# 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) |
| Purchase: | Purchase Amount |

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from google.colab import files
import io
import pandas as pd

# Upload the file
uploaded = files.upload()

# Read the file into a pandas DataFrame
# Assuming the file name is 'walmart_data.csv'
df = pd.read_csv(io.BytesIO(uploaded['walmart_data.csv']))
df.head(10)
```

Choose Files walmart_data.csv

- **walmart_data.csv**(text/csv) - 23027994 bytes, last modified: 30/12/2024 - 100% done

```
Saving walmart_data.csv to walmart_data.csv
```

| | User_ID | Product_ID | Gender | Age | Occupation | City_Category | Stay_In_Current_City_Years | Marital_Status | Product_Category | Purcha |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1000001 | P00069042 | F | 0-17 | 10 | A | 2 | 0 | 3 | 83 |
| 1 | 1000001 | P00248942 | F | 0-17 | 10 | A | 2 | 0 | 1 | 152 |
| 2 | 1000001 | P00087842 | F | 0-17 | 10 | A | 2 | 0 | 12 | 14 |
| 3 | 1000001 | P00085442 | F | 0-17 | 10 | A | 2 | 0 | 12 | 10 |
| 4 | 1000002 | P00285442 | M | 55+ | 16 | C | 4+ | 0 | 8 | 79 |
| 5 | 1000003 | P00193542 | M | 26-35 | 15 | A | 3 | 0 | 1 | 152 |
| 6 | 1000004 | P00184942 | M | 46- | 7 | B | 2 | 1 | 1 | 192 |

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

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

```
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`

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

```
df.dtypes
```

| | 0 |
|---|---|
| **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

```
df.memory_usage()
```

| | 0 |
|---|---|
| **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

```
df.describe()
```

| | 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.

```
# checking null values
df.isnull().sum()
```

| | 0 |
|---|---|
| User_ID | 0 |
| Product_ID | 0 |
| Gender | 0 |
| Age | 0 |
| Occupation | 0 |
| City_Category | 0 |
| Stay_In_Current_City_Years | 0 |
| Marital_Status | 0 |
| Product_Category | 0 |
| Purchase | 0 |

dtype: int64

**How many users are there in the dataset?**

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

```
5891
```

**How many products are there?**

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

```
3631
```

**Value_counts for the following:**

- Gender
- Age
- Occupation
- City_Category
- Stay_In_Current_City_Years
- Marital_Status
- Product_Category

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

| 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 |
| | 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 |
| | 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 |

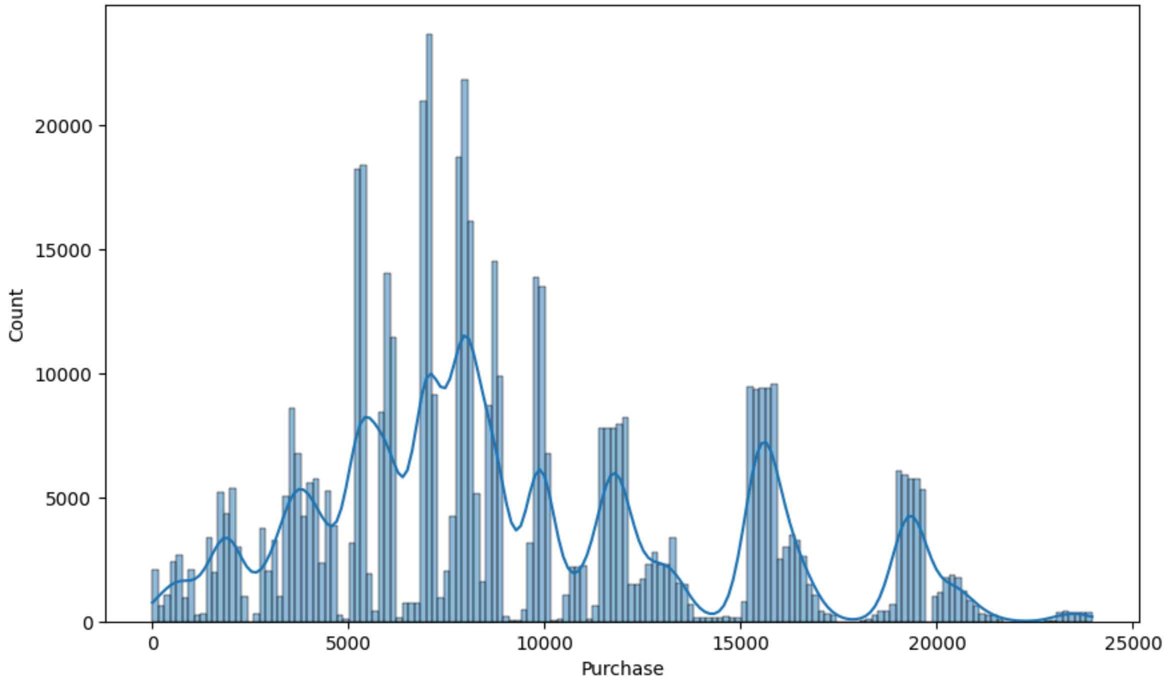
Observations

- ~ 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

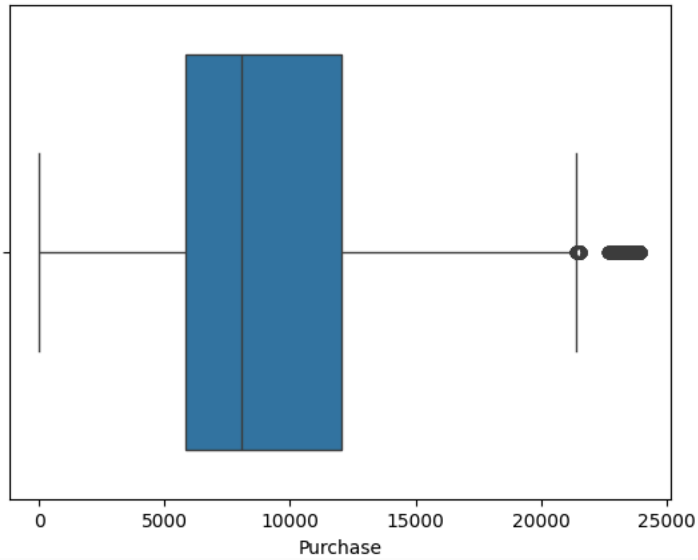
## Univariate Analysis

### Understanding the distribution of data and detecting outlies for continuous variables

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




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



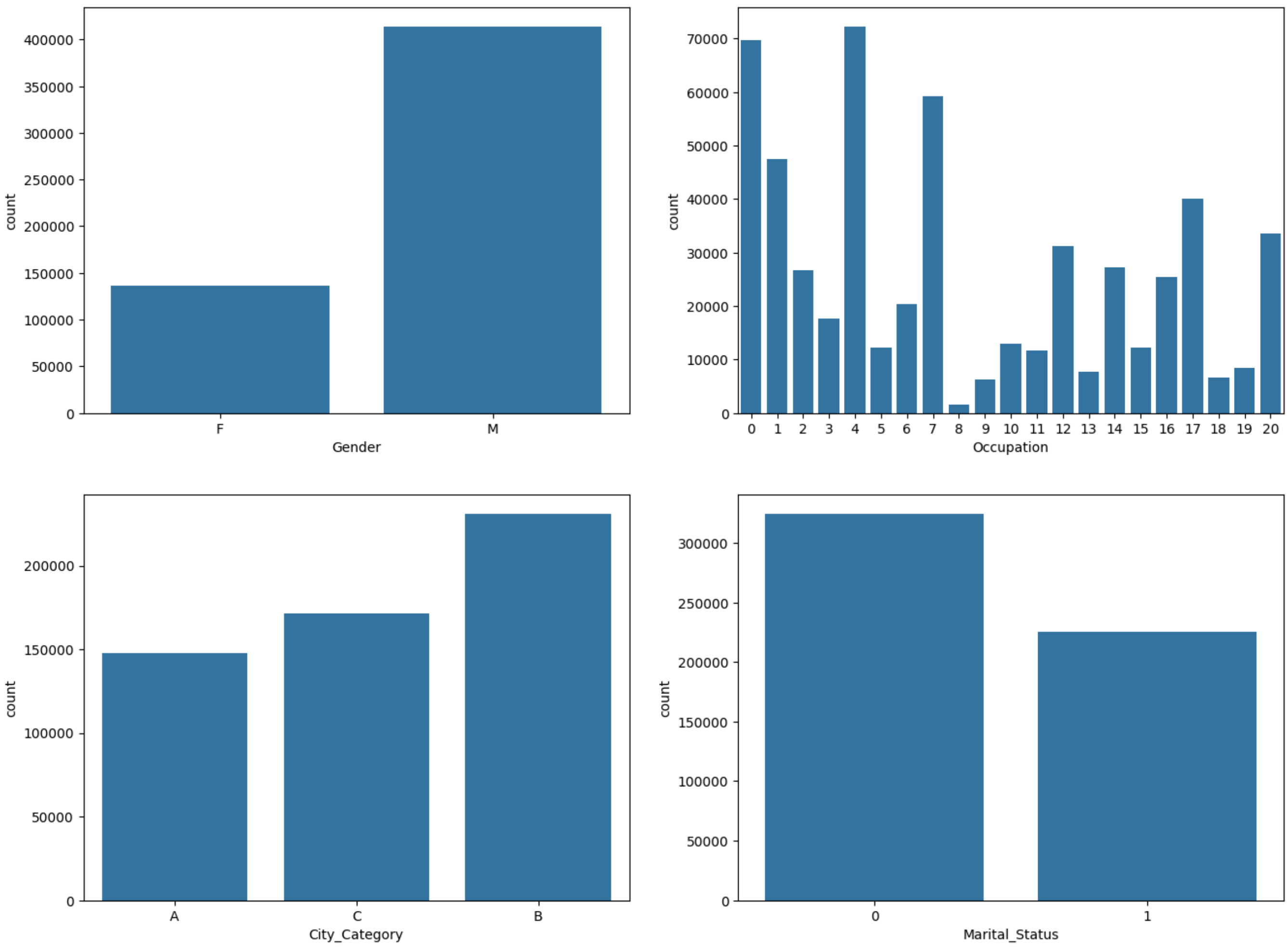

Observation

- Purchase is having outliers

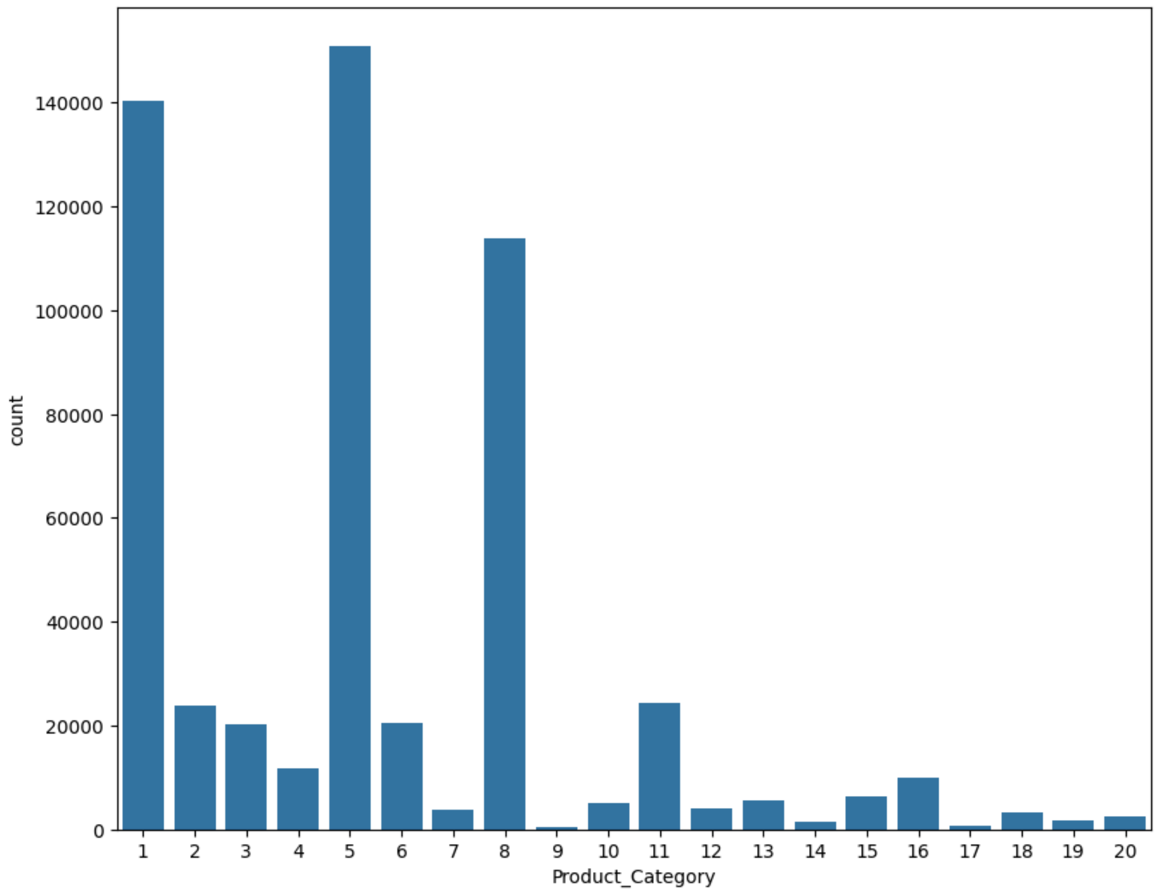
## Understanding the distribution of data for the categorical variables

- Gender
- Age
- Occupation
- City_Category
- Stay_In_Current_City_Years
- Marital_Status
- Product_Category

```
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
0
50000
100000
150000
200000
250000
300000
350000
400000
F
M
Gender
count
0
10000
20000
30000
40000
50000
60000
70000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Occupation
count
0
50000
100000
150000
200000
A
C
B
City_Category
count
0
50000
100000
150000
200000
250000
300000
0
1
Marital_Status

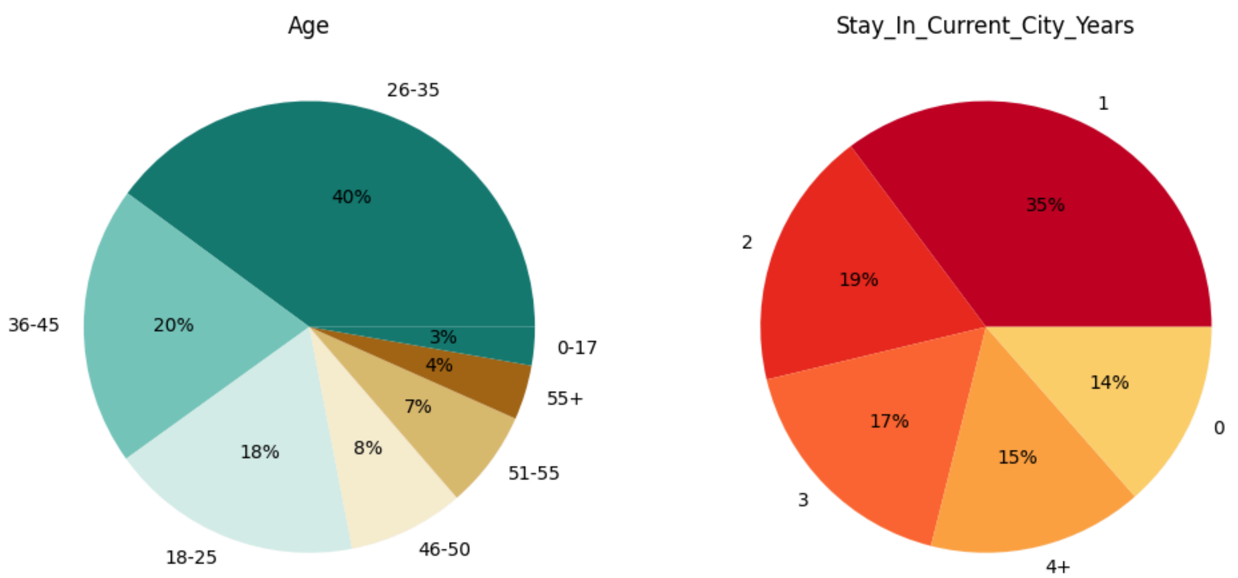



count
0
20000
40000
60000
80000
100000
120000
140000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Product_Category

## 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.

```
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()
```



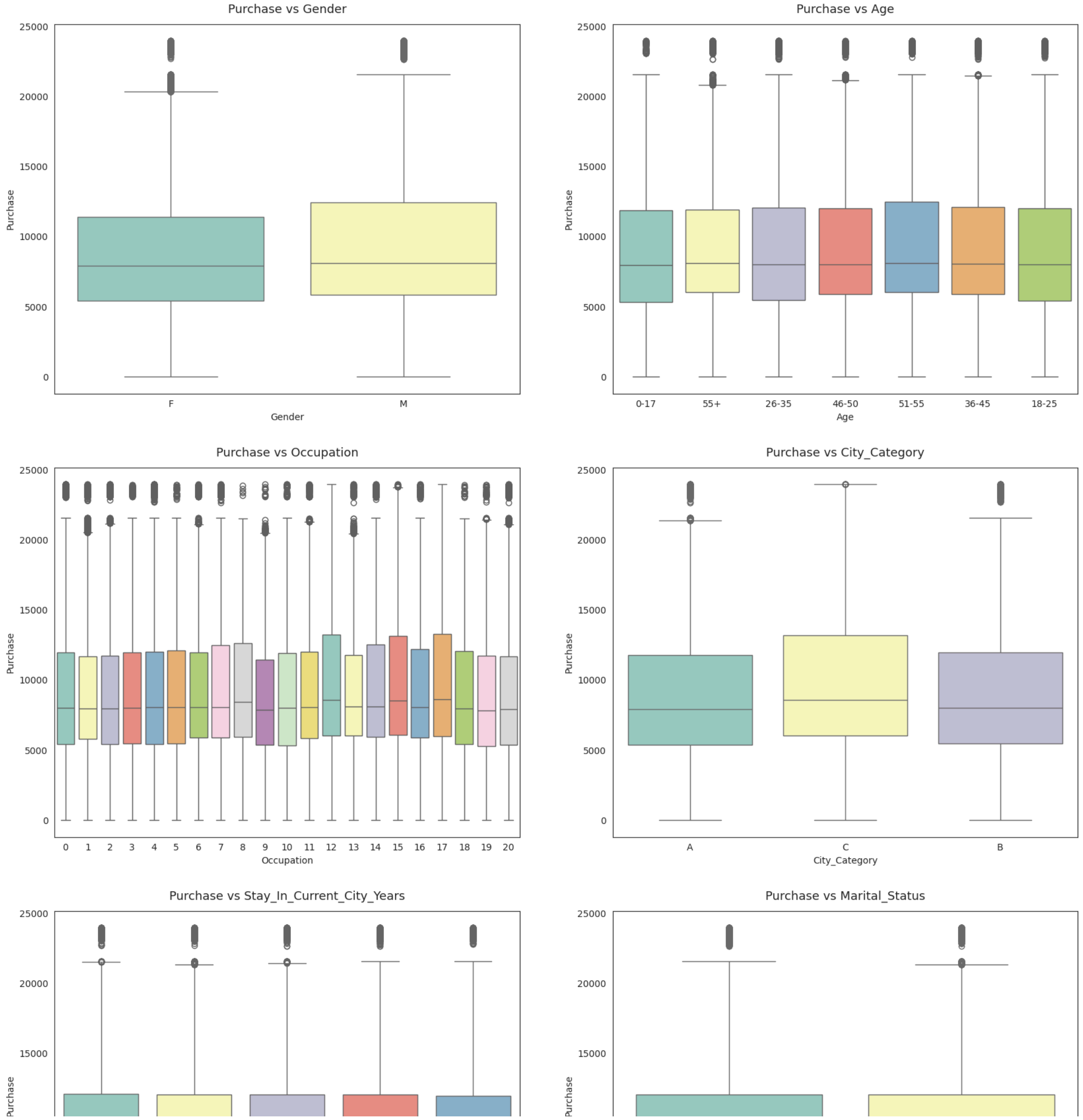

Observations

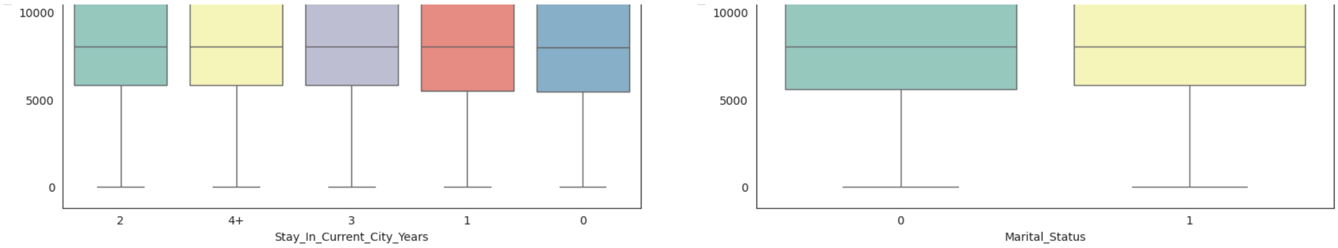
- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years, 15% from 4 years+, 14% are new to city

## Bi-variate Analysis

```
attrs = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
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='Set3')
        axs[row,col].set_title(f"Purchase vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
plt.show()
```

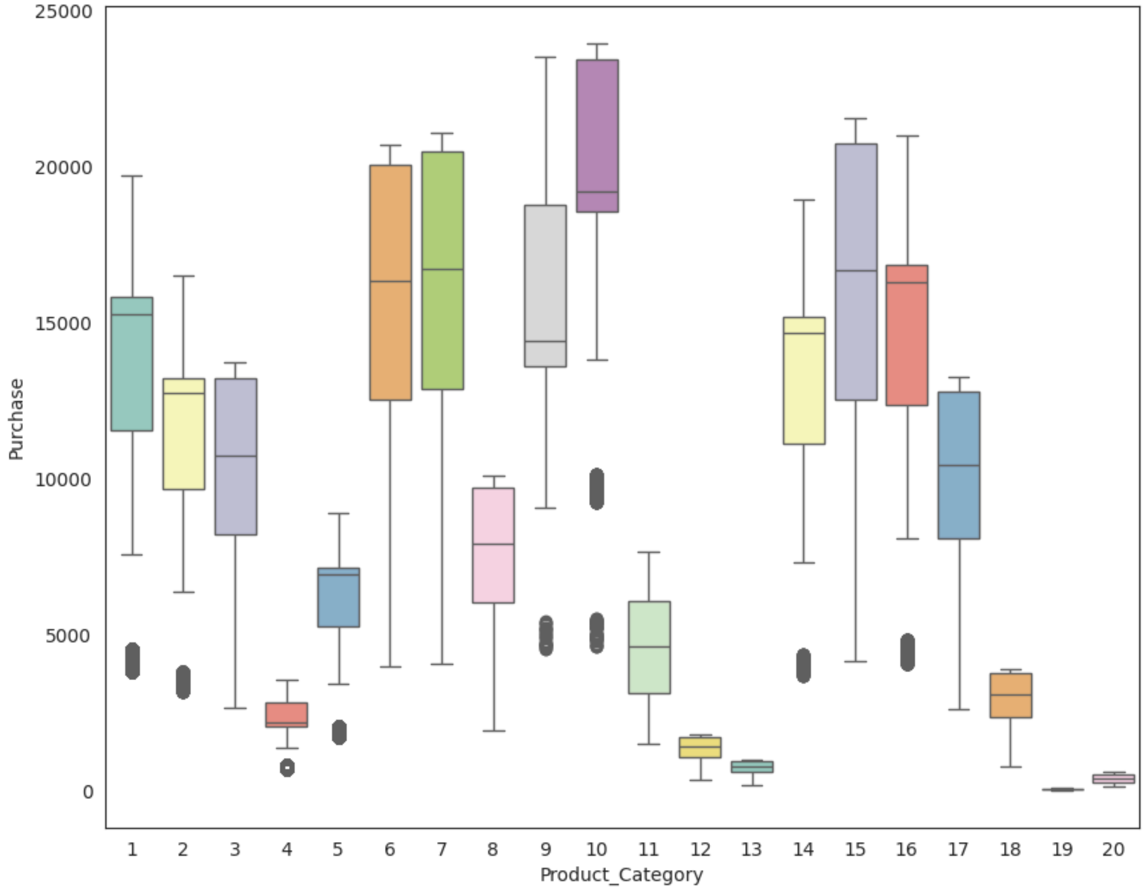
```
<ipython-input-18-88a4bed87712>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
<ipython-input-18-88a4bed87712>: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 `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
<ipython-input-18-88a4bed87712>: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 `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
<ipython-input-18-88a4bed87712>: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 `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
<ipython-input-18-88a4bed87712>: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 `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
<ipython-input-18-88a4bed87712>: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 `le

  sns.boxplot(data=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='Set3')
```





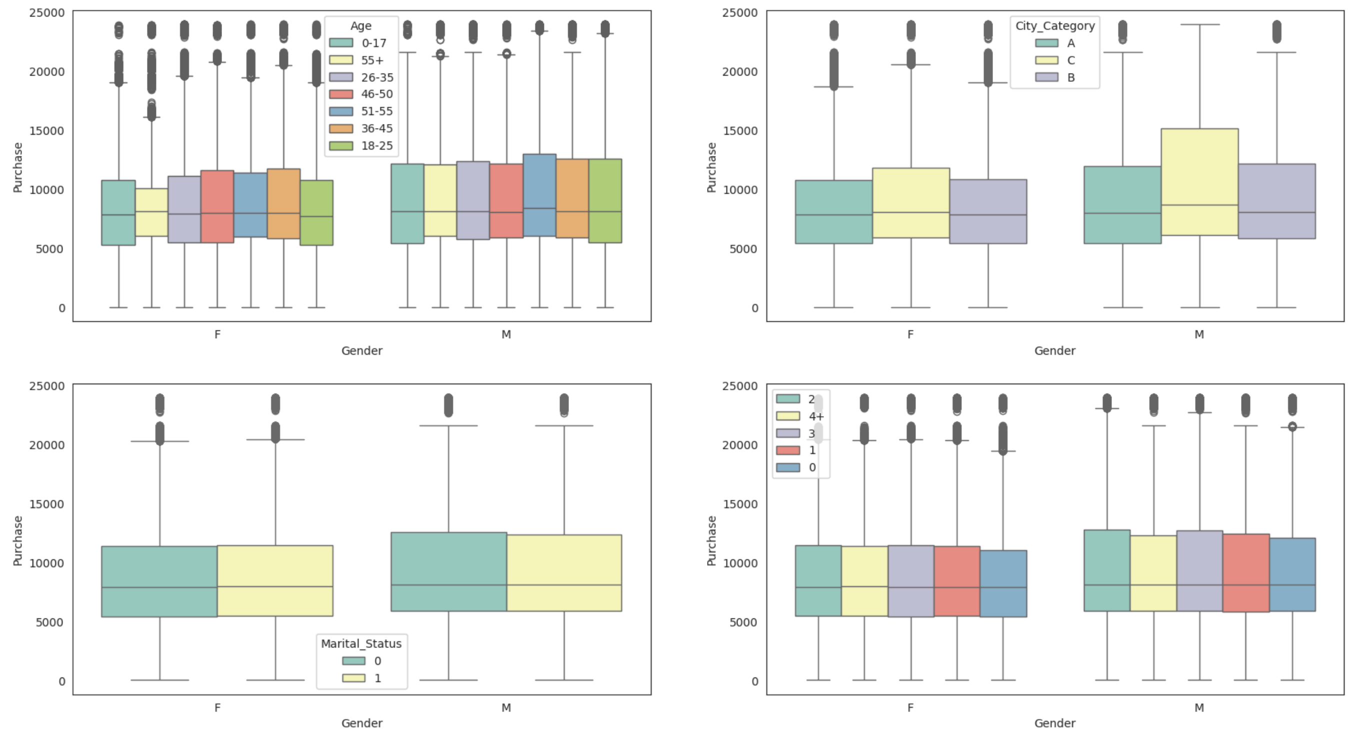

```
plt.figure(figsize=(10, 8))
sns.boxplot(data=df, y='Purchase', x=attrs[-1], palette='Set3')
plt.show()
```

```
<ipython-input-19-962dca1427f4>: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 `le

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



## Multivariate Analysis

```
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()
```




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

| | User_ID | Product_ID | Gender | Age | Occupation | City_Category | Stay_In_Current_City_Years | Marital_Status | Product_Category | Purcha |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1000001 | P00069042 | F | 0-17 | 10 | A | 2 | 0 | 3 | 83 |
| **1** | 1000001 | P00248942 | F | 0-17 | 10 | A | 2 | 0 | 1 | 152 |
| **2** | 1000001 | P00087842 | F | 0-17 | 10 | A | 2 | 0 | 12 | 14 |
| **3** | 1000001 | P00085442 | F | 0-17 | 10 | A | 2 | 0 | 12 | 10 |
| **4** | 1000002 | P00285442 | M | 55+ | 16 | C | 4+ | 0 | 8 | 79 |
| **5** | 1000003 | P00193542 | M | 26-35 | 15 | A | 3 | 0 | 1 | 152 |
| **6** | 1000004 | P00184942 | M | 46- | 7 | B | 2 | 1 | 1 | 192 |

## 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**

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

| | 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

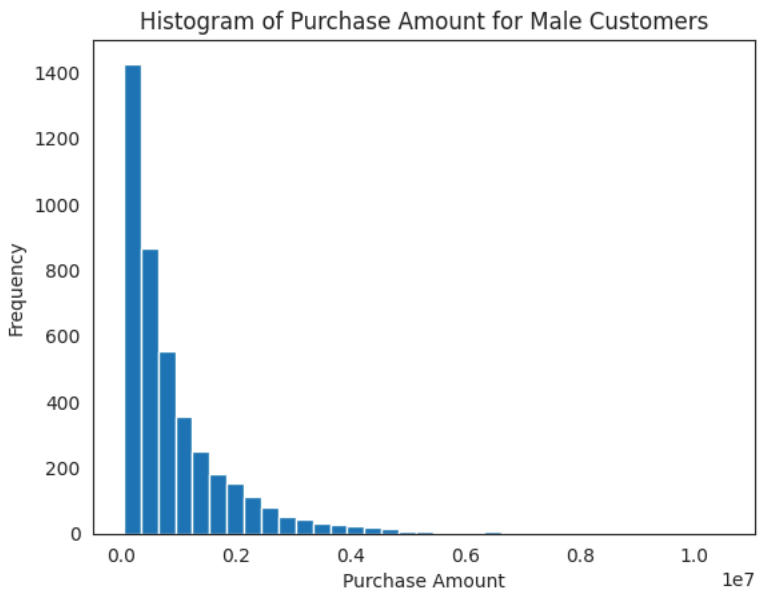
Next steps: Generate code with amt_df   View recommended plots   New interactive sheet

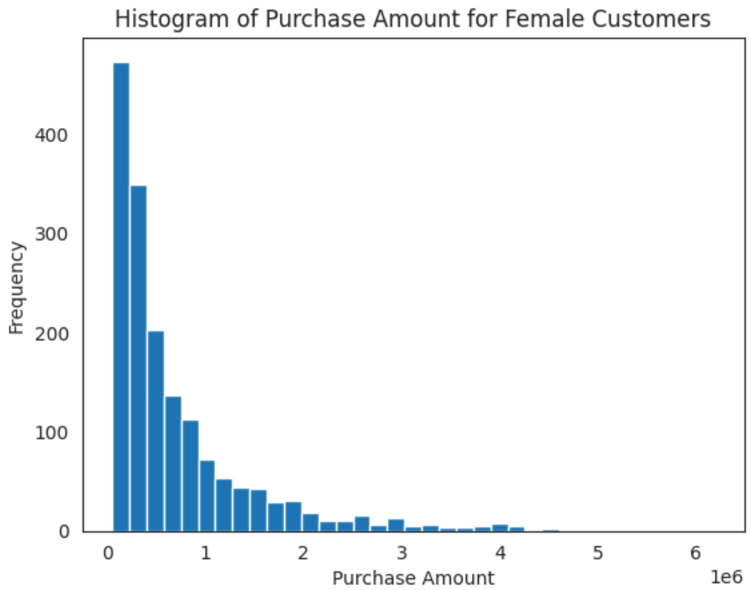
```
# Gender wise value counts in avg_amt_df
avg_amt_df = amt_df['Gender'].value_counts()
avg_amt_df
```

| | count |
|---|---|
| **Gender** | |
| **M** | 4225 |
| **F** | 1666 |

dtype: int64

```
# 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()
```




```
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

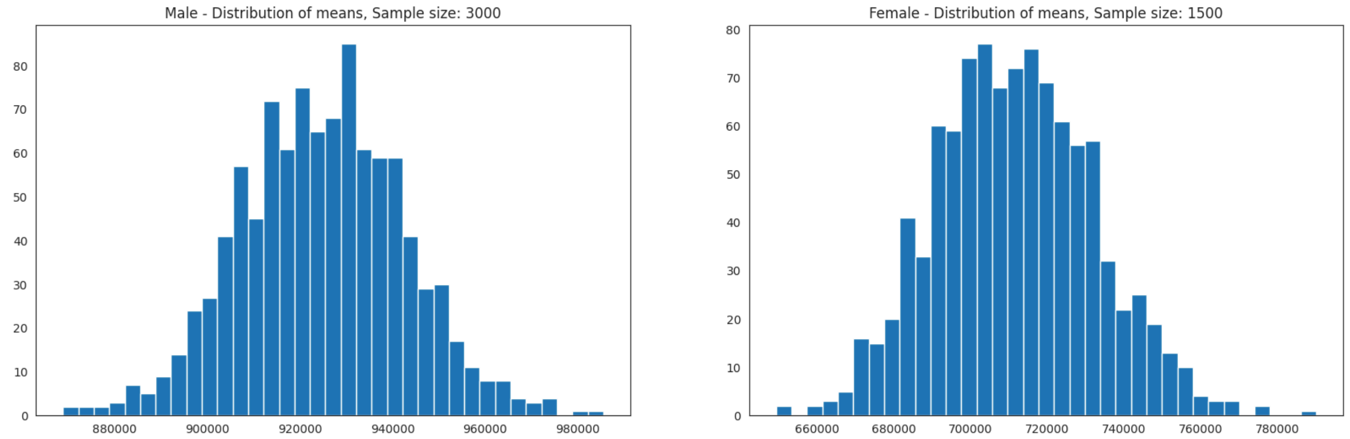
**Sample Size:**

male_sample_size = 3000

female_sample_size = 1500

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

```
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)


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()
```




```
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: 924653.76
Population mean - Mean of sample means of amount spend for Female: 712523.71

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:

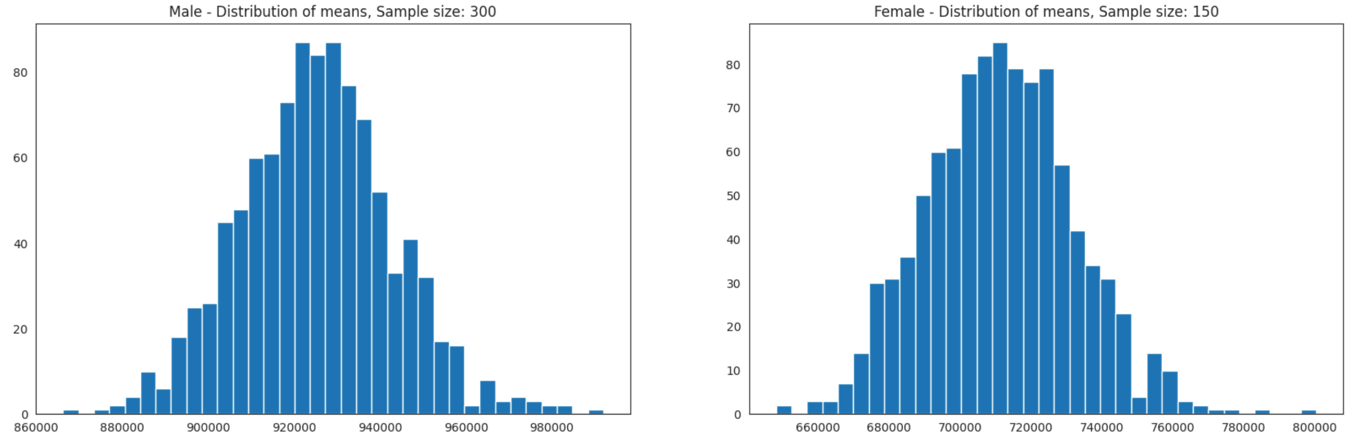
1. Average amount spend by male customers is **925344.40**
2. Average amount spend by female customers is **712024.39**

**Sample Size:**

male_sample_size = 300
female_sample_size = 150

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

```
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)


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()
```




```
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: 925237.59
Population mean - Mean of sample means of amount spend for Female: 711445.27

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

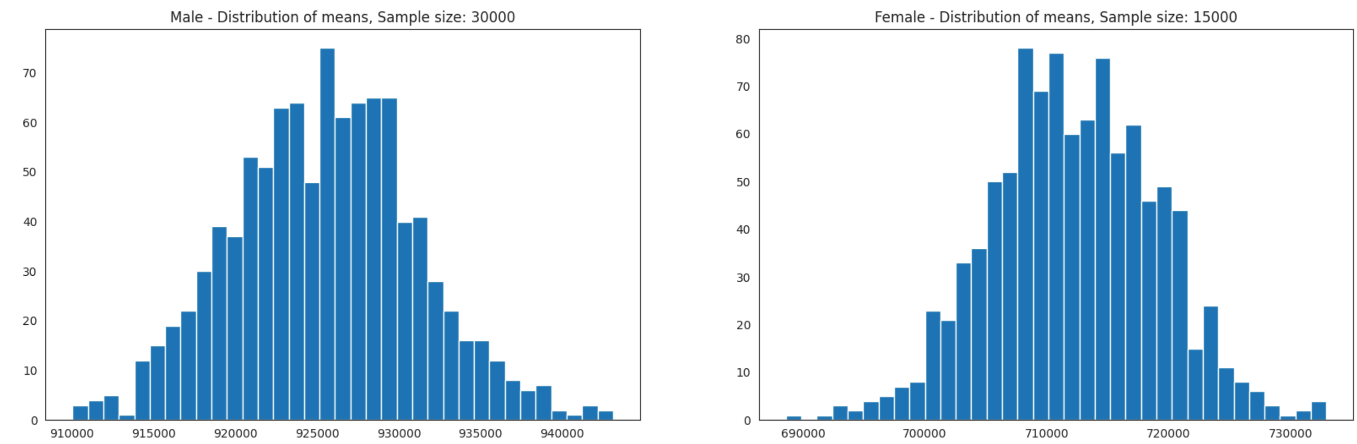
**Sample Size:**

male_sample_size = 30000

female_sample_size = 15000

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


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)


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()
```




```
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: 925480.17
Population mean - Mean of sample means of amount spend for Female: 712196.39

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:**

```
#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:**

```
#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:**

```
#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

```
amt_df
```

| | 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

Next steps: Generate code with amt_df | View recommended plots | New interactive sheet

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

| | 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 |
| **5888** | 1006038 | 0 | 90034 |
| **5889** | 1006039 | 1 | 590319 |
| **5890** | 1006040 | 0 | 1653299 |

5891 rows × 3 columns

Next steps: Generate code with `amt_df` View recommended plots New interactive sheet

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

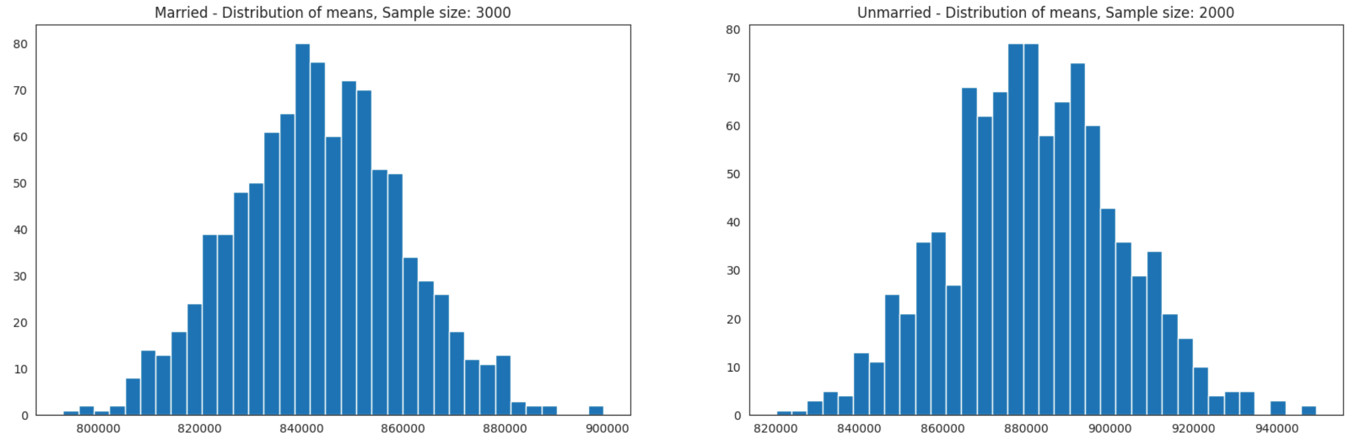
| | count |
|---|---|
| **Marital_Status** | |
| **0** | 3417 |
| **1** | 2474 |

dtype: int64

**Sample Size:**

marid_samp_size = 3000
unmarid_sample_size = 2000

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



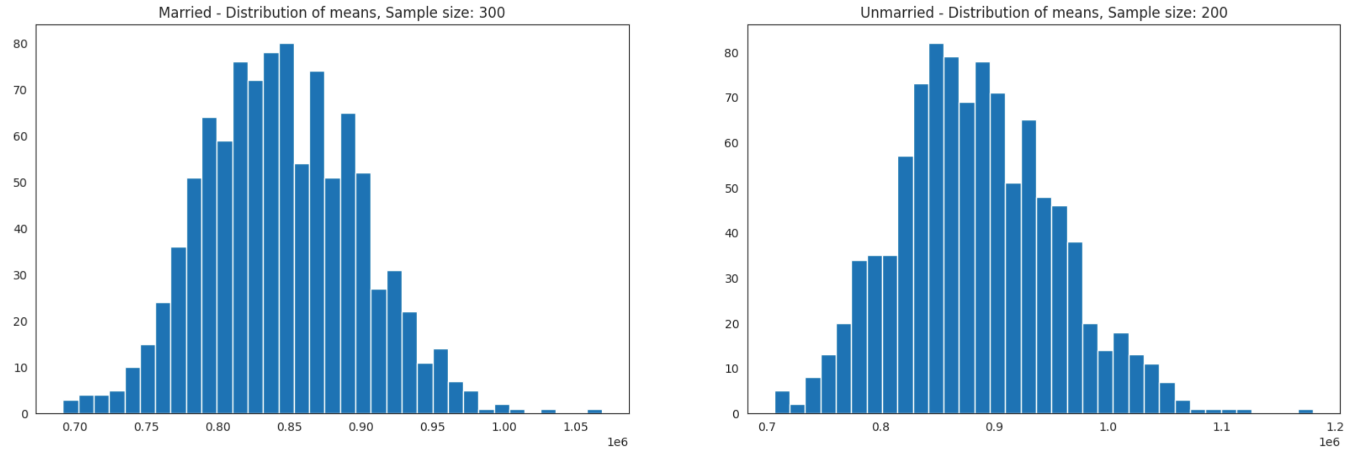

```
Population mean - Mean of sample means of amount spend for Married: 843307.93
Population mean - Mean of sample means of amount spend for Unmarried: 881601.18

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

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




```
Population mean - Mean of sample means of amount spend for Married: 844544.32
Population mean - Mean of sample means of amount spend for Unmarried: 884225.50

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

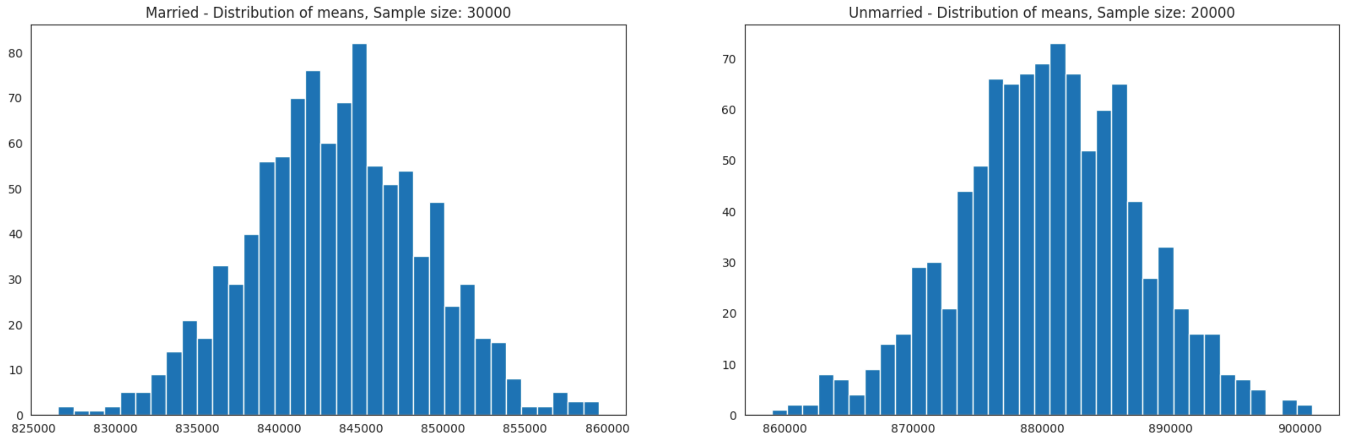
Start coding or generate with AI.

**Sample Size:**

marid_samp_size = 30000

unmarid_sample_size = 20000

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




```
Population mean - Mean of sample means of amount spend for Married: 843502.51
Population mean - Mean of sample means of amount spend for Unmarried: 880481.51

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:**

```
#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:**

```
#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:**

```
#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:**

```
#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:**

```
#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

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

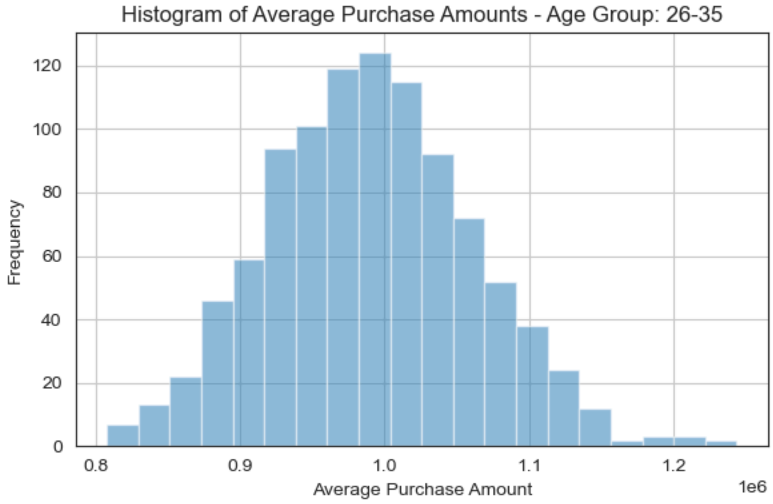
| | User_ID | Age | Purchase |
|---|---|---|---|
| **0** | 1000001 | 0-17 | 334093 |
| **1** | 1000002 | 55+ | 810472 |
| **2** | 1000003 | 26-35 | 341635 |
| **3** | 1000004 | 46-50 | 206468 |
| **4** | 1000005 | 26-35 | 821001 |
| **...** | ... | ... | ... |
| **5886** | 1006036 | 26-35 | 4116058 |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

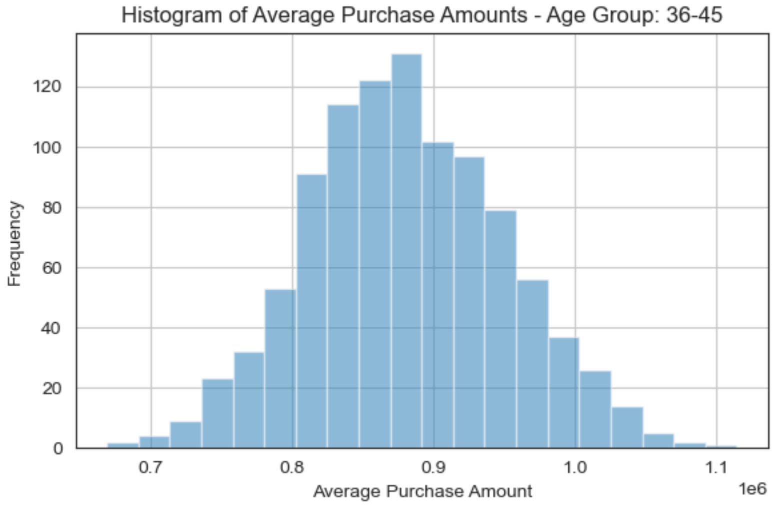
5891 rows × 3 columns

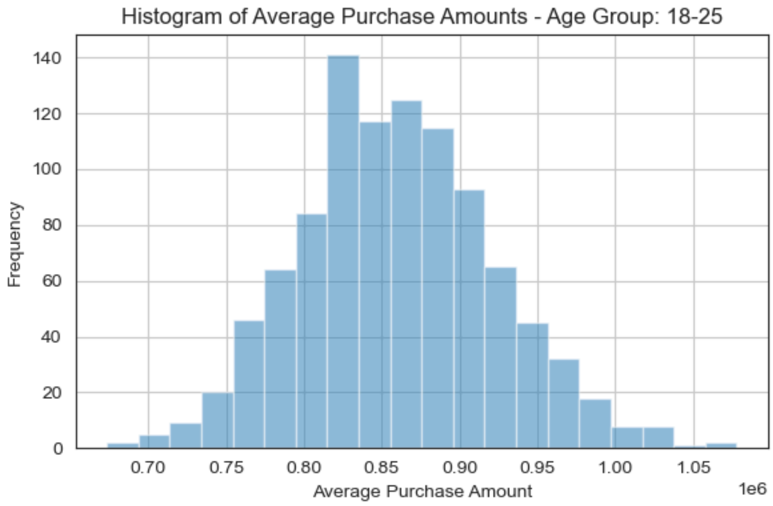
```
amt_df['Age'].value_counts()
```

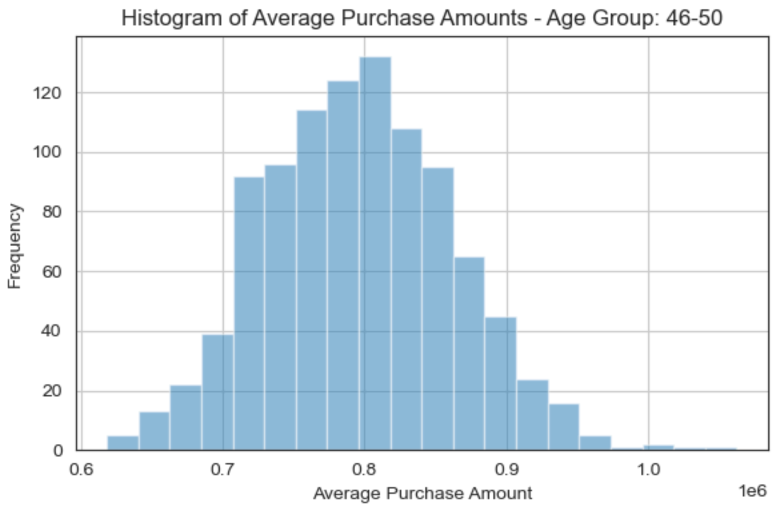
```
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: Age, dtype: int64
```

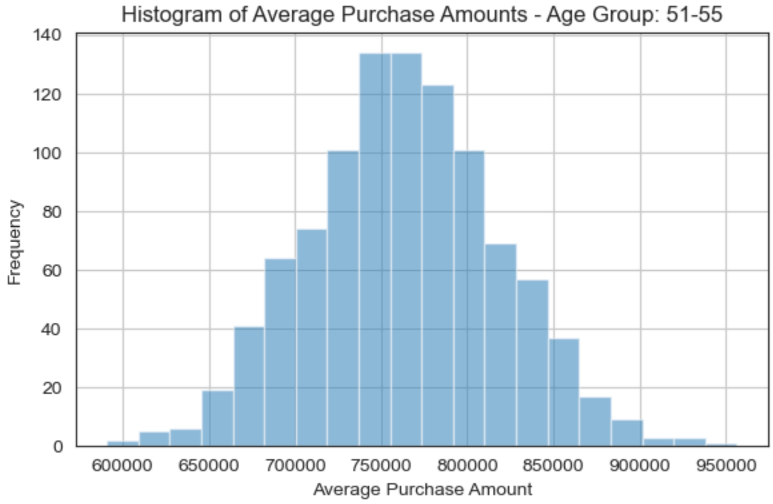
```
sample_size = 200
num_repitions = 1000

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)


# 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()
```

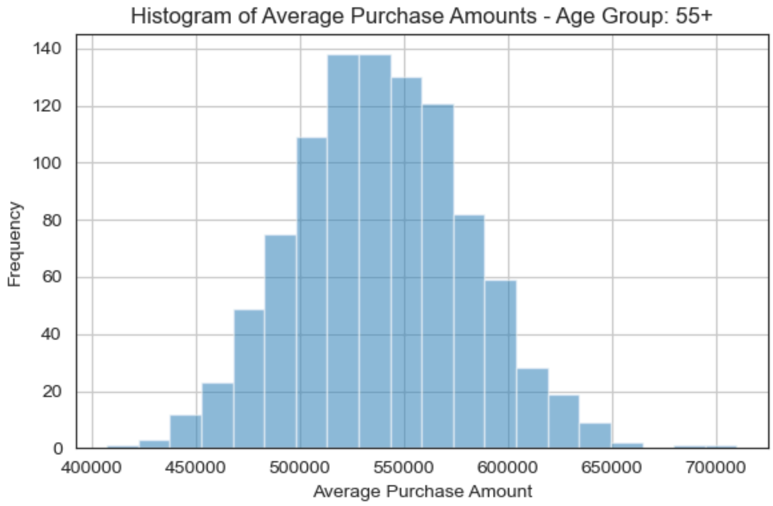

Histogram of Average Purchase Amounts - Age Group: 26-35
Frequency
Average Purchase Amount
1e6
0
20
40
60
80
100
120
0.8
0.9
1.0
1.1
1.2

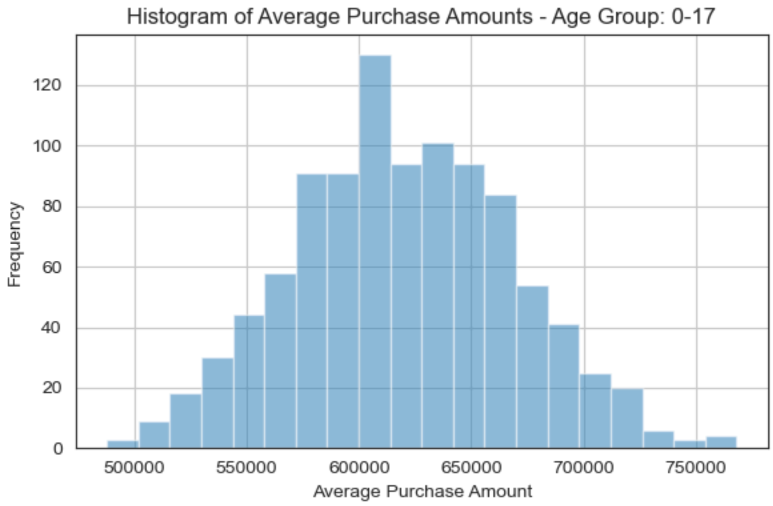

Histogram of Average Purchase Amounts - Age Group: 36-45
Frequency
Average Purchase Amount
1e6
0
20
40
60
80
100
120
0.7
0.8
0.9
1.0
1.1


Histogram of Average Purchase Amounts - Age Group: 18-25
Frequency
Average Purchase Amount
1e6
0
20
40
60
80
100
120
140
0.70
0.75
0.80
0.85
0.90
0.95
1.00
1.05


Histogram of Average Purchase Amounts - Age Group: 46-50
Frequency
Average Purchase Amount
1e6
0
20
40
60
80
100
120
0.6
0.7
0.8
0.9
1.0




**99% Confidence Interval:**

```
#99% Confidence Interval

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