Walmart

March 10, 2024

1 About Walmart

Walmart is an American multinational retail corporation that operates a chain of supercenters, discount departmental stores, and grocery stores from the United States. Walmart has more than 100 million customers worldwido blem

The Management team at Walmart Inc. wants to analyze the customer purchase behavior (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions. They want to understand if the spending habits differ between male and female customers: Do women spend more on Black Friday than men? (Assume 50 million customers are male and 50 million are female).

[98]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm
```

[99]:
```
df = pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
↪000/001/293/original/walmart_data.csv?1641285094")
df
```

[99]:
```
        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
…           …          …     …     …           …
550063  1006033  P00372445      M 51-55          13             B
550064  1006035  P00375436      F 26-35           1             C
550065  1006036  P00375436      F 26-35          15             B
550066  1006038  P00375436      F   55+           1             C
550067  1006039  P00371644      F 46-50           0             B

       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
…                                …          …          …        …
550063                             1          1           20      368
550064                             3          0           20      371
550065                            4+          1           20      137
550066                             2          0           20      365
550067                            4+          1           20      490

[550068 rows x 10 columns]
```

2 Explore the Dataset

[100]:
```python
df.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
```

[101]:
```python
df.shape
```

[101]:
```
(550068, 10)
```

[102]:
```python
df.columns
```

[102]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

3 To find Null values

[103]:
```
df.isna().sum()
```

[103]:
```
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
```

Insight as follows : The above dataset contain zero Null values. No Missing values.

4 To change the datatype of the variables

[104]:
```
df['Marital_Status'] = df['Marital_Status'].apply(lambda x: 'Married' if x == 1␣
↪else 'Single')
columns = ['Marital_Status','Age','Stay_In_Current_City_Years']
df[columns] = df[columns].astype('category')
df.dtypes
```

[104]:
```
User_ID                          int64
Product_ID                      object
Gender                          object
Age                           category
Occupation                       int64
City_Category                   object
Stay_In_Current_City_Years    category
Marital_Status                category
Product_Category                 int64
Purchase                         int64
dtype: object
```

[105]:
```
df.head()
```

[105]:
```
   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	Single	3	8370
1	2	Single	1	15200
2	2	Single	12	1422
3	2	Single	12	1057
4	4+	Single	8	7969

[106]:
```python
# For measurable quantities
df.describe(include='all')
```

[106]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	\
count	5.500680e+05	550068	550068	550068	550068.000000	550068	
unique	NaN	3631	2	7	NaN	3	
top	NaN	P00265242	M	26-35	NaN	B	
freq	NaN	1880	414259	219587	NaN	231173	
mean	1.003029e+06	NaN	NaN	NaN	8.076707	NaN	
std	1.727592e+03	NaN	NaN	NaN	6.522660	NaN	
min	1.000001e+06	NaN	NaN	NaN	0.000000	NaN	
25%	1.001516e+06	NaN	NaN	NaN	2.000000	NaN	
50%	1.003077e+06	NaN	NaN	NaN	7.000000	NaN	
75%	1.004478e+06	NaN	NaN	NaN	14.000000	NaN	
max	1.006040e+06	NaN	NaN	NaN	20.000000	NaN	

	Stay_In_Current_City_Years	Marital_Status	Product_Category	\
count	550068	550068	550068.000000	
unique	5	2	NaN	
top	1	Single	NaN	
freq	193821	324731	NaN	
mean	NaN	NaN	5.404270	
std	NaN	NaN	3.936211	
min	NaN	NaN	1.000000	
25%	NaN	NaN	1.000000	
50%	NaN	NaN	5.000000	
75%	NaN	NaN	8.000000	
max	NaN	NaN	20.000000	

	Purchase
count	550068.000000
unique	NaN
top	NaN
freq	NaN
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000

```
max      23961.000000
```

5 Perform Value counts on the categorical variables

[107]:
```
cols = df.columns
print(cols)
for i in cols:
    if (df[i].dtype == 'category') or (df[i].dtype=='object') and not(i ==␣
 ↪'Product_ID'):
        print(f'\n {df[i].value_counts()}')
        print("-"*50)
        print(f'Percentage distribution:\n {np.round((df[i].value_counts()/
 ↪len(df))*100,2)}')
        print("="*80)
```

```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')

 Gender
M    414259
F    135809
Name: count, dtype: int64
--------------------------------------------------
Percentage distribution:
 Gender
M    75.31
F    24.69
Name: count, dtype: float64
================================================================================

 Age
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: count, dtype: int64
--------------------------------------------------
Percentage distribution:
 Age
26-35    39.92
36-45    20.00
18-25    18.12
```

```
46-50     8.31
51-55     7.00
55+       3.91
0-17      2.75
Name: count, dtype: float64
================================================================================

 City_Category
B    231173
C    171175
A    147720
Name: count, dtype: int64
--------------------------------------------------
Percentage distribution:
 City_Category
B    42.03
C    31.12
A    26.85
Name: count, dtype: float64
================================================================================

 Stay_In_Current_City_Years
1     193821
2     101838
3      95285
4+     84726
0      74398
Name: count, dtype: int64
--------------------------------------------------
Percentage distribution:
 Stay_In_Current_City_Years
1     35.24
2     18.51
3     17.32
4+    15.40
0     13.53
Name: count, dtype: float64
================================================================================

 Marital_Status
Single     324731
Married    225337
Name: count, dtype: int64
--------------------------------------------------
Percentage distribution:
 Marital_Status
Single     59.03
Married    40.97
```

```
Name: count, dtype: float64
================================================================================
```

Conclusion : *Basesd on the df.describe and value counts the observations are below*

1. Male gender purchased more- 75% of users are male and 25% are female.

2. 26-35 age people purchased more - Users ages 26–35 are 40%, users ages 36–45 are 20%, users ages 18–25 are 18%, and very low users ages (0–17 & 55+)are 5%

3. City B people purchased more- 35% stay in a city for 1 year, 18% stay in a city for 2 years, 17% stay in a city for 3 years, and 15% stay in a city for 4+ years.

4. Single people purchased more compared to the married people- 60% of users are single, and 40% are married.

6 Unique Attributes

[108]:
```python
df.head()
```

[108]:
```
   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         Single                 3      8370
1                          2         Single                 1     15200
2                          2         Single                12      1422
3                          2         Single                12      1057
4                         4+         Single                 8      7969
```

[109]:
```python
cols=['User_ID','Product_ID']
for i in cols:
    print(f"Unique counts of the {i} : {df[i].nunique()}")
```

```
Unique counts of the User_ID : 5891
Unique counts of the Product_ID : 3631
```

Conclusion::

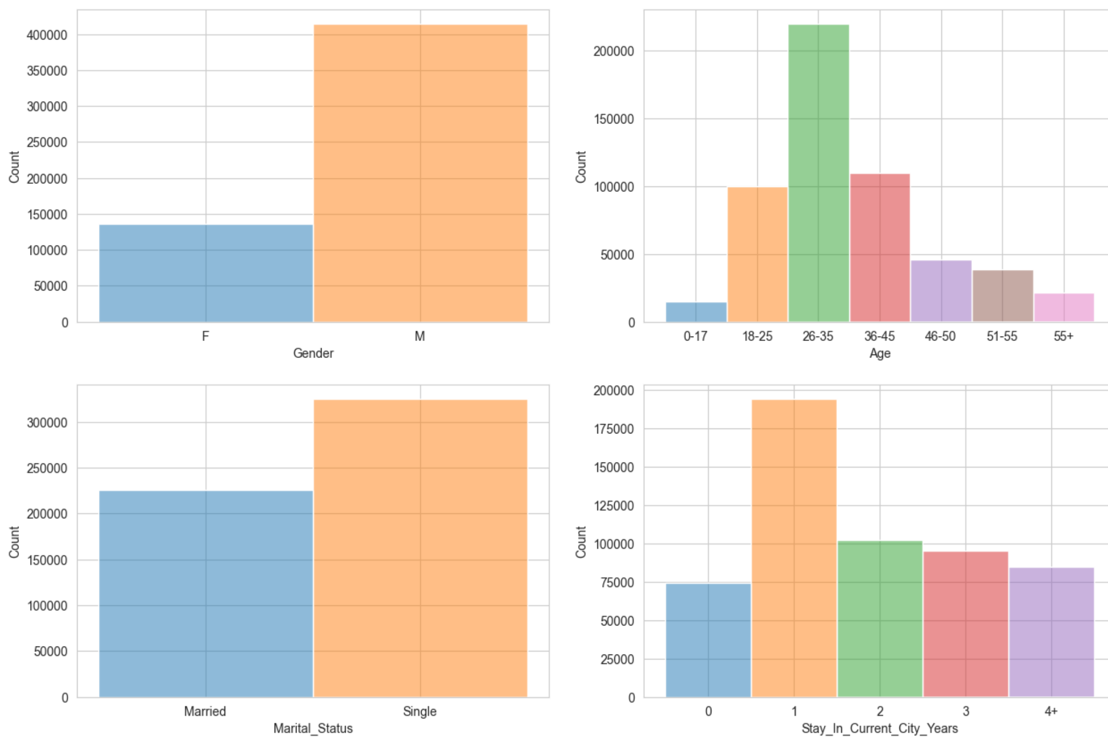
The total number of unique product IDs is 3631

The total number of unique user IDs is 5891

7 Visual Analysis- Univariate & Bivariate*

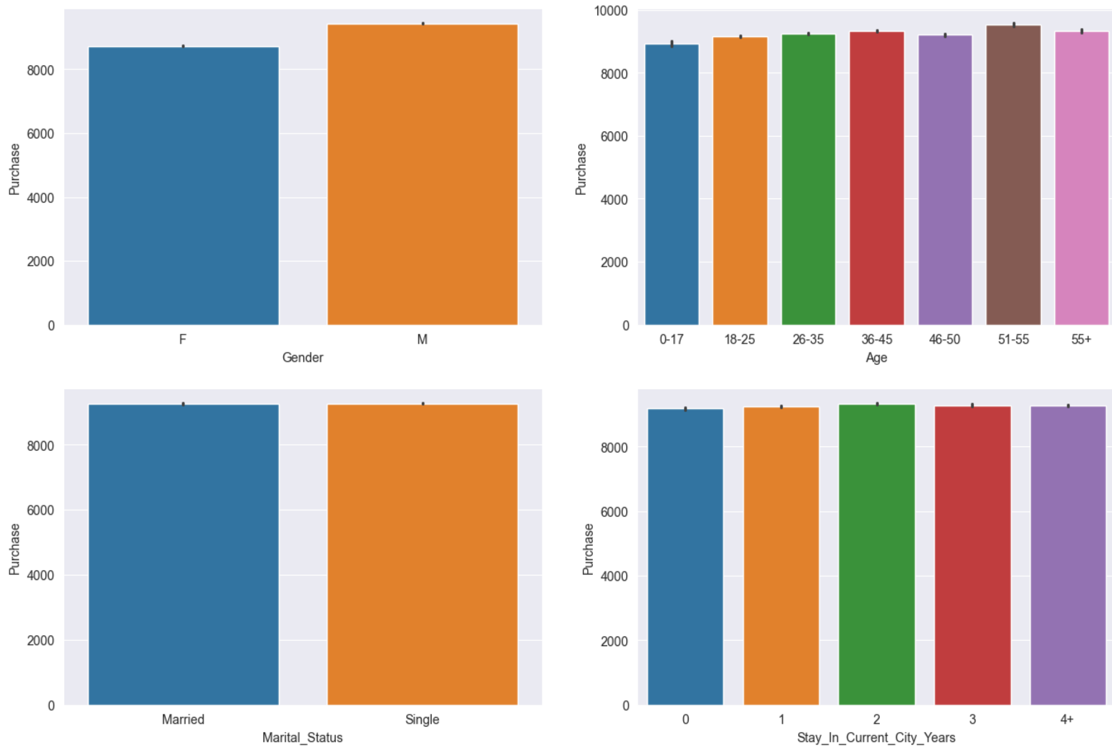
8 BarPlot- Gender vs Purchase

[110]:
```
fig, axis = plt.subplots(nrows = 2, ncols=2, figsize=(15,10))
sns.set_style('darkgrid')
sns.
 ↪histplot(data=df,x='Gender',hue='Gender',legend=False,ax=axis[0,0],color='orange')
sns.histplot(data=df,x='Age',hue='Age',legend=False,ax=axis[0,1],color='blue')
sns.
 ↪histplot(data=df,x='Marital_Status',hue='Marital_Status',legend=False,ax=axis[1,0])
sns.
 ↪histplot(data=df,x='Stay_In_Current_City_Years',hue='Stay_In_Current_City_Years',legend=Fal
plt.show()
```

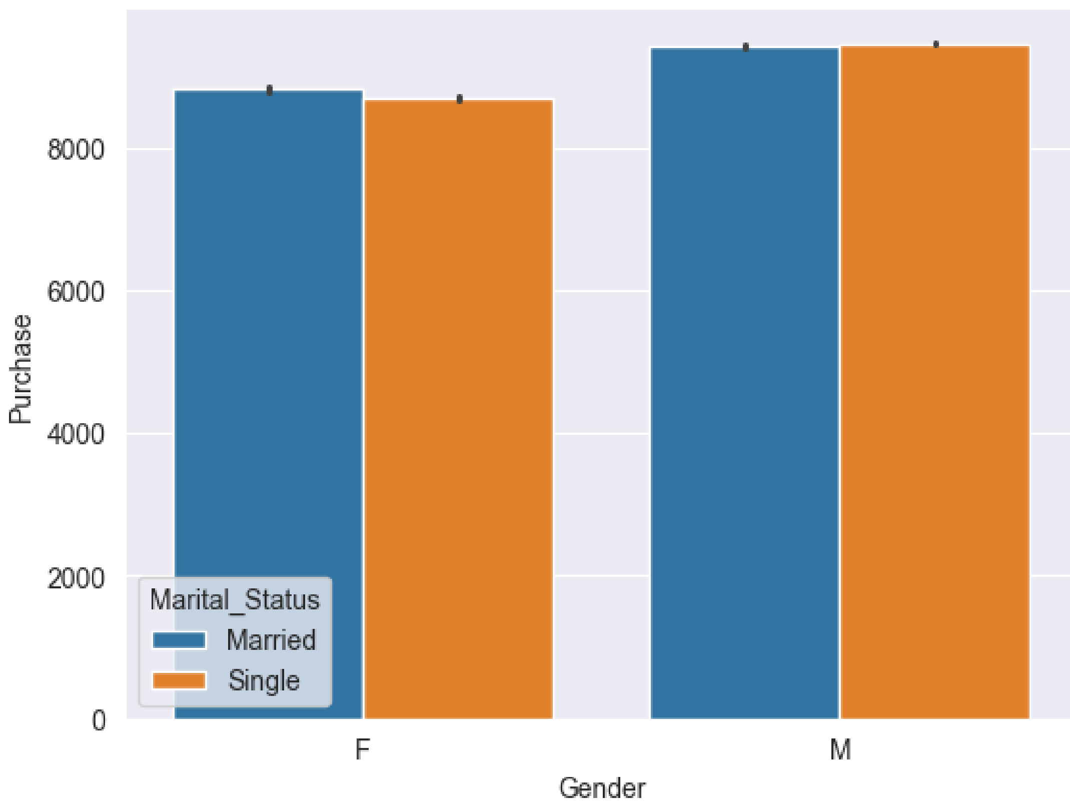


[111]:
```
fig, axis = plt.subplots(nrows = 2, ncols=2, figsize=(15,10))
sns.set_style('darkgrid')
sns.
 ↪barplot(data=df,x='Gender',hue='Gender',y='Purchase',legend=False,ax=axis[0,0])
sns.barplot(data=df,x='Age',hue='Age',y='Purchase',legend=False,ax=axis[0,1])
sns.
 ↪barplot(data=df,x='Marital_Status',y='Purchase',hue='Marital_Status',legend=False,ax=axis[1
```

```
sns.
 ↪barplot(data=df,x='Stay_In_Current_City_Years',y='Purchase',hue='Stay_In_Current_City_Years
plt.show()
```



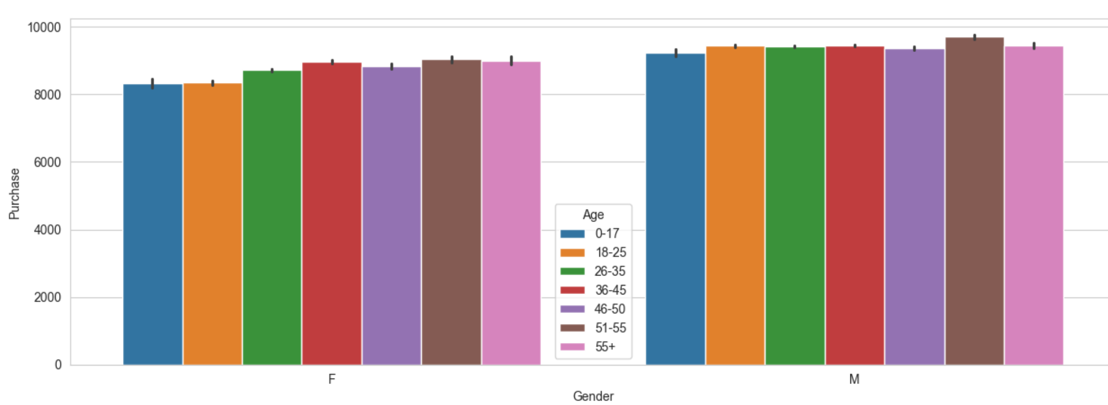
[112]:
```
sns.barplot(x='Gender',y='Purchase',hue='Marital_Status',data=df)
plt.show()
```



Conclusion:

There is no difference in the purchase limit for the married and single category among male and Female

[113]:
```
plt.figure(figsize=(15,5))
sns.set_style('whitegrid')
sns.barplot(x='Gender',y='Purchase',hue='Age',data=df)
plt.show()
```

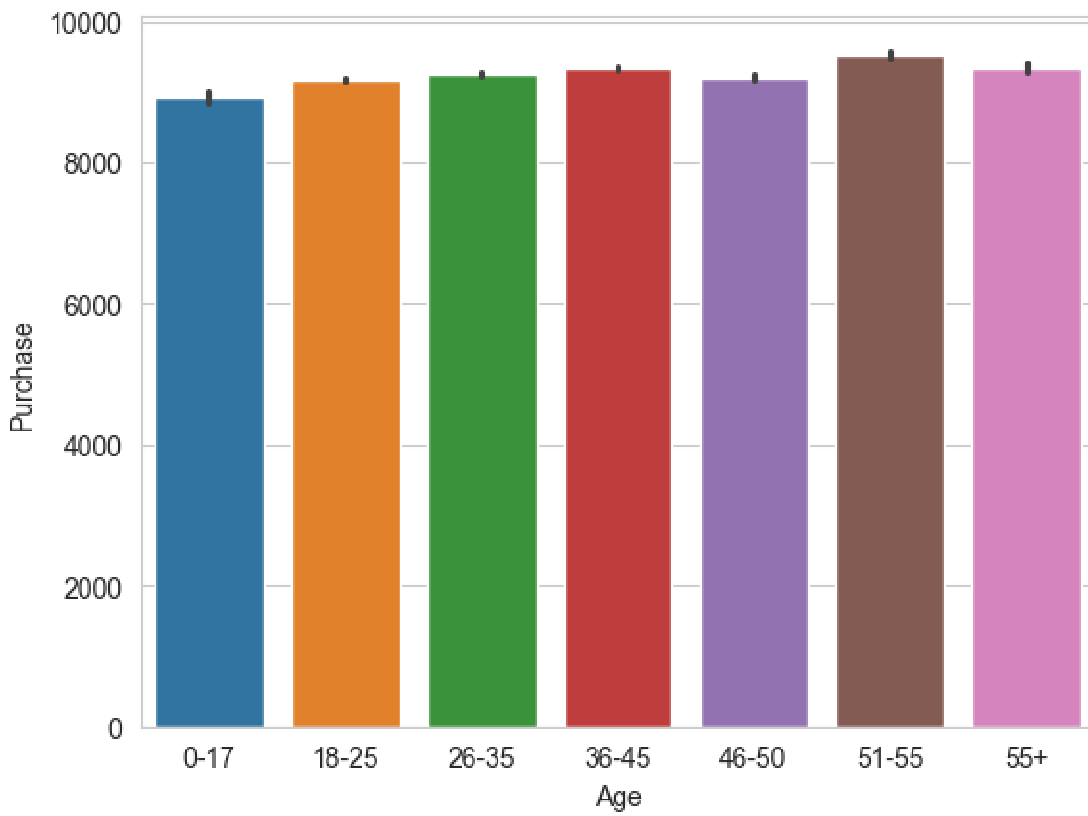


Conclusion:

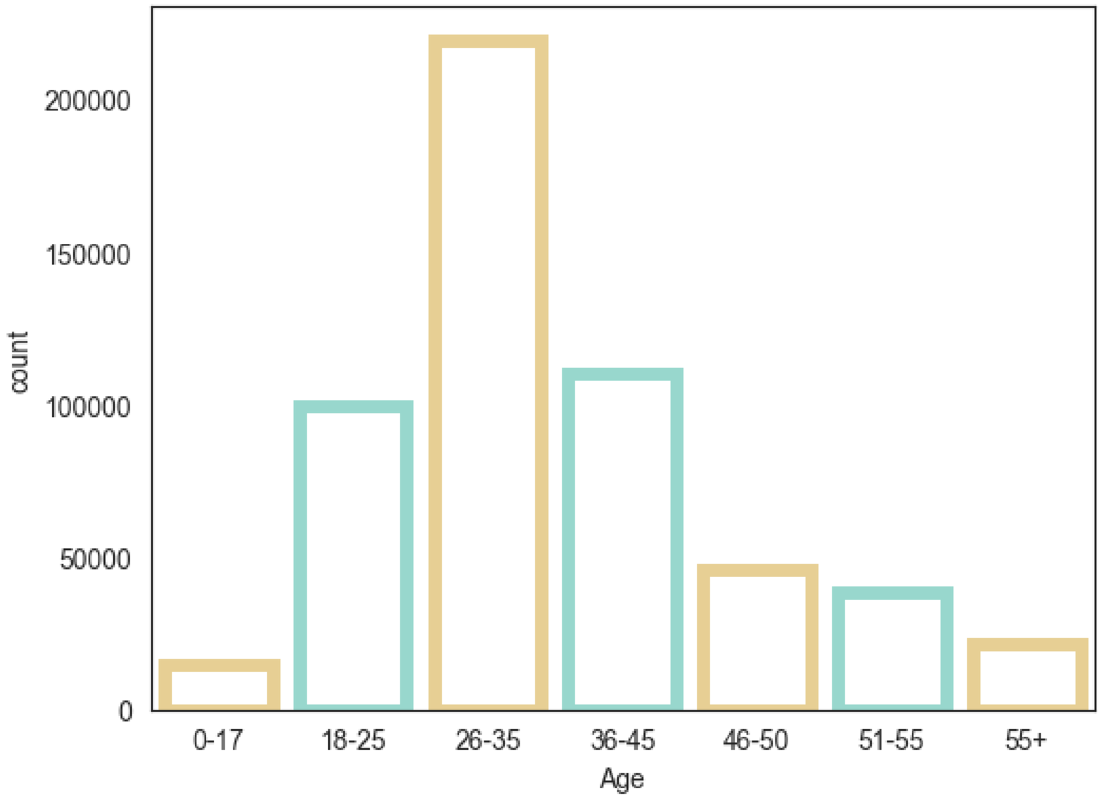
- There is no difference in the purchase limit for thagele category among male and Fema*le

[114]:
```
sns.barplot(y='Purchase',hue='Age',x='Age',data=df,legend=False)
```

[114]: <Axes: xlabel='Age', ylabel='Purchase'>

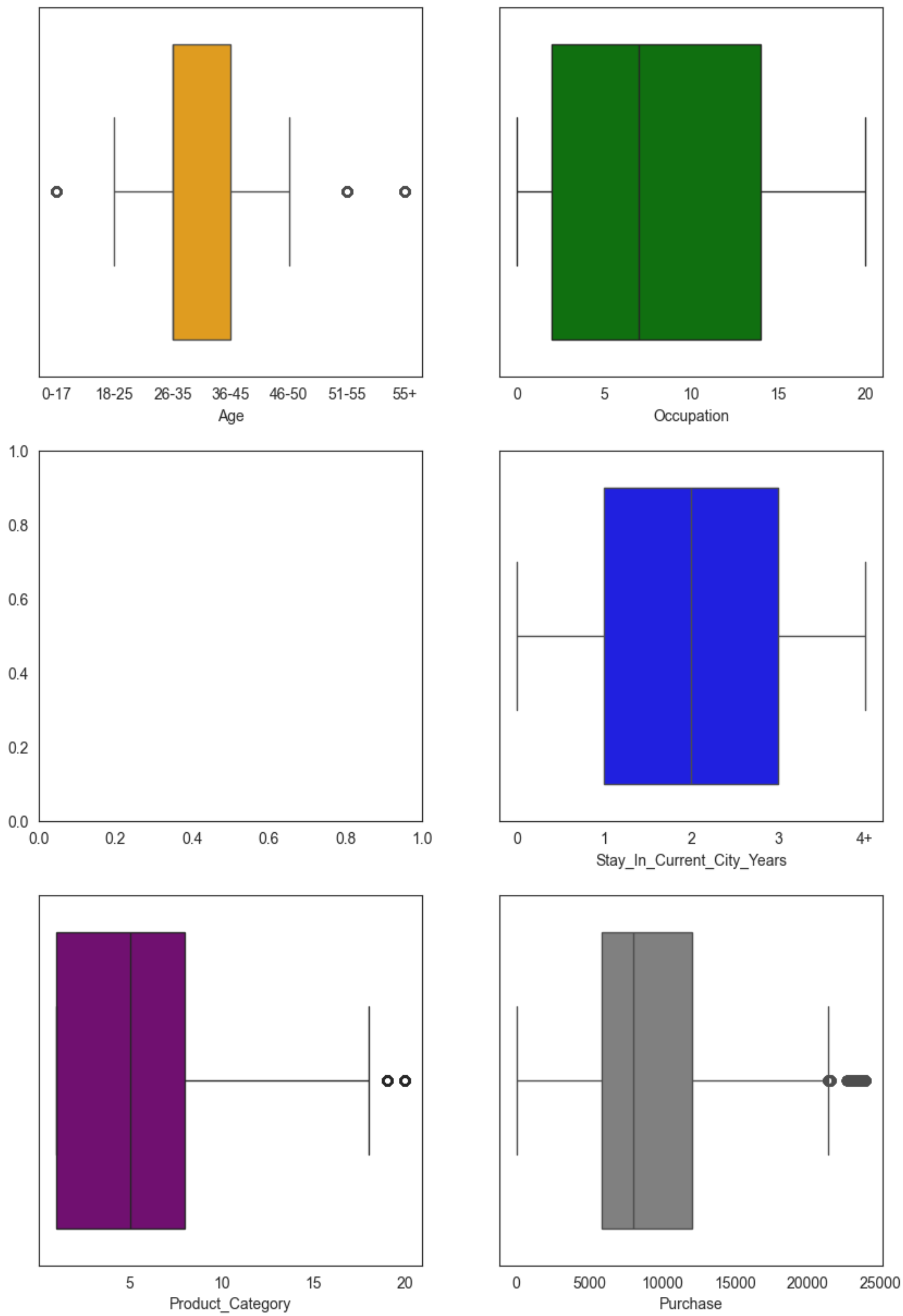


[115]:
```
sns.set_style('white')
sns.countplot(x ='Age', data = df,color="salmon", facecolor=(0, 0, 0, 0),
                    linewidth=5,
                    edgecolor=sns.color_palette("BrBG", 2))
plt.show()
```



9 Outlier detection

[116]:
```
fig,axis = plt.subplots(nrows=3, ncols=2,figsize=(10,15))
sns.set_style('whitegrid')
sns.boxplot(data=df,x='Age',color='orange',ax=axis[0,0])
sns.boxplot(data=df,x='Occupation',color='green',ax=axis[0,1])
sns.boxplot(data=df,x='Stay_In_Current_City_Years',color='blue',ax=axis[1,1])
sns.boxplot(data=df,x='Product_Category',color='purple',ax=axis[2,0])
sns.boxplot(data=df,x='Purchase',color='grey',ax=axis[2,1])
plt.show()
```


0-17
18-25
26-35
36-45
46-50
51-55
55+
Age
0
5
10
15
20
Occupation
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4+
Stay_In_Current_City_Years
5
10
15
20
Product_Category
0
5000
10000
15000
20000
25000
Purchase

Conclusion:

1. ***Age:*** *75% of the people age lies between the age 18-25 and 36-45 ==> outliers are present*

2. ***Occupation:*** *75% of people occupation lies between 0 to 15(approx.) ==> No Outliers*

3. ***Stay_in_current_city:*** *No outliers*

4. ***Product_category:*** *50% of people bought products from 0 to 5 category ==> No outliers*

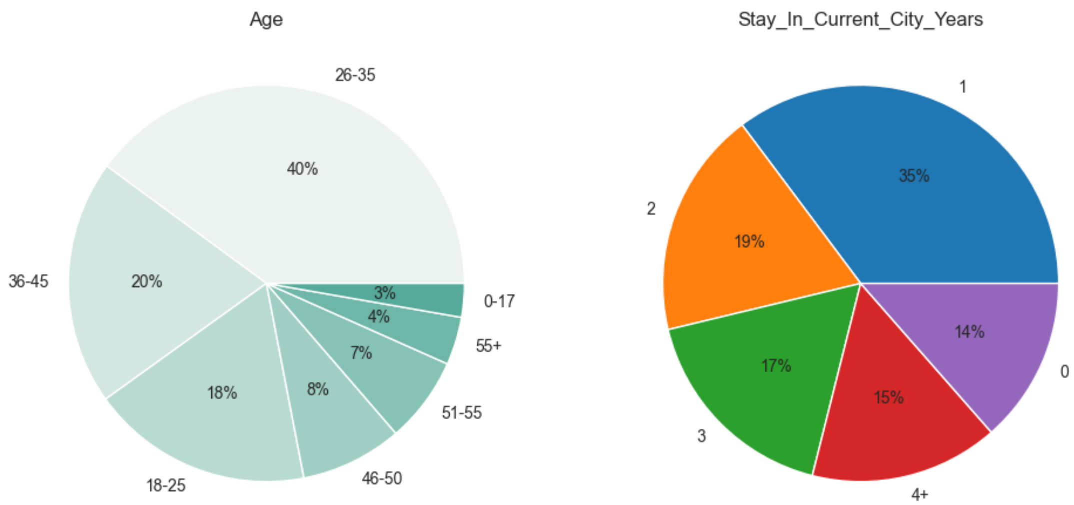
5. ***Purchase****:25% to 75% of puchases are lies between 5000(approx.) to 13000(approx.)==> Outliers are present*

[117]:
```
dataaa=df['Age'].value_counts(normalize=True)
print(dataaa)
dataaa.index
```

```
Age
26-35    0.399200
36-45    0.199999
18-25    0.181178
46-50    0.083082
51-55    0.069993
55+      0.039093
0-17     0.027455
Name: proportion, dtype: float64
```

[117]:
```
CategoricalIndex(['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17'],
categories=['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+'],
ordered=False, dtype='category', name='Age')
```

[118]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 8))
unique_colors_age = sns.color_palette("light:#5A9", len(df['Age'].unique()))

data_age = df['Age'].value_counts(normalize=True) *100
axs[0].pie(x=data_age.values, autopct='%.0f%%',labels=data_age.
 ↪index,colors=unique_colors_age)
axs[0].set_title("Age")

data_city_years = df['Stay_In_Current_City_Years'].value_counts(normalize=True)␣
 ↪* 100
axs[1].pie(x=data_city_years.values,autopct='%.0f%%', labels=data_city_years.
 ↪index)
axs[1].set_title("Stay_In_Current_City_Years")
plt.show()
```



Insights : *.) Users ages 26–35 are 40%, users ages 36–45 are 20%, users ages 18–25 are 18%, users ages 46–50 are 8%, users ages 51–55 are 7%, users ages 55+ are 4%, and very low users ages 0–17 are 2%*

2. 35% stay in a city for 1 year, 19% stay in a city for 2 years, 17% stay in a city for 3 years, and 15% stay in a city for 4+ years.

10 Bivarient analysis

Analyzing the variation in purchases with the following:

Gender vs Purchase

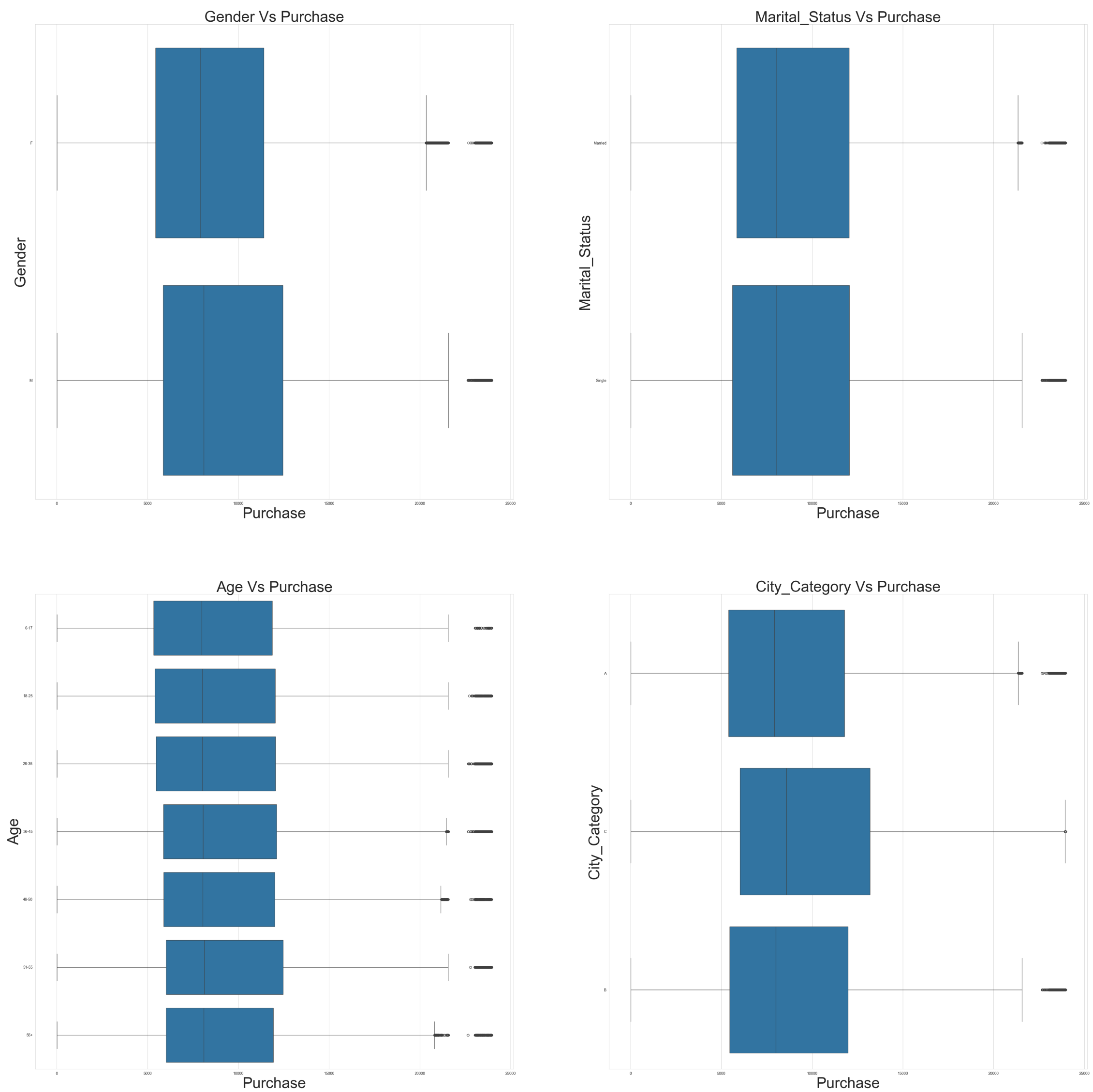
Martial_Status vs Purchase

Age vs Purchase

City_Category vs Purchase

[119]:
```
fig1, axs=plt.subplots(nrows=2,ncols=2, figsize=(50,50))
sns.boxplot(data=df,x='Purchase',y='Gender',orient='h', ax=axs[0,0])
axs[0,0].set_title("Gender Vs Purchase",fontsize=40)
axs[0,0].set_xlabel("Purchase",fontsize=40)
axs[0,0].set_ylabel("Gender",fontsize=40)

sns.boxplot(data=df,x='Purchase',y='Marital_Status',orient='h',ax=axs[0,1])

axs[0,1].set_title("Marital_Status Vs Purchase",fontsize=40)
axs[0,1].set_xlabel("Purchase",fontsize=40)
axs[0,1].set_ylabel("Marital_Status",fontsize=40)
```

```
sns.boxplot(data=df,x='Purchase',y='Age',orient='h',ax=axs[1,0])

axs[1,0].set_title("Age Vs Purchase",fontsize=40)
axs[1,0].set_xlabel("Purchase",fontsize=40)
axs[1,0].set_ylabel("Age",fontsize=40)

sns.boxplot(data=df,x='Purchase',y='City_Category',orient='h',ax=axs[1,1])

axs[1,1].set_title("City_Category Vs Purchase",fontsize=40)
axs[1,1].set_xlabel("Purchase",fontsize=40)
axs[1,1].set_ylabel("City_Category",fontsize=40)

plt.show()
```



Conclusion:

1) Gender vs. Purchase : a) The median for males and females is almost equal. b) Females have more outliers compared to males. c) Males purchased more compared to females.

2) Martial Status vs. Purchase a) The median for married and single people is almost equal. b) Outliers are present in both records.

3) Age vs. Purchase a) The median for all age groups is almost equal. b) Outliers are present in all age groups.

4) City Category vs. Purchase a) The C city region has very low outliers compared to other cities. b) A and B city region medians are almost the same.

11 Detecting Outliers using IQR for the Purchase column

[120]:
```
Q1 = df["Purchase"].quantile(0.25)
Q3 = df["Purchase"].quantile(0.75)
IQR= Q3-Q1
print(f"Quantile 1:{Q1}\nQuantile 2:{Q3}")
print(f"IQR:{IQR}")
```

```
Quantile 1:5823.0
Quantile 2:12054.0
IQR:6231.0
```

[121]:
```
mins= Q1- (1.5*IQR)
maxs= Q3+ (1.5*IQR)
print(mins,maxs)
```

```
-3523.5 21400.5
```

[122]:
```
outliers = df[(df['Purchase']<mins) | (df['Purchase']>maxs)]['Purchase']

print("number of outliers: "+ str(len(outliers)))
print("max outlier value:"+ str(outliers.max()))
print("min outlier value: "+ str(outliers.min()))
```

```
number of outliers: 2677
max outlier value:23961
min outlier value: 21401
```

12 1. Are women spending more money per transaction than men? Why or Why not?

[123]:
```
df.groupby('Gender')['Purchase'].mean()
```

[123]:
```
Gender
F    8734.565765
```

```
M    9437.526040
Name: Purchase, dtype: float64
```

Conclusion:

Overall women not spending more money than men per transaction

13 ======================================

14 Are women spending more money per transaction than men based on the age category? Why or Why not?

15 ======================================

[124]:
```
#Lets see Age wise
a= pd.DataFrame(df.groupby(['Age','Gender'],observed=False)['Purchase'].mean())
a.reset_index(inplace=True)
```

[125]:
```
a
```

[125]:

	Age	Gender	Purchase
0	0-17	F	8338.771985
1	0-17	M	9235.173670
2	18-25	F	8343.180201
3	18-25	M	9440.942971
4	26-35	F	8728.251754
5	26-35	M	9410.337578
6	36-45	F	8959.844056
7	36-45	M	9453.193643
8	46-50	F	8842.098947
9	46-50	M	9357.471509
10	51-55	F	9042.449666
11	51-55	M	9705.094802
12	55+	F	9007.036199
13	55+	M	9438.195603

[126]:
```
a.groupby('Age',observed=False)['Purchase'].aggregate('max')
```

[126]:
```
Age
0-17     9235.173670
18-25    9440.942971
26-35    9410.337578
36-45    9453.193643
46-50    9357.471509
51-55    9705.094802
55+      9438.195603
Name: Purchase, dtype: float64
```

[127]:
```
a[a['Purchase'].isin(a.groupby('Age',observed=False)['Purchase'].
↪aggregate('max').values)]
```

[127]:

	Age	Gender	Purchase
1	0-17	M	9235.173670
3	18-25	M	9440.942971
5	26-35	M	9410.337578
7	36-45	M	9453.193643
9	46-50	M	9357.471509
11	51-55	M	9705.094802
13	55+	M	9438.195603

Conclusion:

For each age category Male gender is higher when compared to female gender in transactions

[128]:
```
cols=['Occupation','City_Category','Stay_In_Current_City_Years','Marital_Status','Product_Cate

for i in cols:
    a= pd.DataFrame(df.groupby([i,'Gender'],observed=False)['Purchase'].mean())
    a.reset_index(inplace=True)
    print(f"Top Gender transaction in {i}:\n{a[a['Purchase'].isin(a.
↪groupby(i,observed=False)['Purchase'].aggregate('max').values)]}")
    print("="*80)
```

```
Top Gender transaction in Occupation:
    Occupation Gender      Purchase
1            0      M   9228.799538
3            1      M   9231.961755
5            2      M   9213.158472
7            3      M   9279.059603
9            4      M   9435.676366
11           5      M   9446.089083
13           6      M   9375.727101
15           7      M   9493.818898
17           8      M   9584.729114
19           9      M   9226.694196
21          10      M   9302.215302
23          11      M   9232.145350
25          12      M   9876.847492
27          13      M   9485.148154
29          14      M   9804.566923
31          15      M   9872.778721
33          16      M   9477.371520
35          17      M   9851.727696
36          18      F  10074.608696
39          19      M   8797.868870
41          20      M   9015.452547
================================================================================
```

```
Top Gender transaction in City_Category:
  City_Category Gender     Purchase
1             A      M  9017.834470
3             B      M  9354.854433
5             C      M  9913.567248
================================================================================
Top Gender transaction in Stay_In_Current_City_Years:
  Stay_In_Current_City_Years Gender     Purchase
1                          0      M  9350.908869
3                          1      M  9421.145380
5                          2      M  9502.486091
7                          3      M  9491.916315
9                         4+      M  9413.589778
================================================================================
Top Gender transaction in Marital_Status:
  Marital_Status Gender     Purchase
1        Married      M  9413.817605
3         Single      M  9453.756740
================================================================================
Top Gender transaction in Product_Category:
    Product_Category Gender      Purchase
1                  1      M  13608.164721
2                  2      F  11407.496819
4                  3      F  10262.656677
6                  4      F   2454.851882
8                  5      F   6307.239532
11                 6      M  15907.851009
12                 7      F  16394.853659
14                 8      F   7499.924787
16                 9      F  15724.314286
18                10      F  19692.076592
21                11      M   4687.425261
22                12      F   1422.909269
24                13      F    733.846785
26                14      F  13747.362761
29                15      M  14797.431350
31                16      M  14793.384056
33                17      M  10209.732558
35                18      M   2990.168793
36                19      F     37.676275
38                20      F    371.564315
================================================================================
```

16 Conclusion:

1. Except 18th Occupation all other occupations male purchase rate is higher compared to the Female

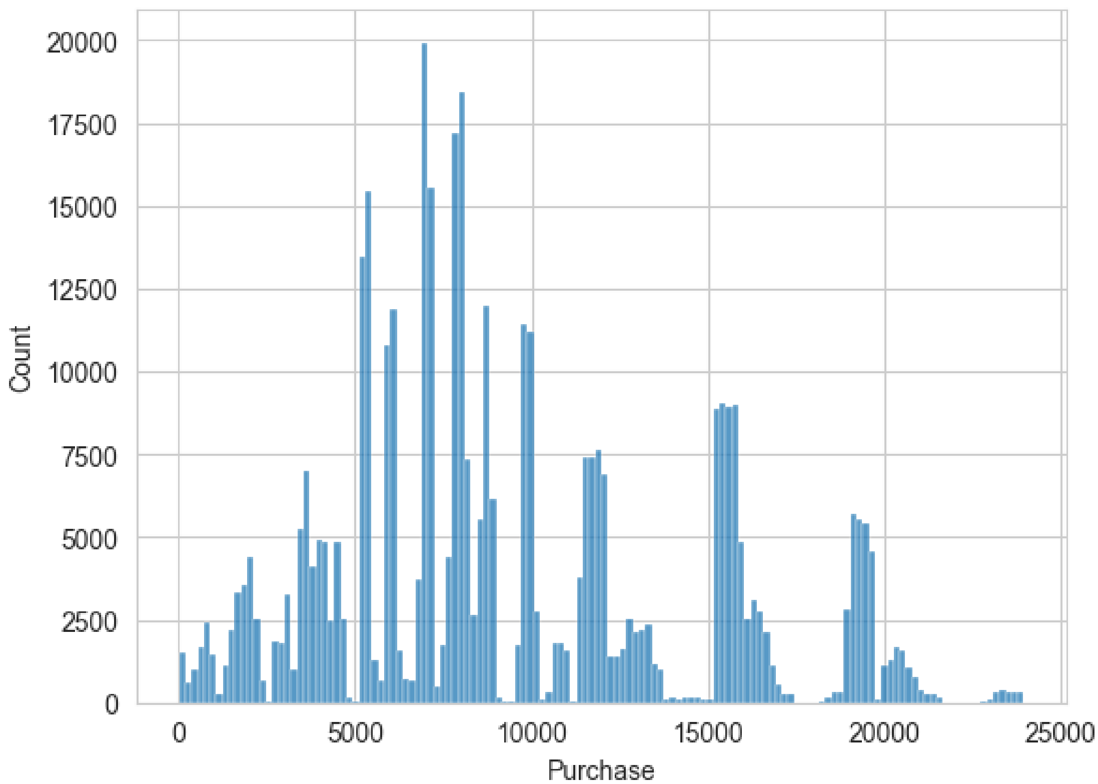
2. In all the 3 City category male purchase rate is higher

3. Based on the Marital Status male purchase rate is higher

4. Based on the product category- 2,3,4,5,7,8,9,10,12,13,14,19,20 For these products female purchase rate is higher when compared to the male

17 Confidence intervals and distribution of the mean of the expenses by female and male customers

[129]:
```
df_male = df[df['Gender']=='M']['Purchase']
sns.histplot(df_male)
plt.show()
```



[130]:
```
df_male
```

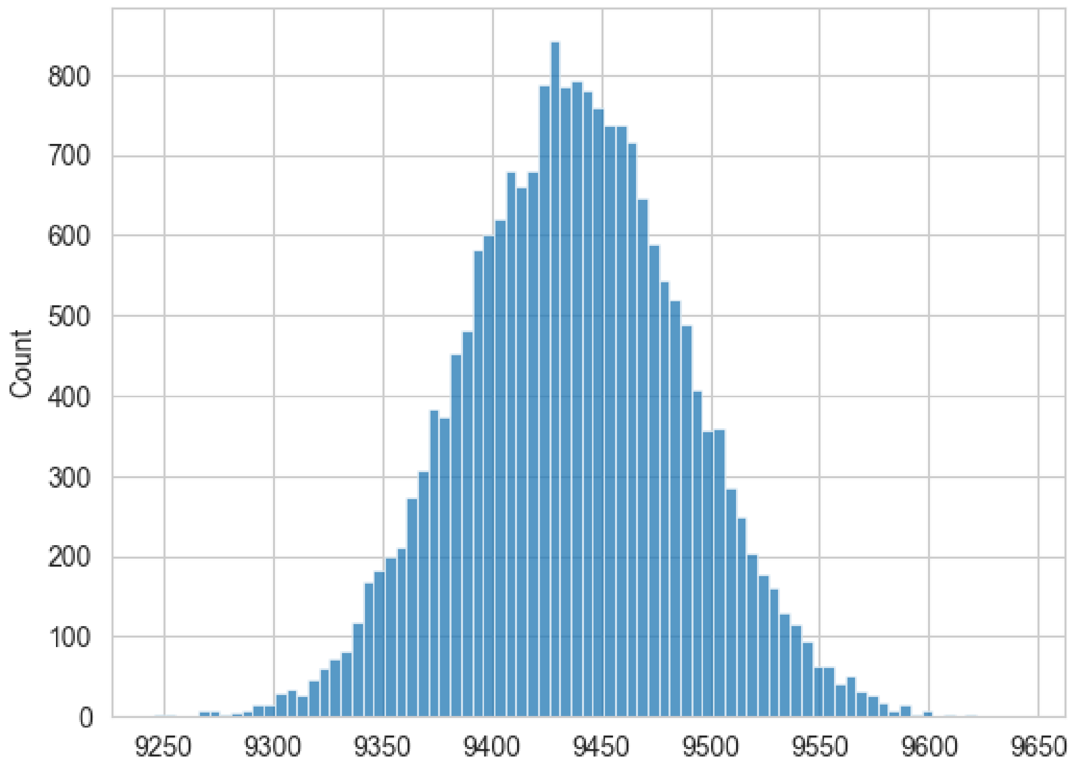
[130]:
```
4           7969
5          15227
6          19215
7          15854
8          15686
           …
```

```
550057       61
550058      121
550060      494
550062      473
550063      368
Name: Purchase, Length: 414259, dtype: int64
```

[131]:
```
sample_10000 = [np.mean(df_male.sample(10000)) for i in range(20000)]
```

[132]:
```
sns.histplot(sample_10000)
```

[132]: <Axes: ylabel='Count'>

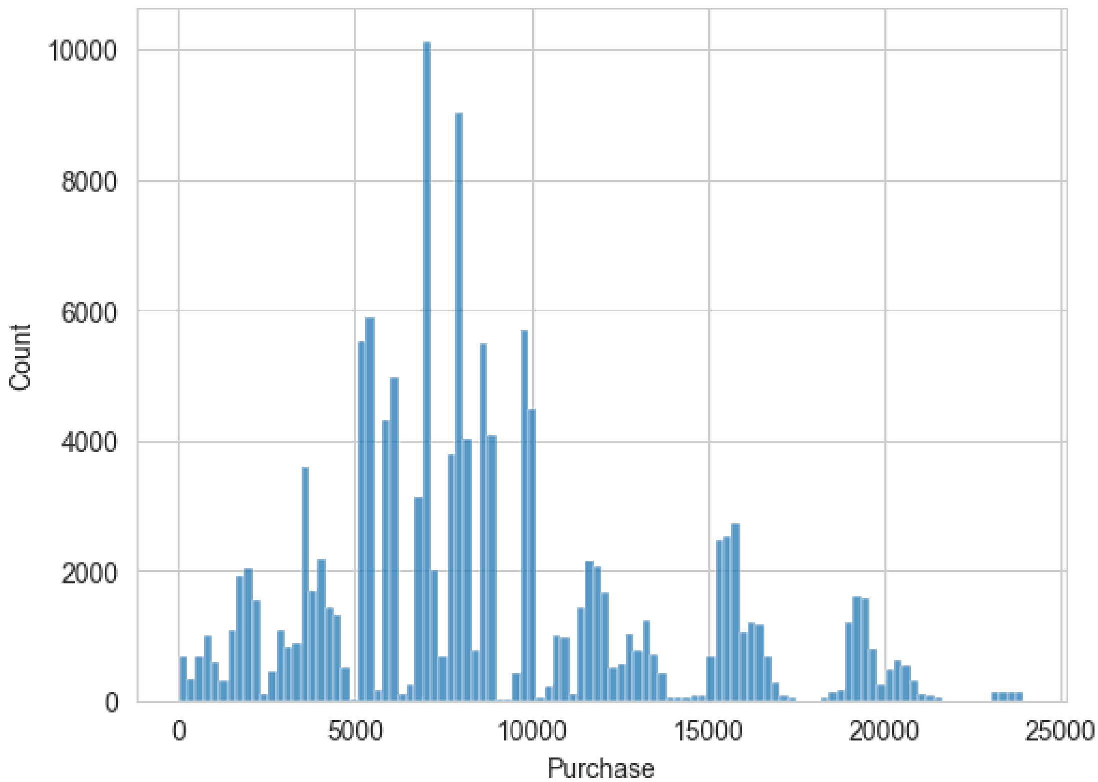


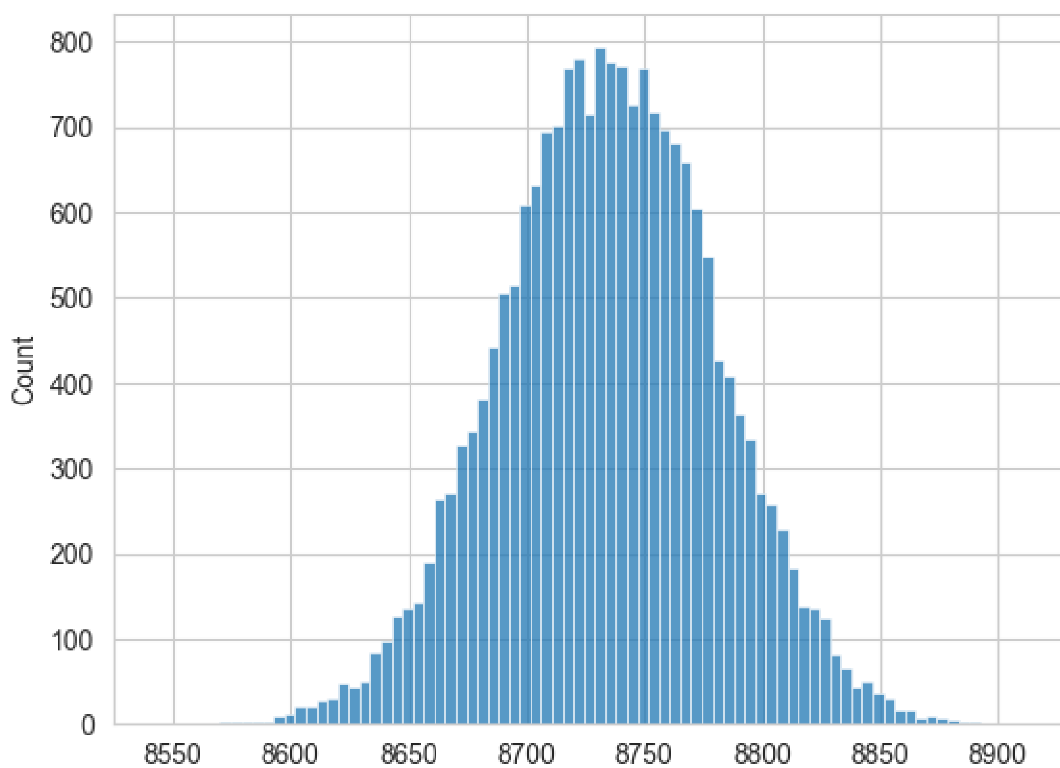
[133]:
```
def confidence_interval(percentage, mean, sigma):
    p1= ((100-percentage)/2)/100
    z1= norm.ppf(p1)
    lower_range=  mean + (z1*sigma)
    p2= p1+ (percentage/100)
    z2= norm.ppf(p2)
    upper_range=  mean + (z2*sigma)
    return np.round(lower_range,3), np.round(upper_range,3)
```

[134]:
```
male_sample_10000 = np.array(sample_10000)

print(f"The Male population mean: {np.round(df_male.mean(),3)}\nThe Male␣
↪Population Standard deviation: {np.round(df_male.std(),3)}")
print(f"The Male sample mean: {np.round(male_sample_10000.mean(),3)}\nThe Male␣
↪sample Standard deviation: {np.round(male_sample_10000.std(),3)}")

male_lower_purchase, male_upper_purchase = confidence_interval(95,␣
↪male_sample_10000.mean(), df_male.std()/np.sqrt(10000))
print(f"The Population average Male purchase ranges from {male_lower_purchase}␣
↪to {male_upper_purchase}")
```

```
The Male population mean: 9437.526
The Male Population Standard deviation: 5092.186
The Male sample mean: 9437.771
The Male sample Standard deviation: 50.801
The Population average Male purchase ranges from 9337.966 to 9537.576
```

[135]:
```
#Calculate the interval for Female purchase
df_female = df[df['Gender']=='F']['Purchase']
sns.histplot(df_female)
plt.show()
sample_10000_female = [np.mean(df_female.sample(10000)) for i in range(20000)]
sns.histplot(sample_10000_female)
plt.show()
female_sample_10000 = np.array(sample_10000_female)
print(f"The Female population mean: {np.round(df_female.mean(),3)}\nThe Female␣
↪Population Standard deviation: {np.round(df_female.std(),3)}")
print(f"The Female sample mean: {np.round(female_sample_10000.mean(),3)}\nThe␣
↪Female sample Standard deviation: {np.round(female_sample_10000.std(),3)}")

female_lower_purchase, female_upper_purchase = confidence_interval(95,␣
↪female_sample_10000.mean(), df_female.std()/np.sqrt(10000))
print(f"The Population average Female purchase ranges from␣
↪{female_lower_purchase} to {female_upper_purchase}")
```


10000
8000
6000
4000
2000
0
Count
0
5000
10000
15000
20000
25000
Purchase


800
700
600
500
400
300
200
100
0
Count
8550
8600
8650
8700
8750
8800
8850
8900

```
The Female population mean: 8734.566
The Female Population Standard deviation: 4767.233
The Female sample mean: 8734.51
The Female sample Standard deviation: 45.819
The Population average Female purchase ranges from 8641.074 to 8827.946
```

18 Conclusion based on the Male and Female purchase range with 95% confidence

*The Population average Male purchase ranges from **9337.667 to 9537.277** with 95% confidence with the sample size of 10k*

*The Population average Female purchase ranges from **8641.108 to 8827.98** with 95% confidence with the sample size of 10k*

Based on the Confidence interval male purchase average is higher compared to the female purchase range. Hence, Male purchase is higher

19 With 90% Confidence and 99% confidence

[136]:
```
confidence=90
male_lower_purchase, male_upper_purchase = confidence_interval(confidence,␣
↪male_sample_10000.mean(), df_male.std()/np.sqrt(10000))
print(f"The Population average Male purchase ranges from {male_lower_purchase}␣
↪to {male_upper_purchase} with 90% confidence")
print("*"*50)

female_lower_purchase, female_upper_purchase = confidence_interval(confidence,␣
↪female_sample_10000.mean(), df_female.std()/np.sqrt(10000))
print(f"The Population average Female purchase ranges from␣
↪{female_lower_purchase} to {female_upper_purchase} with 90% confidence\n\n")

print("="*100)
confidence=99

male_lower_purchase, male_upper_purchase = confidence_interval(confidence,␣
↪male_sample_10000.mean(), df_male.std()/np.sqrt(10000))
print(f"\n\nThe Population average Male purchase ranges from␣
↪{male_lower_purchase} to {male_upper_purchase} with 99% confidence")
print("*"*50)

female_lower_purchase, female_upper_purchase = confidence_interval(confidence,␣
↪female_sample_10000.mean(), df_female.std()/np.sqrt(10000))
```

```
print(f"The Population average Female purchase ranges from␣
↪{female_lower_purchase} to {female_upper_purchase} with 99% confidence")
```

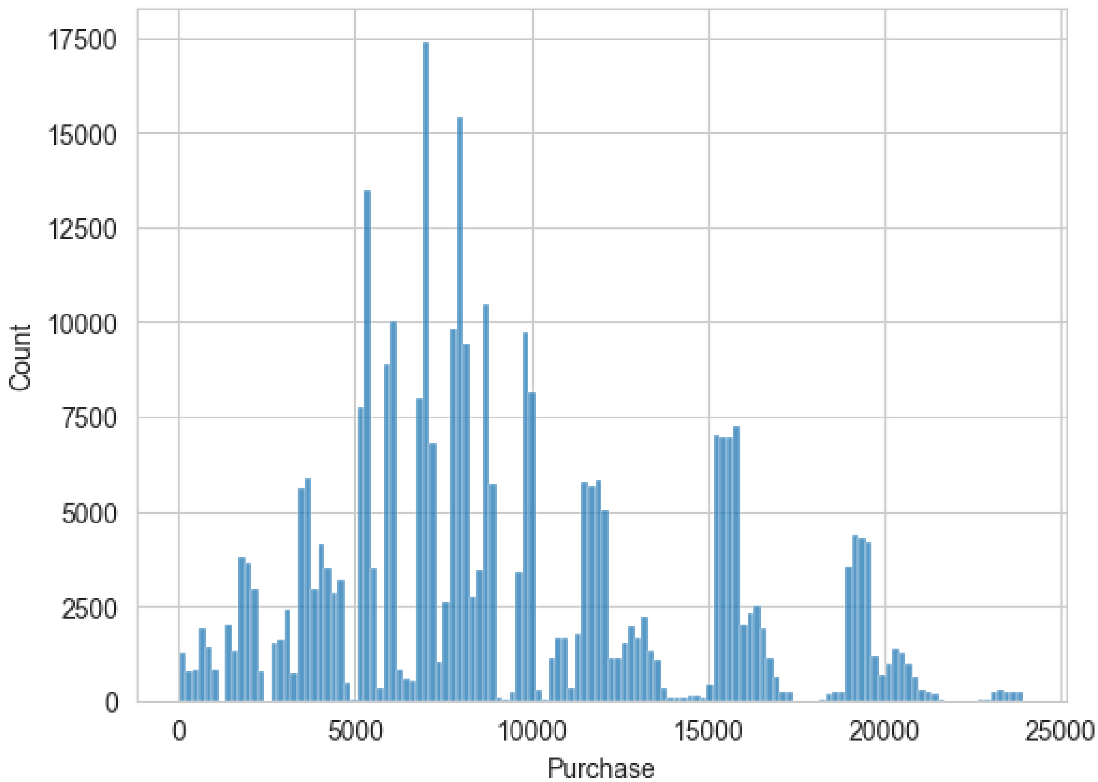
```
The Population average Male purchase ranges from 9354.012 to 9521.53 with 90%
confidence
**************************************************
The Population average Female purchase ranges from 8656.096 to 8812.924 with 90%
confidence


================================================================================
====================


The Population average Male purchase ranges from 9306.605 to 9568.937 with 99%
confidence
**************************************************
The Population average Female purchase ranges from 8611.714 to 8857.305 with 99%
confidence
```

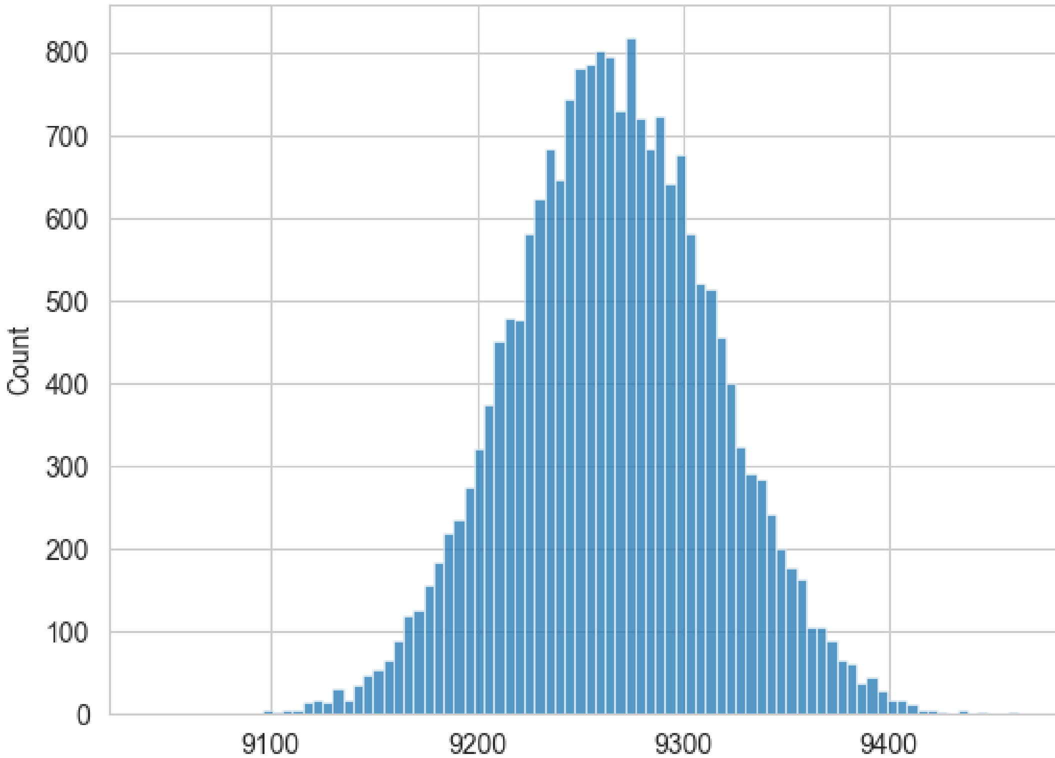
20 Confidence intervals and distribution of the mean of the expenses by Maritial Status with 95% confidence

[137]:

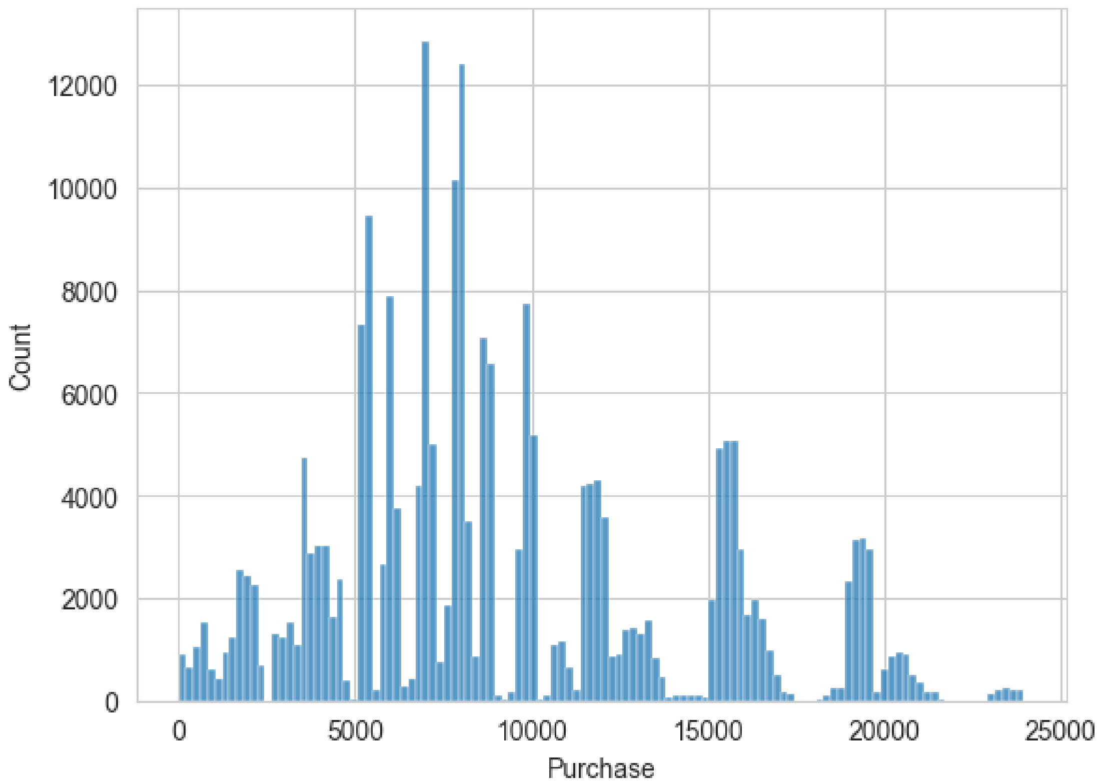
```
#Calculate the interval for Single purchase
df_single = df[df['Marital_Status']=='Single']['Purchase']
sns.histplot(df_single)
plt.show()
sample_10000_Single = [np.mean(df_single.sample(10000)) for i in range(20000)]
sns.histplot(sample_10000_Single)
plt.show()
single_sample_10000 = np.array(sample_10000_Single)
print(f"The Single population mean: {np.round(df_single.mean(),3)}\nThe Single␣
↪Population Standard deviation: {np.round(df_single.std(),3)}")
print(f"The Single sample mean: {np.round(single_sample_10000.mean(),3)}\nThe␣
↪Single sample Standard deviation: {np.round(single_sample_10000.std(),3)}")

single_lower_purchase, single_upper_purchase = confidence_interval(95,␣
↪single_sample_10000.mean(), df_single.std()/np.sqrt(10000))
print(f"The Population average Single purchase ranges from␣
↪{single_lower_purchase} to {single_upper_purchase}")

#Calculate the interval for Married purchase
df_married = df[df['Marital_Status']=='Married']['Purchase']
sns.histplot(df_married)
plt.show()
sample_10000_Married = [np.mean(df_married.sample(10000)) for i in range(20000)]
```

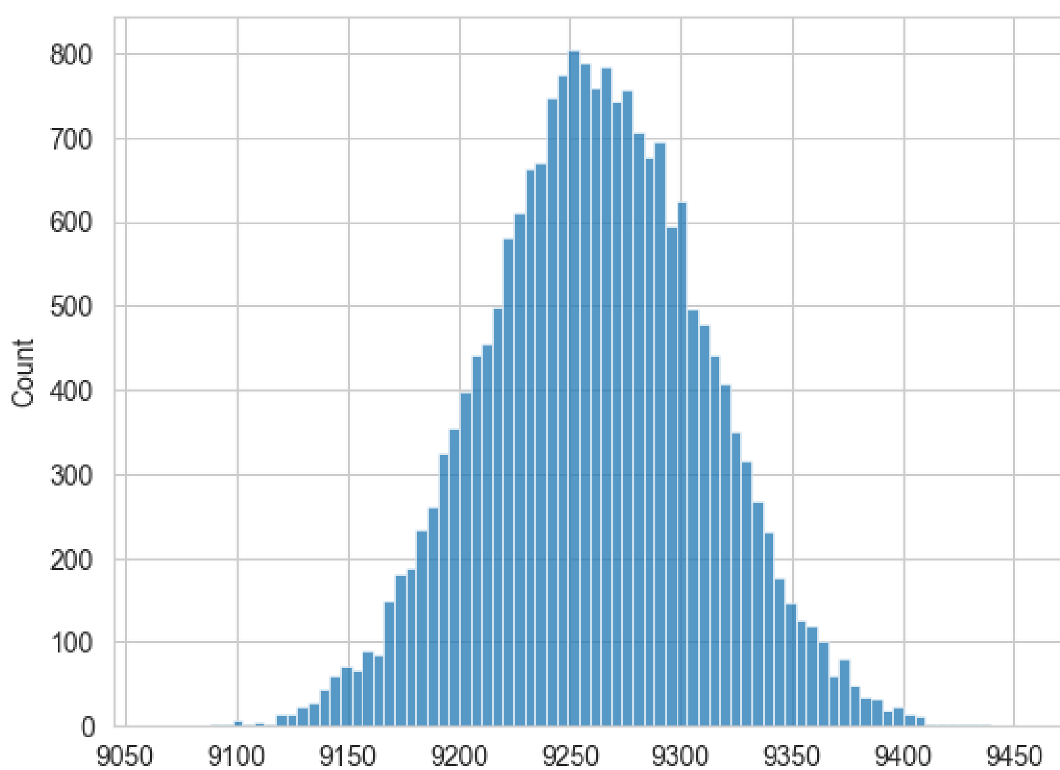
```
sns.histplot(sample_10000_Married)
plt.show()
married_sample_10000 = np.array(sample_10000_Married)
print(f"The Married population mean: {np.round(df_married.mean(),3)}\nThe␣
↪Married Population Standard deviation: {np.round(df_married.std(),3)}")
print(f"The Married sample mean: {np.round(married_sample_10000.mean(),3)}\nThe␣
↪Married sample Standard deviation: {np.round(married_sample_10000.std(),3)}")

married_lower_purchase, married_upper_purchase = confidence_interval(95,␣
↪married_sample_10000.mean(), df_married.std()/np.sqrt(10000))
print(f"The Population average Married purchase ranges from␣
↪{married_lower_purchase} to {married_upper_purchase}")
```






```
The Single population mean: 9265.908
The Single Population Standard deviation: 5027.348
The Single sample mean: 9265.906
The Single sample Standard deviation: 49.764
The Population average Single purchase ranges from 9167.372 to 9364.44
```


Count
Purchase
0
2000
4000
6000
8000
10000
12000
0
5000
10000
15000
20000
25000


Count
0
100
200
300
400
500
600
700
800
9050
9100
9150
9200
9250
9300
9350
9400
9450

```
The Married population mean: 9261.175
The Married Population Standard deviation: 5016.897
The Married sample mean: 9261.189
The Married sample Standard deviation: 49.579
The Population average Married purchase ranges from 9162.859 to 9359.518
```

21 With 90% and 99% confidence

[138]:
```
confidence=90

single_lower_purchase, single_upper_purchase = confidence_interval(confidence,␣
↪single_sample_10000.mean(), df_single.std()/np.sqrt(10000))
print(f"The Population average Single purchase ranges from␣
↪{single_lower_purchase} to {single_upper_purchase} with 90% confidence")

married_lower_purchase, married_upper_purchase =␣
↪confidence_interval(confidence, married_sample_10000.mean(), df_married.
↪std()/np.sqrt(10000))
print(f"The Population average Single purchase ranges from␣
↪{married_lower_purchase} to {married_upper_purchase} with 90% confidence")

print("="*100)
confidence=99
single_lower_purchase, single_upper_purchase = confidence_interval(confidence,␣
↪single_sample_10000.mean(), df_single.std()/np.sqrt(10000))
print(f"The Population average Single purchase ranges from␣
↪{single_lower_purchase} to {single_upper_purchase} with 99% confidence")
married_lower_purchase, married_upper_purchase =␣
↪confidence_interval(confidence, married_sample_10000.mean(), df_married.
↪std()/np.sqrt(10000))
print(f"The Population average Single purchase ranges from␣
↪{married_lower_purchase} to {married_upper_purchase} with 99% confidence")
```

```
The Population average Single purchase ranges from 9183.213 to 9348.598 with 90%
confidence
The Population average Single purchase ranges from 9178.668 to 9343.709 with 90%
confidence
================================================================================
====================
The Population average Single purchase ranges from 9136.41 to 9395.402 with 99%
confidence
The Population average Single purchase ranges from 9131.962 to 9390.415 with 99%
confidence
```

Conclusion:

For all the 90%, 95% and 99% confidence intervals the average purchase of Single and Married people overlaps each other so we cannot determine which maritial status people has high purchase range

22 Confidence intervals and distribution of the mean of the expenses by Age with 95% confidence

[139]:
```
age_category=df['Age'].value_counts().index
for i in age_category:
    print(f"The Analysis for the {i} age category is shown below:\n")
    df_age = df[df['Age']==i]['Purchase']
    #sns.histplot(df_age)
    #plt.show()
    sample_10000_age = [np.mean(df_age.sample(10000)) for i in range(20000)]
    #sns.histplot(sample_10000_age)
    #plt.show()
    age_sample_10000 = np.array(sample_10000_age)
    print(f"The {i} Age population mean: {np.round(df_age.mean(),3)}\nThe {i}␣
↪Age Population Standard deviation: {np.round(df_age.std(),3)}")
    print(f"The {i} Age sample mean: {np.round(age_sample_10000.mean(),3)}\nThe␣
↪{i} Age sample Standard deviation: {np.round(age_sample_10000.std(),3)}")

    lower_purchase, upper_purchase = confidence_interval(95, age_sample_10000.
↪mean(), df_age.std()/np.sqrt(10000))
    print(f"The Population average {i} Age purchase ranges from␣
↪{lower_purchase} to {upper_purchase}")
    print("="*100)
```

```
The Analysis for the 26-35 age category is shown below:

The 26-35 Age population mean: 9252.691
The 26-35 Age Population Standard deviation: 5010.527
The 26-35 Age sample mean: 9252.729
The 26-35 Age sample Standard deviation: 49.191
The Population average 26-35 Age purchase ranges from 9154.525 to 9350.934
================================================================================
====================
The Analysis for the 36-45 age category is shown below:

The 36-45 Age population mean: 9331.351
The 36-45 Age Population Standard deviation: 5022.924
The 36-45 Age sample mean: 9330.989
The 36-45 Age sample Standard deviation: 47.738
The Population average 36-45 Age purchase ranges from 9232.541 to 9429.436
================================================================================
====================
The Analysis for the 18-25 age category is shown below:
```

```
The 18-25 Age population mean: 9169.664
The 18-25 Age Population Standard deviation: 5034.322
The 18-25 Age sample mean: 9169.504
The 18-25 Age sample Standard deviation: 48.261
The Population average 18-25 Age purchase ranges from 9070.833 to 9268.174
================================================================================
====================
The Analysis for the 46-50 age category is shown below:

The 46-50 Age population mean: 9208.626
The 46-50 Age Population Standard deviation: 4967.216
The 46-50 Age sample mean: 9208.997
The 46-50 Age sample Standard deviation: 44.063
The Population average 46-50 Age purchase ranges from 9111.641 to 9306.352
================================================================================
====================
The Analysis for the 51-55 age category is shown below:

The 51-55 Age population mean: 9534.808
The 51-55 Age Population Standard deviation: 5087.368
The 51-55 Age sample mean: 9534.534
The 51-55 Age sample Standard deviation: 43.499
The Population average 51-55 Age purchase ranges from 9434.823 to 9634.244
================================================================================
====================
The Analysis for the 55+ age category is shown below:

The 55+ Age population mean: 9336.28
The 55+ Age Population Standard deviation: 5011.494
The 55+ Age sample mean: 9336.004
The 55+ Age sample Standard deviation: 36.794
The Population average 55+ Age purchase ranges from 9237.78 to 9434.227
================================================================================
====================
The Analysis for the 0-17 age category is shown below:

The 0-17 Age population mean: 8933.465
The 0-17 Age Population Standard deviation: 5111.114
The 0-17 Age sample mean: 8933.391
The 0-17 Age sample Standard deviation: 29.747
The Population average 0-17 Age purchase ranges from 8833.215 to 9033.567
================================================================================
====================
```

Conclusion:

51-55 age category purchase interval is higher than 0-17, 18-25, 26-35, 55+ categories

23 Lets analyse the Married Female and Single female purchase

[140]:
```
female= df[df['Gender']=='F']
df_single_female = female[female['Marital_Status']=='Single']['Purchase']
#sns.histplot(df_single_female)
#plt.show()
sample_10000_single_female = [np.mean(df_single_female.sample(20000)) for i in range(30000)]
#sns.histplot(sample_10000_single_female)
#plt.show()
single_female_sample_10000 = np.array(sample_10000_single_female)
print(f"The single female population mean: {np.round(df_single_female.mean(),3)}\nThe single female Population Standard deviation: {np.round(df_single_female.std(),3)}")
print(f"The single female sample mean: {np.round(single_female_sample_10000.mean(),3)}\nThe single female sample Standard deviation: {np.round(single_female_sample_10000.std(),3)}")

lower_purchase, upper_purchase = confidence_interval(95, single_female_sample_10000.mean(), df_single_female.std()/np.sqrt(20000))
print(f"The Population average single female purchase ranges from {lower_purchase} to {upper_purchase}")

print("="*100)
df_married_female = female[female['Marital_Status']=='Married']['Purchase']
#sns.histplot(df_married_female)
#plt.show()
sample_10000_married_female = [np.mean(df_married_female.sample(20000)) for i in range(30000)]
#sns.histplot(sample_10000_married_female)
#plt.show()
married_female_sample_10000 = np.array(sample_10000_married_female)
print(f"The married female population mean: {np.round(df_married_female.mean(),3)}\nThe married female Population Standard deviation: {np.round(df_married_female.std(),3)}")
print(f"The married female sample mean: {np.round(married_female_sample_10000.mean(),3)}\nThe married female sample Standard deviation: {np.round(married_female_sample_10000.std(),3)}")

lower_purchase, upper_purchase = confidence_interval(95, married_female_sample_10000.mean(), df_married_female.std()/np.sqrt(20000))
print(f"The Population average married female purchase ranges from {lower_purchase} to {upper_purchase}")
```

```
The single female population mean: 8679.846
The single female Population Standard deviation: 4740.048
The single female sample mean: 8679.485
```

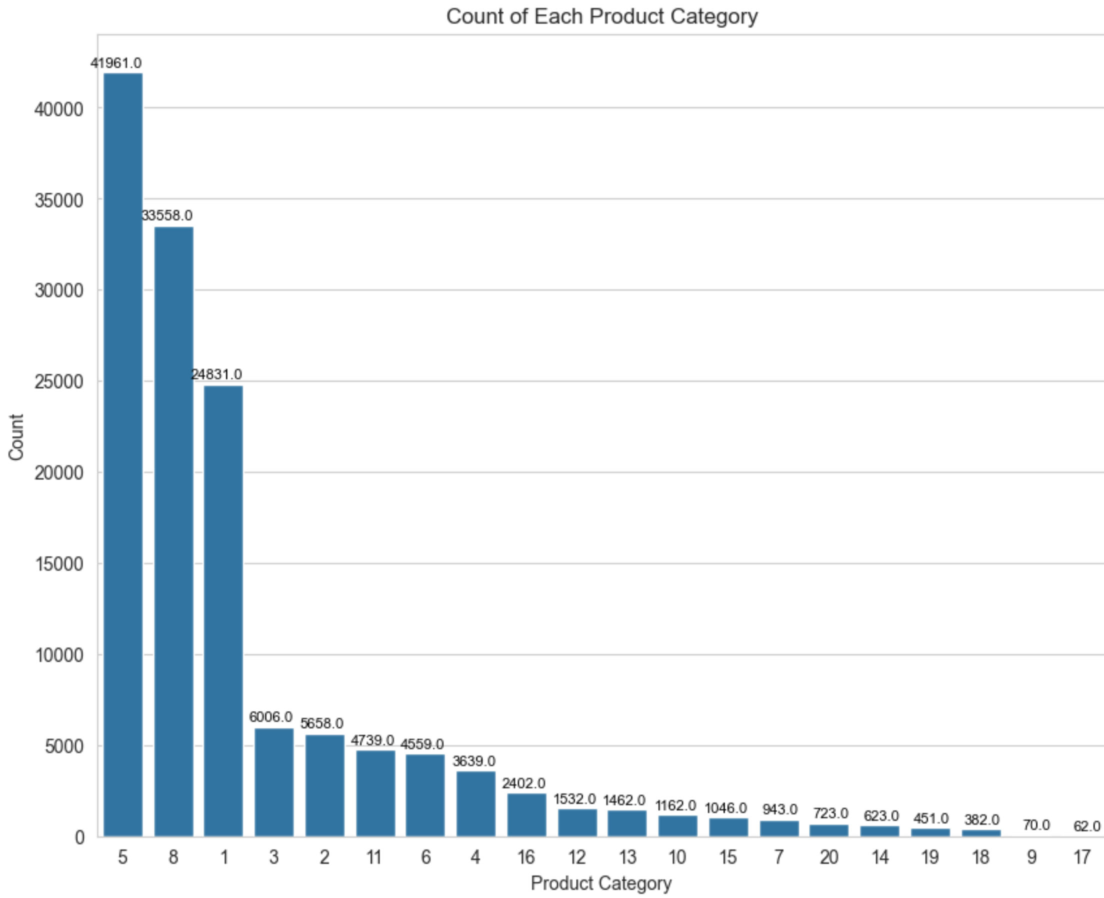
```
The single female sample Standard deviation: 28.887
The Population average single female purchase ranges from 8613.793 to 8745.178
================================================================================
====================
The married female population mean: 8810.25
The married female Population Standard deviation: 4803.594
The married female sample mean: 8810.315
The married female sample Standard deviation: 27.397
The Population average married female purchase ranges from 8743.742 to 8876.888
```

Conclusion:

Married women purchases more when compared to the single women

24 Top selling product cateogry for Female

[141]:
```
plt.figure(figsize=(10, 8))
sns.countplot(data=female, x='Product_Category',␣
 ↪order=female['Product_Category'].value_counts().index)
plt.xlabel('Product Category')
plt.ylabel('Count')
plt.title('Count of Each Product Category')
for p in plt.gca().patches:
    plt.gca().annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 1., p.
 ↪get_height()),
    ha='right', va='center', fontsize=8, color='black', xytext=(0, 5),␣
 ↪textcoords='offset points')
plt.show()
```



Conclusion:

The top selling products categories are 5, 8, 1, 3 and 5

The low selling product categories are 20,14,19,18,9 and 17

25 Lets analyse the Married male and Single male purchase

[142]:
```
male= df[df['Gender']=='M']
df_single_male = male[male['Marital_Status']=='Single']['Purchase']
#sns.histplot(df_single_female)
#plt.show()
sample_10000_single_male = [np.mean(df_single_male.sample(20000)) for i in␣
 ↪range(30000)]
#sns.histplot(sample_10000_single_female)
#plt.show()
single_male_sample_10000 = np.array(sample_10000_single_male)
```

```
print(f"The single male population mean: {np.round(df_single_male.
↪mean(),3)}\nThe single male Population Standard deviation: {np.
↪round(df_single_male.std(),3)}")
print(f"The single male sample mean: {np.round(single_male_sample_10000.
↪mean(),3)}\nThe single male sample Standard deviation: {np.
↪round(single_male_sample_10000.std(),3)}")

lower_purchase, upper_purchase = confidence_interval(95,␣
↪single_male_sample_10000.mean(), df_single_male.std()/np.sqrt(20000))
print(f"The Population average single male purchase ranges from␣
↪{lower_purchase} to {upper_purchase}")

print("="*100)
df_married_male = male[male['Marital_Status']=='Married']['Purchase']
#sns.histplot(df_married_female)
#plt.show()
sample_10000_married_male = [np.mean(df_married_male.sample(20000)) for i in␣
↪range(30000)]
#sns.histplot(sample_10000_married_female)
#plt.show()
married_male_sample_10000 = np.array(sample_10000_married_male)
print(f"The married male population mean: {np.round(df_married_male.
↪mean(),3)}\nThe married male Population Standard deviation: {np.
↪round(df_married_male.std(),3)}")
print(f"The married male sample mean: {np.round(married_male_sample_10000.
↪mean(),3)}\nThe married male sample Standard deviation: {np.
↪round(married_male_sample_10000.std(),3)}")

lower_purchase, upper_purchase = confidence_interval(95,␣
↪married_male_sample_10000.mean(), df_married_male.std()/np.sqrt(20000))
print(f"The Population average married male purchase ranges from␣
↪{lower_purchase} to {upper_purchase}")
```

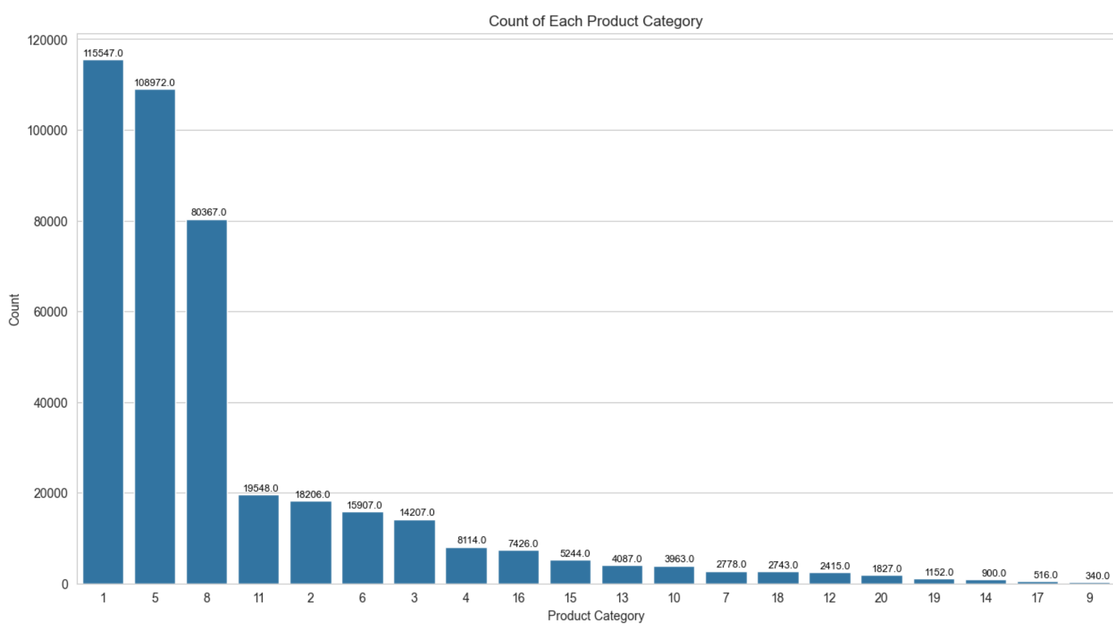
```
The single male population mean: 9453.757
The single male Population Standard deviation: 5101.803
The single male sample mean: 9453.425
The single male sample Standard deviation: 34.512
The Population average single male purchase ranges from 9382.719 to 9524.131
================================================================================
====================
The married male population mean: 9413.818
The married male Population Standard deviation: 5078.027
The married male sample mean: 9413.635
The married male sample Standard deviation: 33.697
The Population average married male purchase ranges from 9343.258 to 9484.011
```

Conclusion:

The confidence interval overlaps the married male and single male hence we cannot conclude which marital status men purchases more

26 Top selling product cateogry for Male

[143]:
```
plt.figure(figsize=(15, 8))
sns.countplot(data=male, x='Product_Category', order=male['Product_Category'].
 ↪value_counts().index)
plt.xlabel('Product Category')
plt.ylabel('Count')
plt.title('Count of Each Product Category')
for p in plt.gca().patches:
    plt.gca().annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 1., p.
 ↪get_height()),
    ha='right', va='center', fontsize=8, color='black', xytext=(0, 5),␣
 ↪textcoords='offset points')
plt.show()
```



Conclusion:

- The top selling products categories ae r1, 5,8, 11 and 2**

The low selling product categories 12, 20, 19, 14, 17 and 9* 17

27 ==

28 Final Insights

1. Using the Bi-varient and univarient analysis- Expense of Men is higher compared to the women during the black friday sale of Walmart

2. Male gender purchased more- 75% of users are male and 25% are female.

3. 26-35 age people purchased more - Users ages 26–35 are 40%, users ages 36–45 are 20%, users ages 18–25 are 18%, and very low users ages (0–17 & 55+)are 5%

4. City B people purchased more- 35% stay in a city for 1 year, 18% stay in a city for 2 years, 17% stay in a city for 3 years, and 15% stay in a city for 4+ years.

5. Single people purchased more compared to the married people- 60% of users are single, and 40% are married.

6. For each ***age*** *category Male gender is higher when compared to female gender in transactions*

7. Except 18th Occupation all other occupations male purchase rate is higher compared to the Female

8. In all the 3 City category male purchase rate is higher

9. Based on the Marital Status male purchase rate is higher

10. Based on the product category- 2,3,4,5,7,8,9,10,12,13,14,19,20 For these products female purchase rate is higher when compared to the male

29 Final Recommendations:

1. Based on the confidence interval the purchase rate of men is higher to women statistically hence Walmart has to focus on retaining female customers and getting more female customers by providing offers.

2. Especially Single marital status women purchase rate is less compared to married women statistically, Walmart has to focus on the Single women Caegory products and discounts.

3. Male customers and their purchase is already higher so walmart can focus on retaining the existing customers with new offers.

4. ***51-55 age category purchase interval is higher*** *than 0-17, 18-25, 26-35, 55+ categories. So, Walmart can focus on the other category people especially 0-17 and 18-25 Category people*

5. The top selling products categories for females are 5, 8, 1, 3 and 5

6. The low selling product categories for females are 20,14,19,18,9 and 17

7. The top selling products categories for male are 5, 8, 1, 11, and 2

8. The low selling product categories for male are 20, 19, 18, 14, 9 and 17

9. Hence the product categories which are low selling such as ***20, 14, 19, 18, 9 and 17*** *walmart has to take necessary actions to improve the sales of these cateogries like offers, discounts.*