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.

In [ ]:

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

import os
for dirname, _, filenames in os.walk('https://d2beiqkhq929f0.cloudfront.net/public_assets
/assets/000/001/293/original/walmart_data.csv?1641285094'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

In [ ]:

```
df = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/
original/walmart_data.csv?1641285094")
df.head()
```

Out[ ]:

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

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.dtypes
```

Out[ ]:

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

In [ ]:

```
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	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

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_Cit
y_Years', 'Marital_Status', 'Product_Category']
df[categorical_cols].melt().groupby(['variable', 'value'])[['value']].count()/len(df)
```

Out[ ]:

		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

variable	value	value
	...	[illegible]
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

variable	value	value
	2	0.185137
	3	0.173224
	4+	0.154028

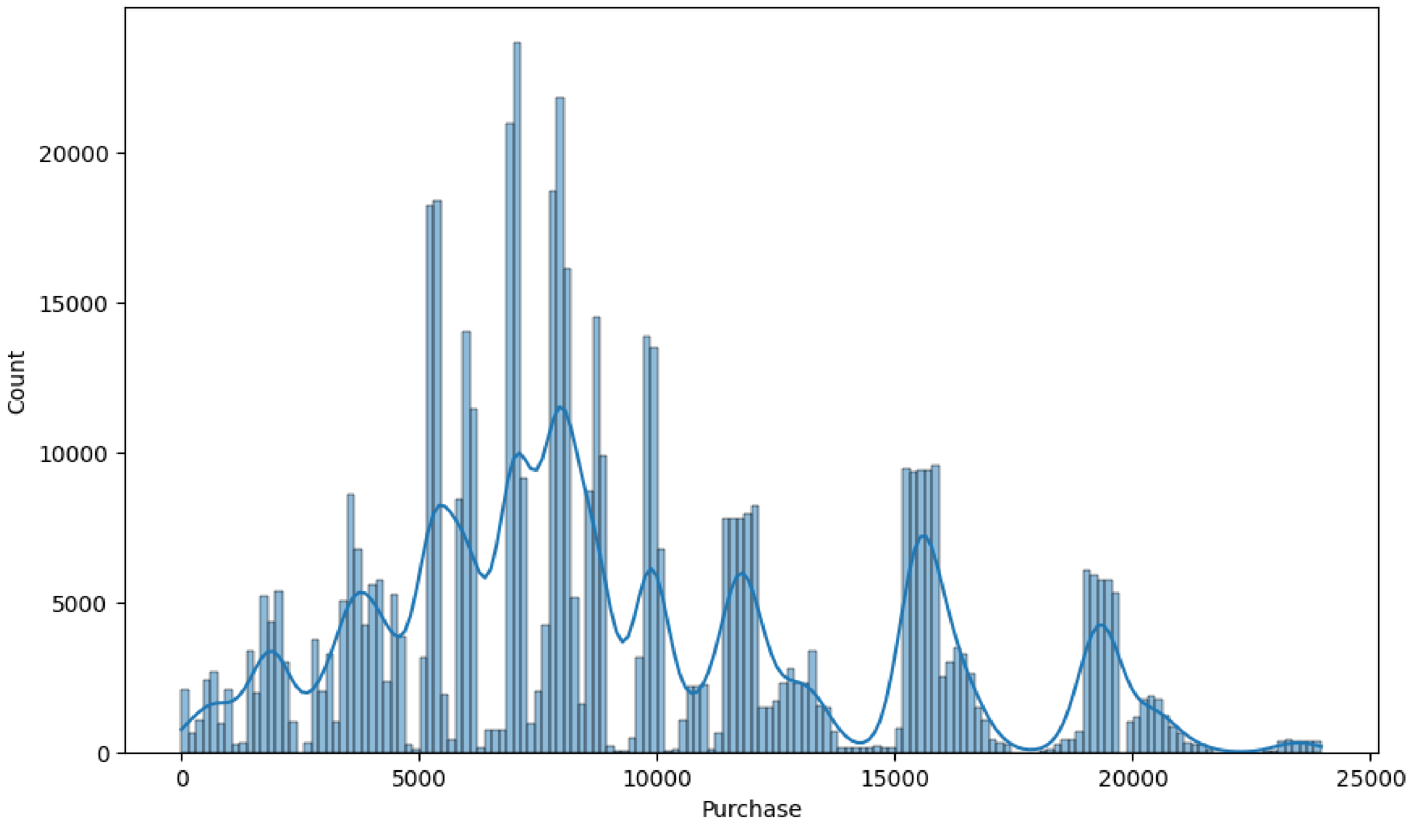
Observations

- ~ 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 diffenent types of occupations in the city

Univariate Analysis

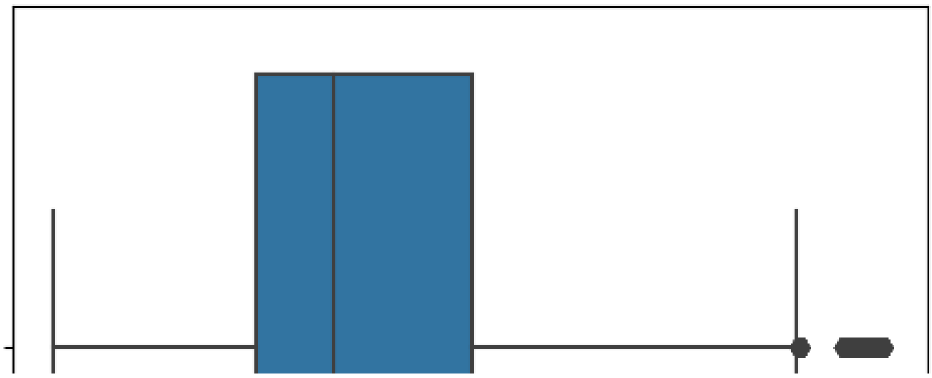
In [ ]:

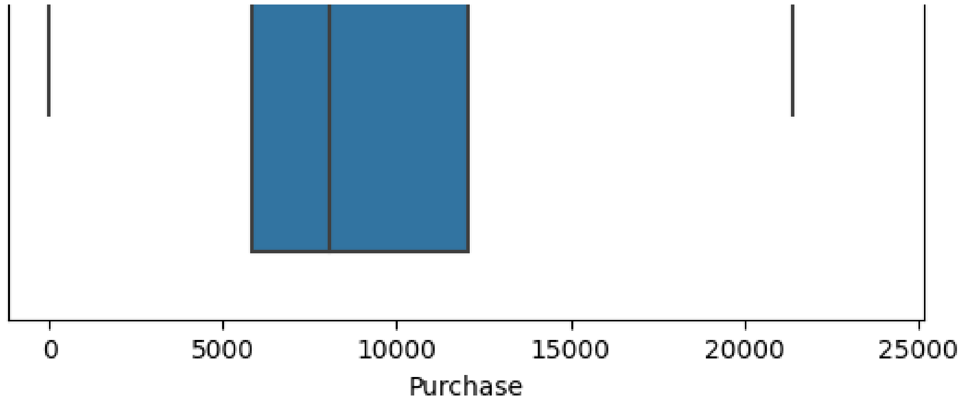
```
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='Purchase', kde=True)
plt.show()
```



In [ ]:

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





Observation

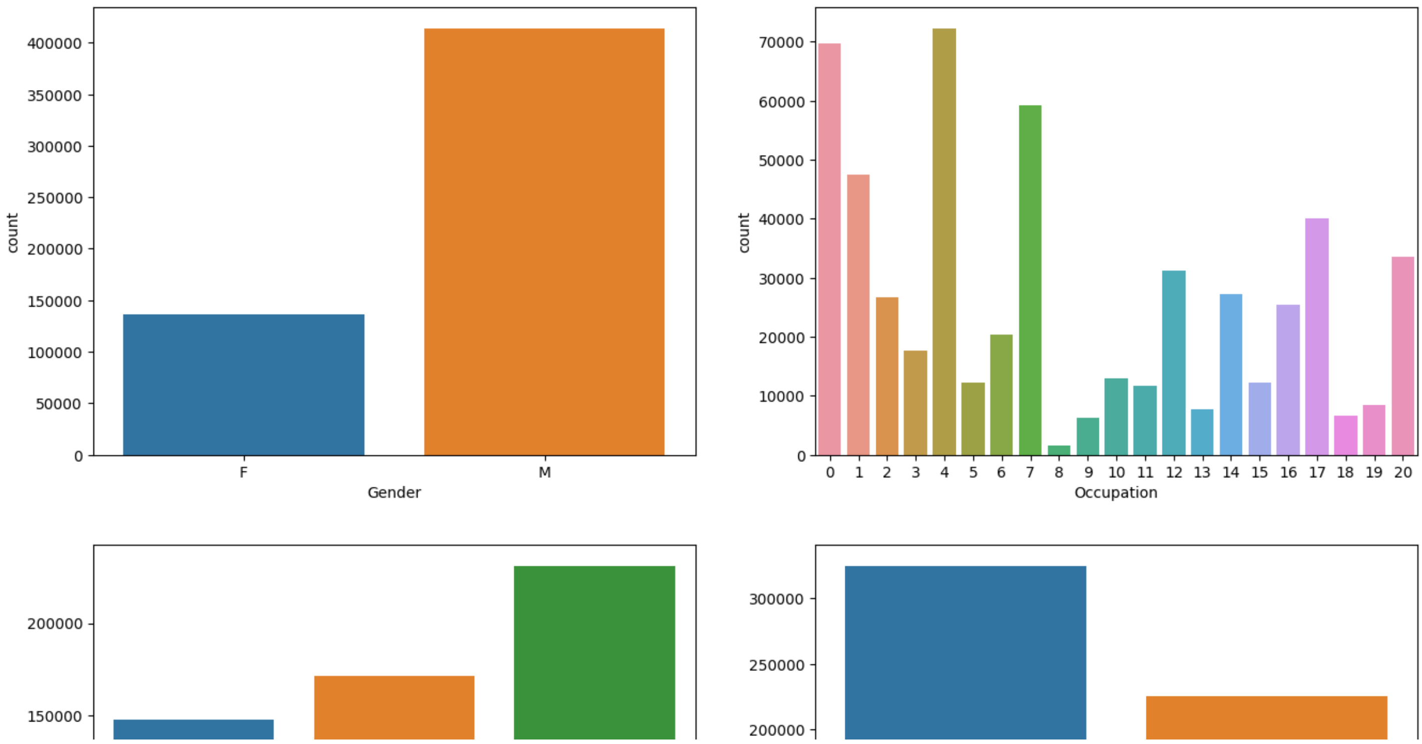
- **Purchase is having outliers**

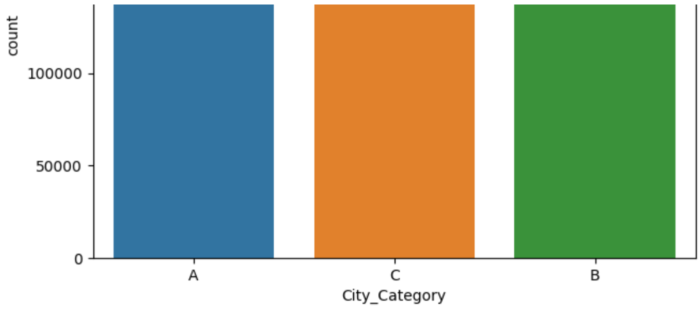
Understanding the distribution of data for the categorical variables

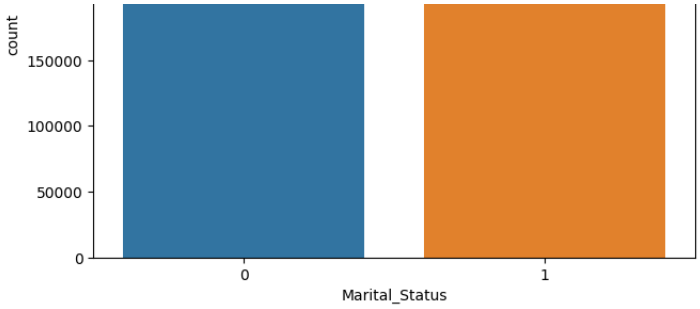
- **Gender**
- **Age**
- **Occupation**
- **City_Category**
- **Stay_In_Current_City_Years**
- **Marital_Status**
- **Product_Category**

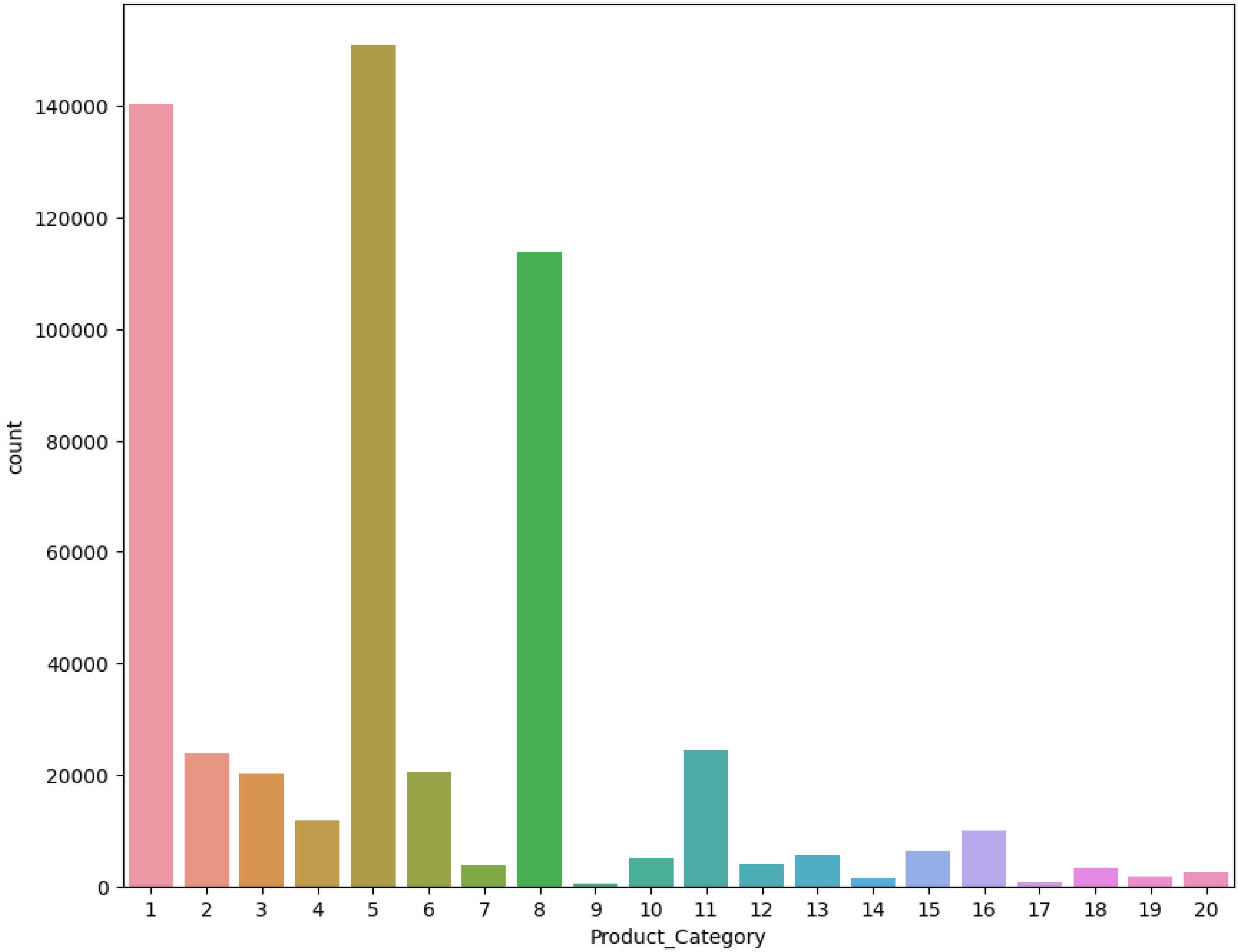
In [ ]:

```
categorical_cols = ['Gender', 'Occupation','City_Category','Marital_Status','Product_Cate
gory']

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()
```









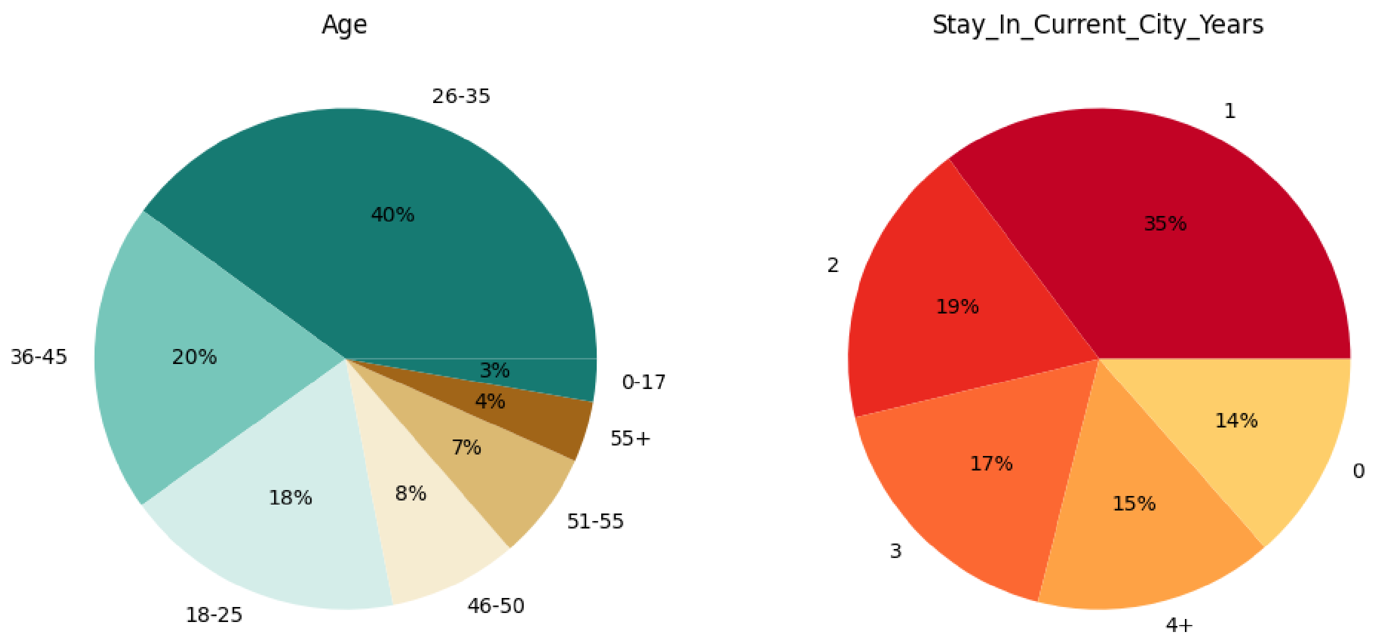
Observations

- **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")
```

```python
plt.show()
```

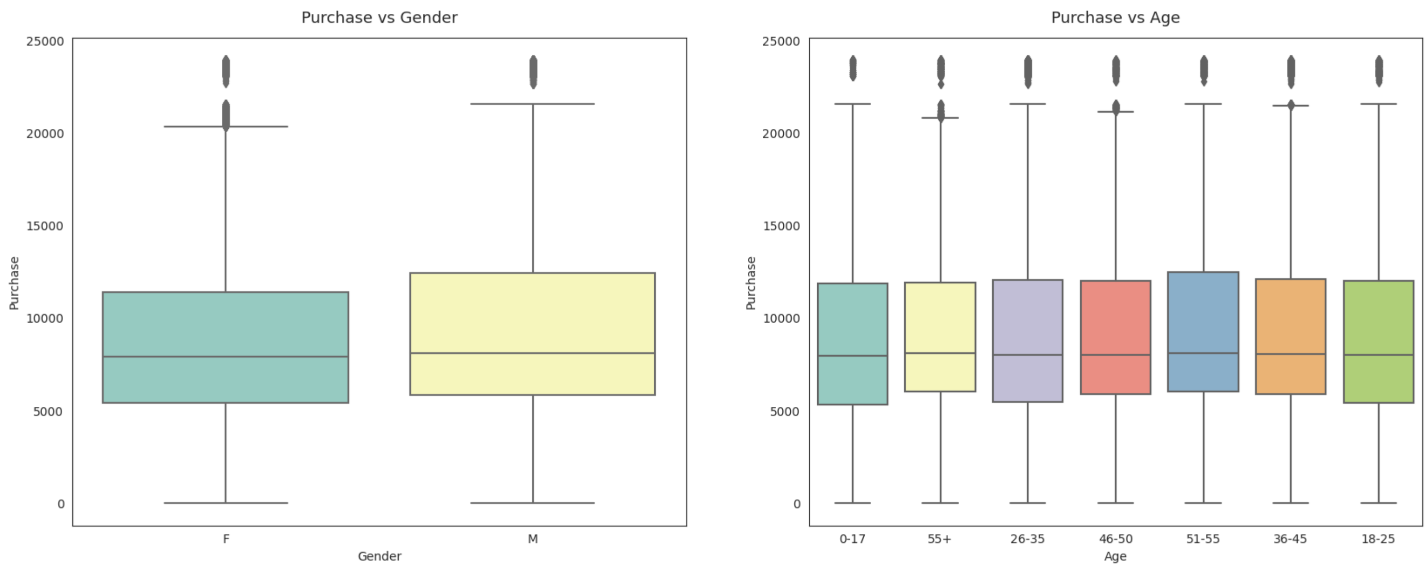


Upper two graphs are self-explanatory.

Bi-variate Analysis

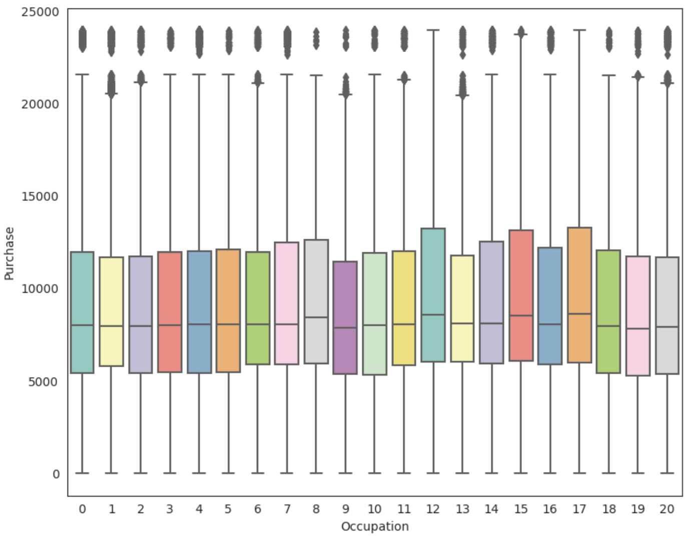
In [ ]:

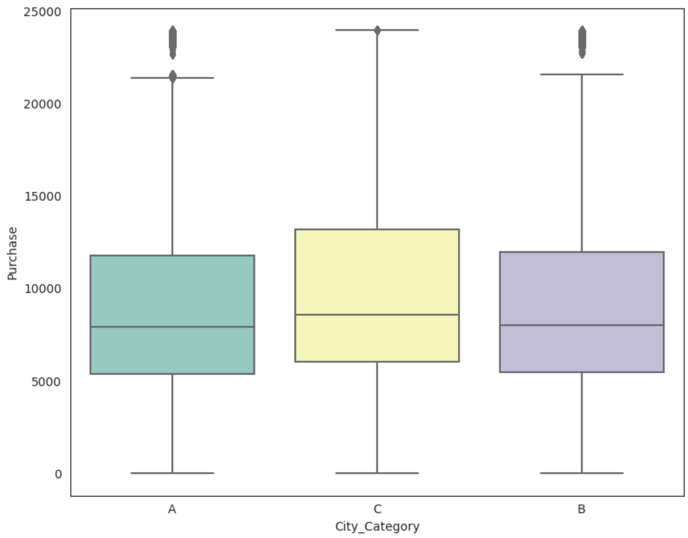
```python
attrs = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', '
Marital_Status', 'Product_Category']
sns.set_style("white")

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='Se
t3')
        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()
```



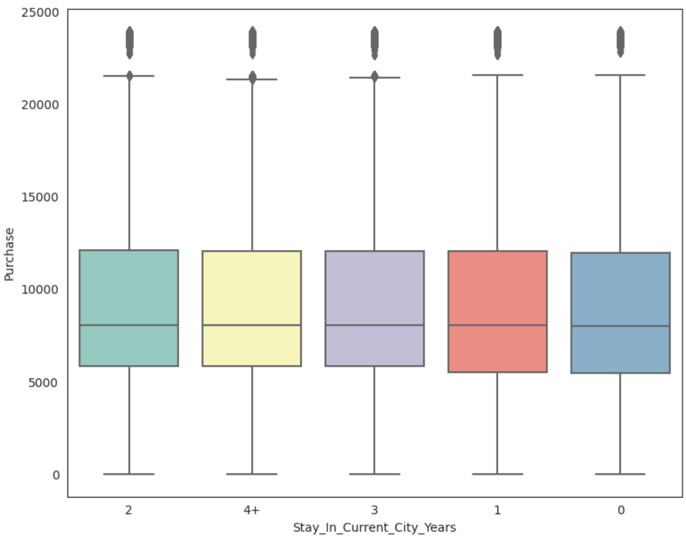
Purchase vs Occupation

Purchase vs City_Category

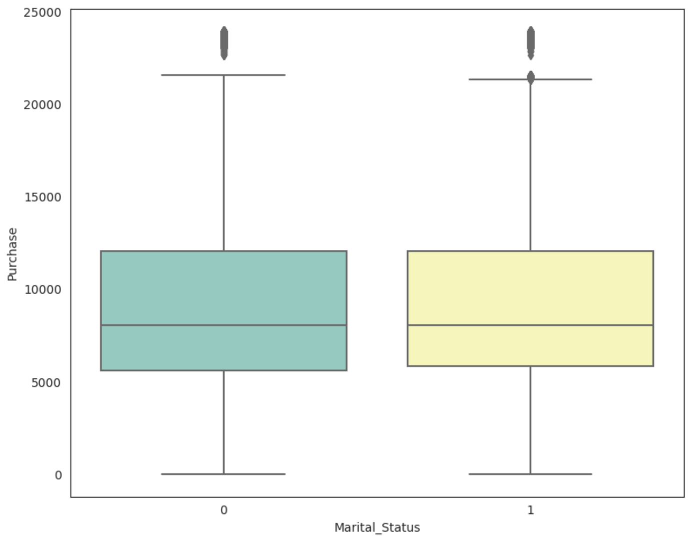


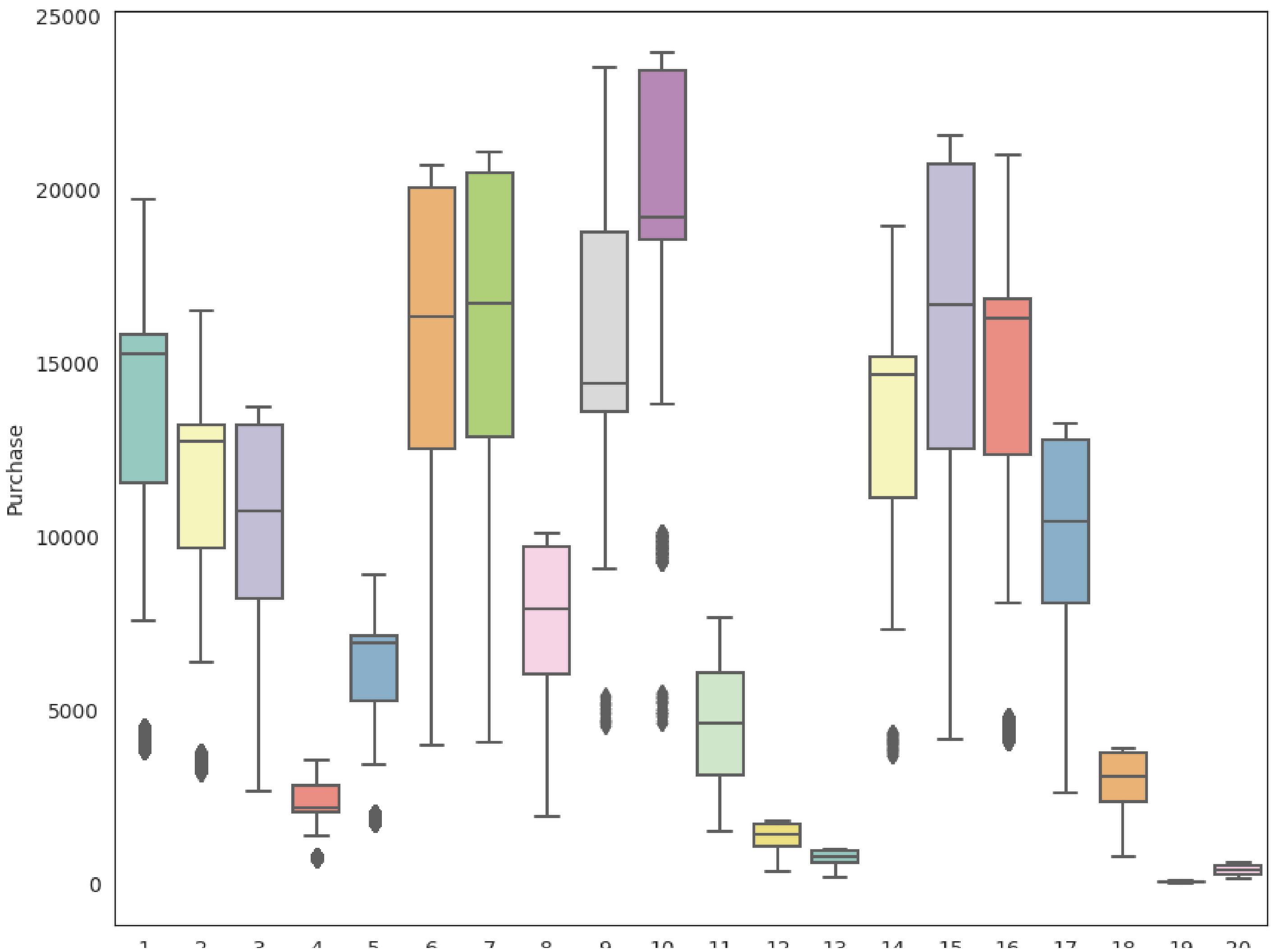


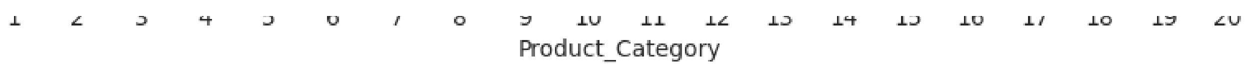
Purchase vs Stay_In_Current_City_Years



Purchase vs Marital_Status



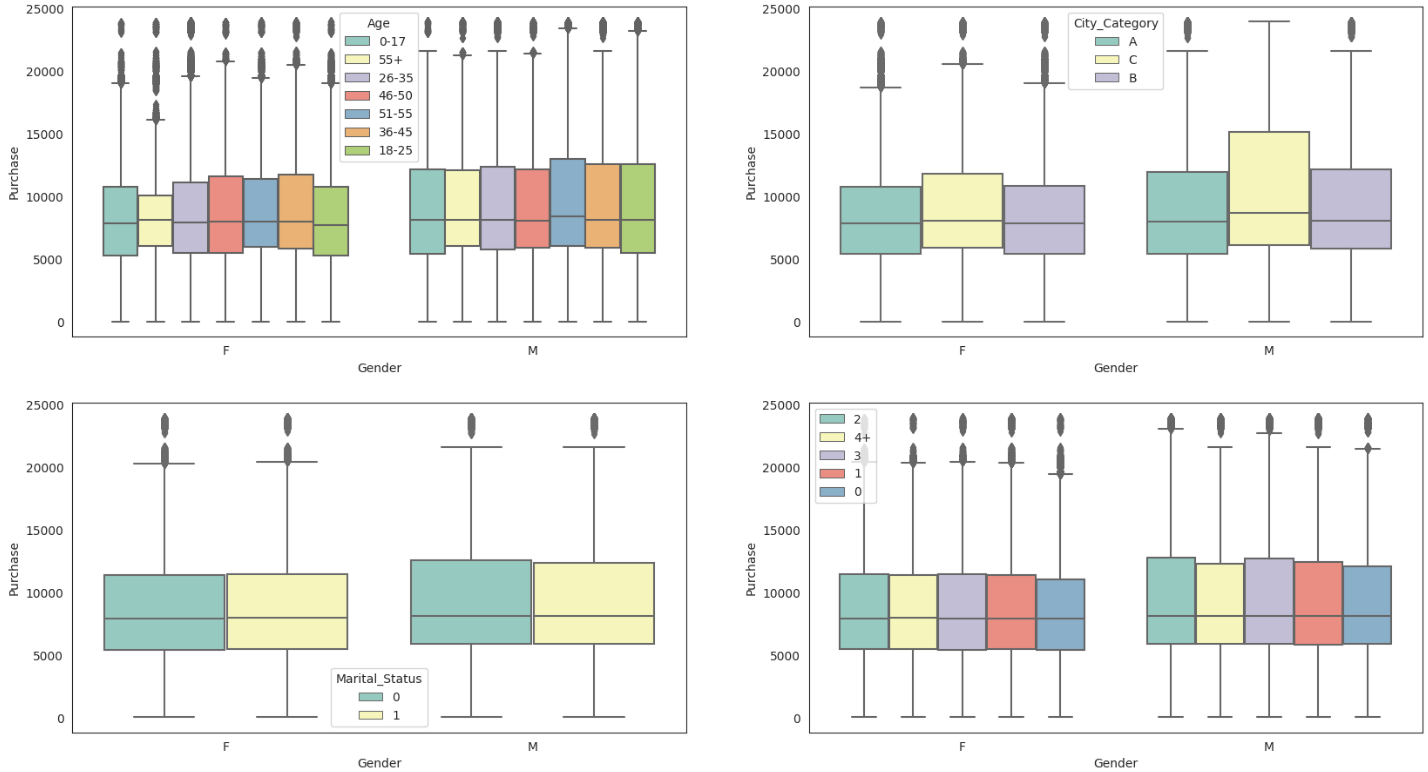




Multivariate Analysis

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=a
xs[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_Catego
0	1000001	P00069042	F	0-17	10	A	2	0	
1	1000001	P00248942	F	0-17	10	A	2	0	
2	1000001	P00087842	F	0-17	10	A	2	0	1
3	1000001	P00085442	F	0-17	10	A	2	0	1
4	1000002	P00285442	M	55+	16	C	4+	0	
5	1000003	P00193542	M	26-35	15	A	3	0	
6	1000004	P00184942	M	46-50	7	B	2	1	

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Catego
7	1000004	P00346142	M	46-50	7	B	2	1	
8	1000004	P0097242	M	46-50	7	B	2	1	
9	1000005	P00274942	M	26-35	20	A	1	1	

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
...	...	...	...
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 [ ]:

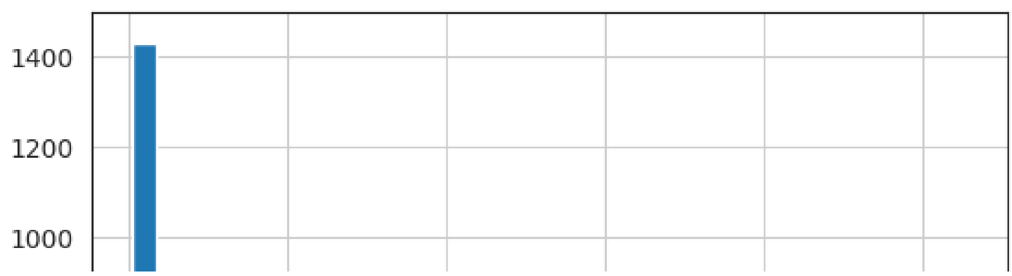
```
# Gender wise value counts in avg_amt_df
df['Gender'].value_counts()
```

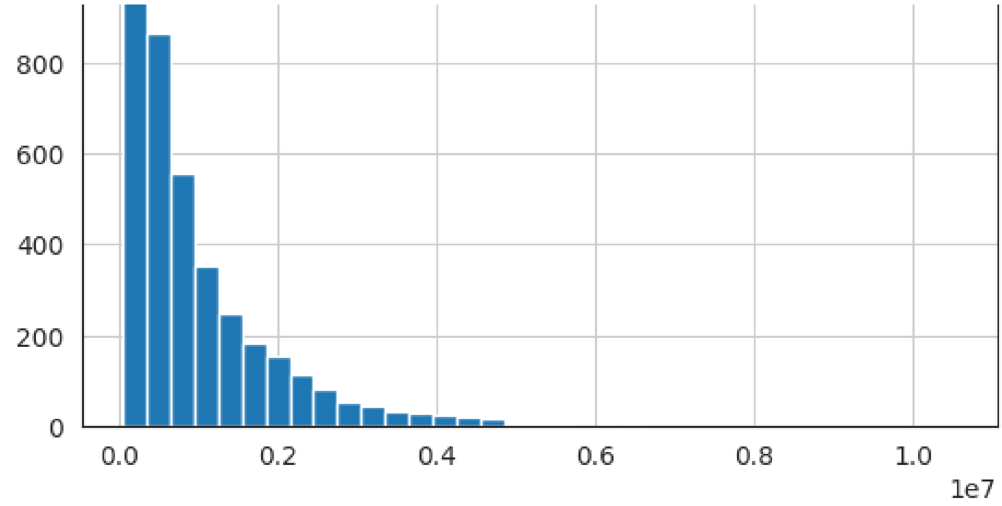
Out[ ]:

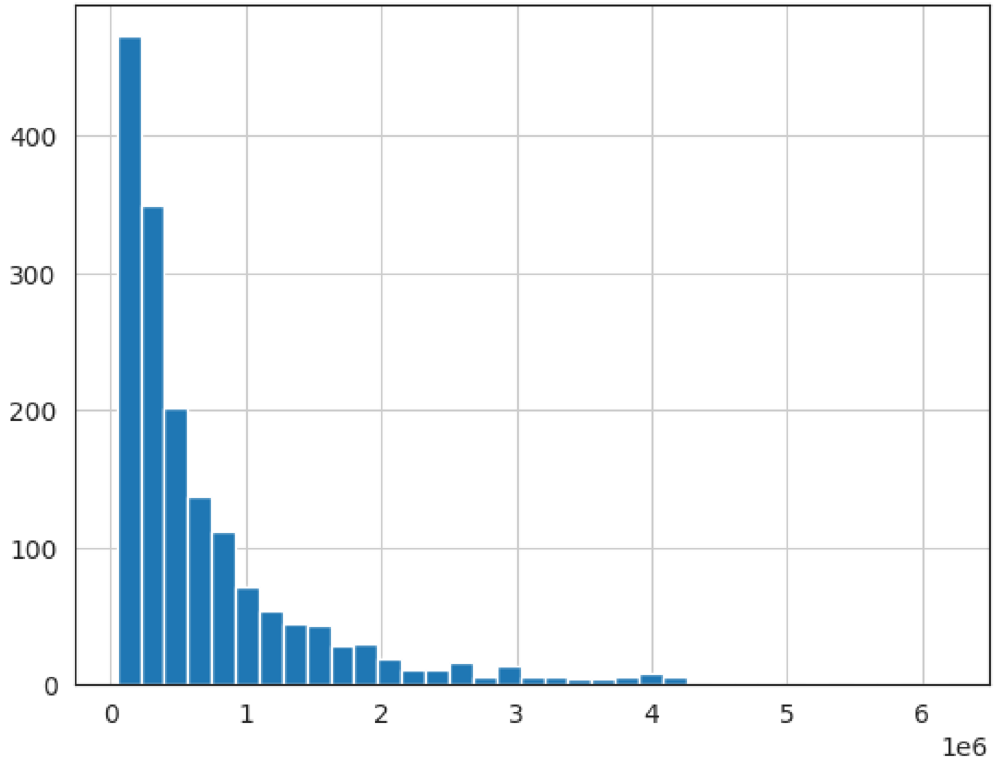
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [ ]:

```
# 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()
```







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**

In [ ]:

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

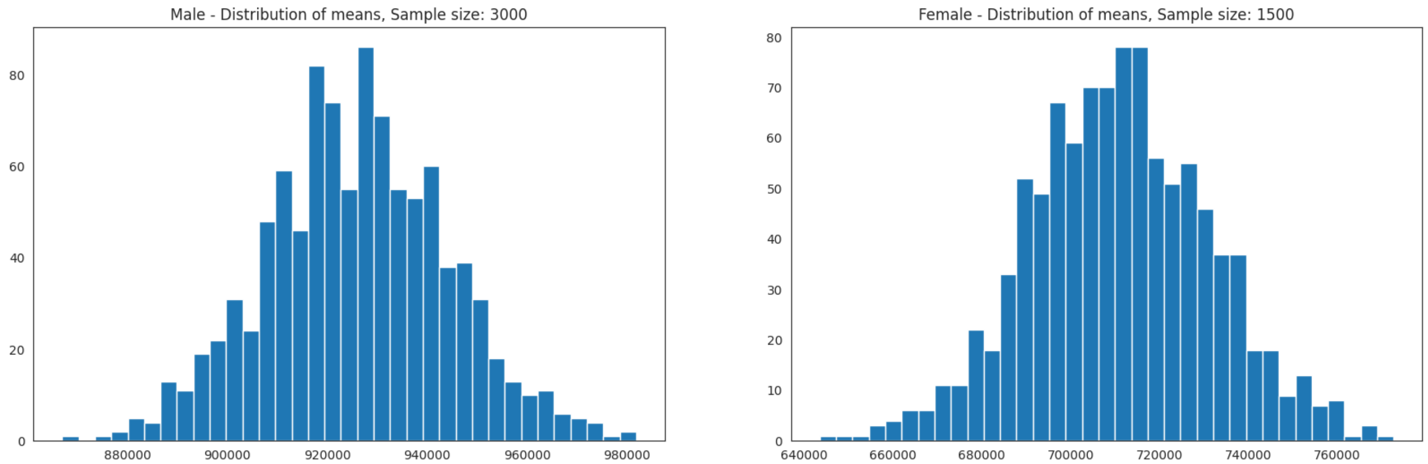
In [ ]:

```
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(n
p.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'].mea
n(), female_df['Purchase'].std()))
```

```
Population mean - Mean of sample means of amount spend for Male: 925877.07
Population mean - Mean of sample means of amount spend for Female: 710935.46

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:

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

In [ ]:

```
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, f
emale_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:

- **Average amount spend by male customer will lie in between: (895617.83, 955070.97)**
- **Average amount spend by female customer will lie in between: (673254.77, 750794.02)**

Doing the same activity 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

	User_ID	Marital_Status	Purchase
5887	1006037	0	1119538
5888	1006038	0	90034
5889	1006039	1	590319
5890	1006040	0	1653299

5891 rows × 3 columns

In [ ]:

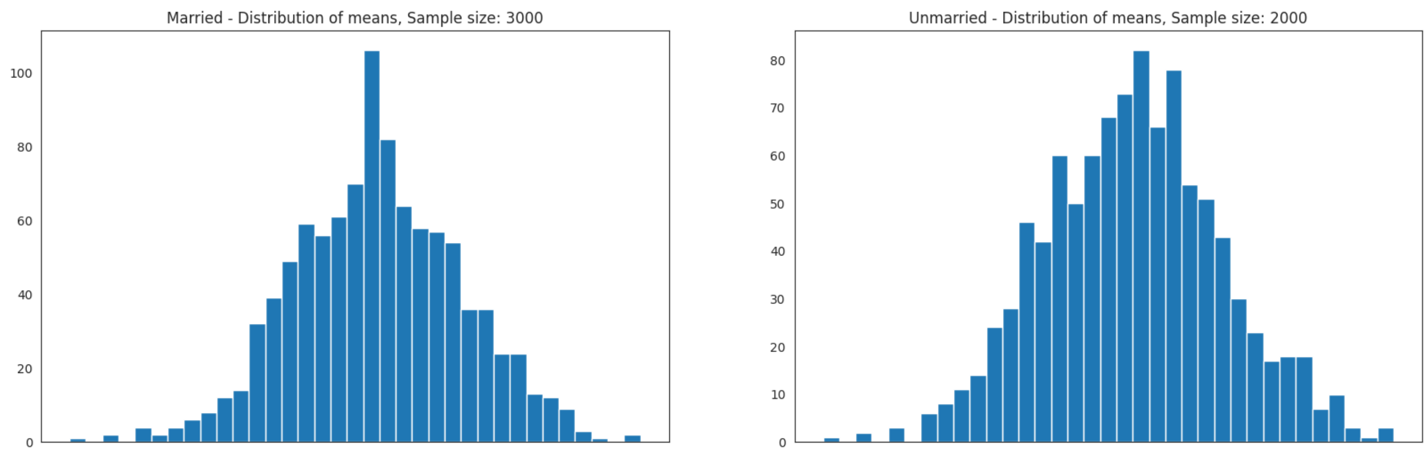
```
amt_df['Marital_Status'].value_counts()
```

Out[ ]:

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

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(), 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: 843731.50
Population mean - Mean of sample means of amount spend for Unmarried: 880327.02

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

In [ ]:

```python
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, upp
er_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

In [ ]:

```python
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 [ ]:

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

Out[ ]:

```
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
```

```
Name: Age, 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)['Pu
rchase'].mean()
        all_means[age_interval].append(mean)
```

In [ ]:

```
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, lo
wer_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 diffenent 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**:

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

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

- Average amount spend by male customer will lie in between: **(895617.83, 955070.97)**
- Average amount spend by female customer will lie in between: **(673254.77, 750794.02)**

Confidence Interval by Marital_Status

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

Confidence Interval by Age

- 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)**

Recommendations

- Men spent more money than women, So company should focus on retaining the male customers and getting more male customers.
- **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.
- **Unmarried customers** spend more money than married customers, So company should focus on acquisition of Unmarried customers.
- 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**
- 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.