About Walmart

Walmart is an American multinational retail corporation that operates a chain of supercentres, 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 analyse the customer purchase behaviour (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).

1. Defining Problem Statement and Analysing basic metrics

In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [7]:
```python
df = pd.read_csv(r"C:\Users\mahesh\Desktop\Scaler\walmart_data.csv")
df.head()
```

Out[7]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969

In [ ]:

In [3]:
```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
```

conversion of categorical attributes to 'category' :

Change the data types of - Occupation, Marital_Status, Product_Category

```
In [4]: #Change the data types of - Occupation, Marital_Status, Product_Category
        cols = ['Occupation', 'Marital_Status', 'Product_Category']
        df[cols] = df[cols].astype('object')
```

```
In [5]: df.dtypes
```

```
Out[5]: 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
```

statistical summary:

```
In [7]: print(df.memory_usage())
        df.describe()
```

```
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
```

Out[7]:

	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

```
# checking null values
In [11]: print(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
```

Observations

- There are no missing values in the dataset.

- **Purchase amount might have outliers.:** the max Purchase amount is 23961 while its mean is 9263.96. The mean is sensitive to outliers, but the fact the mean is so small compared to the max value indicates the max value is an outlier

2: Non-Graphical Analysis: Value counts and unique attributes :

unique attributes :

```
In [12]: # How many users are there in the dataset?
         print(df['User_ID'].nunique())
         # How many products are there?
         print(df['Product_ID'].nunique())
```

```
5891
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)
```

Out[13]:

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

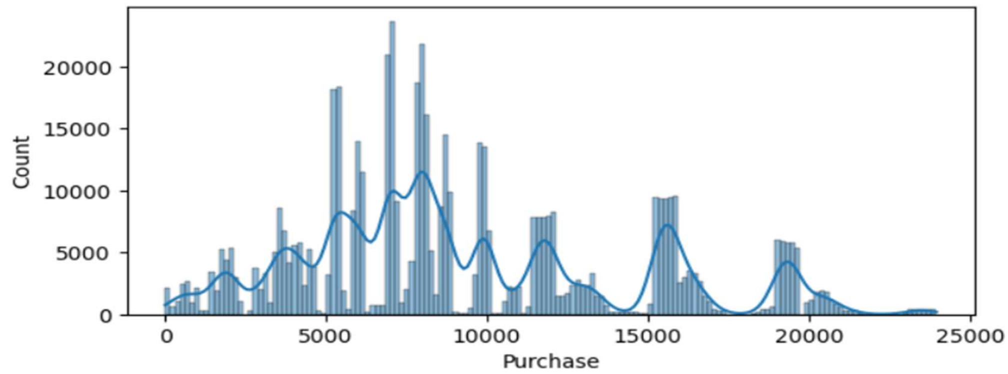
- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are **`Male`** and 25% are **`Female`**
- 60% Single, 40% Married
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- Total of 20 product categories are there
- There are 20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

3: Visual Analysis - Univariate & Bivariate

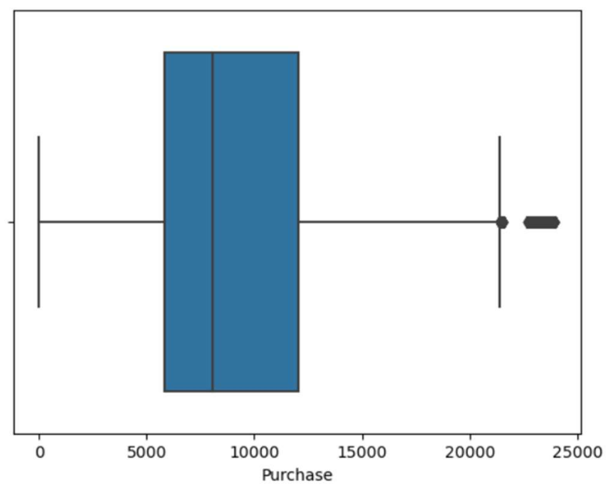
Univariate

- For continuous variable(s): Boxplot, histogram for univariate analysis: *Understanding the distribution of data and detecting outlies for continuous variables*

```
plt.figure(figsize=(7, 3))
sns.histplot(data=df, x='Purchase', kde=True)
plt.show()
```




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



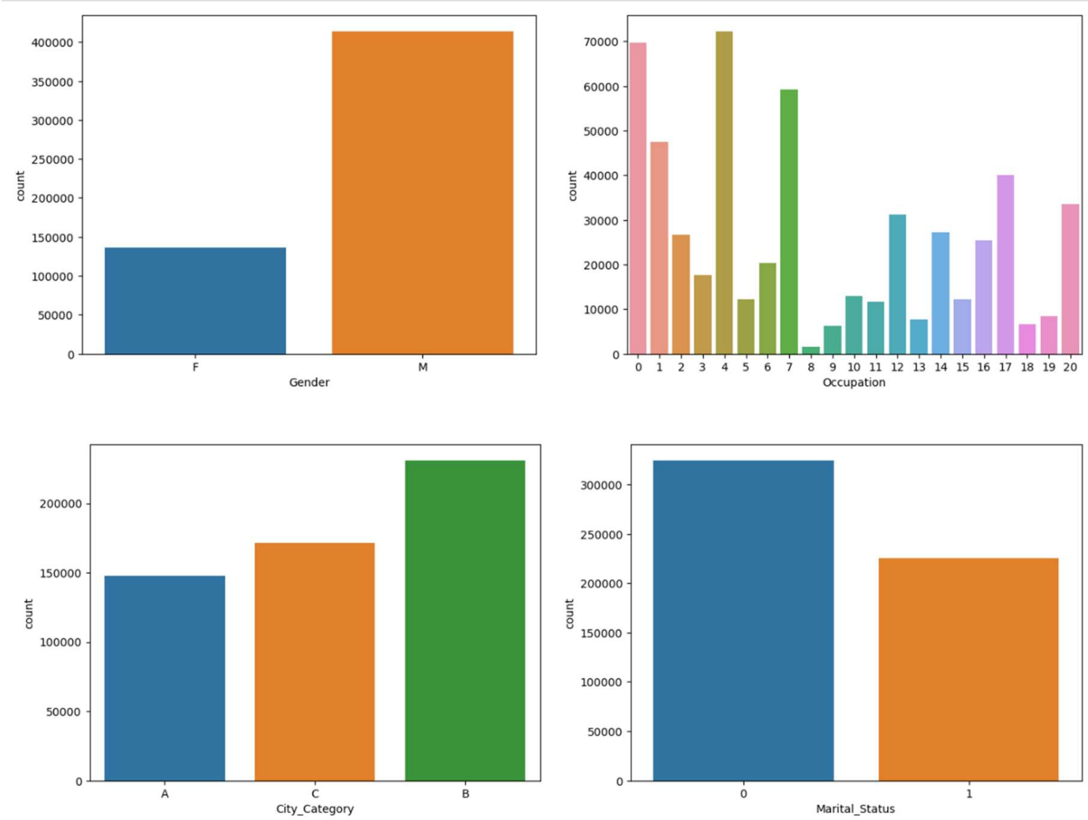
Observation

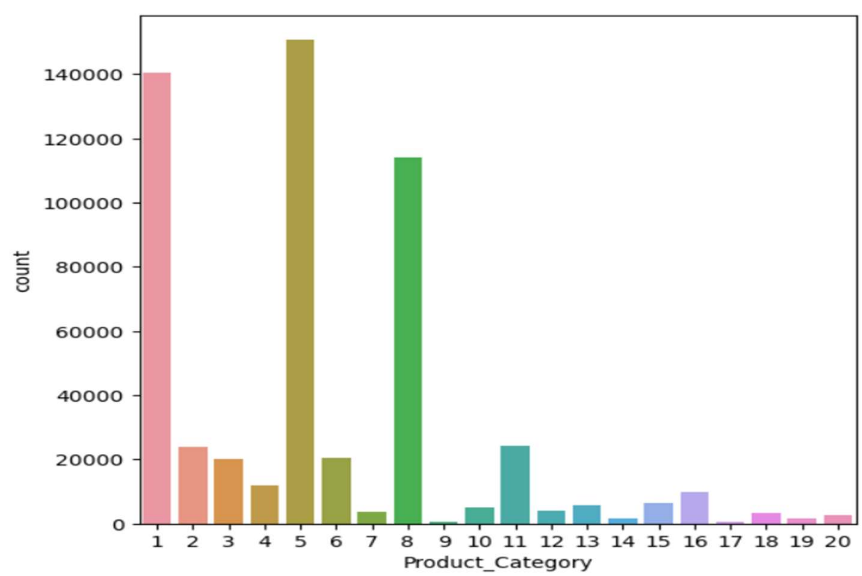
- Purchase is having outliers

- For categorical variable(s): countplot
  Understanding the distribution of data for the categorical variables

```
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()
```

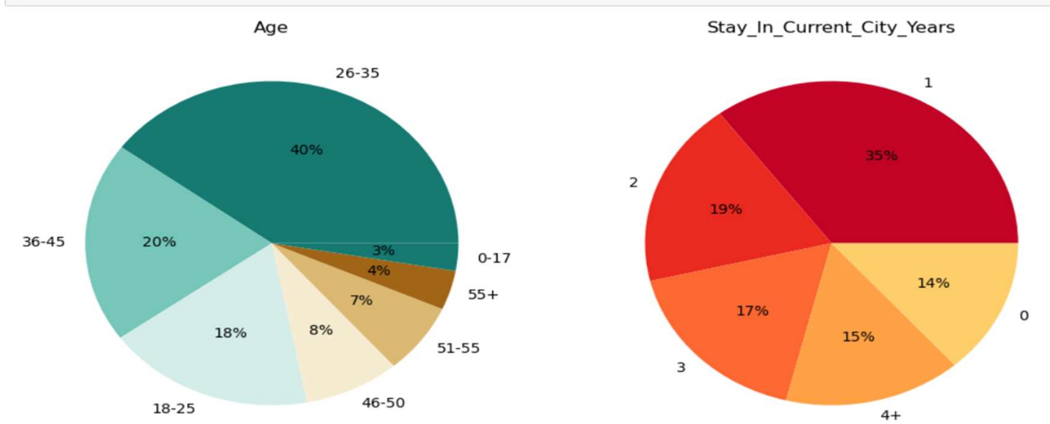
```
plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Product_Category')
plt.show()
```






```
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()
```



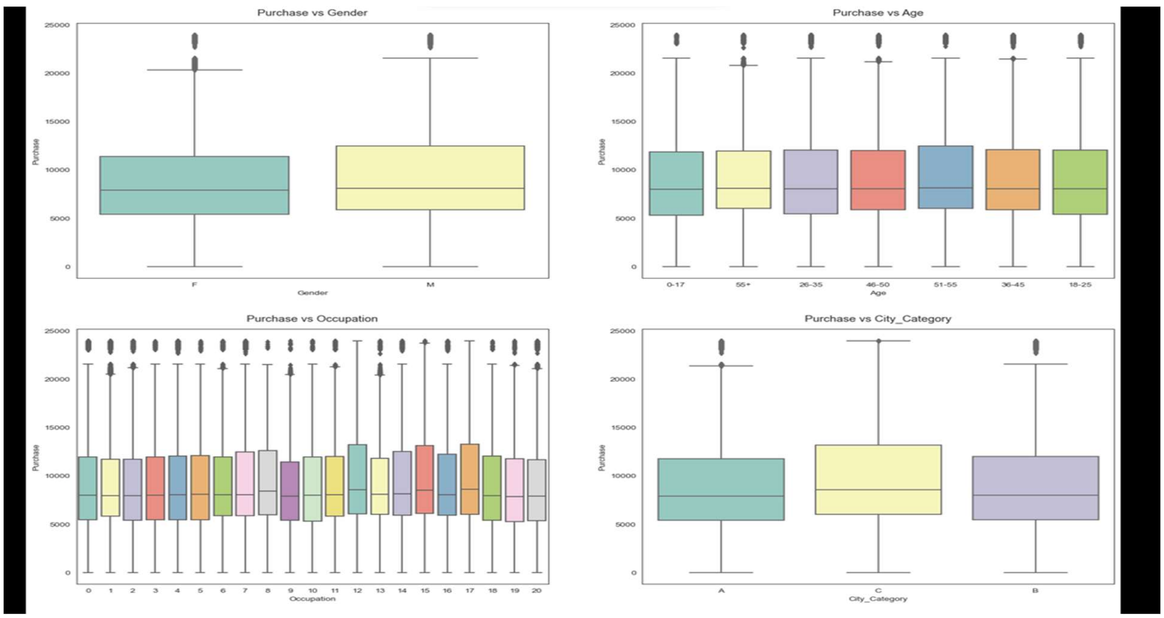
Observations

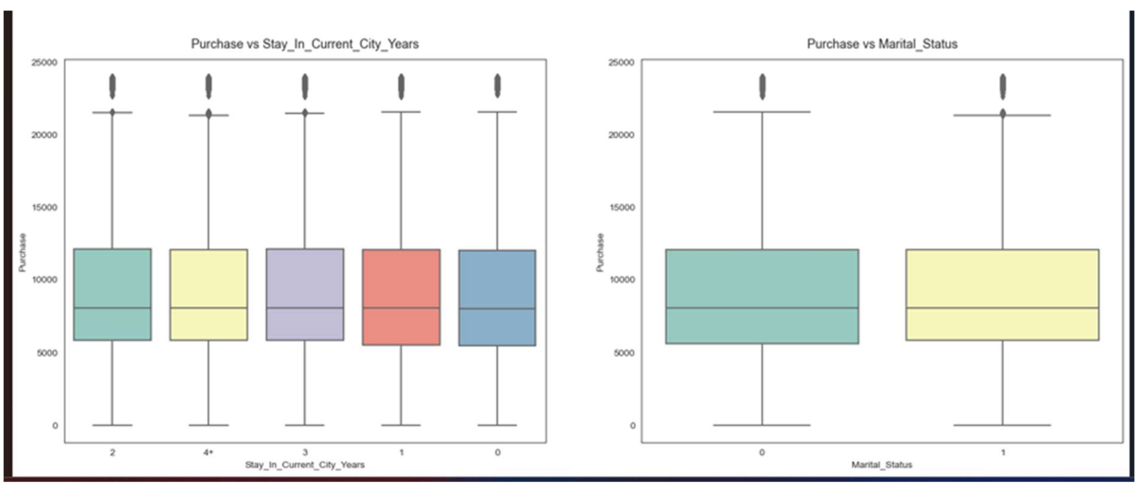
- Most of the users are `Male`
- There are 20 different types of `Occupation` and `Product_Category`
- More users belong to B `City_Category`
- More users are `Single` as compare to `Married`
- `Product_Category` - `1, 5, 8, & 11` have highest purchasing frequency.

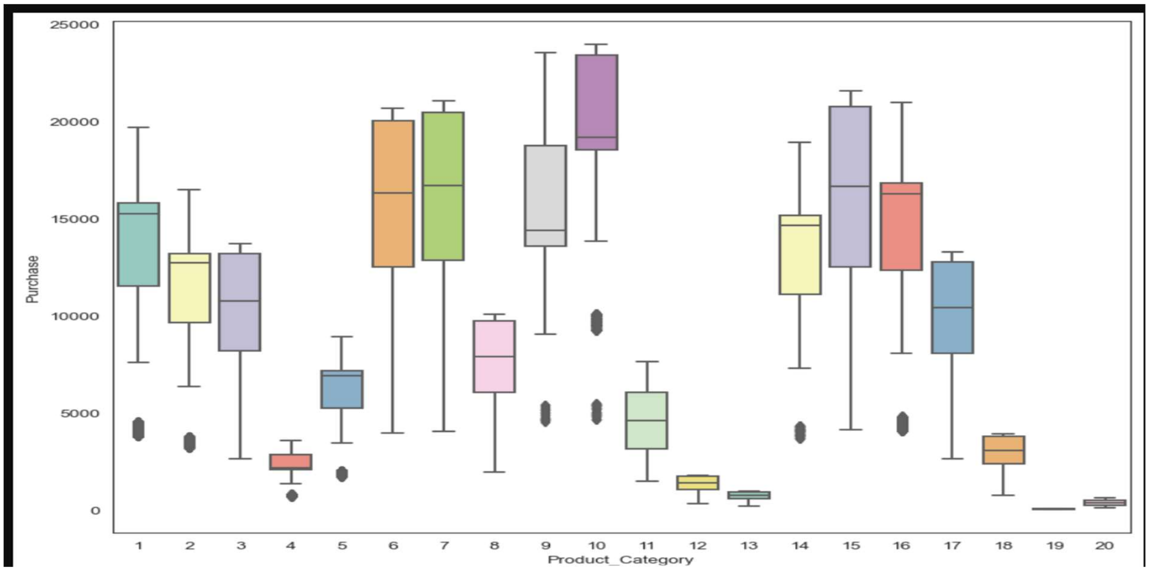
Bivariate

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

Missing Value & Outlier Detection

Missing Value:

```
# checking null values
In [11]: print(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
```

Observations

- There are no missing values in the dataset.

Using pandas describe() to find outliers:

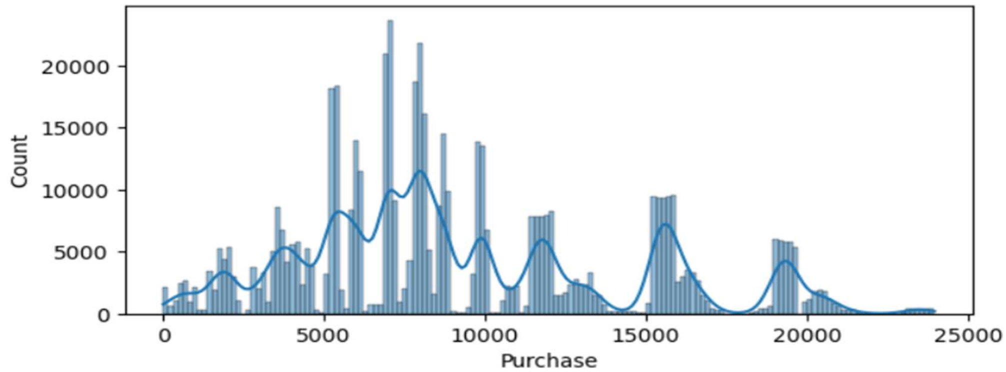
```
In [9]: df.describe()
Out[9]:
```

	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

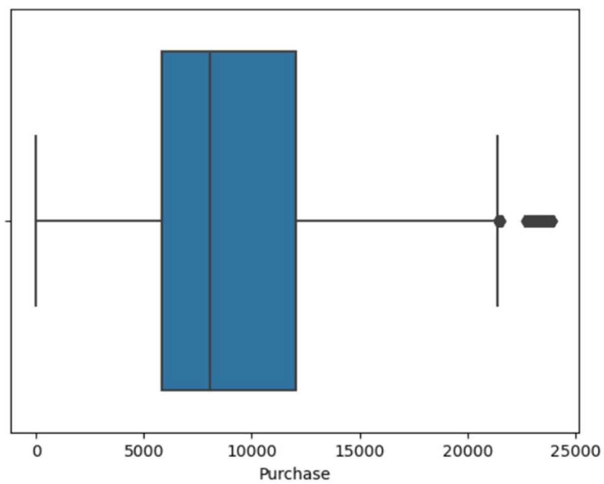
- **Purchase amount might have outliers.:** the max Purchase amount is 23961 while its mean is 9263.96. The mean is sensitive to outliers, but the fact the mean is so small compared to the max value indicates the max value is an outlier

visualize outliers:

```
plt.figure(figsize=(7, 3))
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

Using the convenient pandas .quantile() function

```
#create a function to find outliers using IQR

def find_outliers_IQR(df):

   q1=df.quantile(0.25)

   q3=df.quantile(0.75)

   IQR=q3-q1
```

```
    outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]

    return outliers
```

```
outliers = find_outliers_IQR(df["Purchase"])

print("number of outliers: "+ str(len(outliers)))

print("max outlier value:"+ str(outliers.max()))

print("min outlier value: "+ str(outliers.min()))
```

```
number of outliers: 2677
max outlier value:23961
min outlier value: 21401
```

Answering questions (50 Points)

1. Are women spending more money per transaction than men? Why or Why not?
   Average amount spends per customer for Male and Female

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

Out[20]:

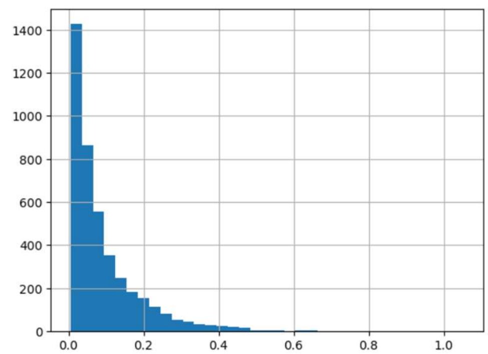
	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001

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

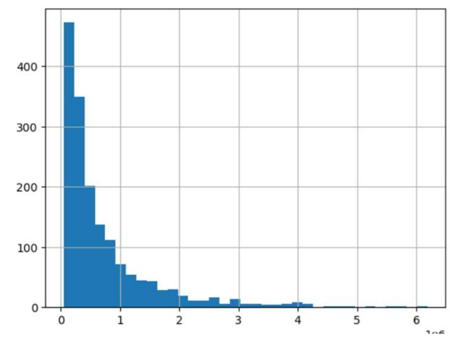
```
Out[22]: M    4225
         F    1666
         Name: Gender, dtype: int64
```

```
# 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()
```

Male Purchase:



Female Purchase:




```
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
```

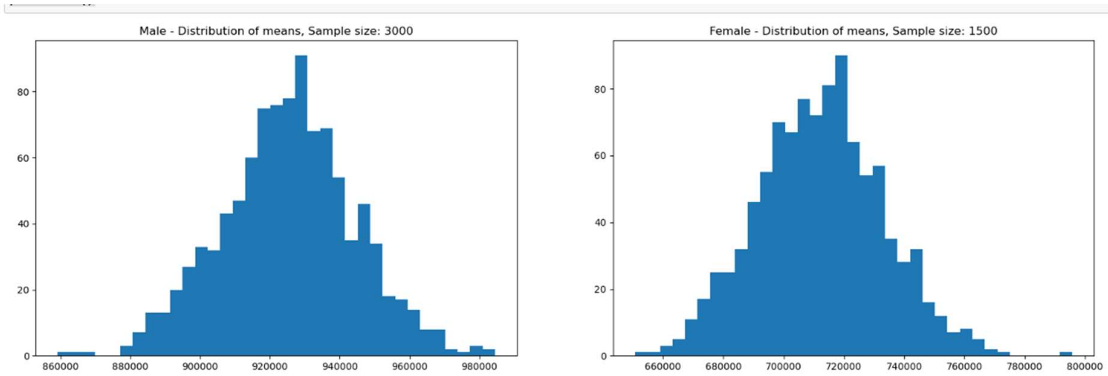
Observation

Male customers spend more money than female customers

2. Confidence intervals and distribution of the mean of the expenses by female and male 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: 925462.34
Population mean - Mean of sample means of amount spend for Female: 712249.43

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**

3: Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

```
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)**

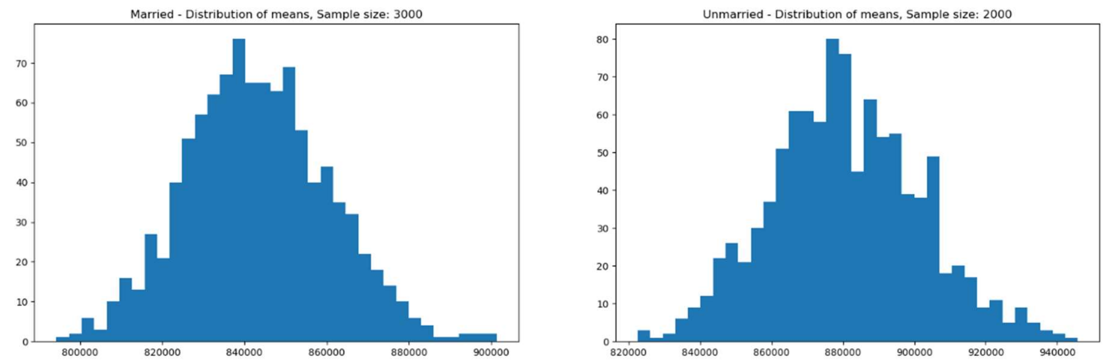
4: Results when the same activity is performed for Married vs Unmarried:

Doing the same activity for married vs unmarried

```
      amt_df

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




```
Population mean - Mean of sample means of amount spend for Married: 843182.67
Population mean - Mean of sample means of amount spend for Unmarried: 880788.23

Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
Married confidence interval of means: (806668.83, 880384.76)
Unmarried confidence interval of means: (848741.18, 912410.38)
```

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
amt_df['Age'].value_counts()
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.