Walmart_CS (1)

September 5, 2024

#

Walmart - Confidence Interval and CLT

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0.1 What is Walmart?

`Walmart`, founded in `1962 by Sam Walton`, is a retail giant and one of the world's largest and most influential companies. Headquartered in `Bentonville, Arkansas`, this American multinational corporation has established itself as a global powerhouse in the retail industry. Walmart operates a vast network of hypermarkets, discount department stores, and grocery stores under various brand names across the United States and in numerous countries around the world.

Known for its `"Everyday Low Prices"` strategy, Walmart has redefined the retail landscape with its commitment to offering a wide range of products at affordable prices. With its extensive supply chain and efficient distribution systems, the company has played a pivotal role in shaping consumer expectations and shopping habits. Beyond retail, Walmart has also ventured into e-commerce, technology innovation, and sustainability initiatives, further solidifying its position as a key player in the modern retail ecosystem.

0.2 Objective

The objective of this project is to conduct a comprehensive analysis of customer purchase behavior, with a specific focus on purchase amounts at Walmart. This study aims to provide valuable insights that can assist the management team at Walmart. in making data-driven decisions.

0.3 About Data

The company collected the transactional data of customers who purchased products from the Walmart Stores.

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm

import statistics
from scipy import stats
```

```
import math
```

[ ]:
```
data=pd.read_csv('/content/walmart_data.csv')
```

[ ]:
```
#@title 1: Initial data exploration
```

[ ]:
```
data.head()
```

[ ]:
```
   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
```

[ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 149490 entries, 0 to 150254
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     149490 non-null  object
 1   Product_ID                  149490 non-null  object
 2   Gender                      149490 non-null  object
 3   Age                         149490 non-null  object
 4   Occupation                  149490 non-null  object
 5   City_Category               149490 non-null  object
 6   Stay_In_Current_City_Years  149490 non-null  object
 7   Marital_Status              149490 non-null  object
 8   Product_Category            149490 non-null  object
 9   Purchase                    149490 non-null  int64
dtypes: int64(1), object(9)
memory usage: 12.5+ MB
```

There are total:

```
*   10 columns:
*   5 columns are of type object, rest are of type Integer
*   550068 rows are there in the given data
```

There are no null values in the data

[ ]:
```
data.nunique()
```

[ ]:
```
User_ID                       5873
Product_ID                    3417
Gender                           2
Age                              7
Occupation                      21
City_Category                    3
Stay_In_Current_City_Years       5
Marital_Status                   2
Product_Category                18
Purchase                     14522
dtype: int64
```

There are:

```
* 5891 different users
* 3631 products
* 2 genders(F=Female,M=Male)
* 7 different age groups
* Customers belong to 21 different occupations
* 3 city categories
* Marital status to know if customers are married or unmarried
* 20 different product categories
```

We are gonna convert all the columns except "Purchase" into object data type to use as categorical data

[ ]:
```
data=data.astype({
    'User_ID':'object',
    'Occupation':'object',
    'Marital_Status':'object',
    'Product_Category':'object',
}

)
```

[ ]:
```
data.head()
```

[ ]:
```
   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         Single                3      8370
1                          2         Single                1     15200
2                          2         Single               12      1422
3                          2         Single               12      1057
4                         4+         Single                8      7969
```

[ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 149490 entries, 0 to 150254
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     149490 non-null  object
 1   Product_ID                  149490 non-null  object
 2   Gender                      149490 non-null  object
 3   Age                         149490 non-null  object
 4   Occupation                  149490 non-null  object
 5   City_Category               149490 non-null  object
 6   Stay_In_Current_City_Years  149490 non-null  object
 7   Marital_Status              149490 non-null  object
 8   Product_Category            149490 non-null  object
 9   Purchase                    149490 non-null  int64
dtypes: int64(1), object(9)
memory usage: 12.5+ MB
```

[ ]:
```
data['Marital_Status']=data['Marital_Status'].replace({0:'Single',1:'Married'})
```

Marital Status data has been converted as:

```
* 0-> Single
* 1-> Married
```

[ ]:
```
data.head()
```

[ ]:
```
   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         Single                3      8370
1                          2         Single                1     15200
2                          2         Single               12      1422
3                          2         Single               12      1057
```

```
4                          4+         Single                  8      7969
```

[ ]:
```
#@title 2: Null value detection and outlier treatment
```

[ ]:
```
data.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
```

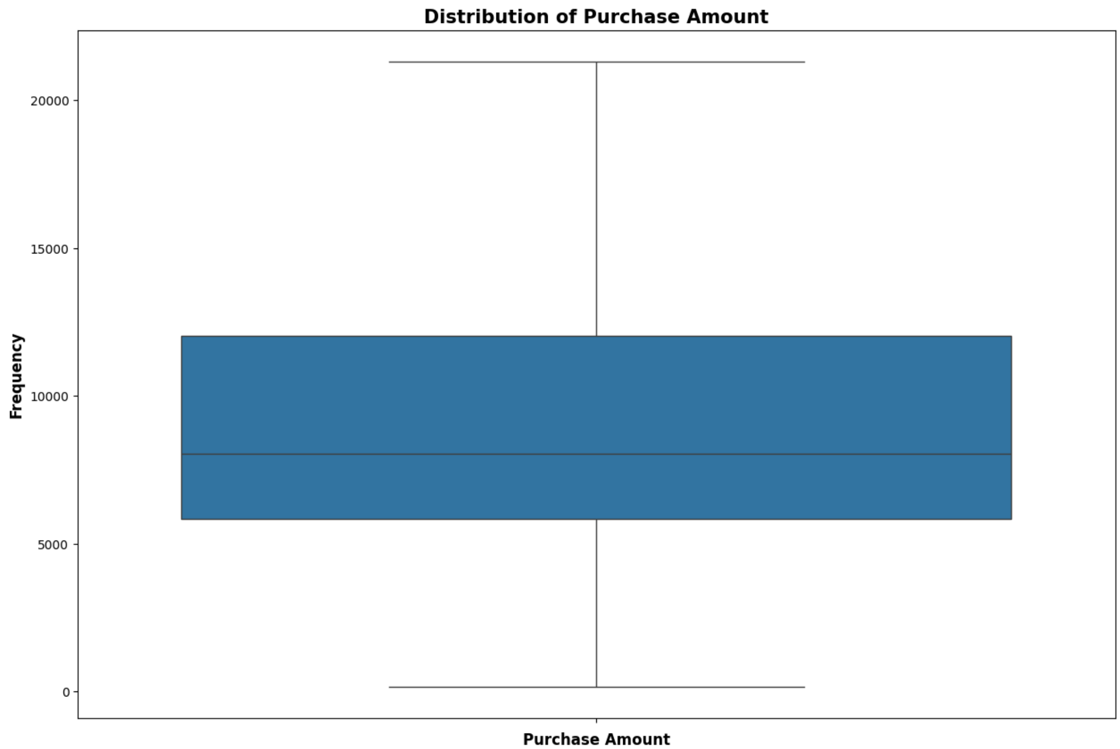
[ ]:
```
data.duplicated().sum()
```

[ ]:
```
0
```

There are no null or duplicate values in the data

[ ]:
```
#@title Outlier detection in purchase amount and clipping of data
```

[ ]:
```
plt.figure(figsize=(15,10))
sns.boxplot(data['Purchase'])
plt.xlabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Distribution of Purchase Amount',fontsize = 15,fontweight = 'bold')
plt.show()
```



[ ]:
```
percentiles = data['Purchase'].quantile([0.25, 0.75])
IQR=percentiles.iloc[1]-percentiles.iloc[0]
lower_bound=percentiles.iloc[0]-1.5*IQR
upper_bound=percentiles.iloc[1]+1.5*IQR
print("Lower Bound:",lower_bound)
print("Upper Bound:",upper_bound)


data = data[
    (data['Purchase'] >= lower_bound) & (data['Purchase'] <= upper_bound)
]
```

```
Lower Bound: -3448.875
Upper Bound: 21314.125
```

Data outside of lower and upper bound calculated using 1.5 times of the Inter Quartile Range has been clipped off and data has been finalised for further analysis

[ ]:
```
data.shape
```

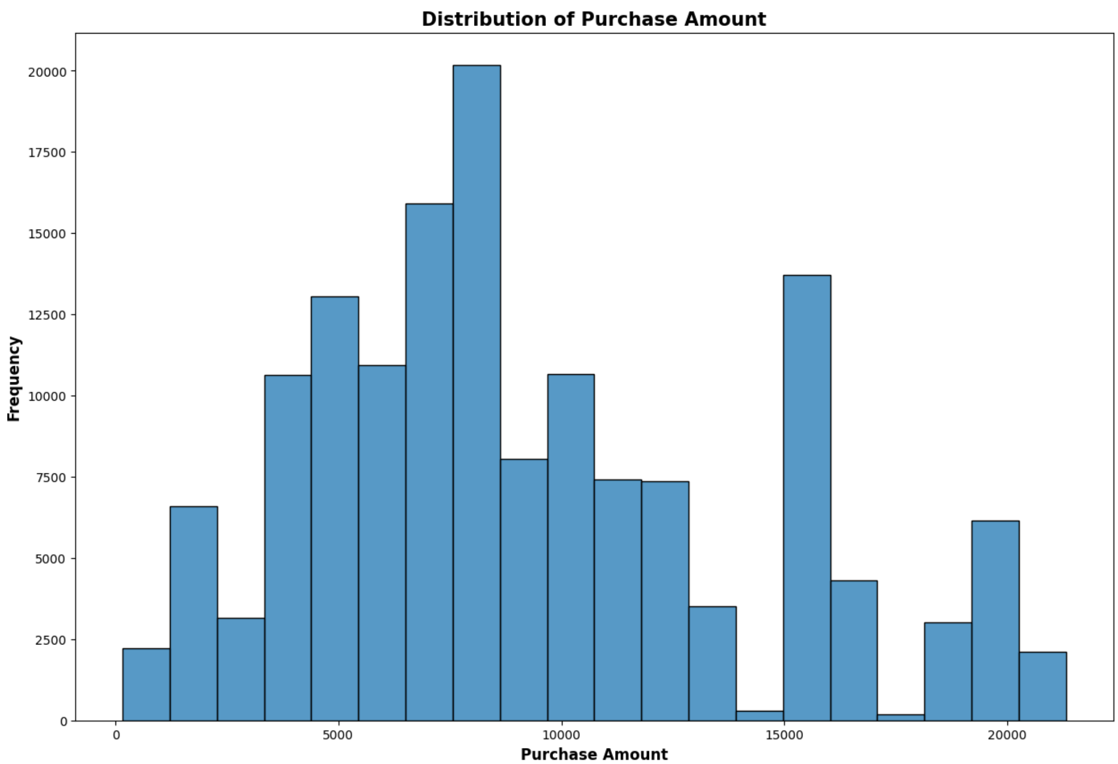
[ ]: (149490, 10)

Our Final data for use has a total of 547391 rows of data

```
[ ]: #@title  3:Univariate Analysis
```

```
[ ]: #@title 3.1: Purchase amount distribution
```

```
[ ]: plt.figure(figsize=(15,10))

     sns.histplot(data=data,x='Purchase',bins=20)
     plt.xlabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
     plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
     plt.title('Distribution of Purchase Amount',fontsize = 15,fontweight = 'bold')
     plt.show()
```

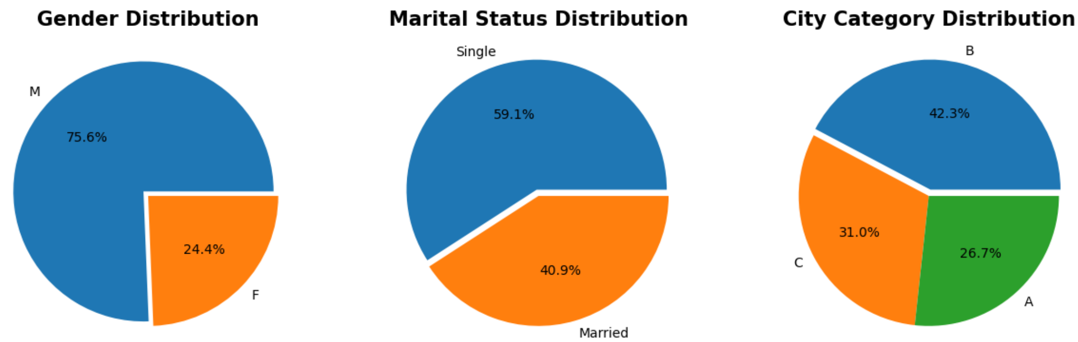


- Highest no of purchase order value falls in the range of 7000
- Customers ordering in values between 5000-10000 per order has been found to be the highest
- Orders in the range of 16000 have also been much frequent

```
[ ]: #@title 3.2: Gender, Marital Status  and City Category Distribution
```

```
[ ]: plt.figure(figsize=(15,10))

     plt.subplot(1,3,1)
     plt.pie(data['Gender'].value_counts(),labels=data['Gender'].value_counts().
      ↪index,autopct='%1.1f%%',explode=(0.05,0))
```

```
plt.title('Gender Distribution',fontsize = 15,fontweight = 'bold')

plt.subplot(1,3,2)
plt.pie(data['Marital_Status'].value_counts(),labels=data['Marital_Status'].
 ↪value_counts().index,autopct='%1.1f%%',explode=(0.05,0))
plt.title('Marital Status Distribution',fontsize = 15,fontweight = 'bold')

plt.subplot(1,3,3)
plt.pie(data['City_Category'].value_counts(),labels=data['City_Category'].
 ↪value_counts().index,autopct='%1.1f%%',explode=(0.05,0,0))
plt.title('City Category Distribution',fontsize = 15,fontweight = 'bold')

plt.show()
```



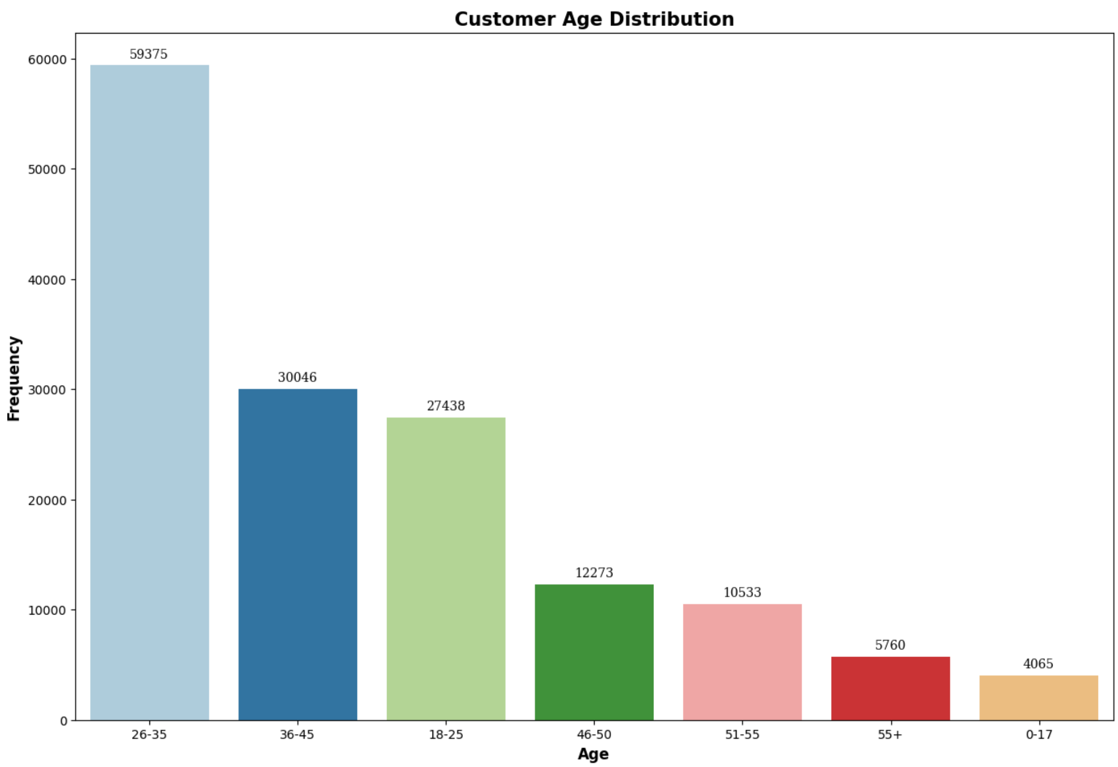
* 75% of the customers are male
* 60% of the customers are unmarried
* Cities lying in category 'B' have generated the highest no of orders

[ ]:
```
#@title 3.3: Customer Age Distribution
```

[ ]:
```
plt.figure(figsize=(15,10))
temp1=data['Age'].sort_values().value_counts()
color_map=sns.color_palette("Paired", len(temp1))

ax1 = plt.subplot()

for i in temp1.index:
    ax1.text(i, temp1[i] + 1000, temp1[i],{'font':'serif','size' : 10},ha =␣
 ↪'center',va = 'center')

sns.barplot(x=temp1.index,y=temp1.values, palette=color_map)
plt.xlabel('Age',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Customer Age Distribution',fontsize = 15,fontweight = 'bold')
```

```
plt.show()
```

```
<ipython-input-978-a8b81cdcdece>:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=temp1.index,y=temp1.values, palette=color_map)
```



[ ]:
```
#@title 3.4: Customer Stay In current City Distribution
```

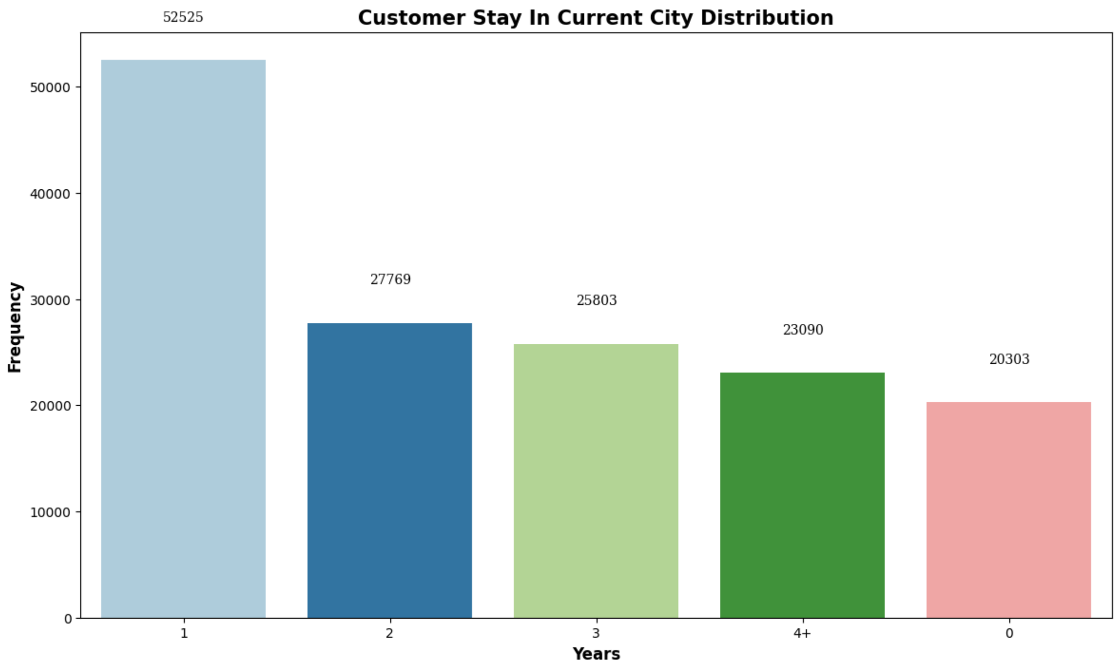
[ ]:
```
plt.figure(figsize=(14,8))
temp1=data['Stay_In_Current_City_Years'].sort_values().value_counts()
color_map=sns.color_palette("Paired", len(temp1))

ax1 = plt.subplot()

for i in temp1.index:
    ax1.text(i,temp1[i]+4000,temp1[i],{'font':'serif','size' : 10},ha =␣
 ↪'center',va = 'center')
sns.barplot(x=temp1.index,y=temp1.values, ax=ax1,palette=color_map)
plt.xlabel('Years',fontsize = 12,fontweight = 'bold')
```

```
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Customer Stay In Current City Distribution',fontsize = 15,fontweight␣
 ↪= 'bold')
plt.show()
```

<ipython-input-980-6304d29c1992>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=temp1.index,y=temp1.values, ax=ax1,palette=color_map)



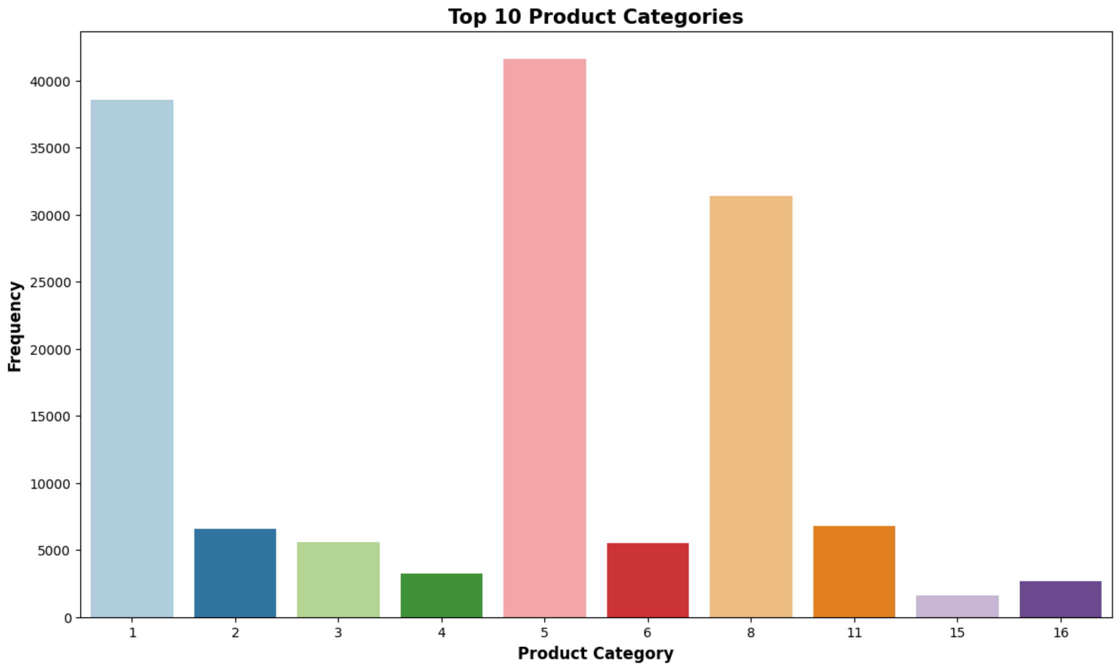

```
[ ]: #@title 3.5: Top 10 Products and Categories
```

```
[ ]: plt.figure(figsize=(14,8))
temp1=data['Product_Category'].value_counts()[0:10]
sns.barplot(x=temp1.index, y=temp1.values,palette='Paired')
plt.xlabel('Product Category',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Top 10 Product Categories',fontsize = 15,fontweight = 'bold')
plt.show()
```

<ipython-input-982-1f6412ede65f>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

```
  sns.barplot(x=temp1.index, y=temp1.values,palette='Paired')
```



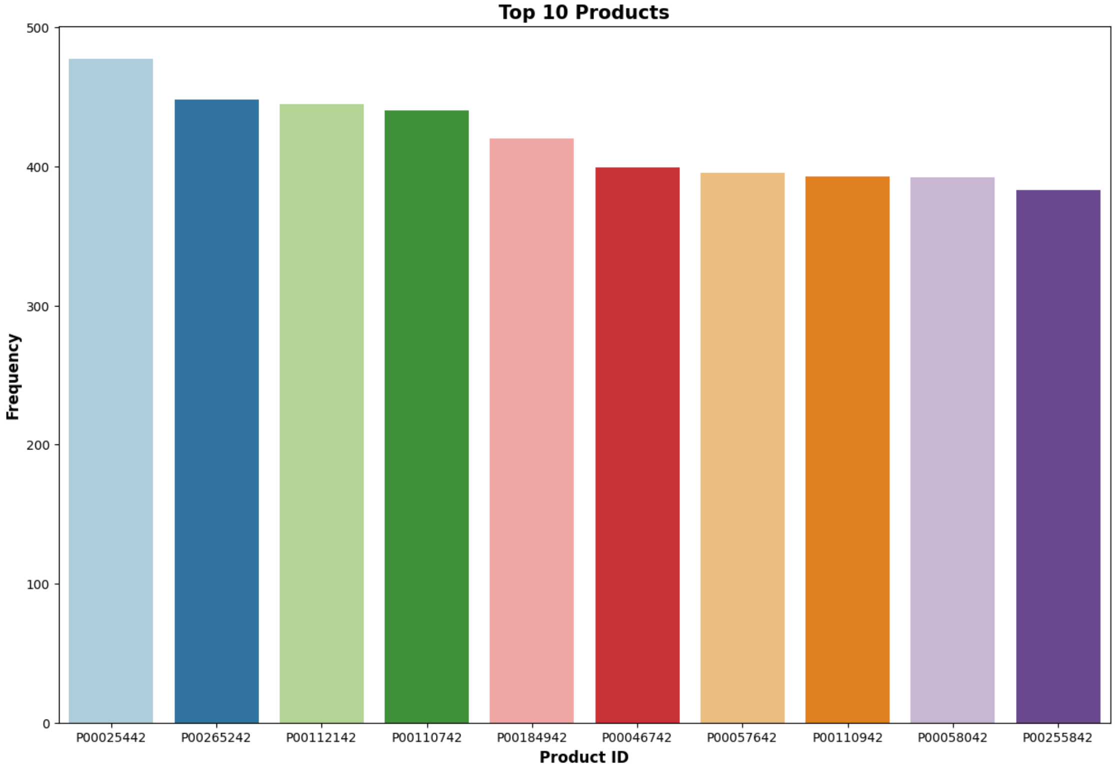
* Products of category 5 have been sold most followed by 1 & 8

```
[ ]: plt.figure(figsize=(15,10))
temp1=data['Product_ID'].value_counts()

sns.barplot(x=temp1.index[:10],y=temp1.values[:10],palette='Paired')
plt.xlabel('Product ID',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Top 10 Products',fontsize = 15,fontweight = 'bold')
plt.show()
```

<ipython-input-983-88f0dfc18f23>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

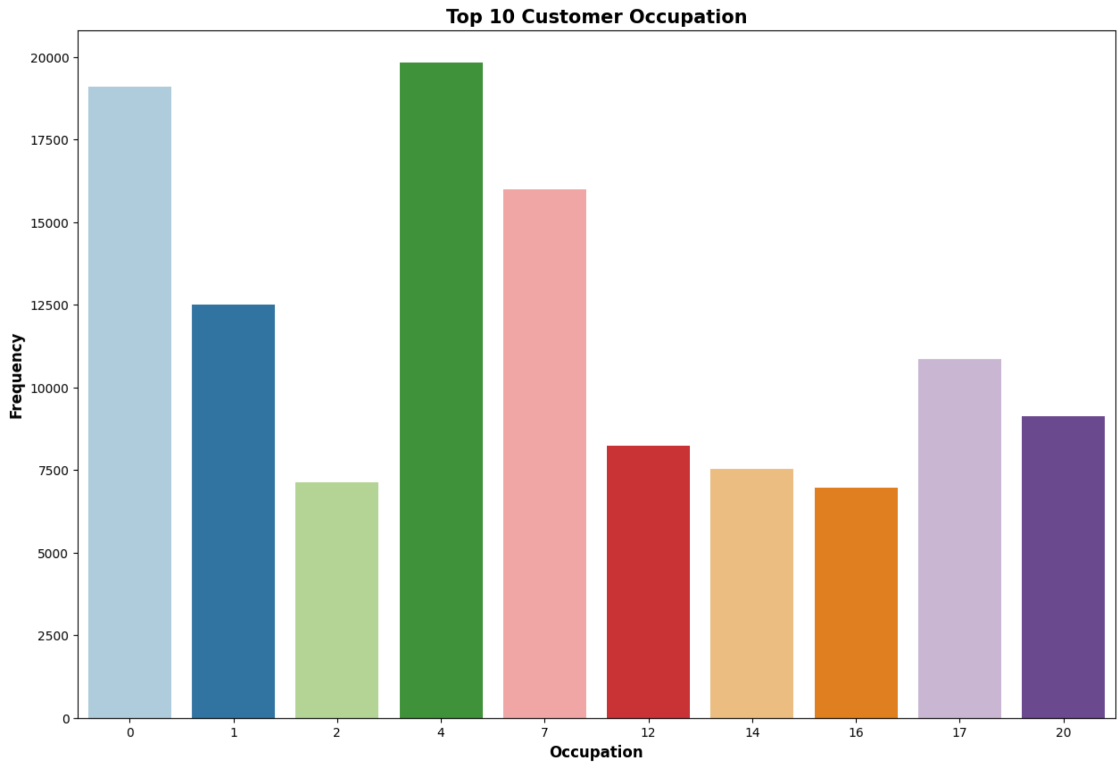
```
  sns.barplot(x=temp1.index[:10],y=temp1.values[:10],palette='Paired')
```



[ ]:
```
#@title 3.6: Top 10 Customer Occupation
```

[ ]:
```
plt.figure(figsize=(15,10))
temp1=data['Occupation'].sort_values(ascending=False).value_counts()


sns.barplot(x=temp1.index[:10],y=temp1.values[:10],palette='Paired')
plt.xlabel('Occupation',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')
plt.title('Top 10 Customer Occupation',fontsize = 15,fontweight = 'bold')
plt.show()
```

```
<ipython-input-985-4fce35c26511>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=temp1.index[:10],y=temp1.values[:10],palette='Paired')
```




```
* Customers of occupation of type 4 have ordered most no of orders
```

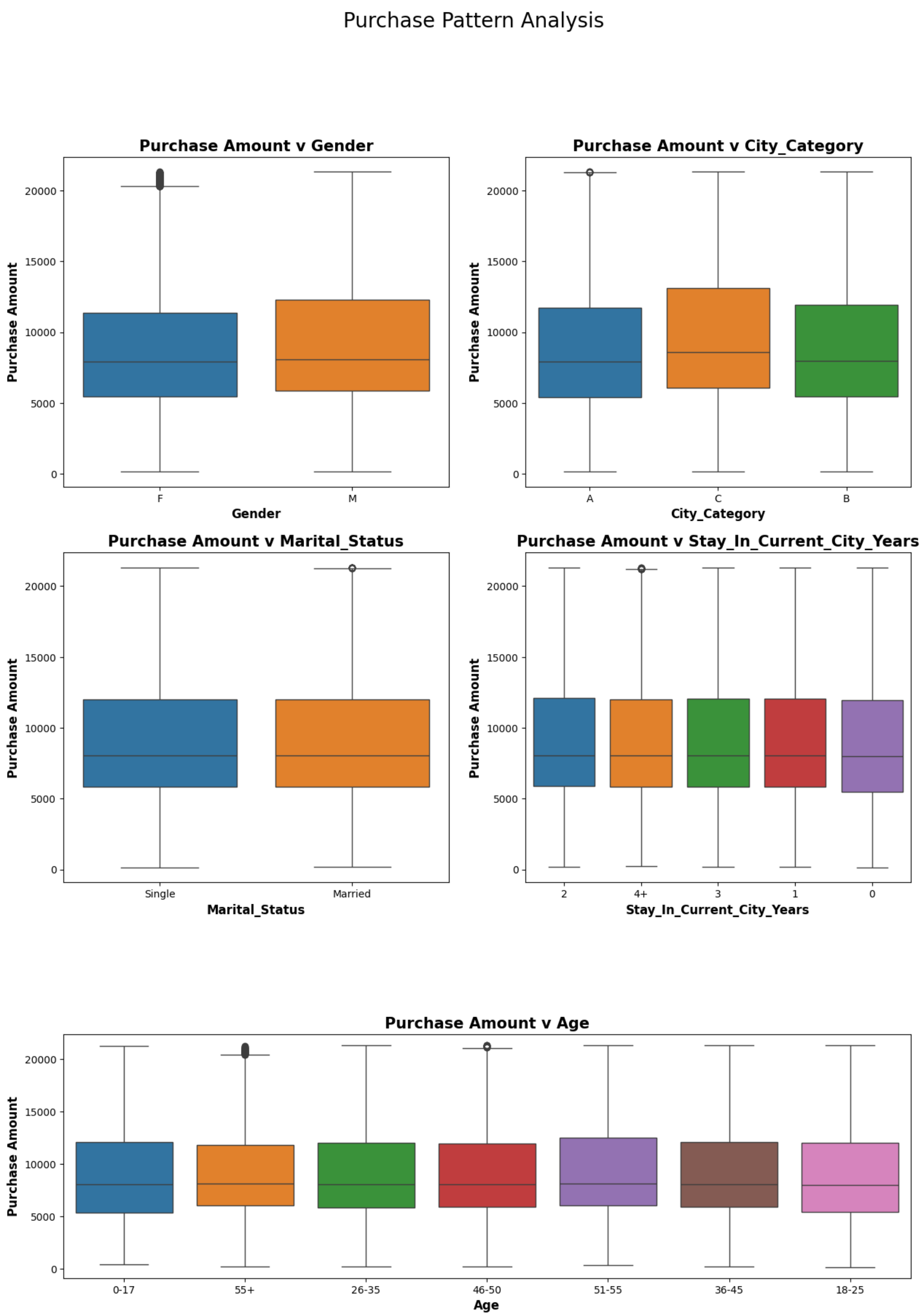
[ ]:
```
#@title 4: Bivariate Analysis:- Purchase Pattern Analysis
```

[ ]:
```
plt.figure(figsize=(15,20)).suptitle("Purchase Pattern Analysis",fontsize=20)



plt.subplot(3,2,1)
sns.boxplot(data=data,x='Gender',y='Purchase',palette="tab10")
plt.xlabel('Gender',fontsize = 12,fontweight = 'bold')
plt.ylabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.title('Purchase Amount v Gender',fontsize = 15,fontweight = 'bold')

plt.subplot(3,2,2)
sns.boxplot(data=data,x='City_Category',y='Purchase',palette="tab10")
plt.xlabel('City_Category',fontsize = 12,fontweight = 'bold')
plt.ylabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.title('Purchase Amount v City_Category',fontsize = 15,fontweight = 'bold')

plt.subplot(3,2,3)
sns.boxplot(data=data,x='Marital_Status',y='Purchase',palette="tab10")
plt.xlabel('Marital_Status',fontsize = 12,fontweight = 'bold')
plt.ylabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
```

```
plt.title('Purchase Amount v Marital_Status',fontsize = 15,fontweight = 'bold')

plt.subplot(3,2,4)
sns.
 ↪boxplot(data=data,x='Stay_In_Current_City_Years',y='Purchase',palette="tab10")
plt.xlabel('Stay_In_Current_City_Years',fontsize = 12,fontweight = 'bold')
plt.ylabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.title('Purchase Amount v Stay_In_Current_City_Years',fontsize =␣
 ↪15,fontweight = 'bold')

plt.subplot(4,1,4)
sns.boxplot(data=data,x='Age',y='Purchase',palette="tab10")
plt.xlabel('Age',fontsize = 12,fontweight = 'bold')
plt.ylabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.title('Purchase Amount v Age',fontsize = 15,fontweight = 'bold')


plt.show()
```

```
<ipython-input-987-8c30eb8f3d06>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=data,x='Gender',y='Purchase',palette="tab10")
<ipython-input-987-8c30eb8f3d06>:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=data,x='City_Category',y='Purchase',palette="tab10")
<ipython-input-987-8c30eb8f3d06>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=data,x='Marital_Status',y='Purchase',palette="tab10")
<ipython-input-987-8c30eb8f3d06>:23: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=data,x='Stay_In_Current_City_Years',y='Purchase',palette="tab
```

```
10")
<ipython-input-987-8c30eb8f3d06>:29: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=data,x='Age',y='Purchase',palette="tab10")
```


Purchase Pattern Analysis
Purchase Amount v Gender
Purchase Amount
20000
15000
10000
5000
0
F
M
Gender
Purchase Amount v City_Category
A
C
B
City_Category
Purchase Amount v Marital_Status
Single
Married
Marital_Status
Purchase Amount v Stay_In_Current_City_Years
2
4+
3
1
0
Stay_In_Current_City_Years
Purchase Amount v Age
0-17
55+
26-35
46-50
51-55
36-45
18-25
Age

- Out of all the variables analysed above, it's noteworthy that the purchase amount remains relatively stable regardless of the variable under consideration. As indicated in the data, the median purchase amount consistently hovers around 8,000 bucks, regardless of the specific variable being examined.

[ ]:
```
#@title 5: 95% Confidence Interval for Gender v Purchase amount
```

[ ]:
```
male_data_purchase=data.loc[data['Gender']=='M','Purchase']
female_data_purchase=data.loc[data['Gender']=='F','Purchase']
```

[ ]:
```
male_data_purchase.describe()
```

[ ]:
```
count    113071.000000
mean       9403.735281
std        4972.467396
min         185.000000
25%        5873.000000
50%        8094.000000
75%       12277.000000
max       21314.000000
Name: Purchase, dtype: float64
```

[ ]:
```
female_data_purchase.describe()
```

[ ]:
```
count    36419.000000
mean      8722.028282
std       4609.771933
min        160.000000
25%       5445.000000
50%       7916.000000
75%      11382.500000
max      21309.000000
Name: Purchase, dtype: float64
```

[ ]:
```
#@title 5.1: Using CLT
```

[ ]:
```
male95_df=pd.
↪DataFrame(columns=['Gender','Lower_limit','Upper_limit','Range','Sample_size','CI','Confide
```

[ ]:
```
alpha=0.05
z_critical=norm.ppf(1-alpha/2)
list1=[300,3000,10000,len(male_data_purchase)]

for i in list1:

    sample1M=male_data_purchase.sample(i)
```

```
    mean2=round(sample1M.mean(),2)
    mstd2=sample1M.std()
    lower_limit2=round(mean2-z_critical*(mstd2/math.sqrt(len(sample1M))),2)
    upper_limit2=round(mean2+z_critical*(mstd2/math.sqrt(len(sample1M))),2)
    range2=round(upper_limit2-lower_limit2,2)


    male_samp1 = pd.DataFrame({'Gender': ['M'],
                        'Lower_limit': [lower_limit2],
                        'Upper_limit': [upper_limit2],
                        'Range': [range2],
                        'Sample_size': [len(sample1M)],
                        'CI': [[lower_limit2,upper_limit2]],
                        'Confidence_pct': [(1-alpha)*100]})

    male95_df = pd.concat([male95_df, male_samp1], ignore_index=True)
```

```
<ipython-input-994-2b1919ee2acd>:24: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  male95_df = pd.concat([male95_df, male_samp1], ignore_index=True)
```

[ ]:
```
male95_df
```

[ ]:
```
  Gender  Lower_limit  Upper_limit    Range Sample_size                   CI  \
0      M      9102.98     10224.68  1121.70         300  [9102.98, 10224.68]
1      M      9203.30      9547.74   344.44        3000     [9203.3, 9547.74]
2      M      9355.25      9552.83   197.58       10000   [9355.25, 9552.83]
3      M      9374.76      9432.72    57.96      113071   [9374.76, 9432.72]

   Confidence_pct
0            95.0
1            95.0
2            95.0
3            95.0
```

[ ]:
```
female95_df=pd.
 ↪DataFrame(columns=['Gender','Lower_limit','Upper_limit','Range','Sample_size','CI','Confide
```

[ ]:
```
alpha=0.05
z_critical=norm.ppf(1-alpha/2)
list1=[300,3000,10000,len(female_data_purchase)]

for i in list1:
```

```
    sample1f=female_data_purchase.sample(i)

    mean2=sample1f.mean()
    mstd2=sample1f.std()
    lower_limit2=round(mean2-z_critical*(mstd2/math.sqrt(len(sample1f))),2)
    upper_limit2=round(mean2+z_critical*(mstd2/math.sqrt(len(sample1f))),2)
    range2=round(upper_limit2-lower_limit2,2)


    female_samp1 = pd.DataFrame({'Gender': ['F'],
                        'Lower_limit': [lower_limit2],
                        'Upper_limit': [upper_limit2],
                        'Range': [range2],
                        'Sample_size': [len(sample1f)],
                        'CI': [[lower_limit2,upper_limit2]],
                        'Confidence_pct': [(1-alpha)*100]})

    female95_df = pd.concat([female95_df, female_samp1], ignore_index=True)
```

```
<ipython-input-997-3ea4a114c68b>:24: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  female95_df = pd.concat([female95_df, female_samp1], ignore_index=True)
```

[ ]:
```
female95_df
```

[ ]:
```
  Gender  Lower_limit  Upper_limit   Range Sample_size                  CI  \
0      F      8079.44      9048.17  968.73         300  [8079.44, 9048.17]
1      F      8615.76      8947.07  331.31        3000  [8615.76, 8947.07]
2      F      8666.74      8848.43  181.69       10000  [8666.74, 8848.43]
3      F      8674.68      8769.37   94.69       36419  [8674.68, 8769.37]

   Confidence_pct
0            95.0
1            95.0
2            95.0
3            95.0
```

[ ]:
```
Gender_df=pd.concat([male95_df,female95_df],ignore_index=True)
```

[ ]:
```
Gender_df.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Gender  Lower_limit  Upper_limit    Range Sample_size                   CI  \
0      M      9102.98     10224.68  1121.70         300  [9102.98, 10224.68]
```

```
1      F      8079.44      9048.17    968.73          300    [8079.44, 9048.17]
2      M      9203.30      9547.74    344.44         3000     [9203.3, 9547.74]
3      F      8615.76      8947.07    331.31         3000    [8615.76, 8947.07]
4      M      9355.25      9552.83    197.58        10000    [9355.25, 9552.83]
5      F      8666.74      8848.43    181.69        10000    [8666.74, 8848.43]
6      F      8674.68      8769.37     94.69        36419    [8674.68, 8769.37]
7      M      9374.76      9432.72     57.96       113071    [9374.76, 9432.72]

   Confidence_pct
0            95.0
1            95.0
2            95.0
3            95.0
4            95.0
5            95.0
6            95.0
7            95.0
```

[ ]:
```python
#@title 5.2: Using bootstrapping
```

[ ]:
```python
male95_bt=pd.
↪DataFrame(columns=['Gender','Lower_limit','Upper_limit','Range','Sample_size','CI','Confide
```

[ ]:
```python
sample_list=[300,3000,30000,len(male_data_purchase)]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(male_data_purchase,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Gender':'M','Lower_limit':lower_limit,'Upper_limit':
↪upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    male95_bt=pd.concat([male95_bt,temp_bt],ignore_index=True)
```

```
<ipython-input-1003-3e8f703596c6>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  male95_bt=pd.concat([male95_bt,temp_bt],ignore_index=True)
```

[ ]:
```
male95_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Gender  Lower_limit  Upper_limit    Range Sample_size                 CI  \
0      M      8849.36      9985.47  1136.11         300  [8849.36, 9985.47]
1      M      9225.42      9582.20   356.78        3000   [9225.42, 9582.2]
2      M      9346.57      9460.58   114.01       30000  [9346.57, 9460.58]
3      M      9373.81      9432.76    58.95      113071  [9373.81, 9432.76]

  Confidence_pct
0             95
1             95
2             95
3             95
```

[ ]:
```
female95_bt=pd.
↪DataFrame(columns=['Gender','Lower_limit','Upper_limit','Range','Sample_size','CI','Confide
```

[ ]:
```
sample_list=[300,3000,30000,len(female_data_purchase)]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.
↪choice(female_data_purchase,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Gender':'F','Lower_limit':lower_limit,'Upper_limit':
↪upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    female95_bt=pd.concat([female95_bt,temp_bt],ignore_index=True)
```

```
<ipython-input-1006-cefe05eef21a>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  female95_bt=pd.concat([female95_bt,temp_bt],ignore_index=True)
```

[ ]:
```
female95_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Gender  Lower_limit  Upper_limit    Range Sample_size                 CI  \
0      F      8198.52      9250.55  1052.03         300  [8198.52, 9250.55]
```

```
1      F      8559.75      8887.03    327.28         3000  [8559.75, 8887.03]
2      F      8669.25      8774.11    104.86        30000  [8669.25, 8774.11]
3      F      8675.35      8769.17     93.82        36419  [8675.35, 8769.17]

  Confidence_pct
0             95
1             95
2             95
3             95
```

[ ]:
```
Gender_final_bt=pd.concat([male95_bt,female95_bt],ignore_index=True)
```

[ ]:
```
Gender_final_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Gender  Lower_limit  Upper_limit    Range Sample_size                  CI  \
0      M      8849.36      9985.47  1136.11         300  [8849.36, 9985.47]
1      F      8198.52      9250.55  1052.03         300  [8198.52, 9250.55]
2      M      9225.42      9582.20   356.78        3000   [9225.42, 9582.2]
3      F      8559.75      8887.03   327.28        3000  [8559.75, 8887.03]
4      M      9346.57      9460.58   114.01       30000  [9346.57, 9460.58]
5      F      8669.25      8774.11   104.86       30000  [8669.25, 8774.11]
6      F      8675.35      8769.17    93.82       36419  [8675.35, 8769.17]
7      M      9373.81      9432.76    58.95      113071  [9373.81, 9432.76]

  Confidence_pct
0             95
1             95
2             95
3             95
4             95
5             95
6             95
7             95
```

###Inference###

1. Sample Size - The analysis highlights the importance of sample size in estimating population parameters. It suggests that `as the sample size increases, the confidence intervals become narrower and more precise`. In business, this implies that larger sample sizes can provide more reliable insights and estimates.

2. Confidence Intervals - From the above analysis, we can see that except for the Sample Size of 300, `the confidence interval do not overlap` as the sample size increases. This means that there is a statistically significant difference between the average spending per transaction for men and women within the given samples.

3. Population Average - We are `95% confident` that the true population average for falls between * Using CLT for male `9374` and `9,432`, and for `females`, it falls between `8,674' and 8,769`. * Using Bootstrapping for male `9373' and '9,432`, and for `females`, it falls between

8,674' and 8,769

4. Women spend less - `Men tend to spend more money per transaction on average than women`, as the upper bounds of the confidence intervals for men are consistently higher than those for women across different sample sizes.

How can Walmart leverage this conclusion to make changes or improvements?

1. Segmentation Opportunities - Walmart can create targeted marketing campaigns, loyalty programs, or product bundles to cater to the distinct spending behaviors of male and female customers. This approach may help maximize revenue from each customer segment.

2. Pricing Strategies - Based on the above data of average spending per transaction by gender, they might adjust pricing or discount strategies to incentivize higher spending among male customers while ensuring competitive pricing for female-oriented products.

[ ]:
```python
#@title 6: 95% Confidence Interval for Marital Status v Purchase amount
```

[ ]:
```python
unmarried_data_purchase=data.loc[data['Marital_Status']=='Single','Purchase'].
  ↪reset_index(drop=True)
married_data_purchase=data.loc[data['Marital_Status']=='Married','Purchase'].
  ↪reset_index(drop=True)
```

[ ]:
```python
unmarried_data_purchase.describe()
```

[ ]:
```
count    88400.000000
mean      9229.317534
std       4907.645716
min        160.000000
25%       5818.000000
50%       8037.000000
75%      12028.000000
max      21309.000000
Name: Purchase, dtype: float64
```

[ ]:
```python
married_data_purchase.describe()
```

[ ]:
```
count    61090.000000
mean      9249.723850
std       4877.461565
min        187.000000
25%       5867.000000
50%       8054.000000
75%      12028.000000
max      21314.000000
Name: Purchase, dtype: float64
```

[ ]:
```python
#@title 6.1: Using CLT
```

[ ]:
```
unmarried_df=pd.
↪DataFrame(columns=['Marital_Status','Lower_limit','Upper_limit','Range','Sample_size','CI',
```

[ ]:
```
alpha=0.05
z_critical=norm.ppf(1-alpha/2)
list1=[300,3000,30000,len(unmarried_data_purchase)]

for i in list1:

    sample1M=unmarried_data_purchase.sample(i)

    mean2=sample1M.mean()
    mstd2=sample1M.std()
    lower_limit2=round(mean2-z_critical*(mstd2/math.sqrt(len(sample1M))),2)
    upper_limit2=round(mean2+z_critical*(mstd2/math.sqrt(len(sample1M))),2)
    range2=round(upper_limit2-lower_limit2,2)


    unmarried_samp1 = pd.DataFrame({'Marital_Status': ['Single'],
                        'Lower_limit': [lower_limit2],
                        'Upper_limit': [upper_limit2],
                        'Range': [range2],
                        'Sample_size': [len(sample1M)],
                        'CI': [[lower_limit2,upper_limit2]],
                        'Confidence_pct': [(1-alpha)*100]})

    unmarried_df = pd.concat([unmarried_df, unmarried_samp1], ignore_index=True)
```

```
<ipython-input-1016-797d36f16c3a>:24: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  unmarried_df = pd.concat([unmarried_df, unmarried_samp1], ignore_index=True)
```

[ ]:
```
unmarried_df
```

[ ]:
```
  Marital_Status  Lower_limit  Upper_limit    Range Sample_size  \
0         Single      9028.78     10161.89  1133.11         300
1         Single      8990.44      9343.93   353.49        3000
2         Single      9147.74      9258.52   110.78       30000
3         Single      9196.97      9261.67    64.70       88400

                  CI  Confidence_pct
0  [9028.78, 10161.89]           95.0
1   [8990.44, 9343.93]           95.0
2   [9147.74, 9258.52]           95.0
```

```
3   [9196.97, 9261.67]           95.0
```

[ ]:
```
married_df=pd.
↪DataFrame(columns=['Marital_Status','Lower_limit','Upper_limit','Range','Sample_size','CI',
```

[ ]:
```
alpha=0.05
z_critical=norm.ppf(1-alpha/2)
list1=[300,3000,30000,len(married_data_purchase)]

for i in list1:

    sample1U=married_data_purchase.sample(i)

    mean2=sample1U.mean()
    mstd2=sample1U.std()
    lower_limit2=round(mean2-z_critical*(mstd2/math.sqrt(len(sample1U))),2)
    upper_limit2=round(mean2+z_critical*(mstd2/math.sqrt(len(sample1U))),2)
    range2=round(upper_limit2-lower_limit2,2)


    married_samp1 = pd.DataFrame({'Marital_Status': ['Married'],
                        'Lower_limit': [lower_limit2],
                        'Upper_limit': [upper_limit2],
                        'Range': [range2],
                        'Sample_size': [len(sample1U)],
                        'CI': [[lower_limit2,upper_limit2]],
                        'Confidence_pct': [(1-alpha)*100]})

    married_df = pd.concat([married_df, married_samp1], ignore_index=True)
```

```
<ipython-input-1019-88afbaff02f3>:24: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  married_df = pd.concat([married_df, married_samp1], ignore_index=True)
```

[ ]:
```
married_df
```

[ ]:
```
  Marital_Status  Lower_limit  Upper_limit    Range Sample_size  \
0        Married      8691.10      9795.28  1104.18         300
1        Married      9005.36      9351.91   346.55        3000
2        Married      9214.48      9325.45   110.97       30000
3        Married      9211.05      9288.40    77.35       61090

                   CI  Confidence_pct
0   [8691.1, 9795.28]            95.0
```

```
1  [9005.36, 9351.91]            95.0
2  [9214.48, 9325.45]            95.0
3   [9211.05, 9288.4]            95.0
```

[ ]:
```
Marital_Status_df=pd.concat([unmarried_df,married_df],ignore_index=True)
```

[ ]:
```
Marital_Status_df.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Marital_Status  Lower_limit  Upper_limit    Range Sample_size  \
0         Single      9028.78     10161.89  1133.11         300
1        Married      8691.10      9795.28  1104.18         300
2         Single      8990.44      9343.93   353.49        3000
3        Married      9005.36      9351.91   346.55        3000
4         Single      9147.74      9258.52   110.78       30000
5        Married      9214.48      9325.45   110.97       30000
6        Married      9211.05      9288.40    77.35       61090
7         Single      9196.97      9261.67    64.70       88400

                   CI  Confidence_pct
0  [9028.78, 10161.89]            95.0
1    [8691.1, 9795.28]            95.0
2   [8990.44, 9343.93]            95.0
3   [9005.36, 9351.91]            95.0
4   [9147.74, 9258.52]            95.0
5   [9214.48, 9325.45]            95.0
6    [9211.05, 9288.4]            95.0
7   [9196.97, 9261.67]            95.0
```

[ ]:
```
#@title 6.2: Using bootstrappig
```

[ ]:
```
Unmarried95_bt=pd.
 ↪DataFrame(columns=['Marital_status','Lower_limit','Upper_limit','Range','Sample_size','CI',
```

[ ]:
```
sample_list=[300,3000,30000,len(unmarried_data_purchase)]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.
 ↪choice(unmarried_data_purchase,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)
```

```
    temp_bt=pd.DataFrame({'Marital_status':'Single','Lower_limit':
↪lower_limit,'Upper_limit':upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    Unmarried95_bt=pd.concat([Unmarried95_bt,temp_bt],ignore_index=True)
```

```
<ipython-input-1025-7bdf52a03aeb>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  Unmarried95_bt=pd.concat([Unmarried95_bt,temp_bt],ignore_index=True)
```

[ ]:
```
Unmarried95_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Marital_status  Lower_limit  Upper_limit    Range  Sample_size  \
0         Single      8667.95      9784.09  1116.14          300
1         Single      9054.06      9408.18   354.12         3000
2         Single      9173.10      9283.08   109.98        30000
3         Single      9196.60      9262.20    65.60        88400

                   CI  Confidence_pct
0  [8667.95, 9784.09]              95
1  [9054.06, 9408.18]              95
2   [9173.1, 9283.08]              95
3    [9196.6, 9262.2]              95
```

[ ]:
```
Married95_bt=pd.
↪DataFrame(columns=['Marital_status','Lower_limit','Upper_limit','Range','Sample_size','CI',
```

[ ]:
```
sample_list=[300,3000,30000,len(married_data_purchase)]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.
↪choice(married_data_purchase,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Marital_status':'Married','Lower_limit':
↪lower_limit,'Upper_limit':upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    Married95_bt=pd.concat([Married95_bt,temp_bt],ignore_index=True)
```

```
<ipython-input-1028-127b9e41b637>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  Married95_bt=pd.concat([Married95_bt,temp_bt],ignore_index=True)
```

[ ]:
```
Married95_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Marital_status  Lower_limit  Upper_limit    Range Sample_size  \
0        Married      8702.47      9804.66  1102.19         300
1        Married      9074.70      9427.71   353.01        3000
2        Married      9194.11      9305.23   111.12       30000
3        Married      9210.47      9288.40    77.93       61090

                  CI Confidence_pct
0  [8702.47, 9804.66]             95
1   [9074.7, 9427.71]             95
2  [9194.11, 9305.23]             95
3   [9210.47, 9288.4]             95
```

[ ]:
```
Marital_final_bt=pd.concat([Unmarried95_bt,Married95_bt],ignore_index=True)
```

[ ]:
```
Marital_final_bt.sort_values(by='Sample_size',ignore_index=True)
```

[ ]:
```
  Marital_status  Lower_limit  Upper_limit    Range Sample_size  \
0         Single      8667.95      9784.09  1116.14         300
1        Married      8702.47      9804.66  1102.19         300
2         Single      9054.06      9408.18   354.12        3000
3        Married      9074.70      9427.71   353.01        3000
4         Single      9173.10      9283.08   109.98       30000
5        Married      9194.11      9305.23   111.12       30000
6        Married      9210.47      9288.40    77.93       61090
7         Single      9196.60      9262.20    65.60       88400

                  CI Confidence_pct
0  [8667.95, 9784.09]             95
1  [8702.47, 9804.66]             95
2  [9054.06, 9408.18]             95
3   [9074.7, 9427.71]             95
4   [9173.1, 9283.08]             95
5  [9194.11, 9305.23]             95
6   [9210.47, 9288.4]             95
7    [9196.6, 9262.2]             95
```

0.3.1 Inference

1. Sample Size - The analysis highlights the importance of sample size in estimating population parameters. It suggests that `as the sample size increases, the confidence intervals become narrower and more precise`. In business, this implies that larger sample sizes can provide more reliable insights and estimates.

2. Confidence Intervals - From the above analysis, we can see that `the confidence interval overlap` for all the sample sizes. This means that there is `no statistically significant difference` between the average spending per transaction for married and unmarried customers within the given samples.

3. Population Average - We are `95% confident` that the true population average for falls between * Using CLT For `Single` between `9196` and `9261`, and for `Married`, it falls between `9211` and `9288` * Using Bootstrapping For `Single` between `9196` and `9262`, and for `Married`, it falls between `9210' and '9288`

4. Both the customers spend equal - The overlapping confidence intervals of average spending for married and unmarried customers indicate that `both married and single customers spend a similar amount per transaction`. This implies a resemblance in spending behavior between the two groups.

How can Walmart leverage this conclusion to make changes or improvements?

1. Marketing Resources - Walmart may not need to allocate marketing resources specifically targeting one group over the other. Instead, they can focus on broader marketing strategies that appeal to both groups.

[ ]:
```
#@title 7: 95% Confidence interval for different age groups v Purchase amount
```

[ ]:
```
data.groupby(['Age']).size().reset_index(name='Count')
```

[ ]:

	Age	Count
0	0-17	4065
1	18-25	27438
2	26-35	59375
3	36-45	30046
4	46-50	12273
5	51-55	10533
6	55+	5760

Here we are gonna use only bootstrapping method as the sizes of a few population are less and bootstrapping can give us more accurate results

[ ]:
```
df_1 = data.loc[data['Age'] == '0-17','Purchase']
    df_2 = data.loc[data['Age'] == '18-25','Purchase']
    df_3 = data.loc[data['Age'] == '26-35','Purchase']
    df_4 = data.loc[data['Age'] == '36-45','Purchase']
    df_5 = data.loc[data['Age'] == '46-50','Purchase']
    df_6 = data.loc[data['Age'] == '51-55','Purchase']
    df_7 = data.loc[data['Age'] == '55+','Purchase']
```

[ ]:
```
age_df1=pd.
↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_1,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'0-17','Lower_limit':lower_limit,'Upper_limit':
↪upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df1=pd.concat([age_df1,temp_bt],ignore_index=True)
```

```
<ipython-input-1036-a75feb17640c>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df1=pd.concat([age_df1,temp_bt],ignore_index=True)
```

[ ]:
```
age_df1
```

[ ]:
```
    Age  Lower_limit  Upper_limit   Range Sample_size                  CI  \
0  0-17      8633.58      9520.80  887.22         500   [8633.58, 9520.8]
1  0-17      8754.11      9380.36  626.25        1000  [8754.11, 9380.36]
2  0-17      8851.29      9296.64  445.35        2000  [8851.29, 9296.64]

  Confidence_pct
0             95
1             95
2             95
```

[ ]:
```
age_df2=pd.
↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
```

```
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_2,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'18-25','Lower_limit':lower_limit,'Upper_limit':
 ↪upper_limit,'Range':range2,'Sample_size':i,'CI':
 ↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df2=pd.concat([age_df2,temp_bt],ignore_index=True)
```

```
<ipython-input-1039-7ed29c48d8c6>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df2=pd.concat([age_df2,temp_bt],ignore_index=True)
```

[ ]:
```
age_df2
```

[ ]:
```
     Age  Lower_limit  Upper_limit   Range Sample_size                    CI  \
0  18-25      8697.09      9563.21  866.12         500  [8697.09, 9563.21]
1  18-25      8827.18      9429.23  602.05        1000  [8827.18, 9429.23]
2  18-25      8914.94      9343.34  428.40        2000  [8914.94, 9343.34]

  Confidence_pct
0             95
1             95
2             95
```

[ ]:
```
age_df3=pd.
 ↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_3,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
```

```
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'26-35','Lower_limit':lower_limit,'Upper_limit':
  ↪upper_limit,'Range':range2,'Sample_size':i,'CI':
  ↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df3=pd.concat([age_df3,temp_bt],ignore_index=True)
```

```
<ipython-input-1042-900ee932bf39>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df3=pd.concat([age_df3,temp_bt],ignore_index=True)
```

[ ]:
```
age_df3
```

[ ]:
```
     Age  Lower_limit  Upper_limit   Range Sample_size                  CI  \
0  26-35      8808.40      9666.07  857.67         500   [8808.4, 9666.07]
1  26-35      8937.47      9543.86  606.39        1000  [8937.47, 9543.86]
2  26-35      9023.04      9449.00  425.96        2000   [9023.04, 9449.0]

  Confidence_pct
0             95
1             95
2             95
```

[ ]:
```
age_df4=pd.
  ↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_4,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'36-45','Lower_limit':lower_limit,'Upper_limit':
  ↪upper_limit,'Range':range2,'Sample_size':i,'CI':
  ↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df4=pd.concat([age_df4,temp_bt],ignore_index=True)
```

```
<ipython-input-1045-f341ae1d5ddc>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df4=pd.concat([age_df4,temp_bt],ignore_index=True)
```

[ ]:
```
age_df4
```

[ ]:
```
     Age  Lower_limit  Upper_limit   Range Sample_size                   CI  \
0  36-45      8868.86      9731.36  862.50         500  [8868.86, 9731.36]
1  36-45      8982.90      9593.69  610.79        1000   [8982.9, 9593.69]
2  36-45      9074.07      9501.08  427.01        2000  [9074.07, 9501.08]

  Confidence_pct
0             95
1             95
2             95
```

[ ]:
```
age_df5=pd.
 ↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_5,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'46-50','Lower_limit':lower_limit,'Upper_limit':
 ↪upper_limit,'Range':range2,'Sample_size':i,'CI':
 ↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df5=pd.concat([age_df5,temp_bt],ignore_index=True)
```

```
<ipython-input-1048-60d411bbe4e8>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df5=pd.concat([age_df5,temp_bt],ignore_index=True)
```

[ ]:
```
age_df5
```

[ ]:
```
     Age  Lower_limit  Upper_limit   Range Sample_size                  CI  \
0  46-50      8757.90      9600.61  842.71         500   [8757.9, 9600.61]
1  46-50      8876.31      9473.75  597.44        1000  [8876.31, 9473.75]
2  46-50      8969.71      9386.22  416.51        2000  [8969.71, 9386.22]

  Confidence_pct
0             95
1             95
2             95
```

[ ]:
```
age_df6=pd.
↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_6,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'51-55','Lower_limit':lower_limit,'Upper_limit':
↪upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df6=pd.concat([age_df6,temp_bt],ignore_index=True)
```

```
<ipython-input-1051-4d9604f14c01>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df6=pd.concat([age_df6,temp_bt],ignore_index=True)
```

[ ]:
```
age_df6
```

[ ]:
```
     Age  Lower_limit  Upper_limit   Range Sample_size                  CI  \
0  51-55      9082.82      9951.85  869.03         500  [9082.82, 9951.85]
1  51-55      9200.03      9824.07  624.04        1000  [9200.03, 9824.07]
2  51-55      9298.80      9726.66  427.86        2000   [9298.8, 9726.66]
```

```
   Confidence_pct
0              95
1              95
2              95
```

[ ]:
```
age_df7=pd.
↪DataFrame(columns=['Age','Lower_limit','Upper_limit','Range','Sample_size','CI','Confidence
```

[ ]:
```
sample_list=[500,1000,2000]
samples_taken={}
for i in sample_list:
    sample_means=[]
    for j in np.arange(10000):
        bootstrapped_samples=np.random.choice(df_7,i,replace=True)
        sample_means.append(bootstrapped_samples.mean())

    samples_taken[i]=sample_means
    lower_limit=round(np.percentile(sample_means,2.5),2)
    upper_limit=round(np.percentile(sample_means,97.5),2)
    range2=round(upper_limit-lower_limit,2)

    temp_bt=pd.DataFrame({'Age':'55+','Lower_limit':lower_limit,'Upper_limit':
↪upper_limit,'Range':range2,'Sample_size':i,'CI':
↪[[lower_limit,upper_limit]],'Confidence_pct':[95]})
    age_df7=pd.concat([age_df7,temp_bt],ignore_index=True)
```

```
<ipython-input-1054-ce74b51fbeb2>:15: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  age_df7=pd.concat([age_df7,temp_bt],ignore_index=True)
```

[ ]:
```
age_df7
```

[ ]:
```
   Age  Lower_limit  Upper_limit   Range Sample_size                    CI  \
0  55+      8826.05      9658.24  832.19         500  [8826.05, 9658.24]
1  55+      8943.37      9528.84  585.47        1000  [8943.37, 9528.84]
2  55+      9033.91      9445.71  411.80        2000  [9033.91, 9445.71]

   Confidence_pct
0              95
1              95
2              95
```

[ ]:
```
final_age_df=pd.
↪concat([age_df1,age_df2,age_df3,age_df4,age_df5,age_df6,age_df7],ignore_index=True)
```

```
[ ]: final_age_df=final_age_df[['Age','CI','Range','Sample_size']]
```

```
[ ]: final_age_df
```

```
[ ]:      Age                 CI   Range Sample_size
     0     0-17   [8633.58, 9520.8]  887.22         500
     1     0-17  [8754.11, 9380.36]  626.25        1000
     2     0-17  [8851.29, 9296.64]  445.35        2000
     3    18-25  [8697.09, 9563.21]  866.12         500
     4    18-25  [8827.18, 9429.23]  602.05        1000
     5    18-25  [8914.94, 9343.34]  428.40        2000
     6    26-35   [8808.4, 9666.07]  857.67         500
     7    26-35  [8937.47, 9543.86]  606.39        1000
     8    26-35   [9023.04, 9449.0]  425.96        2000
     9    36-45  [8868.86, 9731.36]  862.50         500
     10   36-45   [8982.9, 9593.69]  610.79        1000
     11   36-45  [9074.07, 9501.08]  427.01        2000
     12   46-50   [8757.9, 9600.61]  842.71         500
     13   46-50  [8876.31, 9473.75]  597.44        1000
     14   46-50  [8969.71, 9386.22]  416.51        2000
     15   51-55  [9082.82, 9951.85]  869.03         500
     16   51-55  [9200.03, 9824.07]  624.04        1000
     17   51-55   [9298.8, 9726.66]  427.86        2000
     18     55+  [8826.05, 9658.24]  832.19         500
     19     55+  [8943.37, 9528.84]  585.47        1000
     20     55+  [9033.91, 9445.71]  411.80        2000
```

```
[ ]: final_age_df.pivot(index='Age',columns='Sample_size',values=['CI','Range'])
```

```
[ ]:                                 CI                                        \
     Sample_size                500                 1000                2000
     Age
     0-17            [8633.58, 9520.8]  [8754.11, 9380.36]  [8851.29, 9296.64]
     18-25          [8697.09, 9563.21]  [8827.18, 9429.23]  [8914.94, 9343.34]
     26-35           [8808.4, 9666.07]  [8937.47, 9543.86]   [9023.04, 9449.0]
     36-45          [8868.86, 9731.36]   [8982.9, 9593.69]  [9074.07, 9501.08]
     46-50           [8757.9, 9600.61]  [8876.31, 9473.75]  [8969.71, 9386.22]
     51-55          [9082.82, 9951.85]  [9200.03, 9824.07]   [9298.8, 9726.66]
     55+            [8826.05, 9658.24]  [8943.37, 9528.84]  [9033.91, 9445.71]

                     Range
     Sample_size      500     1000    2000
     Age
     0-17           887.22  626.25  445.35
     18-25          866.12  602.05   428.4
     26-35          857.67  606.39  425.96
     36-45           862.5  610.79  427.01
```

```
46-50         842.71  597.44  416.51
51-55         869.03  624.04  427.86
55+           832.19  585.47   411.8
```

0.3.2 Inference

1. Sample Size - The analysis highlights the importance of sample size in estimating population parameters. It suggests that `as the sample size increases, the confidence intervals become narrower and more precise`. In business, this implies that larger sample sizes can provide more reliable insights and estimates.

2. Confidence Intervals and customer spending patterns - From the above analysis, we can see that `the confidence interval overlap` for some of the age groups. We can club the average spending into following age groups - - 0 - 17 - Customers in this age group have the lowest spending per transaction - 18 - 25, 26 - 35, 46 - 50 - Customers in these age groups have overlapping confidence intervals indicating similar buying characteristics - 36 - 45, 55+ - Customers in these age groups have overlapping confidence intervals indicating and similar spending patterns - 51 - 55 - Customers in this age group have the highest spending per transaction

3. Population Average - We are `95% confident` that for 2000 samples average for following age groups falls between the below range -

```
- 0 - 17  = (8851-9296)
- 18 - 25 = (8914-9343)
- 26 - 35 = (9023-9449)
- 36 - 45 = (9074-9501)
- 46 - 50 = (8969-9386)
- 51 - 55 = (9298-9726)
- 55+     = (9033-9445)
```

How can Walmart leverage this conclusion to make changes or improvements?

1. Targeted Marketing - Knowing that customers in the 0 - 17 age group have the lowest spending per transaction, Walmart can try to increase their spending per transaction by offering them more attractive discounts, coupons, or rewards programs. Walmart can also tailor their product selection and marketing strategies to appeal to the preferences and needs of this age group

2. Customer Segmentation - Since customers in the 18 - 25, 26 - 35, and 46 - 50 age groups exhibit similar buying characteristics, and so do the customers in 36 - 45 and 55+, Walmart can optimize its product selection to cater to the preferences of these age groups. Also, Walmart can use this information to adjust their pricing strategies for different age groups.

3. Premium Services - Recognizing that customers in the 51 - 55 age group have the highest spending per transaction, Walmart can explore opportunities to enhance the shopping experience for this demographic. This might involve offering premium services, personalized recommendations, or loyalty programs that cater to the preferences and spending habits of this age group.

0.3.3 Recommendations

1.Target Male Shoppers - Since male customers account for a significant portion of Black Friday sales and tend to spend more per transaction on average, Walmart should tailor its marketing strategies and product offerings to incentivize higher spending among male customers while ensuring competitive pricing for female-oriented products.

2. Focus on 26 - 45 Age Group - With the age group between 26 and 45 contributing to the majority of sales, Walmart should specifically cater to the preferences and needs of this demographic.This could include offering exclusive deals on products that are popular among this age group.

3. Engaging Younger Shoppers - Knowing that customers in the 0 - 17 age group have the lowest spending per transaction, Walmart can try to increase their spending per transaction by offering them more attractive discounts, coupons, or rewards programs. It's essential to start building brand loyalty among younger consumers.

4. Customer Segmentation - Since customers in the 18 - 25, 26 - 35, and 46 - 50 age groups exhibit similar buying characteristics, and so do the customers in 36 - 45 and 55+, Walmart can optimize its product selection to cater to the preferences of these age groups. Also, Walmart can use this information to adjust their pricing strategies for different age groups.

5. Enhance the 51 - 55 Age Group Shopping Experience - Considering that customers aged 51 - 55 have the highest spending per transaction, Walmart offer them exclusive pre-sale access, special discount or provide personalized product recommendations for this age group. Walmart can also introduce loyalty programs specifically designed to reward and retain customers in the 51 - 55 age group.