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#CHAPTER 1: DEFINITIONS OF THE PROBLEM STATEMENT AND ANALYSING BASIC METRICS ON DATA

##**Introduction to Aerofit**

HISTORY:

> Walmart Inc is an `American multinational retail corporation` that operates a chain of `hypermarkets, discount department stores and grocery stores` in the United States. Headquarter is in `Bentonville, Arkansas.`. The company was founded by `Sam Walton and James Bud Walton` in 1962.
>
> By 2022, Walmart has `10586 stores and clubs in 24 countries`, operating under `46 different names`. For eg: In India, It is named as `Flipkart Wholesale`.
>
> Walmart is the `world's largest company by revenue`, with about `US\$570 billion in annual revenue`, according to `Fortune Global 500 list` of 2022. It has more than `100 million customers` worldwide.

##**Problem Definition**

> 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`.

###Importing the required Libraries

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import bernoulli,binom,norm,expon,geom,poisson,lognorm
import math
import io
```

###Importing the dataset `Walmart_data.csv`

[2]:
```
# from google.colab import files
# uploaded = files.upload()
# print("Done")
```

[3]:
```
# walmart = pd.read_csv(io.BytesIO(uploaded['walmart_data.csv']))
walmart = pd.read_csv("walmart_data.csv")
```

[4]:
```
walmart.head()
```

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

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

###Details regarding each column in dataset

Details	Regarding Information
User__ID:	User ID
Product__ID:	Product ID
Gender:	Sex of User
Age:	Age in bins
Occupation:	Occupation(Masked)
City__Category:	Category of the City (A,B,C)
StayInCurrentCityYears:	Number of years stay in current city
Marital__Status:	Marital Status
ProductCategory:	Product Category (Masked)
Purchase:	Purchase Amount

##**Analysing Basic Metrics**

###Number of rows, columns, datatypes

[5]:
```
#Number of rows and columns
print("Number of rows: {},\nNumber of columns: {}".format(walmart.
 ↪shape[0],walmart.shape[1]))
```

```
Number of rows: 550068,
```

```
Number of columns: 10
```

[6]:
```
walmart.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
```

`Occupation, Marital Status and Product Category` can be changed from `int64 datatype` to `object datatype` as they are categorical attributes

[7]:
```
#Convert the Occupation, Marital Status and Product Category columns data type␣
↪to 'object'
Columns_to_convert_as_object =␣
↪["Occupation","Marital_Status","Product_Category"]
walmart[Columns_to_convert_as_object] = walmart[Columns_to_convert_as_object].
↪astype("object")
```

[8]:
```
#Checking datatypes
walmart.dtypes
```

[8]:
```
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
```

Except User_ID and Purchase columns, remaining all columns are `object` data type.

###nunique and unique

[9]:
```
#number of unique values in each column of given dataset
for i in walmart.columns:
    print(i,":",walmart[i].nunique())
```

```
User_ID : 5891
Product_ID : 3631
Gender : 2
Age : 7
Occupation : 21
City_Category : 3
Stay_In_Current_City_Years : 5
Marital_Status : 2
Product_Category : 20
Purchase : 18105
```

How many users are there in the given dataset? Ans: `5891 unique users`

How many products are there in the given dataset? Ans: `3631 unique products`

Number of User_ID's are less than Number of actual rows of dataset. So it cannot taken as primary key.

[10]:
```
#unique values for "Gender","Age","Occupation","City_category",
#"Stay_In_Current_City_Years","Marital_Status","Product_Category" columns
for i in walmart.columns:
    if i in ["User_ID","Product_ID","Purchase"]:
        continue
    print(i,sorted(walmart[i].unique()),"",sep = "\n")
```

```
Gender
['F', 'M']

Age
['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']

Occupation
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]

City_Category
['A', 'B', 'C']

Stay_In_Current_City_Years
['0', '1', '2', '3', '4+']

Marital_Status
[0, 1]

Product_Category
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]
```

Observations:

How many occupations are there in the given dataset? Ans: 21 unique occupations(masked)(range 0 to 20)

How many product categories are there in the given dataset? Ans: 20 unique product categories (range 1 to 20)

Age column consists of 7 unique values in BINS.

'City Category' = A,B,C, Marital_Status = `{"0": "Not Married","1":"Married"}`

range of 'Stay_In_current_city_years' = 0 to 3 and 4+

###Range of One transaction Purchase amount

[11]:
```
#Minimum and Maximum value for Numerical Column --> "Purchase"
print("Maximum Purchase Value of a customer for one product/one transaction is␣
 ↪$",walmart["Purchase"].max(),sep = "")
print("Minimum Purchase Value of a customer for one product/one transaction is␣
 ↪$",walmart["Purchase"].min(),sep = "")
```

```
Maximum Purchase Value of a customer for one product/one transaction is $23961
Minimum Purchase Value of a customer for one product/one transaction is $12
```

range of Purchase Value of a customer for one product/one transaction is $12 to $23961

[12]:
```
#memory used by each column
walmart.memory_usage()
```

[12]:
```
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
```

all columns are using same amount of memory

#CHAPTER 2: NULL VALUES AND OUTLIERS DETECTION OF DATA

##**Finding Null Values**

[13]:
```
#checking null values
walmart.isnull().sum()
```

[13]:
```
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:

> Interestingly, There are `no null values` in any of the column. So no need to handle the null values. (Imputation of null values is not required)

##**Descriptive Statistics of Dataset**

[14]:
```
walmart.describe(include = "all")
```

[14]:
```
             User_ID Product_ID  Gender     Age  Occupation City_Category  \
count   5.500680e+05     550068  550068  550068    550068.0        550068
unique           NaN       3631       2       7        21.0             3
top              NaN  P00265242       M   26-35         4.0             B
freq             NaN       1880  414259  219587     72308.0        231173
mean    1.003029e+06        NaN     NaN     NaN         NaN           NaN
std     1.727592e+03        NaN     NaN     NaN         NaN           NaN
min     1.000001e+06        NaN     NaN     NaN         NaN           NaN
25%     1.001516e+06        NaN     NaN     NaN         NaN           NaN
50%     1.003077e+06        NaN     NaN     NaN         NaN           NaN
75%     1.004478e+06        NaN     NaN     NaN         NaN           NaN
max     1.006040e+06        NaN     NaN     NaN         NaN           NaN

       Stay_In_Current_City_Years  Marital_Status  Product_Category  \
count                      550068        550068.0          550068.0
unique                          5             2.0              20.0
top                             1             0.0               5.0
freq                       193821        324731.0          150933.0
mean                          NaN             NaN               NaN
std                           NaN             NaN               NaN
min                           NaN             NaN               NaN
25%                           NaN             NaN               NaN
50%                           NaN             NaN               NaN
75%                           NaN             NaN               NaN
```

```
max                                NaN              NaN                 NaN

             Purchase
count   550068.000000
unique            NaN
top               NaN
freq              NaN
mean      9263.968713
std       5023.065394
min         12.000000
25%       5823.000000
50%       8047.000000
75%      12054.000000
max      23961.000000
```

Observations:

MODE (High frequency values of dataset)

- `Product_ID P00265242` : 1880 times
- `Gender Male` : 414259 times
- `Age group of 26-35` : 219587 times
- `Occupation 4` : 72308 times
- `City Category B` : 231173 times
- `Stay in current city years 1` : 193821 times
- `Marital Status (Not Married)` : 324731 times
- `Product Category 5` : 150933 times

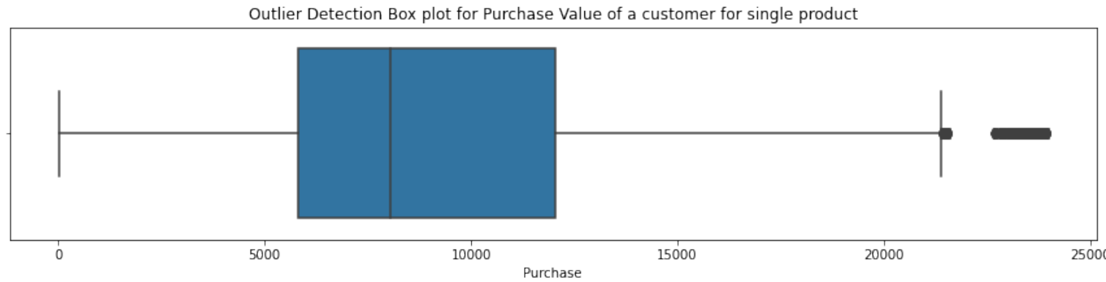
Descriptive Statistics of Purchase Column:

- `mean` of Purchase value by a customer of one product = `$9263.96`
- `50 percentile` or Median of Purchase value by a customer of one product = `$8047`
- `Standard Deviation` of Purchase value by a customer of one product = `$5023.06`. This indicates that data has more dispersion.
- `25 percentile "Q1"` of Purchase value by a customer of one product = `$5823`
- `75 percentile "Q3"` of Purchase value by a customer of one product = `$12054`
- The difference between Mean and Median Purchase values are significant. So it indicates presence of outliers for that column.

##**Outlier detection of Purchase column**

###Box plot on each transaction purchase amount and finding IQR Statistically

[15]:
```python
#Box plot for Purchase column
fig = plt.figure(figsize = (15,3))
plt.title("Outlier Detection Box plot for Purchase Value of a customer for␣
 ↪single product")
sns.boxplot(data=walmart, x = walmart["Purchase"],orient="h")
plt.show()
```



[16]:
```python
#create a function to find outliers using IQR (Statistical way)
def find_outliers_IQR(df):
    q1=df.quantile(0.25)
    q3=df.quantile(0.75)
    IQR=q3-q1
    upper_whisker = q3+1.5*IQR
    lower_whisker = q1-1.5*IQR
    outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]
    return outliers,IQR,upper_whisker,lower_whisker

outliers,IQR,uw,lw = find_outliers_IQR(walmart["Purchase"])
print("Outliers of Purchase Value of a customer for single product")
print("number of outliers =", (len(outliers)))
print("max outlier value =", (outliers.max()))
print("min outlier value =", (outliers.min()))
print("Inter Quartile range =",IQR)
print("upper_whisker =", uw)
print("lower whisker =", lw)
```

```
Outliers of Purchase Value of a customer for single product
number of outliers = 2677
max outlier value = 23961
min outlier value = 21401
Inter Quartile range = 6231.0
upper_whisker = 21400.5
lower whisker = -3523.5
```

Observations:

Difference between Max Oultier Value and Min Outlier Values is $2560, which is large value. and Number of ouliers are fairly large value 2677. So bounding/deleting of outliers is not good. `Use the dataset without bounding the outliers`

lower whisker is negative value so It is equal to `zero`

#CHAPTER 3: EXPLORATORY DATA ANALYSIS (Non Graphical and Visual Analysis)

##**Non Graphical analysis**

###Number of Transactions with respect each category of every column

[17]:
```
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category',
                    'Stay_In_Current_City_Years', 'Marital_Status',␣
 ↪'Product_Category']
for i in categorical_cols:
    print("Number of Transactions in {} column".format(i),end="\n\n")
    print(walmart[i].value_counts(),end="\n\n")
```

```
Number of Transactions in Gender column

M    414259
F    135809
Name: Gender, dtype: int64

Number of Transactions in Age column

26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64

Number of Transactions in Occupation column

4     72308
0     69638
7     59133
1     47426
17    40043
20    33562
12    31179
14    27309
2     26588
16    25371
6     20355
3     17650
10    12930
```

```
5      12177
15     12165
11     11586
19      8461
13      7728
18      6622
9       6291
8       1546
Name: Occupation, dtype: int64

Number of Transactions in City_Category column

B    231173
C    171175
A    147720
Name: City_Category, dtype: int64

Number of Transactions in Stay_In_Current_City_Years column

1     193821
2     101838
3      95285
4+     84726
0      74398
Name: Stay_In_Current_City_Years, dtype: int64

Number of Transactions in Marital_Status column

0    324731
1    225337
Name: Marital_Status, dtype: int64

Number of Transactions in Product_Category column

5     150933
1     140378
8     113925
11     24287
2      23864
6      20466
3      20213
4      11753
16      9828
15      6290
13      5549
10      5125
12      3947
7       3721
```

```
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64
```

Observations: According to number of transactions

`Male : Female` = 414259:135809 = approx `75%:25%`

More number of transactions by `26-35 Age` group (40% transactions)

Top five occupations are `4,0,7,1,17`

City Category `B` = 231173 (`42%`)

Most transactions from customers who are staying from `1 year`

Unmarried:Married = 324731:225337 = `60:40`

Top five product categories are `5,1,8,11,2`

###Average and total Purchase amount of all columns with respect to each of their category

[18]:
```python
for i in categorical_cols:
    print("Average Purchase amount for {} categories is: ".format(i),walmart.
 ↪groupby(i)["Purchase"].mean().sort_values(ascending = False),sep =␣
 ↪"\n",end="\n\n")
    print("Total Purchase amount for {} categories is: ".format(i),walmart.
 ↪groupby(i)["Purchase"].sum().sort_values(ascending = False),sep =␣
 ↪"\n",end="\n\n")
```

```
Average Purchase amount for Gender categories is:
Gender
M    9437.526040
F    8734.565765
Name: Purchase, dtype: float64

Total Purchase amount for Gender categories is:
Gender
M    3909580100
F    1186232642
Name: Purchase, dtype: int64

Average Purchase amount for Age categories is:
Age
51-55    9534.808031
55+      9336.280459
36-45    9331.350695
```

```
26-35    9252.690633
46-50    9208.625697
18-25    9169.663606
0-17     8933.464640
Name: Purchase, dtype: float64

Total Purchase amount for Age categories is:
Age
26-35    2031770578
36-45    1026569884
18-25     913848675
46-50     420843403
51-55     367099644
55+       200767375
0-17      134913183
Name: Purchase, dtype: int64

Average Purchase amount for Occupation categories is:
Occupation
17    9821.478236
12    9796.640239
15    9778.891163
8     9532.592497
14    9500.702772
7     9425.728223
16    9394.464349
5     9333.149298
13    9306.351061
6     9256.535691
4     9213.980251
11    9213.845848
3     9178.593088
18    9169.655844
0     9124.428588
10    8959.355375
1     8953.193270
2     8952.481683
20    8836.494905
19    8710.627231
9     8637.743761
Name: Purchase, dtype: float64

Total Purchase amount for Occupation categories is:
Occupation
4     666244484
0     635406958
7     557371587
1     424614144
```

```
17    393281453
12    305449446
20    296570442
14    259454692
16    238346955
2     238028583
6     188416784
3     162002168
15    118960211
10    115844465
5     113649759
11    106751618
19     73700617
13     71919481
18     60721461
9      54340046
8      14737388
Name: Purchase, dtype: int64

Average Purchase amount for City_Category categories is:
City_Category
C    9719.920993
B    9151.300563
A    8911.939216
Name: Purchase, dtype: float64

Total Purchase amount for City_Category categories is:
City_Category
B    2115533605
C    1663807476
A    1316471661
Name: Purchase, dtype: int64

Average Purchase amount for Stay_In_Current_City_Years categories is:
Stay_In_Current_City_Years
2     9320.429810
3     9286.904119
4+    9275.598872
1     9250.145923
0     9180.075123
Name: Purchase, dtype: float64

Total Purchase amount for Stay_In_Current_City_Years categories is:
Stay_In_Current_City_Years
1     1792872533
2      949173931
3      884902659
4+     785884390
```

```
0      682979229
Name: Purchase, dtype: int64

Average Purchase amount for Marital_Status categories is:
Marital_Status
0    9265.907619
1    9261.174574
Name: Purchase, dtype: float64

Total Purchase amount for Marital_Status categories is:
Marital_Status
0    3008927447
1    2086885295
Name: Purchase, dtype: int64

Average Purchase amount for Product_Category categories is:
Product_Category
10    19675.570927
7     16365.689600
6     15838.478550
9     15537.375610
15    14780.451828
16    14766.037037
1     13606.218596
14    13141.625739
2     11251.935384
17    10170.759516
3     10096.705734
8      7498.958078
5      6240.088178
11     4685.268456
18     2972.864320
4      2329.659491
12     1350.859894
13      722.400613
20      370.481176
19       37.041797
Name: Purchase, dtype: float64

Total Purchase amount for Product_Category categories is:
Product_Category
1     1910013754
5      941835229
8      854318799
6      324150302
2      268516186
3      204084713
16     145120612
```

```
11     113791115
10     100837301
15      92969042
7       60896731
4       27380488
14      20014696
18       9290201
9        6370324
17       5878699
12       5331844
13       4008601
20        944727
19         59378
Name: Purchase, dtype: int64
```

Observations

> Average Purchase amount in Age column is highest for 51-55 bin Total Purchase amount in Age column is highest for 26-35 bin
>
> Average Purchase amount in Occupation column is highest for 17 bin Total Purchase amount in Occupation column is highest for 4 bin
>
> Average Purchase amount in City_category column is highest for C bin Total Purchase amount in City_category column is highest for B bin
>
> Average Purchase amount in Stay_in_city column is highest for 2 year bin Total Purchase amount in Stay_in_city column is highest for 1 year bin
>
> Average Purchase amount in Product_category column is highest for 10 bin Total Purchase amount in Product_category column is highest for 1 year bin
>
> These type of differences because, `Number of smaller amount transactions in a bin is dominating the mean purchase amount of other bin.`
>
> Above Value counts are based on given dataset. `Given dataset consists of same customer buying multiple products`. So Primary key for above dataset is "User_ID + Product_ID"

###Value_counts by percentage format

> It is better to analyse based number of customers (other than number of transactions bought)

[19]:
```
#melt the Categorical columns of walmart data and then group by (attribute and␣
↪bins), Then get the Count Percentage of each bin
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category',␣
↪'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
(walmart[categorical_cols].melt().groupby(['variable', 'value'])[['value']].
↪count()/len(walmart))*100
```

[19]:

variable	value	value
Age	0-17	2.745479
	18-25	18.117760
	26-35	39.919974
	36-45	19.999891
	46-50	8.308246
	51-55	6.999316
	55+	3.909335
City_Category	A	26.854862
	B	42.026259
	C	31.118880
Gender	F	24.689493
	M	75.310507
Marital_Status	0	59.034701
	1	40.965299
Occupation	0	12.659889
	1	8.621843
	2	4.833584
	3	3.208694
	4	13.145284
	5	2.213726
	6	3.700452
	7	10.750125
	8	0.281056
	9	1.143677
	10	2.350618
	11	2.106285
	12	5.668208
	13	1.404917
	14	4.964659
	15	2.211545
	16	4.612339
	17	7.279645
	18	1.203851
	19	1.538173
	20	6.101427
Product_Category	1	25.520118
	2	4.338373
	3	3.674637
	4	2.136645
	5	27.438971
	6	3.720631
	7	0.676462
	8	20.711076
	9	0.074536
	10	0.931703

```
                              11        4.415272
                              12        0.717548
                              13        1.008784
                              14        0.276875
                              15        1.143495
                              16        1.786688
                              17        0.105078
                              18        0.568112
                              19        0.291419
                              20        0.463579
Stay_In_Current_City_Years    0        13.525237
                              1        35.235825
                              2        18.513711
                              3        17.322404
                              4+       15.402823
```

Observations from categorically grouped data:

approximately `78% of users` are having age between `18 to 45`

City Category Users ratio approx = `27:42:31`

Male:Female = `75:25`

NotMarried:Married = `60:40`

`35% customers staying from 1 year.` remaining all years customers are almost around 13 to 18 %(similar)

###CrossTab analysis

Cross tab between City Category and Age

[20]:
```
pd.crosstab(index = walmart["City_Category"],columns = walmart["Age"],margins =
 ↪True, normalize="index")*100
```

[20]:
```
Age                0-17      18-25      26-35      36-45      46-50     51-55  \
City_Category
A              1.722177  18.639995  49.922150  18.018549   5.149607  4.128757
B              2.351053  18.707635  39.617083  20.589775   8.827155  7.674339
C              4.161238  16.870454  31.697386  20.913101  10.333285  8.564919
All            2.745479  18.117760  39.919974  19.999891   8.308246  6.999316

Age                 55+
City_Category
A              2.418765
B              2.232960
C              7.459617
All            3.909335
```

Observations:

Large percentage of number of transactions are observed in 26-35 age group in all city categories

0-17 and 55+ has very less percentage share in all city categories.

[21]:
```
pd.crosstab(index = walmart["City_Category"],columns = walmart["Age"],margins =␣
↪True, normalize="columns")*100
```

[21]:
```
Age                 0-17      18-25      26-35      36-45      46-50  \
City_Category
A              16.845451  27.628938  33.583500  24.194413  16.645150
B              35.988611  43.394541  41.707387  43.265796  44.651102
C              47.165938  28.976520  24.709113  32.539791  38.703748

Age                51-55        55+        All
City_Category
A              15.841147  16.615513  26.854862
B              46.079323  24.004836  42.026259
C              38.079530  59.379650  31.118880
```

Comparison between Gender and Total Purchase amount

[22]:
```
df = pd.DataFrame(walmart.groupby(["Gender"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df
```

[22]:
```
          Purchase  percentage
Gender
F       1186232642   23.278576
M       3909580100   76.721424
```

Observations:

Male spent more purchase amount than Female (76:24)

Comparison between Age group and Total Purchase amount

[23]:
```
df = pd.DataFrame(walmart.groupby(["Age"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df
```

[23]:
```
         Purchase  percentage
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
```

Observations:

with respect to total purchase amount also, Age group 26-35 dominates other groups.

Comparison between marital status and total purchase amount

[24]:
```python
df = pd.DataFrame(walmart.groupby(["Marital_Status"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df
```

[24]:
```
                  Purchase  percentage
Marital_Status
0               3008927447   59.047057
1               2086885295   40.952943
```

Observations:

With respect to total purchase amount, Unmarried : Married = 59:41

Comparison between City Category and Total Purchase amount

[25]:
```python
df = pd.DataFrame(walmart.groupby(["City_Category"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df
```

[25]:
```
                 Purchase  percentage
City_Category
A              1316471661   25.834381
B              2115533605   41.515136
C              1663807476   32.650483
```

Observations:

A: B: C = 25.8 : 41.5 : 32.7

Comparison between Occupation and Total Purchase amount

[26]:
```python
df = pd.DataFrame(walmart.groupby(["Occupation"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df.sort_values("percentage",ascending = False)
```

[26]:
```
             Purchase  percentage
Occupation
4           666244484   13.074352
0           635406958   12.469198
7           557371587   10.937835
1           424614144    8.332609
17          393281453    7.717738
```

```
12          305449446   5.994126
20          296570442   5.819885
14          259454692   5.091527
16          238346955   4.677310
2           238028583   4.671062
6           188416784   3.697482
3           162002168   3.179123
15          118960211   2.334470
10          115844465   2.273327
5           113649759   2.230258
11          106751618   2.094889
19           73700617   1.446298
13           71919481   1.411345
18           60721461   1.191595
9            54340046   1.066367
8            14737388   0.289206
```

Observations:

Occupation like 4,0, 7 has contributed more towards the total purchase amount

Comparison between Product_Category and Total Purchase amount

[27]:
```python
df = pd.DataFrame(walmart.groupby(["Product_Category"])[["Purchase"]].sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df.sort_values("percentage",ascending = False)
```

[27]:

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

```
19                      59378    0.001165
```

Observations:

Product Categories like 1,5,8 has contributed more towards the total purchase amount

Comparison between Stay_In_Current_City_Years and Total Purchase amount

[28]:
```
df = pd.DataFrame(walmart.groupby(["Stay_In_Current_City_Years"])[["Purchase"]].
  ↪sum())
df["percentage"] = df["Purchase"]/df["Purchase"].sum()*100
df.sort_values("percentage",ascending = False)
```

[28]:
```
                              Purchase  percentage
Stay_In_Current_City_Years
1                           1792872533   35.183250
2                            949173931   18.626547
3                            884902659   17.365290
4+                           785884390   15.422160
0                            682979229   13.402754
```

###User concentrated analysis

[29]:
```
walmart.groupby(["User_ID"])["Purchase"].count().sort_values(ascending = False)
```

[29]:
```
User_ID
1001680    1026
1004277     979
1001941     898
1001181     862
1000889     823
           …
1002111       7
1005391       7
1002690       7
1005608       7
1000708       6
Name: Purchase, Length: 5891, dtype: int64
```

Observations:

1001680 has done more number of transactions

[30]:
```
walmart.groupby(["User_ID"])["Purchase"].sum().sort_values(ascending = False)
```

[30]:
```
User_ID
1004277    10536909
1001680     8699596
1002909     7577756
1001941     6817493
```

```
1000424     6573609
              …
1004991       52371
1005117       49668
1003883       49349
1000094       49288
1004464       46681
Name: Purchase, Length: 5891, dtype: int64
```

Observations:

1004277 has made highest total purchase amount

[31]:
```python
walmart.groupby(["User_ID"])["Purchase"].mean().sort_values(ascending = False)
```

[31]:
```
User_ID
1003902    18577.893617
1005069    18490.166667
1005999    18345.944444
1001349    18162.739130
1003461    17508.700000
               …
1004636     3612.812500
1005944     3599.733333
1002744     3421.521739
1003598     2698.357143
1004486     2318.733333
Name: Purchase, Length: 5891, dtype: float64
```

Observations:

On average, 1003902 User spent more purchase amount.

##**Visual Analysis**

###Reset the index of above melted walmart data

[32]:
```python
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category',␣
↪'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
Attribute_melt_group= (walmart[categorical_cols].melt().groupby(['variable',␣
↪'value'])[['value']].count()/len(walmart))*100
```

[33]:
```python
Attribute_melt_group.columns = ["Percentages"]
Attribute_melt_group = Attribute_melt_group.reset_index()
Attribute_melt_group.columns = ["Attribute","Bins","Percentages"]
Attribute_melt_group
```

[33]:

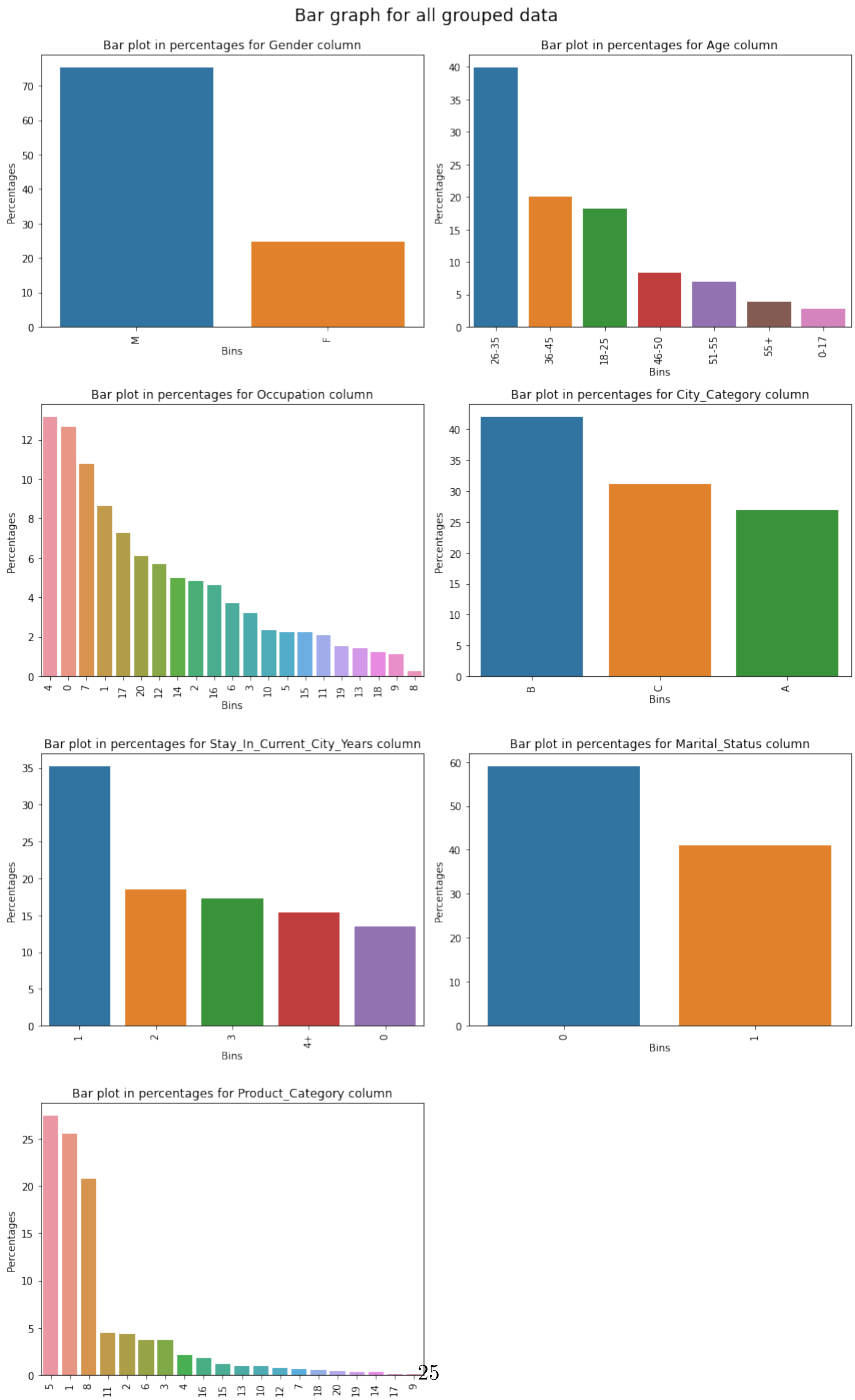
	Attribute	Bins	Percentages
0	Age	0-17	2.745479
1	Age	18-25	18.117760

2	Age	26-35	39.919974
3	Age	36-45	19.999891
4	Age	46-50	8.308246
5	Age	51-55	6.999316
6	Age	55+	3.909335
7	City_Category	A	26.854862
8	City_Category	B	42.026259
9	City_Category	C	31.118880
10	Gender	F	24.689493
11	Gender	M	75.310507
12	Marital_Status	0	59.034701
13	Marital_Status	1	40.965299
14	Occupation	0	12.659889
15	Occupation	1	8.621843
16	Occupation	2	4.833584
17	Occupation	3	3.208694
18	Occupation	4	13.145284
19	Occupation	5	2.213726
20	Occupation	6	3.700452
21	Occupation	7	10.750125
22	Occupation	8	0.281056
23	Occupation	9	1.143677
24	Occupation	10	2.350618
25	Occupation	11	2.106285
26	Occupation	12	5.668208
27	Occupation	13	1.404917
28	Occupation	14	4.964659
29	Occupation	15	2.211545
30	Occupation	16	4.612339
31	Occupation	17	7.279645
32	Occupation	18	1.203851
33	Occupation	19	1.538173
34	Occupation	20	6.101427
35	Product_Category	1	25.520118
36	Product_Category	2	4.338373
37	Product_Category	3	3.674637
38	Product_Category	4	2.136645
39	Product_Category	5	27.438971
40	Product_Category	6	3.720631
41	Product_Category	7	0.676462
42	Product_Category	8	20.711076
43	Product_Category	9	0.074536
44	Product_Category	10	0.931703
45	Product_Category	11	4.415272
46	Product_Category	12	0.717548
47	Product_Category	13	1.008784
48	Product_Category	14	0.276875

```
49              Product_Category     15      1.143495
50              Product_Category     16      1.786688
51              Product_Category     17      0.105078
52              Product_Category     18      0.568112
53              Product_Category     19      0.291419
54              Product_Category     20      0.463579
55  Stay_In_Current_City_Years        0     13.525237
56  Stay_In_Current_City_Years        1     35.235825
57  Stay_In_Current_City_Years        2     18.513711
58  Stay_In_Current_City_Years        3     17.322404
59  Stay_In_Current_City_Years       4+     15.402823
```

###Bivariate Analysis between Bins of each column and respective Number of transactions in percentages

[34]:
```
# Bar graph for all grouped data
fig = plt.figure(figsize = (12,20))
fig.suptitle("Bar graph for all grouped data \n",fontsize = "xx-large" )
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category',
                    'Stay_In_Current_City_Years', 'Marital_Status',␣
 ↪'Product_Category']
k = 1
for i in categorical_cols:
    plt.subplot(4,2,k)
    plt.title("Bar plot in percentages for {} column".format(i))
    mask = Attribute_melt_group[Attribute_melt_group["Attribute"] ==i]
    sns.barplot(data=mask, x = mask["Bins"],y = mask["Percentages"],
                order = mask.sort_values("Percentages",ascending = False).Bins)
    plt.xticks(rotation = 90)
    k = k+1
plt.tight_layout()
plt.show()
```


Bar graph for all grouped data
Bar plot in percentages for Gender column
Percentages
Bins
M
F
Bar plot in percentages for Age column
26-35
36-45
18-25
46-50
51-55
55+
0-17
Bar plot in percentages for Occupation column
4 0 7 1 17 20 12 14 2 16 6 3 10 5 15 11 19 13 18 9 8
Bar plot in percentages for City_Category column
B
C
A
Bar plot in percentages for Stay_In_Current_City_Years column
1
2
3
4+
0
Bar plot in percentages for Marital_Status column
0
1
Bar plot in percentages for Product_Category column
5 1 8 11 2 6 3 4 16 15 13 10 12 7 18 20 19 14 17 9

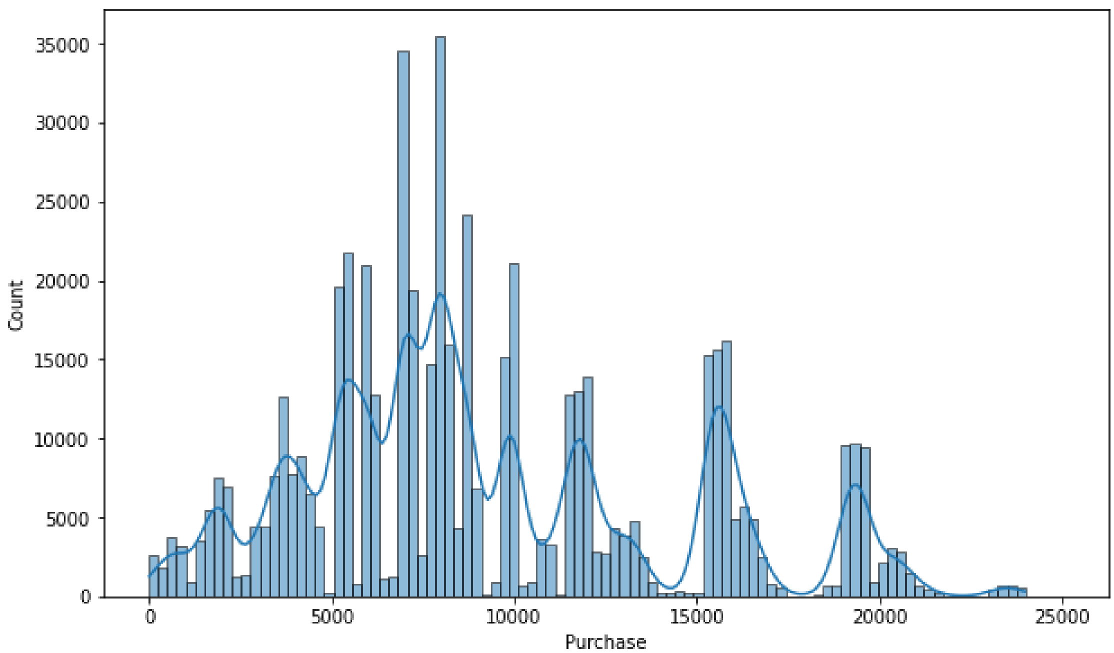
Observations:

Product Category - 1,5,8 have high purchasing frequencies

Occupation Category - 4, 0 ,7, 1, 17, 20 occupy approxmately 50% of dataset

###Univariate analysis on Purchase column bins with step size = $2500

[35]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=walmart, x='Purchase', kde=True,bins = np.
 ↪linspace(0,25000,100))
plt.show()
```



Observations

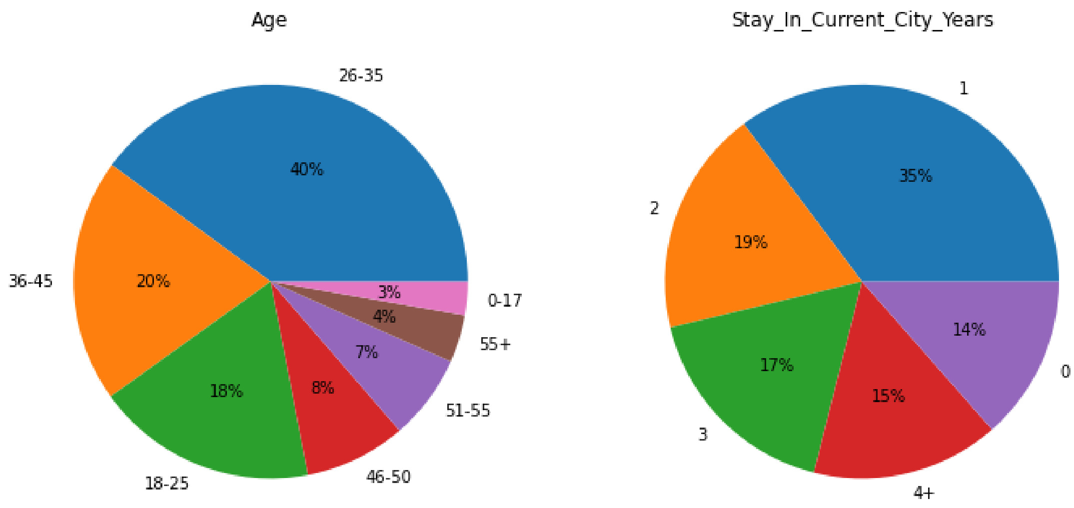
$5000 to $10000 bin consists of more transactions

The Kde distribution of purchase column is like `multi modal distribution`i.e., more than one maxima locally

###Pie plots on Age and Stay in city columns

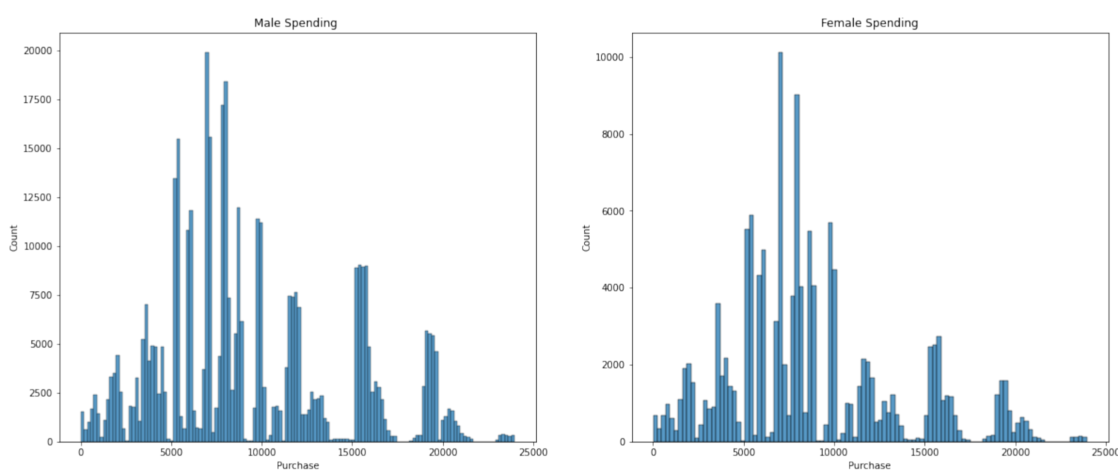
[36]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 8))
data = walmart['Age'].value_counts(normalize=True)*100
axs[0].pie(x=data.values, labels=data.index, autopct='%.0f%%')
axs[0].set_title("Age")
data = walmart['Stay_In_Current_City_Years'].value_counts(normalize=True)*100
```

```
axs[1].pie(x=data.values, labels=data.index, autopct='%.0f%%')
axs[1].set_title("Stay_In_Current_City_Years")
plt.show()
```



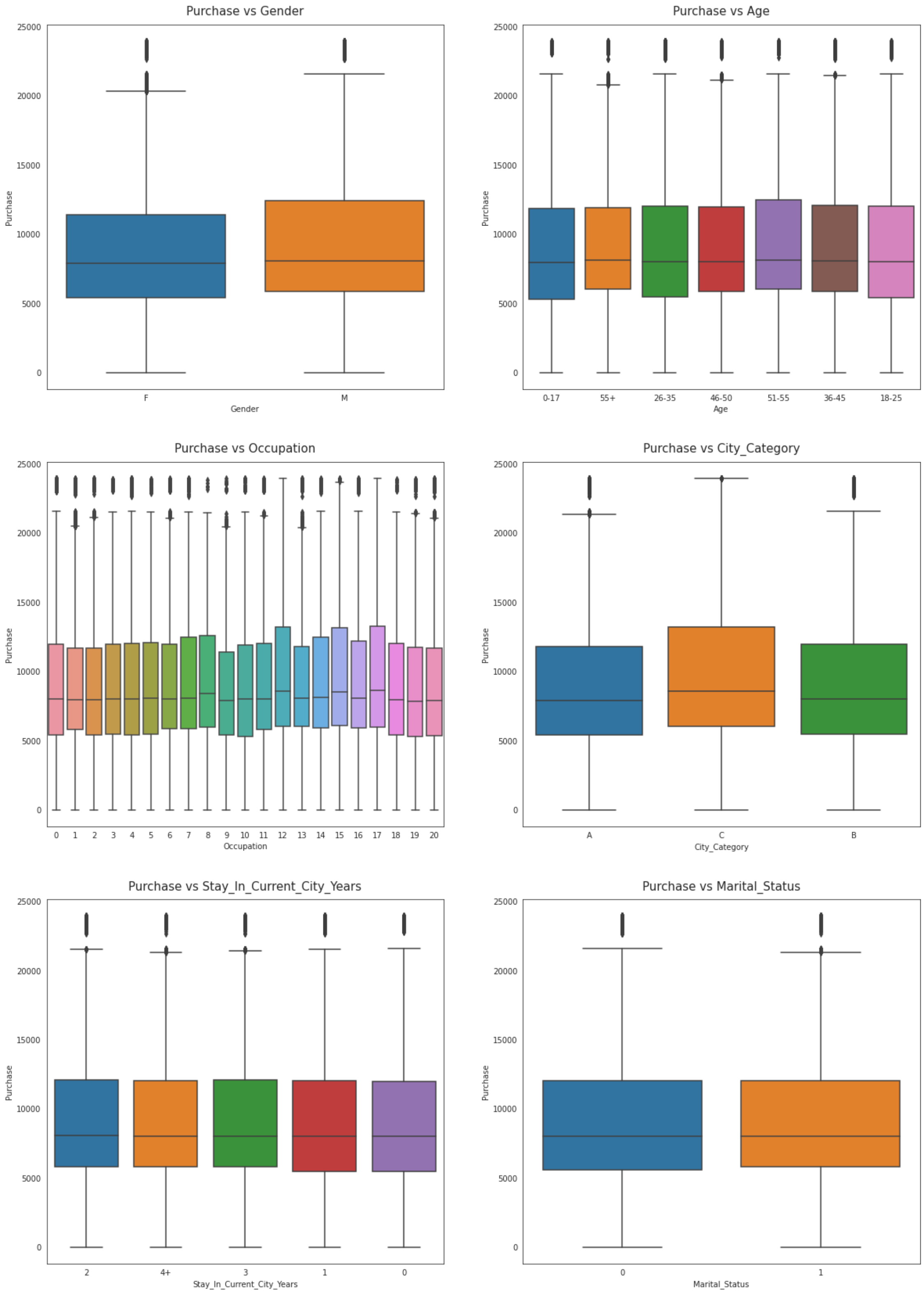
###Bivariate analysis between Purchase amount and Number of customers grouped by Gender

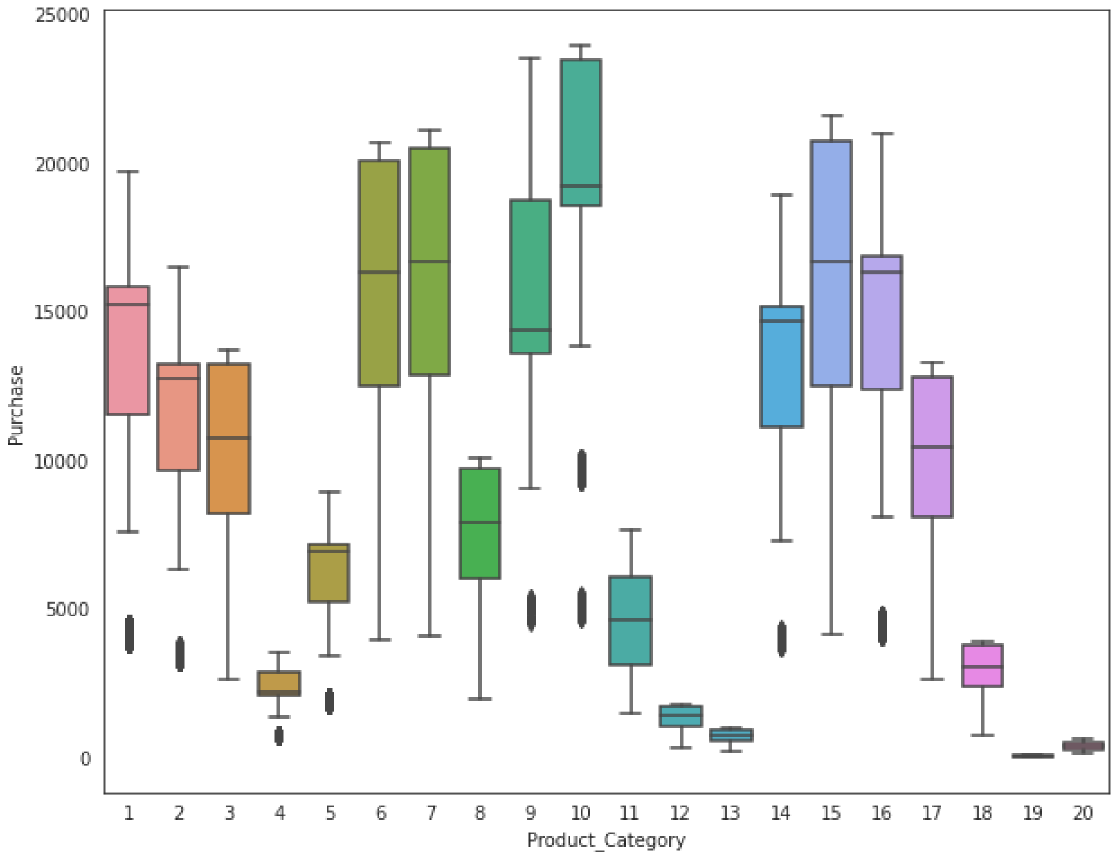
[37]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20,8))
sns.histplot(data=walmart[walmart['Gender']=='M']['Purchase'], ax=axs[0]).
  ↪set_title("Male Spending ")
sns.histplot(data=walmart[walmart['Gender']=='F']['Purchase'], ax=axs[1]).
  ↪set_title("Female Spending")
plt.show()
```



###Bivariate analysis using box plot on all categorical columns

[38]:
```
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=1.5)
count = 0
for row in range(3):
    for col in range(2):
        sns.boxplot(data=walmart, y='Purchase', x=attrs[count], ax=axs[row,␣
 ↪col])
        axs[row,col].set_title(f"Purchase vs {attrs[count]}", pad=12,␣
 ↪fontsize=15)
        count += 1
plt.show()
plt.figure(figsize=(10, 8))
sns.boxplot(data=walmart, y='Purchase', x=attrs[-1])
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
25000
20000
15000
10000
5000
0



Observations

Outliers are present in all graphs. Outliers are on upper side for graps except Product category vs Purchase

Median values are approximately similar in all graphs except Product category vs Purchase.

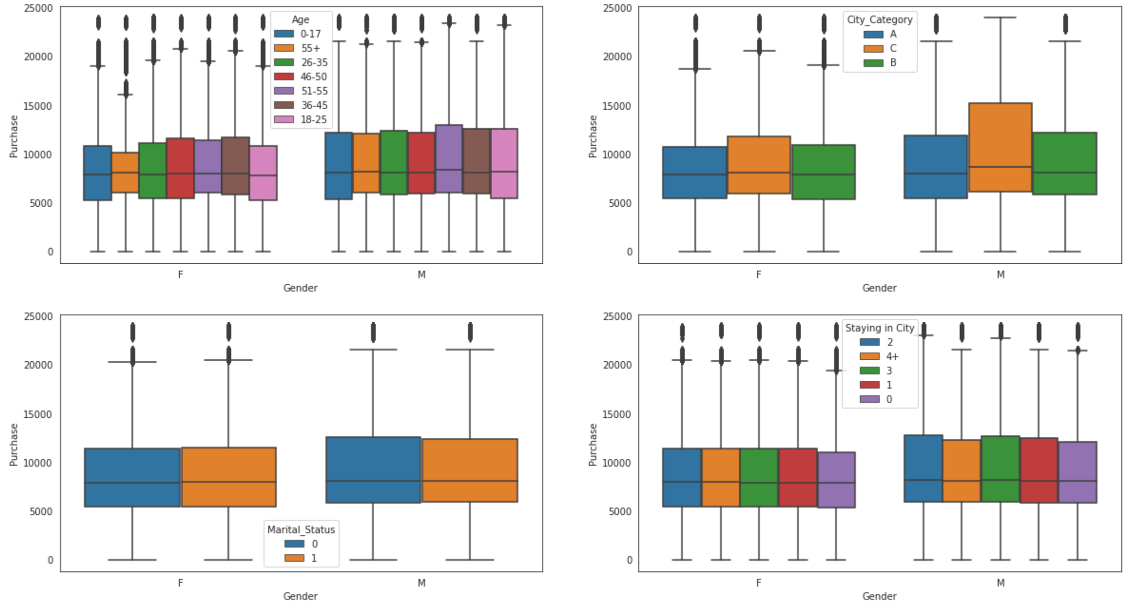
Median of 10 Product Category is highest and 19 is lowest.

It indicates that product category 10 is the costliest category and Product 19 is cheapest category

###Multi variate analysis using box plot by taking Gender column as common vs Purchase. Legends are varied among remaining categorical columns

[39]:
```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.boxplot(data=walmart, y='Purchase', x='Gender', hue='Age', ax=axs[0,0])
sns.boxplot(data=walmart, y='Purchase', x='Gender', hue='City_Category',␣
 ↪ax=axs[0,1])
sns.boxplot(data=walmart, y='Purchase', x='Gender', hue='Marital_Status',␣
 ↪ax=axs[1,0])
```

```
sns.boxplot(data=walmart, y='Purchase', x='Gender',␣
↪hue='Stay_In_Current_City_Years', ax=axs[1,1])
axs[1,1].legend(loc='best',title="Staying in City")
plt.show()
```



Observations:

For Male and Female, With respect to Age Bins, Median Purchase values are almost similar.

For Male and Female, With respect to Marital Status, Median Purchase values are almost similar.

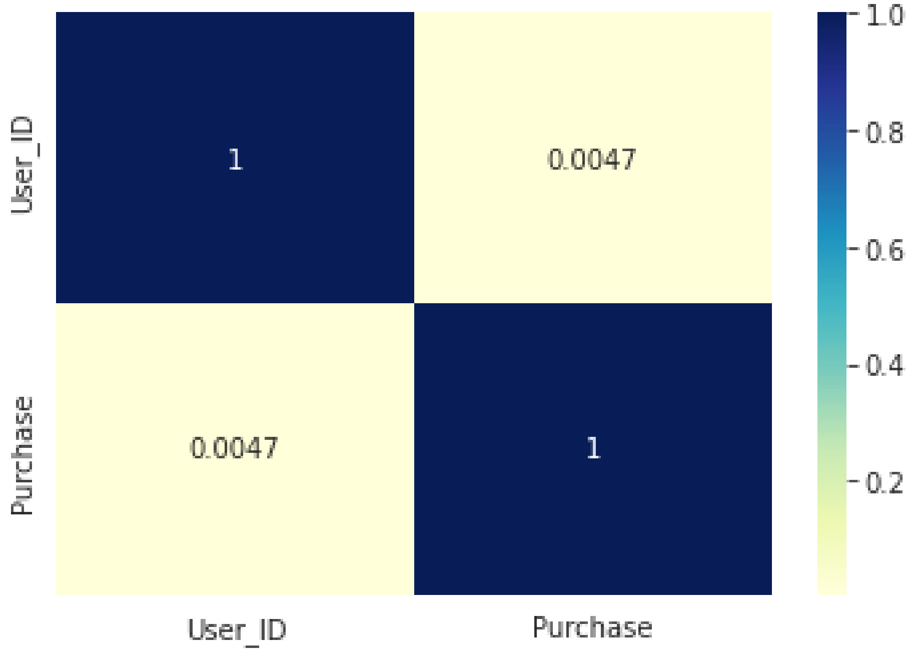
For Male and Female, With respect to City Category, slightly Category B Median Purchase value is higher for both female and male

For Male and Female, With respect to Stay in city column, Median Purchase values are almost similar

###Correlation heat maps and pair plots

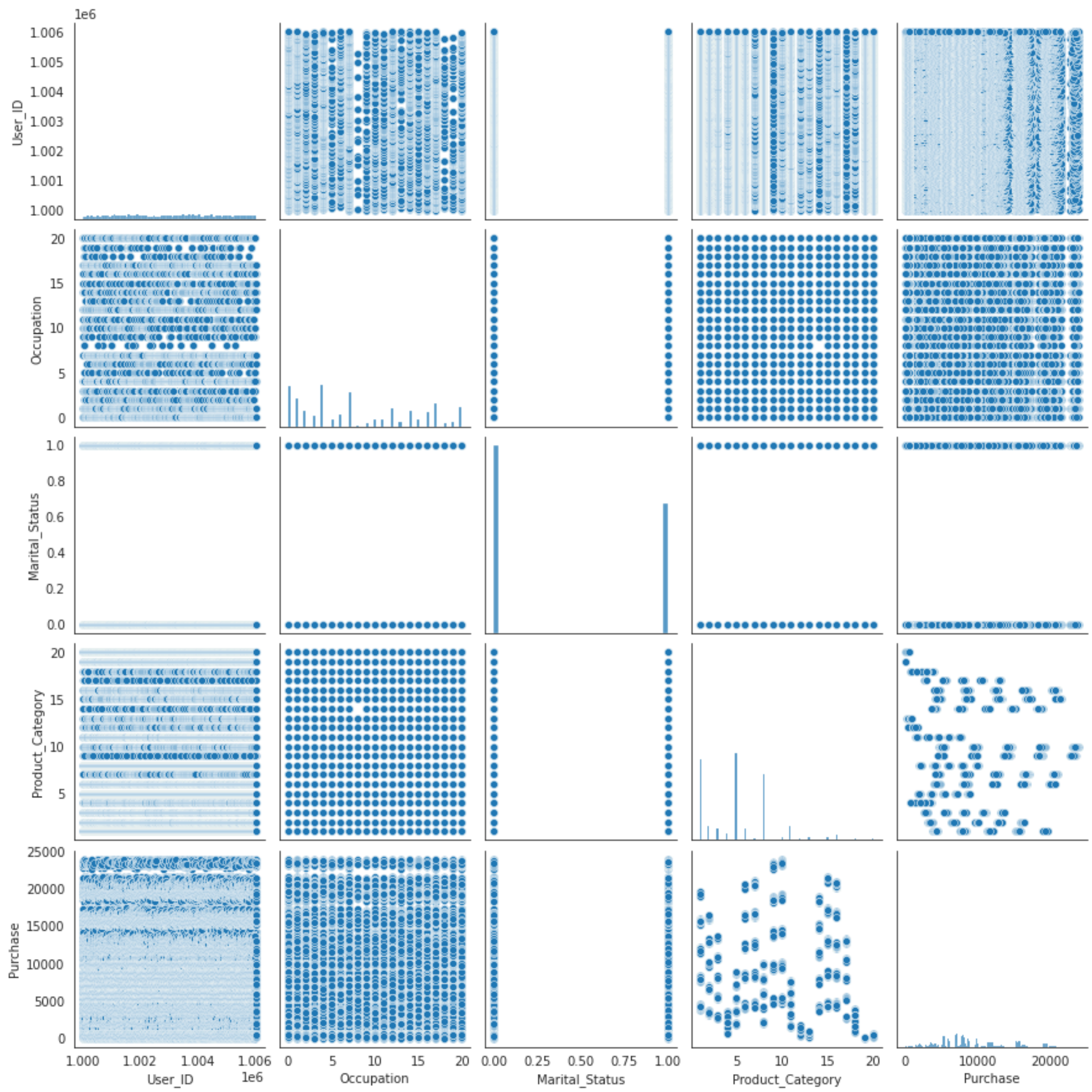
[40]:
```
sns.heatmap(walmart.corr(), cmap="YlGnBu", annot=True)
```

[40]: <Axes: >



[41]:
```
sns.pairplot(walmart)
```

[41]: <seaborn.axisgrid.PairGrid at 0x7f9a9e8f8a90>



#CHAPTER 4: APPLICATION OF CENTRAL LIMIT THEOREM AND OBTAINING CONFIDENCE INTERVALS OF THE DATA

##Applying CLT for Gender Vs Purchase and finding the distribution and mean

Important Note for Boot Strapping the data to 50 Million Female Customers and 50 Million Male customers:

> Given 550068 transactions data regarding `5891 unique` customers. Among them `4225 Male and 1666 female customers`. Same customers have bought multiple products. Each buy is treated as a transaction.
>
> So walmart data should be fancy masked by Gender and separate Male and Female Transactions. So that we can take sample from 550068 transactions and bootstrap it. (Not from 5891 unique customers average data)

Population data should be multiplied by `Random OverSampling by replacement and bootstrapping techniques` and Use this data, To estimate the answers for `50 Million Female` (from 1666) and `50 Million Male`(from 4225) customers

The distribution followed by samples point estimates are similar to the distribution of 50 million customers.

Note:

According central limit theorem, The mean of sample means are closer to the population mean

###Considering Average Purchase Value

```
[ ]: #Number of unique male and female customers
avg_amt_gender_walmart = walmart.groupby(['User_ID', 'Gender'])[['Purchase']].
↪mean()
avg_amt_gender_walmart = avg_amt_gender_walmart.reset_index()
avg_amt_gender_walmart["Gender"].value_counts()
```

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

Available Population data with Mean Purchase value of each Customer

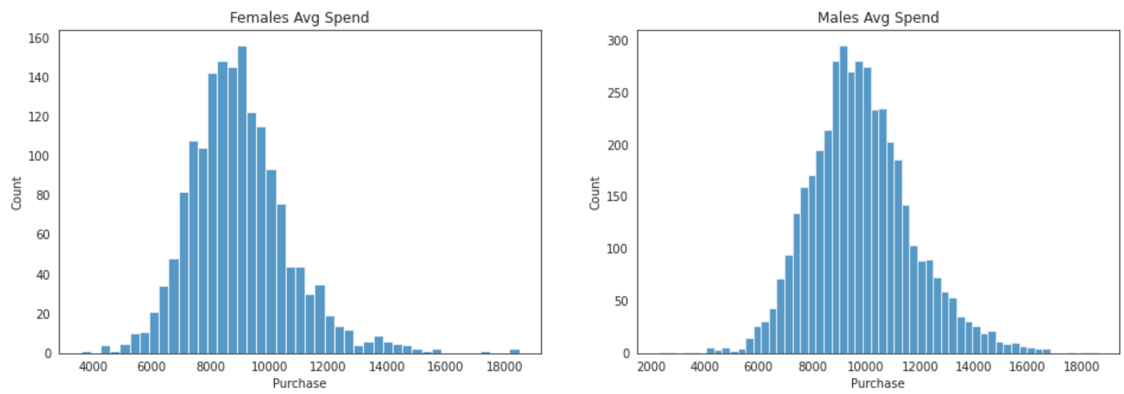
```
[ ]: #Population data
avg_amt_gender_walmart.sort_values("Purchase",ascending = False)
```

```
[ ]:       User_ID Gender      Purchase
3801  1003902      M  18577.893617
4943  1005069      F  18490.166667
5849  1005999      F  18345.944444
1307  1001349      M  18162.739130
3367  1003461      M  17508.700000
…         …    …           …
4521  1004636      M   3612.812500
5794  1005944      F   3599.733333
2667  1002744      M   3421.521739
3500  1003598      M   2698.357143
4373  1004486      M   2318.733333

[5891 rows x 3 columns]
```

```
[ ]: fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,5))
sns.
↪histplot(data=avg_amt_gender_walmart[avg_amt_gender_walmart['Gender']=='F']['Purchase'],␣
↪ax=axs[0]).set_title("Females Avg Spend")
```

```
sns.
↪histplot(data=avg_amt_gender_walmart[avg_amt_gender_walmart['Gender']=='M']['Purchase'],␣
↪ax=axs[1]).set_title("Males Avg Spend")
```

[ ]: Text(0.5, 1.0, 'Males Avg Spend')



[ ]:
```
df = avg_amt_gender_walmart.groupby(["Gender"])[["Purchase"]].mean()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

[ ]:

	Purchase	Percentage
Gender		
F	8965.198464	47.758187
M	9806.867524	52.241813

[ ]:
```
df = avg_amt_gender_walmart.groupby(["Gender"])[["Purchase"]].sum()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

[ ]:

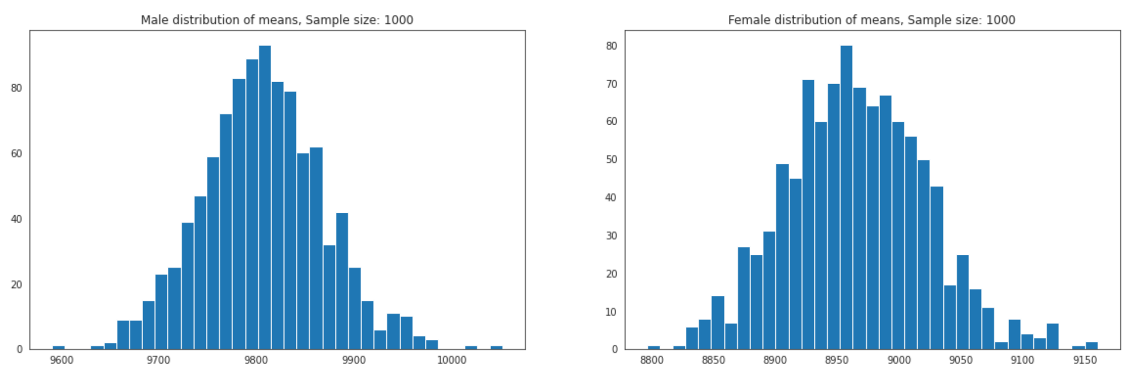
	Purchase	Percentage
Gender		
F	1.493602e+07	26.496383
M	4.143402e+07	73.503617

[116]:
```
avg_amt_male = avg_amt_gender_walmart[avg_amt_gender_walmart["Gender"]=="M"]
avg_amt_female = avg_amt_gender_walmart[avg_amt_gender_walmart["Gender"]=="F"]
```

[117]:
```
#Finding the sample(sample size=1000) for avg purchase amount for males and␣
↪females
genders = ["M", "F"]
sample_size = 1000
num_repitions = 1000
avg_male_means = []
```

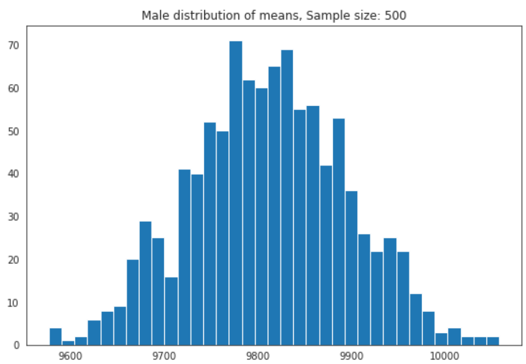
```
avg_female_means = []
for i in range(num_repitions):
    avg_male_mean = avg_amt_male.sample(sample_size, replace=True)['Purchase'].
 ↪mean()
    avg_female_mean = avg_amt_female.sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
    avg_male_means.append(avg_male_mean)
    avg_female_means.append(avg_female_mean)
```

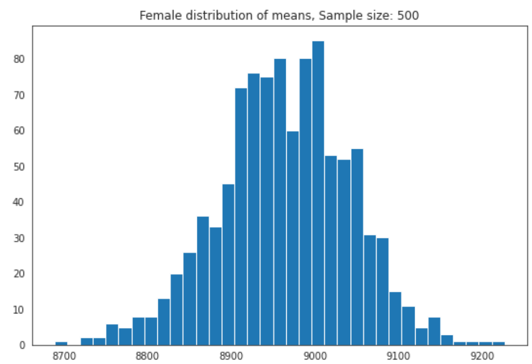
[119]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(avg_male_means, bins=35)
axis[1].hist(avg_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()
```

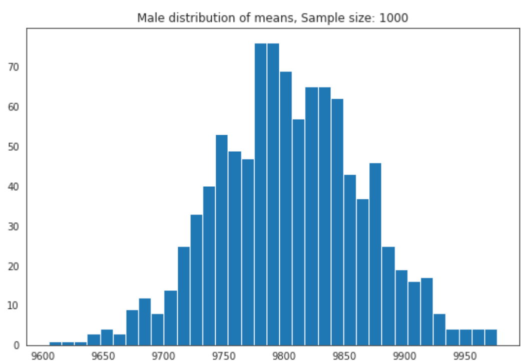


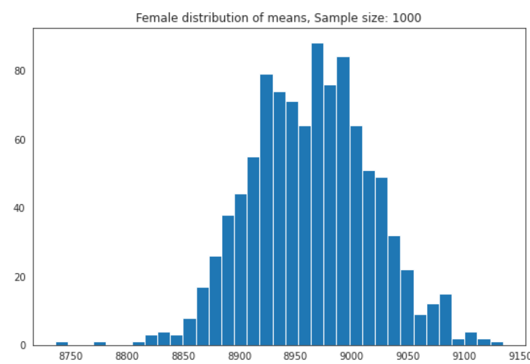
[120]:
```
#Finding the sample(sample size=variable) for avg purchase amount for males and␣
 ↪females
genders = ["M", "F"]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
    avg_male_means = []
    avg_female_means = []
    for i in range(num_repitions):
        avg_male_mean = avg_amt_male.sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
        avg_female_mean = avg_amt_female.sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
        avg_male_means.append(avg_male_mean)
        avg_female_means.append(avg_female_mean)
```

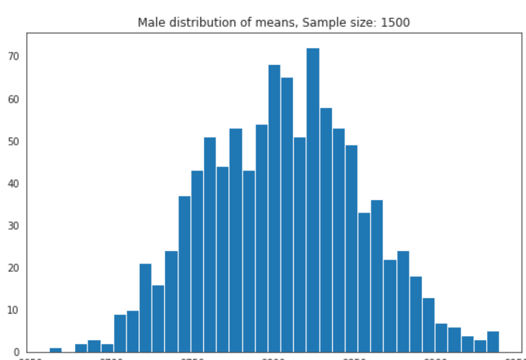
```python
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(avg_male_means, bins=35)
axis[1].hist(avg_female_means, bins=35)
axis[0].set_title("Male distribution of means, Sample size: {}".format(sample_size))
axis[1].set_title("Female distribution of means, Sample size: {}".format(sample_size))
plt.show()
```

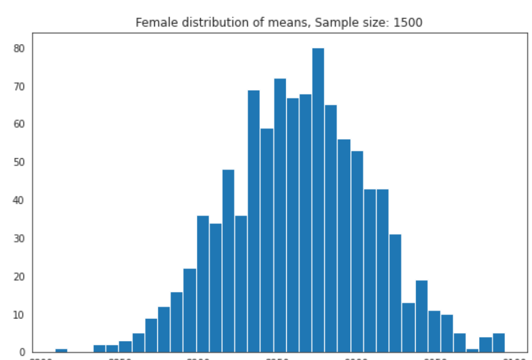


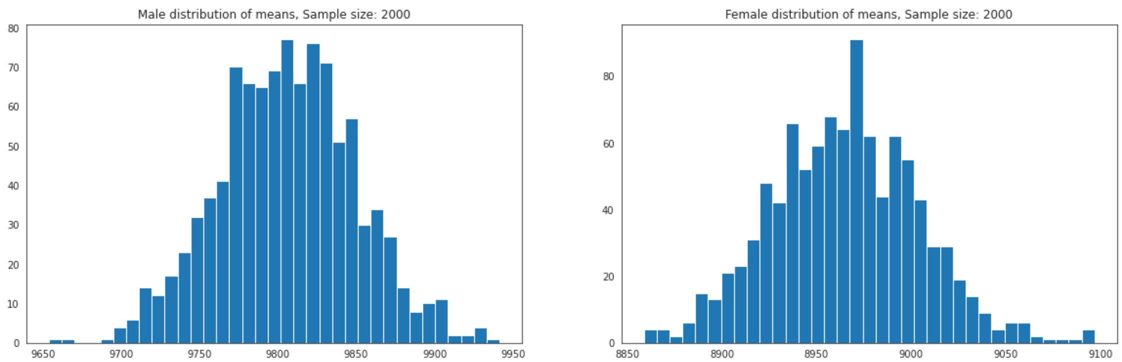




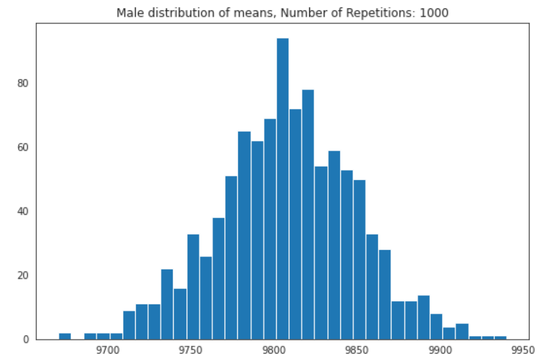


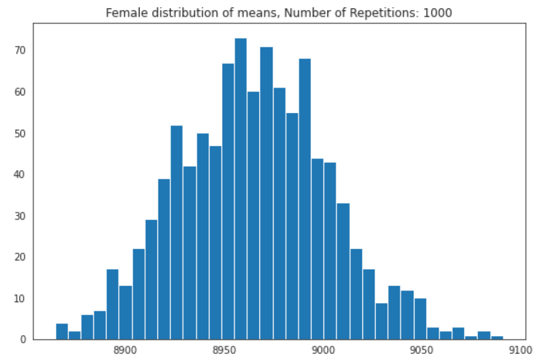


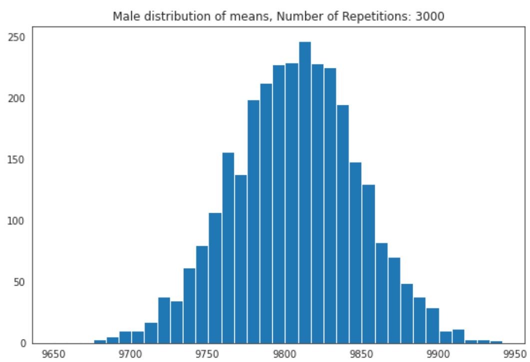


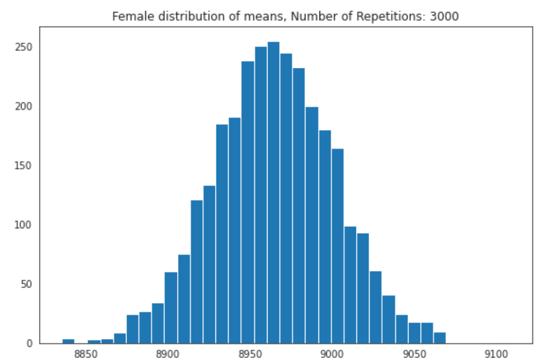


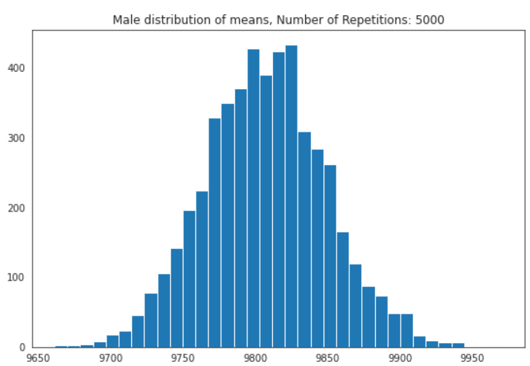
[121]:
```
#Finding the sample(sample size=1000) for avg purchase amount for males and␣
↪females
genders = ["M", "F"]
sample_size_range = 1000
num_repitions_range= np.arange(1000,11001,2000)
for num_repitions in num_repitions_range:
    avg_male_means = []
    avg_female_means = []
    for i in range(num_repitions):
        avg_male_mean = avg_amt_male.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_female_mean = avg_amt_female.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_male_means.append(avg_male_mean)
        avg_female_means.append(avg_female_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(avg_male_means, bins=35)
    axis[1].hist(avg_female_means, bins=35)
    axis[0].set_title("Male distribution of means, Number of Repetitions: {}".
↪format(num_repitions))
    axis[1].set_title("Female distribution of means, Number of Repetitions: {}".
↪format(num_repitions))
    plt.show()
```

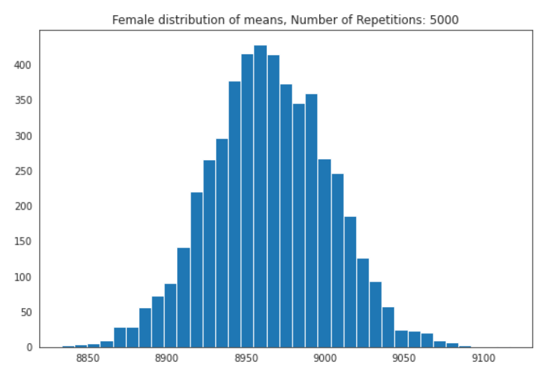

Male distribution of means, Number of Repetitions: 1000
0
20
40
60
80
9700
9750
9800
9850
9900
9950

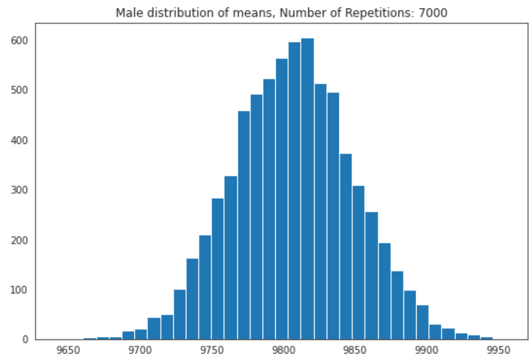

Female distribution of means, Number of Repetitions: 1000
0
10
20
30
40
50
60
70
8900
8950
9000
9050
9100

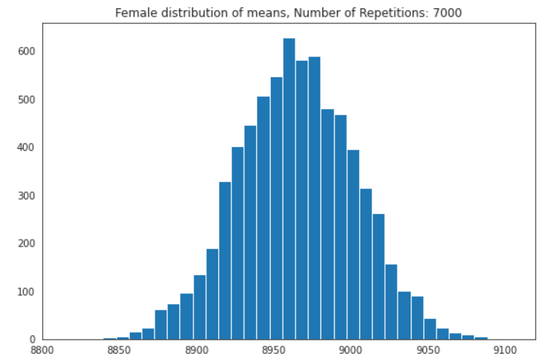

Male distribution of means, Number of Repetitions: 3000
0
50
100
150
200
250
9650
9700
9750
9800
9850
9900
9950

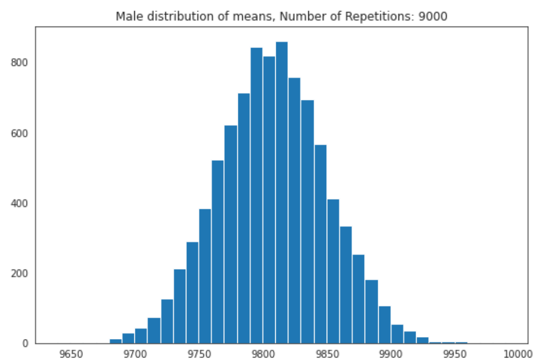

Female distribution of means, Number of Repetitions: 3000
0
50
100
150
200
250
8850
8900
8950
9000
9050
9100

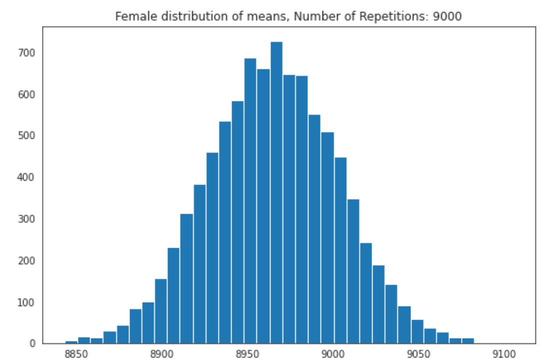

Male distribution of means, Number of Repetitions: 5000
0
100
200
300
400
9650
9700
9750
9800
9850
9900
9950

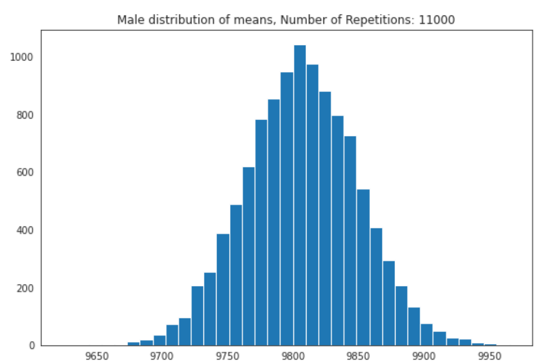

Female distribution of means, Number of Repetitions: 5000
0
50
100
150
200
250
300
350
400
8850
8900
8950
9000
9050
9100

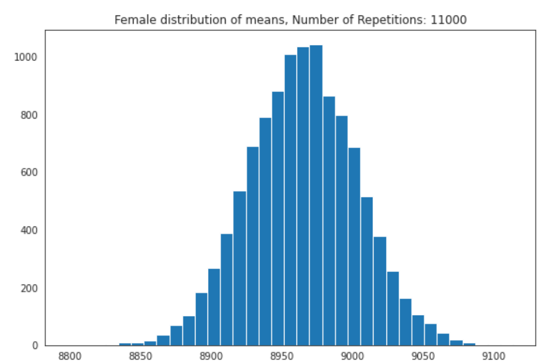








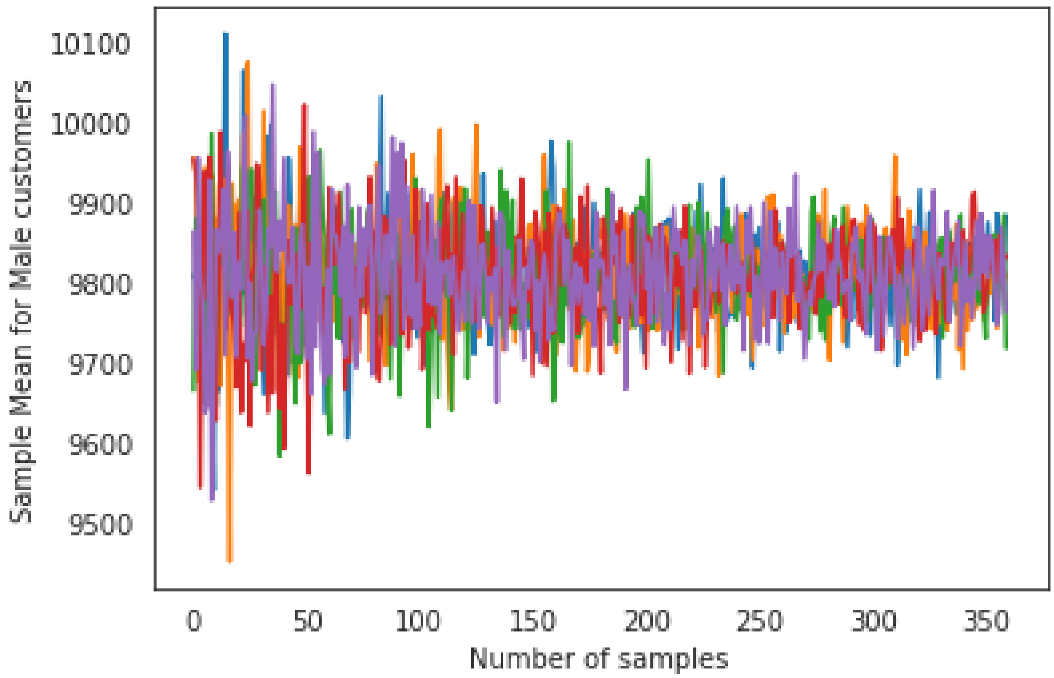




[ ]:
```
sample_mean_male_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_male = avg_amt_male.sample(num_samples,replace = True)
        sample_mean_male = np.mean(sample_male["Purchase"])
        sample_mean_male_trend.append(sample_mean_male)
    plt.plot(sample_mean_male_trend)
    sample_mean_male_trend = []
```

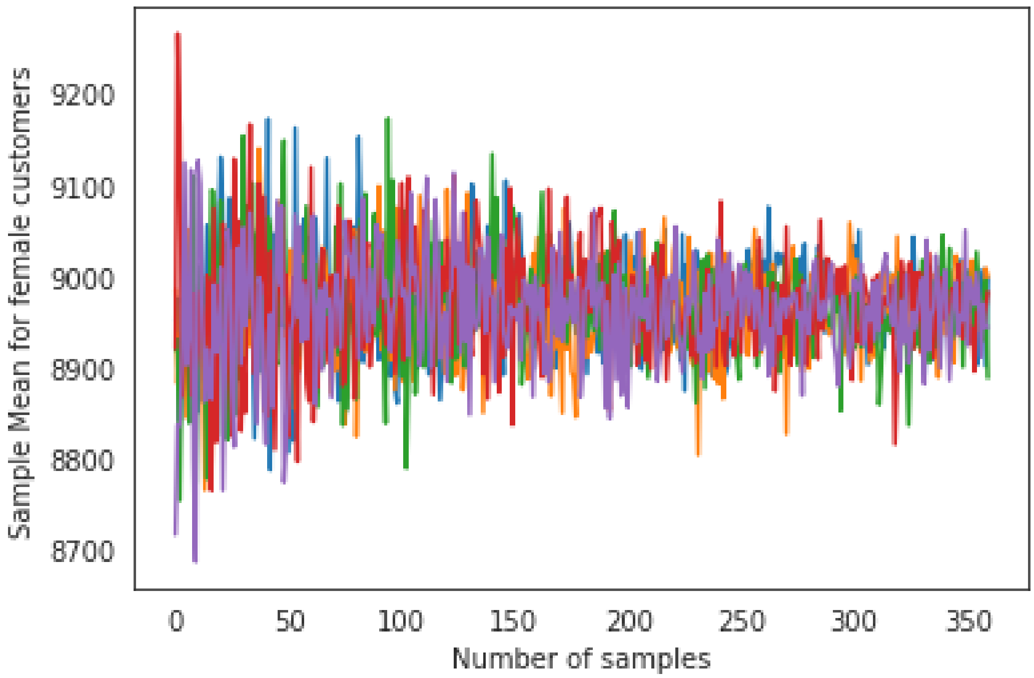
```
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Male customers")
```

[ ]: Text(0, 0.5, 'Sample Mean for Male customers')



[ ]:
```
sample_mean_female_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_female = avg_amt_female.sample(num_samples,replace = True)
        sample_mean_female = np.mean(sample_female["Purchase"])
        sample_mean_female_trend.append(sample_mean_female)
    plt.plot(sample_mean_female_trend)
    sample_mean_female_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for female customers")
```

[ ]: Text(0, 0.5, 'Sample Mean for female customers')



0.0.1 Considering Total Purchase Value

[ ]:
```
#Number of unique male and female customers
tot_amt_gender_walmart = walmart.groupby(['User_ID', 'Gender'])[['Purchase']].
 ↪sum()
tot_amt_gender_walmart = tot_amt_gender_walmart.reset_index()
tot_amt_gender_walmart.sort_values("Purchase",ascending = False)
```

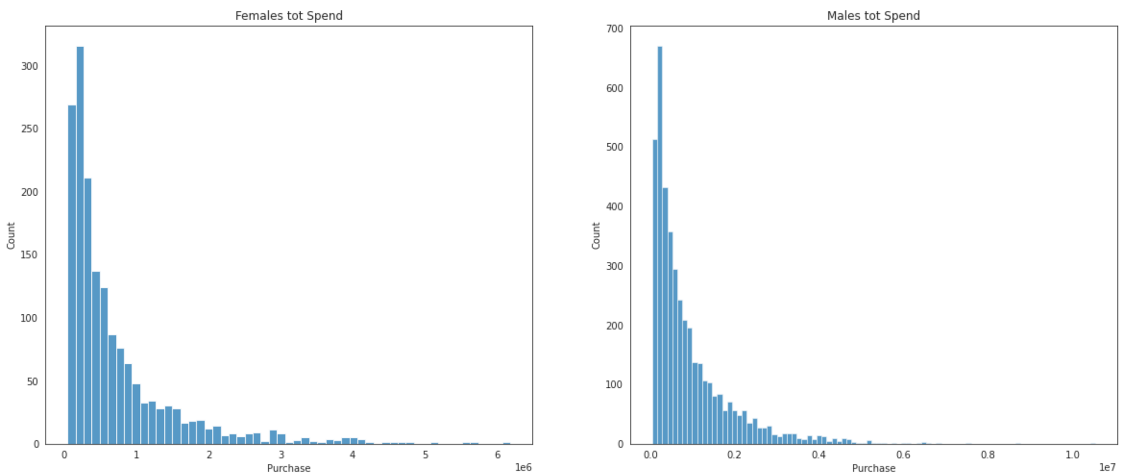
[ ]:

	User_ID	Gender	Purchase
4166	1004277	M	10536909
1634	1001680	M	8699596
2831	1002909	M	7577756
1885	1001941	M	6817493
416	1000424	M	6573609
…	…	…	…
4866	1004991	F	52371
4989	1005117	F	49668
3782	1003883	M	49349
91	1000094	M	49288
4351	1004464	F	46681

[5891 rows x 3 columns]

```
[ ]: fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20,8))
sns.
 ↪histplot(data=tot_amt_gender_walmart[tot_amt_gender_walmart['Gender']=='F']['Purchase'],␣
 ↪ax=axs[0]).set_title("Females tot Spend")
sns.
 ↪histplot(data=tot_amt_gender_walmart[tot_amt_gender_walmart['Gender']=='M']['Purchase'],␣
 ↪ax=axs[1]).set_title("Males tot Spend")
```

```
[ ]: Text(0.5, 1.0, 'Males tot Spend')
```




```
[ ]: df = tot_amt_gender_walmart.groupby(["Gender"])[["Purchase"]].mean()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

```
[ ]:              Purchase  Percentage
Gender
F       712024.394958    43.48589
M       925344.402367    56.51411
```

```
[ ]: df = tot_amt_gender_walmart.groupby(["Gender"])[["Purchase"]].sum()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

```
[ ]:          Purchase  Percentage
Gender
F       1186232642   23.278576
M       3909580100   76.721424
```

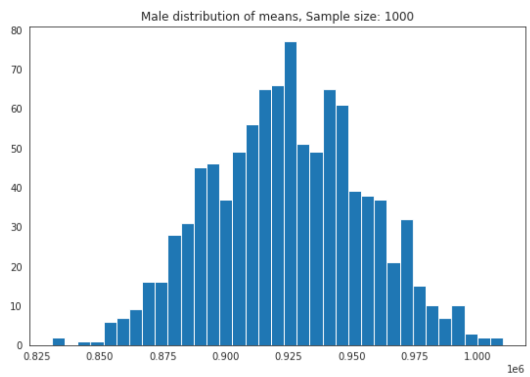
```
[122]: tot_amt_male = tot_amt_gender_walmart[tot_amt_gender_walmart["Gender"]=="M"]
tot_amt_female = tot_amt_gender_walmart[tot_amt_gender_walmart["Gender"]=="F"]
```

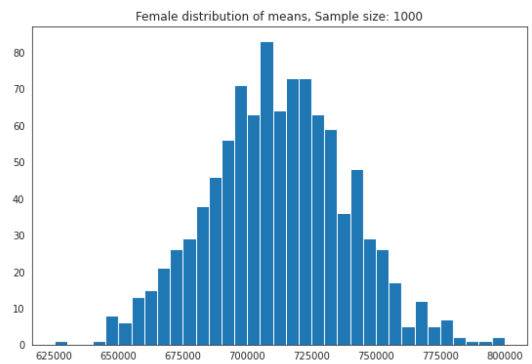
[123]:

```
#Finding the sample(sample size=1000) for tot purchase amount for males and␣
↪females
genders = ["M", "F"]
sample_size = 1000
num_repitions = 1000
tot_male_means = []
tot_female_means = []
for i in range(num_repitions):
    tot_male_mean = tot_amt_male.sample(sample_size, replace=True)['Purchase'].
↪mean()
    tot_female_mean = tot_amt_female.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
    tot_male_means.append(tot_male_mean)
    tot_female_means.append(tot_female_mean)
```

[125]:

```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(tot_male_means, bins=35)
axis[1].hist(tot_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()
```

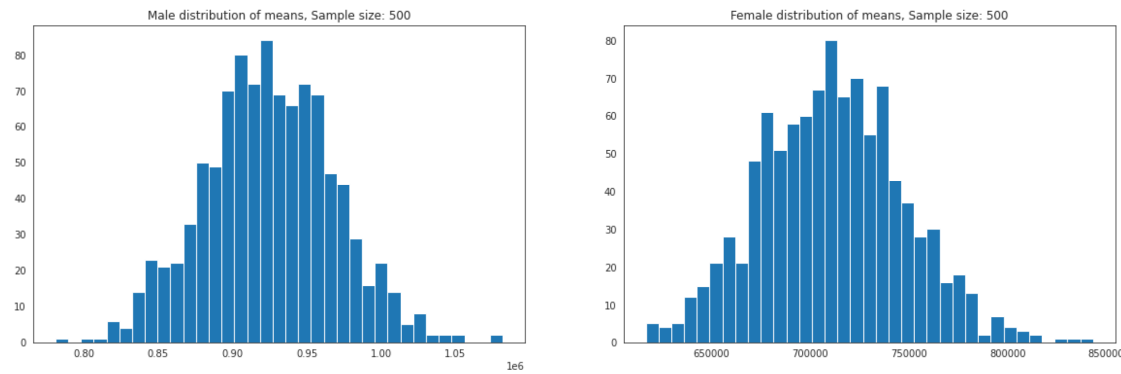


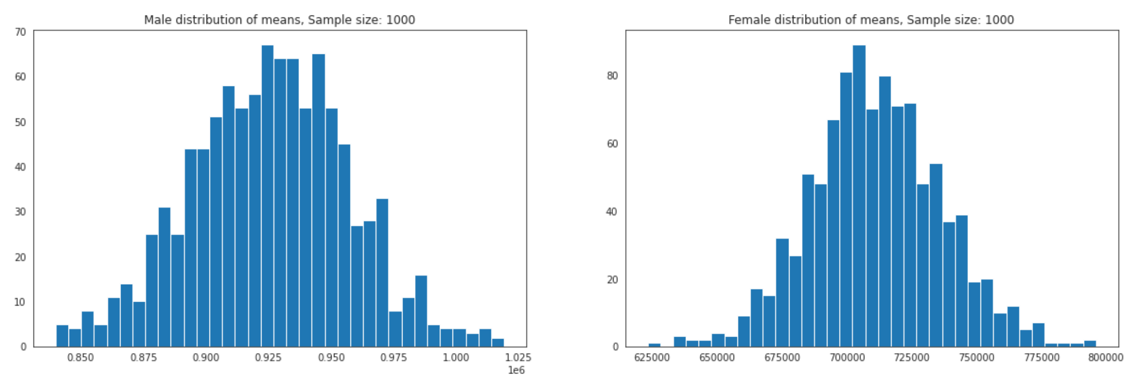


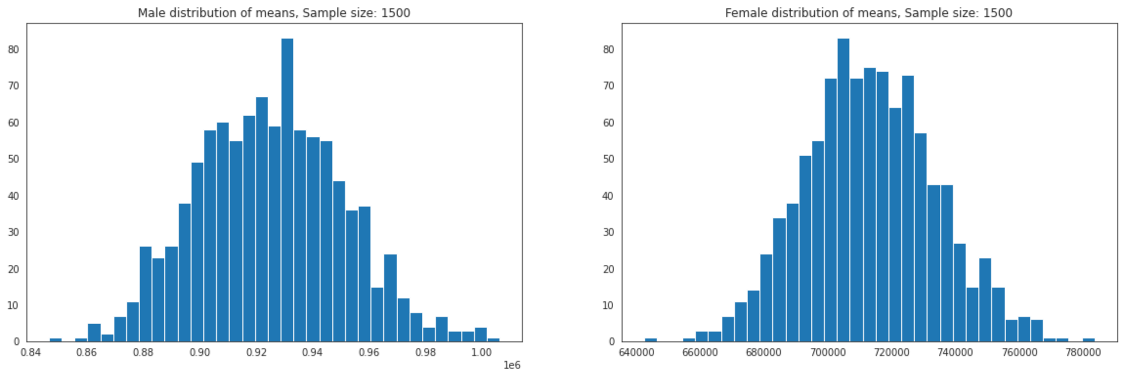
[ ]:

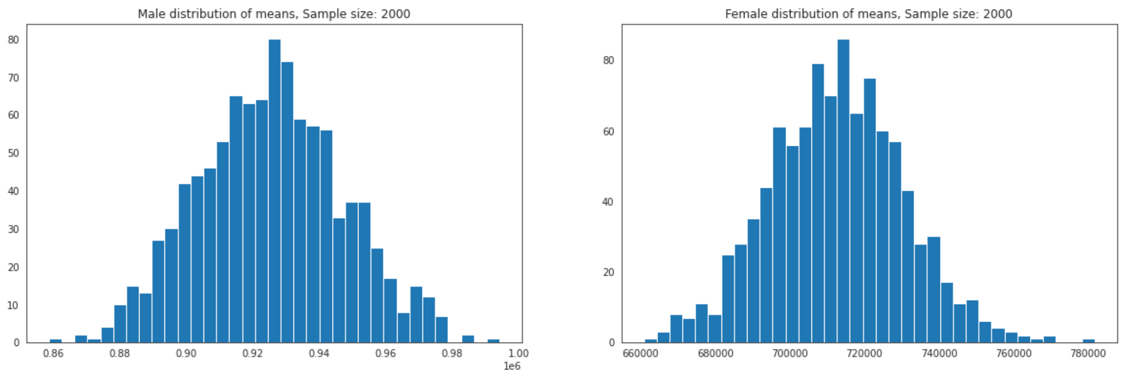
```
#Finding the sample(sample size=1000) for tot purchase amount for males and␣
↪females
genders = ["M", "F"]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
    tot_male_means = []
    tot_female_means = []
    for i in range(num_repitions):
        tot_male_mean = tot_amt_male.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
```

```
        tot_female_mean = tot_amt_female.sample(sample_size, replace=True)['Purchase'].mean()
        tot_male_means.append(tot_male_mean)
        tot_female_means.append(tot_female_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(tot_male_means, bins=35)
    axis[1].hist(tot_female_means, bins=35)
    axis[0].set_title("Male distribution of means, Sample size: {}".format(sample_size))
    axis[1].set_title("Female distribution of means, Sample size: {}".format(sample_size))
    plt.show()
```





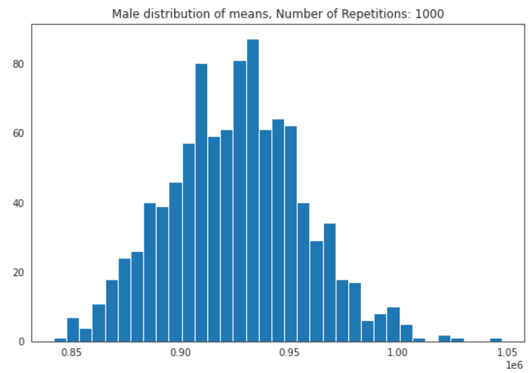


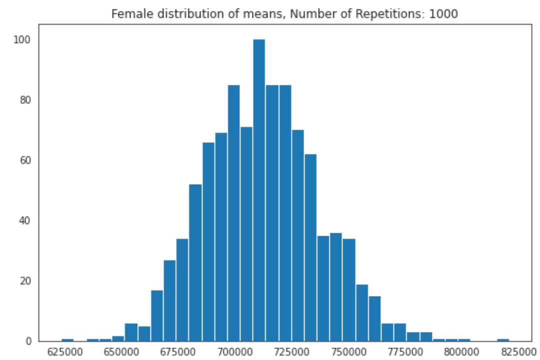


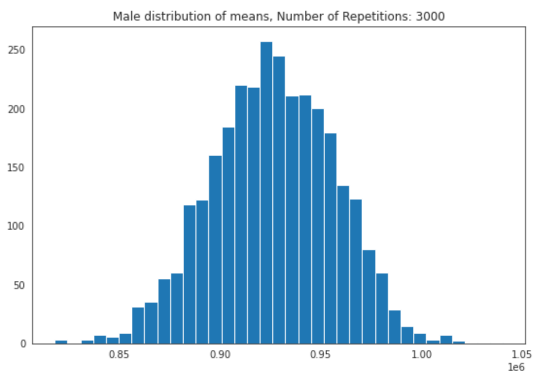
[126]:

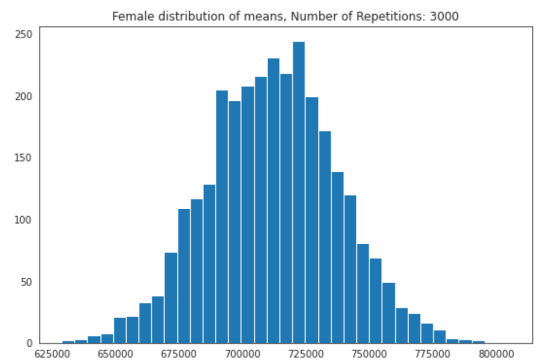
```
#Finding the sample(sample size=1000) for tot purchase amount for males and␣
↪females
genders = ["M", "F"]
sample_size_range = 1000
num_repitions_range= np.arange(1000,11001,2000)
for num_repitions in num_repitions_range:
    tot_male_means = []
    tot_female_means = []
    for i in range(num_repitions):
        tot_male_mean = tot_amt_male.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_female_mean = tot_amt_female.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_male_means.append(tot_male_mean)
        tot_female_means.append(tot_female_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(tot_male_means, bins=35)
    axis[1].hist(tot_female_means, bins=35)
    axis[0].set_title("Male distribution of means, Number of Repetitions: {}".
↪format(num_repitions))
```

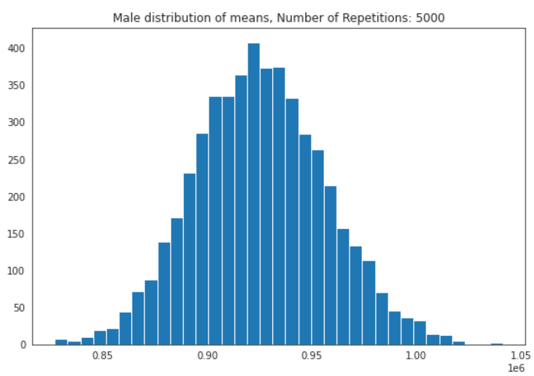
```
    axis[1].set_title("Female distribution of means, Number of Repetitions: {}".
↪format(num_repitions))
    plt.show()
```

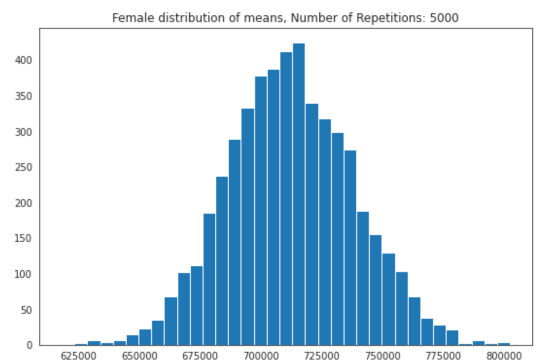


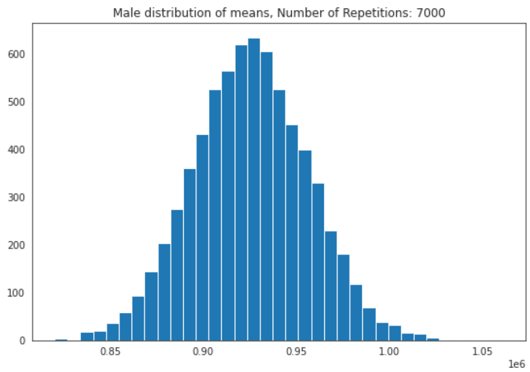


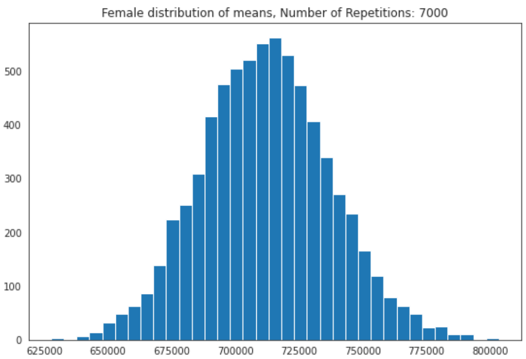


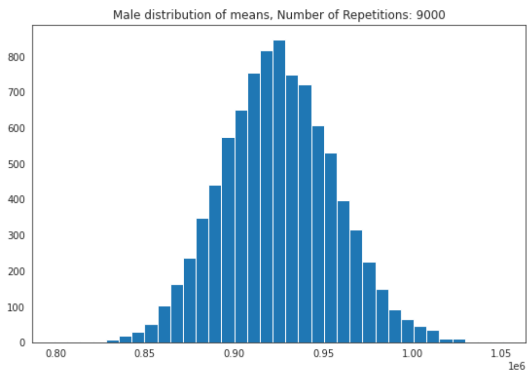


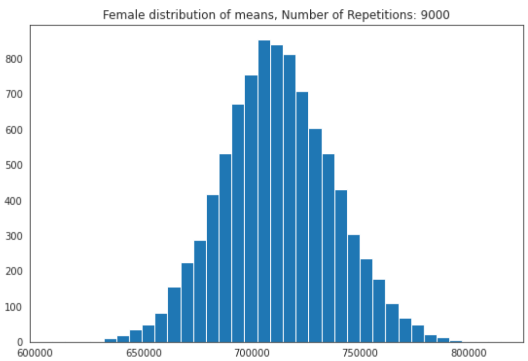


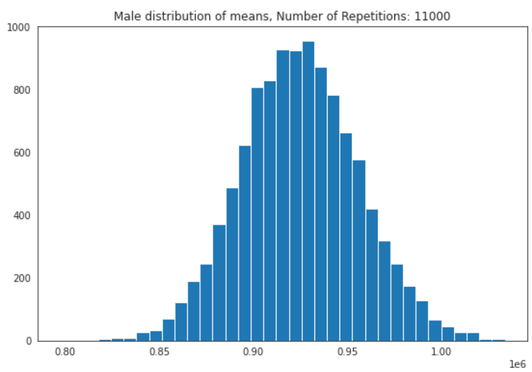


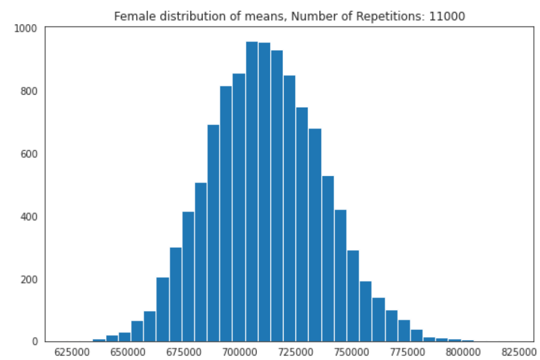








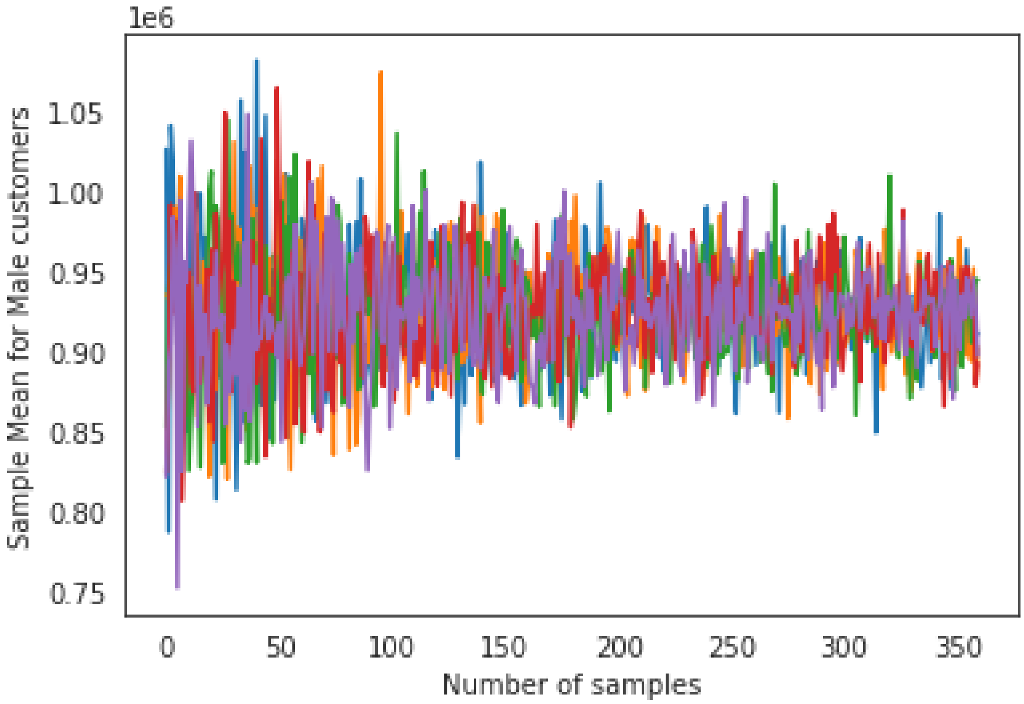




[ ]:
```
sample_mean_male_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_male = tot_amt_male.sample(num_samples,replace = True)
        sample_mean_male = np.mean(sample_male["Purchase"])
        sample_mean_male_trend.append(sample_mean_male)
    plt.plot(sample_mean_male_trend)
```

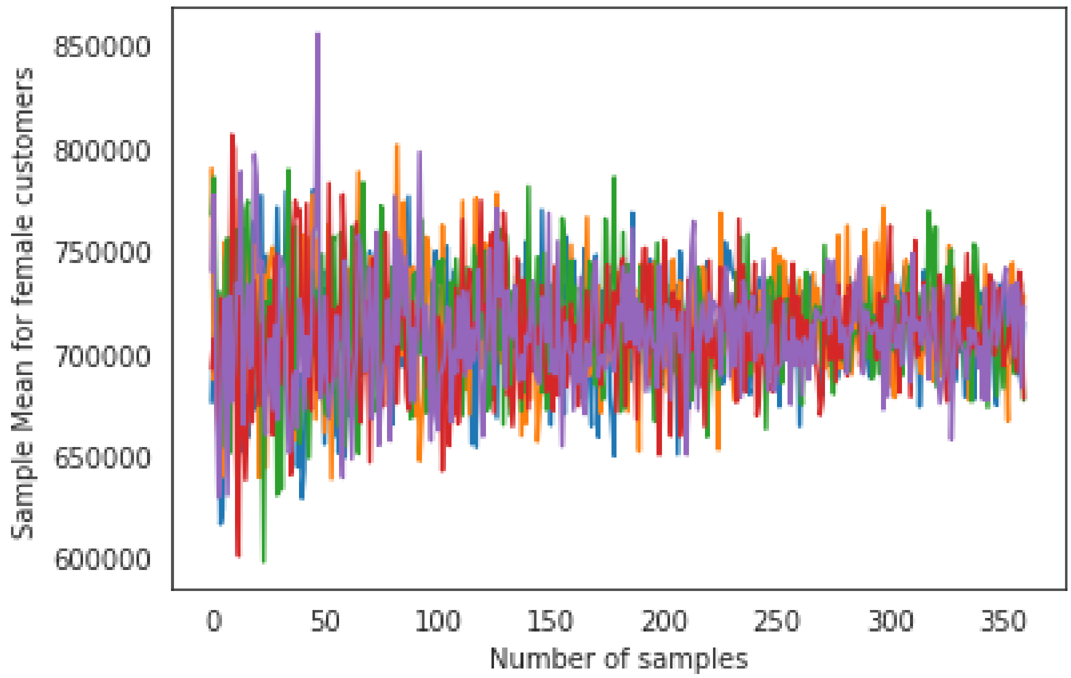
```
    sample_mean_male_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Male customers")
```

[ ]: Text(0, 0.5, 'Sample Mean for Male customers')



[ ]:
```
sample_mean_female_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_female = tot_amt_female.sample(num_samples,replace = True)
        sample_mean_female = np.mean(sample_female["Purchase"])
        sample_mean_female_trend.append(sample_mean_female)
    plt.plot(sample_mean_female_trend)
    sample_mean_female_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for female customers")
```

[ ]: Text(0, 0.5, 'Sample Mean for female customers')



##Calculating 90%, 95% and 99% confidence intervals for Gender Vs Purchase for various sample sizes and number of repetitions:

###Considering Average Purchase value

[ ]:
```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

L = [z90,z95,z99]
P = [90,95,99]
k = 0
for i in L:
    print(f"For {P[k]}% confidence interval",end="\n\n")
    k += 1

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

    print("Sample avg spend amount for Male: {:.2f}".format(np.
 ↪mean(avg_male_means)))
```

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

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

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

    sample_mean_male=np.mean(avg_male_means)
    sample_mean_female=np.mean(avg_female_means)

    sample_std_male=pd.Series(avg_male_means).std()
    sample_std_female=pd.Series(avg_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=i*sample_std_error_male + sample_mean_male
    Lower_Limit_male=sample_mean_male - i*sample_std_error_male

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

    print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
    print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female],end="\n"*4)
```

```
For 90% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9800.38
Sample avg spend amount for Female: 8966.96

Sample std for Male: 134.96
Sample std for Female: 119.61

Sample std error for Male: 4.27
Sample std error for Female: 3.78

Male_CI:  [9793.362178087145, 9807.401544678165]
Female_CI:  [8960.734025589201, 8973.176916867775]
```

```
For 95% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9800.38
Sample avg spend amount for Female: 8966.96

Sample std for Male: 134.96
Sample std for Female: 119.61

Sample std error for Male: 4.27
Sample std error for Female: 3.78

Male_CI:  [9792.017392826521, 9808.74632993879]
Female_CI:  [8959.542161505984, 8974.368780950992]



For 99% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9800.38
Sample avg spend amount for Female: 8966.96

Sample std for Male: 134.96
Sample std for Female: 119.61

Sample std error for Male: 4.27
Sample std error for Female: 3.78

Male_CI:  [9789.3890863187, 9811.37463644661]
Female_CI:  [8957.21273076482, 8976.698211692155]
```

[127]:

```
#Finding the sample(sample size=varies from 500 to 2000) for avg purchase␣
↪amount for males and females
genders = ["M", "F"]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
```

```
    print("FOR SAMPLE SIZE = {}".format(sample_size),end="\n"*2)
    avg_male_means = []
    avg_female_means = []
    for i in range(num_repitions):
        avg_male_mean = avg_amt_male.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_female_mean = avg_amt_female.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_male_means.append(avg_male_mean)
        avg_female_means.append(avg_female_mean)

    #Taking the values for z at 90%, 95% and 99% confidence interval as:
    z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
    z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
    z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

    L = [z90,z95,z99]
    P = [90,95,99]
    k = 0
    for i in L:
        print(f"For {P[k]}% confidence interval",end="\n\n")
        k += 1

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

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

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

        print("Sample std error for Male: {:.2f}".format(pd.
↪Series(avg_male_means).std()/np.sqrt(sample_size)))
        print("Sample std error for Female: {:.2f}\n".format(pd.
↪Series(avg_female_means).std()/np.sqrt(sample_size)))

        sample_mean_male=np.mean(avg_male_means)
        sample_mean_female=np.mean(avg_female_means)
```

```python
        sample_std_male=pd.Series(avg_male_means).std()
        sample_std_female=pd.Series(avg_female_means).std()

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

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

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

        print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
        print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female],end="\n"*4)
```

```
FOR SAMPLE SIZE = 500

For 90% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.27
Sample avg spend amount for Female: 8963.79

Sample std for Male: 89.09
Sample std for Female: 75.85

Sample std error for Male: 3.98
Sample std error for Female: 3.39

Male_CI:  [9803.720275371403, 9816.827398562551]
Female_CI:  [8958.213459866189, 8969.37237874474]



For 95% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.27
Sample avg spend amount for Female: 8963.79

Sample std for Male: 89.09
Sample std for Female: 75.85
```

```
Sample std error for Male: 3.98
Sample std error for Female: 3.39

Male_CI:  [9802.464786673792, 9818.082887260161]
Female_CI:  [8957.144583322857, 8970.441255288071]



For 99% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.27
Sample avg spend amount for Female: 8963.79

Sample std for Male: 89.09
Sample std for Female: 75.85

Sample std error for Male: 3.98
Sample std error for Female: 3.39

Male_CI:  [9800.011005232958, 9820.536668700996]
Female_CI:  [8955.055524751831, 8972.530313859097]



FOR SAMPLE SIZE = 1000

For 90% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.55
Sample avg spend amount for Female: 8964.47

Sample std for Male: 60.54
Sample std for Female: 56.86

Sample std error for Male: 1.91
Sample std error for Female: 1.80

Male_CI:  [9804.403617210439, 9810.701960443497]
Female_CI:  [8961.512755009608, 8967.42805966546]
```

```
For 95% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.55
Sample avg spend amount for Female: 8964.47

Sample std for Male: 60.54
Sample std for Female: 56.86

Sample std error for Male: 1.91
Sample std error for Female: 1.80

Male_CI:  [9803.800319398442, 9811.305258255494]
Female_CI:  [8960.946147217033, 8967.994667458035]



For 99% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.55
Sample avg spend amount for Female: 8964.47

Sample std for Male: 60.54
Sample std for Female: 56.86

Sample std error for Male: 1.91
Sample std error for Female: 1.80

Male_CI:  [9802.621208047469, 9812.484369606467]
Female_CI:  [8959.838744427747, 8969.102070247322]



FOR SAMPLE SIZE = 1500

For 90% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.29
Sample avg spend amount for Female: 8967.23
```

```
Sample std for Male: 49.73
Sample std for Female: 45.31

Sample std error for Male: 1.28
Sample std error for Female: 1.17

Male_CI:  [9808.173207171278, 9812.397221460118]
Female_CI:  [8965.30894029565, 8969.15742639628]



For 95% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.29
Sample avg spend amount for Female: 8967.23

Sample std for Male: 49.73
Sample std for Female: 45.31

Sample std error for Male: 1.28
Sample std error for Female: 1.17

Male_CI:  [9807.768602581786, 9812.80182604961]
Female_CI:  [8964.940306329845, 8969.526060362085]



For 99% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9810.29
Sample avg spend amount for Female: 8967.23

Sample std for Male: 49.73
Sample std for Female: 45.31

Sample std error for Male: 1.28
Sample std error for Female: 1.17

Male_CI:  [9806.977825863156, 9813.59260276824]
Female_CI:  [8964.21983215475, 8970.24653453718]
```

```
FOR SAMPLE SIZE = 2000

For 90% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.18
Sample avg spend amount for Female: 8966.01

Sample std for Male: 42.61
Sample std for Female: 36.23

Sample std error for Male: 0.95
Sample std error for Female: 0.81

Male_CI:  [9805.610294962125, 9808.744800041712]
Female_CI:  [8964.675924023466, 8967.340769887216]



For 95% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.18
Sample avg spend amount for Female: 8966.01

Sample std for Male: 42.61
Sample std for Female: 36.23

Sample std error for Male: 0.95
Sample std error for Female: 0.81

Male_CI:  [9805.310050915996, 9809.045044087841]
Female_CI:  [8964.420667105986, 8967.596026804697]



For 99% confidence interval

Population avg spend amount for Male: 9806.87
Population avg spend amount for Female: 8965.20

Sample avg spend amount for Male: 9807.18
Sample avg spend amount for Female: 8966.01
```

```
Sample std for Male: 42.61
Sample std for Female: 36.23

Sample std error for Male: 0.95
Sample std error for Female: 0.81

Male_CI:  [9804.72324095943, 9809.631854044406]
Female_CI:  [8963.921781940431, 8968.09491197025]
```

###Considering Total Purchase Value

[178]:
```python
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

L = [z90,z95,z99]
P = [90,95,99]
k = 0
for i in L:
    print(f"For {P[k]}% confidence interval",end="\n\n")
    k += 1

    print("Population tot spend amount for Male: {:.2f}".
 ↪format(tot_amt_male['Purchase'].mean()))
    print("Population tot spend amount for Female: {:.2f}\n".
 ↪format(tot_amt_female['Purchase'].mean()))

    print("Sample tot spend amount for Male: {:.2f}".format(np.
 ↪mean(tot_male_means)))
    print("Sample tot spend amount for Female: {:.2f}\n".format(np.
 ↪mean(tot_female_means)))

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

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

    sample_mean_male=np.mean(tot_male_means)
```

```
    sample_mean_female=np.mean(tot_female_means)

    sample_std_male=pd.Series(tot_male_means).std()
    sample_std_female=pd.Series(tot_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=i*sample_std_error_male + sample_mean_male
    Lower_Limit_male=sample_mean_male - i*sample_std_error_male

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

    print("Male_CI: ",[Lower_Limit_male,Upper_Limit_male])
    print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female],end="\n"*4)
```

```
For 90% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 924555.04
Sample tot spend amount for Female: 710115.59

Sample std for Male: 70675.37
Sample std for Female: 59496.85

Sample std error for Male: 2234.95
Sample std error for Female: 1881.46

Male_CI:  [920878.8715874696, 928231.2073825303]
Female_CI:  [707020.874182807, 713210.3124171929]



For 95% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 924555.04
Sample tot spend amount for Female: 710115.59

Sample std for Male: 70675.37
Sample std for Female: 59496.85
```

```
Sample std error for Male: 2234.95
Sample std error for Female: 1881.46

Male_CI:  [920174.6152562278, 928935.4637137721]
Female_CI:  [706428.0080264049, 713803.178573595]



For 99% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 924555.04
Sample tot spend amount for Female: 710115.59

Sample std for Male: 70675.37
Sample std for Female: 59496.85

Sample std error for Male: 2234.95
Sample std error for Female: 1881.46

Male_CI:  [918798.186206344, 930311.8927636559]
Female_CI:  [705269.2847545444, 714961.9018454555]
```

[128]:

```
#Finding the sample(sample size=varies from 200 to 2000) for tot purchase␣
↪amount for males and females
genders = ["M", "F"]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
    print("FOR SAMPLE SIZE = {}".format(sample_size),end="\n"*2)
    tot_male_means = []
    tot_female_means = []
    for i in range(num_repitions):
        tot_male_mean = tot_amt_male.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_female_mean = tot_amt_female.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_male_means.append(tot_male_mean)
        tot_female_means.append(tot_female_mean)

    #Taking the values for z at 90%, 95% and 99% confidence interval as:
    z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
```

```
z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

L = [z90,z95,z99]
P = [90,95,99]
k = 0
for i in L:
    print(f"For {P[k]}% confidence interval",end="\n\n")
    k += 1

    print("Population tot spend amount for Male: {:.2f}".
↪format(tot_amt_male['Purchase'].mean()))
    print("Population tot spend amount for Female: {:.2f}\n".
↪format(tot_amt_female['Purchase'].mean()))

    print("Sample tot spend amount for Male: {:.2f}".format(np.
↪mean(tot_male_means)))
    print("Sample tot spend amount for Female: {:.2f}\n".format(np.
↪mean(tot_female_means)))

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

    print("Sample std error for Male: {:.2f}".format(pd.
↪Series(tot_male_means).std()/np.sqrt(sample_size)))
    print("Sample std error for Female: {:.2f}\n".format(pd.
↪Series(tot_female_means).std()/np.sqrt(sample_size)))

    sample_mean_male=np.mean(tot_male_means)
    sample_mean_female=np.mean(tot_female_means)

    sample_std_male=pd.Series(tot_male_means).std()
    sample_std_female=pd.Series(tot_female_means).std()

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

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

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

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

```python
        print("Female_CI: ",[Lower_Limit_female,Upper_Limit_female],end="\n"*4)
```

```
FOR SAMPLE SIZE = 500

For 90% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 923808.85
Sample tot spend amount for Female: 711065.24

Sample std for Male: 45111.39
Sample std for Female: 36756.98

Sample std error for Male: 2017.44
Sample std error for Female: 1643.82

Male_CI:  [920490.4471935608, 927127.2435784392]
Female_CI:  [708361.3956577323, 713769.0893302677]



For 95% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 923808.85
Sample tot spend amount for Female: 711065.24

Sample std for Male: 45111.39
Sample std for Female: 36756.98

Sample std error for Male: 2017.44
Sample std error for Female: 1643.82

Male_CI:  [919854.7300550219, 927762.9607169781]
Female_CI:  [707843.4102701691, 714287.0747178309]



For 99% confidence interval

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

```
Sample tot spend amount for Male: 923808.85
Sample tot spend amount for Female: 711065.24

Sample std for Male: 45111.39
Sample std for Female: 36756.98

Sample std error for Male: 2017.44
Sample std error for Female: 1643.82

Male_CI:  [918612.256969333, 929005.433802667]
Female_CI:  [706831.0372133304, 715299.4477746696]



FOR SAMPLE SIZE = 1000

For 90% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925953.06
Sample tot spend amount for Female: 711629.93

Sample std for Male: 30440.43
Sample std for Female: 25004.43

Sample std error for Male: 962.61
Sample std error for Female: 790.71

Male_CI:  [924369.7097010091, 927536.4173409909]
Female_CI:  [710329.3259169975, 712930.5287770025]



For 95% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925953.06
Sample tot spend amount for Female: 711629.93

Sample std for Male: 30440.43
Sample std for Female: 25004.43

Sample std error for Male: 962.61
Sample std error for Female: 790.71
```

```
Male_CI:  [924066.3810763634, 927839.7459656366]
Female_CI:  [710080.1651558374, 713179.6895381626]



For 99% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925953.06
Sample tot spend amount for Female: 711629.93

Sample std for Male: 30440.43
Sample std for Female: 25004.43

Sample std error for Male: 962.61
Sample std error for Female: 790.71

Male_CI:  [923473.5424860629, 928432.5845559371]
Female_CI:  [709593.194582002, 713666.660111998]



FOR SAMPLE SIZE = 1500

For 90% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925247.00
Sample tot spend amount for Female: 712259.25

Sample std for Male: 25094.76
Sample std for Female: 21155.49

Sample std error for Male: 647.94
Sample std error for Female: 546.23

Male_CI:  [924181.2312889253, 926312.777132408]
Female_CI:  [711360.7788281697, 713157.7237064971]



For 95% confidence interval
```

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

Sample tot spend amount for Male: 925247.00
Sample tot spend amount for Female: 712259.25

Sample std for Male: 25094.76
Sample std for Female: 21155.49

Sample std error for Male: 647.94
Sample std error for Female: 546.23

Male_CI:  [923977.0574457485, 926516.9509755848]
Female_CI:  [711188.6553231055, 713329.8472115613]



For 99% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925247.00
Sample tot spend amount for Female: 712259.25

Sample std for Male: 25094.76
Sample std for Female: 21155.49

Sample std error for Male: 647.94
Sample std error for Female: 546.23

Male_CI:  [923578.0112511908, 926915.9971701425]
Female_CI:  [710852.2496963071, 713666.2528383597]



FOR SAMPLE SIZE = 2000

For 90% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925994.56
Sample tot spend amount for Female: 711532.16

Sample std for Male: 21856.81
Sample std for Female: 17963.69
```

```
Sample std error for Male: 488.73
Sample std error for Female: 401.68

Male_CI:  [925190.6690386124, 926798.4577023878]
Female_CI:  [710871.4546307928, 712192.8651582072]



For 95% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925994.56
Sample tot spend amount for Female: 711532.16

Sample std for Male: 21856.81
Sample std for Female: 17963.69

Sample std error for Male: 488.73
Sample std error for Female: 401.68

Male_CI:  [925036.6641920813, 926952.4625489189]
Female_CI:  [710744.8810144563, 712319.4387745438]



For 99% confidence interval

Population tot spend amount for Male: 925344.40
Population tot spend amount for Female: 712024.39

Sample tot spend amount for Male: 925994.56
Sample tot spend amount for Female: 711532.16

Sample std for Male: 21856.81
Sample std for Female: 17963.69

Sample std error for Male: 488.73
Sample std error for Female: 401.68

Male_CI:  [924735.67045559, 927253.4562854102]
Female_CI:  [710497.5000613206, 712566.8197276795]
```

##CLT and Confindence Intervals of Marital Status Vs Purchase

###Considering Average Purchase Value

[81]:
```
#Number of unique male and female customers
avg_amt_Marital_Status_walmart = walmart.groupby(['User_ID',␣
↪'Marital_Status'])[['Purchase']].mean()
avg_amt_Marital_Status_walmart = avg_amt_Marital_Status_walmart.reset_index()
avg_amt_Marital_Status_walmart["Marital_Status"].value_counts()
```

[81]:
```
0    3417
1    2474
Name: Marital_Status, dtype: int64
```

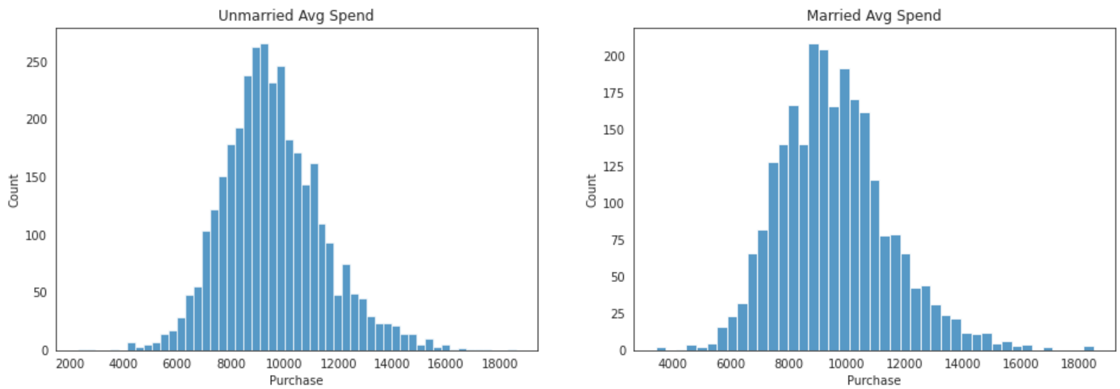
Available Population data with Mean Purchase value of each Customer

[82]:
```
#Population data
avg_amt_Marital_Status_walmart.sort_values("Purchase",ascending = False)
```

[82]:
```
      User_ID  Marital_Status      Purchase
3801  1003902               0  18577.893617
4943  1005069               1  18490.166667
5849  1005999               1  18345.944444
1307  1001349               1  18162.739130
3367  1003461               0  17508.700000
…       …              …            …
4521  1004636               1   3612.812500
5794  1005944               0   3599.733333
2667  1002744               1   3421.521739
3500  1003598               0   2698.357143
4373  1004486               0   2318.733333

[5891 rows x 3 columns]
```

[84]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,5))
sns.
↪histplot(data=avg_amt_Marital_Status_walmart[avg_amt_Marital_Status_walmart['Marital_Status
↪ax=axs[0]).set_title("Unmarried Avg Spend")
sns.
↪histplot(data=avg_amt_Marital_Status_walmart[avg_amt_Marital_Status_walmart['Marital_Status
↪ax=axs[1]).set_title("Married Avg Spend")
```

[84]:
```
Text(0.5, 1.0, 'Married Avg Spend')
```



[85]:
```
df = avg_amt_Marital_Status_walmart.groupby(["Marital_Status"])[["Purchase"]].
    ↪mean()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

[85]:

	Purchase	Percentage
Marital_Status		
0	9564.407142	49.972426
1	9574.962299	50.027574

[86]:
```
df = avg_amt_Marital_Status_walmart.groupby(["Marital_Status"])[["Purchase"]].
    ↪sum()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

[86]:

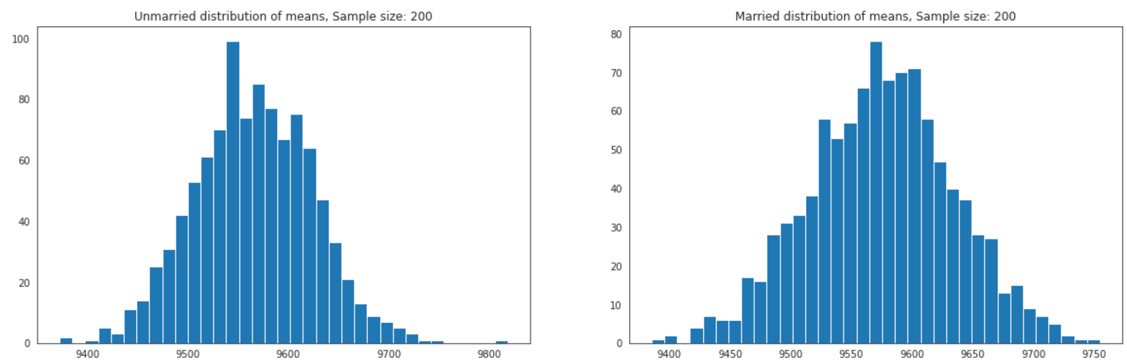
	Purchase	Percentage
Marital_Status		
0	3.268158e+07	57.976864
1	2.368846e+07	42.023136

[129]:
```
avg_amt_Married =␣
    ↪avg_amt_Marital_Status_walmart[avg_amt_Marital_Status_walmart["Marital_Status"]==1]
avg_amt_Unmarried =␣
    ↪avg_amt_Marital_Status_walmart[avg_amt_Marital_Status_walmart["Marital_Status"]==0]
```

[130]:
```
#Finding the sample(sample size=1000) for avg purchase amount for males and␣
    ↪females
Marital_Statuses = [0,1]
sample_size = 1000
num_repitions = 1000
avg_Unmarried_means = []
avg_Married_means = []
for i in range(num_repitions):
```

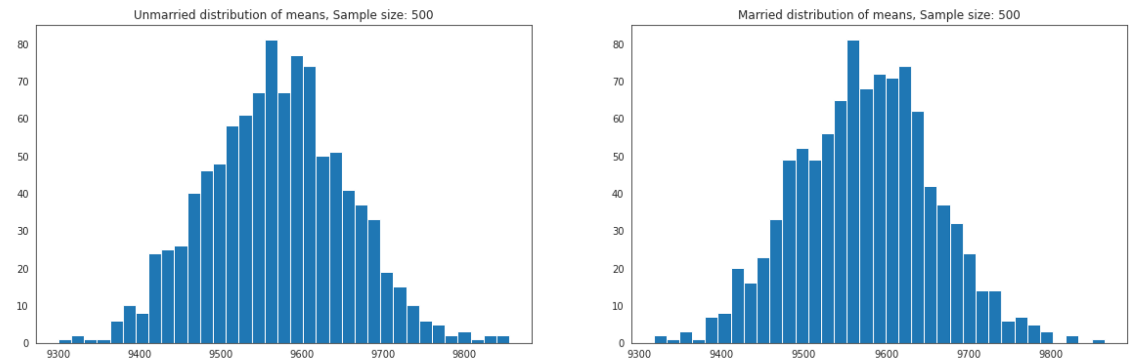
```
    avg_Unmarried_mean = avg_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
    avg_Married_mean = avg_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
    avg_Unmarried_means.append(avg_Unmarried_mean)
    avg_Married_means.append(avg_Married_mean)
```

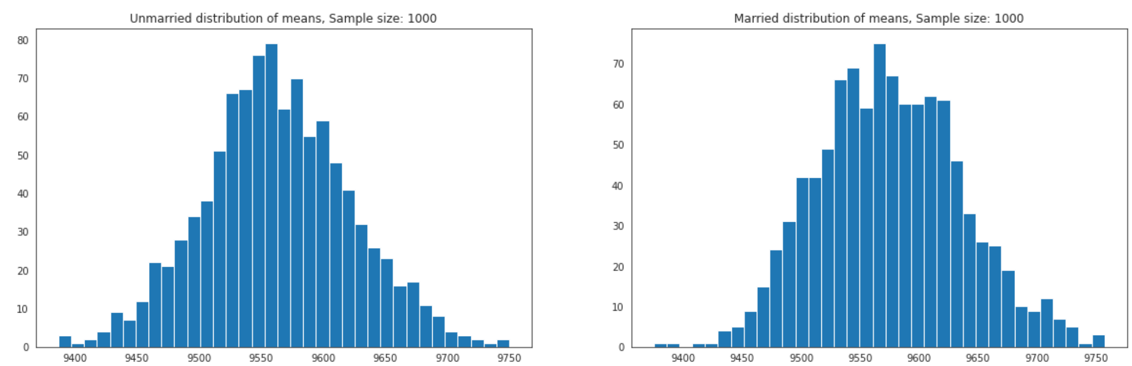
[131]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(avg_Unmarried_means, bins=35)
axis[1].hist(avg_Married_means, bins=35)
axis[0].set_title("Unmarried distribution of means, Sample size: 200")
axis[1].set_title("Married distribution of means, Sample size: 200")

plt.show()
```

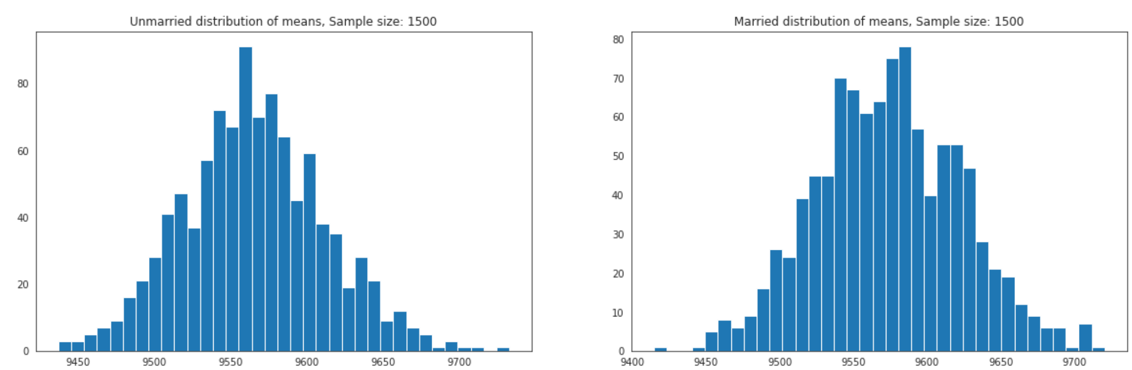


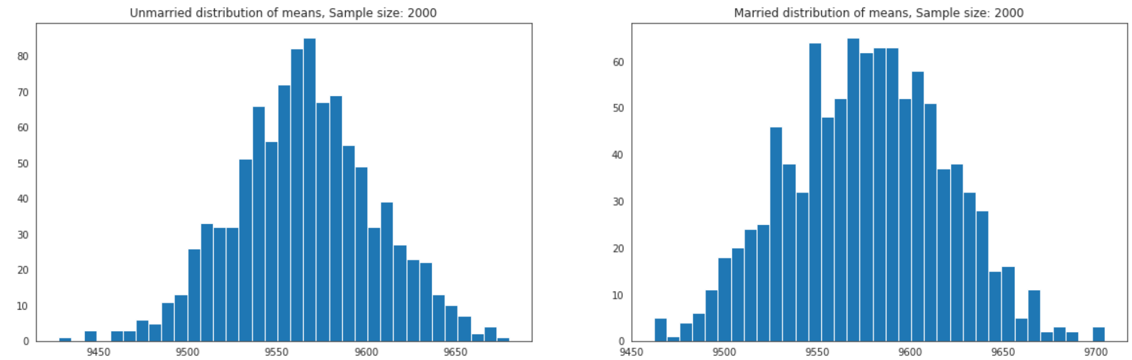
[90]:
```
#Finding the sample(sample size=1000) for avg purchase amount for Unmarrieds␣
↪and Marrieds
Marital_Statuses = [0,1]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
    avg_Unmarried_means = []
    avg_Married_means = []
    for i in range(num_repitions):
        avg_Unmarried_mean = avg_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_Married_mean = avg_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_Unmarried_means.append(avg_Unmarried_mean)
        avg_Married_means.append(avg_Married_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(avg_Unmarried_means, bins=35)
```

```
    axis[1].hist(avg_Married_means, bins=35)
    axis[0].set_title("Unmarried distribution of means, Sample size: {}".format(sample_size))
    axis[1].set_title("Married distribution of means, Sample size: {}".format(sample_size))
    plt.show()
```



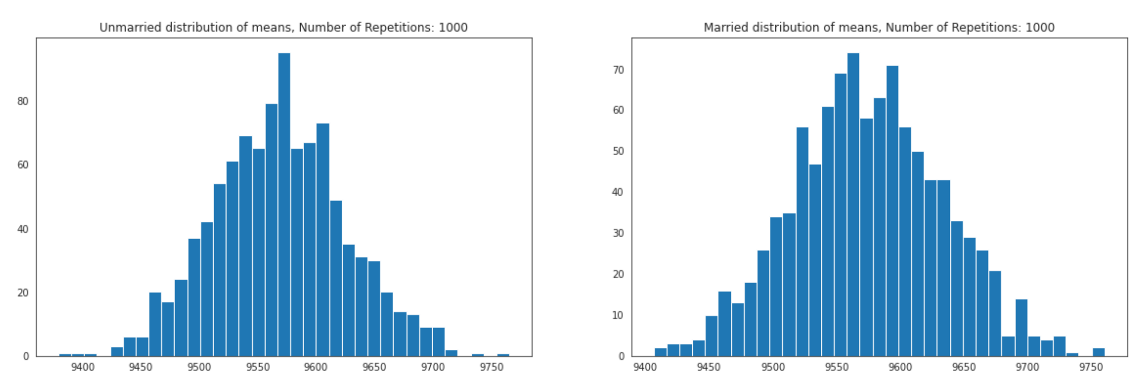


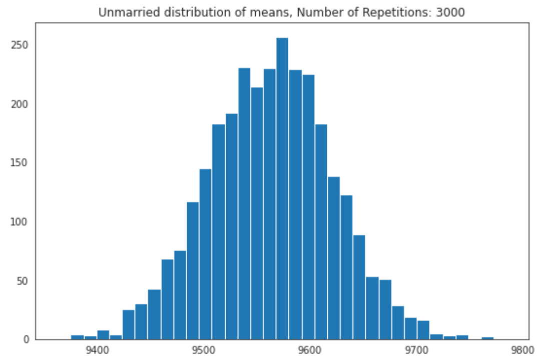


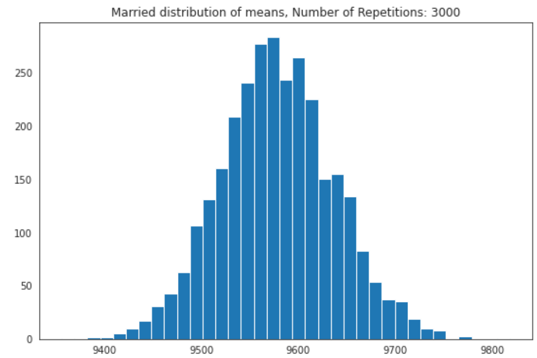


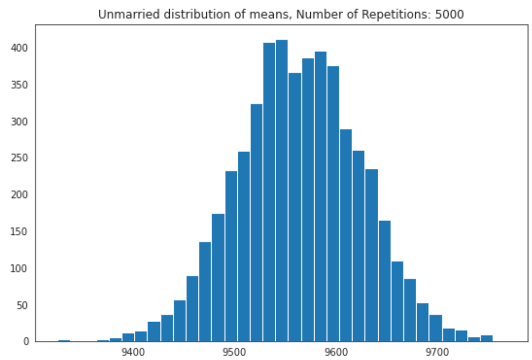
[132]:

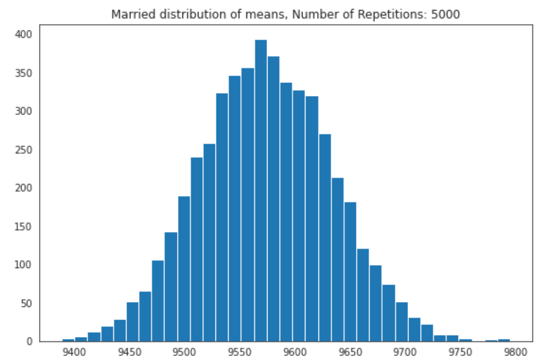
```
#Finding the sample(sample size=1000) for avg purchase amount for Unmarrieds␣
↪and Marrieds
Marital_Statuses = [0,1]
sample_size_range = 1000
num_repitions_range= np.arange(1000,11001,2000)
for num_repitions in num_repitions_range:
    avg_Unmarried_means = []
    avg_Married_means = []
    for i in range(num_repitions):
        avg_Unmarried_mean = avg_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_Married_mean = avg_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        avg_Unmarried_means.append(avg_Unmarried_mean)
        avg_Married_means.append(avg_Married_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(avg_Unmarried_means, bins=35)
    axis[1].hist(avg_Married_means, bins=35)
    axis[0].set_title("Unmarried distribution of means, Number of Repetitions:␣
↪{}".format(num_repitions))
    axis[1].set_title("Married distribution of means, Number of Repetitions:␣
↪{}".format(num_repitions))
    plt.show()
```

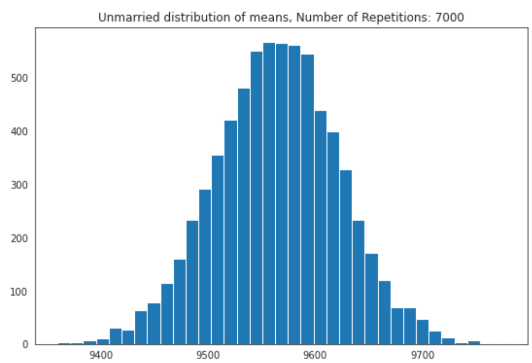


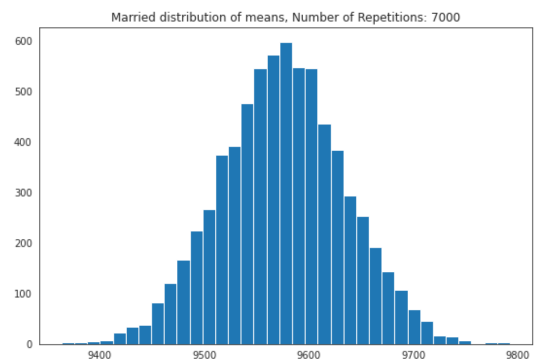

Unmarried distribution of means, Number of Repetitions: 3000

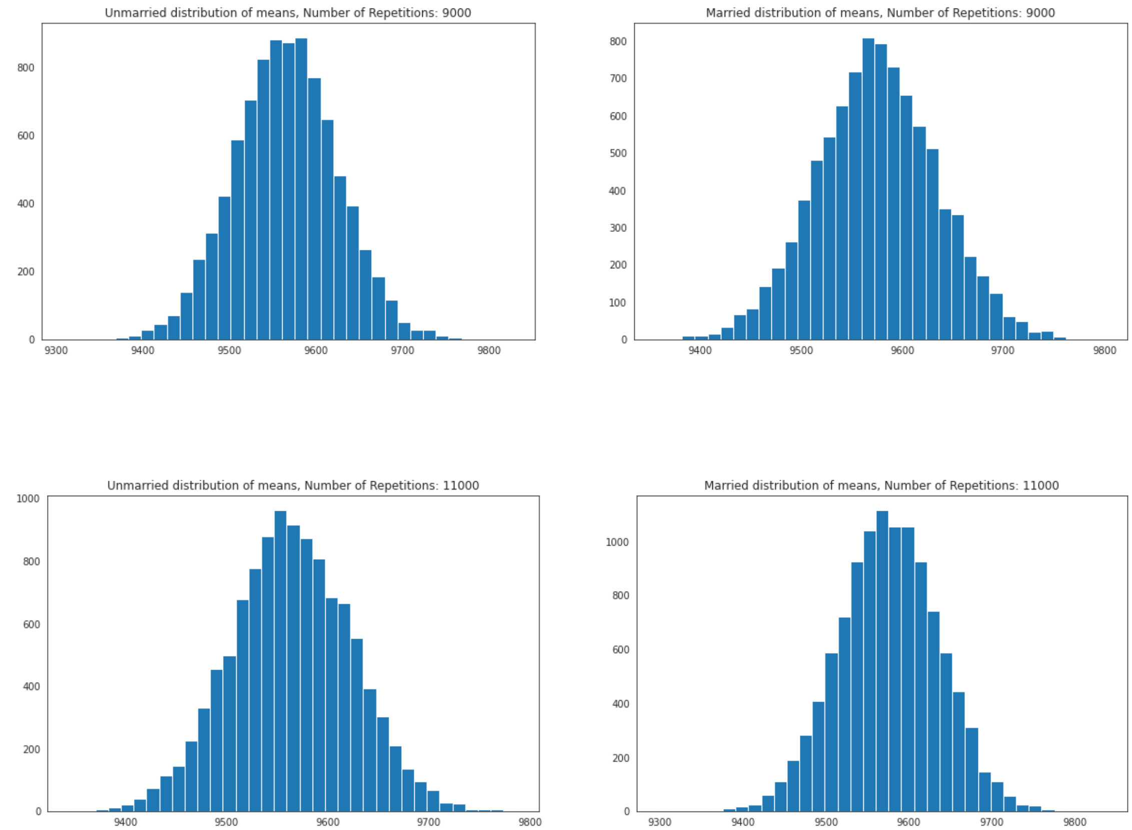

Married distribution of means, Number of Repetitions: 3000


Unmarried distribution of means, Number of Repetitions: 5000


Married distribution of means, Number of Repetitions: 5000


Unmarried distribution of means, Number of Repetitions: 7000

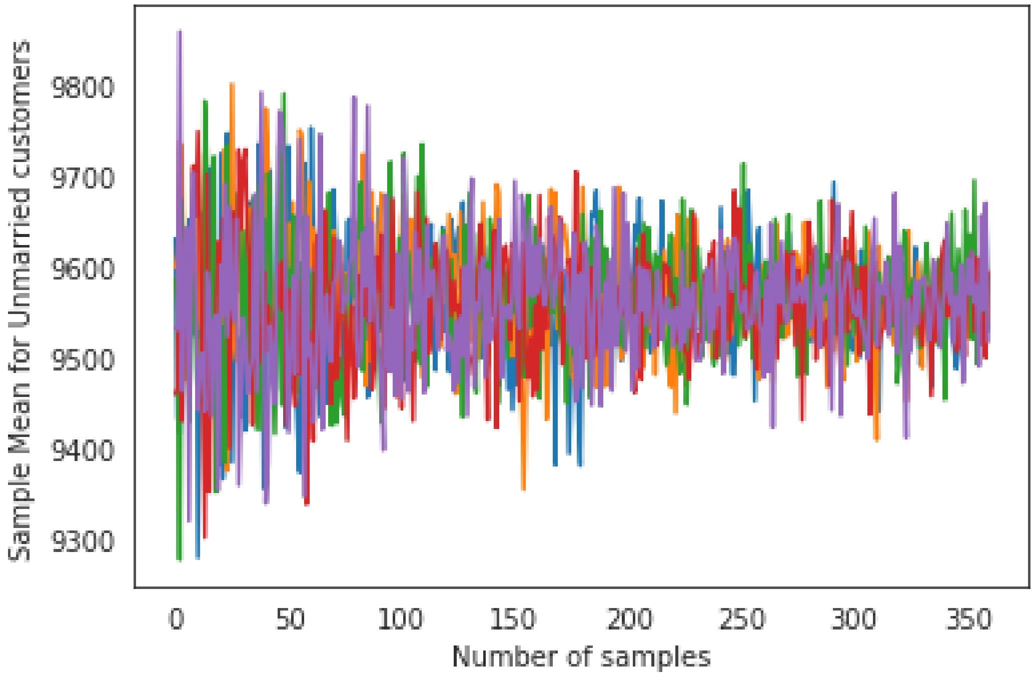

Married distribution of means, Number of Repetitions: 7000



[92]:

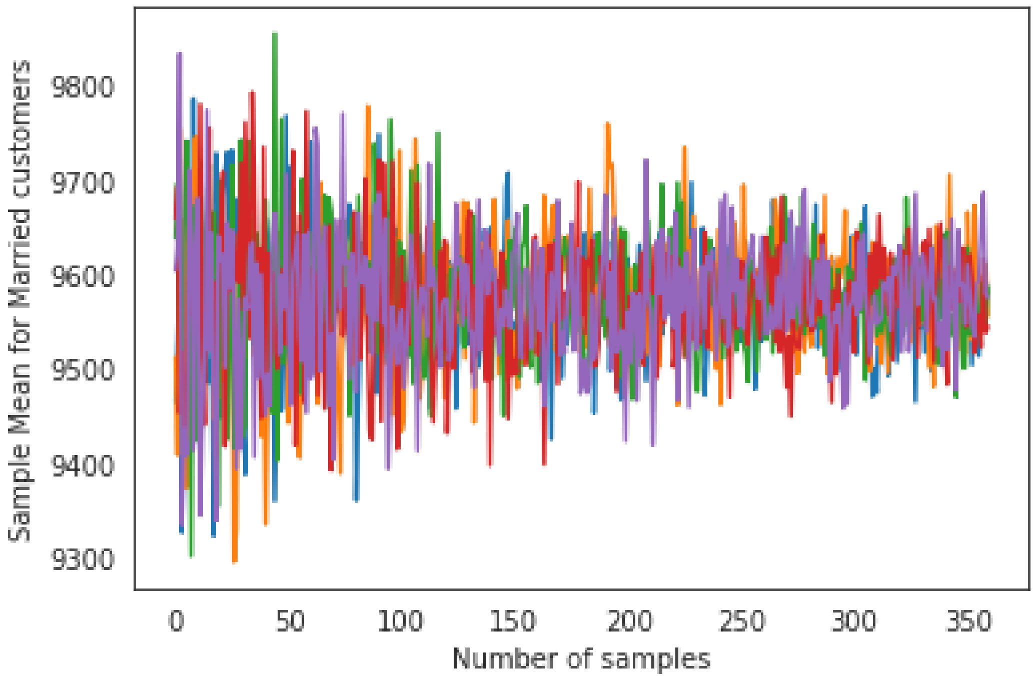
```
sample_mean_Unmarried_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_Unmarried = avg_amt_Unmarried.sample(num_samples,replace = True)
        sample_mean_Unmarried = np.mean(sample_Unmarried["Purchase"])
        sample_mean_Unmarried_trend.append(sample_mean_Unmarried)
    plt.plot(sample_mean_Unmarried_trend)
    sample_mean_Unmarried_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Unmarried customers")
```

[92]: Text(0, 0.5, 'Sample Mean for Unmarried customers')



[93]:
```
sample_mean_Married_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_Married = avg_amt_Married.sample(num_samples,replace = True)
        sample_mean_Married = np.mean(sample_Married["Purchase"])
        sample_mean_Married_trend.append(sample_mean_Married)
    plt.plot(sample_mean_Married_trend)
    sample_mean_Married_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Married customers")
```

[93]: Text(0, 0.5, 'Sample Mean for Married customers')



0.0.2 Considering Total Purchase Value

[94]:
```python
#Number of unique male and female customers
tot_amt_Marital_Status_walmart = walmart.groupby(['User_ID',␣
↪'Marital_Status'])[['Purchase']].sum()
tot_amt_Marital_Status_walmart = tot_amt_Marital_Status_walmart.reset_index()
tot_amt_Marital_Status_walmart.sort_values("Purchase",ascending = False)
```

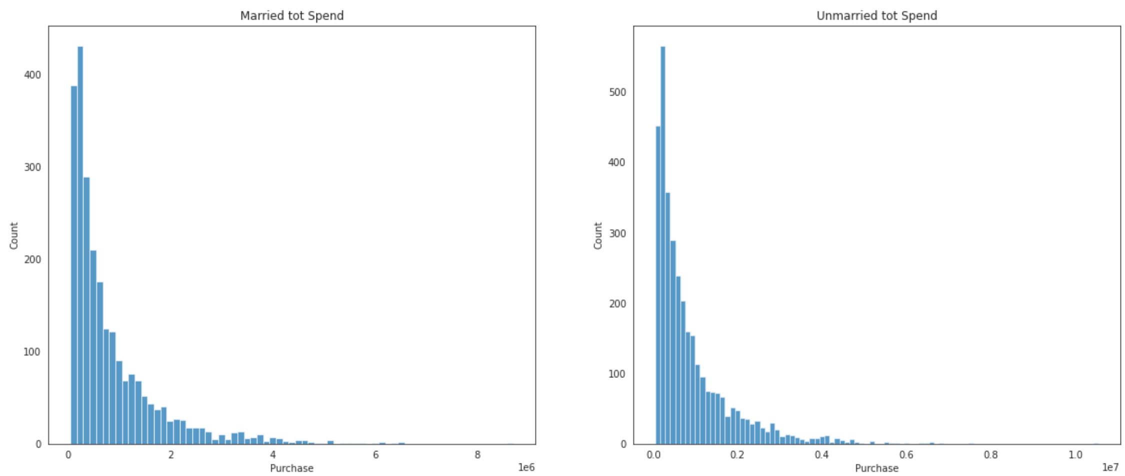
[94]:

	User_ID	Marital_Status	Purchase
4166	1004277	0	10536909
1634	1001680	1	8699596
2831	1002909	0	7577756
1885	1001941	0	6817493
416	1000424	0	6573609
…	…	…	…
4866	1004991	1	52371
4989	1005117	0	49668
3782	1003883	1	49349
91	1000094	0	49288
4351	1004464	0	46681

[5891 rows x 3 columns]

[95]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20,8))
sns.
 ↪histplot(data=tot_amt_Marital_Status_walmart[tot_amt_Marital_Status_walmart['Marital_Status
 ↪ax=axs[0]).set_title("Married tot Spend")
sns.
 ↪histplot(data=tot_amt_Marital_Status_walmart[tot_amt_Marital_Status_walmart['Marital_Status
 ↪ax=axs[1]).set_title("Unmarried tot Spend")
```

[95]: Text(0.5, 1.0, 'Unmarried tot Spend')



[96]:
```
df = tot_amt_Marital_Status_walmart.groupby(["Marital_Status"])[["Purchase"]].
 ↪mean()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

[96]:

	Purchase	Percentage
Marital_Status		
0	880575.781972	51.074443
1	843526.796686	48.925557

[97]:
```
df = tot_amt_Marital_Status_walmart.groupby(["Marital_Status"])[["Purchase"]].
 ↪sum()
df["Percentage"] = (df["Purchase"]/df["Purchase"].sum())*100
df
```

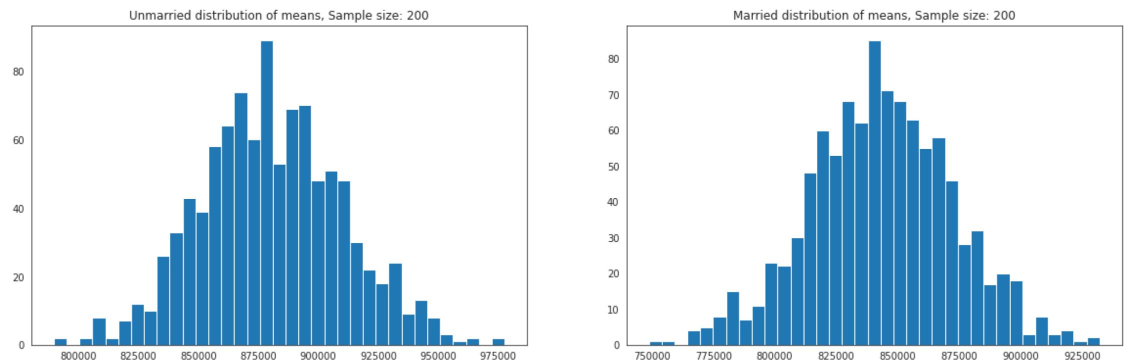
[97]:

	Purchase	Percentage
Marital_Status		
0	3008927447	59.047057
1	2086885295	40.952943

[98]:
```
tot_amt_Unmarried =␣
↪tot_amt_Marital_Status_walmart[tot_amt_Marital_Status_walmart["Marital_Status"]==0]
tot_amt_Married =␣
↪tot_amt_Marital_Status_walmart[tot_amt_Marital_Status_walmart["Marital_Status"]==1]
```

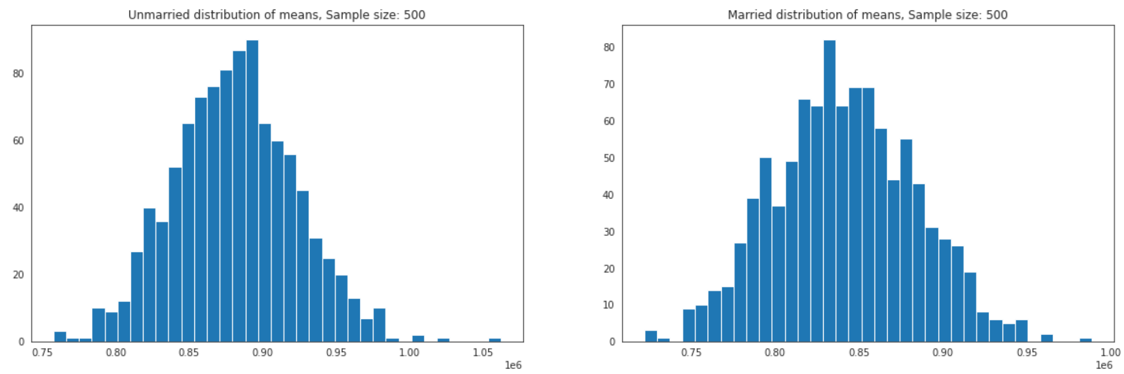
[133]:
```
#Finding the sample(sample size=1000) for tot purchase amount for Unmarrieds␣
↪and Marrieds
Marital_Statuses = [0,1]
sample_size = 1000
num_repitions = 1000
tot_Unmarried_means = []
tot_Married_means = []
for i in range(num_repitions):
    tot_Unmarried_mean = tot_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
    tot_Married_mean = tot_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
    tot_Unmarried_means.append(tot_Unmarried_mean)
    tot_Married_means.append(tot_Married_mean)
```

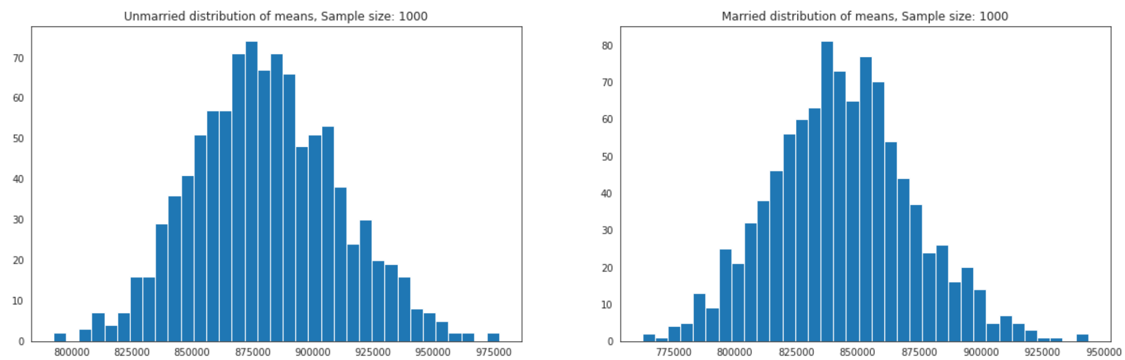
[134]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(tot_Unmarried_means, bins=35)
axis[1].hist(tot_Married_means, bins=35)
axis[0].set_title("Unmarried distribution of means, Sample size: 200")
axis[1].set_title("Married distribution of means, Sample size: 200")
plt.show()
```

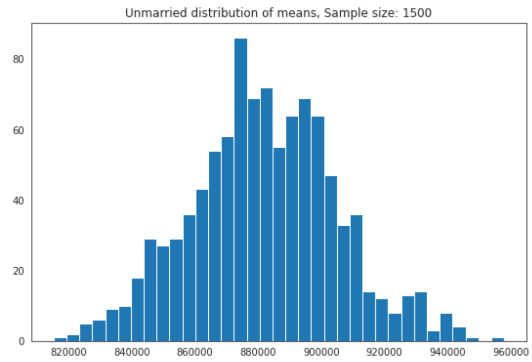


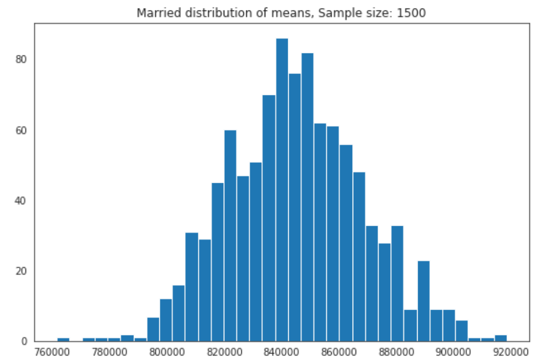
[101]:
```
#Finding the sample(sample size=1000) for tot purchase amount for Unmarrieds␣
↪and Marrieds
Marital_Statuses = [0,1]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
```

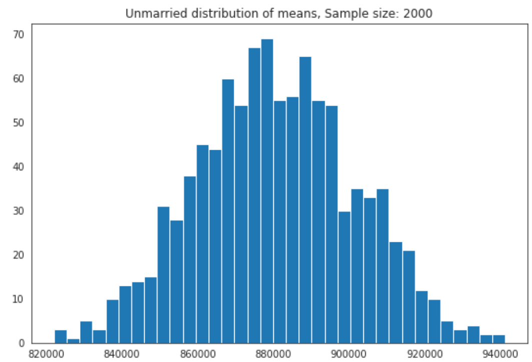
```
    tot_Unmarried_means = []
    tot_Married_means = []
    for i in range(num_repitions):
        tot_Unmarried_mean = tot_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_Married_mean = tot_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_Unmarried_means.append(tot_Unmarried_mean)
        tot_Married_means.append(tot_Married_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(tot_Unmarried_means, bins=35)
    axis[1].hist(tot_Married_means, bins=35)
    axis[0].set_title("Unmarried distribution of means, Sample size: {}".
↪format(sample_size))
    axis[1].set_title("Married distribution of means, Sample size: {}".
↪format(sample_size))
    plt.show()
```

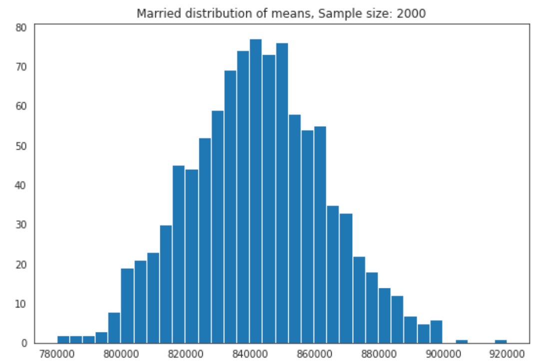






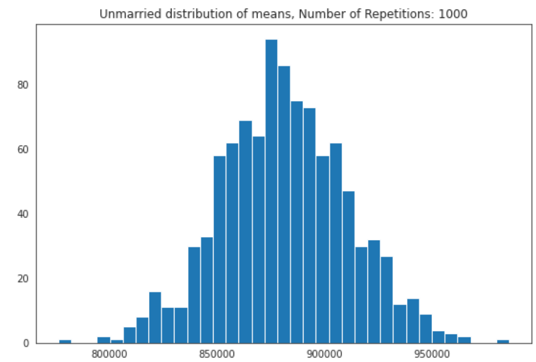


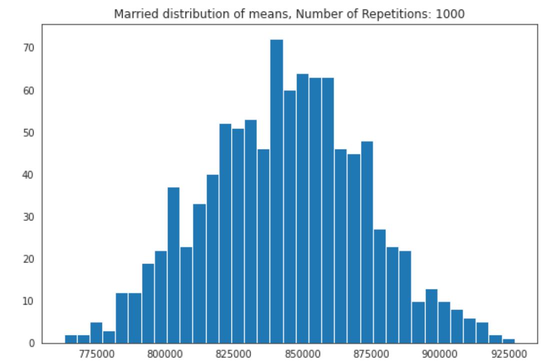


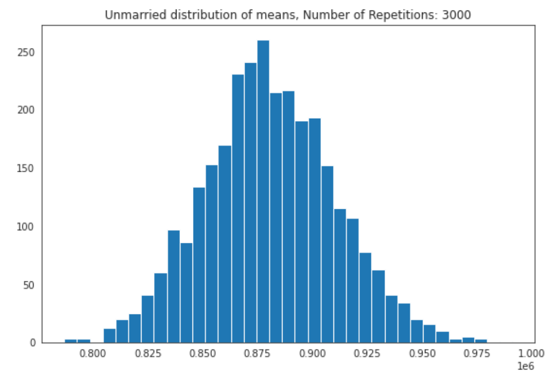


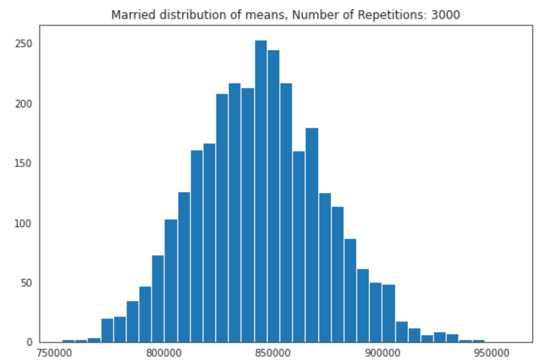
[135]:
```
#Finding the sample(sample size=1000) for tot purchase amount for Unmarrieds␣
↪and Marrieds
Marital_Statuses = [0,1]
sample_size_range = 1000
num_repitions_range= np.arange(1000,11001,2000)
for num_repitions in num_repitions_range:
    tot_Unmarried_means = []
    tot_Married_means = []
    for i in range(num_repitions):
        tot_Unmarried_mean = tot_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_Married_mean = tot_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_Unmarried_means.append(tot_Unmarried_mean)
        tot_Married_means.append(tot_Married_mean)
    fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
    axis[0].hist(tot_Unmarried_means, bins=35)
    axis[1].hist(tot_Married_means, bins=35)
    axis[0].set_title("Unmarried distribution of means, Number of Repetitions:␣
↪{}".format(num_repitions))
```

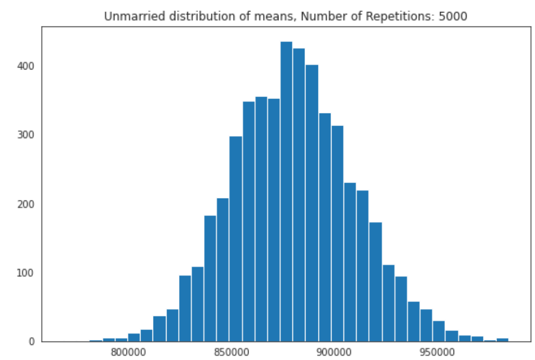
```
    axis[1].set_title("Married distribution of means, Number of Repetitions: {}".format(num_repitions))
    plt.show()
```

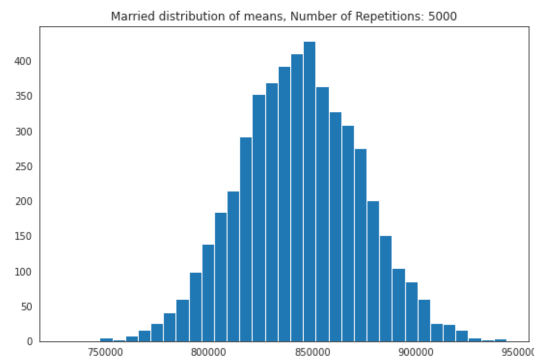


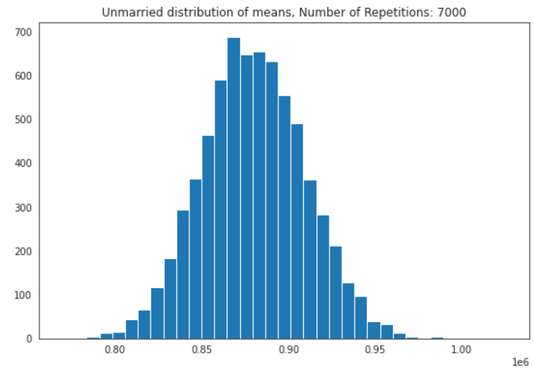


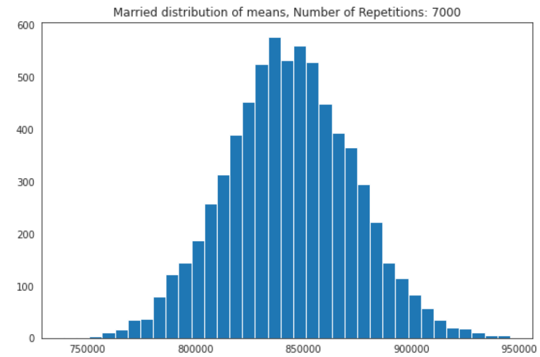


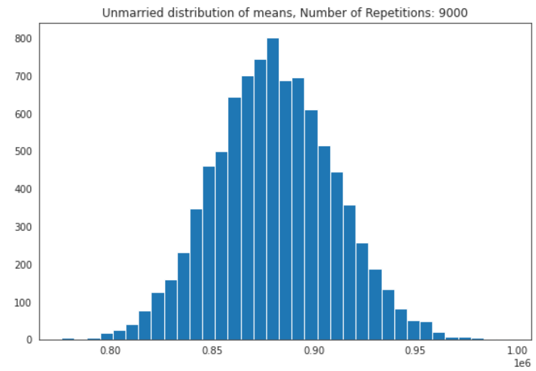


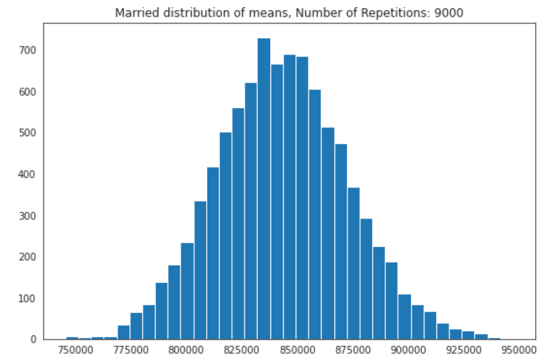


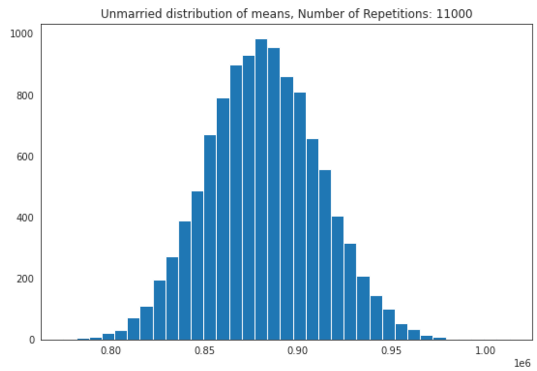


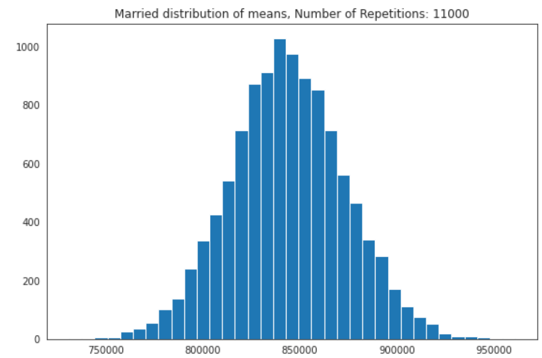










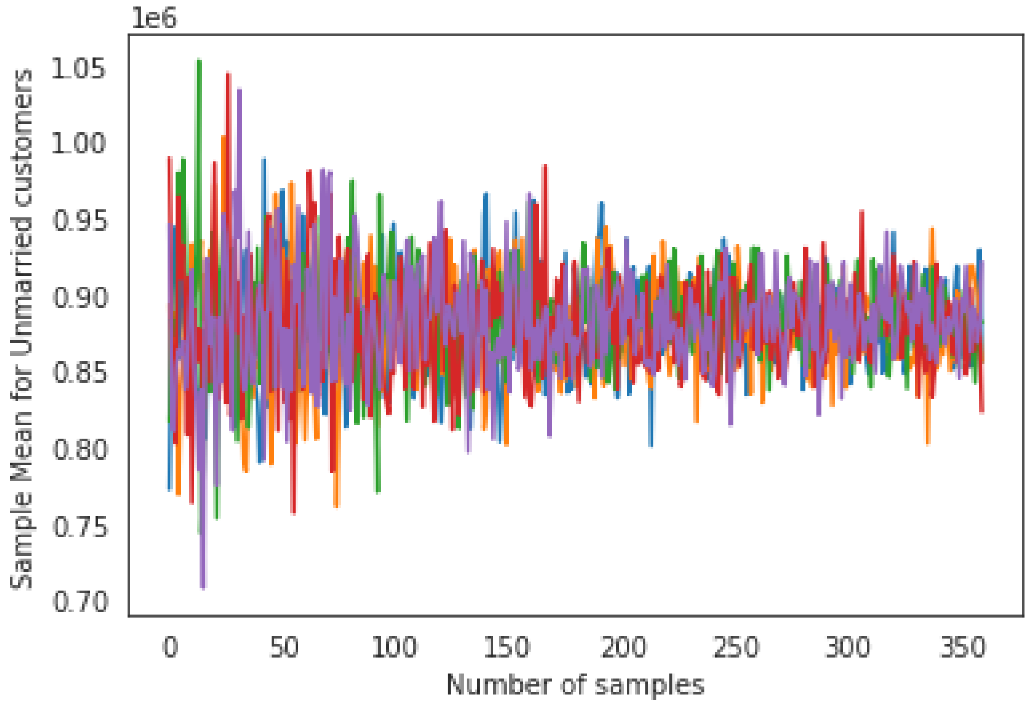


[103]:

```
sample_mean_Unmarried_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_Unmarried = tot_amt_Unmarried.sample(num_samples,replace = True)
        sample_mean_Unmarried = np.mean(sample_Unmarried["Purchase"])
        sample_mean_Unmarried_trend.append(sample_mean_Unmarried)
    plt.plot(sample_mean_Unmarried_trend)
```

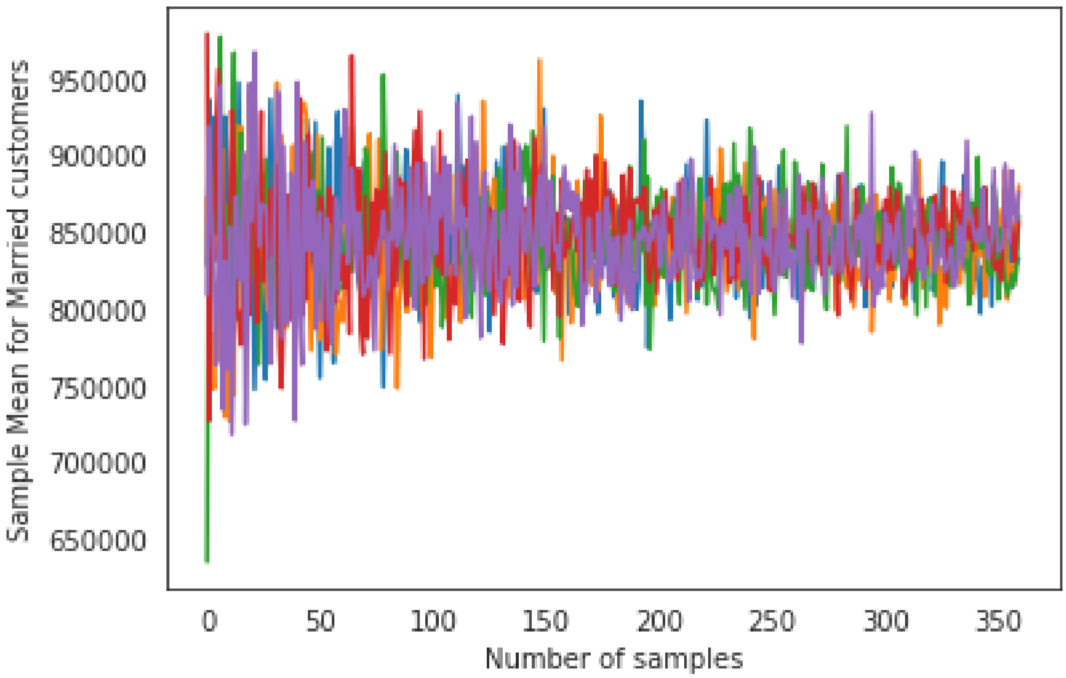
```
    sample_mean_Unmarried_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Unmarried customers")
```

[103]: Text(0, 0.5, 'Sample Mean for Unmarried customers')



[104]:
```
sample_mean_Married_trend = []
for person in range(5):
    for num_samples in range(200,2000,5):
        sample_Married = tot_amt_Married.sample(num_samples,replace = True)
        sample_mean_Married = np.mean(sample_Married["Purchase"])
        sample_mean_Married_trend.append(sample_mean_Married)
    plt.plot(sample_mean_Married_trend)
    sample_mean_Married_trend = []
plt.xlabel("Number of samples")
plt.ylabel("Sample Mean for Married customers")
```

[104]: Text(0, 0.5, 'Sample Mean for Married customers')



##Calculating 90%, 95% and 99% confidence intervals Marital Status Vs Purchase for various sample sizes and number of repetitions:

###Considering Average Purchase value

[105]:
```
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

L = [z90,z95,z99]
P = [90,95,99]
k = 0
for i in L:
    print(f"For {P[k]}% confidence interval",end="\n\n")
    k += 1

    print("Population avg spend amount for Unmarried: {:.2f}".
 ↪format(avg_amt_Unmarried['Purchase'].mean()))
    print("Population avg spend amount for Married: {:.2f}\n".
 ↪format(avg_amt_Married['Purchase'].mean()))

    print("Sample avg spend amount for Unmarried: {:.2f}".format(np.
 ↪mean(avg_Unmarried_means)))
```

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

    print("Sample std for Unmarried: {:.2f}".format(pd.
 ↪Series(avg_Unmarried_means).std()))
    print("Sample std for Married: {:.2f}\n".format(pd.
 ↪Series(avg_Married_means).std()))

    print("Sample std error for Unmarried: {:.2f}".format(pd.
 ↪Series(avg_Unmarried_means).std()/np.sqrt(1000)))
    print("Sample std error for Married: {:.2f}\n".format(pd.
 ↪Series(avg_Married_means).std()/np.sqrt(1000)))

    sample_mean_Unmarried=np.mean(avg_Unmarried_means)
    sample_mean_Married=np.mean(avg_Married_means)

    sample_std_Unmarried=pd.Series(avg_Unmarried_means).std()
    sample_std_Married=pd.Series(avg_Married_means).std()

    sample_std_error_Unmarried=sample_std_Unmarried/np.sqrt(1000)
    sample_std_error_Married=sample_std_Married/np.sqrt(1000)

    Upper_Limit_Unmarried=i*sample_std_error_Unmarried + sample_mean_Unmarried
    Lower_Limit_Unmarried=sample_mean_Unmarried - i*sample_std_error_Unmarried

    Upper_Limit_Married=i*sample_std_error_Married + sample_mean_Married
    Lower_Limit_Married=sample_mean_Married - i*sample_std_error_Married

    print("Unmarried_CI: ",[Lower_Limit_Unmarried,Upper_Limit_Unmarried])
    print("Married_CI: ",[Lower_Limit_Married,Upper_Limit_Married],end="\n"*4)
```

```
For 90% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.01
Sample avg spend amount for Married: 9574.87

Sample std for Unmarried: 42.10
Sample std for Married: 42.87

Sample std error for Unmarried: 1.33
Sample std error for Married: 1.36

Unmarried_CI:  [9561.824451457214, 9566.203667684382]
Married_CI:  [9572.640874361774, 9577.100797339675]
```

```
For 95% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.01
Sample avg spend amount for Married: 9574.87

Sample std for Unmarried: 42.10
Sample std for Married: 42.87

Sample std error for Unmarried: 1.33
Sample std error for Married: 1.36

Unmarried_CI:  [9561.404980578867, 9566.623138562729]
Married_CI:  [9572.213672846285, 9577.527998855165]



For 99% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.01
Sample avg spend amount for Married: 9574.87

Sample std for Unmarried: 42.10
Sample std for Married: 42.87

Sample std error for Unmarried: 1.33
Sample std error for Married: 1.36

Unmarried_CI:  [9560.585148541973, 9567.442970599623]
Married_CI:  [9571.378731717623, 9578.362939983826]
```

[136]:
```
#Finding the sample(sample size=varies from 500 to 2000) for avg purchase
 ↪amount for Unmarrieds and Marrieds
Marital_Statuses = [0,1]
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
```

```python
for sample_size in sample_size_range:
    print("FOR SAMPLE SIZE = {}".format(sample_size),end="\n"*2)
    avg_Unmarried_means = []
    avg_Married_means = []
    for i in range(num_repitions):
        avg_Unmarried_mean = avg_amt_Unmarried.sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
        avg_Married_mean = avg_amt_Married.sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
        avg_Unmarried_means.append(avg_Unmarried_mean)
        avg_Married_means.append(avg_Married_mean)

    #Taking the values for z at 90%, 95% and 99% confidence interval as:
    z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
    z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
    z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

    L = [z90,z95,z99]
    P = [90,95,99]
    k = 0
    for i in L:
        print(f"For {P[k]}% confidence interval",end="\n\n")
        k += 1

        print("Population avg spend amount for Unmarried: {:.2f}".
 ↪format(avg_amt_Unmarried['Purchase'].mean()))
        print("Population avg spend amount for Married: {:.2f}\n".
 ↪format(avg_amt_Married['Purchase'].mean()))

        print("Sample avg spend amount for Unmarried: {:.2f}".format(np.
 ↪mean(avg_Unmarried_means)))
        print("Sample avg spend amount for Married: {:.2f}\n".format(np.
 ↪mean(avg_Married_means)))

        print("Sample std for Unmarried: {:.2f}".format(pd.
 ↪Series(avg_Unmarried_means).std()))
        print("Sample std for Married: {:.2f}\n".format(pd.
 ↪Series(avg_Married_means).std()))

        print("Sample std error for Unmarried: {:.2f}".format(pd.
 ↪Series(avg_Unmarried_means).std()/np.sqrt(sample_size)))
        print("Sample std error for Married: {:.2f}\n".format(pd.
 ↪Series(avg_Married_means).std()/np.sqrt(sample_size)))

        sample_mean_Unmarried=np.mean(avg_Unmarried_means)
        sample_mean_Married=np.mean(avg_Married_means)
```

```
        sample_std_Unmarried=pd.Series(avg_Unmarried_means).std()
        sample_std_Married=pd.Series(avg_Married_means).std()

        sample_std_error_Unmarried=sample_std_Unmarried/np.sqrt(sample_size)
        sample_std_error_Married=sample_std_Married/np.sqrt(sample_size)

        Upper_Limit_Unmarried=i*sample_std_error_Unmarried +␣
↪sample_mean_Unmarried
        Lower_Limit_Unmarried=sample_mean_Unmarried -␣
↪i*sample_std_error_Unmarried

        Upper_Limit_Married=i*sample_std_error_Married + sample_mean_Married
        Lower_Limit_Married=sample_mean_Married - i*sample_std_error_Married

        print("Unmarried_CI: ",[Lower_Limit_Unmarried,Upper_Limit_Unmarried])
        print("Married_CI:␣
↪",[Lower_Limit_Married,Upper_Limit_Married],end="\n"*4)
```

```
FOR SAMPLE SIZE = 500

For 90% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9562.06
Sample avg spend amount for Married: 9574.88

Sample std for Unmarried: 86.32
Sample std for Married: 85.20

Sample std error for Unmarried: 3.86
Sample std error for Married: 3.81

Unmarried_CI:  [9555.711748986765, 9568.41116443106]
Married_CI:  [9568.608087319108, 9581.142063179776]



For 95% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9562.06
Sample avg spend amount for Married: 9574.88
```

```
Sample std for Unmarried: 86.32
Sample std for Married: 85.20

Sample std error for Unmarried: 3.86
Sample std error for Married: 3.81

Unmarried_CI:  [9554.495313288096, 9569.627600129728]
Married_CI:  [9567.407498540038, 9582.342651958845]



For 99% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9562.06
Sample avg spend amount for Married: 9574.88

Sample std for Unmarried: 86.32
Sample std for Married: 85.20

Sample std error for Unmarried: 3.86
Sample std error for Married: 3.81

Unmarried_CI:  [9552.117858718379, 9572.005054699446]
Married_CI:  [9565.061015875746, 9584.689134623137]



FOR SAMPLE SIZE = 1000

For 90% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.92
Sample avg spend amount for Married: 9577.92

Sample std for Unmarried: 61.17
Sample std for Married: 58.70

Sample std error for Unmarried: 1.93
Sample std error for Married: 1.86

Unmarried_CI:  [9561.73742002977, 9568.100528132909]
```

```
Married_CI:  [9574.862511889623, 9580.968668218924]


For 95% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.92
Sample avg spend amount for Married: 9577.92

Sample std for Unmarried: 61.17
Sample std for Married: 58.70

Sample std error for Unmarried: 1.93
Sample std error for Married: 1.86

Unmarried_CI:  [9561.127918601527, 9568.710029561153]
Married_CI:  [9574.277623036021, 9581.553557072526]


For 99% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9564.92
Sample avg spend amount for Married: 9577.92

Sample std for Unmarried: 61.17
Sample std for Married: 58.70

Sample std error for Unmarried: 1.93
Sample std error for Married: 1.86

Unmarried_CI:  [9559.936682634503, 9569.901265528177]
Married_CI:  [9573.134490949968, 9582.69668915858]


FOR SAMPLE SIZE = 1500

For 90% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96
```

```
Sample avg spend amount for Unmarried: 9563.03
Sample avg spend amount for Married: 9575.09

Sample std for Unmarried: 49.95
Sample std for Married: 47.83

Sample std error for Unmarried: 1.29
Sample std error for Married: 1.24

Unmarried_CI:  [9560.908281779959, 9565.151272212306]
Married_CI:  [9573.06178074709, 9577.124667900125]



For 95% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9563.03
Sample avg spend amount for Married: 9575.09

Sample std for Unmarried: 49.95
Sample std for Married: 47.83

Sample std error for Unmarried: 1.29
Sample std error for Married: 1.24

Unmarried_CI:  [9560.501859527401, 9565.557694464864]
Married_CI:  [9572.672610001846, 9577.51383864537]



For 99% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9563.03
Sample avg spend amount for Married: 9575.09

Sample std for Unmarried: 49.95
Sample std for Married: 47.83

Sample std error for Unmarried: 1.29
Sample std error for Married: 1.24
```

```
Unmarried_CI:  [9559.707530289423, 9566.352023702842]
Married_CI:  [9571.911997856303, 9578.274450790912]



FOR SAMPLE SIZE = 2000

For 90% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9566.76
Sample avg spend amount for Married: 9575.27

Sample std for Unmarried: 41.74
Sample std for Married: 43.16

Sample std error for Unmarried: 0.93
Sample std error for Married: 0.97

Unmarried_CI:  [9565.223641271437, 9568.293885173272]
Married_CI:  [9573.680776064648, 9576.855605145214]



For 95% confidence interval

Population avg spend amount for Unmarried: 9564.41
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9566.76
Sample avg spend amount for Married: 9575.27

Sample std for Unmarried: 41.74
Sample std for Married: 43.16

Sample std error for Unmarried: 0.93
Sample std error for Married: 0.97

Unmarried_CI:  [9564.929552594507, 9568.587973850203]
Married_CI:  [9573.376669513626, 9577.159711696237]



For 99% confidence interval

Population avg spend amount for Unmarried: 9564.41
```

```
Population avg spend amount for Married: 9574.96

Sample avg spend amount for Unmarried: 9566.76
Sample avg spend amount for Married: 9575.27

Sample std for Unmarried: 41.74
Sample std for Married: 43.16

Sample std error for Unmarried: 0.93
Sample std error for Married: 0.97

Unmarried_CI:  [9564.35477295787, 9569.16275348684]
Married_CI:  [9572.782310510349, 9577.754070699513]
```

###Considering Total Purchase Value

[107]:
```python
#Taking the values for z at 90%, 95% and 99% confidence interval as:
z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

L = [z90,z95,z99]
P = [90,95,99]
k = 0
for i in L:
    print(f"For {P[k]}% confidence interval",end="\n\n")
    k += 1

    print("Population tot spend amount for Unmarried: {:.2f}".
 ↪format(tot_amt_Unmarried['Purchase'].mean()))
    print("Population tot spend amount for Married: {:.2f}\n".
 ↪format(tot_amt_Married['Purchase'].mean()))

    print("Sample tot spend amount for Unmarried: {:.2f}".format(np.
 ↪mean(tot_Unmarried_means)))
    print("Sample tot spend amount for Married: {:.2f}\n".format(np.
 ↪mean(tot_Married_means)))

    print("Sample std for Unmarried: {:.2f}".format(pd.
 ↪Series(tot_Unmarried_means).std()))
    print("Sample std for Married: {:.2f}\n".format(pd.
 ↪Series(tot_Married_means).std()))
```

```
    print("Sample std error for Unmarried: {:.2f}".format(pd.
↪Series(tot_Unmarried_means).std()/np.sqrt(1000)))
    print("Sample std error for Married: {:.2f}\n".format(pd.
↪Series(tot_Married_means).std()/np.sqrt(1000)))

    sample_mean_Unmarried=np.mean(tot_Unmarried_means)
    sample_mean_Married=np.mean(tot_Married_means)

    sample_std_Unmarried=pd.Series(tot_Unmarried_means).std()
    sample_std_Married=pd.Series(tot_Married_means).std()

    sample_std_error_Unmarried=sample_std_Unmarried/np.sqrt(1000)
    sample_std_error_Married=sample_std_Married/np.sqrt(1000)

    Upper_Limit_Unmarried=i*sample_std_error_Unmarried + sample_mean_Unmarried
    Lower_Limit_Unmarried=sample_mean_Unmarried - i*sample_std_error_Unmarried

    Upper_Limit_Married=i*sample_std_error_Married + sample_mean_Married
    Lower_Limit_Married=sample_mean_Married - i*sample_std_error_Married

    print("Unmarried_CI: ",[Lower_Limit_Unmarried,Upper_Limit_Unmarried])
    print("Married_CI: ",[Lower_Limit_Married,Upper_Limit_Married],end="\n"*4)
```

```
For 90% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 880567.63
Sample tot spend amount for Married: 843576.17

Sample std for Unmarried: 21244.35
Sample std for Married: 21364.19

Sample std error for Unmarried: 671.81
Sample std error for Married: 675.60

Unmarried_CI:  [879462.6040186816, 881672.6466136823]
Married_CI:  [842464.9152250631, 844687.4252572096]



For 95% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80
```

```
Sample tot spend amount for Unmarried: 880567.63
Sample tot spend amount for Married: 843576.17

Sample std for Unmarried: 21244.35
Sample std for Married: 21364.19

Sample std error for Unmarried: 671.81
Sample std error for Married: 675.60

Unmarried_CI:  [879250.9112269991, 881884.3394053647]
Married_CI:  [842252.0282181286, 844900.3122641441]



For 99% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 880567.63
Sample tot spend amount for Married: 843576.17

Sample std for Unmarried: 21244.35
Sample std for Married: 21364.19

Sample std error for Unmarried: 671.81
Sample std error for Married: 675.60

Unmarried_CI:  [878837.1696741062, 882298.0809582577]
Married_CI:  [841835.9526392685, 845316.3878430042]
```

[137]:

```
#Finding the sample(sample size=varies from 200 to 2000) for tot purchase␣
↪amount for Unmarrieds and Marrieds
sample_size_range = np.arange(500,2100,500)
num_repitions = 1000
for sample_size in sample_size_range:
    print("FOR SAMPLE SIZE = {}".format(sample_size),end="\n"*2)
    tot_Unmarried_means = []
    tot_Married_means = []
    for i in range(num_repitions):
        tot_Unmarried_mean = tot_amt_Unmarried.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
        tot_Married_mean = tot_amt_Married.sample(sample_size,␣
↪replace=True)['Purchase'].mean()
```

```
        tot_Unmarried_means.append(tot_Unmarried_mean)
        tot_Married_means.append(tot_Married_mean)

    #Taking the values for z at 90%, 95% and 99% confidence interval as:
    z90=(norm.ppf(0.95)-norm.ppf(0.05))/2#90% Confidence Interval
    z95=(norm.ppf(0.975)-norm.ppf(0.025))/2 #95% Confidence Interval
    z99=(norm.ppf(0.995)-norm.ppf(0.005))/2 #99% Confidence Interval

    L = [z90,z95,z99]
    P = [90,95,99]
    k = 0
    for i in L:
        print(f"For {P[k]}% confidence interval",end="\n\n")
        k += 1

        print("Population tot spend amount for Unmarried: {:.2f}".
↪format(tot_amt_Unmarried['Purchase'].mean()))
        print("Population tot spend amount for Married: {:.2f}\n".
↪format(tot_amt_Married['Purchase'].mean()))

        print("Sample tot spend amount for Unmarried: {:.2f}".format(np.
↪mean(tot_Unmarried_means)))
        print("Sample tot spend amount for Married: {:.2f}\n".format(np.
↪mean(tot_Married_means)))

        print("Sample std for Unmarried: {:.2f}".format(pd.
↪Series(tot_Unmarried_means).std()))
        print("Sample std for Married: {:.2f}\n".format(pd.
↪Series(tot_Married_means).std()))

        print("Sample std error for Unmarried: {:.2f}".format(pd.
↪Series(tot_Unmarried_means).std()/np.sqrt(sample_size)))
        print("Sample std error for Married: {:.2f}\n".format(pd.
↪Series(tot_Married_means).std()/np.sqrt(sample_size)))

        sample_mean_Unmarried=np.mean(tot_Unmarried_means)
        sample_mean_Married=np.mean(tot_Married_means)

        sample_std_Unmarried=pd.Series(tot_Unmarried_means).std()
        sample_std_Married=pd.Series(tot_Married_means).std()

        sample_std_error_Unmarried=sample_std_Unmarried/np.sqrt(sample_size)
        sample_std_error_Married=sample_std_Married/np.sqrt(sample_size)

        Upper_Limit_Unmarried=i*sample_std_error_Unmarried +␣
↪sample_mean_Unmarried
```

```
        Lower_Limit_Unmarried=sample_mean_Unmarried -␣
↪i*sample_std_error_Unmarried

        Upper_Limit_Married=i*sample_std_error_Married + sample_mean_Married
        Lower_Limit_Married=sample_mean_Married - i*sample_std_error_Married

        print("Unmarried_CI: ",[Lower_Limit_Unmarried,Upper_Limit_Unmarried])
        print("Married_CI:␣
↪",[Lower_Limit_Married,Upper_Limit_Married],end="\n"*4)
```

```
FOR SAMPLE SIZE = 500

For 90% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 878480.12
Sample tot spend amount for Married: 842814.59

Sample std for Unmarried: 43217.95
Sample std for Married: 43282.54

Sample std error for Unmarried: 1932.77
Sample std error for Married: 1935.65

Unmarried_CI:  [875301.0019179899, 881659.2338620103]
Married_CI:  [839630.7191889907, 845998.4543030096]



For 95% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 878480.12
Sample tot spend amount for Married: 842814.59

Sample std for Unmarried: 43217.95
Sample std for Married: 43282.54

Sample std error for Unmarried: 1932.77
Sample std error for Married: 1935.65

Unmarried_CI:  [874691.9675611685, 882268.2682188317]
Married_CI:  [839020.7745544256, 846608.3989375746]
```

```
For 99% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 878480.12
Sample tot spend amount for Married: 842814.59

Sample std for Unmarried: 43217.95
Sample std for Married: 43282.54

Sample std error for Unmarried: 1932.77
Sample std error for Married: 1935.65

Unmarried_CI:  [873501.6444587434, 883458.5913212568]
Married_CI:  [837828.6723657867, 847800.5011262135]



FOR SAMPLE SIZE = 1000

For 90% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 881225.72
Sample tot spend amount for Married: 842605.10

Sample std for Unmarried: 29866.24
Sample std for Married: 29543.86

Sample std error for Unmarried: 944.45
Sample std error for Married: 934.26

Unmarried_CI:  [879672.2279472066, 882779.2032527934]
Married_CI:  [841068.3774654779, 844141.816132522]



For 95% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80
```

```
Sample tot spend amount for Unmarried: 881225.72
Sample tot spend amount for Married: 842605.10

Sample std for Unmarried: 29866.24
Sample std for Married: 29543.86

Sample std error for Unmarried: 944.45
Sample std error for Married: 934.26

Unmarried_CI:  [879374.6208885844, 883076.8103114156]
Married_CI:  [840773.9827723788, 844436.210825621]



For 99% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 881225.72
Sample tot spend amount for Married: 842605.10

Sample std for Unmarried: 29866.24
Sample std for Married: 29543.86

Sample std error for Unmarried: 944.45
Sample std error for Married: 934.26

Unmarried_CI:  [878792.964774516, 883658.466425484]
Married_CI:  [840198.6050445011, 845011.5885534987]



FOR SAMPLE SIZE = 1500

For 90% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 881612.52
Sample tot spend amount for Married: 844209.61

Sample std for Unmarried: 23440.50
Sample std for Married: 23248.16

Sample std error for Unmarried: 605.23
Sample std error for Married: 600.26
```

```
Unmarried_CI:  [880616.9992202143, 882608.0323237856]
Married_CI:  [843222.259328686, 845196.9551313139]



For 95% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 881612.52
Sample tot spend amount for Married: 844209.61

Sample std for Unmarried: 23440.50
Sample std for Married: 23248.16

Sample std error for Unmarried: 605.23
Sample std error for Married: 600.26

Unmarried_CI:  [880426.2846353549, 882798.746908645]
Married_CI:  [843033.1096407446, 845386.1048192553]



For 99% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 881612.52
Sample tot spend amount for Married: 844209.61

Sample std for Unmarried: 23440.50
Sample std for Married: 23248.16

Sample std error for Unmarried: 605.23
Sample std error for Married: 600.26

Unmarried_CI:  [880053.5437976911, 883171.4877463088]
Married_CI:  [842663.4273053368, 845755.7871546631]



FOR SAMPLE SIZE = 2000

For 90% confidence interval
```

```
Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 880505.79
Sample tot spend amount for Married: 842920.38

Sample std for Unmarried: 21535.27
Sample std for Married: 20591.32

Sample std error for Unmarried: 481.54
Sample std error for Married: 460.44

Unmarried_CI:  [879713.7180547146, 881297.8548202855]
Married_CI:  [842163.02726735, 843677.72637665]



For 95% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 880505.79
Sample tot spend amount for Married: 842920.38

Sample std for Unmarried: 21535.27
Sample std for Married: 20591.32

Sample std error for Unmarried: 481.54
Sample std error for Married: 460.44

Unmarried_CI:  [879561.9787465814, 881449.5941284187]
Married_CI:  [842017.9391664545, 843822.8144775456]



For 99% confidence interval

Population tot spend amount for Unmarried: 880575.78
Population tot spend amount for Married: 843526.80

Sample tot spend amount for Unmarried: 880505.79
Sample tot spend amount for Married: 842920.38

Sample std for Unmarried: 21535.27
Sample std for Married: 20591.32

Sample std error for Unmarried: 481.54
```

```
Sample std error for Married: 460.44

Unmarried_CI:  [879265.4128763737, 881746.1599986263]
Married_CI:  [841734.372703498, 844106.380940502]
```

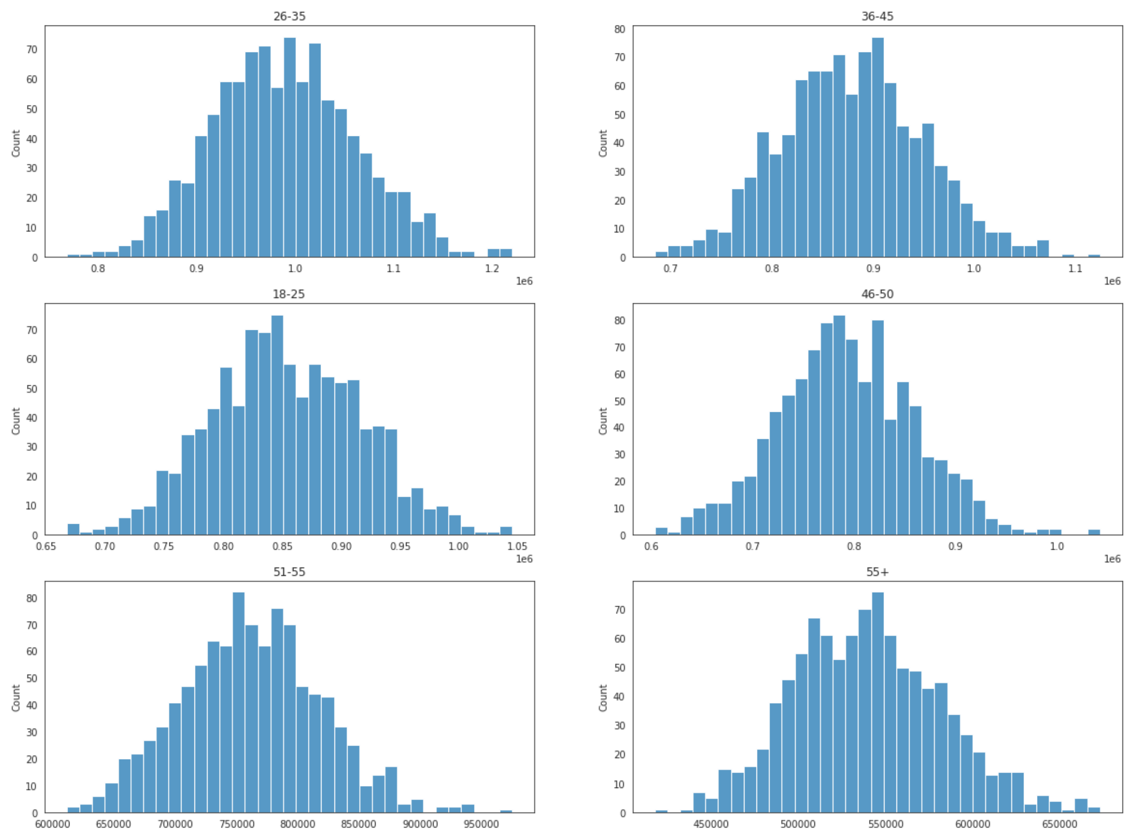
##Similarly CLT and Confidence Interval for Age Column Vs Purchase

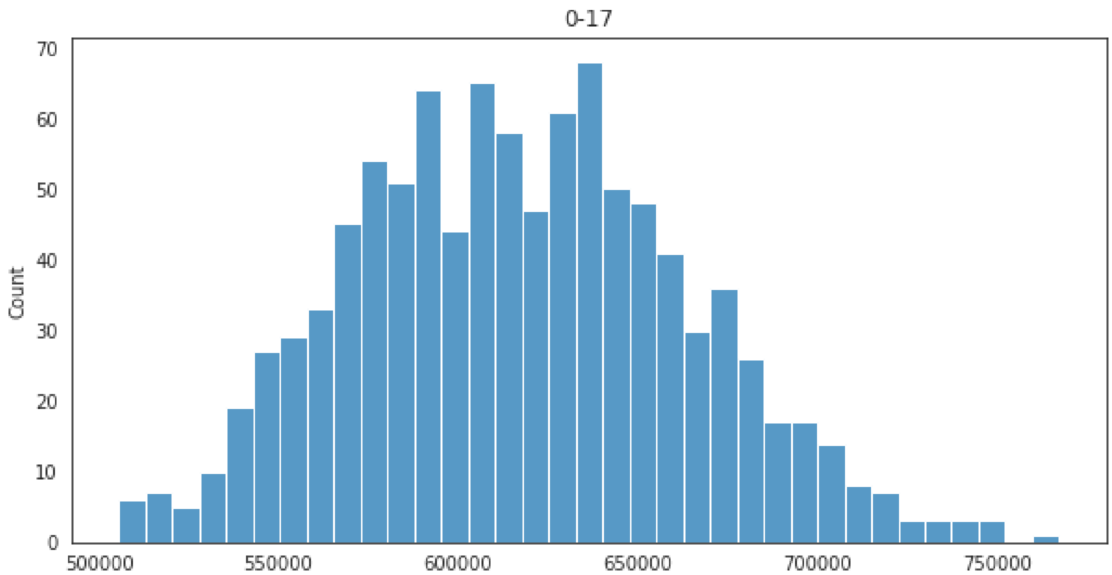
[109]:
```
avgamt_age = walmart.groupby(['User_ID', 'Age'])[['Purchase']].sum()
avgamt_age = avgamt_age.reset_index()

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

[109]:
```
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: Age, dtype: int64
```

[112]:
```
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]).set(title =␣
 ↪"26-35")
sns.histplot(all_sample_means['36-45'],bins=35,ax=axis[0,1]).set(title =␣
 ↪"36-45")
```

```
sns.histplot(all_sample_means['18-25'],bins=35,ax=axis[1,0]).set(title = "18-25")
sns.histplot(all_sample_means['46-50'],bins=35,ax=axis[1,1]).set(title = "46-50")
sns.histplot(all_sample_means['51-55'],bins=35,ax=axis[2,0]).set(title = "51-55")
sns.histplot(all_sample_means['55+'],bins=35,ax=axis[2,1]).set(title = "55+")

plt.show()

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





####90% Confidence Interval

[113]:
```
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)
```

####95% Confidence Interval

[114]:
```
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)
```

####99% Confidence Interval

[115]:
```
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 = 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)
```

#CHAPTER 7: RECOMMENDATIONS AND QUESTIONS

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).

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

Ans: 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.

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

Ans: 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

4. 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%.

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

Ans: 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]

6. Results when the same activity is performed for Age

Ans: 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)

[ ]:

```

```