```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from scipy.stats import norm

data = pd.read_csv('walmart_data.txt')
data.head()

   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category
Purchase
0                          2               0                 3
8370
1                          2               0                 1
15200
2                          2               0                12
1422
3                          2               0                12
1057
4                         4+               0                 8
7969

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     550068 non-null  int64
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64
 8   Product_Category            550068 non-null  int64
 9   Purchase                    550068 non-null  int64
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

```
data.describe()
```

```
             User_ID     Occupation  Marital_Status  
Product_Category  \
count  5.500680e+05  550068.000000  550068.000000     550068.000000

mean   1.003029e+06       8.076707       0.409653          5.404270

std    1.727592e+03       6.522660       0.491770          3.936211

min    1.000001e+06       0.000000       0.000000          1.000000

25%    1.001516e+06       2.000000       0.000000          1.000000

50%    1.003077e+06       7.000000       0.000000          5.000000

75%    1.004478e+06      14.000000       1.000000          8.000000

max    1.006040e+06      20.000000       1.000000         20.000000


             Purchase
count  550068.000000
mean     9263.968713
std      5023.065394
min        12.000000
25%      5823.000000
50%      8047.000000
75%     12054.000000
max     23961.000000
```

```
data.describe(include= 'object')
```

```
       Product_ID  Gender     Age City_Category 
Stay_In_Current_City_Years
count       550068  550068  550068        550068 
550068
unique        3631       2       7             3 
5
top      P00265242       M   26-35             B 
1
freq          1880  414259  219587        231173 
193821
```

```
data.shape
```

```
(550068, 10)
```

```
data.isna().sum()
```

```
User_ID                       0
Product_ID                    0
```

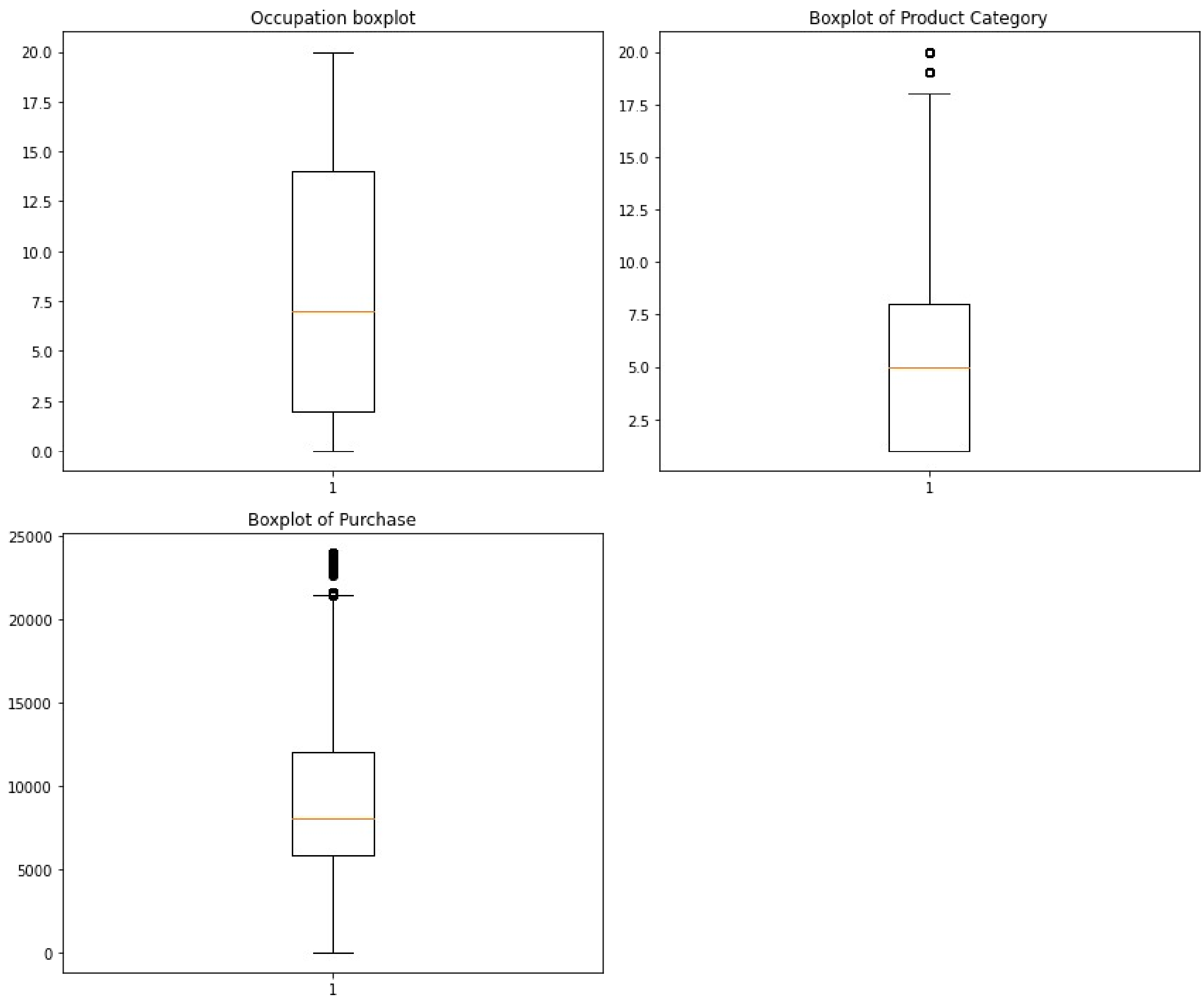
```
Gender                        0
Age                           0
Occupation                    0
City_Category                 0
Stay_In_Current_City_Years    0
Marital_Status                0
Product_Category              0
Purchase                      0
dtype: int64
```

There are no missing value at all

```
data.duplicated().sum()

0
```

There are no duplicate values

```
data.Age.unique()

array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)

data.Marital_Status.unique()

array([0, 1], dtype=int64)

fig, ax = plt.subplots(2,2, figsize =(12, 10))
ax[0,0].boxplot(data['Occupation'])
ax[0,0].set_title('Occupation boxplot')

ax[0,1].boxplot(data.Product_Category)
ax[0,1].set_title('Boxplot of Product Category')

ax[1,0].boxplot(data.Purchase)
ax[1,0].set_title('Boxplot of Purchase')

ax[1,1].axis('off')



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



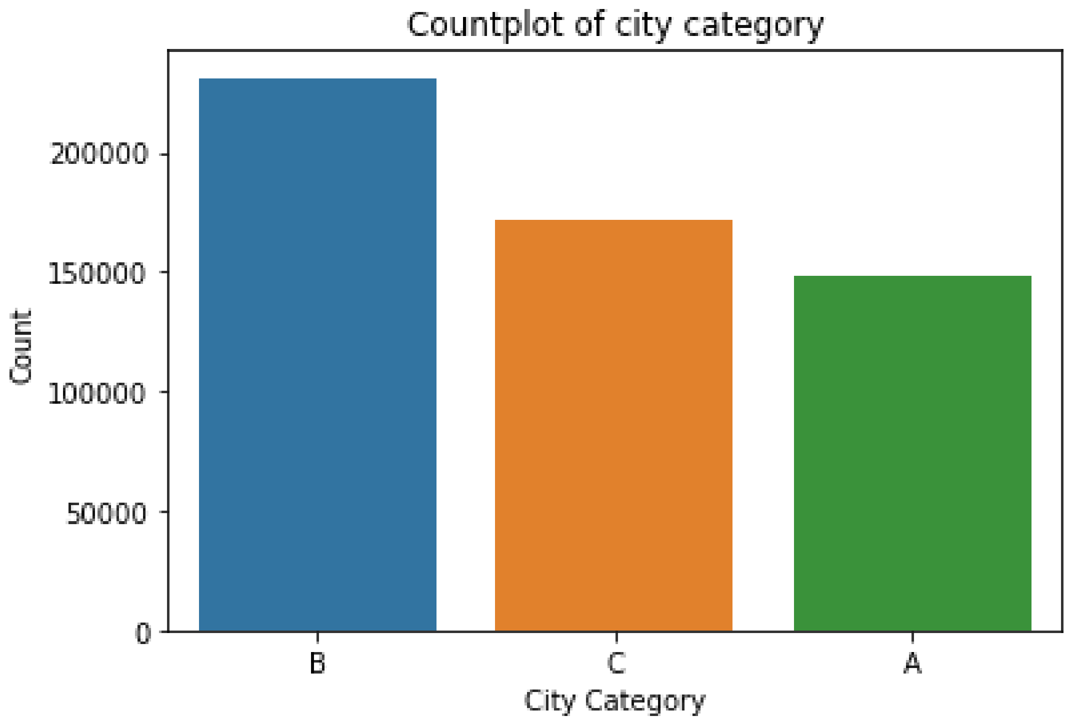
Purchase and product category has some outliers

```
category = data.City_Category.value_counts()
category
```

```
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

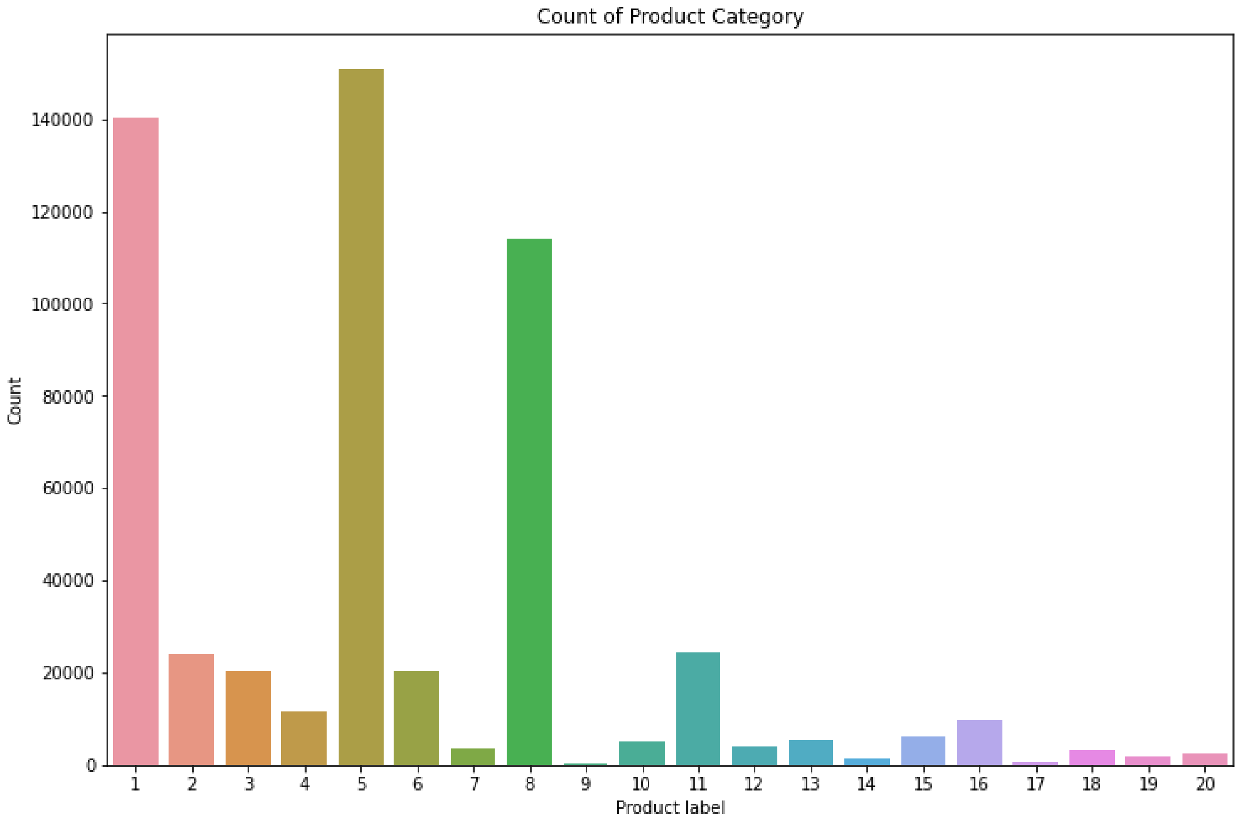
```
sns.barplot(category.index, category.values)
plt.title('Countplot of city category')
plt.xlabel('City Category')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```

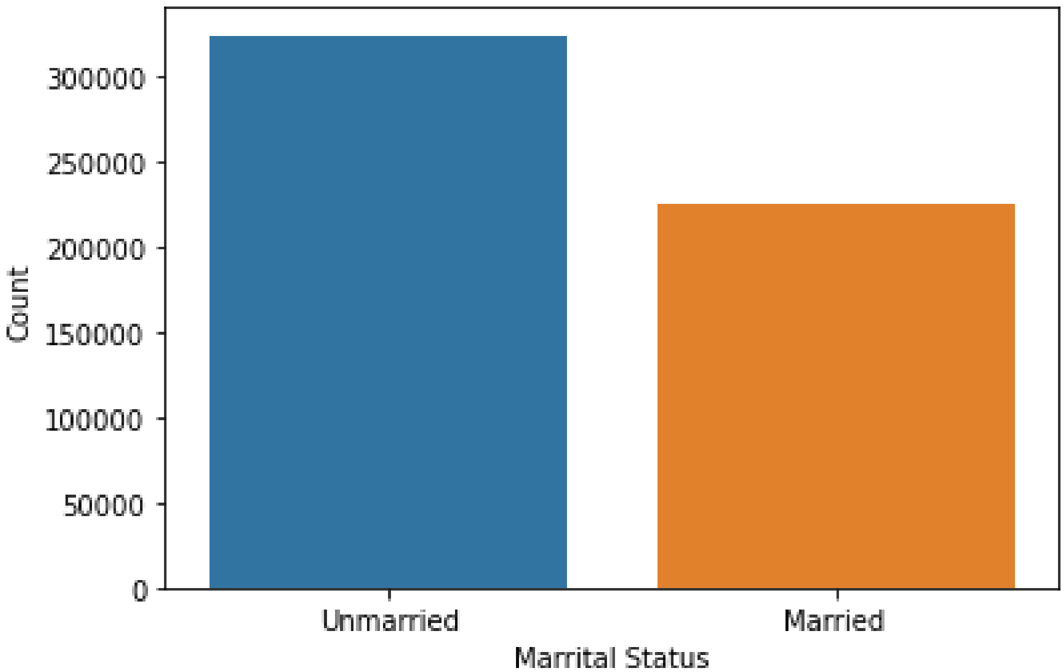


City B has more purchase followed by city C and A

```
clipped_columns['Product_Category']

0          3.0
1          1.0
2         12.0
3         12.0
4          8.0
          ...
550063    13.0
550064    13.0
550065    13.0
550066    13.0
550067    13.0
Name: Product_Category, Length: 550068, dtype: float64

product = data.Product_Category.value_counts()

plt.figure(figsize = (12, 8))
sns.barplot(product.index, product.values)
plt.title('Count of Product Category')
plt.xlabel('Product label')
plt.ylabel('Count')

Text(0, 0.5, 'Count')
```

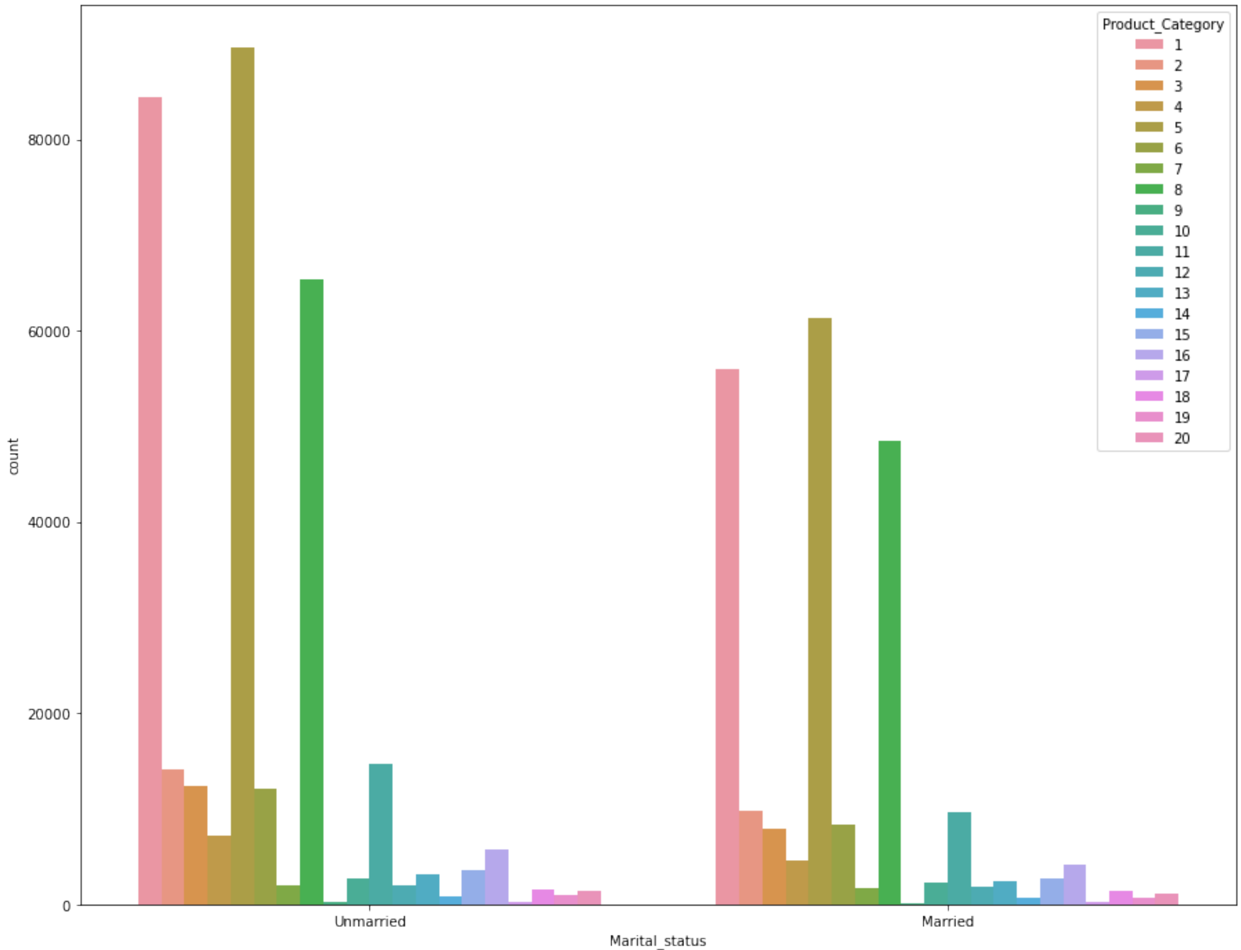



```
data['Marital_status'] = data.Marital_Status.map({0: 'Unmarried', 1:
'Married'})

marital_s = data.Marital_status.value_counts()

sns.barplot(marital_s.index, marital_s.values)
plt.xlabel('Marrital Status')
plt.ylabel('Count')

Text(0, 0.5, 'Count')
```

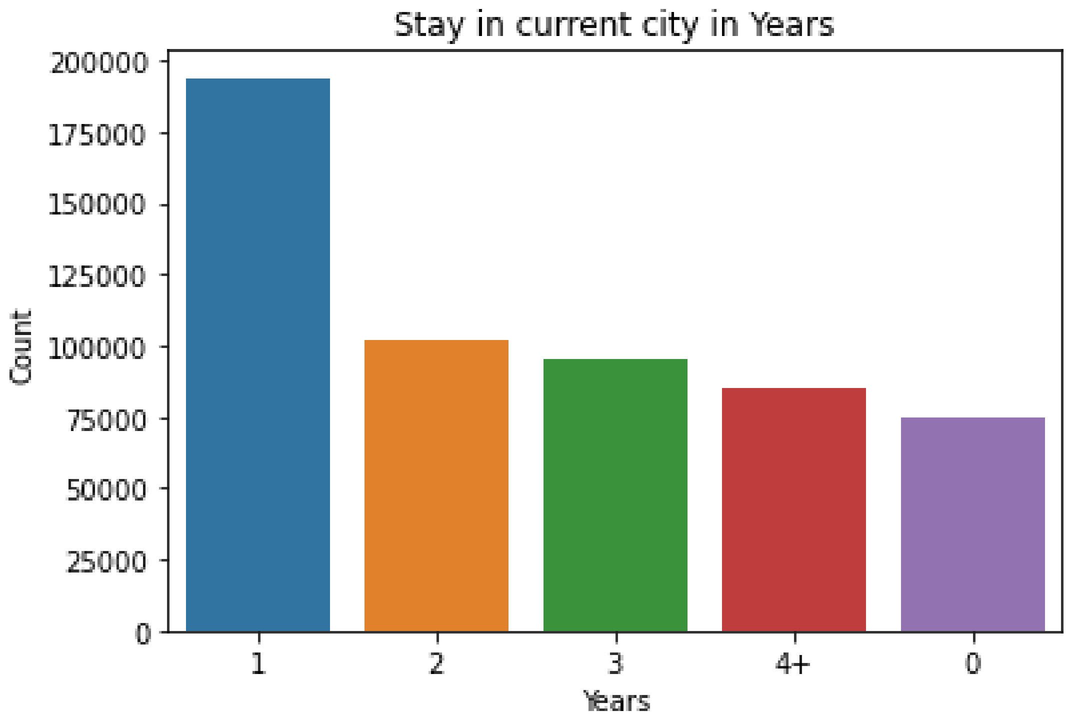



```
plt.figure(figsize = (15, 12))
sns.countplot(x= 'Marital_status', hue = 'Product_Category', data =
data)
```

```
<AxesSubplot:xlabel='Marital_status', ylabel='count'>
```



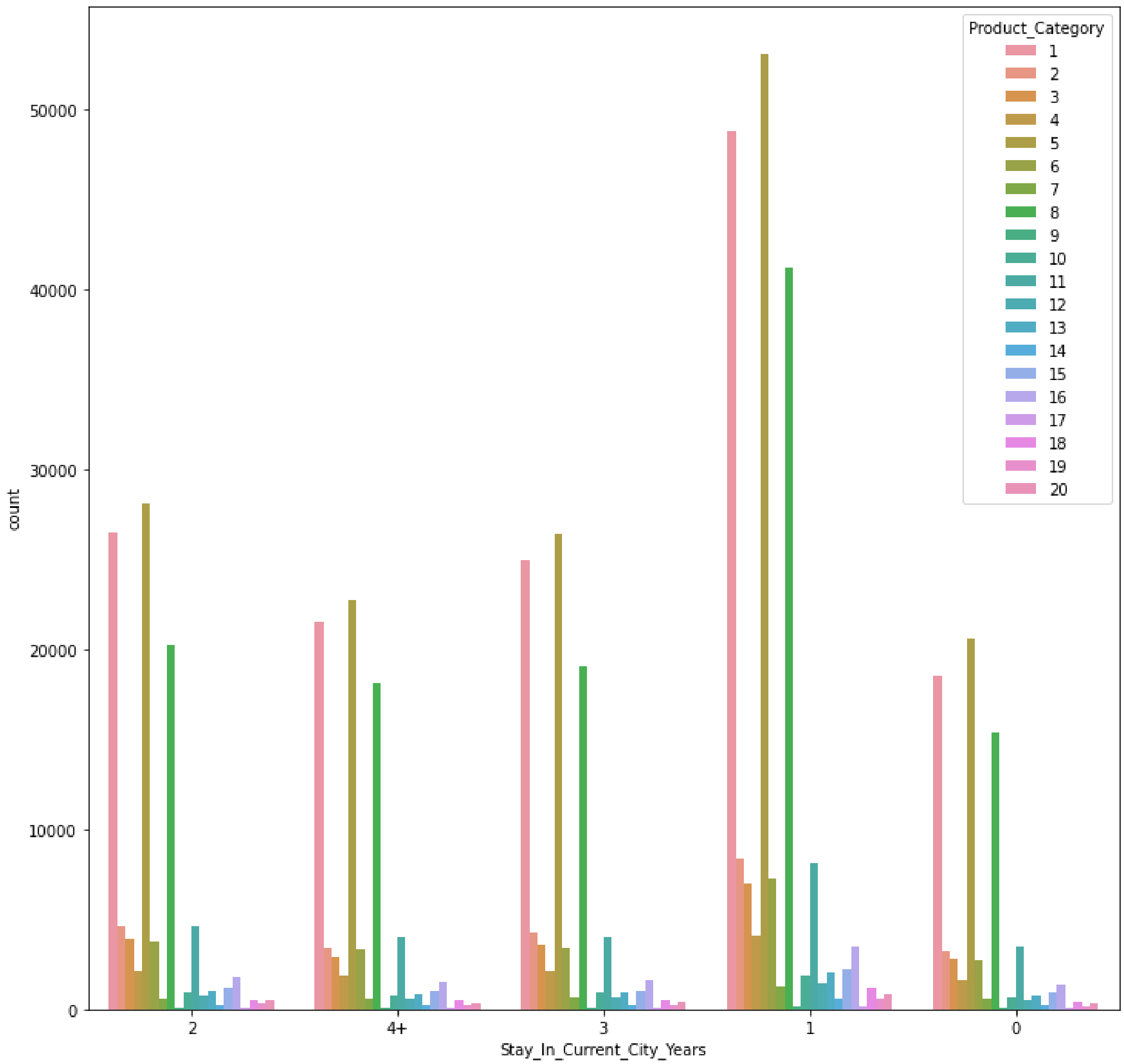

```
Current_city_year = data.Stay_In_Current_City_Years.value_counts()

sns.barplot(Current_city_year.index, Current_city_year.values)
plt.title('Stay in current city in Years')
plt.xlabel('Years')
plt.ylabel('Count')

Text(0, 0.5, 'Count')
```



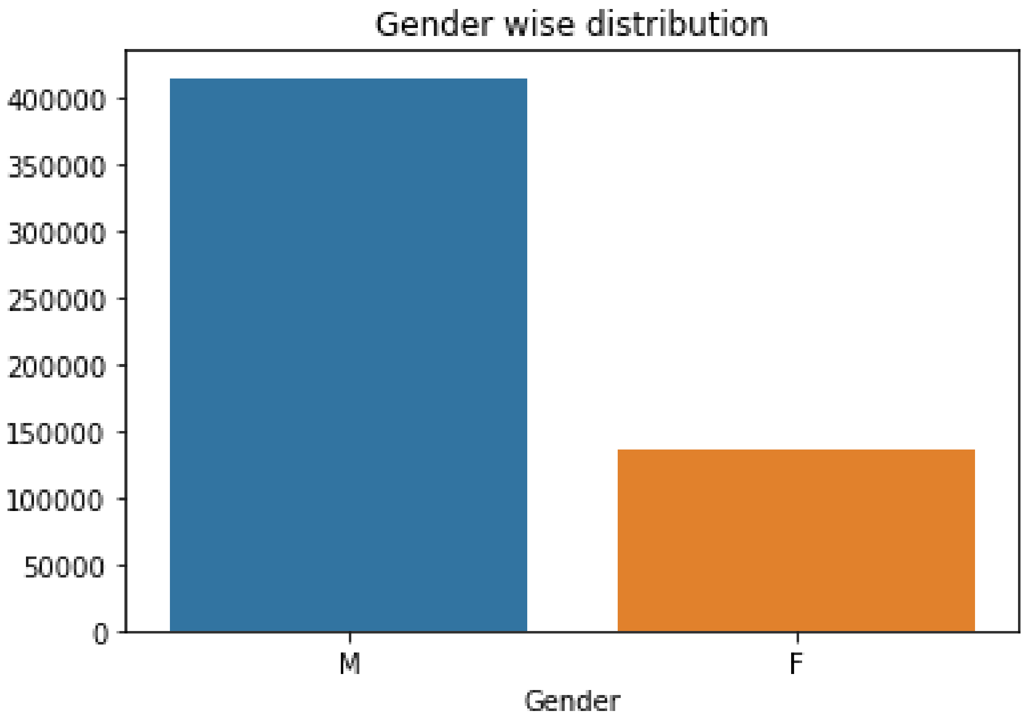
Those who are living in city for 1 year has more purchase history than others

```
plt.figure(figsize = (12, 12))
sns.countplot('Stay_In_Current_City_Years', hue = 'Product_Category', data=data)
```

```
<AxesSubplot:xlabel='Stay_In_Current_City_Years', ylabel='count'>
```




```
gender = data.Gender.value_counts()

sns.barplot(gender.index, gender.values)
plt.title('Gender wise distribution')
plt.xlabel('Gender')

Text(0.5, 0, 'Gender')
```



It seems Male Purchase history is more than female

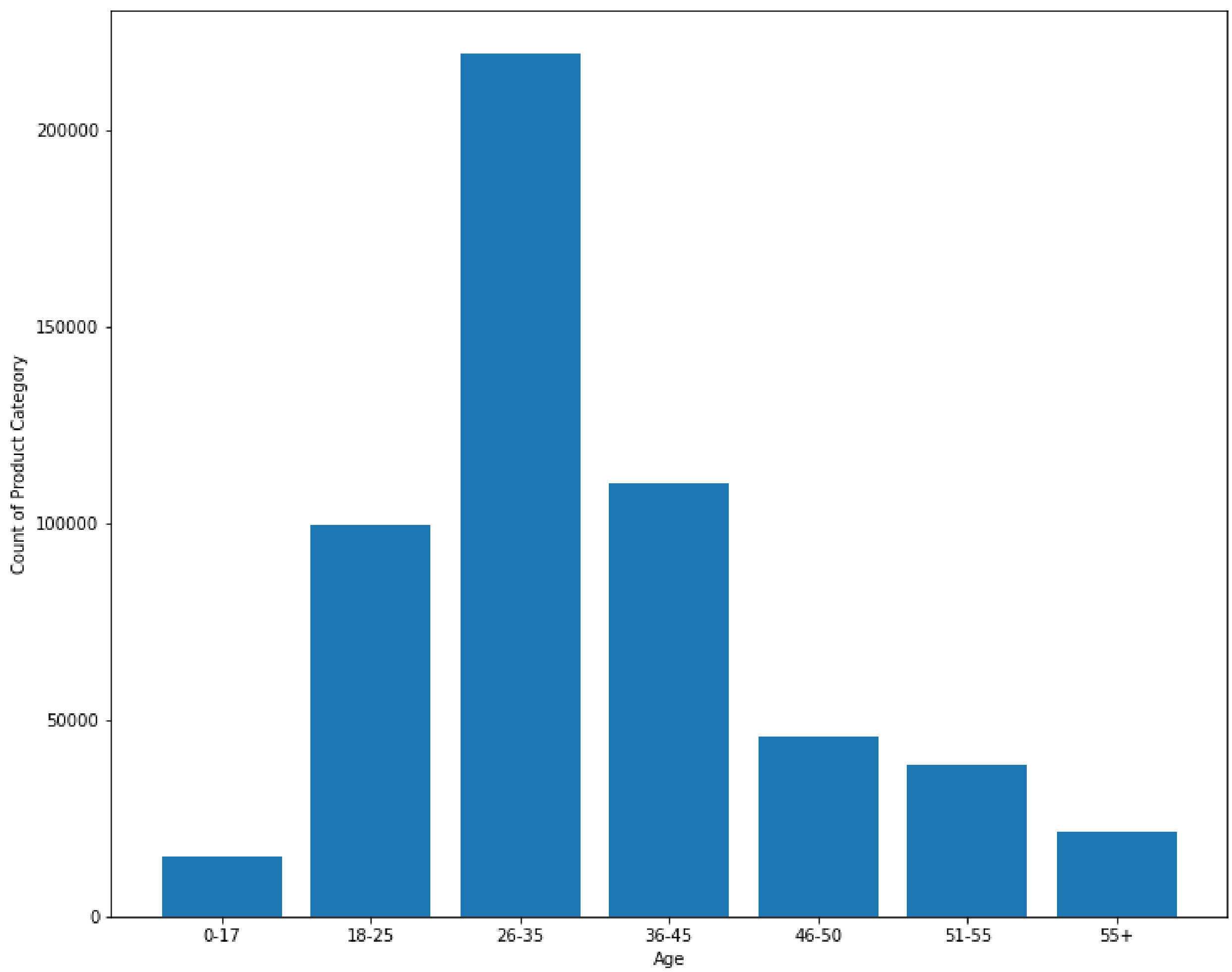
Data between the 5 percentile and 95 percentile

```
columns_to_clip = ['Product_Category', 'Purchase']

clipped_columns = {}

for column in columns_to_clip:
    percentile_5_val = np.percentile(data[column], 5)
    percentile_95_val = np.percentile(data[column],95)
    clipped_column = np.clip(data[column], percentile_5_val,
percentile_95_val)
    clipped_columns[column] = clipped_column

clipped_columns['Product_Category'].value_counts()

5.0     150933
1.0     140378
8.0     113925
13.0     31046
11.0     24287
2.0      23864
6.0      20466
3.0      20213
4.0      11753
10.0      5125
12.0      3947
```

```
7.0        3721
9.0         410
Name: Product_Category, dtype: int64
```

```
df = data.copy()

df['Product_Category'] = clipped_columns['Product_Category']
df['Purchase'] = clipped_columns['Purchase']

age = data.groupby('Age')['Product_Category'].count()

plt.figure(figsize = (12, 10))
plt.bar(age.index, age.values)
plt.xlabel('Age')
plt.ylabel('Count of Product Category')
```

```
Text(0, 0.5, 'Count of Product Category')
```

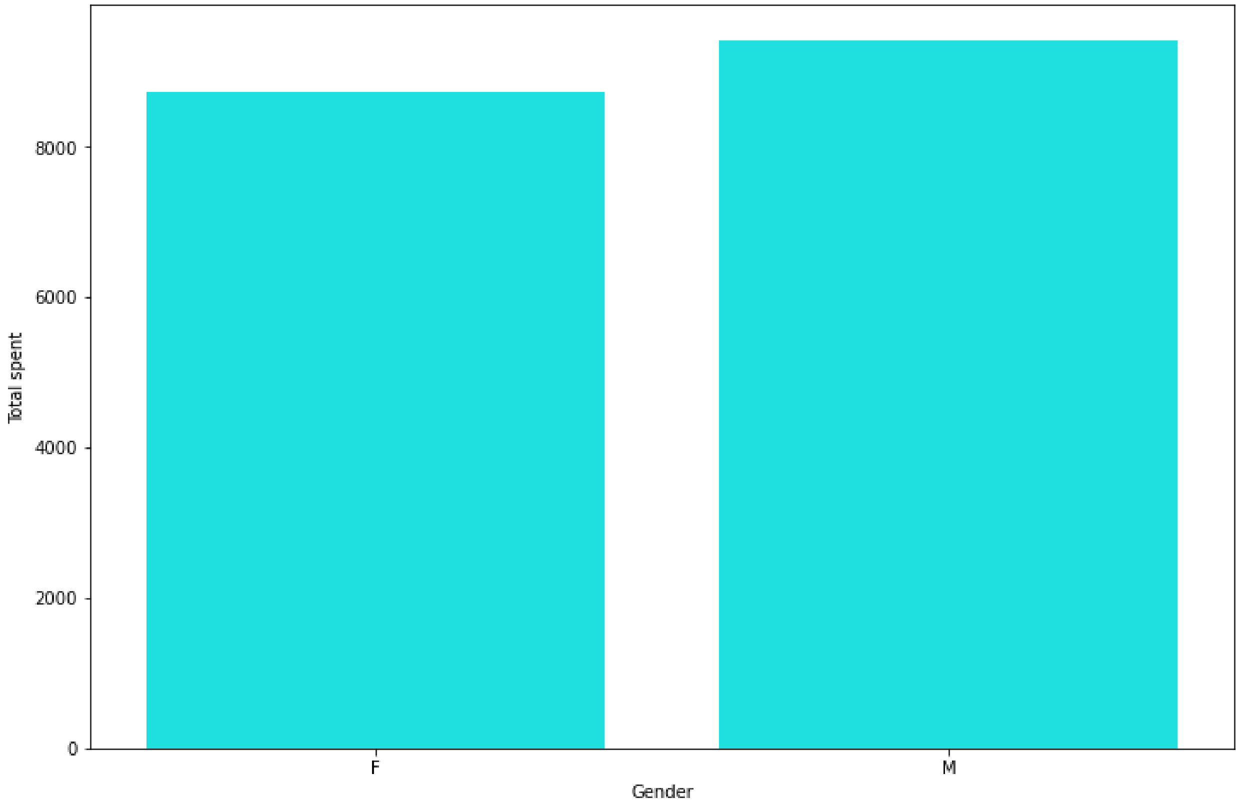


Age group 26-35 orders more comarative to other age group

```
# Q 4: How does gender affect the amount spent?


def get_average_spent_per_gender(data):
  """Calculates the average amount spent per gender."""
  return data.groupby('Gender')['Purchase'].mean()

def bootstrap_ci(data, sample_size, n_bootstraps=50000):
  """Computes the confidence interval using bootstrapping."""
  gender_means = get_average_spent_per_gender(data)
  bootstrapped_means = []
  for i in range(n_bootstraps):
    sample = data.sample(sample_size, replace=True)
    bootstrapped_means.append(get_average_spent_per_gender(sample))

    bootstrapped_means_df = pd.DataFrame(bootstrapped_means)
  # Assuming a 95% confidence interval
    quantiles = bootstrapped_means_df.quantile([0.025, 0.975], axis=1)
    return quantiles.T

spent = get_average_spent_per_gender(df)
spent
```

```
Gender
F    8736.540266
M    9427.240997
Name: Purchase, dtype: float64
```

```
plt.figure(figsize= (12, 8))
sns.barplot(spent.index, spent.values, color = 'cyan')
plt.xlabel('Gender')
plt.ylabel('Total spent')
plt.show()
```




```
bootstrap_ci(data, len(data))

                0.025        0.975
Purchase  8764.625474  9427.446337

# C. I. for different sizes
sample_sizes = [300, 3000, 30000]
for sample_size in sample_sizes:
        sample_ci = bootstrap_ci(data.sample(sample_size,
replace=True), sample_size)
        print(f"Confidence Interval for Sample Size {sample_size}:")
        print(sample_ci)

Confidence Interval for Sample Size 300:
                0.025        0.975
Purchase  8986.642475  9710.329238
Confidence Interval for Sample Size 3000:
                0.025        0.975
Purchase  8994.249609  9618.148917
Confidence Interval for Sample Size 30000:
                0.025        0.975
Purchase  8714.402089  9410.657681
```

How does gender affect the amount spent?

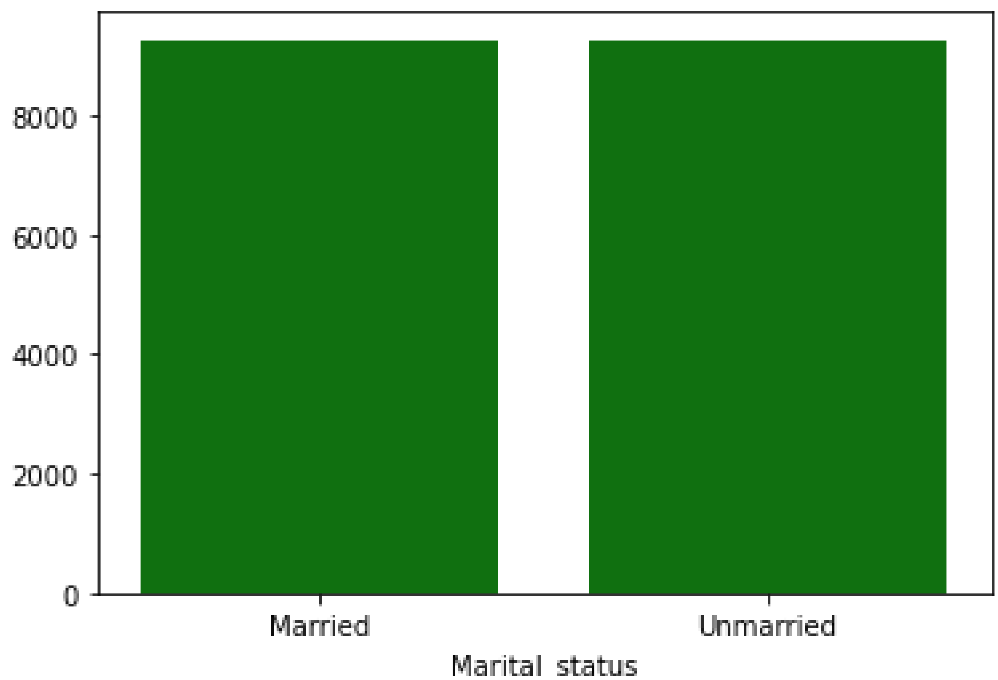
Sample size 300: round(8975.46379-8720.402612,2) = 255.06 Sample size 3000: round(9568.542328-8874.368952,2) = 694.17 Sample size 30000: round(9453.213589 - 8658.600629, 2) = 794.61 This confirms that a larger sample size leads to a larger confidence interval, reflecting a more precise estimate of the average purchase amount. The confidence interval width varies across sample sizes for gender

```
# Q5 How does Marital_Status affect the amount spent

def get_average_spent_per_marital_status(data):
  """Calculates the average amount spent per marital status."""
  return data.groupby('Marital_status')['Purchase'].mean()

def bootstrap_ci_1(data, sample_size, n_bootstraps=1000):
  """Computes the confidence interval using bootstrapping."""
  marital_means = get_average_spent_per_marital_status(data)
  bootstrapped_means = []
  for _ in range(n_bootstraps):
    sample = data.sample(sample_size, replace=True)

bootstrapped_means.append(get_average_spent_per_marital_status(sample)
)

    bootstrapped_means_df = pd.DataFrame(bootstrapped_means)
  # Assuming a 95% confidence interval
    quantiles = bootstrapped_means_df.quantile([0.025, 0.975], axis=1)
    return quantiles.T

ms = get_average_spent_per_marital_status(data)
ms
```

```
Marital_status
Married      9261.174574
Unmarried    9265.907619
Name: Purchase, dtype: float64
```

```
sns.barplot(ms.index, ms.values, color = 'green')
```

```
<AxesSubplot:xlabel='Marital_status'>
```




```
bootstrap_ci_1(data, len(data))

                0.025        0.975
Purchase  9256.720884  9283.345125

sample_size = [300, 3000, 30000]
for sample in sample_size:
        sample_ci = bootstrap_ci_1(data.sample(sample, replace=True),
sample)
        print(f"Confidence Interval for Sample Size {sample}:")
        print(sample_ci)

Confidence Interval for Sample Size 300:
                0.025        0.975
Purchase  9539.995967  9679.967696
Confidence Interval for Sample Size 3000:
                0.025        0.975
Purchase  9005.888774  9205.681198
Confidence Interval for Sample Size 30000:
                0.025        0.975
Purchase  9225.509386  9231.802087
```

5. How does Marital_Status affect the amount spent?

Sample size 300: round(9723.721992-9035.276332, 2) = 688.45

Sample size 3000: round(9177.663179- 9118.895905, 2) = 58.77

Sample size 30000: round(9301.357872 - 9293.477086, 2) = 7.88

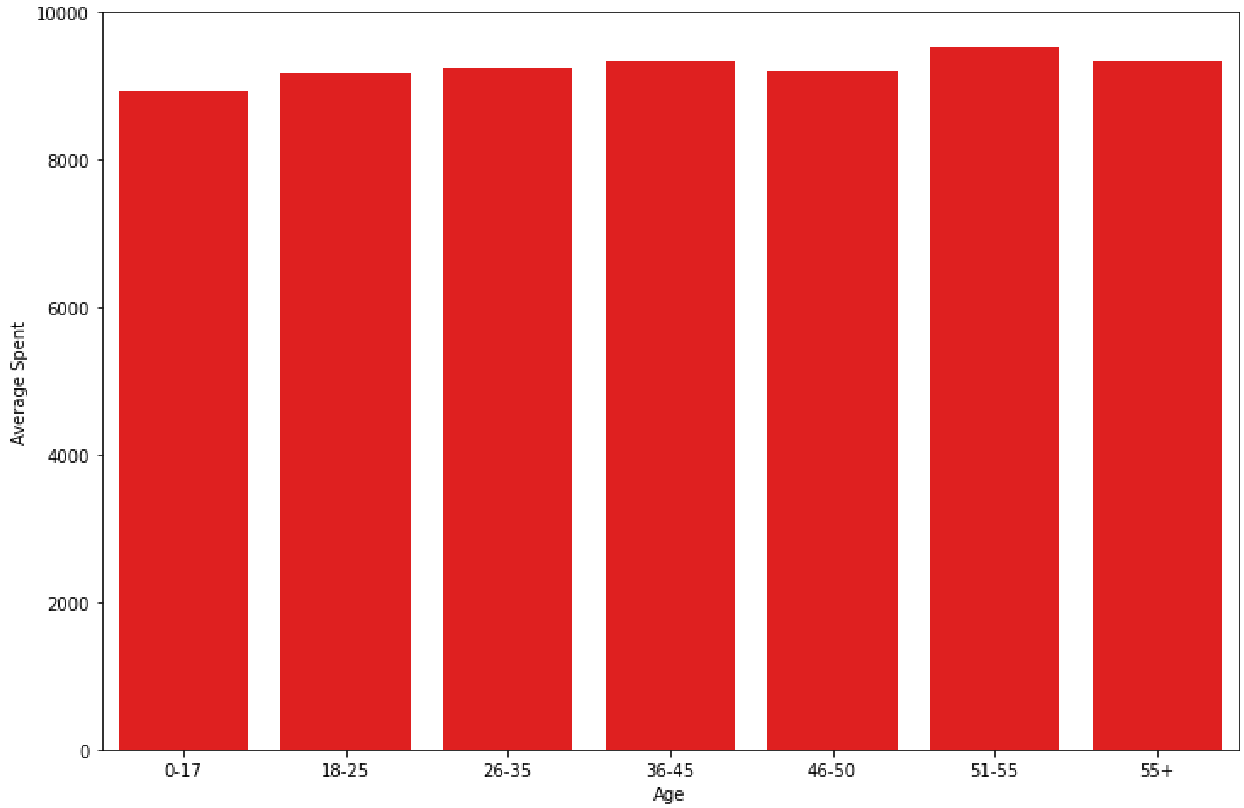
This confirms that a larger sample size leads to a narrower confidence interval, reflecting a more precise estimate of the average purchase amount.

```
# Q6:  6. How does Age affect the amount spent?

def get_average_spent_per_age(data):
  """Calculates the average amount spent per age."""
  return data.groupby('Age')['Purchase'].mean()

def bootstrap_ci_2(data, sample_size, n_bootstraps=1000):
  """Computes the confidence interval using bootstrapping."""
  age_means = get_average_spent_per_age(data)
  bootstrapped_means = []
  for _ in range(n_bootstraps):
    sample = data.sample(sample_size, replace=True)
    bootstrapped_means.append(get_average_spent_per_age(sample))

    bootstrapped_means_df = pd.DataFrame(bootstrapped_means)
  # Assuming a 95% confidence interval
    quantiles = bootstrapped_means_df.quantile([0.025, 0.975], axis=1)
    return quantiles.T

Age = get_average_spent_per_age(data)
Age
```

```
Age
0-17     8933.464640
18-25    9169.663606
26-35    9252.690633
36-45    9331.350695
46-50    9208.625697
51-55    9534.808031
55+      9336.280459
Name: Purchase, dtype: float64
```

```
plt.figure(figsize = (12, 8))
sns.barplot(Age.index, Age.values, color = 'red')
plt.xlabel('Age')
plt.ylabel('Average Spent')
```

```
Text(0, 0.5, 'Average Spent')
```




```
bootstrap_ci_2(data, len(data))

                 0.025        0.975
Purchase  8908.251741  9507.729568

sample_size = [300, 3000, 30000]
for sample in sample_size:
        sample_ci = bootstrap_ci_2(data.sample(sample, replace=True),
sample)
        print(f"Confidence Interval for Sample Size {sample}:")
        print(sample_ci)

Confidence Interval for Sample Size 300:
              0.025        0.975
Purchase  5336.975  10609.53604
Confidence Interval for Sample Size 3000:
                 0.025         0.975
Purchase  8880.919758  10312.672085
Confidence Interval for Sample Size 30000:
                0.025        0.975
Purchase  8548.42964  9496.231911
```

How is the width of the confidence interval affected by the sample size?

1.Sample Size 300: Widest interval (10815.920186 - 6106.863441 ≈ 4709.06)

2.Sample Size 3000: Narrower interval (10086.178888 - 9125.641289 ≈ 960.54)

3.Sample Size 30000: Narrowest interval (9520.499949 - 8838.930224 ≈ 681.57)

This confirms the principle that a larger sample size leads to a narrower confidence interval, reflecting a more precise estimate of the average purchase amount.

Do the confidence intervals for different sample sizes overlap?

Larger sample sizes lead to narrower confidence intervals, indicating a more precise estimate of the average purchase amount.

How does the sample size affect the shape of the distributions of the means?

Sample size primarily affects the spread of the distribution of means, not necessarily the underlying shape of the purchase amount data.

Report

1.Overlapping CI for overall data suggests no significant difference in average spending between genders based on this sample. Suggestion: Walmart could use gender-neutral marketing and analyze purchase behavior within genders for targeted promotions.

1. YES, the confidence intervals for the average amount spent by married and unmarried (computed using all the data) overlap. Suggestion: Implement unified marketing strategies.Analyze spending behavior within each group for further insights.

Recommondations

1.Targeted marketing: Since the majority of transactions are made by males, it would be beneficial to tailor marketing strategies to cater to their preferences and needs. This could include specific promotions, product offerings, or advertising campaigns designed to attract male customers.

1. Engage with new residents: As a significant portion of transactions come from customers who have recently moved to the current city, it presents an opportunity to engage with these new residents. Targeted marketing, welcoming offers, and incentives for newcomers can help capture their loyalty and increase their spending.

2. Increase focus on single customers: Given that 59.05% of total revenue is generated by single customers, dedicating efforts to cater to their needs and preferences can help drive more sales. Understanding their motivations and targeting them with personalized offers can enhance their shopping experience and loyalty.

3. Location-based marketing: With a significant number of customers belonging to specific cities, tailoring marketing strategies to target these locations can lead to better results. Allocating resources, promotions, and events based on the customer concentration in each city can help drive sales

4. Optimize revenue from specific age groups: Since a majority of transactions are made by customers between the ages of 26 and 45, it is important to focus

marketing efforts on this demographic. Offering products and services that align with their interests and values can maximize revenue generation.