WALMART BIZ CASE STUDY

To analyse,interprete and visualize the given Walmart data and to solve the related problems like

1. Analysing customer purchase behaviour against gender and other factors
2. To underrstand if the spending habit differ between male and female customers
3. Do women spend more than men on black friday? And to get insights and make better business decision, we need functions and methods, so we must import Python libraries into our work notebook.

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

To get the data into our work space we use the below code(to read csv files) and saving the whole set of data into a single variable(dataframe) which makes analysis easier

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094 -O walmart.csv
```

```
--2023-09-27 12:38:14--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 18.172.139.46, 18.172.139.61, 18.172.139.210, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|18.172.139.46|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 23027994 (22M) [text/plain]
Saving to: ‘walmart.csv’

walmart.csv         100%[===================>]  21.96M   107MB/s    in 0.2s

2023-09-27 12:38:15 (107 MB/s) - ‘walmart.csv’ saved [23027994/23027994]
```

```
df = pd.read_csv('walmart.csv')
```

```
df.head(2)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Yea
0	1000001	P00069042	F	0-17	10	A	

```
df.tail(2)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_Cit
550066	1006038	P00375436	F	55+	1	C	
550067	1006039	P00371644	F	46-	0	B	

```
df.sample(2)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_Cit
337427	1003940	P00116842	M	36-45	20	B	

```
# TO GET NO. OF ROWS & COLUMNS:

df.shape
```

```
(550068, 10)
```

```
# TO GET TOTAL ELEMENTS IN THE DATASET (i.e., the dot product of no. of rows & columns)

df.size
```

```
5500680
```

```
# To get index

df.index
```

```
RangeIndex(start=0, stop=550068, step=1)
```

```
# TO GET THE NAMES OF THE COLUMNS

df.columns
```

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

```
# TO GET THE NAMES OF THE COLUMNS(alternate method)

df.keys()
```

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

```
# To get memory usage of each column

df.memory_usage()
```

```
Index                             128
User_ID                       4400544
Product_ID                    4400544
Gender                        4400544
Age                           4400544
Occupation                    4400544
City_Category                 4400544
Stay_In_Current_City_Years    4400544
Marital_Status                4400544
Product_Category              4400544
Purchase                      4400544
dtype: int64
```

```
# TO GET THE TOTAL INFORMATION ABOUT THE DATASET.
# info function let us know the columns with their data types and no. of non-null values & the total memory usage


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
```

From the above analysis we get to know that 5 columns are integer data type and the other 5 are of object data type

MISSING VALUE DETECTION

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

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

INFERENCE:

No missing values found

TO ANALYSE THE BASIC METRICS

```
# To get the data type of each column

df.dtypes
```

```
User_ID                        int64
Product_ID                    object
Gender                        object
Age                           object
Occupation                     int64
City_Category                 object
Stay_In_Current_City_Years    object
Marital_Status                 int64
Product_Category               int64
Purchase                       int64
dtype: object
```

STATISTICAL SUMMERY

```
df.describe()
```

	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

Describe function returns the glimpse of the data with the statistical values from all over the data just to predict the normal ranges and average ranges to the particular elements. Note: it will display only the numerical values and return from the numerical values.

NOTE:

Here, marital status is considered as numerical data which has to be converted to categorical values

CONVERSION TO CATEGORICAL ATTRIBUTE

```
df['Marital_Status_categ'] = df['Marital_Status'].replace({0:'Single',1:'Married'})
```

```
df.sample(5)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_Cit
105323	1004227	P00206442	M	26-35	19	A	
220112	1003934	P00126242	M	26-35	0	B	
464234	1005511	P00277442	M	46-50	1	B	
48220	1001391	P00296242	M	36-45	15	C	
219382	1003824	P00018342	M	26-35	17	A	

```
# To get statistical values for the object data type
```

```
df.describe(include = object)
```

	Product_ID	Gender	Age	City_Category	Stay_In_Current_City_Years	Marital_S
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	

INFERENCE:

1. **Male** customers are more than Female customers
2. Most customers belong to the age group of **26-35**
3. Majority of the customers are from city_category **B**
4. The Product which made the top in the sales is **P00265242**
5. Many customers stay in the current city for **1 year**
6. Number of **Unmarried** customers dominate married customers

```
# Accessing the rows with their iloc(integer location) values
```

```
df.iloc[:4]
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422

```
# Accessing selected range of rows using external location values
```

```
df.loc[3:6]
```

User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase

```
# Accessing the specified columns for all rows using external location

df.loc[:,['Product_ID','Gender','Age']]
```

	Product_ID	Gender	Age
0	P00069042	F	0-17
1	P00248942	F	0-17
2	P00087842	F	0-17
3	P00085442	F	0-17
4	P00285442	M	55+
...	...	...	...
550063	P00372445	M	51-55
550064	P00375436	F	26-35
550065	P00375436	F	26-35
550066	P00375436	F	55+
550067	P00371644	F	46-50

550068 rows × 3 columns

NON-GRAPHICAL ANALYSIS:

```
df['User_ID'].nunique()
```

```
5891
```

```
df['User_ID'].value_counts()
```

```
1001680    1026
1004277     979
1001941     898
1001181     862
1000889     823
           ...
1002690       7
1002111       7
1005810       7
1004991       7
1000708       6
Name: User_ID, Length: 5891, dtype: int64
```

INFERENCE:

1. There are **5891** unique customers
2. Among all the customers, user_id **1001680** contributed the most purchase

```
df['Product_ID'].unique()
```

```
array(['P00069042', 'P00248942', 'P00087842', ..., 'P00370293',
       'P00371644', 'P00370853'], dtype=object)
```

```
df['Product_ID'].nunique()
```

```
3631
```

```
df['Product_ID'].value_counts()
```

```
P00265242    1880
P00025442    1615
P00110742    1612
P00112142    1562
P00057642    1470
             ...
P00314842       1
P00298842       1
P00231642       1
P00204442       1
P00066342       1
Name: Product_ID, Length: 3631, dtype: int64
```

INFERENCE:

1. There are **3631** unique products in Walmart
2. Among them **P00265242** product is the most sold (ie., 1880 customers brought)

```
df['Gender'].value_counts()
```

```
M    414259
F    135809
Name: Gender, dtype: int64
```

INFERENCE:

Its a clear evidance that Male customers are more than Female

```
df['Marital_Status'].value_counts()
```

```
0    324731
1    225337
Name: Marital_Status, dtype: int64
```

INFERENCE:

Unmarried customers are more than the Married customers

```
df['Age'].value_counts()
```

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

INFERENCE:

Customers belonging to the age group of **26-35** are more compared to other age groups

```
df['Occupation'].value_counts()
```

```
4     72308
0     69638
7     59133
1     47426
17    40043
20    33562
12    31179
14    27309
2     26588
16    25371
6     20355
3     17650
10    12930
5     12177
```

```
15    12165
11    11586
19     8461
13     7728
18     6622
9      6291
8      1546
Name: Occupation, dtype: int64
```

INFERENCE:

Occupation of most of the customer is **4**

```
df_cc = df.groupby(['User_ID','City_Category']).agg({'Purchase':'sum'}).reset_index()
df_cc.groupby('City_Category').agg({'Purchase':'sum'}).reset_index()
```

	City_Category	Purchase
0	A	1316471661
1	B	2115533605
2	C	1663807476

INFERENCE:

Customers belonging to **city_category B** are likely to purchase more

```
df_cc['City_Category'].value_counts()
```

```
C    3139
B    1707
A    1045
Name: City_Category, dtype: int64
```

INFERENCE:

There are **more number of customers** who belongs to City Category **C(3139)**

```
df.groupby(['User_ID','Gender']).agg({'Gender':'count'}).rename(columns={'Gender':'count'}).reset_index().head(5)
```

	User_ID	Gender	count
0	1000001	F	35
1	1000002	M	77
2	1000003	M	29
3	1000004	M	14
4	1000005	M	106

```
df.groupby('Gender').agg({'Purchase':'mean'}).reset_index()
```

	Gender	Purchase
0	F	8734.565765
1	M	9437.526040

INFERENCE:

Male customers purchase for more amount than female customers

```
df.groupby('Age').agg({'Age':'count'}). rename(columns ={'Age':'Age','Age':'Count'}).reset_index().sort_values('Count',ascending = False)
```

	Age	Count
2	26-35	219587
3	36-45	110013
1	18-25	99660
4	46-50	45701
5	51-55	38501
6	55+	21504

INFERENCE:

1. customers of age group **26-35** contribute more with a count of **219587**
2. Least contributed age group is **0-17** with a count of **15102**

```
df['Product_Category'].nunique()
```

```
20
```

```
df['Product_Category'].value_counts()
```

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

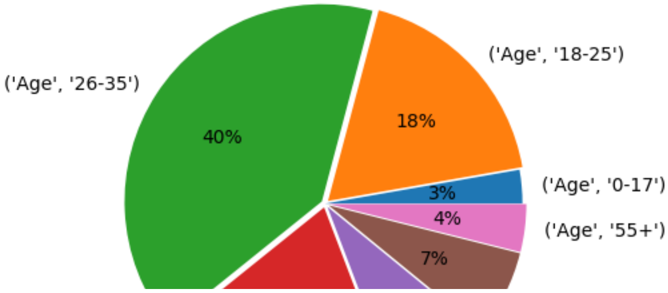
INFERENCE:

1. There are **20** unique product categories
2. Product category **5(150933)** is purchased more followed by Product category **1(140378)**

VISUAL ANALYSIS:

UNIVARIATE

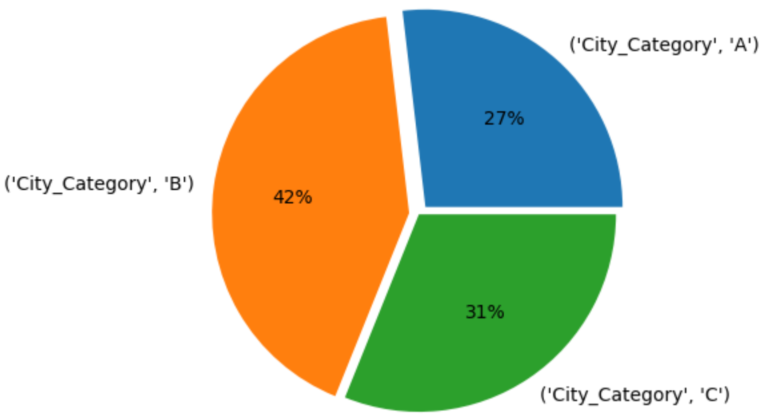
```
age = ['Age']

df1=df[age].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode=[0,0.02,0.02,0.02,0.02,0.02,0.02],autopct='%.0f%%')
plt.show()
```



INFERENCE:

Most customer belong to the age group of **26-35(40%)** whereas customers of age group **0-17(3%)** is the **least**


```
City_Category = ['City_Category']

df1=df[City_Category].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode = [0.05,0.05,0],autopct='%.0f%%')
plt.show()
```



INFERENCE:

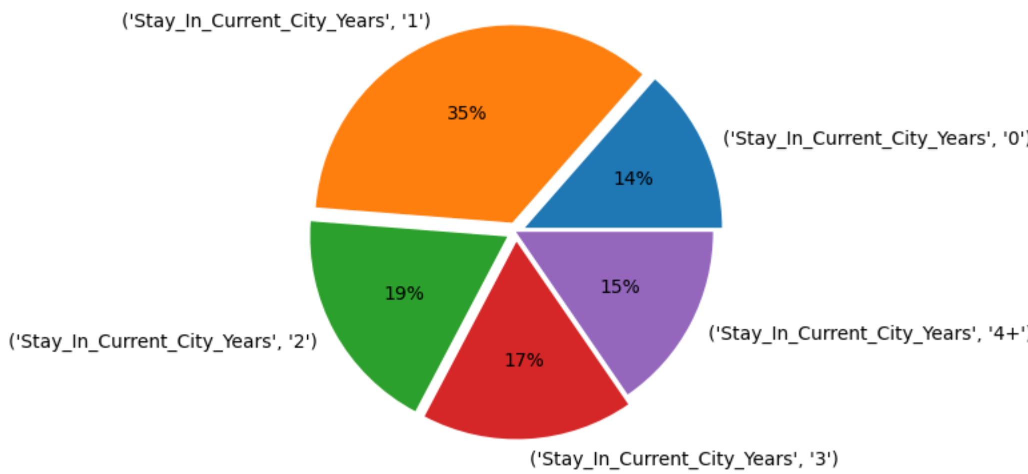
Most customers belong to city_category **B (42%)**.

```
Gender = ['Gender']

df1=df[Gender].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode= [0.05,0],autopct='%.0f%%')
plt.show()
```

INFERENCE:

75% contribution is from **Male** constomers whereas only **25%** is contributed by **Female**

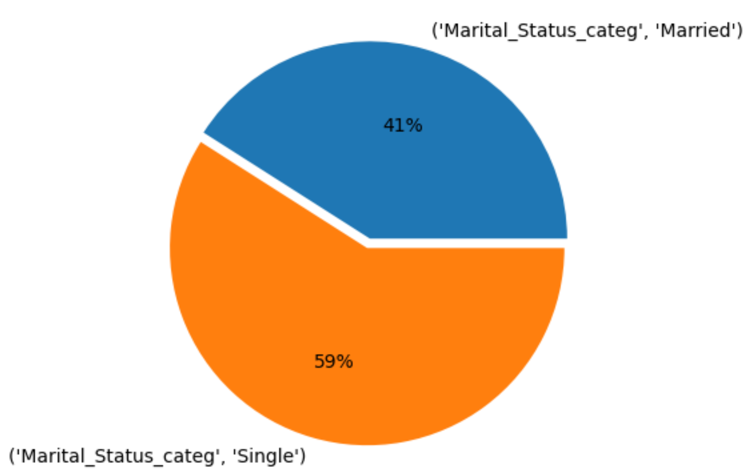
```
Stay_In_Current_City_Years = ['Stay_In_Current_City_Years']

df1=df[Stay_In_Current_City_Years].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode=[0.05,0.05,0.05,0.05,0],autopct='%.0f%%')
plt.show()
```



INFERENCE:

Most customers Stay in current city for just **1 year**

```
Marital_Status = ['Marital_Status_categ']

df1=df[Marital_Status].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode=[0,0.05],autopct='%.0f%%')
plt.show()
```

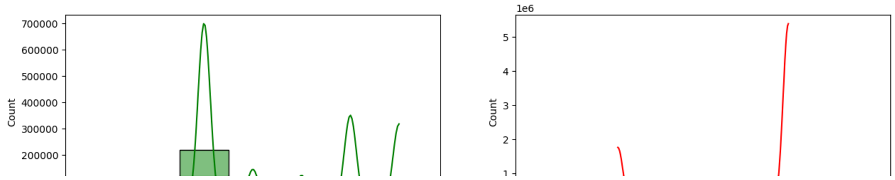


INFERENCE:

59% of customers are **Single**

HISTPLOT

```
# plotting charts in subplots

plt.figure(figsize=(15,12))

plt.subplot(3,2,1)
sns.histplot(data = df, x='Age', kde=True, color='green', bins = 30)


plt.subplot(3,2,2)
sns.histplot(data = df, x='Gender', kde=True, color='red', bins = 10)


plt.subplot(3,2,3)
sns.histplot(data = df, x='Purchase', kde=True, color='green', bins = 5)

plt.subplot(3,2,4)
sns.histplot(data = df, x='Marital_Status', kde=True, color='red', bins = 5)

plt.subplot(3,2,5)
sns.histplot(data = df, x='City_Category', kde=True, color='green', bins = 5)

plt.subplot(3,2,6)
sns.histplot(data = df, x='Occupation', kde=True, color='red', bins = 20)

plt.show()
```

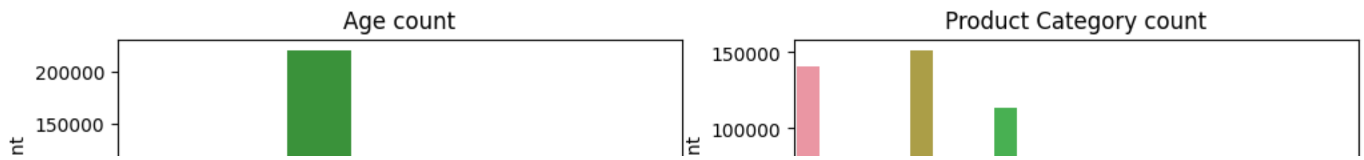


INFERENCE:

1. Most customers belong to the age group of **26-35** whereas the second most purchased age group is **36-45**
2. **Female** purchase more than male
3. Maximum purchased amount is around **23000**
4. Married customers count less than that of the **single** customers
5. Most customers are from** city_category B** followed by C
6. **Most** Customer belong to occupation **4** whereas **least** number of customer's occupation is **9**

COUNTPLOT ANALYSIS:

```
plt.figure(figsize=(12,8))

plt.subplot(3,2,1)
sns.countplot(data = df,x='Age')
plt.xticks(rotation =90)
plt.title('Age count')

plt.subplot(3,2,2)
sns.countplot(data = df,x='Product_Category')
plt.title('Product Category count')

plt.subplot(3,2,5)
sns.countplot(data = df,x='Gender')
plt.title('Gender count')

plt.subplot(3,2,6)
sns.countplot(data = df,x='Marital_Status')
plt.title('Marital Status count')

plt.show()
```

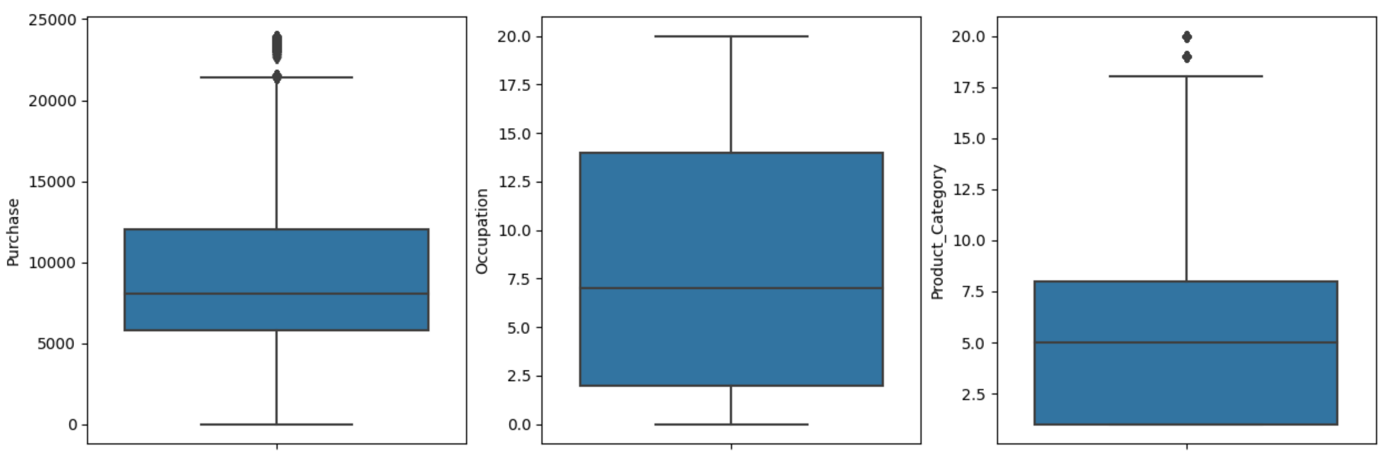


INFERENCE:

The above analysis gives the clear visualisation of the parameters involved.

BOXPLOT - CHECK FOR OUTLIERS

```
plt.figure(figsize=(15,5))

plt.subplot(1,3,1)
sns.boxplot(data = df, y='Purchase',orient='v')

plt.subplot(1,3,2)
sns.boxplot(data = df, y='Occupation',orient='v')

plt.subplot(1,3,3)
sns.boxplot(data = df, y='Product_Category',orient ='v')

plt.show()
```



INFERENCE:

1. Average Purchase value is approximately around **7000** with a ver few outliers
2. There is no outliers in case of occupation
3. Mostly brought product category is **5** and outliers at **18** and **20**

Even one outlier can have a great impact in the range of Dataset and its mean.

Range of Data is not Robust.

To overcome the issues in Range we can use IQR(Integrated Quartile Range).

IQR is defined as difference between 75th percentile and 25th percentile.

IQR = 75% -25%

From the outlier plot involving purchase we can observe the below values,

25% = 100 50% = 8000 75% = 22000

Now, IQR = 75% - 25% which is around 21000.

Thereby overcoming the problem of Range issues.

BIVARIATE ANALYSIS:

```
attributes = ['Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
sns.set_style("whitegrid")

fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 12))
fig.subplots_adjust(top=1.3)
count = 0
for row in range(3):
    for col in range(2):
        sns.countplot(data=df, x=attributes[count], hue='Gender',ax=axs[row, col])
        axs[row,col].set_title(f"Purchase vs {attributes[count]} for each gender", pad=12, fontsize=13)
        count += 1
plt.show()
```

INFERENCES:

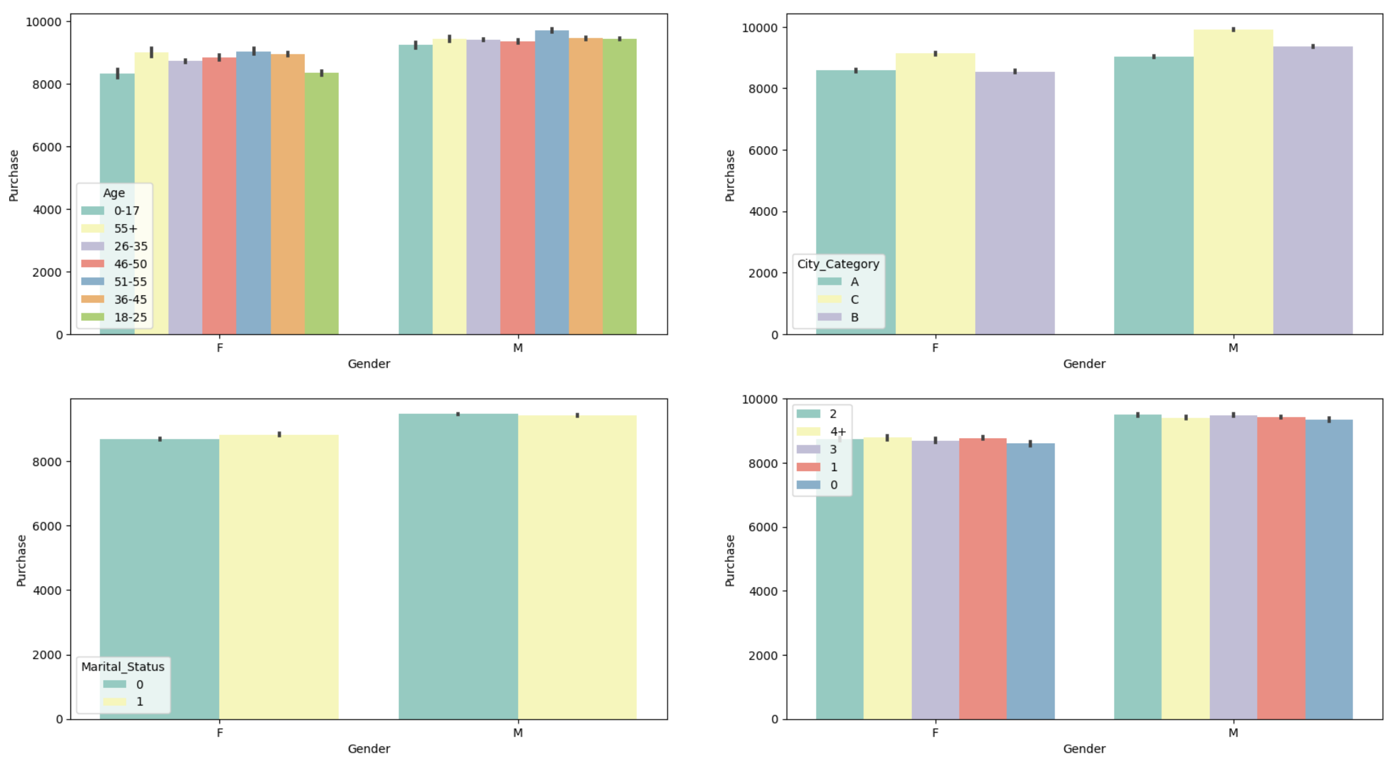
Here is yet another visual analysis which confirms the above mentioned fact that Men purchase more than women. Also we can observe,

1. Both Gender belonging to age group **26-35** spend more

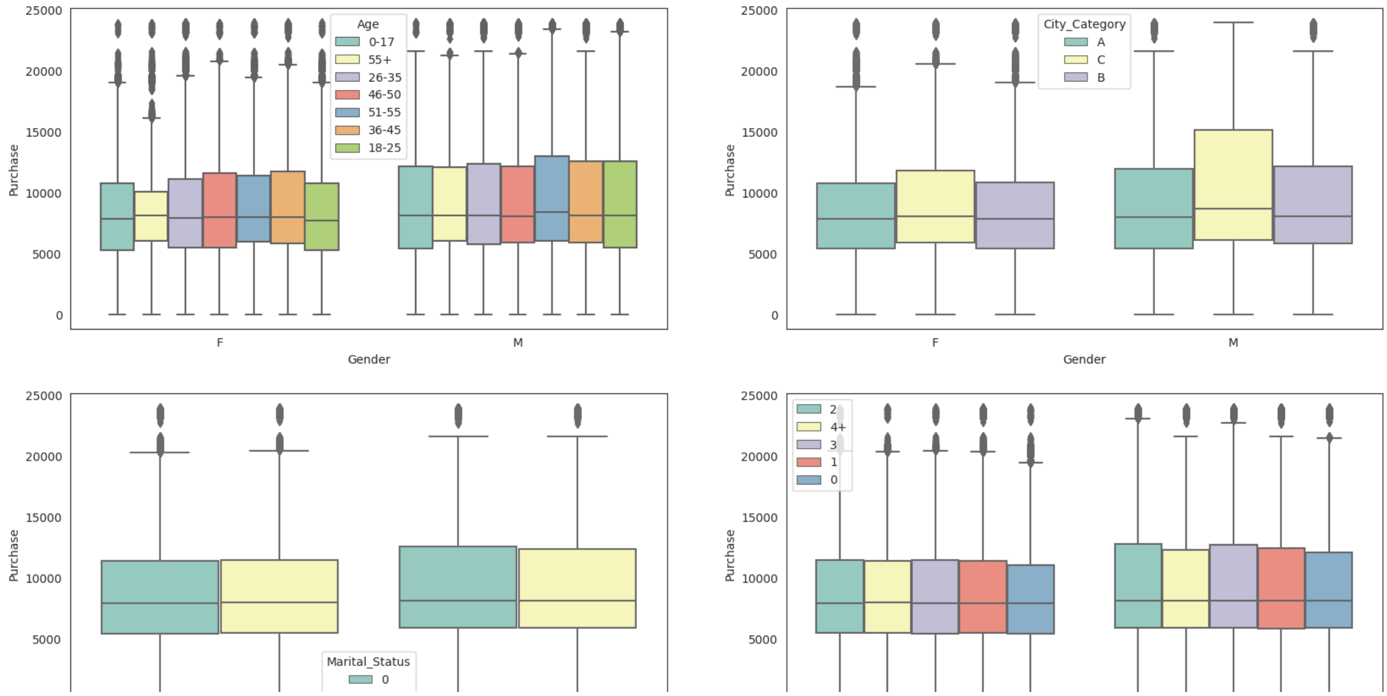
2. **Male** whose Occupation **4** spend more and **Female** whose Occupation is **0,1 or 4** spend more
3. Both Gender from city category **B** purchase more
4. Customers who stay in the current city for **1 year** tend to purchase more irrespective of their
5. Irrespective of their gender, **Single** customers purchase a lot
6. **Male** are interested in product category **1** where as **Female** are interested in product category **5**

MULTIVARIANT ANALYSIS:

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.barplot(data=df, y='Purchase', x='Gender', hue='Age', palette='Set3', ax=axs[0,0])
sns.barplot(data=df, y='Purchase', x='Gender', hue='City_Category', palette='Set3', ax=axs[0,1])

sns.barplot(data=df, y='Purchase', x='Gender', hue='Marital_Status', palette='Set3', ax=axs[1,0])
sns.barplot(data=df, y='Purchase', x='Gender', hue='Stay_In_Current_City_Years', palette='Set3', ax=axs[1,1])
axs[1,1].legend(loc='upper left')

plt.show()
```




```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.boxplot(data=df, y='Purchase', x='Gender', hue='Age', palette='Set3', ax=axs[0,0])
sns.boxplot(data=df, y='Purchase', x='Gender', hue='City_Category', palette='Set3', ax=axs[0,1])

sns.boxplot(data=df, y='Purchase', x='Gender', hue='Marital_Status', palette='Set3', ax=axs[1,0])
sns.boxplot(data=df, y='Purchase', x='Gender', hue='Stay_In_Current_City_Years', palette='Set3', ax=axs[1,1])
axs[1,1].legend(loc='upper left')

plt.show()
```



INEFERENCE:

1. FEMALE:

1. Majority number of purchases are done by those belonging to age category of** 55+**
2. City category **C** hits the more number of purchases
3. **Married** female just overtakes the single female in terms of number of purchases
4. Those who stay for **more than 4 years** purchase more often than others

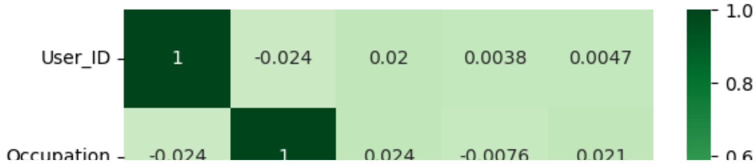
2. MALE:

1. Majority number of purchases are done by those belonging to age category of** 51-55**
2. City category **C** hits the more number of purchases
3. Botn **married** and **single** male contribute the same in terms of number of purchases
4. Those who stay for **2 years** purchase just a little more often than others

HEATMAP

```
sns.heatmap(df.corr(),cmap='Greens',annot = True)
plt.show()
```

```
<ipython-input-29-d8d28ea6e5da>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  sns.heatmap(data.corr(),cmap='Greens',annot = True)
```



INFERENCE:

Most attributes are categorical so, correlation between then wont give an effective idea.

PAIRPLOT

```
sns.pairplot(data = df)
```

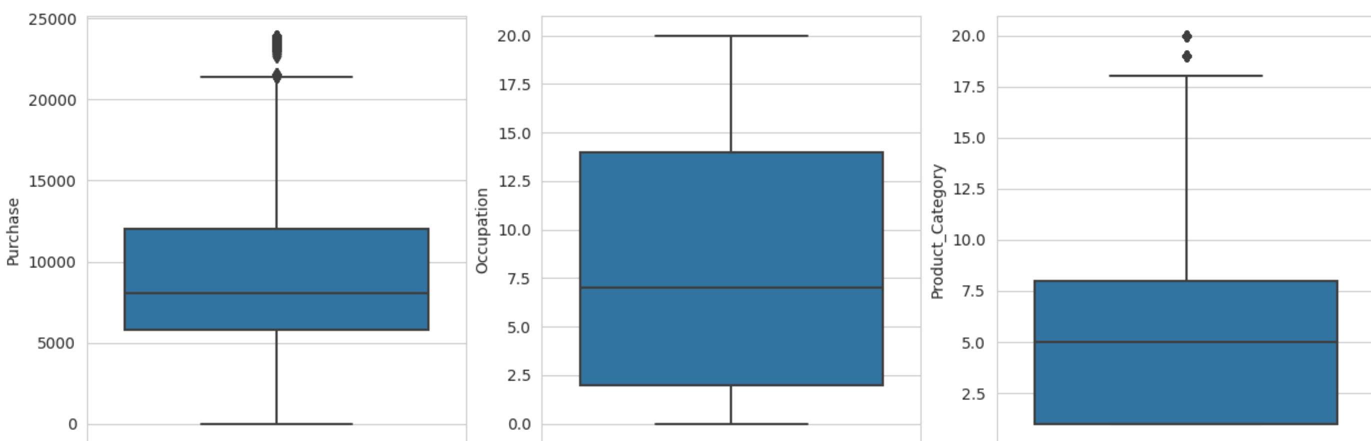
INFERENCE:

The above pairplot clearly states that moost attributes are categorical and their dependencies upon each other cant be given by pairplots.

```
<seaborn.axisgrid.PairGrid at 0x7eb68eac9a80>
```

DETECTING DATA OF OUTLIER VALUES

```
sns.set_style(style='whitegrid')

plt.figure(figsize=(15,5))

plt.subplot(1,3,1)
sns.boxplot(data = df, y='Purchase',orient='v')

plt.subplot(1,3,2)
sns.boxplot(data = df, y='Occupation',orient='v')

plt.subplot(1,3,3)
sns.boxplot(data = df, y='Product_Category',orient ='v')

plt.show()
```



DATA OF OUTLIERS IN PURCHASE COLUMN

```
df[df['Purchase']>21000]
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purch
343	1000058	P00117642	M	26-35	2	B	3	0	10	23
375	1000062	P00119342	F	36-45	3	A	1	0	10	23
652	1000126	P00087042	M	18-25	9	B	1	0	10	23
731	1000139	P00020142	F	26-35	20	C	2	0	7	21
736	1000139	P00159542	F	26-35	20	C	2	0	10	23
...	...	...	...	...	...	...	...	...	...	
545101	1005915	P00174242	M	18-25	4	C	0	0	15	21
545663	1006002	P00116142	M	51-55	0	C	1	1	10	23

DATA OF OUTLIERS IN PRODUCT CATEGORY COLUMN

```
df[df['Product_Category']>18]
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purch
545915	1000001	P00375436	F	0-17	10	A	2	0	20	
545916	1000002	P00372445	M	55+	16	C	4+	0	20	
545917	1000004	P00375436	M	46-50	7	B	2	1	20	
545918	1000006	P00375436	F	51-55	9	A	1	0	20	
545919	1000007	P00372445	M	36-45	1	B	1	1	20	
...	...	...	...	...	...	...	...	...	...	
550063	1006033	P00372445	M	51-55	13	B	1	1	20	
550064	1006035	P00375436	F	26-35	1	C	3	0	20	

INFERENCE:

1. There is no outliers in occupation column
2. On the contrary, there are a lot of outliers in case of **purchase** and **product_category**

CONDITIONAL PROBABILITY:

PROBABILITY OF PURCHASE MORE THAN AVERAGE FOR A GIVEN PARAMETER

```
average=df['Purchase'].mean()
```

```
df['Marital_Status_categ'].where(df['Purchase']>=average).value_counts()
```

```
Single     129299
Married     89710
Name: Marital_Status_categ, dtype: int64
```

```
df['Stay_In_Current_City_Years'].where(df['Purchase']>=average).value_counts()
```

```
1     77143
2     40934
3     37860
4+    33941
0     29131
Name: Stay_In_Current_City_Years, dtype: int64
```

```
df['Occupation'].where(df['Purchase']>=average).value_counts()
```

```
4.0     28412
0.0     27029
7.0     24321
17.0    18262
1.0     17521
12.0    13784
20.0    11965
14.0    11380
16.0    10369
2.0      9784
6.0      8061
3.0      6800
15.0     5287
5.0      4990
10.0     4973
11.0     4496
13.0     3123
19.0     2966
18.0     2631
9.0      2164
```

```
8.0        691
Name: Occupation, dtype: int64
```

```
df['Age'].where(df['Purchase']>=average).value_counts()
```

```
26-35    86784
36-45    44538
18-25    38996
46-50    17910
51-55    16193
55+       8838
0-17      5750
Name: Age, dtype: int64
```

```
df['Gender'].where(df['Purchase']>=average).value_counts()
```

```
M    171753
F     47256
Name: Gender, dtype: int64
```

```
df['City_Category'].where(df['Purchase']>=average).value_counts()
```

```
B    90015
C    74725
A    54269
Name: City_Category, dtype: int64
```

INFERENCE :

The details of customers whose purchase is greater than average purchase is given below:

1. **Single** customer's **(129299)** average purchase is more than that of **married** customers**(89710)**
2. Customers who stay in the current city for **a year** contribute the **most** whereas who stay for **less than a year** contribute the **least**
3. Customers whose occupation is **4** purchase **more** than others then comes **0** and **7** whereas occupation **8** contributes the **least**
4. Age group of customer who purchase a **lot** is **26-35** and the **least** is **0 -17**
5. **Male** spend more than Female
6. Customers from city **B** purchase more than others

```
df.groupby('Age').agg({'Age':'count'}). rename(columns ={'Age':'Age','Age':'Count'}).reset_index().sort_values('Count',ascending = False)
```

	Age	Count
2	26-35	219587
3	36-45	110013
1	18-25	99660
4	46-50	45701
5	51-55	38501
6	55+	21504
0	0-17	15102

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

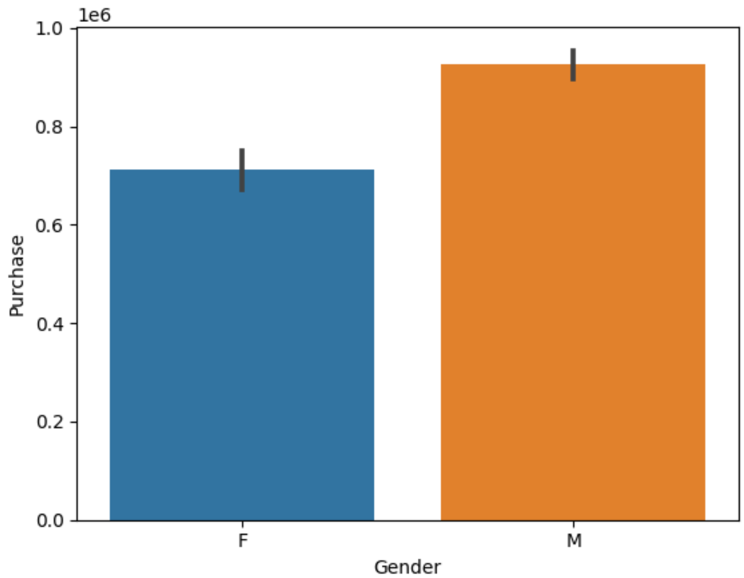
```
df_gender = df.groupby(['User_ID','Gender']).agg({'Purchase':'sum'}).reset_index()
df_gender.sample(5)
```

	User_ID	Gender	Purchase
1891	1001947	M	762558
1301	1001343	M	1621007

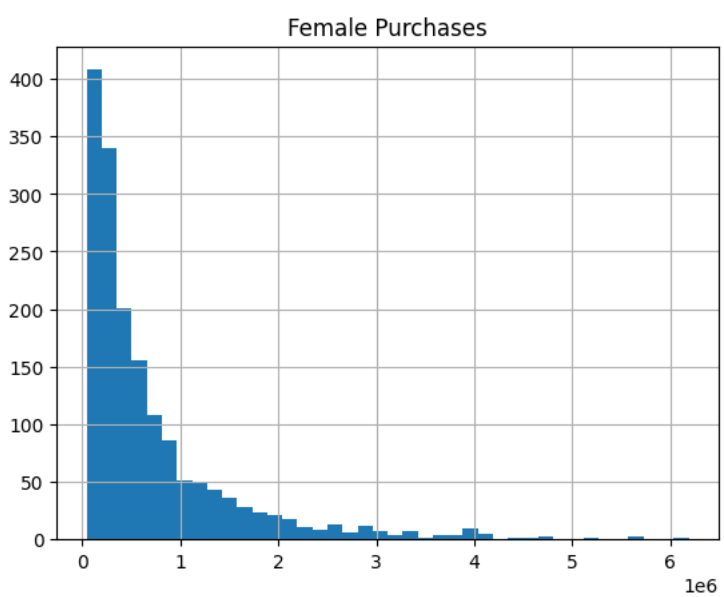
```
gender_count = df_gender['Gender'].value_counts()
gender_count
```

```
M    4225
F    1666
Name: Gender, dtype: int64
```

```
sns.barplot(data = df_gender, x='Gender', y='Purchase')
plt.show()
```

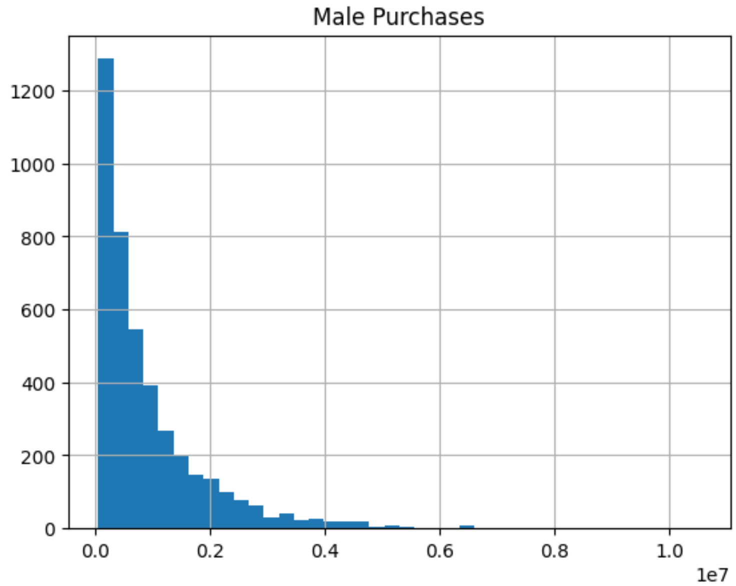



```
df_gender[df_gender['Gender']=='F']['Purchase'].hist(bins=40)
plt.title('Female Purchases')


plt.show()
```




```
df_gender[df_gender['Gender']=='M']['Purchase'].hist(bins=40)
plt.title('Male Purchases')
```

```
Text(0.5, 1.0, 'Male Purchases')
```




```
df_gender1 = df_gender.groupby(['Gender']).agg({'Purchase':'mean'}).reset_index().rename(columns={'Purchase':'Average_Purchase'})
df_gender1
```

	Gender	Average_Purchase
0	F	712024.394958
1	M	925344.402367

INFERENCE:

It is clearly evident that Men purchased more than women interms of total amount spent or no of products brought. So, **Average purchase** of **men(~=925344)** is more than that of **women(~=712024)**.

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

Distribution (Kdeplot) of the expenses of male and female customers:

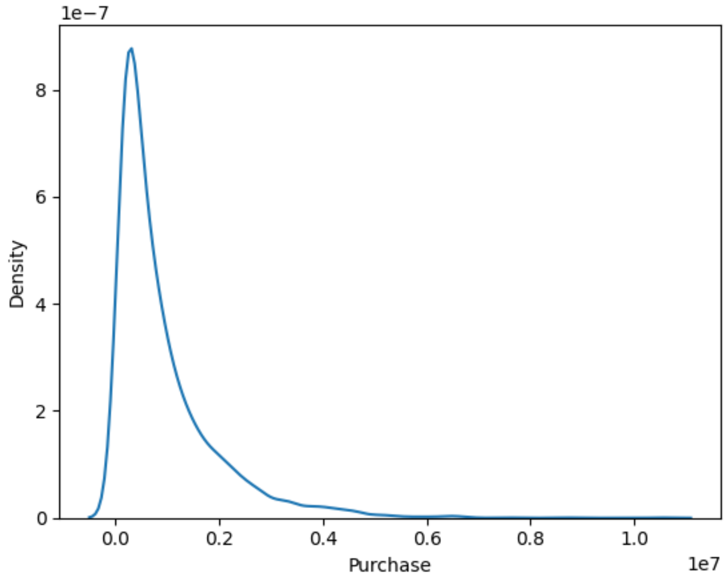
```
df_female = df_gender[df_gender['Gender']=='F'][['Purchase']]
sns.kdeplot(df_female['Purchase'])
```

```
<Axes: xlabel='Purchase', ylabel='Density'>
```

```
df_male = df_gender[df_gender['Gender']=='M'][['Purchase']]
```

```
sns.kdeplot(df_male['Purchase'])
```

```
<Axes: xlabel='Purchase', ylabel='Density'>
```



INFERENCE:

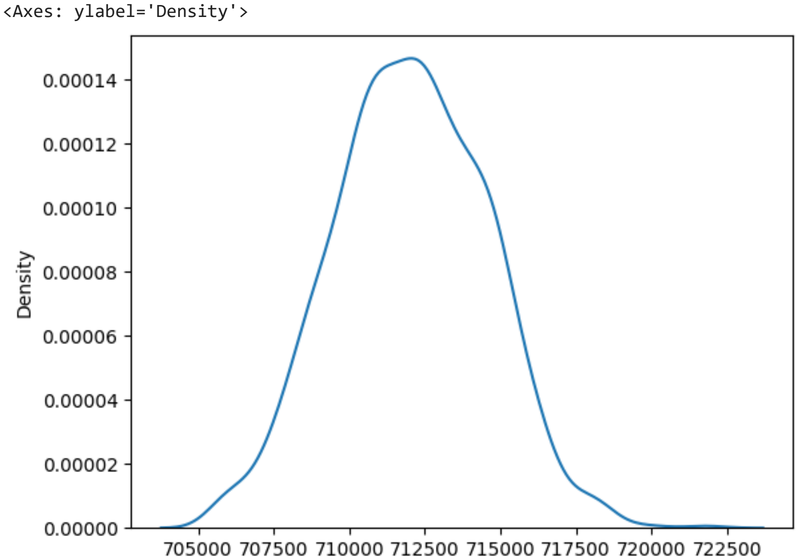
The Kdeplot shows that the **distribution is not normal** or gaussian. so we take **sampling distribution of sample means** which follows normal distribution to **perform CLT** to get confidence interval

CENTRAL LIMIT THEOREM - TO GET CONFIDENCE INTERVAL

```
sampling_df_female = [df_female['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
sampling_df_male = [df_male['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
```

```
sampling_df_female = pd.Series(sampling_df_female)
sns.kdeplot(sampling_df_female)
```

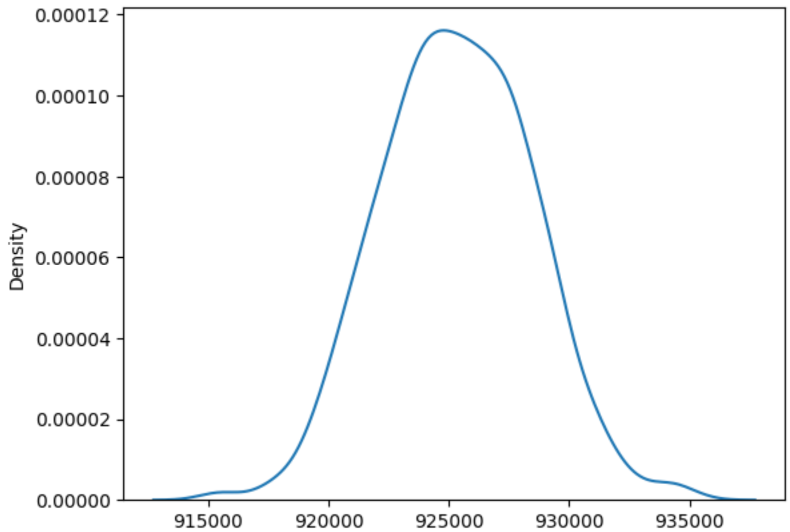
```
<Axes: ylabel='Density'>
```




```
sampling_df_male = pd.Series(sampling_df_male)
```

```
sns.kdeplot(sampling_df_male)
```

```
<Axes: ylabel='Density'>
```




```
np.mean(sampling_df_female)
```

```
712034.0230193799
```

```
np.std(sampling_df_female)
```

```
2504.1451389941653
```

```
np.mean(sampling_df_male)
```

```
925333.72352391
```

```
np.std(sampling_df_male)
```

```
3137.2283436803896
```

Analysis of average purchase values by gender with 90% confidence

```
gender = ['M','F']

for i in range(len(gender)):
  if gender[i] == 'M':
    print('CI - Male Customers for 90% confidence')
    print(round(norm(np.mean(sampling_df_male),np.std(sampling_df_male)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_male),np.std(sampl
  else:
    print('CI - Female Customers for 90% confidence')
    print(round(norm(np.mean(sampling_df_female),np.std(sampling_df_female)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_female),np.std
```

```
CI - Male Customers for 90% confidence
920173.44 , 930494.0
CI - Female Customers for 90% confidence
707915.07 , 716152.98
```

Analysis of average purchase values by gender with 95% confidence

```
gender = ['M','F']

for i in range(len(gender)):
  if gender[i] == 'M':
    print('CI - Male Customers for 95% confidence')
    print(round(norm(np.mean(sampling_df_male),np.std(sampling_df_male)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_male),np.std(samp
  else:
    print('CI - Female Customers for 95% confidence')
```

```
    print(round(norm(np.mean(sampling_df_female),np.std(sampling_df_female)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_female),np.st
```

```
CI - Male Customers for 95% confidence
919184.87 , 931482.58
CI - Female Customers for 95% confidence
707125.99 , 716942.06
```

Analysis of average purchase values by gender with 99% confidence

```
gender = ['M','F']

for i in range(len(gender)):
  if gender[i] == 'M':
    print('CI - Male Customers for 99% confidence')
    print(round(norm(np.mean(sampling_df_male),np.std(sampling_df_male)).ppf(0.005),2), ',', round(norm(np.mean(sampling_df_male),np.std(samp
  else:
    print('CI - Female Customers for 99% confidence')
    print(round(norm(np.mean(sampling_df_female),np.std(sampling_df_female)).ppf(0.005),2), ',', round(norm(np.mean(sampling_df_female),np.st
```

```
CI - Male Customers for 99% confidence
917252.76 , 933414.69
CI - Female Customers for 99% confidence
705583.77 , 718484.27
```

INFERENCE:

Based on mean expanses we observe that,

1. For **Male**:
    1. **90%** Confidence interval range - [920173.44 , 930494.0]
    2. **95%** Confidence interval range - [919184.87 , 931482.58]
    3. **99%** Confidence interval range - [917252.76 , 933414.69]
2. For **Female**:
    1. **90%** Confidence interval range - [707915.07 , 716152.98]
    2. **95%** Confidence interval range - [707125.99 , 716942.06]
    3. **99%** Confidence interval range - [705583.77 , 718484.27]

3. Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

```
n=[10,100,1000,100000]
gender = ['M','F']


for i in range(len(n)):
  sampling_df_female = [df_female['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
  sampling_df_male = [df_male['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]

  for j in range(len(gender)):
    if gender[j] == 'M':
      print('CI - Male Customers for 95% confidence with sample size',n[i])
      print(round(norm(np.mean(sampling_df_male),np.std(sampling_df_male)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_male),np.std(sa
    else:
      print('CI - Female Customers for 95% confidence with sample size', n[i])
      print(round(norm(np.mean(sampling_df_female),np.std(sampling_df_female)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_female),np.
```

```
CI - Male Customers for 95% confidence with sample size 10
336383.56 , 1486803.06
CI - Female Customers for 95% confidence with sample size 10
230504.21 , 1162337.64
CI - Male Customers for 95% confidence with sample size 100
732690.74 , 1117507.95
CI - Female Customers for 95% confidence with sample size 100
```

```
556328.71 , 875023.01
CI - Male Customers for 95% confidence with sample size 1000
864306.86 , 984992.57
CI - Female Customers for 95% confidence with sample size 1000
664440.84 , 760932.51
CI - Male Customers for 95% confidence with sample size 100000
919461.82 , 931512.4
CI - Female Customers for 95% confidence with sample size 100000
706793.04 , 717166.15
```

We can observe that for **95**% confidence interval,

1. For sample size **10**:
    1. Male - [336383.56 , 1486803.06]
    2. Female - [230504.21 , 1162337.64]

For Sample size 10 the confidence interval for both Male and Female is **overlapping**

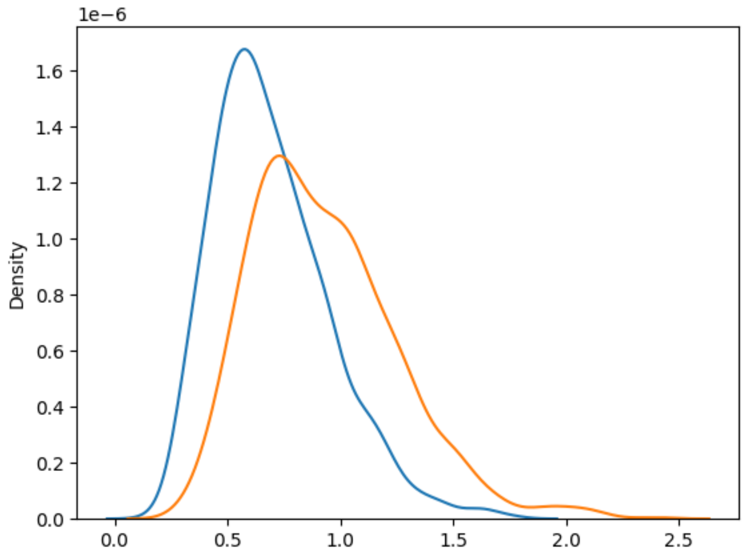
and as the **sample size increases**, we can see the **interval** ranges **seperating** and then finally they both **dont overalap**.

2. For sample size **100000**:
    1. Male - [919461.82 , 931512.4]
    2. Female - [706793.04 , 717166.15]

For Sample size 100000 the confidence interval for both Male and Female is now **not overlapping**.

```
n=[10,100,1000,100000]
gender = ['M','F']


for i in range(len(n)):
  sampling_df_female = [df_female['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
  sampling_df_male = [df_male['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]

  for j in range(len(gender)):
    if gender[j] == 'M':
      print('CI - Male Customers for 90% confidence with sample size',n[i])
      print(round(norm(np.mean(sampling_df_male),np.std(sampling_df_male)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_male),np.std(samp

    else:
      print('CI - Female Customers for 90% confidence with sample size', n[i])
      print(round(norm(np.mean(sampling_df_female),np.std(sampling_df_female)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_female),np.s


  sns.kdeplot(data = sampling_df_female)
  sns.kdeplot(data = sampling_df_male)
  plt.show()
```

```
CI - Male Customers for 90% confidence with sample size 10
398239.18 , 1460303.15
CI - Female Customers for 90% confidence with sample size 10
272905.21 , 1120068.76
```



INFERENCE:

The above graphs are the visual confirmation about the fact that as sample size increases the overlapping fades away.

So, to do business analysis Walmart has to involve in analysing samples of bigger sizes.

CONCLUSION TO MAKE CHANGES:

Its clearly evident that female customers spend much lesser than male so company has to focus on products that attracts more female customers and increase their spendings.

4. Results when the same activity is performed for Married vs Unmarried

```
df_marital_status = df.groupby(['User_ID','Marital_Status'])[['Purchase']].agg({'Purchase':'sum'}).reset_index()
df_marital_status.sample(5)
```

	User_ID	Marital_Status	Purchase
1651	1001700	0	221795
5267	1005406	1	462689
687	1000709	0	272784
1144	1001183	0	970956
4260	1004373	1	1770654

```
df_single = df_marital_status[df_marital_status['Marital_Status']==0][['Purchase']]
df_married = df_marital_status[df_marital_status['Marital_Status']==1][['Purchase']]
```

```
sns.kdeplot(df_single['Purchase'])
sns.kdeplot(df_married['Purchase'])
plt.show()
```

INFERENCE:

The Kdeplot shows that the **distribution is not normal** or gaussian. so we take **sampling distribution of sample means** which follows normal distribution to **perform CLT** to get confidence interval

Analysis of average purchase values by marital status with 90% confidence

```
sampling_df_single = [df_single['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
sampling_df_married = [df_married['Purchase'].sample(100000,replace="True").mean() for _ in range(1000)]
```

```
marital_status = [0,1]

for i in range(len(marital_status)):
  if marital_status[i] == 0:
    print('CI - Unmarried Customers for 90% confidence')
    print(round(norm(np.mean(sampling_df_single),np.std(sampling_df_single)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_single),np.std
  else:
    print('CI - Married Customers for 90% confidence')
    print(round(norm(np.mean(sampling_df_married),np.std(sampling_df_married)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_married),np.:
```

```
CI - Unmarried Customers for 90% confidence
875551.66 , 885586.1
CI - Married Customers for 90% confidence
838763.13 , 848506.47
```

Analysis of average purchase values by marital status with 95% confidence

```
marital_status = [0,1]

for i in range(len(marital_status)):
  if marital_status[i] == 0:
    print('CI - Unmarried Customers for 95% confidence')
    print(round(norm(np.mean(sampling_df_single),np.std(sampling_df_single)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_single),np.st
  else:
    print('CI - Married Customers for 95% confidence')
    print(round(norm(np.mean(sampling_df_married),np.std(sampling_df_married)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_married),np
```

```
CI - Unmarried Customers for 95% confidence
874384.43 , 886694.53
CI - Married Customers for 95% confidence
837743.29 , 849155.68
```

Analysis of average purchase values by marital status with 99% confidence

```
marital_status = [0,1]

for i in range(len(marital_status)):
  if marital_status[i] == 0:
    print('CI - Unmarried Customers for 99% confidence')
    print(round(norm(np.mean(sampling_df_single),np.std(sampling_df_single)).ppf(0.005),2), ',', round(norm(np.mean(sampling_df_single),np.st
  else:
```

```
    print('CI - Married Customers for 99% confidence')
    print(round(norm(np.mean(sampling_df_married),np.std(sampling_df_married)).ppf(0.005),2), ',', round(norm(np.mean(sampling_df_married),np
```

```
CI - Unmarried Customers for 99% confidence
872450.38 , 888628.58
CI - Married Customers for 99% confidence
835950.28 , 850948.7
```

INFERENCE:

Based on mean expanses we observe that,

1. For **Single**:
   1. **90%** Confidence interval range - [875551.66 , 885586.1]
   2. **95%** Confidence interval range - [874384.43 , 886694.53]
   3. **99%** Confidence interval range - [872450.38 , 888628.58]
2. For **Married**:
   1. **90%** Confidence interval range - [838763.13 , 848506.47]
   2. **95%** Confidence interval range - [837743.29 , 849155.68]
   3. **99%** Confidence interval range - [835950.28 , 850948.7]

To check for overlapping

```
n=[10,100,1000,100000]
marital_status = [0,1]


for i in range(len(n)):
  sampling_df_single = [df_single['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
  sampling_df_married = [df_married['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]

  for j in range(len(marital_status)):
    if marital_status[j] == 0:
      print('CI - Single Customers for 90% confidence with sample size',n[i])
      print(round(norm(np.mean(sampling_df_single),np.std(sampling_df_single)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_single),np.s
    else:
      print('CI - Married Customers for 90% confidence with sample size', n[i])
      print(round(norm(np.mean(sampling_df_married),np.std(sampling_df_married)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_married),np
```

```
CI - Single Customers for 90% confidence with sample size 10
367230.03 , 1368949.38
CI - Married Customers for 90% confidence with sample size 10
365940.17 , 1322729.0
CI - Single Customers for 90% confidence with sample size 100
720769.03 , 1032080.28
CI - Married Customers for 90% confidence with sample size 100
692075.18 , 997054.24
CI - Single Customers for 90% confidence with sample size 1000
829114.43 , 931893.02
CI - Married Customers for 90% confidence with sample size 1000
795454.36 , 894526.33
CI - Single Customers for 90% confidence with sample size 100000
875469.22 , 885467.44
CI - Married Customers for 90% confidence with sample size 100000
838780.52 , 848580.3
```

We can observe that for **90**% confidence interval,

1. For sample size **10**:
   1. Single - [367230.03 , 1368949.38]
   2. Married - [365940.17 , 1322729.0]

For Sample size 10 the confidence interval for both Single and Married is **overlapping**

and as the **sample size increases**, we can see the **interval** ranges **seperating** and then finally they both **dont overalap**.

2. For sample size **100000**:
    1. Single - [875469.22 , 885467.44]
    2. Married - [838780.52 , 848580.3]

For Sample size 100000 the confidence interval for both Single and Married is now **not overlapping**.

```
n=[10,100,1000,100000]
marital_status = [0,1]


for i in range(len(n)):
  sampling_df_single = [df_single['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
  sampling_df_married = [df_married['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]

  for j in range(len(marital_status)):
    if marital_status[j] == 0:
      print('CI - Single Customers for 95% confidence with sample size',n[i])
      print(round(norm(np.mean(sampling_df_single),np.std(sampling_df_single)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_single),np.:

    else:
      print('CI - Married Customers for 95% confidence with sample size', n[i])
      print(round(norm(np.mean(sampling_df_married),np.std(sampling_df_married)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_married),


  sns.kdeplot(data = sampling_df_single)
  sns.kdeplot(data = sampling_df_married)
  plt.show()
```

```
CI - Single Customers for 95% confidence with sample size 10
292672.72 , 1435888.8
CI - Married Customers for 95% confidence with sample size 10
264556.24 , 1451405.08
```

1e-6

INFERENCE:

The above graphs are the visual confirmation about the fact that as sample size increases the overlapping fades away.

CONCLUSION TO MAKE CHANGES:

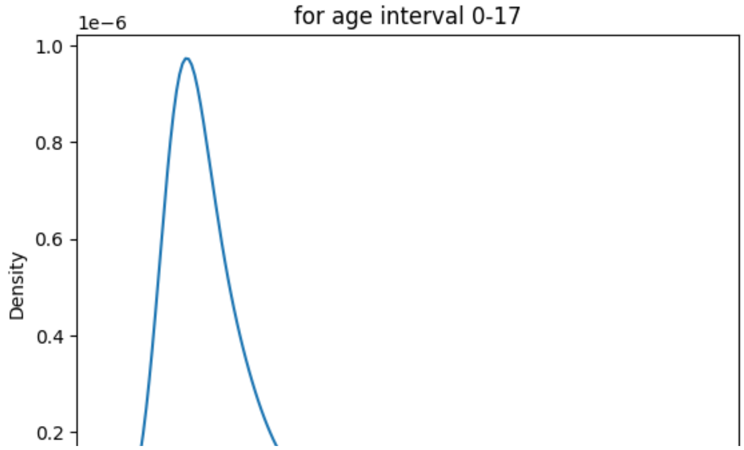
Its obvious that married customers spend less. Taking steps to improve their purchase rate will contribute to the positive side for the company

5. Results when the same activity is performed for Age

```
df_age = df.groupby(['User_ID','Age'])[['Purchase']].agg({'Purchase':'sum'}).reset_index()
df_age.sample(5)
```

	User_ID	Age	Purchase
582	1000598	36-45	160192
2629	1002705	26-35	180128
3389	1003483	46-50	4002639
1956	1002013	46-50	464609
2097	1002157	18-25	669912

```
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']


for i in range(len(age_interval)):
  df_age1 = df_age[df_age['Age']==age_interval[i]][['Purchase']]
  sns.kdeplot(df_age1['Purchase'])
  plt.title(f'for age interval {age_interval[i]}')
  plt.show()
```



INFERENCE:

The Kdeplot shows that the **distribution is not normal** or gaussian. so we take **sampling distribution of sample means** which follows normal distribution to **perform CLT** to get confidence interval

Analysis of average purchase values by age with 90% confidence

```
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']


for i in range(len(age_interval)):
  df_age1 = df_age[df_age['Age']==age_interval[i]][['Purchase']]
  sampling_df_age1 = [df_age1['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
  print(f'CI - Customers of age group {age_interval[i]} for 90% confidence')
  print(round(norm(np.mean(sampling_df_age1),np.std(sampling_df_age1)).ppf(0.05),2), ',', round(norm(np.mean(sampling_df_age1),np.std(samplin
```

```
CI - Customers of age group 0-17 for 90% confidence
615282.36 , 622325.19
CI - Customers of age group 18-25 for 90% confidence
850330.0 , 859366.09
CI - Customers of age group 26-35 for 90% confidence
984083.04 , 995015.16
CI - Customers of age group 36-45 for 90% confidence
874731.09 , 884692.66
CI - Customers of age group 46-50 for 90% confidence
787644.11 , 797175.58
CI - Customers of age group 51-55 for 90% confidence
759285.82 , 767249.93
CI - Customers of age group 55+ for 90% confidence
536355.25 , 542997.96
```

Analysis of average purchase values by age with 95% confidence

```
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']


for i in range(len(age_interval)):
  df_age1 = df_age[df_age['Age']==age_interval[i]][['Purchase']]
  sampling_df_age1 = [df_age1['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
  print(f'CI - Customers of age group {age_interval[i]} for 95% confidence')
  print(round(norm(np.mean(sampling_df_age1),np.std(sampling_df_age1)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_age1),np.std(sampli
```

```
CI - Customers of age group 0-17 for 95% confidence
614506.54 , 623140.43
CI - Customers of age group 18-25 for 95% confidence
849312.29 , 860481.06
CI - Customers of age group 26-35 for 95% confidence
983336.45 , 996088.19
CI - Customers of age group 36-45 for 95% confidence
873602.74 , 885641.41
CI - Customers of age group 46-50 for 95% confidence
786620.71 , 798496.92
CI - Customers of age group 51-55 for 95% confidence
```

```
758186.14 , 768268.92
CI - Customers of age group 55+ for 95% confidence
535695.8 , 543637.84
```

Analysis of average purchase values by age with 99% confidence

```
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']


for i in range(len(age_interval)):
  df_age1 = df_age[df_age['Age']==age_interval[i]][['Purchase']]
  sampling_df_age1 = [df_age1['Purchase'].sample(100000,replace='True').mean() for _ in range(1000)]
  print(f'CI - Customers of age group {age_interval[i]} for 99% confidence')
  print(round(norm(np.mean(sampling_df_age1),np.std(sampling_df_age1)).ppf(0.005),2), ',', round(norm(np.mean(sampling_df_age1),np.std(sampli
```

```
CI - Customers of age group 0-17 for 99% confidence
613346.06 , 624375.53
CI - Customers of age group 18-25 for 99% confidence
847581.86 , 862194.84
CI - Customers of age group 26-35 for 99% confidence
981576.12 , 998086.96
CI - Customers of age group 36-45 for 99% confidence
871681.74 , 887590.69
CI - Customers of age group 46-50 for 99% confidence
785019.86 , 800113.81
CI - Customers of age group 51-55 for 99% confidence
756921.62 , 769629.79
CI - Customers of age group 55+ for 99% confidence
534450.29 , 544933.81
```

INFERENCE:

Based on mean expanses we observe that,

1. For **90%** confidence:
    1. age group - '**0-17**' CI range - [615282.36 , 622325.19]
    2. age group - '**18-25**' CI range - [850330.0 , 859366.09]
    3. age group - '**26-35**' CI range - [984083.04 , 995015.16]
    4. age group - '**36-45**' CI range - [874731.09 , 884692.66]
    5. age group - '**46-50**' CI range - [787644.11 , 797175.58]
    6. age group - '**51-55**' CI range - [759285.82 , 767249.93]
    7. age group - '**55+**' CI range - [536355.25 , 542997.96]
2. For **95%** confidence:
    1. age group - '**0-17**' CI range - [614506.54 , 623140.43]
    2. age group - '**18-25**' CI range - [849312.29 , 860481.06]
    3. age group - '**26-35**' CI range - [983336.45 , 996088.19]
    4. age group - '**36-45**' CI range - [873602.74 , 885641.41]
    5. age group - '**46-50**' CI range - [786620.71 , 798496.92]
    6. age group - '**51-55**' CI range - [758186.14 , 768268.92]
    7. age group - '**55+**' CI range - [535695.8 , 543637.84]
3. For **99%** confidence:
    1. age group - '**0-17**' CI range - [613346.06 , 624375.53]
    2. age group - '**18-25**' CI range - [847581.86 , 862194.84]
    3. age group - '**26-35**' CI range - [981576.12 , 998086.96]
    4. age group - '**36-45**' CI range - [871681.74 , 887590.69]
    5. age group - '**46-50**' CI range - [785019.86 , 800113.81]
    6. age group - '**51-55**' CI range - [756921.62 , 769629.79]
    7. age group - '**55+**' CI range - [534450.29 , 544933.81]

To check for overlapping

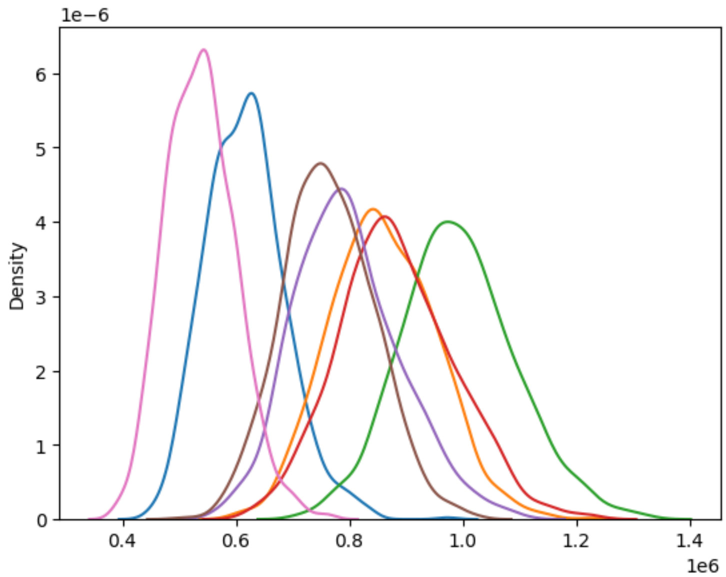
```
n=[10,100,1000,10000]
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']

for i in range(len(n)):

  for j in range(len(age_interval)):
    df_age1 = df_age[df_age['Age']==age_interval[j]][['Purchase']]
    sampling_df_age1 = [df_age1['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
    print(f'CI - Customers of age group {age_interval[j]} with sample size {n[i]} for 95% confidence')
    print(round(norm(np.mean(sampling_df_age1),np.std(sampling_df_age1)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_age1),np.std(samp
```

```
CI - Customers of age group 0-17 with sample size 10 for 95% confidence
195817.37 , 1065754.52
CI - Customers of age group 18-25 with sample size 10 for 95% confidence
309850.12 , 1406347.17
CI - Customers of age group 26-35 with sample size 10 for 95% confidence
351959.79 , 1653236.6
CI - Customers of age group 36-45 with sample size 10 for 95% confidence
277320.97 , 1456148.13
CI - Customers of age group 46-50 with sample size 10 for 95% confidence
213903.92 , 1381808.27
CI - Customers of age group 51-55 with sample size 10 for 95% confidence
289205.2 , 1254322.15
CI - Customers of age group 55+ with sample size 10 for 95% confidence
150397.31 , 918647.36
CI - Customers of age group 0-17 with sample size 100 for 95% confidence
485884.37 , 751729.42
CI - Customers of age group 18-25 with sample size 100 for 95% confidence
682403.24 , 1024157.04
CI - Customers of age group 26-35 with sample size 100 for 95% confidence
791117.75 , 1187911.33
CI - Customers of age group 36-45 with sample size 100 for 95% confidence
681968.66 , 1063859.57
CI - Customers of age group 46-50 with sample size 100 for 95% confidence
610772.05 , 970090.88
CI - Customers of age group 51-55 with sample size 100 for 95% confidence
604351.57 , 925260.68
CI - Customers of age group 55+ with sample size 100 for 95% confidence
421266.79 , 657245.97
CI - Customers of age group 0-17 with sample size 1000 for 95% confidence
575750.39 , 662680.49
CI - Customers of age group 18-25 with sample size 1000 for 95% confidence
800142.98 , 908045.24
CI - Customers of age group 26-35 with sample size 1000 for 95% confidence
923009.37 , 1055496.65
CI - Customers of age group 36-45 with sample size 1000 for 95% confidence
823246.9 , 939085.82
CI - Customers of age group 46-50 with sample size 1000 for 95% confidence
734687.94 , 847758.06
CI - Customers of age group 51-55 with sample size 1000 for 95% confidence
712222.96 , 811998.73
CI - Customers of age group 55+ with sample size 1000 for 95% confidence
500994.44 , 578246.4
CI - Customers of age group 0-17 with sample size 10000 for 95% confidence
605612.65 , 632018.86
CI - Customers of age group 18-25 with sample size 10000 for 95% confidence
837561.44 , 872340.08
CI - Customers of age group 26-35 with sample size 10000 for 95% confidence
968847.93 , 1009312.34
CI - Customers of age group 36-45 with sample size 10000 for 95% confidence
859751.31 , 898496.63
CI - Customers of age group 46-50 with sample size 10000 for 95% confidence
775526.45 , 811248.98
CI - Customers of age group 51-55 with sample size 10000 for 95% confidence
747567.77 , 778527.52
CI - Customers of age group 55+ with sample size 10000 for 95% confidence
527397.73 , 551774.38
```

```
n=[100,100000]
age_interval = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']

for i in range(len(n)):

  for j in range(len(age_interval)):
    df_age1 = df_age[df_age['Age']==age_interval[j]][['Purchase']]
    sampling_df_age1 = [df_age1['Purchase'].sample(n[i],replace='True').mean() for _ in range(1000)]
    print(f'CI - Customers of age group {age_interval[j]} with sample size {n[i]} for 95% confidence')
    sns.kdeplot(sampling_df_age1)
    print(round(norm(np.mean(sampling_df_age1),np.std(sampling_df_age1)).ppf(0.025),2), ',', round(norm(np.mean(sampling_df_age1),np.std(samp
```

```
plt.show()
```

```
CI - Customers of age group 0-17 with sample size 100 for 95% confidence
481441.56 , 752900.07
CI - Customers of age group 18-25 with sample size 100 for 95% confidence
678238.45 , 1042195.75
CI - Customers of age group 26-35 with sample size 100 for 95% confidence
795674.73 , 1189895.3
CI - Customers of age group 36-45 with sample size 100 for 95% confidence
683173.01 , 1082822.36
CI - Customers of age group 46-50 with sample size 100 for 95% confidence
614058.53 , 978894.98
CI - Customers of age group 51-55 with sample size 100 for 95% confidence
606290.29 , 921536.0
CI - Customers of age group 55+ with sample size 100 for 95% confidence
419080.94 , 658052.1
```




```
CI - Customers of age group 0-17 with sample size 100000 for 95% confidence
614784.8 , 623288.93
CI - Customers of age group 18-25 with sample size 100000 for 95% confidence
849505.72 , 860370.36
CI - Customers of age group 26-35 with sample size 100000 for 95% confidence
983123.02 , 996207.82
CI - Customers of age group 36-45 with sample size 100000 for 95% confidence
873798.29 , 885616.97
CI - Customers of age group 46-50 with sample size 100000 for 95% confidence
786736.32 , 798096.0
CI - Customers of age group 51-55 with sample size 100000 for 95% confidence
758380.77 , 768128.68
CI - Customers of age group 55+ with sample size 100000 for 95% confidence
535826.01 , 543489.54
```

INFERENCE:

As the sample size increases the overlapping vividly fades away.

CONCLUSION TO MAKE CHANGES:

Age group 0-17 contribute less spending products attracting them would increase their spending

INSIGHTS:

1. AGE:

1. **80%** of the customers are between the age **18-50** (40%: 26-35, 18%: 18-25, 20%: 36-45)
2. Majority customers fall in age group of **26-35**

2. Gender:

1. **75%** of the users are **Male** and 25% are Female. Obviously, Males purchase more than females.

3. Marital Status:

1. **59%** - **Single**, 41% - Married. Single customers purchase more than married customers

4. Stay in current city:

1. **35%** Staying in the city for **1 year**, 18% for 2 years, 17% for 3 years

5.City Category:

1. The **majority number** of customers come from City Category **C**
2. But, people from City Category **B tend to purchase more**.

6.Product Category:

1. There are **20 unique product category**
2. The most frequently bought product category is **5(150933)**
3. Product **5 and 8** is more popular among **females** and **1** among **male**.

7. Occupation:

1. Customers whose occupation is **4** purchase **more** than others then comes **0** and **7**
2. Customers whose occupation is **8** spend the **least**

8. Product ID:

1. The Product which made the top in the sales is **P00265242**(ie., 1880 times it is bought)

RECOMMENDATIONS:

1. Male spent more than female, So company should focus on retaining the male customers and attracting more female customers.
2. Product_Category - 1, 5, 8, & 11 have highest purchasing frequency. So these products has to be restocked more frequently.
3. Product_Category - 17,9and 14 are least sold.So, those products are to be restocked in less quantity.
4. Focusing on offers that would attract married customers would increase their purchase rate
5. More number of customers are from city category C but their Purchase rate is low . So, emphasis on attracting customers in city C is important
6. In light of the fact that females spend less than males on average, management needs to focus on their specific needs differently. Adding some additional offers for women can increase their spending on Black Friday.
7. Management should come-up with more kids loving products like snacks, ice creams, beverages to attract more younger generation to increase the sale.
8. Installing baby care facilities and play zone for kids too would attract more married and female customers.
9. Taking surveys especially involving customers whose occupation is 18,9,8 about their product of interest and their needs and restocking accordingly would increase their purchase rate.
10. City category A purchase rate is very low which can be improved by creating seasonal offers and digital marketing and also can provide home delivery on a minimum spend.