Walmart:Customer Purchase Behavior

Business Statement:

Analyzing the customers purchase behavior against the customer's gender based on various factors like purchase amount,age,occupation,marital status,etc.

Packages

```
import pandas as pd
import numpy as np
import scipy.stats as st
import matplotlib.pyplot as plt
import seaborn as sns
```

```
data_tran=pd.read_csv("/content/walmart_data.txt")
```

1.1 - Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary

```
data_tran.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Ca
0	1000001	P00069042	F	0-17	10	A	2	0	
1	1000001	P00248942	F	0-17	10	A	2	0	

1.1.1 - Shape of the data

```
print("Shape of the data:",data_tran.shape)
```

```
Shape of the data: (550068, 10)
```

1.1.2 - Data type as well as other things like memory usage

```
print(data_tran.info()) # data types as well as other information like memory usage
```

```
<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
None
```

42 MB memory has been taken by the dataset

1.1.3 - Convert a column into a categorical column if possible

```
# convert some columns to categorical column
# the advantage of converting a column(if possible) into a categorical column
# will reduce the substancial amount of memory usage,this can be very much helpful if the
# dataset is very huge
# convert all the columns except column Purchase into categorical columns

for col in data_tran.columns[:-1]:
  data_tran[col]=data_tran[col].astype("category")

# Now again print the information about the data,this time meory will be reduced
# substancial amount
data_tran.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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
```

```
 9   Purchase                    550068 non-null  int64
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

Here only 10.3 MB memory usage. Almost 4 times less memory usage.This proves converting columns into categorical columns(if possible) will reduce the substancial amount of memory usage

1.1.4 - Statistical Summary

```
data_tran.describe(include="all")
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Pr

The mean and median(50% quantile) of **Purchase** are not same.There is a significant difference.For example **mean** is 9263.96 whereas **median** is 8047.This indicates Purchase column as a whole seems to have outliers.

Range of **Purchase** is 12.0 to 23961

1.2 - Non-Graphical Analysis: Value counts and unique attributes

1.2.1 - Value counts

```
for col in data_tran.columns:
  print(f"Value counts of the column {col}:\n")
  print(data_tran[col].value_counts())
  print()
```

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

Value counts of the column Stay_In_Current_City_Years:

1     193821
2     101838
3      95285
4+     84726
0      74398
Name: Stay_In_Current_City_Years, dtype: int64

Value counts of the column Marital_Status:

0    324731
1    225337
```

```
Name: Marital_Status, dtype: int64

Value counts of the column Product_Category:

5     150933
1     140378
8     113925
11     24287
2      23864
6      20466
3      20213
4      11753
16      9828
15      6290
13      5549
10      5125
12      3947
7       3721
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64

Value counts of the column Purchase:

7011     191
7193     188
6855     187
6891     184
7012     183
        ...
23491      1
18345      1
3372       1
855        1
21489      1
Name: Purchase, Length: 18105, dtype: int64
```

1.2.2 - Unique Attributes

```
d={}
for col in data_tran.columns:
  d[col]=data_tran[col].nunique()
df=pd.DataFrame(d,index=["No. of unique values"])
df
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Produ
No. of unique values	5891	3631	2	7	21	3	5	2	

There are 550068 records ,no attributes are unique

Range of the attributes

```
for col in data_tran.columns[2:-1]:
  print(f"{col} has the following values:\n")
  print(data_tran[col].unique())
  print()
```

```
Gender has the following values:

['F', 'M']
Categories (2, object): ['F', 'M']
```

```
Age has the following values:

['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']

Occupation has the following values:

[10, 16, 15, 7, 20, ..., 18, 5, 14, 13, 6]
Length: 21
Categories (21, int64): [0, 1, 2, 3, ..., 17, 18, 19, 20]

City_Category has the following values:

['A', 'C', 'B']
Categories (3, object): ['A', 'B', 'C']

Stay_In_Current_City_Years has the following values:

['2', '4+', '3', '1', '0']
Categories (5, object): ['0', '1', '2', '3', '4+']

Marital_Status has the following values:

[0, 1]
Categories (2, int64): [0, 1]

Product_Category has the following values:

[3, 1, 12, 8, 5, ..., 10, 17, 9, 20, 19]
Length: 20
Categories (20, int64): [1, 2, 3, 4, ..., 17, 18, 19, 20]
```

Missing values and outlier detection

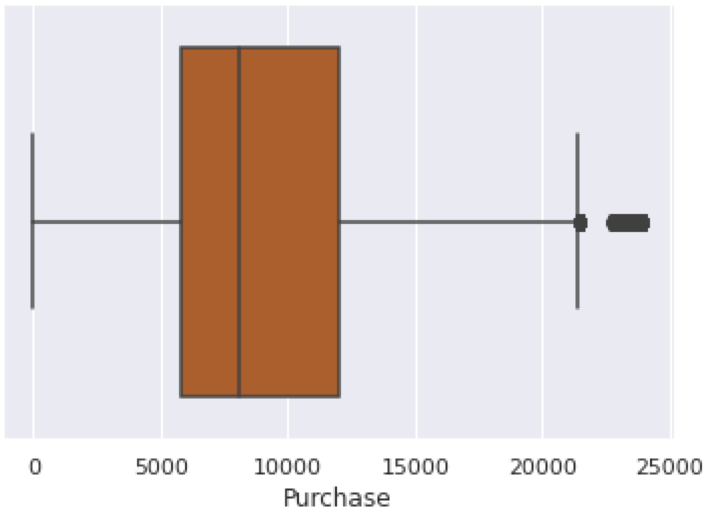
```
data_tran.isna().sum() # detect missing values
```

```
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 values

```
# outliet detection in Purchase column
sns.boxplot(x='Purchase',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730fa52710>
```

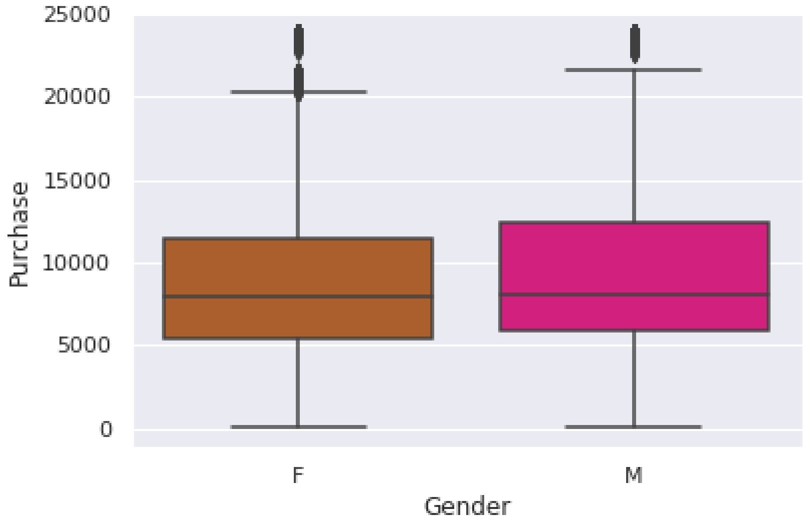


There are a few outliers in the **Purchase** attribute.

Outlier in Purchase column against male and female

```
sns.boxplot(x='Gender',y='Purchase',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730fa27910>
```

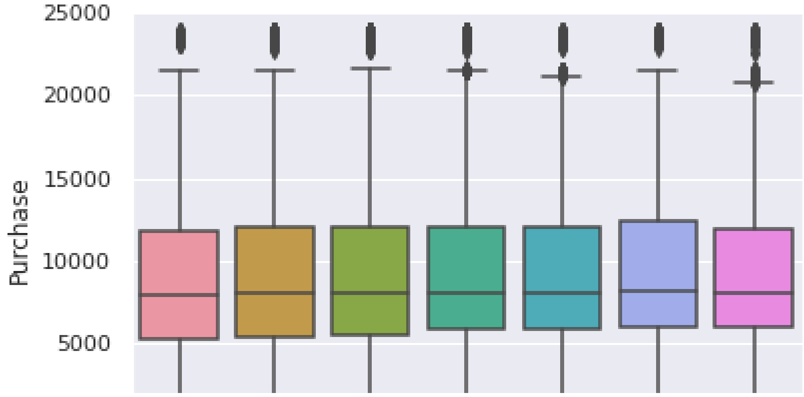


Female spendings have more outliers than **male** spendings.

Outliers against age category

```
sns.boxplot(x='Age',y='Purchase',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730f9feb90>
```



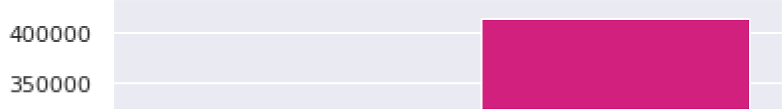
Every age category seems to have outliers.

1.3 - Visual Analysis - Univariate & Bivariate

Number of female and male transactions

```
sns.countplot(x='Gender',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730f8f0550>
```

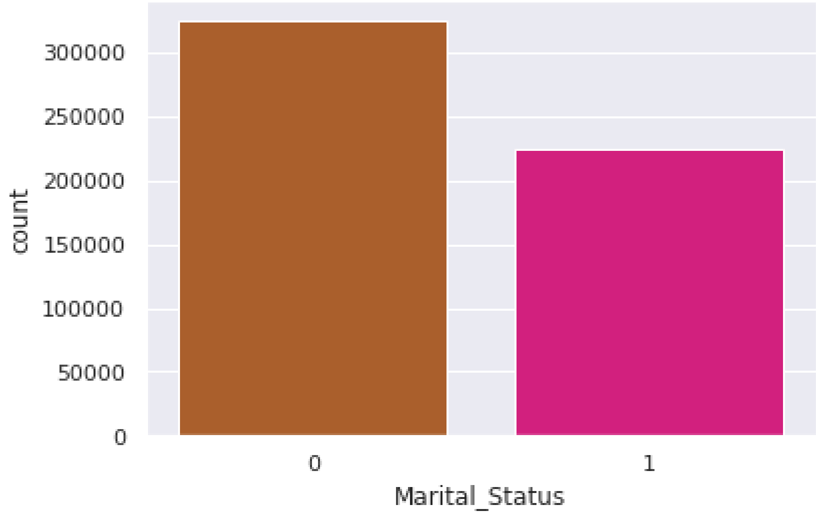


Number of male transactions is way more than the number of female transactions.More than two times of female transaction is male transactions.

number of married and unmarried

```
sns.countplot(x='Marital_Status',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730f9a2a50>
```

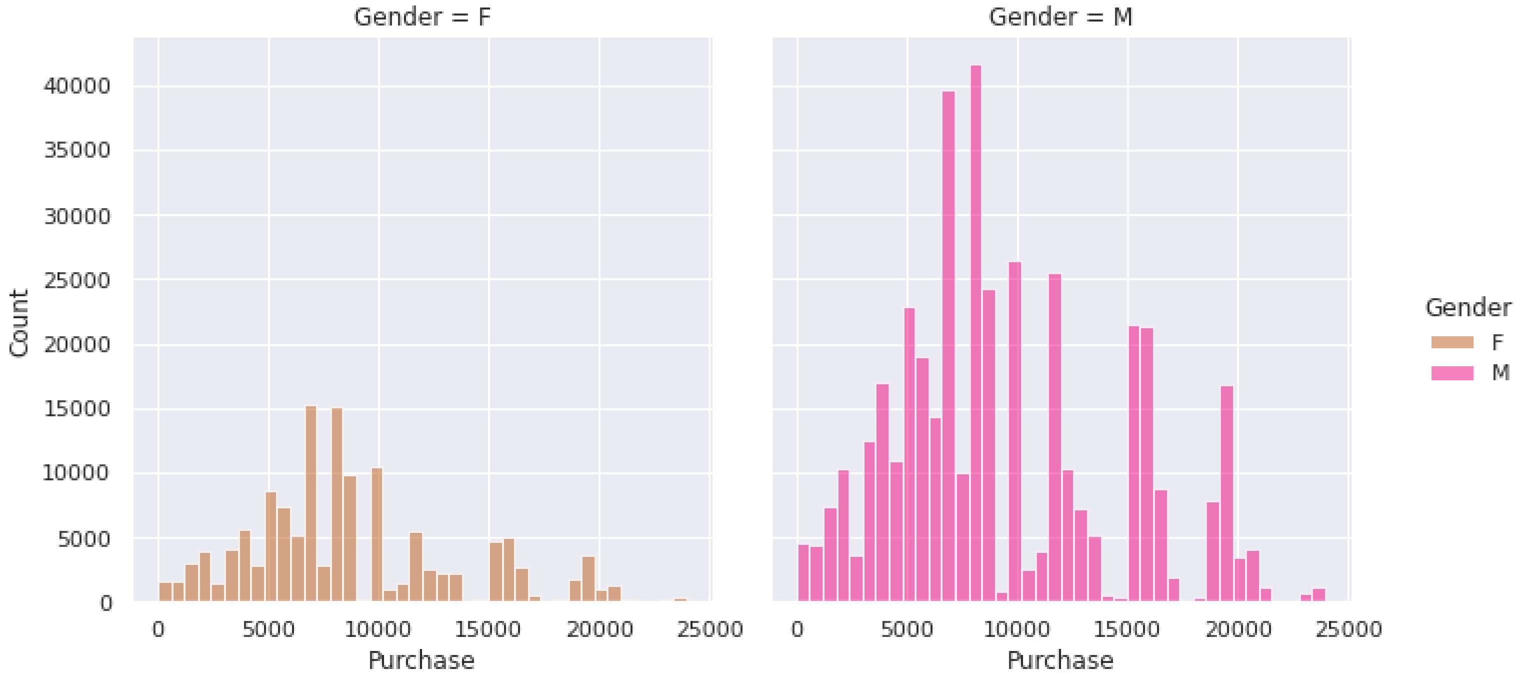


Unmarried customers visited Walmart stores in bulk numbers than married customers.

Distribution plot for Male and Female

```
sns.set_theme(palette="Accent_r")
sns.displot(data=data_tran,x='Purchase',hue='Gender',kind='hist',col='Gender',bins=40)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730fcce990>
```



The **males** outnumbered **females** in spending.For example people who have spend between 5000 and 10000 are most males.

Conclusion:In overall **males** spending more than **females**

Distribution plot based on age category for male and female

```
sns.set_theme(palette='Accent_r')
```

```
sns.displot(data=data_tran,x='Purchase',hue='Gender',kind='hist',col='Age',col_wrap=3,bins=30,
            multiple='dodge')
```

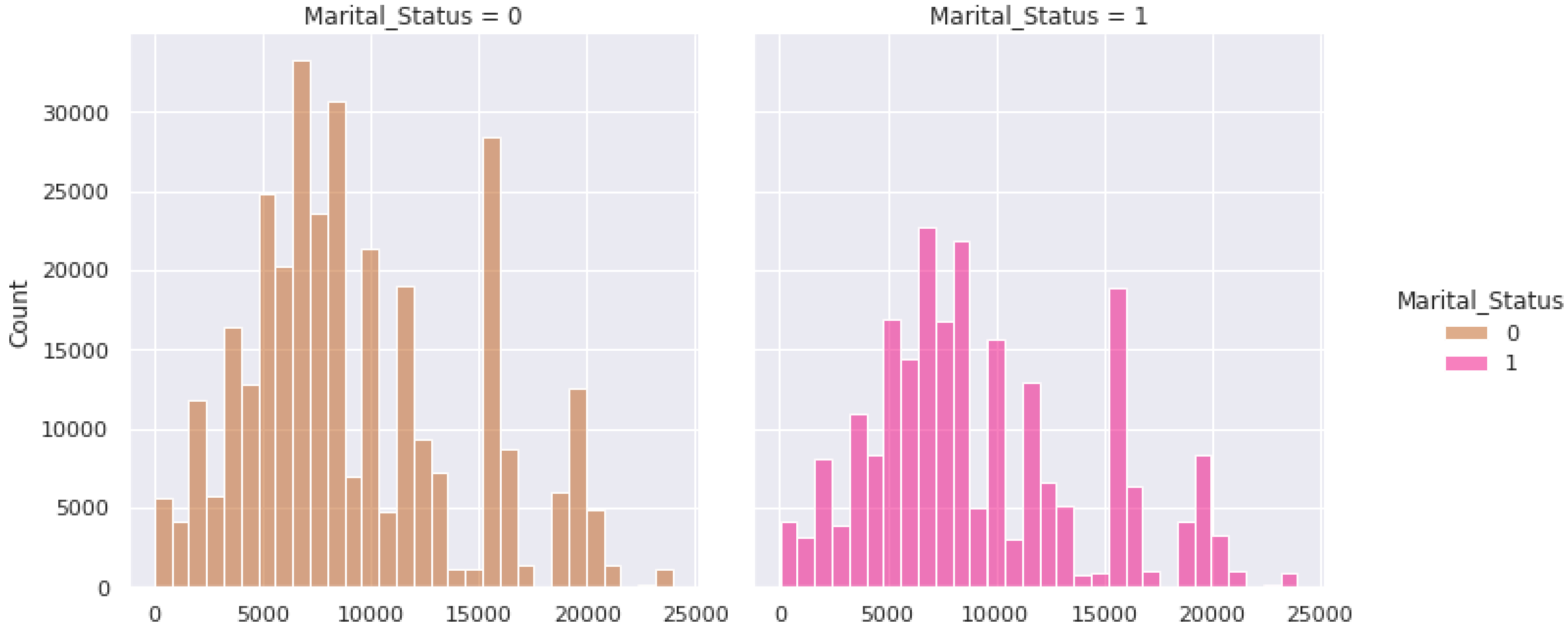
```
<seaborn.axisgrid.FacetGrid at 0x7f730f708310>
```

In almost all age category **males** outnumbered **females** in spending.In particular customers belong to age range from 51 to 55 spending more than any another age range.In this case **male** outnumbered **female**.

Distribution plot for married and unmarried


```
sns.displot(x='Purchase',hue='Marital_Status',data=data_tran,col='Marital_Status',bins=30)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730f279810>
```

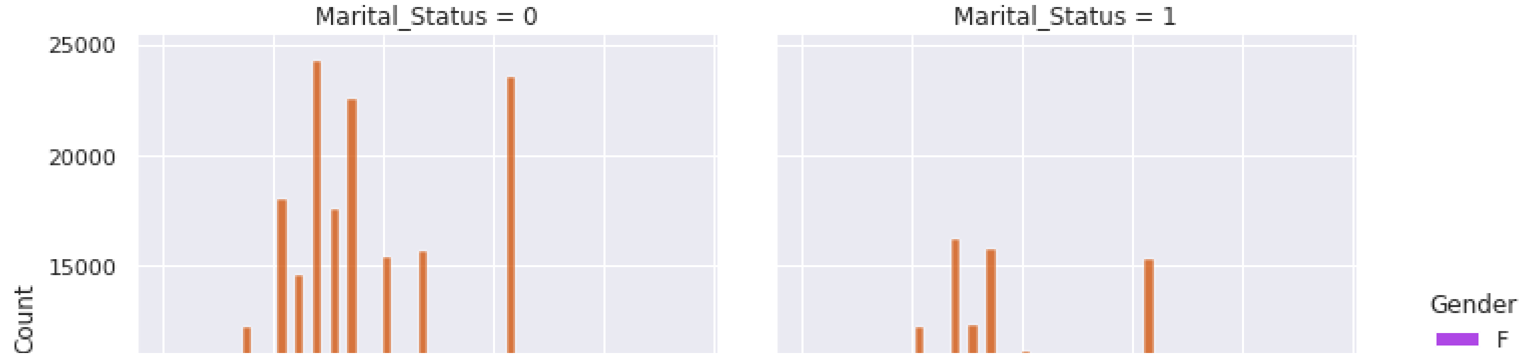


It's very strange that unmarried people spending more than married people.

Distribution plot for male and female against marital status

```
sns.displot(x='Purchase',hue='Gender',col='Marital_Status',data=data_tran,palette='gnuplot',bins=30,multiple='dodge')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730f764110>
```

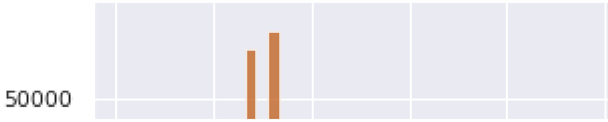


Unmarried male happens to spend more than married male.There is not much significant difference between married females vs unmarried females.Still unmarried females spending a little over money than married females.

Histogram plot for the **Purchase** column

```
sns.displot(x='Purchase',kind='hist',data=data_tran,palette='deep',bins=40)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730f16ead0>
```

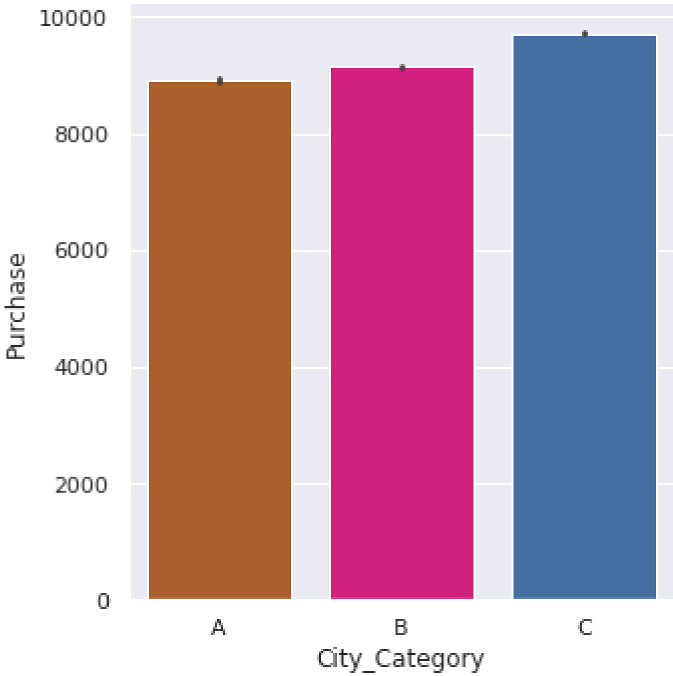


There is a peak around 8000.This distribution is not unimodal that is it has more than one peak.

Spending nature per city(On average)

```
sns.catplot(x='City_Category',y='Purchase',data=data_tran,kind='bar',estimator=np.mean)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730ec35c10>
```

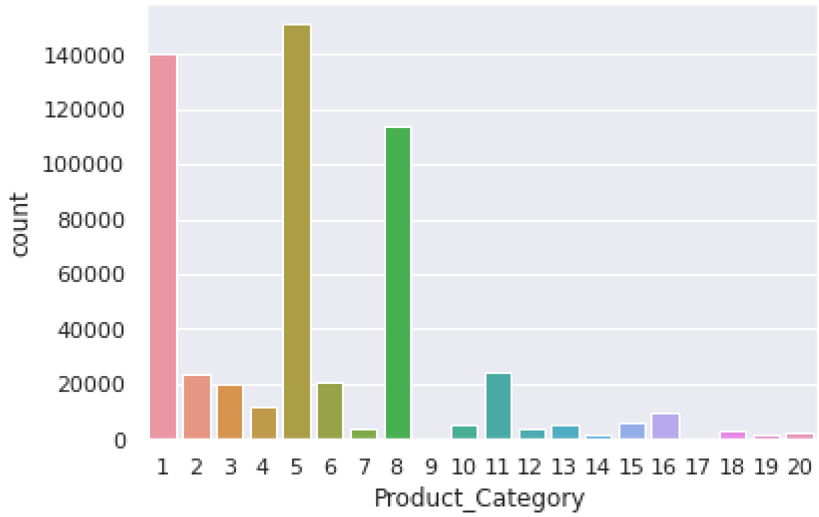


Customers from city **C** happend to spend more on average than city citites.

Count plot for Product Category

```
sns.countplot(x='Product_Category',data=data_tran)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730eae5310>
```



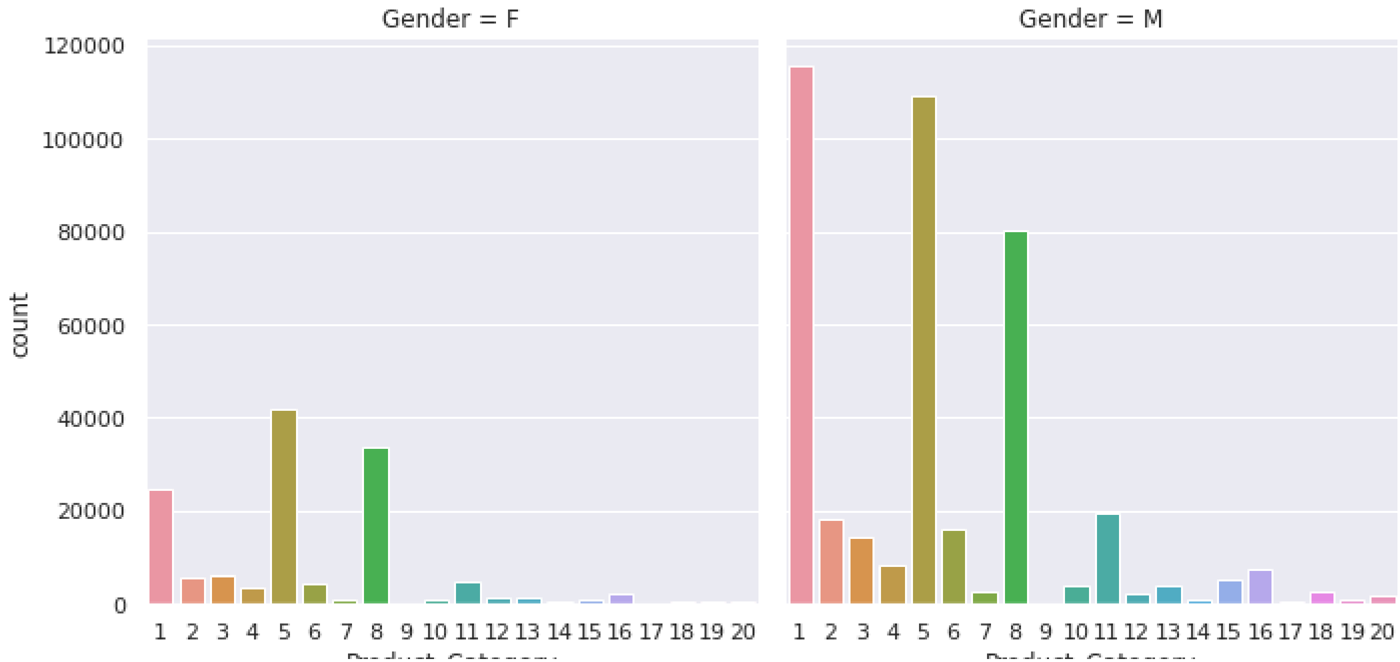
Majority products belong to category 1,5,and 8.Total is more than 4 lakhs which is more than 70% of the total transactions(550068).

Conclusion: These product categories are more famous than other categories.

Count plot for Product Category agains male and female

```
sns.catplot(x='Product_Category',col='Gender',data=data_tran,kind='count')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730eb8ae50>
```



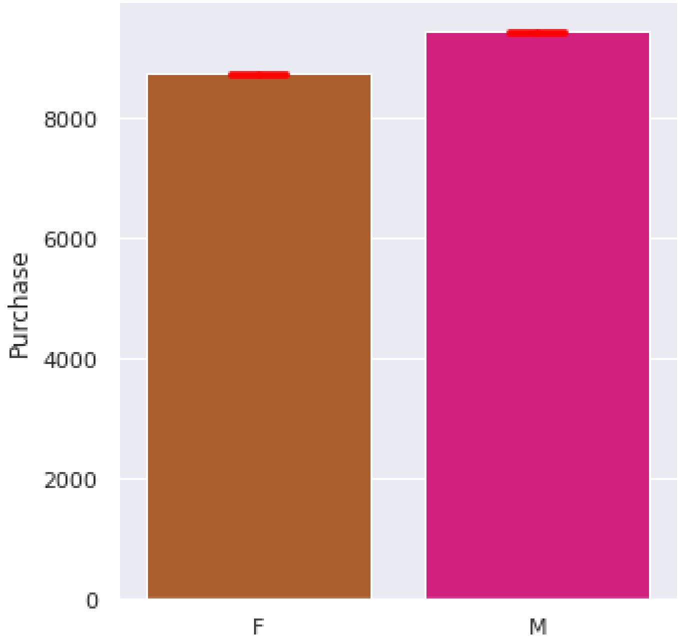
Product categories 1,5,and 8 are more famous to males as well as females.But these product categories are way more famous in male camp than female.

Barplot for male and female with mean estimator and confidence interval using bootstrapping:

This is using seaborn ,later will explicitly find confidence intervals

```
sns.catplot(x='Gender',y='Purchase',data=data_tran,ci=95,errcolor='red',estimator=np.mean,kind='bar',
            capsize=0.2) # 95% boostrap confidence interval
                         # around average spending for male and female
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730cfd0790>
```



The average female spending per transaction is slighly less than the average male spending.

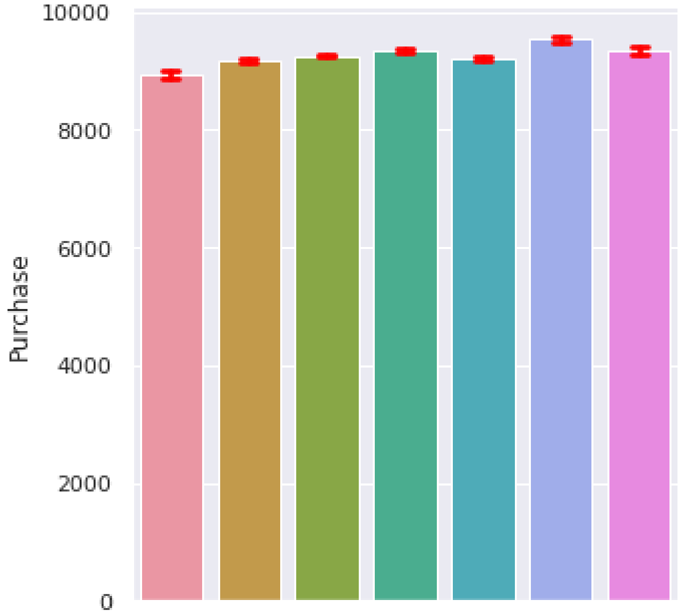
The bootstrap confidence interval around mean for both male and female seems to be very much narrow.

Nevertheless,will explicitly find condfidence interval around mean.

Barplot along with bootstrap 95% confidence interval around mean for each age category.

```
sns.catplot(x='Age',y='Purchase',data=data_tran,ci=95,errcolor='red',estimator=np.mean,kind='bar',
            capsize=0.2)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730e9a1f90>
```



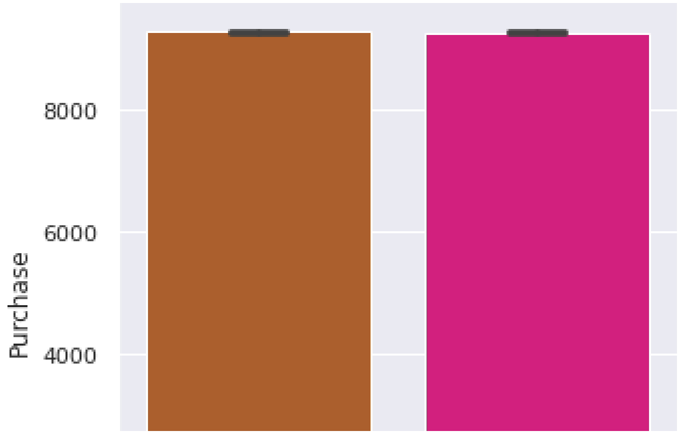
Age category 0-17 and 55+ seems to have a wider confidence interval compared to others.

Nevertheless will find confidence intervals explicitly later.

Barplot of mean for maried vs unmarried.

```
sns.catplot(x='Marital_Status',y='Purchase',data=data_tran,
            ci=95,kind='bar',estimator=np.mean,capsize=0.2) # 95% bootstrap confidence interval around mean
```

```
<seaborn.axisgrid.FacetGrid at 0x7f730cff7850>
```



Bootstrap confidence interval seems to be very much narrow for both married and unmarried.

Nevertheless will construct them explicitly.

Constructing bootstraped confidence interval for male and female

```
male_mean=np.mean(data_tran[data_tran['Gender']=='M'].Purchase)
female_mean=np.mean(data_tran[data_tran['Gender']=='F'].Purchase)
print("Avergae spending per transaction for male is ",male_mean)
print()
print("Avergae spending per transaction for female is ",female_mean)
```

```
Avergae spending per transaction for male is  9437.526040472265

Avergae spending per transaction for female is  8734.565765155476
```

Conclusion: The average spending per transaction for female is little less than the average male spending.

Nevertheless the difference in average spending amongst male and female is not much significant.

On average still male spending more per transaction than female does.

```
def construct_confidence_interval(n_sim,sample_size,data,ci=95):
  # by default 95% confidence interval
  boots_mean=[]
  for _ in range(n_sim):
    boot_sample=np.random.choice(data,size=sample_size,replace=True)
    boots_mean.append(np.mean(boot_sample))

  # calculate the confidence interval
  conf=np.percentile(boots_mean,[(100-ci)/2, ci+((100-ci)/2)])
  return list(conf)
```

confidence for female spending:Around population mean

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000,100000] # different different sample sizes
data=data_tran[data_tran['Gender']=='F'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for female spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for female spending:
```

	sample size	CI
0	30	[7096.71, 10515.97]
1	100	[7822.28, 9684.35]
2	1000	[8440.93, 9033.03]
3	10000	[8643.26, 8827.12]
4	30000	[8679.8, 8789.9]
5	50000	[8693.41, 8776.72]

As sample size increasing the confidence intervals become narrower and narrower.

with **100** samples confidence interval is not much of use as it is much wider.

With **1000** samples the confidence interval seems to be reliable.

```
intervals=[]
ci=99 # 99% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("99% confidence interval for female spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
99% confidence interval for female spending:
```

	sample size	CI
0	30	[6609.27, 11057.87]
1	100	[7532.47, 9995.36]

As sample size is increasing the 90% and 95% confidence intervals are becoming more and more identical.

```
intervals=[]
ci=90 # 90% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("90% confidence interval for female spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
90% confidence interval for female spending:
```

	sample size	CI
0	30	[7307.57, 10219.32]
1	100	[7954.87, 9531.82]
2	1000	[8491.63, 8982.01]
3	10000	[8657.16, 8812.27]
4	30000	[8689.2, 8780.52]
5	50000	[8698.59, 8769.42]
6	100000	[8709.32, 8759.06]

As sample size is increasing the 90%,95% and 99% confidence intervals are becoming more and more identical.

```
# calculate average spending of each female customer
avg_spending=data_tran[data_tran['Gender']=='F'].groupby('User_ID')['Purchase'].mean()

# get the minimum avergae spending and maximum average spending
print("Minimum average spending: ",avg_spending.min())
print("Maximum average spending: ",avg_spending.max())
```

```
Minimum average spending:  3599.733333333333
Maximum average spending:  18490.166666666668
```

With keeping in mind the minimum and maximum average spending of female customers ,we can select 95% confidence interval(**[8441.75, 9026.34]**) with sample size 1000 as a worthy candidate.

Confidence interval for male spending

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000,100000] # different different sample sizes
data=data_tran[data_tran['Gender']=='M'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for male spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for male spending:
```

	sample size	CI
0	30	[7683.1, 11282.64]
1	100	[8456.58, 10452.78]
2	1000	[9125.27, 9756.72]
3	10000	[9336.46, 9539.07]
4	30000	[9379.59, 9495.39]
5	50000	[9393.81, 9482.32]

```
intervals=[]
ci=99 # 99% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("99% confidence interval for male spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
99% confidence interval for male spending:
```

```
intervals=[]
ci=90 # 90% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("90% confidence interval for male spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
90% confidence interval for male spending:
```

	sample size	CI
0	30	[7961.52, 10959.01]
1	100	[8604.42, 10275.25]
2	1000	[9170.74, 9700.77]
3	10000	[9354.06, 9520.55]
4	30000	[9388.5, 9486.54]
5	50000	[9399.46, 9474.64]
6	100000	[9410.97, 9464.47]

```
# calculate average spending of each male customer
avg_spending=data_tran[data_tran['Gender']=='M'].groupby('User_ID')['Purchase'].mean()

# get the minimum avergae spending and maximum average spending
print("Minimum average spending: ",avg_spending.min())
print("Maximum average spending: ",avg_spending.max())
```

```
Minimum average spending:  2318.733333333333
Maximum average spending:  18577.893617021276
```

Interestingly the minimum average(**2318**) spending of a male customer is little less than the minimum average(**3599**) spending of a female customer .

Maximum average spending is almost same for both a male and female.

This way we can draw another conclusion that on average a female customer spends a minimum of **3599** dollars whereas a male customer spending a minimum of **2318** dollars.

So in this perspective female are more oriented towards shopping.

Interestingly with sample size 1000 both the male and the female 95% confidence intervals are not overlapping at all.

Male confidence interval(95%): [9114.96, 9747.34]

Female confidence interval(95%): [8441.75, 9026.34]

Also male happens to spend more on average than a female customer does.

Conclusion: On average male spending more than female

Women are not spending more than men

Reason:

1. Men spending more on average
2. Spending confidence interval for men is [9114.96, 9747.34] whereas confidence interval for women is [8441.75, 9026.34]

Confidence interval for married customers

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000,100000] # different different sample sizes
data=data_tran[data_tran['Marital_Status']==1].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for married customers's spending:
```

	sample size	CI
0	30	[7552.28, 11113.97]
1	100	[8289.44, 10256.0]
2	1000	[8952.24, 9567.01]
3	10000	[9162.19, 9358.05]
4	30000	[9206.28, 9317.66]
5	50000	[9216.56, 9305.4]
6	100000	[9229.91, 9291.62]

With 1000 samples ,the 95% confidence interval is **[8949.88, 9577.5]** which is not bad.

```
intervals=[]
ci=99 # 99% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
```

```
print("99% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
99% confidence interval for married customers's spending:
```

	sample size	CI
0	30	[7098.73, 11759.03]
1	100	[8036.42, 10542.52]
2	1000	[8861.52, 9672.79]
3	10000	[9133.89, 9385.96]
4	30000	[9189.58, 9336.11]
5	50000	[9203.4, 9319.63]
6	100000	[9219.75, 9302.35]

With 1000 samples the 99% confidence interval is **[8865.55, 9679.69]**

```
intervals=[]
ci=90 # 90% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("90% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
90% confidence interval for married customers's spending:
```

	sample size	CI
0	30	[7793.34, 10797.7]
1	100	[8448.92, 10098.21]
2	1000	[9005.79, 9516.49]
3	10000	[9179.2, 9343.47]

With 1000 samples 90% confidence interval is **[9003.21, 9519.72]**

5	50000	[9224.18, 9299.12]

With 1000 samples ,the 95%,99% ,and 90% confidence intervals are [8949.88, 9577.5],[8865.55, 9679.69],[9003.21, 9519.72] respectively.

Confidence interval for unmarried customers spending

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000,100000] # different different sample sizes
data=data_tran[data_tran['Marital_Status']==0].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for married customers's spending:
```

	sample size	CI
0	30	[7551.24, 11106.94]
1	100	[8293.34, 10280.18]
2	1000	[8960.99, 9579.68]
3	10000	[9166.44, 9362.76]
4	30000	[9208.71, 9322.65]

With 1000 samples the 95% confidence interval is [8956.61, 9584.18]

6	100000	[9234.66, 9297.48]

```
intervals=[]
ci=99 # 99% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("99% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
99% confidence interval for married customers's spending:
```

With 1000 samples the 99% confidence interval is [8858.94, 9679.09]

```
intervals=[]
ci=90 # 90% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=ci)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("90% confidence interval for married customers's spending:\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
90% confidence interval for married customers's spending:
```

	sample size	CI
0	30	[7806.45, 10785.24]
1	100	[8447.01, 10081.7]
2	1000	[9009.54, 9527.03]
3	10000	[9183.03, 9348.56]
4	30000	[9217.39, 9314.51]
5	50000	[9228.77, 9303.27]
6	100000	[9240.24, 9291.78]

With 1000 samples the 90% confidence interval is [9005.89, 9530.48]

With 1000 samples ,the 95%,99% ,and 90% confidence intervals are [8956.61, 9584.18],[8858.94, 9679.09],[9005.89, 9530.48] respectively.

Conclusion: If we consider 95% confidence interval then the intervals are overlapping.

married: [8949.88, 9577.5]

Unmarried: [8956.61, 9584.18]

They are almost identical that is spending nature of married customers and unmarried customers are almost same.

Those who are married should have been more active on **Black Friday** as they are more responsible towards family but on the contray this is not the case.Unmarried customers seems to be in par with married customers in responsibility,shopping,etc.

confidence intervals for all age category

Mean for each age category

```
data_tran.groupby('Age')['Purchase'].mean().sort_values()
```

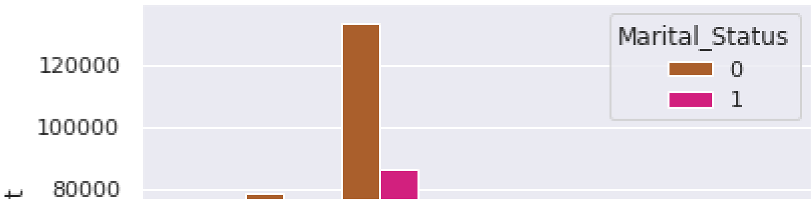
```
Age
0-17     8933.464640
18-25    9169.663606
46-50    9208.625697
26-35    9252.690633
36-45    9331.350695
55+      9336.280459
51-55    9534.808031
Name: Purchase, dtype: float64
```

```
# number of married and unmarried customers in each age range
data=data_tran.groupby(['Age','Marital_Status'])['User_ID'].count().reset_index()
data.columns=['Age','Marital_Status','Count']
data
```

	Age	Marital_Status	Count
0	0-17	0	15102
1	0-17	1	0
2	18-25	0	78544
3	18-25	1	21116
4	26-35	0	133296
5	26-35	1	86291
6	36-45	0	66377
7	36-45	1	43636
8	46-50	0	12690
9	46-50	1	33011
10	51-55	0	10839
11	51-55	1	27662
12	55+	0	7883
13	55+	1	13621

```
sns.barplot(x='Age',y='Count',hue='Marital_Status',data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f730e75f810>



Customers in the age range 51-55 on average spends more than any other range.

Customers in the age range 0-17 on average spends 8933 dollars which is the lowest.

Conlsuion: 0-17 age range customers are not married ,so they have less family burden than other customers belong to different age group.

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000,100000] # different different sample sizes, for age:26-35  which has around 2
                                                    # lakh customers
data=data_tran[data_tran['Age']=='26-35'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 26-35 :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 26-35 :
```

	sample size	CI
0	30	[7472.71, 11056.47]

Customers in the age group 26-35 with 1000 samples the 95% confidence interval is [8943.88, 9563.55]

2	1000	[8944.37, 9561.68]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000] # different different sample sizes, for age:36-45  which has around 1
                                                                          # lakh customers
data=data_tran[data_tran['Age']=='36-45'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 36-45 :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 36-45 :
```

	sample size	CI
0	30	[7636.83, 11181.4]
1	100	[8364.74, 10315.35]
2	1000	[9021.58, 9645.37]
3	10000	[9233.22, 9429.74]
4	30000	[9274.23, 9387.44]
5	50000	[9287.31, 9375.69]

Customers in the age group 36-45 with 1000 samples the 95% confidence interval is [9021.32, 9648.72]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000,50000] # different different sample sizes, for age:18-25  which has around 1
                                                    # lakh customers
data=data_tran[data_tran['Age']=='18-25'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 18-25 :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 18-25 :
```

	sample size	CI
0	30	[7406.52, 11025.01]
1	100	[8213.39, 10188.03]
2	1000	[8854.19, 9474.36]
3	10000	[9070.65, 9269.55]
4	30000	[9113.63, 9225.32]
5	50000	[9125.14, 9213.61]

Customers in the age group 18-25 with 1000 samples the 95% confidence interval is [8858.76, 9478.65]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,30000] # different different sample sizes, for age:46-50  which has around 40
                                                    # thousands customers
data=data_tran[data_tran['Age']=='46-50'].Purchase
```

```
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 46-50 :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 46-50 :
```

	sample size	CI
0	30	[7546.14, 11029.95]
1	100	[8244.64, 10194.67]
2	1000	[8894.5, 9520.95]
3	10000	[9111.08, 9305.98]
4	30000	[9152.49, 9265.57]

Customers in the age group 46-50 with 1000 samples the 95% : confidence interval is [8903.42, 9522.41]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,20000] # different different sample sizes, for age:51-55  which has around 40
                                                    # thousands customers
data=data_tran[data_tran['Age']=='51-55'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 51-55 :\n")
```

```
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 51-55 :
```

	sample size	CI
0	30	[7765.36, 11402.98]
1	100	[8565.87, 10534.76]
2	1000	[9228.51, 9856.74]
3	10000	[9435.35, 9632.5]
4	20000	[9465.51, 9604.59]

Customers in the age group 51-55 with 1000 samples the 95% confidence interval is [9226.18, 9859.68]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,10000,15000] # different different sample sizes, for age:55+  which has around 20
                                                    # thousands customers
data=data_tran[data_tran['Age']=='55+'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 55+ :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 55+ :
```

	sample size	CI
0	30	[7603.19, 11135.99]

Customers in the age group 55+ with 1000 samples the 95% confidence interval is [9020.52, 9649.17]

2	1000	[9031.56, 9643.53]

```
n_sim=10000 # number of simulations
sample_sizes=[30,100,1000,5000,10000] # different different sample sizes, for age:0-17  which has around 15
                                                    # thousands customers
data=data_tran[data_tran['Age']=='0-17'].Purchase
intervals=[]
ci=95 # 95% confidence interval
for sample_size in sample_sizes:
  interval=construct_confidence_interval(n_sim,sample_size,data,ci=95)
  intervals.append([round(interval[0],2),round(interval[1],2)])
print("95% confidence interval for spending by customers belong to the age group 0-17 :\n")
df=pd.DataFrame({'sample size':sample_sizes,'CI':intervals})
df
```

```
95% confidence interval for spending by customers belong to the age group 0-17 :
```

	sample size	CI
0	30	[7162.12, 10792.79]
1	100	[7931.97, 9949.64]
2	1000	[8621.05, 9249.24]
3	5000	[8793.02, 9075.95]
4	10000	[8834.67, 9034.22]

Customers in the age group 0-17 with 1000 samples the 95% confidence interval is [8618.78, 9249.09]

Conclusion: The 95% confidence intervals all the age category more or less overlapping.

And more or less every customer spending from 8800 dollars to 9800 dollars on average.

Nevertheless customers belonging to age group 51-55 happens to spend more money on average than any other age category customers

Age group 51-55 happens to spend on average maximum of 9859.68 dollars.

Recommendation:

1. Store more products of category 1,5,and 8 for both men and women on Black Friday.
2. Store more men related products.
3. Customers in the age range 51-55 are valuable customers as they are in heighest spending customers on average.
4. 95% confidence interval for married and unmarried are [8949.88, 9577.5] and [8956.61, 9584.18] respectively.They are almost identical but number of unmarried customers outnumbered married one.**So,we should pay more focus towards unmmarried customers.**
5. Walmart should store more products for city **C** customers.

0s completed at 10:40