```
#pip install pandas_profiling

import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import seaborn as sns
import numpy as np
import warnings
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from pandas_profiling import ProfileReport

warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt

# Load the sales data into a pandas DataFrame
df = pd.read_csv('full_gen_data.csv')

df.head()
```

```
   country article  sales  regular_price  current_price     ratio
retailweek  \
0  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
1  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
2  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
3  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
4  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27

   promo1  promo2  customer_id  ...    style                sizes
gender  \
0       0       0       1003.0  ...     slim  xxs,xs,s,m,l,xl,xxl
women
1       0       0       1003.0  ...  regular  xxs,xs,s,m,l,xl,xxl
women
2       0       0       1003.0  ...  regular  xxs,xs,s,m,l,xl,xxl
women
3       0       0       1003.0  ...  regular  xxs,xs,s,m,l,xl,xxl
kids
4       0       0       1003.0  ...  regular  xxs,xs,s,m,l,xl,xxl
women

   rgb_r_main_col rgb_g_main_col rgb_b_main_col rgb_r_sec_col
rgb_g_sec_col  \
0             205            104             57           255
```

```
187
1             188             238             104             255
187
2             205             173               0             255
187
3             205             140             149             164
211
4             138              43             226             164
211

   rgb_b_sec_col  label
0            255      0
1            255      0
2            255      0
3            238      0
4            238      0

[5 rows x 24 columns]
```

```
# Check Number of column and column names
print(df.columns)
```

```
Index(['country', 'article', 'sales', 'regular_price',
'current_price',
       'ratio', 'retailweek', 'promo1', 'promo2', 'customer_id',
'article.1',
       'productgroup', 'category', 'cost', 'style', 'sizes', 'gender',
       'rgb_r_main_col', 'rgb_g_main_col', 'rgb_b_main_col',
'rgb_r_sec_col',
       'rgb_g_sec_col', 'rgb_b_sec_col', 'label'],
      dtype='object')
```

"article" refers to a unique identifier for a specific product or item. It is represented by a 6-digit article number.

```
df.describe()
```

```
                sales  regular_price  current_price          ratio  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean       56.781800      52.391200      28.290800       0.545646
std        87.934743      35.272128      22.578343       0.194363
min         1.000000       3.950000       1.950000       0.296482
25%        10.000000      25.950000      11.950000       0.354839
50%        26.000000      40.950000      20.950000       0.525044
75%        64.000000      79.950000      37.950000       0.699248
max       898.000000     197.950000     195.950000       1.000000

               promo1         promo2    customer_id           cost  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean        0.061900       0.004900    2721.726500       6.517000
```

```
std          0.240975       0.069829    1908.085499       3.914728
min          0.000000       0.000000       1.000000       1.290000
25%          0.000000       0.000000    1017.000000       2.290000
50%          0.000000       0.000000    2091.000000       6.950000
75%          0.000000       0.000000    4570.250000       9.600000
max          1.000000       1.000000    5999.000000      13.290000

       rgb_r_main_col  rgb_g_main_col  rgb_b_main_col
rgb_r_sec_col  \
count   100000.000000   100000.000000   100000.000000  100000.000000

mean       161.400000      139.600000      133.500000     207.700000

std         39.790147       63.641814       81.148727      35.313205

min         79.000000       26.000000        0.000000     164.000000

25%        138.000000      104.000000       57.000000     164.000000

50%        160.000000      144.000000      143.000000     205.000000

75%        205.000000      181.000000      205.000000     255.000000

max        205.000000      238.000000      250.000000     255.000000


       rgb_g_sec_col  rgb_b_sec_col          label
count  100000.000000  100000.000000  100000.00000
mean      181.400000     209.900000       0.13928
std        23.474359      45.306849       0.34624
min       155.000000     155.000000       0.00000
25%       155.000000     155.000000       0.00000
50%       187.000000     238.000000       0.00000
75%       211.000000     255.000000       0.00000
max       211.000000     255.000000       1.00000

df.shape

(100000, 24)

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 24 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   country         100000 non-null  object
 1   article         100000 non-null  object
 2   sales           100000 non-null  int64
 3   regular_price   100000 non-null  float64
```

```
 4   current_price   100000 non-null  float64
 5   ratio           100000 non-null  float64
 6   retailweek      100000 non-null  object
 7   promo1          100000 non-null  int64
 8   promo2          100000 non-null  int64
 9   customer_id     100000 non-null  float64
 10  article.1       100000 non-null  object
 11  productgroup    100000 non-null  object
 12  category        100000 non-null  object
 13  cost            100000 non-null  float64
 14  style           100000 non-null  object
 15  sizes           100000 non-null  object
 16  gender          100000 non-null  object
 17  rgb_r_main_col  100000 non-null  int64
 18  rgb_g_main_col  100000 non-null  int64
 19  rgb_b_main_col  100000 non-null  int64
 20  rgb_r_sec_col   100000 non-null  int64
 21  rgb_g_sec_col   100000 non-null  int64
 22  rgb_b_sec_col   100000 non-null  int64
 23  label           100000 non-null  int64
dtypes: float64(5), int64(10), object(9)
memory usage: 18.3+ MB
```

```
df.isnull().sum()
```

```
country           0
article           0
sales             0
regular_price     0
current_price     0
ratio             0
retailweek        0
promo1            0
promo2            0
customer_id       0
article.1         0
productgroup      0
category          0
cost              0
style             0
sizes             0
gender            0
rgb_r_main_col    0
rgb_g_main_col    0
rgb_b_main_col    0
rgb_r_sec_col     0
rgb_g_sec_col     0
rgb_b_sec_col     0
label             0
dtype: int64
```

```
profile = ProfileReport(df, title='Data Analysis Report',
explorative=True)
profile.to_widgets()
```

{"model_id":"cd202af2a20747dcb52785ab185c199b","version_major":2,"vers
ion_minor":0}

{"model_id":"3273c12fb9514db19c60ca77316c96fb","version_major":2,"vers
ion_minor":0}

{"model_id":"761fd20f217642b3bd33a40ddcc4d5ef","version_major":2,"vers
ion_minor":0}

{"model_id":"c3c518d1d7534cc78b0413cf473e8978","version_major":2,"vers
ion_minor":0}

```
profile.to_file('data_analysis_report.html')
```

{"model_id":"fa4f2a84470c416484ad5413833801e3","version_major":2,"vers
ion_minor":0}

{"model_id":"379ca52318394e1b84207c02f398579e","version_major":2,"vers
ion_minor":0}

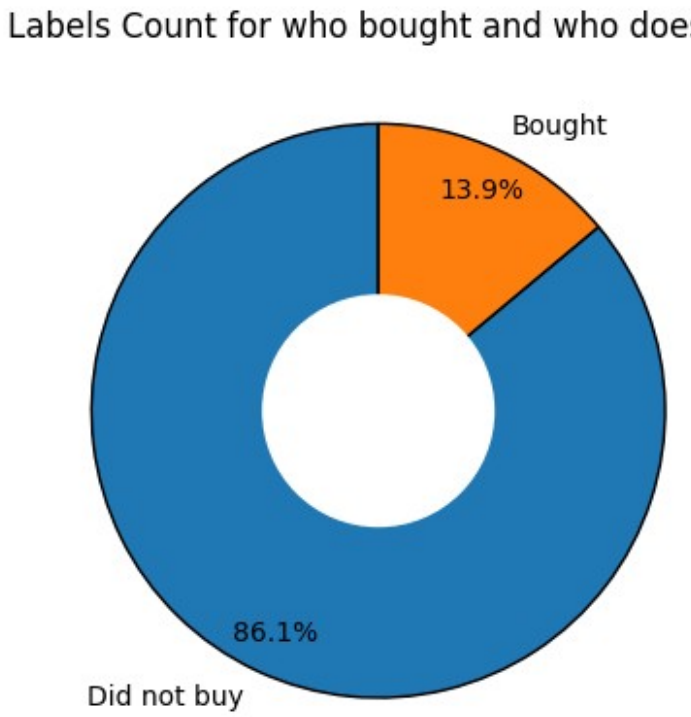
```
# Get descriptive statistics of numerical features
num_features = ['sales', 'regular_price', 'current_price', 'ratio',
'cost']
num_stats = df[num_features].describe()
print(num_stats)
```

```
                sales  regular_price  current_price          ratio  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean       56.781800      52.391200      28.290800       0.545646
std        87.934743      35.272128      22.578343       0.194363
min         1.000000       3.950000       1.950000       0.296482
25%        10.000000      25.950000      11.950000       0.354839
50%        26.000000      40.950000      20.950000       0.525044
75%        64.000000      79.950000      37.950000       0.699248
max       898.000000     197.950000     195.950000       1.000000

                cost
count  100000.000000
mean        6.517000
std         3.914728
min         1.290000
25%         2.290000
50%         6.950000
75%         9.600000
max        13.290000
```

```
# Get value counts of categorical features
cat_features = ['country', 'promo1', 'promo2', 'productgroup',
```

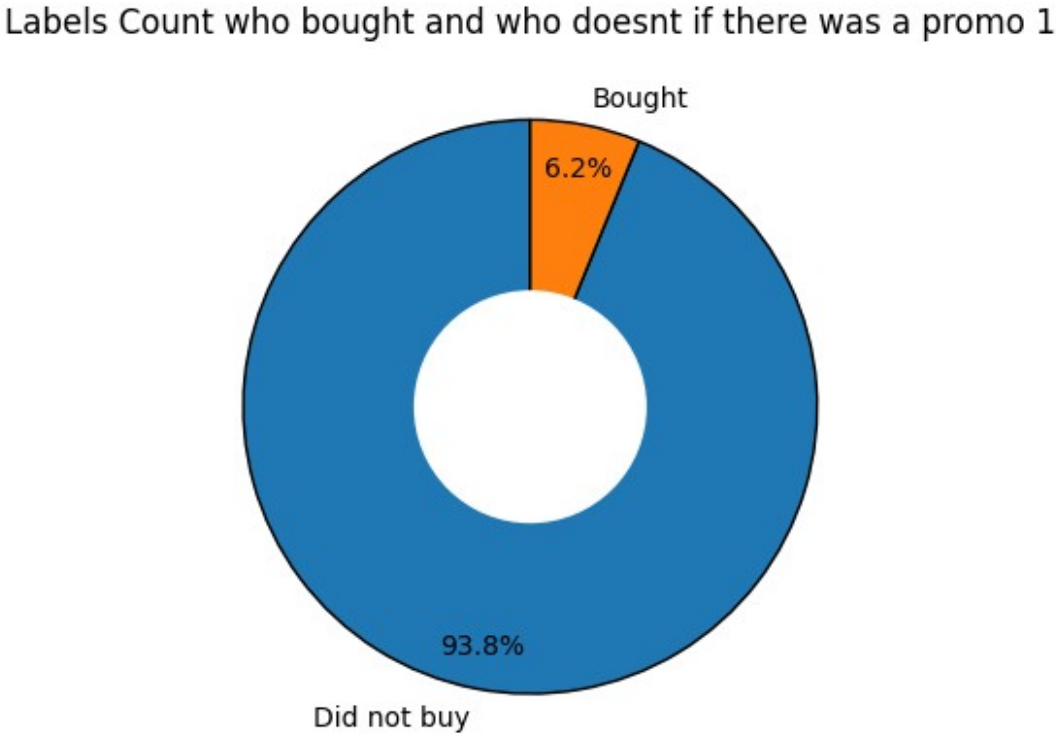
```
'category', 'gender']
for feature in cat_features:
    value_counts = df[feature].value_counts()
    print(f"\nValue counts for {feature}:")
    print(value_counts)


Value counts for country:
Germany    49400
Austria    35140
France     15460
Name: country, dtype: int64

Value counts for promo1:
0    93810
1     6190
Name: promo1, dtype: int64

Value counts for promo2:
0    99510
1      490
Name: promo2, dtype: int64

Value counts for productgroup:
SHOES                    60000
HARDWARE ACCESSORIES     20000
SHORTS                   10000
SWEATSHIRTS              10000
Name: productgroup, dtype: int64

Value counts for category:
TRAINING             30000
RUNNING              20000
FOOTBALL GENERIC     20000
GOLF                 10000
RELAX CASUAL         10000
INDOOR               10000
Name: category, dtype: int64

Value counts for gender:
women     70000
kids      10000
unisex    10000
men       10000
Name: gender, dtype: int64

# Create a pie chart of label
label_counts_maps = {
0: 'Did not buy',
1: 'Bought' }
```

```
colors = ['red', 'yellow', 'orange', 'purple']
hole_size = 0.4  # Size of the hole in the center

label_counts = df['label'].value_counts()
plt.pie(label_counts.values,
labels=label_counts.index.map(label_counts_maps), autopct='%1.1f%%',
startangle=90, pctdistance=0.85, wedgeprops={'edgecolor': 'black'})

centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Labels Count for who bought and who doesnt ')
plt.show()
```

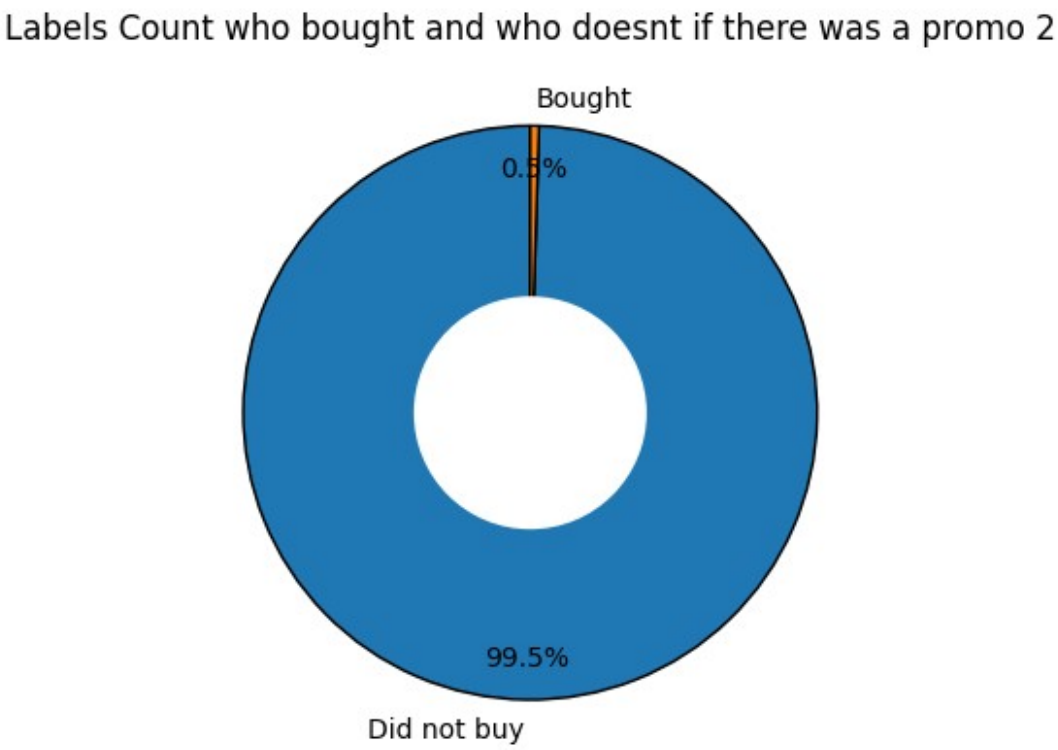



```
# Create a pie chart of promo1
promo1_counts = df['promo1'].value_counts()
plt.pie(promo1_counts.values,
labels=promo1_counts.index.map(label_counts_maps), autopct='%1.1f%%',
startangle=90, pctdistance=0.85, wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
```

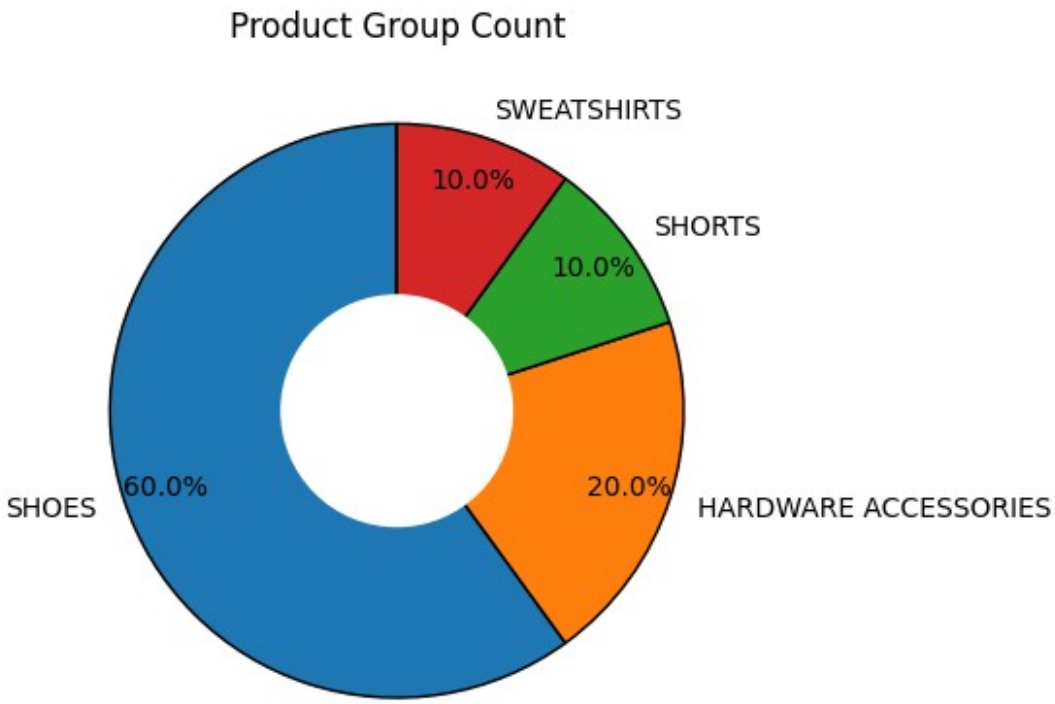
```
fig.gca().add_artist(centre_circle)

plt.title('Labels Count who bought and who doesnt if there was a promo
1')

plt.show()
```



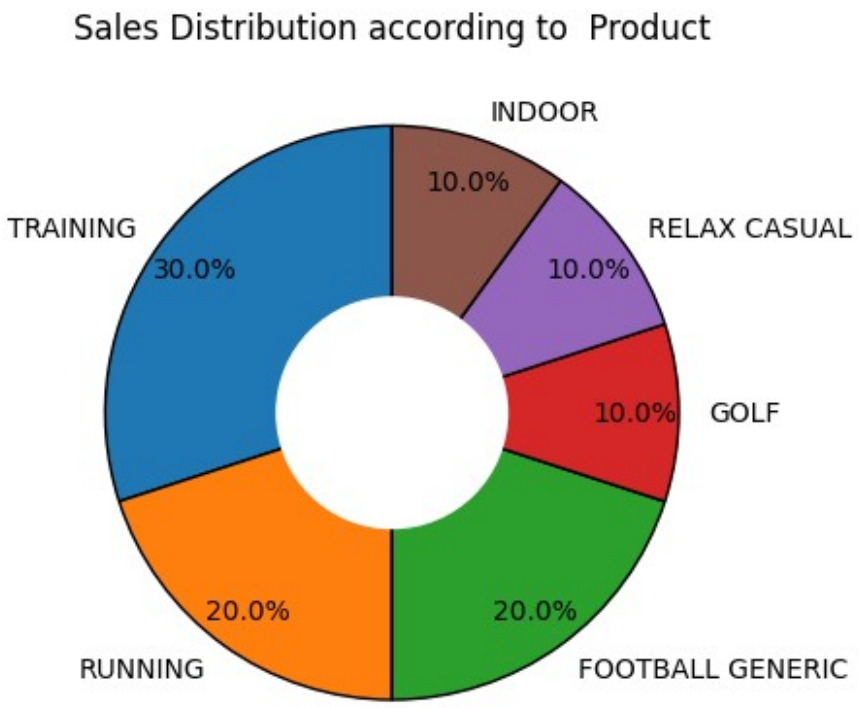

```
# Create a pie chart of promo2
promo2_counts = df['promo2'].value_counts()
plt.pie(promo2_counts.values,
labels=promo1_counts.index.map(label_counts_maps), autopct='%1.1f%
%',startangle=90, pctdistance=0.85, wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title('Labels Count who bought and who doesnt if there was a promo
2')
plt.show()
```



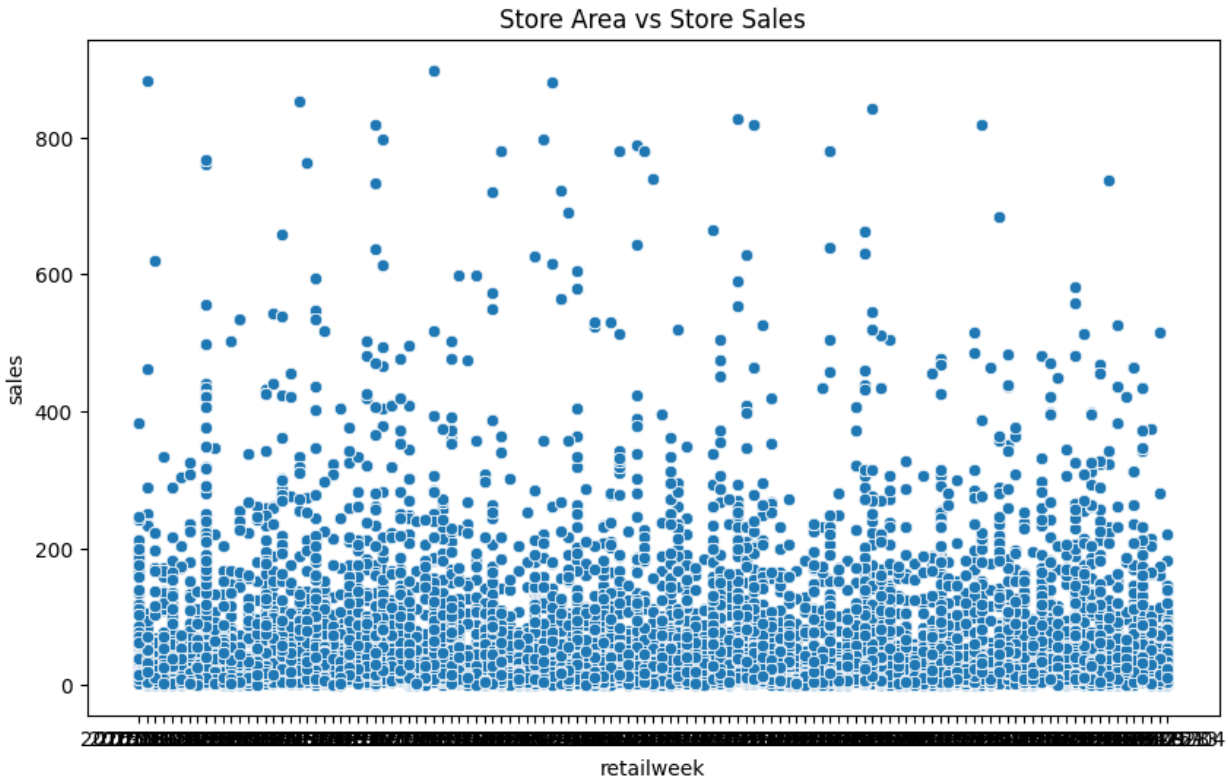

```
# Create a pie chart of gender
productgroup_counts = df['productgroup'].value_counts()
plt.pie(productgroup_counts.values, labels=productgroup_counts.index,
autopct='%1.1f%%',startangle=90, pctdistance=0.85,
wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title('Product Group Count')


plt.show()
```




```
# Create a pie chart of gender
country_counts = df['category'].value_counts()
plt.pie(country_counts.values, labels=country_counts.index,
autopct='%1.1f%%',startangle=90, pctdistance=0.85,
wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Sales Distribution according to  Product')
plt.show()
```

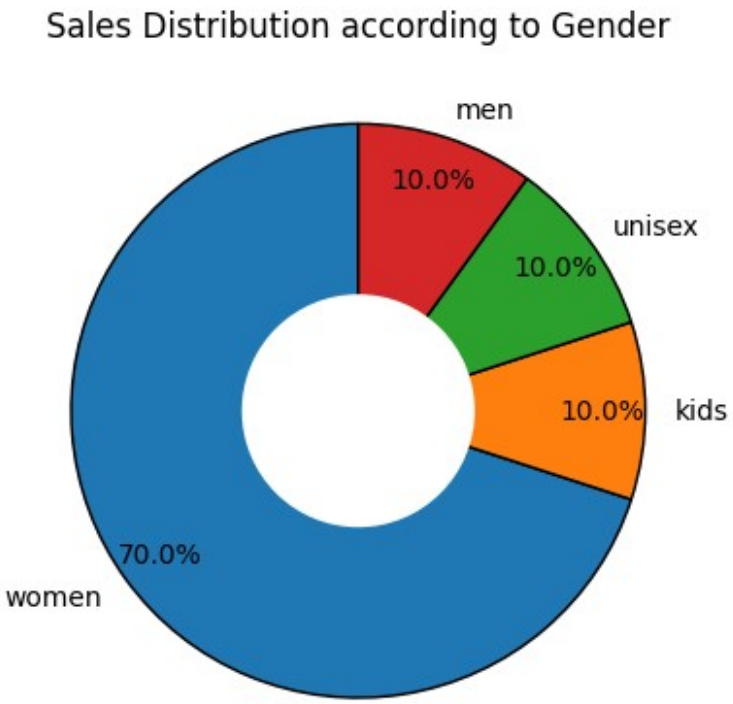



```
# Create visualizations
plt.figure(figsize=(10, 6))
sns.scatterplot(df, x='retailweek', y='sales')
plt.title('Store Area vs Store Sales')
plt.show()
```



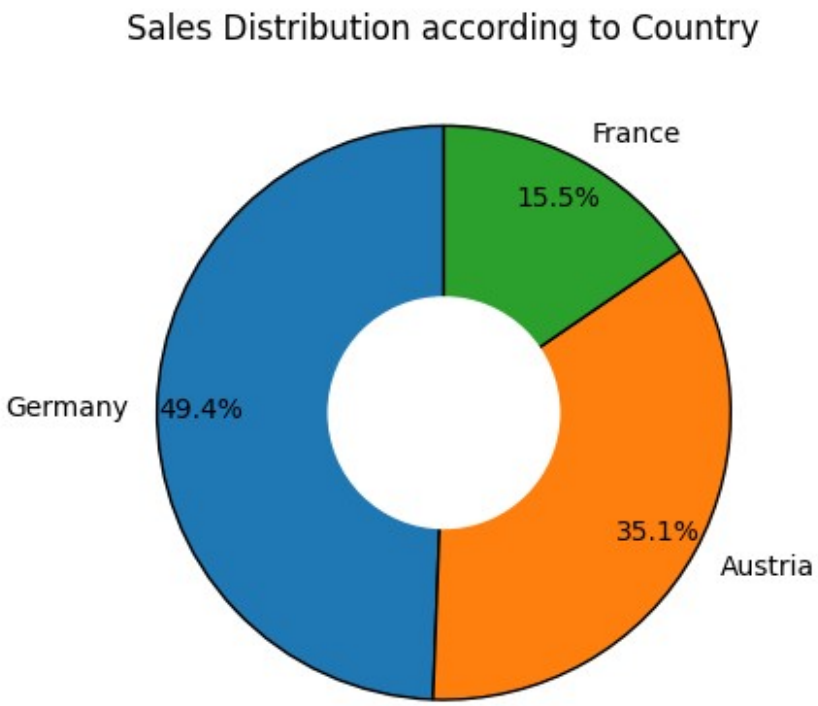
What is the most gender interested in our products?

```
# Create a pie chart of gender
gender_counts = df['gender'].value_counts()
plt.pie(gender_counts.values, labels=gender_counts.index,
autopct='%1.1f%%',startangle=90, pctdistance=0.85,
wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title('Sales Distribution according to Gender')
plt.show()
```



What is the most country interested in our products?

```
# Create a pie chart of gender
country_counts = df['country'].value_counts()
plt.pie(country_counts.values, labels=country_counts.index,
autopct='%1.1f%%',startangle=90, pctdistance=0.85,
wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title('Sales Distribution according to Country')
plt.show()
```



Add Month Column

```
df['month']=df['retailweek'].str[5:7]
df['month'].astype(int)
```

```
0         3
1         3
2         3
3         3
4         3
        ..
99995     6
99996     6
99997     6
99998     6
99999     6
Name: month, Length: 100000, dtype: int64
```

```
df['year']=df['retailweek'].str[0:4]
df['year'].astype(int)
```

```
0         2016
1         2016
2         2016
3         2016
4         2016
```

```
         ...
99995    2016
99996    2016
99997    2016
99998    2016
99999    2016
Name: year, Length: 100000, dtype: int64
```

```
df.head()
```

```
   country article  sales  regular_price  current_price     ratio
retailweek  \
0  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
1  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
2  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
3  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27
4  Germany  YN8639     28           5.95           3.95  0.663866
2016-03-27

   promo1  promo2  customer_id  ... gender rgb_r_main_col
rgb_g_main_col  \
0       0       0       1003.0  ...  women            205
104
1       0       0       1003.0  ...  women            188
238
2       0       0       1003.0  ...  women            205
173
3       0       0       1003.0  ...   kids            205
140
4       0       0       1003.0  ...  women            138
43

   rgb_b_main_col rgb_r_sec_col rgb_g_sec_col rgb_b_sec_col  label
month  \
0              57           255           187           255      0
03
1             104           255           187           255      0
03
2               0           255           187           255      0
03
3             149           164           211           238      0
03
4             226           164           211           238      0
03

   year
```

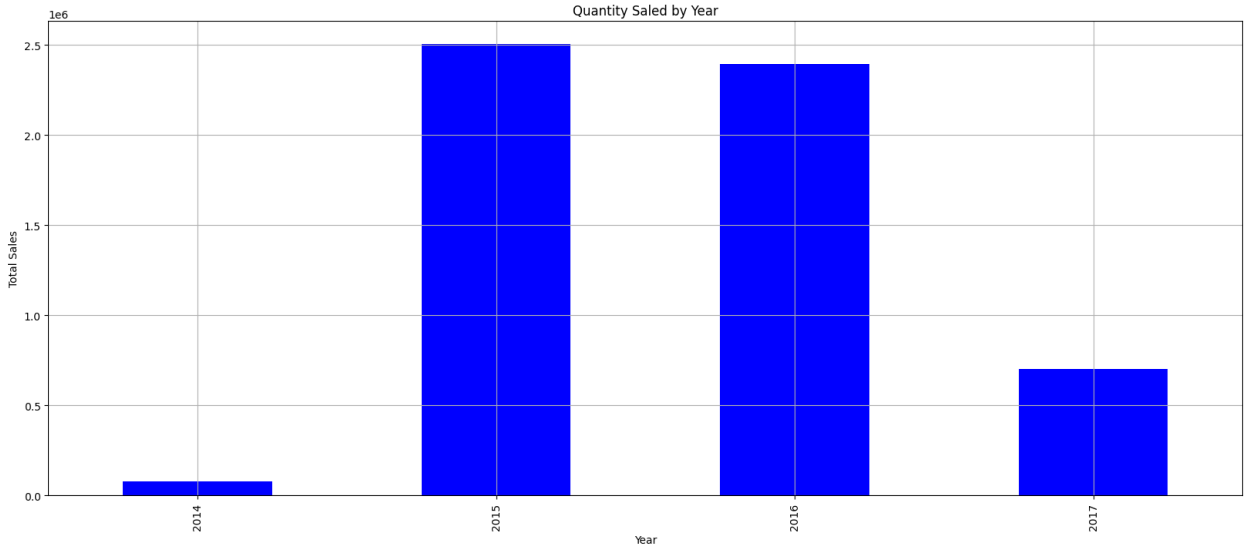
```
0  2016
1  2016
2  2016
3  2016
4  2016

[5 rows x 26 columns]
```

```
sales_by_year=df.groupby('year')['sales'].sum()
print(sales_by_year)
```

```
year
2014      78010
2015    2505760
2016    2392740
2017     701670
Name: sales, dtype: int64
```

What is the year that has the best and worst sales ?

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(20, 8))
sales_by_year.plot(kind='bar', color='blue')
plt.xlabel('Year')
plt.ylabel('Total Sales')
plt.title('Quantity Saled by Year')
plt.grid(True)
plt.show()
```

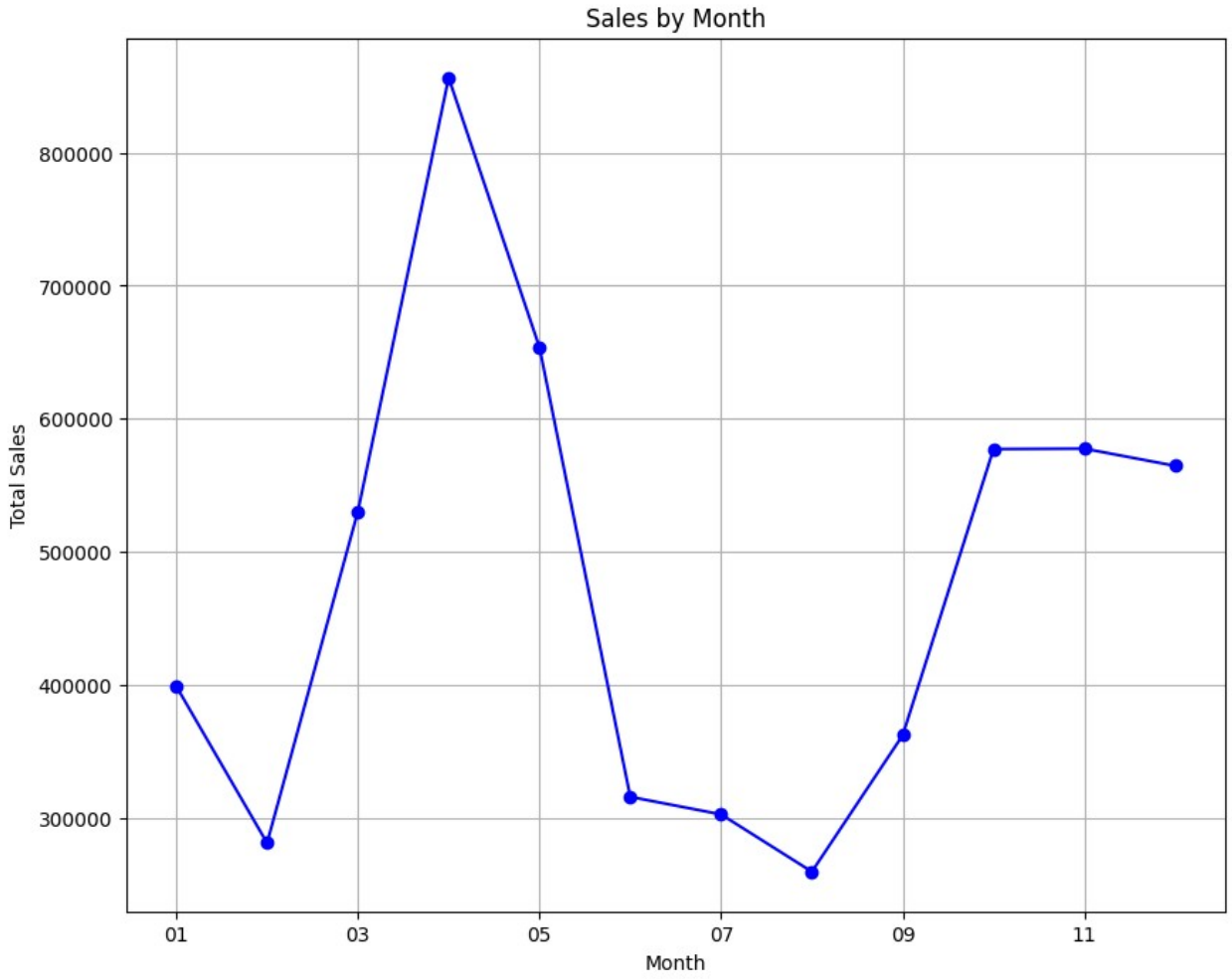



```
sales_by_month=df.groupby('month')['sales'].sum()
print(sales_by_month)
```

```
month
01    398810
02    280870
03    530130
04    856430
05    653640
06    315580
07    302390
08    259290
09    361940
10    577110
11    577460
12    564530
Name: sales, dtype: int64
```

What is the month that has best Sales ?

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 8))
sales_by_month.plot(kind='line', marker='o',
linestyle='-',color='blue')
plt.xlabel('Month')
plt.ylabel('Total Sales')
plt.title('Sales by Month')
plt.grid(True)
plt.show()
```



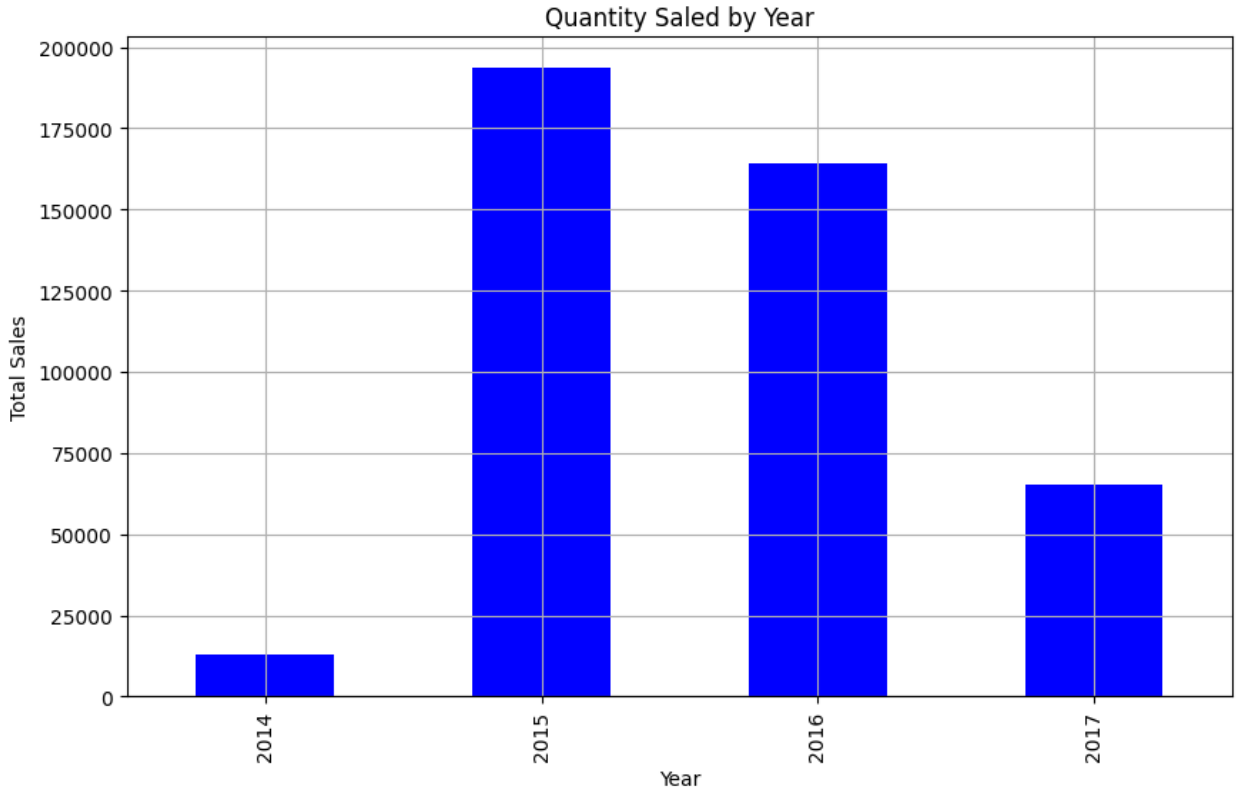
What is the year that has best and worst advertisement result ?

```
filtered_df = df[df['label'] == 1]

sales_by_year=filtered_df.groupby('year')['sales'].sum()
print(sales_by_year)
```

```
year
2014     12819
2015    193457
2016    164304
2017     65120
Name: sales, dtype: int64
```

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
sales_by_year.plot(kind='bar', color='blue')
plt.xlabel('Year')
plt.ylabel('Total Sales')
```

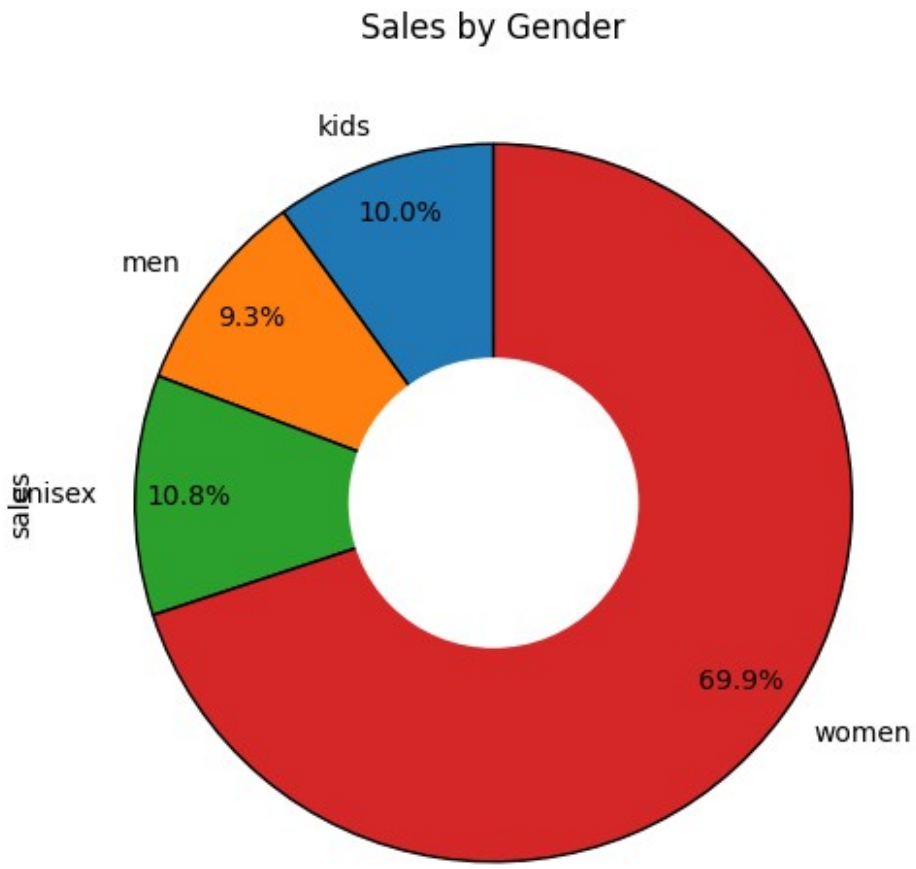
```
plt.title('Quantity Saled by Year')
plt.grid(True)
plt.show()
```



Which gender responds to the advertisements the most?

```
sales_by_gender=filtered_df.groupby('gender')['sales'].sum()
print(sales_by_gender)

gender
kids       43457
men        40409
unisex     47128
women     304706
Name: sales, dtype: int64

# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
sales_by_gender.plot(kind='pie',autopct='%1.1f%%',startangle=90,
pctdistance=0.85, wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
```

```
plt.title('Sales by Gender')
plt.grid(True)
plt.show()
```



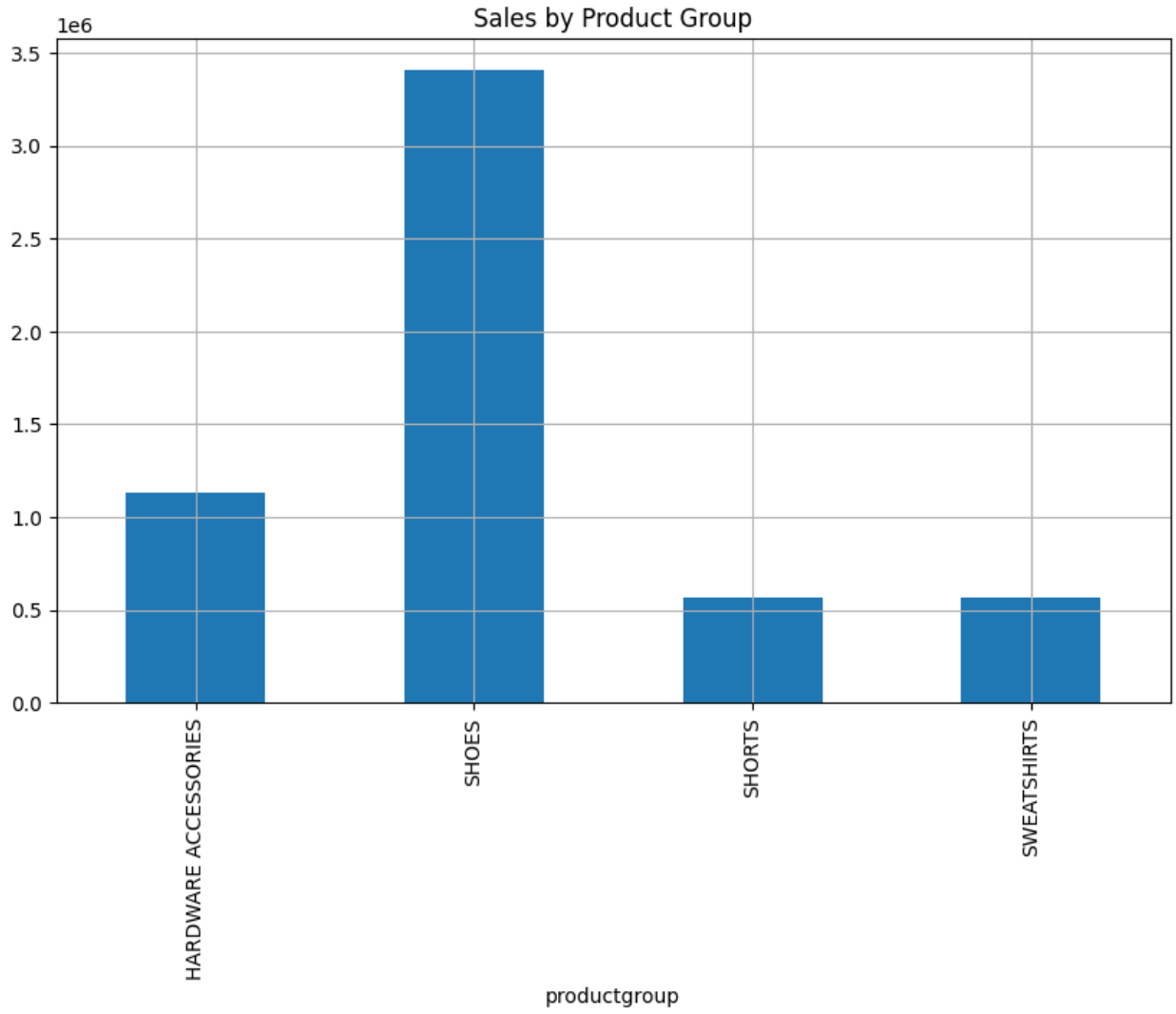
What is the most Product sold ?

```
sales_by_productgroup=df.groupby('productgroup')['sales'].sum()
print(sales_by_productgroup)
```

```
productgroup
HARDWARE ACCESSORIES    1135636
SHOES                   3406908
SHORTS                   567818
SWEATSHIRTS              567818
Name: sales, dtype: int64
```

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
sales_by_productgroup.plot(kind='bar')
```

```
plt.title('Sales by Product Group')
plt.grid(True)
plt.show()
```



What is the Average Discount

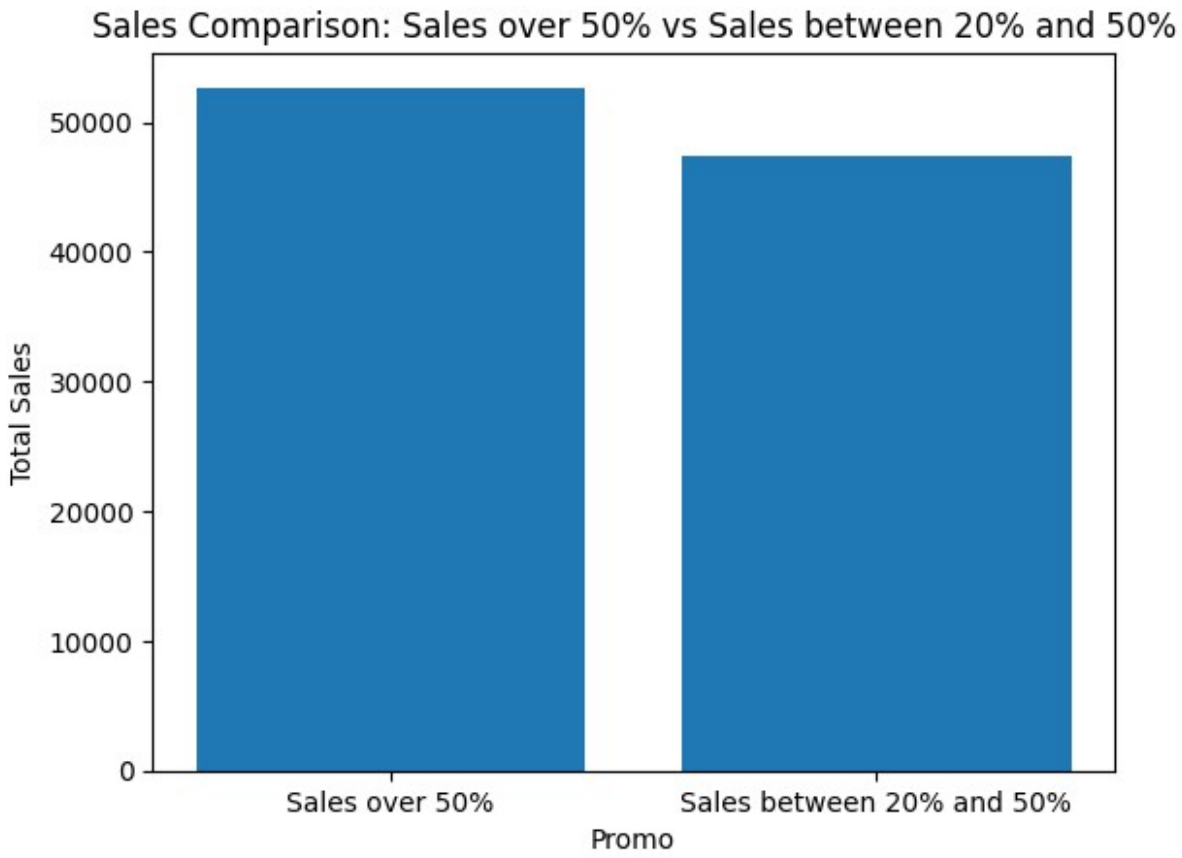
```
df['ratio'].mean()
```

```
0.545645863457212
```

What is the impact of discouts activities on sales?

```
df_ratio_over_50 = df['ratio'].where(df['ratio'] > 0.5)
count_ratio_over_50 = df_ratio_over_50.count()

df_ratio_over_20 = df['ratio'].where((df['ratio'] > 0.2) &
(df['ratio'] < 0.5))
```

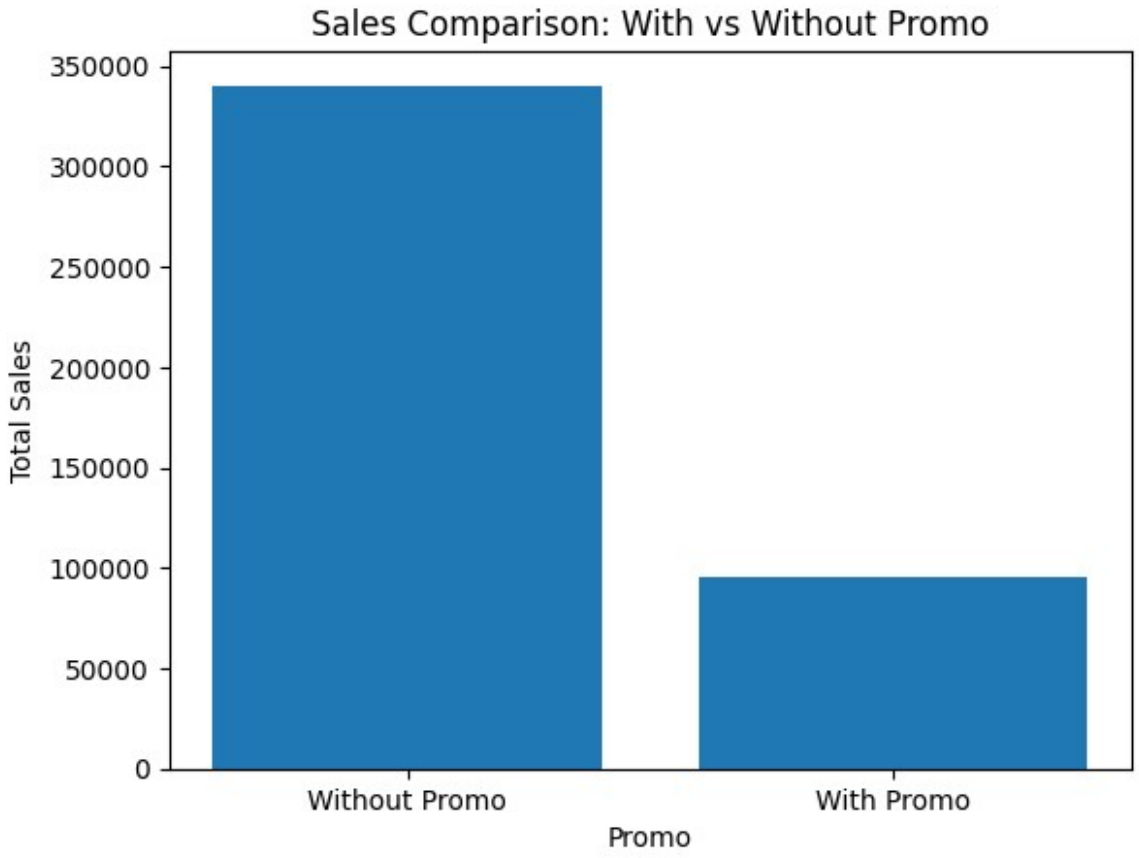
```
count_ratio_over_20 = df_ratio_over_20.count()

# Create a bar plot
labels = ['Sales over 50%', 'Sales between 20% and 50%']
values = [count_ratio_over_50, count_ratio_over_20]

plt.bar(labels, values)
plt.xlabel('Promo')
plt.ylabel('Total Sales')
plt.title('Sales Comparison: Sales over 50% vs Sales between 20% and
50%')

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



What is the impact of promotional activities (promo1 and promo2) on sales?

```
saleswithoutpromo = filtered_df[(filtered_df['promo1'] == 0) &
(filtered_df['promo2'] == 0)]
```

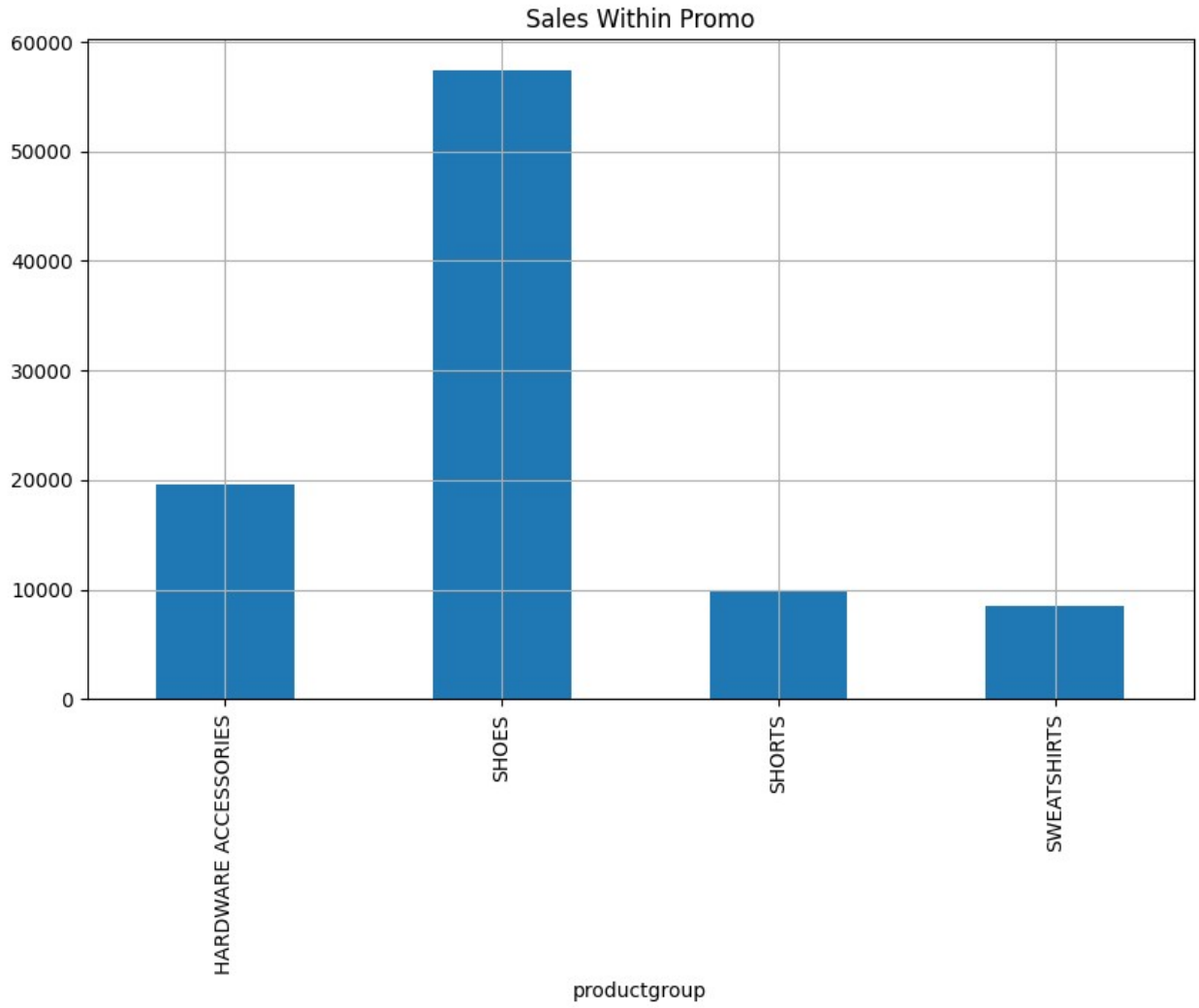
```
saleswithpromo = filtered_df[(filtered_df['promo1'] == 1) |
(filtered_df['promo2'] == 1)]

# Create a bar plot
labels = ['Without Promo', 'With Promo']
values = [saleswithoutpromo['sales'].sum(),
saleswithpromo['sales'].sum()]

plt.bar(labels, values)
plt.xlabel('Promo')
plt.ylabel('Total Sales')
plt.title('Sales Comparison: With vs Without Promo')

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




```
promo = filtered_df[(filtered_df['promo1'] == 1) |
(filtered_df['promo2'] == 1)]
promo=promo.groupby('productgroup')['sales'].sum()

promo.head()
```

```
productgroup
HARDWARE ACCESSORIES    19599
SHOES                   57371
SHORTS                   9843
SWEATSHIRTS              8506
Name: sales, dtype: int64
```

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
promo.plot(kind='bar')

plt.title('Sales Within Promo')
plt.grid(True)
plt.show()
```

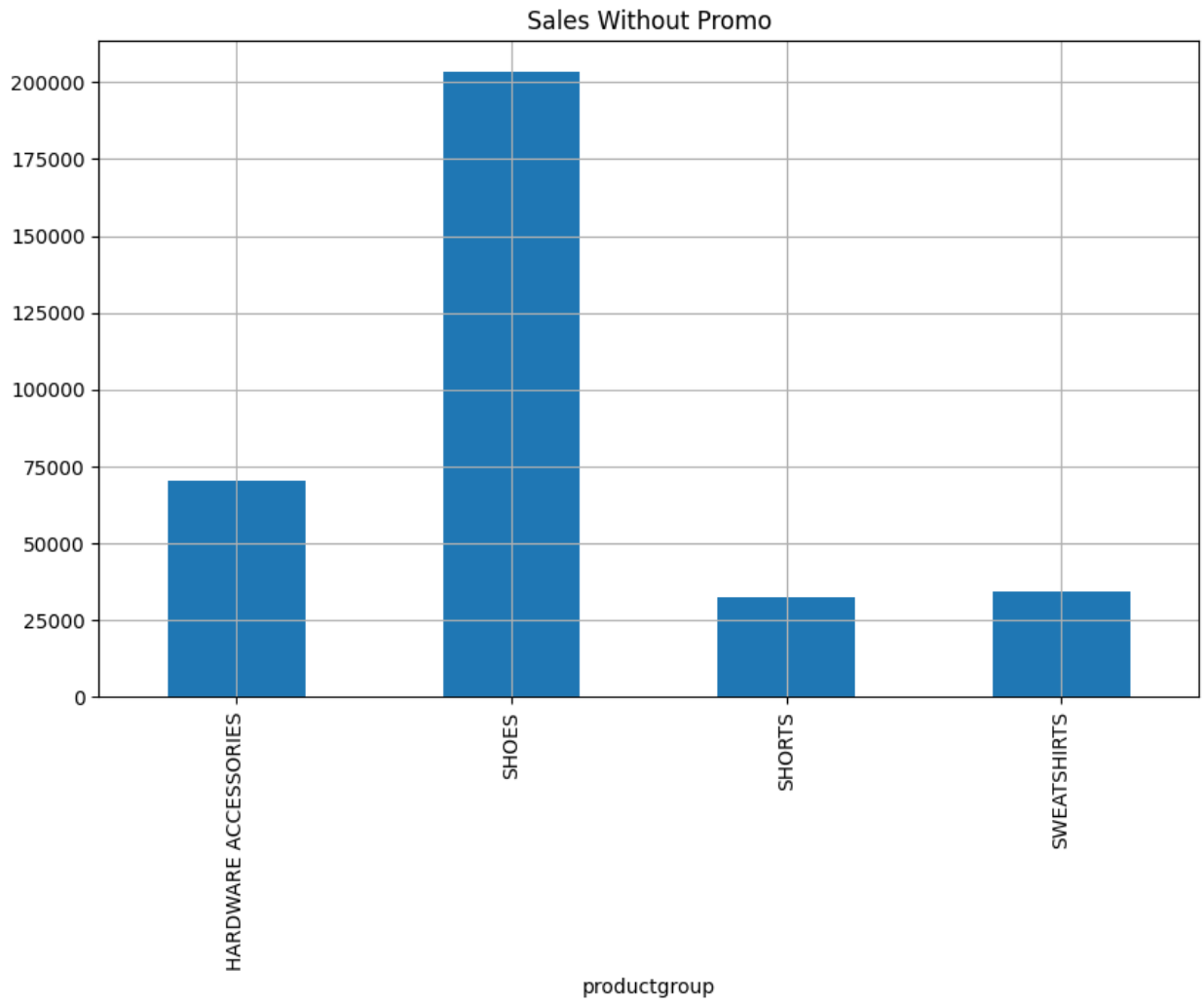



```
withoutpromo = filtered_df[(filtered_df['promo1'] == 0) &
(filtered_df['promo2'] == 0)]
```

```
withoutpromo=withoutpromo.groupby('productgroup')['sales'].sum()

promo.head()
```

```
productgroup
HARDWARE ACCESSORIES    19599
SHOES                   57371
SHORTS                   9843
SWEATSHIRTS              8506
Name: sales, dtype: int64
```

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
withoutpromo.plot(kind='bar')

plt.title('Sales Without Promo')
plt.grid(True)
plt.show()
```

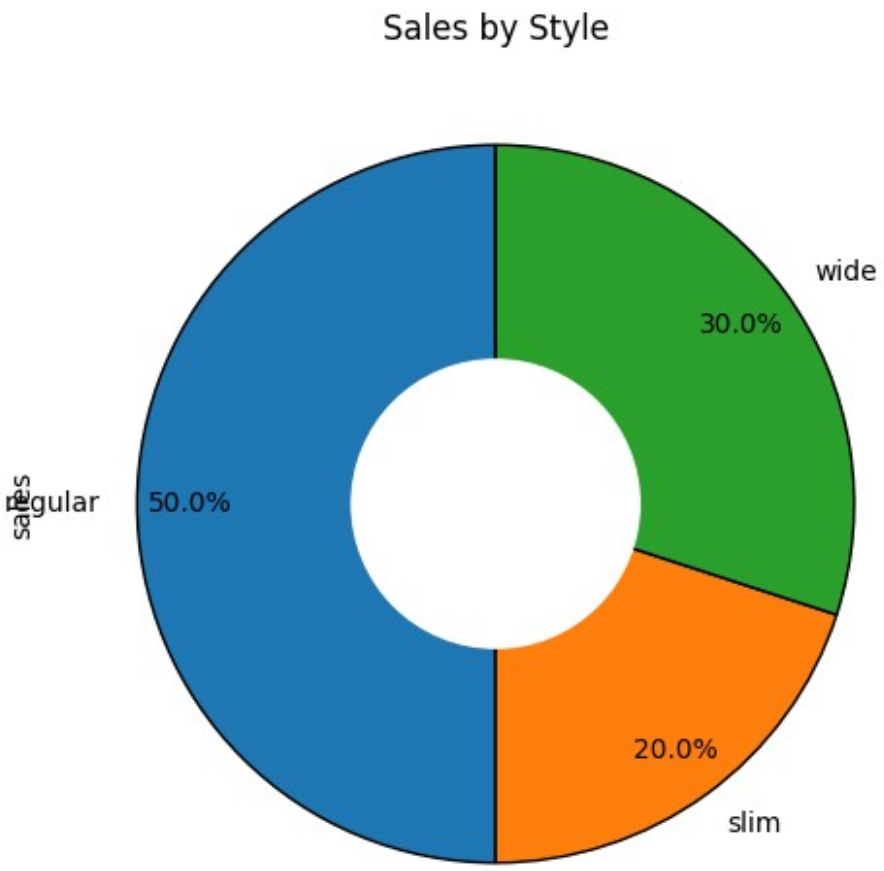


```
sales_by_style=df.groupby('style')['sales'].sum()
print(sales_by_style)
```

```
style
regular    2839090
slim       1135636
wide       1703454
Name: sales, dtype: int64
```

What is the most Style sold ?

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
sales_by_style.plot(kind='pie',autopct='%1.1f%%',startangle=90,
pctdistance=0.85, wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Sales by Style')
plt.grid(True)
plt.show()
```




```
sales_by_style.nlargest(1)
```

```
style
regular    2839090
Name: sales, dtype: int64
```

What is the most category required ?

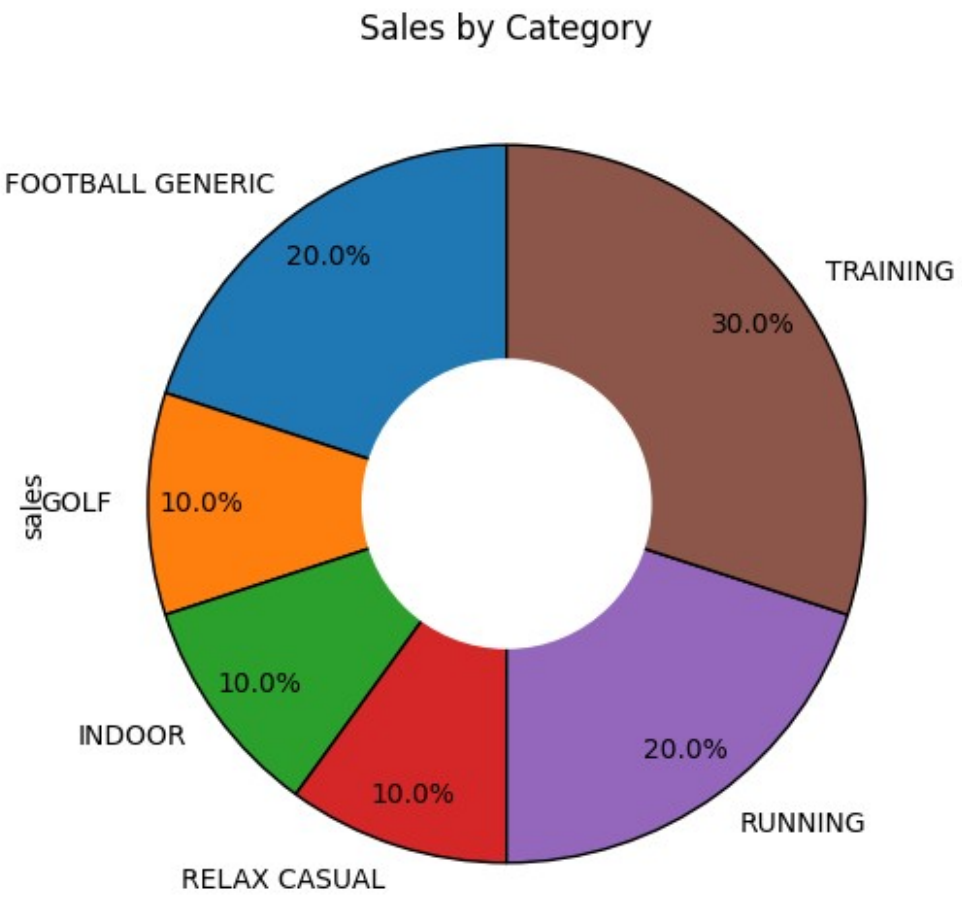
```
sales_by_category=df.groupby('category')['sales'].sum()
print(sales_by_category)
```

```
category
FOOTBALL GENERIC    1135636
GOLF                 567818
INDOOR               567818
RELAX CASUAL         567818
RUNNING             1135636
TRAINING            1703454
Name: sales, dtype: int64
```

```
sales_by_category.nlargest(1)
```

```
category
TRAINING    1703454
Name: sales, dtype: int64
```

```
# Create a bar plot of sales by retail week
plt.figure(figsize=(10, 6))
sales_by_category.plot(kind='pie',autopct='%1.1f%%',startangle=90,
pctdistance=0.85, wedgeprops={'edgecolor': 'black'})
centre_circle = plt.Circle((0,0), hole_size, color='white',
fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Sales by Category')
plt.grid(True)
plt.show()
```



What Products are often most sold together?

```
# Group the data by 'customer_id' and 'article' and calculate the
count of unique articles
grouped_df = filtered_df.groupby('customer_id')
['productgroup'].agg([('products', lambda x: ','.join(x)), ('count',
'count')]).reset_index()

# Print the resulting grouped DataFrame
grouped_df=grouped_df[grouped_df['count']>1]
grouped_df=grouped_df.sort_values('count')

grouped_df.head()
```

```
      customer_id                    products  count
1504       2514.0  SHOES,HARDWARE ACCESSORIES      2
1802       3530.0           SWEATSHIRTS,SHOES      2
1796       3505.0  HARDWARE ACCESSORIES,SHOES      2
548         803.0                SHOES,SHOES      2
1795       3500.0  SHOES,HARDWARE ACCESSORIES      2
```

```
# Group the data by desired features and calculate the revenue
revenue_table = df.groupby(['productgroup', 'category',
'retailweek']).agg({'sales': 'sum', 'cost': 'sum', 'current_price':
'mean'})
revenue_table = revenue_table.rename(columns={'sales': 'total_sales',
'cost': 'total_cost', 'current_price': 'average_price'})

# Add additional calculated columns
revenue_table['revenue'] = revenue_table['total_sales'] *
revenue_table['average_price']
revenue_table['profit'] = revenue_table['revenue'] -
revenue_table['total_cost']

# Display the revenue table
print(revenue_table)
```

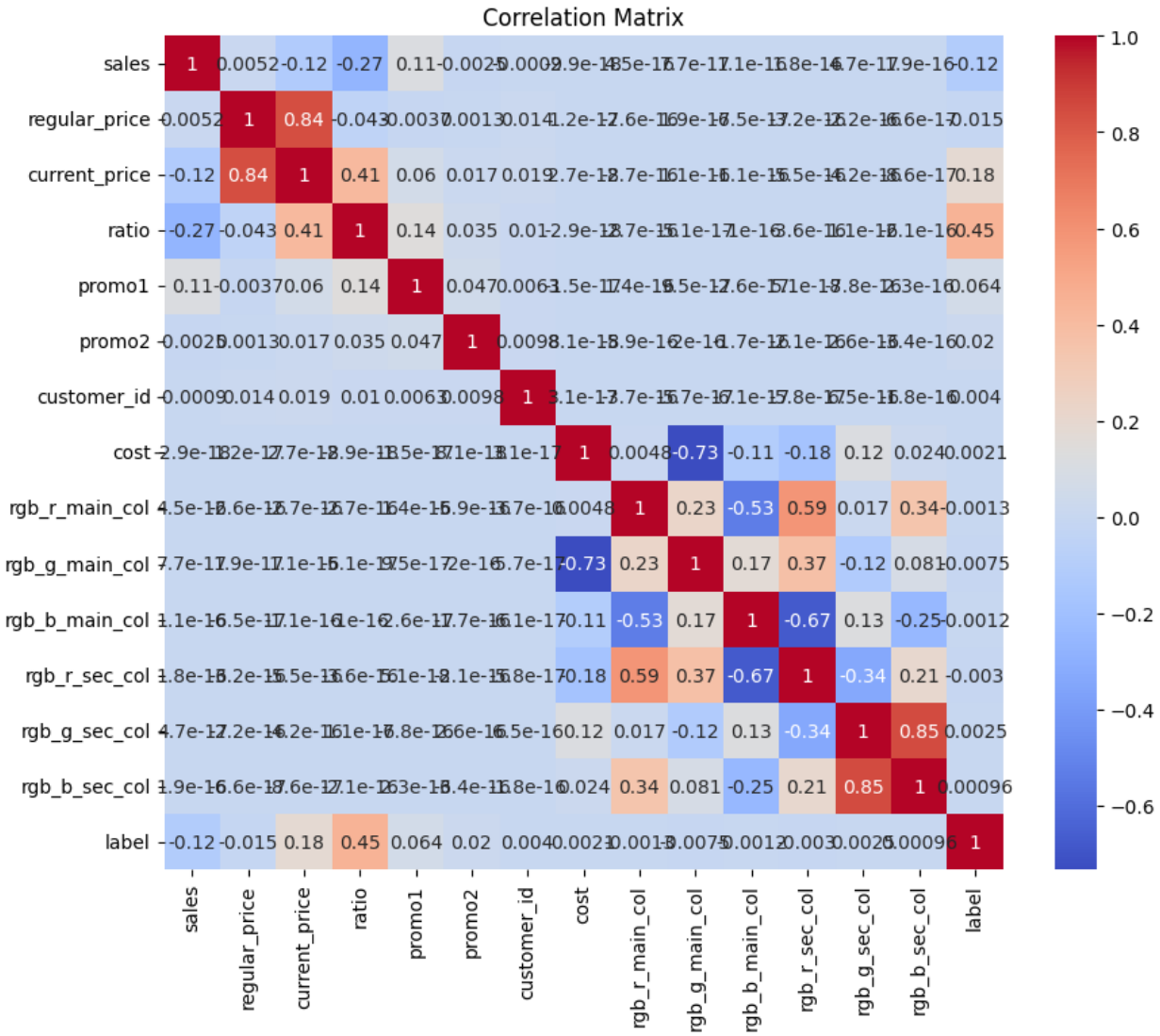
```
                                        total_sales  total_cost  \
productgroup         category retailweek
HARDWARE ACCESSORIES GOLF     2014-12-28         7801       132.6
                              2015-01-04         3024       142.8
                              2015-01-11         2326       141.1
                              2015-01-18         2878       153.0
                              2015-01-25         4089       151.3
...                                               ...         ...
SWEATSHIRTS          TRAINING 2017-04-02         6430       357.0
                              2017-04-09         5657       340.2
                              2017-04-16         6840       357.0
                              2017-04-23         7312       369.6
                              2017-04-30         5682       348.6
```

```
                                          average_price         revenue
\
productgroup         category retailweek

HARDWARE ACCESSORIES GOLF     2014-12-28      32.257692  251642.257692

                              2015-01-04      35.747619  108100.800000

                              2015-01-11      33.431928   77762.663855

                              2015-01-18      35.616667  102504.766667

                              2015-01-25      38.197191  156188.314045

...                                                 ...            ...

SWEATSHIRTS          TRAINING 2017-04-02      19.879412  127824.617647

                              2017-04-09      15.456173   87435.569753

                              2017-04-16      18.702941  127928.117647

                              2017-04-23      19.688636  143963.309091

                              2017-04-30      18.901807  107400.068675


                                                 profit
productgroup         category retailweek
HARDWARE ACCESSORIES GOLF     2014-12-28  251509.657692
                              2015-01-04  107958.000000
                              2015-01-11   77621.563855
                              2015-01-18  102351.766667
                              2015-01-25  156037.014045
...                                                 ...
SWEATSHIRTS          TRAINING 2017-04-02  127467.617647
                              2017-04-09   87095.369753
                              2017-04-16  127571.117647
                              2017-04-23  143593.709091
                              2017-04-30  107051.468675

[1107 rows x 5 columns]
```

```
# Checking unique values

column_values = df["country"].values
unique_values =  np.unique(column_values)
print(unique_values)
```

```
['Austria' 'France' 'Germany']
```

```
# Calculate correlation matrix
corr_matrix = df.corr()

# Visualize correlation matrix as a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```




```
import numpy as np
#print(np.unique(df.category))
#print(np.unique(df.productgroup))
#print(np.unique(df.style))
print(np.unique(df.gender))
```

```
['kids' 'men' 'unisex' 'women']
```

```
df.category.replace(['FOOTBALL GENERIC','GOLF', 'INDOOR','RELAX
CASUAL','RUNNING','TRAINING'],
                        [0, 1,2,3,4,5], inplace=True)

df.productgroup.replace(['HARDWARE ACCESSORIES','SHOES',
'SHORTS','SWEATSHIRTS'],
                        [0, 1,2,3], inplace=True)

df.gender.replace(['kids','men', 'unisex','women'],
                        [0, 1,2,3], inplace=True)

df['month']=df['month'].astype('int')
```

Remove the outliers in the data

```
df['sales'].describe()
```

```
count    100000.000000
mean         56.781800
std          87.934743
min           1.000000
25%          10.000000
50%          26.000000
75%          64.000000
max         898.000000
Name: sales, dtype: float64
```

```
import plotly.express as px
fig=px.box(df,y='sales')
fig.show()

# Calculate the first and third quartiles (Q1 and Q3)
Q1 = np.percentile(df['sales'], 25)
Q3 = np.percentile(df['sales'], 75)

# Calculate the Interquartile Range (IQR)
IQR = Q3 - Q1

# Define the lower and upper bounds to identify outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
filtered_data = [x for x in df['sales'] if lower_bound <= x <=
upper_bound]

# Update the DataFrame with filtered data
df = df[(df['sales'] >= lower_bound) & (df['sales'] <= upper_bound)]
```

```
import plotly.express as px
fig=px.box(df,y='sales')
fig.show()
```

```
import plotly.express as px
fig=px.box(df,y='sales')
fig.show()
```

```
# Select relevant features for the analysis
features = ['category','cost','productgroup','ratio','regular_price',
'current_price', 'promo1', 'promo2','gender','rgb_r_main_col',
'rgb_g_main_col', 'rgb_b_main_col','month']
target = 'label'
```

```
df.info()
```

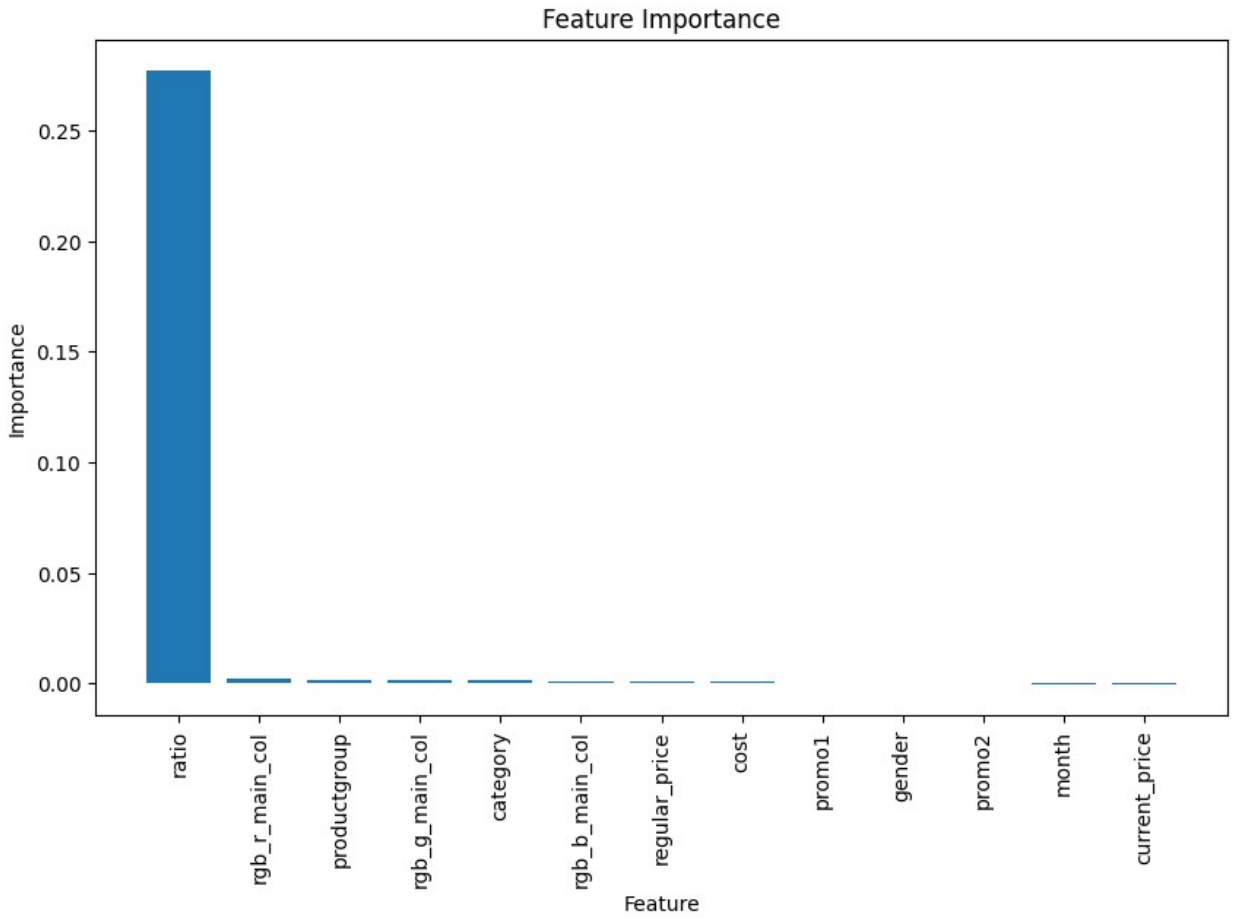
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90460 entries, 0 to 99979
Data columns (total 26 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   country         90460 non-null  object
 1   article         90460 non-null  object
 2   sales           90460 non-null  int64
 3   regular_price   90460 non-null  float64
 4   current_price   90460 non-null  float64
 5   ratio           90460 non-null  float64
 6   retailweek      90460 non-null  object
 7   promo1          90460 non-null  int64
 8   promo2          90460 non-null  int64
 9   customer_id     90460 non-null  float64
 10  article.1       90460 non-null  object
 11  productgroup    90460 non-null  int64
 12  category        90460 non-null  int64
 13  cost            90460 non-null  float64
 14  style           90460 non-null  object
 15  sizes           90460 non-null  object
 16  gender          90460 non-null  int64
 17  rgb_r_main_col  90460 non-null  int64
 18  rgb_g_main_col  90460 non-null  int64
 19  rgb_b_main_col  90460 non-null  int64
 20  rgb_r_sec_col   90460 non-null  int64
 21  rgb_g_sec_col   90460 non-null  int64
 22  rgb_b_sec_col   90460 non-null  int64
 23  label           90460 non-null  int64
 24  month           90460 non-null  int64
 25  year            90460 non-null  object
dtypes: float64(5), int64(14), object(7)
memory usage: 18.6+ MB
```

```
# Assuming you have a DataFrame called 'df' containing the
'regular_price' and 'current_price' columns

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Select the columns to be normalized
columns_to_normalize = ['regular_price','ratio',
'current_price','cost','rgb_r_main_col', 'rgb_g_main_col',
'rgb_b_main_col','month']

# Apply Min-Max scaling to the selected columns
df[columns_to_normalize] =
scaler.fit_transform(df[columns_to_normalize])

# Fit and transform the selected column
# Initialize the StandardScaler
scaler = StandardScaler()

df['ratio'] = scaler.fit_transform(df[['ratio']])

# Split the data into training and testing sets
X = df[features]
y = df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

Accuracy: 0.8488282113641389

# Split the dataset into majority and minority classes
majority_class = df[df['label'] == 0]
minority_class = df[df['label'] == 1]

# Undersample the majority class
undersampled_majority = majority_class.sample(n=len(minority_class),
random_state=42)

# Combine the undersampled majority class with the minority class
balanced_df = pd.concat([undersampled_majority, minority_class])
```

```
# Split the data into training and testing sets
X = balanced_df[features]
y = balanced_df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7870508982035929
```

```
from sklearn.inspection import permutation_importance

# Assuming you have a trained model called 'model'
results = permutation_importance(model, X, y, scoring='accuracy')
importances = results.importances_mean

# Assuming you have calculated the feature importances and stored them
in the 'importances' variable
# Assuming you have a list of feature names called 'feature_names'

# Sort the feature importances and feature names in descending order

sorted_indices = importances.argsort()[::-1]
sorted_importances = importances[sorted_indices]
sorted_feature_names = [features[i] for i in sorted_indices]

# Create a bar plot of feature importances
plt.figure(figsize=(10, 6))
plt.bar(range(len(sorted_importances)), sorted_importances)
plt.xticks(range(len(sorted_importances)), sorted_feature_names,
rotation='vertical')
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance')
plt.show()
```




```
from sklearn.metrics import classification_report

# Assuming you have actual labels in 'y_true' and predicted labels in
'y_pred'
report = classification_report(y_test, y_pred)

# Print the classification report
print(report)
```

```
              precision    recall  f1-score   support

           0       0.82      0.74      0.78      2699
           1       0.76      0.83      0.79      2645

    accuracy                           0.79      5344
   macro avg       0.79      0.79      0.79      5344
weighted avg       0.79      0.79      0.79      5344
```

Conclusion : The Most Answered Question

1. What is the year that has the best and worst sales ?

2. What is the month that has best Sales?
3. What is the year that has best and worst advertisement result ?
4. What is the most gender interested in our products?
5. Which gender responds to the advertisements the most?
6. What is the most country interested in our products?
7. What is the impact of promotional activities (promo1 and promo2) on sales?
8. What is the impact of discount activities 20% or 50% on sales?
9. What is the most Product sold ?
10. What is the most category required ?
11. What is the most Style sold ?
12. What Products are often most sold together?
13. What is the Average Discount