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).

```
#Import the libraries:

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

#Read the Walmart data:

df = pd.read_csv("walmart_data.csv")
df

---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-3-cfa996cb6bff> in <cell line: 3>()
      1 #Read the Walmart data:
      2
----> 3 df = pd.read_csv("walmart_data.csv")
      4 df

/usr/local/lib/python3.10/dist-packages/pandas/util/_decorators.py in wrapper(*args, **kwargs)
    209                 else:
    210                     kwargs[new_arg_name] = new_arg_value
--> 211             return func(*args, **kwargs)
    212
    213         return cast(F, wrapper)

/usr/local/lib/python3.10/dist-packages/pandas/util/_decorators.py in wrapper(*args, **kwargs)
    329                     stacklevel=find_stack_level(),
    330                 )
--> 331             return func(*args, **kwargs)
```

```
    332
    333         # error: "Callable[[VarArg(Any), KwArg(Any)], Any]"
has no

/usr/local/lib/python3.10/dist-packages/pandas/io/parsers/readers.py
in read_csv(filepath_or_buffer, sep, delimiter, header, names,
index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine,
converters, true_values, false_values, skipinitialspace, skiprows,
skipfooter, nrows, na_values, keep_default_na, na_filter, verbose,
skip_blank_lines, parse_dates, infer_datetime_format, keep_date_col,
date_parser, dayfirst, cache_dates, iterator, chunksize, compression,
thousands, decimal, lineterminator, quotechar, quoting, doublequote,
escapechar, comment, encoding, encoding_errors, dialect,
error_bad_lines, warn_bad_lines, on_bad_lines, delim_whitespace,
low_memory, memory_map, float_precision, storage_options)
    948     kwds.update(kwds_defaults)
    949
--> 950     return _read(filepath_or_buffer, kwds)
    951
    952

/usr/local/lib/python3.10/dist-packages/pandas/io/parsers/readers.py
in _read(filepath_or_buffer, kwds)
    603
    604     # Create the parser.
--> 605     parser = TextFileReader(filepath_or_buffer, **kwds)
    606
    607     if chunksize or iterator:

/usr/local/lib/python3.10/dist-packages/pandas/io/parsers/readers.py
in __init__(self, f, engine, **kwds)
   1440
   1441         self.handles: IOHandles | None = None
-> 1442         self._engine = self._make_engine(f, self.engine)
   1443
   1444     def close(self) -> None:

/usr/local/lib/python3.10/dist-packages/pandas/io/parsers/readers.py
in _make_engine(self, f, engine)
   1733                 if "b" not in mode:
   1734                     mode += "b"
-> 1735             self.handles = get_handle(
   1736                 f,
   1737                 mode,

/usr/local/lib/python3.10/dist-packages/pandas/io/common.py in
get_handle(path_or_buf, mode, encoding, compression, memory_map,
is_text, errors, storage_options)
    854         if ioargs.encoding and "b" not in ioargs.mode:
    855             # Encoding
```

```
--> 856             handle = open(
    857                 handle,
    858                 ioargs.mode,

FileNotFoundError: [Errno 2] No such file or directory:
'walmart_data.csv'

#Checking missing values:
df.isnull().sum()/len(df)*100

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-4-f2655f955b56> in <cell line: 2>()
      1 #Checking missing values:
----> 2 df.isnull().sum()/len(df)*100

NameError: name 'df' is not defined

#Checking the characteristics of the data:
df.describe(include='all')

df.info()
```

Initial Observations:

1. There are no missing values in the data.
2. There are 3631 unique product IDs in the dataset. P00265242 is the most sold Product ID.
3. There are 7 unique age groups and most of the purchase belongs to age 26-35 group.
4. There are 3 unique citi categories with category B being the highest.
5. 5 unique values for Stay_in_current_citi_years with 1 being the highest.
6. The difference between mean and median seems to be significant for purchase that suggests outliers in the data.
7. Minimum & Maximum purchase is 12 and 23961 suggests the purchasing behaviour is quite spread over a aignificant range of values. Mean is 9264 and 75% of purchase is of less than or equal to 12054. It suggest most of the purchase is not more than 12k.
8. Few categorical variable are of integer data type. It can be converted to character type.

9. Out of 550068 data points, 414259's gender is Male and rest are the female. Male purchase count is much higher than female.

10. Standard deviation for purchase have significant value which suggests data is more spread out for this attribute.

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

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-5-e9231eb29805> in <cell line: 2>()
      1 columns=['User_ID','Occupation', 'Marital_Status',
'Product_Category']
----> 2 df[columns]=df[columns].astype('object')

NameError: name 'df' is not defined

df.info()

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-6-a74c58233b9e> in <cell line: 1>()
----> 1 df.info()

NameError: name 'df' is not defined

df.describe(include='all')

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-7-174ba9bf1a5c> in <cell line: 1>()
----> 1 df.describe(include='all')

NameError: name 'df' is not defined
```

Observation post modifying the categorical variable's data type:

1. There are 5891 unique users, and userid 1001680 being with the highest count.
2. The customers belongs to 21 distinct occupation for the purchases being made with Occupation 4 being the highest.
3. Marital status unmarried contribute more in terms of the count for the purchase.
4. There are 20 unique product categories with 5 being the highest.

```
# Checking how categorical variables contributes to the entire data
categ_cols = ['Gender', 'Age', 'City_Category',
'Stay_In_Current_City_Years', 'Marital_Status']
df[categ_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
Stay_In_Current_City_Years  0      0.135252
                            1      0.352358
                            2      0.185137
                            3      0.173224
                            4+     0.154028
```

Observations:

```
1. 40% of the purchase done by aged 26-35 and 78% purchase are done by
the customers aged between the age 18-45 (40%: 26-35, 18%: 18-25, 20%:
36-45)
2. 75% of the purchase count are done by Male and 25% by Female
3. 60% Single, 40% Married contributes to the purchase count.
4. 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3
years
5. There are 20 product categories in total.
6. There are 20 different types of occupations in the city.

#Checking how the data is spread basis distinct users

df2=df.groupby(['User_ID'])['Age'].unique()
df2.value_counts()/len(df2)
```

```
[26-35]    0.348498
[36-45]    0.198099
[18-25]    0.181463
[46-50]    0.090137
[51-55]    0.081650
```

```
[55+]      0.063147
[0-17]     0.037006
Name: Age, dtype: float64
```

Observation:

```
1. We can see 35% of the users are aged 26-35. 73% of users are aged
between 18-45.
2. From the previous observation we saw 40% of the purchase are done
by users aged 26-35. And, we have 35% of users aged between 26-35 and
they are contributing 40% of total purchase count.So, we can infer
users aged 26-35 are more frequent  customers.
```

```
df2=df.groupby(['User_ID'])['Gender'].unique()
df2.value_counts()/len(df2)
```

```
[M]    0.717196
[F]    0.282804
Name: Gender, dtype: float64
```

Observation:

```
1. We have 72% male users and 28% female users. Combining with
previous observations we can see 72% of male users contributing to 75%
of the purchase count and 28% of female users are contributing to 25%
of the purchase count.
```

```
df2=df.groupby(['User_ID'])['Marital_Status'].unique()
df2.value_counts()/len(df2)
```

```
[0]    0.580037
[1]    0.419963
Name: Marital_Status, dtype: float64
```

Observation: 1. We have 58% of the single users and 42% of married users. Combining with previous observation, single users contributes more as 58% of the single contributes to the 60% of the purchase count.

```
df2=df.groupby(['User_ID'])['City_Category'].unique()
df2.value_counts()/len(df2)
```

```
[C]    0.532847
[B]    0.289764
[A]    0.177389
Name: City_Category, dtype: float64
```

Observation:

```
1. 53% of the users belong to city category C whereas 29% to category
B and 18% belong to category A. Combining from the previous
observation category B purchase count is 42% and Category C purchase
count is 31%. We can clearly see category B are more actively
purchasing inspite of the fact they are only 28% of the total users.
On the other hand, we have 53% of category C users but they only
contribute 31% of the total purchase count.

#Checking the age group distribution in different city categories
pd.crosstab(index=df["City_Category"],columns=df["Age"],margins=True,n
ormalize="index")

Age                   0-17     18-25     26-35     36-45     46-50
51-55  \
City_Category

A               0.017222  0.186400  0.499222  0.180185  0.051496
0.041288
B               0.023511  0.187076  0.396171  0.205898  0.088272
0.076743
C               0.041612  0.168705  0.316974  0.209131  0.103333
0.085649
All             0.027455  0.181178  0.399200  0.199999  0.083082
0.069993

Age                  55+
City_Category
A               0.024188
B               0.022330
C               0.074596
All             0.039093
```

Observation:

```
1. We have seen earlier that city category B and A constitutes less
percentage of total population, but they contribute more towards
purchase count. We can see from above results large percentage of
customers aged 26-35 for B(40%) and A (50%) which can be the reason
for these city categories to be more actively purchasing.

#Checking how genders are contributing towards toatl purchase amount
df2=pd.DataFrame(df.groupby(['Gender'])[['Purchase']].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2

          Purchase    percent
Gender
```

```
F       1186232642  23.278576
M       3909580100  76.721424
```

Observation:

1. We can see male(72% of the population) contributes to more than 76% of the total purchase amount whereas female(28% of the population) contributes 23% of the total purchase amount.

```
#Checking how purchase value are spread among diffrent age categories
df2=pd.DataFrame(df.groupby(['Age'])[['Purchase']].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2

         Purchase    percent
Age
0-17    134913183   2.647530
18-25   913848675  17.933325
26-35  2031770578  39.871374
36-45  1026569884  20.145361
46-50   420843403   8.258612
51-55   367099644   7.203947
55+     200767375   3.939850
```

Observation:

```
1. We can see the net purchase amount spread is similar to the
purchase count spread among the different age groups.

df2=pd.DataFrame(df.groupby(['Marital_Status'])['Purchase'].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2

                  Purchase    percent
Marital_Status
0               3008927447  59.047057
1               2086885295  40.952943
```

Observations:

```
1. Single users are contributing 59% towards the total purchase amount
in comparison to 41% by married users.

df2=pd.DataFrame(df.groupby(['City_Category'])['Purchase'].sum())

df2['percent'] = (df2['Purchase'] /
```

```
                  df2['Purchase'].sum()) * 100
df2
```

```
                Purchase    percent
City_Category
A             1316471661  25.834381
B             2115533605  41.515136
C             1663807476  32.650483
```

Observations:

```
1. City_category contribution to the total purchase amount is also
similar to their contribution towards Purchase count. Still, combining
with previous observation we can City_category C although has
percentage purchase count of 31% but they contribute more in terms of
purchase amount i.e. 32.65%. We can infer City category C purchase
higher value products.
```

```
# Users with highest number of purchases
df.groupby(['User_ID'])['Purchase'].count().nlargest(10)
```

```
User_ID
1001680    1026
1004277     979
1001941     898
1001181     862
1000889     823
1003618     767
1001150     752
1001015     740
1005795     729
1005831     727
Name: Purchase, dtype: int64
```

```
#Users with highest purchases amount
df.groupby(['User_ID'])['Purchase'].sum().nlargest(10)
```

```
User_ID
1004277    10536909
1001680     8699596
1002909     7577756
1001941     6817493
1000424     6573609
1004448     6566245
1005831     6512433
1001015     6511314
1003391     6477160
1001181     6387961
Name: Purchase, dtype: int64
```

Observation:

```
1. The users with high number of purchases contribute more to the
purchase amount. Still, we can see there are few users not in the list
of top 10 purchase counts are there in list of top 10 purchase amount.
Also, the user 1004277 with lesser purchase count(979) has a much
higher purchase amount than the user(1001680) with top purchase count.
```

```
df2=pd.DataFrame(df.groupby(['Occupation'])[['Purchase']].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2
```

Occupation	Purchase	percent
0	635406958	12.469198
1	424614144	8.332609
2	238028583	4.671062
3	162002168	3.179123
4	666244484	13.074352
5	113649759	2.230258
6	188416784	3.697482
7	557371587	10.937835
8	14737388	0.289206
9	54340046	1.066367
10	115844465	2.273327
11	106751618	2.094889
12	305449446	5.994126
13	71919481	1.411345
14	259454692	5.091527
15	118960211	2.334470
16	238346955	4.677310
17	393281453	7.717738
18	60721461	1.191595
19	73700617	1.446298
20	296570442	5.819885

Observations:

```
1. Some of the Occupation like 0, 4, 7 has contributed more towards
total purchase amount.
```

```
df2=pd.DataFrame(df.groupby(['Product_Category'])[['Purchase']].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2
```

```
                        Purchase    percent
Product_Category
1                     1910013754  37.482024
2                      268516186   5.269350
3                      204084713   4.004949
4                       27380488   0.537313
5                      941835229  18.482532
6                      324150302   6.361111
7                       60896731   1.195035
8                      854318799  16.765114
9                        6370324   0.125011
10                     100837301   1.978827
11                     113791115   2.233032
12                       5331844   0.104632
13                       4008601   0.078665
14                      20014696   0.392767
15                      92969042   1.824420
16                     145120612   2.847840
17                       5878699   0.115363
18                       9290201   0.182310
19                         59378   0.001165
20                        944727   0.018539
```

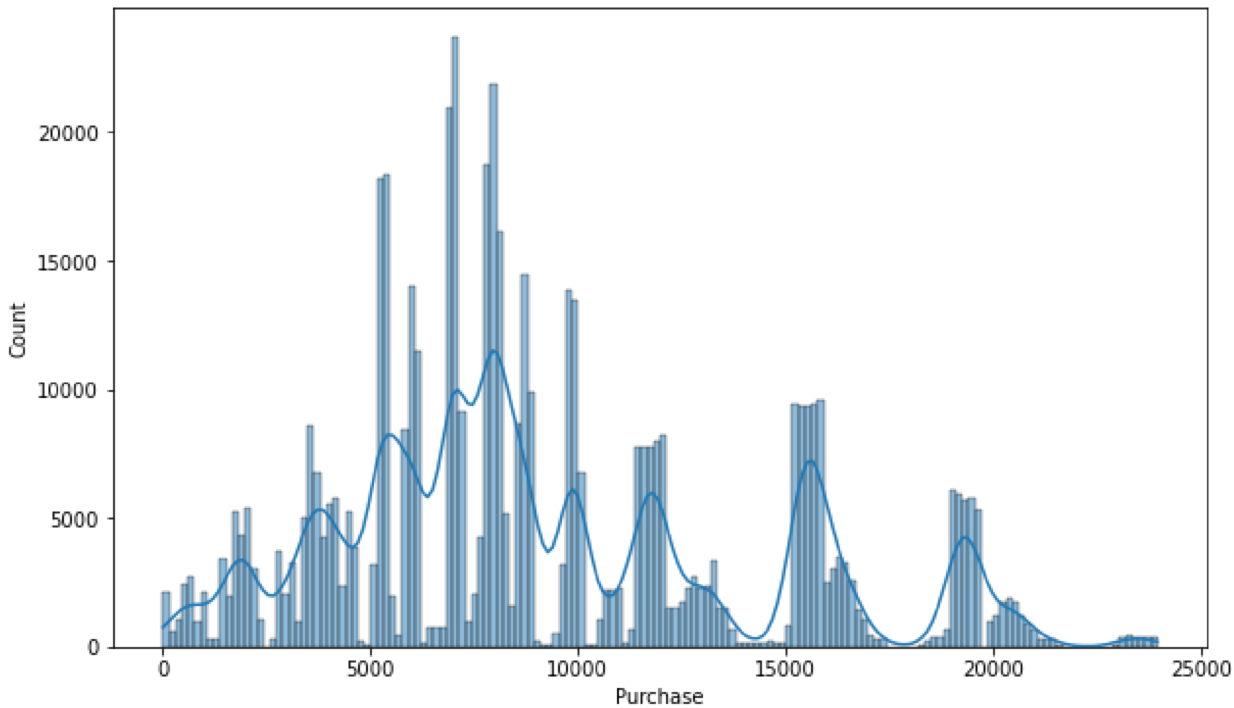
Observations:

```
1. 1, 8, 5 are among the highest yielding product categories and 19,
20, 13 are among the lowest in terms of their contribution to total
amount.

df2=pd.DataFrame(df.groupby(['Stay_In_Current_City_Years'])
[['Purchase']].sum())

df2['percent'] = (df2['Purchase'] /
                  df2['Purchase'].sum()) * 100
df2

                            Purchase    percent
Stay_In_Current_City_Years
0                          682979229  13.402754
1                         1792872533  35.183250
2                          949173931  18.626547
3                          884902659  17.365290
4+                         785884390  15.422160
```

Univariate Analysis:

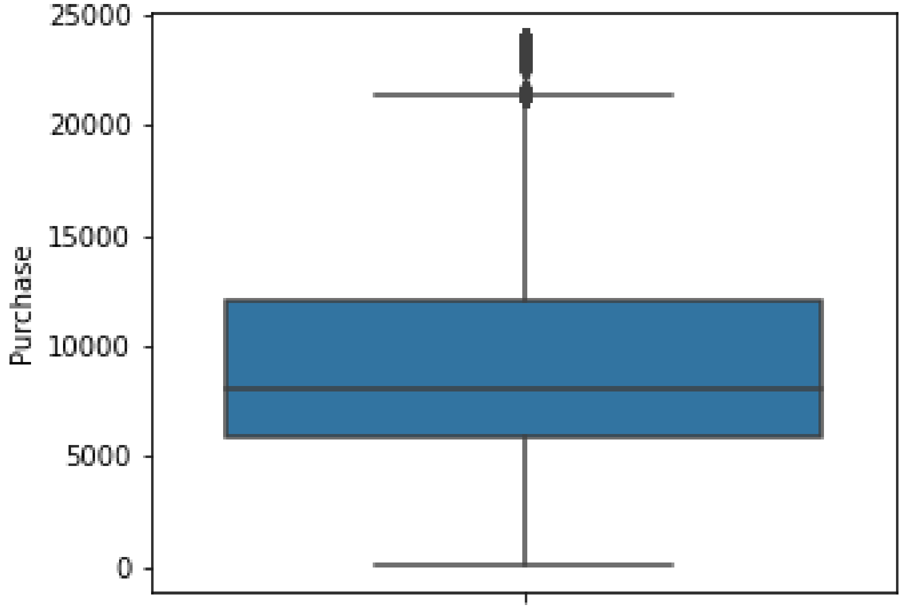
We can explore the distribution of the data for the quantitative attributes using histplot.

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



Observation:

```
1. We can see purchase value between 5000 and 10000 have higher count.
From the initial observation we have already seen the mean and median
is 9263 and 8047 respectively. Also, we can see there are outliers in
the data.

plt.figure(figsize=(5, 4))
sns.boxplot(data=df, y='Purchase')
plt.show()
```

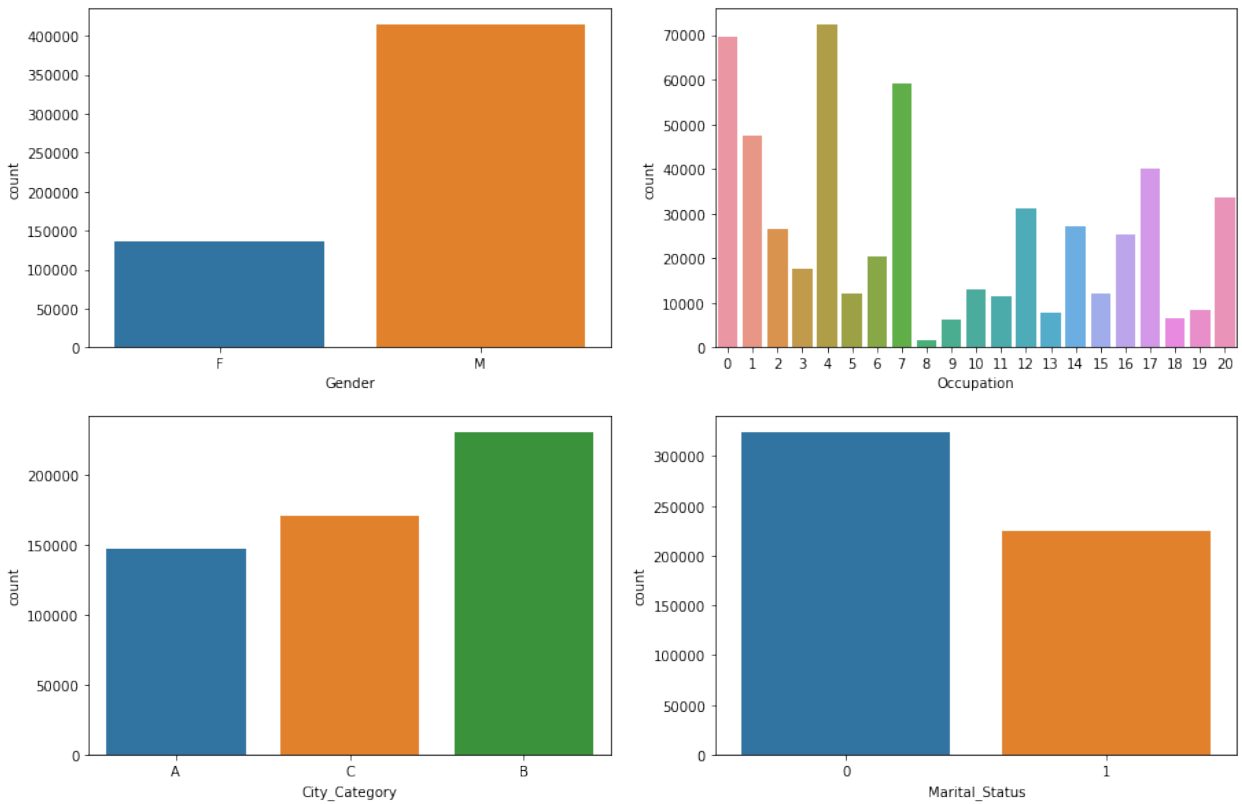


Observation:

```
We can see there are outliers in the data for purchase.
```

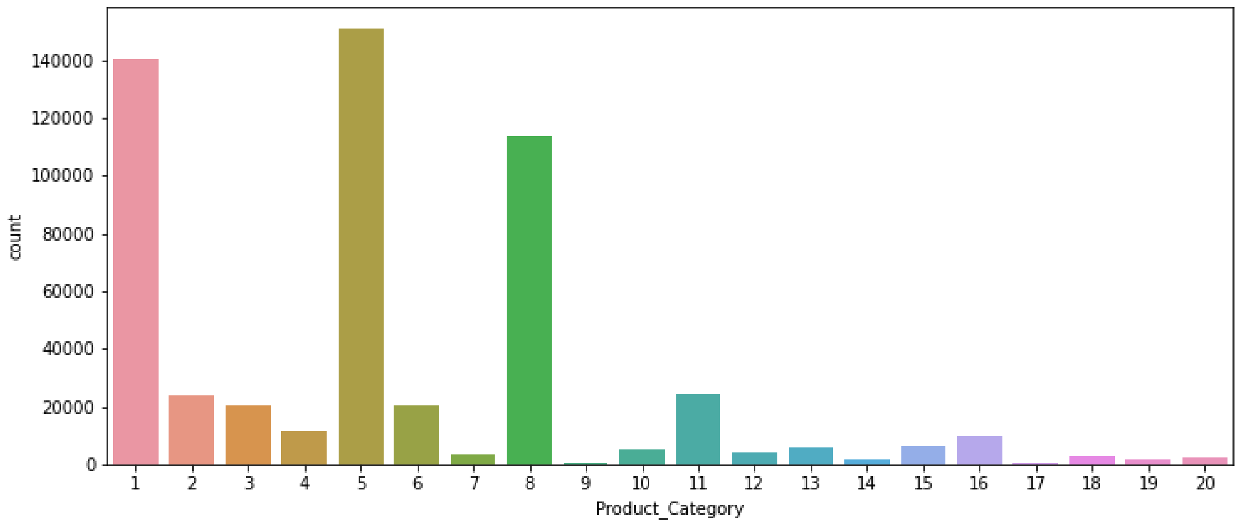
Univariate analysis for qualitative variables:

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))
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()
```



Observations:

```
1. We can clearly see from the graphs above the purchases done by
males are much higher than females.
2. We have 21 occupations categories. Occupation category 4, 0, and 7
are with higher number of purchases and category 8 with the lowest
number of purchaes.
3. The purchases are highest from City category B.
4. Single customer purchases are higher than married users.

plt.figure(figsize=(12, 5))
sns.countplot(data=df, x='Product_Category')
plt.show()
```

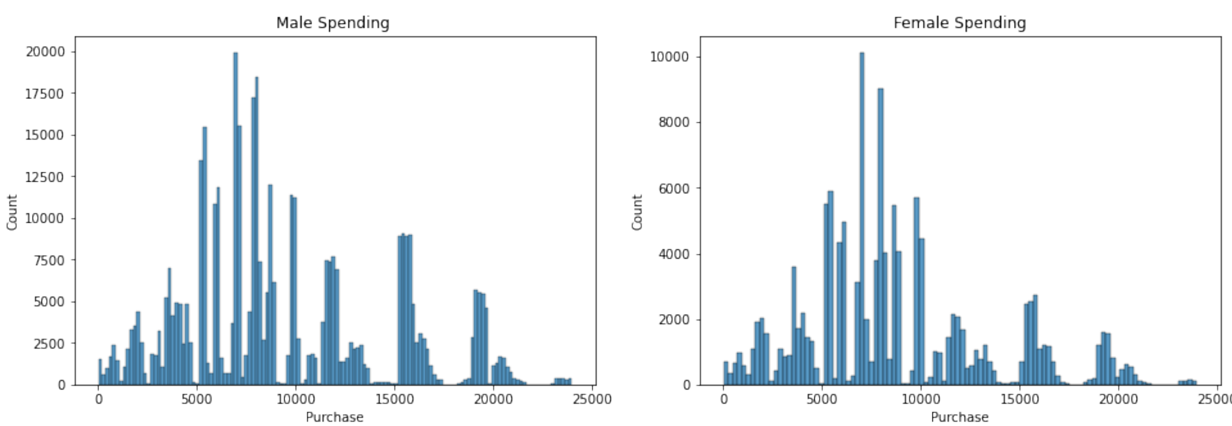


Observations:

```
1. There are 20 product categories with product category 1, 5 and  8
having higher purchasing frequency.
```

Bivariate Analysis:

```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,5))
sns.histplot(data=df[df['Gender']=='M']['Purchase'],
ax=axs[0]).set_title("Male Spending ")
sns.histplot(data=df[df['Gender']=='F']['Purchase'],
ax=axs[1]).set_title("Female Spending")
plt.show()
```

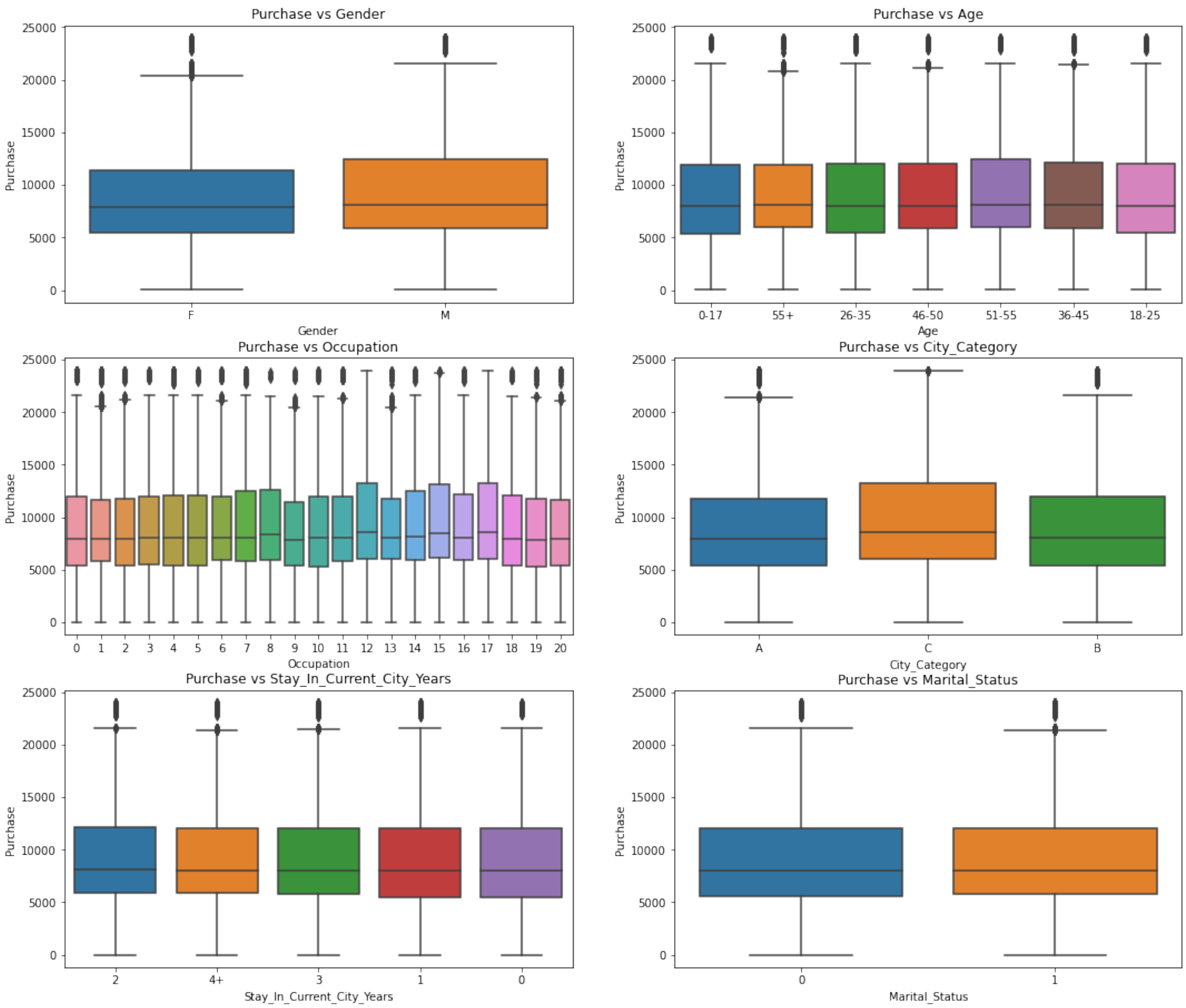


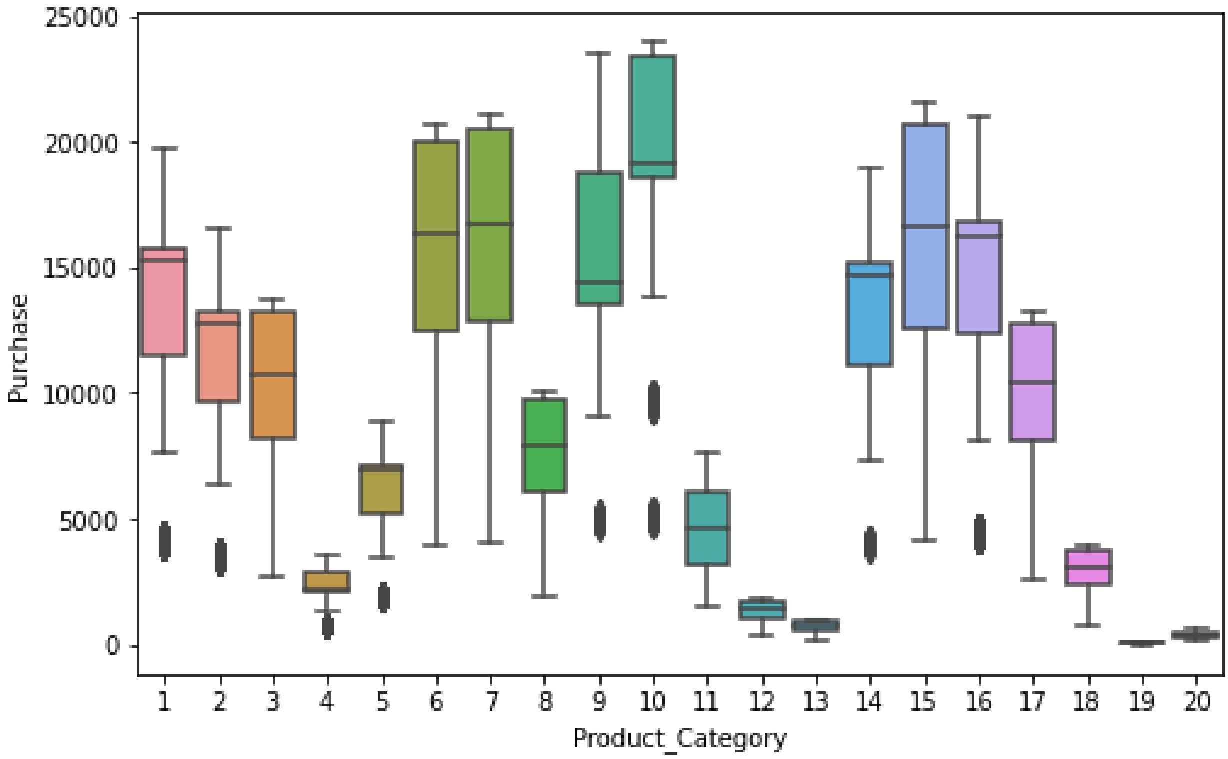
Observations:

```
1. From the above histplot, we can clearly see spending behaviour is
very much similar in nature for both males and females as the maximum
```

```
purchase count are between the purchase value range of 5000-10000 for
both. But, the purchase count are more in case of males.
```

```python
attr = ['Gender', 'Age', 'Occupation', 'City_Category',
'Stay_In_Current_City_Years', 'Marital_Status']

fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 10))
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=attr[count], ax=axs[row,
col],)
        axs[row,col].set_title(f"Purchase vs {attr[count]}")
        count += 1
plt.show()

plt.figure(figsize=(8, 5))
sns.boxplot(data=df, y='Purchase', x='Product_Category')
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
0
5000
10000
15000
20000
25000



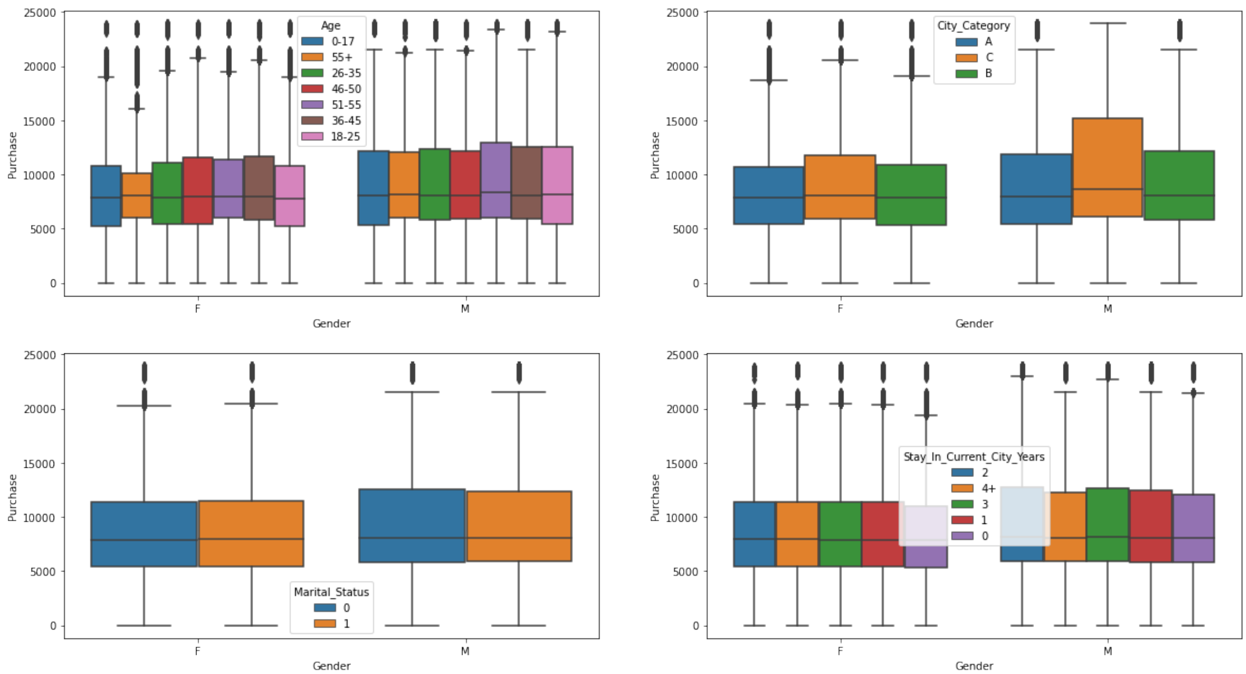
Observations:

```
1. The spending behaviour for males and females are similar as we had
seen from the above histplot. Males purchasing value are in the little
higher range than females.
2. Among diffent age categories, we see similar purchase behaviour.
For all age groups, most of the purchases are of the values between 5k
to 12k with all have some outliers.
3. Among different occupation as well, we see similar purchasing
behaviour in terms of the purchase values.
4. Similarly for City category, stay in current city years, marital
status - we see the users spends mostly in the range of 5k to 12k.
5. We see variations among product categories. Product category 10
products are the costliest ones. Also, there are few outliers for some
of the product categories.
```

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', ax=axs[0,0])
sns.boxplot(data=df, y='Purchase', x='Gender', hue='City_Category',
ax=axs[0,1])

sns.boxplot(data=df, y='Purchase', x='Gender', hue='Marital_Status',
ax=axs[1,0])
```

```
sns.boxplot(data=df, y='Purchase', x='Gender',
hue='Stay_In_Current_City_Years', ax=axs[1,1])

plt.show()
```

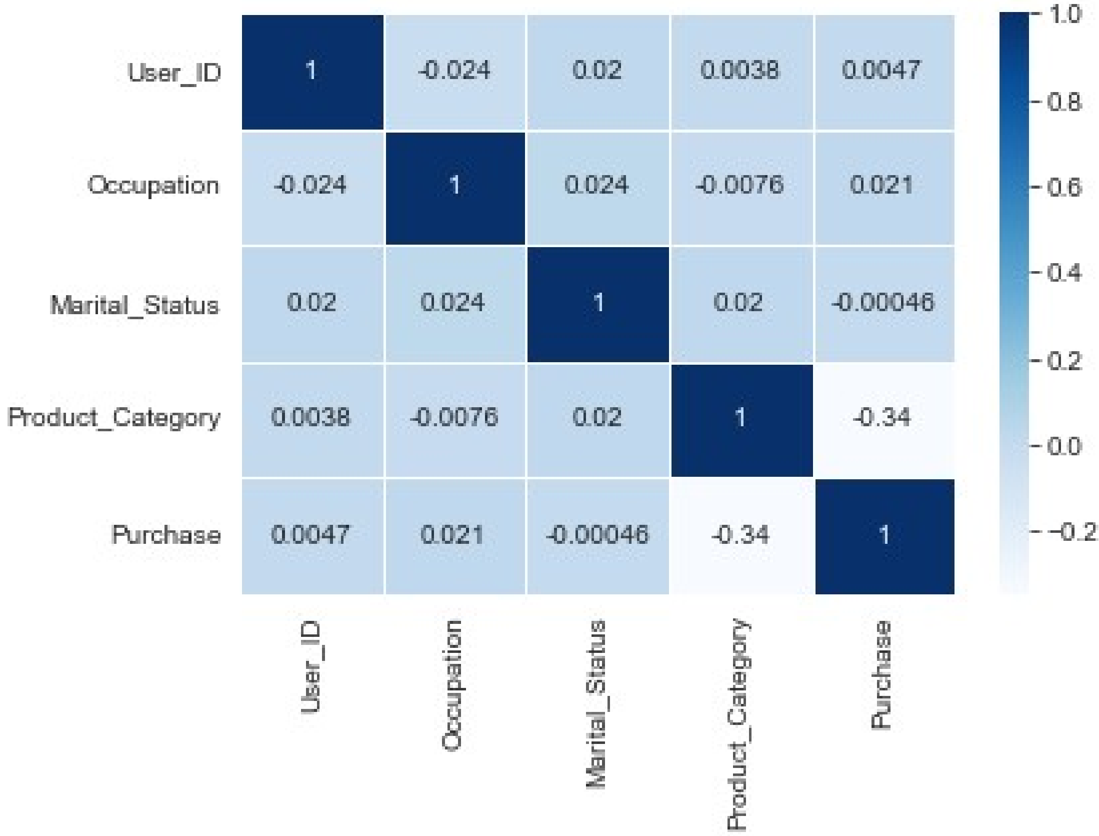


Observations:

```
1. The purchasing pattern is very much similar for males and females
even among differnt age groups.
2. The purchasing behaviour of males and females basis different citi
categories is also similar in nature. Still,  males from city category
B tends to purchase costlier products in comparison to females.
3. Males and females spending behaviour remains similar even when take
into account their marital status.
4. Purchase values are similar for males and females basis
Stay_in_current_city_years. Although, Males buy slightly high value
products.
```

Correlation between categorical variables:

```
sns.heatmap(df.corr(), annot=True, cmap="Blues", linewidth=.5)

<AxesSubplot:>
```

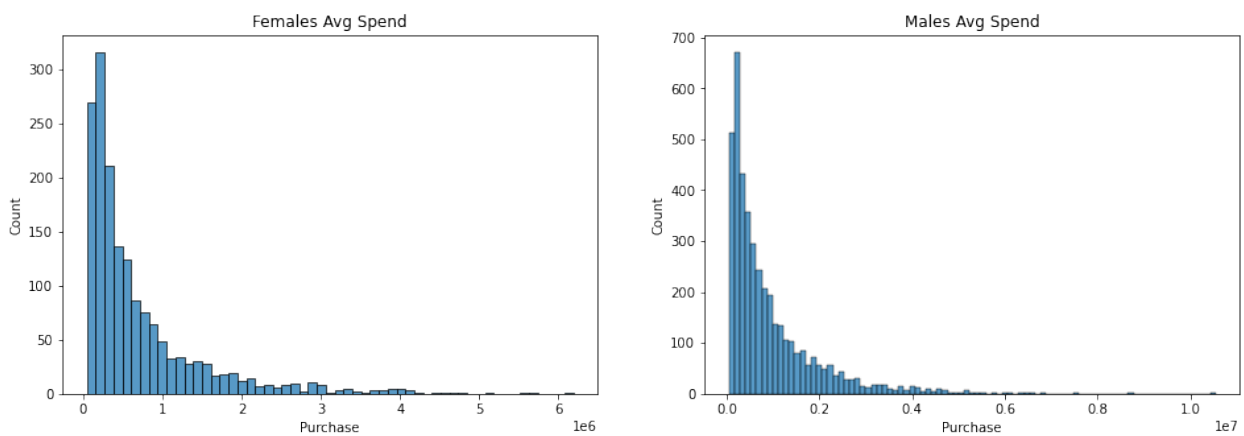


Average amount spend per males and females:

Observations:

```
1. From the above correlation plot, we can see the correlation is not
significant between any pair of variables.

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

      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 count in the entire data
avgamt_gender['Gender'].value_counts()

M    4225
F    1666
Name: Gender, dtype: int64

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,5))

sns.histplot(data=avgamt_gender[avgamt_gender['Gender']=='F']
['Purchase'], ax=axs[0]).set_title("Females Avg Spend")
sns.histplot(data=avgamt_gender[avgamt_gender['Gender']=='M']
['Purchase'], ax=axs[1]).set_title("Males Avg Spend")

Text(0.5, 1.0, 'Males Avg Spend')
```

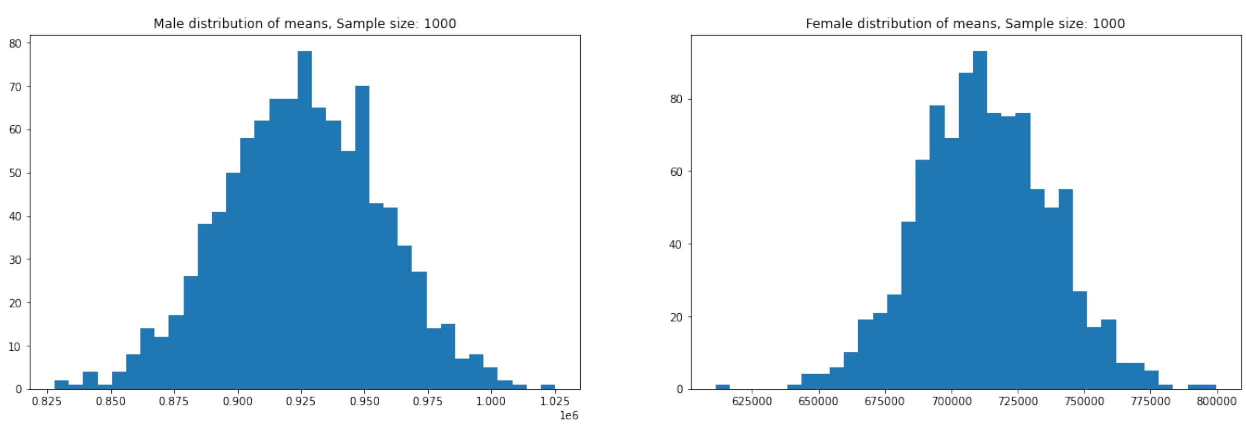


Observations:

```
1. Average amount spend by males are higher than females.

avgamt_gender.groupby(['Gender'])[['Purchase']].mean()

             Purchase
Gender
F       712024.394958
M       925344.402367

avgamt_gender.groupby(['Gender'])['Purchase'].sum()

Gender
F    1186232642
M    3909580100
Name: Purchase, dtype: int64
```

Observations:

```
1. Average amount for the males is 925344 for the entire population whereas it's much lesser for females(712024).
2. Total amount spend by males is around 4 billion whereas for females it's 1.2 billion.

avgamt_male = avgamt_gender[avgamt_gender['Gender']=='M']
avgamt_female = avgamt_gender[avgamt_gender['Gender']=='F']

#Finding the sample(sample size=1000) for avg purchase amount for males and females
genders = ["M", "F"]

sample_size = 1000

num_repitions = 1000
male_means = []
female_means = []

for i in range(num_repitions):
    male_mean = avgamt_male.sample(sample_size, replace=True)['Purchase'].mean()
    female_mean = avgamt_female.sample(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: 1000")
axis[1].set_title("Female distribution of means, Sample size: 1000")

plt.show()
```



Observations:

```
1. The means sample seems to be normally distributed for both males
and females. Also, we can see the mean of the sample means are closer
to the population mean as per central limit theorem.
```

Calculating 90% confidence interval for sample size 1000:

```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Male:
{:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\
n".format(avgamt_female['Purchase'].mean()))

print("Sample avg spend amount for Male:
{:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\
n".format(np.mean(female_means)))

print("Sample std for Male:
{:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\
n".format(pd.Series(female_means).std()))

print("Sample std error for Male:
{:.2f}".format(pd.Series(male_means).std()/np.sqrt(1000)))
print("Sample std error for Female: {:.2f}\
n".format(pd.Series(female_means).std()/np.sqrt(1000)))

sample_mean_male=np.mean(male_means)
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1000)
sample_std_error_female=sample_std_female/np.sqrt(1000)

Upper_Limit_male=z90*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z90*sample_std_error_male

Upper_Limit_female=z90*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z90*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39

Sample avg spend amount for Male: 924582.94
Sample avg spend amount for Female: 711745.10

Sample std for Male: 31569.60
Sample std for Female: 25364.68

Sample std error for Male: 998.32
Sample std error for Female: 802.10

Male_CI:  [922940.710869628, 926225.1781143723]
Female_CI:  [710425.6393085682, 713064.5538614319]
```

Observation:

Now using the Confidence interval at 90%, we can say that:

Average amount spend by male customers lie in the range 9,22,940.71 - 9,26,225.18

Average amount spend by female customers lie in range 7,10,425.64 - 7,13,064.55

Calculating 95% confidence interval for sample size 1000:

```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Male:
{:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\
n".format(avgamt_female['Purchase'].mean()))

print("Sample avg spend amount for Male:
{:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\
n".format(np.mean(female_means)))

print("Sample std for Male:
{:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\
n".format(pd.Series(female_means).std()))

print("Sample std error for Male:
{:.2f}".format(pd.Series(male_means).std()/np.sqrt(1000)))
print("Sample std error for Female: {:.2f}\
n".format(pd.Series(female_means).std()/np.sqrt(1000)))

sample_mean_male=np.mean(male_means)
```

```
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1000)
sample_std_error_female=sample_std_female/np.sqrt(1000)

Upper_Limit_male=z95*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z95*sample_std_error_male

Upper_Limit_female=z95*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z95*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39

Sample avg spend amount for Male: 924582.94
Sample avg spend amount for Female: 711745.10

Sample std for Male: 31569.60
Sample std for Female: 25364.68

Sample std error for Male: 998.32
Sample std error for Female: 802.10

Male_CI:  [922626.2406015142, 926539.6483824861]
Female_CI:  [710172.977276911, 713317.2158930891]
```

Observation:

Now using the Confidence interval at 95%, we can say that:

Average amount spend by male customers lie in the range 9,22,626.24 - 9,26,539.65

Average amount spend by female customers lie in range 7,10,172.98 - 7,13,317.21

Calculating 99% confidence interval for sample size 1000:

```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Male:
{:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\
n".format(avgamt_female['Purchase'].mean()))
```

```
print("Sample avg spend amount for Male:
{:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\
n".format(np.mean(female_means)))

print("Sample std for Male:
{:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\
n".format(pd.Series(female_means).std()))

print("Sample std error for Male:
{:.2f}".format(pd.Series(male_means).std()/np.sqrt(1000)))
print("Sample std error for Female: {:.2f}\
n".format(pd.Series(female_means).std()/np.sqrt(1000)))

sample_mean_male=np.mean(male_means)
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1000)
sample_std_error_female=sample_std_female/np.sqrt(1000)

Upper_Limit_male=z99*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z99*sample_std_error_male

Upper_Limit_female=z99*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z99*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39

Sample avg spend amount for Male: 924582.94
Sample avg spend amount for Female: 711745.10

Sample std for Male: 31569.60
Sample std for Female: 25364.68

Sample std error for Male: 998.32
Sample std error for Female: 802.10

Male_CI:  [922011.2765216472, 927154.6124623531]
Female_CI:  [709678.8826372258, 713811.3105327743]
```

Observation:

Now using the Confidence interval at 99%, we can say that:

Average amount spend by male customers lie in the range 9,22,011.28 - 9,27,154.61

Average amount spend by female customers lie in range 7,09,678.88 - 7,13,811.31

Calculating 90% confidence interval for sample size 1500:

```
#Finding the sample(sample size=1000) avg purchase amount for males
and females
genders = ["M", "F"]

sample_size = 1500

num_repitions = 1000
male_means = []
female_means = []

for i in range(num_repitions):
    male_mean = avgamt_male.sample(sample_size, replace=True)
['Purchase'].mean()
    female_mean = avgamt_female.sample(sample_size, replace=True)
['Purchase'].mean()

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

#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Male:
{:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\
n".format(avgamt_female['Purchase'].mean()))

print("Sample avg spend amount for Male:
{:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\
n".format(np.mean(female_means)))

print("Sample std for Male:
{:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\
n".format(pd.Series(female_means).std()))

print("Sample std error for Male:
{:.2f}".format(pd.Series(male_means).std()/np.sqrt(1500)))
print("Sample std error for Female: {:.2f}\
n".format(pd.Series(female_means).std()/np.sqrt(1500)))
```

```
sample_mean_male=np.mean(male_means)
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1500)
sample_std_error_female=sample_std_female/np.sqrt(1500)

Upper_Limit_male=z90*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z90*sample_std_error_male

Upper_Limit_female=z90*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z90*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39

Sample avg spend amount for Male: 925248.16
Sample avg spend amount for Female: 712079.47

Sample std for Male: 25209.48
Sample std for Female: 21005.90

Sample std error for Male: 650.91
Sample std error for Female: 542.37

Male_CI:  [924177.4154154606, 926318.8960552063]
Female_CI:  [711187.2675015299, 712971.6650158035]
```

Observation:

Now using the Confidence interval at 90%, we can say that:

Average amount spend by male customers lie in the range 9,24,177.41 - 9,26,318.90

Average amount spend by female customers lie in range 7,11,187.27 - 7,12,971.67

By increasing the sample size we can see confidence interval is more closer to the population mean.

Calculating 95% confidence interval for sample size 1500:

```
print("Population avg spend amount for Male:
{:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\
n".format(avgamt_female['Purchase'].mean()))
```

```
print("Sample avg spend amount for Male:
{:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\
n".format(np.mean(female_means)))

print("Sample std for Male:
{:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\
n".format(pd.Series(female_means).std()))

print("Sample std error for Male:
{:.2f}".format(pd.Series(male_means).std()/np.sqrt(1500)))
print("Sample std error for Female: {:.2f}\
n".format(pd.Series(female_means).std()/np.sqrt(1500)))

sample_mean_male=np.mean(male_means)
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1500)
sample_std_error_female=sample_std_female/np.sqrt(1500)

Upper_Limit_male=z95*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z95*sample_std_error_male

Upper_Limit_female=z95*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z95*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39

Sample avg spend amount for Male: 925248.16
Sample avg spend amount for Female: 712079.47

Sample std for Male: 25209.48
Sample std for Female: 21005.90

Sample std error for Male: 650.91
Sample std error for Female: 542.37

Male_CI:  [923972.3800350594, 926523.9314356075]
Female_CI:  [711016.4209310142, 713142.5115863192]
```

Observation:

Now using the Confidence interval at 95%, we can say that:

Average amount spend by male customers lie in the range 9,23,972.41 - 9,26,523.93

Average amount spend by female customers lie in range 7,11,016.42 - 7,13,142.51

By increasing the sample size we can see confidence interval is more closer to the population mean.

Calculating 99% confidence interval for sample size 1500:

```
print("Population avg spend amount for Male: {:.2f}".format(avgamt_male['Purchase'].mean()))
print("Population avg spend amount for Female: {:.2f}\n".format(avgamt_female['Purchase'].mean()))

print("Sample avg spend amount for Male: {:.2f}".format(np.mean(male_means)))
print("Sample avg spend amount for Female: {:.2f}\n".format(np.mean(female_means)))

print("Sample std for Male: {:.2f}".format(pd.Series(male_means).std()))
print("Sample std for Female: {:.2f}\n".format(pd.Series(female_means).std()))

print("Sample std error for Male: {:.2f}".format(pd.Series(male_means).std()/np.sqrt(1500)))
print("Sample std error for Female: {:.2f}\n".format(pd.Series(female_means).std()/np.sqrt(1500)))

sample_mean_male=np.mean(male_means)
sample_mean_female=np.mean(female_means)

sample_std_male=pd.Series(male_means).std()
sample_std_female=pd.Series(female_means).std()

sample_std_error_male=sample_std_male/np.sqrt(1500)
sample_std_error_female=sample_std_female/np.sqrt(1500)

Upper_Limit_male=z99*sample_std_error_male + sample_mean_male
Lower_Limit_male=sample_mean_male - z99*sample_std_error_male

Upper_Limit_female=z99*sample_std_error_female + sample_mean_female
Lower_Limit_female=sample_mean_female - z99*sample_std_error_female

print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female])
```

```
Population avg spend amount for Male: 925344.40
Population avg spend amount for Female: 712024.39
```

```
Sample avg spend amount for Male: 925248.16
Sample avg spend amount for Female: 712079.47

Sample std for Male: 25209.48
Sample std for Female: 21005.90

Sample std error for Male: 650.91
Sample std error for Female: 542.37

Male_CI:  [923571.4219578304, 926924.8895128365]
Female_CI:  [710682.3209708949, 713476.6115464385]
```

Observation:

Now using the Confidence interval at 99%, we can say that:

Average amount spend by male customers lie in the range 923571.42 - 926924.89

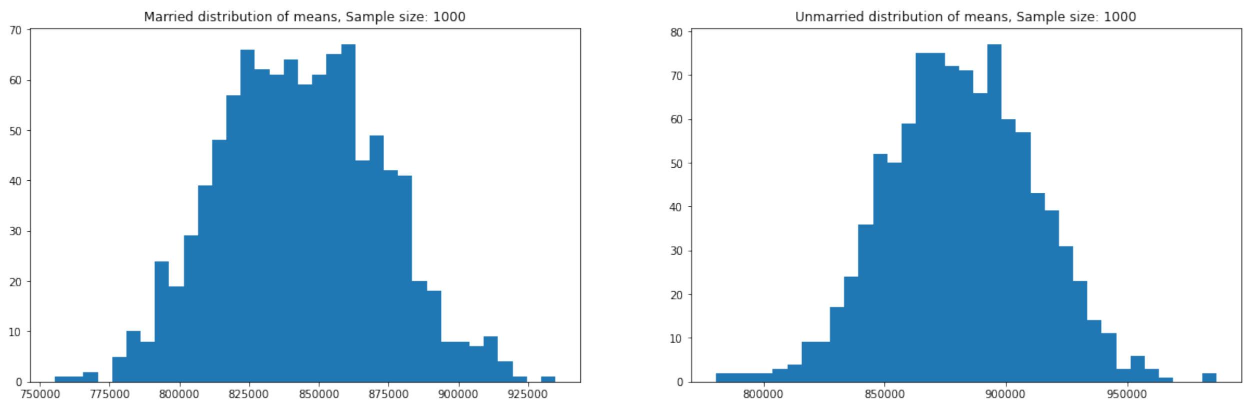
Average amount spend by female customers lie in range 710682.32 - 713476.61

By increasing the sample size we can see confidence interval is more closer to the population mean.

CLT and Confidence interval considering marital status:

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

avgamt_married = avg_Marital[avg_Marital['Marital_Status']==1]
avgamt_single = avg_Marital[avg_Marital['Marital_Status']==0]

sample_size = 1000
num_repitions = 1000
married_means = []
single_means = []

for i in range(num_repitions):
    avg_married =
avg_Marital[avg_Marital['Marital_Status']==1].sample(sample_size,
replace=True)['Purchase'].mean()
    avg_single =
avg_Marital[avg_Marital['Marital_Status']==0].sample(sample_size,
replace=True)['Purchase'].mean()

    married_means.append(avg_married)
    single_means.append(avg_single)


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

```
axis[0].hist(married_means, bins=35)
axis[1].hist(single_means, bins=35)
axis[0].set_title("Married distribution of means, Sample size: 1000")
axis[1].set_title("Unmarried distribution of means, Sample size: 1000")

plt.show()
```



Observations:

1. The means sample seems to be normally distributed for both married and singles. Also, we can see the mean of the sample means are closer to the population mean as per central limit theorem.

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

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

Calculating 90% confidence interval for avg expenses for married/single for sample size 1000:

```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Married: {:.2f}".format(avgamt_married['Purchase'].mean()))
print("Population avg spend amount for Single: {:.2f}\n".format(avgamt_single['Purchase'].mean()))

print("Sample avg spend amount for Married: {:.2f}".format(np.mean(married_means)))
print("Sample avg spend amount for Single: {:.2f}\n".format(np.mean(single_means)))
```

```
print("Sample std for Married:
{:.2f}".format(pd.Series(married_means).std()))
print("Sample std for Single: {:.2f}\
n".format(pd.Series(single_means).std()))

print("Sample std error for Married:
{:.2f}".format(pd.Series(married_means).std()/np.sqrt(1000)))
print("Sample std error for Single: {:.2f}\
n".format(pd.Series(single_means).std()/np.sqrt(1000)))

sample_mean_married=np.mean(married_means)
sample_mean_single=np.mean(single_means)

sample_std_married=pd.Series(married_means).std()
sample_std_single=pd.Series(single_means).std()

sample_std_error_married=sample_std_married/np.sqrt(1000)
sample_std_error_single=sample_std_single/np.sqrt(1000)

Upper_Limit_married=z90*sample_std_error_male + sample_mean_married
Lower_Limit_married=sample_mean_married - z90*sample_std_error_married

Upper_Limit_single=z90*sample_std_error_single + sample_mean_single
Lower_Limit_single=sample_mean_single - z90*sample_std_error_single

print("Married_CI: ",[Lower_Limit_married,Upper_Limit_married])
print("Single_CI: ",[Lower_Limit_single,Upper_Limit_single])
```

```
Population avg spend amount for Married: 843526.80
Population avg spend amount for Single: 880575.78

Sample avg spend amount for Married: 843401.41
Sample avg spend amount for Single: 881586.01

Sample std for Married: 28747.45
Sample std for Single: 30599.76

Sample std error for Married: 909.07
Sample std error for Single: 967.65

Married_CI:  [841905.9791311473, 844472.1467098729]
Single_CI:  [879994.2306792004, 883177.7968027996]
```

Calculating 95% confidence interval for avg expenses for married/single for sample size 1000:

```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval
```

```
print("Population avg spend amount for Married:
{:.2f}".format(avgamt_married['Purchase'].mean()))
print("Population avg spend amount for Single: {:.2f}\
n".format(avgamt_single['Purchase'].mean()))

print("Sample avg spend amount for Married:
{:.2f}".format(np.mean(married_means)))
print("Sample avg spend amount for Single: {:.2f}\
n".format(np.mean(single_means)))

print("Sample std for Married:
{:.2f}".format(pd.Series(married_means).std()))
print("Sample std for Single: {:.2f}\
n".format(pd.Series(single_means).std()))

print("Sample std error for Married:
{:.2f}".format(pd.Series(married_means).std()/np.sqrt(1000)))
print("Sample std error for Single: {:.2f}\
n".format(pd.Series(single_means).std()/np.sqrt(1000)))

sample_mean_married=np.mean(married_means)
sample_mean_single=np.mean(single_means)

sample_std_married=pd.Series(married_means).std()
sample_std_single=pd.Series(single_means).std()

sample_std_error_married=sample_std_married/np.sqrt(1000)
sample_std_error_single=sample_std_single/np.sqrt(1000)

Upper_Limit_married=z95*sample_std_error_male + sample_mean_married
Lower_Limit_married=sample_mean_married - z95*sample_std_error_married

Upper_Limit_single=z95*sample_std_error_single + sample_mean_single
Lower_Limit_single=sample_mean_single - z95*sample_std_error_single

print("Married_CI: ",[Lower_Limit_married,Upper_Limit_married])
print("Single_CI: ",[Lower_Limit_single,Upper_Limit_single])
```

```
Population avg spend amount for Married: 843526.80
Population avg spend amount for Single: 880575.78

Sample avg spend amount for Married: 843401.41
Sample avg spend amount for Single: 881586.01

Sample std for Married: 28747.45
Sample std for Single: 30599.76

Sample std error for Married: 909.07
Sample std error for Single: 967.65
```

```
Married_CI:  [841619.6207198777, 844677.1820902741]
Single_CI:  [879689.4211567282, 883482.6063252718]
```

Calculating 99% confidence interval for avg expenses for married/single for sample size 1000:

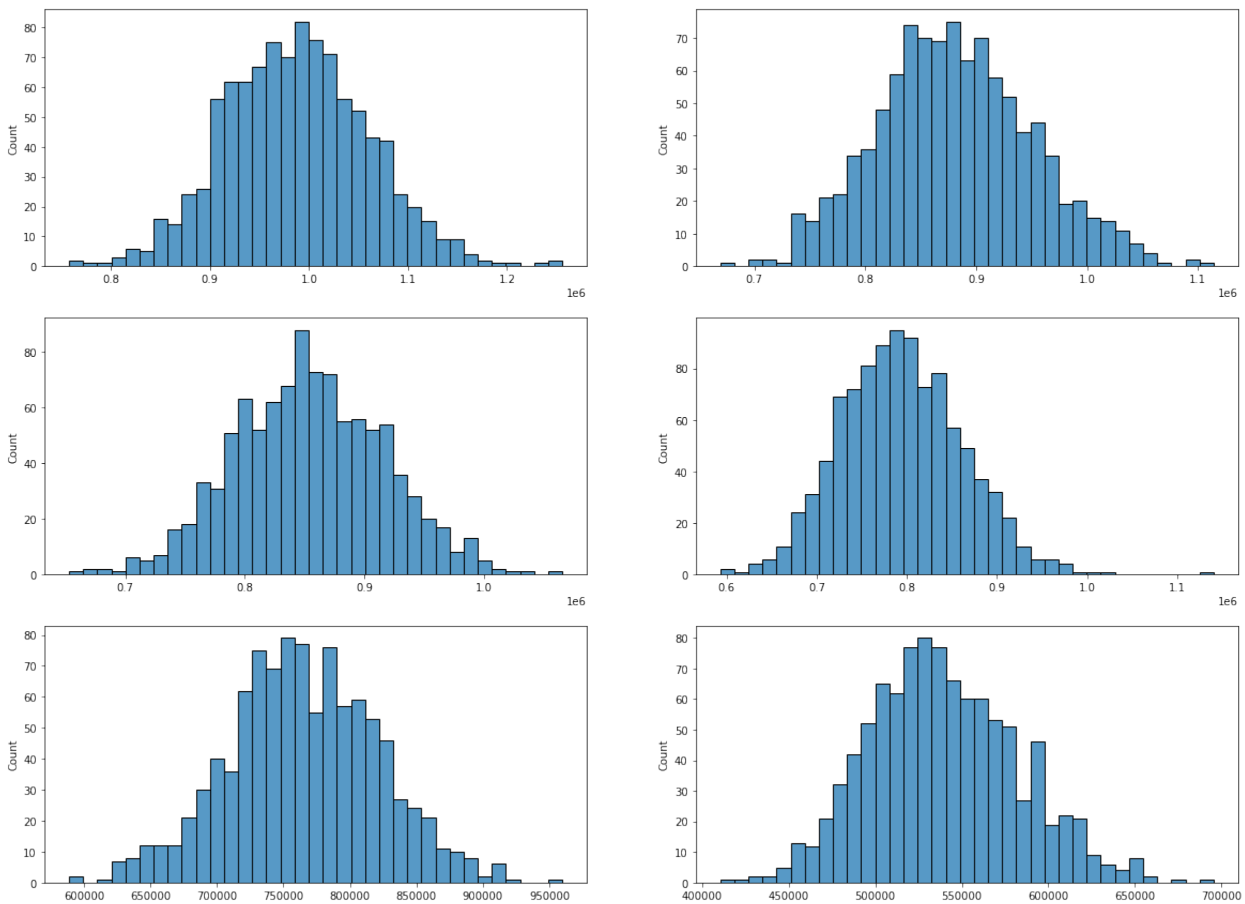
```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

print("Population avg spend amount for Married:
{:.2f}".format(avgamt_married['Purchase'].mean()))
print("Population avg spend amount for Single: {:.2f}\
n".format(avgamt_single['Purchase'].mean()))

print("Sample avg spend amount for Married:
{:.2f}".format(np.mean(married_means)))
print("Sample avg spend amount for Single: {:.2f}\
n".format(np.mean(single_means)))

print("Sample std for Married:
{:.2f}".format(pd.Series(married_means).std()))
print("Sample std for Single: {:.2f}\
n".format(pd.Series(single_means).std()))

print("Sample std error for Married:
{:.2f}".format(pd.Series(married_means).std()/np.sqrt(1000)))
print("Sample std error for Single: {:.2f}\
n".format(pd.Series(single_means).std()/np.sqrt(1000)))

sample_mean_married=np.mean(married_means)
sample_mean_single=np.mean(single_means)

sample_std_married=pd.Series(married_means).std()
sample_std_single=pd.Series(single_means).std()

sample_std_error_married=sample_std_married/np.sqrt(1000)
sample_std_error_single=sample_std_single/np.sqrt(1000)

Upper_Limit_married=z99*sample_std_error_male + sample_mean_married
Lower_Limit_married=sample_mean_married - z99*sample_std_error_married

Upper_Limit_single=z99*sample_std_error_single + sample_mean_single
Lower_Limit_single=sample_mean_single - z99*sample_std_error_single

print("Married_CI: ",[Lower_Limit_married,Upper_Limit_married])
print("Single_CI: ",[Lower_Limit_single,Upper_Limit_single])

Population avg spend amount for Married: 843526.80
Population avg spend amount for Single: 880575.78
```

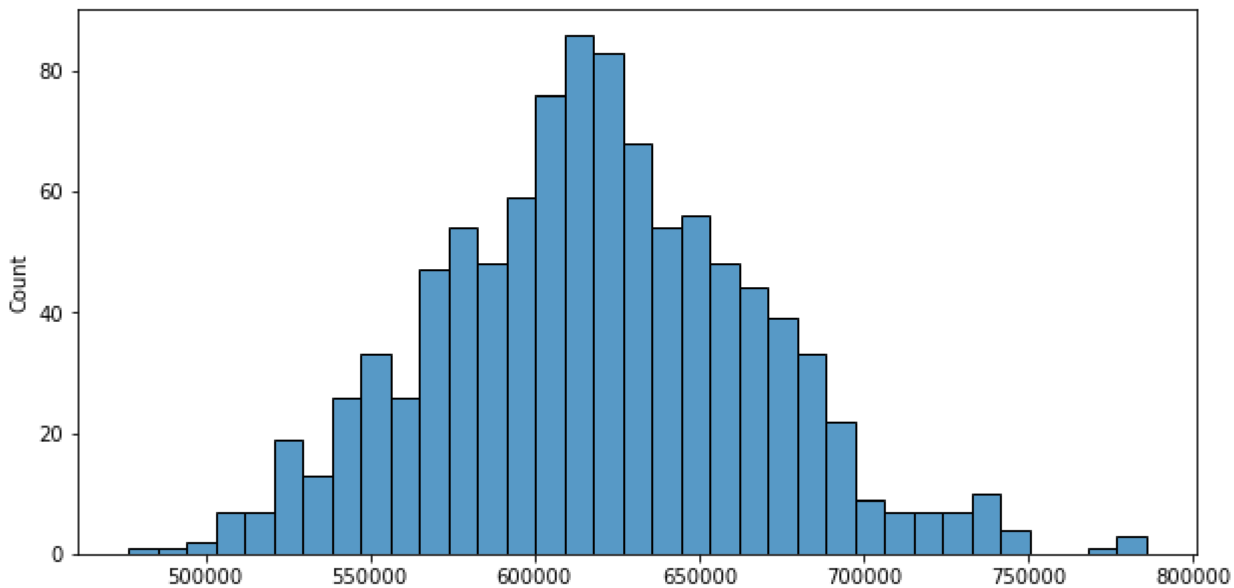
```
Sample avg spend amount for Married: 843401.41
Sample avg spend amount for Single: 881586.01

Sample std for Married: 28747.45
Sample std for Single: 30599.76

Sample std error for Married: 909.07
Sample std error for Single: 967.65

Married_CI:  [841059.6309378392, 845078.140167503]
Single_CI:  [879093.3492016713, 884078.6782803286]
```

Observation:

```
For married and singles, it can be seen with larger sample size the
sample mean gets closer to tthe population mean. And at greater
confidence interval, the range increases.

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

avgamt_age['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_sample_means = {}

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

for i in age_intervals:
    for j in range(num_repitions):

        mean = avgamt_age[avgamt_age['Age']==i].sample(sample_size,
replace=True)['Purchase'].mean()
        all_sample_means[i].append(mean)
```

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(20, 15))

sns.histplot(all_sample_means['26-35'],bins=35,ax=axis[0,0])
sns.histplot(all_sample_means['36-45'],bins=35,ax=axis[0,1])
sns.histplot(all_sample_means['18-25'],bins=35,ax=axis[1,0])
sns.histplot(all_sample_means['46-50'],bins=35,ax=axis[1,1])
sns.histplot(all_sample_means['51-55'],bins=35,ax=axis[2,0])
sns.histplot(all_sample_means['55+'],bins=35,ax=axis[2,1])

plt.show()

plt.figure(figsize=(10, 5))
sns.histplot(all_sample_means['0-17'],bins=35)
plt.show()
```





Observations:

1. The means sample seems to be normally distributed for all age groups. Also, we can see the mean of the sample means are closer to the population mean as per central limit theorem.

Calculating 90% confidence interval for avg expenses for different age groups for sample size 200:

```
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

sample_size = 200
num_repitions = 1000

all_population_means={}
all_sample_means = {}

age_intervals = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+',
'0-17']
for i in age_intervals:
    all_sample_means[i] = []
    all_population_means[i]=[]
    population_mean=avgamt_age[avgamt_age['Age']==i]
['Purchase'].mean()
    all_population_means[i].append(population_mean)

print("All age group population mean: \n", all_population_means)
print("\n")

for i in age_intervals:
```

```
    for j in range(num_repitions):

        mean = avgamt_age[avgamt_age['Age']==i].sample(sample_size, 
replace=True)['Purchase'].mean()
        all_sample_means[i].append(mean)


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

    new_df = avgamt_age[avgamt_age['Age']==val]

    std_error = z90*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - std_error
    upper_lim = sample_mean + std_error

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

```
All age group population mean:
 {'26-35': [989659.3170969313], '36-45': [879665.7103684661], '18-25': 
[854863.119738073], '46-50': [792548.7815442561], '51-55': 
[763200.9230769231], '55+': [539697.2446236559], '0-17': 
[618867.8119266055]}


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

Calculating 95% confidence interval for avg expenses for different age groups for sample size 200:

```
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

sample_size = 200
num_repitions = 1000

all_means = {}

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

```
    all_means[i] = []

for i in age_intervals:
    for j in range(num_repitions):
        mean = avgamt_age[avgamt_age['Age']==i].sample(sample_size,
replace=True)['Purchase'].mean()
        all_means[i].append(mean)
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-
17']:

    new_df = avgamt_age[avgamt_age['Age']==val]

    std_error = z95*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - std_error
    upper_lim = sample_mean + std_error

    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)
```

Calculating 99% confidence interval for avg expenses for different age groups for sample size 200:

```
z90=1.645 #90% Confidence Interval
z95=1.960 #95% Confidence Interval
z99=2.576 #99% Confidence Interval

sample_size = 200
num_repitions = 1000

all_means = {}

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

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

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

    new_df = avgamt_age[avgamt_age['Age']==val]

    std_error = z99*new_df['Purchase'].std()/np.sqrt(len(new_df))
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - std_error
    upper_lim = sample_mean + std_error

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

```
For age 26-35 confidence interval of means: (931009.46, 1048309.18)
For age 36-45 confidence interval of means: (805647.89, 953683.53)
For age 18-25 confidence interval of means: (784903.24, 924823.00)
For age 46-50 confidence interval of means: (688663.50, 896434.06)
For age 51-55 confidence interval of means: (670138.33, 856263.52)
For age 55+ confidence interval of means: (457227.15, 622167.34)
For age 0-17 confidence interval of means: (498997.92, 738737.71)
```

Observation:

```
1. We can see the sample means are closer to the population mean for
the diffrent age groups. And, with greater confidence interval we have
the upper limit and lower limit range increases. As we have seen for
gender and marital status, by increasing the sample size we can have
the mean of the sample means closer to the population.
```

Recommendations:

```
1. Men spent more money than women, company can focus on retaining the
male customers and getting more male customers.

2. Product_Category - 1, 5, 8 have highest purchasing frequency. it
means these are the products in these categories are in more demand.
Company can focus on selling more of these products.

3. Unmarried customers spend more money than married customers, So
company should focus on acquisition of Unmarried customers.

4. Customers in the age 26-35 spend more money than the others, So
company should focus on acquisition of customers who are in the age
26-35.

5. We have more customers aged 26-35 in the city category B and A,
company can focus more on these customers for these cities to increase
the business.

6. 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.

7. Some of the Product category like 19,20,13 have very less purchase.
Company can think of dropping it.

8. The top 10 users who have purchased more company should give more
offers and discounts so that they can be retained and can be helpful
for companies business.

9. The occupation which are contributing more company can think of
offering credit cards or other benefits to those customers by liasing
with some financial partners to increase the sales.

10. The top products should be given focus in order to maintain the
quality in order to further increase the sales of those products.

11. People who are staying in city for an year have contributed to 35%
of the total purchase amount. Company can focus on such customer base
who are neither too old nor too new residents in the city.

12. We have highest frequency of purchase order between 5k and 10k,
company can focus more on these mid range products to increase the
sales.
```

Question:

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

Ans: No. CI's of male and female do not overlap and upper limits of
female purchase CI are lesser than lower limits of male purchase CI.
This proves that men usually spend more than women (NOTE: as per data
77% contibutions are from men and only 23% purchases are from women).

The reason for less purchase by women could have several factors:

  Males might be doing the purchase for females.
  Salary can be a factor in less purchase.
  We also need to see whether male-based products were sold more than
women-based products to clearly identify difference in spending
pattern.
  If the female based products quality/quantity needs to be improved
for women purchasing.

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

At 99% Confidence Interval with sample size 1000
```

Average amount spend by male customers lie in the range 9,22,011.28 - 9,27,154.61

Average amount spend by female customers lie in range 7,09,678.88 - 7,13,811.31

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

Ans: No. Confidence intervals of average male and female spending are not overlapping. This trend can be changed via introducing female centric marketing strategies by Walmart so that more female customers are attracted to increase female purchases to achieve comparable statistics close to 50%.

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

At 99% Confidence Interval with sample size 1000

Average amount spend by married customers lie in the range: [841059.6309378392, 845078.140167503]
Average amount spend by unmarried customers lie in the range: [879093.3492016713, 884078.6782803286]

5. Results when the same activity is performed for Age

At 99% Confidence Interval with sample size 200

For age 26-35 confidence interval of means: (931009.46,1048309.18)
For age 36-45 confidence interval of means: (805647.89, 953683.53)
For age 18-25 confidence interval of means: (784903.24, 924823.00)
For age 46-50 confidence interval of means: (688663.50, 896434.06)
For age 51-55 confidence interval of means: (670138.33, 856263.52)
For age 55+ confidence interval of means: (457227.15, 622167.34)
For age 0-17 confidence interval of means: (498997.92, 738737.71)