Notebook

July 16, 2023

```python
import pandas as pd
import os
import re
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

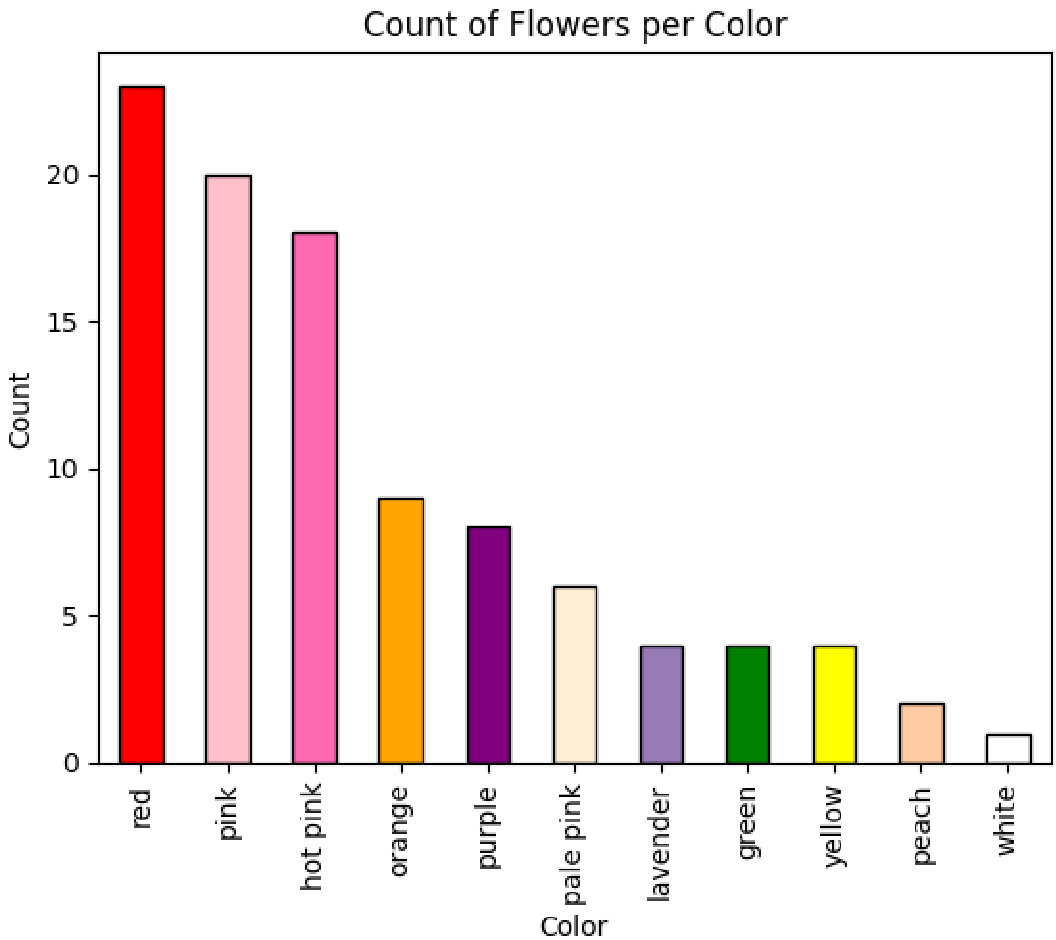
```python
# Get a list of all Excel files in the directory
excel_files = [f for f in os.listdir('Recipes/') if f.endswith('.xlsx')]

# Specify your new directory
new_dir = './csv_files/'

# Create the new directory if it doesn't exist
os.makedirs(new_dir, exist_ok=True)
for excel_file in excel_files:
    # Extract the year from the file name using regular expressions
    year_match = re.search(r'\d{4}', excel_file)  # Looks for four digits in a␣
↪row
    year = year_match.group() if year_match else 'unknown'

    # Load spreadsheet
    xl = pd.ExcelFile(os.path.join('Recipes/', excel_file), engine='openpyxl')

    # Load a sheet into a DataFrame by its name
    for sheet_name in xl.sheet_names:
        df = xl.parse(sheet_name)
        df = df.iloc[:, :11]

        # Write DataFrame to a CSV file with year prefix in the specified␣
↪directory
        df.to_csv(new_dir + f'{year}_{sheet_name}.csv', index=False)

# Get a list of all CSV files in the new directory
csv_files = [f for f in os.listdir(new_dir) if f.endswith('.csv')]

# Read each CSV file and store the data in a dictionary
```

```
data = {}
for csv_file in csv_files:
    data[csv_file] = pd.read_csv(new_dir + csv_file)
```

```
# Get a list of all CSV files in the subdirectory
csv_files = [f for f in os.listdir('csv_files/') if f.endswith('.csv')]

# Check if the 'processed_csv' directory exists, if not create it
if not os.path.exists('processed_csv'):
    os.makedirs('processed_csv')

data = {}
for csv_file in csv_files:
    df = pd.read_csv('csv_files/' + csv_file, header=None)
    df.columns = ['Colors', 'Flowers', 'StemPrice', 'SQty', 'SPrice',␣
 ↪'DQty','DPrice','PQty','PPrice','EQty','EPrice']
    df = df.iloc[4:16]

    # Save this DataFrame to a new CSV file in the 'processed_csv' subdirectory
    df.to_csv('processed_csv/' + csv_file[:-4] + '_processed.csv', index=False)

    data[csv_file] = df
```

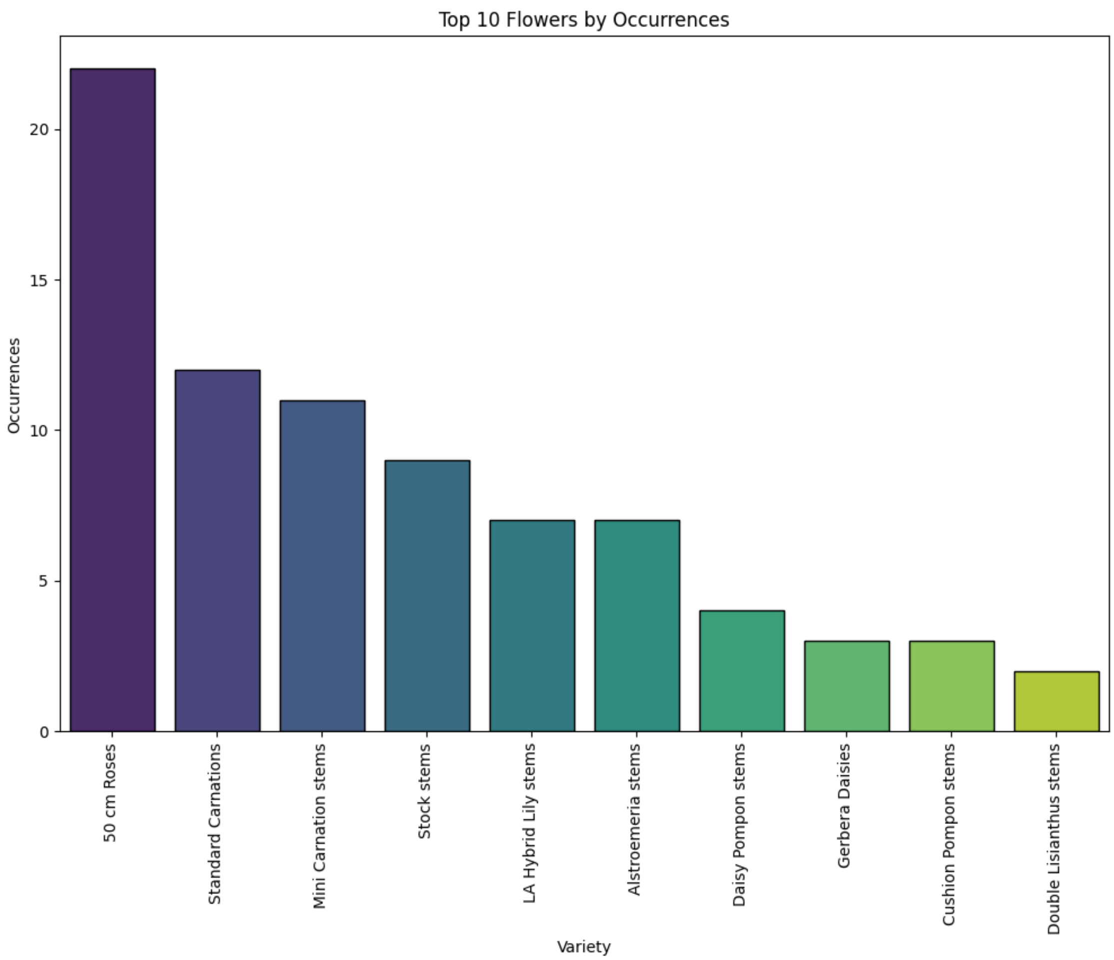
```
# Get a list of all processed CSV files in the processed_csvs directory
csv_files = [f for f in os.listdir('processed_csv') if f.endswith('.csv')]

data = {}
for csv_file in csv_files:
    df = pd.read_csv(f'processed_csv/{csv_file}')
    df = df.iloc[0:9]
    data[csv_file] = df

# Concatenate all dataframes in the dictionary into a single dataframe
# Create a new column 'Arrangement' which is the key in the dictionary
all_data = pd.concat([df.assign(Arrangement=os.path.splitext(name)[0]) for␣
 ↪name, df in data.items()])

# Convert the color names to lowercase
all_data['Colors'] = all_data['Colors'].str.lower().str.strip()

# Define the custom colors
custom_colors = {
    'hot pink': '#FF69B4',
    'orange': '#FFA500',
    'pink': '#FFC0CB',
    'green': '#008000',
```

```
    'purple': '#800080',
    'yellow': '#FFFF00',
    'white': '#FFFFFF',
    'peach': '#ffcba4',
    'lavender': '#967bb6',
    'light pink': '#FFB6C1',
    'red': '#FF0000',
    'pale pink': '#FFEFD5',
    'blue': '#8EA5C5',
    'ivory': '#f5f5dc'
}

# Count the number of flowers per color
color_counts = all_data['Colors'].value_counts()
color_names = color_counts.index

# Plot the bar chart with custom colors and outline
color_counts.plot(kind='bar', color=[custom_colors.get(c, 'gray') for c in␣
 ↪color_names], edgecolor='black')

plt.title('Count of Flowers per Color')
plt.xlabel('Color')
plt.ylabel('Count')
plt.savefig('Count of Flowers per Color')
plt.show()
```



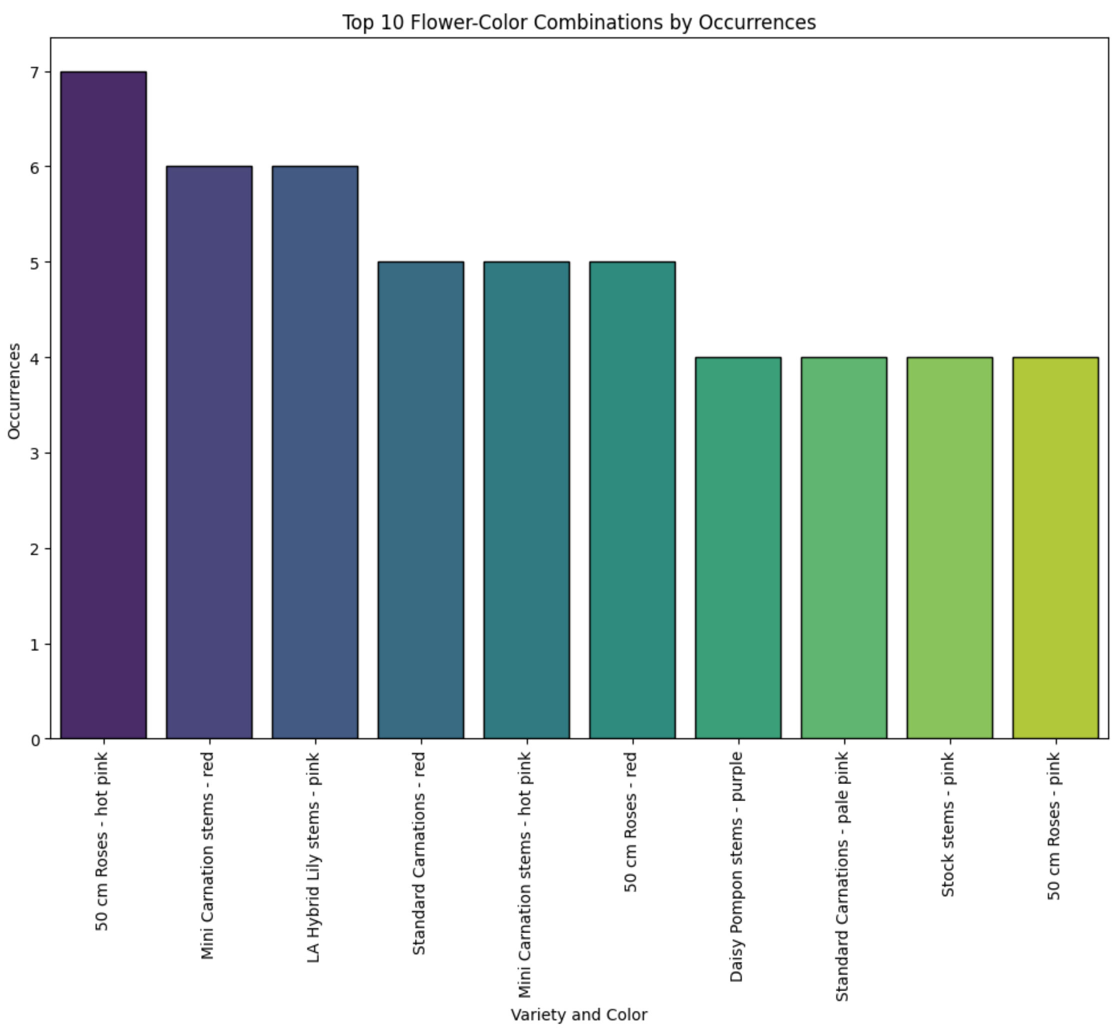

```python
# Remove rows where 'Colors' is NaN
all_data = all_data[all_data['Colors'].notna()]

# Count the occurrences of each flower variety
variety_counts = all_data['Flowers'].value_counts()

# Select the top 10 varieties
top_varieties = variety_counts.head(10)

# Create a bar plot for the top 10 varieties
plt.figure(figsize=(12, 8))
sns.barplot(x=top_varieties.index, y=top_varieties.values, palette='viridis',
    edgecolor='black')

# Set title and labels
plt.title('Top 10 Flowers by Occurrences')
plt.xlabel('Variety')
```

```
plt.ylabel('Occurrences')
plt.savefig('Top 10 Flowers by Occurrences')
plt.xticks(rotation=90)  # Rotate the x-axis labels for better readability

plt.show()
```

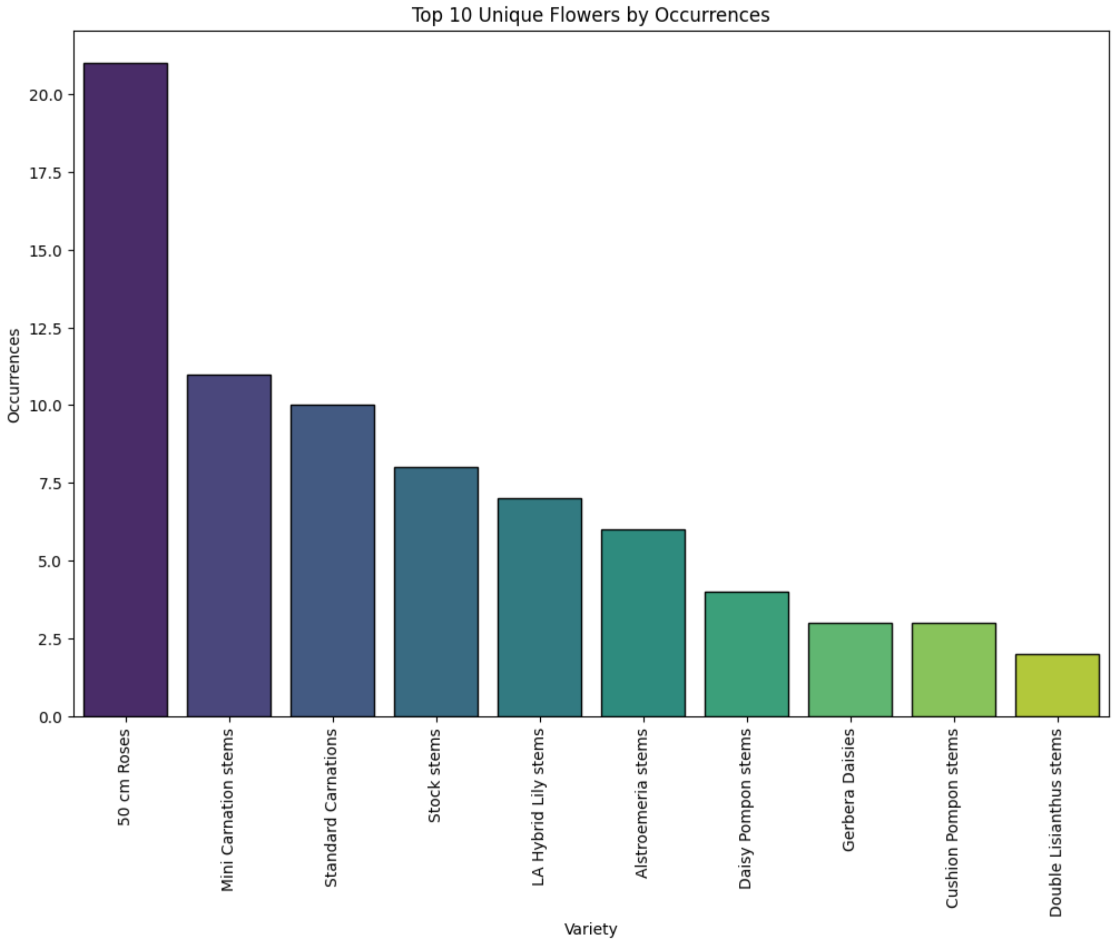



```
# Remove rows where 'Colors' is NaN
all_data = all_data[all_data['Colors'].notna()]

# Count the occurrences of each unique combination of 'Flowers' and 'Colors'
variety_color_counts = all_data.groupby(['Flowers', 'Colors']).size()

# Select the top 10 combinations
top_varieties_colors = variety_color_counts.sort_values(ascending=False).
 ↪head(10)
```

```
# Convert the MultiIndex to a single index by joining the levels with a
↪separator
top_varieties_colors.index = top_varieties_colors.index.map(' - '.join)

# Create a bar plot for the top 10 combinations
plt.figure(figsize=(12, 8))
sns.barplot(x=top_varieties_colors.index, y=top_varieties_colors.values,
↪palette='viridis', edgecolor='black')

# Set title and labels
plt.title('Top 10 Flower-Color Combinations by Occurrences')
plt.xlabel('Variety and Color')
plt.ylabel('Occurrences')
plt.savefig('Top 10 Flower-Color Combinations by Occurrences')
plt.xticks(rotation=90)  # Rotate the x-axis labels for better readability

plt.show()
```

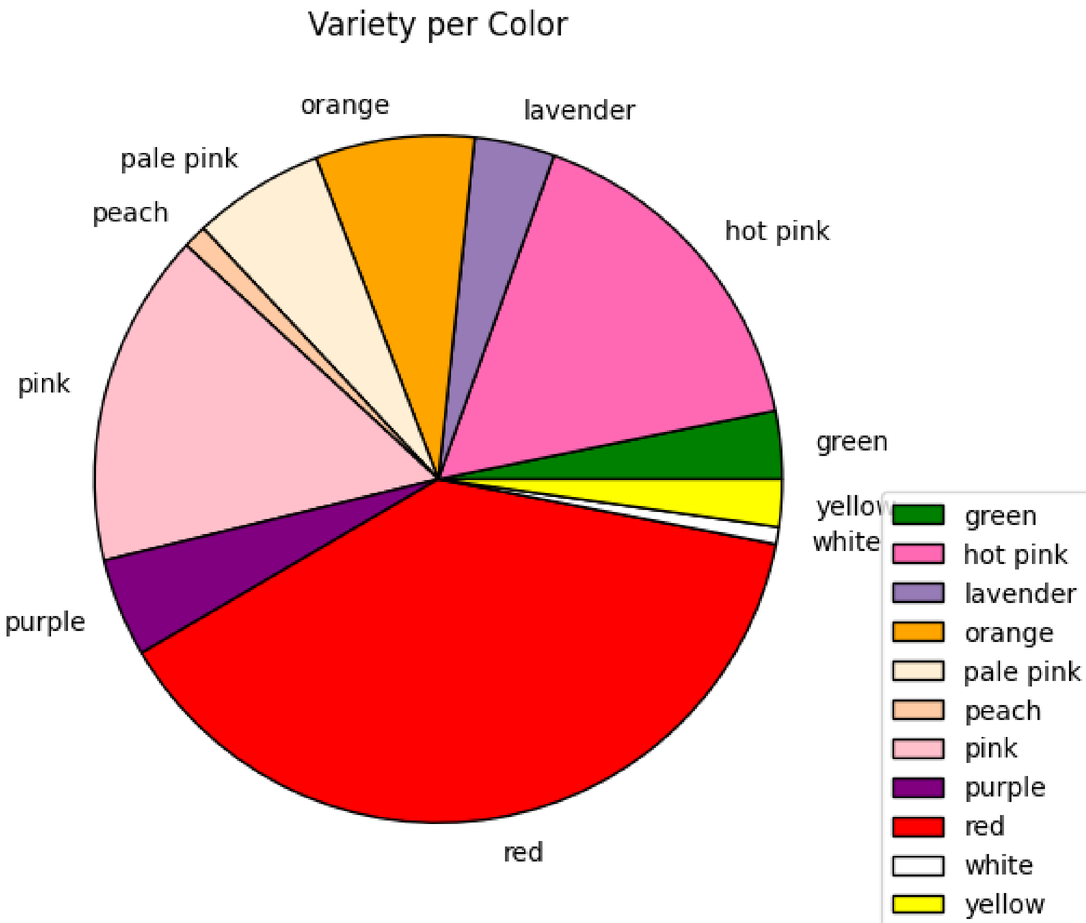


```
# Drop duplicates based on 'Arrangement' and 'Flowers'
all_data_unique_flowers = all_data.drop_duplicates(subset=['Arrangement',␣
↪'Flowers'])

# Count the occurrences of each 'Flowers' type
variety_counts = all_data_unique_flowers['Flowers'].value_counts()

# Select the top 10 varieties
top_varieties = variety_counts.head(10)

# Create a bar plot for the top 10 varieties
plt.figure(figsize=(12, 8))
sns.barplot(x=top_varieties.index, y=top_varieties.values, palette='viridis',␣
↪edgecolor='black')

# Set title and labels
plt.title('Top 10 Unique Flowers by Occurrences')
plt.xlabel('Variety')
plt.ylabel('Occurrences')
plt.savefig('Top 10 Unique Flowers by Occurrences')
plt.xticks(rotation=90)  # Rotate the x-axis labels for better readability

plt.show()
```



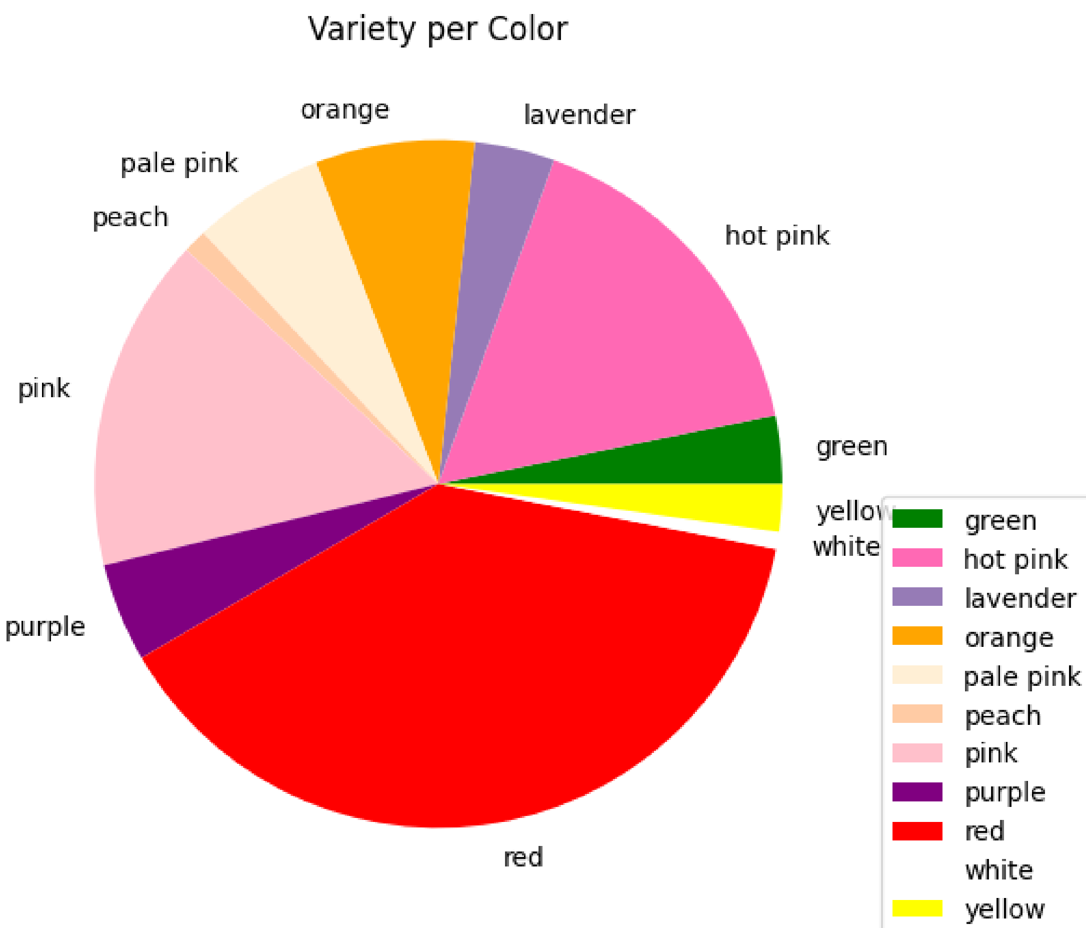

```
all_data['Colors'] = all_data['Colors'].str.lower()
all_data['Colors'] = all_data['Colors'].str.strip()
# Remove rows with NaN values in the 'Colors' column
all_data = all_data[all_data['Colors'].notna()]

# Convert the quantity columns to numeric
for col in ['SQty', 'DQty', 'PQty', 'EQty']:
    all_data[col] = pd.to_numeric(all_data[col], errors='coerce')

# Calculate the total volume for each color
color_volume = all_data.groupby('Colors')[['SQty', 'DQty', 'PQty', 'EQty']].
↪sum().sum(axis=1)

# Filter out colors with 0 sales volume
color_volume = color_volume[color_volume != 0]

# Define the custom colors
```

```
custom_colors = {
    'hot pink': '#FF69B4',
    'orange': '#FFA500',
    'pink': '#FFC0CB',
    'green': '#008000',
    'purple': '#800080',
    'yellow': '#FFFF00',
    'white': '#FFFFFF',
    'peach': '#ffcba4',
    'lavender': '#967bb6',
    'light pink': '#FFB6C1',
    'red': '#FF0000',
    'pale pink': '#FFEFD5',
    'blue': '#8EA5C5',
    'ivory': '#f5f5dc'
}

# Create the pie chart with custom colors
custom_colors = {color: custom_colors.get(color, 'gray') for color in color_volume.index}
colors = [custom_colors[color] for color in color_volume.index]

# Adjust the figure size
plt.figure(figsize=(8, 6))

# Create the pie chart with updated colors
patches, texts = plt.pie(color_volume.values, labels=color_volume.index, colors=colors, wedgeprops = {"edgecolor" : "black", 'linewidth': 1,'antialiased': True})


plt.title('Variety per Color')

# Position the legend outside the chart area
plt.legend(patches, color_volume.index, bbox_to_anchor=(1, 0.5), loc='best')
plt.savefig('Variety per Color Border')
plt.show()
```



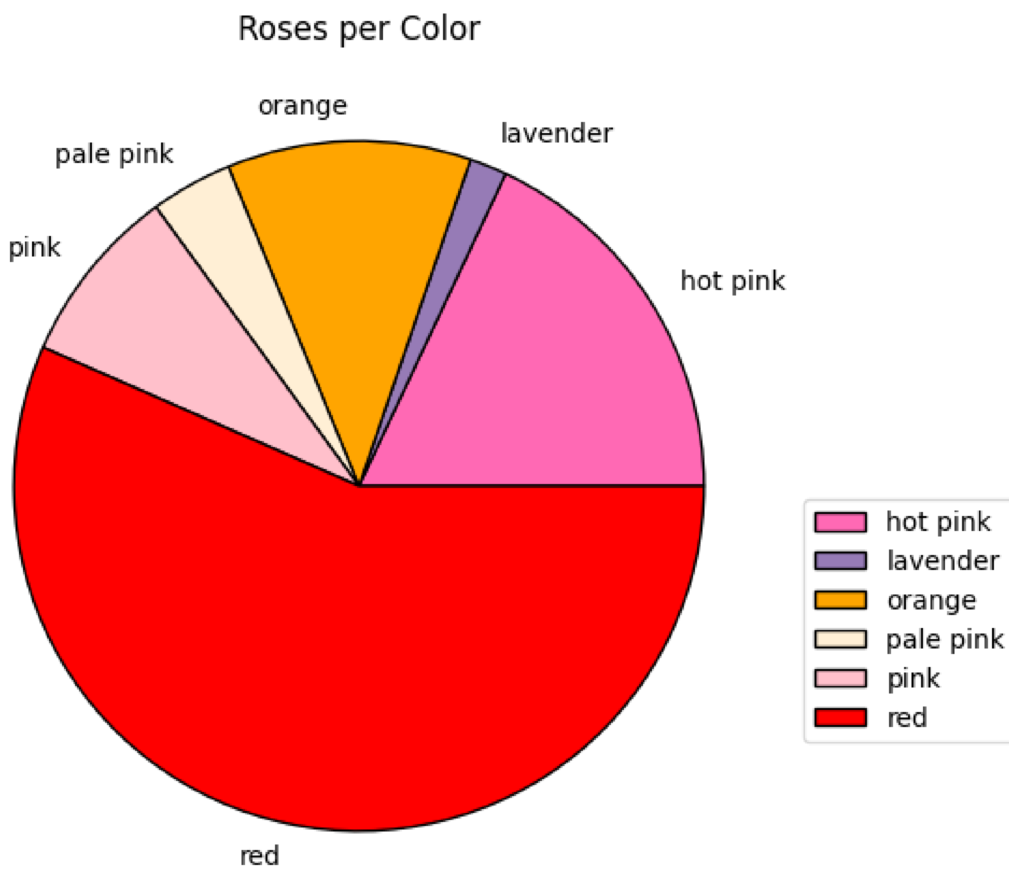

```
# Convert the quantity columns to numeric
for col in ['SQty', 'DQty', 'PQty', 'EQty']:
    all_data[col] = pd.to_numeric(all_data[col], errors='coerce')

# Calculate the total volume for each color
color_volume = all_data.groupby('Colors')[['SQty', 'DQty', 'PQty', 'EQty']].
↪sum().sum(axis=1)

# Filter out colors with 0 sales volume
color_volume = color_volume[color_volume != 0]

# Define the custom colors
custom_colors = {
    'hot pink': '#FF69B4',
    'orange': '#FFA500',
    'pink': '#FFC0CB',
    'green': '#008000',
```

```
    'purple': '#800080',
    'yellow': '#FFFF00',
    'white': '#FFFFFF',
    'peach': '#ffcba4',
    'lavender': '#967bb6',
    'light pink': '#FFB6C1',
    'red': '#FF0000',
    'pale pink': '#FFEFD5',
    'blue': '#8EA5C5',
    'ivory': '#f5f5dc'
}

# Create the pie chart with custom colors
custom_colors = {color: custom_colors.get(color, 'gray') for color in␣
 ↪color_volume.index}
colors = [custom_colors[color] for color in color_volume.index]

# Adjust the figure size
plt.figure(figsize=(8, 6))

# Create the pie chart with updated colors
patches, texts = plt.pie(color_volume.values, labels=color_volume.index,␣
 ↪colors=colors)


plt.title('Variety per Color')

# Position the legend outside the chart area
plt.legend(patches, color_volume.index, bbox_to_anchor=(1, 0.5), loc='best')
plt.savefig('Variety per Color Borderless')
plt.show()
```




```
all_data['Flowers'] = all_data['Flowers'].str.lower()
all_data['Flowers'] = all_data['Flowers'].str.strip()
# Remove rows with NaN values in the 'Flowers' column
all_data = all_data[all_data['Flowers'].notna()]
# Filter rows for roses
roses_data = all_data[all_data['Flowers'].str.contains('rose', case=False)]

# Calculate the total volume for each color
color_volume = roses_data.groupby('Colors')[['SQty', 'DQty', 'PQty', 'EQty']].
 ↪sum().sum(axis=1)

# Filter out colors with 0 sales volume
color_volume = color_volume[color_volume != 0]

# Define the custom colors
custom_colors = {
    'hot pink': '#FF69B4',
```

```python
    'orange': '#FFA500',
    'pink': '#FFC0CB',
    'green': '#008000',
    'purple': '#800080',
    'yellow': '#FFFF00',
    'white': '#FFFFFF',
    'peach': '#ffcba4',
    'lavender': '#967bb6',
    'light pink': '#FFB6C1',
    'red': '#FF0000',
    'pale pink': '#FFEFD5',
    'blue': '#8EA5C5',
    'ivory': '#f5f5dc'
}

# Create the pie chart with custom colors
custom_colors = {color: custom_colors.get(color, 'gray') for color in␣
↪color_volume.index}
colors = [custom_colors[color] for color in color_volume.index]

# Adjust the figure size
plt.figure(figsize=(8, 6))

# Create the pie chart with updated colors
patches, texts = plt.pie(color_volume.values, labels=color_volume.index,␣
↪colors=colors,
                         wedgeprops={"edgecolor": "black", 'linewidth': 1,␣
↪'antialiased': True})

plt.title('Roses per Color')

# Position the legend outside the chart area
plt.legend(patches, color_volume.index, bbox_to_anchor=(1, 0.5), loc='best')
plt.savefig('Roses per Color Border')
plt.show()
```




```python
# Remove the filter to include all arrangements
all_arrangements = all_data

# Drop duplicates to ensure each flower type is counted only once per␣
↪arrangement
all_unique_flowers = all_arrangements.drop_duplicates(subset=['Arrangement',␣
↪'Flowers'])

# Count the occurrences of each color and flower type
color_counts = all_arrangements['Colors'].value_counts()
flower_counts = all_unique_flowers['Flowers'].value_counts()

print("Most common colors among all arrangements:")
print(color_counts)
print("\nMost common flower types among all arrangements:")
print(flower_counts)
```

```
Most common colors among all arrangements:
```

```
Colors
red          23
pink         20
hot pink     18
orange        9
purple        8
pale pink     6
lavender      4
green         4
yellow        4
peach         2
white         1
Name: count, dtype: int64

Most common flower types among all arrangements:
Flowers
50 cm roses                 21
mini carnation stems        11
standard carnations         10
stock stems                  8
la hybrid lily stems         7
alstroemeria stems           6
daisy pompon stems           4
gerbera daisies              3
cushion pompon stems         3
double lisianthus stems      2
waxflower stems              2
hypericum berry stems        2
spray rose stems             2
snapdragon stems             2
fuji mums                    2
la lily stems                2
sunflowers                   2
button pompon stems          2
60 cm roses                  2
hydrangea blooms             1
Name: count, dtype: int64
```

```python
# Load the data for each year
df_2022 = pd.read_excel('Top10/Top 10 22 vs 23 VDay.xlsx', sheet_name='2022') #␣
 ↪Replace with your 2022 sheet name
df_2023 = pd.read_excel('Top10/Top 10 22 vs 23 VDay.xlsx', sheet_name='2023') #␣
 ↪Replace with your 2023 sheet name

# Define a function to clean up the data
def clean_data(df):
```

```python
    df['Gross Order Line Group Amt'] = df['Gross Order Line Group Amt'].replace({'\$': '', ',': ''}, regex=True).astype(float)
    df['AOV'] = df['AOV'].replace({'\$': '', ',': ''}, regex=True).astype(float)
    df['Order Line Group Cnt'] = df['Order Line Group Cnt'].replace({',': ''}, regex=True).astype(int)
    return df

# Clean the data
df_2022 = clean_data(df_2022)
df_2023 = clean_data(df_2023)
```

```
<>:7: DeprecationWarning: invalid escape sequence '\$'
<>:8: DeprecationWarning: invalid escape sequence '\$'
<>:7: DeprecationWarning: invalid escape sequence '\$'
<>:8: DeprecationWarning: invalid escape sequence '\$'
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1430136236.py:7:
DeprecationWarning: invalid escape sequence '\$'
  df['Gross Order Line Group Amt'] = df['Gross Order Line Group
Amt'].replace({'\$': '', ',': ''}, regex=True).astype(float)
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1430136236.py:8:
DeprecationWarning: invalid escape sequence '\$'
  df['AOV'] = df['AOV'].replace({'\$': '', ',': ''}, regex=True).astype(float)
```

```python
def basic_stats(df, year):
    # Basic statistics
    total_order_cnt = df['Order Line Group Cnt'].sum()
    total_order_amt = df['Gross Order Line Group Amt'].sum()
    avg_aov = df['AOV'].mean()

    print(f"Stats for {year}:")
    print(f"Total Order Count: {total_order_cnt}")
    print(f"Total Order Amount: ${total_order_amt}")
    print(f"Average AOV: ${avg_aov}")

    # Highest Gross Order Line Group Amt, Order Line Group Cnt, and AOV
    highest_order_amt_code = df.loc[df['Gross Order Line Group Amt'].idxmax(), 'Featured Product Set Code']
    highest_order_cnt_code = df.loc[df['Order Line Group Cnt'].idxmax(), 'Featured Product Set Code']
    highest_aov_code = df.loc[df['AOV'].idxmax(), 'Featured Product Set Code']

    print(f"Product with Highest Order Amount: {highest_order_amt_code}")
    print(f"Product with Highest Order Count: {highest_order_cnt_code}")
    print(f"Product with Highest AOV: {highest_aov_code}")

basic_stats(df_2022, 2022)
print("---")
```

```
basic_stats(df_2023, 2023)
```

```
Stats for 2022:
Total Order Count: 117614
Total Order Amount: $12725541.82
Average AOV: $109.03099999999999
Product with Highest Order Amount: B59
Product with Highest Order Count: C5375
Product with Highest AOV: V1R
---
Stats for 2023:
Total Order Count: 92182
Total Order Amount: $9928045.36
Average AOV: $108.175
Product with Highest Order Amount: YPB
Product with Highest Order Count: C5375
Product with Highest AOV: V1R
```

```
# The path to the directory where your csv files are stored
directory = 'processed_csv/'

# Initialize an empty list to hold all transactions
transactions = []

# Loop through every file in the directory
for filename in os.listdir(directory):
    if filename.endswith(".csv"):  # check if the file is a CSV
        # Create a dataframe from the csv file
        df = pd.read_csv(directory + filename)

        # Fill NaNs in 'Colors' and 'Flowers' with an empty string
        df['Colors'].fillna('', inplace=True)
        df['Flowers'].fillna('', inplace=True)

        # Merge the 'Colors' and 'Flowers' columns into a single column
        df['Items'] = df.apply(lambda row: row['Colors'] + ' ' + row['Flowers']␣
↪if row['Colors'] and row['Flowers'] else row['Colors'] or row['Flowers'],␣
↪axis=1)

        # Drop rows where 'Items' is empty or whitespace
        df = df[df['Items'].str.strip() != '']

        # Extract the items into a list
        items = df['Items'].tolist()

        # Add this list to the transactions list
        transactions.append(items)
```

```python
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

# 'transactions' is your list of transactions
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)
df = pd.DataFrame(te_ary, columns=te.columns_)

# Generate frequent itemsets
frequent_itemsets = apriori(df, min_support=0.01, use_colnames=True)

# Generate association rules
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
```

```python
# Display the top 10 rules, sorted by lift in descending order
top_rules = rules.sort_values("lift", ascending=False).head(10)
print(top_rules)
```

```
                                              antecedents  \
371430  (2120S Small Cinched Vase, Hot Pink Stock stem…
472959  (Pink Hydrangea blooms, Purple Daisy Pompon st…
472952  (Purple Alstroemeria stems, Purple Daisy Pompo…
472953  (Purple Daisy Pompon stems, Hot Pink Alstroeme…
472954  (Purple Daisy Pompon stems, Hot Pink Alstroeme…
472955  (Purple Alstroemeria stems, Lavender 50 cm Ros…
472956  (Purple Alstroemeria stems, Hot Pink Alstroeme…
472957  (Lavender 50 cm Roses, Hot Pink Alstroemeria s…
472958  (Pink Hydrangea blooms, Purple Alstroemeria st…
472960  (Pink Hydrangea blooms, Purple Daisy Pompon st…

                                              consequents  antecedent support  \
371430        (Pink Hydrangea blooms, Purple Stock stems)            0.041667
472959  (Purple Stock stems, Hot Pink Stock stems, Hot…           0.041667
472952  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472953  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472954  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472955  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472956  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472957  (Purple Stock stems, Hot Pink Stock stems, Pin…           0.041667
472958  (Purple Stock stems, Hot Pink Stock stems, Hot…           0.041667
472960  (Purple Stock stems, Hot Pink Stock stems, Hot…           0.041667

        consequent support   support  confidence  lift  leverage  conviction  \
371430            0.041667  0.041667         1.0  24.0  0.039931         inf
472959            0.041667  0.041667         1.0  24.0  0.039931         inf
472952            0.041667  0.041667         1.0  24.0  0.039931         inf
472953            0.041667  0.041667         1.0  24.0  0.039931         inf
```

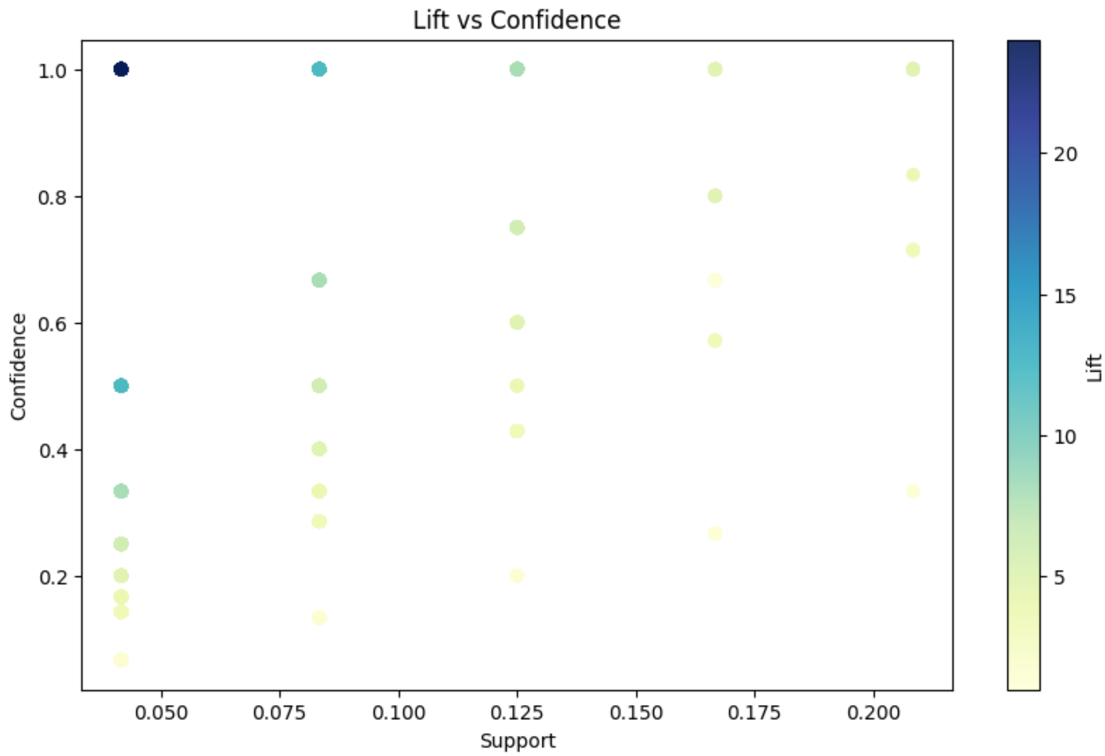
```
472954            0.041667  0.041667        1.0   24.0  0.039931          inf
472955            0.041667  0.041667        1.0   24.0  0.039931          inf
472956            0.041667  0.041667        1.0   24.0  0.039931          inf
472957            0.041667  0.041667        1.0   24.0  0.039931          inf
472958            0.041667  0.041667        1.0   24.0  0.039931          inf
472960            0.041667  0.041667        1.0   24.0  0.039931          inf

        zhangs_metric
371430            1.0
472959            1.0
472952            1.0
472953            1.0
472954            1.0
472955            1.0
472956            1.0
472957            1.0
472958            1.0
472960            1.0
```

```python
filtered_rules = rules[ (rules['lift'] >= 2) &
                        (rules['confidence'] >= 0.5) ]
print(filtered_rules)
```

```
                                                antecedents  \
1       (2097 Medium Oval Woodchip Basket (Giftwares))
2                                        (Green Fuji Mums)
3       (2097 Medium Oval Woodchip Basket (Giftwares))
5       (2097 Medium Oval Woodchip Basket (Giftwares))
6       (2097 Medium Oval Woodchip Basket (Giftwares))
…                                                    …
794287                          (Pink Standard Carnations)
794288                       (Hot Pink Alstroemeria stems)
794289                             (Pink Hydrangea blooms)
794293                        (Purple Alstroemeria stems)
794294                              (Lavender 50 cm Roses)

                                                consequents  antecedent support  \
1                                       (Floral Foam blocks)            0.083333
2          (2097 Medium Oval Woodchip Basket (Giftwares))            0.083333
3                                          (Green Fuji Mums)            0.083333
5                                     (Israeli Ruscus stems)            0.083333
6                                        (Leatherleaf stems)            0.083333
…                                                         …                 …
794287  (2120S Small Cinched Vase, Purple Stock stems,…            0.041667
794288  (2120S Small Cinched Vase, Purple Stock stems,…            0.041667
794289  (2120S Small Cinched Vase, Purple Stock stems,…            0.041667
794293  (2120S Small Cinched Vase, Purple Stock stems,…            0.041667
794294  (2120S Small Cinched Vase, Purple Stock stems,…            0.041667
```

```
        consequent support   support  confidence       lift  leverage  \
1                 0.208333  0.083333         1.0   4.800000  0.065972
2                 0.083333  0.083333         1.0  12.000000  0.076389
3                 0.083333  0.083333         1.0  12.000000  0.076389
5                 0.250000  0.083333         1.0   4.000000  0.062500
6                 0.291667  0.083333         1.0   3.428571  0.059028
…                      …         …         …          …         …
794287            0.041667  0.041667         1.0  24.000000  0.039931
794288            0.041667  0.041667         1.0  24.000000  0.039931
794289            0.041667  0.041667         1.0  24.000000  0.039931
794293            0.041667  0.041667         1.0  24.000000  0.039931
794294            0.041667  0.041667         1.0  24.000000  0.039931

        conviction  zhangs_metric
1              inf       0.863636
2              inf       1.000000
3              inf       1.000000
5              inf       0.818182
6              inf       0.772727
…             …              …
794287         inf       1.000000
794288         inf       1.000000
794289         inf       1.000000
794293         inf       1.000000
794294         inf       1.000000

[759908 rows x 10 columns]
```

```
plt.figure(figsize=(10,6))
plt.scatter(rules['support'], rules['confidence'], c=rules['lift'], alpha=0.9, cmap='YlGnBu')
plt.title('Lift vs Confidence')
plt.xlabel('Support')
plt.ylabel('Confidence')
plt.colorbar(label='Lift')
plt.savefig('Lift vs Confidence Apriori Analysis')
plt.show()
```




```
frequent_itemsets = apriori(df, min_support=0.01, use_colnames=True)

# Filter out the itemsets with only one item
single_item_sets = frequent_itemsets[frequent_itemsets['itemsets'].apply(lambda␣
↪x: len(x) == 1)]

# Sort by support
sorted_single_item_sets = single_item_sets.sort_values('support',␣
↪ascending=False)

print(sorted_single_item_sets)
```

```
     support                      itemsets
58  0.625000                  (Salal tips)
42  0.291667   (Pink LA Hybrid Lily stems)
23  0.291667        (Hot Pink 50 cm Roses)
31  0.291667           (Leatherleaf stems)
28  0.250000        (Israeli Ruscus stems)
..       …                             …
41  0.041667       (Pink Hydrangea blooms)
21  0.041667                      (Greens)
49  0.041667          (Purple Stock stems)
43  0.041667    (Pink Standard Carnations)
```

```
15  0.041667             (Focal Flowers)

[67 rows x 2 columns]
```

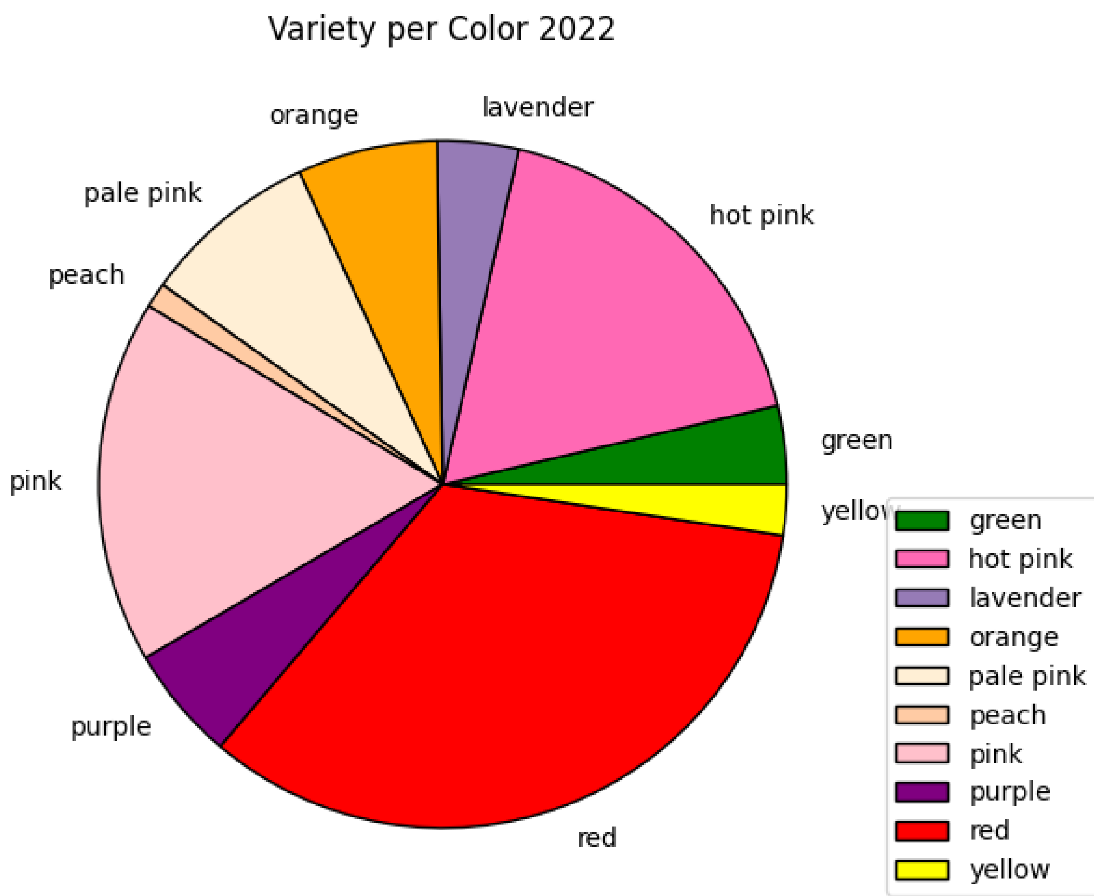
```
# Define the column names for Good, Better, Best, Exquisite
column_names = ["Unnamed: 4", "Unnamed: 6", "Unnamed: 8", "Unnamed: 10"]

# Get a list of all CSV files in the subdirectory
csv_files = [f for f in os.listdir('csv_files/') if f.endswith('.csv')]

# Check if the 'price_csv' directory exists, if not create it
if not os.path.exists('price_csv'):
    os.makedirs('price_csv')

data = {}
for csv_file in csv_files:
    df = pd.read_csv('csv_files/' + csv_file)

    # Select only the columns of interest
    df = df[column_names]

    df = df.iloc[1:3]

    # Save this DataFrame to a new CSV file in the 'price_csv' subdirectory
    df.to_csv('price_csv/' + csv_file[:-4] + '_price.csv', index=False)

    data[csv_file] = df
```

```
# Specify the directory containing your CSV files
data_directory = 'processed_csv'

# Get a list of all CSV files in the directory
files = [os.path.join(data_directory, f) for f in os.listdir(data_directory) if␣
 ↪f.endswith('.csv')]

dfs = []
for filename in files:
    df = pd.read_csv(filename)
    df = df.iloc[0:9]
    # Extract the year from the filename
    year = re.search(r'\d{4}', filename).group(0)
    df['Year'] = int(year)

    dfs.append(df)

# Concatenate all the DataFrames
all_data = pd.concat(dfs, ignore_index=True)
```

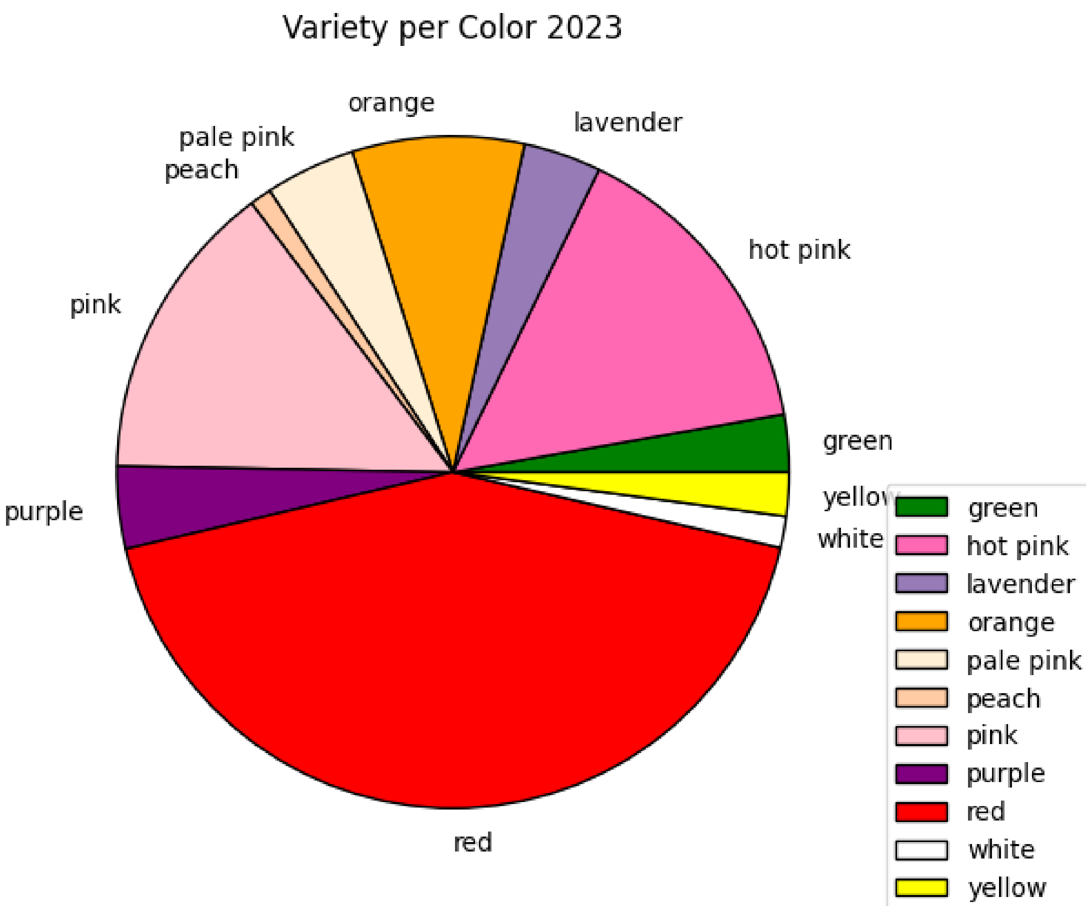
```
# Split the data based on the year
data_2022 = all_data[all_data['Year'] == 2022]
data_2023 = all_data[all_data['Year'] == 2023]

for data, year in zip([data_2022, data_2023], ['2022', '2023']):
    data['Colors'] = data['Colors'].str.lower()
    data['Colors'] = data['Colors'].str.strip()
    # Remove rows with NaN values in the 'Colors' column
    data = data[data['Colors'].notna()]

    # Convert the quantity columns to numeric
    for col in ['SQty', 'DQty', 'PQty', 'EQty']:
        data.loc[:, col] = pd.to_numeric(data.loc[:, col], errors='coerce')
    # Calculate the total volume for each color
    color_volume = data.groupby('Colors')[['SQty', 'DQty', 'PQty', 'EQty']].
 ↪sum().sum(axis=1)

    # Filter out colors with 0 sales volume
    color_volume = color_volume[color_volume != 0]
    # Define the custom colors
    custom_colors = {
        'hot pink': '#FF69B4',
        'orange': '#FFA500',
        'pink': '#FFC0CB',
        'green': '#008000',
        'purple': '#800080',
        'yellow': '#FFFF00',
        'white': '#FFFFFF',
        'peach': '#ffcba4',
        'lavender': '#967bb6',
        'light pink': '#FFB6C1',
        'red': '#FF0000',
        'pale pink': '#FFEFD5',
        'blue': '#8EA5C5',
        'ivory': '#f5f5dc'
    }
    # Create the pie chart with custom colors
    custom_colors = {color: custom_colors.get(color, 'gray') for color in␣
 ↪color_volume.index}
    colors = [custom_colors[color] for color in color_volume.index]

    # Adjust the figure size
    plt.figure(figsize=(8, 6))

    # Create the pie chart with updated colors
```

```
    patches, texts = plt.pie(color_volume.values, labels=color_volume.index,␣
↪colors=colors, wedgeprops = {"edgecolor" : "black", 'linewidth':␣
↪1,'antialiased': True})

    plt.title(f'Variety per Color {year}')

    # Position the legend outside the chart area
    plt.legend(patches, color_volume.index, bbox_to_anchor=(1, 0.5), loc='best')
    plt.savefig(f'Variety per Color Borders {year}')
    plt.show()
```

```
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1653350726.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.lower()
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1653350726.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.strip()
```




```
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1653350726.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.lower()
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/1653350726.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.strip()
```

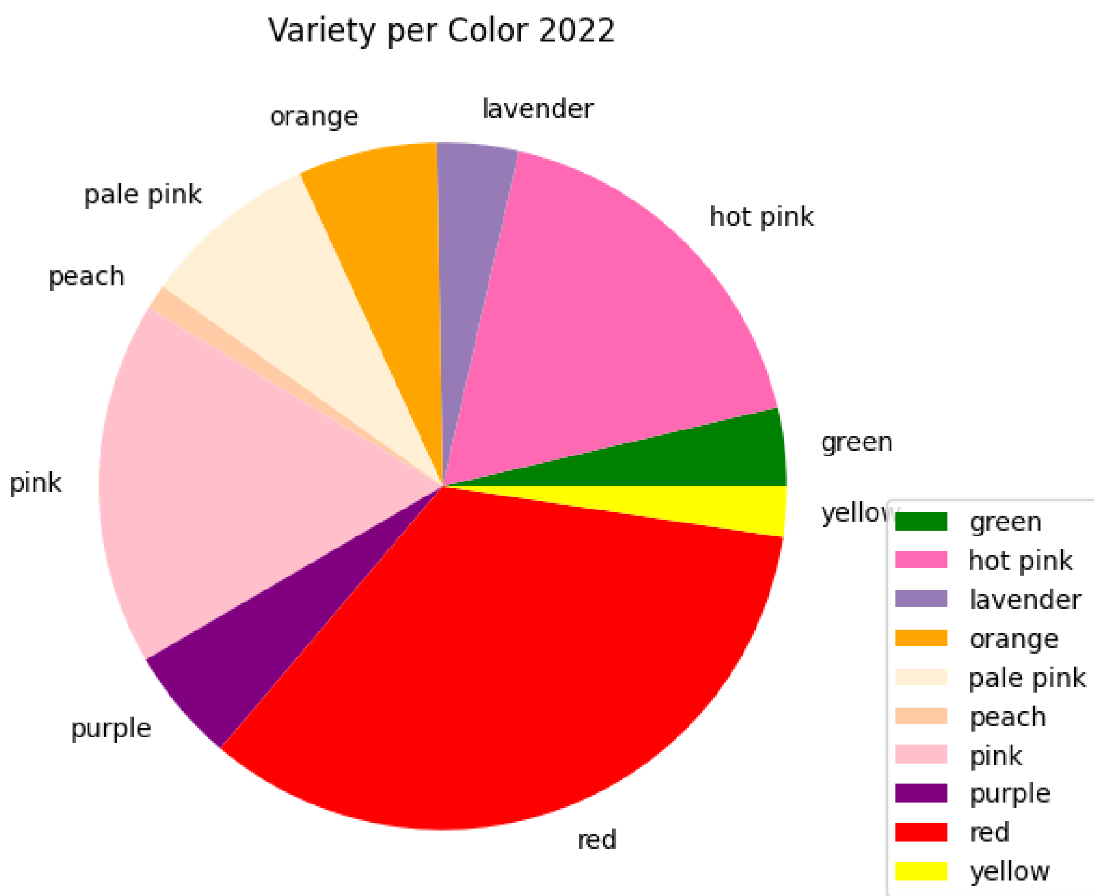



```
# Split the data based on the year
data_2022 = all_data[all_data['Year'] == 2022]
data_2023 = all_data[all_data['Year'] == 2023]

for data, year in zip([data_2022, data_2023], ['2022', '2023']):
    data['Colors'] = data['Colors'].str.lower()
    data['Colors'] = data['Colors'].str.strip()
    # Remove rows with NaN values in the 'Colors' column
    data = data[data['Colors'].notna()]

    # Convert the quantity columns to numeric
    for col in ['SQty', 'DQty', 'PQty', 'EQty']:
        data.loc[:, col] = pd.to_numeric(data.loc[:, col], errors='coerce')
    # Calculate the total volume for each color
    color_volume = data.groupby('Colors')[['SQty', 'DQty', 'PQty', 'EQty']].
↪sum().sum(axis=1)

    # Filter out colors with 0 sales volume
```

```
    color_volume = color_volume[color_volume != 0]
    # Define the custom colors
    custom_colors = {
        'hot pink': '#FF69B4',
        'orange': '#FFA500',
        'pink': '#FFC0CB',
        'green': '#008000',
        'purple': '#800080',
        'yellow': '#FFFF00',
        'white': '#FFFFFF',
        'peach': '#ffcba4',
        'lavender': '#967bb6',
        'light pink': '#FFB6C1',
        'red': '#FF0000',
        'pale pink': '#FFEFD5',
        'blue': '#8EA5C5',
        'ivory': '#f5f5dc'
    }
    # Create the pie chart with custom colors
    custom_colors = {color: custom_colors.get(color, 'gray') for color in␣
↪color_volume.index}
    colors = [custom_colors[color] for color in color_volume.index]

    # Adjust the figure size
    plt.figure(figsize=(8, 6))

    # Create the pie chart with updated colors
    patches, texts = plt.pie(color_volume.values, labels=color_volume.index,␣
↪colors=colors)

    plt.title(f'Variety per Color {year}')

    # Position the legend outside the chart area
    plt.legend(patches, color_volume.index, bbox_to_anchor=(1, 0.5), loc='best')
    plt.savefig(f'Variety per Color Borderless {year}')
    plt.show()
```

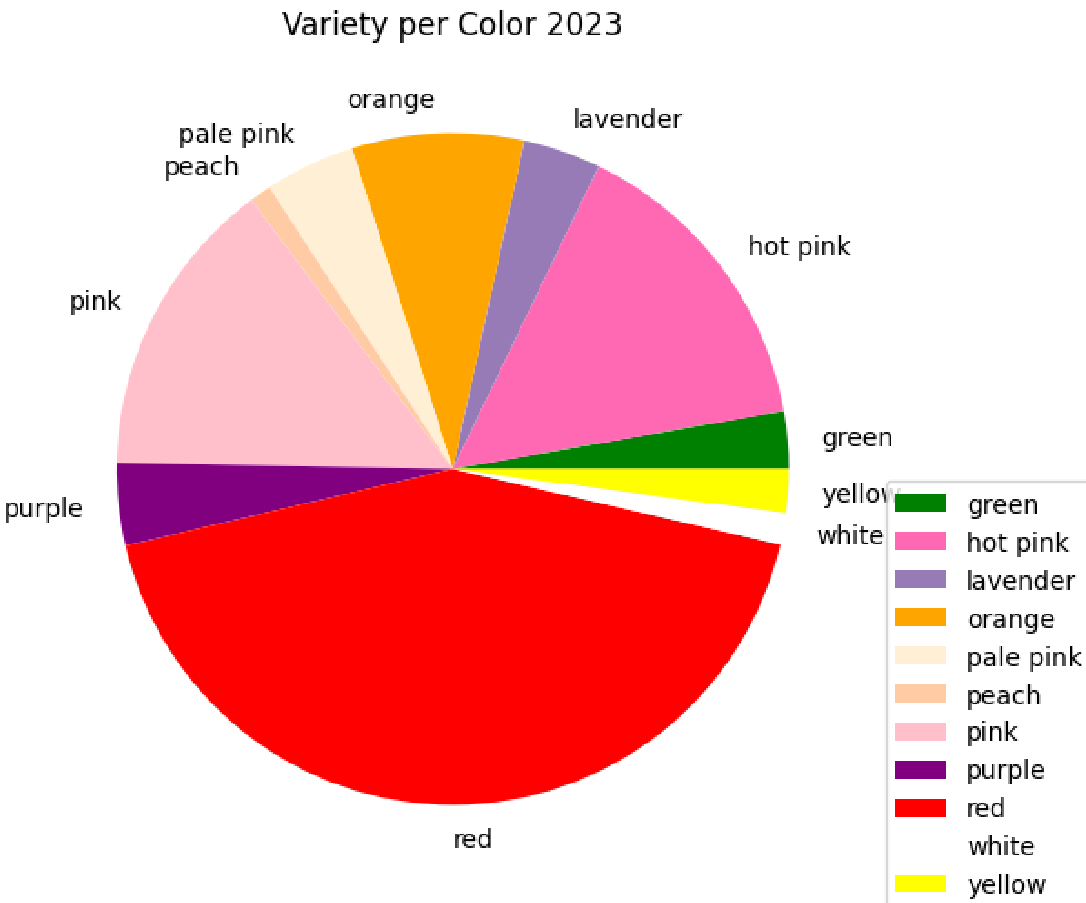
```
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/3347232594.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.lower()
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/3347232594.py:7:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.strip()
```




```
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/3347232594.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.lower()
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/3347232594.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Colors'] = data['Colors'].str.strip()
```




```
# Assuming all_arrangements is your original dataframe, you create a copy of it
# that includes only columns from index 0 up to index 13 (not including 13).
all_arrangements_copy = all_arrangements.iloc[:, 0:12].copy()

# Make sure 'Year' and 'Arrangement_Code' are not in the dataframe columns
if 'Year' in all_arrangements_copy.columns:
    all_arrangements_copy = all_arrangements_copy.drop(columns='Year')

if 'Arrangement_Code' in all_arrangements_copy.columns:
    all_arrangements_copy = all_arrangements_copy.
 ↪drop(columns='Arrangement_Code')
```

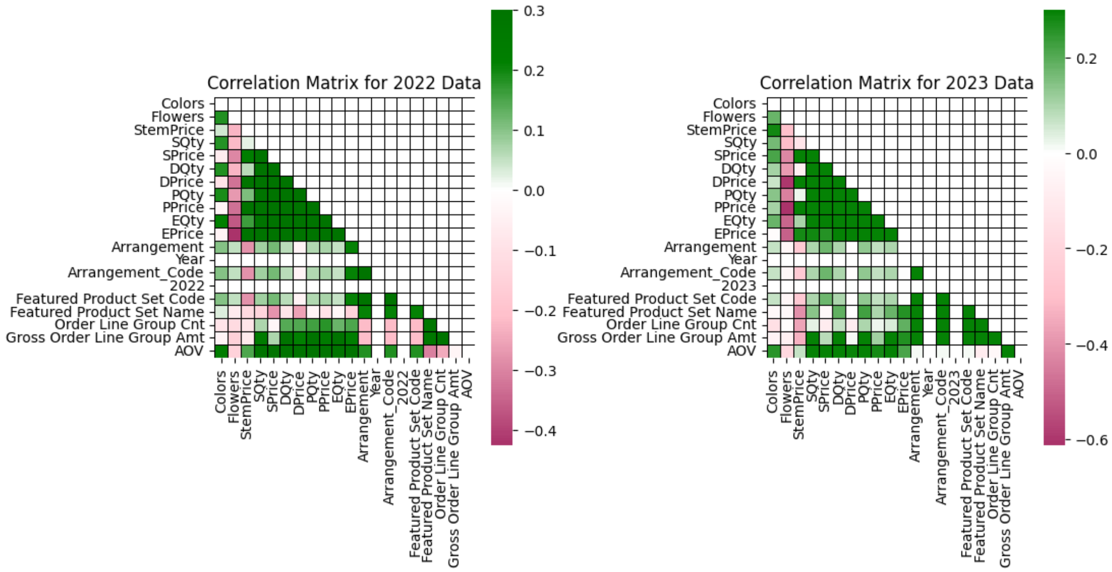
```
# Now, remove "_processed" from 'Arrangement' and split it into two columns:␣
↪'Year' and 'Arrangement_Code'
all_arrangements_copy['Arrangement'] = all_arrangements_copy['Arrangement'].str.
↪rstrip('_processed')
split_arrangement = all_arrangements_copy['Arrangement'].str.split('_', n=1,␣
↪expand=True)
all_arrangements_copy['Year'] = split_arrangement[0]
all_arrangements_copy['Arrangement_Code'] = split_arrangement[1]

# For df_2022 dataframe
if df_2022['Featured Product Set Code'].str.contains('_').any():
    split_df_2022 = df_2022['Featured Product Set Code'].str.split('_',␣
↪expand=True)
    df_2022['Year'] = split_df_2022[0]
    df_2022['Arrangement_Code'] = split_df_2022[1]
else:
    df_2022['Year'] = '2022'  # Assigning 2022 as default year
    df_2022['Arrangement_Code'] = df_2022['Featured Product Set Code']

# For df_2023 dataframe
if df_2023['Featured Product Set Code'].str.contains('_').any():
    split_df_2023 = df_2023['Featured Product Set Code'].str.split('_',␣
↪expand=True)
    df_2023['Year'] = split_df_2023[0]
    df_2023['Arrangement_Code'] = split_df_2023[1]
else:
    df_2023['Year'] = '2023'  # Assigning 2023 as default year
    df_2023['Arrangement_Code'] = df_2023['Featured Product Set Code']

# Merging all three dataframes
df_merged_2022 = pd.merge(all_arrangements_copy, df_2022, how='left',␣
↪on=['Year', 'Arrangement_Code'])
df_merged_2023 = pd.merge(all_arrangements_copy, df_2023, how='left',␣
↪on=['Year', 'Arrangement_Code'])

# For df_2022, keep only the rows where Year is '2022'
df_merged_2022 = df_merged_2022[df_merged_2022['Year'] == '2022']

# For df_2023, keep only the rows where Year is '2023'
df_merged_2023 = df_merged_2023[df_merged_2023['Year'] == '2023']
df_merged_2023.dropna(subset=['Featured Product Set Code'], inplace=True)
```

```
# Making a copy to avoid changing the original data
df_2022C = df_merged_2022.copy()
df_2023C = df_merged_2023.copy()
```

```
# Convert object columns to category and encode
for col in df_2022C.select_dtypes('object'):
    df_2022C[col] = df_2022C[col].astype('category').cat.codes

for col in df_2023C.select_dtypes('object'):
    df_2023C[col] = df_2023C[col].astype('category').cat.codes

# Now you can compute correlation
corr_2022 = df_2022C.corr()
corr_2023 = df_2023C.corr()
```

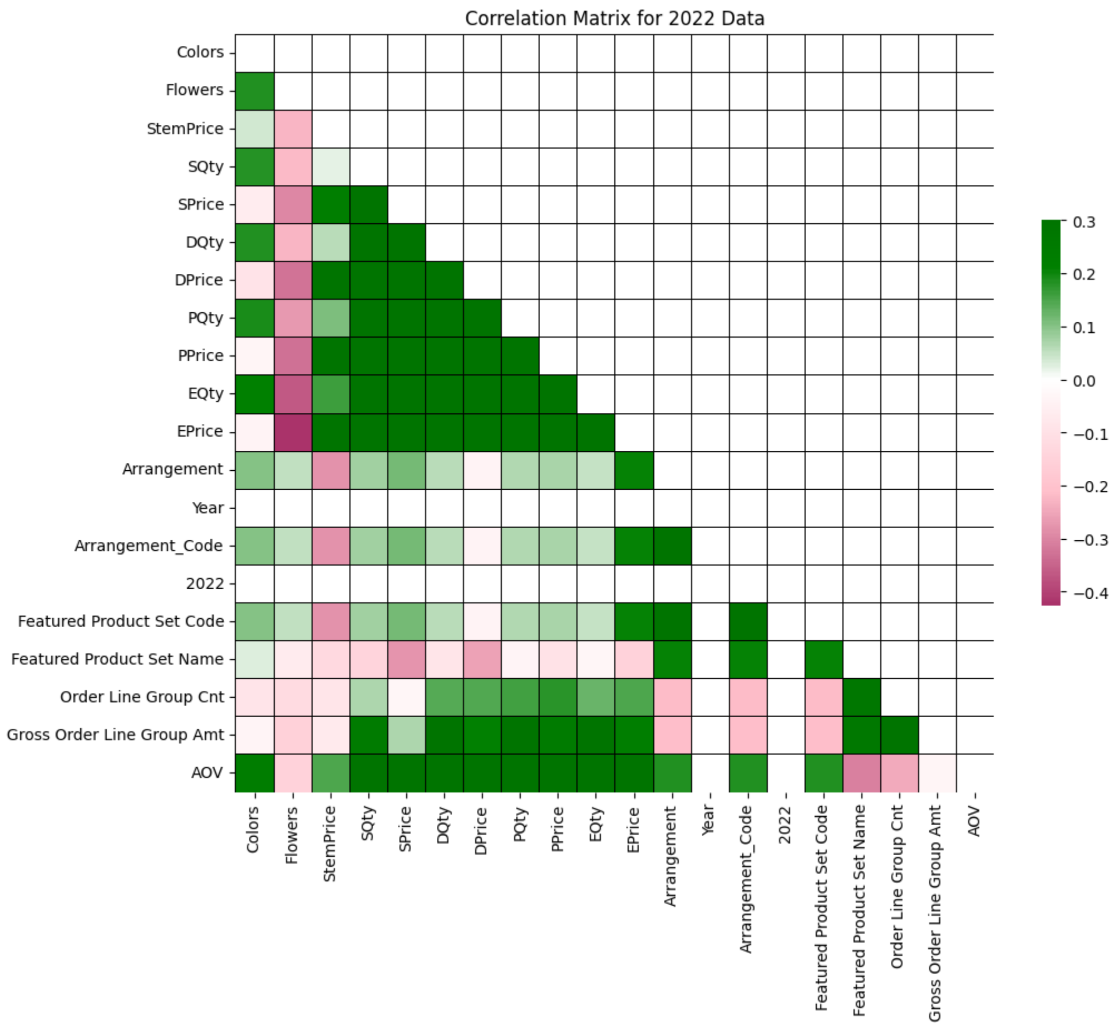
```
import matplotlib.colors as mcolors
import seaborn as sns
# Calculate the correlation matrix
corr_2022 = df_2022C.corr()
corr_2023 = df_2023C.corr()

# Generate a mask for the upper triangle of each correlation matrix
mask_2022 = np.triu(np.ones_like(corr_2022, dtype=bool))
mask_2023 = np.triu(np.ones_like(corr_2023, dtype=bool))

# Define the colors for the gradient colormap
colors = ['#AA336A', 'pink', 'white', 'green', 'darkgreen']

# Create a custom colormap with a gradient
cmap = mcolors.LinearSegmentedColormap.from_list('custom', colors)

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Draw the heatmap with the custom colormap for 2022 data
plt.subplot(1, 2, 1)
sns.heatmap(corr_2022, mask=mask_2022, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},
 ↪linecolor='black')
plt.title('Correlation Matrix for 2022 Data')

# Draw the heatmap with the custom colormap for 2023 data
plt.subplot(1, 2, 2)
sns.heatmap(corr_2023, mask=mask_2023, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},
 ↪linecolor='black')
plt.title('Correlation Matrix for 2023 Data')

plt.tight_layout()
plt.savefig('Correlation Matrices Combined')
plt.show()
```

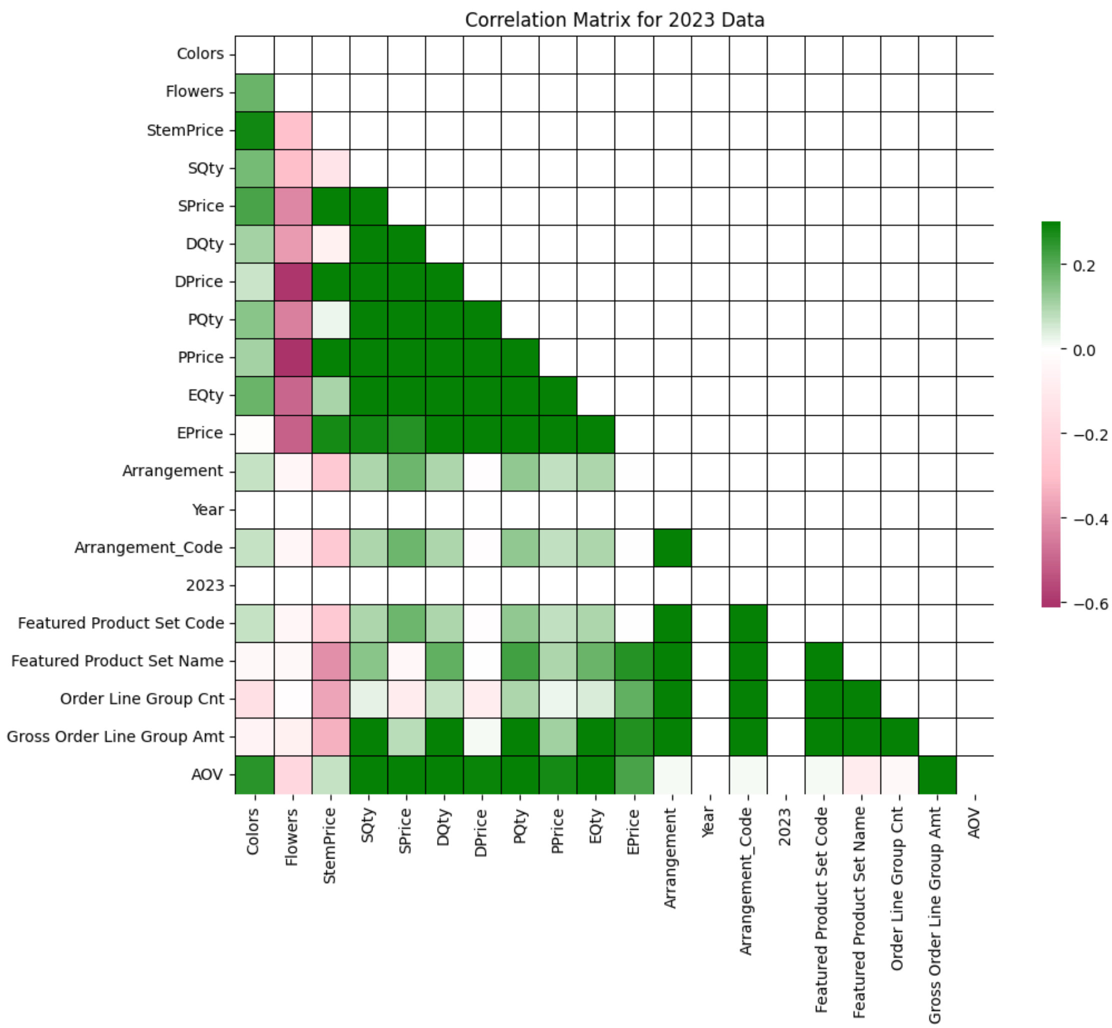
```
/var/folders/d8/qgb_8zcs7vl6pjzppspg_0sw0000gn/T/ipykernel_7237/80074052.py:21:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated
since 3.6 and will be removed two minor releases later; explicitly call
ax.remove() as needed.
  plt.subplot(1, 2, 1)
```




```python
# Calculate the correlation matrix
corr_2022 = df_2022C.corr()
corr_2023 = df_2023C.corr()

# Generate a mask for the upper triangle of each correlation matrix
mask_2022 = np.triu(np.ones_like(corr_2022, dtype=bool))
mask_2023 = np.triu(np.ones_like(corr_2023, dtype=bool))

# Define the colors for the gradient colormap
colors = ['#AA336A', 'pink', 'white', 'green', 'darkgreen']

# Create a custom colormap with a gradient
cmap = mcolors.LinearSegmentedColormap.from_list('custom', colors)

# Set up the matplotlib figure for 2022
f, ax = plt.subplots(figsize=(11, 9))

# Draw the heatmap with the custom colormap for 2022 data
sns.heatmap(corr_2022, mask=mask_2022, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},␣
 ↪linecolor='black')
plt.title('Correlation Matrix for 2022 Data')
```

```
plt.savefig('Correlation Matrix for 2022 Data')
plt.show()

# Set up the matplotlib figure for 2023
f, ax = plt.subplots(figsize=(11, 9))

# Draw the heatmap with the custom colormap for 2023 data
sns.heatmap(corr_2023, mask=mask_2023, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},
 ↪linecolor='black')
plt.title('Correlation Matrix for 2023 Data')
plt.savefig('Correlation Matrix for 2023 Data')
plt.show()
```






```python
# For DataFrame df_2022
print("---- Descriptive Statistics for 2022 Data ----")
print(df_2022.describe(include='all'))

# For DataFrame df_2023
print("---- Descriptive Statistics for 2023 Data ----")
print(df_2023.describe(include='all'))
```

```
---- Descriptive Statistics for 2022 Data ----
                    2022 Featured Product Set Code Featured Product Set Name  \
count                 10                        10                        10
unique                 1                        10                        10
top     Florist Delivered                    C5375   Light of My Life Bouquet
freq                  10                         1                         1
mean                 NaN                       NaN                       NaN
std                  NaN                       NaN                       NaN
```

```
min                     NaN                       NaN                       NaN
25%                     NaN                       NaN                       NaN
50%                     NaN                       NaN                       NaN
75%                     NaN                       NaN                       NaN
max                     NaN                       NaN                       NaN

        Order Line Group Cnt  Gross Order Line Group Amt         AOV  Year  \
count              10.000000                1.000000e+01   10.000000    10
unique                   NaN                         NaN         NaN     1
top                      NaN                         NaN         NaN  2022
freq                     NaN                         NaN         NaN    10
mean            11761.400000                1.272554e+06  109.031000   NaN
std              8799.115589                9.827513e+05   22.939076   NaN
min              5062.000000                5.173360e+05   88.470000   NaN
25%              6183.500000                6.316731e+05   95.662500   NaN
50%              7686.500000                8.370735e+05  101.085000   NaN
75%             13095.250000                1.323885e+06  108.080000   NaN
max             31203.000000                3.341509e+06  157.550000   NaN

       Arrangement_Code
count                10
unique               10
top               C5375
freq                  1
mean                NaN
std                 NaN
min                 NaN
25%                 NaN
50%                 NaN
75%                 NaN
max                 NaN
---- Descriptive Statistics for 2023 Data ----
                    2023 Featured Product Set Code Featured Product Set Name  \
count                 10                        10                        10
unique                 1                        10                        10
top     Florist Delivered                    C5375  Light of My Life Bouquet
freq                  10                         1                         1
mean                 NaN                       NaN                       NaN
std                  NaN                       NaN                       NaN
min                  NaN                       NaN                       NaN
25%                  NaN                       NaN                       NaN
50%                  NaN                       NaN                       NaN
75%                  NaN                       NaN                       NaN
max                  NaN                       NaN                       NaN

        Order Line Group Cnt  Gross Order Line Group Amt         AOV  Year  \
count              10.000000                1.000000e+01   10.000000    10
unique                   NaN                         NaN         NaN     1
```

```
top                 NaN                        NaN         NaN  2023
freq                NaN                        NaN         NaN    10
mean        9218.200000               9.928045e+05  108.175000   NaN
std         3230.496584               3.580617e+05   22.851048   NaN
min         5112.000000               4.946269e+05   85.640000   NaN
25%         6623.750000               6.737672e+05   97.222500   NaN
50%         8839.000000               1.063513e+06  100.970000   NaN
75%        11006.250000               1.334562e+06  103.135000   NaN
max        14664.000000               1.365605e+06  152.480000   NaN

       Arrangement_Code
count                10
unique               10
top               C5375
freq                  1
mean                NaN
std                 NaN
min                 NaN
25%                 NaN
50%                 NaN
75%                 NaN
max                 NaN
```

```
print(df_2022['AOV'].describe())
print(df_2023['Order Line Group Cnt'].describe())
```

```
count     10.000000
mean     109.031000
std       22.939076
min       88.470000
25%       95.662500
50%      101.085000
75%      108.080000
max      157.550000
Name: AOV, dtype: float64
count       10.000000
mean      9218.200000
std       3230.496584
min       5112.000000
25%       6623.750000
50%       8839.000000
75%      11006.250000
max      14664.000000
Name: Order Line Group Cnt, dtype: float64
```

The descriptive statistics give us a detailed overview of the numerical variables in the dataset for 2022 and 2023.

For the 2022 data:

1. **Order Line Group Cnt**: This variable shows the count of order lines. The average count in 2022 is about 11,761 with a standard deviation of about 8,799. The minimum count is 5,062 and the maximum is 31,203. The median (50th percentile) is 7,687.
2. **Gross Order Line Group Amt**: This is likely the total monetary amount for the order lines. The average amount in 2022 is about $1,272,554 with a standard deviation of about $982,751. The minimum amount is about $517,336 and the maximum is about $3,341,509.
3. **AOV (Average Order Value)**: The average order value in 2022 is about $109.03 with a standard deviation of about $22.94. The minimum AOV is $88.47 and the maximum is $157.55.

For the 2023 data:

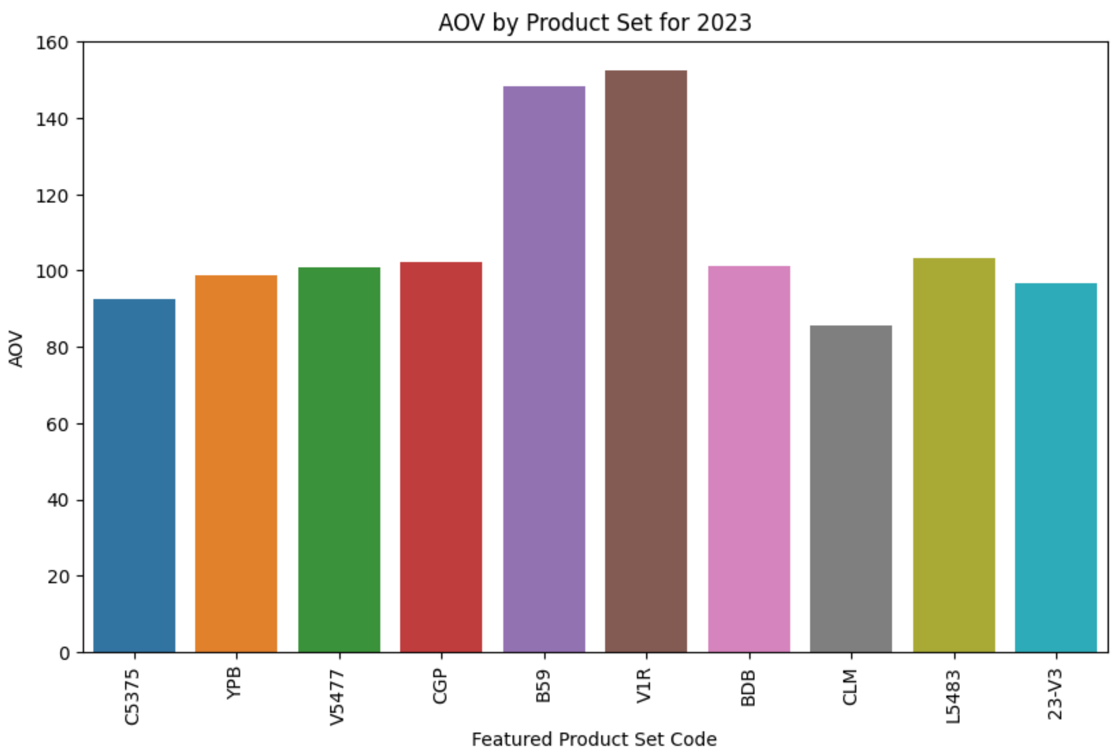
1. **Order Line Group Cnt**: The average count in 2023 is about 9,218 with a standard deviation of about 3,230. The minimum count is 5,112 and the maximum is 14,664. The median (50th percentile) is 8,839.
2. **Gross Order Line Group Amt**: The average amount in 2023 is about $992,804 with a standard deviation of about $358,061. The minimum amount is about $494,626 and the maximum is about $1,365,605.
3. **AOV (Average Order Value)**: The average order value in 2023 is about $108.17 with a standard deviation of about $22.85. The minimum AOV is $85.64 and the maximum is $152.48.

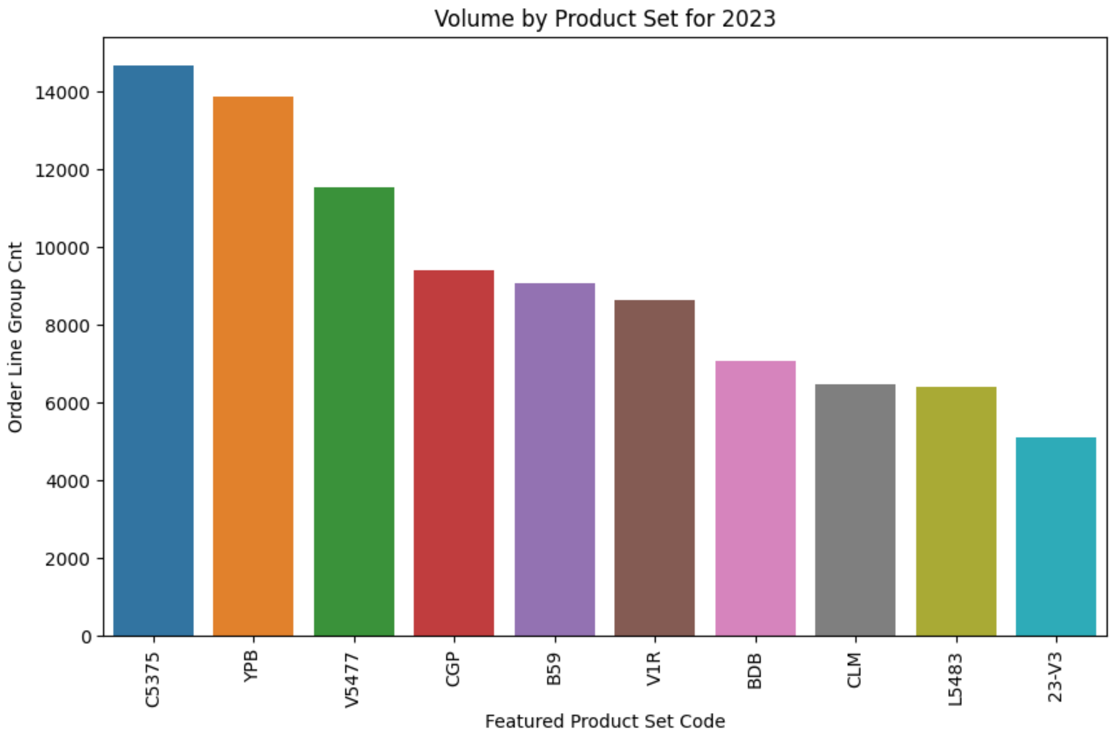
From the summary statistics, you can observe that the average order value (AOV) seems relatively stable from 2022 to 2023, while the number of order lines ("Order Line Group Cnt") seems to have decreased on average in 2023 compared to 2022. Similarly, the gross order line group amount also seems to have decreased in 2023 compared to 2022.

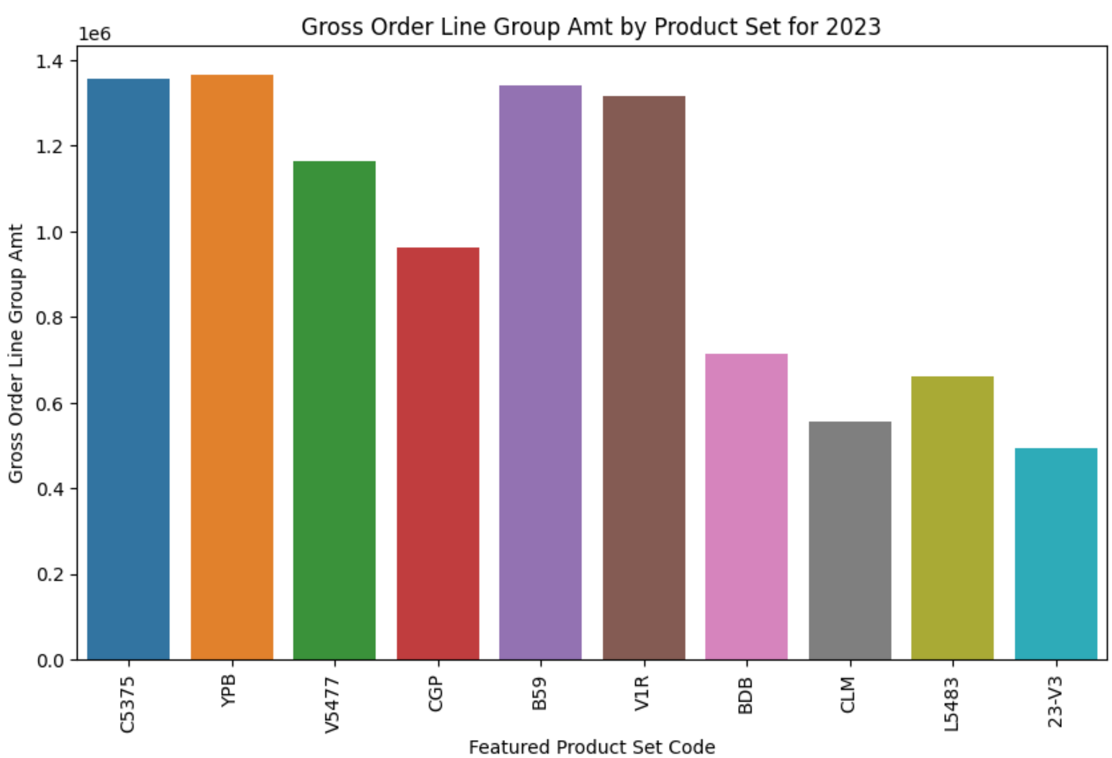
Please note that these interpretations are based on the assumption that the dataset is representative and random. For a more in-depth analysis, you may want to perform hypothesis testing or use inferential statistics.

```
import matplotlib.pyplot as plt
import seaborn as sns
df_2023_top10 = df_2023.copy()
# Assuming you've converted your data to a DataFrame named 'df_2023_top10'

# Convert 'Gross Order Line Group Amt' and 'AOV' to numeric values
# (they appear to be strings with dollar signs)
df_2023_top10['Gross Order Line Group Amt'] = df_2023_top10['Gross Order Line Group Amt'].replace('[\\$,]', '', regex=True).astype(float)
df_2023_top10['AOV'] = df_2023_top10['AOV'].replace('[\\$,]', '', regex=True).astype(float)

# For AOV
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='AOV', data=df_2023_top10)
plt.title('AOV by Product Set for 2023')
```

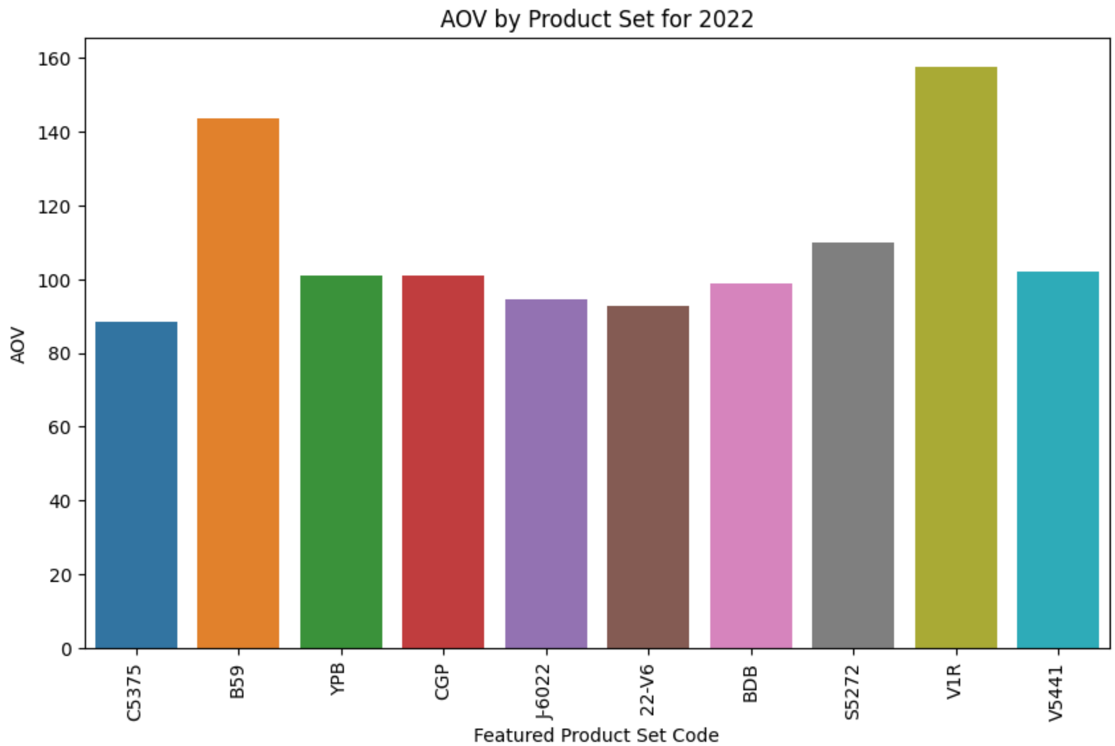
```
plt.savefig('AOV by Product Set for 2023')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are␣
  ↪long
plt.show()

# For Order Line Group Cnt
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='Order Line Group Cnt',␣
  ↪data=df_2023_top10)
plt.title('Volume by Product Set for 2023')
plt.savefig('Volume by Product Set for 2023')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are␣
  ↪long
plt.show()

# For Gross Order Line Group Amt
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='Gross Order Line Group Amt',␣
  ↪data=df_2023_top10)
plt.title('Gross Order Line Group Amt by Product Set for 2023')
plt.savefig('Gross Order Line Group Amt by Product Set for 2023')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are␣
  ↪long
plt.show()
```

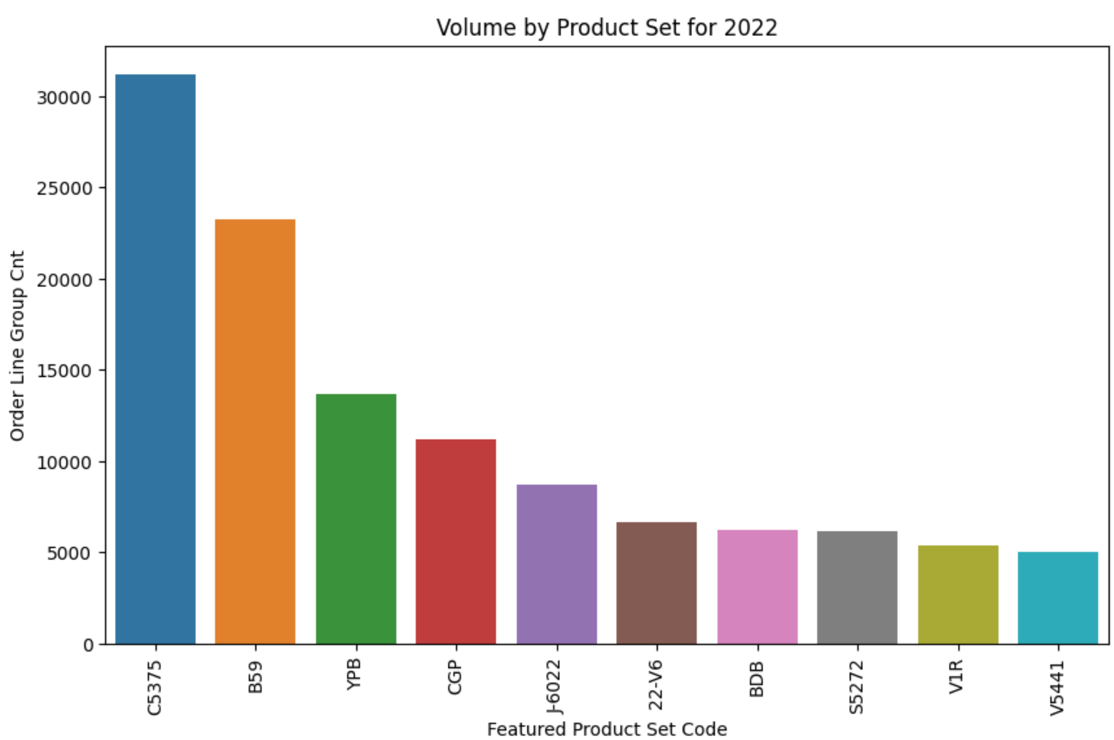


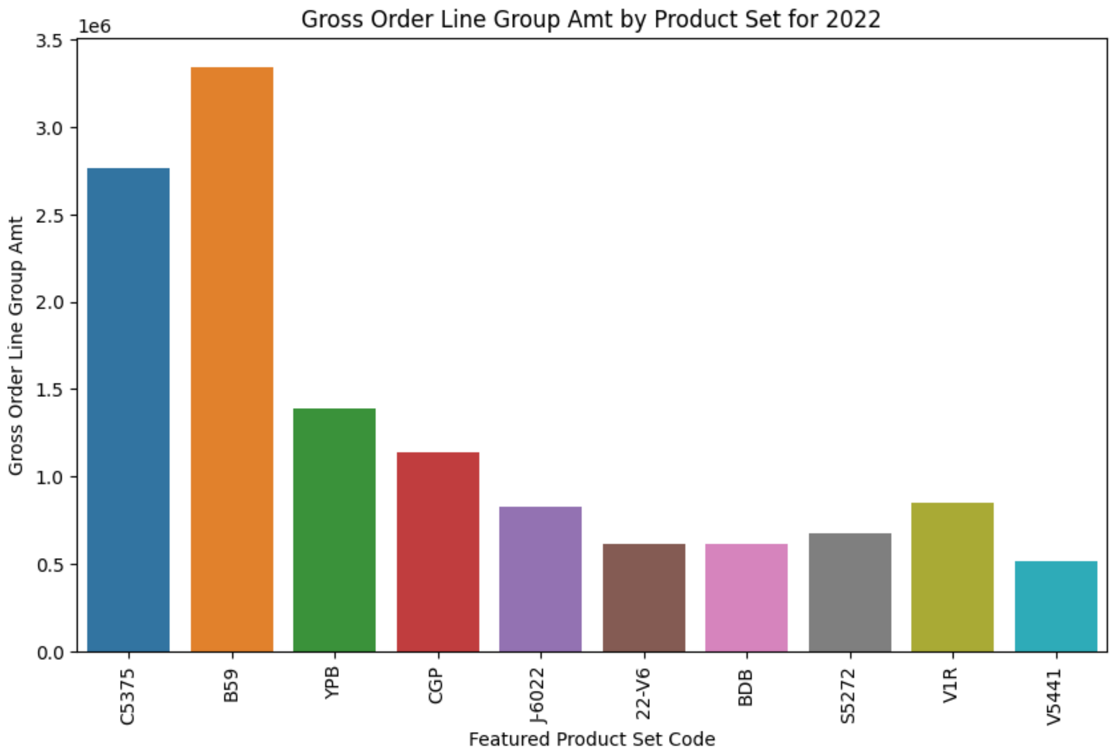

Volume by Product Set for 2023
Order Line Group Cnt
0
2000
4000
6000
8000
10000
12000
14000
C5375
YPB
V5477
CGP
B59
V1R
BDB
CLM
L5483
23-V3
Featured Product Set Code


Gross Order Line Group Amt by Product Set for 2023
1e6
Gross Order Line Group Amt
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
C5375
YPB
V5477
CGP
B59
V1R
BDB
CLM
L5483
23-V3
Featured Product Set Code

```python
import matplotlib.pyplot as plt
import seaborn as sns
df_2022_top10 = df_2022.copy()
# Assuming you've converted your data to a DataFrame named 'df_2023_top10'

# Convert 'Gross Order Line Group Amt' and 'AOV' to numeric values
# (they appear to be strings with dollar signs)
df_2022_top10['Gross Order Line Group Amt'] = df_2022_top10['Gross Order Line Group Amt'].replace('[\\$,]', '', regex=True).astype(float)
df_2022_top10['AOV'] = df_2022_top10['AOV'].replace('[\\$,]', '', regex=True).astype(float)

# For AOV
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='AOV', data=df_2022_top10)
plt.title('AOV by Product Set for 2022')
plt.savefig('AOV by Product Set for 2022')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are long
plt.show()

# For Order Line Group Cnt
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='Order Line Group Cnt', data=df_2022_top10)
plt.title('Volume by Product Set for 2022')
plt.savefig('Volume by Product Set for 2022')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are long
plt.show()

# For Gross Order Line Group Amt
plt.figure(figsize=(10,6))
sns.barplot(x='Featured Product Set Code', y='Gross Order Line Group Amt', data=df_2022_top10)
plt.title('Gross Order Line Group Amt by Product Set for 2022')
plt.savefig('Gross Order Line Group Amt by Product Set for 2022')
plt.xticks(rotation=90) # Rotating x labels for better visibility if they are long
plt.show()
```


AOV by Product Set for 2022
AOV
160
140
120
100
80
60
40
20
0
C5375
B59
YPB
CGP
J-6022
22-V6
BDB
S5272
V1R
V5441
Featured Product Set Code


Volume by Product Set for 2022
Order Line Group Cnt
30000
25000
20000
15000
10000
5000
0
C5375
B59
YPB
CGP
J-6022
22-V6
BDB
S5272
V1R
V5441
Featured Product Set Code




```
# Summary statistics for numerical columns
df_2022.describe(include=[np.number])
```

	Order Line Group Cnt	Gross Order Line Group Amt	AOV
count	10.000000	1.000000e+01	10.000000
mean	11761.400000	1.272554e+06	109.031000
std	8799.115589	9.827513e+05	22.939076
min	5062.000000	5.173360e+05	88.470000
25%	6183.500000	6.316731e+05	95.662500
50%	7686.500000	8.370735e+05	101.085000
75%	13095.250000	1.323885e+06	108.080000
max	31203.000000	3.341509e+06	157.550000

```
df_2023.describe(include=[np.number])
```

	Order Line Group Cnt	Gross Order Line Group Amt	AOV
count	10.000000	1.000000e+01	10.000000
mean	9218.200000	9.928045e+05	108.175000
std	3230.496584	3.580617e+05	22.851048
min	5112.000000	4.946269e+05	85.640000
25%	6623.750000	6.737672e+05	97.222500
50%	8839.000000	1.063513e+06	100.970000

```
75%          11006.250000                1.334562e+06  103.135000
max          14664.000000                1.365605e+06  152.480000
```

```
df_merged = pd.concat([df_merged_2022, df_merged_2023])
```

```
import statsmodels.api as sm
from statsmodels.formula.api import ols

# ANOVA on Colors
model_colors = ols('Q("Gross Order Line Group Amt") ~ C(Colors)',␣
 ↪data=df_merged_2022).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("Gross Order Line Group Amt") ~ C(Flowers)',␣
 ↪data=df_merged_2022).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                 sum_sq    df         F   PR(>F)
C(Colors)  2.539476e+12   9.0  0.464199  0.88879
Residual   2.188267e+13  36.0       NaN      NaN
                  sum_sq    df         F    PR(>F)
C(Flowers)  1.243020e+13  19.0  1.418432  0.201184
Residual    1.199194e+13  26.0       NaN       NaN
```

```
import statsmodels.api as sm
from statsmodels.formula.api import ols

# ANOVA on Colors
model_colors = ols('Q("Gross Order Line Group Amt") ~ C(Colors)',␣
 ↪data=df_merged_2023).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("Gross Order Line Group Amt") ~ C(Flowers)',␣
 ↪data=df_merged_2023).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                 sum_sq    df         F    PR(>F)
C(Colors)  6.108511e+11  10.0  0.490318  0.882921
Residual   3.737477e+12  30.0       NaN       NaN
                  sum_sq    df         F   PR(>F)
C(Flowers)  1.184109e+12  16.0  0.561327  0.88249
```

```
Residual     3.164220e+12   24.0        NaN       NaN
```

```python
import statsmodels.api as sm
from statsmodels.formula.api import ols

# ANOVA on Colors
model_colors = ols('Q("Gross Order Line Group Amt") ~ C(Colors)',␣
 ↪data=df_merged).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("Gross Order Line Group Amt") ~ C(Flowers)',␣
 ↪data=df_merged).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                 sum_sq    df         F    PR(>F)
C(Colors)   1.874336e+12  10.0  0.517572  0.872724
Residual    2.752267e+13  76.0       NaN       NaN
                  sum_sq    df         F    PR(>F)
C(Flowers)  7.164528e+12  19.0  1.136373  0.337928
Residual    2.223248e+13  67.0       NaN       NaN
```

```python
import statsmodels.api as sm
from statsmodels.formula.api import ols

# ANOVA on Colors
model_colors = ols('Q("AOV") ~ C(Colors)', data=df_merged_2022).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("AOV") ~ C(Flowers)', data=df_merged_2022).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                sum_sq    df         F    PR(>F)
C(Colors)   2278.891873   9.0  2.033239  0.063785
Residual    4483.273851  36.0       NaN       NaN
                 sum_sq    df         F    PR(>F)
C(Flowers)  2550.208611  19.0  0.828536  0.659491
Residual    4211.957113  26.0       NaN       NaN
```

```python
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

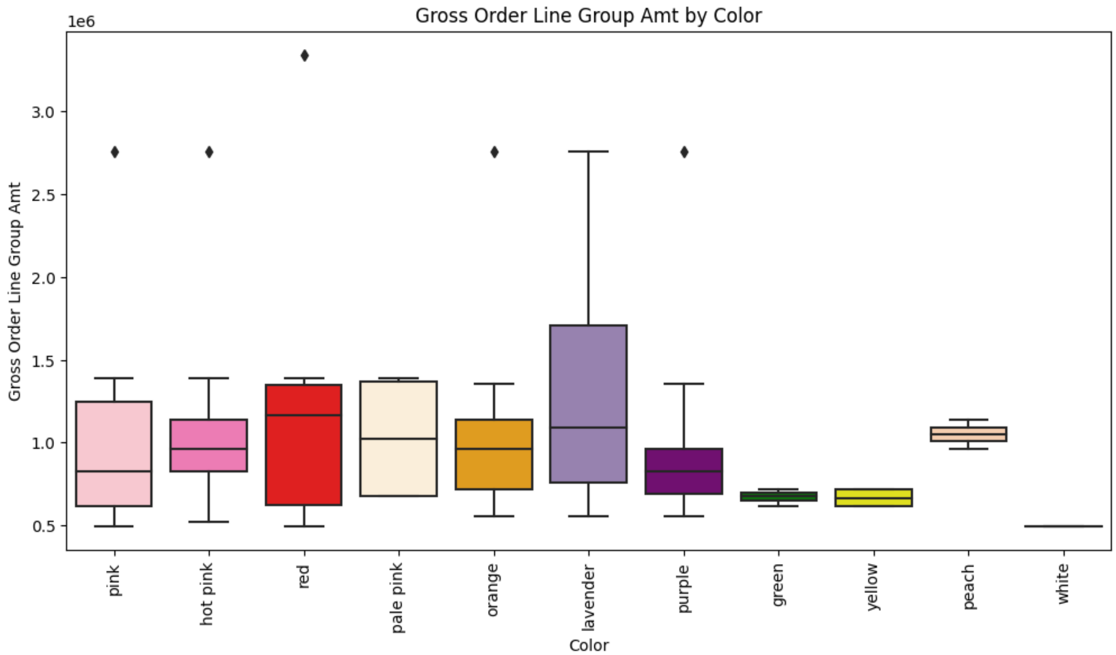
```
# ANOVA on Colors
model_colors = ols('Q("AOV") ~ C(Colors)', data=df_merged_2023).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("AOV") ~ C(Flowers)', data=df_merged_2023).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                  sum_sq    df         F   PR(>F)
C(Colors)    1455.173158  10.0  0.860961  0.57747
Residual     5070.517490  30.0       NaN      NaN
                  sum_sq    df        F    PR(>F)
C(Flowers)   3168.324165  16.0  1.41554  0.214973
Residual     3357.366483  24.0      NaN       NaN
```

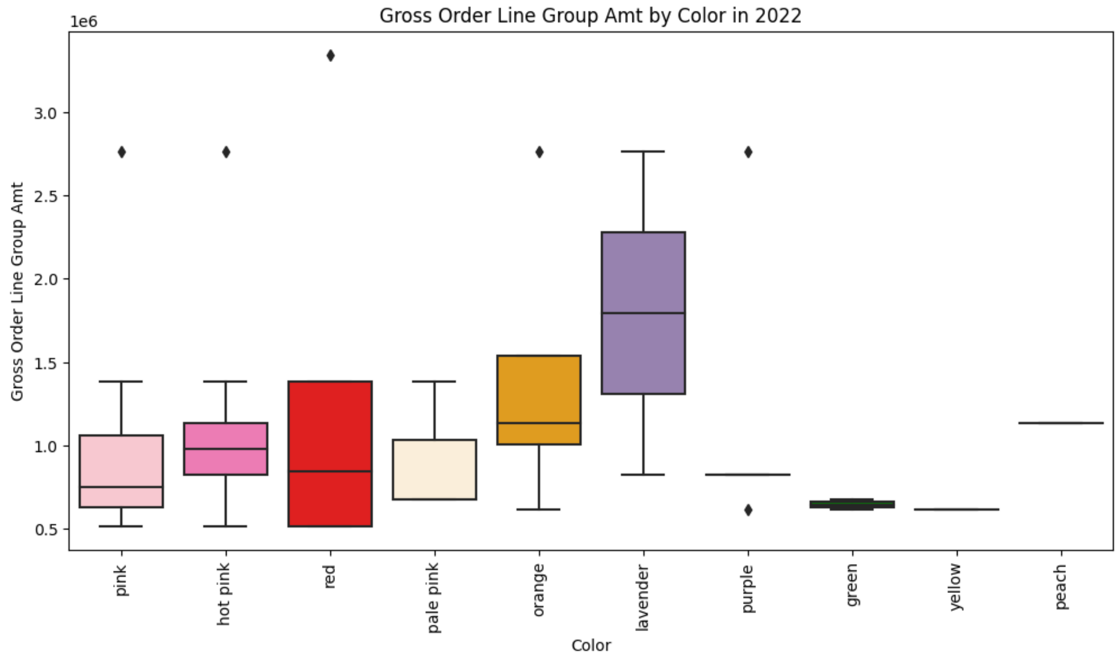
```
import statsmodels.api as sm
from statsmodels.formula.api import ols

# ANOVA on Colors
model_colors = ols('Q("AOV") ~ C(Colors)', data=df_merged).fit()
anova_table_colors = sm.stats.anova_lm(model_colors, typ=2)
print(anova_table_colors)

# ANOVA on Flowers
model_flowers = ols('Q("AOV") ~ C(Flowers)', data=df_merged).fit()
anova_table_flowers = sm.stats.anova_lm(model_flowers, typ=2)
print(anova_table_flowers)
```

```
                  sum_sq    df         F    PR(>F)
C(Colors)    3363.693266  10.0  2.571874  0.009774
Residual     9939.861357  76.0       NaN       NaN
                  sum_sq    df         F   PR(>F)
C(Flowers)   5650.522066  19.0  2.603612  0.00212
Residual     7653.032557  67.0       NaN      NaN
```

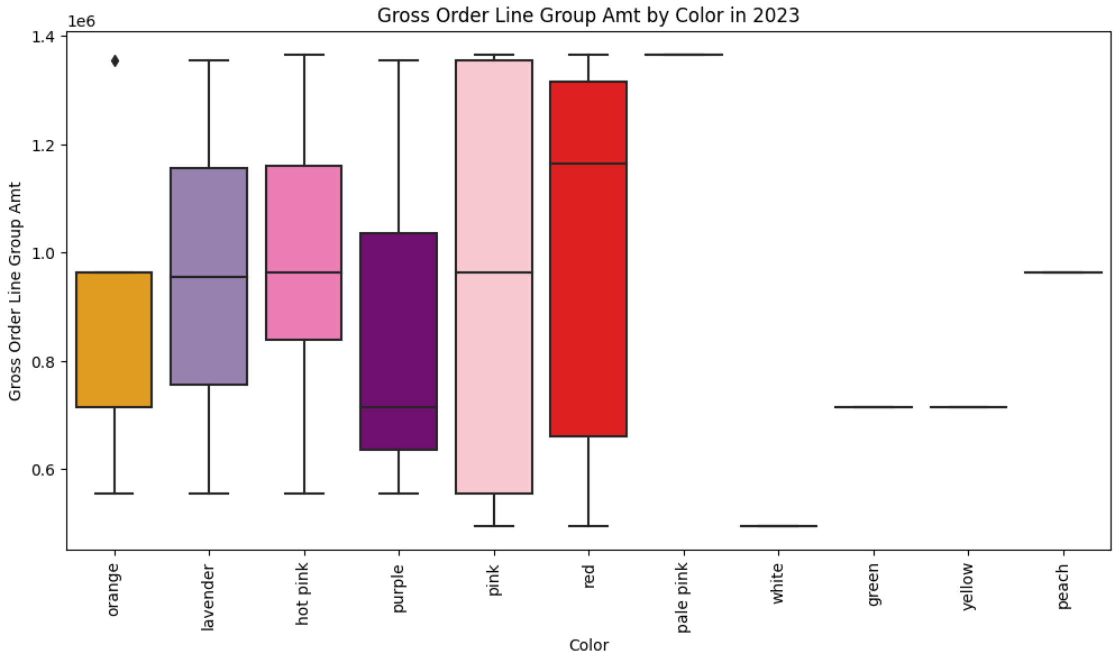
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Colors', y='Gross Order Line Group Amt', data=df_merged,␣
 ↪palette=custom_colors)
plt.title('Gross Order Line Group Amt by Color')
plt.xlabel('Color')
plt.ylabel('Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Gross Order Line Group Amt by Color')
plt.show()
```



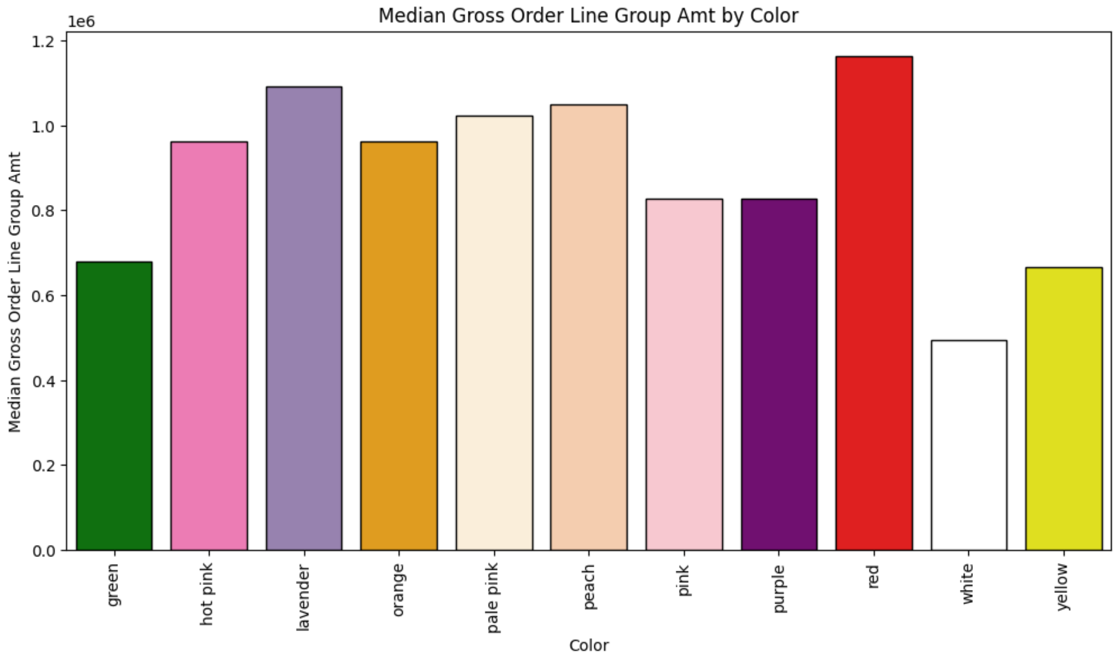

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Colors', y='Gross Order Line Group Amt', data=df_merged_2022,␣
 ↪palette=custom_colors)
plt.title('Gross Order Line Group Amt by Color in 2022')
plt.xlabel('Color')
plt.ylabel('Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Gross Order Line Group Amt by Color in 2022')
plt.show()
```



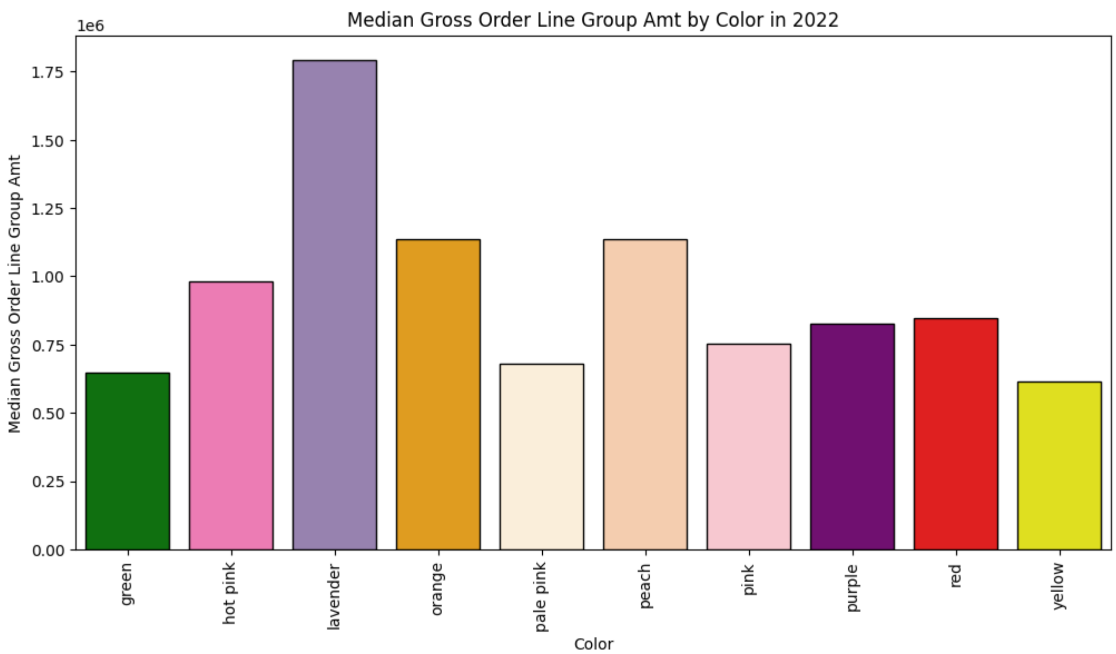

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Colors', y='Gross Order Line Group Amt', data=df_merged_2023,␣
 ↪palette=custom_colors)
plt.title('Gross Order Line Group Amt by Color in 2023')
plt.xlabel('Color')
plt.ylabel('Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Gross Order Line Group Amt by Color in 2023')
plt.show()
```



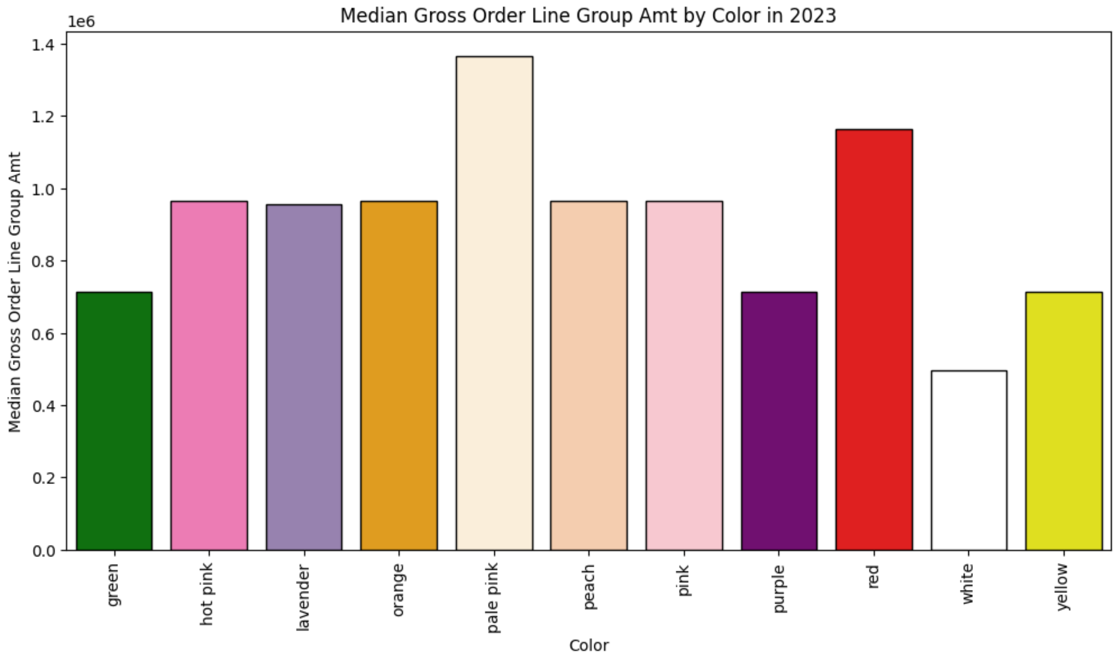

```
# Calculate median 'Gross Order Line Group Amt' for each color
color_median = df_merged.groupby('Colors')['Gross Order Line Group Amt'].
  ↪median().reset_index()

# Map each color to your custom color palette
color_palette = color_median['Colors'].map(custom_colors).fillna('#000000')  #␣
  ↪Colors not in custom_colors will be black

# Create the plot
plt.figure(figsize=(12, 6))
barplot = sns.barplot(x='Colors', y='Gross Order Line Group Amt',␣
  ↪data=color_median, palette=color_palette)

# Add borders to each bar
for rectangle in barplot.patches:
    rectangle.set_edgecolor('black')

plt.title('Median Gross Order Line Group Amt by Color')
plt.xlabel('Color')
plt.ylabel('Median Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Median Gross Order Line Group Amt by Color')
plt.show()
```




```
# Calculate median 'Gross Order Line Group Amt' for each color
color_median_2022 = df_merged_2022.groupby('Colors')['Gross Order Line Group␣
↪Amt'].median().reset_index()

# Map each color to your custom color palette
color_palette = color_median_2022['Colors'].map(custom_colors).
↪fillna('#000000')  # Colors not in custom_colors will be black

# Create the plot
plt.figure(figsize=(12, 6))
barplot = sns.barplot(x='Colors', y='Gross Order Line Group Amt',␣
↪data=color_median_2022, palette=color_palette)

# Add borders to each bar
for rectangle in barplot.patches:
    rectangle.set_edgecolor('black')

plt.title('Median Gross Order Line Group Amt by Color in 2022')
plt.xlabel('Color')
plt.ylabel('Median Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Median Gross Order Line Group Amt by Color in 2022')
plt.show()
```




```
# Calculate median 'Gross Order Line Group Amt' for each color
color_median_2023 = df_merged_2023.groupby('Colors')['Gross Order Line Group␣
↪Amt'].median().reset_index()

# Map each color to your custom color palette
color_palette = color_median_2023['Colors'].map(custom_colors).
↪fillna('#000000')  # Colors not in custom_colors will be black

# Create the plot
plt.figure(figsize=(12, 6))
barplot = sns.barplot(x='Colors', y='Gross Order Line Group Amt',␣
↪data=color_median_2023, palette=color_palette)

# Add borders to each bar
for rectangle in barplot.patches:
    rectangle.set_edgecolor('black')

plt.title('Median Gross Order Line Group Amt by Color in 2023')
plt.xlabel('Color')
plt.ylabel('Median Gross Order Line Group Amt')
plt.xticks(rotation=90)  # Rotates X-Axis Labels for better visibility
plt.savefig('Median Gross Order Line Group Amt by Color in 2023')
plt.show()
```



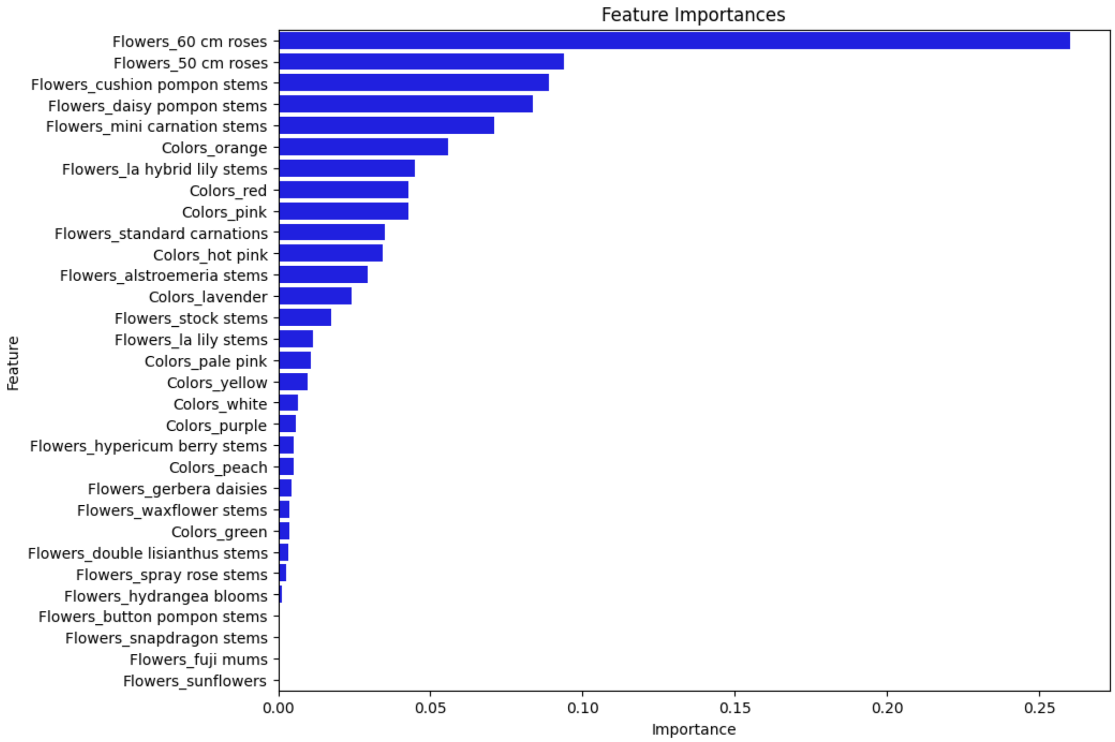

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestRegressor
```

```
df_merged.columns
```

```
Index([                    'Colors',                       'Flowers',
                        'StemPrice',                          'SQty',
                           'SPrice',                          'DQty',
                           'DPrice',                          'PQty',
                           'PPrice',                          'EQty',
                           'EPrice',                   'Arrangement',
                             'Year',              'Arrangement_Code',
                               2022,  'Featured Product Set Code',
        'Featured Product Set Name',        'Order Line Group Cnt',
       'Gross Order Line Group Amt',                           'AOV',
                               2023],
      dtype='object')
```

```
top_10 = df_merged[['Colors', 'Flowers','Gross Order Line Group Amt']]
# One-hot encode the categorical features
encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
encoded_data = encoder.fit_transform(top_10[['Colors', 'Flowers']])

# Create a DataFrame from the encoded data
```

```
encoded_df = pd.DataFrame(encoded_data, columns=encoder.get_feature_names_out())

# Concatenate the encoded data with the original DataFrame
top_10_encoded = pd.concat([top_10.drop(['Colors', 'Flowers'], axis=1).
 ↪reset_index(drop=True), encoded_df], axis=1)

# Separate target variable and features
y = top_10_encoded['Gross Order Line Group Amt']
X = top_10_encoded.drop(['Gross Order Line Group Amt'], axis=1)

X.columns = X.columns.astype(str)

# Impute missing values with the median
imputer = SimpleImputer(strategy='median')
X_imputed = imputer.fit_transform(X)

# Create a DataFrame from the imputed data
X_imputed_df = pd.DataFrame(X_imputed, columns=X.columns)

# Fit a Random Forest model
model = RandomForestRegressor(random_state=0)
model.fit(X_imputed_df, y)

# Get feature importances
importances = model.feature_importances_

# Create a DataFrame for the importances
importances_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
})

# Sort the DataFrame by importance
importances_df = importances_df.sort_values(by='Importance', ascending=False)

# Create a bar plot for the feature importances
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=importances_df, color='b')
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.savefig('Feature Importances by Flowers and Colors')
plt.show()
```




```python
# Select only the columns corresponding to 'Flowers' and 'Colors'
X = top_10_encoded.filter(regex='Flowers|Colors')

# Impute missing values with the most frequent
imputer = SimpleImputer(strategy='most_frequent')
X_imputed = imputer.fit_transform(X)

# Create a DataFrame from the imputed data
X_imputed_df = pd.DataFrame(X_imputed, columns=X.columns)

# Fit a Random Forest model
model = RandomForestRegressor(random_state=0)
model.fit(X_imputed_df, y)

# Get feature importances
importances = model.feature_importances_

# Create a DataFrame for the importances
importances_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
})
```

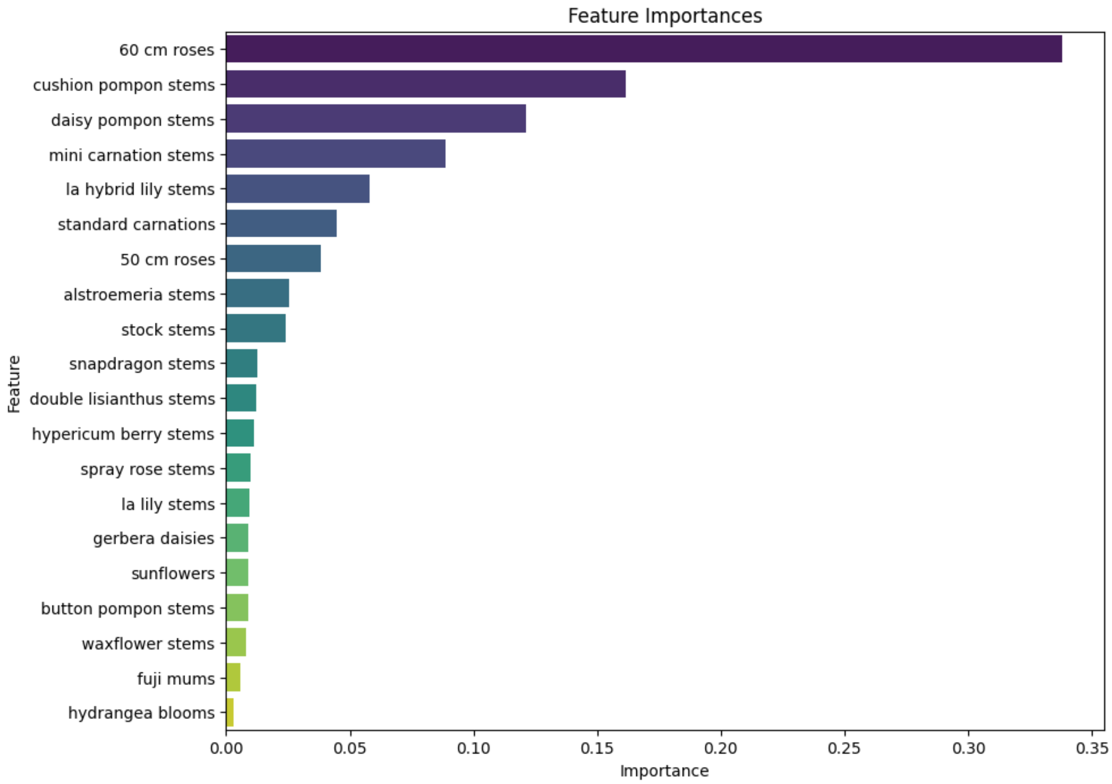
```
# Sum the importances of the binary columns corresponding to each unique flower␣
↪and color
flower_importances = importances_df[importances_df['Feature'].str.
↪startswith('Flowers')].sum()
color_importances = importances_df[importances_df['Feature'].str.
↪startswith('Colors')].sum()

print("Importance of Flowers: ", flower_importances)
print("Importance of Colors: ", color_importances)
```

```
Importance of Flowers:  Feature       Flowers_50 cm rosesFlowers_60 cm
rosesFlowers_…
Importance                                                  0.758488
dtype: object
Importance of Colors:  Feature       Colors_greenColors_hot
pinkColors_lavenderColo…
Importance                                                  0.241512
dtype: object
```

```
# Select only the columns corresponding to 'Flowers'
X_flowers = top_10_encoded.filter(regex='Flowers')

# Impute missing values with the most frequent
imputer = SimpleImputer(strategy='most_frequent')
X_flowers_imputed = imputer.fit_transform(X_flowers)

# Create a DataFrame from the imputed data
X_flowers_imputed_df = pd.DataFrame(X_flowers_imputed, columns=X_flowers.
↪columns)

# Fit a Random Forest model
model = RandomForestRegressor(random_state=0)
model.fit(X_flowers_imputed_df, y)

# Get feature importances
importances = model.feature_importances_

# Create a DataFrame for the importances
importances_df = pd.DataFrame({
    'Feature': X_flowers.columns,
    'Importance': importances
})

# Print the importances of each unique flower
print(importances_df.sort_values(by='Importance', ascending=False))
# Sort the DataFrame by importance
```

```
importances_df_sorted = importances_df.sort_values(by='Importance',␣
↪ascending=False)
# Remove 'Flowers_' prefix from feature names
importances_df_sorted['Feature'] = importances_df_sorted['Feature'].str.
↪replace('Flowers_', '')

# Plot the feature importances
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=importances_df_sorted,␣
↪palette='viridis')
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.savefig('Feature Importances by Flowers')
plt.show()
```

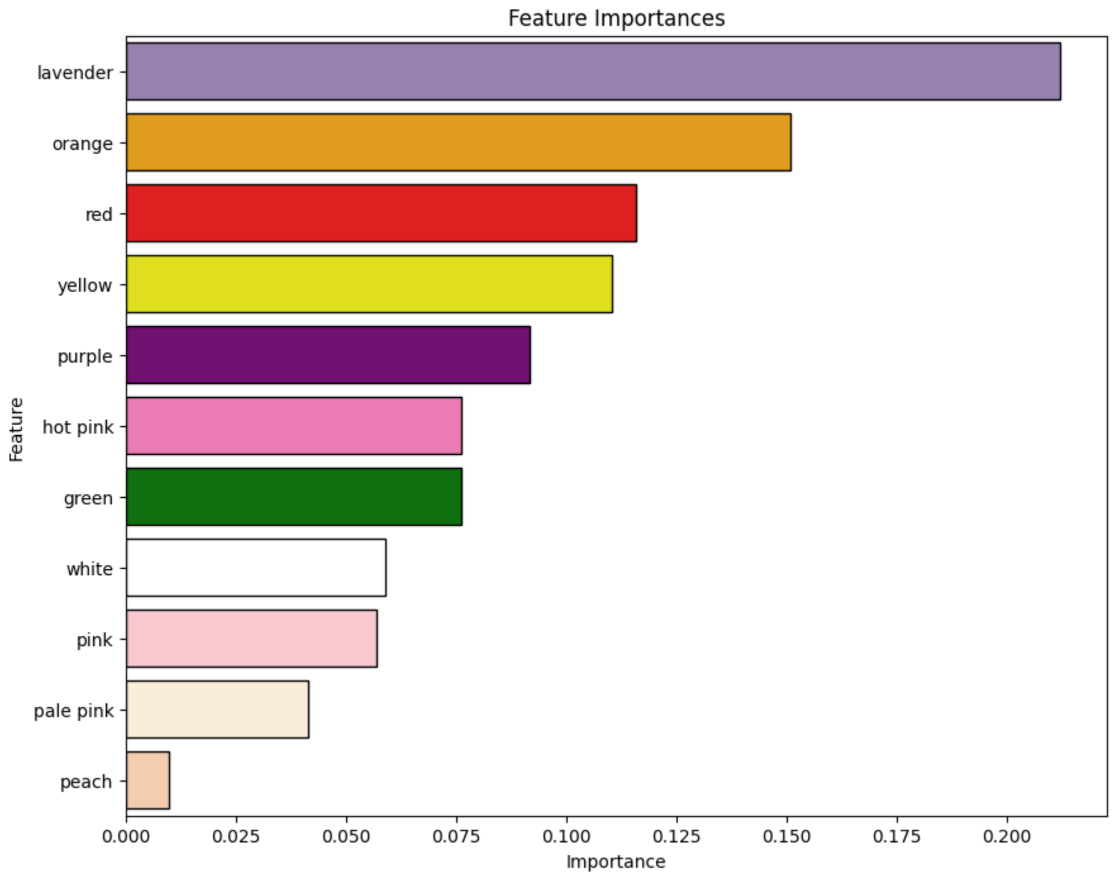
```
                          Feature  Importance
1              Flowers_60 cm roses    0.338269
4      Flowers_cushion pompon stems    0.161600
5        Flowers_daisy pompon stems    0.121315
13     Flowers_mini carnation stems    0.088589
11      Flowers_la hybrid lily stems    0.057986
16      Flowers_standard carnations    0.044919
0              Flowers_50 cm roses    0.038382
2        Flowers_alstroemeria stems    0.025571
17              Flowers_stock stems    0.024067
14         Flowers_snapdragon stems    0.012609
6   Flowers_double lisianthus stems    0.012108
10    Flowers_hypericum berry stems    0.011259
15         Flowers_spray rose stems    0.009720
12            Flowers_la lily stems    0.009329
8           Flowers_gerbera daisies    0.009153
18              Flowers_sunflowers    0.009083
3        Flowers_button pompon stems    0.008968
19           Flowers_waxflower stems    0.008094
7                 Flowers_fuji mums    0.005724
9          Flowers_hydrangea blooms    0.003252
```




```
# Select only the columns corresponding to 'Colors'
X_colors = top_10_encoded.filter(regex='Colors')

# Impute missing values with the most frequent
imputer = SimpleImputer(strategy='most_frequent')
X_colors_imputed = imputer.fit_transform(X_colors)

# Create a DataFrame from the imputed data
X_colors_imputed_df = pd.DataFrame(X_colors_imputed, columns=X_colors.columns)

# Fit a Random Forest model
model = RandomForestRegressor(random_state=0)
model.fit(X_colors_imputed_df, y)

# Get feature importances
importances = model.feature_importances_

# Create a DataFrame for the importances
importances_df = pd.DataFrame({
    'Feature': X_colors.columns,
    'Importance': importances
})
```

```python
# Print the importances of each unique color
print(importances_df.sort_values(by='Importance', ascending=False))
# Sort the DataFrame by importance
importances_df_sorted = importances_df.sort_values(by='Importance',␣
↪ascending=False)
# Remove 'Colors_' prefix from feature names
importances_df_sorted['Feature'] = importances_df_sorted['Feature'].str.
↪replace('Colors_', '')

# Create a list of colors for the barplot
colors = [custom_colors.get(feature, 'gray') for feature in␣
↪importances_df_sorted['Feature']]

# Create the barplot
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=importances_df_sorted,␣
↪palette=colors, edgecolor='black')
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.savefig('Feature Importances by Colors')
plt.show()
```

```
            Feature  Importance
2   Colors_lavender    0.212144
3     Colors_orange    0.150827
8        Colors_red    0.115897
10    Colors_yellow    0.110274
7     Colors_purple    0.091763
1   Colors_hot pink    0.076252
0      Colors_green    0.076066
9      Colors_white    0.058775
6       Colors_pink    0.056859
4  Colors_pale pink    0.041279
5      Colors_peach    0.009862
```




```
# Select all arrangements instead of just the top 10

# Create a DataFrame with unique flowers and colors for each arrangement
df_merged_unique = df_merged.groupby('Arrangement').agg({'Flowers': 'nunique',␣
↪'Colors': 'nunique'}).reset_index()

# Encode the categorical variables
encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
encoded_data = encoder.fit_transform(df_merged_unique[['Colors', 'Flowers']])

# Create a DataFrame from the encoded data
encoded_df = pd.DataFrame(encoded_data, columns=encoder.
↪get_feature_names_out(['Colors', 'Flowers']))

# Concatenate the encoded data with the original DataFrame
all_arrangements_encoded = pd.concat([df_merged_unique.drop(['Colors',␣
↪'Flowers'], axis=1), encoded_df], axis=1)
# Drop the 'Arrangement' column
all_arrangements_encoded = all_arrangements_encoded.drop('Arrangement', axis=1)
```

```python
# Impute missing values with the median
imputer = SimpleImputer(strategy='median')
imputed_data = imputer.fit_transform(all_arrangements_encoded)

# Create a DataFrame from the imputed data
all_arrangements_imputed = pd.DataFrame(imputed_data,␣
↪columns=all_arrangements_encoded.columns)

# Create a new target variable that only contains the GOLGA for the␣
↪arrangements in 'all_arrangements_imputed'
y = df_merged.loc[all_arrangements_imputed.index, 'Gross Order Line Group Amt']

# Fit a Random Forest model
model = RandomForestRegressor(random_state=0)
model.fit(all_arrangements_imputed, y)

# Get feature importances
importances = model.feature_importances_

# Create a DataFrame of feature importances
importances_df = pd.DataFrame({'Feature': all_arrangements_imputed.columns,␣
↪'Importance': importances})

# Sort the DataFrame by importance
importances_df_sorted = importances_df.sort_values(by='Importance',␣
↪ascending=False)

# Print the DataFrame
print(importances_df_sorted)
```

```
      Feature  Importance
5   Flowers_2    0.140609
7   Flowers_4    0.120313
4   Flowers_1    0.114643
8   Flowers_5    0.110416
10  Flowers_7    0.093777
0    Colors_1    0.085963
9   Flowers_6    0.074904
1    Colors_3    0.071351
3    Colors_5    0.069342
6   Flowers_3    0.059667
2    Colors_4    0.059015
```

```python
# Print categories for 'Colors'
print("Colors categories:")
for i, category in enumerate(encoder.categories_[0]):
```

```
    print(f"Colors_{i+1}: {category}")

# Print categories for 'Flowers'
print("\nFlowers categories:")
for i, category in enumerate(encoder.categories_[1]):
    print(f"Flowers_{i+1}: {category}")
```

```
Colors categories:
Colors_1: 1
Colors_2: 3
Colors_3: 4
Colors_4: 5

Flowers categories:
Flowers_1: 1
Flowers_2: 2
Flowers_3: 3
Flowers_4: 4
Flowers_5: 5
Flowers_6: 6
Flowers_7: 7
```

```
import nbformat
from nbconvert import PDFExporter, HTMLExporter, LatexExporter, MarkdownExporter

# Read the Jupyter Notebook file
with open('FTD_VDay.ipynb', 'r', encoding='utf-8') as f:
    nb = nbformat.read(f, as_version=4)

# Configure the exporters
pdf_exporter = PDFExporter()
pdf_exporter.exclude_input_prompt = True
pdf_exporter.exclude_output_prompt = True

html_exporter = HTMLExporter()
latex_exporter = LatexExporter()
markdown_exporter = MarkdownExporter()

# Export the notebook to PDF
pdf_output, _ = pdf_exporter.from_notebook_node(nb)

# Export the notebook to HTML
html_output, _ = html_exporter.from_notebook_node(nb)

# Export the notebook to LaTeX
latex_output, _ = latex_exporter.from_notebook_node(nb)
```

```python
# Export the notebook to Markdown
markdown_output, _ = markdown_exporter.from_notebook_node(nb)

# Save the outputs to files
with open('FTD_VDay.pdf', 'wb') as f:
    f.write(pdf_output)

with open('FTD_VDay.html', 'w', encoding='utf-8') as f:
    f.write(html_output)

with open('FTD_VDay.tex', 'w', encoding='utf-8') as f:
    f.write(latex_output)

with open('FTD_VDay.md', 'w', encoding='utf-8') as f:
    f.write(markdown_output)
```