#### Walmart

Walmart is an American multinational retail corporation that operates a chain of supercentres, discount departmental stores, and grocery stores from the United States. Walmart has more than 100 million customers worldwide

#### **Business Problem**

The Management team at Walmart Inc. wants to analyse the customer purchase behaviour (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions. They want to understand if the spending habits differ between male and female customers: Do women spend more on Black Friday than men? (Assume 50 million customers are male and 50 million are female).

# Defining Problem Statement and Analysing basic metrics

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

df=pd.read_csv('walmart_data.txt')

df.head(10)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0- 17	10	А	2	0	3	8370
1	1000001	P00248942	F	0- 17	10	А	2	0	1	15200
2	1000001	P00087842	F	0- 17	10	А	2	0	12	1422
3	1000001	P00085442	F	0- 17	10	А	2	0	12	1057
4	1000002	P00285442	М	55+	16	С	4+	0	8	7969
5	1000003	P00193542	М	26- 35	15	А	3	0	1	15227
6	1000004	P00184049	M	46-	7	R	2	1	1	10215

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
# Column
                                     Non-Null Count Dtype
                         550068 non-null int64
550068 non-null object
550068 non-null object
550068 non-null object
550068 non-null int64
550068 non-null object
0 User_ID
1
     Product_ID
2 Gender
3
    Age
    Occupation
    City_Category
     Stay_In_Current_City_Years 550068 non-null object
     Marital_Status
                                      550068 non-null int64
    Product_Category
                                      550068 non-null int64
                                     550068 non-null int64
     Purchase
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

Occupation, Marital\_Status and Product Category needs to be in object type

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

# df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
                               Non-Null Count Dtype
# Column
0 User_ID
                               550068 non-null int64
   Product_ID
                              550068 non-null object
1
2 Gender
                               550068 non-null object
                               550068 non-null object
3
    Age
                            550068 non-null object
   Occupation
                               550068 non-null object
5
   City_Category
    Stay_In_Current_City_Years 550068 non-null object
    Marital Status
                               550068 non-null object
                               550068 non-null object
   Product_Category
    Purchase
                               550068 non-null int64
dtypes: int64(2), object(8)
memory usage: 42.0+ MB
```

#### df.describe().T

	count	mean	std	min	25%	50%	75%
User_ID	550068.0	1.003029e+06	1727.591586	1000001.0	1001516.0	1003077.0	1004478.0
Purchase	550068.0	9.263969e+03	5023.065394	12.0	5823.0	8047.0	12054.0

# df.describe(include=object).T

	count	unique	top	freq	$\blacksquare$
Product_ID	550068	3631	P00265242	1880	ıl.
Gender	550068	2	M	414259	
Age	550068	7	26-35	219587	
Occupation	550068	21	4	72308	
City_Category	550068	3	В	231173	
Stay_In_Current_City_Years	550068	5	1	193821	
Marital_Status	550068	2	0	324731	
Product_Category	550068	20	5	150933	

#### Observations:

- 2 unique genders where Male are more
- 7 unique Age categories where 26-35 are most
- 21 unique Occupation categories where 4 number occupation are more
- 3 unique City\_category where B city are more
- 2 unique Marital\_Status where 0 are more (more unmarried)
- 20 unique Product\_Category where 5th product category are most

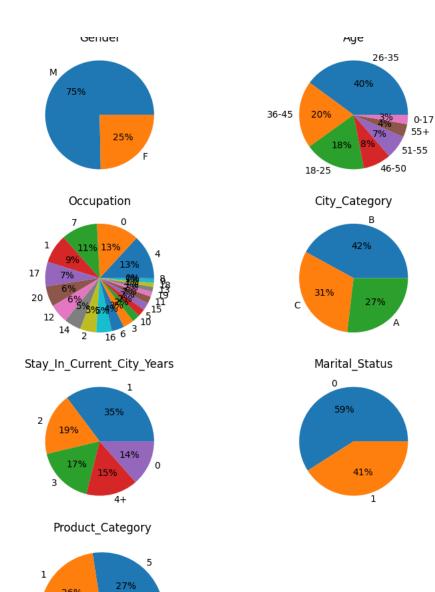
# Value Count and Frequency count of categorical columns

```
col=list(df.columns)
col.remove('Purchase')
col.remove('User_ID')
col.remove('Product_ID')
temp=[]
unique_categories=[]
for i in col:
    temp=df[i].unique()
    unique_categories.append(temp)
Unique_df=pd.DataFrame(unique_categories)
```

	0	1	2	3	4	5	6	7	8	9	• • •
Gender	F	М	None	None	None	None	None	NaN	NaN	NaN	
Age	0- 17	55+	26- 35	46- 50	51- 55	36- 45	18- 25	NaN	NaN	NaN	
Occupation	10	16	15	7	20	9	1	12.0	17.0	0.0	
City_Category	Α	С	В	None	None	None	None	NaN	NaN	NaN	
Stay_In_Current_City_Years	2	4+	3	1	0	None	None	NaN	NaN	NaN	
Marital_Status	0	1	None	None	None	None	None	NaN	NaN	NaN	
Product_Category	3	1	12	8	5	4	2	6.0	14.0	11.0	
7 rows x 21 columns											•

categorical\_cols = ['Gender', 'Age', 'Occupation', 'City\_Category', 'Stay\_In\_Current\_City\_Years', 'Marital\_Status', 'Product\_Category']
df[categorical\_cols].melt().groupby(['variable','value'])[['value']].count()/len(df)

```
0.049647
                                   14
                                   15
                                        0.022115
                                   16
                                        0.046123
                                   17
                                        0.072796
                                   18
                                        0.012039
                                   19
                                        0.015382
                                        0.061014
                                   20
          Product_Category
                                        0.255201
                                   1
                                   2
                                        0.043384
                                   3
                                        0.036746
                                   4
                                        0.021366
                                   5
                                        0.274390
                                        0.037206
                                   6
                                   7
                                        0.006765
                                   8
                                        0.207111
                                   9
                                        0.000745
                                        0.009317
                                   10
                                   11
                                        0.044153
                                   12
                                        0.007175
                                   13
                                        0.010088
                                   14
                                        0.002769
                                   15
                                        0.011435
                                   16
                                        0.017867
                                        0.001051
                                   17
                                   18
                                        0.005681
                                   19
                                        0.002914
                                        0.004636
                                   20
      Stay_In_Current_City_Years
                                   0
                                        0.135252
                                   1
                                        0.352358
                                   2
                                        0.185137
Categorical columns visualization
                                       0 454000
categorical_cols=categorical_cols[:6]
c_cols=np.array(categorical_cols).reshape(3,2)
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(9,9))
for i in range(3):
  for j in range(2):
    data=df[c_cols[i][j]].value_counts(normalize=True)*100
    axs[i,j].pie(x=data.values,labels=data.index,autopct='\%.0f\%')\\
    axs[i,j].set_title(c_cols[i][j])
plt.figure(figsize=(3,3))
data=df['Product_Category'].value_counts(normalize=True)*100
plt.pie(x=data.values,labels=data.index,autopct='%.0f%%')
plt.title('Product_Category')
plt.show()
```



# Observations

- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are Male and 25% are Female
- 60% Single, 40% Married
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- Total of 20 product categories are there
- Product\_Category 1, 5 & 8 have highest purchasing frequency.
- There are 20 different types of occupations in the city
- More users belong to B City\_Category

Unique categories are well ranged without any gaps

# Checking Null Values

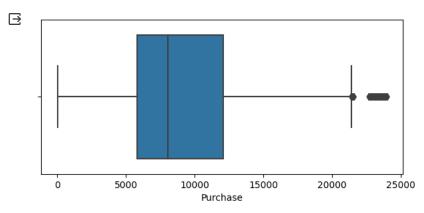
# df.isnull().sum()

User_ID	0
Product_ID	0
Gender	0
Age	0
Occupation	0
City_Category	0
Stay_In_Current_City_Years	0
Marital_Status	0
Product_Category	0
Purchase	0
dtype: int64	

# Visual Analysis

Only Purchase is numerical column where outliers might be there

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



# Observation:

• Purchase have outliers on right side

```
def find_outliers_IQR(df):
    q1=df.quantile(0.25)
    q3=df.quantile(0.75)
    IQR=q3-q1
    #as the outliers are on right side we will check right side outliers
    outliers = df[df>(q3+1.5*IQR)]
    return outliers

outliers = find_outliers_IQR(df["Purchase"])
    print("number of outliers: "+ str(len(outliers)))
    print("max outlier value:"+ str(outliers.max()))
    print("min outlier value: "+ str(outliers.min()))

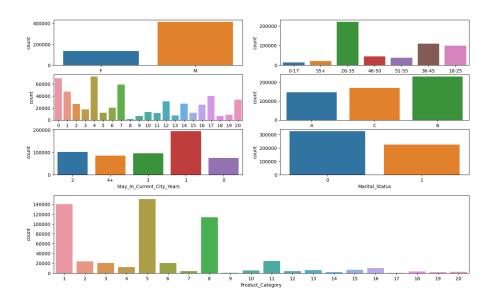
    number of outliers: 2677
    max outlier value: 23961
    min outlier value: 21401
```

# Categorical variables

```
coll=df.columns
coll=col1[2:8]
coll=np.array(col1)
coll=coll.reshape(3,2)

fig,axs=plt.subplots(nrows=3,ncols=2,figsize=(16,6))
for i in range(3):
    for j in range(2):
        sns.countplot(data=df,x=col1[i][j],ax=axs[i,j])

plt.figure(figsize=(16,3))
sns.countplot(data=df,x='Product_Category')
plt.show()
```

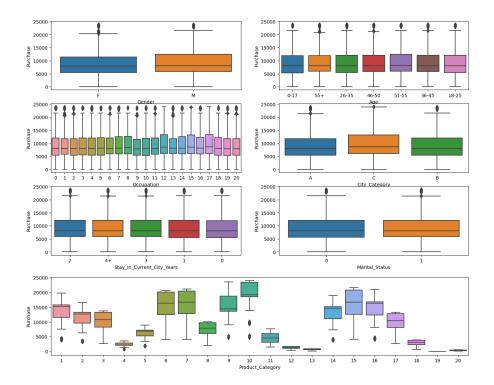


# Observations:

- Most of the users are Male
- There are 20 different types of Occupation and Product\_Category
- More users belong to B City\_Category
- More users are Single as compare to Married
- Product\_Category 1, 5 & 8 have highest purchasing frequency.
- 26-35 age group are more frequent buyers

```
col2=df.columns
col2=col2[2:8]

fig,axs=plt.subplots(nrows=3,ncols=2,figsize=(16,9))
count=0
for i in range(3):
    for j in range(2):
        sns.boxplot(data=df,x=col2[count],y='Purchase',ax=axs[i,j])
        count+=1
plt.show()
plt.figure(figsize=(16,3))
sns.boxplot(data=df,x='Product_Category',y='Purchase')
plt.show()
```



# Answers of questions

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

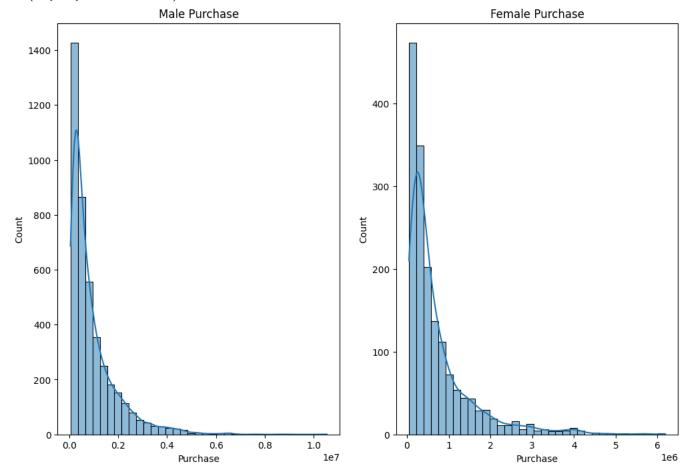
df.head()

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0- 17	10	А	2	0	3	8370
1	1000001	P00248942	F	0- 17	10	А	2	0	1	15200
2	1000001	P00087842	F	0- 17	10	А	2	0	12	1422
4										<b></b>

data=df.groupby(['User\_ID','Gender'])['Purchase'].sum()
data=data.reset\_index()
data.head()

	User_ID	Gender	Purchase	⊞
0	1000001	F	334093	ıl.
1	1000002	М	810472	
2	1000003	М	341635	
3	1000004	М	206468	
4	1000005	М	821001	

```
df1=data[data['Gender']=='M']
df2=data[data['Gender']=='F']
fig, axs=plt.subplots(nrows=1,ncols=2,figsize=(12,8))
sns.histplot(data=df1,x='Purchase',kde=True,bins=35,ax=axs[0])
axs[0].set_title('Male Purchase')
sns.histplot(data=df2,x='Purchase',kde=True,bins=35,ax=axs[1])
axs[1].set_title('Female Purchase')
```



```
male_avg=df1['Purchase'].mean()
m_s=df1["Purchase"].std()
female_avg=df2['Purchase'].mean()
print("Average amount spend by Male customers:{:.2f}".format(male_avg))
print("Average amount spend by Female customers:{:.2f}".format(female_avg))

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

# Observation:

16394.853659

• Male customers spend more money than female customers on average on a unit

```
df1=df[df['Gender']=='M']
df2=df[df['Gender']=='F']
male_top10_product_cat=df1.groupby('Product_Category')['Purchase'].mean().nlargest(10)
female\_top10\_product\_cat=df2.groupby('Product\_Category')['Purchase'].mean().nlargest(10)
male_top10_product_cat,female_top10_product_cat
     (Product_Category
           19670.731264
      10
            16355.789777
      6
            15907.851009
            15498.888235
      15
            14797.431350
      16
            14793.384056
            13608.164721
      14
            12722.321111
      2
            11203.590520
            10209.732558
      Name: Purchase, dtype: float64,
      Product_Category
            19692.076592
```

```
9 15724.314286
6 15596.428164
15 14695.326960
16 14681.491257
14 13747.362761
1 13597.162619
2 11407.496819
3 10262.656677
Name: Purchase, dtype: float64)
```

# Observation:

• Top 10 average price for product category for male and female are quite similar just male buy 17th category more and female buy 3rd category more then other

col2

```
dtype='object')
for i in col2:
 male_top10=df1.groupby(i)['Purchase'].mean().nlargest(10)
 female_top10=df2.groupby(i)['Purchase'].mean().nlargest(10)
 print(f'Male Top 10 {i}{male_top10},Female Top 10 {i}{female_top10}')
    0-17
             8338.771985
    Name: Purchase, dtype: float64
    Occupation
    Male Top 10 OccupationOccupation
    12
          9876.847492
    15
          9872.778721
    17
          9851.727696
    14
          9804.566923
    8
          9584.729114
          9493.818898
          9485.148154
    13
    16
          9477.371520
          9446.089083
    4
          9435,676366
    Name: Purchase, dtype: float64, Female Top 10 OccupationOccupation
    18
          10074.608696
    17
           9543.435734
    15
           9394.894979
    8
           9361.451524
           9155.953301
    12
           9092,302553
    11
           9090.800000
           9078.405882
           9055.138149
    3
    16
           8965.212320
    Name: Purchase, dtype: float64
    City_Category
    Male Top 10 City_CategoryCity_Category
         9913.567248
    В
         9354.854433
         9017.834470
```

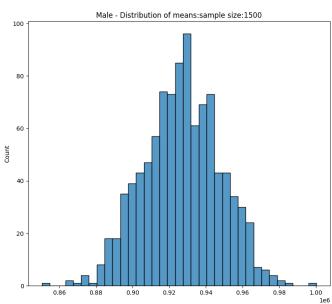
```
1 9413.81/605
Name: Purchase, dtype: float64,Female Top 10 Marital_StatusMarital_Status
1 8810.249789
0 8679.845815
Name: Purchase, dtype: float64
```

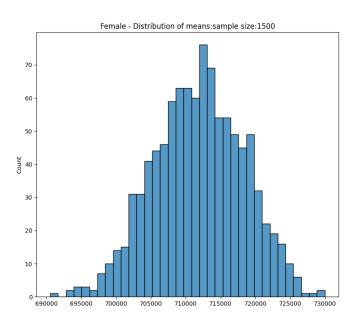
#### Observations:

- Age range of 0-50 age female's mean purchase cost is lower then 0-50 age male's
- Leaving occupation type 18,17 & 8 all are below average purchase mean of male whereas all occupation type of male is above average purchase mean of male
- Clearly from Marital\_Status,Stay\_in\_Current\_city & city\_category we can determine female's purchase mean is lower whereas male's of every type have higher and similar mean than female

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

```
df1=data[data['Gender']=='M']
df2=data[data['Gender']=='F']
sample_size=1500
male_means=[]
female_means=[]
for i in range(1000):
 male_mean=df1.sample(sample_size)['Purchase'].mean()
 male_means.append(male_mean)
 female_mean=df2.sample(sample_size)['Purchase'].mean()
 female_means.append(female_mean)
fig,axs= plt.subplots(nrows=1,ncols=2,figsize=(20,8))
sns.histplot(data=male_means,bins=35,ax=axs[0])
sns.histplot(data=female_means,bins=35,ax=axs[1])
axs[0].set title('Male - Distribution of means:sample size:1500')
axs[1].set_title('Female - Distribution of means:sample size:1500')
plt.show()
```





```
print("Population mean - Mean of sample means of amount spend for Male:{:.2f}".format(np.mean(male_means)))
print("Population mean - Mean of sample means of amount spend forFemale: {:.2f}".format(np.mean(female_means)))
print("\nMale - Sample mean: {:.2f} Sample std:{:.2f}".format(df1['Purchase'].mean(), df1['Purchase'].std()))
print("Female - Sample mean: {:.2f} Sample std:{:.2f}".format(df2['Purchase'].mean(),df2['Purchase'].std()))

Population mean - Mean of sample means of amount spend for Male:926901.98
Population mean - Mean of sample means of amount spend forFemale: 711849.24

Male - Sample mean: 925344.40 Sample std:985830.10
Female - Sample mean: 712024.39 Sample std:807370.73
```

#### Observation:

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

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

```
male_df=df1
female_df=df2

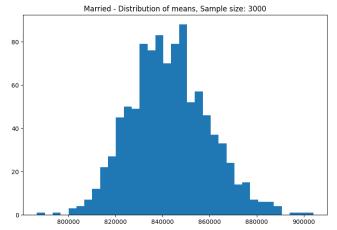
male_margin_of_error_clt =1.96*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt
female_margin_of_error_clt =1.96*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt
print("Male confidence interval of means: ({:.2f},{:.2f})".format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: (895617.83,955070.97)
Female confidence interval of means: (673254.77,750794.02)
```

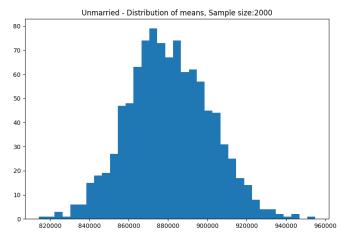
Now we can infer about the population that, 95% of the times:

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

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

```
amt df=data
amt_df = df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt df
amt_df['Marital_Status'].value_counts()
marid_samp_size = 3000
unmarid_sample_size = 2000
num_repitions = 1000
marid_means = []
unmarid_means = []
for in range(num repitions):
      marid_mean =amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size,replace=True)['Purchase'].mean()
      unmarid_mean =amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size,replace=True)['Purchase'].mean()
      marid means.append(marid mean)
      unmarid_means.append(unmarid_mean)
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 3000")
axis[1].set_title("Unmarried - Distribution of means, Sample size:2000")
plt.show()
print("Population mean - Mean of sample means of amount spend forMarried: {:.2f}".format(np.mean(marid_means)))
print("Population mean - Mean of sample means of amount spend forUnmarried: {:.2f}".format(np.mean(unmarid means)))
print("\nMarried - Sample mean: {:.2f} Sample std:{:.2f}".format(amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']==1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=1]['Purchase'].mean(),amt_df['Marital_Status']=
print("Unmarried - Sample mean: {:.2f} Sample std:{:.2f}".format(amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df[amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']==0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purchase'].mean(),amt_df['Marital_Status']=0]['Purc
for val in ["Married", "Unmarried"]:
      new_val = 1 if val == "Married" else 0
      new_df = amt_df[amt_df['Marital_Status']==new_val]
      margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
      sample_mean = new_df['Purchase'].mean()
      lower_lim = sample_mean - margin_of_error_clt
      upper_lim = sample_mean + margin_of_error_clt
      print("{} confidence interval of means: ({:.2f},{:.2f})".format(val, lower_lim, upper_lim))
```





Population mean - Mean of sample means of amount spend forMarried: 843007.66 Population mean - Mean of sample means of amount spend forUnmarried: 880417.21

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

# 5: Results when the same activity is performed for Age:

```
amt_df = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
amt_df['Age'].value_counts()
sample\_size = 200
num_repitions = 1000
all_means = {}
age_intervals = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+','0-17']
for age_interval in age_intervals:
  all_means[age_interval] = []
for age_interval in age_intervals:
  for _ in range(num_repitions):
   mean = amt_df[amt_df['Age']==age_interval].sample(sample_size,replace=True)['Purchase'].mean()
    all_means[age_interval].append(mean)
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:
  new_df = amt_df[amt_df['Age']==val]
  margin_of_error_clt =1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
sample_mean = new_df['Purchase'].mean()
lower_lim = sample_mean - margin_of_error_clt
upper_lim = sample_mean + margin_of_error_clt
 print("For age {} --> confidence interval of means: ({:.2f},{:.2f})".format(val, lower_lim, upper_lim)) 
     For age 0-17 --> confidence interval of means: (527662.46,710073.17)
```

# Insights

- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are Male and 25% are Female
- 60% Single, 40% Married
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- · Total of 20 product categories are there
- There are 20 differnent types of occupations in the city
- · Most of the users are Male
- · There are 20 different types of Occupation and Product\_Category
- More users belong to B City\_Category
- · More users are Single as compare to Married
- Product\_Category 1, 5, 8, & 11 have highest purchasing frequency.
- Average amount spend by Male customers: 925344.40

- Average amount spend by Female customers: 712024.39 Confidence Interval by Gender Now using the Central Limit Theorem for the population:
- 1. Average amount spend by male customers is 9,26,341.86
- 2. Average amount spend by female customers is 7,11,704.09 Now we can infer about the population that, 95% of the times:
- 3. Average amount spend by male customer will lie in between: (895617.83, 955070.97)
- 4. Average amount spend by female customer will lie in between: (673254.77, 750794.02) Confidence Interval by Marital\_Status
- 5. Married confidence interval of means: (806668.83, 880384.76)
- 6. Unmarried confidence interval of means: (848741.18, 912410.38) Confidence Interval by Age
- 7. For age 26-35 --> confidence interval of means: (945034.42, 1034284.21)
- 8. For age 36-45 --> confidence interval of means: (823347.80, 935983.62)
- 9. For age 18-25 --> confidence interval of means: (801632.78, 908093.46)
- 10. For age 46-50 --> confidence interval of means: (713505.63, 871591.93)
- 11. For age 51-55 --> confidence interval of means: (692392.43, 834009.42)
- 12. For age 55+ --> confidence interval of means: (476948.26, 602446.23)
- 13. For age 0-17 --> confidence interval of means: (527662.46, 710073.17)

# Recommendations

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

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