In [461…

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind, chisquare, chi2_contingency, norm, ttest_1samp,
import scipy.stats as stats
```

In [462…

```python
data = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/
```

In [463…

```python
data
```

Out[463]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
0	1000001	P00069042	F	0-17	10	A	2
1	1000001	P00248942	F	0-17	10	A	2
2	1000001	P00087842	F	0-17	10	A	2
3	1000001	P00085442	F	0-17	10	A	2
4	1000002	P00285442	M	55+	16	C	4+
...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1
550064	1006035	P00375436	F	26-35	1	C	3
550065	1006036	P00375436	F	26-35	15	B	4+
550066	1006038	P00375436	F	55+	1	C	2
550067	1006039	P00371644	F	46-50	0	B	4+

550068 rows × 10 columns

In [464…

```python
data.shape
#5.5 Million rows with 10 columns
```

Out[464]:

```
(550068, 10)
```

In [465…

```python
data.describe(include = 'all')
```

Out[465]:

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

In [466…

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

Out[466]:

	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 [467…

```
data.dtypes
```

Out[467]:

```
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
```

In [468…

```
data.isna().sum()/len(data)*100
#No null values
```

Out[468]:

```
User_ID                       0.0
Product_ID                    0.0
Gender                        0.0
Age                           0.0
Occupation                    0.0
City_Category                 0.0
Stay_In_Current_City_Years    0.0
Marital_Status                0.0
Product_Category              0.0
Purchase                      0.0
dtype: float64
```

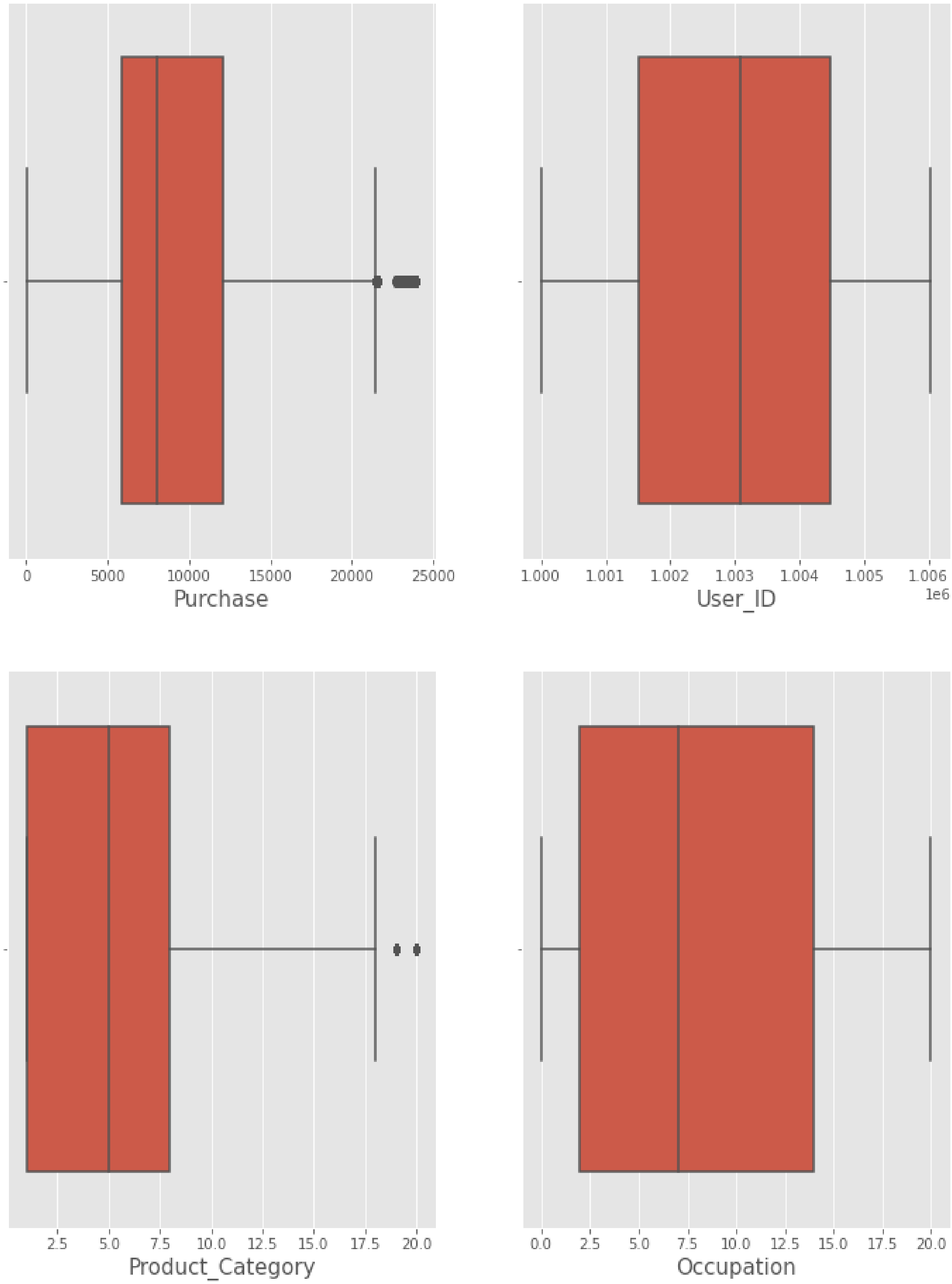
In [469…

```python
plt.figure(figsize = (12, 16))
plt.suptitle('Outliers detection using Boxplot', fontsize = 20)

plt.subplot(2, 2, 1)
plt.xlabel('Purchase', fontsize = 15)
sns.boxplot(x = "Purchase", data = data)

plt.subplot(2, 2, 2)
plt.xlabel('User_ID', fontsize = 15)
sns.boxplot(x = "User_ID", data = data)

plt.subplot(2, 2, 3)
plt.xlabel('Product_Category', fontsize = 15)
sns.boxplot(x = "Product_Category", data = data)

plt.subplot(2, 2, 4)
plt.xlabel('Occupation', fontsize = 15)
sns.boxplot(x = "Occupation", data = data)

#No outliers observed in the figure
```

Out[469]:

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

Outliers detection using Boxplot



In [470…

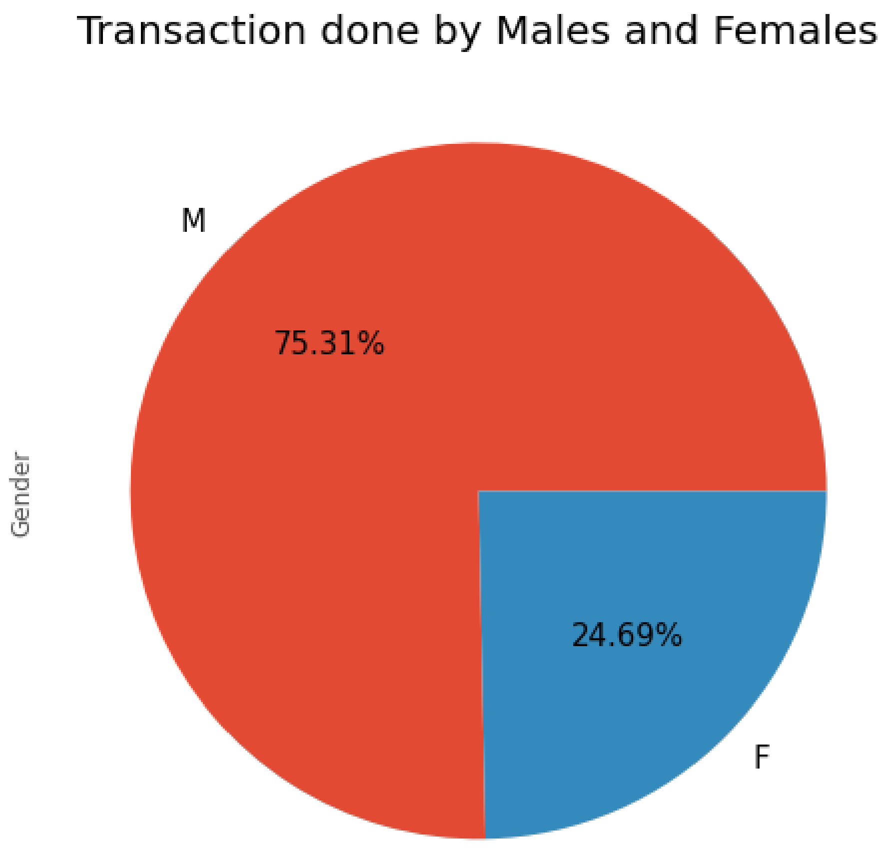
```
data.dtypes
#Age, Stay_In_Current_City_Years is object
```

Out[470]:
```
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
```

In [471…
```
data['Gender'].value_counts()
#Total 414259 transactions was done by males and 135809 by females
```

Out[471]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [472…
```
Gender_percent = data['Gender'].value_counts()/len(data)*100
plt.figure(figsize=(8, 8))
Gender_percent.plot(kind='pie', y = Gender_percent, autopct='%.2f%%', fontsize = 15
plt.title('Transaction done by Males and Females', fontsize = 20)
plt.show()
#Observation: Approximately 75% of the transactions were done by males and 25% by f
```



In [473…
```
#Total Unique Customers:
data['User_ID'].nunique()
#5891 are the unique customers
```

Out[473]: 5891

In [474…
```
#Out of 5891 how many are males and how many are females?
data.groupby(['Gender'])['User_ID'].nunique()
```

```
#Females are 1666 and males are 4225, males are more than females but how much more
```

Out[474]:

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

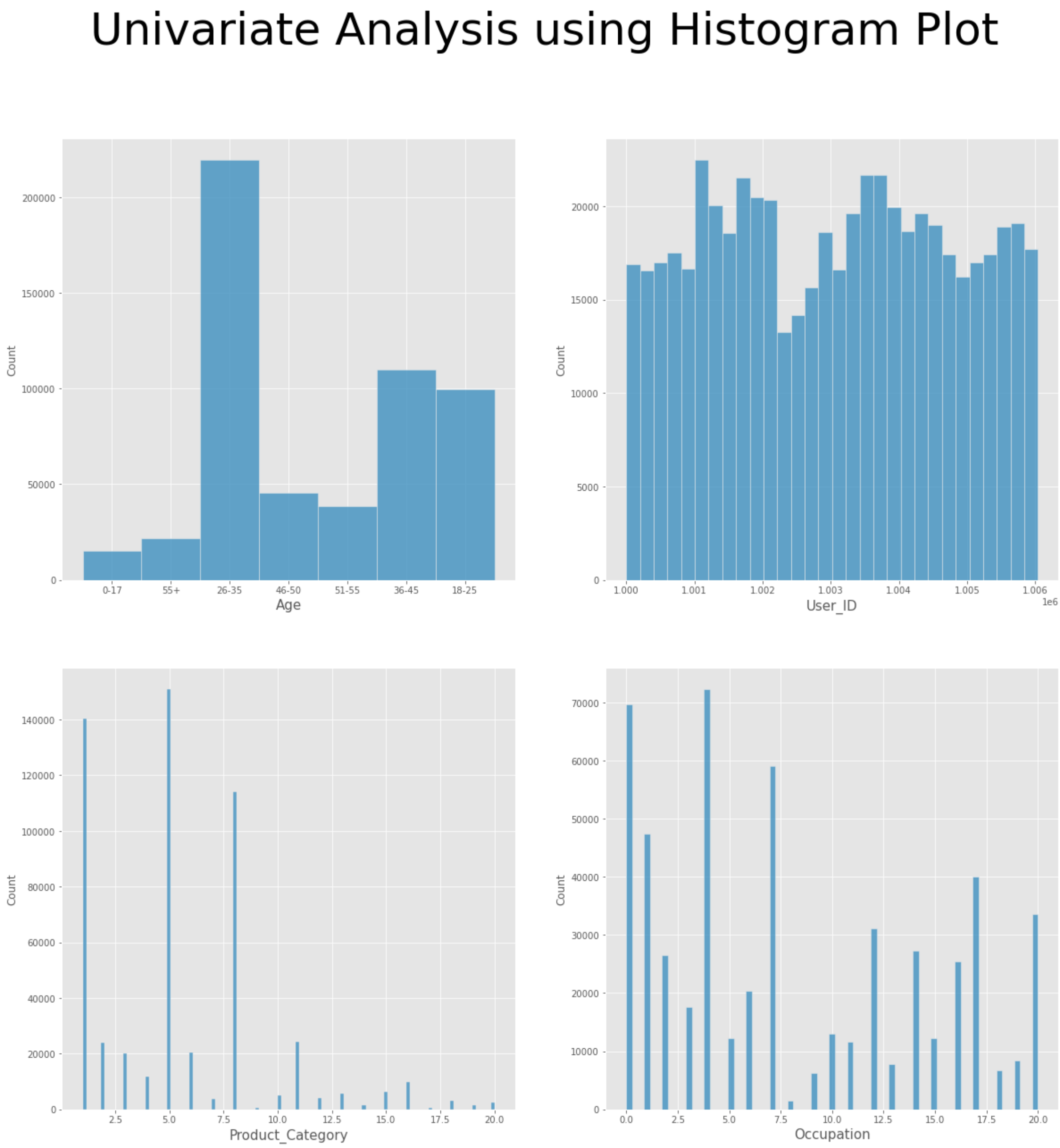
UNIVARIATE ANALYSIS

In [475…

```
plt.figure(figsize = (20, 20))
plt.suptitle('Univariate Analysis using Histogram Plot', fontsize = 50)

plt.subplot(2, 2, 1)
plt.xlabel('Age', fontsize = 15)
sns.histplot(x = "Age", data = data)

plt.subplot(2, 2, 2)
plt.xlabel('User_ID', fontsize = 15)
sns.histplot(x = "User_ID", bins = 30, data = data)

plt.subplot(2, 2, 3)
plt.xlabel('Product_Category', fontsize = 15)
sns.histplot(x = "Product_Category", data = data)

plt.subplot(2, 2, 4)
plt.xlabel('Occupation', fontsize = 15)
sns.histplot(x = "Occupation", data = data)
```

Out[475]:

```
<AxesSubplot:xlabel='Occupation', ylabel='Count'>
```

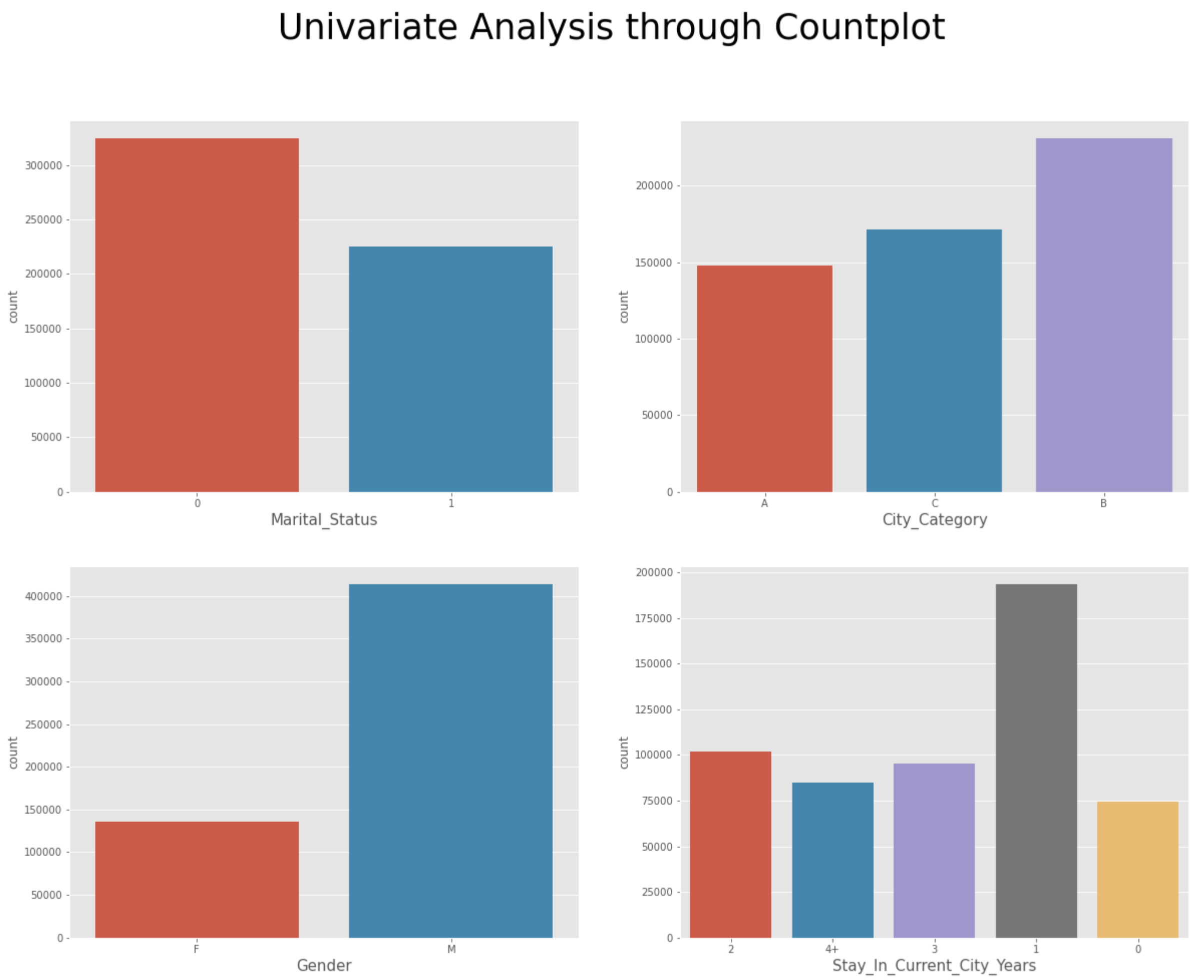


In [476…

```python
plt.figure(figsize = (20, 15))
plt.suptitle('Univariate Analysis through Countplot', fontsize = 35)

plt.subplot(2, 2, 1)
plt.xlabel('Marital_Status', fontsize = 15)
sns.countplot(x = "Marital_Status", data = data)

plt.subplot(2, 2, 2)
plt.xlabel('City_Category', fontsize = 15)
sns.countplot(x = "City_Category", data = data)

plt.subplot(2, 2, 3)
plt.xlabel('Gender', fontsize = 15)
sns.countplot(x = "Gender", data = data)

plt.subplot(2, 2, 4)
plt.xlabel('Stay_In_Current_City_Years', fontsize = 15)
sns.countplot(x = "Stay_In_Current_City_Years", data = data)
```

Out[476]:

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



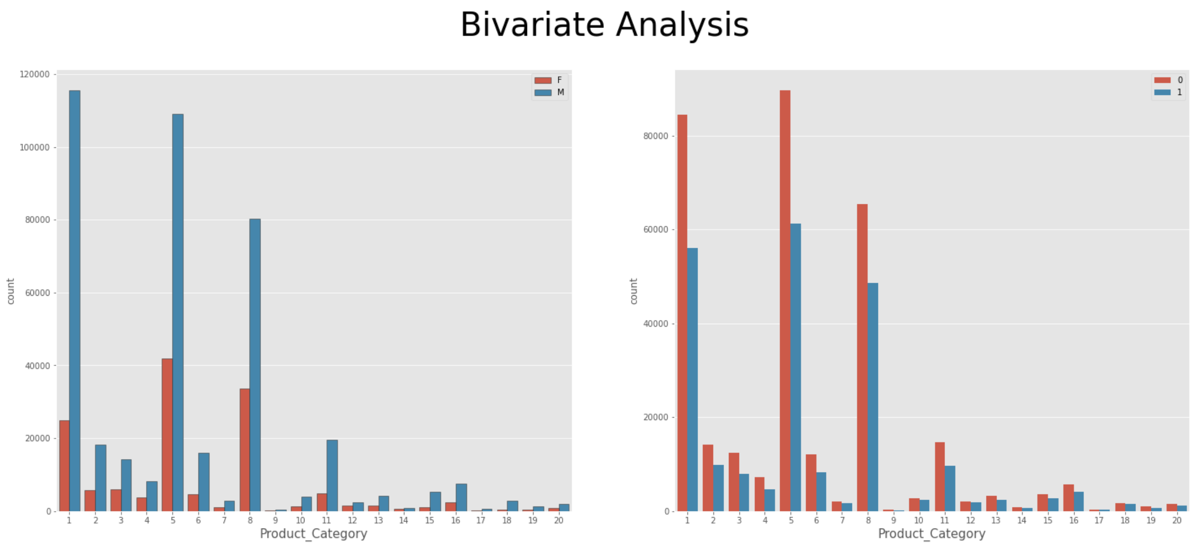
BIVARIATE ANALYSIS

In [477…

```
plt.figure(figsize = (25, 10))
plt.suptitle('Bivariate Analysis', fontsize = 40)

plt.subplot(1, 2, 1)
plt.xlabel('Product_Category wrt Gender', fontsize = 15)
sns.countplot(data = data, x = "Product_Category", hue = "Gender", edgecolor="0.15'
plt.legend(loc = 'upper right')


plt.subplot(1, 2, 2)
plt.xlabel('Product_Category wrt Mariage', fontsize = 15)
sns.countplot(data = data, x = "Product_Category", hue = "Marital_Status")
plt.legend(loc = 'upper right')
```

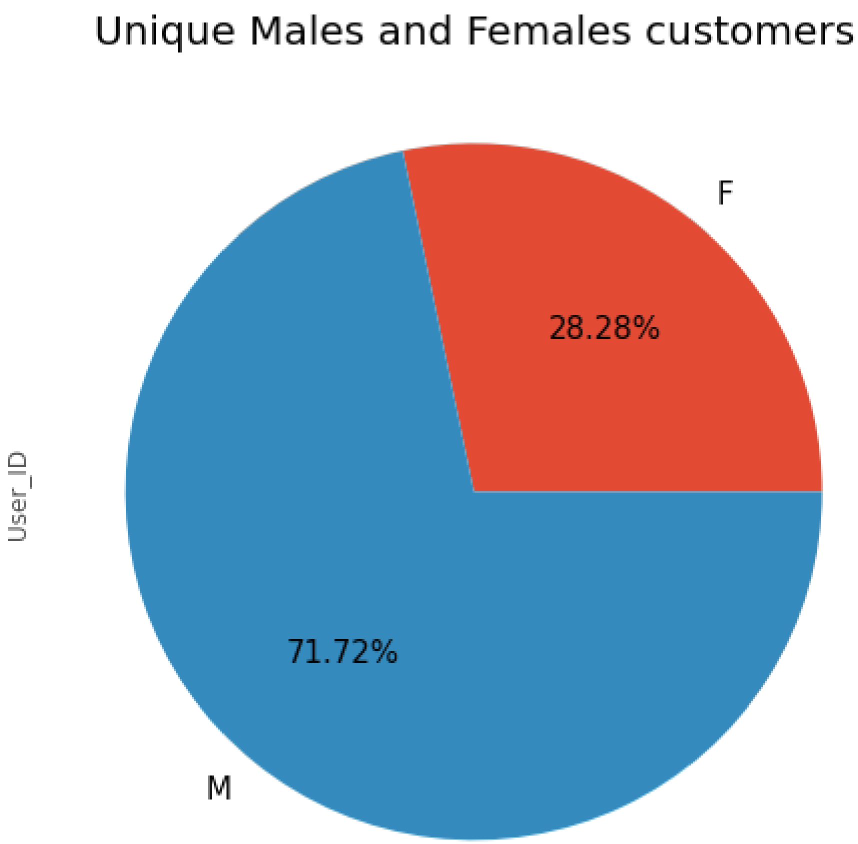
Out[477]:

```
<matplotlib.legend.Legend at 0x164b224c9a0>
```



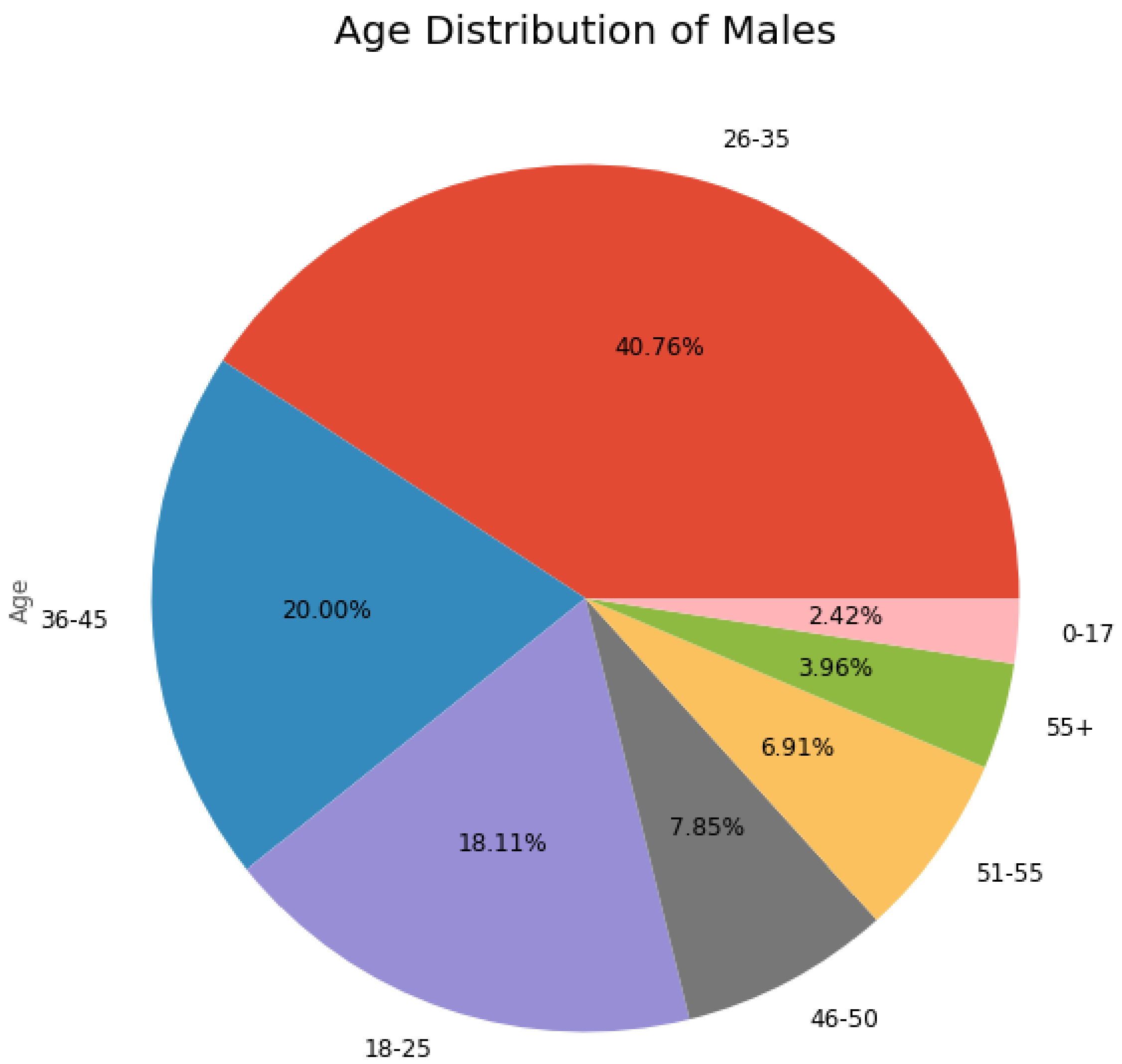
In [478…

```
Gender_percent = (data.groupby(['Gender'])['User_ID'].nunique()/data['User_ID'].nur
plt.figure(figsize=(8, 8))
Gender_percent.plot(kind='pie', y = Gender_percent, autopct='%.2f%%', fontsize = 15
plt.title('Unique Males and Females customers', fontsize = 20)
plt.show()
#Observation: Approximately 72% are males and 28% are females in the given dataset
```



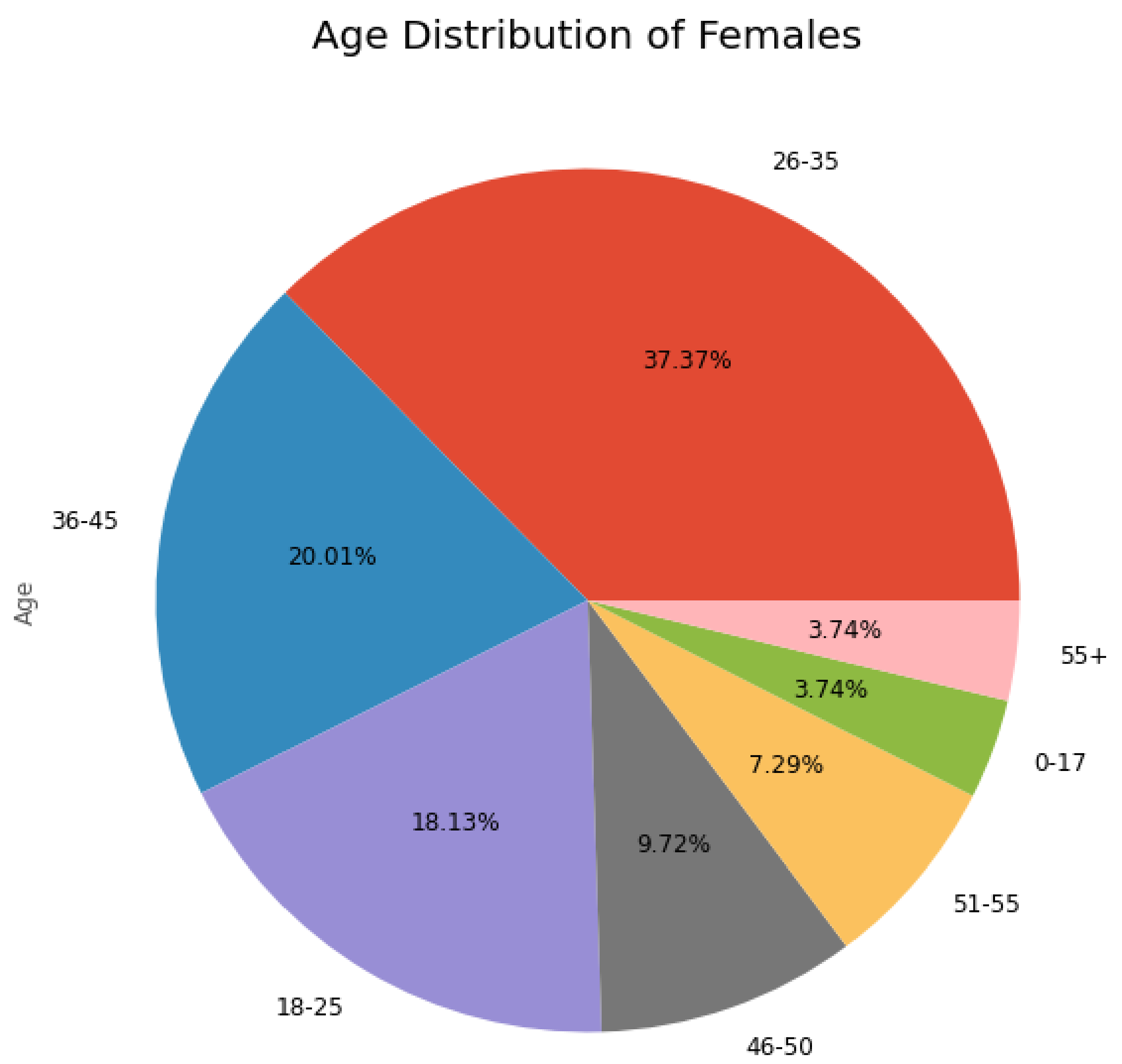
In [449…

```
plt.figure(figsize=(10, 10))
Male_population = data[data['Gender'] == 'M']
MaleAge_distn = Male_population['Age'].value_counts()/len(data)*100
MaleAge_distn.plot(kind = 'pie', y = MaleAge_distn, autopct='%.2f%%', fontsize = 12
plt.title('Age Distribution of Males', fontsize = 20)
plt.show()
```



In [450…

```
plt.figure(figsize=(10, 10))
Female_population = data[data['Gender'] == 'F']
FemaleAge_distn = Female_population['Age'].value_counts()/len(data)*100
FemaleAge_distn.plot(kind = 'pie', y = FemaleAge_distn, autopct='%.2f%%', fontsize
plt.title('Age Distribution of Females', fontsize = 20)
plt.show()
```



CORRELATION DATA

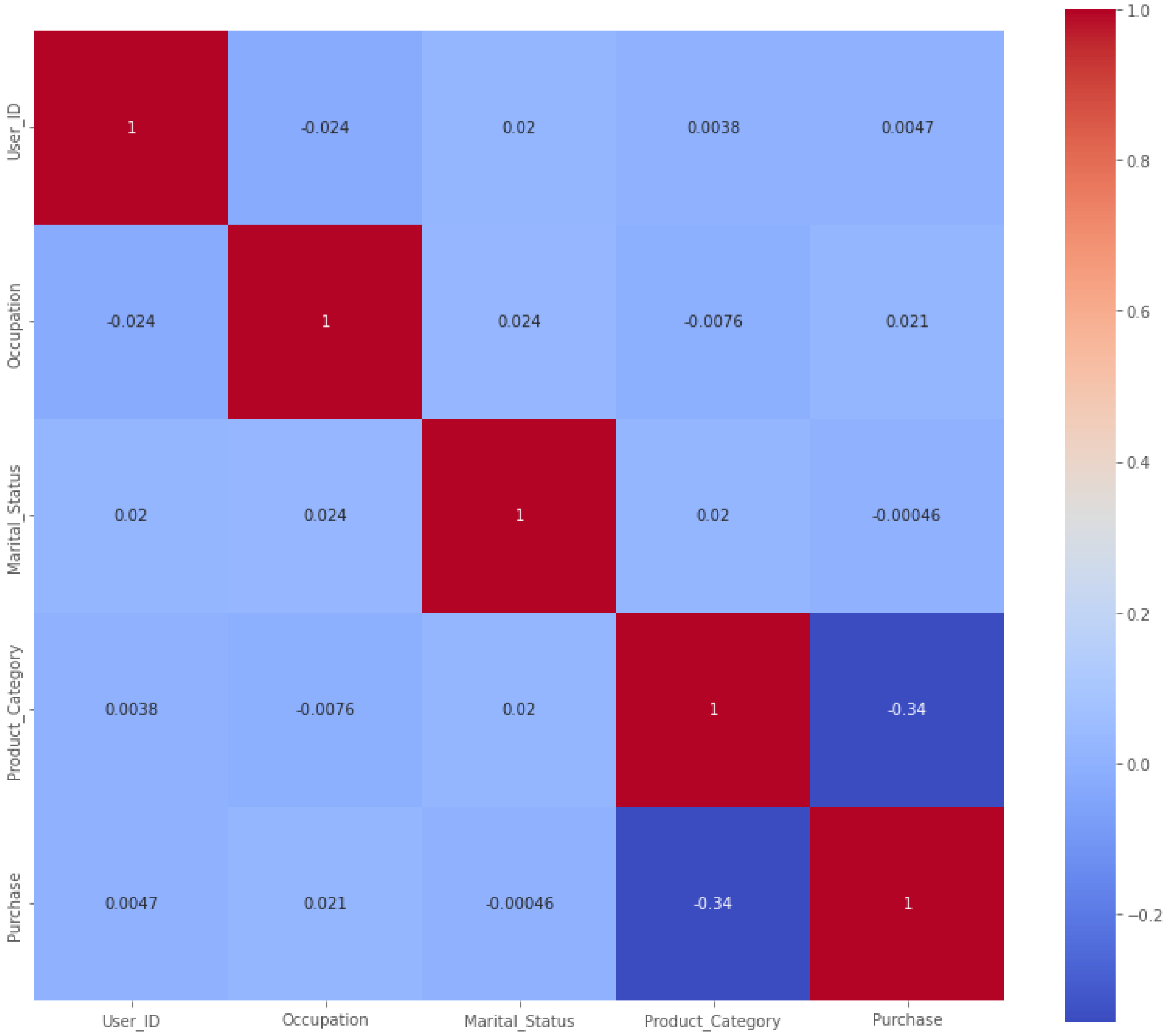
In [451…

```
plt.figure(figsize = (14, 12))
sns.heatmap(data.corr(method = 'pearson'), square = True, annot = True, cmap = 'coo
```

```
C:\Users\Chanchal Gupta\AppData\Local\Temp\ipykernel_24416\3584284474.py:2: Future
Warning: The default value of numeric_only in DataFrame.corr is deprecated. In a f
uture version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  sns.heatmap(data.corr(method = 'pearson'), square = True, annot = True, cmap =
'coolwarm')
```

Out[451]:

```
<AxesSubplot:>
```



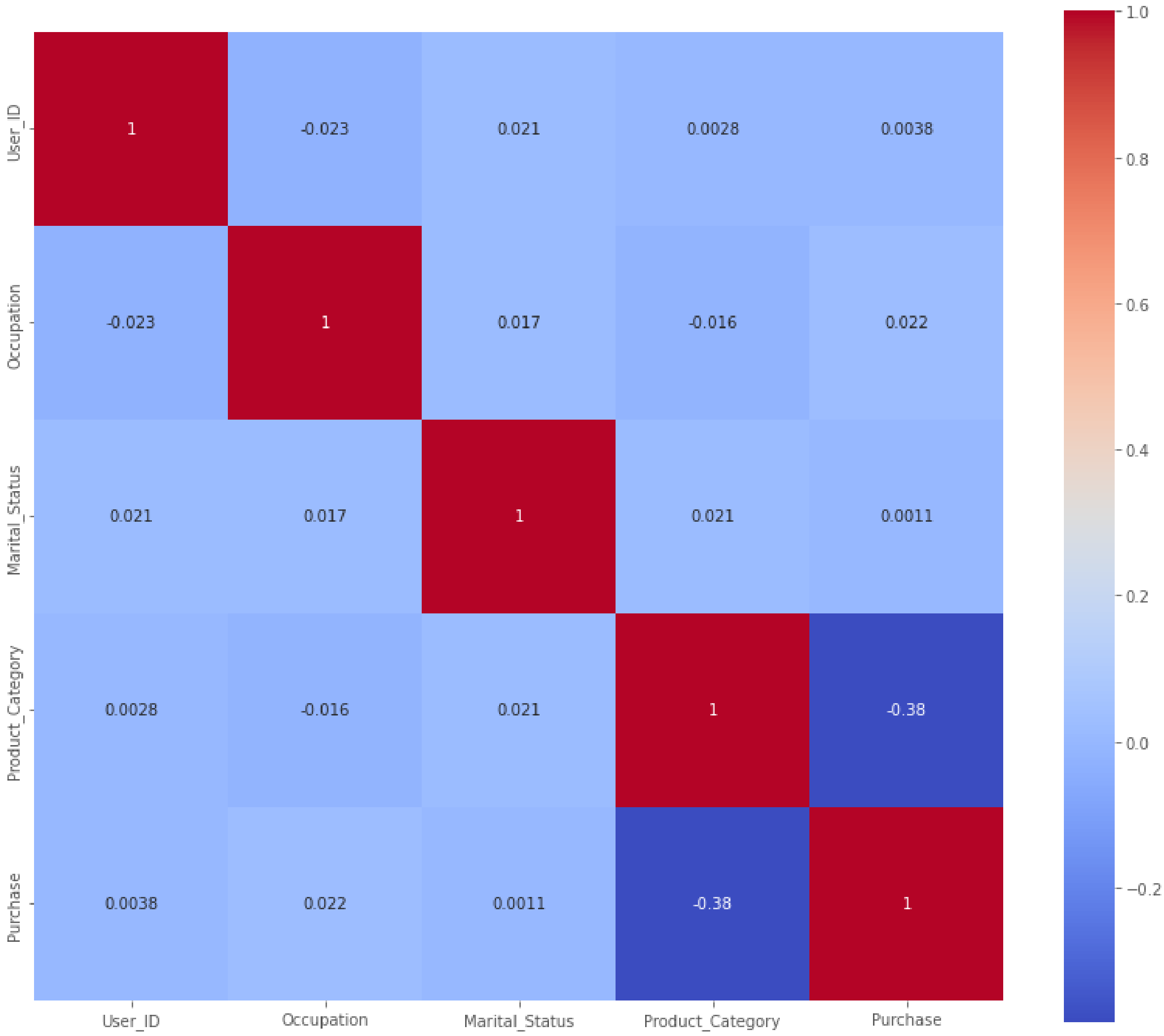
In [452…

```
plt.figure(figsize = (14, 12))
sns.heatmap(data.corr(method = 'spearman'), square = True, annot = True, cmap = 'cc
```

```
C:\Users\Chanchal Gupta\AppData\Local\Temp\ipykernel_24416\2790631011.py:2: Future
Warning: The default value of numeric_only in DataFrame.corr is deprecated. In a f
uture version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  sns.heatmap(data.corr(method = 'spearman'), square = True, annot = True, cmap =
'coolwarm')
```

Out[452]:

```
<AxesSubplot:>
```



In [453…

```
#How many transactions done by unmarital?
data[data['Marital_Status']==0]['Gender'].value_counts()
#Males > Females
```

Out[453]:

```
M    245910
F     78821
Name: Gender, dtype: int64
```

In [454…

```
#How many transactions done by marital?
data[data['Marital_Status']==1]['Gender'].value_counts()
#males > Females
```

Out[454]:

```
M    168349
F     56988
Name: Gender, dtype: int64
```

In [455…

```
#Products are mostly ordered by Males?
MaritalStatus = pd.crosstab(data['Product_Category'], data['Gender'], normalize = '
MaritalStatus
```

Out[455]:

Gender	F	M
Product_Category		
1	17.688669	82.311331
2	23.709353	76.290647
3	29.713551	70.286449
4	30.962307	69.037693
5	27.801077	72.198923
6	22.275970	77.724030
7	25.342650	74.657350
8	29.456221	70.543779
9	17.073171	82.926829
10	22.673171	77.326829
11	19.512496	80.487504
12	38.814289	61.185711
13	26.347090	73.652910
14	40.906106	59.093894
15	16.629571	83.370429
16	24.440374	75.559626
17	10.726644	89.273356
18	12.224000	87.776000
19	28.134747	71.865253
20	28.352941	71.647059

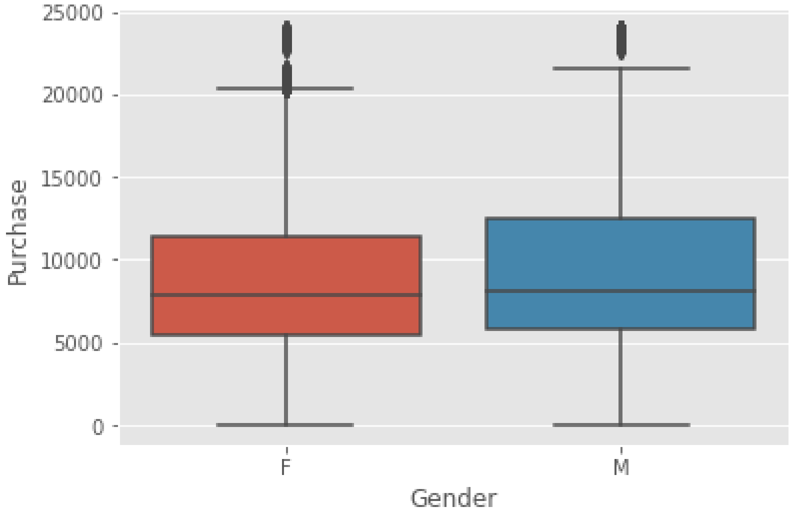
Are women spending more money per transaction than men? Why or Why not?

In [456…

```
sns.boxplot(x = 'Gender', y = 'Purchase', data = data)
#There is no major difference between males and females spending
```

Out[456]:

```
<AxesSubplot:xlabel='Gender', ylabel='Purchase'>
```



In [457…

```
#Main data, will not change
data.groupby(['Gender'])['Purchase'].describe()
```

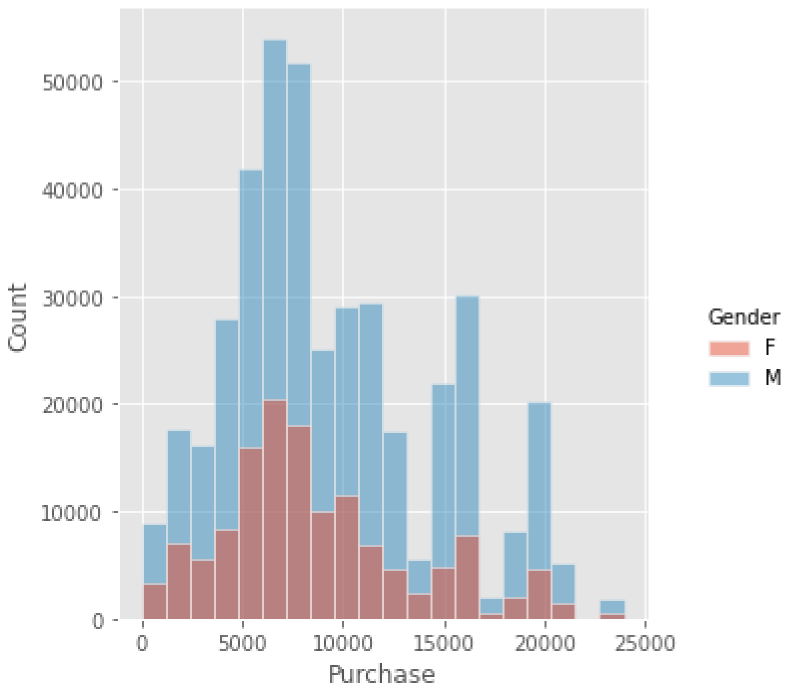
Out[457]:

Gender	count	mean	std	min	25%	50%	75%	max
F	135809.0	8734.565765	4767.233289	12.0	5433.0	7914.0	11400.0	23959.0
M	414259.0	9437.526040	5092.186210	12.0	5863.0	8098.0	12454.0	23961.0

In [458…

```
GenderSpends = data[['Gender', 'Purchase']]
sns.displot(x = 'Purchase', data = GenderSpends, hue = 'Gender', bins = 20)
#This is not a normal distribution
#to check how the sample is related to population we will do CLT
```

Out[458]: <seaborn.axisgrid.FacetGrid at 0x1648bfc6b50>



In [459…

```
#randomly selecting 300 samples, this will change as an when you click
sample = GenderSpends.sample(1000)
sample.groupby(['Gender'])['Purchase'].describe()
```

Out[459]:

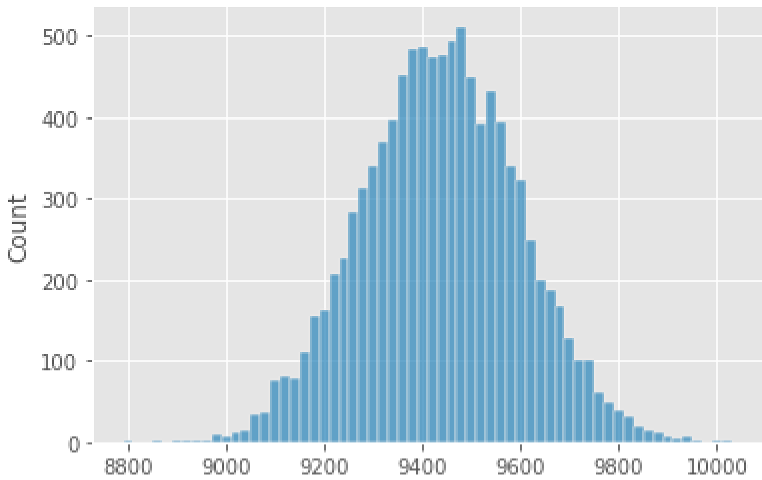
Gender	count	mean	std	min	25%	50%	75%	max
F	270.0	8610.574074	4581.051148	14.0	5370.75	7876.0	11412.25	20690.0
M	730.0	9257.576712	4984.396146	25.0	5492.00	8032.5	12001.25	23893.0

GENDER VS PURCHASE

In [479…

```
M = int(input('Enter the number of samples to be chosen randomly:'))
Male_Data = data[data['Gender'] == 'M']
Average_Male_Spends = [Male_Data['Purchase'].sample(M, replace = True).mean() for i
sns.histplot(Average_Male_Spends)
print('The average mean for randomly selected samples is ', np.mean(Average_Male_Sp
#This is the Normal distribution
```

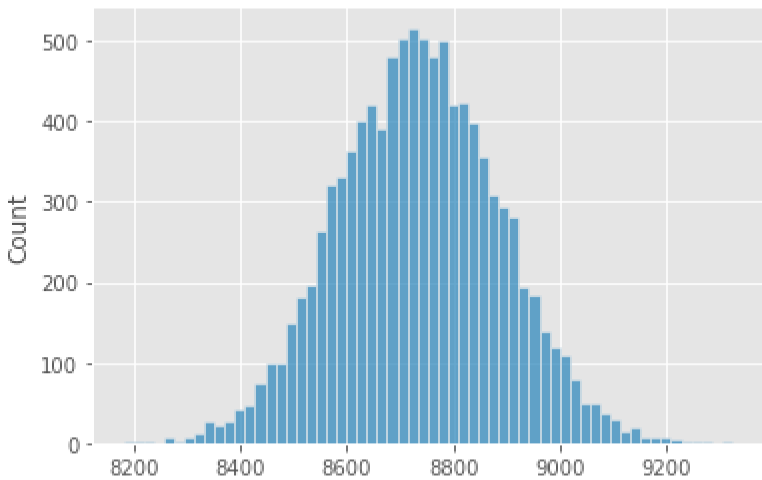
```
Enter the number of samples to be chosen randomly:1000
The average mean for randomly selected samples is  9438.1258214
```



In [480…

```
F = int(input('Enter the number of samples to be chosen randomly:'))
Female_Data = data[data['Gender'] == 'F']
Average_Female_Spends = [Female_Data['Purchase'].sample(F, replace = True).mean() f
sns.histplot(Average_Female_Spends)
print('The average mean for randomly selected samples is ', np.mean(Average_Female_
#This is the Normal distribution
```

```
Enter the number of samples to be chosen randomly:1000
The average mean for randomly selected samples is  8733.623187199999
```



In [ ]:
```
#Confidence interval can be identified by z score or percentile
```

In [481…
```
#Using z score:
#NOTE: Here std deviation is of sample and not population, hence not divide by n

def cal_ci(Value,confidence):
    upper_limit = np.mean(Value) - norm.ppf((1-confidence/100)/2) * np.std(Value)
    lower_limit = np.mean(Value) + norm.ppf((1-confidence/100)/2) * np.std(Value)

    return lower_limit, upper_limit

#What is the confidence interval for 95%Confidence?
confidence = float(input())
print(f'At {confidence} Interval the Average spend by Male is', cal_ci(Average_Male
print(f'At {confidence} Interval the Average spend by Female is', cal_ci(Average_Fe
```

```
95
At 95.0 Interval the Average spend by Male is (9125.569301321953, 9750.68234147804
8)
At 95.0 Interval the Average spend by Female is (8436.486840108448, 9030.759534291
55)
```

In [482…
```
#Using Percentile:
print('Using percentile, At 95% Confidence Interval the Average spend by Male is',
print('Using percentile, At 95% Confidence Interval the Average spend by Male is',
```

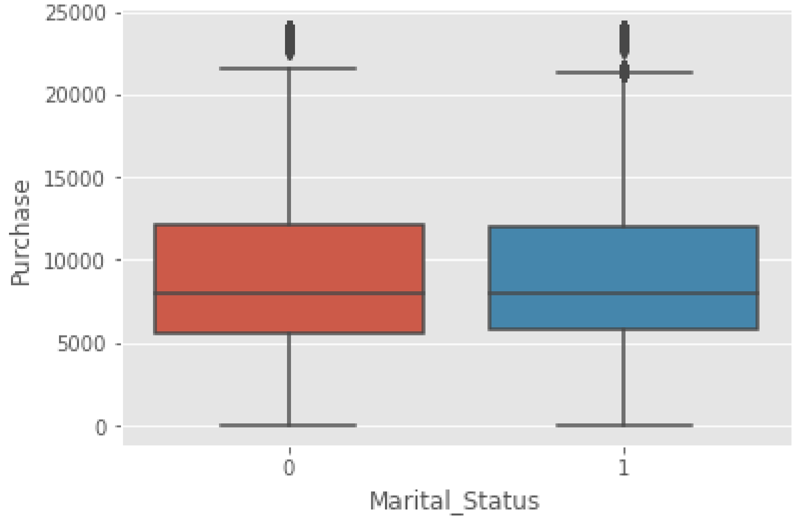
```
Using percentile, At 95% Confidence Interval the Average spend by Male is [9124.58
875 9749.73175]
Using percentile, At 95% Confidence Interval the Average spend by Male is [8441.87
2425 9030.324725]
```

In [ ]:
```
'''
OBSERVATIONS/INSIGHTS:

-> Overlappig was observed when randomly selected samples were less like 300

TO ELIMINATE OVERLAPPING:
-> Increase in Number of samples e.g., 1000 it tends to eliminates the overlapping
-> The range of values gets closer with Decrease in the Confidence, overlapping car

-> Womens are spending less than Males, the reason may be due to economic opportuni
the Income is not mentioned we cannot conclude that.

'''
```

Are unmarried spending more money per transaction than married? Why or Why not?

In [483…
```
sns.boxplot(x = 'Marital_Status', y = 'Purchase', data = data)
#There is no major difference in spending habits of Married and Unmarried
```

Out[483]:
```
<AxesSubplot:xlabel='Marital_Status', ylabel='Purchase'>
```



In [484…

```
#The Average spending habits is not significantly different irrespective of Marital
data.groupby(['Marital_Status'])['Purchase'].describe()
```

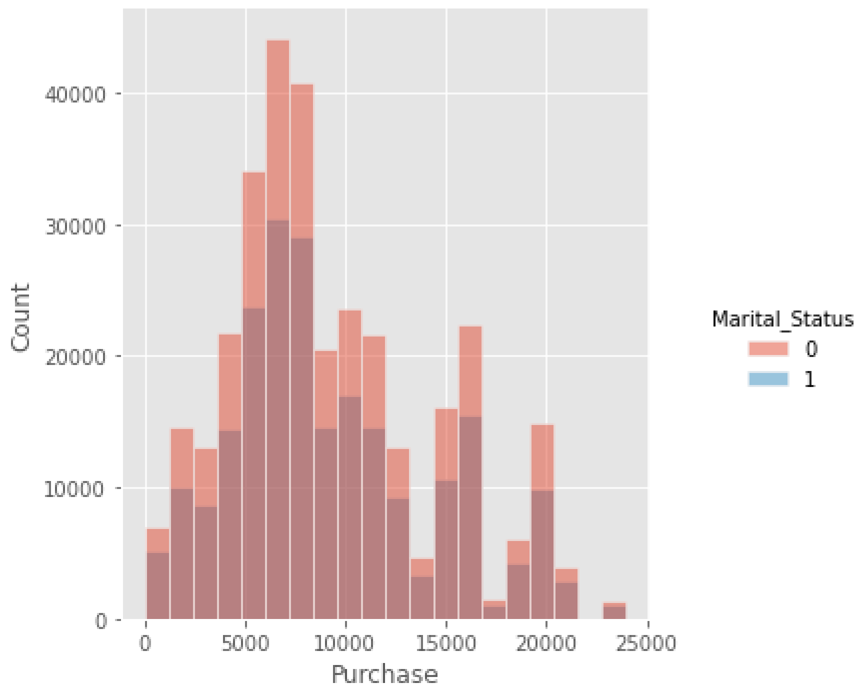
Out[484]:

Marital_Status	count	mean	std	min	25%	50%	75%	max
0	324731.0	9265.907619	5027.347859	12.0	5605.0	8044.0	12061.0	23961.0
1	225337.0	9261.174574	5016.897378	12.0	5843.0	8051.0	12042.0	23961.0

In [485…

```
MaritalSpends = data[['Marital_Status', 'Purchase']]
sns.displot(x = 'Purchase', data = MaritalSpends, hue = 'Marital_Status', bins = 20
#This is not a normal distribution
#to check how the sample is related to population we will do CLT
```

Out[485]: <seaborn.axisgrid.FacetGrid at 0x164a826be20>



MARITAL STATUS VS PURCHASE

In [486…

```
#randomly selecting 300 samples, this will change as an when you click
sample = MaritalSpends.sample(1000)
sample.groupby(['Marital_Status'])['Purchase'].describe()
```

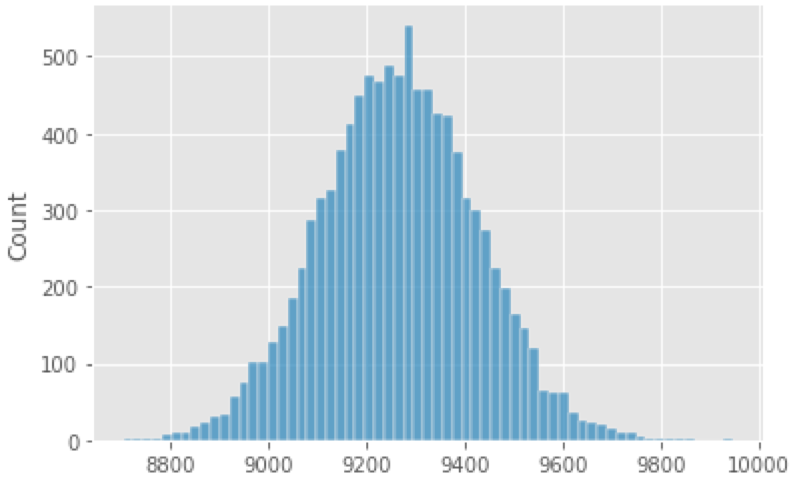
Out[486]:

	count	mean	std	min	25%	50%	75%	max
Marital_Status								
0	581.0	9096.445783	5088.983119	13.0	5419.0	8014.0	11939.0	23792.0
1	419.0	9250.178998	5003.273113	48.0	5896.0	8080.0	12138.0	23958.0

In [488…

```
Married = int(input('Enter the number of samples to be chosen randomly:'))
Married_Data = data[data['Marital_Status'] == 0]
Average_Married_Spends = [Married_Data['Purchase'].sample(Married, replace = True).
sns.histplot(Average_Married_Spends)
print('The average mean for randomly selected samples is ', np.mean(Average_Marriec
#This is the Normal distribution
```

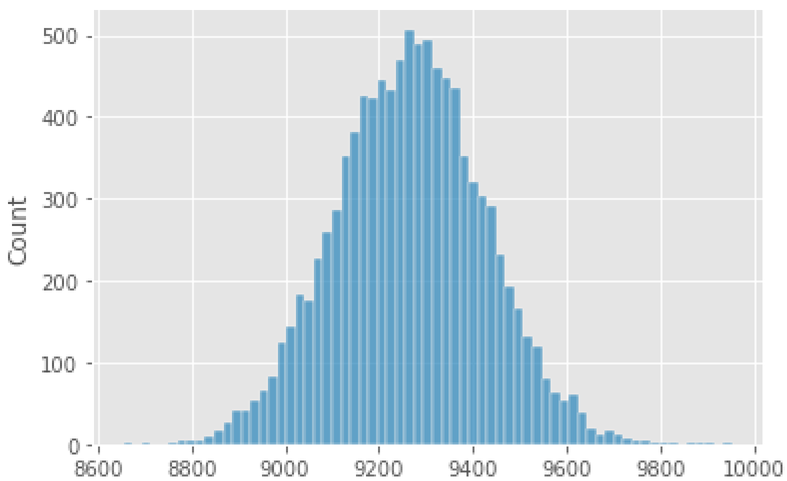
```
Enter the number of samples to be chosen randomly:1000
The average mean for randomly selected samples is  9265.6559863
```



In [489…

```
Unmarried = int(input('Enter the number of samples to be chosen randomly:'))
Unmarried_Data = data[data['Marital_Status'] == 0]
Average_Unmarried_Spends = [Unmarried_Data['Purchase'].sample(Unmarried, replace =
sns.histplot(Average_Unmarried_Spends)
print('The average mean for randomly selected samples is ', np.mean(Average_Unmarri
#This is the Normal distribution
```

```
Enter the number of samples to be chosen randomly:1000
The average mean for randomly selected samples is  9266.3197373
```



In [ ]:
```
#Confidence interval can be identified by z score or percentile
```

In [490…
```
#Using z score:
#NOTE: Here std deviation is of sample and not population, hence not divide by n

def cal_ci(Value,confidence):
    upper_limit = np.mean(Value) - norm.ppf((1-confidence/100)/2) * np.std(Value)
    lower_limit = np.mean(Value) + norm.ppf((1-confidence/100)/2) * np.std(Value)

    return lower_limit, upper_limit

#What is the confidence interval for 95%Confidence?
confidence = float(input('Enter the % confidence interval:'))
print(f'At {confidence} % Confidence Interval the Average spend by Unmarried people
print(f'At {confidence} % Confidence Interval the Average spend by Married people i
```

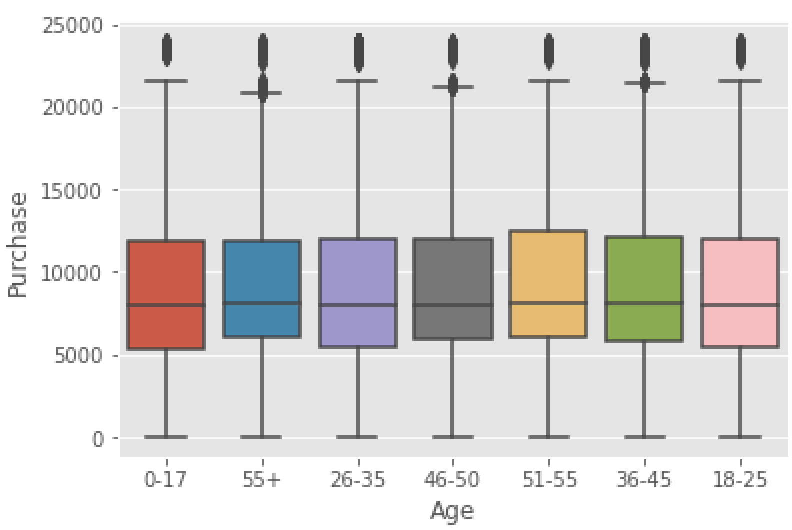
```
Enter the % confidence interval:95
At 95.0 % Confidence Interval the Average spend by Unmarried people is (8956.66485
9333483, 9575.974615266518)
At 95.0 % Confidence Interval the Average spend by Married people is (8953.1607347
47227, 9578.151237852773)
```

In [ ]:
```
'''
OBSERVATIONS/INSIGHTS:

-> Overlappig was observed

TO ELIMINATE OVERLAPPING:
-> Increase in Number of samples
-> The range of values gets closer with Decrease in the Confidence, overlapping car

'''
```

AGE vs PURCHASE

In [491…
```
sns.boxplot(x = 'Age', y = 'Purchase', data = data)
#There is no major difference in spending habits of Married and Unmarried
```

Out[491]: <AxesSubplot:xlabel='Age', ylabel='Purchase'>



In [492…
```
data.groupby(['Age'])['Purchase'].describe()
```

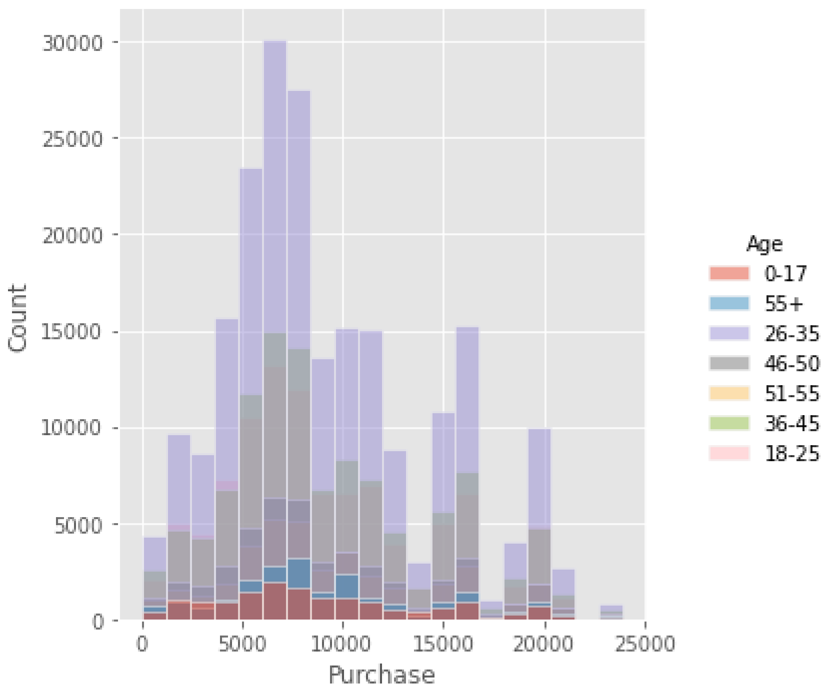
Out[492]:

Age	count	mean	std	min	25%	50%	75%	max
0-17	15102.0	8933.464640	5111.114046	12.0	5328.0	7986.0	11874.0	23955.0
18-25	99660.0	9169.663606	5034.321997	12.0	5415.0	8027.0	12028.0	23958.0
26-35	219587.0	9252.690633	5010.527303	12.0	5475.0	8030.0	12047.0	23961.0
36-45	110013.0	9331.350695	5022.923879	12.0	5876.0	8061.0	12107.0	23960.0
46-50	45701.0	9208.625697	4967.216367	12.0	5888.0	8036.0	11997.0	23960.0
51-55	38501.0	9534.808031	5087.368080	12.0	6017.0	8130.0	12462.0	23960.0
55+	21504.0	9336.280459	5011.493996	12.0	6018.0	8105.5	11932.0	23960.0

In [493…

```
Age_Spends = data[['Age', 'Purchase']]
sns.displot(x = 'Purchase', data = Age_Spends, hue = 'Age', bins = 20)
#This is not a normal distribution
#to check how the sample is related to population we will do CLT
```

Out[493]: <seaborn.axisgrid.FacetGrid at 0x164d93490d0>



In [494…

```
#randomly selecting 1000 samples, this will change as an when you click
sample = Age_Spends.sample(1000)
sample.groupby(['Age'])['Purchase'].describe()
```

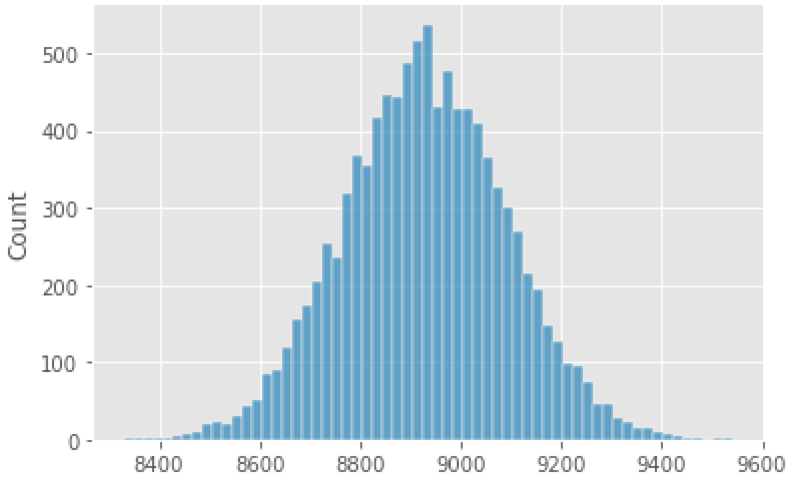
Out[494]:

Age	count	mean	std	min	25%	50%	75%	max
0-17	26.0	9317.115385	6545.133199	388.0	5150.50	7035.5	15787.00	20793.0
18-25	153.0	9352.784314	5095.655416	587.0	5561.00	8161.0	13017.00	20907.0
26-35	395.0	9217.635443	5034.461804	26.0	5449.00	7980.0	12028.50	20976.0
36-45	223.0	9142.843049	4923.214375	762.0	5907.50	7933.0	12640.00	23279.0
46-50	78.0	8222.269231	4879.928988	48.0	5164.75	7819.0	11491.00	23073.0
51-55	72.0	8776.750000	4875.384191	37.0	5892.00	7877.5	9923.25	21325.0
55+	53.0	9222.547170	5467.113718	25.0	6058.00	7932.0	12011.00	20611.0

In [495…

```
Age = int(input('Enter the number of samples to be chosen randomly:'))
Age_Data = data[data['Age'] == '0-17']
Age_Spends = [Age_Data['Purchase'].sample(Age, replace = True).mean() for i in rang
sns.histplot(Age_Spends)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends))
#This is the Normal distribution
```

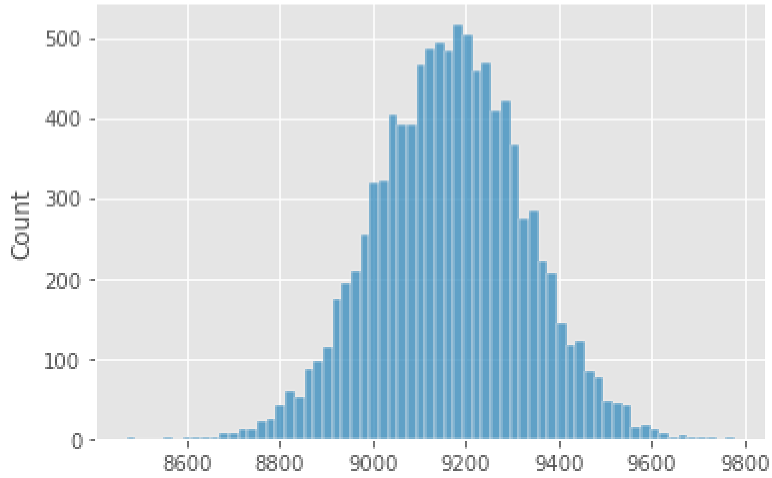
```
Enter the number of samples to be chosen randomly:1000
The average mean for randomly selected samples is  8930.6897681
```



In [496…

```
Age_Data2 = data[data['Age'] == '18-25']
Age_Spends2 = [Age_Data2['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends2)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends2))
#This is the Normal distribution
```

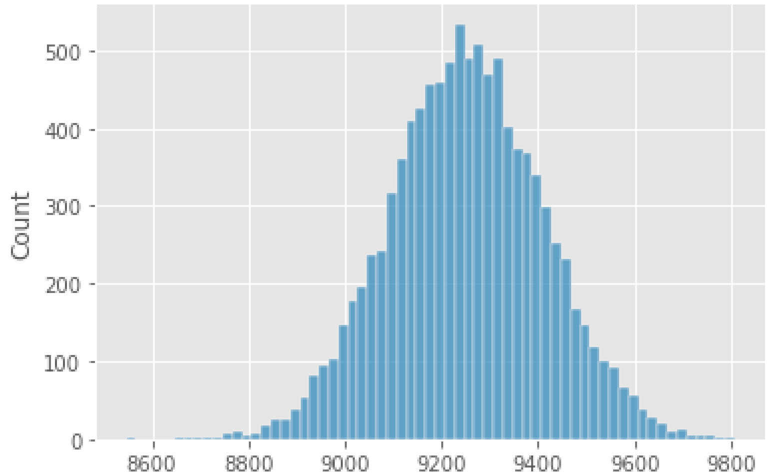
```
The average mean for randomly selected samples is  9167.880292700002
```



In [497…

```
Age_Data3 = data[data['Age'] == '26-35']
Age_Spends3 = [Age_Data3['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends3)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends3))
#This is the Normal distribution
```

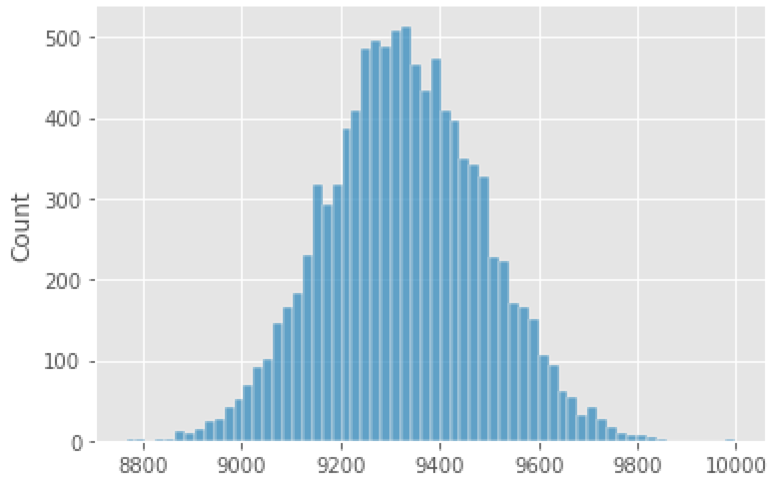
```
The average mean for randomly selected samples is  9251.991360299999
```



In [498…

```
Age_Data4 = data[data['Age'] == '36-45']
Age_Spends4 = [Age_Data4['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends4)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends4))
#This is the Normal distribution
```

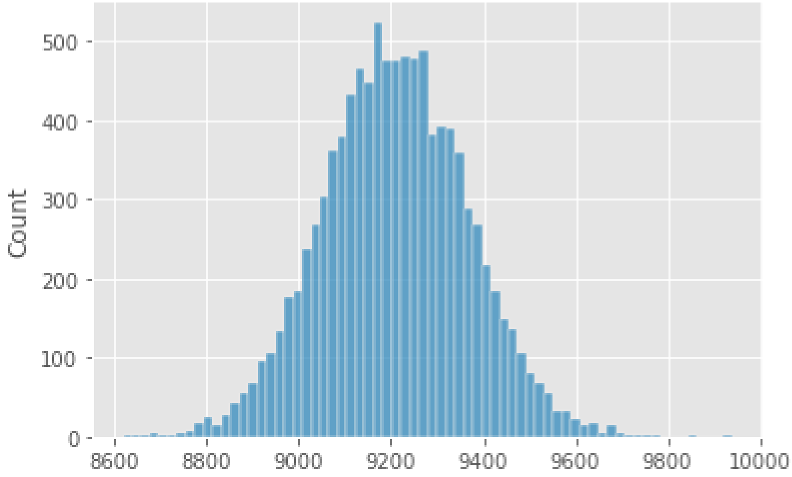
```
The average mean for randomly selected samples is  9329.5723834
```



In [499…

```
Age_Data5 = data[data['Age'] == '46-50']
Age_Spends5 = [Age_Data5['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends5)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends5))
#This is the Normal distribution
```

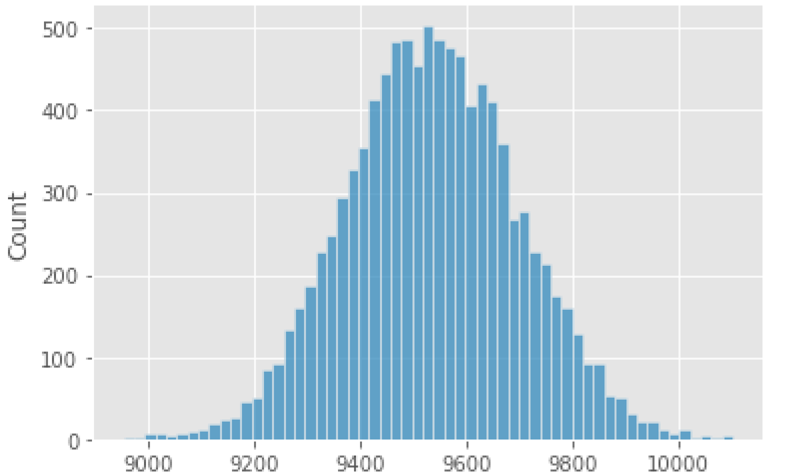
The average mean for randomly selected samples is 9208.7526209



In [500…

```
Age_Data6 = data[data['Age'] == '51-55']
Age_Spends6 = [Age_Data6['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends6)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends6))
#This is the Normal distribution
```

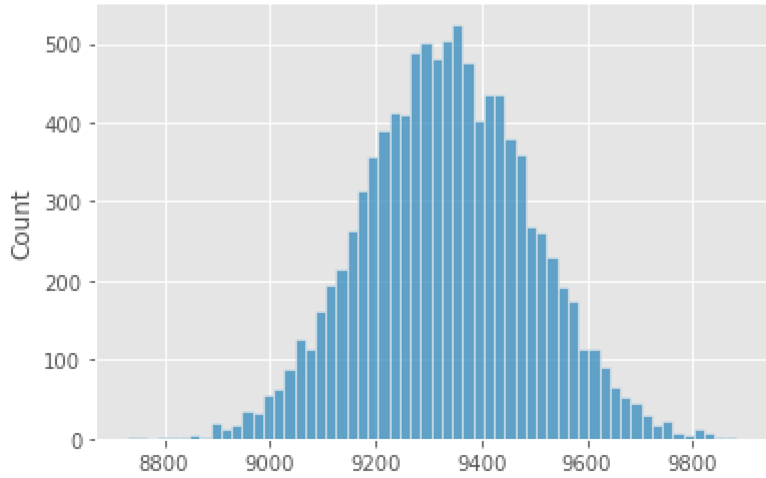
The average mean for randomly selected samples is 9534.6121624



In [501…

```
Age_Data7 = data[data['Age'] == '55+']
Age_Spends7 = [Age_Data7['Purchase'].sample(Age, replace = True).mean() for i in ra
sns.histplot(Age_Spends7)
print('The average mean for randomly selected samples is ', np.mean(Age_Spends7))
#This is the Normal distribution
```

The average mean for randomly selected samples is 9334.680548



In [502…

```
#Using z score:
#NOTE: Here std deviation is of sample and not population, hence not divide by n

def cal_ci(Value,confidence):
    upper_limit = np.mean(Value) - norm.ppf((1-confidence/100)/2) * np.std(Value)
    lower_limit = np.mean(Value) + norm.ppf((1-confidence/100)/2) * np.std(Value)

    return lower_limit, upper_limit

#What is the confidence interval for 95%Confidence?
confidence = float(input('Enter the % confidence interval:'))
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
print(f'At {confidence} % Confidence Interval the Average spend by the Age group of
```

```
Enter the % confidence interval:95
At 95.0 % Confidence Interval the Average spend by the Age group of 0-17 yrs (861
3.562164475896, 9247.817371724102)
At 95.0 % Confidence Interval the Average spend by the Age group of 18-25 yrs (885
3.935823662674, 9481.824761737329)
At 95.0 % Confidence Interval the Average spend by the Age group of 26-35 yrs (894
0.194767743336, 9563.787952856661)
At 95.0 % Confidence Interval the Average spend by the Age group of 36-45 yrs (901
7.626757229147, 9641.518009570853)
At 95.0 % Confidence Interval the Average spend by the Age group of 46-50 yrs (890
0.43284498233, 9517.072396817672)
At 95.0 % Confidence Interval the Average spend by the Age group of 51-55 yrs (921
6.6952843351, 9852.529040464902)
At 95.0 % Confidence Interval the Average spend by the Age group of 55+ yrs (9023.
67419081036, 9645.686905189641)
```

In [ ]:

```
'''
OBSERVATIONS/INSIGHTS:

-> The Dataset of Walmart company is the transactional data of customers who purcha
stores during Black Friday.

-> Dataset is a distribution of total 550068 rows with 10 columns.

-> User_ID is the detail of Each unique Customers and Product_ID is the ID of each
Product ID.

-> From the Boxplot data, No null values were observed in the data
```

```
-> Transaction Data is segregation for Unmarried/Married Males and Females along wi
As per dataset, the Unmarried population seems to buy more products than Married.

-> Major transactions are done by Males than Female. Around 75% of the transactions
and 25% (Total 135809) by females.

-> There are Total 5891 Unique customers, Approximately 72% (4225) are males and 28

-> 40% of the products are purchased by people at an Age group of 26-35, and least
hence age group can be an great target for Sales Marketing.

->Product_category 1, 5, 8 are mostly ordered by the customers, Mostly by the Male

-> Amongst the three cities, most products were purchased from people who stay in C
seems to stay for only a year and few stay for a longer time

-> From the boxplot data there was no major difference observed on spending habits
how sample is related to population data? we performed CLT and Bootstrapping.

-> Insights are mentioned for each question.

'''
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: