Walmart Case Study

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In [ ]:

Dataset link - https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_d
1641285094

Collab Link- https://colab.research.google.com/drive/1sxEzmi7gPT2TQRKoFkKWRqQvPOqqlksz#scrollTo=

Walmart

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 worldwide.

Objective

In this analysis, we try to find out the effect of different user types on Purchase.

In [ ]:

```
# loading dataset in collab
!wget --no-check-certificate https://d2beiqkhq929f0.cloudfront.net/public_assets
```

```
--2025-01-30 20:08:15--  https://d2beiqkhq929f0.cloudfront.net/public_assets/asse
ts/000/001/293/original/walmart_data.csv?1641285094
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 18.16
4.173.110, 18.164.173.117, 18.164.173.58, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|18.16
4.173.110|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 23027994 (22M) [text/plain]
Saving to: ‘Walmart.csv’


Walmart.csv           0%[                    ]       0  --.-KB/s
Walmart.csv         100%[===================>]  21.96M  --.-KB/s    in 0.1s

2025-01-30 20:08:15 (182 MB/s) - ‘Walmart.csv’ saved [23027994/23027994]
```

In [ ]:

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```python
import seaborn as sns

from scipy.stats import norm

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```python
# reading dataset
walmart_df = pd.read_csv('Walmart.csv')
walmart_df.head()
```

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_`
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	

In [ ]:
```python
walmart_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
```

In [ ]:
```python
# checking for structure of data
walmart_df.shape
```

Out[ ]: (550068, 10)

This tell that the total data entries are 550068 (0.55 million) with 10 features.

In [ ]:
```python
walmart_df.columns
```

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

In [ ]:
```
walmart_df.describe()
```

Out[ ]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

In [ ]:
```
walmart_df.describe(include= object)
```

Out[ ]:

	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

In [ ]:
```
walmart_df.isnull().sum()
```

Out[ ]:

	0
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

This shows that there are no null values in the data.

In [ ]:

```
 #checking for no of unique values in each feature and displaying the count with
for col in walmart_df.columns:
  # No of unique values in each column
  print(f"Number of unique values in feature '{col}': {walmart_df[col].nunique()

  # Displaying unique values in different features
  print(f"Unique values in feature '{col}': {walmart_df[col].unique()}",end="\n\
  print("-"*108)
```

```
Number of unique values in feature 'User_ID': 5891
Unique values in feature 'User_ID': [1000001 1000002 1000003 ... 1004113 1005391
1001529]

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Product_ID': 3631
Unique values in feature 'Product_ID': ['P00069042' 'P00248942' 'P00087842' ...
'P00370293' 'P00371644'
 'P00370853']

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Gender': 2
Unique values in feature 'Gender': ['F' 'M']

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Age': 7
Unique values in feature 'Age': ['0-17' '55+' '26-35' '46-50' '51-55' '36-45' '18
-25']

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Occupation': 21
Unique values in feature 'Occupation': [10 16 15  7 20  9  1 12 17  0  3  4 11  8
19  2 18  5 14 13  6]

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'City_Category': 3
Unique values in feature 'City_Category': ['A' 'C' 'B']

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Stay_In_Current_City_Years': 5
Unique values in feature 'Stay_In_Current_City_Years': ['2' '4+' '3' '1' '0']

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Marital_Status': 2
Unique values in feature 'Marital_Status': [0 1]

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Product_Category': 20
Unique values in feature 'Product_Category': [ 3  1 12  8  5  4  2  6 14 11 13 15
7 16 18 10 17  9 20 19]

--------------------------------------------------------------------------------
--------------------------
Number of unique values in feature 'Purchase': 18105
Unique values in feature 'Purchase': [ 8370 15200  1422 ...   135   123   613]

--------------------------------------------------------------------------------
--------------------------
```

Here we can see that there are multiple purchases made from the same user so to know the exact analysis if customers we create a new data set of customers and analyse that.

Similarily for better analysis, I do the same for product analysis.

User Analysis

In [ ]:

```
#Here we have found a new dataframe which contains all the unique users data wit
users_df = walmart_df[['User_ID',    'Gender',   'Age'    ,'Occupation',  'City_C
users_df.drop_duplicates(inplace=True)

users_df.reset_index(inplace=True)
users_df.drop("index",axis=1, inplace=True)
users_df
```

Out[ ]:

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Ma
0	1000001	F	0-17	10	A	2	
1	1000002	M	55+	16	C	4+	
2	1000003	M	26-35	15	A	3	
3	1000004	M	46-50	7	B	2	
4	1000005	M	26-35	20	A	1	
...	...	...	...	...	...	...	
5886	1004588	F	26-35	4	C	0	
5887	1004871	M	18-25	12	C	2	
5888	1004113	M	36-45	17	C	3	
5889	1005391	M	26-35	7	A	0	
5890	1001529	M	18-25	4	C	4+	

5891 rows × 7 columns

In [ ]:

```
# in this cell, we have found the total for all transactions per user
user_sum= walmart_df.groupby('User_ID')['Purchase'].sum().reset_index()
user_sum.rename(columns={'Purchase':'Purchase_total'},inplace=True)

#finding the mean of the purchase for each user
user_pur_mean=walmart_df.groupby('User_ID')['Purchase'].mean().reset_index()
user_pur_mean.rename(columns={'Purchase':'Purchase_mean'},inplace=True)

#merging  the datatset
users_df = pd.merge(users_df, user_pur_mean,on='User_ID')
```

```
users_df= pd.merge(users_df, user_sum, on='User_ID')
users_df
```

Out[ ]:

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Ma
0	1000001	F	0-17	10	A	2	
1	1000002	M	55+	16	C	4+	
2	1000003	M	26-35	15	A	3	
3	1000004	M	46-50	7	B	2	
4	1000005	M	26-35	20	A	1	
...	...	...	...	...	...	...	
5886	1004588	F	26-35	4	C	0	
5887	1004871	M	18-25	12	C	2	
5888	1004113	M	36-45	17	C	3	
5889	1005391	M	26-35	7	A	0	
5890	1001529	M	18-25	4	C	4+	

5891 rows × 9 columns

In [ ]:

```
user_pur_mean=walmart_df.groupby('User_ID')['Purchase'].mean().reset_index()
```

In [ ]:

```
for i in users_df.columns:
    print(users_df[i].value_counts())
    print("-"*25)
```

```
User_ID
1000001    1
1004451    1
1004460    1
1004459    1
1004458    1
          ..
1002206    1
1002205    1
1002204    1
1002203    1
1001529    1
Name: count, Length: 5891, dtype: int64
-------------------------
Gender
M    4225
F    1666
Name: count, dtype: int64
-------------------------
Age
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: count, dtype: int64
-------------------------
Occupation
4     740
0     688
7     669
1     517
17    491
12    376
14    294
20    273
2     256
16    235
6     228
10    192
3     170
15    140
13    140
11    128
5     111
9      88
19     71
18     67
8      17
Name: count, dtype: int64
-------------------------
City_Category
C    3139
B    1707
A    1045
Name: count, dtype: int64
-------------------------
Stay_In_Current_City_Years
```

```
1      2086
2      1145
3       979
4+      909
0       772
Name: count, dtype: int64
-------------------------
Marital_Status
0    3417
1    2474
Name: count, dtype: int64
-------------------------
Purchase_mean
9042.000000     2
10513.000000    2
8460.500000     2
8158.411765     2
7992.153846     2
               ..
8652.418301     1
10826.888889    1
8881.734177     1
7281.917910     1
11764.769231    1
Name: count, Length: 5886, dtype: int64
-------------------------
Purchase_total
985855     2
784192     2
243379     2
365501     2
329348     2
          ..
97442      1
701657     1
1951554    1
187017     1
152942     1
Name: count, Length: 5876, dtype: int64
-------------------------
```

We can see that the there are total 5891 users with multiple transactions in the dataset. Further we found out that the probability of users for gender, city category, age, marital status, stay in current city years.

In [ ]:

```
#finding the probability for each value in each feature
for i in users_df[["Gender",    'Age',  'Occupation',   'City_Category',    'Sta
  print(f"{i}:")
  # print("")
  for j in users_df[i].unique():
    print(f"P({j})={users_df[i].value_counts()[j]/5891}")
  print("-"*75)
```

```
Gender:
P(F)=0.2828042777117637
P(M)=0.7171957222882362
---------------------------------------------------------------------------
Age:
P(0-17)=0.03700560176540486
P(55+)=0.06314717365472755
P(26-35)=0.34849770836869803
P(46-50)=0.09013749787811917
P(51-55)=0.08164997453742998
P(36-45)=0.19809879477168563
P(18-25)=0.18146324902393482
---------------------------------------------------------------------------
Occupation:
P(10)=0.03259208962824648
P(16)=0.03989135970123918
P(15)=0.023765065353929724
P(7)=0.11356306229842132
P(20)=0.04634187744016296
P(9)=0.014938041079612968
P(1)=0.08776099134272619
P(12)=0.06382617552198269
P(17)=0.08334747920556781
P(0)=0.11678832116788321
P(3)=0.028857579358343235
P(4)=0.12561534544219996
P(11)=0.021728059752164318
P(8)=0.0028857579358343237
P(19)=0.012052283143778646
P(2)=0.043456119504328636
P(18)=0.01137328127652351
P(5)=0.018842301816329995
P(14)=0.04990663724325242
P(13)=0.023765065353929724
P(6)=0.03870310643354269
---------------------------------------------------------------------------
City_Category:
P(A)=0.177389237820404
P(C)=0.5328467153284672
P(B)=0.28976404685112883
---------------------------------------------------------------------------
Stay_In_Current_City_Years:
P(2)=0.1943642845017824
P(4+)=0.15430317433372942
P(3)=0.16618570701069427
P(1)=0.3540994737735529
P(0)=0.13104736038024103
---------------------------------------------------------------------------
Marital_Status:
P(0)=0.580037345102699
P(1)=0.41996265489730095
---------------------------------------------------------------------------
```

Observations:

After checking the probability from the columns we learn that,

- the choosen user to be a male has the probabilty to be 0.71 while to be female is 0.28.

- the highest number of transactions are from 26-35 followed by36-45 followed by 18-25. the total orders from these three age groups cover almost 73% of the transactions.
- 36% of users have only three occupations 0, 4, 7.
- almost half(53%) of transactions are made by users from C city category. The following city category is B followed by A.
- the purchases are 35% made by the users who have stayed only for 1 year in the current city.
- It is also noticable that the probability of a married user making purchase is 16% less than the transaction from an unmarried user.

In [ ]:
```
pd.crosstab( users_df['Age'], users_df['Gender'],margins=True, margins_name='Tot
```

Out[ ]:

Gender Age	F	M	Total
0-17	78	140	218
18-25	287	782	1069
26-35	545	1508	2053
36-45	333	834	1167
46-50	182	349	531
51-55	142	339	481
55+	99	273	372
Total	1666	4225	5891

It is observed that the make customers are more than twice of the female customers for any age group.

In [ ]:
```
pd.crosstab( users_df['Marital_Status'],  users_df['Gender'],margins=True, margi
```

Out[ ]:

Gender Marital_Status	F	M	Total
0	947	2470	3417
1	719	1755	2474
Total	1666	4225	5891

In [ ]:
```
print(f"P(Married)={2474/5891}")
print(f"P(Male | Married)={1755/2474}")
print(f"P(Female | Married)={719/2474}")
```

```
P(Married)=0.41996265489730095
P(Male | Married)=0.7093775262732417
P(Female | Married)=0.2906224737267583
```

It is also observed that the 41% of users are married. Out of 41% married users, 71% are males and 29% are females.

In [ ]:
```
pd.pivot_table(users_df,index='Age',columns='Marital_Status',values='Purchase_me
```

Out[ ]:

Marital_Status	0	1
Age		
0-17	8986.318305	NaN
18-25	9496.626961	9579.910647
26-35	9610.621910	9601.752614
36-45	9726.657491	9625.127350
46-50	9480.415066	9601.566956
51-55	9665.239747	9616.769687
55+	9635.488925	9280.161837

It is observed that all the unmarried people in any age group have made a marginal more purchase than the married ones. Yet it is unconsiderable for large dataset and shouldn't be considered.

In [ ]:
```
pd.pivot_table(users_df,index='Age',columns='Gender',values='Purchase_mean')
```

Out[ ]:

Gender	F	M
Age		
0-17	8269.299254	9385.800348
18-25	8744.027127	9798.823088
26-35	8983.785208	9832.406222
36-45	9166.297271	9894.155126
46-50	9018.311828	9851.574802
51-55	9235.564079	9795.893948
55+	8890.472041	9594.585985

On observing, we can find that the average purchase for any age group is 6% more in males than in females.

In [ ]:
```
pd.pivot_table(users_df,index='Age',columns=['Gender','Marital_Status'],values='
```

Out[ ]:

Gender	F		M	
Marital_Status	**0**	**1**	**0**	**1**
Age				
0-17	8269.299254	NaN	9385.800348	NaN
18-25	8836.752484	8456.578520	9732.141371	10031.825871
26-35	8847.939262	9176.988331	9874.754429	9765.403237
36-45	9244.240095	9046.110627	9920.391713	9854.285026
46-50	9051.421907	9006.113378	9676.869877	9928.820368
51-55	9172.521061	9268.780294	9942.747972	9745.194344
55+	8990.159986	8842.859887	9839.949579	9450.506201

The stats show that

- unmarried males spent more than unmarried females.
- unmarried males for any age group(except 18-25) spent more than married males.
- for any age except 26-35, 51-55 unmarried females spent more than the married females.
- married females spent even less than the married males.

In [ ]:
```
pd.pivot_table(users_df,index='Age',columns=['Gender','City_Category'],values='P
```

Out[ ]:

Gender		F			
City_Category	**A**	**B**	**C**	**A**	**B**
Age					
0-17	7852.785762	8177.812747	8431.863298	9840.517758	9277.309509	9370.0
18-25	8615.777108	8473.521360	8982.052990	9457.413641	9907.518655	9871.6
26-35	8969.027619	8788.251549	9142.580908	9622.670675	9664.628865	10045.2
36-45	9111.625484	8907.949621	9321.328449	9549.234359	9705.202029	10078.1
46-50	9329.446041	8645.383461	9169.532861	9224.727138	9965.263110	9904.3
51-55	8718.713347	9235.803048	9363.155403	9727.611770	9803.772901	9808.0
55+	9214.383039	8872.290007	8850.385831	9341.858299	9729.891498	9615.7

- It is noticable that users from city C spent more than the other cities.
- Also the higher aged users 55+ from city A spent more than the users from any cities.
- Further, males from any city spent more than the corresponding city's female users.

Product Analysis

In [ ]:

```
#df_product for products

'''Here we have only extracted three columns for products.
We have also added a new column that shows a counts of the product purchased. ''

product_count= walmart_df.groupby('Product_ID')['Purchase'].count().reset_index(
df_product = pd.merge(walmart_df[['Product_ID','Product_Category','Purchase']],
# df_product=walmart_df[['Product_ID','Product_Category','Purchase']].groupby('P
df_product=df_product.groupby('Product_ID',as_index=False)
df_product=df_product.apply(lambda x: x.sort_values(["Purchase_count","Purchase"
df_product.head(10)
```

Out[ ]:

	Product_ID	Product_Category	Purchase	Purchase_count
0 206583	P00000142	3	13716	1152
470193	P00000142	3	13715	1152
412824	P00000142	3	13713	1152
199327	P00000142	3	13707	1152
208925	P00000142	3	13707	1152
49189	P00000142	3	13706	1152
170156	P00000142	3	13706	1152
12937	P00000142	3	13704	1152
209903	P00000142	3	13704	1152
124887	P00000142	3	13697	1152

After this sample data, we can find that the same product has been sold at different prices to different users. So we also remove the Purchase column and only find the products along with the no of sales.

In [ ]:

```
df_product.drop(["Purchase"],axis=1, inplace=True)
df_product.drop_duplicates(inplace=True)
df_product.sort_values("Purchase_count",ascending=False,inplace=True)
df_product.head(20)
```

Out[ ]:

		Product_ID	Product_Category	Purchase_count
2536	**187227**	P00265242	5	1880
249	**143485**	P00025442	1	1615
1016	**344941**	P00110742	1	1612
1030	**109706**	P00112142	1	1562
565	**164847**	P00057642	1	1470
1745	**91543**	P00184942	1	1440
458	**40760**	P00046742	1	1438
569	**238155**	P00058042	8	1422
1355	**126618**	P00145042	1	1406
582	**239375**	P00059442	6	1406
2263	**211446**	P00237542	1	1394
2443	**54201**	P00255842	16	1383
1088	**58604**	P00117942	5	1364
1018	**48495**	P00110942	1	1360
104	**135822**	P00010742	1	1350
2096	**249370**	P00220442	5	1282
1017	**162948**	P00110842	1	1281
1083	**129205**	P00117442	5	1260
505	**86966**	P00051442	8	1249
937	**15064**	P00102642	4	1246

Here it is noticable that the most of the high sold products are from 1st category. While the most sold product is from 5 category products.

Dataset Analysis

In [ ]:

```
numerical_cols = walmart_df.select_dtypes(include=np.number).columns
numerical_cols
```

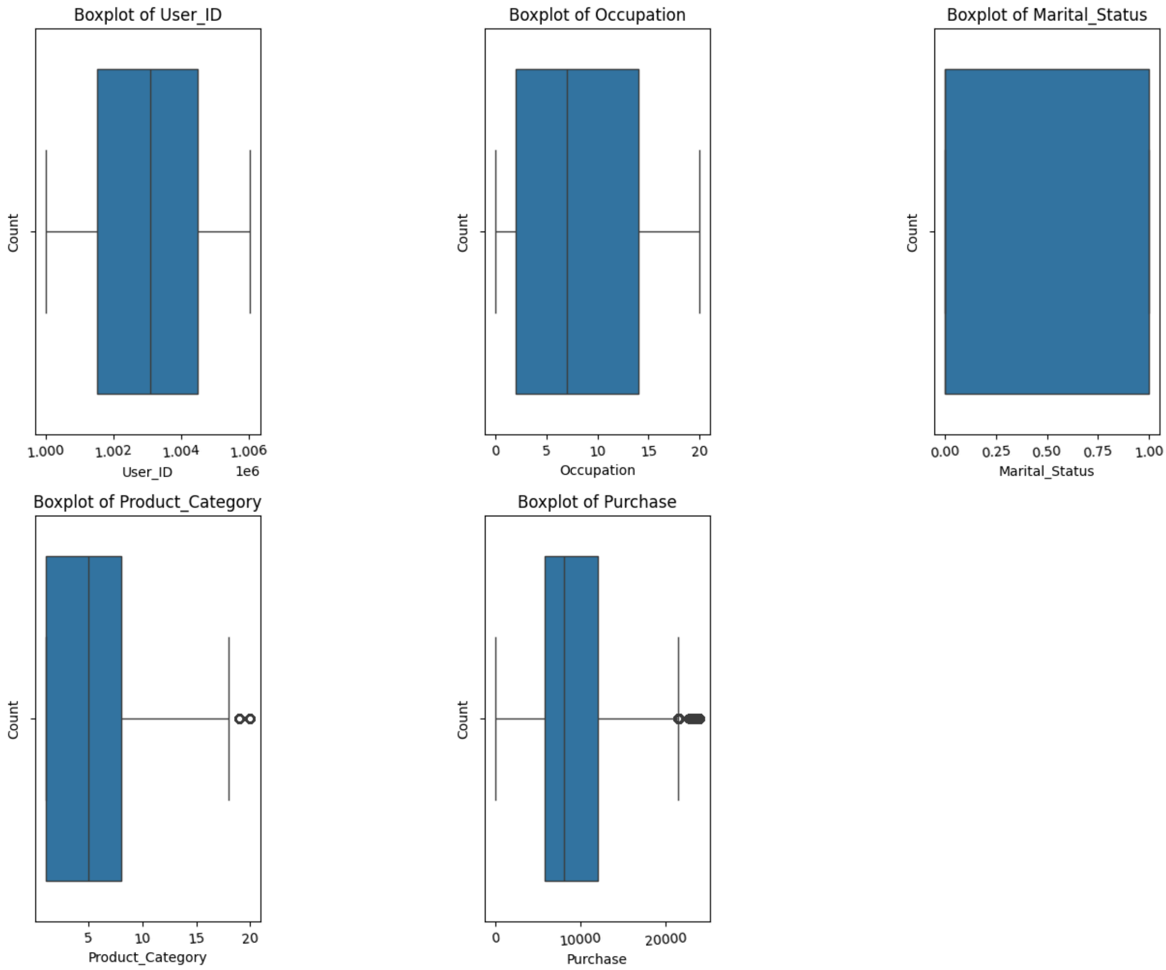
Out[ ]:

```
Index(['User_ID', 'Occupation', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

In [ ]:

```
plt.figure(figsize=(15,12))
j=0
for i in numerical_cols:
    j=j+1
    plt.subplot(2,3,j)
    plt.subplots_adjust(wspace=1, hspace=0.2)
```

```
    sns.boxplot(x=walmart_df[i])
    plt.title(f'Boxplot of {i}')
    plt.xticks(rotation=5)
    plt.xlabel(f'{i}')
    plt.ylabel('Count')
```



After checking the boxplots, we can see that only product_catgory and purchase has outliers. Lets treat the range and outliers values.

In [ ]:
```
r_whis_purchase= walmart_df['Purchase'].quantile(0.75)+1.5*(walmart_df['Purchase
print(f"value or right whisker in Purchase feature = {r_whis_purchase}")
print("No of outliers in purchase column=",(walmart_df['Purchase']> r_whis_purch
```

```
value or right whisker in Purchase feature = 21400.5
No of outliers in purchase column= 2677
```

In [ ]:
```
r_whis_product= walmart_df['Product_Category'].quantile(0.75)+1.5*(walmart_df['P
print(f"value or right whisker in Purchase feature = {r_whis_product}")
print("No of outliers in product category column=",(walmart_df['Product_Category
```

```
value or right whisker in Purchase feature = 18.5
No of outliers in product category column= 4153
```

In [ ]:
```
pd.crosstab( walmart_df['Age'],  walmart_df['Gender'],margins=True, margins_name
```

Out[ ]:

Gender	F	M	Total
Age			
0-17	5083	10019	15102
18-25	24628	75032	99660
26-35	50752	168835	219587
36-45	27170	82843	110013
46-50	13199	32502	45701
51-55	9894	28607	38501
55+	5083	16421	21504
Total	135809	414259	550068

In [ ]:

```
pd.crosstab( walmart_df['Marital_Status'],  walmart_df['Gender'], margins=True,m
```

Out[ ]:

Gender	F	M	All
Marital_Status			
0	78821	245910	324731
1	56988	168349	225337
All	135809	414259	550068

In [ ]:

```
# Probability that the customer is married
print("P(Married)=",(225337/550068))

#probability that a female customer is married
print("P(Married|Female)=",(56988/135809))
#probability that a male customer is married
print("P(Married|Male)=",(168349/414259))
```

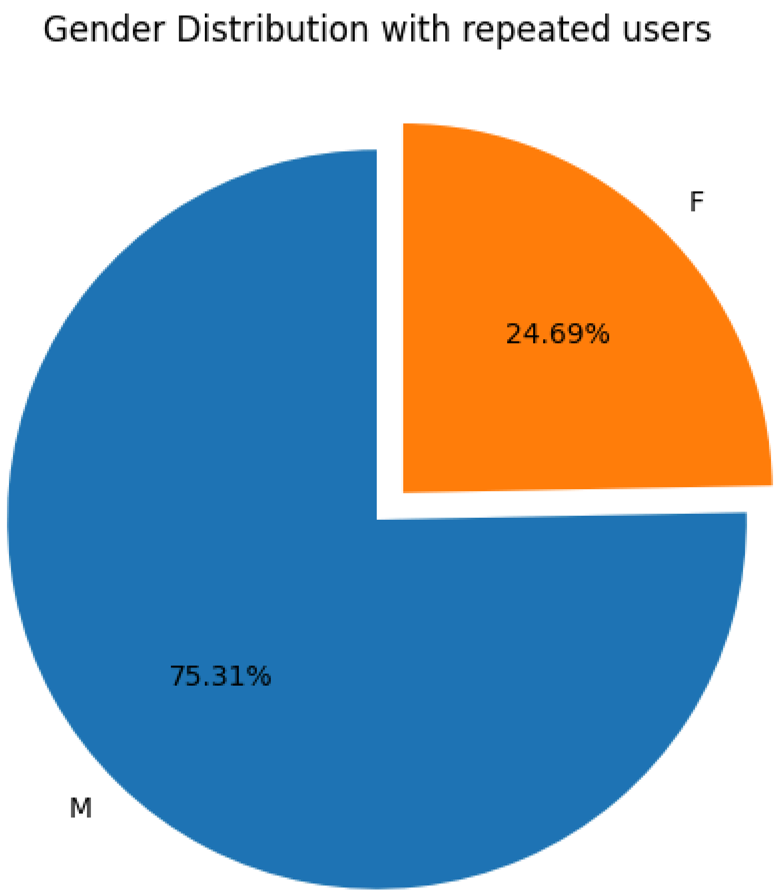
```
P(Married)= 0.40965298835780306
P(Married|Female)= 0.41961872924474813
P(Married|Male)= 0.4063858600537345
```

Visual Analysis

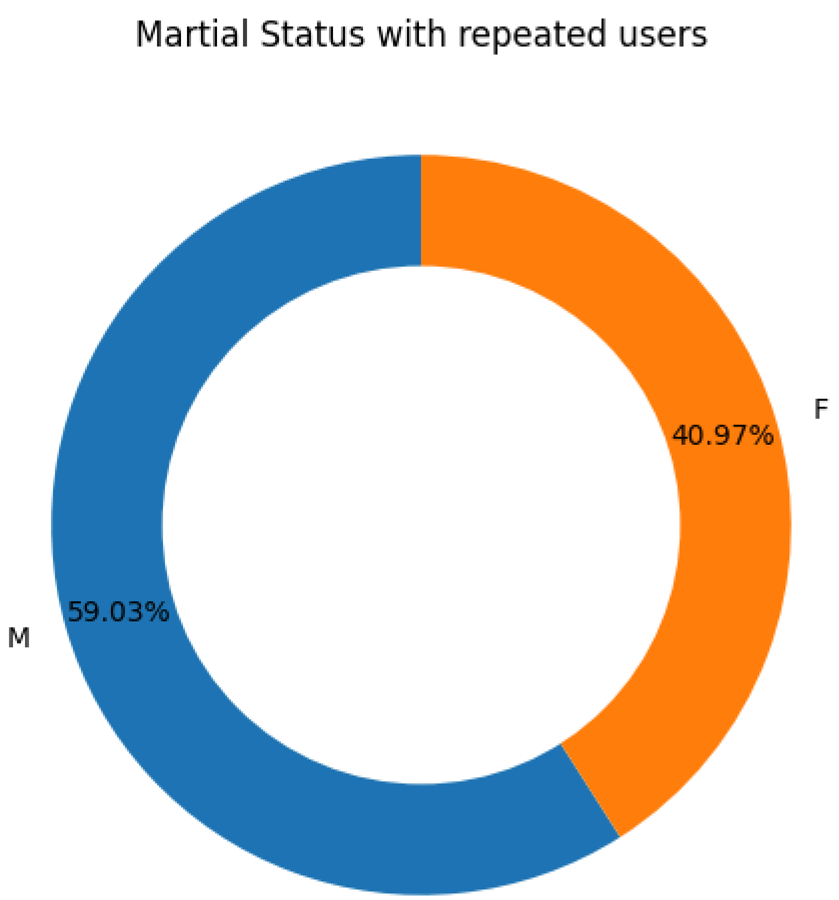
Here are the different plots

- Gender Distribution (Pie chart)
- Marital Status (Donut Chart)
- Age (Countplot)
- Purchase (Hist plot)
- Occupation (Piechart)
- Gender vs Marital Status (Stacked bar chart)
- City vs Purchase (Box Plot)

In [ ]:
```
plt.figure(figsize=(8,6))
plt.pie(walmart_df['Gender'].value_counts(),labels=walmart_df['Gender'].value_cc
plt.title('Gender Distribution with repeated users')
plt.show()
```

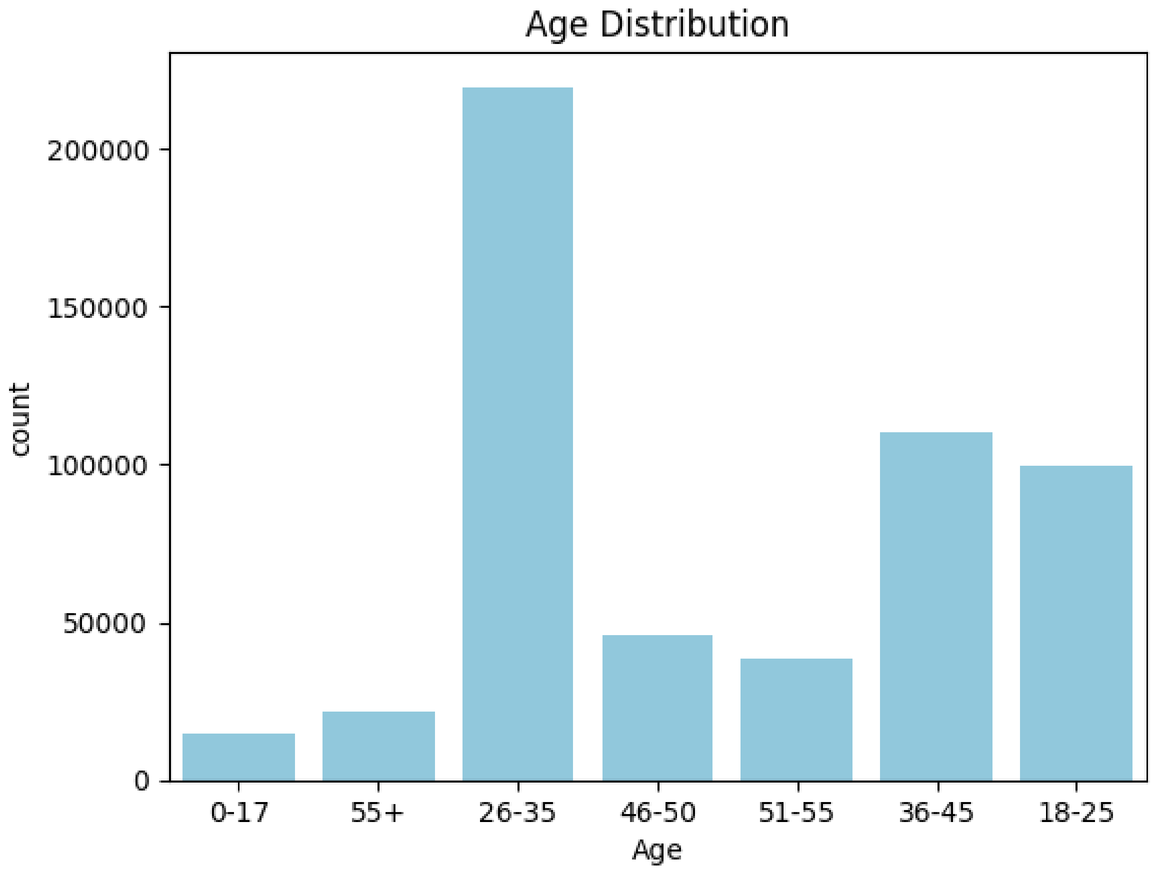


In [ ]:
```
plt.figure(figsize=(8,6))
plt.pie(walmart_df['Marital_Status'].value_counts(),labels=walmart_df['Gender'].
centre_circle = plt.Circle((0, 0), 0.70, fc='white')
fig = plt.gcf()

# Adding Circle in Pie chart
fig.gca().add_artist(centre_circle)
plt.title('Martial Status with repeated users')
plt.show()
```



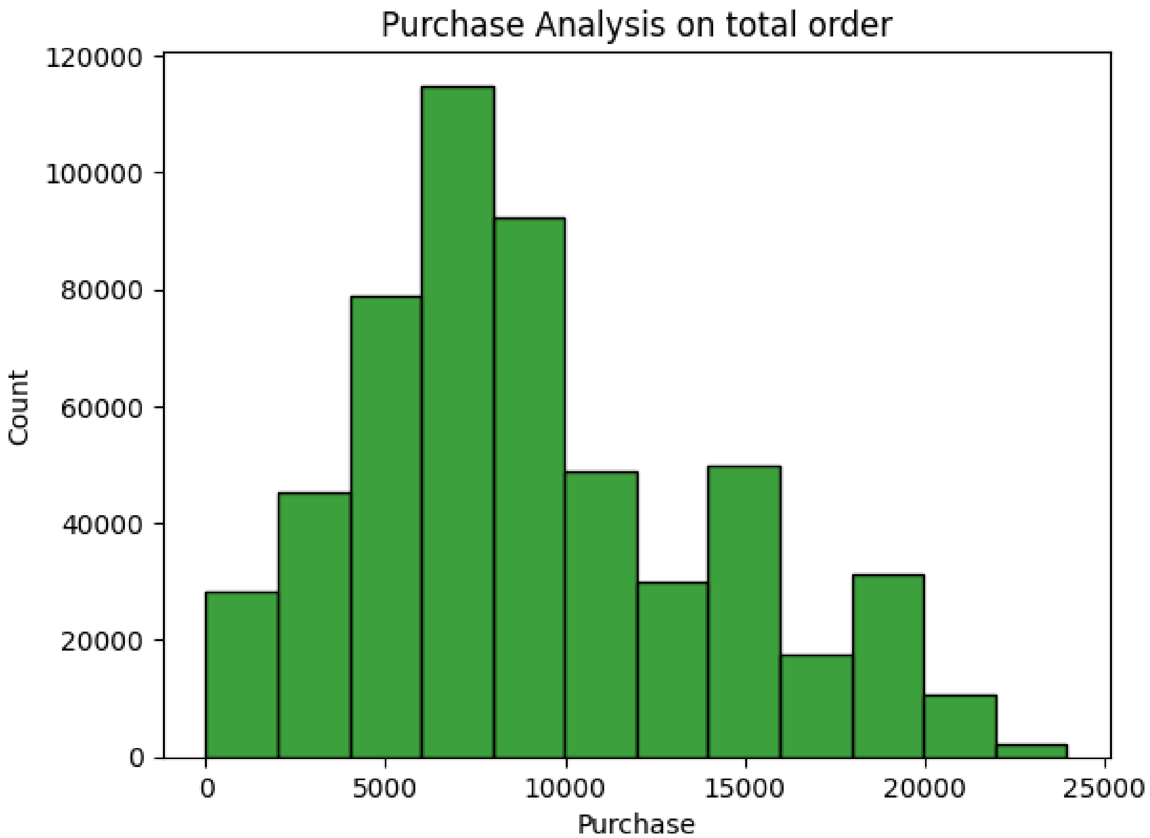
In [ ]:

```
sns.countplot(data=walmart_df,x='Age',hue_order='Age',color="skyblue")
plt.title('Age Distribution')
plt.show()
```



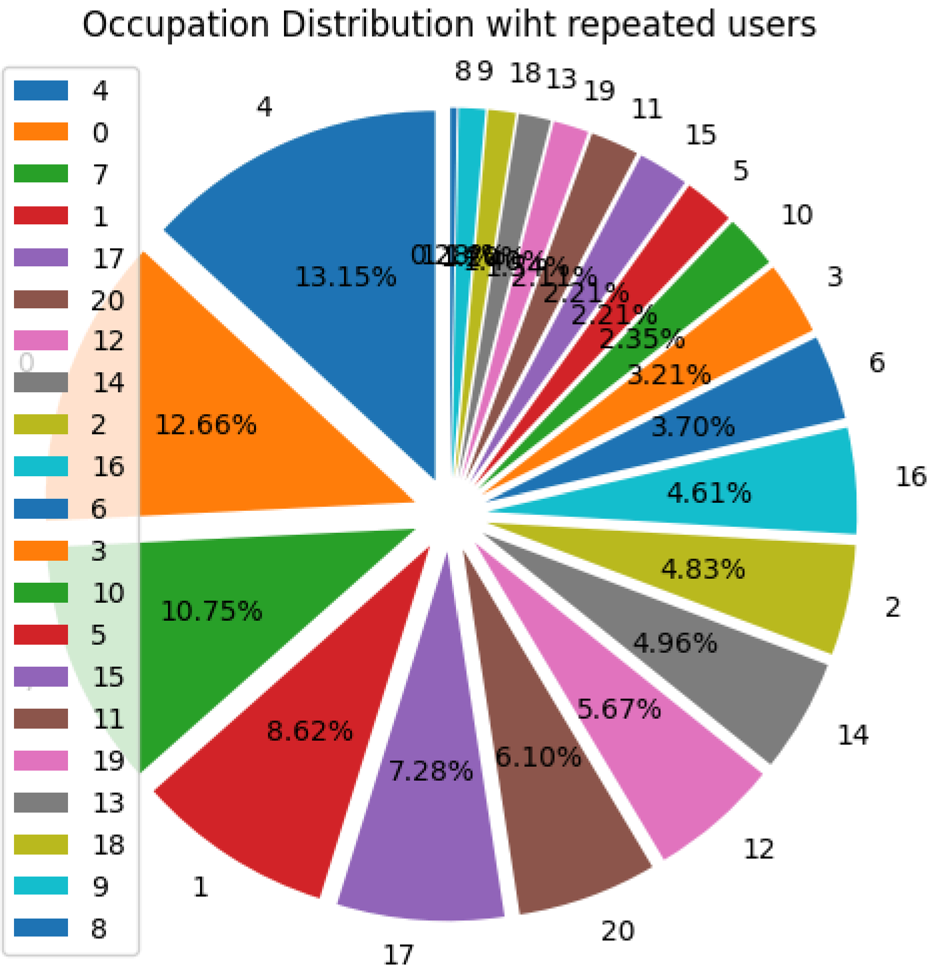
In [ ]:
```
sns.histplot(walmart_df['Purchase'],bins=12,color='g')
plt.title('Purchase Analysis on total order')
plt.ylabel('Count')
```

Out[ ]: Text(0, 0.5, 'Count')



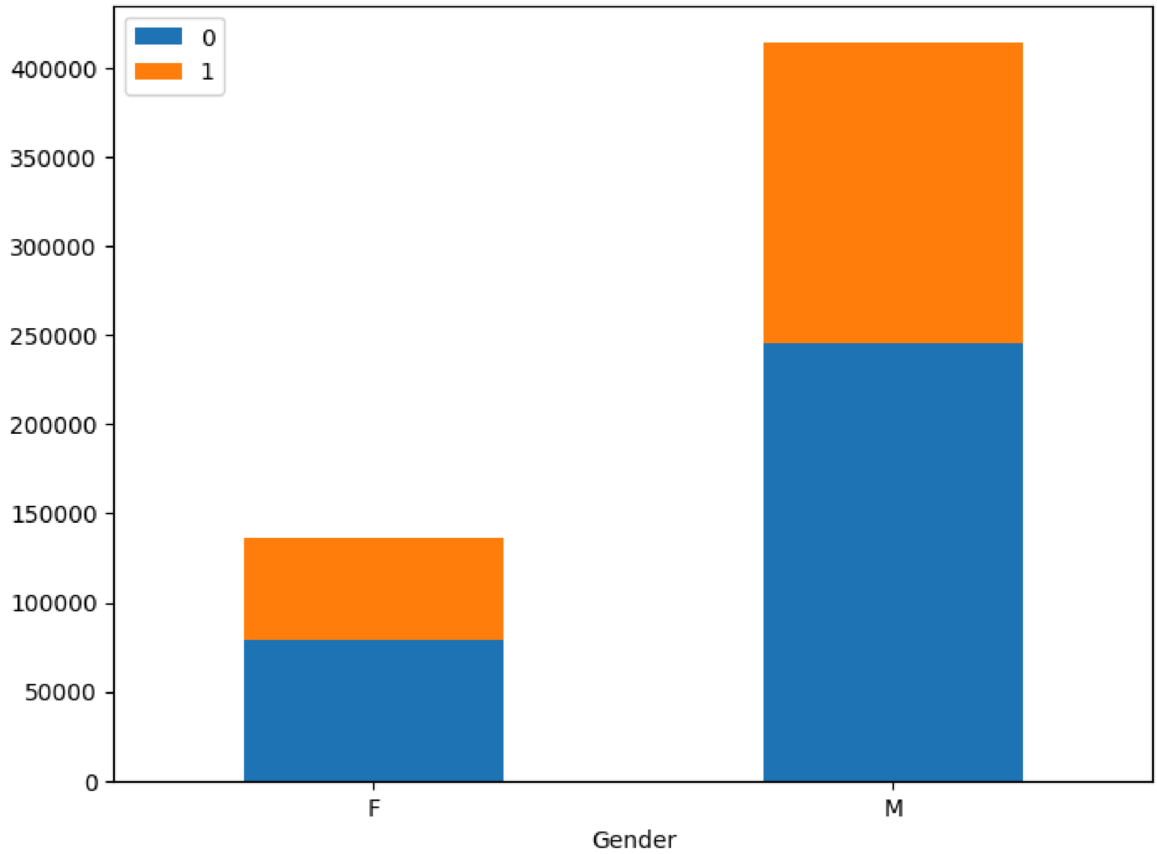
In [ ]:

```
plt.figure(figsize=(8,6))
plt.pie(walmart_df['Occupation'].value_counts(),labels=walmart_df['Occupation'].
plt.title('Occupation Distribution wiht repeated users')
plt.legend()
plt.show()
```

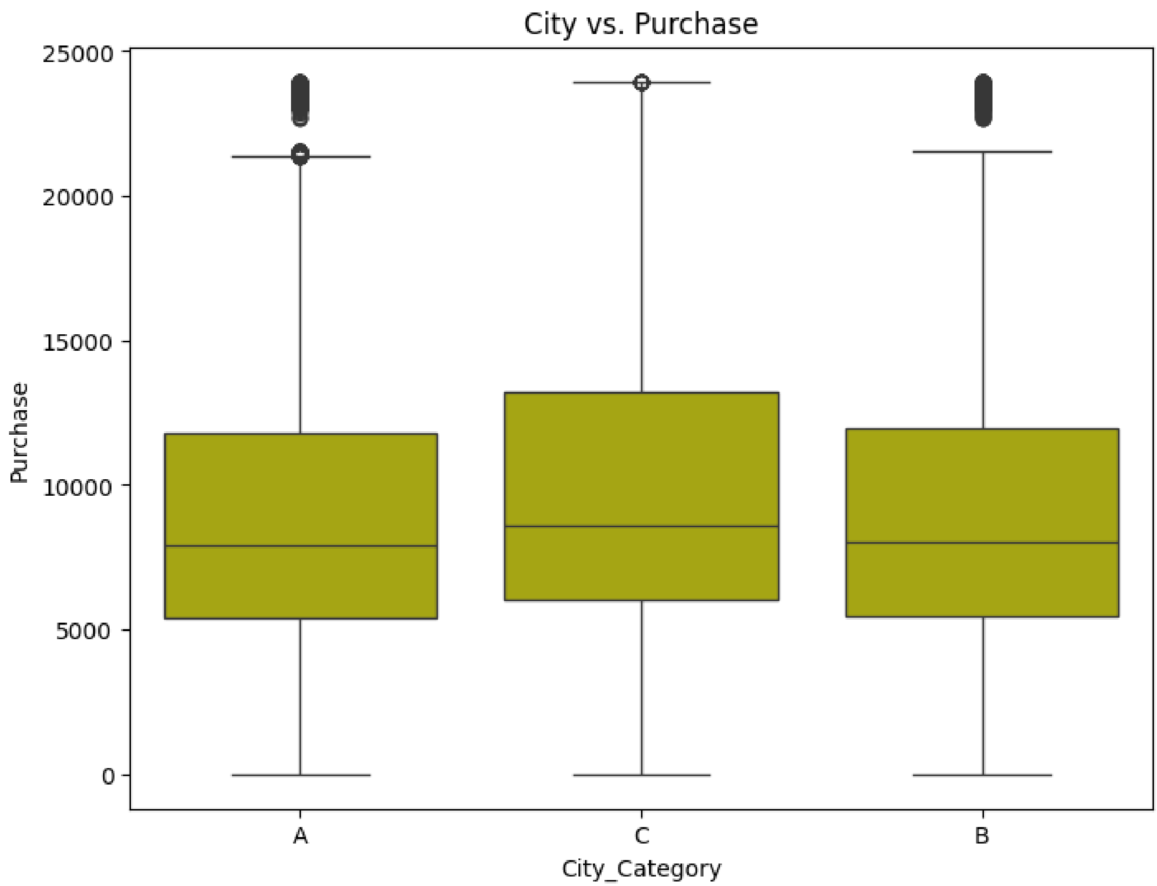


In [ ]:

```
df_stacked_plot= pd.crosstab(walmart_df['Gender'], walmart_df['Marital_Status'])
df_stacked_plot.plot(kind='bar', stacked=True, figsize=(8, 6))
plt.xticks(rotation=0)
plt.legend(loc='upper left')
plt.show()
```



In [ ]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(x='City_Category', y='Purchase', data=walmart_df,color='y')
plt.title('City vs. Purchase')
plt.show()
```



Insights from visual analysis

- In gender pie chart, we found out that 75% transactions are made by male users while only 25% are made from female users.
- From donut chart, we can see that 59% transactions are made by married users. This means that married purchase more variety of products than females.
- From Age distribution, we can see that most of the transactions are made from 26-35 agr group and that is the same age group with the highest purchasing amount.
- From the occupation pie chart, we can see that 35% of transactions are made by users following occupation 4,0,7.
- In Stacked bar chart, it is clearly visible that unmarried users are more in count to married users.
- The city bs purchase bar plot suggests that users from city C spent more than B and have less outliers. While the transactions made in City B and City A have small interquartile range with less mean and median vaalues than City C.

In [ ]:

Confidence Interval

Confidence Interval is a range where we are certain that true value exists.

Confidence Interval using Random Sampling Technique

In this technique, we select some random data for multiple times from the given dataset and try to find the mean and the median for the dataset.

In [ ]:

```
#defining functions to define and print Confidence interval with different confi
def confidence_interval(data, confidence_level):
  mean=np.mean(data)
  std=np.std(data)
  return norm.interval(confidence_level, loc=mean, scale=std)
def ci(data):
  print("Confidence Interval of 90% = ", confidence_interval(data,0.90))
  print("Confidence Interval of 95% = ", confidence_interval(data,0.95))
  print("Confidence Interval of 99% = ", confidence_interval(data,0.99))
  print("."*25)
```

Gender Based Confidence Interval

In [ ]:

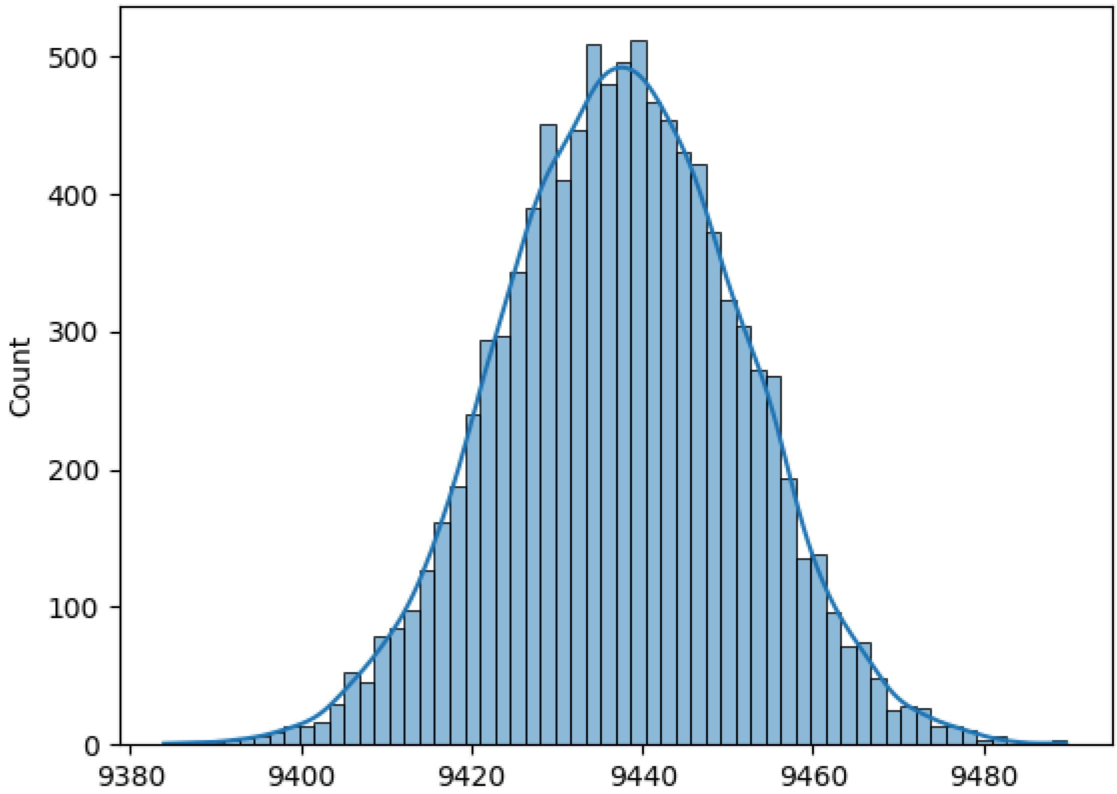
```
df_user_male=walmart_df[walmart_df["Gender"]=="M"]
df_user_female=walmart_df[walmart_df["Gender"]=="F"]
print("size of male user data",len(df_user_male))
print("size of female user data",len(df_user_female))
```

```
size of male user data 414259
size of female user data 135809
```

In [ ]:

```
sample_male_mean_purchase=[np.mean(df_user_male['Purchase'].sample(100000)) for
sns.histplot(sample_male_mean_purchase,kde=True)
```

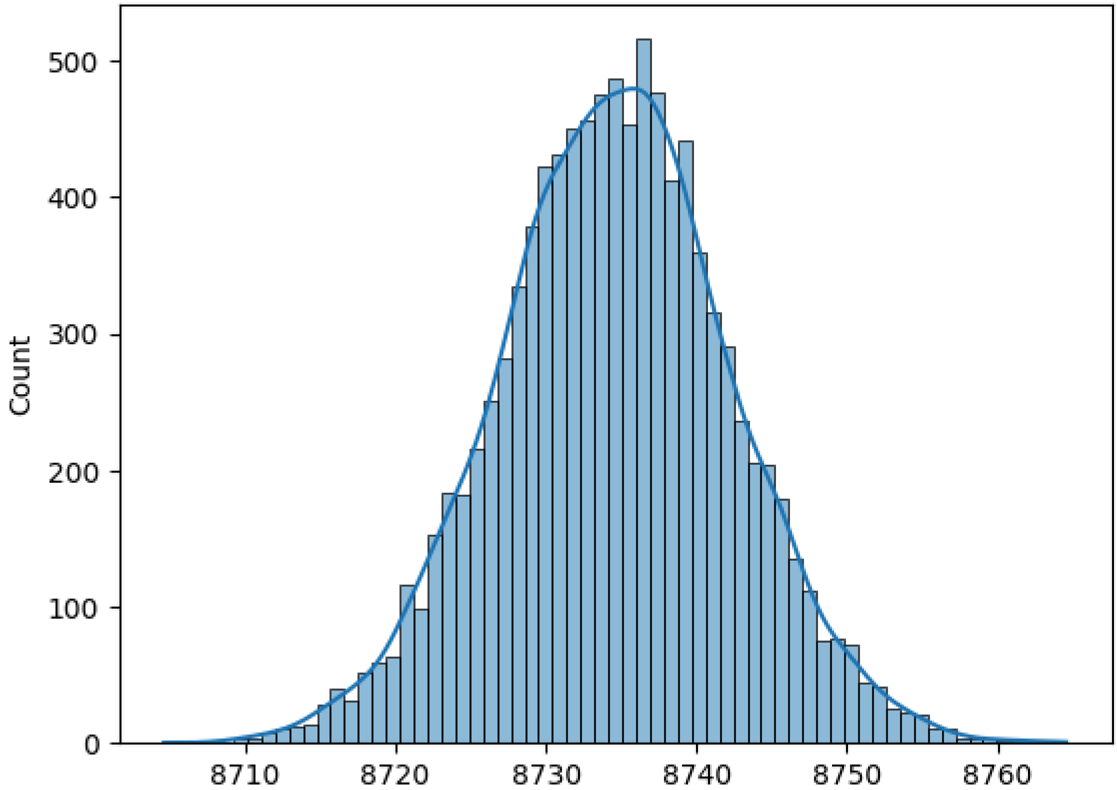
```
plt.show()
print("Confidence Interval for mean of male users")
ci(sample_male_mean_purchase)
```




```
Confidence Interval for mean of male users
Confidence Interval of 90% =  (9414.384812991535, 9460.670116960468)
Confidence Interval of 95% =  (9409.951294274197, 9465.103635677806)
Confidence Interval of 99% =  (9401.286233436205, 9473.768696515797)
.........................
```

In [ ]:

```
sample_female_mean_purchase=[np.mean(df_user_female['Purchase'].sample(100000))
sns.histplot(sample_female_mean_purchase,kde=True)
plt.show()
print("Confidence Interval for mean of female users")
ci(sample_female_mean_purchase)
```




```
Confidence Interval for mean of female users
Confidence Interval of 90% =  (8721.80910344745, 8747.27654186455)
Confidence Interval of 95% =  (8719.36966035811, 8749.71598495389)
Confidence Interval of 99% =  (8714.601907219445, 8754.483738092555)
.........................
```

According to the available data, we have tried to predict the interval for mean using a random sample of 100000 (1 lakh).

- It is found that the interval for males is larger than the intervals in females.
- Also it is found that the mean for females is approximately 580 lesser than the mean for males.

Confidence Interval using Bootstrapping

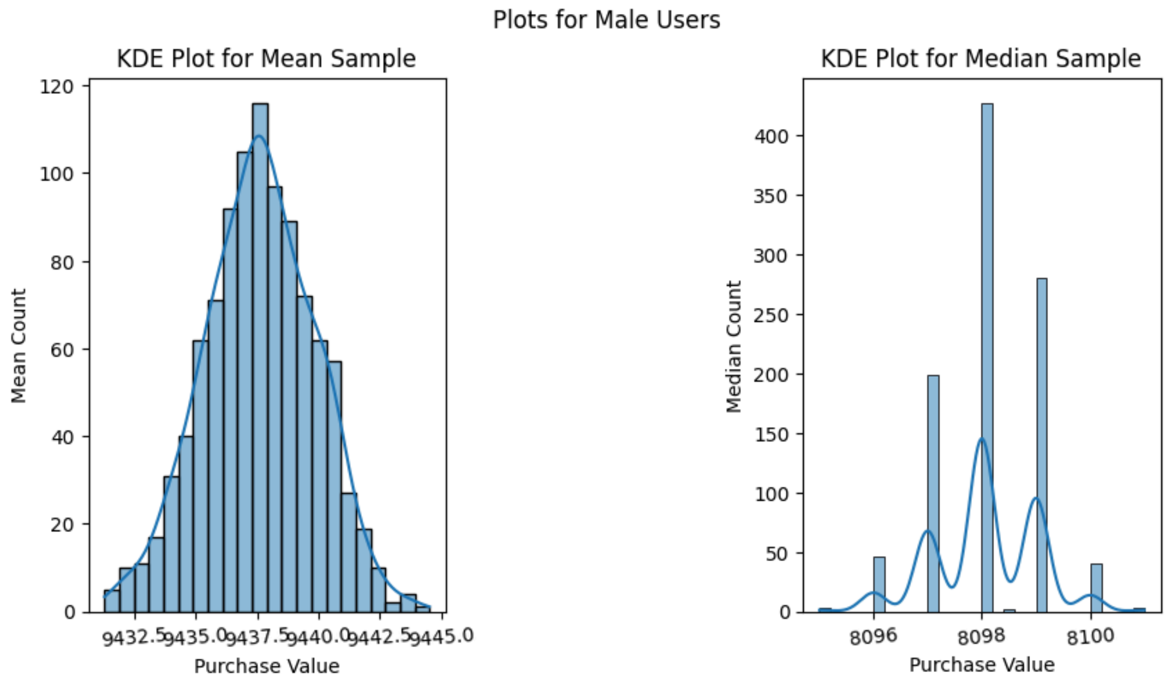
Bootstrapping is a statistical procedure that resamples a single dataset to create many simulated samples.

In [ ]:
```
# this function will process and plot the mean and median for the given datafram
def ci_using_bootstrap(d,t):
    plt.figure(figsize=(10,5))
    plt.suptitle(t)
    boot_mean, boot_median= bootstrapping(d)

    plt.subplot(1,2,1)
    mean_hist(boot_mean)

    plt.subplot(1,2,2)
    median_hist(boot_median)
    plt.show()

    print("Confidence Intervals for mean calculation")
```

```
    ci(boot_mean)

    print("Confidence Intervals for median calculation")
    ci(boot_median)

# bootstrapping values for 5 million data and returning the mean and the median
def bootstrapping(data):
  bootstrapped_median=[]
  bootstrapped_mean=[]
  for reps in range(1000):
    bootstrapped_sample=np.random.choice(data["Purchase"],size=5000000)
    bootstrapped_median.append(np.median(bootstrapped_sample))
    bootstrapped_mean.append(np.mean(bootstrapped_sample))
  return (bootstrapped_mean, bootstrapped_median)

# drawing plots with all the details

def mean_hist(data):
  sns.histplot(data,kde= True)
  plt.subplots_adjust(wspace=1, hspace=0.2)
  plt.title(f'KDE Plot for Mean Sample')
  plt.xticks(rotation=5)
  plt.xlabel("Purchase Value")
  plt.ylabel('Mean Count')

def median_hist(data):
  sns.histplot(data,kde= True)
  plt.subplots_adjust(wspace=1, hspace=0.2)
  plt.title(f'KDE Plot for Median Sample')
  plt.xticks(rotation=5)
  plt.xlabel("Purchase Value")
  plt.ylabel('Median Count')
```

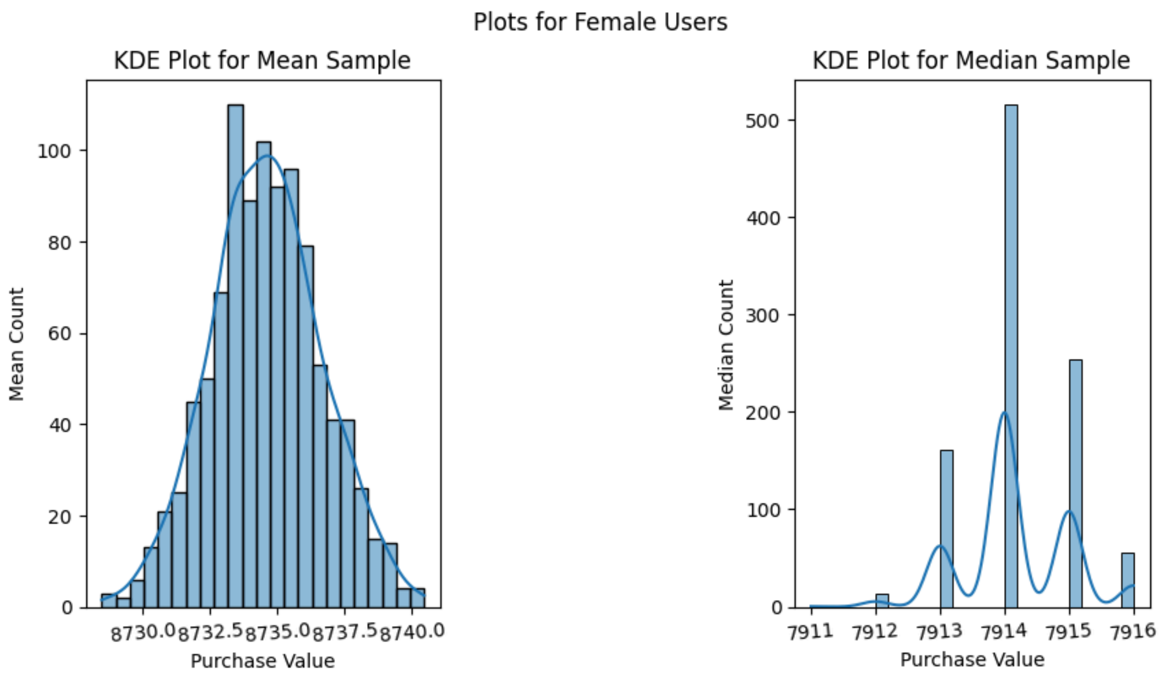
Gender

In [ ]:
```
ci_using_bootstrap(df_user_male,"Plots for Male Users" )
```



```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9433.92852905488, 9441.293328212723)
Confidence Interval of 95% =  (9433.223078898656, 9441.998778368947)
Confidence Interval of 99% =  (9431.844316585566, 9443.377540682037)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8096.533491875048, 8099.606508124952)
Confidence Interval of 95% =  (8096.239137643913, 8099.900862356087)
Confidence Interval of 99% =  (8095.663838996647, 8100.476161003352)
.........................
```

In [ ]:
```
ci_using_bootstrap(df_user_female,"Plots for Female Users" )
```

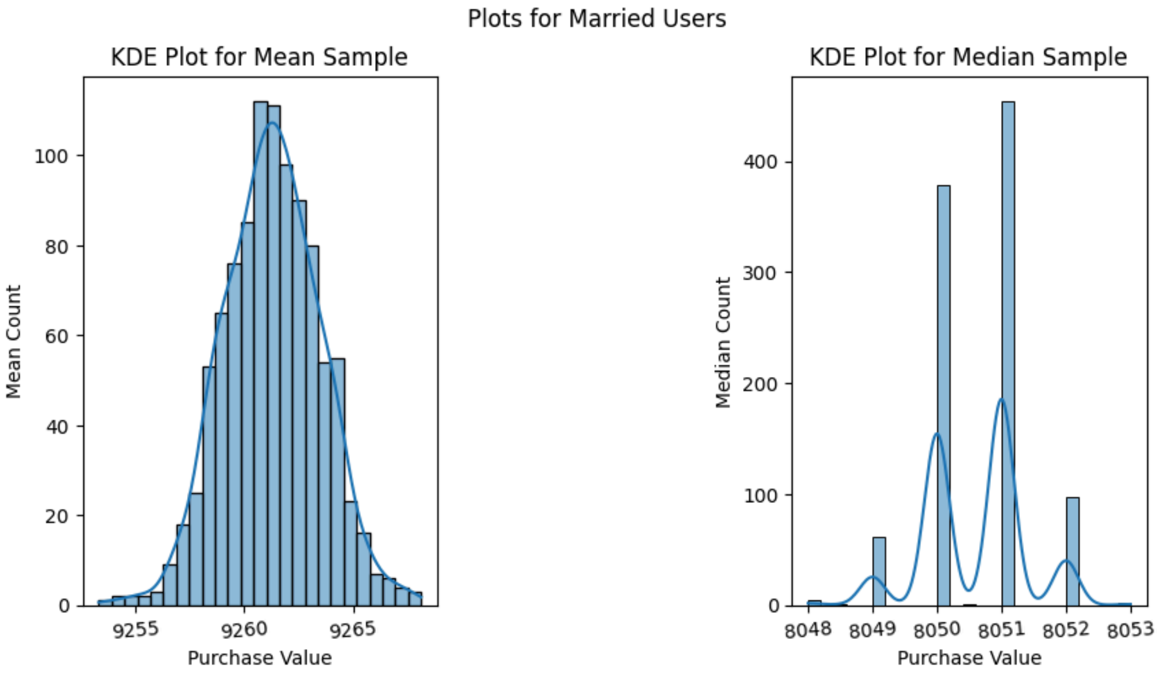



```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (8731.212456155936, 8737.979942940463)
Confidence Interval of 95% =  (8730.564220609105, 8738.628178487294)
Confidence Interval of 99% =  (8729.297281004525, 8739.895118091874)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (7912.823547207869, 7915.522452792131)
Confidence Interval of 95% =  (7912.565027820544, 7915.780972179456)
Confidence Interval of 99% =  (7912.059766342747, 7916.2862336572525)
.........................
```

The difference between the mean and the median interval is large indicating the plots are left skewed. This shows that more purchases are made from lower amounts lesser than the average. But at the same time the overall purchase amount is bigger.

Marital Status

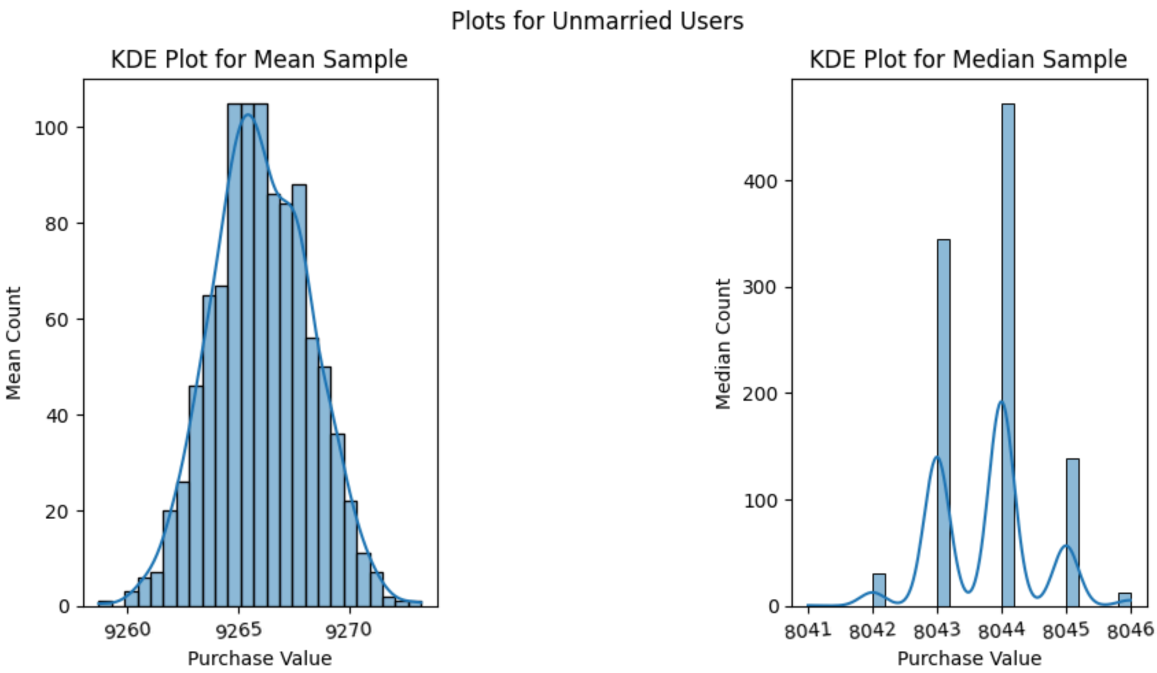
In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df['Marital_Status']==1],"Plots for Marrie
```




```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9257.68921194703, 9264.872780752166)
Confidence Interval of 95% =  (9257.001121256813, 9265.560871442383)
Confidence Interval of 99% =  (9255.656287035305, 9266.905705663892)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8049.308488666789, 8051.861511333211)
Confidence Interval of 95% =  (8049.063942929659, 8052.106057070341)
Confidence Interval of 99% =  (8048.5859921585, 8052.5840078415)
.........................
```

In [ ]:

```
ci_using_bootstrap(walmart_df[walmart_df['Marital_Status']==0],"Plots for Unmarr
```

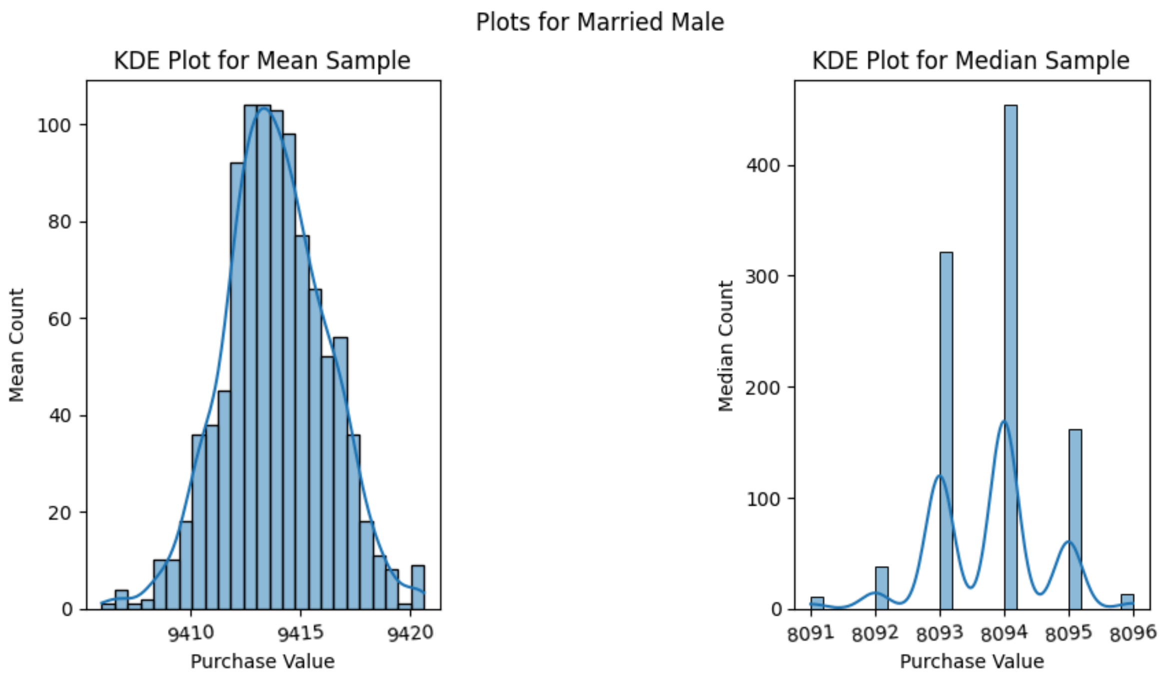


```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9262.453114513817, 9269.644303477784)
Confidence Interval of 95% =  (9261.764293913373, 9270.333124078228)
Confidence Interval of 99% =  (9260.418033123726, 9271.679384867875)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8042.472946691579, 8045.039053308422)
Confidence Interval of 95% =  (8042.227147685395, 8045.284852314606)
Confidence Interval of 99% =  (8041.746747470963, 8045.765252529038)
.........................
```

Through these plots, we can observe that the mean and median values have a slight difference. This tells that the purchasing style for both married and unmarried doesn't have musch difference.

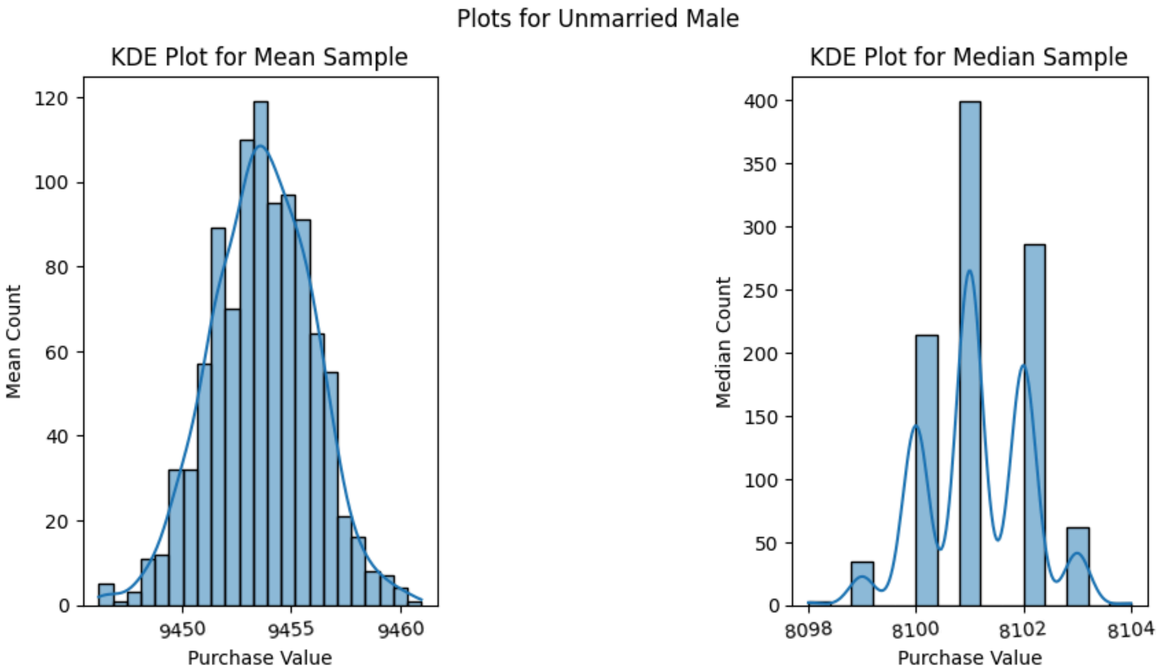
Marital Status and Gender

In [ ]:
```
ci_using_bootstrap(df_user_male[df_user_male["Marital_Status"]==1],"Plots for Ma
```



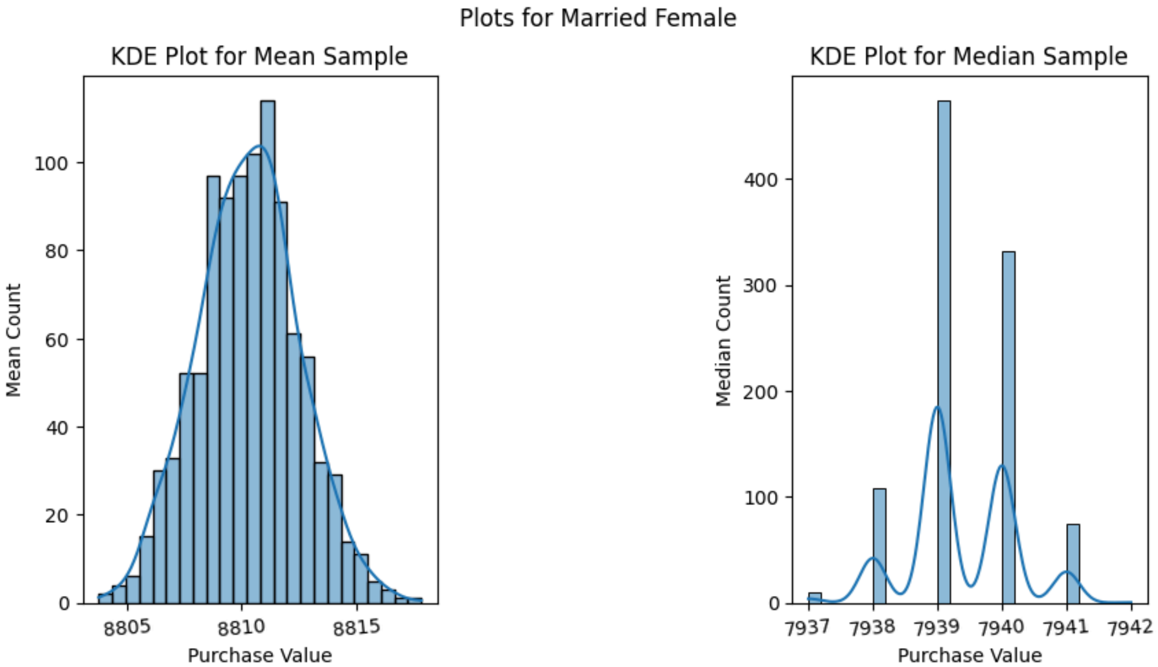

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9410.04984102865, 9417.686798918552)
Confidence Interval of 95% =  (9409.318321672718, 9418.418318274484)
Confidence Interval of 99% =  (9407.888608587597, 9419.848031359605)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8092.353610152896, 8095.160389847103)
Confidence Interval of 95% =  (8092.084757855458, 8095.429242144542)
Confidence Interval of 99% =  (8091.559301290984, 8095.954698709015)
.........................
```

In [ ]:
```
ci_using_bootstrap(df_user_male[df_user_male["Marital_Status"]==0],"Plots for Un
```



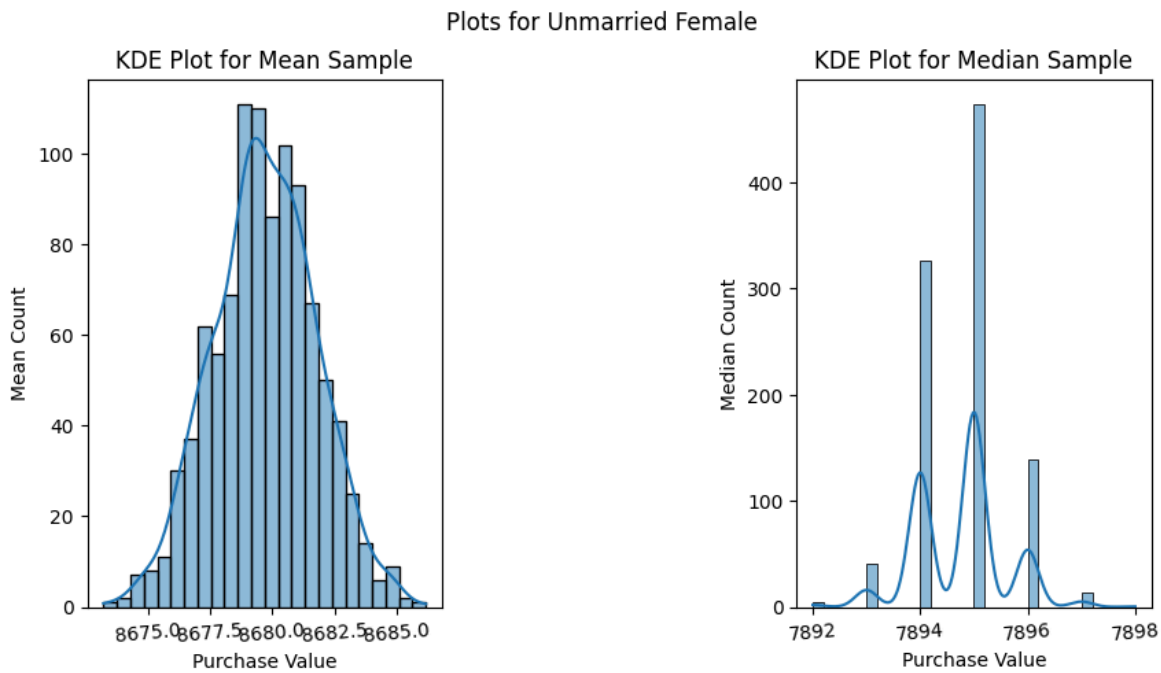

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9449.861048953695, 9457.486332064705)
Confidence Interval of 95% =  (9449.130647886861, 9458.21673313154)
Confidence Interval of 99% =  (9447.703120434342, 9459.644260584058)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8099.55300262329, 8102.69699737671)
Confidence Interval of 95% =  (8099.25184959217, 8102.99815040783)
Confidence Interval of 99% =  (8098.663263076006, 8103.586736923994)
.........................
```

In [ ]:
```
ci_using_bootstrap(df_user_female[df_user_female["Marital_Status"]==1],"Plots fc
```



```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (8806.673657620542, 8813.909936248258)
Confidence Interval of 95% =  (8805.980518027865, 8814.603075840934)
Confidence Interval of 99% =  (8804.625816012905, 8815.957777855894)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (7938.019145382487, 7940.694854617513)
Confidence Interval of 95% =  (7937.762847898007, 7940.951152101993)
Confidence Interval of 99% =  (7937.261929003279, 7941.452070996721)
.........................
```

In [ ]:
```
ci_using_bootstrap(df_user_female[df_user_female["Marital_Status"]==0],"Plots fo
```

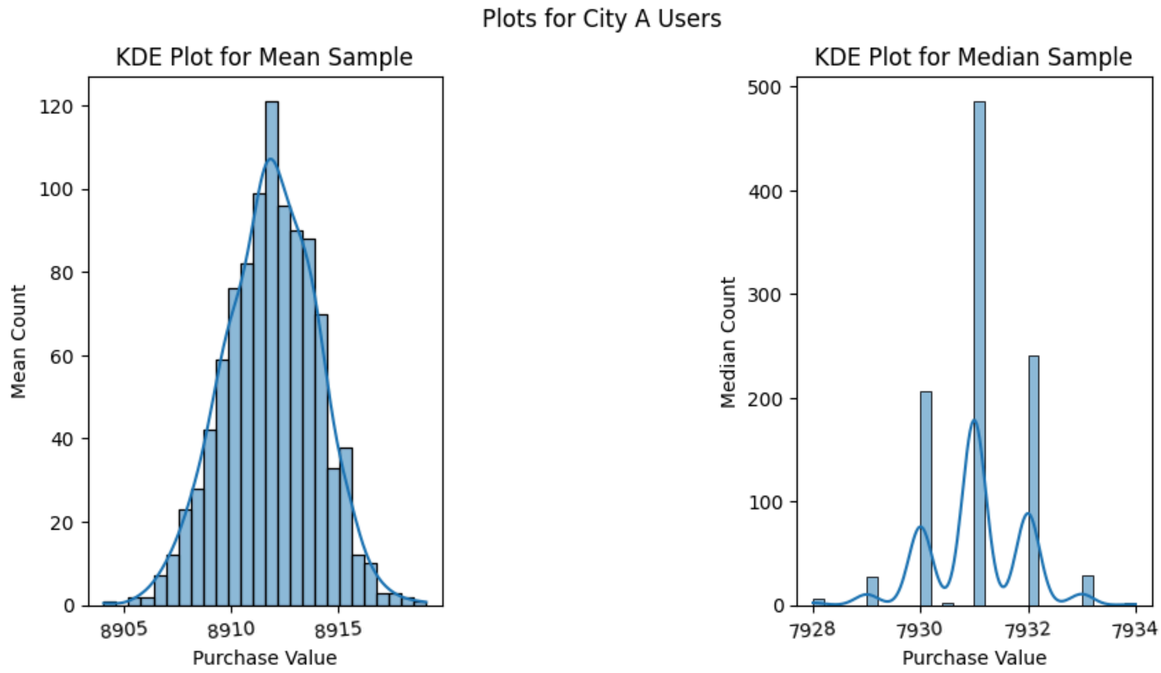



```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (8676.32877169584, 8683.100851847757)
Confidence Interval of 95% =  (8675.680096165286, 8683.749527378312)
Confidence Interval of 99% =  (8674.412296637482, 8685.017326906116)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (7893.397163155239, 7896.090836844761)
Confidence Interval of 95% =  (7893.139144914094, 7896.348855085906)
Confidence Interval of 99% =  (7892.634862898077, 7896.853137101923)
.........................
```

It is noticable that the purchasing pattern for married male users is dfiferent from that of purchasing pattern of unmarried males. We can also observe the same for female users. Therefore it is indicative that purchasing style differs with difference in marital status for each gender.

City

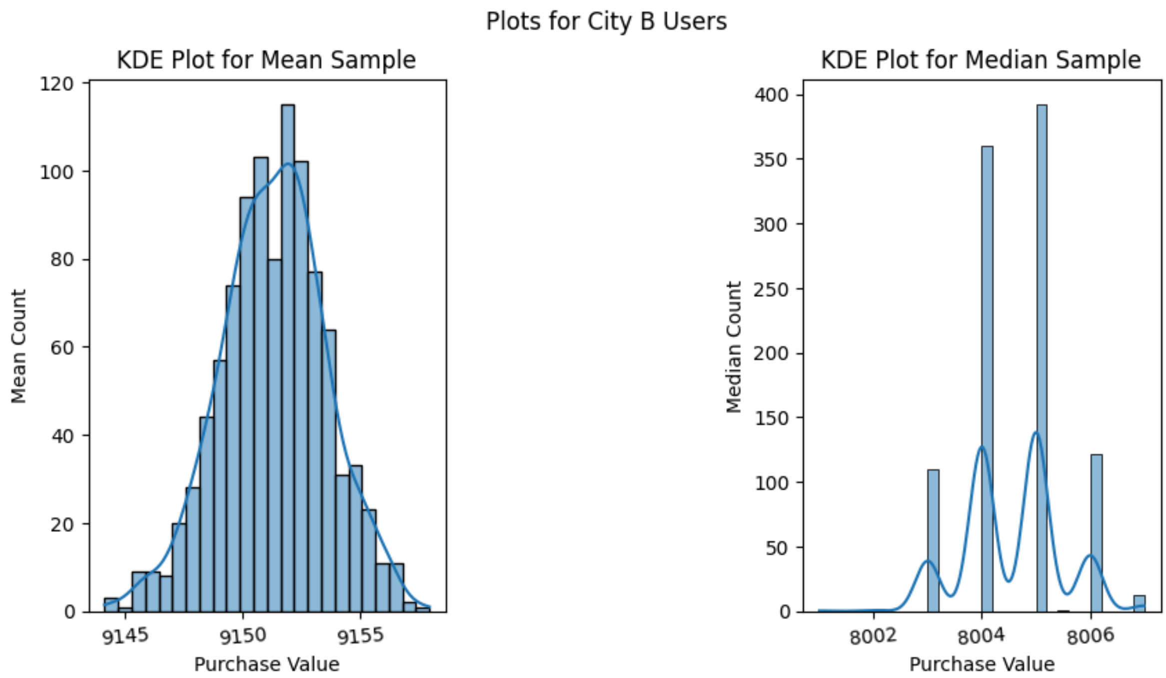
In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["City_Category"]=='A'],"Plots for City
```




```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (8908.30035275608, 8915.438305630323)
Confidence Interval of 95% =  (8907.616631467512, 8916.12202691889)
Confidence Interval of 99% =  (8906.280336993665, 8917.458321392738)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (7929.602439118818, 7932.445560881182)
Confidence Interval of 95% =  (7929.330105732878, 7932.717894267123)
Confidence Interval of 99% =  (7928.797845578398, 7933.250154421603)
.........................
```

In [ ]:

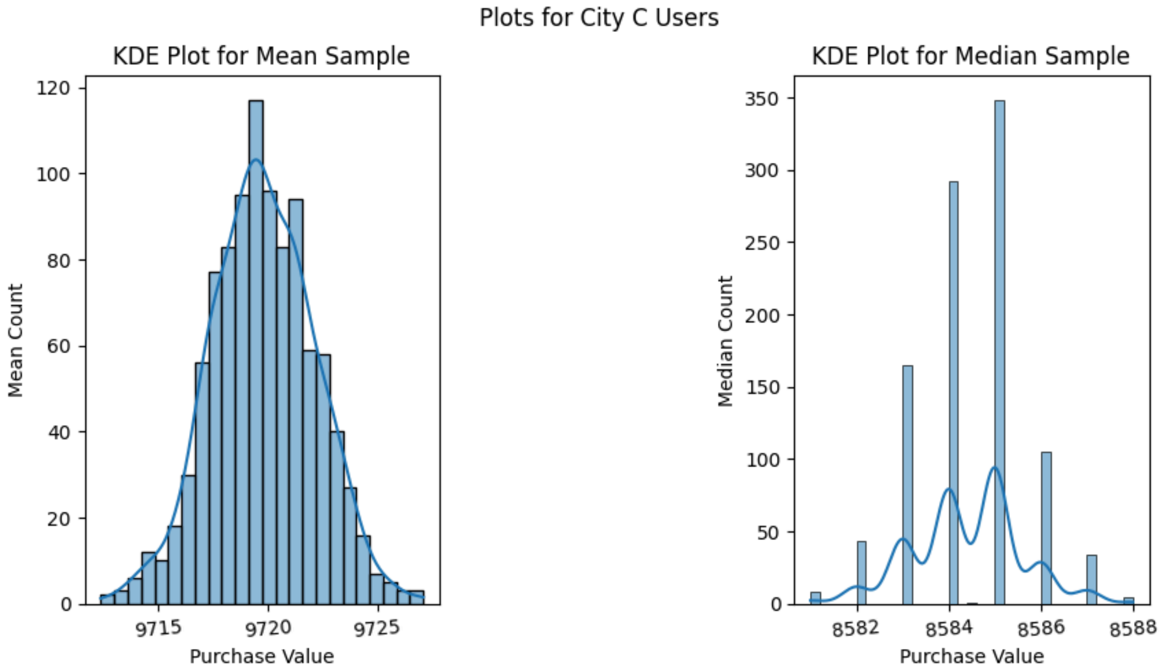
```
ci_using_bootstrap(walmart_df[walmart_df["City_Category"]=='B'],"Plots for City
```



```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9147.645498363347, 9154.993162661855)
Confidence Interval of 95% =  (9146.941689499567, 9155.696971525635)
Confidence Interval of 99% =  (9145.56613499945, 9157.072526025751)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8003.078365167071, 8006.0346348329285)
Confidence Interval of 95% =  (8002.795193711486, 8006.317806288514)
Confidence Interval of 99% =  (8002.241751164683, 8006.871248835317)
.........................
```

In [ ]:

```
ci_using_bootstrap(walmart_df[walmart_df["City_Category"]=='C'],"Plots for City
```



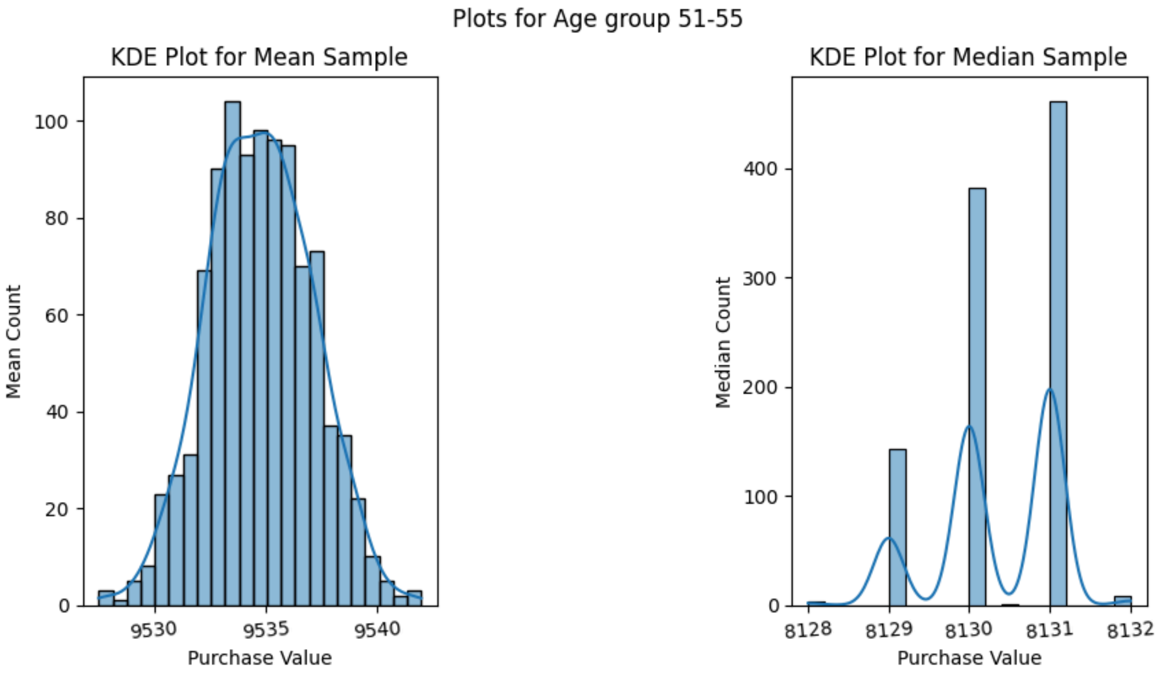

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9715.93209216745, 9723.66053145295)
Confidence Interval of 95% =  (9715.191810106193, 9724.400813514207)
Confidence Interval of 99% =  (9713.744970810581, 9725.847652809818)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8582.465005120823, 8586.337994879177)
Confidence Interval of 95% =  (8582.094024029348, 8586.708975970652)
Confidence Interval of 99% =  (8581.368962530269, 8587.434037469731)
.........................
```

We found out that the users from city C have purchased more products than the other cities.

Age

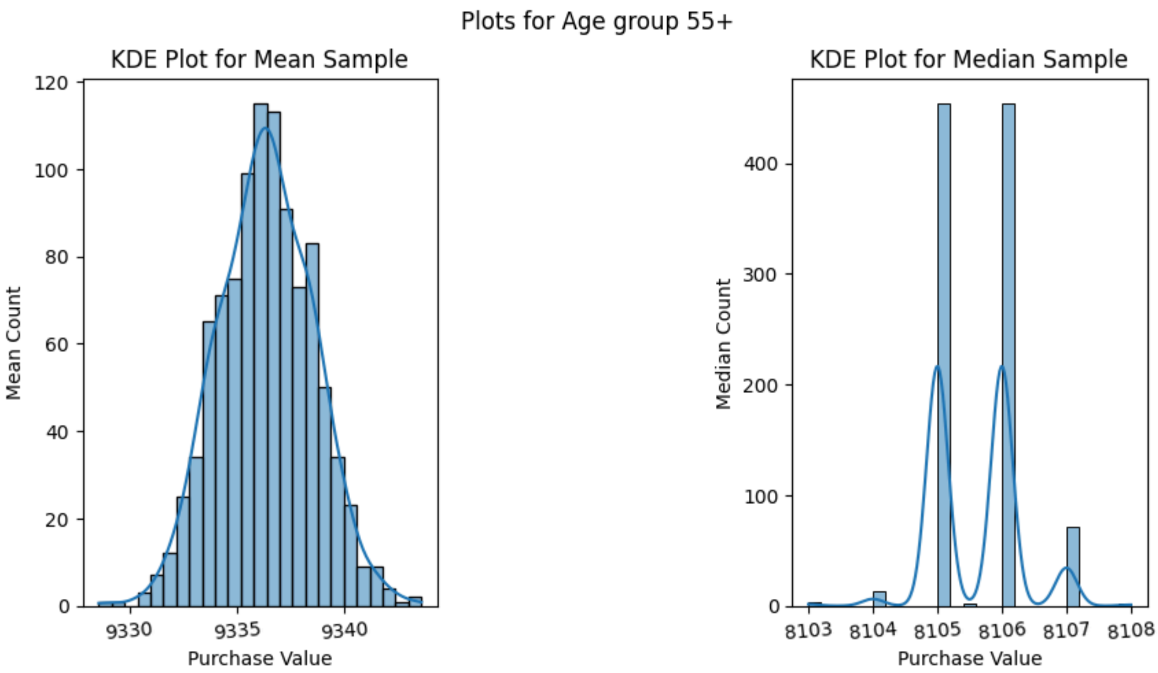
In [ ]:

```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='51-55'],"Plots for Age group 5
```



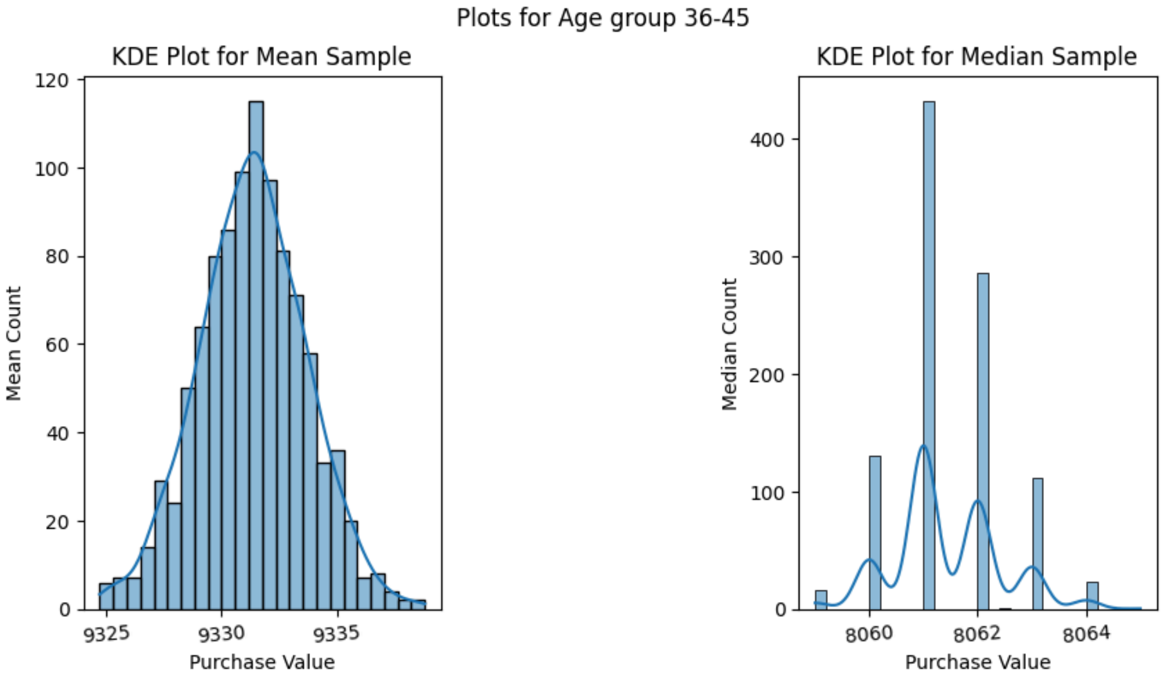

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9530.943202018349, 9538.604927499655)
Confidence Interval of 95% =  (9530.209310255397, 9539.338819262606)
Confidence Interval of 99% =  (9528.774960435332, 9540.773169082671)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8129.110488665838, 8131.546511334162)
Confidence Interval of 95% =  (8128.877149977966, 8131.779850022033)
Confidence Interval of 99% =  (8128.421102748852, 8132.235897251147)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='55+'],"Plots for Age group 55+
```



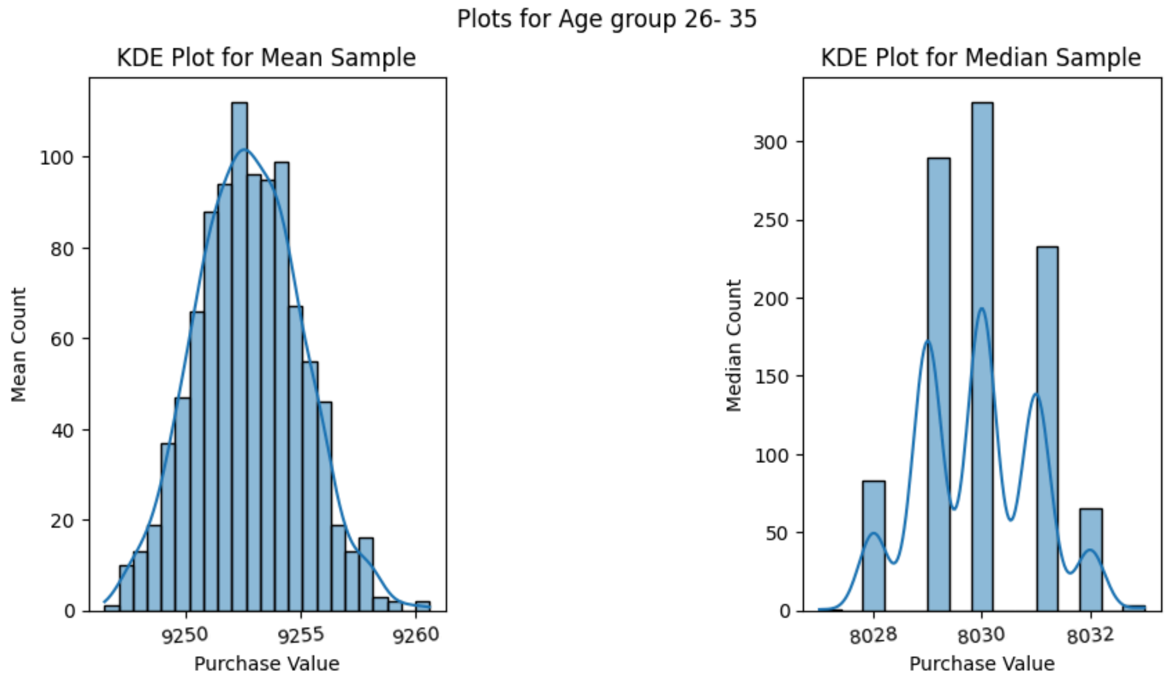
```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9332.775631462864, 9339.943090461933)
Confidence Interval of 95% =  (9332.08908387857, 9340.629638046226)
Confidence Interval of 99% =  (9330.747265570055, 9341.971456354742)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8104.492321992893, 8106.679678007107)
Confidence Interval of 95% =  (8104.282802274993, 8106.889197725008)
Confidence Interval of 99% =  (8103.873307871538, 8107.298692128463)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='36-45'],"Plots for Age group 3
```



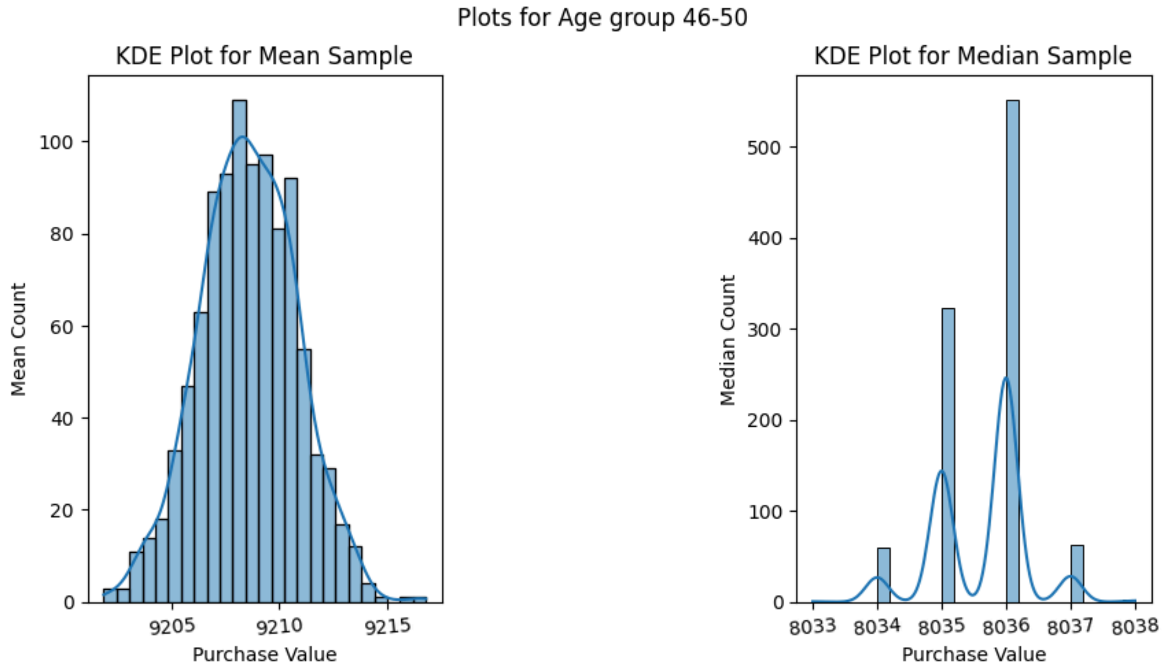

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9327.511669617928, 9335.163190178871)
Confidence Interval of 95% =  (9326.778755351106, 9335.896104445694)
Confidence Interval of 99% =  (9325.346315991776, 9337.328543805024)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8059.798479363671, 8063.04252063633)
Confidence Interval of 95% =  (8059.487743201889, 8063.353256798111)
Confidence Interval of 99% =  (8058.8804270004575, 8063.960572999543)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='26-35'],"Plots for Age group 2
```



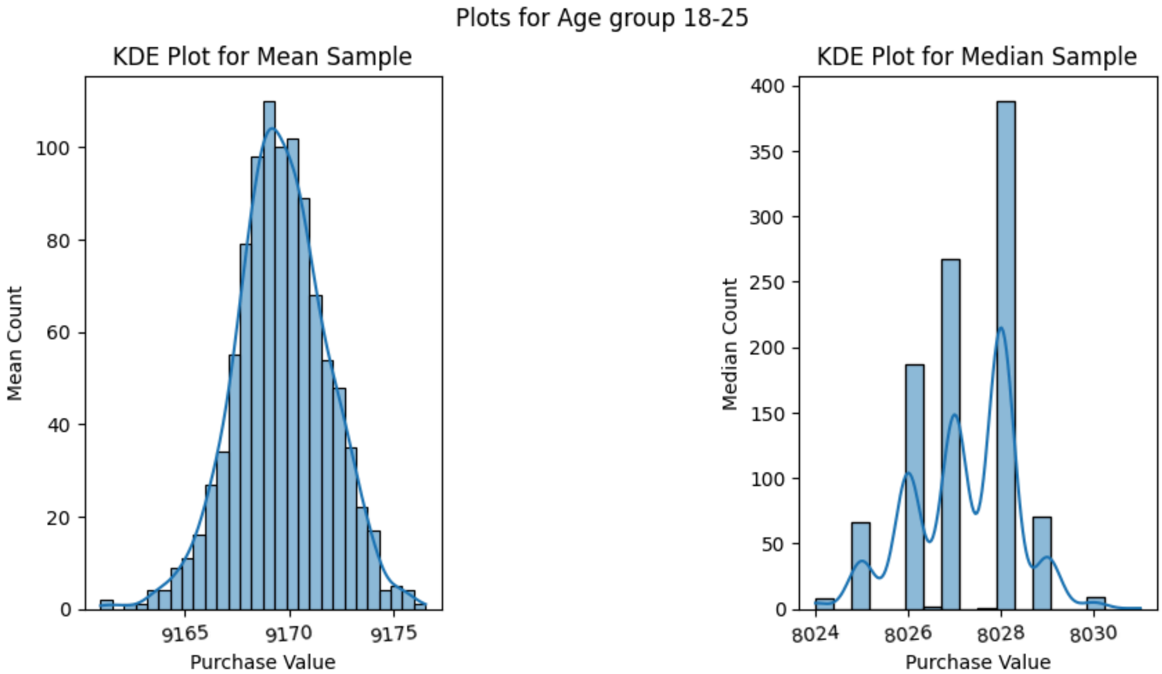

```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9249.014239863782, 9256.500489155818)
Confidence Interval of 95% =  (9248.29715639424, 9257.21757262536)
Confidence Interval of 99% =  (9246.895657430176, 9258.619071589424)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8028.154136089044, 8031.671863910955)
Confidence Interval of 95% =  (8027.817184382918, 8032.008815617081)
Confidence Interval of 99% =  (8027.1586313871585, 8032.667368612841)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='46-50'],"Plots for Age group 4
```



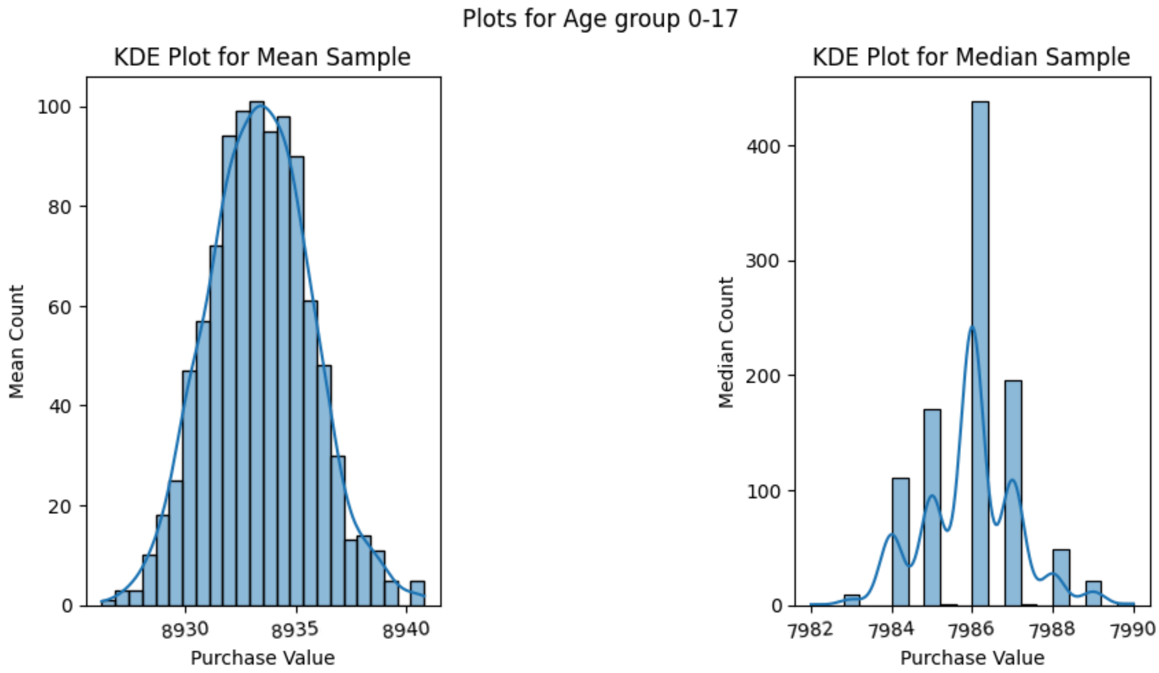
```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9204.876969926037, 9212.249970669563)
Confidence Interval of 95% =  (9204.170734166599, 9212.956206429002)
Confidence Interval of 99% =  (9202.790436436588, 9214.336504159013)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8034.45554710836, 8036.792452891639)
Confidence Interval of 95% =  (8034.231702504515, 8037.016297495485)
Confidence Interval of 99% =  (8033.794210924069, 8037.45378907593)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='18-25'],"Plots for Age group 1
```




```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (9166.009248891325, 9173.230571144275)
Confidence Interval of 95% =  (9165.317541921142, 9173.922278114458)
Confidence Interval of 99% =  (9163.965639885573, 9175.274180150027)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (8025.381852379878, 8029.053147620121)
Confidence Interval of 95% =  (8025.0301909502505, 8029.404809049749)
Confidence Interval of 99% =  (8024.34288863433, 8030.09211136567)
.........................
```

In [ ]:
```
ci_using_bootstrap(walmart_df[walmart_df["Age"]=='0-17'],"Plots for Age group 0-
```




```
Confidence Intervals for mean calculation
Confidence Interval of 90% =  (8929.574452259803, 8937.188451854996)
Confidence Interval of 95% =  (8928.845132004248, 8937.917772110552)
Confidence Interval of 99% =  (8927.419716936065, 8939.343187178734)
.........................
Confidence Intervals for median calculation
Confidence Interval of 90% =  (7984.049248699081, 7987.834751300919)
Confidence Interval of 95% =  (7983.686647717762, 7988.197352282238)
Confidence Interval of 99% =  (7982.977964668617, 7988.9060353313835)
.........................
```

Insights:

- It is found that the difference in mean and median values is very large for any feature. This indicates that the purchase curve is left skewed and the transactions for higher purchase values is less in count.
- All of the graphs are left skewed.
- Most of the transactions are made for the products ranging 5000 to 10000.
- Occupation plays an important role in the users purchasing style. We can see that certain types of occupation has more users purchasing products.
- Noticingly, the users have purchased most of the products from the product category of 1 and 5.
- The number of transactions are higher fromthe age group of 26-35 but thre highest average purchasing price is from 55+. That means the age group 26-35 purchase a variety of products but for less price. The same is true for 18-25 age group.

Recommendations

- It seems like that there are less variety of female products available. Enrich the varety of products for female customers.

- It is also noticed that certain occupations have made only a few percentage of transactions. We can check if they didn't found the variety they needed pr there is some different problem.
- It is recommended to run campiagns in city A and city B to grab users attention and increase sales.
- It is better to spread awareness for products of other categories than 1 and 5. Also maintain a high stock for these two categories so that there is high profits from these two categories.
- There are too many potential customers seen from age froup 18-25. It is better to be variety of cheaper product to increase the sales.

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