Business Case: Walmart - Confidence Interval and CLT

What is Walmart?

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

Objective

The objective is to analyze the customer purchase behavior (specifically, purchase amount) against the customer’s gender and the various other factors to help the business make better decisions and 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).

About Data

The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday.It has information of about 0.5 Million transactions during Black Friday throughout various years.

Exploratory Data Analysis

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

In [ ]:
```
!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/origina
```

```
Downloading...
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/origina
l/walmart_data.csv?1641285094
To: /content/walmart_data.csv?1641285094
100% 23.0M/23.0M [00:00<00:00, 151MB/s]
```

In [ ]:
```
walmart = pd.read_csv("walmart_data.csv?1641285094")
```

In [ ]:
```
walmart.head(10)
```

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_
0	1000001	P00069042	F	0-17	10	A	2	
1	1000001	P00248942	F	0-17	10	A	2	
2	1000001	P00087842	F	0-17	10	A	2	
3	1000001	P00085442	F	0-17	10	A	2	
4	1000002	P00285442	M	55+	16	C	4+	
5	1000003	P00193542	M	26-35	15	A	3	
6	1000004	P00184942	M	46-50	7	B	2	
7	1000004	P00346142	M	46-50	7	B	2	
8	1000004	P0097242	M	46-50	7	B	2	
9	1000005	P00274942	M	26-35	20	A	1	

In [ ]:

```
walmart.shape
```

Out[ ]:

```
(550068, 10)
```

In [ ]:

```
walmart.info()
```

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

In [ ]:

```
## Changing the Data Type of the columns to Category
for column in walmart.columns[:-1]:
  walmart[column] =  walmart[column].astype("category")
walmart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype   
---  ------                      --------------   -----   
 0   User_ID                     550068 non-null  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64   
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

In [ ]:
```
## Replacing Marital Status to Unmarried and Married
walmart['Marital_Status'] = walmart['Marital_Status'].replace({0:'Unmarried',1:'Marri
```

In [ ]:
```
## Replacing Product Category names
d1 = {}
for i in walmart["Product_Category"].value_counts().index:
  d1[i] = f"Product {i}"
walmart['Product_Category'] = walmart['Product_Category'].replace(d1)
```

In [ ]:
```
## Replacing Occupation Category names
d2 = {}
for i in walmart["Occupation"].value_counts().index:
  d2[i] = f"Occupation {i}"
walmart['Occupation'] = walmart['Occupation'].replace(d2)
```

In [ ]:
```
walmart.isna().sum()
```

Out[ ]:
```
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
```

Statstical Analysis

In [ ]:
```
walmart.describe(include = "category")
```

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
count	550068	550068	550068	550068	550068	550068	550068
unique	5891	3631	2	7	21	3	5
top	1001680	P00265242	M	26-35	Occupation 4	B	1
freq	1026	1880	414259	219587	72308	231173	193821

Insights

1. User_ID - Among 5,50,068 transactions there are 5891 unique user_id, indicating same customers buying multiple products.

2. Product_ID - Among 5,50,068 transactions there are 3631 unique products,with the product having the code P00265242 being the highest seller, with a maximum of 1,880 units sold.

3. Gender - Out of 5,50,068 transactions, 4,14,259 (nearly 75%) were done by male gender indicating a significant disparity in purchase behavior between males and females during the Black Friday event.

4. Age - We have 7 unique age groups in the dataset. 26 - 35 Age group has maximum of 2,19,587 transactions. We will analyse this feature in detail in future

5. Stay_In_Current_City_Years - Customers with 1 year of stay in current city accounted to maximum of 1,93,821 transactions among all the other customers with (0,2,3,4+) years of stay in current city

6. Marital_Status - 59% of the total transactions were done by Unmarried Customers and 41% by Married Customers.

In [ ]:
```
walmart.describe()
```

Out[ ]:

	Purchase
count	550068.000000
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000
max	23961.000000

Insights

`The purchase amounts` vary widely, with the minimum recorded purchase being `$12` and the maximum reaching `$23961`. The `median` purchase amount of `$8047` is notably lower than the `mean` purchase amount of `$9264`, indicating a `right-skewed distribution` where a few high-value purchases pull up the mean italicized text

In [ ]:
```
walmart.duplicated().sum()
```

Out[ ]:
```
0
```

Insights

There are no duplicate entries in the dataset

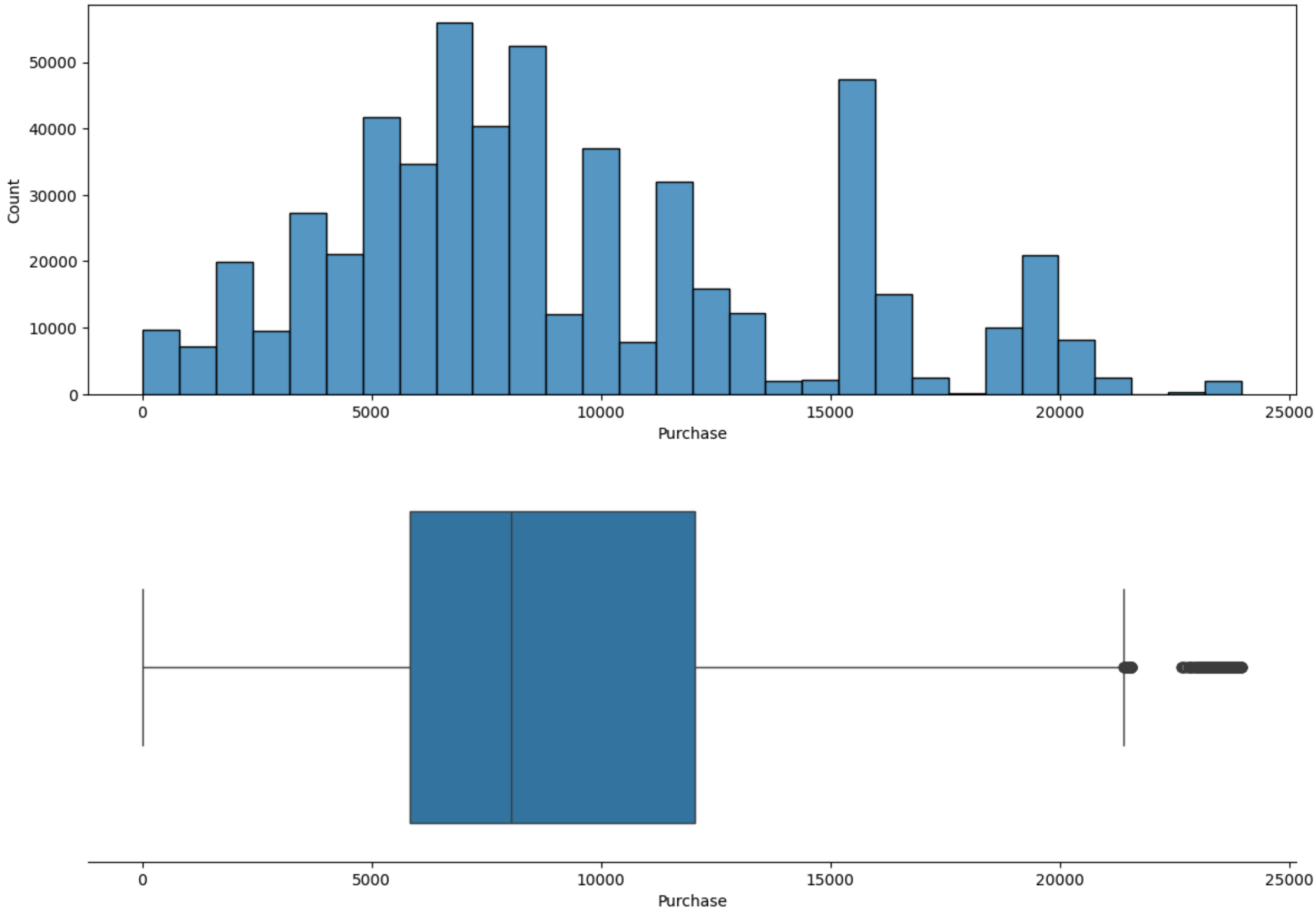
In [ ]:
```
for columns in walmart.columns[:-1]:
  print(f"Unique values in {columns} column")
  print((walmart[columns].unique()))
  print("*"*150)
```

```
Unique values in User_ID column
[1000001, 1000002, 1000003, 1000004, 1000005, ..., 1004588, 1004871, 1004113, 100539
1, 1001529]
Length: 5891
Categories (5891, int64): [1000001, 1000002, 1000003, 1000004, ..., 1006037, 1006038,
1006039, 1006040]
*************************************************************************************
*****************************************************************
Unique values in Product_ID column
['P00069042', 'P00248942', 'P00087842', 'P00085442', 'P00285442', ..., 'P00375436',
'P00372445', 'P00370293', 'P00371644', 'P00370853']
Length: 3631
Categories (3631, object): ['P00000142', 'P00000242', 'P00000342', 'P00000442', ...,
'P0099642',
                            'P0099742', 'P0099842', 'P0099942']
*************************************************************************************
*****************************************************************
Unique values in Gender column
['F', 'M']
Categories (2, object): ['F', 'M']
*************************************************************************************
*****************************************************************
Unique values in Age column
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
*************************************************************************************
*****************************************************************
Unique values in Occupation column
['Occupation 10', 'Occupation 16', 'Occupation 15', 'Occupation 7', 'Occupation 20',
..., 'Occupation 18', 'Occupation 5', 'Occupation 14', 'Occupation 13', 'Occupation
6']
Length: 21
Categories (21, object): ['Occupation 0', 'Occupation 1', 'Occupation 2', 'Occupation
3', ...,
                          'Occupation 17', 'Occupation 18', 'Occupation 19', 'Occupat
ion 20']
*************************************************************************************
*****************************************************************
Unique values in City_Category column
['A', 'C', 'B']
Categories (3, object): ['A', 'B', 'C']
*************************************************************************************
*****************************************************************
Unique values in Stay_In_Current_City_Years column
['2', '4+', '3', '1', '0']
Categories (5, object): ['0', '1', '2', '3', '4+']
*************************************************************************************
*****************************************************************
Unique values in Marital_Status column
['Unmarried', 'Married']
Categories (2, object): ['Unmarried', 'Married']
*************************************************************************************
*****************************************************************
Unique values in Product_Category column
['Product 3', 'Product 1', 'Product 12', 'Product 8', 'Product 5', ..., 'Product 10',
'Product 17', 'Product 9', 'Product 20', 'Product 19']
Length: 20
Categories (20, object): ['Product 1', 'Product 2', 'Product 3', 'Product 4', ..., 'P
roduct 17',
                          'Product 18', 'Product 19', 'Product 20']
*************************************************************************************
*****************************************************************
```

Univariate Analysis

In [ ]:
```
##Purchase amount Distribution
fig, ax = plt.subplots(nrows=2, ncols = 1, figsize=(14, 10))
sns.histplot(data = walmart, x = "Purchase", bins = 30, ax = ax[0])
sns.boxplot(x = walmart["Purchase"], vert = False, patch_artist=True,ax = ax[1])
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)
ax[1].set_yticks([])
```

Out[ ]:
```
[]
```



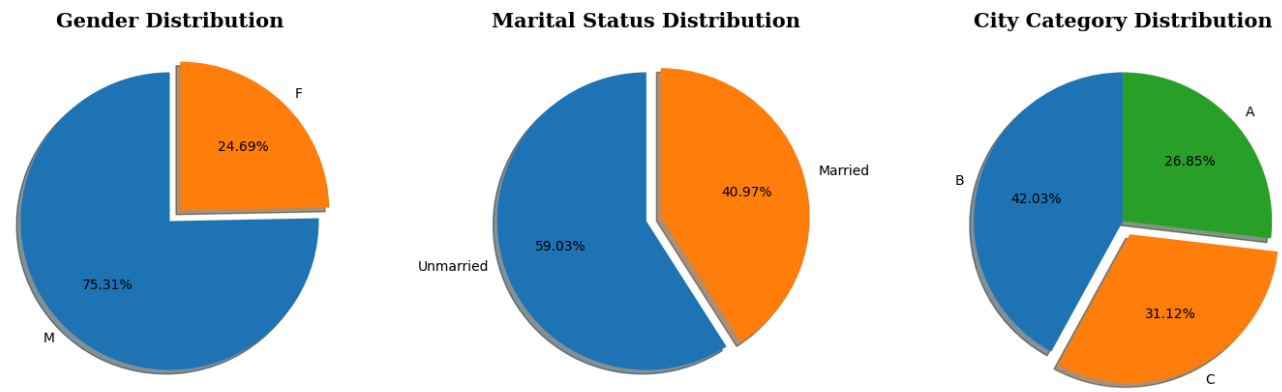
Distribution

Data suggests that the majority of customers spent between `5,823 USD` and `12,054 USD`, with the `median` purchase amount being `8,047 USD`.

The lower limit of `12 USD` while the upper limit of `21,399 USD` reveal significant variability in customer spending

In [ ]:
```
fig, ax = plt.subplots(nrows=1, ncols = 3, figsize=(18, 5))
values_0 = walmart["Gender"].value_counts()
labels_0 = walmart["Gender"].value_counts().index
ax[0].pie(values_0, labels = labels_0, autopct = "%2.2f%%", shadow=True, startangle=9
ax[0].set_title('Gender Distribution',{'font':'serif', 'size':15,'weight':'bold'})

values_1 = walmart["Marital_Status"].value_counts()
labels_1 = walmart["Marital_Status"].value_counts().index
ax[1].pie(values_1, labels = labels_1, autopct = "%2.2f%%", shadow=True, startangle=9
ax[1].set_title('Marital Status Distribution',{'font':'serif', 'size':15,'weight':'bo

values_2 = walmart["City_Category"].value_counts()
labels_2 = walmart["City_Category"].value_counts().index
ax[2].pie(values_2, labels = labels_2, autopct = "%2.2f%%", shadow=True, startangle=9
ax[2].set_title('City Category Distribution',{'font':'serif', 'size':15,'weight':'bol
```

```
plt.show()
```



Insights

Gender Distribution** - Data indicates a significant disparity in purchase behavior between males and females during the Black Friday event.

Marital Status** - Given that unmarried customers account for a higher percentage of transactions, it may be worthwhile to consider specific marketing campaigns or promotions that appeal to this group.

City Category** - City B saw the most number of transactions followed by City C and City A respectively

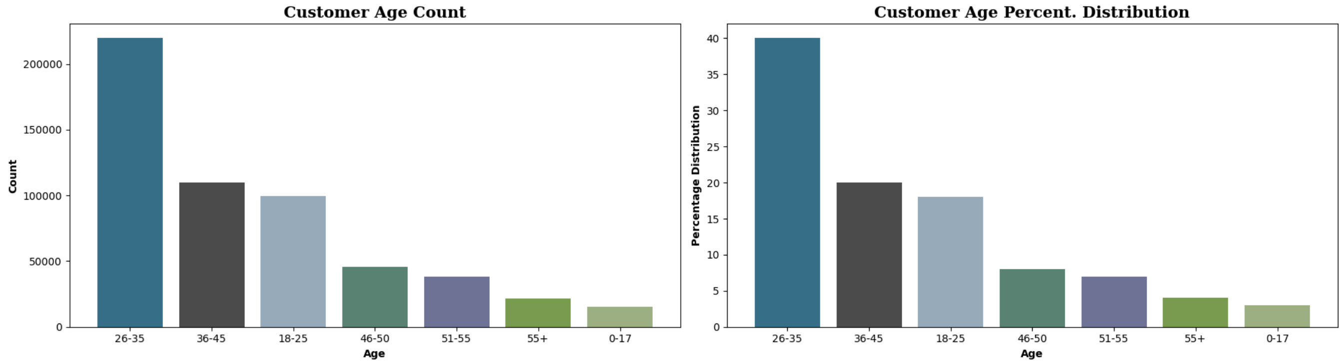
In [ ]:
```
walmart.head()
```

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_!
0	1000001	P00069042	F	0-17	Occupation 10	A	2	Unn
1	1000001	P00248942	F	0-17	Occupation 10	A	2	Unn
2	1000001	P00087842	F	0-17	Occupation 10	A	2	Unn
3	1000001	P00085442	F	0-17	Occupation 10	A	2	Unn
4	1000002	P00285442	M	55+	Occupation 16	C	4+	Unn

In [ ]:
```
fig, ax = plt.subplots(nrows=1, ncols = 2, figsize=(18, 5))

value = walmart["Age"].value_counts()
index = walmart["Age"].value_counts().index
ax[0].bar(index, value, color = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','
ax[0].set_title("Customer Age Count",{'font':'serif', 'size':15,'weight':'bold'})
ax[0].set_ylabel("Count", fontweight = "bold")
ax[0].set_xlabel("Age", fontweight = "bold")

age_info = []
for i in range(0,len(value)):
  x = [index[i], round((value[i]/value.sum())*100)]
  age_info.append(x)
age_info_df = pd.DataFrame(age_info)
ax[1].bar(age_info_df[0], age_info_df[1], color = ["#3A7089", "#4b4b4c",'#99AEBB','#5
ax[1].set_title('Customer Age Percent. Distribution',{'font':'serif', 'size':15,'weig
```

```
ax[1].set_ylabel("Percentage Distribution", fontweight = "bold")
ax[1].set_xlabel("Age", fontweight = "bold")

fig.tight_layout()
```



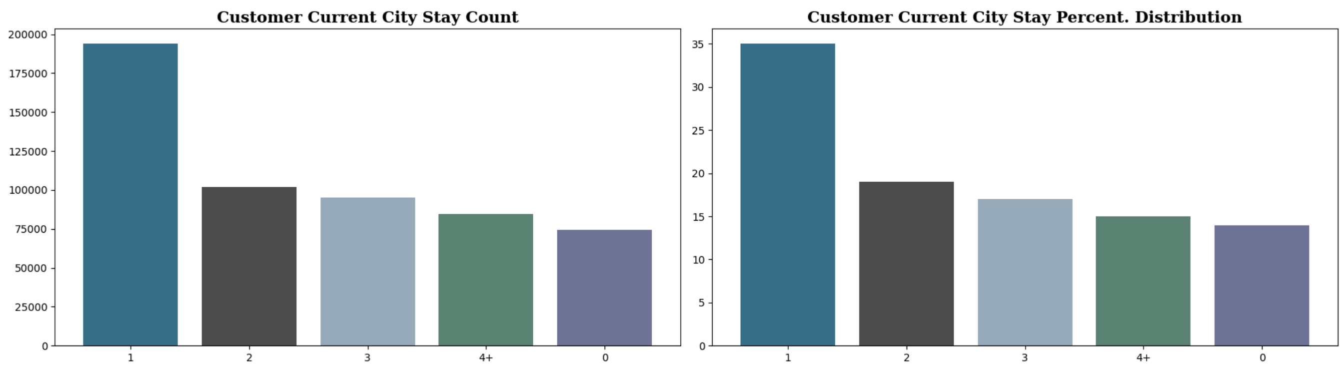
Insights

The age group of 26-35 represents the largest share of Walmart's Black Friday sales, accounting for 40% of the sales. This suggests that the young and middle-aged adults are the most active and interested in shopping for deals and discounts.

The 36-45 and 18-25 age groups are the second and third largest segments, respectively, with 20% and 18% of the sales. This indicates that Walmart has a diverse customer base that covers different life stages and preferences.

The 46-50, 51-55, 55+, and 0-17 age groups are the smallest customer segments, with less than 10% of the total sales each. This implies that Walmart may need to improve its marketing strategies and product offerings to attract more customers from these age groups, especially the seniors and the children.

In [ ]:
```
fig, ax = plt.subplots(nrows=1, ncols = 2, figsize=(18, 5))

value_1 = walmart["Stay_In_Current_City_Years"].value_counts()
index_1 = walmart["Stay_In_Current_City_Years"].value_counts().index
ax[0].bar(index_1, value_1, color = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F759
ax[0].set_title('Customer Current City Stay Count',{'font':'serif', 'size':15,'weight


city_info = []
for i in range(0,len(value_1)):
  x = [index_1[i], round((value_1[i]/value_1.sum())*100)]
  city_info.append(x)
city_info_df = pd.DataFrame(city_info)
ax[1].bar(city_info_df[0], city_info_df[1], color = ["#3A7089", "#4b4b4c",'#99AEBB','
ax[1].set_title('Customer Current City Stay Percent. Distribution',{'font':'serif', '

fig.tight_layout()
```



Insights

The data suggests that the customers are either new to the city or move frequently, and may have different preferences and needs than long-term residents.

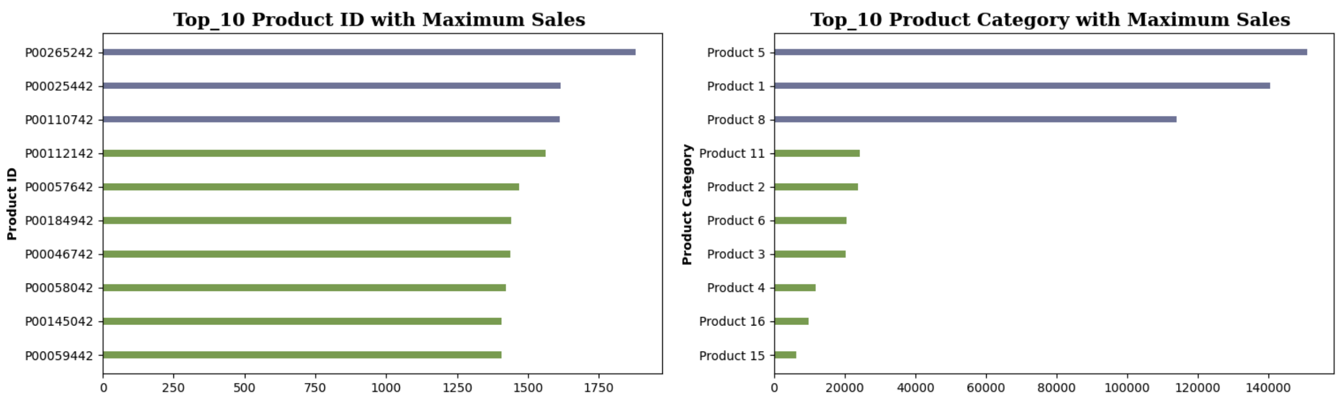
The majority of the customers (49%) have stayed in the current city for one year or less. This suggests that Walmart has a strong appeal to newcomers who may be looking for affordable and convenient shopping options.

4+ years category (14%) customers indicates that Walmart has a loyal customer base who have been living in the same city for a long time.

The percentage of customers decreases as the stay in the current city increases which suggests that Walmart may benefit from targeting long-term residents for loyalty programs and promotions.

In [ ]:
```
fig, ax = plt.subplots(nrows=1, ncols = 2, figsize=(18, 5))

top_10_productID = walmart["Product_ID"].value_counts()[9::-1].reset_index()
ax[0].barh(top_10_productID["index"], top_10_productID["Product_ID"], color = ['#7A9D
ax[0].set_title('Top_10 Product ID with Maximum Sales ',{'font':'serif', 'size':15,'w
ax[0].set_ylabel("Product ID", fontweight = "bold")

top_10_Product_Category = walmart["Product_Category"].value_counts()[9::-1].reset_ind
ax[1].barh(top_10_Product_Category["index"], top_10_Product_Category["Product_Categor
ax[1].set_title('Top_10 Product Category with Maximum Sales ',{'font':'serif', 'size'
ax[1].set_ylabel("Product Category", fontweight = "bold")
```

Out[ ]:
```
Text(0, 0.5, 'Product Category')
```



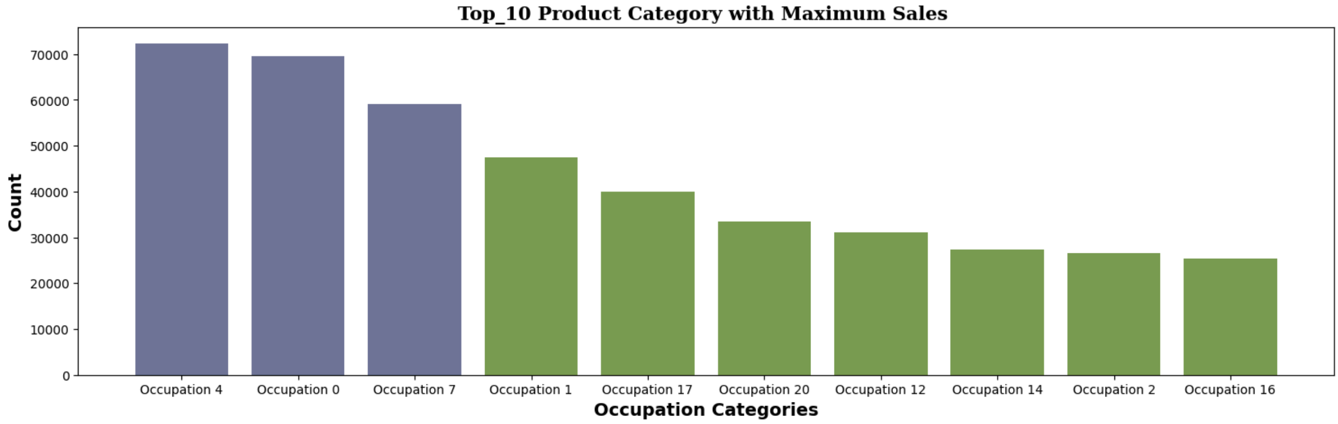
Insights

Top 10 Products Sold - The top-selling products during Walmart's Black Friday sales are characterized by a relatively small variation in sales numbers, suggesting that Walmart offers a variety of products that many different customers like to buy.

Top 10 Product Categories - Categories 5,1 and 8 have significantly outperformed other categories with combined Sales of nearly 75% of the total sales suggesting a strong preference for these products among customers.

In [ ]:
```
fig, ax = plt.subplots(nrows=1, ncols = 1, figsize=(18, 5))

top_10_Customers_Occupation = walmart["Occupation"].value_counts()[0:10].reset_index(
plt.bar(top_10_Customers_Occupation["index"], top_10_Customers_Occupation["Occupation
ax.set_title('Top_10 Product Category with Maximum Sales ',{'font':'serif', 'size':15
plt.xlabel("Occupation Categories",fontweight='bold', fontsize=14)
plt.ylabel("Count",fontweight='bold',fontsize=14)
```

Out[ ]: Text(0, 0.5, 'Count')



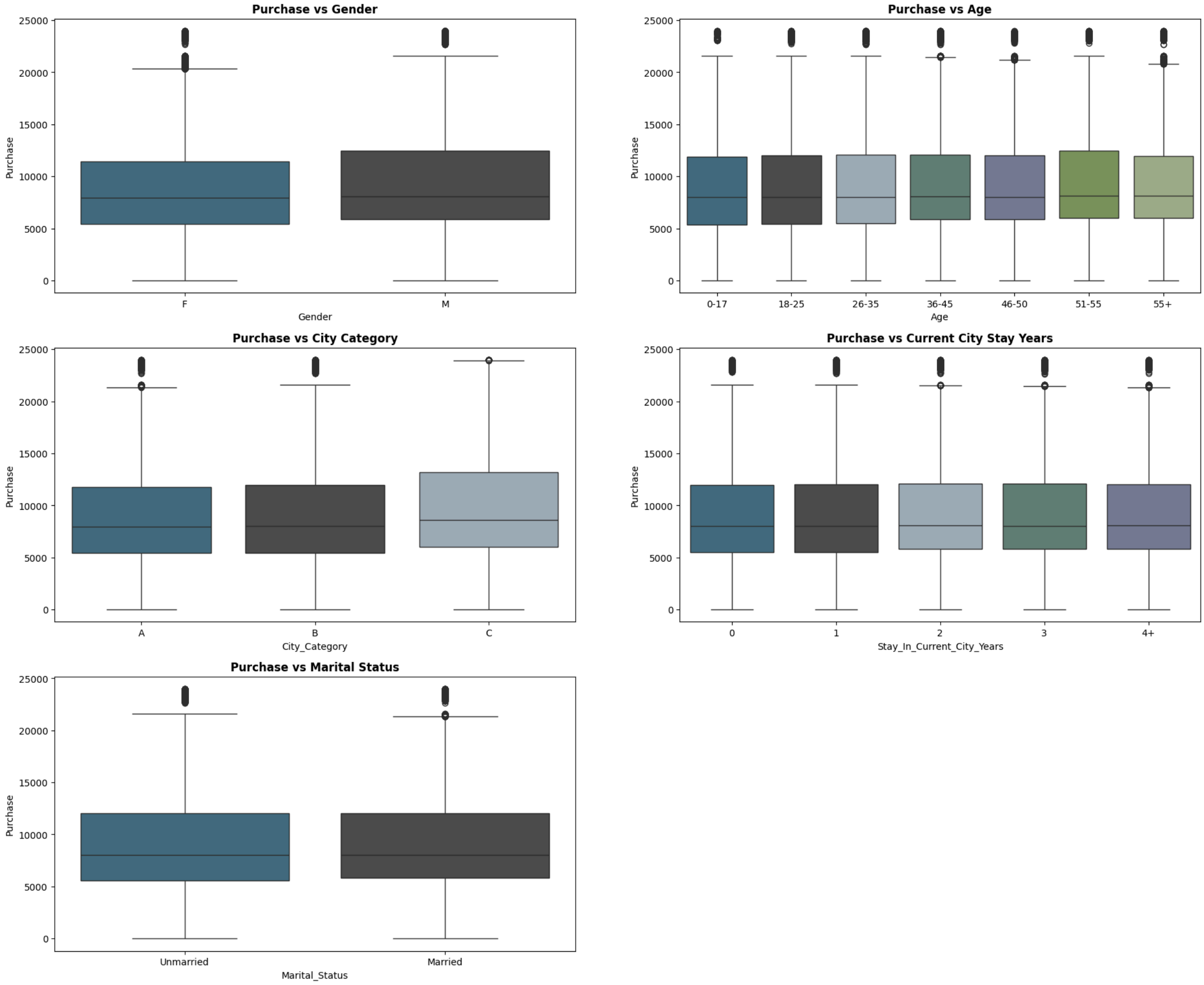
Insights

Customers with Occupation category 4,0 and 7 contributed significantly i.e. almost 37% of the total purchases suggesting that these occupations have a high demand for Walmart products or services, or that they have more disposable income to spend on Black Friday.

In [ ]:

```
plt.figure(figsize = (22,18))
plt.subplot(3,2,1)
sns.boxplot(data = walmart, x = "Gender", y = "Purchase", palette = ["#3A7089", "#4b4
plt.title("Purchase vs Gender", fontweight = "bold")
plt.subplot(3,2,2)
sns.boxplot(data = walmart, x = "Age", y = "Purchase", palette = ["#3A7089", "#4b4b4c
plt.title("Purchase vs Age", fontweight = "bold")
plt.subplot(3,2,3)
sns.boxplot(data = walmart, x = "City_Category", y = "Purchase", palette = ["#3A7089"
plt.title("Purchase vs City Category", fontweight = "bold")
plt.subplot(3,2,4)
sns.boxplot(data = walmart, x = "Stay_In_Current_City_Years", y = "Purchase", palette
plt.title("Purchase vs Current City Stay Years", fontweight = "bold")
plt.subplot(3,2,5)
sns.boxplot(data = walmart, x = "Marital_Status", y = "Purchase", palette = ["#3A7089
plt.title("Purchase vs Marital Status", fontweight = "bold")
plt.subplots_adjust()

plt.show()
```

```
<ipython-input-23-692e3c9d6433>: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.boxplot(data = walmart, x = "Gender", y = "Purchase", palette = ["#3A7089", "#4
b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:3: UserWarning: The palette list has more values (7)
than needed (2), which may not be intended.
  sns.boxplot(data = walmart, x = "Gender", y = "Purchase", palette = ["#3A7089", "#4
b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:6: 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 = walmart, x = "Age", y = "Purchase", palette = ["#3A7089", "#4b4b
4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>: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.boxplot(data = walmart, x = "City_Category", y = "Purchase", palette = ["#3A708
9", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:9: UserWarning: The palette list has more values (7)
than needed (3), which may not be intended.
  sns.boxplot(data = walmart, x = "City_Category", y = "Purchase", palette = ["#3A708
9", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:12: 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 = walmart, x = "Stay_In_Current_City_Years", y = "Purchase", palet
te = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:12: UserWarning: The palette list has more values (7)
than needed (5), which may not be intended.
  sns.boxplot(data = walmart, x = "Stay_In_Current_City_Years", y = "Purchase", palet
te = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:15: 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 = walmart, x = "Marital_Status", y = "Purchase", palette = ["#3A70
89", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
<ipython-input-23-692e3c9d6433>:15: UserWarning: The palette list has more values (7)
than needed (2), which may not be intended.
  sns.boxplot(data = walmart, x = "Marital_Status", y = "Purchase", palette = ["#3A70
89", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384'])
```



Insights

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 USD, regardless of the specific variable being examined.

Gender VS Purchase Amount

Data Visualization

In [ ]:

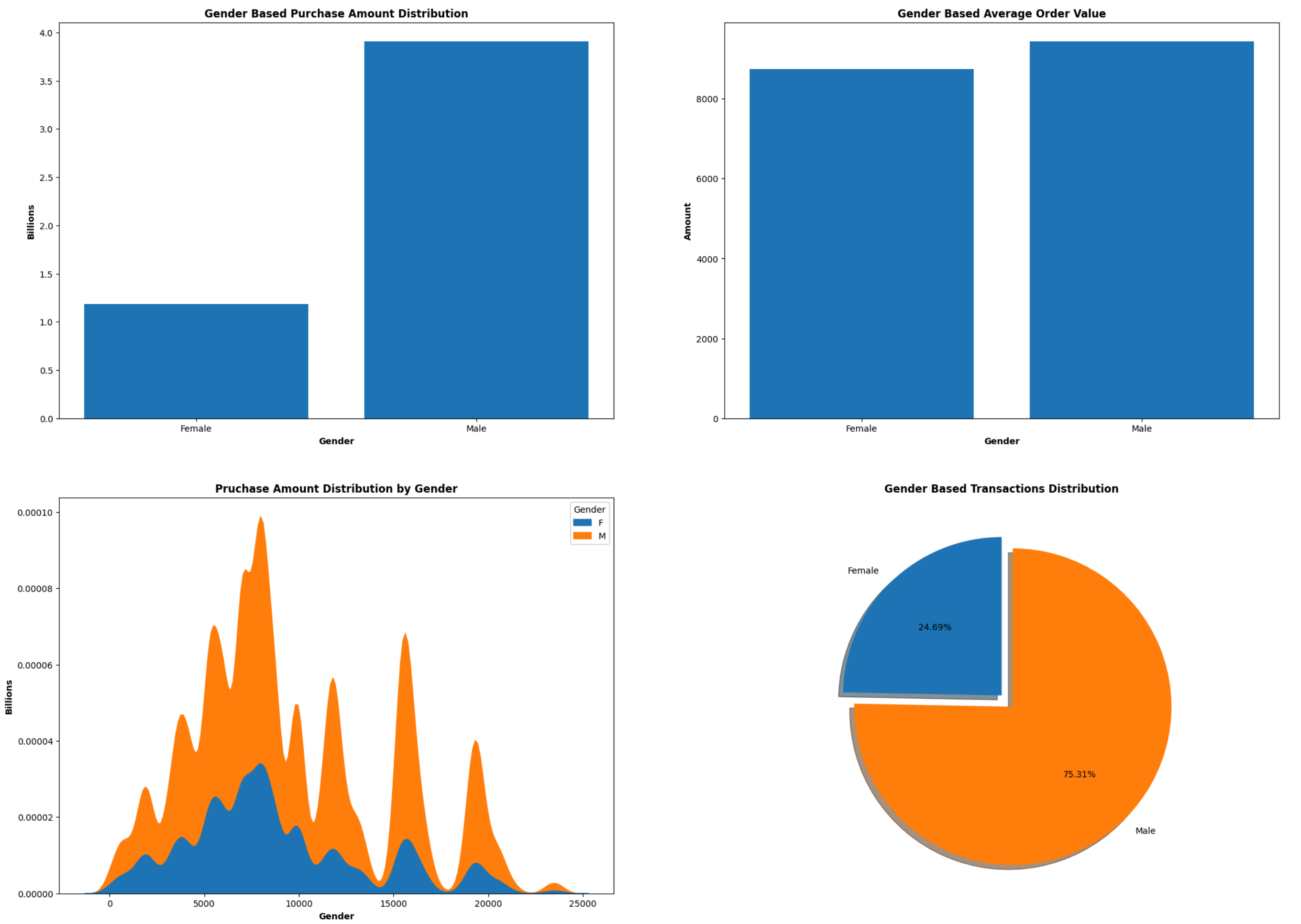
```
#creating a df for purchase amount vs gender
temp = walmart.groupby('Gender')['Purchase'].agg(['sum','count']).reset_index()

#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)

#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)

#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])

#renaming the gender
temp['Gender'] = temp['Gender'].replace({'F':'Female','M':'Male'})

temp
```

Out[ ]:

	Gender	sum	count	sum_in_billions	%sum	per_purchase
0	Female	1186232642	135809	1.19	0.233	8735.0
1	Male	3909580100	414259	3.91	0.767	9438.0

In [ ]:

```
plt.figure(figsize = (25,18))

plt.subplot(2,2,1)
plt.bar(temp["Gender"],temp["sum"]/10**9)
plt.title("Gender Based Purchase Amount Distribution", fontweight = "bold", fontsize
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("Gender",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,2)
plt.bar(temp["Gender"],temp["per_purchase"])
plt.title("Gender Based Average Order Value", fontweight = "bold", fontsize = 12)
plt.ylabel("Amount",fontweight = "bold", fontsize = 10)
plt.xlabel("Gender",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,3)
sns.kdeplot(data = walmart, x = 'Purchase', hue = 'Gender',fill = True, alpha = 1)
plt.title("Pruchase Amount Distribution by Gender", fontweight = "bold", fontsize = 1
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("Gender",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,4)
plt.pie(temp["count"], labels = temp["Gender"], autopct = "%2.2f%%", shadow=True, sta
plt.title("Gender Based Transactions Distribution", fontweight = "bold", fontsize = 1
plt.show()
plt.subplots_adjust()
```



<Figure size 640x480 with 0 Axes>

Insights

Total Sales and Transactions Comparison: The total purchase amount and number of transactions by male customers was more than three times the amount and transactions by female customers indicating that they had a more significant impact on the Black Friday sales.

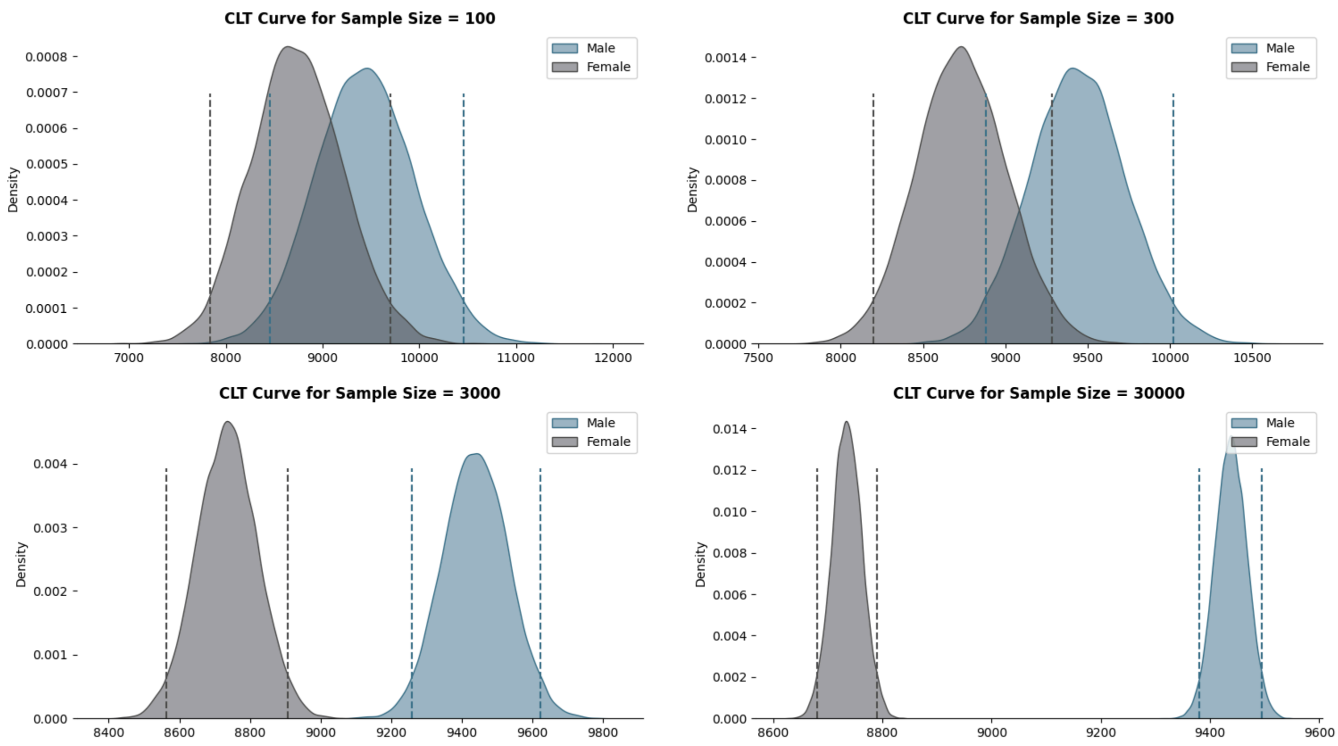
Average Transaction Value: The average purchase amount per transaction was slightly higher for male customers than female customers 9438 vs 8735.

Distribution of Purchase Amount: As seen above, the purchase amount for both the genders is not normally distributed.

In [ ]:
```
##### Confidence Interval = 95
##### Sample Size = 100
plt.figure(figsize = (18,10))

samp_size = 100
ci = 95

walmart_male = walmart[walmart["Gender"] == "M"]["Purchase"]
walmart_female = walmart[walmart["Gender"] == "F"]["Purchase"]

male_samples_100 = []
female_samples_100 = []

for i in range(0,20000):
  male_bootstrapped_means = np.mean(np.random.choice(walmart_male, size= samp_size))
  female_bootstrapped_means = np.mean(np.random.choice(walmart_female, size= samp_siz


  male_samples_100.append(round(male_bootstrapped_means))
  female_samples_100.append(round(female_bootstrapped_means))

plt.subplot(2,2,1)
sns.kdeplot(male_samples_100,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'Male
sns.kdeplot(female_samples_100,color ="#4b4b4c" ,fill = True, alpha = 0.5,label = 'Fe
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_male_100 = np.percentile(male_samples_100, [(100-ci)/2, (100+ci)/2])
interval_female_100 = np.percentile(female_samples_100, [(100-ci)/2, (100+ci)/2])

for i in interval_male_100:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_female_100:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")


##### Confidence Interval = 95
##### Sample Size = 300

samp_size = 300
ci = 95

walmart_male = walmart[walmart["Gender"] == "M"]["Purchase"]
walmart_female = walmart[walmart["Gender"] == "F"]["Purchase"]

male_samples_300 = []
female_samples_300 = []

for i in range(0,20000):
  male_bootstrapped_means = np.mean(np.random.choice(walmart_male, size= samp_size))
  female_bootstrapped_means = np.mean(np.random.choice(walmart_female, size= samp_siz
```

```
  male_samples_300.append(round(male_bootstrapped_means))
  female_samples_300.append(round(female_bootstrapped_means))

plt.subplot(2,2,2)
sns.kdeplot(male_samples_300,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'Male
sns.kdeplot(female_samples_300,color ="#4b4b4c" ,fill = True, alpha = 0.5,label = 'Fe
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_male_300 = np.percentile(male_samples_300, [(100-ci)/2, (100+ci)/2])
interval_female_300 = np.percentile(female_samples_300, [(100-ci)/2, (100+ci)/2])

for i in interval_male_300:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_female_300:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")

##### Confidence Interval = 95
##### Sample Size = 3000
samp_size = 3000
ci = 95

walmart_male = walmart[walmart["Gender"] == "M"]["Purchase"]
walmart_female = walmart[walmart["Gender"] == "F"]["Purchase"]

male_samples_3000 = []
female_samples_3000 = []

for i in range(0,20000):
  male_bootstrapped_means = np.mean(np.random.choice(walmart_male, size= samp_size))
  female_bootstrapped_means = np.mean(np.random.choice(walmart_female, size= samp_siz


  male_samples_3000.append(round(male_bootstrapped_means))
  female_samples_3000.append(round(female_bootstrapped_means))

plt.subplot(2,2,3)
sns.kdeplot(male_samples_3000,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'Mal
sns.kdeplot(female_samples_3000,color ="#4b4b4c" ,fill = True, alpha = 0.5,label = 'F
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_male_3000 = np.percentile(male_samples_3000, [(100-ci)/2, (100+ci)/2])
interval_female_3000 = np.percentile(female_samples_3000, [(100-ci)/2, (100+ci)/2])

for i in interval_male_3000:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_female_3000:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")



##### Confidence Interval = 95
##### Sample Size = 30000

samp_size = 30000
ci = 95

walmart_male = walmart[walmart["Gender"] == "M"]["Purchase"]
walmart_female = walmart[walmart["Gender"] == "F"]["Purchase"]
```

```
male_samples_30000 = []
female_samples_30000 = []

for i in range(0,20000):
  male_bootstrapped_means = np.mean(np.random.choice(walmart_male, size= samp_size))
  female_bootstrapped_means = np.mean(np.random.choice(walmart_female, size= samp_siz


  male_samples_30000.append(round(male_bootstrapped_means))
  female_samples_30000.append(round(female_bootstrapped_means))

plt.subplot(2,2,4)
sns.kdeplot(male_samples_30000,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'Ma
sns.kdeplot(female_samples_30000,color ="#4b4b4c" ,fill = True, alpha = 0.5,label = '
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_male_30000 = np.percentile(male_samples_30000, [(100-ci)/2, (100+ci)/2])
interval_female_30000 = np.percentile(female_samples_30000, [(100-ci)/2, (100+ci)/2])

for i in interval_male_30000:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_female_30000:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")
```



In [ ]:

```
male_100_left , male_100_right = interval_male_100
female_100_left , female_100_right = interval_female_100

male_300_left , male_300_right = interval_male_300
female_300_left , female_300_right = interval_female_300

male_3000_left , male_3000_right = interval_male_3000
female_3000_left , female_3000_right = interval_female_3000

male_30000_left , male_30000_right = interval_male_30000
female_30000_left , female_30000_right = interval_female_30000

print("*"*100)
print("Sample Size 100")
print("*"*100)
```

```python
print(f"Confidence Interval Male = {male_100_left} - {male_100_right.round(0)}")
print(f"Range = {(male_100_right - male_100_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Female = {female_100_left} - {female_100_right}")
print(f"Range = {female_100_right - female_100_left}")

print("\n\n")

print("*"*100)
print("Sample Size 300")
print("*"*100)
print(f"Confidence Interval Male = {male_300_left} - {male_300_right.round(0)}")
print(f"Range = {(male_300_right - male_300_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Female = {female_300_left} - {female_300_right}")
print(f"Range = {female_300_right - female_300_left}")

print("\n\n")

print("*"*100)
print("Sample Size 3000")
print("*"*100)
print(f"Confidence Interval Male = {male_3000_left} - {male_3000_right.round(0)}")
print(f"Range = {(male_3000_right - male_3000_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Female = {female_3000_left} - {female_3000_right}")
print(f"Range = {female_3000_right - female_3000_left}")

print("\n\n")

print("*"*100)
print("Sample Size 30000")
print("*"*100)
print(f"Confidence Interval Male = {male_30000_left} - {male_30000_right.round(0)}")
print(f"Range = {(male_30000_right - male_30000_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Female = {female_30000_left} - {female_30000_right}")
print(f"Range = {female_30000_right - female_30000_left}")
```

```
*************************************************************************************
***************
Sample Size 100
*************************************************************************************
***************
Confidence Interval Male = 8454.0 - 10456.0
Range = 2002.0
--------------------------------------------------
Confidence Interval Female = 7841.0 - 9699.0
Range = 1858.0



*************************************************************************************
***************
Sample Size 300
*************************************************************************************
***************
Confidence Interval Male = 8880.0 - 10021.0
Range = 1141.0
--------------------------------------------------
Confidence Interval Female = 8199.0 - 9282.0
Range = 1083.0



*************************************************************************************
***************
Sample Size 3000
*************************************************************************************
***************
Confidence Interval Male = 9258.0 - 9623.0
Range = 365.0
--------------------------------------------------
Confidence Interval Female = 8564.0 - 8907.0
Range = 343.0



*************************************************************************************
***************
Sample Size 30000
*************************************************************************************
***************
Confidence Interval Male = 9380.0 - 9495.0
Range = 115.0
--------------------------------------------------
Confidence Interval Female = 8680.0 - 8790.0
Range = 110.0
```

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.

1. Confidence Intervals

From the above analysis, we can see that except for the Sample Size of 100, 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.

1. Population Average

We are 95% confident that the true population average for males falls between 9,393 and 9,483, and for females, it falls between 8,692 and 8,777.

1. 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.

1. How can Walmart leverage this conclusion to make changes or improvements? 5.1. 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.

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.

Marital Status VS Purchase Amount

In [ ]:

```
#creating a df for purchase amount vs marital status
temp = walmart.groupby('Marital_Status')['Purchase'].agg(['sum','count']).reset_index

#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)

#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)

#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])

temp
```

Out[ ]:

	Marital_Status	sum	count	sum_in_billions	%sum	per_purchase
0	Unmarried	3008927447	324731	3.01	0.59	9266.0
1	Married	2086885295	225337	2.09	0.41	9261.0

Insights

1. Total Sales and Transactions Comparison

The total purchase amount and number of transactions by Unmarried customers was more than 20% the amount and transactions by married customers indicating that they had a more significant impact on the Black Friday sales.

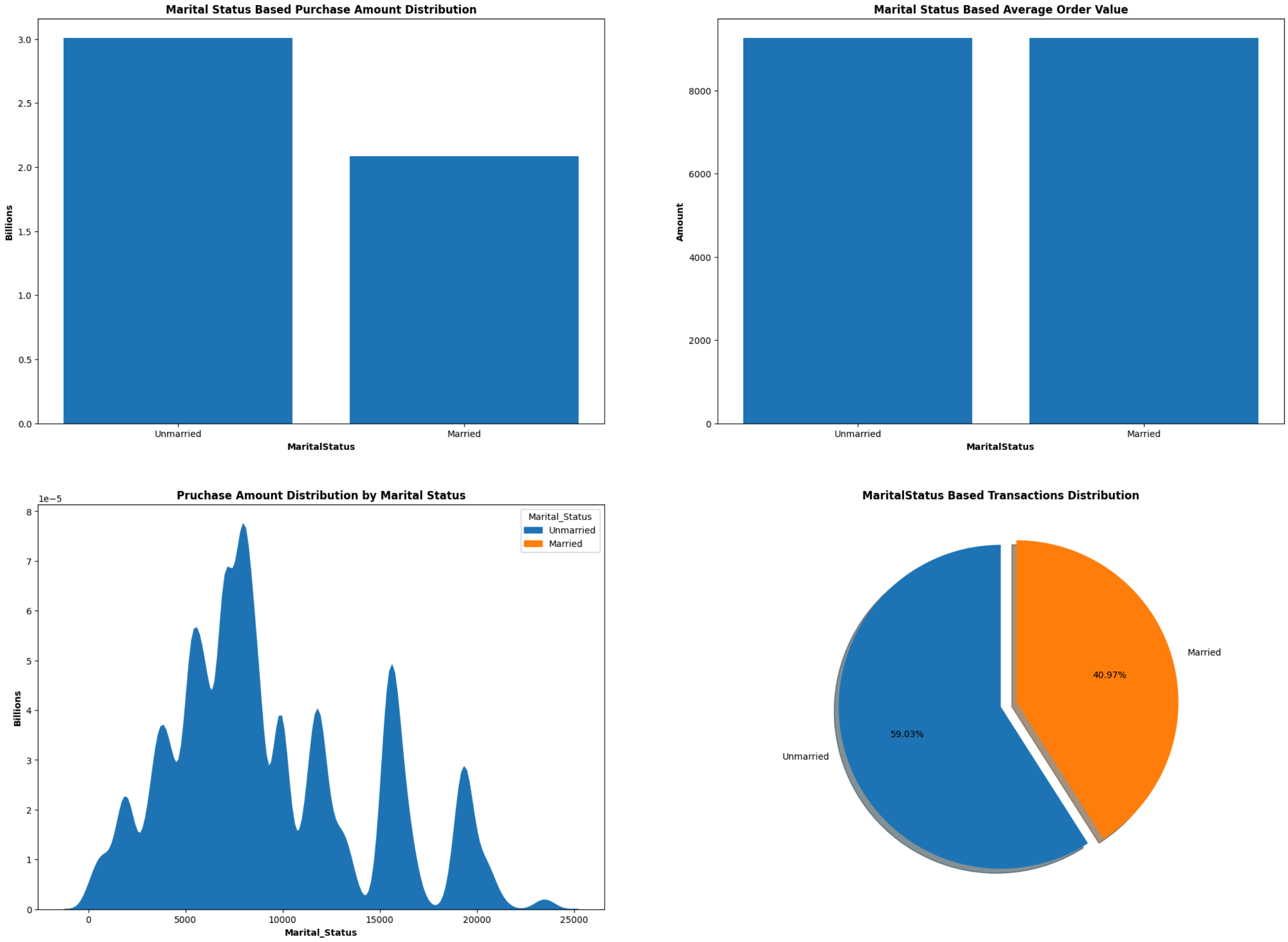
1. Average Transaction Value

The average purchase amount per transaction was almost similar for married and unmarried customers 9261 vs 9266.

1. Distribution of Purchase Amount

As seen above, the purchase amount for both married and unmarried customers is not normally distributed.

In [ ]:
```
plt.figure(figsize = (25,18))

plt.subplot(2,2,1)
plt.bar(temp["Marital_Status"],temp["sum"]/10**9)
plt.title("Marital Status Based Purchase Amount Distribution", fontweight = "bold", f
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("MaritalStatus",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,2)
plt.bar(temp["Marital_Status"],temp["per_purchase"])
plt.title("Marital Status Based Average Order Value", fontweight = "bold", fontsize =
plt.ylabel("Amount",fontweight = "bold", fontsize = 10)
plt.xlabel("MaritalStatus",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,3)
sns.kdeplot(data = walmart, x = 'Purchase', hue = 'Marital_Status',fill = True, alpha
plt.title("Pruchase Amount Distribution by Marital Status", fontweight = "bold", font
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("Marital_Status",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,4)
plt.pie(temp["count"], labels = temp["Marital_Status"], autopct = "%2.2f%%", shadow=T
plt.title("MaritalStatus Based Transactions Distribution", fontweight = "bold", fonts
plt.show()
plt.subplots_adjust()
```



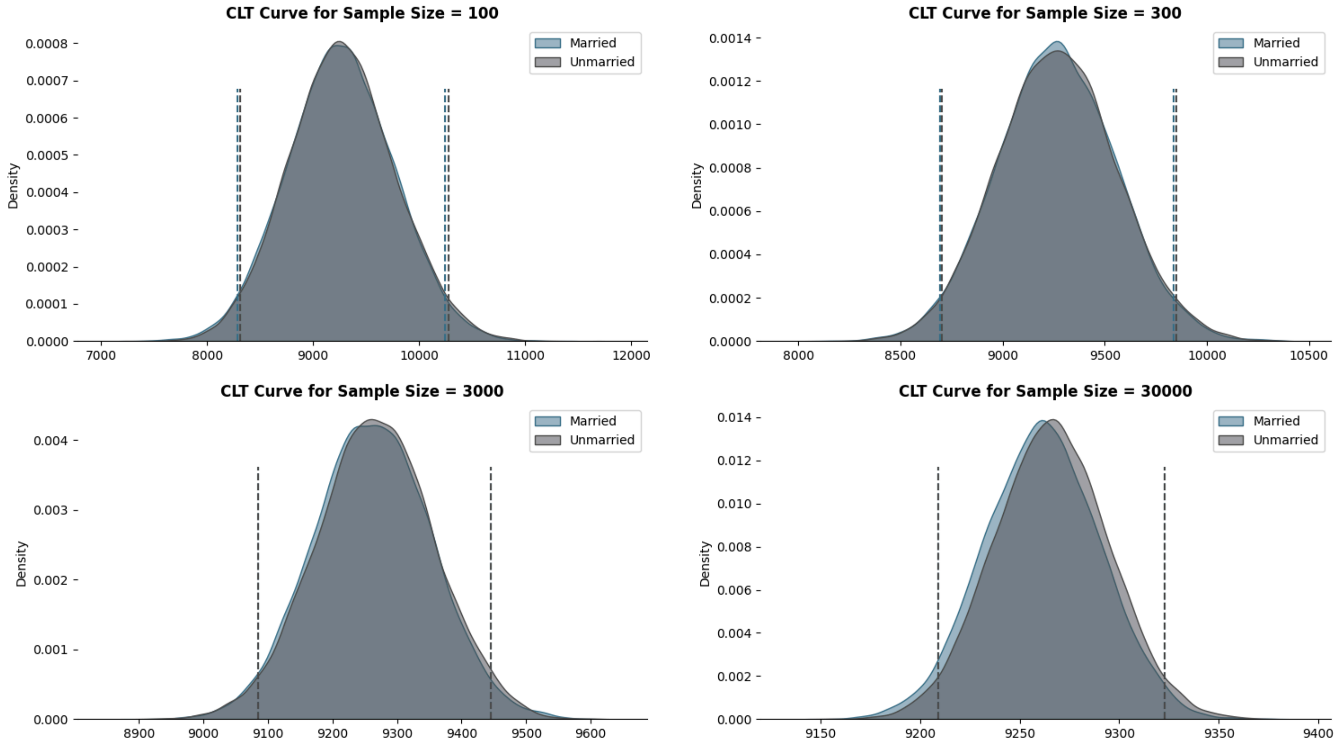

```
<Figure size 640x480 with 0 Axes>
```

In [ ]:

```
##### Confidence Interval = 95
##### Sample Size = 100
plt.figure(figsize = (18,10))

samp_size = 100
ci = 95

walmart_married = walmart[walmart["Marital_Status"] == "Married"]["Purchase"]
walmart_unmarried = walmart[walmart["Marital_Status"] == "Unmarried"]["Purchase"]

married_samples_100 = []
unmarried_samples_100 = []

for i in range(0,20000):
  married_bootstrapped_means = np.mean(np.random.choice(walmart_married, size= samp_s
  unmarried_bootstrapped_means = np.mean(np.random.choice(walmart_unmarried, size= sa


  married_samples_100.append(round(married_bootstrapped_means))
  unmarried_samples_100.append(round(unmarried_bootstrapped_means))

plt.subplot(2,2,1)
sns.kdeplot(married_samples_100,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'M
sns.kdeplot(unmarried_samples_100,color ="#4b4b4c" ,fill = True, alpha = 0.5,label =
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_married_100 = np.percentile(married_samples_100, [(100-ci)/2, (100+ci)/2])
interval_unmarried_100 = np.percentile(unmarried_samples_100, [(100-ci)/2, (100+ci)/2

for i in interval_married_100:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
```

```
for i in interval_unmarried_100:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")


##### Confidence Interval = 95
##### Sample Size = 300

samp_size = 300
ci = 95

walmart_married = walmart[walmart["Marital_Status"] == "Married"]["Purchase"]
walmart_unmarried = walmart[walmart["Marital_Status"] == "Unmarried"]["Purchase"]

married_samples_300 = []
unmarried_samples_300 = []

for i in range(0,20000):
  married_bootstrapped_means = np.mean(np.random.choice(walmart_married, size= samp_s
  unmarried_bootstrapped_means = np.mean(np.random.choice(walmart_unmarried, size= sa


  married_samples_300.append(round(married_bootstrapped_means))
  unmarried_samples_300.append(round(unmarried_bootstrapped_means))

plt.subplot(2,2,2)
sns.kdeplot(married_samples_300,color ="#3A7089" ,fill = True, alpha = 0.5,label = 'M
sns.kdeplot(unmarried_samples_300,color ="#4b4b4c" ,fill = True, alpha = 0.5,label =
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_married_300 = np.percentile(married_samples_300, [(100-ci)/2, (100+ci)/2])
interval_unmarried_300 = np.percentile(unmarried_samples_300, [(100-ci)/2, (100+ci)/2

for i in interval_married_300:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_unmarried_300:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")

##### Confidence Interval = 95
##### Sample Size = 3000
samp_size = 3000
ci = 95

walmart_married = walmart[walmart["Marital_Status"] == "Married"]["Purchase"]
walmart_unmarried = walmart[walmart["Marital_Status"] == "Unmarried"]["Purchase"]

married_samples_3000 = []
unmarried_samples_3000 = []

for i in range(0,20000):
  married_bootstrapped_means = np.mean(np.random.choice(walmart_married, size= samp_s
  unmarried_bootstrapped_means = np.mean(np.random.choice(walmart_unmarried, size= sa


  married_samples_3000.append(round(married_bootstrapped_means))
  unmarried_samples_3000.append(round(unmarried_bootstrapped_means))

plt.subplot(2,2,3)
sns.kdeplot(married_samples_3000,color ="#3A7089" ,fill = True, alpha = 0.5,label = '
sns.kdeplot(unmarried_samples_3000,color ="#4b4b4c" ,fill = True, alpha = 0.5,label =
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)
```

```
interval_married_3000 = np.percentile(married_samples_3000, [(100-ci)/2, (100+ci)/2])
interval_unmarried_3000 = np.percentile(unmarried_samples_3000, [(100-ci)/2, (100+ci)

for i in interval_unmarried_3000:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_unmarried_3000:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")



##### Confidence Interval = 95
##### Sample Size = 30000

samp_size = 30000
ci = 95

walmart_married = walmart[walmart["Marital_Status"] == "Married"]["Purchase"]
walmart_unmarried = walmart[walmart["Marital_Status"] == "Unmarried"]["Purchase"]

married_samples_30000 = []
unmarried_samples_30000 = []

for i in range(0,20000):
  married_bootstrapped_means = np.mean(np.random.choice(walmart_married, size= samp_s
  unmarried_bootstrapped_means = np.mean(np.random.choice(walmart_unmarried, size= sa


  married_samples_30000.append(round(married_bootstrapped_means))
  unmarried_samples_30000.append(round(unmarried_bootstrapped_means))

plt.subplot(2,2,4)
sns.kdeplot(married_samples_30000,color ="#3A7089" ,fill = True, alpha = 0.5,label =
sns.kdeplot(unmarried_samples_30000,color ="#4b4b4c" ,fill = True, alpha = 0.5,label
plt.legend()
plt.title(f'CLT Curve for Sample Size = {samp_size}',fontsize = 12, fontweight = "bol
for axis in ["left","top","right"]:
  plt.gca().spines[axis].set_visible(False)

interval_married_30000 = np.percentile(married_samples_30000, [(100-ci)/2, (100+ci)/2
interval_unmarried_30000 = np.percentile(unmarried_samples_30000, [(100-ci)/2, (100+c

for i in interval_unmarried_30000:
  plt.axvline(x = i, ymax = 0.8, color ='#3A7089', linestyle = "--")
for i in interval_unmarried_30000:
  plt.axvline(x = i, ymax = 0.8, color ='#4b4b4c', linestyle = "--")
```



In [ ]:
```
married_100_left , married_100_right = interval_married_100
unmarried_100_left , unmarried_100_right = interval_unmarried_100

married_300_left , married_300_right = interval_married_300
unmarried_300_left , unmarried_300_right = interval_unmarried_300

married_3000_left , married_3000_right = interval_married_3000
unmarried_3000_left , unmarried_3000_right = interval_unmarried_3000

married_30000_left , married_30000_right = interval_married_30000
unmarried_30000_left , unmarried_30000_right = interval_unmarried_30000

print("*"*100)
print("Sample Size 100")
print("*"*100)
print(f"Confidence Interval Married = {married_100_left} - {married_100_right.round(0
print(f"Range = {(married_100_right - married_100_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Unmarried = {unmarried_100_left} - {unmarried_100_right}"
print(f"Range = {unmarried_100_right - unmarried_100_left}")

print("\n\n")

print("*"*100)
print("Sample Size 300")
print("*"*100)
print(f"Confidence Interval Married = {married_300_left} - {married_300_right.round(0
print(f"Range = {(married_300_right - married_300_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Unmarried = {unmarried_300_left} - {unmarried_300_right}"
print(f"Range = {unmarried_300_right - unmarried_300_left}")

print("\n\n")

print("*"*100)
print("Sample Size 3000")
print("*"*100)
print(f"Confidence Interval Married = {married_3000_left} - {married_3000_right.round
print(f"Range = {(married_3000_right - married_3000_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Unmarried = {unmarried_3000_left} - {unmarried_3000_right
print(f"Range = {unmarried_3000_right - unmarried_3000_left}")
```

```
print("\n\n")

print("*"*100)
print("Sample Size 30000")
print("*"*100)
print(f"Confidence Interval Married = {married_30000_left} - {married_30000_right.rou
print(f"Range = {(married_30000_right - married_30000_left).round(0)}")
print("-"*50)
print(f"Confidence Interval Unmarried = {unmarried_30000_left} - {unmarried_30000_rig
print(f"Range = {unmarried_30000_right - unmarried_30000_left}")
```

```
*************************************************************************************
***************
Sample Size 100
*************************************************************************************
***************
Confidence Interval Married = 8283.0 - 10248.0
Range = 1965.0
--------------------------------------------------
Confidence Interval Unmarried = 8309.975 - 10282.024999999998
Range = 1972.0499999999975



*************************************************************************************
***************
Sample Size 300
*************************************************************************************
***************
Confidence Interval Married = 8694.0 - 9838.0
Range = 1144.0
--------------------------------------------------
Confidence Interval Unmarried = 8703.0 - 9849.0
Range = 1146.0



*************************************************************************************
***************
Sample Size 3000
*************************************************************************************
***************
Confidence Interval Married = 9084.0 - 9440.0
Range = 356.0
--------------------------------------------------
Confidence Interval Unmarried = 9085.0 - 9445.0
Range = 360.0



*************************************************************************************
***************
Sample Size 30000
*************************************************************************************
***************
Confidence Interval Married = 9204.0 - 9318.0
Range = 114.0
--------------------------------------------------
Confidence Interval Unmarried = 9209.0 - 9323.0
Range = 114.0
```

Insights

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.

1. 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.

1. Population Average

We are 95% confident that the true population average for married customers falls between 9,217 and 9,305, and for unmarried customers, it falls between $9,222 and 9,311.

1. Both the customers spend equal

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

1. How can Walmart leverage this conclusion to make changes or improvements? 5.1. 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.

Customer Age VS Purchase Amount

In [ ]:

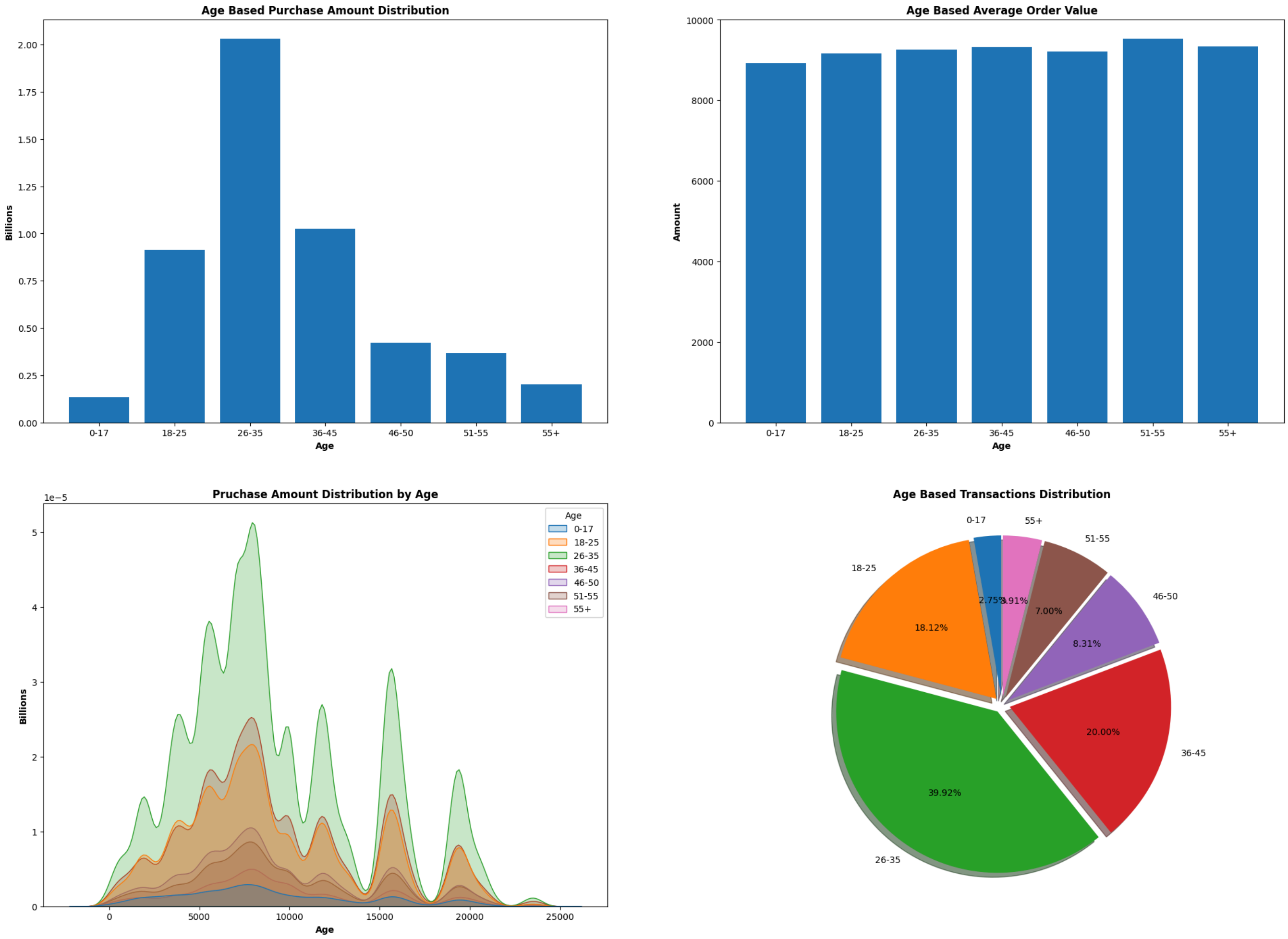
```
#creating a df for purchase amount vs age group
temp = walmart.groupby('Age')['Purchase'].agg(['sum','count']).reset_index()

#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)

#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)

#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])

temp
```

Out[ ]:

	Age	sum	count	sum_in_billions	%sum	per_purchase
0	0-17	134913183	15102	0.13	0.026	8933.0
1	18-25	913848675	99660	0.91	0.179	9170.0
2	26-35	2031770578	219587	2.03	0.399	9253.0
3	36-45	1026569884	110013	1.03	0.201	9331.0
4	46-50	420843403	45701	0.42	0.083	9209.0
5	51-55	367099644	38501	0.37	0.072	9535.0
6	55+	200767375	21504	0.20	0.039	9336.0

In [ ]:

```
plt.figure(figsize = (25,18))

plt.subplot(2,2,1)
plt.bar(temp["Age"],temp["sum"]/10**9)
plt.title("Age Based Purchase Amount Distribution", fontweight = "bold", fontsize = 1
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("Age",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,2)
plt.bar(temp["Age"],temp["per_purchase"])
plt.title("Age Based Average Order Value", fontweight = "bold", fontsize = 12)
plt.ylabel("Amount",fontweight = "bold", fontsize = 10)
plt.xlabel("Age",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,3)
sns.kdeplot(data = walmart, x = 'Purchase', hue = 'Age',fill = True, alpha = 0.25)
plt.title("Pruchase Amount Distribution by Age", fontweight = "bold", fontsize = 12)
plt.ylabel("Billions",fontweight = "bold", fontsize = 10)
plt.xlabel("Age",fontweight = "bold", fontsize = 10)

plt.subplot(2,2,4)
plt.pie(temp["count"], labels = temp["Age"], autopct = "%2.2f%%", shadow=True, starta
plt.title("Age Based Transactions Distribution", fontweight = "bold", fontsize = 12)
plt.show()
plt.subplots_adjust()
```




```
<Figure size 640x480 with 0 Axes>
```

In [ ]:
```python
#creating a function to calculate confidence interval

def confidence_interval(data,ci):
    #converting the list to series
    l_ci = (100-ci)/2
    u_ci = (100+ci)/2

    #calculating lower limit and upper limit of confidence interval
    interval = np.percentile(data,[l_ci,u_ci]).round(0)

    return interval
```

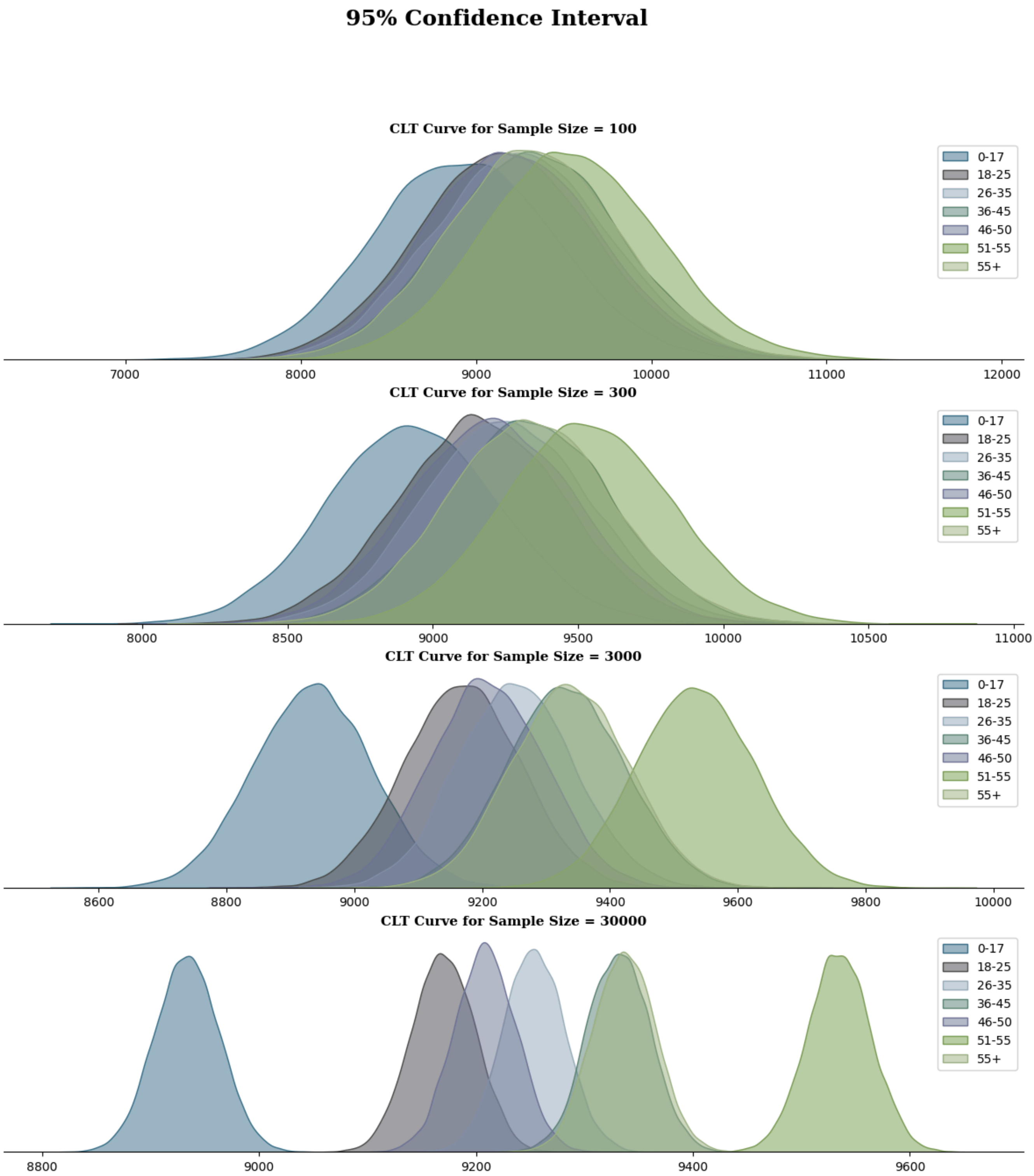
In [ ]:
```python
#defining a function for plotting the visual for given confidence interval

def plot(ci):

    #setting the plot style
    fig = plt.figure(figsize = (15,15))
    gs = fig.add_gridspec(4,1)

    #creating separate data frames

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


    #sample sizes and corresponding plot positions
    sample_sizes = [(100,0),(300,1),(3000,2),(30000,3)]
```

```
#number of samples to be taken from purchase amount
bootstrap_samples = 20000

samples1,samples2,samples3,samples4,samples5,samples6,samples7 = {},{},{},{},{},{

for i,x in sample_sizes:
    l1,l2,l3,l4,l5,l6,l7 = [],[],[],[],[],[],[]

    for j in range(bootstrap_samples):

        #creating random 5000 samples of i sample size
        bootstrapped_samples_1 = np.random.choice(df_1,size = i)
        bootstrapped_samples_2 = np.random.choice(df_2,size = i)
        bootstrapped_samples_3 = np.random.choice(df_3,size = i)
        bootstrapped_samples_4 = np.random.choice(df_4,size = i)
        bootstrapped_samples_5 = np.random.choice(df_5,size = i)
        bootstrapped_samples_6 = np.random.choice(df_6,size = i)
        bootstrapped_samples_7 = np.random.choice(df_7,size = i)

        #calculating mean of those samples
        sample_mean_1 = np.mean(bootstrapped_samples_1)
        sample_mean_2 = np.mean(bootstrapped_samples_2)
        sample_mean_3 = np.mean(bootstrapped_samples_3)
        sample_mean_4 = np.mean(bootstrapped_samples_4)
        sample_mean_5 = np.mean(bootstrapped_samples_5)
        sample_mean_6 = np.mean(bootstrapped_samples_6)
        sample_mean_7 = np.mean(bootstrapped_samples_7)

        #appending the mean to the list
        l1.append(sample_mean_1)
        l2.append(sample_mean_2)
        l3.append(sample_mean_3)
        l4.append(sample_mean_4)
        l5.append(sample_mean_5)
        l6.append(sample_mean_6)
        l7.append(sample_mean_7)

    #storing the above sample generated
    samples1[f'{ci}%_{i}'] = l1
    samples2[f'{ci}%_{i}'] = l2
    samples3[f'{ci}%_{i}'] = l3
    samples4[f'{ci}%_{i}'] = l4
    samples5[f'{ci}%_{i}'] = l5
    samples6[f'{ci}%_{i}'] = l6
    samples7[f'{ci}%_{i}'] = l7


    #creating a temporary dataframe for creating kdeplot
    temp_df = pd.DataFrame(data = {'0-17':l1,'18-25':l2,'26-35':l3,'36-45':l4,'46

                                                #plotting kdeplots
    #plot position
    ax = fig.add_subplot(gs[x])

    #plots
    for p,q in [('#3A7089', '0-17'),('#4b4b4c', '18-25'),('#99AEBB', '26-35'),('#
                ('#7A9D54', '51-55'),('#9EB384', '55+')]:

        sns.kdeplot(data = temp_df,x = q,color =p ,fill = True, alpha = 0.5,ax =


    #removing the axis lines
    for s in ['top','left','right']:
        ax.spines[s].set_visible(False)

    # adjusting axis labels
```

```
        ax.set_yticks([])
        ax.set_ylabel('')
        ax.set_xlabel('')

        #setting title for visual
        ax.set_title(f'CLT Curve for Sample Size = {i}',{'font':'serif', 'size':11,'w

        plt.legend()

    #setting title for visual
    fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size = 18, weight = 'bo

    plt.show()

    return samples1,samples2,samples3,samples4,samples5,samples6,samples7
```

In [ ]:

```
samples1,samples2,samples3,samples4,samples5,samples6,samples7 = plot(95)
```



In [ ]:

```
fig,ax = plt.subplots(figsize = (20,5))
ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7 = ['0-17'],['18-25'],['26-35'],['36-45'],['46-50']
samples = [(samples1,ci_1),(samples2,ci_2),(samples3,ci_3),(samples4,ci_4),(samples5,

for s,c in samples:
    for i in s:
        s_range = confidence_interval(s[i],95)
        c.append(f"CI = ${s_range[0]:.0f} - ${s_range[1]:.0f}, Range = {(s_range[1] -

ci_info = [ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7]
table = ax.table(cellText = ci_info, cellLoc='center',
             colLabels =['Age Group','Sample Size = 100','Sample Size = 1000','Sample
             colLoc = 'center',colWidths = [0.1,0.225,0.225,0.225,0.225],bbox =[0, 0,

table.set_fontsize(13)
ax.axis('off')
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'
plt.show()
```

95% Confidence Interval Summary

Age Group	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
0-17	CI = 7941 – 9948, Range = 2007	CI = 8355 – 9521, Range = 1166	CI = 8753 – 9118, Range = 365	CI = 8875 – 8992, Range = 117
18-25	CI = 8198 – 10202, Range = 2004	CI = 8597 – 9737, Range = 1140	CI = 8990 – 9350, Range = 360	CI = 9113 – 9227, Range = 114
26-35	CI = 8287 – 10256, Range = 1969	CI = 8691 – 9824, Range = 1133	CI = 9075 – 9433, Range = 358	CI = 9196 – 9310, Range = 114
36-45	CI = 8350 – 10324, Range = 1974	CI = 8761 – 9898, Range = 1137	CI = 9148 – 9512, Range = 364	CI = 9274 – 9388, Range = 114
46-50	CI = 8245 – 10211, Range = 1966	CI = 8648 – 9767, Range = 1119	CI = 9033 – 9385, Range = 352	CI = 9152 – 9265, Range = 113
51-55	CI = 8552 – 10551, Range = 1999	CI = 8962 – 10116, Range = 1154	CI = 9352 – 9717, Range = 365	CI = 9477 – 9592, Range = 115
55+	CI = 8357 – 10335, Range = 1978	CI = 8771 – 9911, Range = 1140	CI = 9157 – 9517, Range = 360	CI = 9279 – 9393, Range = 114

Insights

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.

1. 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

1. Population Average

We are 95% confident that the true population average for following age groups falls between the below range -

0 - 17 = 8,888 to 8,979 18 - 25 = 9,125 to 9,213 26 - 35 = 9,209 to 9,297 36 - 45 = 9,288 to 9,376 46 - 50 = 9,165 to 9,253 51 - 55 = 9,490 to 9,579 55+ = 9,292 to 9,381

1. How can Walmart leverage this conclusion to make changes or improvements? 4.1. 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 4.2. 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. 4.3 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.

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. Engage 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.

6. Post-Black Friday Engagement

- After Black Friday, walmart should engage with customers who made purchases by sending follow-up emails or offers for related products. This can help increase customer retention and encourage repeat business throughout the holiday season and beyond.