Business Case: Walmart - Confidence Interval and CLT

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

Business Problem

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

Dataset

The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday. The dataset has the following features:

Variable	Description
User_ID:	User ID
Product_ID:	Product ID
Gender:	Sex of User
Age:	Age in bins
Occupation:	Occupation(Masked)
City_Category:	Category of the City (A,B,C)
StayInCurrentCityYears:	Number of years stay in current city
Marital_Status:	Marital Status
ProductCategory:	Product Category (Masked)

Variable	Description
Purchase:	Purchase Amount

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
!gdown 1uwwhf3deGL1hbe1gRNWQtVO9SVWcnmtX
```

```
Downloading...
From: https://drive.google.com/uc?id=1uwwhf3deGL1hbe1gRNWQtVO9SVWcnmtX
To: /content/04_walmart_data.csv
100% 23.0M/23.0M [00:00<00:00, 186MB/s]
```

In [ ]:
```
df = pd.read_csv('04_walmart_data.csv')
df.head(10)
```

Out[ ]:

	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
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969
5	1000003	P00193542	M	26-35	15	A	3	0	1	15227
6	1000004	P00184942	M	46-50	7	B	2	1	1	19215
7	1000004	P00346142	M	46-50	7	B	2	1	1	15854
8	1000004	P0097242	M	46-50	7	B	2	1	1	15686

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
9	1000005	P00274942	M	26-35	20	A	1	1	8	7871

In [ ]:

```
print(f"Number of rows: {df.shape[0]:,} \nNumber of columns: {df.shape[1]}")
```

```
Number of rows: 550,068
Number of columns: 10
```

In [ ]:

```
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
```

Change the data types of - `Occupation` , `Marital_Status` , `Product_Category`

In [ ]:

```
cols = ['Occupation', 'Marital_Status', 'Product_Category']
df[cols] = df[cols].astype('object')
```

In [ ]:

```
df.dtypes
```

Out[ ]:

```
User_ID                        int64
Product_ID                    object
```

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

In [ ]:

```
df.memory_usage()
```

Out[ ]:

```
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
```

In [ ]:

```
df.describe()
```

Out[ ]:

	User_ID	Purchase
count	5.500680e+05	550068.000000
mean	1.003029e+06	9263.968713
std	1.727592e+03	5023.065394
min	1.000001e+06	12.000000
25%	1.001516e+06	5823.000000
50%	1.003077e+06	8047.000000
75%	1.004478e+06	12054.000000
max	1.006040e+06	23961.000000

Observations

- There are no missing values in the dataset.
- Purchase amount might have outliers.

In [ ]:
```
# checking null values
df.isnull().sum()
```

Out[ ]:
```
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
```

How many users are there in the dataset?

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

Out[ ]:
```
5891
```

How many products are there?

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

Out[ ]:
```
3631
```

Value_counts for the following:

- Gender
- Age
- Occupation

- City_Category
- Stay_In_Current_City_Years
- Marital_Status
- Product_Category

In [ ]:

```
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status', 'Pr
df[categorical_cols].melt().groupby(['variable', 'value'])[['value']].count()/len(df)
```

Out[ ]:

variable	value	value
Age	0-17	0.027455
	18-25	0.181178
	26-35	0.399200
	36-45	0.199999
	46-50	0.083082
	51-55	0.069993
	55+	0.039093
City_Category	A	0.268549
	B	0.420263
	C	0.311189
Gender	F	0.246895
	M	0.753105
Marital_Status	0	0.590347
	1	0.409653
Occupation	0	0.126599
	1	0.086218
	2	0.048336
	3	0.032087

		value
variable	**value**	
	4	0.131453
	5	0.022137
	6	0.037005
	7	0.107501
	8	0.002811
	9	0.011437
	10	0.023506
	11	0.021063
	12	0.056682
	13	0.014049
	14	0.049647
	15	0.022115
	16	0.046123
	17	0.072796
	18	0.012039
	19	0.015382
	20	0.061014
Product_Category	**1**	0.255201
	2	0.043384
	3	0.036746
	4	0.021366
	5	0.274390
	6	0.037206
	7	0.006765

variable	value	value
	8	0.207111
	9	0.000745
	10	0.009317
	11	0.044153
	12	0.007175
	13	0.010088
	14	0.002769
	15	0.011435
	16	0.017867
	17	0.001051
	18	0.005681
	19	0.002914
	20	0.004636
Stay_In_Current_City_Years	0	0.135252
	1	0.352358
	2	0.185137
	3	0.173224
	4+	0.154028

Observations

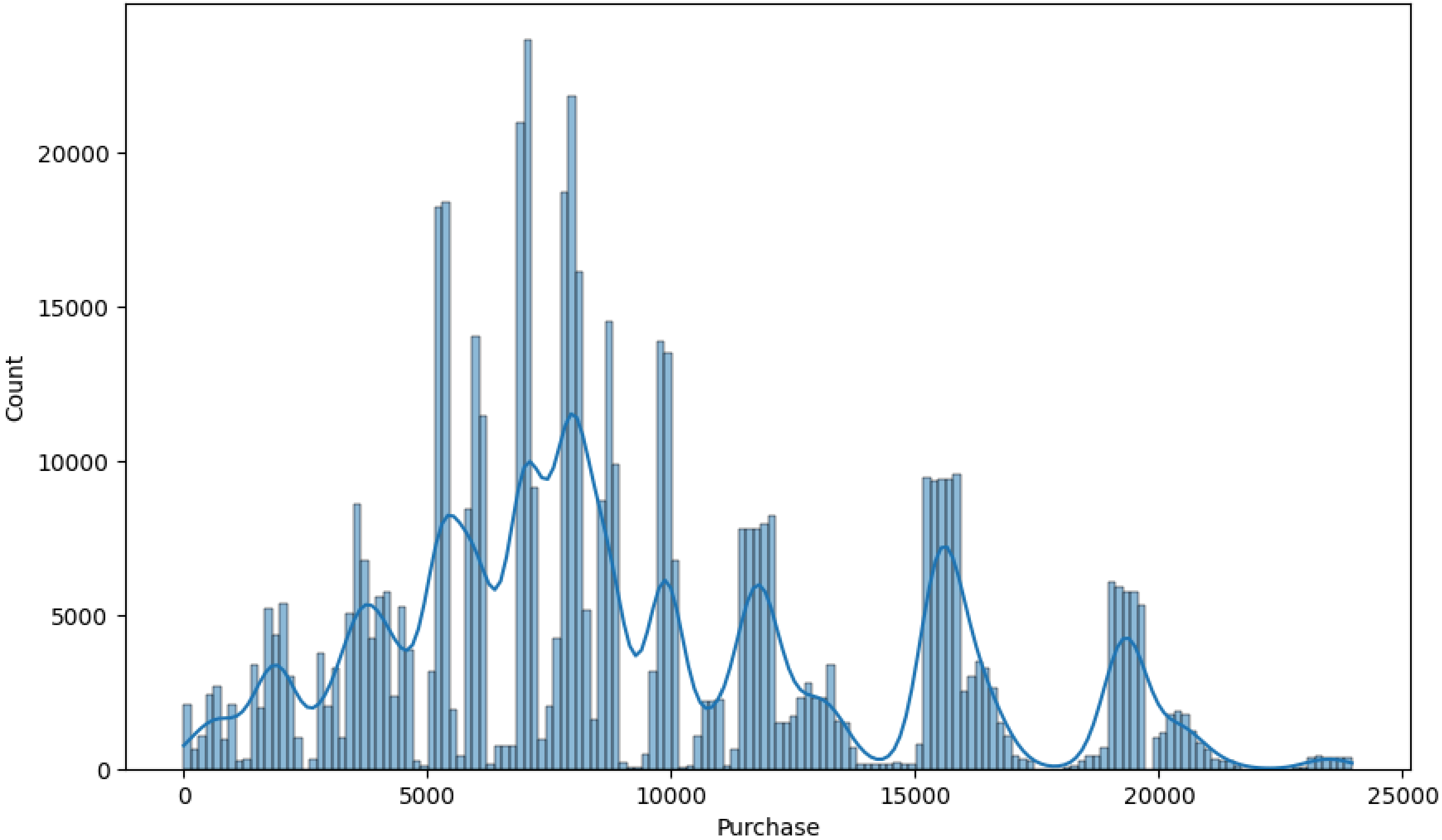
- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are `Male` and 25% are `Female`
- 60% Single, 40% Married
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- Total of 20 product categories are there

- There are 20 differnent types of occupations in the city

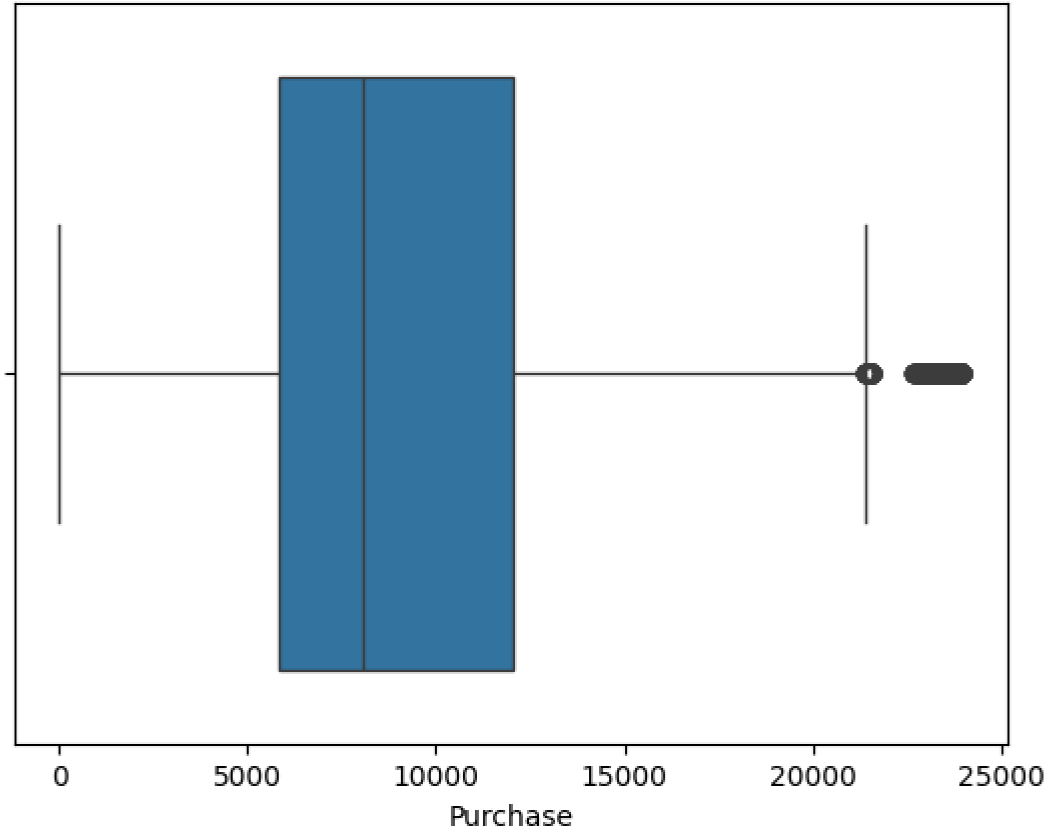
Univariate Analysis

Understanding the distribution of data and detecting outlies for continuous variables

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='Purchase', kde=True)
plt.show()
```



In [ ]:
```
sns.boxplot(data=df, x='Purchase', orient='h')
plt.show()
```



Observation

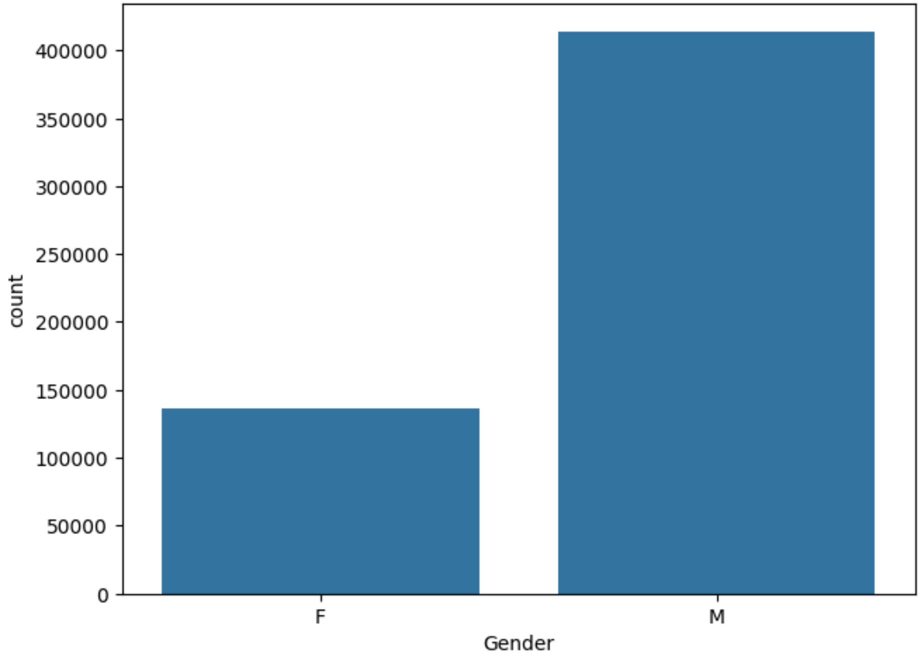
- Purchase is having outliers

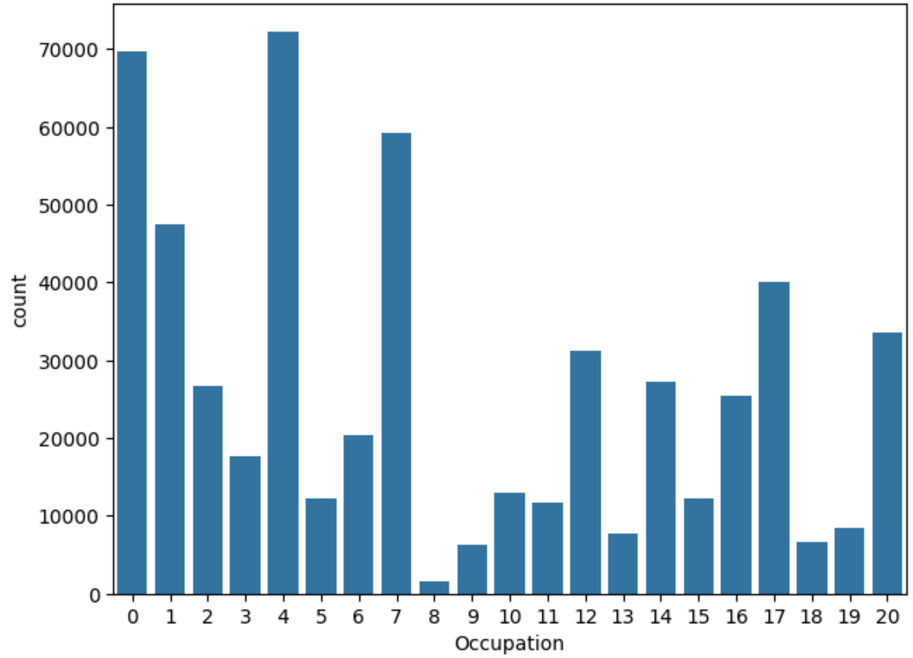
Understanding the distribution of data for the categorical variables

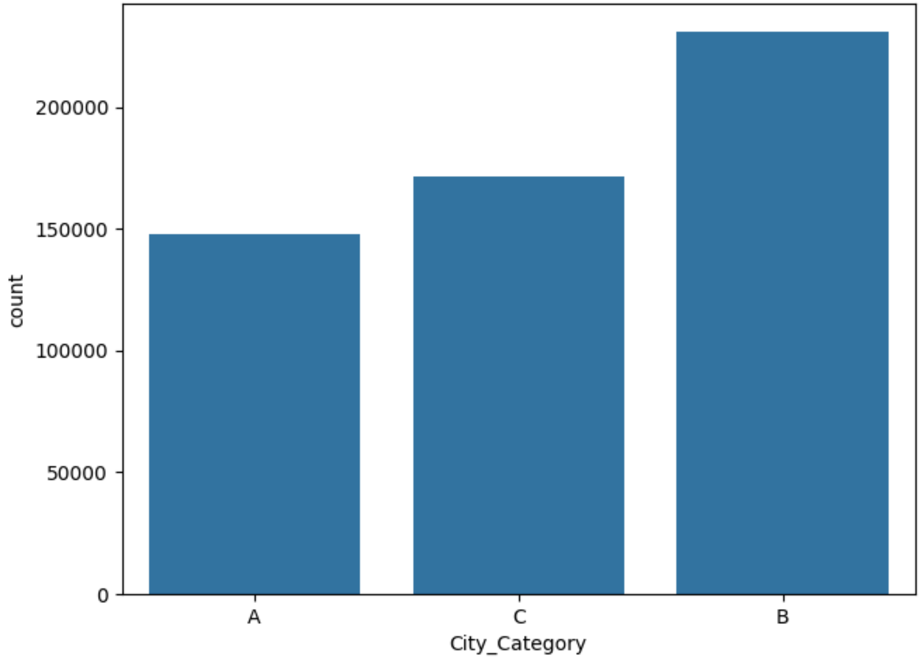
- Gender
- Age
- Occupation
- City_Category

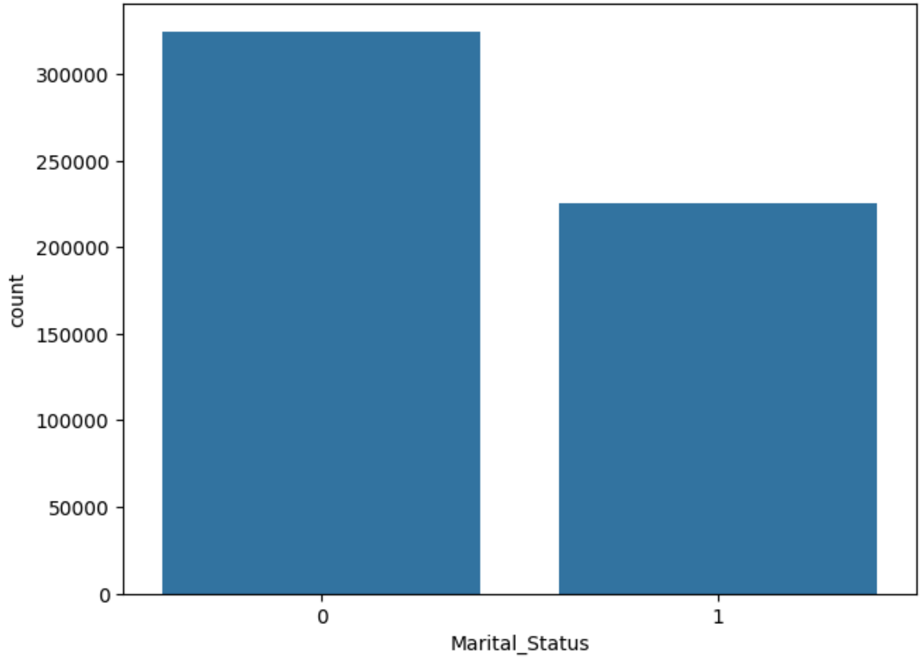
- Stay_In_Current_City_Years
- Marital_Status
- Product_Category

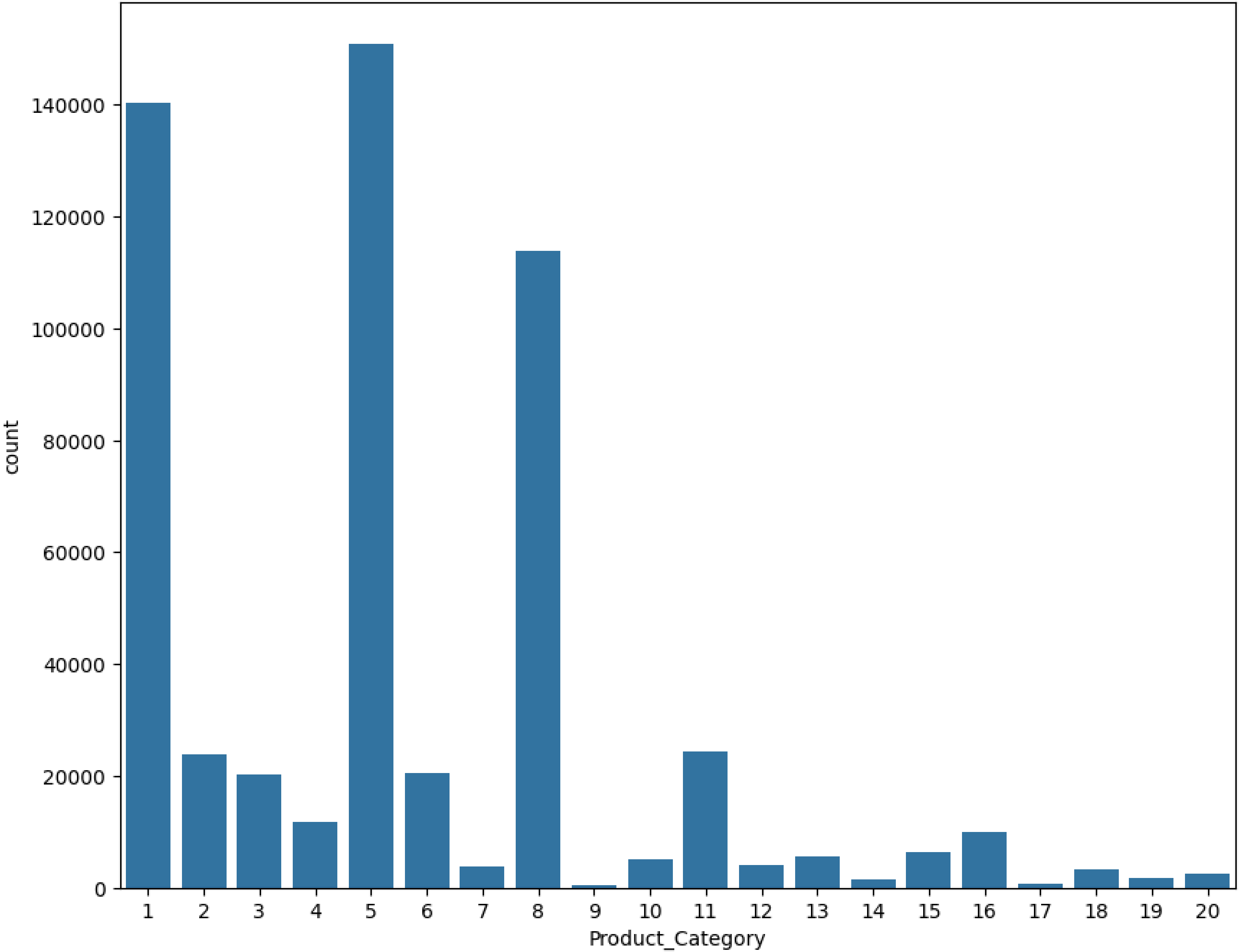
In [ ]:
```
categorical_cols = ['Gender', 'Occupation','City_Category','Marital_Status','Product_Category']

fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
sns.countplot(data=df, x='Gender', ax=axs[0,0])
sns.countplot(data=df, x='Occupation', ax=axs[0,1])
sns.countplot(data=df, x='City_Category', ax=axs[1,0])
sns.countplot(data=df, x='Marital_Status', ax=axs[1,1])
plt.show()

plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Product_Category')
plt.show()
```


count
Gender
F
M


count
Occupation


count
City_Category
A
C
B

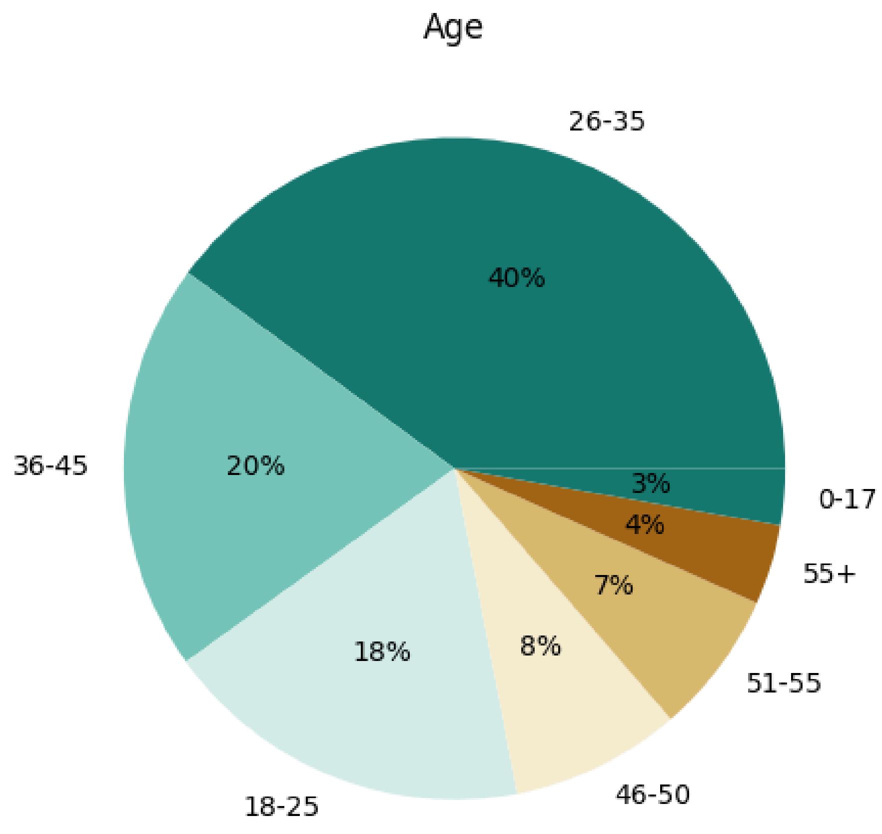

count
Marital_Status
0
1

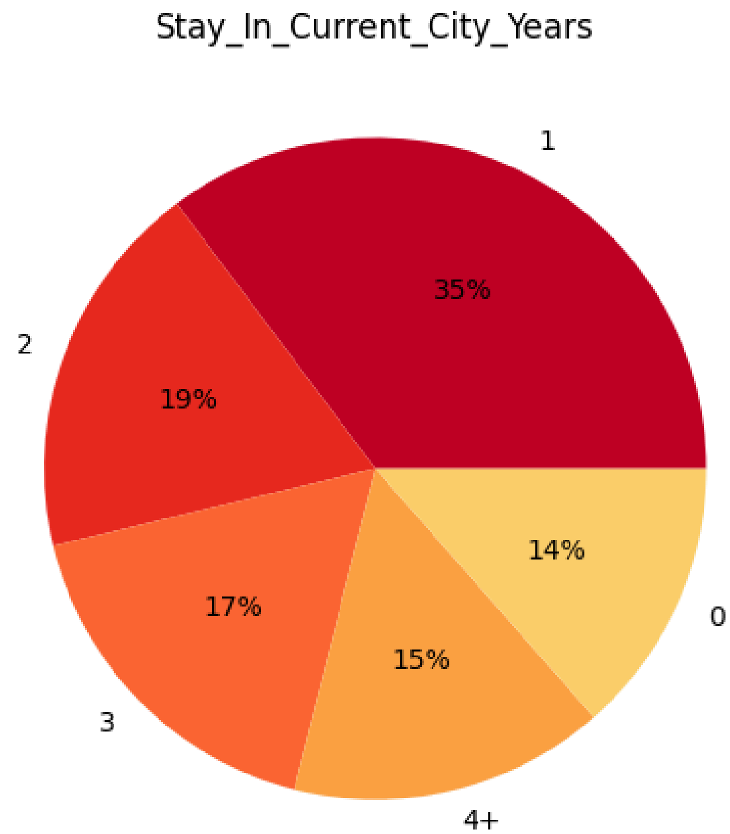


Observations

- Most of the users are `Male`
- There are 20 different types of `Occupation` and `Product_Category`
- More users belong to `B` `City_Category`
- More users are `Single` as compare to `Married`
- `Product_Category` - `1, 5, 8, & 11` have highest purchasing frequency.

In [ ]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 8))

data = df['Age'].value_counts(normalize=True)*100
palette_color = sns.color_palette('BrBG_r')
axs[0].pie(x=data.values, labels=data.index, autopct='%.0f%%', colors=palette_color)
axs[0].set_title("Age")

data = df['Stay_In_Current_City_Years'].value_counts(normalize=True)*100
palette_color = sns.color_palette('YlOrRd_r')
axs[1].pie(x=data.values, labels=data.index, autopct='%.0f%%', colors=palette_color)
axs[1].set_title("Stay_In_Current_City_Years")


plt.show()
```





Observations

- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years, 15% from 4 years+, 14% are new to city

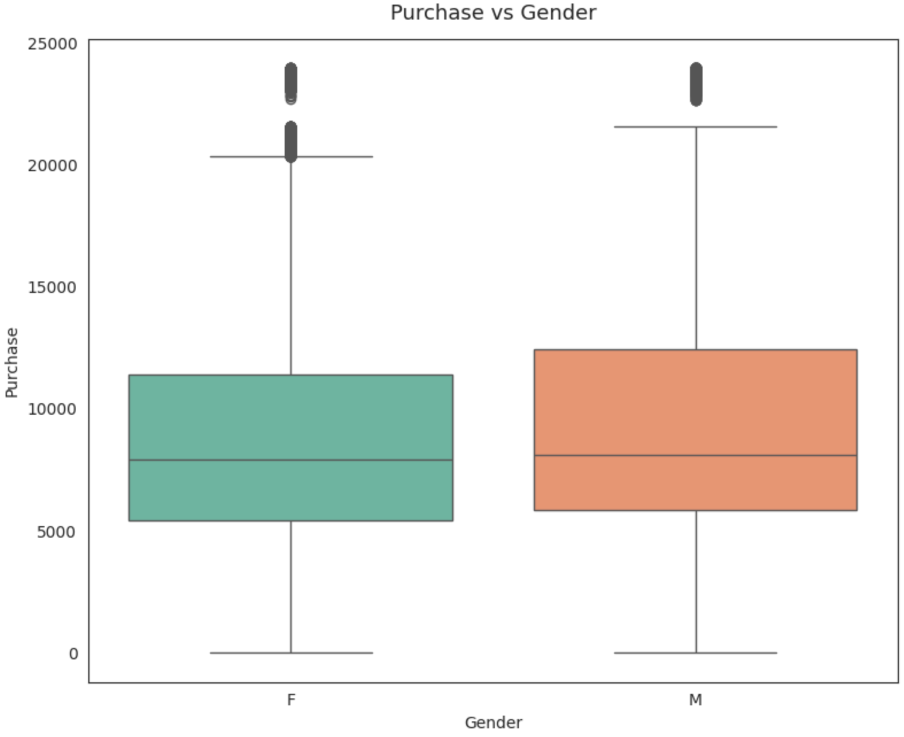
Bi-variate Analysis

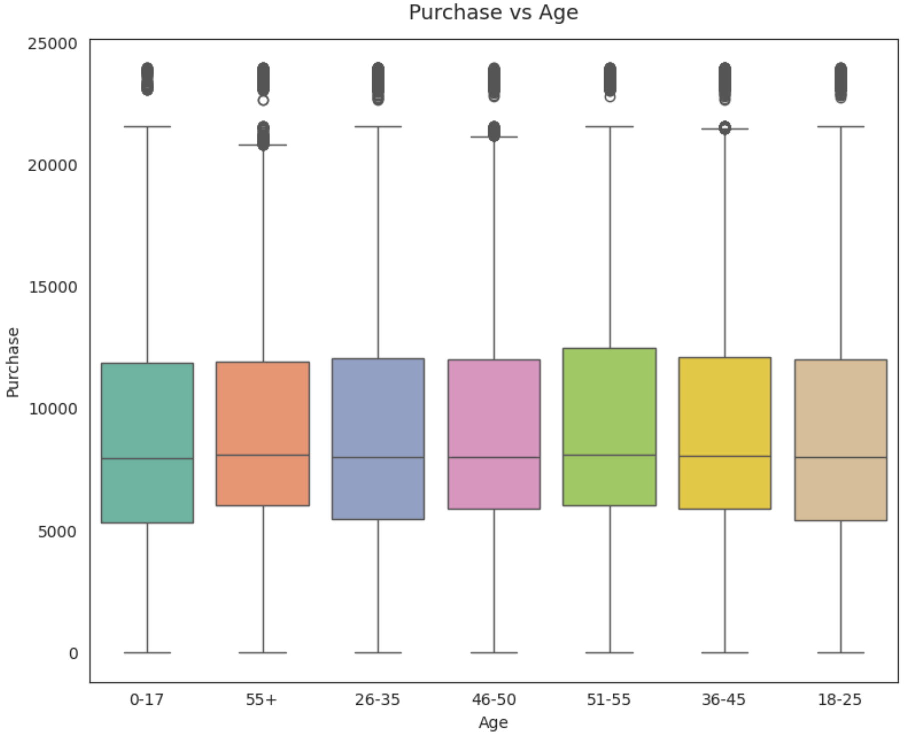
In [ ]:

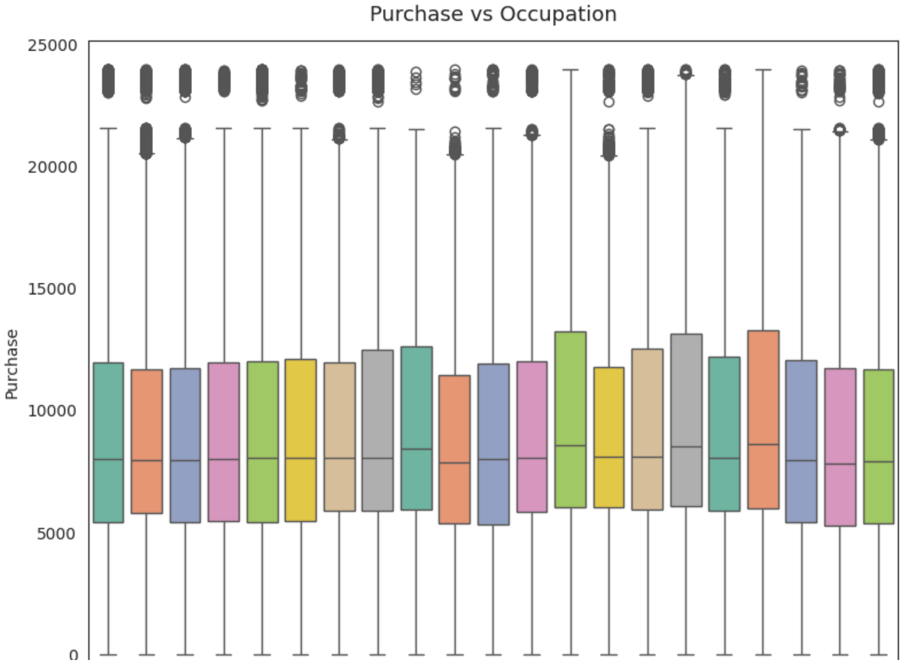
```
attrs = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Categ
sns.set_style("white")

fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(20, 16))
fig.subplots_adjust(top=1.3)
count = 0
```

```
for row in range(3):
    for col in range(2):
        sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
        axs[row,col].set_title(f"Purchase vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
plt.show()
```

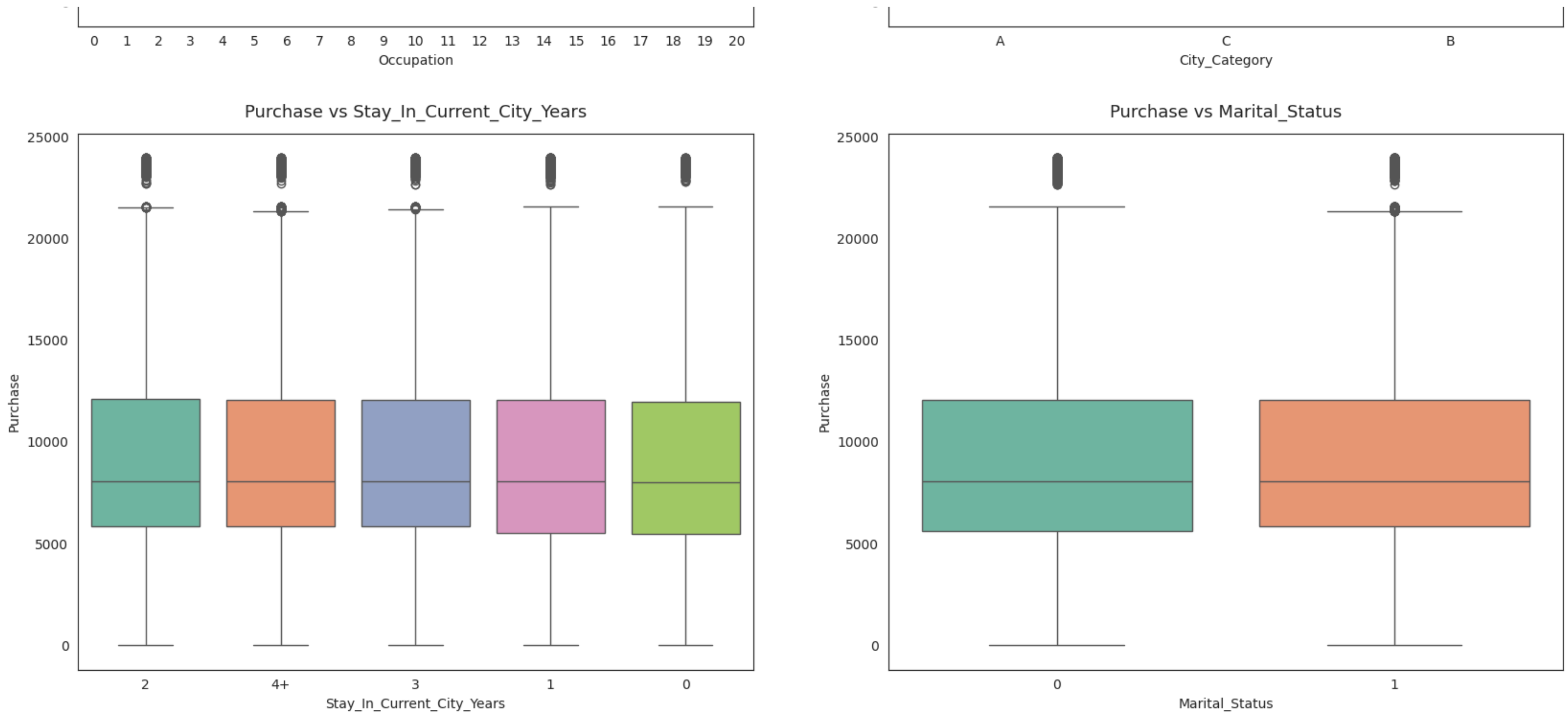
```
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
<ipython-input-67-77a7526bf5f3>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set2')
```


Purchase vs Gender
25000
20000
15000
10000
5000
0
Purchase
F
M
Gender


Purchase vs Age
25000
20000
15000
10000
5000
0
Purchase
0-17
55+
26-35
46-50
51-55
36-45
18-25
Age


Purchase vs Occupation
25000
20000
15000
10000
5000
0
Purchase

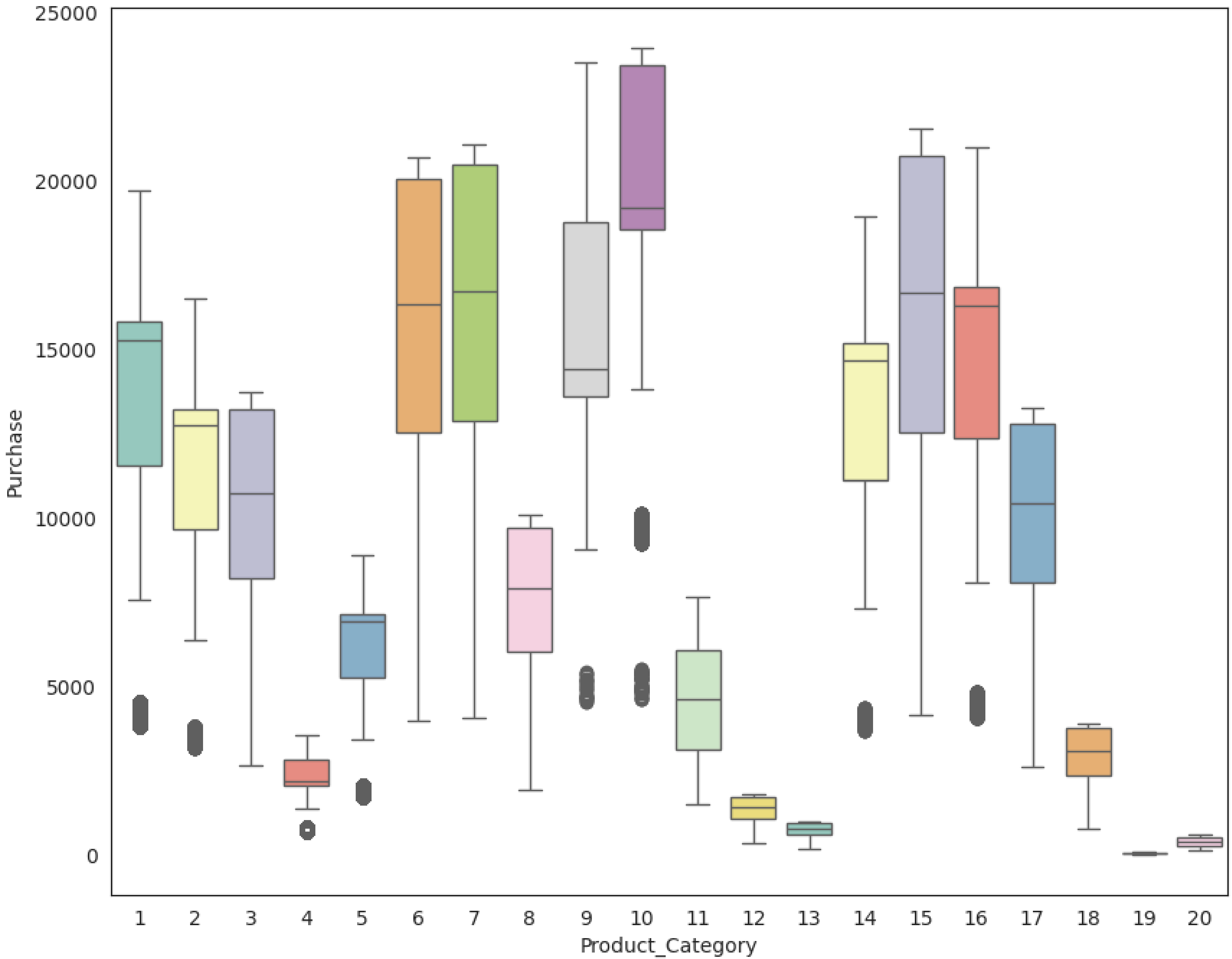

Purchase vs City_Category
25000
20000
15000
10000
5000
0
Purchase



In [ ]:

```
plt.figure(figsize=(10, 8))
sns.boxplot(data=df, y='Purchase', x=attrs[-1], palette='Set3')
plt.show()
```

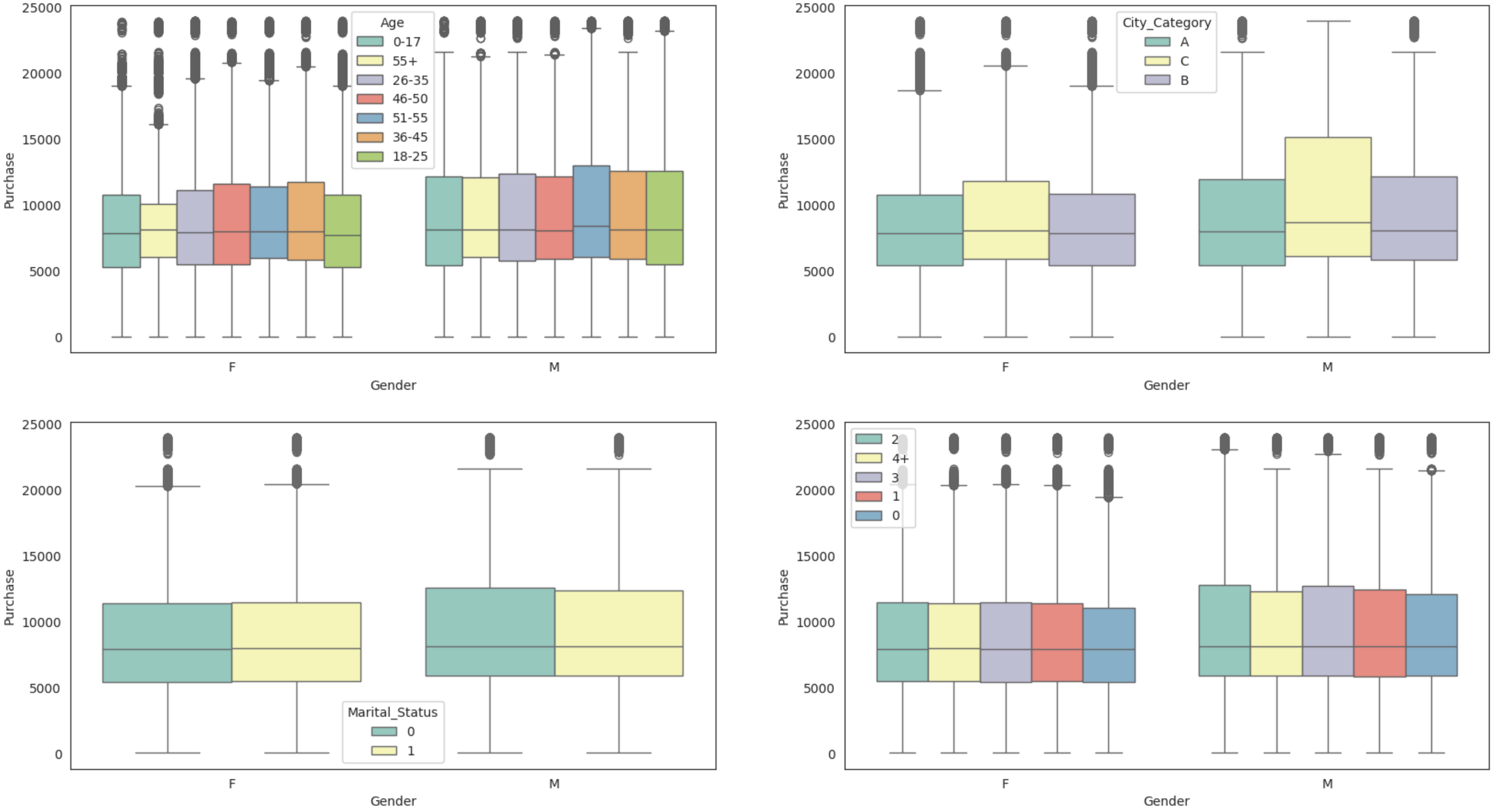
```
<ipython-input-25-962dca1427f4>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue
` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=attrs[-1], palette='Set3')
```


25000
20000
15000
10000
5000
0
Purchase
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
Product_Category

Multivariate Analysis

In [ ]:

```
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()
```



In [ ]:

```
df.head(10)
```

Out[ ]:

	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
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969
5	1000003	P00193542	M	26-35	15	A	3	0	1	15227
6	1000004	P00184942	M	46-50	7	B	2	1	1	19215
7	1000004	P00346142	M	46-50	7	B	2	1	1	15854
8	1000004	P0097242	M	46-50	7	B	2	1	1	15686
9	1000005	P00274942	M	26-35	20	A	1	1	8	7871

Answering questions:

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

Average amount spend per customer for Male and Female

In [ ]:

```
amt_df = df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[ ]:

	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
...	...	...	...

	User_ID	Gender	Purchase
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

5891 rows × 3 columns

In [ ]:

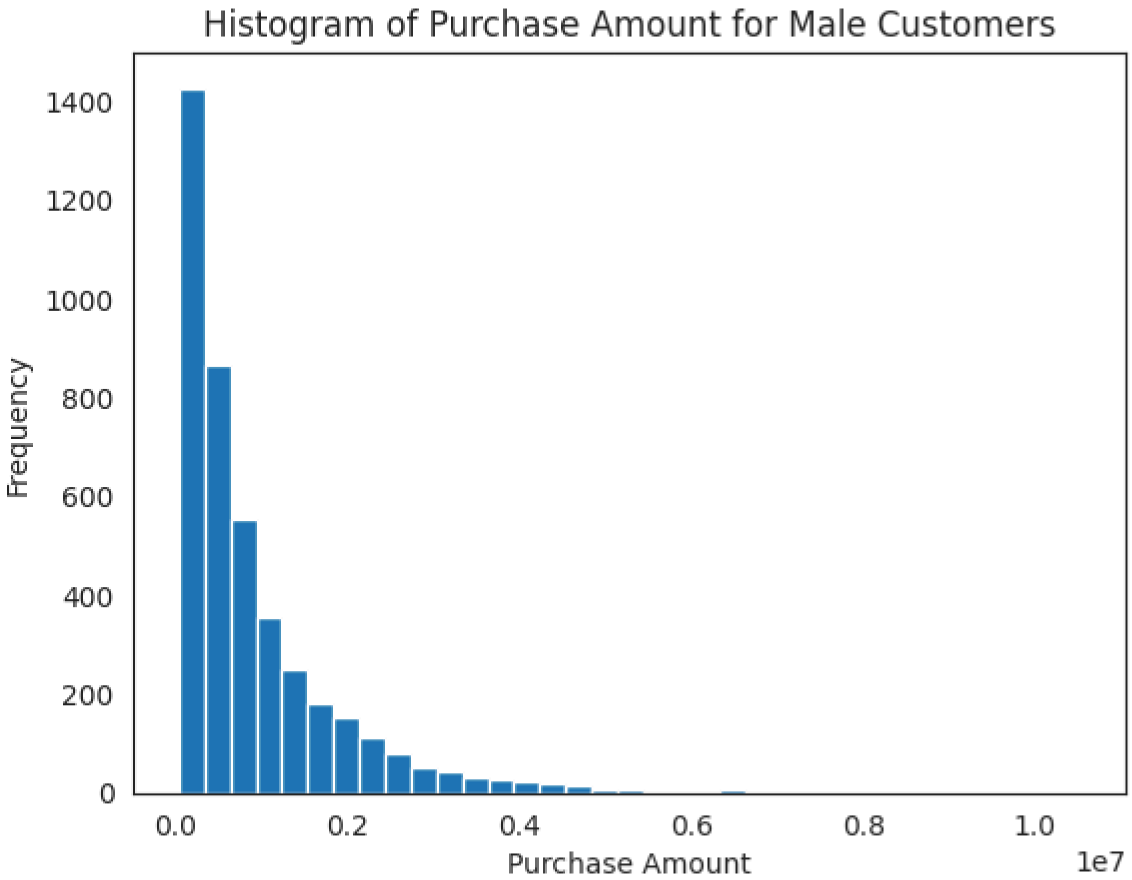
```
# Gender wise value counts in avg_amt_df
avg_amt_df = amt_df['Gender'].value_counts()
avg_amt_df
```

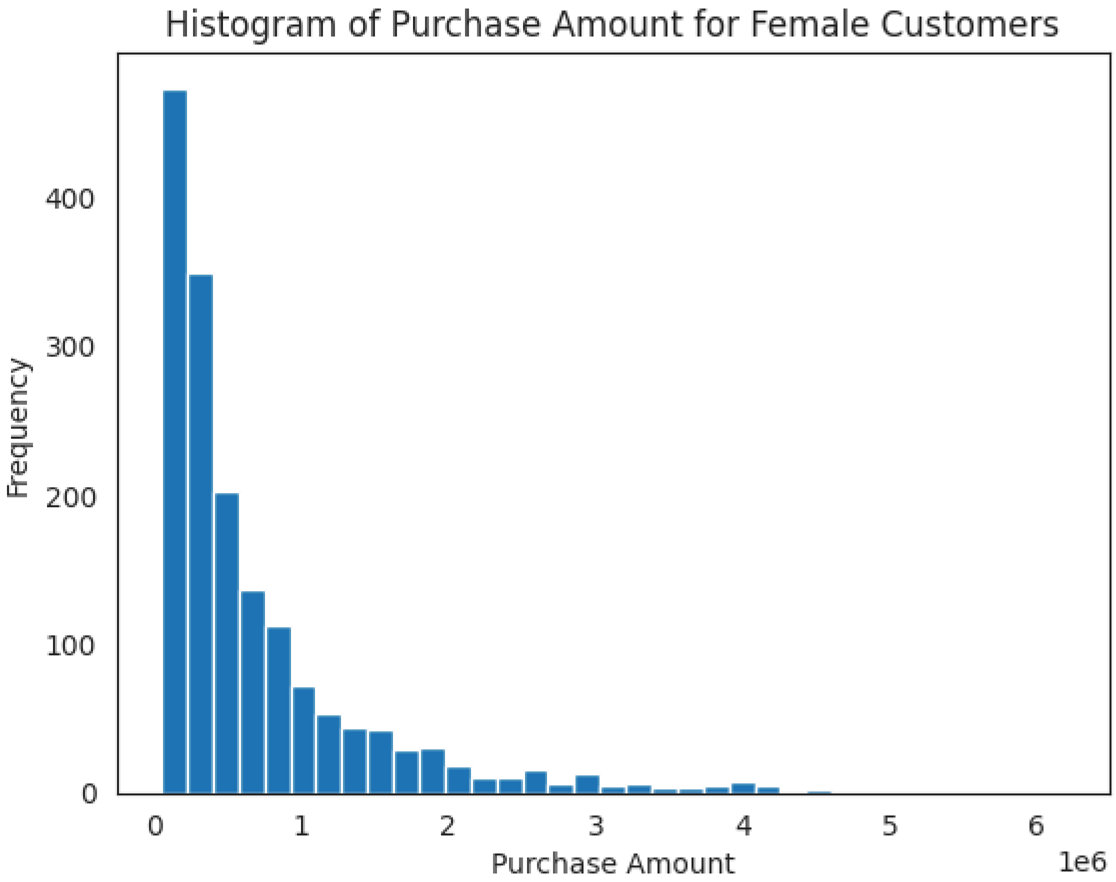
Out[ ]:

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

In [ ]:

```
# histogram of average amount spent for each customer - Male & Female
plt.figure()  # Create a new figure

plt.hist(amt_df[amt_df['Gender']=='M']['Purchase'], bins=35)
plt.title("Histogram of Purchase Amount for Male Customers")
plt.xlabel("Purchase Amount")
plt.ylabel("Frequency")
plt.show()

plt.figure()  # Create a new figure

plt.hist(amt_df[amt_df['Gender']=='F']['Purchase'], bins=35)
plt.title("Histogram of Purchase Amount for Female Customers")
plt.xlabel("Purchase Amount")
plt.ylabel("Frequency")
plt.show()
```


Histogram of Purchase Amount for Male Customers
1400
1200
1000
800
600
400
200
0
Frequency
0.0
0.2
0.4
0.6
0.8
1.0
1e7
Purchase Amount



In [ ]:
```
male_avg = amt_df[amt_df['Gender']=='M']['Purchase'].mean()
female_avg = amt_df[amt_df['Gender']=='F']['Purchase'].mean()

print("Average amount spend by Male customers: {:.2f}".format(male_avg))
print("Average amount spend by Female customers: {:.2f}".format(female_avg))
```

```
Average amount spend by Male customers: 925344.40
Average amount spend by Female customers: 712024.39
```

Observation

Male customers spend more money than female customers

1. The number of total males (4225) is greater than number of total females (1666).

2. Average amount spend by Male customers (925344.40) is greater than Average amount spend by Female customers(712024.39).

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

Sample Size:

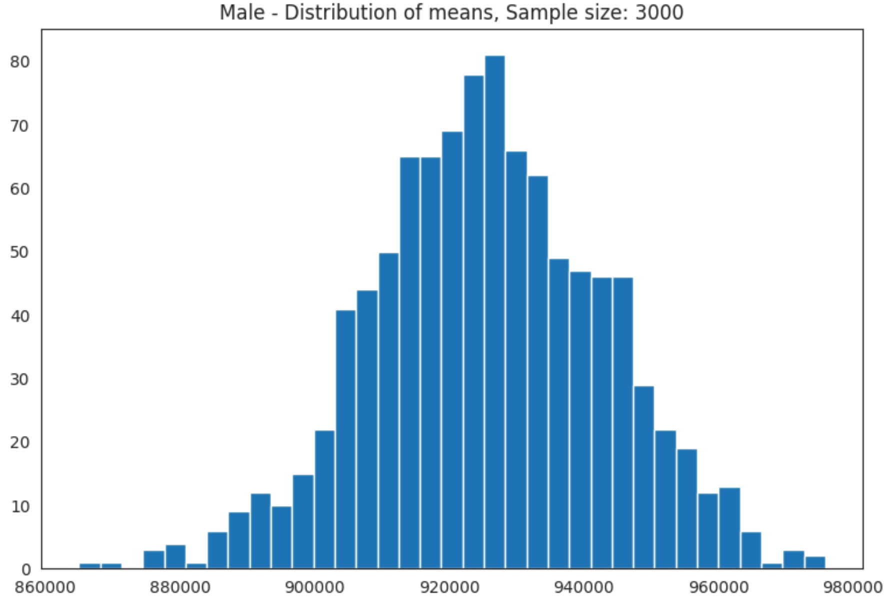
male_sample_size = 3000

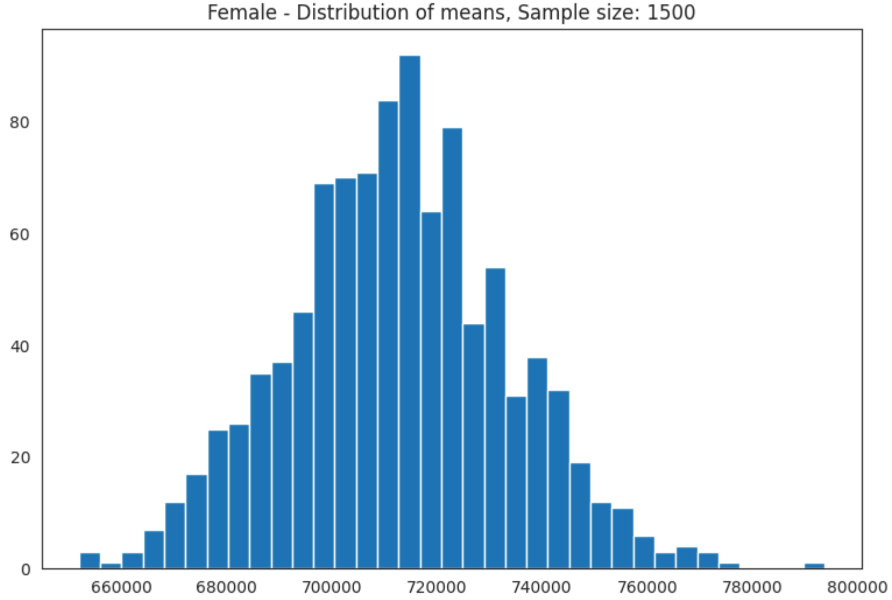
female_sample_size = 1500

In [ ]:
```
male_df = amt_df[amt_df['Gender']=='M']
female_df = amt_df[amt_df['Gender']=='F']
```

In [ ]:
```
genders = ["M", "F"]

male_sample_size = 3000
female_sample_size = 1500
num_repitions = 1000
male_means = []
female_means = []

for _ in range(num_repitions):
    male_mean = male_df.sample(male_sample_size, replace=True)['Purchase'].mean()
    female_mean = female_df.sample(female_sample_size, replace=True)['Purchase'].mean()

    male_means.append(male_mean)
    female_means.append(female_mean)
```

In [ ]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=35)
axis[1].hist(female_means, bins=35)
axis[0].set_title("Male - Distribution of means, Sample size: 3000")
axis[1].set_title("Female - Distribution of means, Sample size: 1500")

plt.show()
```





In [ ]:

```
print("Population mean - Mean of sample means of amount spend for Male: {:.2f}".format(np.mean(male_means)))
print("Population mean - Mean of sample means of amount spend for Female: {:.2f}".format(np.mean(female_means)))

print("\nMale - Sample mean: {:.2f} Sample std: {:.2f}".format(male_df['Purchase'].mean(), male_df['Purchase'].std()))
print("Female - Sample mean: {:.2f} Sample std: {:.2f}".format(female_df['Purchase'].mean(), female_df['Purchase'].std(
```

```
Population mean - Mean of sample means of amount spend for Male: 925621.33
Population mean - Mean of sample means of amount spend for Female: 712502.10

Male - Sample mean: 925344.40 Sample std: 985830.10
Female - Sample mean: 712024.39 Sample std: 807370.73
```

Observation:

Now using the **Central Limit Theorem** for the **population** we can say that:

1. Average amount spend by male customers is **925344.40**
2. Average amount spend by female customers is **712024.39**

Sample Size:

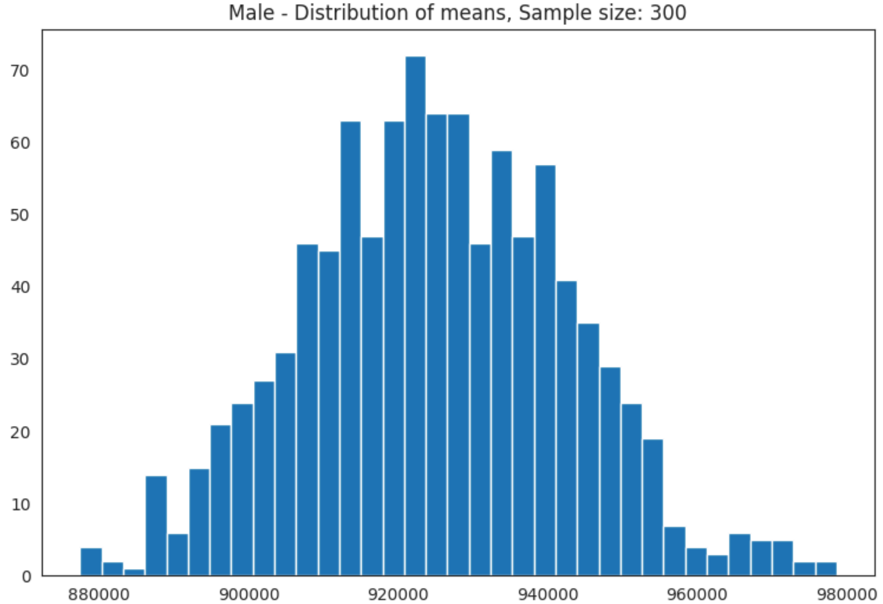
male_sample_size = 300

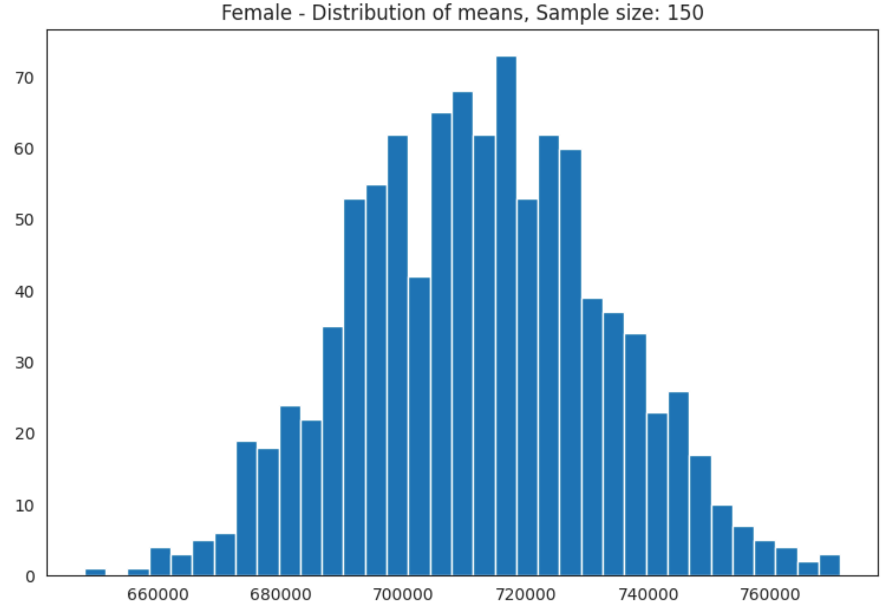
female_sample_size = 150

In [ ]:
```
male_df = amt_df[amt_df['Gender']=='M']
female_df = amt_df[amt_df['Gender']=='F']
```

In [ ]:
```
genders = ["M", "F"]

male_sample_size = 3000
female_sample_size = 1500
num_repitions = 1000
male_means = []
female_means = []

for _ in range(num_repitions):
    male_mean = male_df.sample(male_sample_size, replace=True)['Purchase'].mean()
    female_mean = female_df.sample(female_sample_size, replace=True)['Purchase'].mean()

    male_means.append(male_mean)
    female_means.append(female_mean)
```

In [ ]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=35)
axis[1].hist(female_means, bins=35)
axis[0].set_title("Male - Distribution of means, Sample size: 300")
axis[1].set_title("Female - Distribution of means, Sample size: 150")

plt.show()
```





In [ ]:

```
print("Population mean - Mean of sample means of amount spend for Male: {:.2f}".format(np.mean(male_means)))
print("Population mean - Mean of sample means of amount spend for Female: {:.2f}".format(np.mean(female_means)))

print("\nMale - Sample mean: {:.2f} Sample std: {:.2f}".format(male_df['Purchase'].mean(), male_df['Purchase'].std()))
print("Female - Sample mean: {:.2f} Sample std: {:.2f}".format(female_df['Purchase'].mean(), female_df['Purchase'].std(
```

```
Population mean - Mean of sample means of amount spend for Male: 924978.60
Population mean - Mean of sample means of amount spend for Female: 712356.27

Male - Sample mean: 925344.40 Sample std: 985830.10
Female - Sample mean: 712024.39 Sample std: 807370.73
```

Sample Size:

male_sample_size = 30000

female_sample_size = 15000

In [ ]:

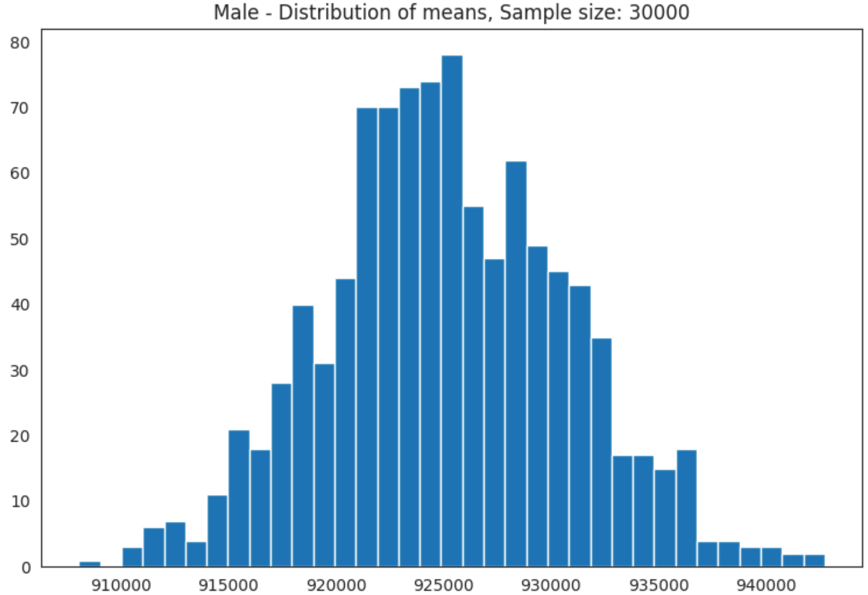
```
male_df = amt_df[amt_df['Gender']=='M']
female_df = amt_df[amt_df['Gender']=='F']
```

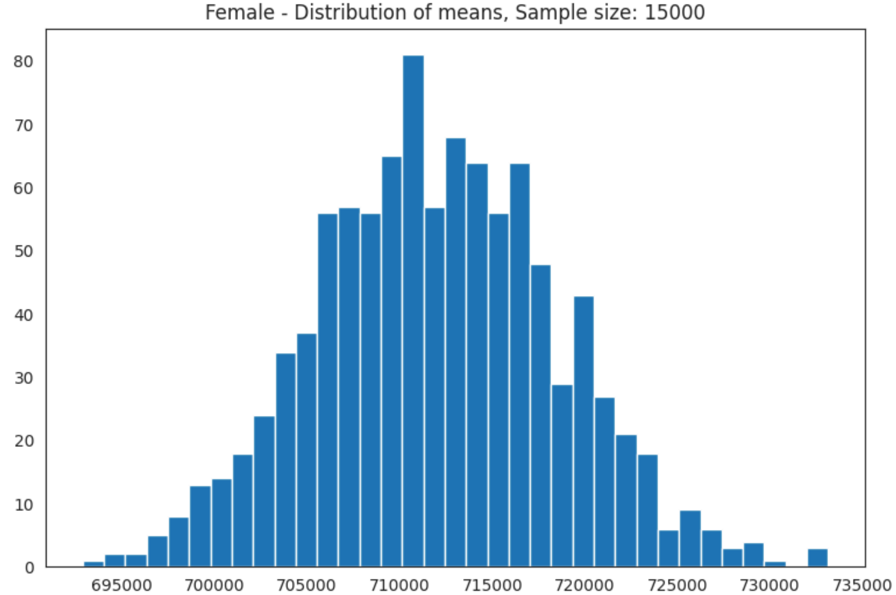
In [ ]:

```
genders = ["M", "F"]

male_sample_size = 30000
female_sample_size = 15000
num_repitions = 1000
male_means = []
female_means = []

for _ in range(num_repitions):
    male_mean = male_df.sample(male_sample_size, replace=True)['Purchase'].mean()
    female_mean = female_df.sample(female_sample_size, replace=True)['Purchase'].mean()

    male_means.append(male_mean)
    female_means.append(female_mean)
```

In [ ]:

```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=35)
axis[1].hist(female_means, bins=35)
axis[0].set_title("Male - Distribution of means, Sample size: 30000")
axis[1].set_title("Female - Distribution of means, Sample size: 15000")

plt.show()
```





In [ ]:
```
print("Population mean - Mean of sample means of amount spend for Male: {:.2f}".format(np.mean(male_means)))
print("Population mean - Mean of sample means of amount spend for Female: {:.2f}".format(np.mean(female_means)))

print("\nMale - Sample mean: {:.2f} Sample std: {:.2f}".format(male_df['Purchase'].mean(), male_df['Purchase'].std()))
print("Female - Sample mean: {:.2f} Sample std: {:.2f}".format(female_df['Purchase'].mean(), female_df['Purchase'].std(
```

```
Population mean - Mean of sample means of amount spend for Male: 925145.94
Population mean - Mean of sample means of amount spend for Female: 712019.70

Male - Sample mean: 925344.40 Sample std: 985830.10
Female - Sample mean: 712024.39 Sample std: 807370.73
```

Observation:

For sample size 300, 3000, and 30000:

Population mean - Mean of sample means of amount spend for Male:

300 -> 924972.04

3000 -> 925321.16

30000 -> 925406.43

Population mean - Mean of sample means of amount spend for Female:

150 -> 712298.71

1500 -> 711995.61

15000 -> 711949.28

We can clearly observe that Mean of sample means for different sample sizes are almost the same.

3)Are confidence intervals of average male and female spending overlapping?

How can Walmart leverage this conclusion to make changes or improvements?

Confidence Interval -> Z

90% -> 1.645

95% -> 1.960

99% -> 2.576

99% Confidence Interval:

In [ ]:
```
#99% Confidence Interval

male_margin_of_error_clt = 2.576*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt

female_margin_of_error_clt = 2.576*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt

print("99% Confidence Interval:")
print("Male confidence interval of means: ({:.2f}, {:.2f})".format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_lower_lim, female_upper_lim))
```

```
99% Confidence Interval:
Male confidence interval of means: (886275.20, 964413.61)
Female confidence interval of means: (661070.03, 762978.76)
```

Observation:

For 99% Confidence Interval, the range for male & female is not overlapping.

Now we can infer about the population that, **99% of the times**:

1. Average amount spend by male customer will lie in between: **(886275.20, 964413.61)**
2. Average amount spend by female customer will lie in between: **(661070.03, 762978.76)**

95% Confidence Interval:

In [ ]:
```
#95% Confidence Interval

male_margin_of_error_clt = 1.96*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt

female_margin_of_error_clt = 1.96*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt

print("95% Confidence Interval:")
print("Male confidence interval of means: ({:.2f}, {:.2f})".format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_lower_lim, female_upper_lim))
```

```
95% Confidence Interval:
Male confidence interval of means: (895617.83, 955070.97)
Female confidence interval of means: (673254.77, 750794.02)
```

Observation:

For 95% Confidence Interval, the range for male & female is not overlapping.

Now we can infer about the population that, **95% of the times**:

1. Average amount spend by male customer will lie in between: **(895617.83, 955070.97)**

2. Average amount spend by female customer will lie in between: **(673254.77, 750794.02)**

90% Confidence Interval:

In [ ]:
```
#90% Confidence Interval

male_margin_of_error_clt = 1.645*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt

female_margin_of_error_clt = 1.645*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt

print("90% Confidence Interval:")
print("Male confidence interval of means: ({:.2f}, {:.2f})".format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_lower_lim, female_upper_lim))
```

```
90% Confidence Interval:
Male confidence interval of means: (900395.32, 950293.49)
Female confidence interval of means: (679485.60, 744563.19)
```

Observation:

For 90% Confidence Interval, the range for male & female is not overlapping.

Now we can infer about the population that, **90% of the times**:

1. Average amount spend by male customer will lie in between: **(900395.32, 950293.49)**
2. Average amount spend by female customer will lie in between: **(679485.60, 744563.19)**

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

Doing the same process for married vs unmarried

In [ ]:
```
amt_df
```

Out[ ]:

	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
...	...	...	...
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

5891 rows × 3 columns

In [ ]:

```
amt_df = df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[ ]:

	User_ID	Marital_Status	Purchase
0	1000001	0	334093
1	1000002	0	810472
2	1000003	0	341635
3	1000004	1	206468
4	1000005	1	821001
...	...	...	...
5886	1006036	1	4116058
5887	1006037	0	1119538

	User_ID	Marital_Status	Purchase
5888	1006038	0	90034
5889	1006039	1	590319
5890	1006040	0	1653299

5891 rows × 3 columns

In [ ]:

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

Out[ ]:

```
Marital_Status
0    3417
1    2474
Name: count, dtype: int64
```

Sample Size:

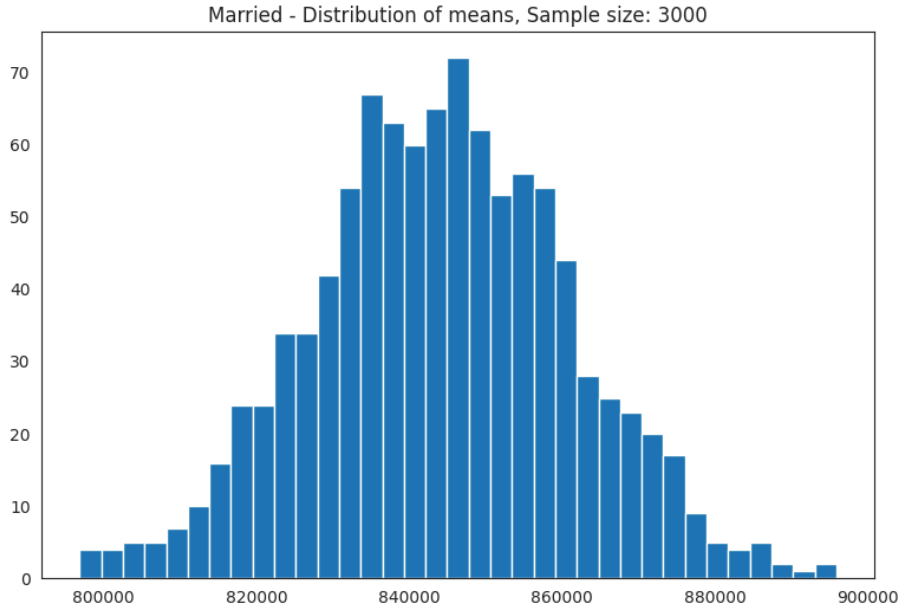
marid_samp_size = 3000

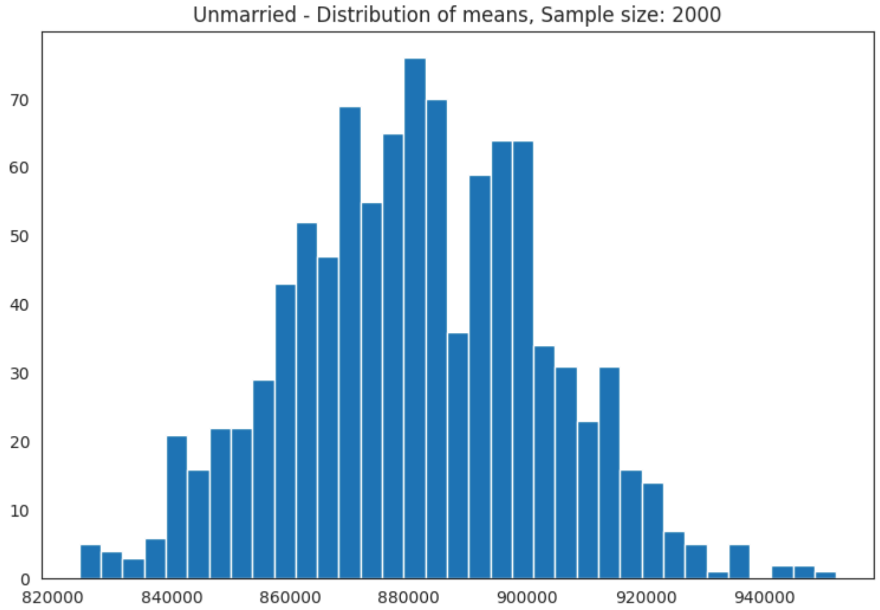
unmarid_sample_size = 2000

In [ ]:

```
marid_samp_size = 3000
unmarid_sample_size = 2000
num_repitions = 1000
marid_means = []
unmarid_means = []

for _ in range(num_repitions):
    marid_mean = amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size, replace=True)['Purchase'].mean()
    unmarid_mean = amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size, replace=True)['Purchase'].mean()

    marid_means.append(marid_mean)
    unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid_means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 3000")
```

```
axis[1].set_title("Unmarried - Distribution of means, Sample size: 2000")

plt.show()

print("Population mean - Mean of sample means of amount spend for Married: {:.2f}".format(np.mean(marid_means)))
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.2f}".format(np.mean(unmarid_means)))

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(
```






```
Population mean - Mean of sample means of amount spend for Married: 844190.17
Population mean - Mean of sample means of amount spend for Unmarried: 881481.84

Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
```

Sample Size:

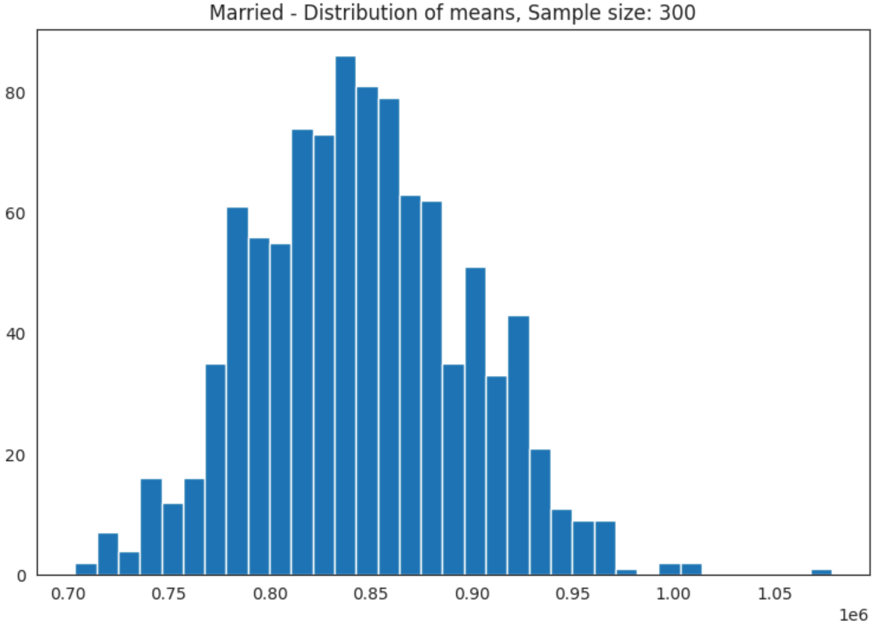
marid_samp_size = 300

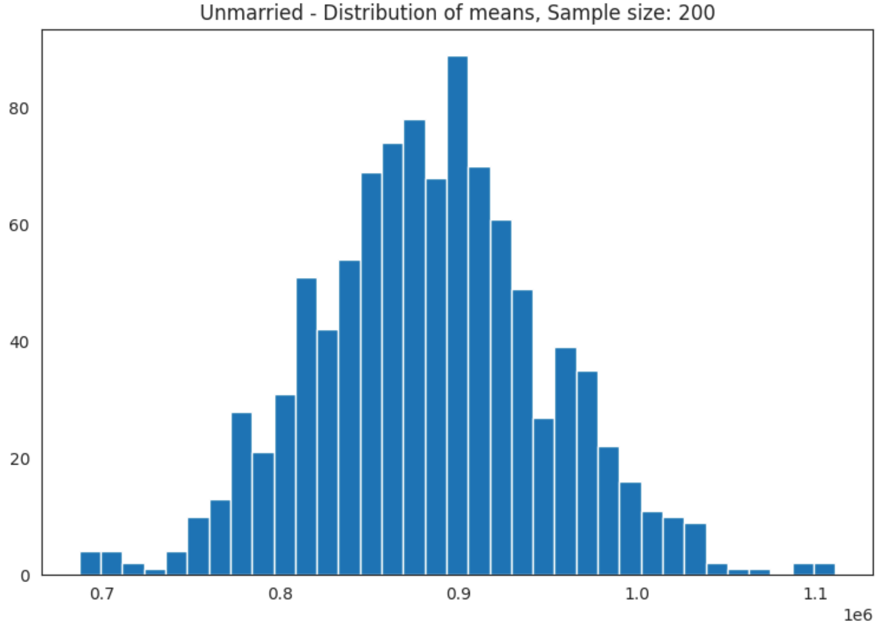
unmarid_sample_size = 200

In [ ]:

```
marid_samp_size = 300
unmarid_sample_size = 200
num_repitions = 1000
```

```
marid_means = []
unmarid_means = []

for _ in range(num_repitions):
    marid_mean = amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size, replace=True)['Purchase'].mean()
    unmarid_mean = amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size, replace=True)['Purchase'].mean()

    marid_means.append(marid_mean)
    unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid_means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 300")
axis[1].set_title("Unmarried - Distribution of means, Sample size: 200")

plt.show()

print("Population mean - Mean of sample means of amount spend for Married: {:.2f}".format(np.mean(marid_means)))
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.2f}".format(np.mean(unmarid_means)))

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(
```






```
Population mean - Mean of sample means of amount spend for Married: 845043.78
Population mean - Mean of sample means of amount spend for Unmarried: 884173.60

Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
```

In [ ]:

```

```

Sample Size:

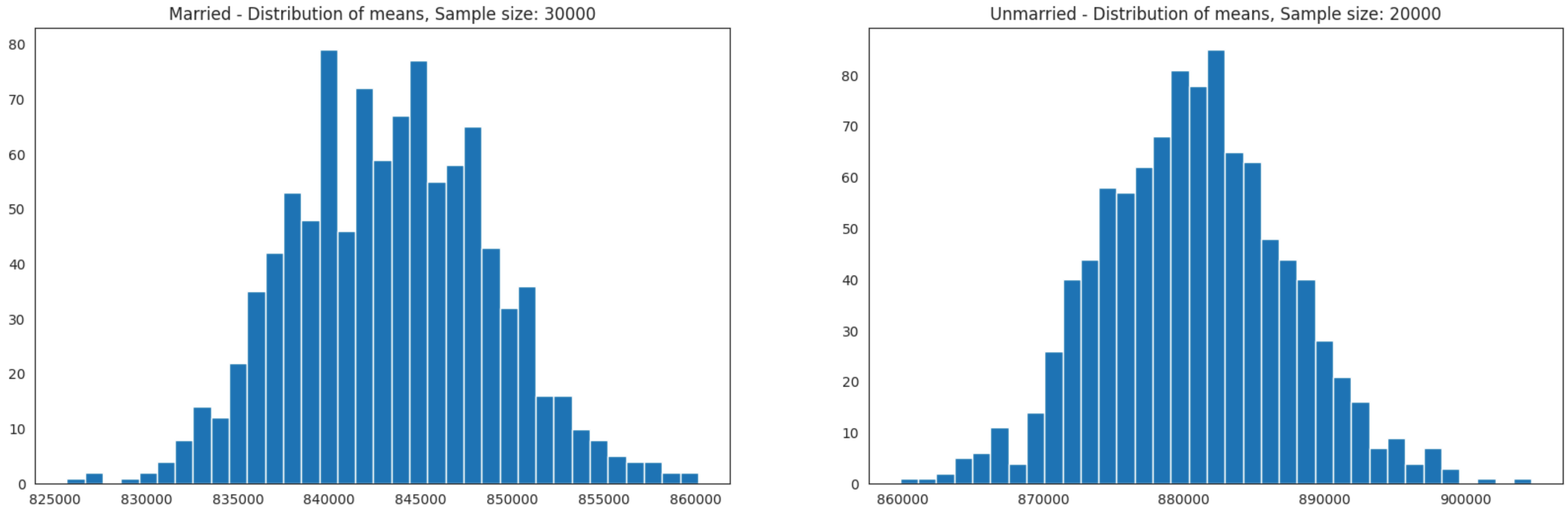
marid_samp_size = 30000

unmarid_sample_size = 20000

In [ ]:

```
marid_samp_size = 30000
unmarid_sample_size = 20000
num_repitions = 1000
marid_means = []
unmarid_means = []

for _ in range(num_repitions):
    marid_mean = amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size, replace=True)['Purchase'].mean()
```

```
    unmarid_mean = amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size, replace=True)['Purchase'].mean()

    marid_means.append(marid_mean)
    unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid_means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 30000")
axis[1].set_title("Unmarried - Distribution of means, Sample size: 20000")

plt.show()

print("Population mean - Mean of sample means of amount spend for Married: {:.2f}".format(np.mean(marid_means)))
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.2f}".format(np.mean(unmarid_means)))

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(
```




```
Population mean - Mean of sample means of amount spend for Married: 843364.51
Population mean - Mean of sample means of amount spend for Unmarried: 880709.36
```

```
Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
```

Observation:

For sample size 300, 3000, and 30000:

Population mean - Mean of sample means of amount spend for Married:

300 -> 843184.78
3000 -> 844173.99
30000 -> 843465.84

Population mean - Mean of sample means of amount spend for Unmarried:

150 -> 879775.58
1500 -> 880847.26
15000 -> 880747.41

We can clearly observe that Mean of sample means for different sample sizes are almost the same.

Confidence Interval -> Z

80% -> 1.282
85% -> 1.440
90% -> 1.645
95% -> 1.960
99% -> 2.576

99% Confidence Interval:

In [ ]:
```
#99% Confidence Interval

print("99% Confidence Interval:")
for val in ["Married", "Unmarried"]:

    new_val = 1 if val == "Married" else 0

    new_df = amt_df[amt_df['Marital_Status']==new_val]
```

```
    margin_of_error_clt = 2.576*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
99% Confidence Interval:
Married confidence interval of means: (795084.90, 891968.69)
Unmarried confidence interval of means: (838736.02, 922415.54)
```

Observation:

For 99% Confidence Interval:

The confidence interval of means of Married and Unmarried is overlapping.

So, we reduce the Confidence Interval to 95% and try again.

95% Confidence Interval:

In [ ]:

```
#95% Confidence Interval

print("95% Confidence Interval:")
for val in ["Married", "Unmarried"]:

    new_val = 1 if val == "Married" else 0

    new_df = amt_df[amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
95% Confidence Interval:
Married confidence interval of means: (806668.83, 880384.76)
Unmarried confidence interval of means: (848741.18, 912410.38)
```

Observation:

For 95% Confidence Interval:

The confidence interval of means of Married and Unmarried is overlapping.

So, we reduce the Confidence Interval to 90% and try again.

90% Confidence Interval:

In [ ]:

```
#90% Confidence Interval

print("90% Confidence Interval:")
for val in ["Married", "Unmarried"]:

    new_val = 1 if val == "Married" else 0

    new_df = amt_df[amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 1.645*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
90% Confidence Interval:
Married confidence interval of means: (812592.43, 874461.16)
Unmarried confidence interval of means: (853857.46, 907294.11)
```

Observation:

For 90% Confidence Interval:

The confidence interval of means of Married and Unmarried is overlapping.

So, we reduce the Confidence Interval to 85% and try again.

85% Confidence Interval:

In [ ]:

```
#85% Confidence Interval

print("85% Confidence Interval:")
for val in ["Married", "Unmarried"]:

    new_val = 1 if val == "Married" else 0
```

```
    new_df = amt_df[amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 1.440*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
85% Confidence Interval:
Married confidence interval of means: (816447.48, 870606.12)
Unmarried confidence interval of means: (857187.10, 903964.47)
```

Observation:

For 85% Confidence Interval:

The confidence interval of means of Married and Unmarried is overlapping.

So, we reduce the Confidence Interval to 80% and try again.

80% Confidence Interval:

In [ ]:
```
#80% Confidence Interval

print("80% Confidence Interval:")
for val in ["Married", "Unmarried"]:

    new_val = 1 if val == "Married" else 0

    new_df = amt_df[amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 1.282*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
80% Confidence Interval:
Married confidence interval of means: (819418.68, 867634.91)
Unmarried confidence interval of means: (859753.36, 901398.21)
```

Observation:

For 80% Confidence Interval:

The confidence interval of means of Married and Unmarried is overlapping.

But the overlapping has significantly reduced.

Now we can infer about the population that, **80% of the times**:

1. Average amount spend by Married customer will lie in between: **(819418.68, 867634.91)**
2. Average amount spend by Unmarried customer will lie in between: **(859753.36, 901398.21)**

5)Results when the same activity is performed for Age

Calculating the average amount spent by Age

In [ ]:

```
amt_df = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[ ]:

	User_ID	Age	Purchase
0	1000001	0-17	334093
1	1000002	55+	810472
2	1000003	26-35	341635
3	1000004	46-50	206468
4	1000005	26-35	821001
...	...	...	...
5886	1006036	26-35	4116058
5887	1006037	46-50	1119538
5888	1006038	55+	90034
5889	1006039	46-50	590319
5890	1006040	26-35	1653299

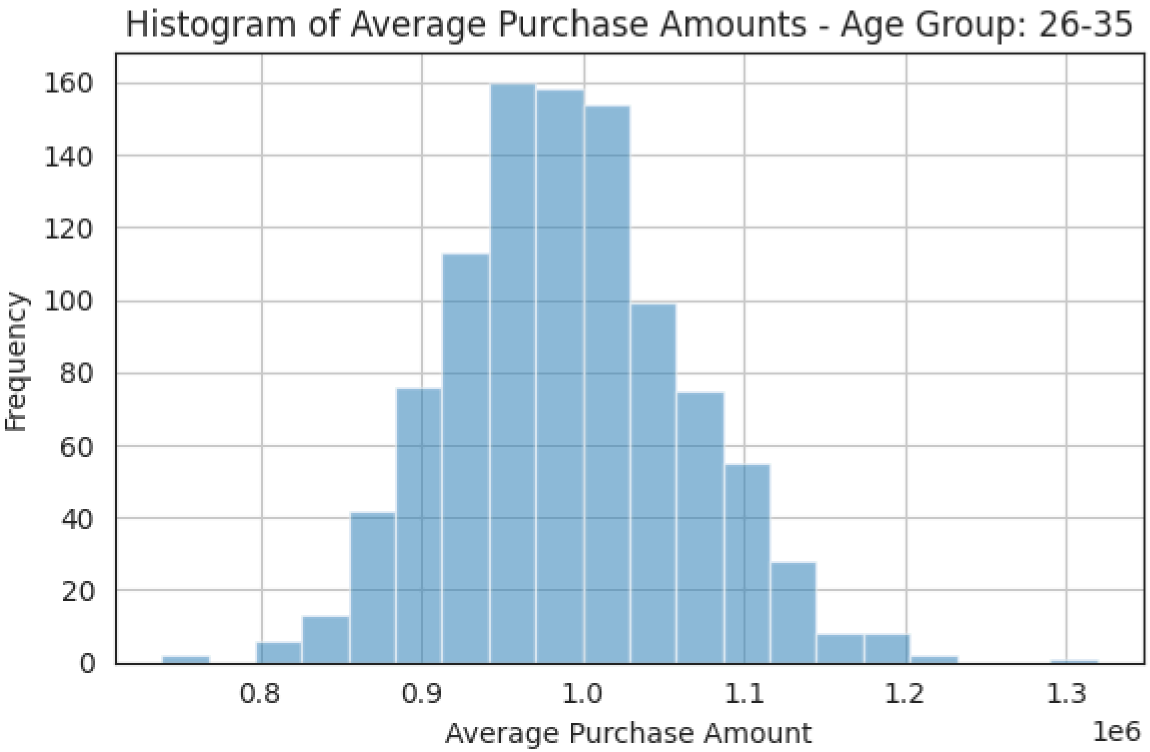
5891 rows × 3 columns

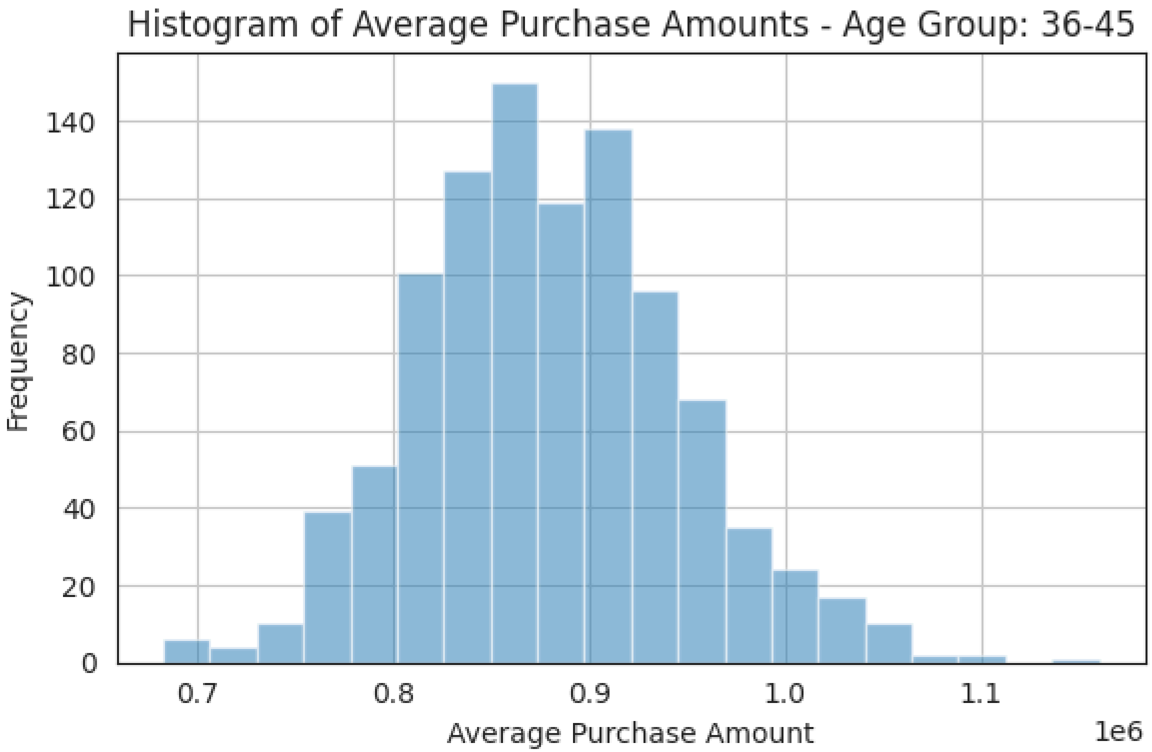
In [ ]:
```
amt_df['Age'].value_counts()
```

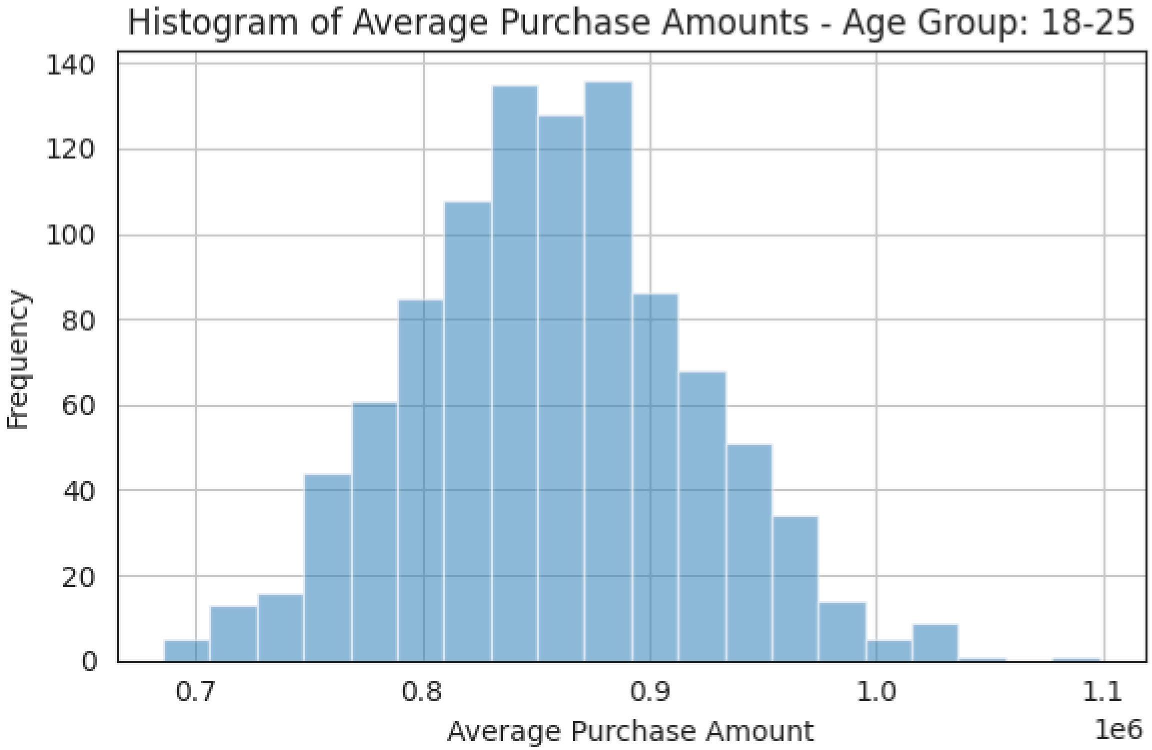
Out[ ]:
```
Age
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: count, dtype: int64
```

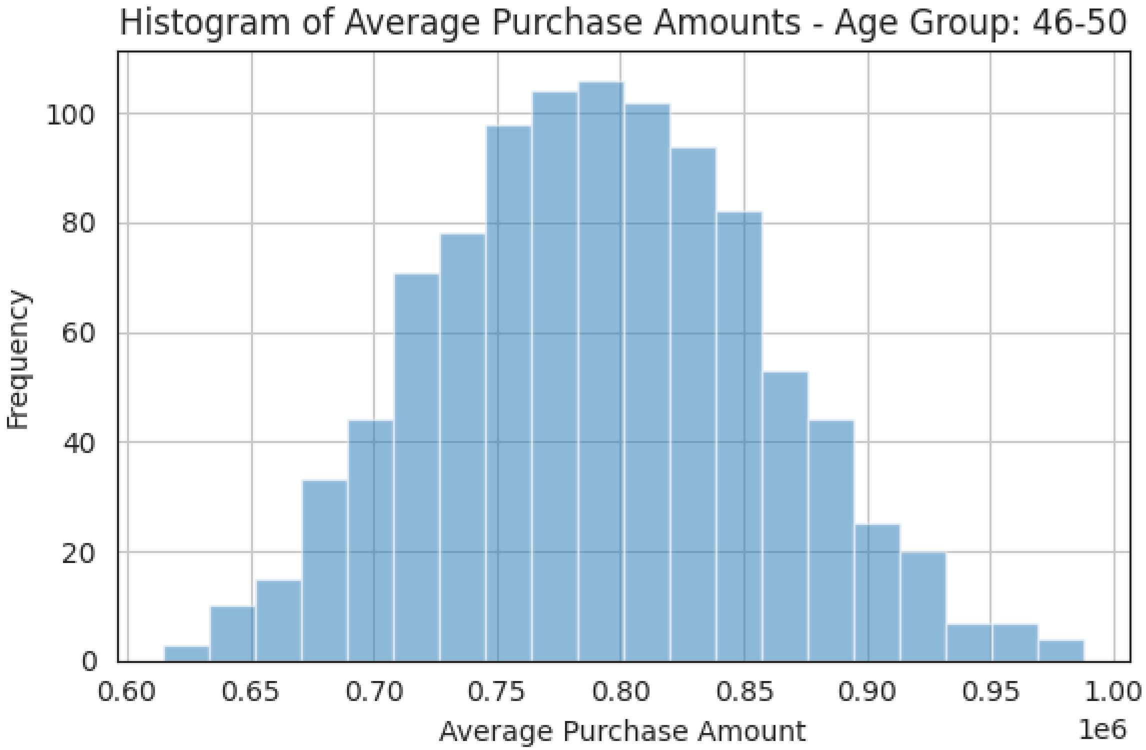
In [ ]:
```
sample_size = 200
num_repitions = 1000

all_means = {}

age_intervals = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
for age_interval in age_intervals:
    all_means[age_interval] = []

for age_interval in age_intervals:
    for _ in range(num_repitions):
        mean = amt_df[amt_df['Age']==age_interval].sample(sample_size, replace=True)['Purchase'].mean()
        all_means[age_interval].append(mean)
```

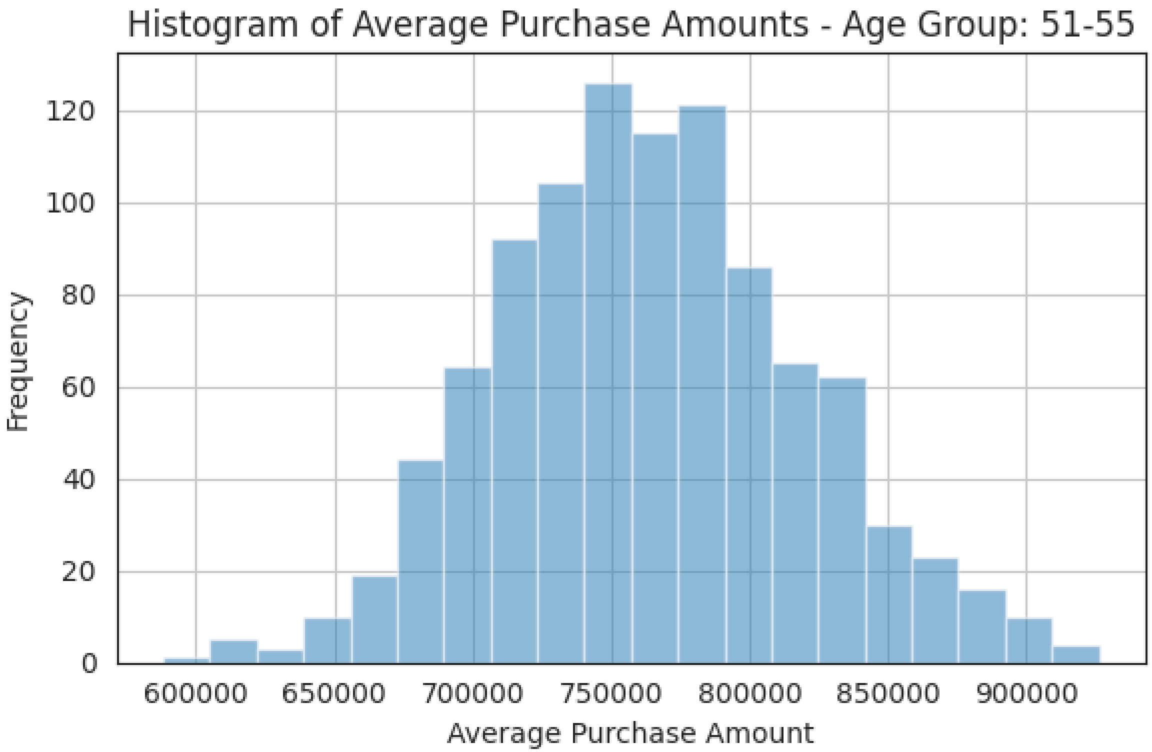
In [ ]:
```
# Create separate histogram plots for each age group's average purchase amounts
for age_interval in age_intervals:
    plt.figure(figsize=(6, 4))  # Adjust the figure size here
    plt.hist(all_means[age_interval], bins=20, alpha=0.5)
    plt.title(f"Histogram of Average Purchase Amounts - Age Group: {age_interval}")
    plt.xlabel("Average Purchase Amount")
    plt.ylabel("Frequency")
    plt.grid(True)
    plt.tight_layout()  # Ensures plots are well-arranged
    plt.show()
```

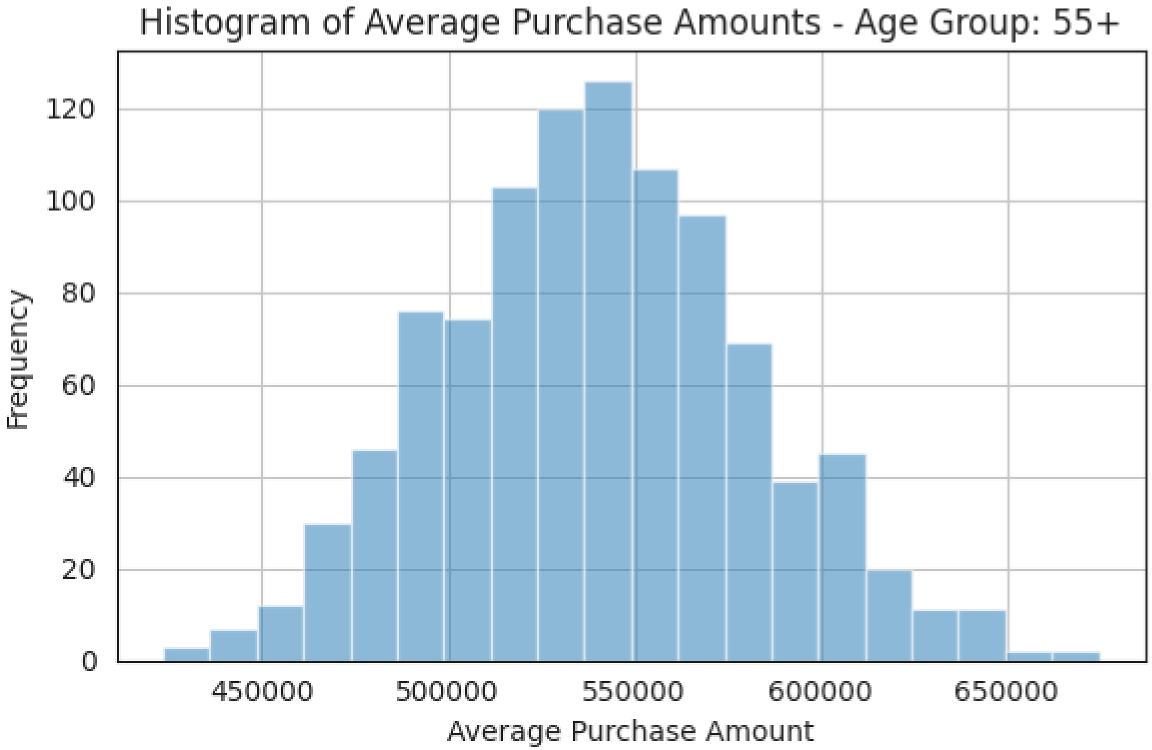

Histogram of Average Purchase Amounts - Age Group: 26-35
Frequency
0
20
40
60
80
100
120
140
160
0.8
0.9
1.0
1.1
1.2
1.3
1e6
Average Purchase Amount

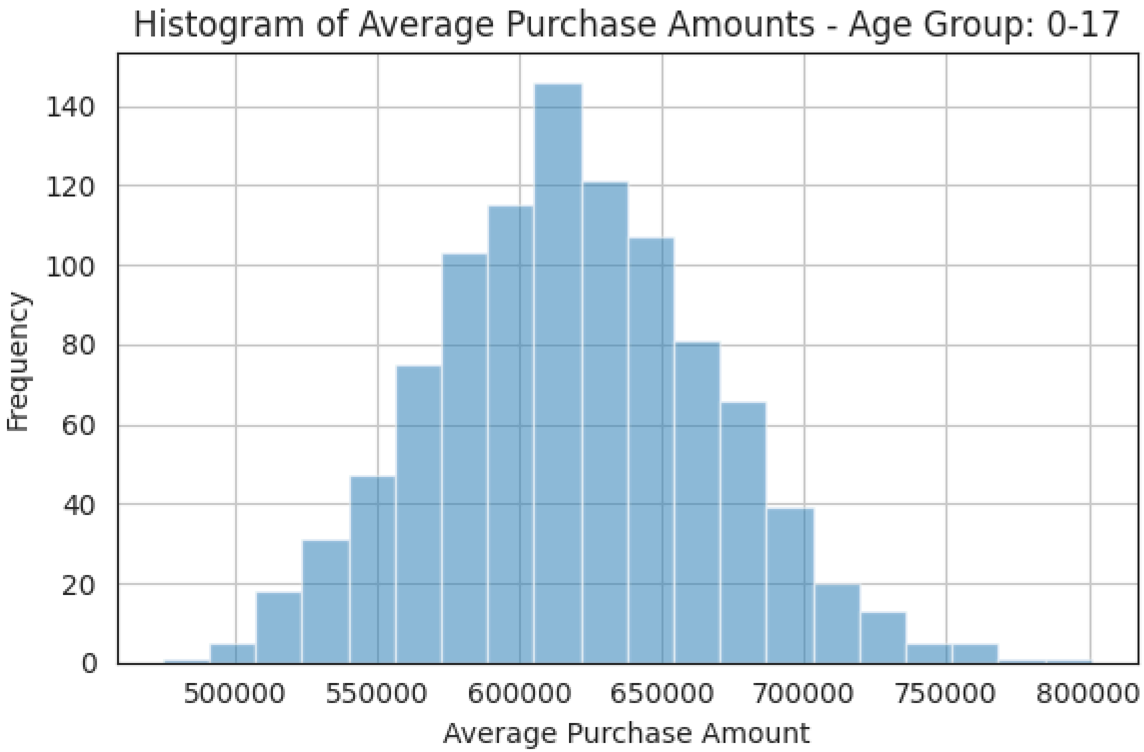

Histogram of Average Purchase Amounts - Age Group: 36-45
Frequency
0
20
40
60
80
100
120
140
0.7
0.8
0.9
1.0
1.1
1e6
Average Purchase Amount


Histogram of Average Purchase Amounts - Age Group: 18-25
Frequency
0
20
40
60
80
100
120
140
0.7
0.8
0.9
1.0
1.1
1e6
Average Purchase Amount


Histogram of Average Purchase Amounts - Age Group: 46-50
Frequency
0
20
40
60
80
100
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
1e6
Average Purchase Amount


Histogram of Average Purchase Amounts - Age Group: 51-55
Frequency
0
20
40
60
80
100
120
600000
650000
700000
750000
800000
850000
900000
Average Purchase Amount


Histogram of Average Purchase Amounts - Age Group: 55+
Frequency
0
20
40
60
80
100
120
450000
500000
550000
600000
650000
Average Purchase Amount



99% Confidence Interval:

In [ ]:
```python
#99% Confidence Interval

for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = amt_df[amt_df['Age']==val]

    margin_of_error_clt = 2.576*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
For age 26-35 --> confidence interval of means: (931009.46, 1048309.18)
For age 36-45 --> confidence interval of means: (805647.89, 953683.53)
For age 18-25 --> confidence interval of means: (784903.24, 924823.00)
```

```
For age 46-50 --> confidence interval of means: (688663.50, 896434.06)
For age 51-55 --> confidence interval of means: (670138.33, 856263.52)
For age 55+ --> confidence interval of means: (457227.15, 622167.34)
For age 0-17 --> confidence interval of means: (498997.92, 738737.71)
```

95% Confidence Interval:

In [ ]:

```
#95% Confidence Interval

for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = amt_df[amt_df['Age']==val]

    margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt

    print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
For age 26-35 --> confidence interval of means: (945034.42, 1034284.21)
For age 36-45 --> confidence interval of means: (823347.80, 935983.62)
For age 18-25 --> confidence interval of means: (801632.78, 908093.46)
For age 46-50 --> confidence interval of means: (713505.63, 871591.93)
For age 51-55 --> confidence interval of means: (692392.43, 834009.42)
For age 55+ --> confidence interval of means: (476948.26, 602446.23)
For age 0-17 --> confidence interval of means: (527662.46, 710073.17)
```

Observation

90% Confidence Interval:

In [ ]:

```
#90% Confidence Interval

for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = amt_df[amt_df['Age']==val]

    margin_of_error_clt = 1.645*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
    upper_lim = sample_mean + margin_of_error_clt
```

```
    print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim))
```

```
For age 26-35 --> confidence interval of means: (952206.28, 1027112.35)
For age 36-45 --> confidence interval of means: (832398.89, 926932.53)
For age 18-25 --> confidence interval of means: (810187.65, 899538.59)
For age 46-50 --> confidence interval of means: (726209.00, 858888.57)
For age 51-55 --> confidence interval of means: (703772.36, 822629.48)
For age 55+ --> confidence interval of means: (487032.92, 592361.57)
For age 0-17 --> confidence interval of means: (542320.46, 695415.16)
```

📊 Insights 📊

Age Distribution 🎂

- ~ 80% of the users are aged between 18-50:
    - 40%: 26-35
    - 18%: 18-25
    - 20%: 36-45

Gender Ratio

- 75% of the users are Male ♂ and 25% are Female ♀

Marital Status

- 60% are Single and 40% are Married

City Residency

- 35% have been staying in the city for 1 year
- 18% have been staying for 2 years
- 17% have been staying for 3 years

Product Categories

- Total of 20 product categories available

Occupations

- 20 different types of occupations in the city

User Demographics

- Most users are Male ♂
- 20 different types of Occupations and Product Categories
- Majority of users belong to City Category B
- More users are Single compared to Married 👤 vs 👫
- Product Categories 1, 5, 8, & 11 have the highest purchasing frequency

Average Spending

- Average amount spent by Male customers: ₹925,344.40
- Average amount spent by Female customers: ₹712,024.39

Confidence Intervals

Gender-wise

Now using the **Central Limit Theorem** for the **population**:

1. Average amount spend by **male** customers is **9,26,341.86**
2. Average amount spend by **female** customers is **7,11,704.09**

For **99% Confidence Interval**:
Now we can infer about the population that, **99% of the times**:

1. Average amount spend by male customer will lie in between: **(886275.20, 964413.61)**
2. Average amount spend by female customer will lie in between: **(661070.03, 762978.76)**

Marital Status-wise

Now using the **Central Limit Theorem** for the **population**:

1. Average amount spend by **Married** customers is **844173.99**
2. Average amount spend by **Unmarried** customers is **880847.26**

For **80% Confidence Interval**:
The confidence interval of means of Married and Unmarried is overlapping.
But the overlapping has significantly reduced.

Now we can infer about the population that, **80% of the times**:

1. Average amount spend by Married customer will lie in between: **(819418.68, 867634.91)**
2. Average amount spend by Unmarried customer will lie in between: **(859753.36, 901398.21)**

Age-wise

For **90% Confidence Interval**:

1. For **age 26-35** --> confidence interval of means: **(952206.28, 1027112.35)**
2. For **age 36-45** --> confidence interval of means: **(832398.89, 926932.53)**
3. For **age 18-25** --> confidence interval of means: **(810187.65, 899538.59)**
4. For **age 46-50** --> confidence interval of means: **(726209.00, 858888.57)**
5. For **age 51-55** --> confidence interval of means: **(703772.36, 822629.48)**
6. For **age 55+** --> confidence interval of means: **(487032.92, 592361.57)**
7. For **age 0-17** --> confidence interval of means: **(542320.46, 695415.16)**

Recommendations

1) Gender-focused Strategy

- Men tend to spend more than women. The company should prioritize retaining existing male customers and attracting new male customers.

2) Product Category Insight

- Products in categories 1, 5, 8, & 11 have the highest purchasing frequency and are favored by customers. The company can consider increasing the promotion and availability of these products, as well as boosting less-purchased items.

3) Marital Status Approach

- Unmarried customers exhibit higher spending compared to married customers. The company should concentrate on attracting and engaging unmarried customers.

4) Targeting Specific Age Group

- Customers aged 18-45 contribute more to the spending. To enhance revenue, the company should focus on acquiring customers within this age range.

5) City Category Strategy

- Male customers residing in City_Category C demonstrate higher spending compared to those in City_Category B or A. To increase revenue, the company should consider emphasizing product offerings in City_Category C.