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


uploaded = files.upload()
```

```
<IPython.core.display.HTML object>

Saving walmart_data.csv to walmart_data.csv
```

```python
df = pd.read_csv("walmart_data.csv")
df.head()
```

```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category
Purchase
0                          2               0                 3
8370
1                          2               0                 1
15200
2                          2               0                12
1422
3                          2               0                12
1057
4                         4+               0                 8
7969
```

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

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

```python
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

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()

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()
```

```
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)
```

```
                                      value
variable                   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
```

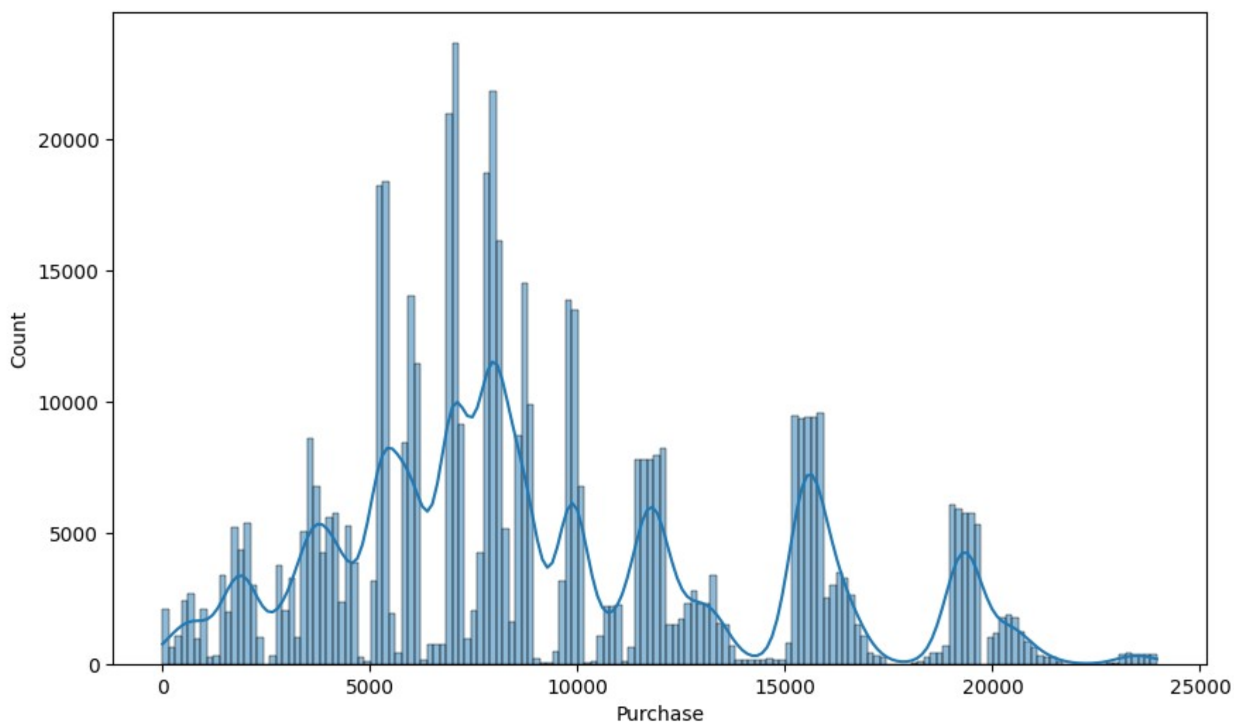
Observations

- ~ 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

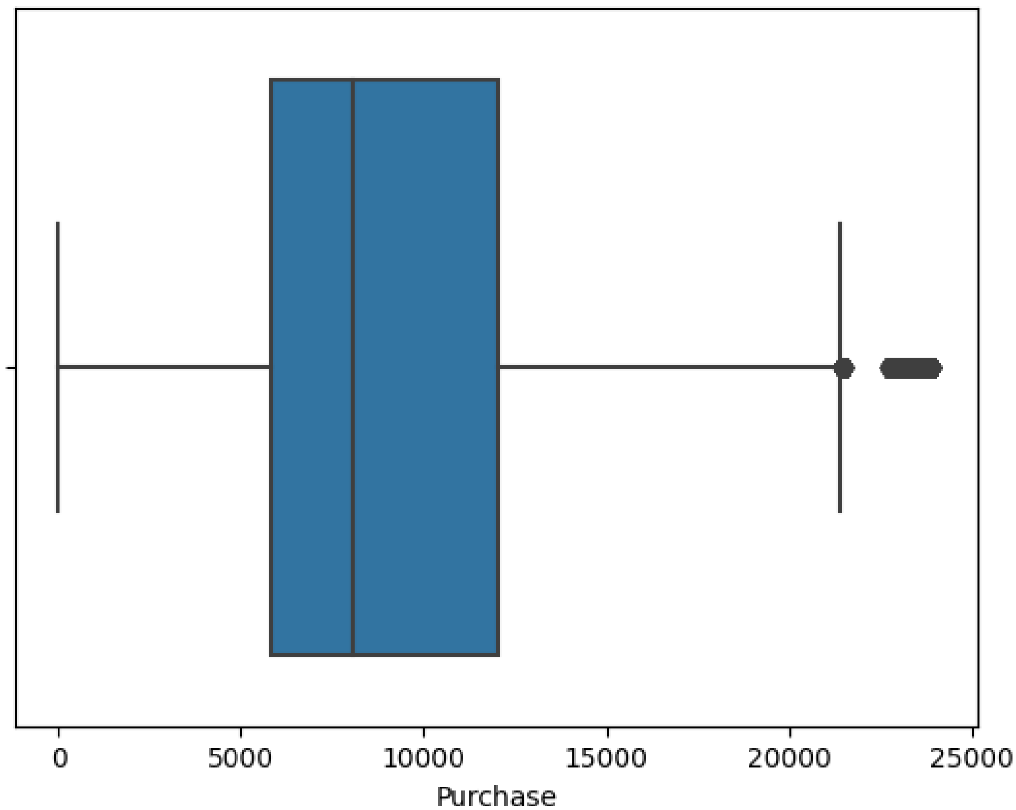
Univariate Analysis

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

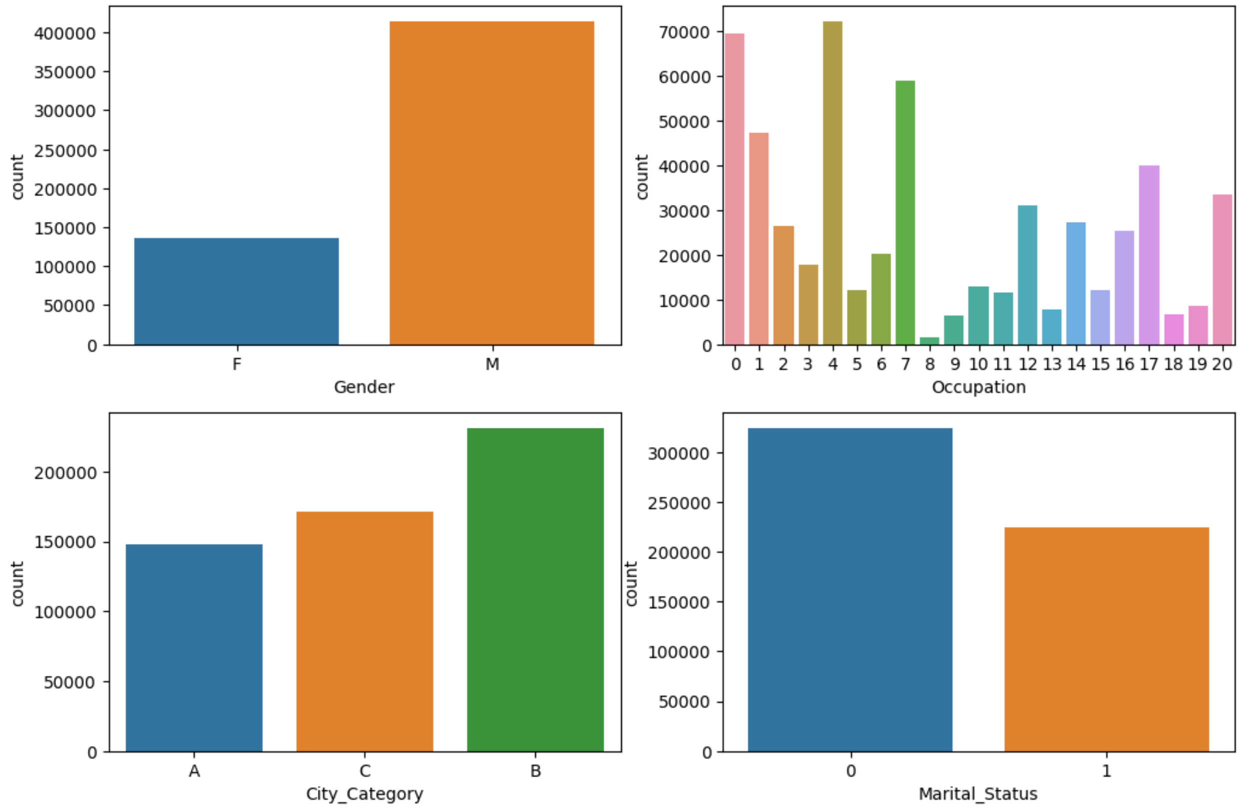
- Purchase is having outliers

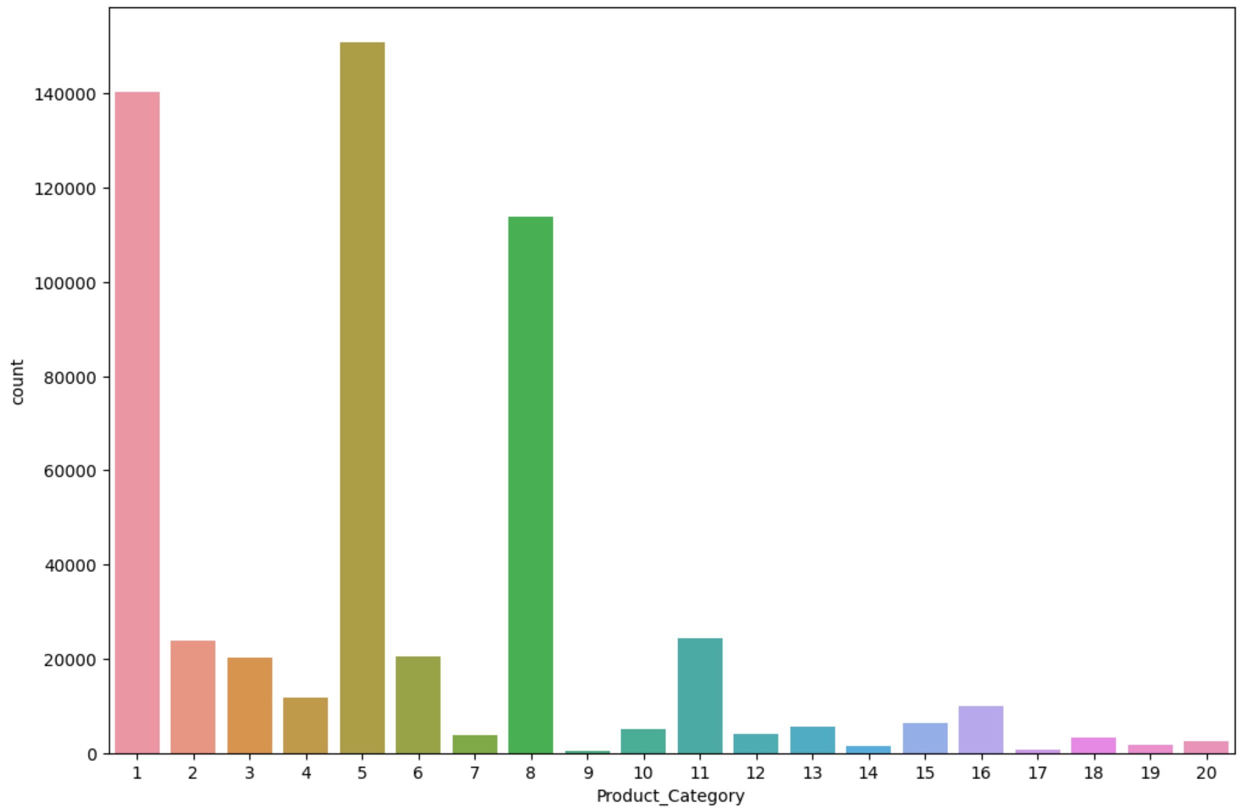
Understanding the distribution of data for the categorical variables

- 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=(12, 8))
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=(12, 8))
```

```
sns.countplot(data=df, x='Product_Category')
plt.show()
```

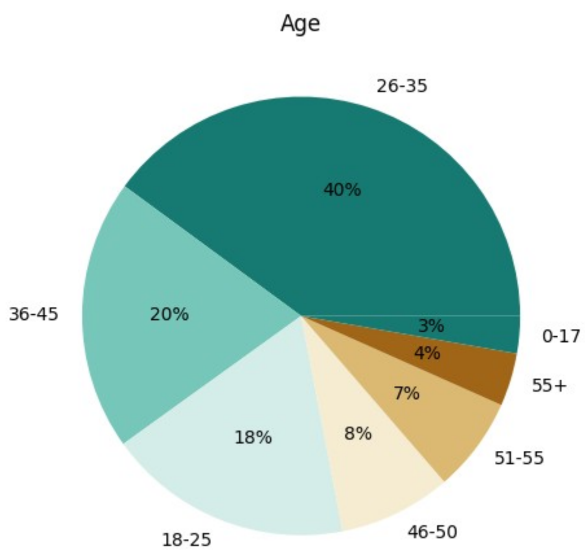


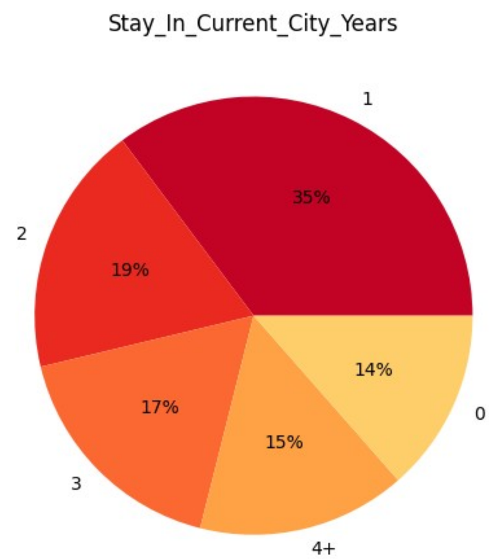


Observations

- 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()
```

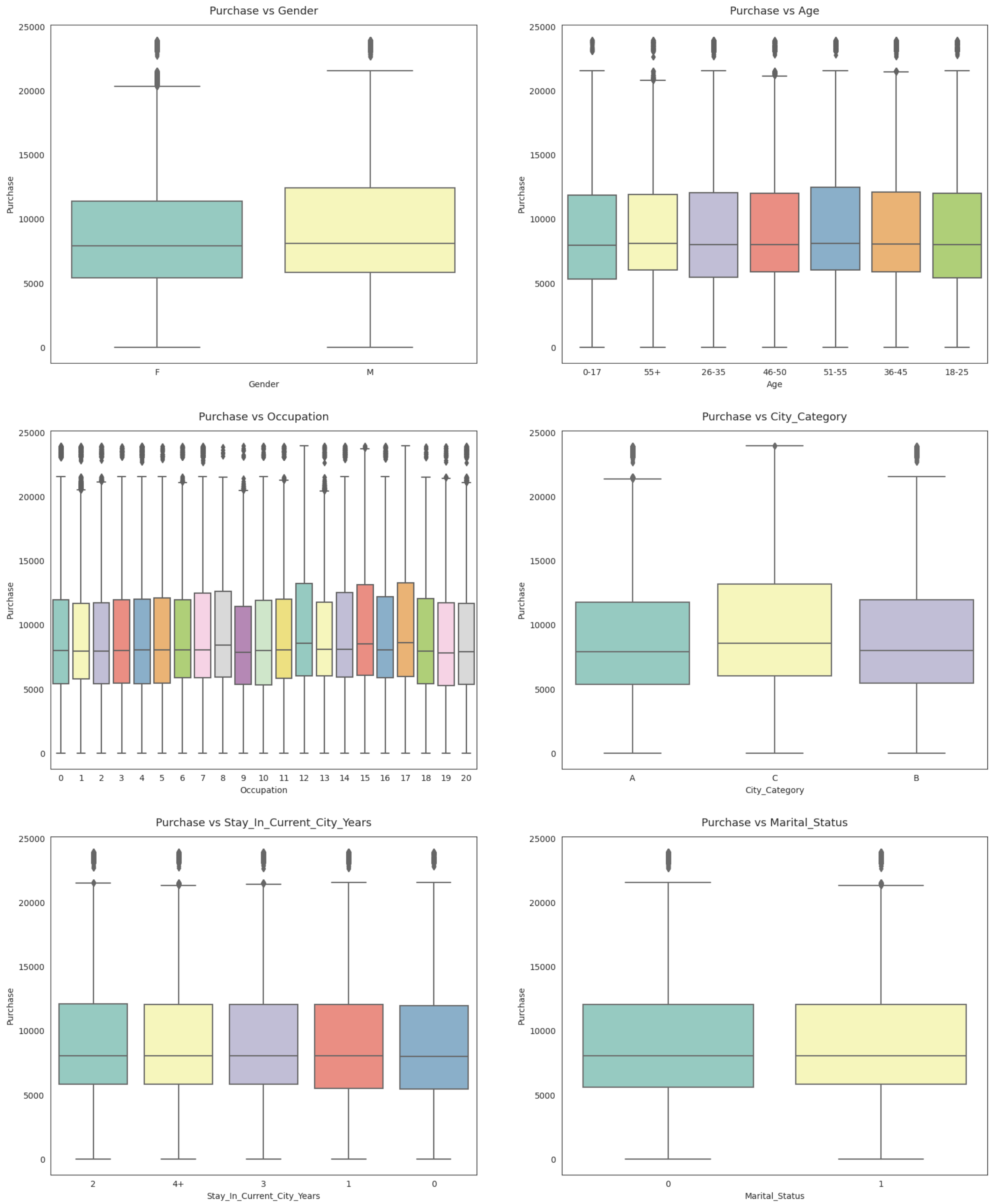


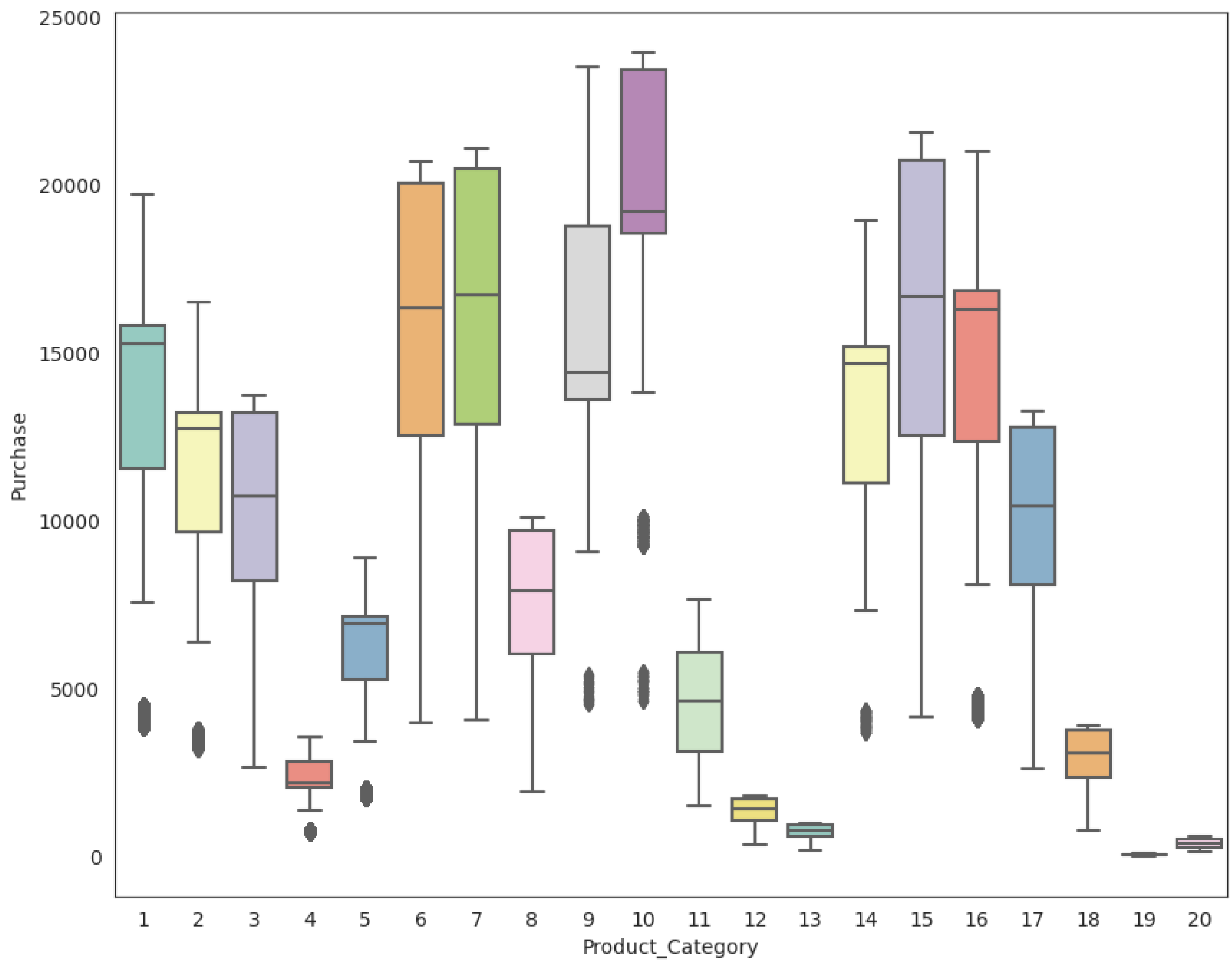


Upper two graphs are self-explanatory.

Bi-variate Analysis

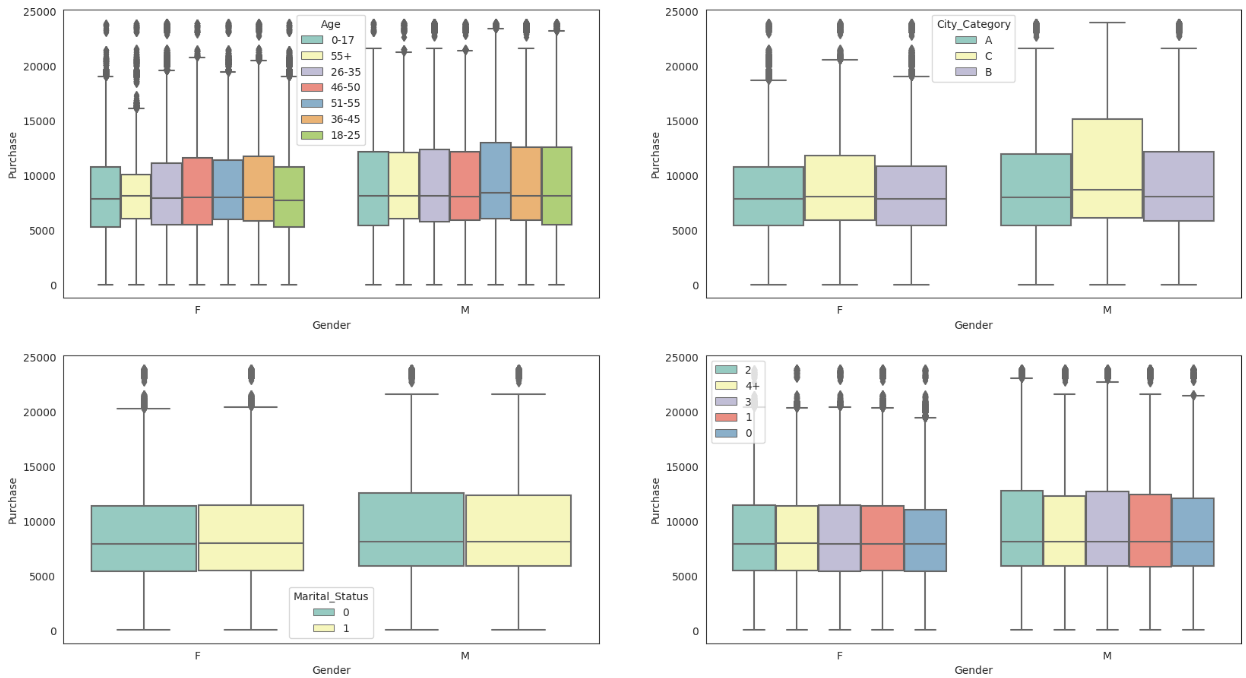
```
attrs = ['Gender', 'Age', 'Occupation', 'City_Category',
'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
sns.set_style("white")

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()

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


Purchase vs Gender
Purchase
Gender
F
M
Purchase vs Age
Age
0-17
55+
26-35
46-50
51-55
36-45
18-25
Purchase vs Occupation
Occupation
Purchase vs City_Category
City_Category
A
C
B
Purchase vs Stay_In_Current_City_Years
Stay_In_Current_City_Years
2
4+
3
1
0
Purchase vs Marital_Status
Marital_Status
0
1



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  \
0  1000001  P00069042      F   0-17          10             A
1  1000001  P00248942      F   0-17          10             A
2  1000001  P00087842      F   0-17          10             A
3  1000001  P00085442      F   0-17          10             A
4  1000002  P00285442      M    55+          16             C
5  1000003  P00193542      M  26-35          15             A
6  1000004  P00184942      M  46-50           7             B
7  1000004  P00346142      M  46-50           7             B
8  1000004   P0097242      M  46-50           7             B
9  1000005  P00274942      M  26-35          20             A

  Stay_In_Current_City_Years  Marital_Status  Product_Category  Purchase

0                          2               0                 3      8370

1                          2               0                 1     15200

2                          2               0                12      1422

3                          2               0                12      1057

4                         4+               0                 8      7969

5                          3               0                 1     15227

6                          2               1                 1     19215
```

7	2	1	1	15854
8	2	1	1	15686
9	1	1	8	7871

Average amount spend per customer for Male and Female

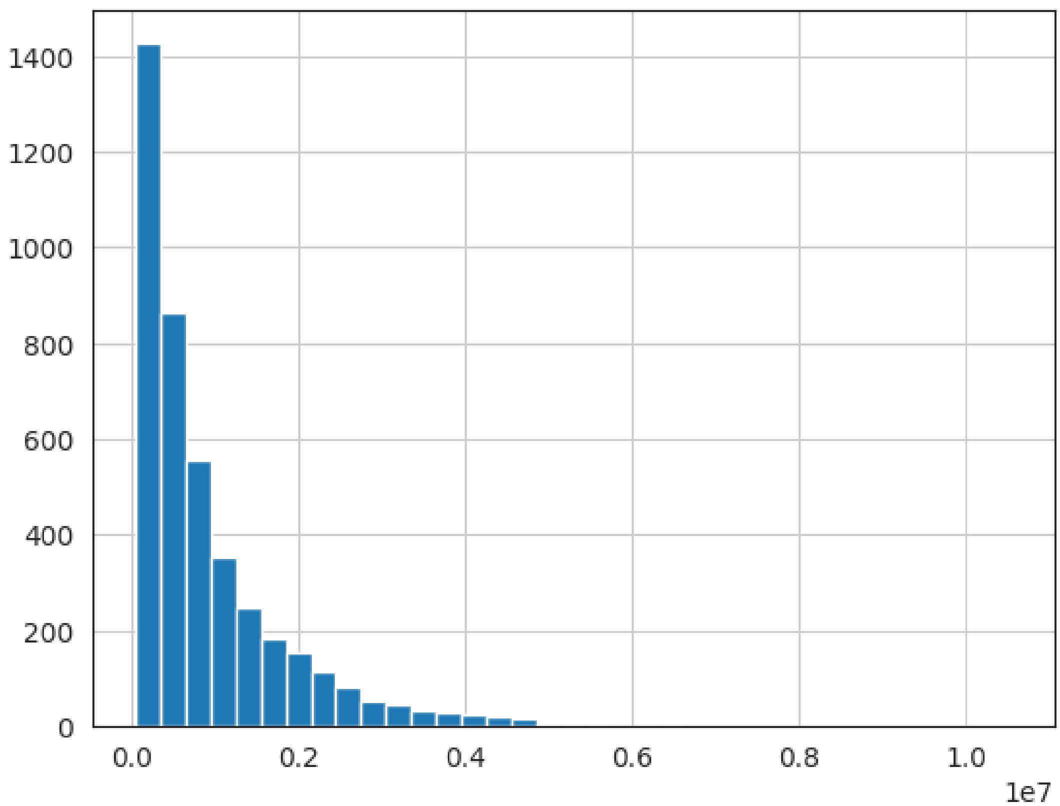
```
amt_df = df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

```
      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 x 3 columns]
```

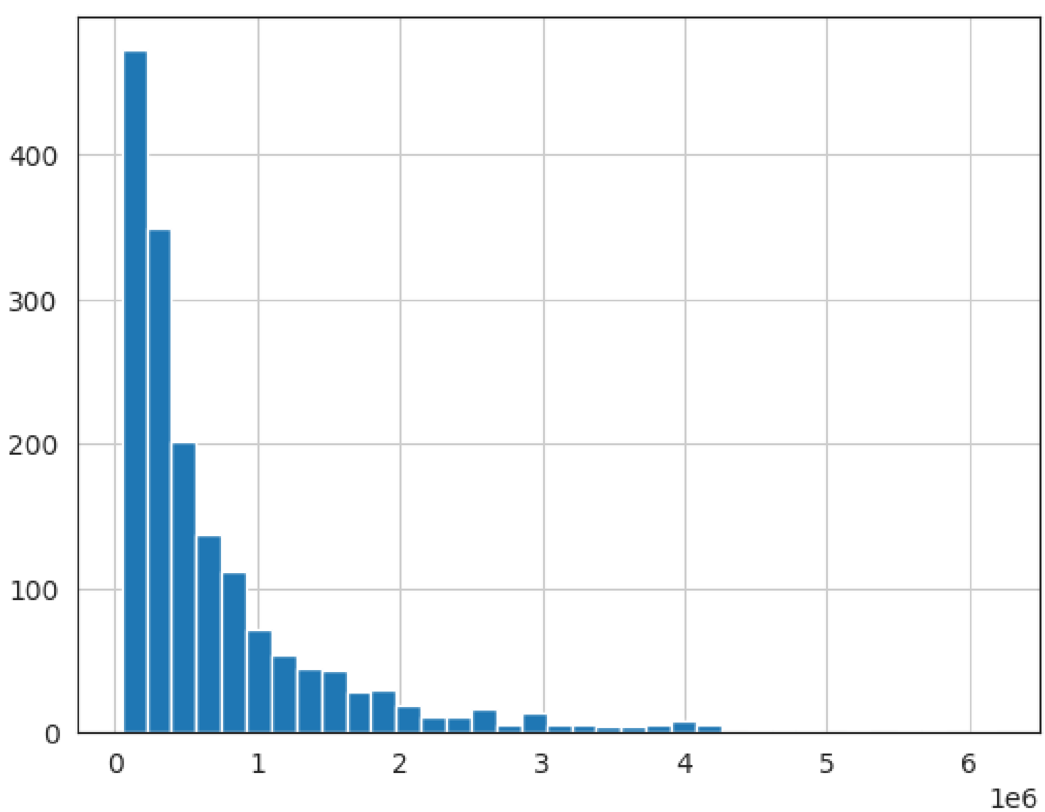
```
# Gender wise value counts in amt_df
amt_df['Gender'].value_counts()
```

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

```
# histogram of average amount spend for each customer - Male & Female
amt_df[amt_df['Gender']=='M']['Purchase'].hist(bins=35)
plt.show()

amt_df[amt_df['Gender']=='F']['Purchase'].hist(bins=35)
plt.show()
```



1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
1e7



400
300
200
100
0
0
1
2
3
4
5
6
1e6

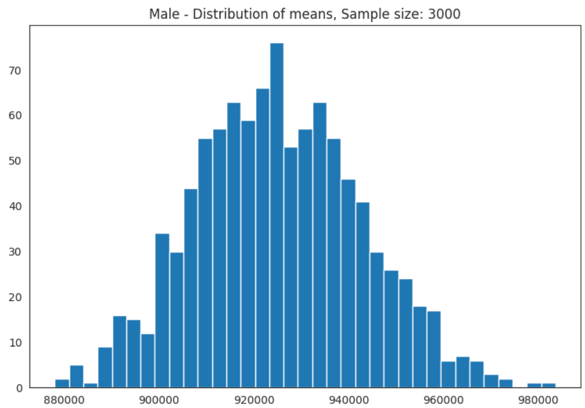
```
male_avg = amt_df[amt_df['Gender']=='M']['Purchase'].mean()
female_avg = amt_df[amt_df['Gender']=='F']['Purchase'].mean()

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

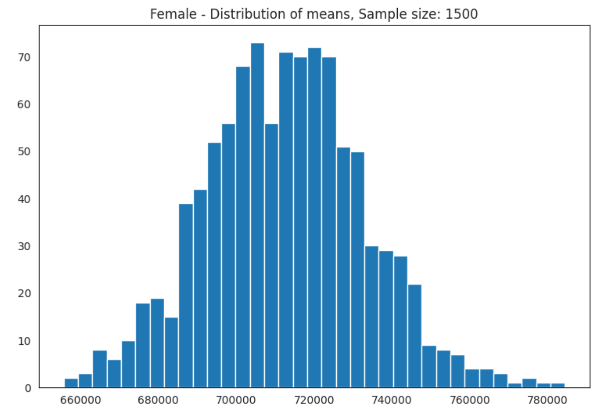
```
Average amount spend by Male customers: 925344.40
Average amount spend by Female customers: 712024.39
```

Observation

1. Male customers spend more money than female customers

```
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: 
925202.04
Population mean - Mean of sample means of amount spend for Female: 
712496.66

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

```
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("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))

Male confidence interval of means: (895617.83, 955070.97)
Female confidence interval of means: (673254.77, 750794.02)
```

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)**

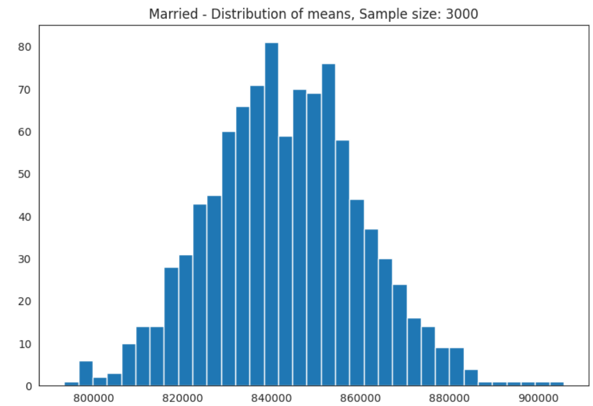
Doing the same activity for married vs unmarried

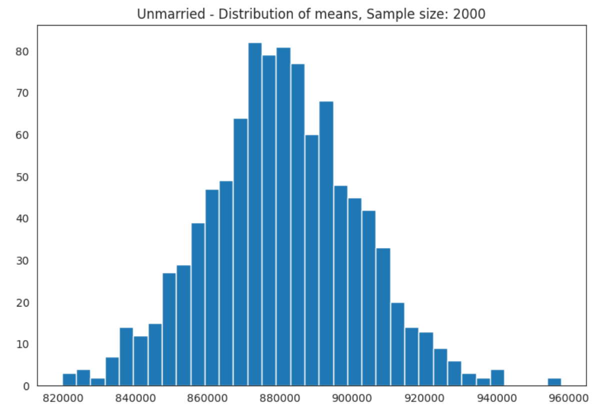
```
amt_df

      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 x 3 columns]

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 x 3 columns]
```

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

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

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






```
Population mean - Mean of sample means of amount spend for Married:
843232.59
Population mean - Mean of sample means of amount spend for Unmarried:
880597.80

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

```
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))
```

```
Married confidence interval of means: (806668.83, 880384.76)
Unmarried confidence interval of means: (848741.18, 912410.38)
```

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 x 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)

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)
```

Insights

- ~ 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

- 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.

- **Average amount** spend by **Male** customers: **925344.40**
- **Average amount** spend by **Female** customers: **712024.39**

Confidence Interval by Gender

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**

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)**

Confidence Interval by Marital_Status

1. **Married** confidence interval of means: **(806668.83, 880384.76)**
2. **Unmarried** confidence interval of means: **(848741.18, 912410.38)**

Confidence Interval by Age

1. For **age 26-35** --> confidence interval of means: **(945034.42, 1034284.21)**
2. For **age 36-45** --> confidence interval of means: **(823347.80, 935983.62)**
3. For **age 18-25** --> confidence interval of means: **(801632.78, 908093.46)**
4. For **age 46-50** --> confidence interval of means: **(713505.63, 871591.93)**
5. For **age 51-55** --> confidence interval of means: **(692392.43, 834009.42)**
6. For **age 55+** --> confidence interval of means: **(476948.26, 602446.23)**
7. For **age 0-17** --> confidence interval of means: **(527662.46, 710073.17)**

Recommendations

1. Men spent more money than women, So company should focus on retaining the male customers and getting more male customers.
2. **Product_Category - 1, 5, 8, & 11** have highest purchasing frequency. it means these are the products in these categories are liked more by customers. Company can focus on selling more of these products or selling more of the products which are purchased less.
3. **Unmarried** customers spend more money than married customers, So company should focus on acquisition of Unmarried customers.
4. Customers in the **age 18-45** spend more money than the others, So company should focus on acquisition of customers who are in the **age 18-45**
5. Male customers living in City_Category C spend more money than other male customers living in B or C, Selling more products in the City_Category C will help the company increase the revenue.