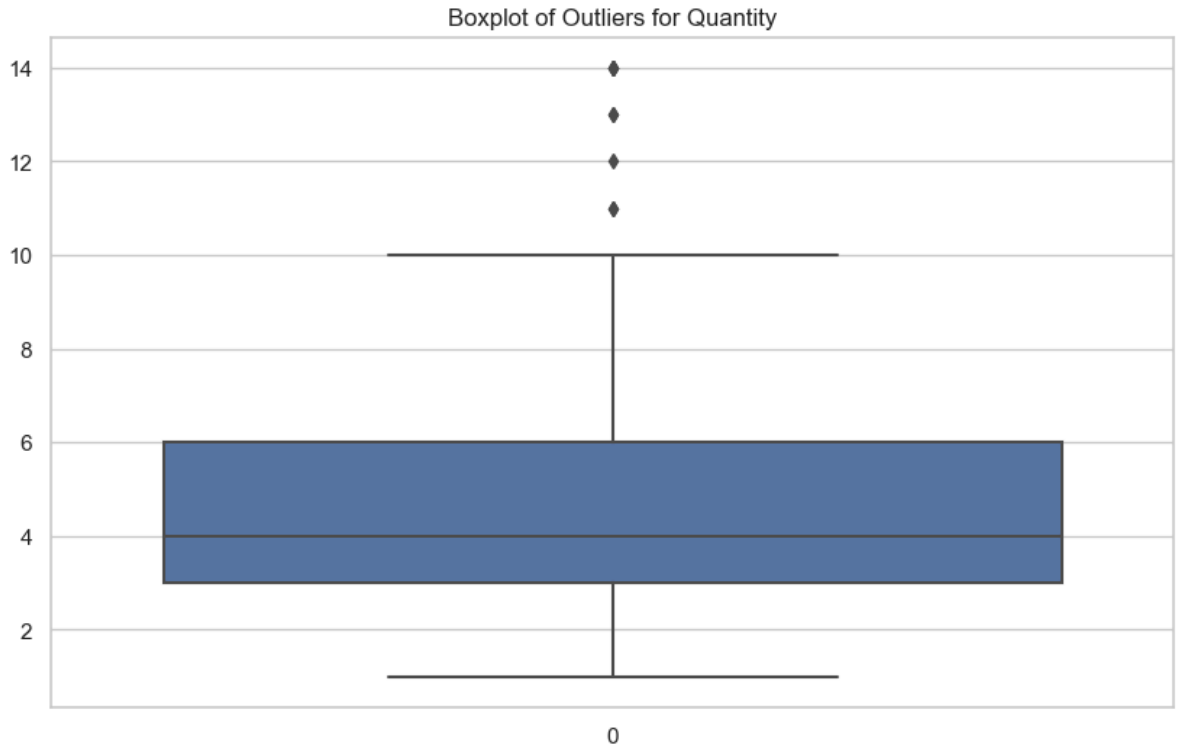
```
    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.
        numerical_feature (str): The name of the numerical feature to analyze.

    Returns:
        None
    """

    q1 = df[numerical_feature].quantile(0.25)
    q3 = df[numerical_feature].quantile(0.75)

    iqr = q3 - q1
    lower_limit = q1 - 1.5 * iqr
    upper_limit = q3 + 1.5 * iqr

    outliers_df = df[(df[numerical_feature] < lower_limit)|(df[numerical_feature] >
    print(f"Outlier numerical feature: {numerical_feature}, Outlier Count: {outlier

    numerical_column = df[numerical_feature]
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=numerical_column)
    plt.title(f'Boxplot of Outliers for {numerical_feature}')
    plt.show()
```

In [ ]:
```
detect_plot_outliers_iqr(global_super_store_df, 'Sales')
detect_plot_outliers_iqr(global_super_store_df, 'Quantity')
detect_plot_outliers_iqr(global_super_store_df, 'Discount')
detect_plot_outliers_iqr(global_super_store_df, 'Loss')
detect_plot_outliers_iqr(global_super_store_df, 'Shipment Days')
```

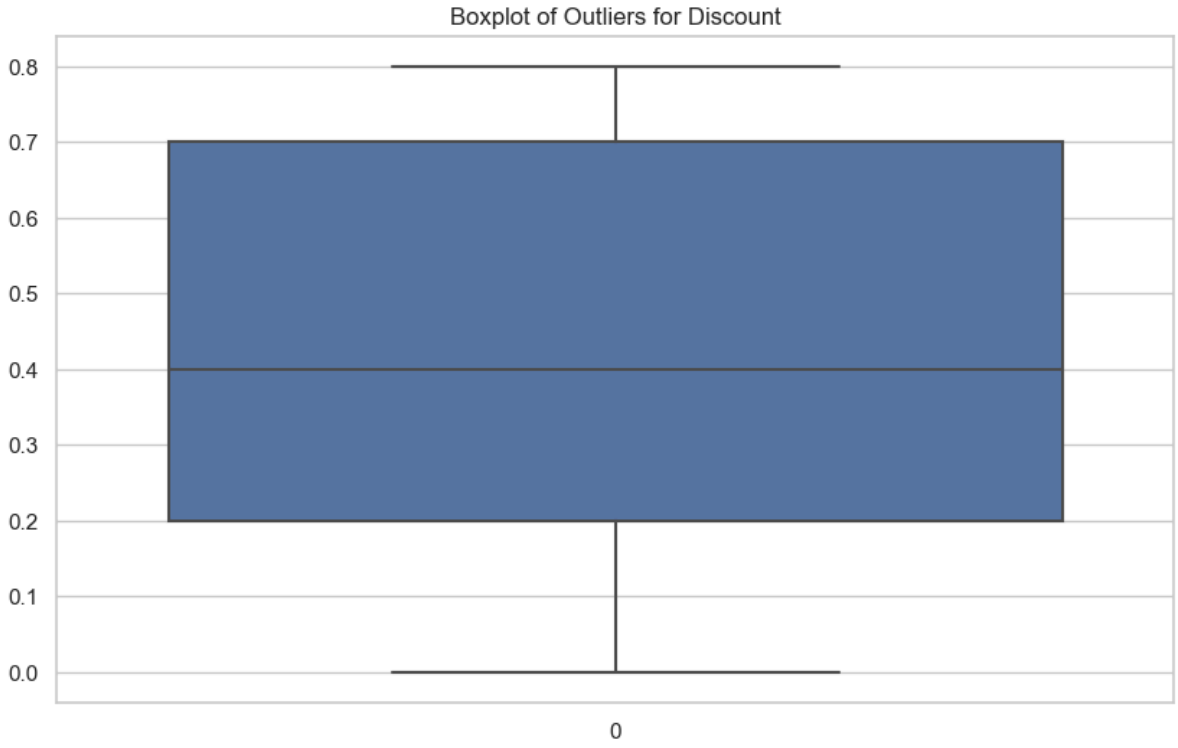
```
Outlier numerical feature: Sales, Outlier Count: 67
```



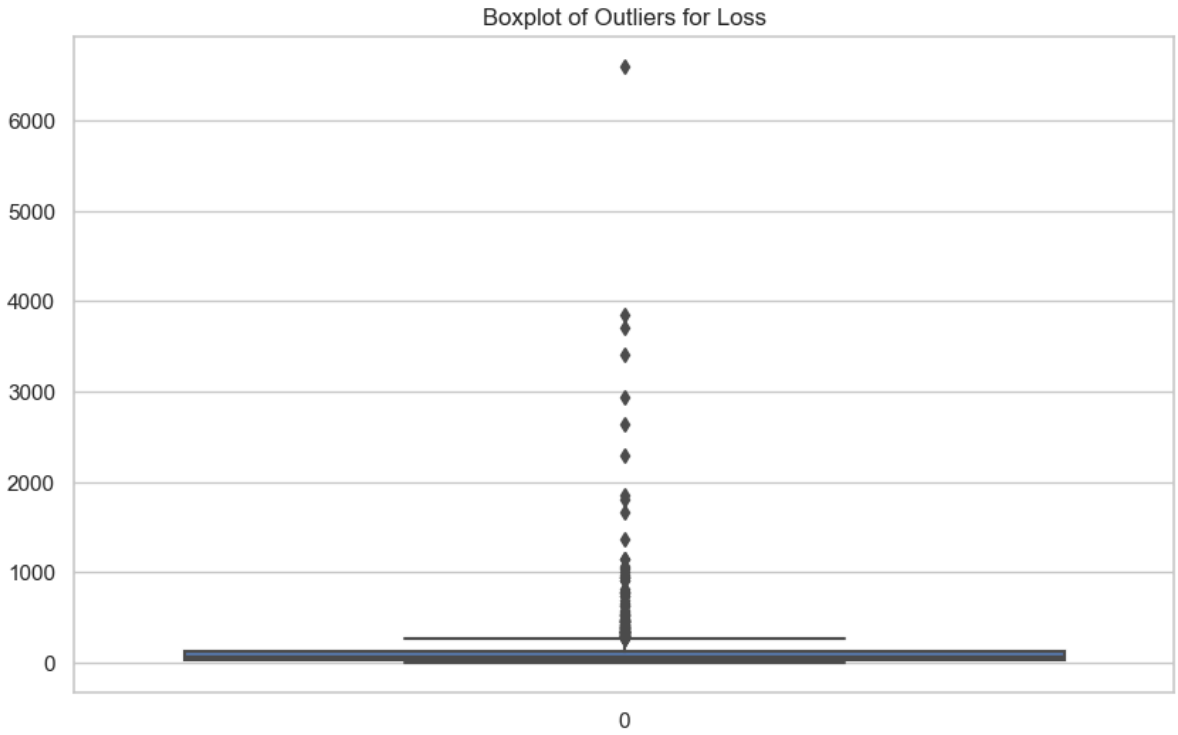

```
Outlier numerical feature: Quantity, Outlier Count: 9
```



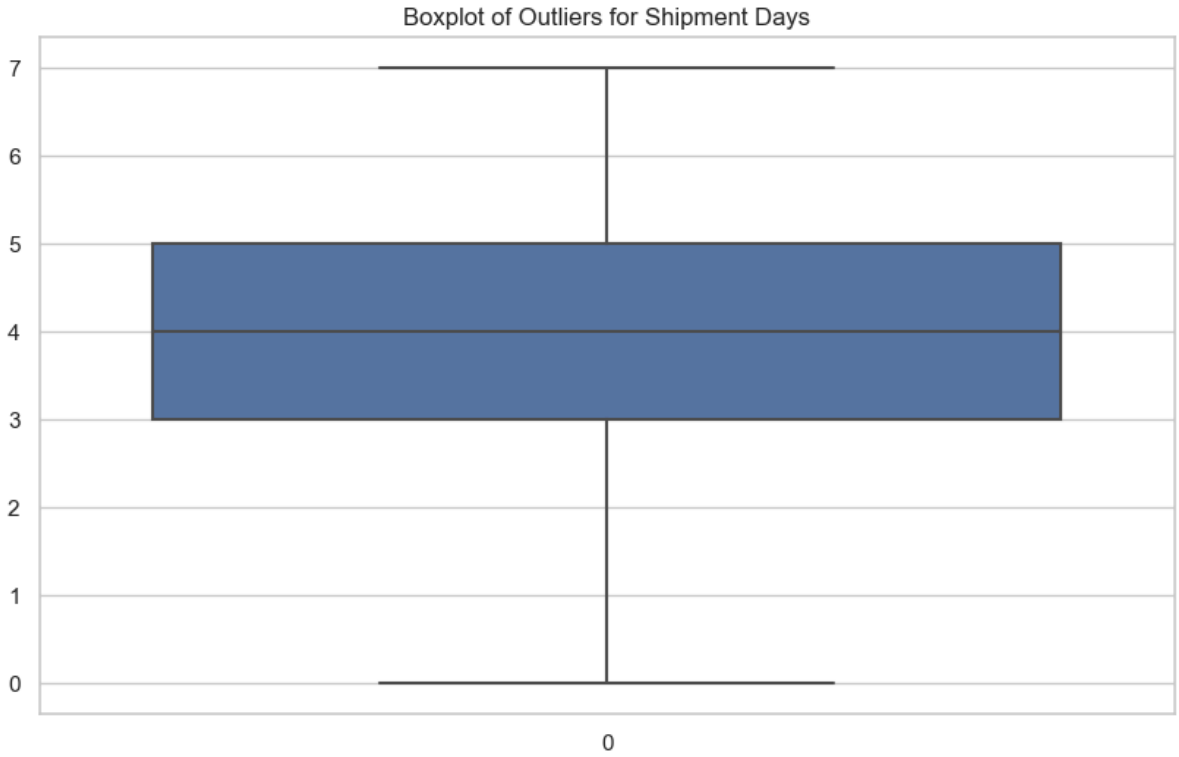

```
Outlier numerical feature: Discount, Outlier Count: 0
```




```
Outlier numerical feature: Loss, Outlier Count: 108
```




```
Outlier numerical feature: Shipment Days, Outlier Count: 0
```



Z-Score Method

Function to detect the outliers using z-score method.

In [ ]:
```
def detect_outliers_zscore(df, numerical_feature, threshold=3):
    """
    Detect outliers in a numerical feature of a DataFrame using the Z-Score method.

    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.
        numerical_feature (str): The name of the numerical feature to analyze.
        threshold (float): The Z-Score threshold for identifying outliers. Default

    Returns:
```

```
        None
    """
    data = df[numerical_feature]
    z_scores = ((data - data.mean()) / data.std()).abs()
    outliers = z_scores > threshold
    outlier_count = outliers.sum()
    print(f"Outlier count for {numerical_feature}: {outlier_count}")
```

In [ ]:
```
detect_outliers_zscore(global_super_store_df, 'Sales')
detect_outliers_zscore(global_super_store_df, 'Quantity')
detect_outliers_zscore(global_super_store_df, 'Discount')
detect_outliers_zscore(global_super_store_df, 'Loss')
detect_outliers_zscore(global_super_store_df, 'Shipment Days')
```

```
Outlier count for Sales: 8
Outlier count for Quantity: 7
Outlier count for Discount: 0
Outlier count for Loss: 11
Outlier count for Shipment Days: 0
```

Removing outliers using IQR method

Function to remove the outliers from the original dataframe.

In [ ]:
```
def remove_outliers_iqr(df):
    """
    Removes outliers from all numerical columns in the DataFrame based on the Inter

    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.

    Returns:
        DataFrame: The DataFrame with outliers removed.
    """
    # Get numerical columns
    numerical_columns = df.select_dtypes(include=['number']).columns

    # Iterate over numerical columns and remove outliers
    for column in numerical_columns:
        df = remove_outliers_iqr_column(df, column)

    return df

def remove_outliers_iqr_column(df, column):
    """
    Removes outliers from a specific numerical column in the DataFrame based on the

    Parameters:
        df (DataFrame): The pandas DataFrame containing the data.
        column (str): The name of the numerical column to remove outliers from.

    Returns:
        DataFrame: The DataFrame with outliers removed.
    """
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Filter out rows where the column value is outside the bounds
    filtered_df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

```
    return filtered_df
```

In [ ]:
```
global_super_store_df = remove_outliers_iqr(global_super_store_df)
```

Conclusion

- Handling missing values in dataset
    - The following columns identified as non-meaningful for EDA, hence been dropped from the dataframe:
        - Row ID, Order ID, Customer ID, Product ID, Product Name
    - Replaced the Faulty values with filler values on categorical columns:
        - Ship Mode, Segment, State, Region, Category, Sub-Category
    - Replaced the following numerical columns were type of object, and data cleansed:
        - Quantity, Profit
        - Applied the `convert_alphabetic_to_float()` library to fix Quantity column
    - Cleansed the date using function: `format_date_in_yyyymmdd()`
    - Populated Geo information:
        - Function `get_city_from_postal_code()` is used to populate the city from postcode
        - Function `get_state_from_postal_code()` is used to populate the state from postcode
- Based on the 1000 order sample, the Global Super Store has:
    - An average sale of $410.
    - Sold ~4 quantities in average.
    - Only made $369 as profit, rest of them are massive losses.
    - Max order to ship turn around 7 days, average being ~4 days.
- Grouped the dataset by categorical columns against the sales and losses
    - **Furniture** is the best sales category and also made bigger losses.
    - **Tables** is the best sales sub category, and **Binders** made the worst losses.
    - **Texas** has the highest sales and well as highest losses.
    - **Consumer** segment making half of the total sales, but also responsible for one-thirds of the total losses.
    - **Standard** shipping method is preferred as the sales percentage is nearly two-thirds of total shipments.
- Univariate analysis and visualization
    - Based on the PDF/CDF graphs, the skewness of **Sales** and **Loss** columns, it is heavily skewed to the right, with a few very high sales/loss values exerting a disproportionate influence on the distribution.
    - Year on year trends
        - Sales numbers are growing year on year, dipping slightly in 2015.
        - Global super store has sold more quantities year on year despite making more losses.

3. Task 3

Categorical Vs. Categorical

The chi-square test of independence is a statistical test used to determine whether there is a significant association between two categorical variables.

Chi-Square Test of Independence

In [ ]:
```
def chi_square_test(df, categorical_feature_1, categorical_feature_2, alpha=0.05):
    """
    Perform chi-square test of independence between two categorical variables.

    Parameters:
        df (DataFrame): Input DataFrame containing the data.
        categorical_feature_1 (str): Name of the first categorical variable.
        categorical_feature_2 (str): Name of the second categorical variable.
        alpha (float): Significance level (default is 0.05).
    """
    # Cross-tabulation
    cross_tab = pd.crosstab(df[categorical_feature_1], df[categorical_feature_2])

    # Perform chi-square test
    chi2, p_value, dof, expected = chi2_contingency(cross_tab)

    # Print results
    print(f"Chi-square statistic: {chi2}")
    print(f"P-value: {p_value}")
    print(f"Degrees of freedom: {dof}")

    # Make decision based on p-value
    if p_value <= alpha:
        print(f"Based on the p-value of {p_value}, we reject the null hypothesis.")
        print(f"There is a significant association between {categorical_feature_1}
    else:
        print(f"Based on the p-value of {p_value}, we fail to reject the null hypot
        print(f"There is no significant association between {categorical_feature_1}
```

Performing Chi-Square test of independence.

In [ ]:
```
# List of categorical variables
categorical_features = ['Ship Mode', 'Segment', 'Region', 'Category', 'Sub-Category

# Loop through all combinations of categorical variables to call chi_square_test
for i in range(len(categorical_features)):
    for j in range(i + 1, len(categorical_features)):
        categorical_feature_1 = categorical_features[i]
        categorical_feature_2 = categorical_features[j]
        print(f"Performing chi-square test between {categorical_feature_1} and {cat
        chi_square_test(global_super_store_df, categorical_feature_1, categorical_f
        print("\n")
```

```
Performing chi-square test between Ship Mode and Segment:
Chi-square statistic: 5.620633935946101
P-value: 0.4669980038187912
Degrees of freedom: 6
Based on the p-value of 0.4669980038187912, we fail to reject the null hypothesis.
There is no significant association between Ship Mode and Segment.


Performing chi-square test between Ship Mode and Region:
Chi-square statistic: 14.294943833673106
P-value: 0.11221352184272178
Degrees of freedom: 9
Based on the p-value of 0.11221352184272178, we fail to reject the null hypothesi
s.
There is no significant association between Ship Mode and Region.


Performing chi-square test between Ship Mode and Category:
Chi-square statistic: 3.1422040665529076
P-value: 0.7907987938955084
Degrees of freedom: 6
Based on the p-value of 0.7907987938955084, we fail to reject the null hypothesis.
There is no significant association between Ship Mode and Category.


Performing chi-square test between Ship Mode and Sub-Category:
Chi-square statistic: 35.80469153873701
P-value: 0.21454116179140625
Degrees of freedom: 30
Based on the p-value of 0.21454116179140625, we fail to reject the null hypothesi
s.
There is no significant association between Ship Mode and Sub-Category.


Performing chi-square test between Segment and Region:
Chi-square statistic: 5.372511621886918
P-value: 0.4969973003222622
Degrees of freedom: 6
Based on the p-value of 0.4969973003222622, we fail to reject the null hypothesis.
There is no significant association between Segment and Region.


Performing chi-square test between Segment and Category:
Chi-square statistic: 3.330745510287931
P-value: 0.5040756934811397
Degrees of freedom: 4
Based on the p-value of 0.5040756934811397, we fail to reject the null hypothesis.
There is no significant association between Segment and Category.


Performing chi-square test between Segment and Sub-Category:
Chi-square statistic: 14.652883814938855
P-value: 0.7959132032930026
Degrees of freedom: 20
Based on the p-value of 0.7959132032930026, we fail to reject the null hypothesis.
There is no significant association between Segment and Sub-Category.


Performing chi-square test between Region and Category:
Chi-square statistic: 103.50328539993852
P-value: 4.6574174516409994e-20
Degrees of freedom: 6
Based on the p-value of 4.6574174516409994e-20, we reject the null hypothesis.
There is a significant association between Region and Category.
```

```
Performing chi-square test between Region and Sub-Category:
Chi-square statistic: 259.59669247851286
P-value: 2.107543089876603e-38
Degrees of freedom: 30
Based on the p-value of 2.107543089876603e-38, we reject the null hypothesis.
There is a significant association between Region and Sub-Category.


Performing chi-square test between Category and Sub-Category:
Chi-square statistic: 1541.9999999999998
P-value: 0.0
Degrees of freedom: 20
Based on the p-value of 0.0, we reject the null hypothesis.
There is a significant association between Category and Sub-Category.
```

According to chi-square test of independence, these categorical features has a significant association:

- *Category* and *Sub-Category*
- *Region* and *Category*
- *Region* and *Sub-Category*

Hence, the bivariate analysis/visualization will be based between these categorical features.

Function: `categorical_analysis()` uses cross-tabulation to plot heatmaps/stacked bar plots.

Function: `bivariate_categorical_sales_figure_analysis()` uses pivot tables to plot heatmaps/stacked bar plots .

Helper Functions for two categorical variables analysis

Function to plot the cross tabulation between two categorical features.

In [ ]:
```python
def categorical_analysis(df, categorical_feature_1, categorical_feature_2):
    """
    Perform bivariate analysis and visualization between two categorical variables

    Parameters:
        df (DataFrame): Input DataFrame containing the data.
        categorical_feature_1 (str): Name of the first categorical variable.
        categorical_feature_2 (str): Name of the second categorical variable.
    """

    # Cross-tab
    cross_tab = pd.crosstab(df[categorical_feature_1], df[categorical_feature_2])
    # Create subplots
    fig, axes = plt.subplots(1, 2, figsize=(20, 10))

    # Visualize cross-tabuate using a heatmap
    sns.heatmap(cross_tab, annot=True, fmt='d', cmap='YlGnBu', ax=axes[0])
    axes[0].set_title(f'Cross-tabulation between {categorical_feature_1} and {categ
    axes[0].set_xlabel(categorical_feature_2)
    axes[0].set_ylabel(categorical_feature_1)

    # Stacked bar plot for better visualization
```

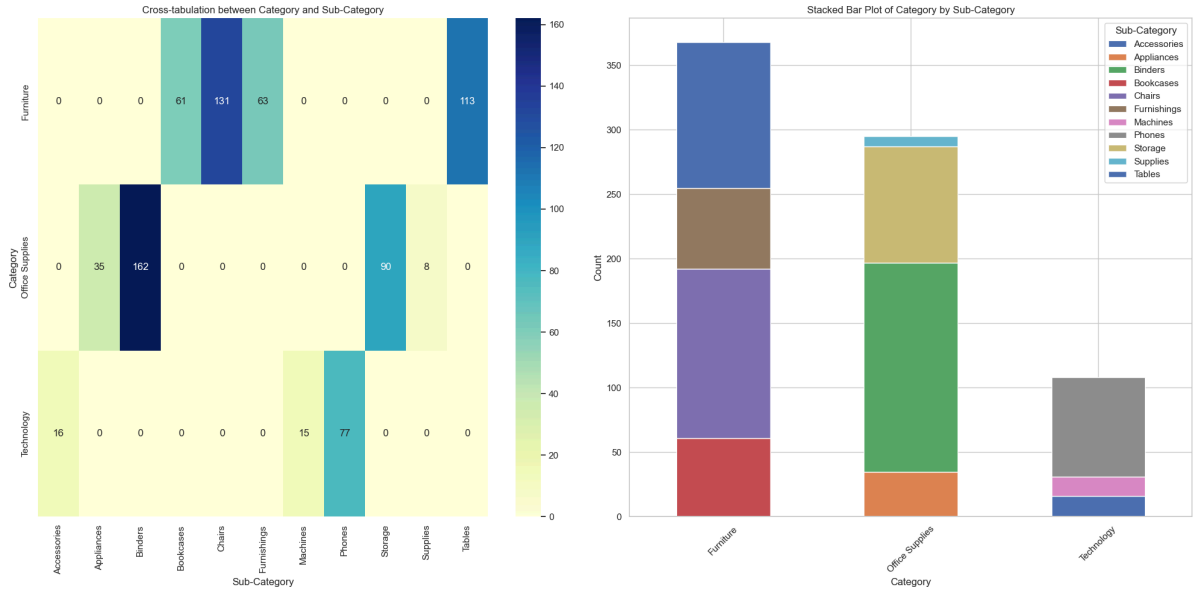
```
    cross_tab.plot(kind='bar', stacked=True, ax=axes[1])
    axes[1].set_title(f'Stacked Bar Plot of {categorical_feature_1} by {categorical
    axes[1].set_xlabel(categorical_feature_1)
    axes[1].set_ylabel('Count')
    axes[1].set_xticklabels(cross_tab.index, rotation=45)
    axes[1].legend(title=categorical_feature_2)

    plt.tight_layout()
    plt.show()
```

Function to plot the pivot table between two categorical features and a numerical feature.

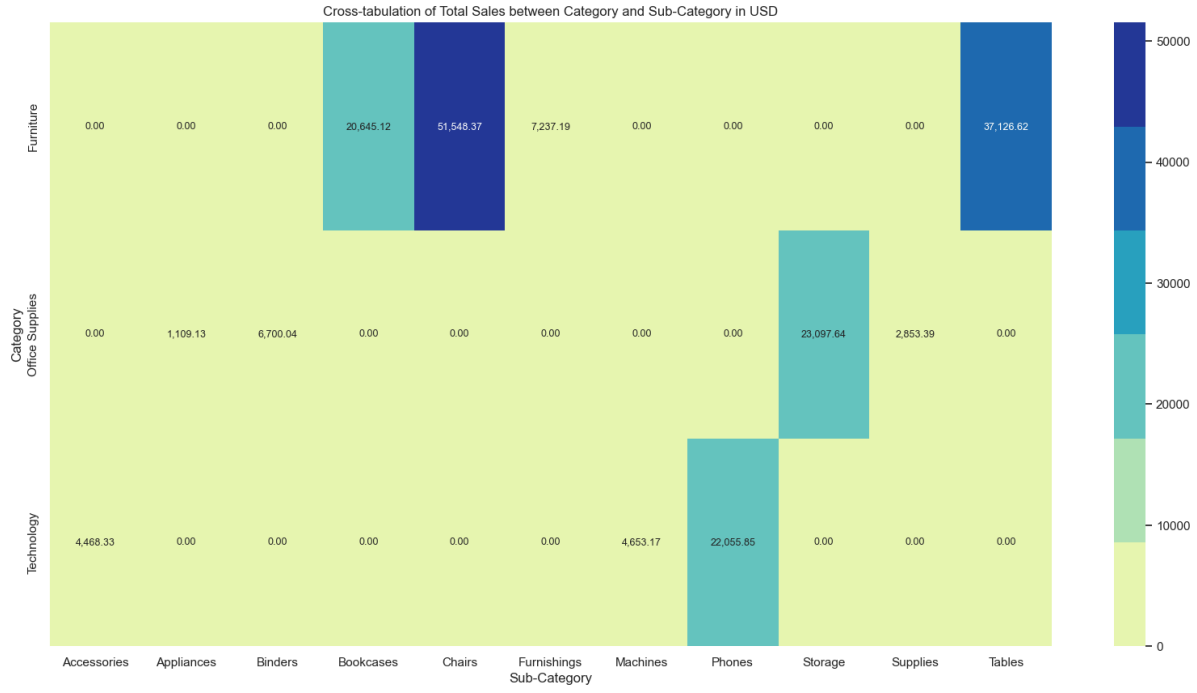
In [ ]:
```
def bivariate_categorical_figure_analysis(df, categorical_feature_1, categorical_fe
    """
    Perform bivariate analysis and visualization between two categorical variables

    Parameters:
        df (DataFrame): Input DataFrame containing the data.
        categorical_feature_1 (str): Name of the first categorical variable.
        categorical_feature_2 (str): Name of the second categorical variable.
    """
    # Create a pivot table with 'Sales' values
    pivot_table = df.pivot_table(values=numerical_feature, index=categorical_featur

    # Define color palette
    color_palette = sns.color_palette("YlGnBu")

    # Plotting the pivot table
    plt.figure(figsize=(20, 10))
    sns.heatmap(pivot_table, annot=True, cmap=color_palette, fmt=',.2f', annot_kws=
    plt.title(f'Cross-tabulation of Total {numerical_feature} between {categorical_
    plt.xlabel(categorical_feature_2)
    plt.ylabel(categorical_feature_1)
    plt.show()

    # Plotting the pivot table as a stacked bar plot
    ax = pivot_table.plot(kind='bar', stacked=True, figsize=(20, 10), color=color_p
    ax.set_title(f'Stacked Bar Plot of Total {numerical_feature} by {categorical_fe
    ax.set_xlabel(categorical_feature_1)
    ax.set_ylabel(f'Total {numerical_feature}')
    ax.set_xticklabels(pivot_table.index, rotation=45)

    # Format y-axis tick labels as currency
    ax.yaxis.set_major_formatter('$ {:,.2f}'.format)

    ax.legend(title=categorical_feature_2)
    plt.show()
```

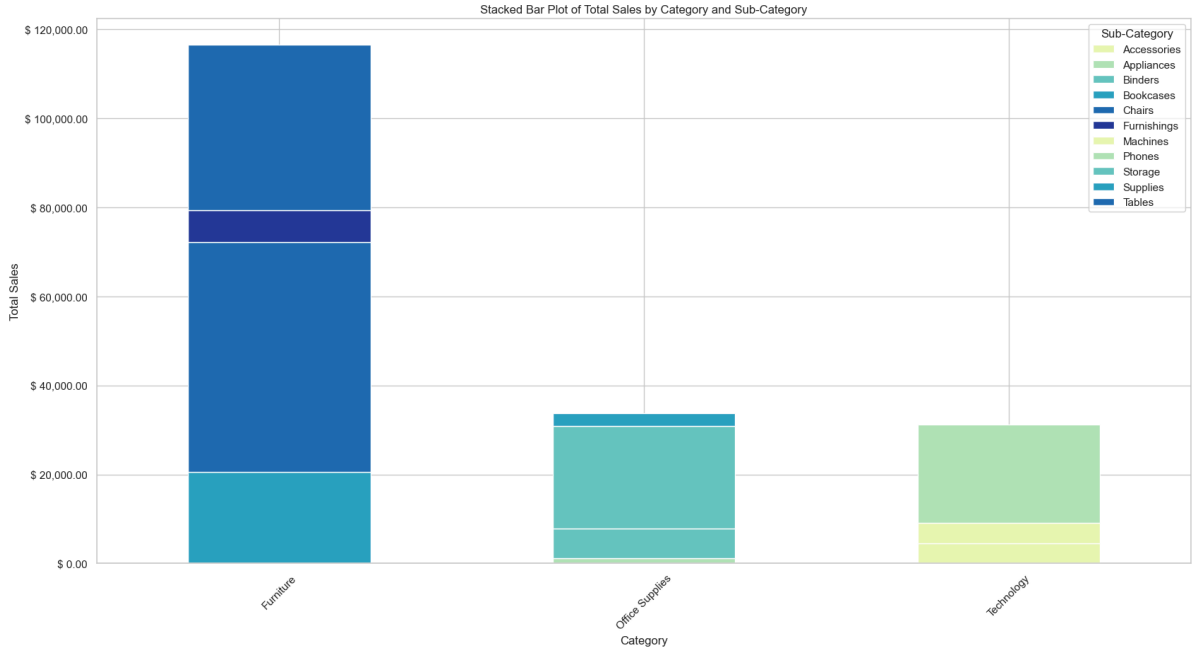
Category Vs. Sub-Category

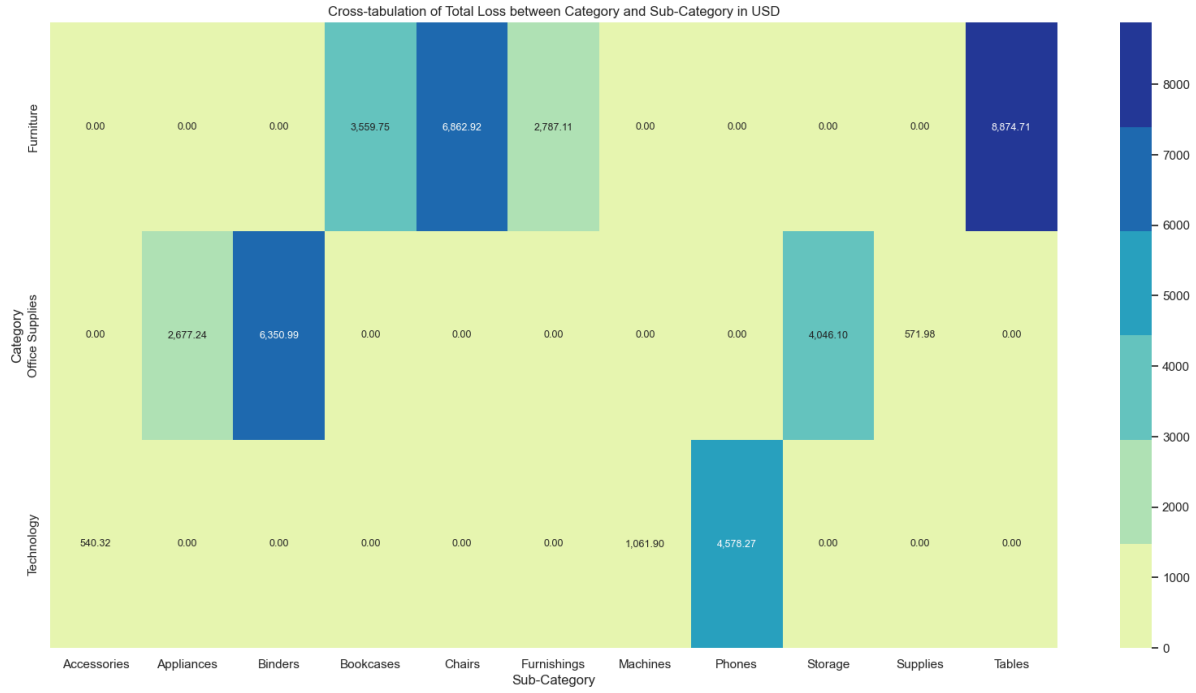
In [ ]:
```
categorical_analysis(global_super_store_df, 'Category', 'Sub-Category')
```

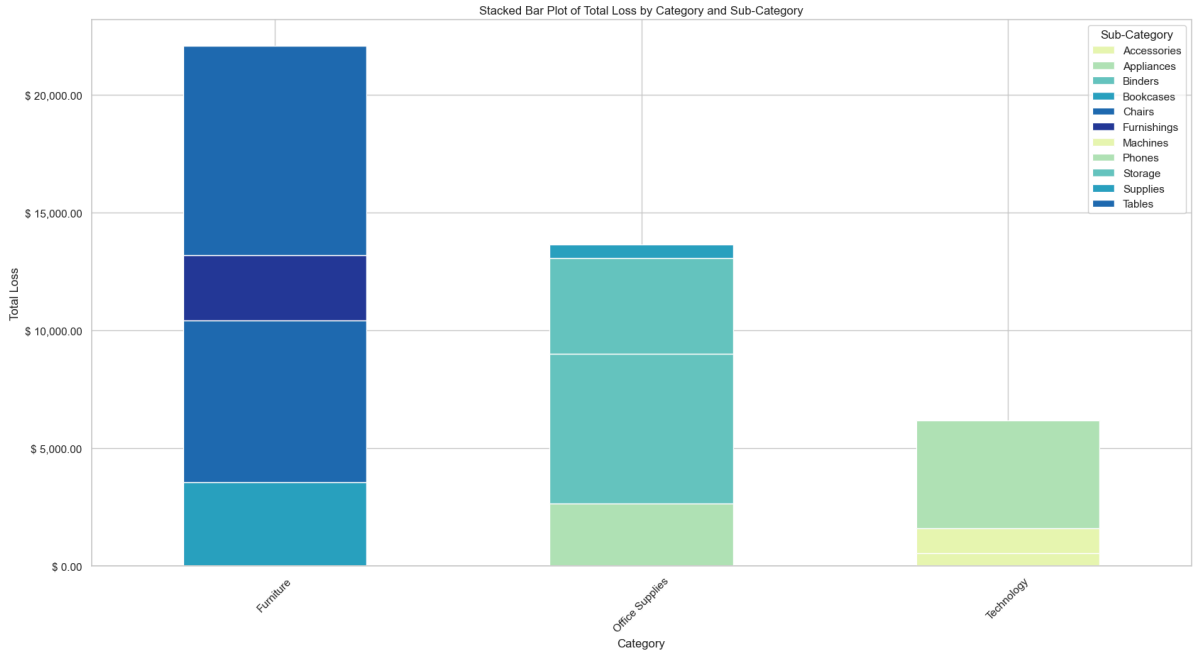


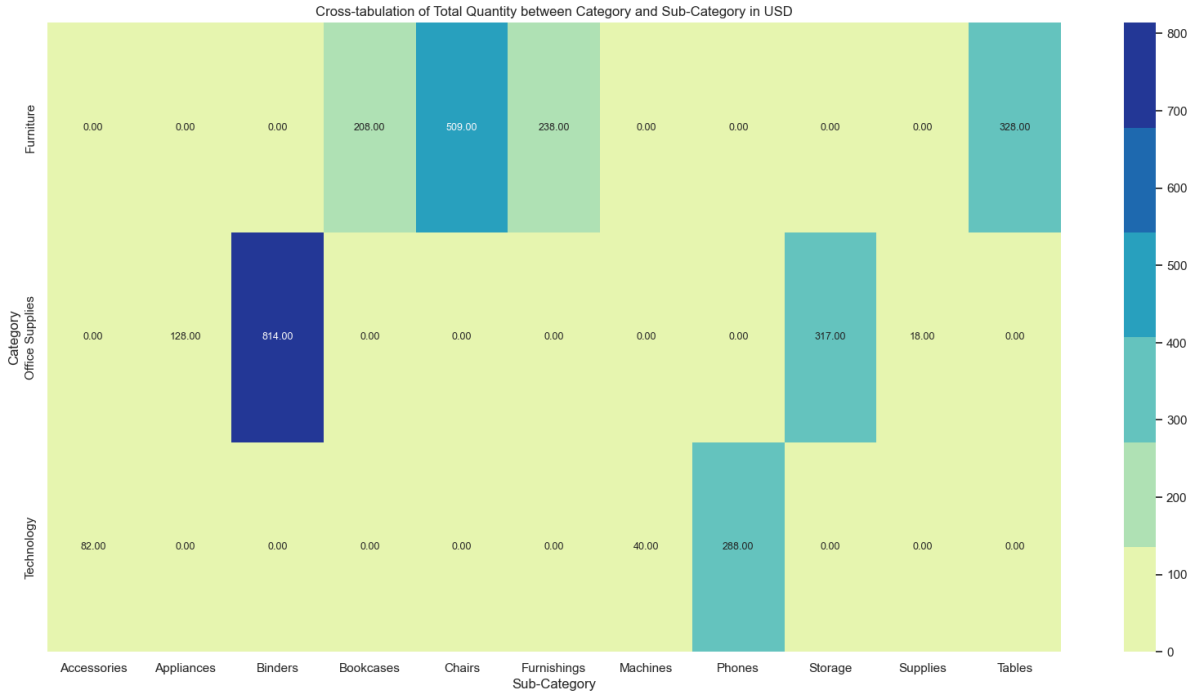
In [ ]:
```
bivariate_categorical_figure_analysis(global_super_store_df, 'Category', 'Sub-Categ
bivariate_categorical_figure_analysis(global_super_store_df, 'Category', 'Sub-Categ
bivariate_categorical_figure_analysis(global_super_store_df, 'Category', 'Sub-Categ
```

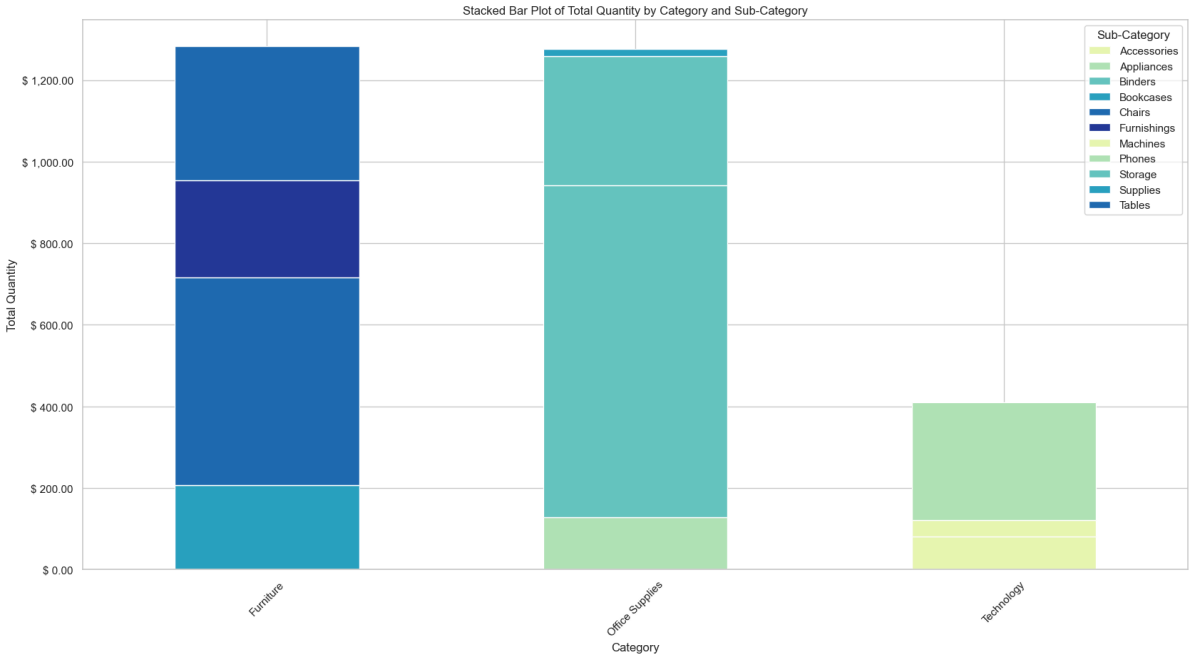



Stacked Bar Plot of Total Sales by Category and Sub-Category
Total Sales
$ 120,000.00
$ 100,000.00
$ 80,000.00
$ 60,000.00
$ 40,000.00
$ 20,000.00
$ 0.00
Furniture
Office Supplies
Technology
Category
Sub-Category
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables


Cross-tabulation of Total Loss between Category and Sub-Category in USD
Category
Furniture
Office Supplies
Technology
0.00 0.00 0.00 3,559.75 6,862.92 2,787.11 0.00 0.00 0.00 0.00 8,874.71
0.00 2,677.24 6,350.99 0.00 0.00 0.00 0.00 0.00 4,046.10 571.98 0.00
540.32 0.00 0.00 0.00 0.00 0.00 1,061.90 4,578.27 0.00 0.00 0.00
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables
Sub-Category
8000
7000
6000
5000
4000
3000
2000
1000
0

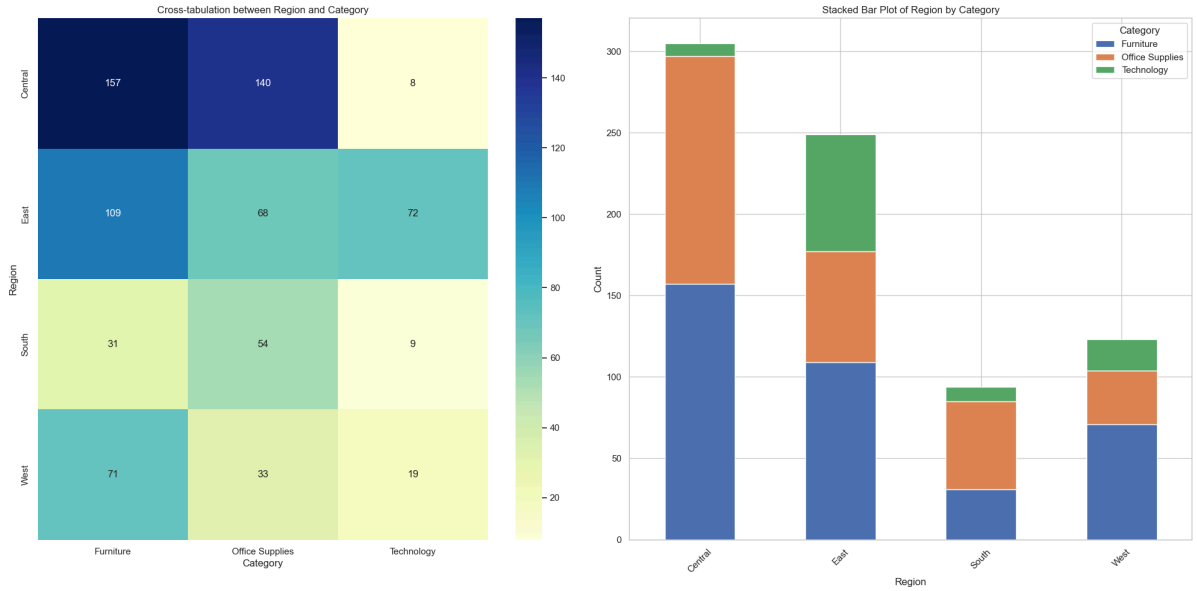

Stacked Bar Plot of Total Loss by Category and Sub-Category
Total Loss
$ 20,000.00
$ 15,000.00
$ 10,000.00
$ 5,000.00
$ 0.00
Furniture
Office Supplies
Technology
Category
Sub-Category
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables



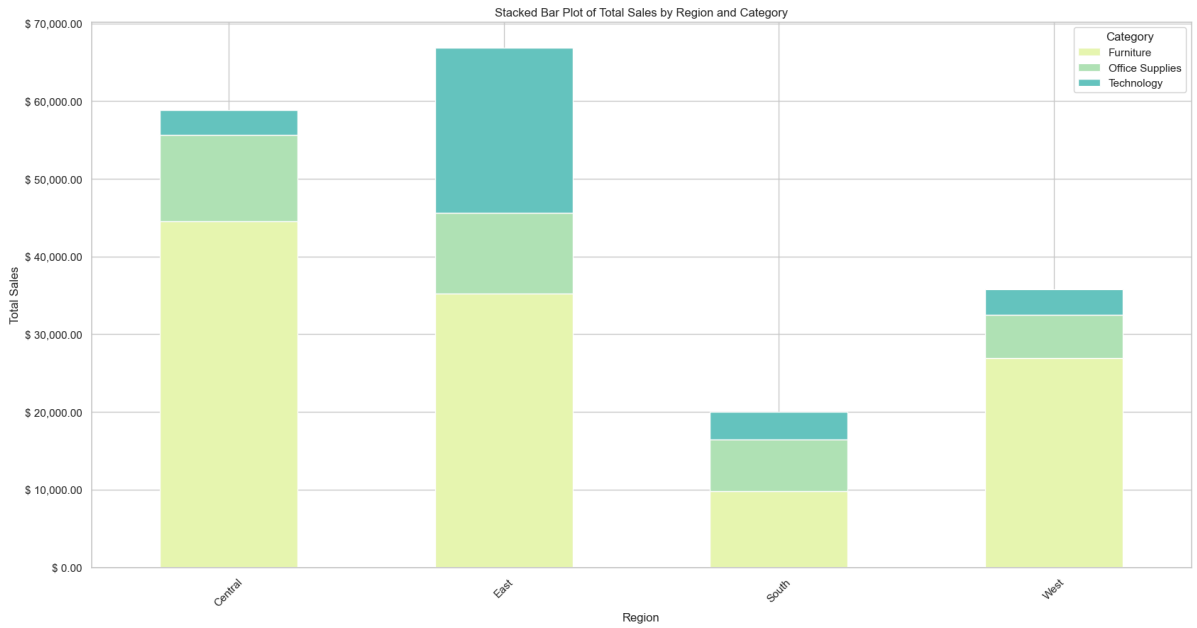


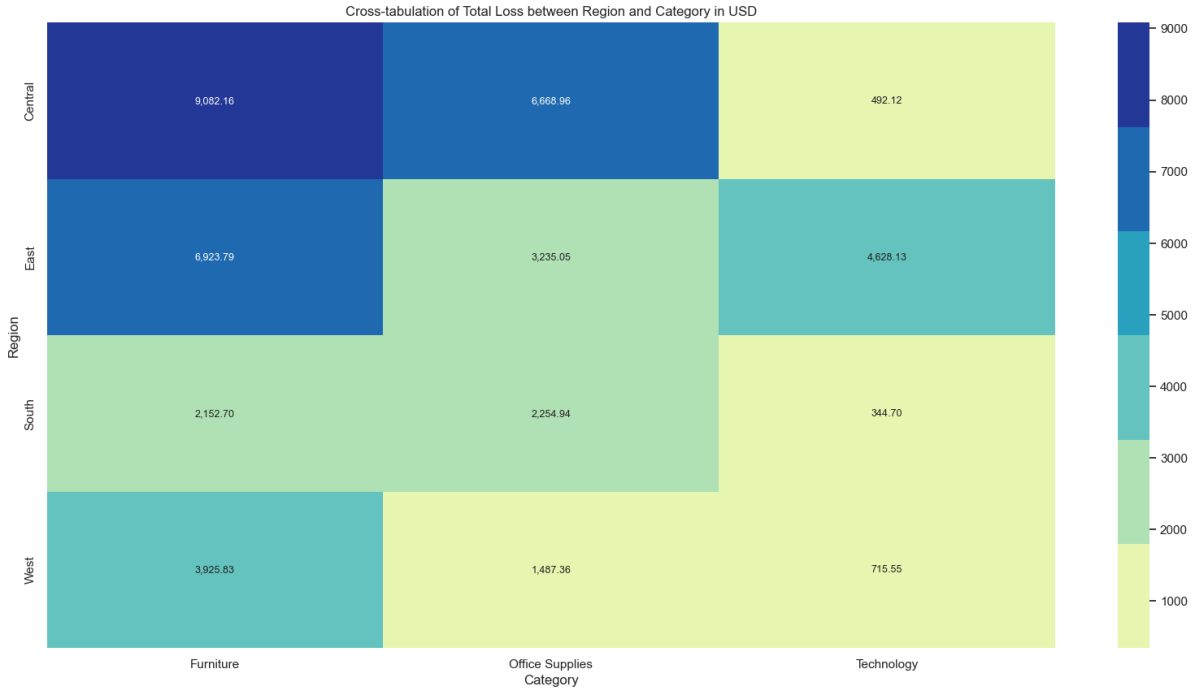
Region Vs. Category

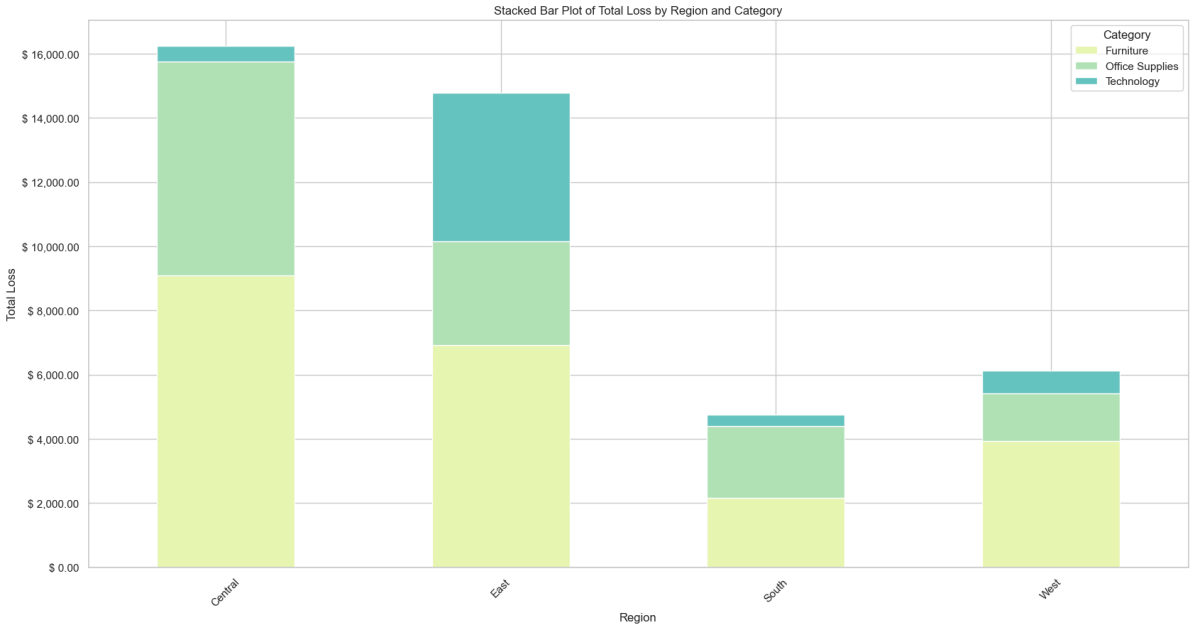
In [ ]:
```
categorical_analysis(global_super_store_df, 'Region', 'Category')
```

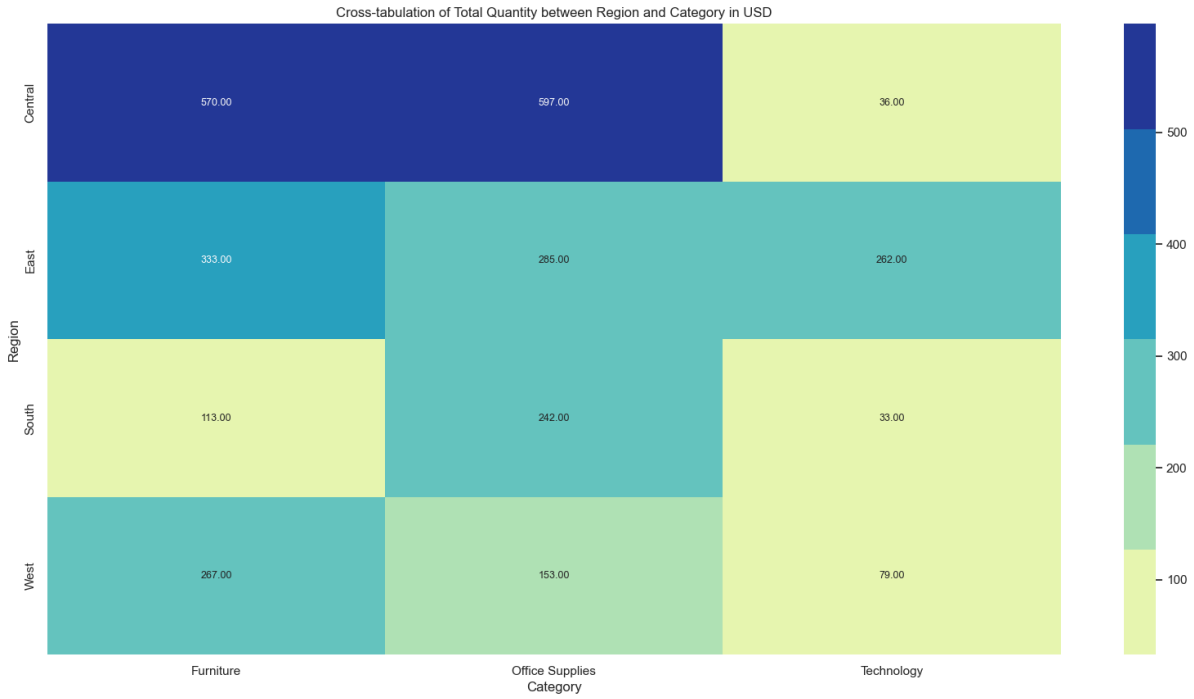


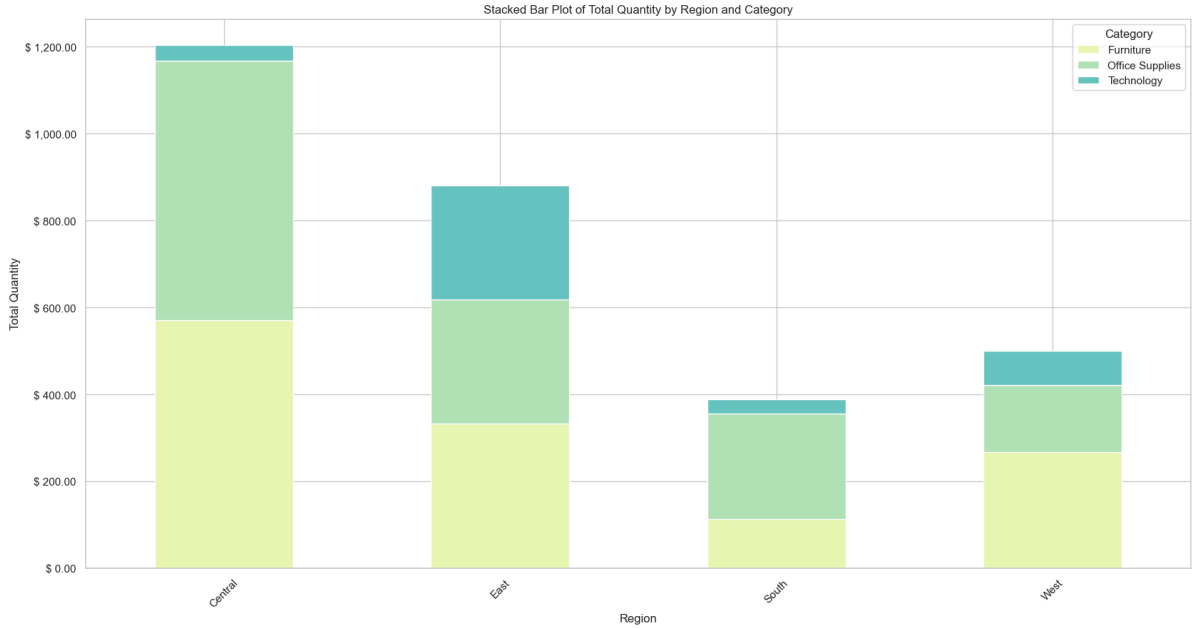
In [ ]:
```
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Category',
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Category',
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Category',
```




Cross-tabulation of Total Loss between Region and Category in USD
Central
East
South
West
Region
9,082.16
6,668.96
492.12
6,923.79
3,235.05
4,628.13
2,152.70
2,254.94
344.70
3,925.83
1,487.36
715.55
Furniture
Office Supplies
Technology
Category
9000
8000
7000
6000
5000
4000
3000
2000
1000

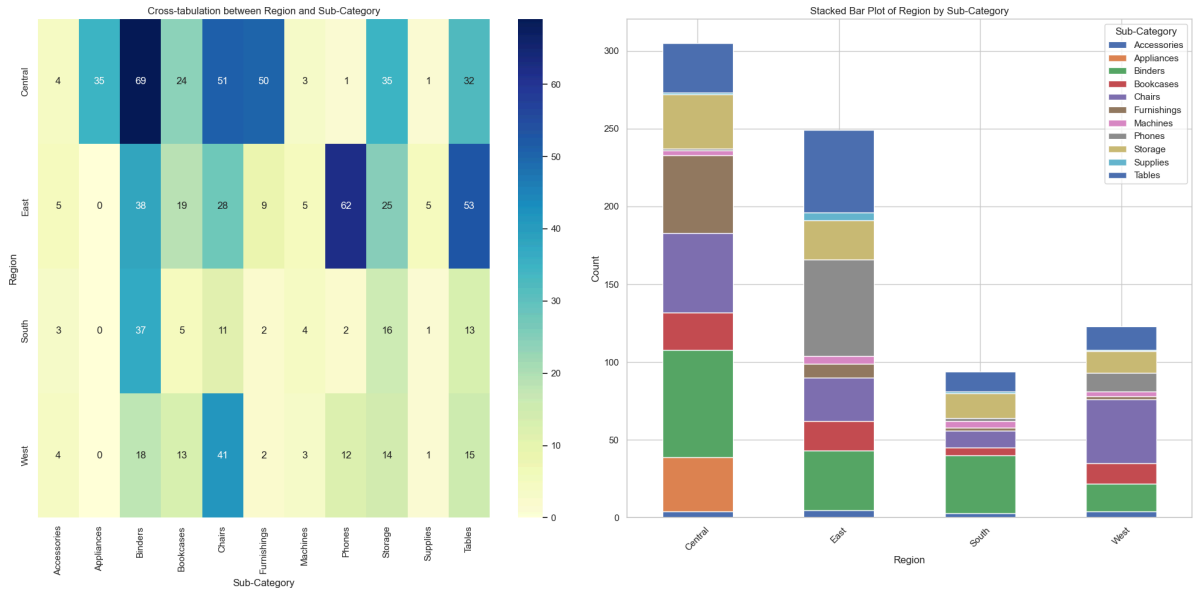

Stacked Bar Plot of Total Loss by Region and Category
Total Loss
$ 16,000.00
$ 14,000.00
$ 12,000.00
$ 10,000.00
$ 8,000.00
$ 6,000.00
$ 4,000.00
$ 2,000.00
$ 0.00
Central
East
South
West
Region
Category
Furniture
Office Supplies
Technology


Cross-tabulation of Total Quantity between Region and Category in USD
Central
East
South
West
Region
570.00
597.00
36.00
333.00
285.00
262.00
113.00
242.00
33.00
267.00
153.00
79.00
Furniture
Office Supplies
Technology
Category
500
400
300
200
100



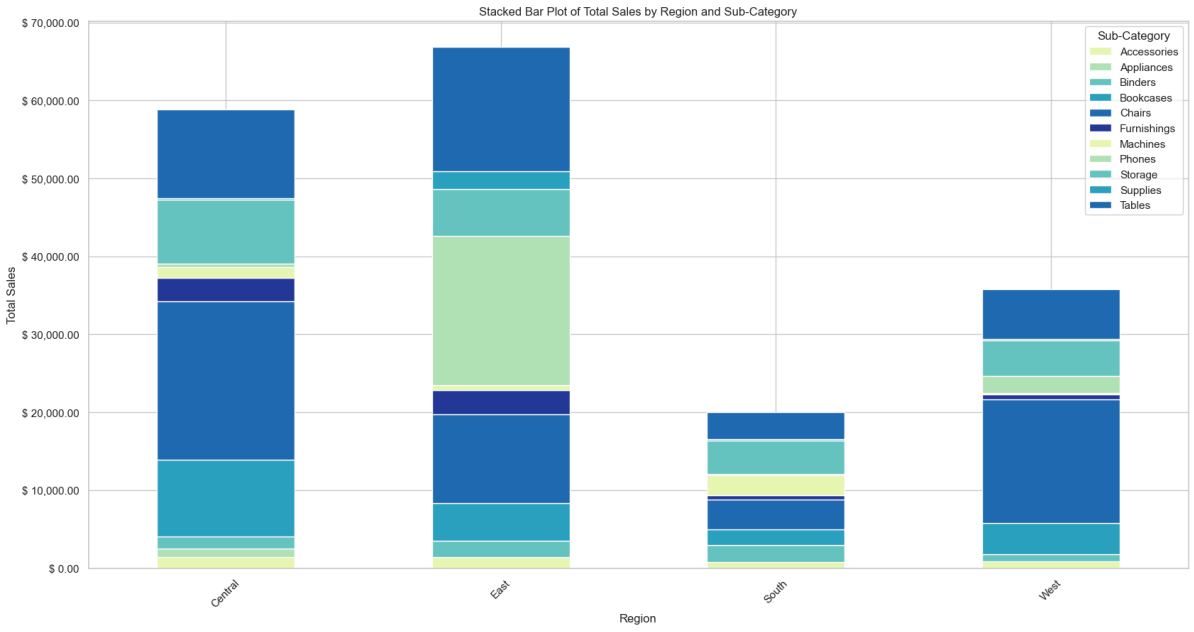
Region Vs. Sub-Category

In [ ]:
```
categorical_analysis(global_super_store_df, 'Region', 'Sub-Category')
```

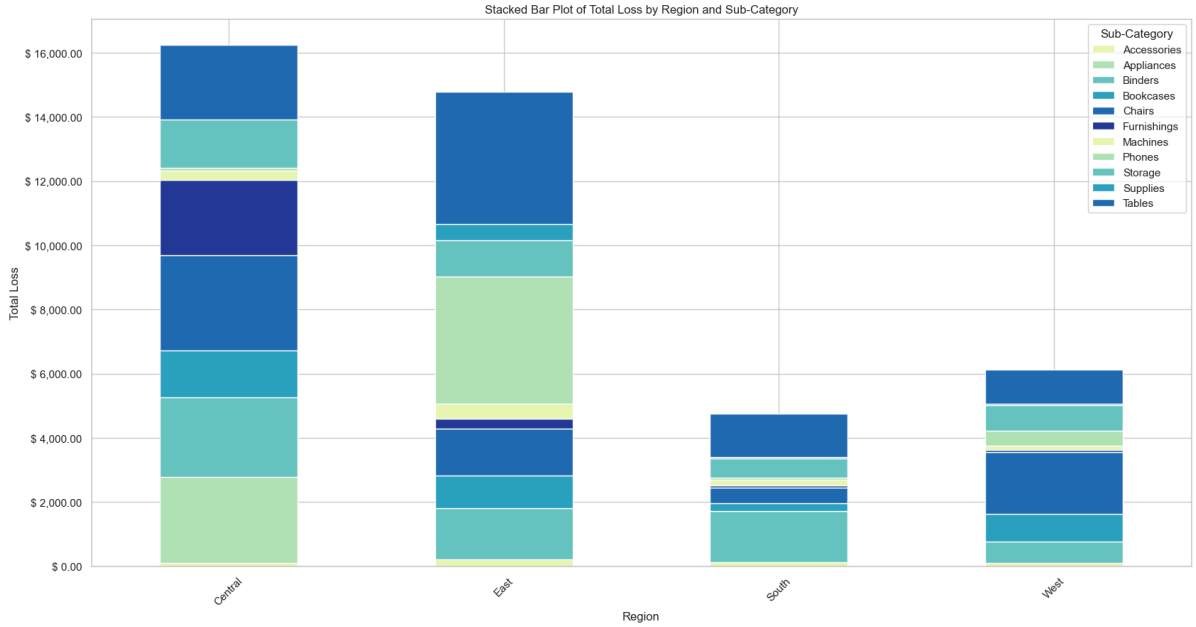


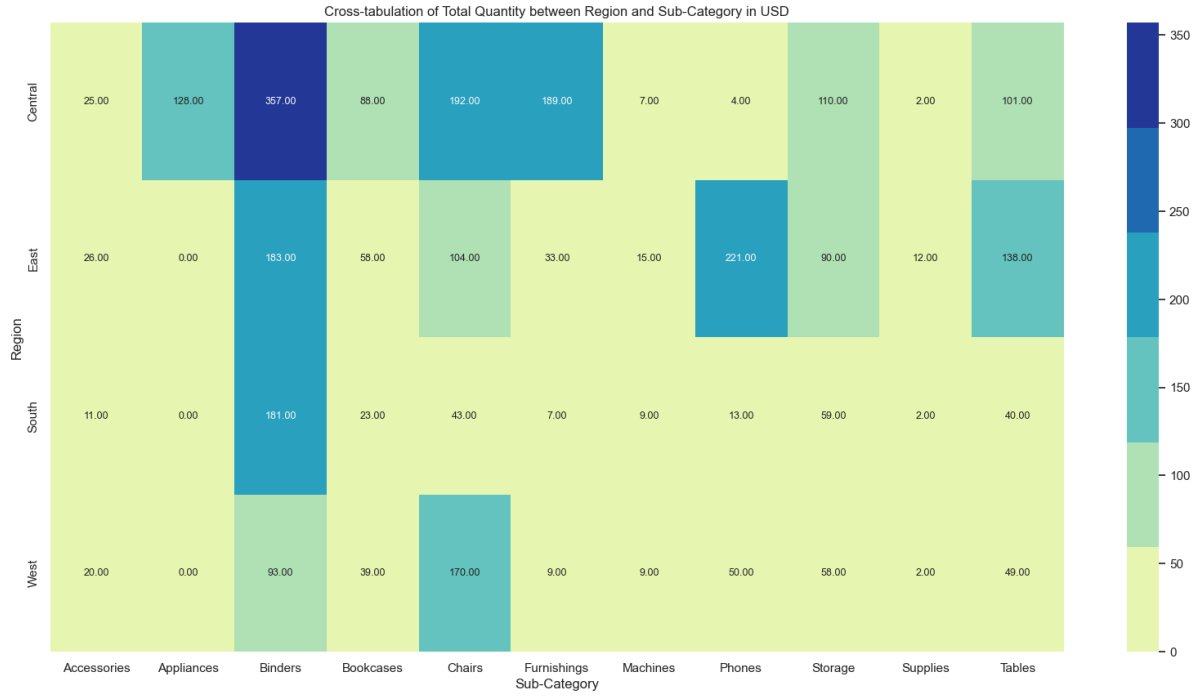
In [ ]:
```
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Sub-Categor
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Sub-Categor
bivariate_categorical_figure_analysis(global_super_store_df, 'Region', 'Sub-Categor
```

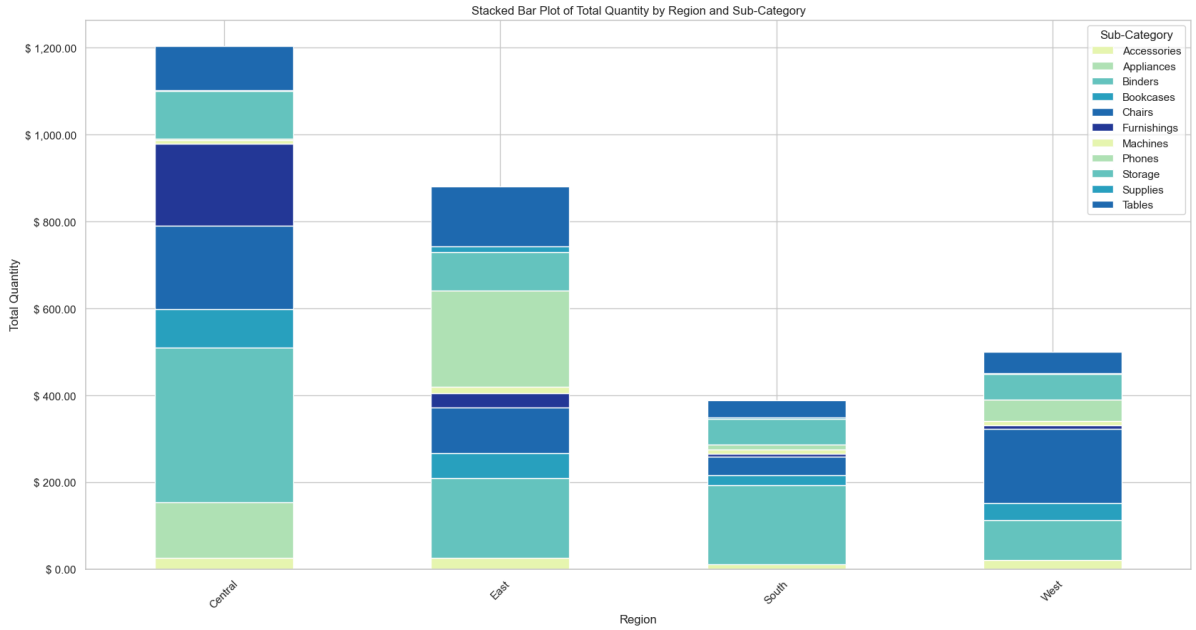

Cross-tabulation of Total Sales between Region and Sub-Category in USD
Region
Central
East
South
West
1,385.46 1,109.13 1,564.55 9,843.61 20,309.82 3,032.60 1,378.05 438.34 8,209.82 185.38 11,378.67
1,449.22 0.00 2,052.59 4,805.04 11,447.60 3,078.96 611.03 19,150.11 6,025.50 2,297.26 15,942.35
799.75 0.00 2,166.13 1,978.03 3,893.01 542.58 2,478.18 217.50 4,324.06 185.38 3,406.66
833.89 0.00 916.78 4,018.43 15,897.94 583.06 185.91 2,249.90 4,538.26 185.38 6,398.94
Accessories Appliances Binders Bookcases Chairs Furnishings Machines Phones Storage Supplies Tables
Sub-Category
20000 17500 15000 12500 10000 7500 5000 2500 0


Stacked Bar Plot of Total Sales by Region and Sub-Category
Total Sales
$ 70,000.00
$ 60,000.00
$ 50,000.00
$ 40,000.00
$ 30,000.00
$ 20,000.00
$ 10,000.00
$ 0.00
Central East South West
Region
Sub-Category
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables


Cross-tabulation of Total Loss between Region and Sub-Category in USD
Region
Central
East
South
West
105.55 2,677.24 2,483.59 1,447.65 2,984.60 2,334.45 298.90 87.67 1,508.13 0.00 2,315.47
211.51 0.00 1,600.98 1,016.15 1,453.97 322.16 447.48 3,969.14 1,131.60 502.46 4,131.52
112.18 0.00 1,607.36 233.34 493.62 69.47 183.58 48.94 612.82 34.76 1,356.27
111.08 0.00 659.05 862.61 1,930.73 61.03 131.94 472.53 793.54 34.76 1,071.45
Accessories Appliances Binders Bookcases Chairs Furnishings Machines Phones Storage Supplies Tables
Sub-Category
4000 3500 3000 2500 2000 1500 1000 500 0


Stacked Bar Plot of Total Loss by Region and Sub-Category
Total Loss
$ 16,000.00
$ 14,000.00
$ 12,000.00
$ 10,000.00
$ 8,000.00
$ 6,000.00
$ 4,000.00
$ 2,000.00
$ 0.00
Central
East
South
West
Region
Sub-Category
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables


Cross-tabulation of Total Quantity between Region and Sub-Category in USD
Region
Central
East
South
West
25.00 128.00 357.00 88.00 192.00 189.00 7.00 4.00 110.00 2.00 101.00
26.00 0.00 183.00 58.00 104.00 33.00 15.00 221.00 90.00 12.00 138.00
11.00 0.00 181.00 23.00 43.00 7.00 9.00 13.00 59.00 2.00 40.00
20.00 0.00 93.00 39.00 170.00 9.00 9.00 50.00 58.00 2.00 49.00
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables
Sub-Category
350
300
250
200
150
100
50
0


Stacked Bar Plot of Total Quantity by Region and Sub-Category
Total Quantity
$ 1,200.00
$ 1,000.00
$ 800.00
$ 600.00
$ 400.00
$ 200.00
$ 0.00
Central
East
South
West
Region
Sub-Category
Accessories
Appliances
Binders
Bookcases
Chairs
Furnishings
Machines
Phones
Storage
Supplies
Tables

Numerical Vs. Numerical

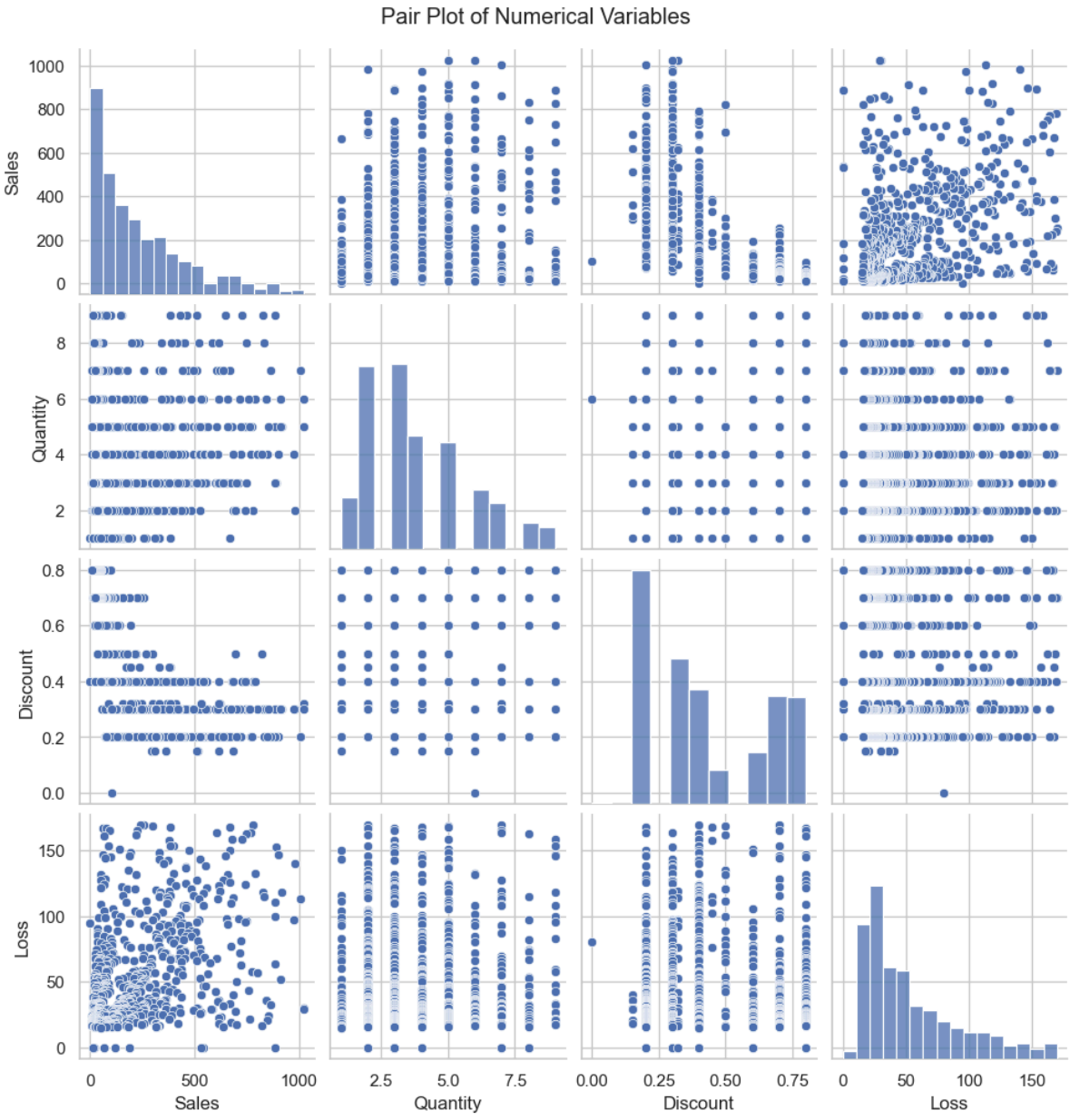
Choosing the numercial features and filter into a new dataframe.

In [ ]:
```
#Select Numerical Features on global_super_store_df dataframe
numerical_features = ['Sales', 'Quantity', 'Discount', 'Loss']
global_super_store_numerial_data = global_super_store_df[numerical_features]
```

Pairplots

In [ ]:
```
sns.pairplot(global_super_store_numerial_data)
plt.suptitle('Pair Plot of Numerical Variables', y=1.02)
plt.show()
```

```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: T
he figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Correlation Matrix

In [ ]:
```
# Create Correlation matrix
correlation_matrix = global_super_store_numerial_data.corr()
```

```
print(tabulate(correlation_matrix.round(4), headers='keys', tablefmt='pretty', stra

# Plot correlation matrix as heatmap
sns.heatmap(correlation_matrix.round(4), annot=True, cmap='coolwarm', linewidths=0.
plt.show()
```

```
+----------+---------+----------+----------+--------+
|          |   Sales | Quantity | Discount |   Loss |
+----------+---------+----------+----------+--------+
|    Sales |     1.0 |   0.1055 |  -0.5794 | 0.4017 |
| Quantity |  0.1055 |      1.0 |   0.1753 | 0.0621 |
| Discount | -0.5794 |   0.1753 |      1.0 | 0.0018 |
|     Loss |  0.4017 |   0.0621 |   0.0018 |    1.0 |
+----------+---------+----------+----------+--------+
```

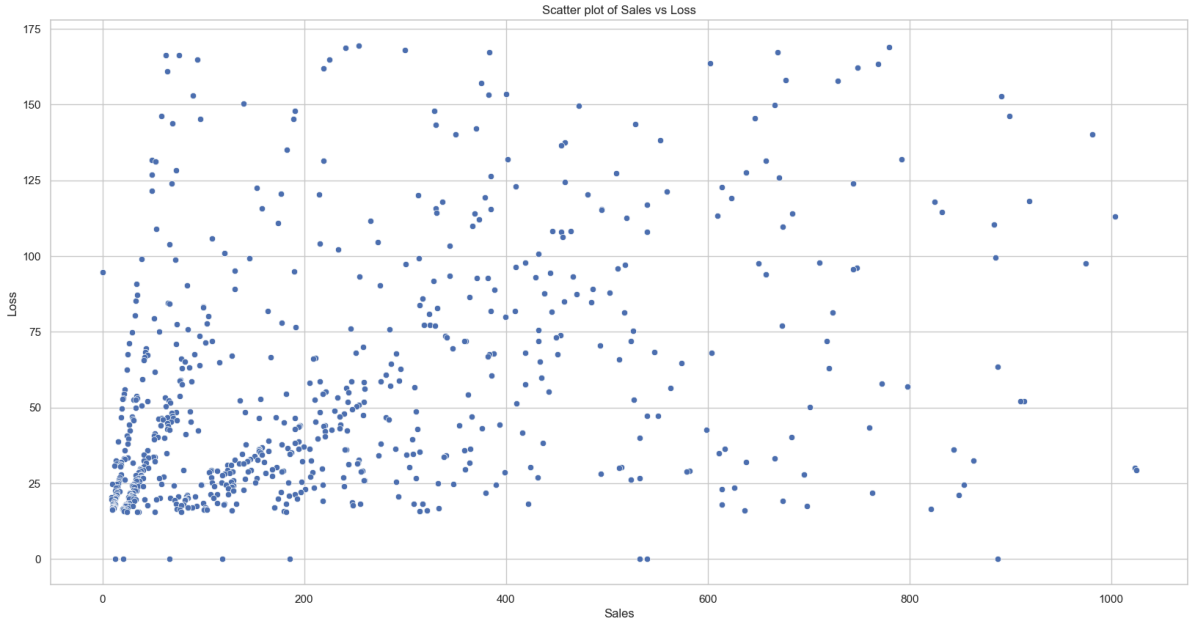
Scatter plots

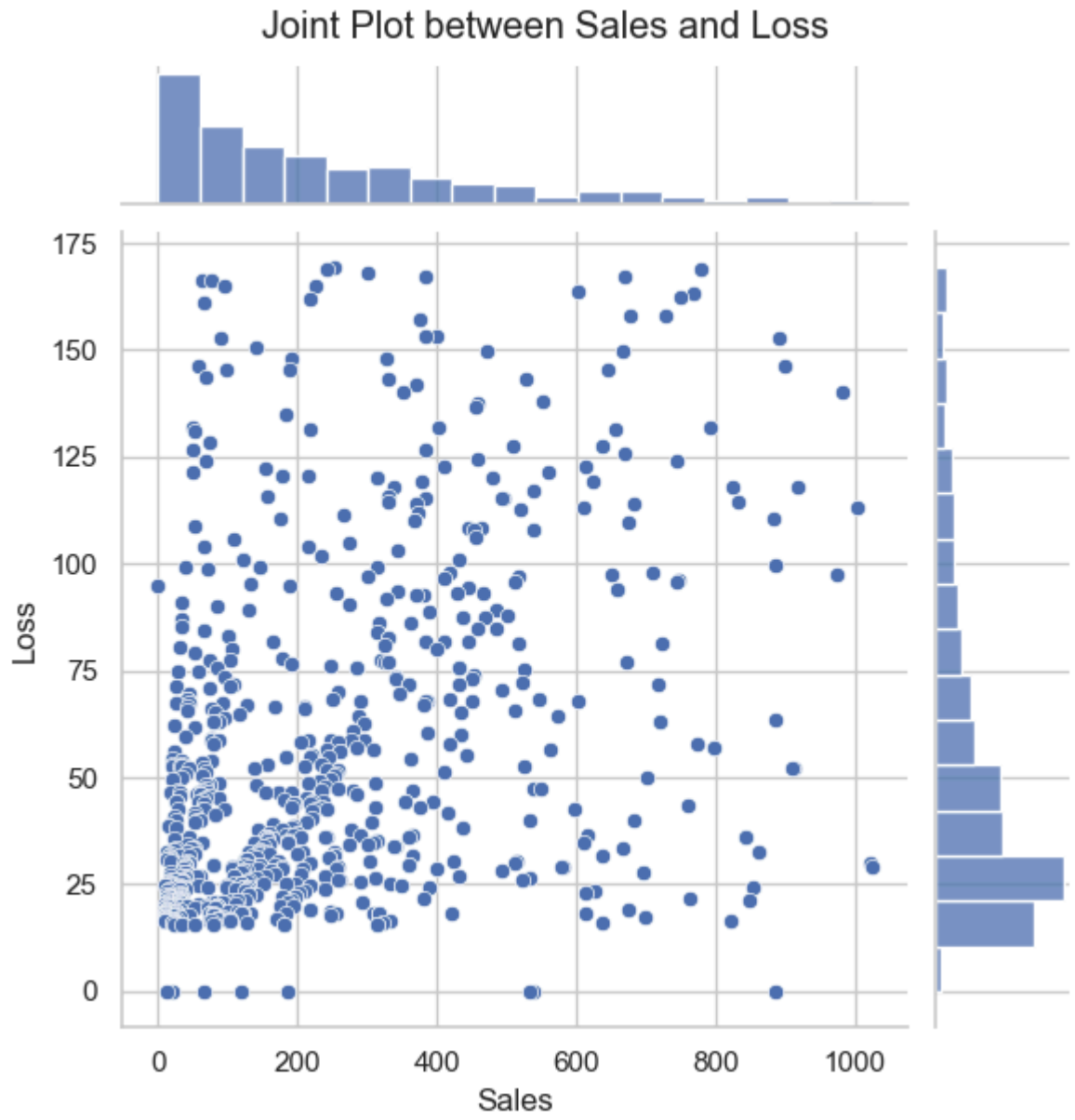
Function to plot scatter and joint plot to perform bivariate analysis between two numerical features.

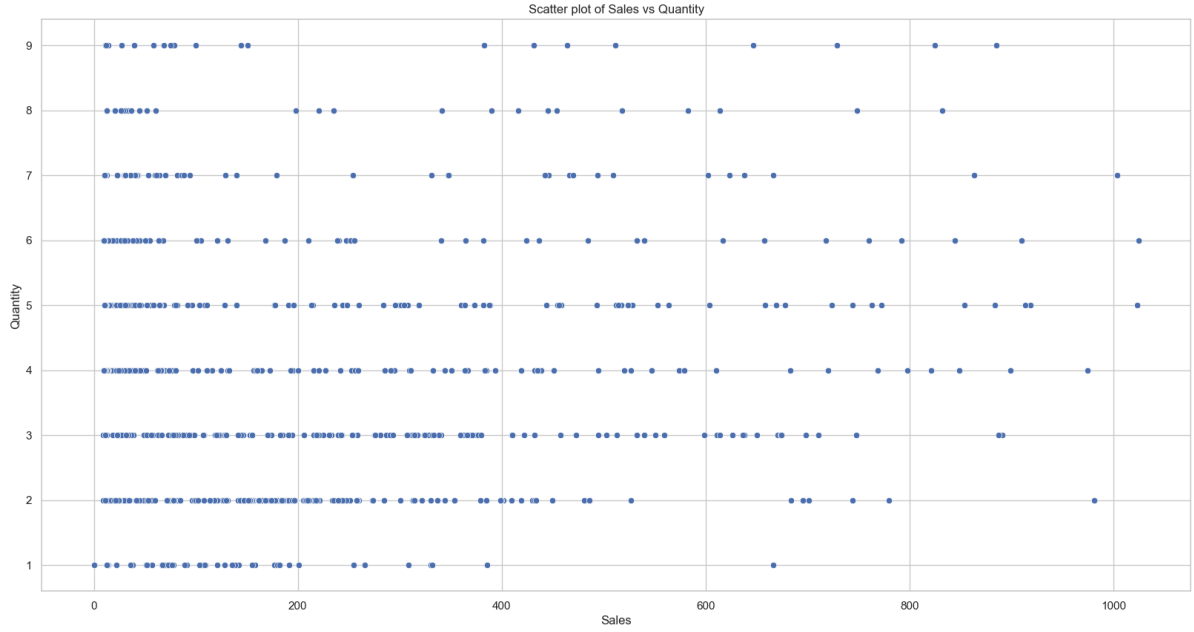
In [ ]:
```
def bivariate_numerical_analysis(df, num_var1, num_var2):
    """
    Perform bivariate analysis and visualization between two numerical variables.

    Parameters:
        df (DataFrame): Input DataFrame containing the data.
        num_var1 (str): Name of the first numerical variable.
        num_var2 (str): Name of the second numerical variable.
    """
    # Scatter plot
    plt.figure(figsize=(20, 10))
    sns.scatterplot(x=num_var1, y=num_var2, data=df)
    plt.title(f'Scatter plot of {num_var1} vs {num_var2}')
    plt.xlabel(num_var1)
    plt.ylabel(num_var2)
    plt.show()
```

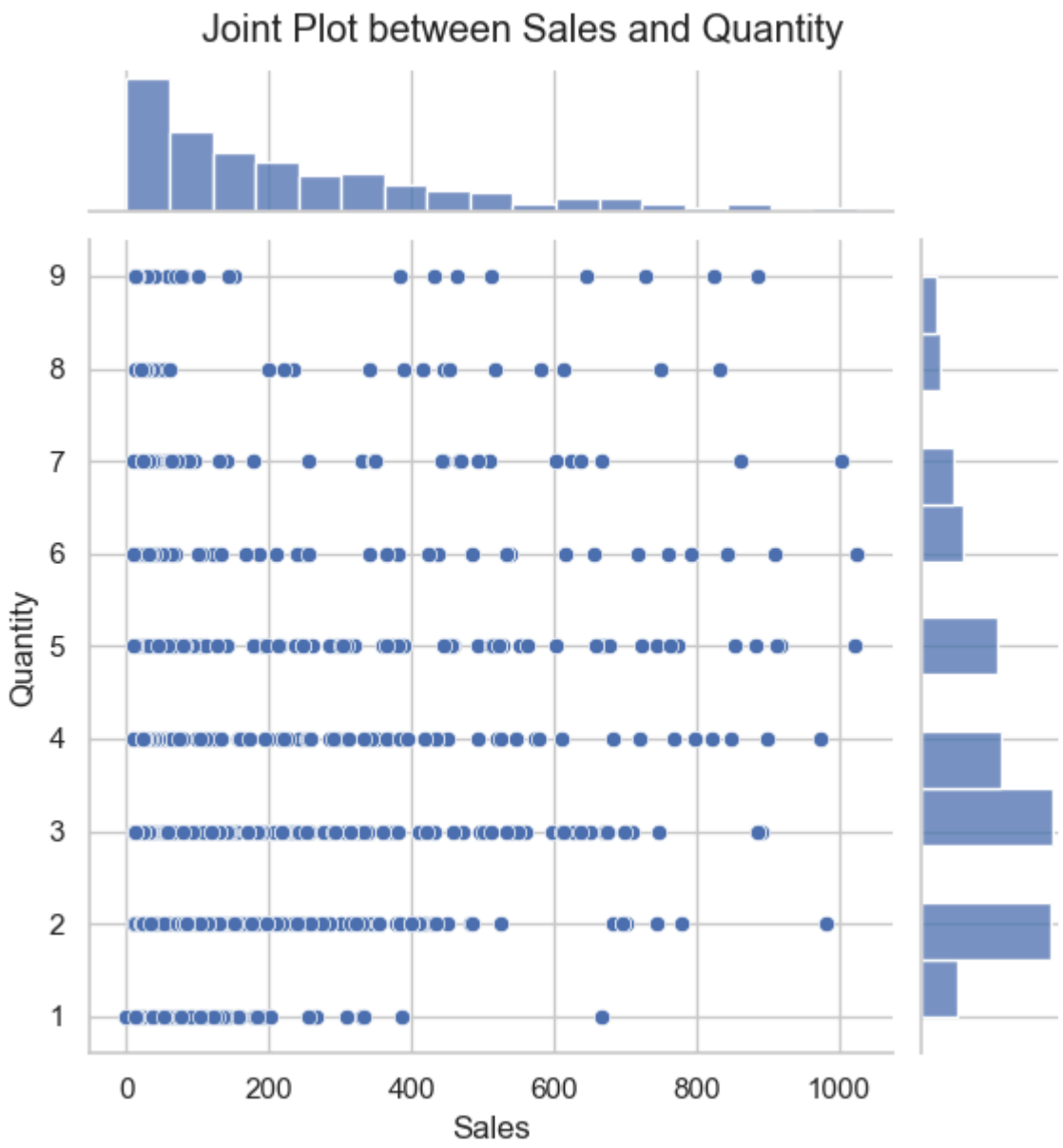
```
    # Joint Plot
    sns.jointplot(x=num_var1, y=num_var2, data=df, kind='scatter')
    plt.xlabel(num_var1)
    plt.ylabel(num_var2)
    plt.suptitle(f'Joint Plot between {num_var1} and {num_var2}', y=1.02)
    plt.show()
```

In [ ]:
```
bivariate_numerical_analysis(global_super_store_df, 'Sales', 'Loss')
bivariate_numerical_analysis(global_super_store_df, 'Sales', 'Quantity')
```




Joint Plot between Sales and Loss
Loss
Sales
0
25
50
75
100
125
150
175
0
200
400
600
800
1000


Scatter plot of Sales vs Quantity
Quantity
Sales
1
2
3
4
5
6
7
8
9
0
200
400
600
800
1000



Categorical Vs. Numerical

Helper Functions

The following function `bivariate_analysis_categorical_numerical` will plot the following in a sub-plot between categorical and numerical features:

- Box Plot
- Violin Plot
- Strip Plot
- Bar Plot

In [ ]:
```
def bivariate_analysis_categorical_numerical(df, cat_var, num_var):
    """
    Perform bivariate analysis and visualization between a categorical variable and
    Produces Box Plot, Violin Plot, Strip Plot and Bar Plot
    Parameters:
    - df (DataFrame): Input DataFrame containing the data.
    - cat_var (str): Name of the categorical variable.
    - num_var (str): Name of the numerical variable.
    """
```

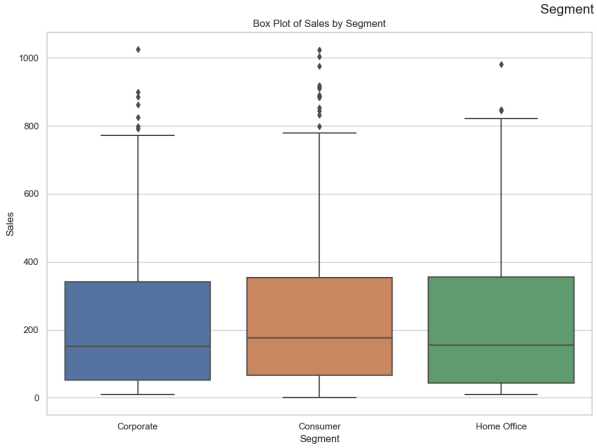
```
    fig, axes = plt.subplots(2, 2, figsize=(20, 15))
    plt.suptitle(f"{cat_var} Vs. {num_var}", fontsize=16)  # Set main title for the

    # Box plot
    sns.boxplot(x=cat_var, y=num_var, data=df, ax=axes[0, 0])
    axes[0, 0].set_title(f'Box Plot of {num_var} by {cat_var}')
    axes[0, 0].set_xlabel(cat_var)
    axes[0, 0].set_ylabel(num_var)

    # Violin plot
    sns.violinplot(x=cat_var, y=num_var, data=df, ax=axes[0, 1])
    axes[0, 1].set_title(f'Violin Plot of {num_var} by {cat_var}')
    axes[0, 1].set_xlabel(cat_var)
    axes[0, 1].set_ylabel(num_var)

    # Strip plot
    sns.stripplot(x=cat_var, y=num_var, data=df, ax=axes[1, 0])
    axes[1, 0].set_title(f'Strip Plot of {num_var} by {cat_var}')
    axes[1, 0].set_xlabel(cat_var)
    axes[1, 0].set_ylabel(num_var)

    # Bar plot
    sns.barplot(x=cat_var, y=num_var, data=df, ax=axes[1, 1])
    axes[1, 1].set_title(f'Bar Plot of {num_var} by {cat_var}')
    axes[1, 1].set_xlabel(cat_var)
    axes[1, 1].set_ylabel(num_var)

    plt.tight_layout()
    plt.show()
```

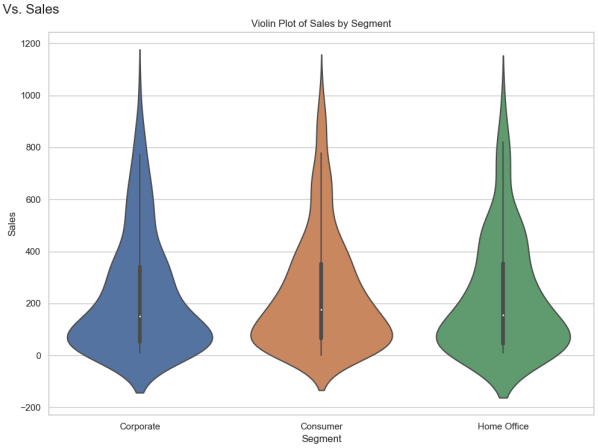
Then the function will run for all categories against one numerical feature.

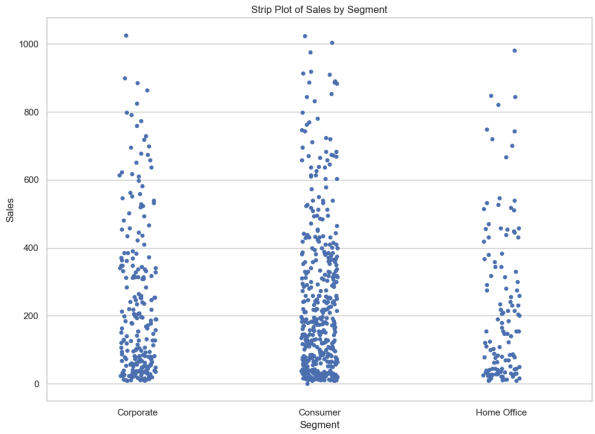
Categories Vs. Sales

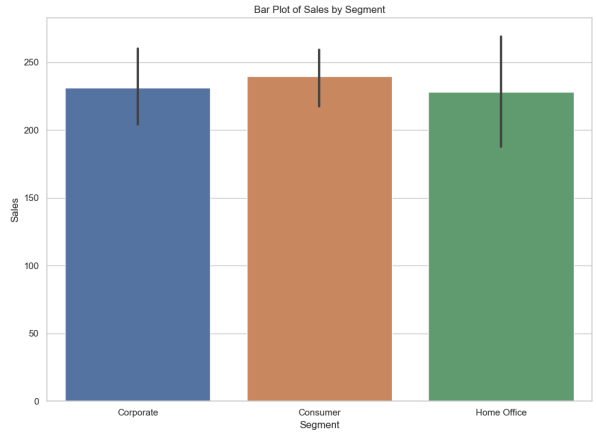
In [ ]:
```
bivariate_analysis_categorical_numerical(global_super_store_df, 'Segment', 'Sales')
bivariate_analysis_categorical_numerical(global_super_store_df, 'Region', 'Sales')
bivariate_analysis_categorical_numerical(global_super_store_df, 'Category', 'Sales'
bivariate_analysis_categorical_numerical(global_super_store_df, 'Sub-Category', 'Sa
```

Segment Vs. Sales

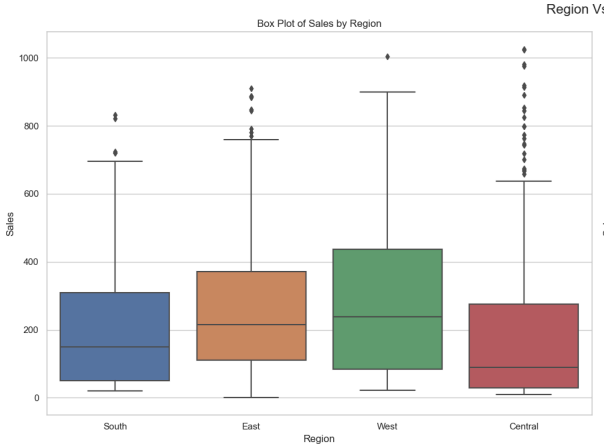


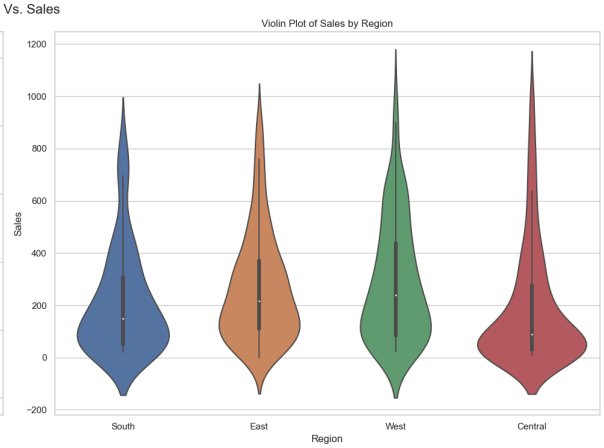


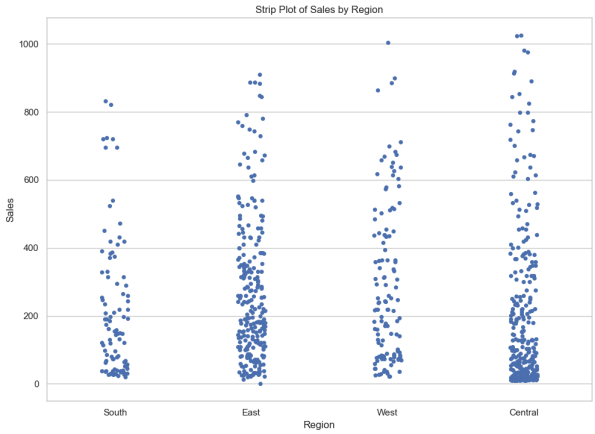


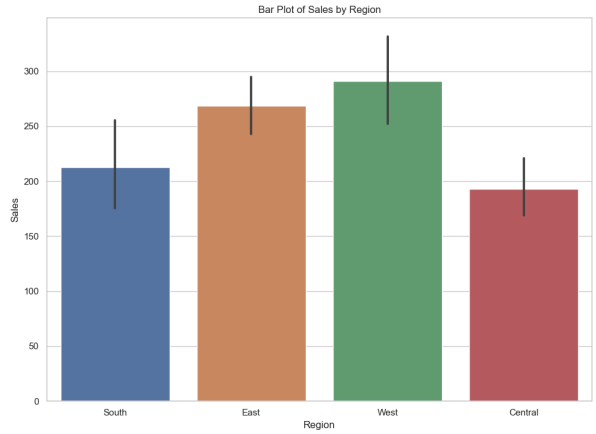


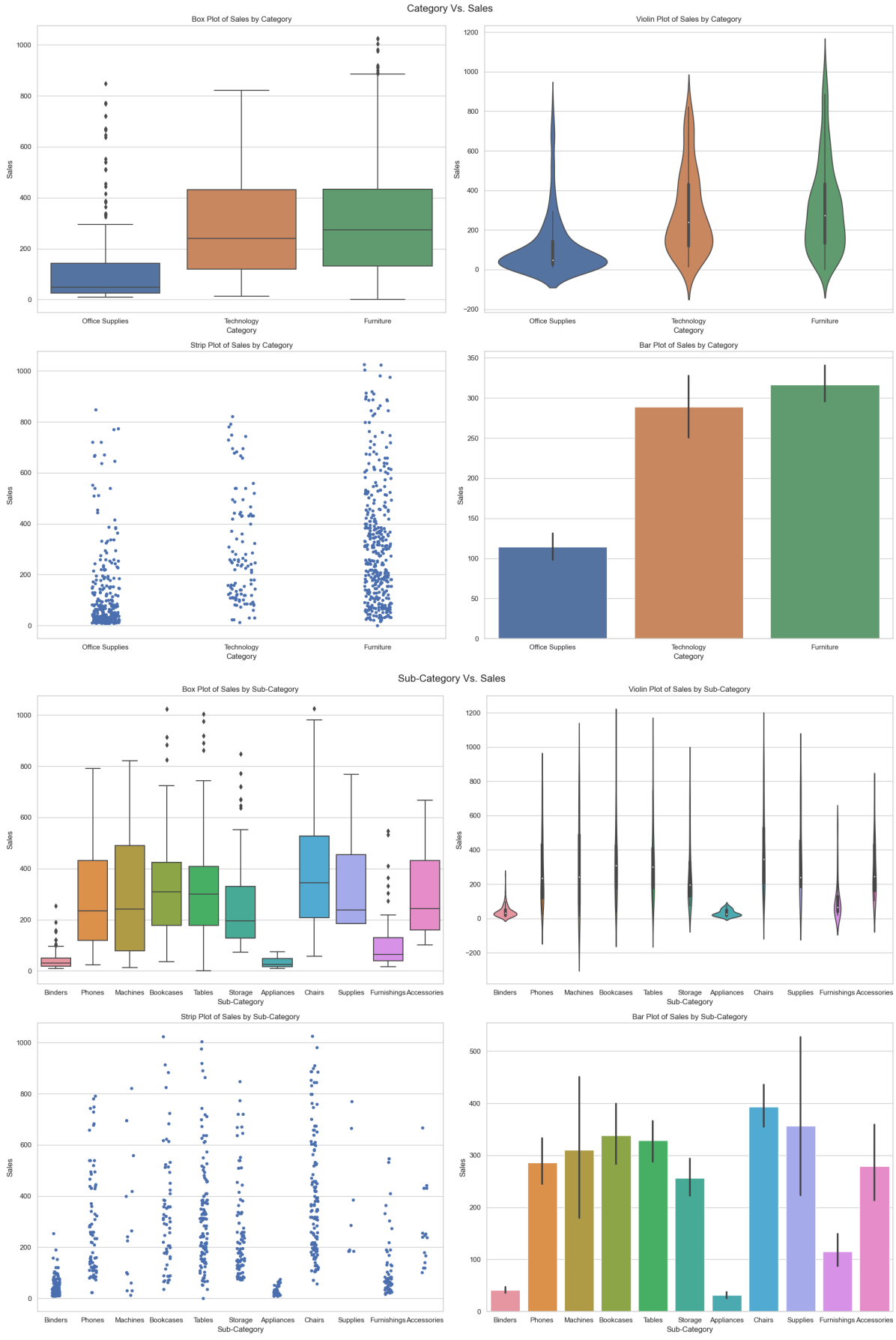
Region Vs. Sales







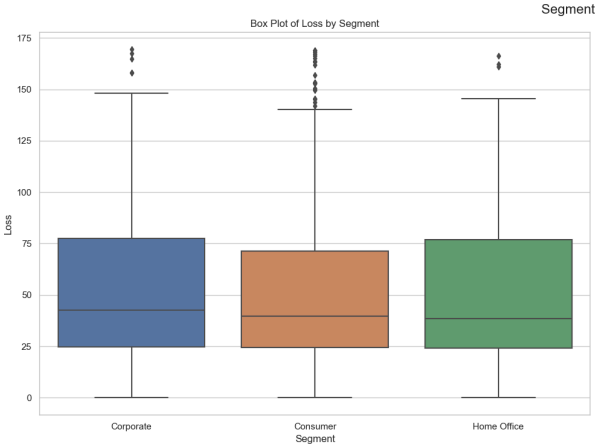


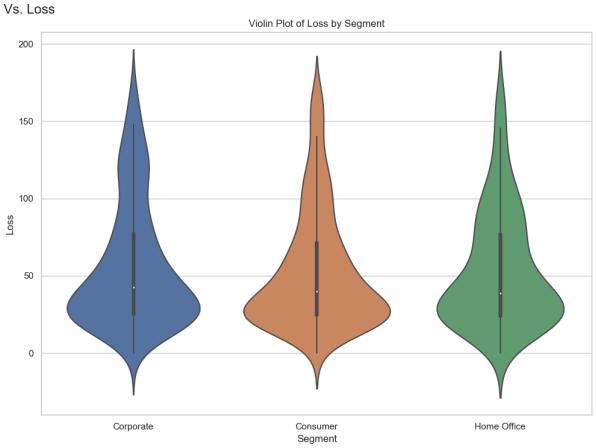


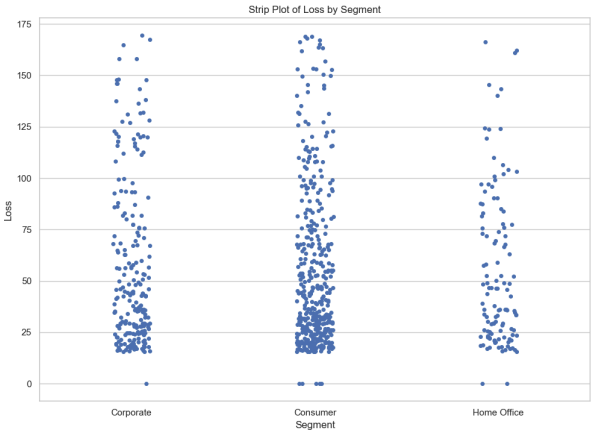
Categories Vs. Loss

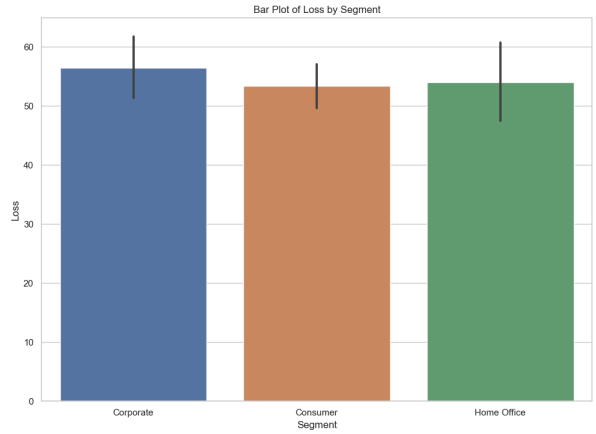
In [ ]:
```
bivariate_analysis_categorical_numerical(global_super_store_df, 'Segment', 'Loss')
bivariate_analysis_categorical_numerical(global_super_store_df, 'Region', 'Loss')
bivariate_analysis_categorical_numerical(global_super_store_df, 'Category', 'Loss')
bivariate_analysis_categorical_numerical(global_super_store_df, 'Sub-Category', 'Lo
```

Segment Vs. Loss

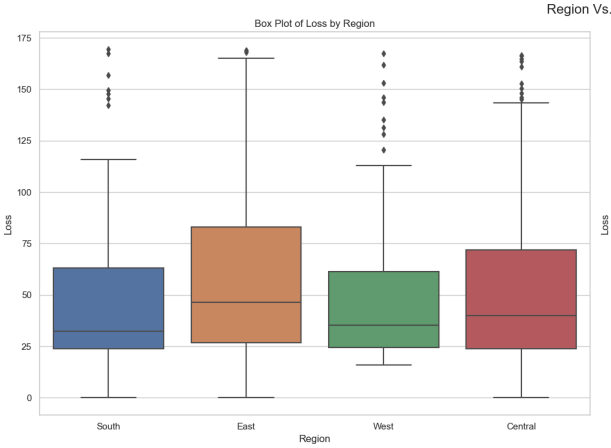


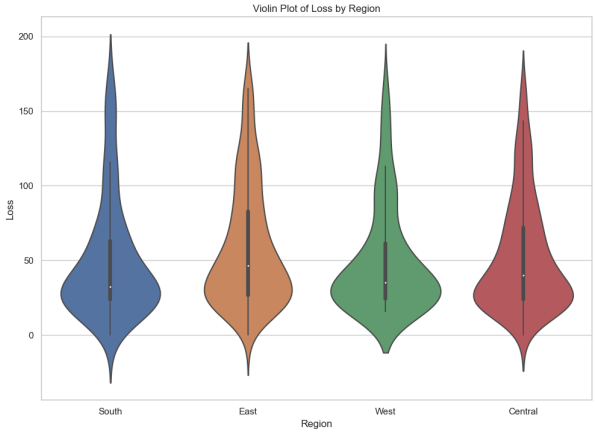


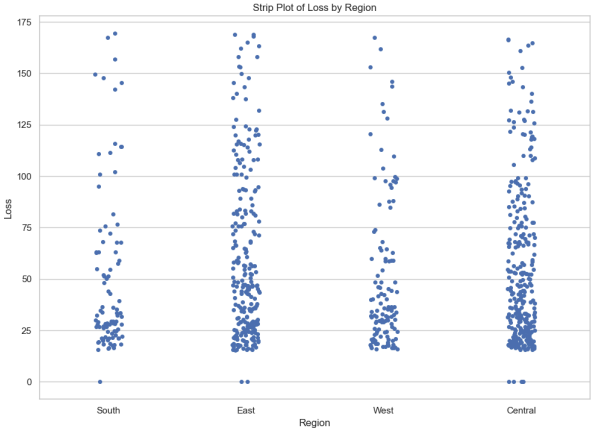


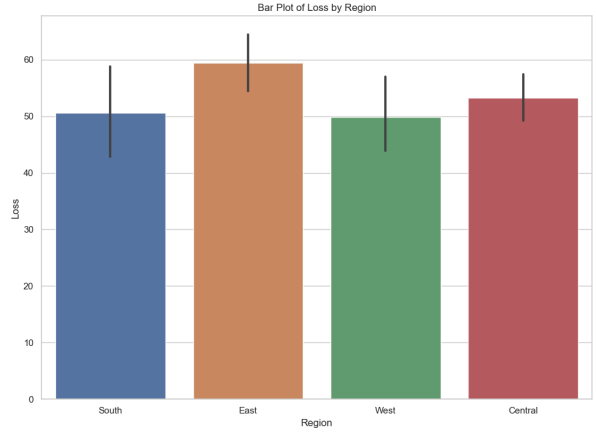


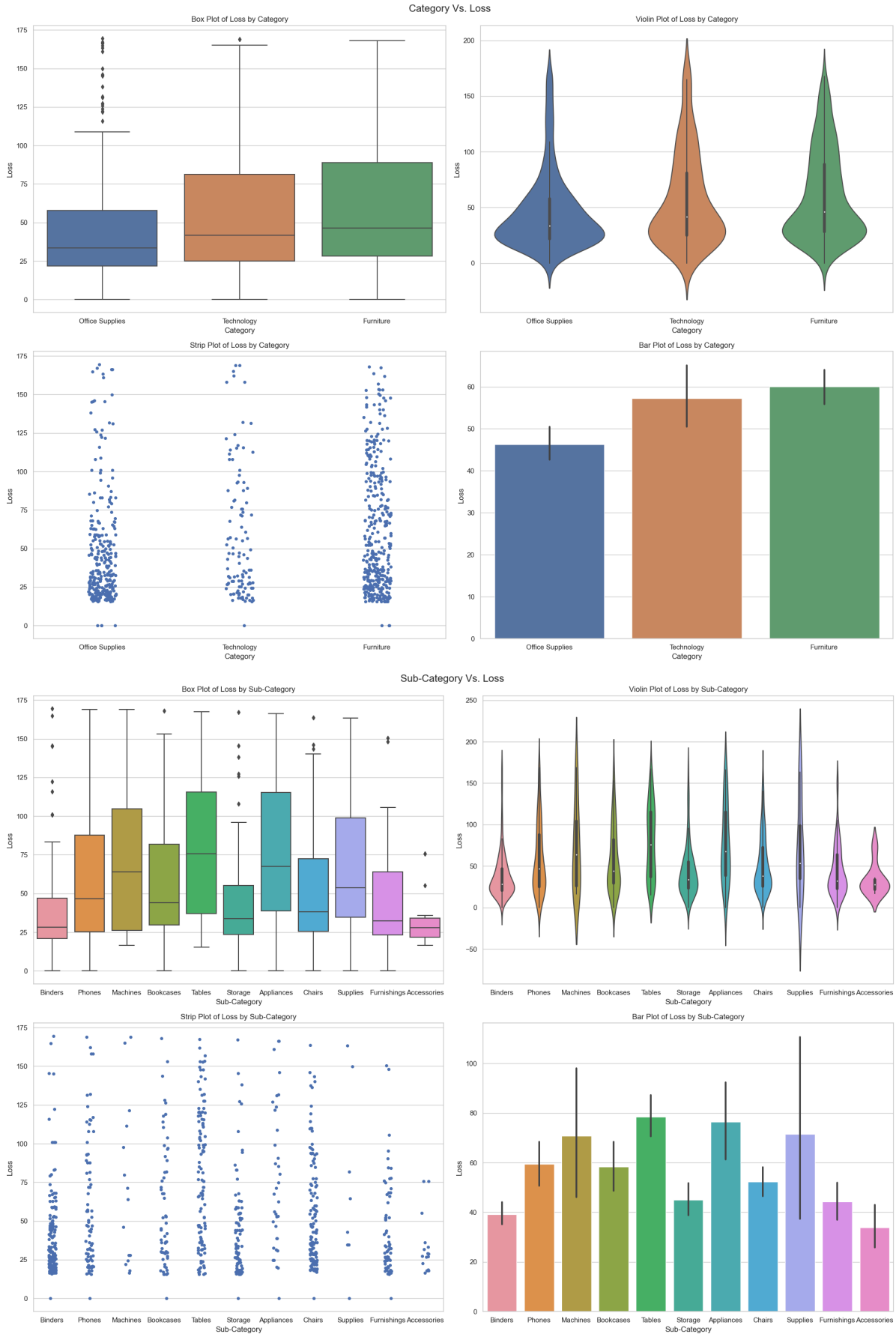
Region Vs. Loss







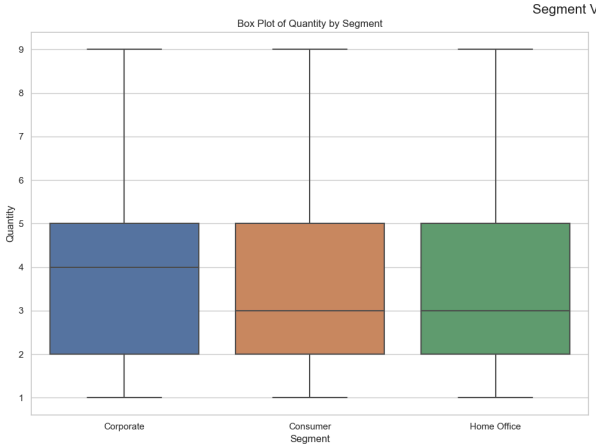


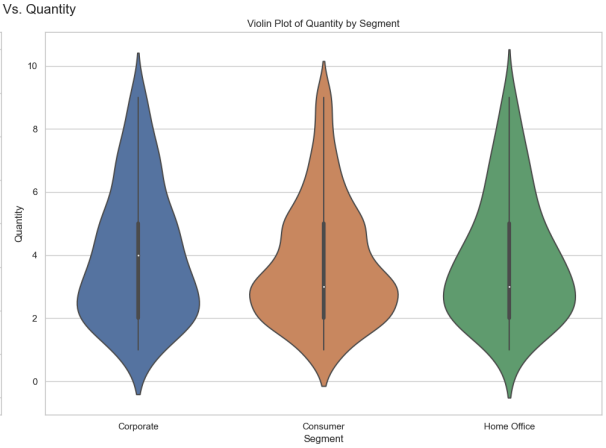


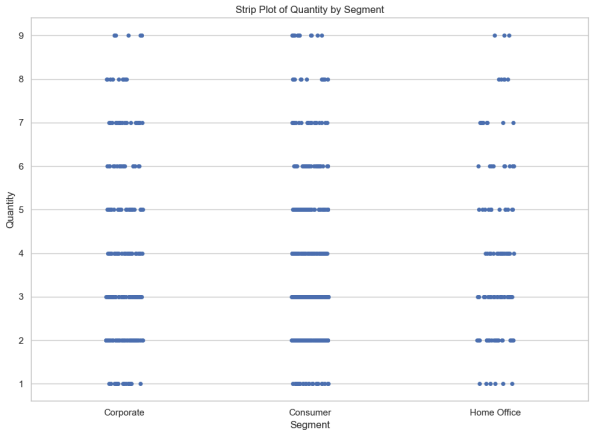
Categories Vs. Quantity

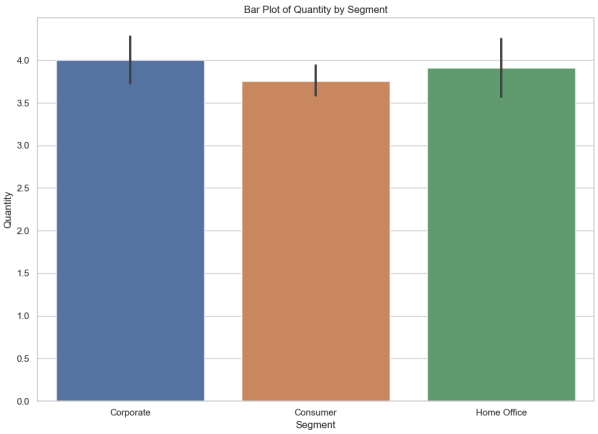
In [ ]:
```
bivariate_analysis_categorical_numerical(global_super_store_df, 'Segment', 'Quantit
bivariate_analysis_categorical_numerical(global_super_store_df, 'Region', 'Quantity
bivariate_analysis_categorical_numerical(global_super_store_df, 'Category', 'Quanti
bivariate_analysis_categorical_numerical(global_super_store_df, 'Sub-Category', 'Qu
```

Segment Vs. Quantity

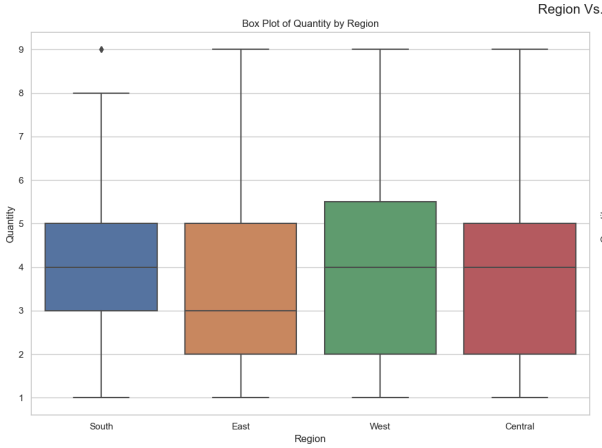


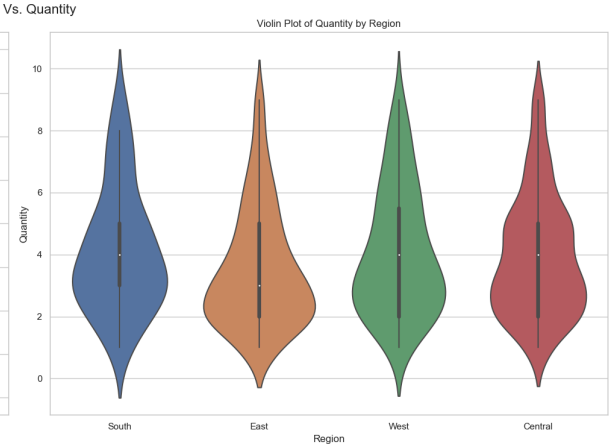


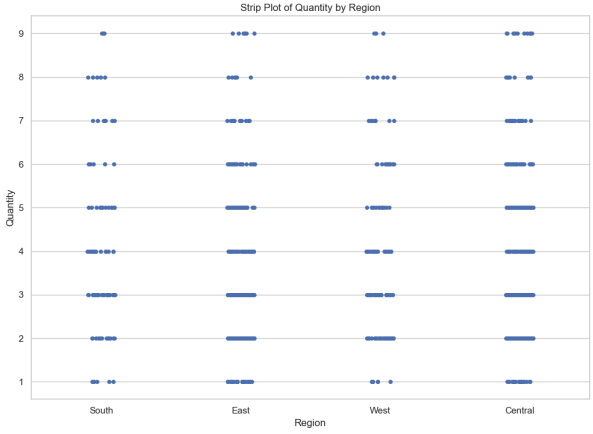


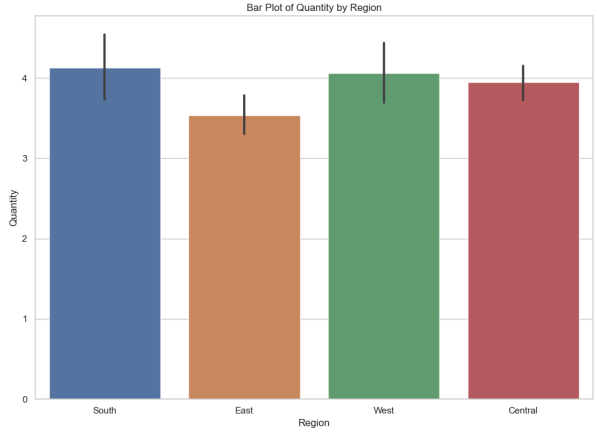


Region Vs. Quantity









Geo Analysis

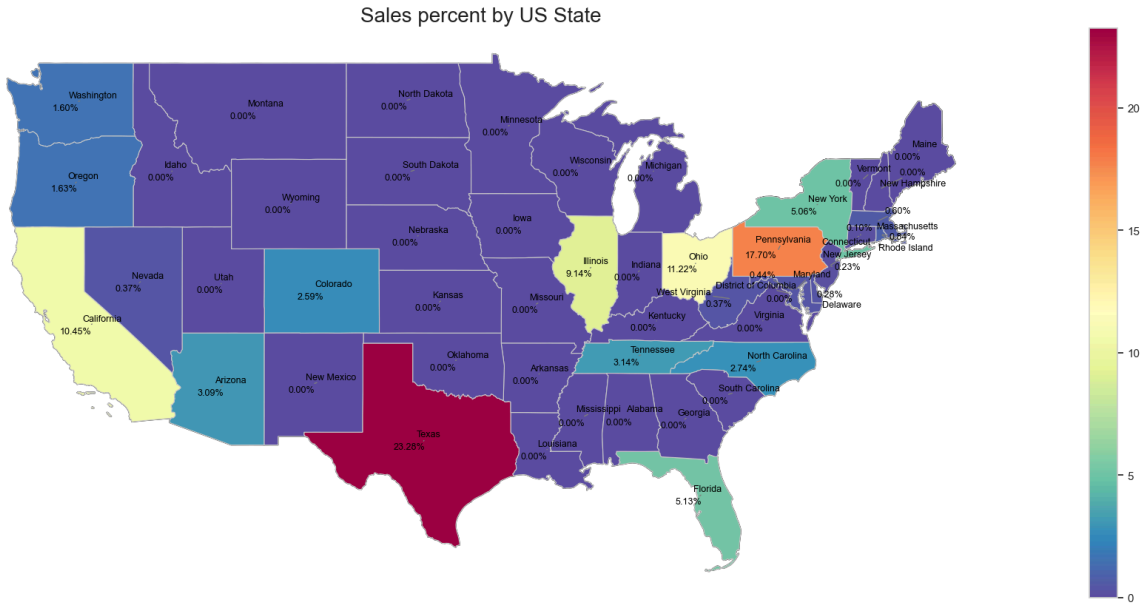
Function to plot the numerical features on a US map.

In [ ]:
```
def geo_analysis_by_state(df, feature_column):
    """
    Plots the feature percentages on a US map grouped by States
```

```
    Args:
    - df (DataFrame): DataFrame containing the feature data.
    - feature_column (str): Name of the numerical feature column.

    Returns:
    - None
    """

    base_folder_path = os.getcwd()
    shp_path = '/data/usa-states-census-2014.shp'

    us_states = gpd.read_file(f'{base_folder_path}{shp_path}')
    us_states = us_states.to_crs("EPSG:3395")

    # Group feature data based on States
    feature_per_states = df.groupby(['State'], as_index=False)[[feature_column]].su

    # Create a new column to see the Feature %
    feature_percent_column_name = feature_column + ' %'

    # Calculate the sum of the feature_column
    total_feature_sum = df[feature_column].sum()

    # Check if the total sum is zero
    if total_feature_sum == 0:
        # If the total sum is zero, set all percentages to zero or handle the scena
        feature_per_states[feature_percent_column_name] = 0
    else:
        # Calculate percentages only if the total sum is not zero
        feature_per_states[feature_percent_column_name] = (feature_per_states[featu

    # Merge sales data with the US map based on state codes or names
    merged_data = us_states.merge(feature_per_states, how='left', left_on='NAME', r

    # Filter out duplicate entries
    merged_data = merged_data.drop_duplicates(subset=['NAME'])

    # Fill NaN values with 0 for the percentage column
    merged_data[feature_percent_column_name].fillna(0, inplace=True)

    # Plot the map
    fig, ax = plt.subplots(1, 1, figsize=(30, 10))
    us_states.plot(ax=ax, color='lightgrey', edgecolor='black')
    merged_data.plot(column=feature_percent_column_name, cmap='Spectral_r', linewic

    # Annotate state names and sales percentages
    texts = []
    for idx, row in merged_data.iterrows():
        x = row['geometry'].centroid.x
        y = row['geometry'].centroid.y
        name = row['NAME']
        feature_percent = row[feature_percent_column_name]
        text = ax.text(x, y, name, fontsize=9, ha='center', va='center', color='bla
        texts.append(text)
        text = ax.text(x, y-0.5, f"{feature_percent:.2f}%", fontsize=9, ha='center'
        texts.append(text)

    # Adjust text labels to avoid overlaps
    adjust_text(texts, arrowprops=dict(arrowstyle='-', color='grey'))

    ax.axis('off')
    ax.set_title(f'{feature_column} percent by US State', loc='center', fontsize=20
    plt.show()
```

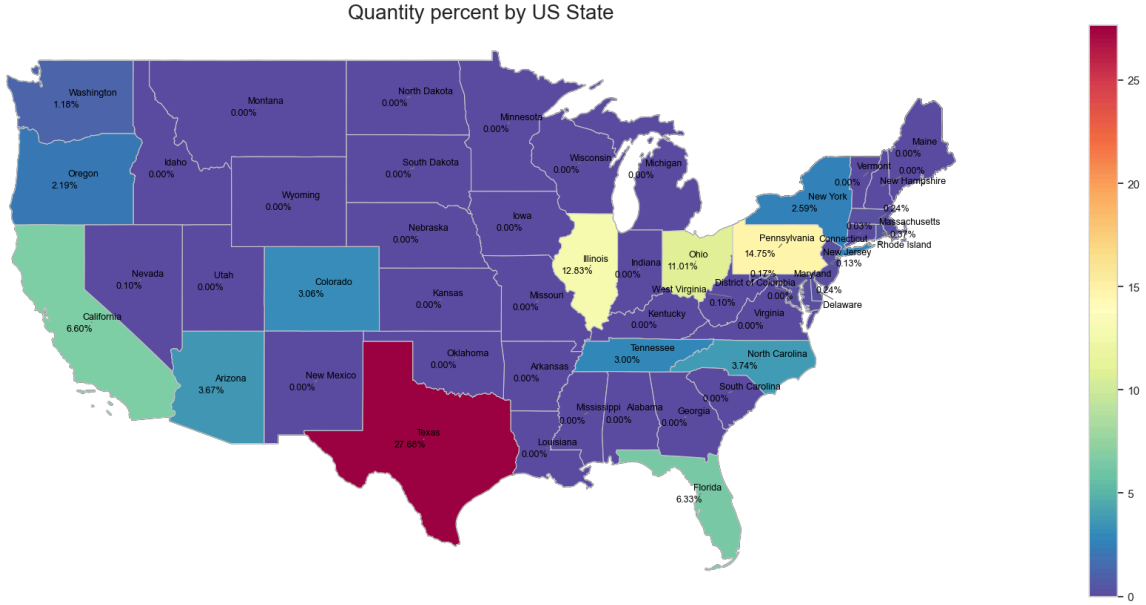
Sales % based on US States

In [ ]:
```
geo_analysis_by_state(global_super_store_df, 'Sales')
```



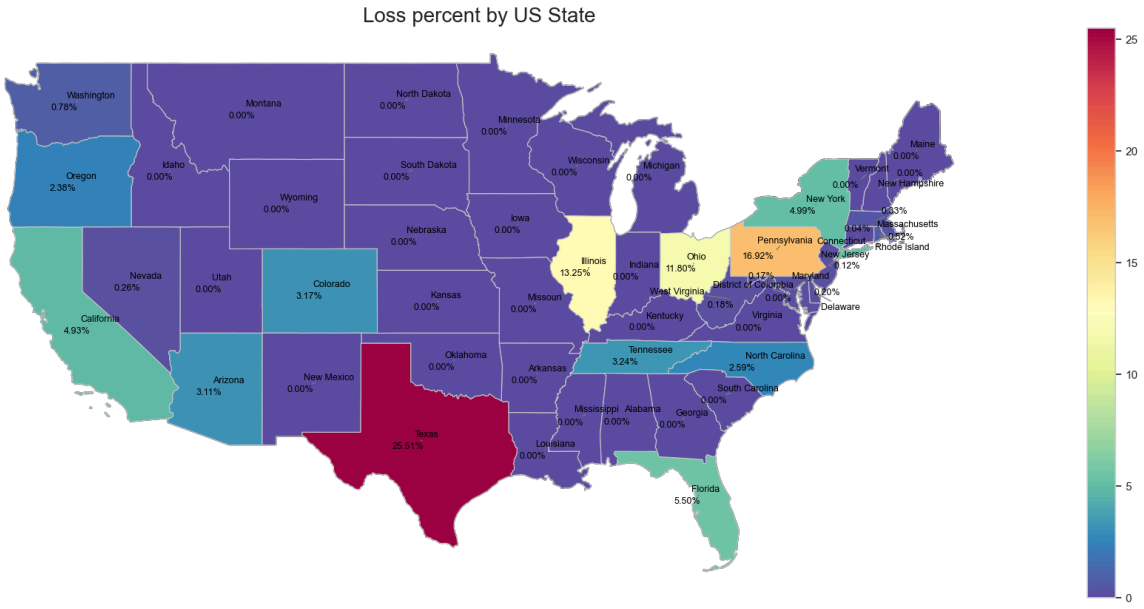
Quantity % based on US States

In [ ]:
```
geo_analysis_by_state(global_super_store_df, 'Quantity')
```



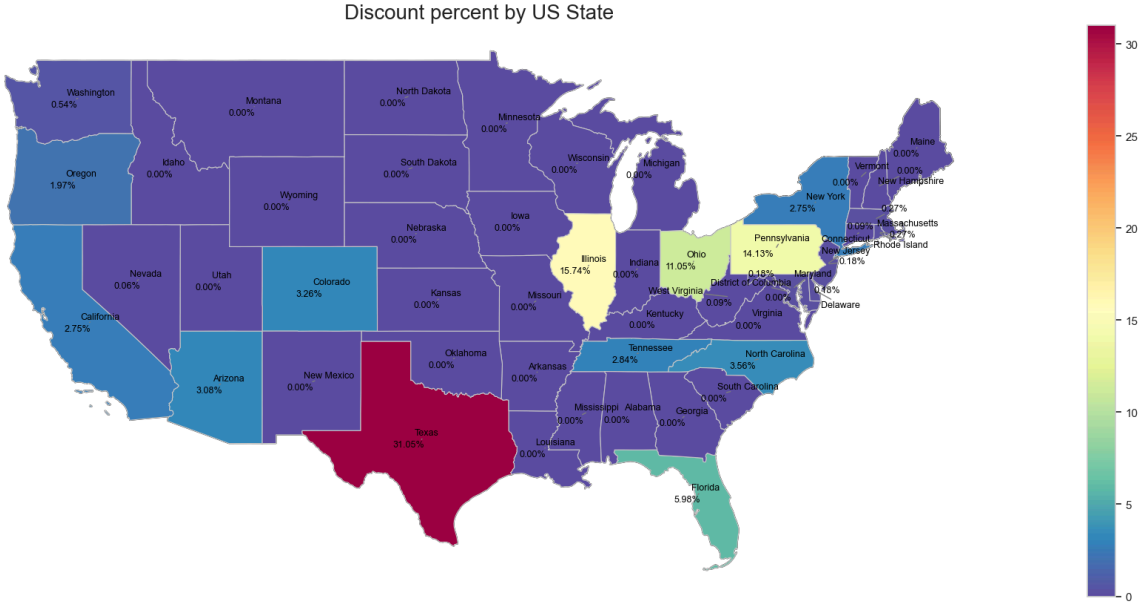
Loss % based on US States

In [ ]:
```
geo_analysis_by_state(global_super_store_df, 'Loss')
```



Discount % based on US States

In [ ]:
```
geo_analysis_by_state(global_super_store_df, 'Discount')
```



- Sales conclusion:
  - **Texas** has the most percentage of Sales with ~23%.
  - The Central and South regions of the country collectively could not match the sales numbers of Texas.
- Quantity conclusion:
  - **Texas** sold ~28% of products.
- Losses conclusion:
  - **Texas** despite of making ~23% of Sales, has grossed an ~26% of losses.

Conclusion

- Categorical Vs. Categorical Conclusion
  - Chi-square test of independence pointed us that the following categories has a significant association:
    - *Category* Vs. *Sub-Category*
    - *Region* Vs. *Category*
    - *Region* Vs. *Sub-Category*
  - Function `categorical_analysis` plotted cross-tabulation and stacked bar plot on the choose categories. Then `bivariate_categorical_figure_analysis` function would plot the pivot-table and heatmaps to given categorical features. In summary:
    - *Category* Vs. *Sub-Category*
      - Binders Sub-Category appeared on most number of Sales, close next is Chairs.
      - But Chairs has the highest sales value, followed by Tables.
      - Binders, and Chairs made almost the same value of loss.
    - *Region* Vs. *Category*
      - Central Region has made highest number of sales on Furniture Category, second close is Office Supplies Category, also from Central Region.
      - Same goes to the sales values, Central Region made the highest sales on Furniture, followed by Furniture category in the East Region.
      - Furniture from Central Region marks the highest loss as well.
    - *Region* Vs. *Sub-Category*
      - Binders Sub-Category on Central Region appeared on most number of Sales, close next is Phones on East Region.
      - But Chairs from Central Region has the highest sales value, followed by Phones on East Region.
      - Tables from East Region marks the highest loss, close second will be Phones on East Region.

- Numerical Vs. Numerical Conclusion
  - Sales and Discount correlation of -0.58
    - Indicates a moderate negative relationship between sales and discounts.
    - Meaning that when discounts increase, sales tend to decrease, and vice versa.
    - Since it is a moderate negative relationship, does not imply causation.
  - Sales and Loss correlation of 0.40
    - Indicates a moderate positive relationship between sales and loss.
    - Meaning that when sales increase, loss tend to increase, and vice versa.
    - Since it is a moderate positive relationship, does not imply causation.
  - The other numerical variable has either a weak positive/negative relationship, we cannot take fruitful decisions, especially causation.

- Categorical Vs. Numerical Conclusion
  - Consumer Segment has ~56% of the sales value, but Corporate Segment has the highest loss percentages.
  - Eastern Region is responsible for ~37% of the sales, most of it coming from Texas. Central Region marks the highest loss percentage.

- Furniture Category has the highest percentage of sales with ~53% and also the losses at ~39%.
- Appliance Sub-category made the highest loss at 241.38%.