```
# Importing necessary libraries for data analysis and visualization
import pandas as pd                             # Pandas for data manipulation and analysis
import numpy as np                              # NumPy for numerical operations
import matplotlib.pyplot as plt                 # Matplotlib for basic plotting
import seaborn as sns                           # Seaborn for statistical data visualization
from statsmodels.tsa.seasonal import seasonal_decompose   # For decomposing time series data
import plotly.express as px                     # Plotly Express for interactive visualizations

# Setting display options to show three decimal places for floating-point numbers in Pandas
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

LOADING DATASET

```
# Display all columns without truncation
pd.set_option('display.max_columns', None)

# Load car-related dataset from URL into 'stores' DataFrame
url = 'https://raw.githubusercontent.com/Vivega28/WEEK_6_PREPINSTA/main/train.csv'
stores = pd.read_csv(url, encoding='unicode_escape')

# Display first two rows of the loaded DataFrame
stores.head(2)
```

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	
0	1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	H
1	2	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	H

Next steps: Generate code with stores View recommended plots

```
# Remove 'Row ID' column from 'stores' DataFrame
del stores["Row ID"]

# Display first two rows
stores.head(2)
```

	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	C
0	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	Henders
1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	United States	Henders

Next steps: Generate code with stores View recommended plots

Preliminary Data Inspection

```
# Display data types of columns in the 'stores' DataFrame
stores.dtypes
```

```
Order ID        object
Order Date      object
Ship Date       object
Ship Mode       object
Customer ID     object
```

```
Customer Name     object
Segment           object
Country           object
City              object
State             object
Postal Code      float64
Region            object
Product ID        object
Category          object
Sub-Category      object
Product Name      object
Sales            float64
dtype: object
```

```
# Display concise information about the 'stores' DataFrame, including data types and memory usage
stores.info(verbose=True)
```

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

```
stores.shape
```

```
(9800, 17)
```

```
stores.describe()
```

	Postal Code	Sales
count	9789.000	9800.000
mean	55273.322	230.769
std	32041.223	626.652
min	1040.000	0.444
25%	23223.000	17.248
50%	58103.000	54.490
75%	90008.000	210.605
max	99301.000	22638.480

Data Cleaning and Viewing

1. Handling the missing values and standardizing Date values

This code checks for duplicate rows in the 'stores' DataFrame and calculates the total number of duplicate rows.

```
# Check for duplicate rows in 'stores' DataFrame
stores.duplicated().sum()
```

```
1
```

```
# Drop duplicate rows from the 'stores' DataFrame
stores = stores.drop_duplicates()
stores.duplicated().sum()
```

```
0
```

```
# Check if there are any missing values in the data
stores.isnull().sum()
```

```
Order ID          0
Order Date        0
Ship Date         0
Ship Mode         0
Customer ID       0
Customer Name     0
Segment           0
Country           0
City              0
State             0
Postal Code      11
Region            0
Product ID        0
Category          0
Sub-Category      0
Product Name      0
Sales             0
dtype: int64
```

```
stores[stores['Postal Code'].isnull()]
```

	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	
2234	CA-2018-104066	05/12/2018	10/12/2018	Standard Class	QJ-19255	Quincy Jones	Corporate	United States	Bu
5274	CA-2016-162887	07/11/2016	09/11/2016	Second Class	SV-20785	Stewart Visinsky	Consumer	United States	Bu
8798	US-2017-150140	06/04/2017	10/04/2017	Standard Class	VM-21685	Valerie Mitchum	Home Office	United States	Bu
9146	US-2017-165505	23/01/2017	27/01/2017	Standard Class	CB-12535	Claudia Bergmann	Corporate	United States	Bu
9147	US-2017-165505	23/01/2017	27/01/2017	Standard Class	CB-12535	Claudia Bergmann	Corporate	United States	Bu
9148	US-2017-165505	23/01/2017	27/01/2017	Standard Class	CB-12535	Claudia Bergmann	Corporate	United States	Bu
9386	US-2018-127292	19/01/2018	23/01/2018	Standard Class	RM-19375	Raymond Messe	Consumer	United States	Bu
9387	US-2018-127292	19/01/2018	23/01/2018	Standard Class	RM-19375	Raymond Messe	Consumer	United States	Bu
9388	US-2018-127292	19/01/2018	23/01/2018	Standard Class	RM-19375	Raymond Messe	Consumer	United States	Bu
9389	US-2018-127292	19/01/2018	23/01/2018	Standard Class	RM-19375	Raymond Messe	Consumer	United States	Bu
9741	CA-2016-117086	08/11/2016	12/11/2016	Standard Class	QJ-19255	Quincy Jones	Corporate	United States	Bu

```
# Replace null values in the 'Postal Code' column of the 'stores' DataFrame with 5401
stores['Postal Code'] = stores['Postal Code'].replace(np.nan, 5401)

# Check for missing values after the replacement
stores.isnull().sum()
```

```
Order ID         0
Order Date       0
Ship Date        0
Ship Mode        0
Customer ID      0
Customer Name    0
Segment          0
Country          0
City             0
State            0
Postal Code      0
Region           0
Product ID       0
Category         0
Sub-Category     0
Product Name     0
Sales            0
dtype: int64
```

```
stores.shape
```

```
(9799, 17)
```

```
# Convert 'Order Date' to the standard format 'YYYY-MM-DD'
stores['Order Date'] = pd.to_datetime(stores['Order Date'], format='%d/%m/%Y')
stores['Order Date']
```

```
0      2017-11-08
1      2017-11-08
2      2017-06-12
3      2016-10-11
4      2016-10-11
          ...
9795   2017-05-21
9796   2016-01-12
9797   2016-01-12
9798   2016-01-12
9799   2016-01-12
Name: Order Date, Length: 9799, dtype: datetime64[ns]
```

```
# Convert 'Ship Date' to the standard format 'YYYY-MM-DD'
stores['Ship Date'] = pd.to_datetime(stores['Ship Date'], format='%d/%m/%Y')
stores['Ship Date']
```

```
0      2017-11-11
1      2017-11-11
2      2017-06-16
3      2016-10-18
4      2016-10-18
          ...
9795   2017-05-28
9796   2016-01-17
9797   2016-01-17
9798   2016-01-17
9799   2016-01-17
Name: Ship Date, Length: 9799, dtype: datetime64[ns]
```

```
# Calculate the days taken to ship and create a new 'Days to Ship' column in the 'stores' DataFrame
stores['Days to Ship'] = (stores['Ship Date'] - stores['Order Date']).dt.days
stores['Days to Ship']
```

```
0       3
1       3
2       4
3       7
4       7
       ..
9795    7
9796    5
9797    5
9798    5
```

```
9799    5
Name: Days to Ship, Length: 9799, dtype: int64
```

```
# Calculate the days taken to ship and create a new 'Days to Ship' column in the 'stores' DataFrame
stores['Days to Ship'] = (stores['Ship Date'] - stores['Order Date']).dt.days
stores['Days to Ship']
```

```
0       3
1       3
2       4
3       7
4       7
       ..
9795    7
9796    5
9797    5
9798    5
9799    5
Name: Days to Ship, Length: 9799, dtype: int64
```

```
# Display a random sample of one row from the 'stores' DataFrame
stores.sample()
```

	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	State
3241	US-2017-140800	2017-02-01	2017-02-03	First Class	CK-12760	Cyma Kinney	Corporate	United States	Arlington	Virginia

2. Viewing Order ID Dataset

This code prints the unique values and the total number of unique values in the 'Order ID' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Order ID' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Order ID'].unique())
print('Total Number of Unique Values: ', stores['Order ID'].nunique())
```

```
Unique Values:
 ['CA-2017-152156' 'CA-2017-138688' 'US-2016-108966' ... 'CA-2015-127166'
 'CA-2017-125920' 'CA-2016-128608']
Total Number of Unique Values:  4922
```

3. Viewing Order Date Dataset

This code prints the unique values and the total number of unique values in the 'Order Date' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Order Date' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Order Date'].unique())
print('Total Number of Unique Values: ', stores['Order Date'].nunique())
```

```
Unique Values:
 ['2017-11-08T00:00:00.000000000' '2017-06-12T00:00:00.000000000'
 '2016-10-11T00:00:00.000000000' ... '2015-06-18T00:00:00.000000000'
 '2018-02-28T00:00:00.000000000' '2016-05-09T00:00:00.000000000']
Total Number of Unique Values:  1230
```

4. Viewing Ship Date Dataset

This code prints the unique values and the total number of unique values in the 'Ship Date' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Ship Date' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Ship Date'].unique())
print('Total Number of Unique Values: ', stores['Ship Date'].nunique())
```

```
Unique Values:
 ['2017-11-11T00:00:00.000000000' '2017-06-16T00:00:00.000000000'
 '2016-10-18T00:00:00.000000000' ... '2015-03-12T00:00:00.000000000'
```

```
 '2018-04-06T00:00:00.000000000' '2016-05-13T00:00:00.000000000']
Total Number of Unique Values:  1326
```

5. Viewing Days to Ship Dataset

This code prints the unique values and the total number of unique values in the 'Days to Ship' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Days to Ship' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Days to Ship'].unique())
print('Total Number of Unique Values: ', stores['Days to Ship'].nunique())
```

```
Unique Values:
 [3 4 7 5 2 6 1 0]
Total Number of Unique Values:  8
```

6. Viewing Customer ID Dataset

This code prints the unique values and the total number of unique values in the 'Customer ID' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Customer ID' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Customer ID'].unique())
print('Total Number of Unique Values: ', stores['Customer ID'].nunique())
```

```
 AG-10810   MH-17440   SS-20515   LD-16855   VP-21760   TC-21145
'IM-15055' 'AR-10570' 'CM-12715' 'FW-14395' 'LC-16960' 'HE-14800'
'BD-11560' 'HD-14785' 'CJ-11875' 'RS-19870' 'SC-20845' 'RE-19405'
'SM-20905']
Total Number of Unique Values:  793
```

7. Viewing Customer Name Dataset

This code prints the unique values and the total number of unique values in the 'Customer Name' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Customer Name' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Customer Name'].unique())
print('Total Number of Unique Values: ', stores['Customer Name'].nunique())
```

```
'Stuart Calhoun' 'Anne McFarland' 'Rick Huthwaite' 'Carol Triggs'
'Matt Collister' 'Corey Catlett' 'Kelly Andreada' 'Tamara Chand'
'Bart Folk' 'Magdelene Morse' 'Adrian Hane' 'Ben Wallace' 'Scot Wooten'
'Brian Stugart' 'Randy Ferguson' 'William Brown' 'Trudy Brown'
'Art Ferguson' 'Richard Bierner' 'Karen Ferguson' 'John Huston'
'Ivan Liston' 'Patrick Bzostek' 'Rob Haberlin' 'Arthur Wiediger'
'Maris LaWare' 'Dorothy Badders' 'Matt Hagelstein' 'Dennis Kane'
'Bobby Trafton' 'Denny Blanton' 'Toby Gnade' 'Barry Franz'
'Justin MacKendrick' 'Maria Zettner' 'Mitch Webber' 'Mark Van Huff'
'Sean Miller' 'Tom Prescott' 'Jim Karlsson' 'Patrick Jones'
'Ricardo Sperren' 'Susan Vittorini' 'Becky Castell' 'Elizabeth Moffitt'
'Brendan Murry' 'Kristina Nunn' 'Kelly Williams' 'Scott Cohen'
'Christina VanderZanden' 'Speros Goranitis' 'Tamara Manning'
'Eleni McCrary' 'Michelle Lonsdale' 'Clay Rozendal' 'Annie Zypern'
'Pierre Wener' 'Shahid Collister' 'Carlos Meador' 'Greg Maxwell'
'Tim Brockman' 'John Murray' 'Sonia Cooley' 'Luke Schmidt' 'Ralph Ritter'
'Daniel Byrd' 'Thomas Thornton' 'Lori Olson' 'Ken Dana' 'Nicole Brennan'
'Brian Derr' 'Chris McAfee' 'Edward Nazzal' 'Kean Nguyen' 'Bill Overfelt'
'Aleksandra Gannaway' 'Matthew Clasen' 'Tom Ashbrook' 'Jason Fortune-'
'Tim Taslimi' 'Sarah Bern' 'Craig Leslie' 'Hunter Glantz'
'Nancy Lomonaco' 'Rick Reed' 'Toby Carlisle' 'Stewart Visinsky'
'Bobby Elias' 'Steve Carroll' 'David Flashing' 'Fred Harton'
'MaryBeth Skach' 'Ritsa Hightower' 'George Ashbrook' 'Julie Prescott'
'Dean percer' 'Michael Oakman' 'Denise Leinenbach' 'Michelle Huthwaite'
'Daniel Raglin' 'Darrin Martin' 'Carol Adams' 'Anna Chung'
'Denise Monton' 'Vicky Freymann' 'Christopher Conant' 'Beth Fritzler'
'Harry Greene' 'Becky Pak' 'Eugene Moren' 'Michelle Arnett' 'Andy Yotov'
'Giulietta Baptist' 'Julia Barnett' 'Michael Grace' 'Sharelle Roach'
'Joy Bell-' 'Dario Medina' 'Tony Chapman' 'Sean Wendt' 'Richard Eichhorn'
'Benjamin Farhat' 'Katrina Bavinger' 'Jason Gross' 'Erin Creighton'
'Eugene Barchas' 'Jennifer Patt' 'Cari Sayre' 'Gary Hansen'
'Pete Takahito' 'Jack Lebron' 'Aaron Hawkins' 'Cindy Chapman'
'David Wiener' 'Sarah Jordon' 'Bruce Geld' 'Laurel Beltran'
'Candace McMahon' 'Evan Henry' 'Tony Sayre' 'Patrick Ryan' 'Liz Carlisle'
'Cindy Schnelling' 'Dave Hallsten' "Jack O'Briant" 'Anna HÃ¤berlin'
'Heather Jas' 'Mark Hamilton' "Russell D'Ascenzo" 'Sam Craven'
'Stephanie Ulpright' 'Fred Chung' 'Randy Bradley' 'Nick Crebassa'
'Darren Budd' 'Maureen Fritzler' 'Roland Murray' 'Vivian Mathis'
'Ed Jacobs' 'Nathan Cano' 'Lycoris Saunders' 'Katrina Edelman'
'Duane Huffman' 'Peter Fuller' 'Valerie Takahito' 'Maureen Gnade'
'Susan Pistek' 'Charles Sheldon' 'Dana Kaydos' 'Khloe Miller'
'Anna Andreadi' 'Dorothy Dickinson' 'Amy Hunt' 'Tracy Poddar'
'Eileen Kiefer' 'Cyra Reiten' 'Susan Gilcrest' 'Angele Hood'
'Neil FranzÃ¶sisch' 'Bill Shonely' 'Stefanie Holloman' 'Roger Demir'
'Alex Grayson' 'Georgia Rosenberg' 'Vivek Sundaresam' 'Tony Molinari'
'Tom Stivers' 'Dennis Bolton' 'Nick Radford' 'Cari Schnelling'
'Monica Federle' 'Liz Willingham' 'Alex Russell' 'Karen Seio'
'Aaron Bergman' 'Lisa Ryan' 'Shahid Shariari' 'Jill Matthias'
'Jason Klamczynski' 'Don Miller' 'Muhammed Lee' 'Marc Harrigan'
'Frank Carlisle' 'Thea Hudgings' 'Juliana Krohn' 'Sarah Brown'
'Barry Gonzalez' 'Barry Weirich' 'Mitch Gastineau' "Doug O'Connell"
'Barry Pond' 'Trudy Schmidt' 'Evan Minnotte' "Anthony O'Donnell"
'Mark Haberlin' 'Shirley Schmidt' 'Lela Donovan' 'Victoria Pisteka'
'Theresa Coyne' 'Ionia McGrath' 'Anemone Ratner' 'Craig Molinari'
'Fred Wasserman' 'Lindsay Castell' 'Harold Engle' 'Brendan Dodson'
'Harold Dahlen' 'Carl Jackson' 'Roy Skaria' 'Sung Chung'
'Ricardo Emerson' 'Susan MacKendrick']
Total Number of Unique Values:  793
```

8. Viewing Segment Dataset

This code prints the unique values and the total number of unique values in the 'Segment' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Segment' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Segment'].unique())
print('Total Number of Unique Values: ', stores['Segment'].nunique())
```

```
Unique Values:
 ['Consumer' 'Corporate' 'Home Office']
Total Number of Unique Values:  3
```

9. Viewing Country Dataset

This code prints the unique values and the total number of unique values in the 'Country' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Country' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Country'].unique())
print('Total Number of Unique Values: ', stores['Country'].nunique())
```

```
Unique Values:
 ['United States']
Total Number of Unique Values:  1
```

10. Viewing City Dataset

This code prints the unique values and the total number of unique values in the 'City' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'City' column of the 'stores' DataFrame
print('Unique Values: \n', stores['City'].unique())
print('Total Number of Unique Values: ', stores['City'].nunique())
```

```
 'Cedar Rapids' 'Providence' 'Pueblo' 'Deltona' 'Murray' 'Middletown'
 'Freeport' 'Pico Rivera' 'Provo' 'Pleasant Grove' 'Smyrna' 'Parma'
 'Mobile' 'New Bedford' 'Irving' 'Vineland' 'Glendale' 'Niagara Falls'
 'Thomasville' 'Westminster' 'Coppell' 'Pomona' 'North Las Vegas'
 'Allentown' 'Tempe' 'Laguna Niguel' 'Bridgeton' 'Everett' 'Watertown'
 'Appleton' 'Bellevue' 'Allen' 'El Paso' 'Grapevine' 'Carrollton' 'Kent'
 'Lafayette' 'Tigard' 'Skokie' 'Plano' 'Suffolk' 'Indianapolis' 'Bayonne'
 'Greensboro' 'Baltimore' 'Kenosha' 'Olathe' 'Tulsa' 'Redmond' 'Raleigh'
 'Muskogee' 'Meriden' 'Bowling Green' 'South Bend' 'Spokane' 'Keller'
 'Port Orange' 'Medford' 'Charlottesville' 'Missoula' 'Apopka' 'Reading'
 'Broomfield' 'Paterson' 'Oklahoma City' 'Chesapeake' 'Lubbock'
 'Johnson City' 'San Bernardino' 'Leominster' 'Bozeman' 'Perth Amboy'
```

```
 Delray Beach   Commerce City   Texas City   Wilson   Rio Rancho
'Goldsboro' 'Montebello' 'El Cajon' 'Beaumont' 'West Palm Beach'
'Abilene' 'Normal' 'Saint Charles' 'Camarillo' 'Hillsboro' 'Burbank'
'Modesto' 'Garden City' 'Atlantic City' 'Longmont' 'Davis' 'Morgan Hill'
'Clifton' 'Sheboygan' 'East Point' 'Rapid City' 'Andover' 'Kissimmee'
'Shelton' 'Danbury' 'Sanford' 'San Marcos' 'Greeley' 'Mansfield' 'Elyria'
'Twin Falls' 'Coral Gables' 'Romeoville' 'Marlborough' 'Laurel' 'Bryan'
'Pine Bluff' 'Aberdeen' 'Hagerstown' 'East Orange' 'Arlington Heights'
'Oswego' 'Coon Rapids' 'San Clemente' 'San Luis Obispo' 'Springdale']
Total Number of Unique Values:  529
```

11. Viewing State Dataset

This code prints the unique values and the total number of unique values in the 'State' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'State' column of the 'stores' DataFrame
print('Unique Values: \n', stores['State'].unique())
print('Total Number of Unique Values: ', stores['State'].nunique())
```

```
Unique Values:
 ['Kentucky' 'California' 'Florida' 'North Carolina' 'Washington' 'Texas'
 'Wisconsin' 'Utah' 'Nebraska' 'Pennsylvania' 'Illinois' 'Minnesota'
 'Michigan' 'Delaware' 'Indiana' 'New York' 'Arizona' 'Virginia'
 'Tennessee' 'Alabama' 'South Carolina' 'Oregon' 'Colorado' 'Iowa' 'Ohio'
 'Missouri' 'Oklahoma' 'New Mexico' 'Louisiana' 'Connecticut' 'New Jersey'
 'Massachusetts' 'Georgia' 'Nevada' 'Rhode Island' 'Mississippi'
 'Arkansas' 'Montana' 'New Hampshire' 'Maryland' 'District of Columbia'
 'Kansas' 'Vermont' 'Maine' 'South Dakota' 'Idaho' 'North Dakota'
 'Wyoming' 'West Virginia']
Total Number of Unique Values:  49
```

12. Viewing Postal Code Dataset

This code prints the unique values and the total number of unique values in the 'Postal Code' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Postal Code' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Postal Code'].unique())
print('Total Number of Unique Values: ', stores['Postal Code'].nunique())
```

```
 98115. 73034. 90045. 19134. 88220. 78207. 77036. 62521. 71203.  6824.
 75051. 92374. 45011.  7090. 19120. 44312. 80219. 75220. 37064. 90604.
 48601. 44256. 43017. 48227. 38401. 33614. 95051. 55044. 92037. 77506.
 94513. 27514.  7960. 45231. 94110. 90301. 33319. 80906.  7109. 48180.
  8701. 22204. 80004.  7601. 33710. 19143. 90805. 92345. 37130. 84041.
 78745.  1852. 31907.  6040. 78550. 85705. 62301.  2038. 33024. 98198.
 61604. 89115.  2886. 33180. 28403. 92646. 40475. 80027.  1841. 39212.
 48187. 10801. 28052. 32216. 47201. 13021. 73071. 94521. 60068. 79109.
 11757. 90008. 92024. 77340. 14609. 72701. 92627. 80134. 30318. 64118.
 59405. 48234. 33801. 36116. 85204. 60653. 54302. 45503. 92804. 98270.
 97301. 78041. 75217. 43123. 10011. 48126. 31088. 94591. 92691. 48307.
  7060. 85635. 98661. 60505. 76017. 40214. 75081. 44105. 75701. 27217.
 22980. 19013. 27511. 32137. 10550. 48205. 33012. 11572. 92105. 60201.
 48183. 55016. 71111. 50315. 93534. 23223. 28806. 92530. 68104. 98026.
 92704. 53209. 41042. 44052.  7036. 93905.  8901. 17602.  3301. 21044.
 75043.  6360. 22304. 43615. 87401. 92503. 90503. 78664. 92054. 33433.
 23464. 92563. 28540. 52601. 98502. 20016. 65109. 63376. 61107. 33142.
 78521. 10701. 94601. 28110. 20735. 30076. 72401. 47374. 94509. 33030.
 46350. 48911. 44221. 89502. 22801. 92025. 48073. 20852. 33065. 14215.
 33437. 39503. 93727. 27834. 11561. 35630. 31204. 52402.  2908. 81001.
 94533. 32725. 42071.  6457. 11520. 90660. 84604. 84062. 30080. 24153.
 44134. 36608.  2740. 75061.  8360. 85301. 14304. 27360. 92683. 38301.
 75019. 91767. 89031. 18103. 19711. 85281. 92677.  8302.  2149. 13601.
 54915. 98006. 75002. 79907. 76051. 75007. 37167. 98031. 70506. 97224.
 60076. 75023. 23434. 46203.  7002. 28314. 27405. 21215. 53142. 66062.
 98002. 74133. 97756. 27604. 74403.  6450. 42104. 46614.  6010. 89015.
 99207. 76248. 45014. 32127. 97504. 22901. 59801. 33178. 29501. 97477.
 32712. 19601. 80020. 65807.  7501. 73120. 23320. 79424. 65203. 37604.
 36830. 92404.  1453. 59715. 85345. 44107.  8861. 91761. 91730. 56560.
 75150. 95207. 32174. 94086.  3820. 17403. 77840. 63116.  2169. 95336.
```

```
 60440. 55369. 95695. 77489. 77581. 94403. 49505. 93277. 66212. 92592.
 92399.  2151. 77301. 60477. 52001. 48127. 87505. 28601. 60188. 56301.
 33161. 46226. 33317. 34952. 29730. 79762. 53214. 91911. 66502. 16602.
 80229. 61821. 47401. 71854. 78539. 77520. 46142. 90712.  2895. 54880.
 76021. 98042. 74012. 33023. 33021. 77536. 67212. 78501. 52240. 83704.
  2920. 61032. 77642. 95610. 75056. 98052. 32114. 86442. 46368. 58103.
 46514. 91776. 33063. 30328. 44060. 73505. 23666. 13440. 54601. 83501.
 39401. 94526. 48858. 84321.  6708. 30605.  4240. 61832. 85323. 30062.
 85364. 54401. 99301. 60302. 32503. 77573. 20877. 84043. 35401. 92553.
 40324. 80538. 85224. 59601. 63122. 76706. 48066. 60423. 18018. 55113.
 68801. 55125. 48237. 72756. 88101. 33458. 93101. 75104. 68701. 84020.
 48104. 91941. 83201. 49423.  6460. 60089. 92630. 96003. 95928. 13501.
 72032. 82001. 42301. 83605. 70065.  3060. 38134. 94061. 37087. 93454.
 60016. 98632. 37075. 50701.  2138. 60067.  1915. 97405. 93030. 98059.
 60025. 33445. 80022. 77590. 27893. 87124. 27534. 98208. 90640. 92020.
 77705. 33407. 79605. 61761. 63301. 60174. 93010. 97123. 91505. 95351.
 67846.  8401. 80501. 95616. 26003. 95037.  7011. 53081. 30344. 57701.
  1810. 34741.  6484.  6810. 52302. 32771. 78666. 80634. 76063. 44035.
 83301. 33134. 60441.  1752. 20707. 77803. 71603. 57401. 21740.  7017.
 60004. 60543. 55433. 92672. 94568. 93405. 72762.]
Total Number of Unique Values:  627
```

13. Viewing Region Dataset

This code prints the unique values and the total number of unique values in the 'Region' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Region' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Region'].unique())
print('Total Number of Unique Values: ', stores['Region'].nunique())
```

```
Unique Values:
 ['South' 'West' 'Central' 'East']
Total Number of Unique Values:  4
```

14. Viewing Product ID Dataset

This code prints the unique values and the total number of unique values in the 'Product ID' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Product ID' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Product ID'].unique())
print('Total Number of Unique Values: ', stores['Product ID'].nunique())
```

```
Unique Values:
 ['FUR-BO-10001798' 'FUR-CH-10000454' 'OFF-LA-10000240' ...
 'TEC-MA-10003589' 'OFF-AP-10003099' 'TEC-PH-10002645']
Total Number of Unique Values:  1861
```

15. Viewing Category Dataset

This code prints the unique values and the total number of unique values in the 'Category' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Category' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Category'].unique())
print('Total Number of Unique Values: ', stores['Category'].nunique())
```

```
Unique Values:
 ['Furniture' 'Office Supplies' 'Technology']
Total Number of Unique Values:  3
```

16. Viewing Sub-Category Dataset

This code prints the unique values and the total number of unique values in the 'Sub-Category' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Sub-Category' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Sub-Category'].unique())
print('Total Number of Unique Values: ', stores['Sub-Category'].nunique())
```

```
Unique Values:
 ['Bookcases' 'Chairs' 'Labels' 'Tables' 'Storage' 'Furnishings' 'Art'
 'Phones' 'Binders' 'Appliances' 'Paper' 'Accessories' 'Envelopes'
 'Fasteners' 'Supplies' 'Machines' 'Copiers']
Total Number of Unique Values:  17
```

*### 17. Viewing Product Name Dataset *

This code prints the unique values and the total number of unique values in the 'Product Name' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Product Name' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Product Name'].unique())
print('Total Number of Unique Values: ', stores['Product Name'].nunique())
```

```
Unique Values:
 ['Bush Somerset Collection Bookcase'
 'Hon Deluxe Fabric Upholstered Stacking Chairs, Rounded Back'
 'Self-Adhesive Address Labels for Typewriters by Universal' ...
 'Cisco 8961 IP Phone Charcoal' 'Eureka Hand Vacuum, Bagless' 'LG G2']
Total Number of Unique Values:  1849
```

18. Viewing Sales Dataset

This code prints the unique values and the total number of unique values in the 'Sales' column of the 'stores' DataFrame.

```
# Display unique values and the total number of unique values in the 'Sales' column of the 'stores' DataFrame
print('Unique Values: \n', stores['Sales'].unique())
print('Total Number of Unique Values: ', stores['Sales'].nunique())
```

```
Unique Values:
 [261.96  731.94   14.62  ... 235.188  26.376  10.384]
Total Number of Unique Values:  5757
```

Viewing & Saving Clean Data

Viewing the final and cleaned data, saving it into .csv format

Here, the column names in the 'stores' DataFrame are modified by replacing spaces with underscores and converting them to lowercase for consistency.

```
stores.columns = [col.replace(' ', '_').replace('-', '_').lower() for col in stores.columns] # Rename columns by replacing spaces with under
```

```
stores.sample(5)                # Display a random sample of 5 rows from the modified 'stores' DataFrame
```

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segment
1709	CA-2018-123491	2018-10-30	2018-11-05	Standard Class	JK-15205	Jamie Kunitz	Consumer
9584	CA-2018-132584	2018-08-26	2018-08-27	First Class	HJ-14875	Heather Jas	Home Office
5361	CA-2018-100951	2018-06-09	2018-06-10	First Class	NC-18625	Noah Childs	Corporate
2791	CA-2015-125514	2015-09-21	2015-09-22	First Class	BM-11650	Brian Moss	Corporate
3894	US-2015-112200	2015-11-22	2015-11-28	Standard Class	TC-21475	Tony Chapman	Home Office

```
print(stores.dtypes)       # Display data types of each column in the modified 'stores' DataFrame
```

```
order_id                object
order_date      datetime64[ns]
ship_date       datetime64[ns]
ship_mode               object
customer_id             object
customer_name           object
segment                 object
country                 object
city                    object
state                   object
postal_code            float64
region                  object
product_id              object
category                object
sub_category            object
product_name            object
sales                  float64
days_to_ship             int64
dtype: object
```

```
print(stores.isnull().sum().sum())
```

```
0
```

```
print(stores.shape)
```

```
(9799, 18)
```

```
print(stores.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   order_id       9799 non-null   object
 1   order_date     9799 non-null   datetime64[ns]
 2   ship_date      9799 non-null   datetime64[ns]
 3   ship_mode      9799 non-null   object
 4   customer_id    9799 non-null   object
 5   customer_name  9799 non-null   object
 6   segment        9799 non-null   object
 7   country        9799 non-null   object
 8   city           9799 non-null   object
 9   state          9799 non-null   object
 10  postal_code    9799 non-null   float64
 11  region         9799 non-null   object
 12  product_id     9799 non-null   object
 13  category       9799 non-null   object
```

```
 14  sub_category   9799 non-null   object
 15  product_name   9799 non-null   object
 16  sales          9799 non-null   float64
 17  days_to_ship   9799 non-null   int64
dtypes: datetime64[ns](2), float64(2), int64(1), object(13)
memory usage: 1.4+ MB
None
```

```
stores.to_csv('stores_data_cleaned.csv', index=False)
```

Statistics & Data Vizualization

Data Analysis

1.1. Descriptive Numeric Analysis

This code generates descriptive statistics, such as mean, standard deviation, minimum, and maximum values, for numerical columns in the 'stores' DataFrame

```
# Generate descriptive statistics for numerical columns in the 'stores' DataFrame
stores.describe()
```

	postal_code	sales	days_to_ship
count	9799.000	9799.000	9799.000
mean	55218.567	230.764	3.961
std	32068.158	626.684	1.750
min	1040.000	0.444	0.000
25%	23223.000	17.248	3.000
50%	57701.000	54.480	4.000
75%	90008.000	210.572	5.000
max	99301.000	22638.480	7.000

```
# Generate descriptive statistics for numerical columns in the 'stores' DataFrame
stores.describe()
```

	postal_code	sales	days_to_ship
count	9799.000	9799.000	9799.000
mean	55218.567	230.764	3.961
std	32068.158	626.684	1.750
min	1040.000	0.444	0.000
25%	23223.000	17.248	3.000
50%	57701.000	54.480	4.000
75%	90008.000	210.572	5.000
max	99301.000	22638.480	7.000

Observation: Gives a desription about the stats on sale price which is only necessary here.

1.2. Descriptive Numeric Analysis

This code generates descriptive statistics for categorical columns in the 'stores' DataFrame, including count, unique values, top value, and frequency.

```
# Generate descriptive statistics for categorical columns in the 'stores' DataFrame
stores.describe(include=['object'])
```

	order_id	ship_mode	customer_id	customer_name	segment	country	city	sta
count	9799	9799	9799	9799	9799	9799	9799	97
unique	4922	4	793	793	3	1	529	
top	CA-2018-100111	Standard Class	WB-21850	William Brown	Consumer	United States	New York City	Californ

Observation:

Gives an idea about the top values of every column, count and frequency of different values.

2. Top Customers:

Identify the top customers based on total sales or order frequency. This helps in understanding who contributes the most to revenue.

This code identifies and prints the top 5 customers in the 'stores' DataFrame based on the sum of their sales.

```
# Find and display the top 5 customers based on the sum of their sales
top_customers = stores.groupby('customer_name')['sales'].sum().sort_values(ascending=False).head(5)
print("Top Customers:\n", top_customers)
```

```
Top Customers:
 customer_name
Sean Miller     25043.050
Tamara Chand    19052.218
Raymond Buch    15117.339
Tom Ashbrook    14595.620
Adrian Barton   14473.571
Name: sales, dtype: float64
```

Observation:

Someone should give them some discount for being so loyal to Superstore. Especially, Sean Miller.

3. Popular Products:

Find the most popular products based on sales or order quantity.

This code identifies and prints the top 10 popular products in the 'stores' DataFrame based on the sum of their sales.

```
# Find and display the top 10 popular products based on the sum of their sales
popular_products = stores.groupby('product_name')['sales'].sum().sort_values(ascending=False).head(10)
print("Popular Products:\n", popular_products)
```

```
Popular Products:
 product_name
Canon imageCLASS 2200 Advanced Copier                                        61599.824
Fellowes PB500 Electric Punch Plastic Comb Binding Machine with Manual Bind  27453.384
Cisco TelePresence System EX90 Videoconferencing Unit                        22638.480
HON 5400 Series Task Chairs for Big and Tall                                 21870.576
GBC DocuBind TL300 Electric Binding System                                   19823.479
GBC Ibimaster 500 Manual ProClick Binding System                             19024.500
Hewlett Packard LaserJet 3310 Copier                                         18839.686
HP Designjet T520 Inkjet Large Format Printer - 24" Color                    18374.895
GBC DocuBind P400 Electric Binding System                                    17965.068
High Speed Automatic Electric Letter Opener                                  17030.312
Name: sales, dtype: float64
```

Observation: Looks like Copier and Binding machine are used so roughly, that they are ordered repeatedly.

4. Customer Segmentation:

Explore different customer segments and their characteristics.

This code calculates and prints the average sales for each customer segment in the 'stores' DataFrame.

```
# Calculate and display the average sales for each customer segment
customer_segmentation = stores.groupby('segment')['sales'].mean()
print("Average Sales by Customer Segment:\n", customer_segmentation)
```

```
Average Sales by Customer Segment:
 segment
Consumer      225.066
Corporate     233.151
Home Office   243.382
Name: sales, dtype: float64
```

Observation: Looks like everyone opted for work from home.

5. Temporal Trends:

Analyze trends over time, such as monthly or yearly sales growth.

This code calculates and prints the sum of sales grouped by month, showing temporal trends in the 'stores' DataFrame.

```
# Calculate and display the sum of sales grouped by month for temporal trends
temporal_trends = stores.groupby(pd.to_datetime(stores['order_date'], format='%m/%d/%Y').dt.to_period("M"))['sales'].sum()
print("Temporal Trends:\n", temporal_trends)
```

```
Temporal Trends:
 order_date
2015-01    14205.707
2015-02     4519.892
2015-03    55205.797
2015-04    27625.483
2015-05    23644.303
2015-06    34322.936
2015-07    33781.543
2015-08    27117.536
2015-09    81623.527
2015-10    31453.393
2015-11    77907.661
2015-12    68167.058
2016-01    18066.958
2016-02    11951.411
2016-03    32339.318
2016-04    34154.469
2016-05    29959.531
2016-06    23599.374
2016-07    28608.259
2016-08    36818.342
2016-09    63133.606
2016-10    31011.737
2016-11    75249.399
2016-12    74543.601
2017-01    18542.491
2017-02    22978.815
2017-03    51165.059
2017-04    38679.767
2017-05    56656.908
2017-06    39724.486
2017-07    38320.783
2017-08    30542.200
2017-09    69193.391
2017-10    59583.033
2017-11    79066.496
2017-12    95739.121
2018-01    43476.474
2018-02    19920.997
2018-03    58863.413
2018-04    35541.910
```

```
2018-05    43825.982
2018-06    48190.728
2018-07    44825.104
2018-08    62837.848
2018-09    86152.888
2018-10    77448.131
2018-11   117938.155
2018-12    83030.389
Freq: M, Name: sales, dtype: float64
```

Observation: Datewise analysis of sales happened in every month.

6. Geographical Analysis:

   Examine sales performance across different regions, states, or cities.

This code conducts geographical analysis by calculating and printing the top 10 sales in regions, states, and cities in the 'stores' DataFrame.

```
# Perform geographical analysis by calculating and displaying the top 10 sales in regions, states, and cities
geographical_analysis = stores.groupby(['region', 'state', 'city'])['sales'].sum().sort_values(ascending=False).head(10)
print("Geographical Analysis:\n", geographical_analysis)
```

```
Geographical Analysis:
 region   state         city
East     New York      New York City   252462.547
West     California    Los Angeles     173420.181
         Washington    Seattle         116106.322
         California    San Francisco   109041.120
East     Pennsylvania  Philadelphia    108841.749
Central  Texas         Houston          63956.143
         Illinois      Chicago          47820.133
West     California    San Diego        47521.029
Central  Michigan      Detroit          42446.944
South    Florida       Jacksonville     39133.328
Name: sales, dtype: float64
```

Observation: The company should open its store in New York city and Los Angeles as the sales are higher there.

7. Shipping Analysis:

```
Investigate the relationship between shipping mode and delivery times.
```

This code calculates and prints the average days to ship for each shipping mode in the 'stores' DataFrame.

```
# Calculate and display the average days to ship for each shipping mode
shipping_analysis = stores.groupby('ship_mode')['days_to_ship'].mean()
print("Average Days to Ship by Shipping Mode:\n", shipping_analysis)
```

```
Average Days to Ship by Shipping Mode:
 ship_mode
First Class      2.179
Same Day         0.045
Second Class     3.249
Standard Class   5.009
Name: days_to_ship, dtype: float64
```

Observation: Seems fair. Same day delivery is too impressive.

8.Correlation Analysis:

bold text

```
Explore correlations between numerical variables [ Correlation isn't necessary for postal code ].
```

This code computes and prints the correlation matrix between the 'days_to_ship' and 'sales' columns in the 'stores' DataFrame.

```
# Calculate and display the correlation matrix between 'days_to_ship' and 'sales' columns
correlation_matrix = stores[['days_to_ship', 'sales']].corr()
print("Correlation Matrix:\n", correlation_matrix)
```

```
Correlation Matrix:
               days_to_ship  sales
days_to_ship         1.000 -0.006
sales               -0.006  1.000
```

Observation: Gives an analysis of days to ship to sales

9. Outliers Detection:

```
Identify and examine outliers in numerical columns.
```

```
Outliers for Sales Column
```

This code filters rows in the 'stores' DataFrame where sales are greater than the mean plus three times the standard deviation.

```
# Filter rows in the 'stores' DataFrame where sales exceed the mean plus 3 times the standard deviation
stores[stores['sales'] > stores['sales'].mean() + 3 * stores['sales'].std()]
```

ship_mode	customer_id	customer_name	segment	country	city	state	postal
Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	1914
Standard Class	BM-11140	Becky Martin	Consumer	United States	San Antonio	Texas	7820
Standard Class	KC-16540	Kelly Collister	Consumer	United States	San Diego	California	9203
Second Class	SB-20290	Sean Braxton	Corporate	United States	Houston	Texas	7703
Second Class	SB-20290	Sean Braxton	Corporate	United States	Houston	Texas	7703
...	...	...	...	...	...	...	
Second Class	JH-15985	Joseph Holt	Consumer	United States	Concord	North Carolina	2802
Standard Class	MS-17365	Maribeth Schnelling	Consumer	United States	Los Angeles	California	9004
Standard Class	ME-17320	Maria Etezadi	Home Office	United States	Santa Barbara	California	9310
Standard Class	QJ-19255	Quincy Jones	Corporate	United States	Burlington	Vermont	540
Standard Class	LF-17185	Luke Foster	Consumer	United States	San Antonio	Texas	7820

Observation: Those days were really memorabe for company for having more sales than its used to.

```
Outliers for days_to_ship Column
```

This code filters rows in the 'stores' DataFrame where the days to ship exceed the mean plus three times the standard deviation.

```
# Filter rows in the 'stores' DataFrame where days to ship exceed the mean plus 3 times the standard deviation
stores[stores['days_to_ship'] > stores['days_to_ship'].mean() + 3 * stores['days_to_ship'].std()]
```

order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segment	count

Observation: Company is more strict to timing

10. Average Sales by Category:

```
Showcasing the average Sales by Category:.
```

This code calculates and prints the average sales for each product category in the 'stores' DataFrame.

```
# Calculate and display the average sales for each product category
average_sales_by_category = stores.groupby('category')['sales'].mean()
print("Average Sales by Category:\n", average_sales_by_category)
```

```
Average Sales by Category:
 category
Furniture         350.687
Office Supplies   119.381
Technology        456.401
Name: sales, dtype: float64
```

Observation: Seems like superstore is popular for its great technology quality.

Data Vizualization: Univariate

Here, we set the style of Seaborn plots to 'whitegrid' for a clean and simple background in visualizations.

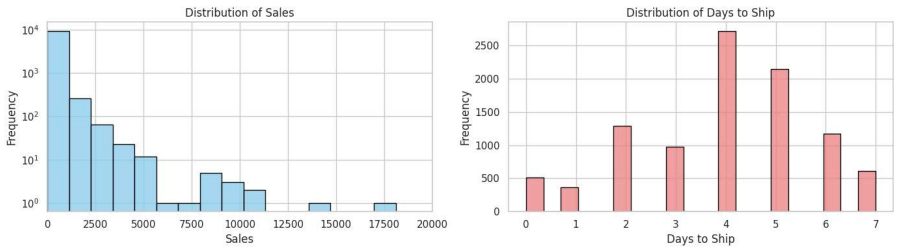
```
# Set the style of Seaborn plots to 'whitegrid'
sns.set(style='whitegrid')
```

1. Histograms

Create histograms to visualize the distribution of key numeric variables. Reference: Link

Here, we create a side-by-side histogram subplot for the distribution of sales and days to ship in the 'stores' DataFrame. The visualizations provide insights into the frequency and patterns of these two variables.

```
# Create a side-by-side histogram subplot for sales and days to ship
fig, axes = plt.subplots(1, 2, figsize=(14, 4))

# First subplot for sales distribution
sns.histplot(stores['sales'], bins=20, color='skyblue', edgecolor='black', ax=axes[0])
axes[0].set_title('Distribution of Sales')
axes[0].set_xlabel('Sales')
axes[0].set_ylabel('Frequency')
axes[0].set_xlim(0, 20000)
axes[0].set_yscale('log')

# Second subplot for days to ship distribution
sns.histplot(stores['days_to_ship'], bins=20, color='lightcoral', edgecolor='black', ax=axes[1])
axes[1].set_title('Distribution of Days to Ship')
axes[1].set_xlabel('Days to Ship')
axes[1].set_ylabel('Frequency')

# Adjust layout for better spacing
plt.tight_layout()

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



Observation:

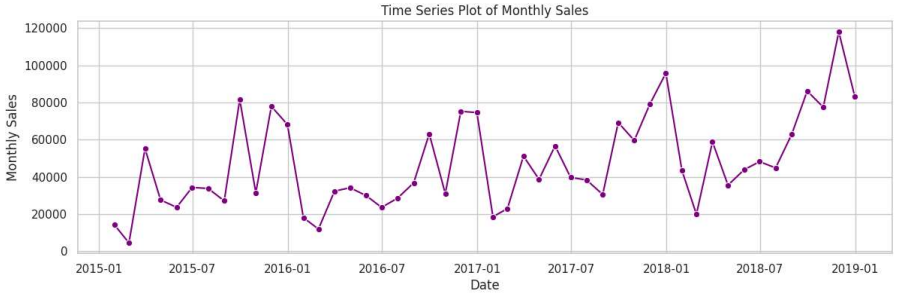
```
Sales less than 5000 are quiet common.
Most shipments take 4 days to ship
```

2. Time Series Plots

Plot time series graphs to understand the trends and patterns in sales over the 4-year period.

Here, we create a time series plot for monthly sales in the 'stores' DataFrame. The plot displays the trend in monthly sales over time using Seaborn.

```
# Create a time series plot for monthly sales
plt.figure(figsize=(14, 4))

# Convert 'order_date' to datetime format
stores['order_date'] = pd.to_datetime(stores['order_date'], format='%m/%d/%Y')

# Resample monthly and sum sales
time_series_sales = stores.resample('M', on='order_date')['sales'].sum().reset_index()

# Plot the time series using Seaborn
sns.lineplot(data=time_series_sales, x='order_date', y='sales', marker='o', color='purple')
plt.title('Time Series Plot of Monthly Sales')
plt.xlabel('Date')
plt.ylabel('Monthly Sales')

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



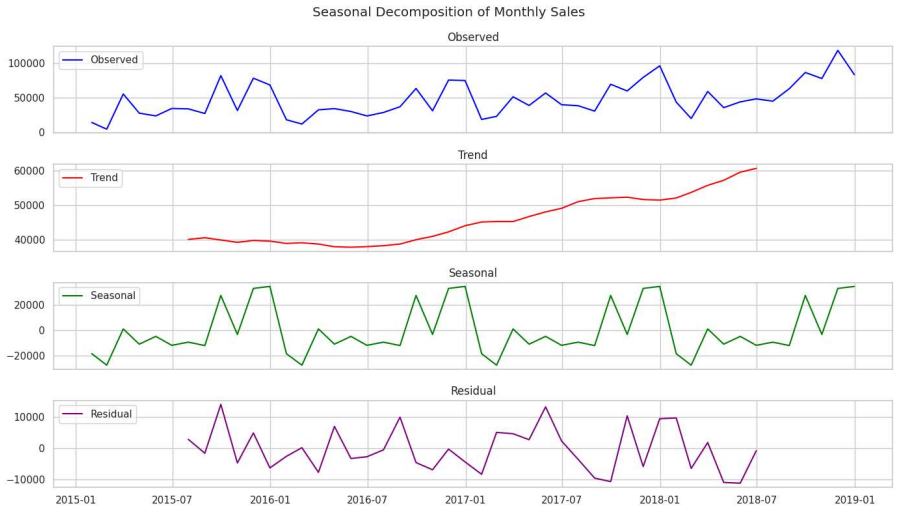
Observation: We couldn't predict, but the company seems to earn in last 2 years and tend to grow more.

3. Seasonal Decomposition

Decompose time series data into components like trend, seasonality, and residuals for deeper insights. Reference : Link

In this code, we perform seasonal decomposition on the 'sales' column in the time_series_sales DataFrame and plot the observed, trend, seasonal, and residual components separately. The resulting visualizations provide insights into the different aspects of the time series data.

```
# Perform seasonal decomposition on the 'sales' column in the time_series_sales DataFrame
result = seasonal_decompose(time_series_sales['sales'], model='additive', period=12)

# Plot individual components
fig, axes = plt.subplots(4, 1, figsize=(14, 8), sharex=True)

axes[0].plot(time_series_sales['order_date'], result.observed, label='Observed', color='blue')
axes[0].legend(loc='upper left')
axes[0].set_title('Observed')

axes[1].plot(time_series_sales['order_date'], result.trend, label='Trend', color='red')
axes[1].legend(loc='upper left')
axes[1].set_title('Trend')

axes[2].plot(time_series_sales['order_date'], result.seasonal, label='Seasonal', color='green')
axes[2].legend(loc='upper left')
axes[2].set_title('Seasonal')

axes[3].plot(time_series_sales['order_date'], result.resid, label='Residual', color='purple')
axes[3].legend(loc='upper left')
axes[3].set_title('Residual')

plt.suptitle('Seasonal Decomposition of Monthly Sales')
plt.tight_layout()
plt.show()
```



Observation: Okay! Now I am sure that company is really growing!

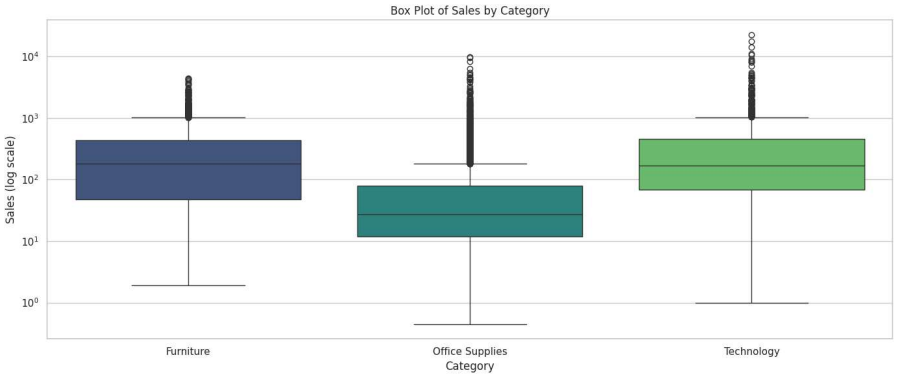
4. Box Plots

Use box plots to identify outliers and understand the distribution of numeric variables.

Here, we use Seaborn to create a box plot of sales by category in the 'stores' DataFrame. The y-axis is set to a logarithmic scale for a better representation of the data distribution.

```
# Create a box plot of sales by category using Seaborn
plt.figure(figsize=(14, 6))
sns.boxplot(x='category', y='sales', data=stores, palette='viridis')
plt.yscale('log')
plt.title('Box Plot of Sales by Category')
plt.xlabel('Category')
plt.ylabel('Sales (log scale)')
plt.tight_layout()
plt.show()
```

```
<ipython-input-60-a3ae334ebd2a>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.

  sns.boxplot(x='category', y='sales', data=stores, palette='viridis')
```



Observation: Outliers seem to be strict.

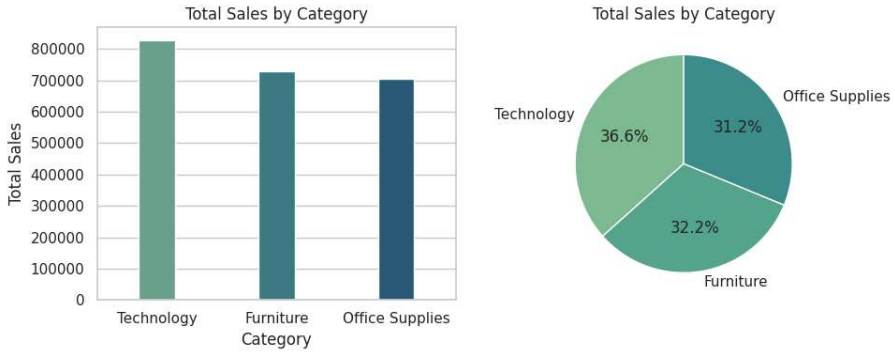
5. Sales Distribution by Category

Visualize the distribution of sales across different categories using bar charts or pie charts.

In this code, we calculate the total sales by category and create subplots with a bar plot and a pie chart to visualize the distribution of sales across categories in the 'stores' DataFrame.

```
# Calculate total sales by category
category_sales = stores.groupby('category')['sales'].sum().reset_index()

# Sort the data by sales in descending order
category_sales = category_sales.sort_values(by='sales', ascending=False)

# Create subplots with two columns
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Bar plot on the first subplot
sns.barplot(x='category', y='sales', data=category_sales, palette='crest', ax=axes[0], order=category_sales['category'], width=0.3)
axes[0].set_title('Total Sales by Category')
axes[0].set_xlabel('Category')
axes[0].set_ylabel('Total Sales')

# Pie chart on the second subplot
axes[1].pie(category_sales['sales'], labels=category_sales['category'], autopct='%1.1f%%', colors=sns.color_palette('crest'), startangle=90)
axes[1].set_title('Total Sales by Category')

# Display the plots
plt.tight_layout()
plt.show()
```

```
<ipython-input-61-7cf5ba9b34cf>:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.

  sns.barplot(x='category', y='sales', data=category_sales, palette='crest', ax=axes[0],
```



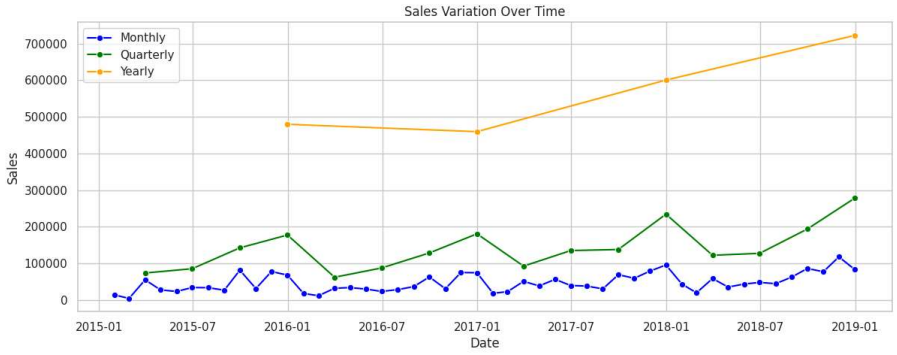
Observation: Its interesting to see that Technology has more amount of sale.

6. Sales Variation Over Time

Plot line charts to observe how sales vary over different time periods (months, quarters, years).

Here, we calculate monthly, quarterly, and yearly sales variations and create a Seaborn-style line plot to visualize how sales vary over time in the 'stores' DataFrame. The plot displays monthly, quarterly, and yearly trends with different colors and markers.

```
# Calculate monthly, quarterly, and yearly sales variations
monthly_sales_variation = stores.resample('M', on='order_date')['sales'].sum()
quarterly_sales_variation = stores.resample('Q', on='order_date')['sales'].sum()
yearly_sales_variation = stores.resample('Y', on='order_date')['sales'].sum()

# Create a Seaborn-style plot using lineplot
plt.figure(figsize=(14, 5))
sns.lineplot(data=monthly_sales_variation, marker='o', color='blue', label='Monthly')
sns.lineplot(data=quarterly_sales_variation, marker='o', color='green', label='Quarterly')
sns.lineplot(data=yearly_sales_variation, marker='o', color='orange', label='Yearly')

# Set titles and labels
plt.title('Sales Variation Over Time')
plt.xlabel('Date')
plt.ylabel('Sales')

# Add legend
plt.legend()

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



Observation: For Yearly, its been growing For month and daily basis, there is a zigzag pattern with a growing trend.

Data Vizualization: Bivariate

1. Correlation Analysis

Examine the correlation between sales and other relevant numeric variables.

In this code, we calculate the correlation matrix for the numeric columns in the 'stores' DataFrame and create a heatmap using Seaborn to visually represent the correlations between different variables. The heatmap includes annotations with correlation values and uses the 'crest' color map.

```
# Calculate the correlation matrix
correlation_matrix = stores.corr()

# Create a heatmap using Seaborn
plt.figure(figsize=(5, 5))
sns.heatmap(correlation_matrix, annot=True, cmap='crest', fmt=".2f", linewidths=.5)
plt.title('Correlation Analysis')
plt.tight_layout()
plt.show()
```

```
of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to
```

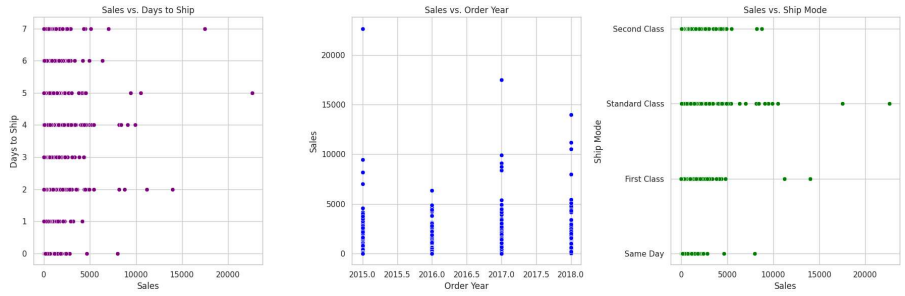
Observation: Gives an understanding to sales to shipment days

2. Scatter Plots

Plot scatter plots to explore the relationship between sales and another numeric variable.

This code creates a figure with three scatter plots side by side to compare the relationships between sales and days to ship, sales and order year, and sales and ship mode in the 'stores' DataFrame. Each subplot is labeled with the respective titles and axis labels for clarity.

```
# Create a figure with three scatter plots side by side
plt.figure(figsize=(18, 6))

# Scatter Plot: Sales vs. Days to Ship
plt.subplot(1, 3, 1)
sns.scatterplot(x='sales', y='days_to_ship', data=stores, color='purple')
plt.title('Sales vs. Days to Ship')
plt.xlabel('Sales')
plt.ylabel('Days to Ship')

# Scatter Plot: Sales vs. Order Date
plt.subplot(1, 3, 2)
sns.scatterplot(x=stores['order_date'].dt.year, y='sales', data=stores, color='blue')
plt.title('Sales vs. Order Year')
plt.xlabel('Order Year')
plt.ylabel('Sales')

# Scatter Plot: Sales vs. Ship Mode
plt.subplot(1, 3, 3)
sns.scatterplot(x='sales', y='ship_mode', data=stores, color='green')
plt.title('Sales vs. Ship Mode')
plt.xlabel('Sales')
plt.ylabel('Ship Mode')

# Adjust layout
plt.tight_layout()
plt.show()
```



Observation:

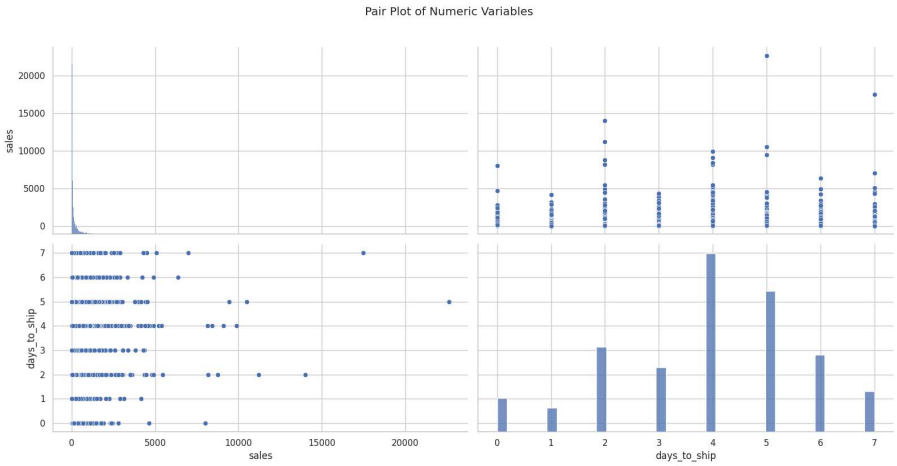
```
It seems that the company is uniform to delivery standards. Order size doesn't priortize the order delivery dates to reduce.
In 2018 seem like they are growing with more number of big sales.
Most of the sale is a Standard Class Delivery.
```

3. Pair Plots

Use pair plots for a quick overview of relationships between multiple numeric variables.

Here, we create a pair plot using Seaborn for the numeric variables 'sales' and 'days_to_ship' in the 'stores' DataFrame. The pair plot provides a visual representation of the relationships between these numeric variables.

```
# Generate a pair plot for selected numeric variables using Seaborn
numeric_columns = ['sales', 'days_to_ship']
sns.pairplot(stores[numeric_columns], height=4, aspect=2)
plt.suptitle('Pair Plot of Numeric Variables', y=1.02)
plt.tight_layout()
plt.show()
```



Observation:

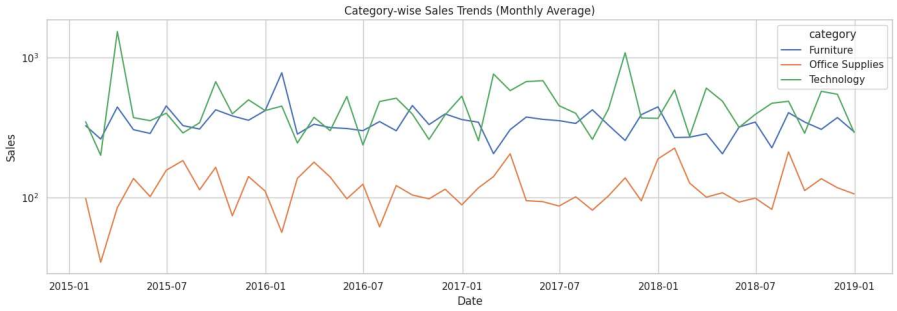
Gives analysis to days to ship and sales. They don't depend on each other.

4. Category-wise Sales Trends

Analyze how sales trends differ across different categories using line charts. Reference: pd.Grouper Saved my Day 🙄

Here, we convert the 'order_date' column to datetime format, then resample the data to calculate the monthly average sales for each category. The resulting trends are visualized using a line plot with a logarithmic scale on the y-axis for better representation.

```
# Convert 'order_date' to datetime format
stores['order_date'] = pd.to_datetime(stores['order_date'])

# Resample the data to monthly average for each category
monthly_avg_sales = stores.groupby(['category', pd.Grouper(key='order_date', freq='M')])['sales'].mean().reset_index()

# Create a line plot with log scale for the y-axis
plt.figure(figsize=(14, 5))
sns.lineplot(x='order_date', y='sales', hue='category', data=monthly_avg_sales)
plt.yscale('log')
plt.title('Category-wise Sales Trends (Monthly Average)')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.tight_layout()
plt.show()
```

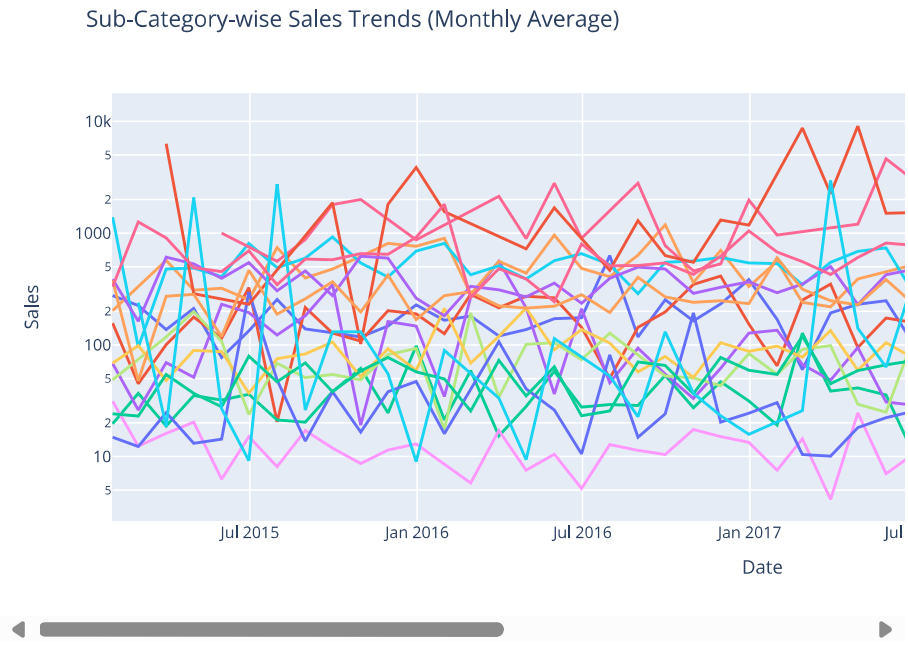


Observation:

Shows that Technology is always on demand than that of Furniture and office supplies.

Here, we convert the 'order_date' column to datetime format and resample the data to calculate the monthly average sales for each sub-category. The trends are visualized using a line plot with a logarithmic scale on the y-axis using Plotly Express for interactive and detailed exploration.

```
# Convert 'order_date' to datetime format
stores['order_date'] = pd.to_datetime(stores['order_date'])

# Resample the data to monthly average for each sub_category
monthly_avg_sales = stores.groupby(['sub_category', pd.Grouper(key='order_date', freq='M')])['sales'].mean().reset_index()

# Create a line plot with log scale for the y-axis using Plotly Express
fig = px.line(monthly_avg_sales, x='order_date', y='sales', color='sub_category',
              labels={'sales': 'Sales', 'order_date': 'Date', 'sub_category': 'Sub-Category'},
              title='Sub-Category-wise Sales Trends (Monthly Average)',
              log_y=True, width=1200, height=500)

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



Observation:

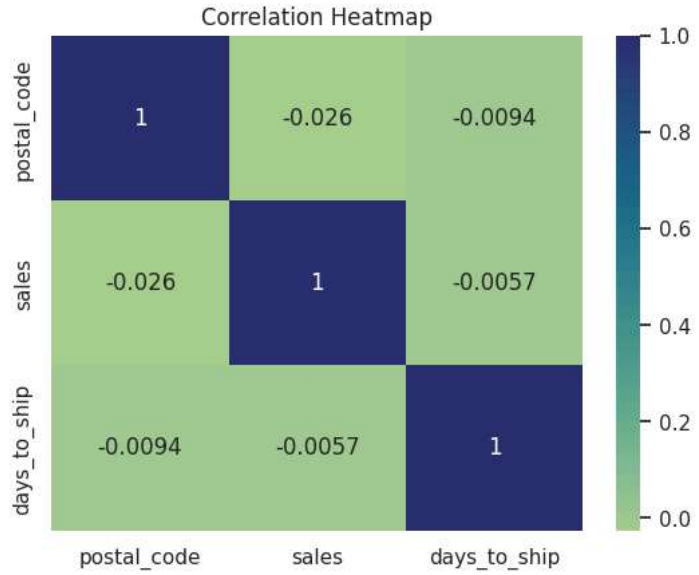
I don't know why they need sooooo many copiers and machines for binding.

5. Heatmaps

Create heatmaps to visualize the correlation matrix for better insights

In this code, we use Seaborn to generate a heatmap for the correlation matrix, visualizing the correlations between different variables. The color intensity and annotations provide insights into the strength and direction of the correlations.

```
# Create a heatmap for the correlation matrix using Seaborn
sns.heatmap(correlation_matrix, annot=True, cmap='crest')
plt.title('Correlation Heatmap')
plt.show()
```



Observation:

Gives an understanding to sales to shipment days

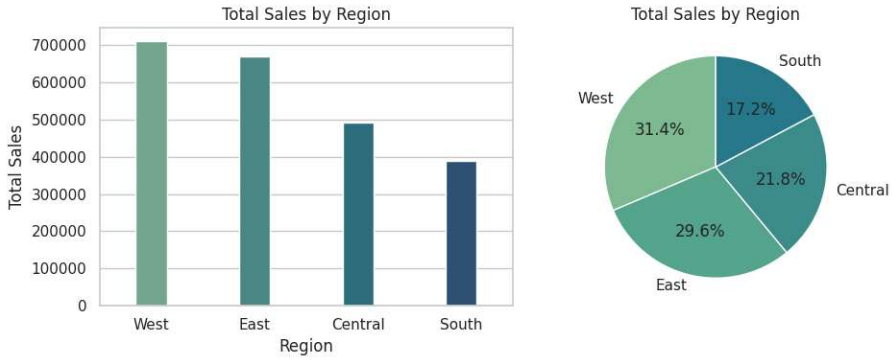
6. Sales by Region

Compare sales across different regions using bar charts or stacked bar charts.

In this code, we calculate the total sales by region and create subplots with a bar plot and a pie chart to visualize the distribution of sales across different regions in the 'stores' DataFrame.

```
# Calculate total sales by region
region_sales = stores.groupby('region')['sales'].sum().reset_index()

# Sort the data by sales in descending order
region_sales = region_sales.sort_values(by='sales', ascending=False)

# Create subplots with two columns
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Bar plot on the first subplot
sns.barplot(x='region', y='sales', data=region_sales, palette='crest', ax=axes[0], order=region_sales['region'], width=0.3)
axes[0].set_title('Total Sales by Region')
axes[0].set_xlabel('Region')
axes[0].set_ylabel('Total Sales')

# Pie chart on the second subplot
axes[1].pie(region_sales['sales'], labels=region_sales['region'], autopct='%1.1f%%', colors=sns.color_palette('crest'), startangle=90)
axes[1].set_title('Total Sales by Region')

# Display the plots
plt.tight_layout()
plt.show()
```

```
<ipython-input-69-e42d015deedd>:11: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
```



Observation:

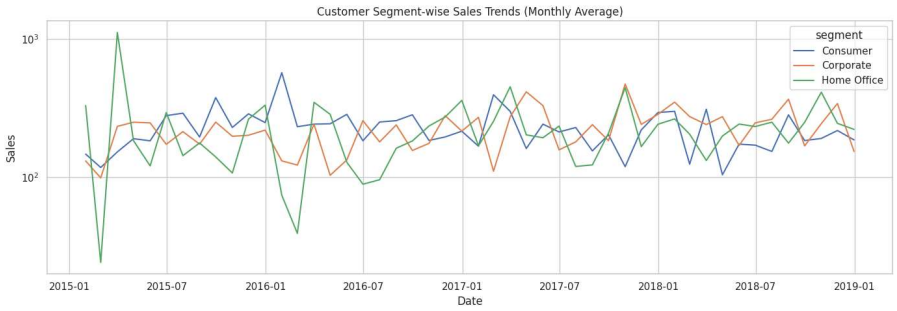
People from West region of US order more supplies from superstore then comes East then Central and South

7. Customer Segment Analysis

Explore sales trends for different customer segments using line charts or bar charts.

Here, we convert the 'order_date' column to datetime format, resample the data to calculate the monthly average sales for each customer segment, and visualize the trends using a line plot with a logarithmic scale on the y-axis.

```
# Convert 'order_date' to datetime format
stores['order_date'] = pd.to_datetime(stores['order_date'])

# Resample the data to monthly average for each segment
monthly_avg_sales = stores.groupby(['segment', pd.Grouper(key='order_date', freq='M')])['sales'].mean().reset_index()

# Create a line plot with log scale for the y-axis
plt.figure(figsize=(14, 5))
sns.lineplot(x='order_date', y='sales', hue='segment', data=monthly_avg_sales)
plt.yscale('log')
plt.title('Customer Segment-wise Sales Trends (Monthly Average)')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.tight_layout()
plt.show()
```



Observation:

I guess there is a clash between the manager who wants work from office and employees who want work from home.

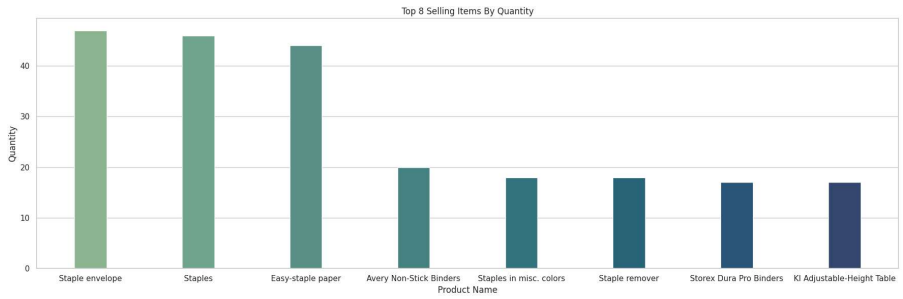
8. Sales vs. Quantity

Investigate the relationship between sales and quantity sold using scatter plots.

Here, we identify and visualize the top 8 selling items by quantity using a count plot. The figure width is increased for better presentation of the information.

```
# Identify the top 8 selling items
top_8_products = stores['product_name'].value_counts().nlargest(8).index

# Create a count plot to visualize the quantity of the top 8 selling items
plt.figure(figsize=(18, 6))  # Increase the width of the figure
sns.countplot(x='product_name', data=stores[stores['product_name'].isin(top_8_products)], order=top_8_products, palette='crest', width=0.3)
plt.title('Top 8 Selling Items By Quantity')
plt.xlabel('Product Name')
plt.ylabel('Quantity')
plt.tight_layout()
plt.show()
```

```
<ipython-input-71-aafa300a1f9b>:6: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
```



Observation:

Envelop and staples ! I agree, to attach and hide secret documents.

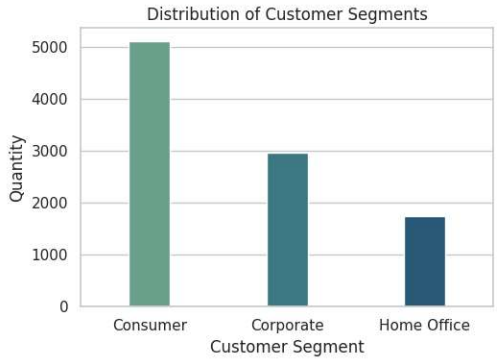
9. Customer Segment vs. Quantity

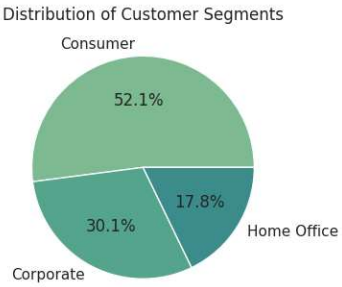
Compare the quantity sold across different customer segments using bar charts.

Here, we analyze and visualize the distribution of customer segments using a bar plot and a pie chart. The bar plot provides a detailed quantity breakdown, while the pie chart offers a proportional representation of customer segments.

```
# Segment distribution
segment_counts = stores['segment'].value_counts().reset_index()

# Create subplots with two columns
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Bar plot on the first subplot
sns.barplot(x='index', y='segment', data=segment_counts, palette='crest', ax=axes[0], width=0.3)
axes[0].set_title('Distribution of Customer Segments')
axes[0].set_xlabel('Customer Segment')
axes[0].set_ylabel('Quantity')

# Pie chart on the second subplot
axes[1].pie(segment_counts['segment'], labels=segment_counts['index'], autopct='%1.1f%%', colors=sns.color_palette('crest'))
axes[1].set_title('Distribution of Customer Segments')

# Display the plots
plt.tight_layout()
plt.show()
```

```
<ipython-input-72-a2d4657ba8a5>:8: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
```





Observation:

The company is mostly B2C as it is customer centric.

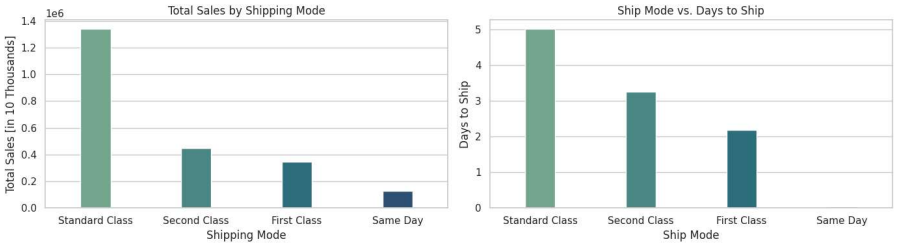
10. Shipping Mode vs. Sales

Explore the relationship between shipping modes and sales using categorical plots.

Here, we analyze and visualize total sales by shipping mode using a bar plot. Additionally, we explore the relationship between ship mode and days to ship using another bar plot on the second subplot. The second plot helps understand how different shipping modes affect the time taken to ship products.

```
# Analyze total sales by shipping mode
ship_mode_sales = stores.groupby('ship_mode')['sales'].sum().reset_index()

# Sort the data by sales in descending order
ship_mode_sales = ship_mode_sales.sort_values(by='sales', ascending=False)

# Create subplots with two columns
fig, axes = plt.subplots(1, 2, figsize=(14, 4))

# Bar plot for total sales by shipping mode on the first subplot
sns.barplot(x='ship_mode', y='sales', data=ship_mode_sales, palette='crest', ax=axes[0], order=ship_mode_sales['ship_mode'], width=0.3)
axes[0].set_title('Total Sales by Shipping Mode')
axes[0].set_xlabel('Shipping Mode')
axes[0].set_ylabel('Total Sales [in 10 Thousands]')

# Analyze the relationship between ship mode and days to ship
ship_mode_days_to_ship = stores.groupby('ship_mode')['days_to_ship'].mean().reset_index()

# Sort the data by days to ship in descending order
ship_mode_days_to_ship = ship_mode_days_to_ship.sort_values(by='days_to_ship', ascending=False)

# Bar plot for ship mode vs. days to ship on the second subplot
sns.barplot(x='ship_mode', y='days_to_ship', data=stores, ax=axes[1], palette='crest', ci=False, order=ship_mode_days_to_ship['ship_mode'],
axes[1].set_title('Ship Mode vs. Days to Ship')
axes[1].set_xlabel('Ship Mode')
axes[1].set_ylabel('Days to Ship')

# Display the plots
plt.tight_layout()
plt.show()
```

```
<ipython-input-73-3c3c9fe2a62b>:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.

<ipython-input-73-3c3c9fe2a62b>:23: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=('ci', False)` for the same effect.

<ipython-input-73-3c3c9fe2a62b>:23: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
```



Observation:

Most people prefer standard class. Who has money for same day deliver?
the comany really works hard on their delivery procedure.

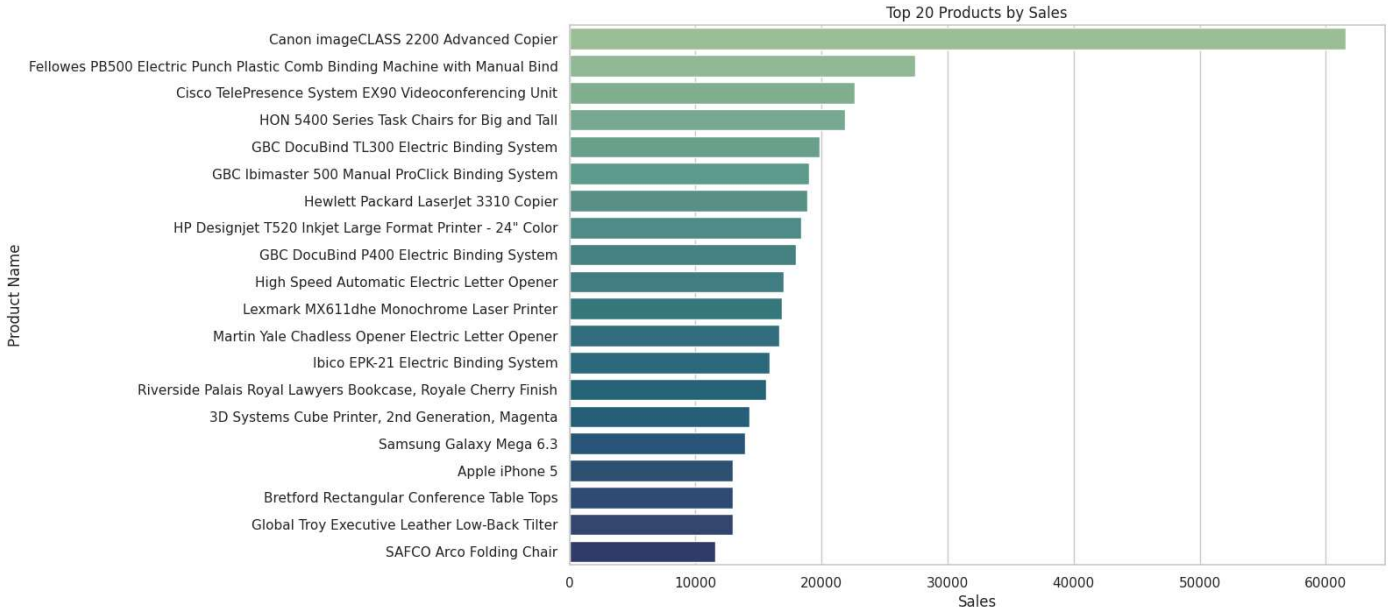
11. Product-wise Sales Analysis

Investigate how sales vary for different products or categories using bar charts or line charts.

Here, we identify and visualize the top 20 products by sales using a horizontal bar plot. The length of each bar represents the sales amount, providing a clear comparison of product performance.

```
# Identify and visualize the top 20 products by sales with a horizontal bar plot
top_products = stores.groupby('product_name')['sales'].sum().sort_values(ascending=False).head(20).reset_index()

# Create a horizontal bar plot
plt.figure(figsize=(12, 8))
sns.barplot(y='product_name', x='sales', data=top_products, palette='crest')
plt.title('Top 20 Products by Sales')
plt.xlabel('Sales')
plt.ylabel('Product Name')
plt.show()
```

```
<ipython-input-74-28c350cff05a>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend
```



Observation:

Again Binder and Copier! Need to catch the person who breaks it !

12. Region-wise Product Sales

Compare product sales across different regions using grouped bar charts.

Here, we use Plotly Express to create a horizontal bar plot that visualizes sales by state. The color of each bar represents the sales amount, and the logarithmic scale on the x-axis provides a clearer view of the distribution. The layout is adjusted for better presentation.

```
# Visualize sales by state using a horizontal bar plot with Plotly Express
fig = px.bar(stores, x='sales', y='state', orientation='h', color='sales',
             color_continuous_scale='viridis', error_x=None,
             labels={'sales': 'Sales', 'state': 'States'},
             title='Sales by State',
             log_x=True)

# Adjust the layout
fig.update_layout(height=600, width=1100)

# Display the plot
fig.show()
```