walmart-business-case-study

February 21, 2024

1 Walmart Business Case Study

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

1.1 Objective/ Purpose of analyzing Walmart data

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

1.2 Importing Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
```

1.3 Importing Dataset

[2]:
```
#Reading the CSV file data for Walmart Dataset
walmart_data = pd.read_csv('walmart_data.csv')
```

1.4 Data analysis like checking the structure & characteristics of the dataset

[3]:
```
walmart_data.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
```

Displaying data types of each column

[4]:
```
walmart_data.dtypes
```

[4]:
```
User_ID                        int64
Product_ID                    object
Gender                        object
Age                           object
Occupation                     int64
City_Category                 object
Stay_In_Current_City_Years    object
Marital_Status                 int64
Product_Category               int64
Purchase                       int64
dtype: object
```

Product_ID, Gender, Age, City_Category, Stay_In_Current_City_Years columns have **Object** datatype

User_ID, Occupation, Marital_Status, Product_Category, Purchase columns have **Integer** datatype

Finding the number of rows and columns given in the dataset

[5]:
```
print(f"'Number of Rows' : {walmart_data.shape[0]}\n'Number of Columns' : 
 ↪{walmart_data.shape[1]}")
```

```
'Number of Rows' : 550068
'Number of Columns' : 10
```

Total number of rows and columns are 550068 and 10 respectively.

Check for the missing values and find the number of missing values in each column

[6]:
```
walmart_data.isna().sum()
```

[6]:
```
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
```

There is no missing value in any of the columns.

Checking Duplicate values in the dataset

[7]:
```
walmart_data.duplicated().value_counts()
```

[7]:
```
False    550068
dtype: int64
```

There are no duplicate entries in the dataset.

Replacing the values in marital_status column

[8]:
```
walmart_data['Marital_Status'] = walmart_data['Marital_Status'].replace({0:
 ↪'Unmarried',1:'Married'})
walmart_data['Marital_Status'].unique()
```

[8]:
```
array(['Unmarried', 'Married'], dtype=object)
```

Here, I have replaced Marital Status from 0, 1 to 'Unmarried', 'Married' respectively for better understanding and analysis.

[9]:
```
# conversion of categorical attributes to 'category'
column=["User_ID","Occupation","Marital_Status","Product_Category"]
walmart_data[column]=walmart_data[column].astype("object")
```

Viewing and understanding few 5 rows of the Netfix dataframe

[10]:
```
walmart_data.head()
```

[10]:
```
   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      Unmarried                3      8370
```

1	2	Unmarried	1	15200
2	2	Unmarried	12	1422
3	2	Unmarried	12	1057
4	4+	Unmarried	8	7969

Checking the unique values for columns

[11]:
```
for i in walmart_data.columns:
    print(f'Unique Values in {i} column are :-\n {walmart_data[i].unique()}\n')
    print('.'*80)
```

```
Unique Values in User_ID column are :-
 [1000001 1000002 1000003 … 1004113 1005391 1001529]


…
Unique Values in Product_ID column are :-
 ['P00069042' 'P00248942' 'P00087842' … 'P00370293' 'P00371644'
 'P00370853']


…
Unique Values in Gender column are :-
 ['F' 'M']


…
Unique Values in Age column are :-
 ['0-17' '55+' '26-35' '46-50' '51-55' '36-45' '18-25']


…
Unique Values in Occupation column are :-
 [10 16 15 7 20 9 1 12 17 0 3 4 11 8 19 2 18 5 14 13 6]


…
Unique Values in City_Category column are :-
 ['A' 'C' 'B']


…
Unique Values in Stay_In_Current_City_Years column are :-
 ['2' '4+' '3' '1' '0']


…
Unique Values in Marital_Status column are :-
 ['Unmarried' 'Married']


…
Unique Values in Product_Category column are :-
 [3 1 12 8 5 4 2 6 14 11 13 15 7 16 18 10 17 9 20 19]


…
```

```
Unique Values in Purchase column are :-
 [ 8370 15200  1422 …   135   123   613]
```

…

Checking the number of unique values for columns

[12]:
```python
for i in walmart_data.columns:
    print('Number of Unique Values in',i,'column :', walmart_data[i].nunique())
    print('-'*70)
```

```
Number of Unique Values in User_ID column : 5891
----------------------------------------------------------------------
Number of Unique Values in Product_ID column : 3631
----------------------------------------------------------------------
Number of Unique Values in Gender column : 2
----------------------------------------------------------------------
Number of Unique Values in Age column : 7
----------------------------------------------------------------------
Number of Unique Values in Occupation column : 21
----------------------------------------------------------------------
Number of Unique Values in City_Category column : 3
----------------------------------------------------------------------
Number of Unique Values in Stay_In_Current_City_Years column : 5
----------------------------------------------------------------------
Number of Unique Values in Marital_Status column : 2
----------------------------------------------------------------------
Number of Unique Values in Product_Category column : 20
----------------------------------------------------------------------
Number of Unique Values in Purchase column : 18105
----------------------------------------------------------------------
```

Statistical summary of All columns

[13]:
```python
walmart_data.describe()
```

[13]:

	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

The dataset provides information on the following variables:

User_ID: It contains unique identification numbers assigned to each user. The dataset includes a total of 550,068 user records.

Occupation: This variable represents the occupation of the users. The dataset includes values ranging from 0 to 20, indicating different occupations.

Product_Category: It indicates the category of the products purchased by the users. The dataset includes values ranging from 1 to 20, representing different product categories.

Purchase: This variable represents the purchase amount made by each user. The dataset includes purchase values ranging from 12 to 23,961.

1.5 Detect Outliers

[14]:
```
continuous_var = ['Purchase']
arr = {'5th percentile': 5, '25th percentile or Q1': 25, '50th percentile or␣
↪Q2': 50, '75th percentile or Q3': 75,
       '95th percentile': 95}
```

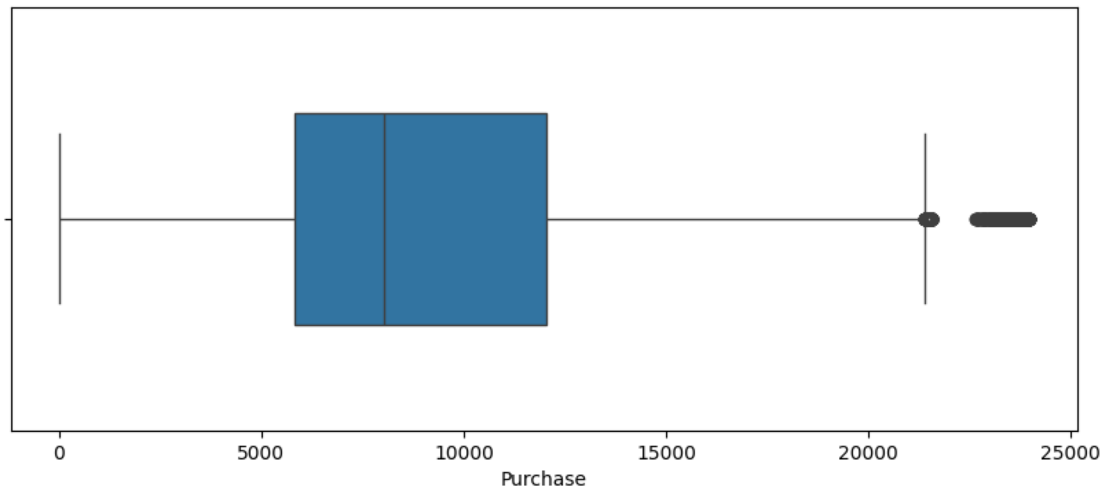
[15]:
```
for key, value in arr.items():
    for var in continuous_var:
        print(f'{var} -> {key} : {np.percentile(walmart_data[var], value):.2f}')
```

```
Purchase -> 5th percentile : 1984.00
Purchase -> 25th percentile or Q1 : 5823.00
Purchase -> 50th percentile or Q2 : 8047.00
Purchase -> 75th percentile or Q3 : 12054.00
Purchase -> 95th percentile : 19336.00
```

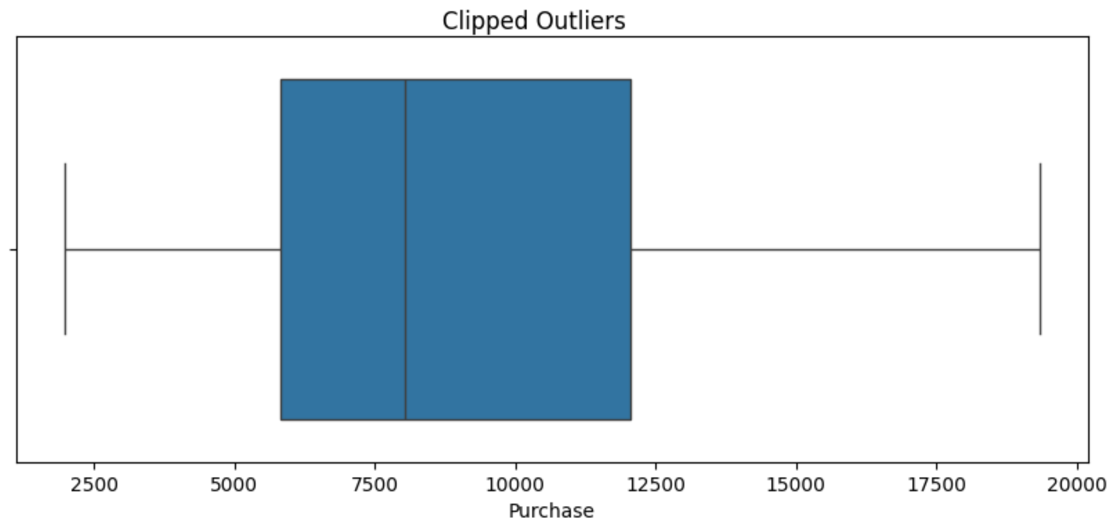
[16]:
```
for var in continuous_var:
    # Calculate the IQR for the variable
    Q1 = np.percentile(walmart_data[var], arr['25th percentile or Q1'])
    Q3 = np.percentile(walmart_data[var], arr['75th percentile or Q3'])
    percentile_95 = np.percentile(walmart_data[var], arr['95th percentile'])
    IQR = Q3 - Q1

    # Define the outlier thresholds
    lower_threshold = Q1 - 1.5 * IQR
    upper_threshold = Q3 + 1.5 * IQR

    # Find the outliers for the variable
    outliers = walmart_data[(walmart_data[var] < lower_threshold) |␣
↪(walmart_data[var] > upper_threshold)]

    # Calculate the percentage of outliers
    outlier_percentage = round(len(outliers) / len(walmart_data[var]) * 100, 2 )

    # Output the percentage of outliers
    print(f"IQR for {var}: {IQR}")
    print(f"Outlier above this Q3 {var} : {upper_threshold}")
    print(f"Percentage of outliers for {var}: {outlier_percentage}% \n")
```

```
IQR for Purchase: 6231.0
Outlier above this Q3 Purchase : 21400.5
Percentage of outliers for Purchase: 0.49%
```

[17]:
```
plt.figure(figsize=(10, 4))

# Box Plot for Purchase
sns.boxplot(x=walmart_data['Purchase'], patch_artist=True, widths=0.5)

plt.show()
```



[18]:
```
clipped_purchase = np.clip(walmart_data['Purchase'], np.
 ↪percentile(walmart_data['Purchase'], 5), np.
 ↪percentile(walmart_data['Purchase'], 95))

plt.figure(figsize=(10, 4))
plt.suptitle("\nClipped Outliers\n\n")
sns.boxplot(data=walmart_data,x=clipped_purchase)
plt.show()
```



Insights

Based on this graphical representation, it is evident that both Purchase has only a minor presence of outliers which is **0.49%**.

1.6 Non-Graphical Analysis:

Description of columns with 'object' datatype

[19]:
```
walmart_data.describe(include = 'object')
```

[19]:
```
        User_ID Product_ID  Gender     Age  Occupation City_Category  \
count    550068     550068  550068  550068      550068        550068
unique     5891       3631       2       7          21             3
top     1001680  P00265242       M   26-35           4             B
freq       1026       1880  414259  219587       72308        231173

       Stay_In_Current_City_Years Marital_Status  Product_Category
count                      550068         550068            550068
unique                          5              2                20
top                             1      Unmarried                 5
freq                       193821         324731            150933
```

The provided data represents summary statistics for two variables: Product_ID and Gender. Here is a breakdown of the information:

Product_ID: There are 3,631 unique values observed in this variable, indicating that there are 3,631 different products. The top value, which appears most frequently, is 'P00265242'. This value occurs 1,880 times in the dataset.

Gender: There are 2 unique values in this variable, which suggests that it represents a binary category. The top value is 'M' (i.e., Male), indicating that 'M' is the most common gender category. It appears 414,259 times in the dataset.

These summary statistics provide insights into the distribution and frequency of the Product_ID and Gender variables. They give an understanding of the number of unique products, the most common product, and the dominant gender category in the dataset.

1.6.1 value_counts and unique attributes

[20]:
```
categorical_columns = ['User_ID', 'Gender', 'Age', 'Occupation',␣
↪'City_Category', 'Marital_Status', 'Product_Category',␣
↪'Stay_In_Current_City_Years']
```

[21]:
```
# How many unique customers' data is given in the dataset?
print(f"Total number of unique customers in dataset are␣
↪{walmart_data['User_ID'].nunique()}")
```

```
Total number of unique customers in dataset are 5891
```

[22]:
```
# Total number of transactions made by each gender
np.round(walmart_data['Gender'].value_counts(normalize = True) * 100, 2)
```

[22]:
```
M    75.31
F    24.69
Name: Gender, dtype: float64
```

We have the data of 5891 customers who made at least one purchase on Black Friday in Walmart.

It is clear from the above that out of every four transactions, three are made by males as Males made more than 75% of purchase.

[23]:
```
np.round(walmart_data['Product_Category'].value_counts(normalize=True) *100, 2).
↪cumsum()
```

[23]:
```
5      27.44
1      52.96
8      73.67
11     78.09
2      82.43
6      86.15
3      89.82
4      91.96
16     93.75
15     94.89
13     95.90
10     96.83
12     97.55
```

```
7      98.23
18     98.80
20     99.26
19     99.55
14     99.83
17     99.94
9     100.01
Name: Product_Category, dtype: float64
```

It can be inferred from the above result that 82.43% of the total transactions are made for only 5 Product Categories. These are **5, 1, 8, 11 and 2**.

[24]:
```
np.round(walmart_data['Stay_In_Current_City_Years'].value_counts(normalize =␣
↪True) * 100, 2).sort_values(ascending=False)
```

[24]:
```
1     35.24
2     18.51
3     17.32
4+    15.40
0     13.53
Name: Stay_In_Current_City_Years, dtype: float64
```

From the above result, it is clear that majority of the transactions (53.75 % of total transactions) are made by the customers having **1 or 2** years of stay in the current city.

[25]:
```
np.round(walmart_data['Occupation'].value_counts(normalize = True) * 100, 2).
↪cumsum()
```

[25]:
```
4     13.15
0     25.81
7     36.56
1     45.18
17    52.46
20    58.56
12    64.23
14    69.19
2     74.02
16    78.63
6     82.33
3     85.54
10    87.89
5     90.10
15    92.31
11    94.42
19    95.96
13    97.36
18    98.56
9     99.70
```

```
8     99.98
Name: Occupation, dtype: float64
```

It can be inferred from the above that 82.33 % of the total transactions are made by the customers belonging to 11 occupations. These are 4, 0, 7, 1, 17, 20, 12, 14, 2, 16, 6 (Ordered in descending order of the total transactions' share.)

How many unique customers are there for each gender

[26]:
```
gender_dist = pd.DataFrame(walmart_data.groupby('Gender')['User_ID'].nunique()).
↪reset_index().rename(columns = {'User_ID' : 'unique_customers'})
gender_dist['percent_share'] = np.round(gender_dist['unique_customers'] /␣
↪gender_dist['unique_customers'].sum() * 100, 2)
gender_dist
```

[26]:

	Gender	unique_customers	percent_share
0	F	1666	28.28
1	M	4225	71.72

There are more unique male customers than female who purchased the products.

How many transactions are made by each gender category ?

[27]:
```
transaction_dist = pd.DataFrame(walmart_data.groupby('Gender')['User_ID'].
↪count()).reset_index()
transaction_dist
```

[27]:

	Gender	User_ID
0	F	135809
1	M	414259

[28]:
```
print('Average number of transactions made by each Male on Black Friday is',␣
↪round(414259 / 4225))
print('Average number of transactions made by each Female on Black Friday is',␣
↪round(135809 / 1666))
```

```
Average number of transactions made by each Male on Black Friday is 98
Average number of transactions made by each Female on Black Friday is 82
```

What is the total Revenue generated by Walmart from each Gender ?

[29]:
```
total_revenue = pd.DataFrame(walmart_data.groupby('Gender')['Purchase'].sum()).
↪reset_index()
total_revenue['Total Revenue Percentage'] = np.round(total_revenue['Purchase'] /
↪ total_revenue['Purchase'].sum() *100,2)
total_revenue
```

[29]:

	Gender	Purchase	Total Revenue Percentage
0	F	1186232642	23.28

```
1      M  3909580100                    76.72
```

What is the average total purchase made by each user in each gender ?

[30]:
```python
total_purchase = walmart_data.groupby(by=['Gender','User_ID'])['Purchase'].
 ↪sum().reset_index().rename(columns={'Purchase':'Average_Purchase'})
total_purchase.groupby(by = 'Gender')['Average_Purchase'].mean()
```

[30]:
```
Gender
F    712024.394958
M    925344.402367
Name: Average_Purchase, dtype: float64
```

What is the Average Revenue generated by Walmart from each Gender per transaction ?

[31]:
```python
average_revenue = np.round(walmart_data.groupby(by=['Gender'])['Purchase'].
 ↪mean().reset_index().rename(columns = {'Purchase' : 'Average_Purchase'}),2)
average_revenue
```

[31]:

	Gender	Average_Purchase
0	F	8734.57
1	M	9437.53

How many unique customers are there for each Marital Status ?

[32]:
```python
unique_customers = walmart_data.groupby('Marital_Status')['User_ID'].nunique()
unique_customers
```

[32]:
```
Marital_Status
Married      2474
Unmarried    3417
Name: User_ID, dtype: int64
```

How many transactions are made by each Marital Status category ?

[33]:
```python
transactions_made = walmart_data.groupby('Marital_Status')['User_ID'].count()
transactions_made
```

[33]:
```
Marital_Status
Married      225337
Unmarried    324731
Name: User_ID, dtype: int64
```

What is the total Revenue generated by Walmart from each Marital Status ?

[34]:
```python
total_revenue = walmart_data.groupby('Marital_Status')['Purchase'].sum()
total_revenue
```

```
[34]: Marital_Status
Married      2086885295
Unmarried    3008927447
Name: Purchase, dtype: int64
```

What is the average total purchase made by each user in each marital status ?

```
[35]: average_purchase = walmart_data.groupby(by=['Marital_Status',␣
       ↪'User_ID'])['Purchase'].mean()
      average_purchase
```

```
[35]: Marital_Status  User_ID
Married         1000004    14747.714286
                1000005     7745.292453
                1000007    13804.000000
                1000008    10345.363636
                1000010     9728.744395
                                …
Unmarried       1006034    16423.833333
                1006035     6293.717105
                1006037     9176.540984
                1006038     7502.833333
                1006040     9184.994444
Name: Purchase, Length: 5891, dtype: float64
```

Top average total purchase from Married users is : 1000004

Top average total purchase from Unmarried users is : 1006034

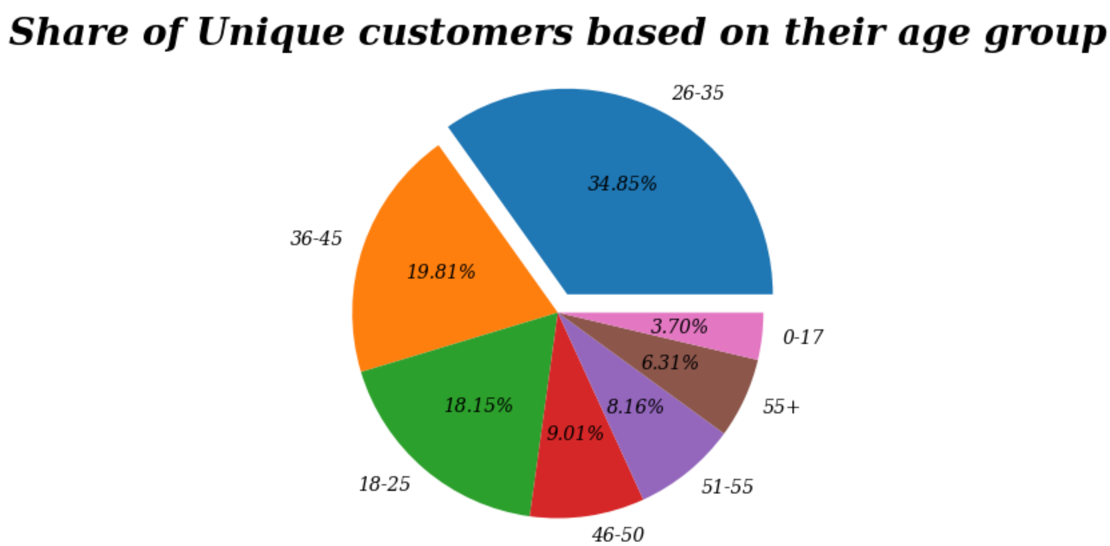
```
[36]: age_dist = walmart_data.groupby(by = ['Age'])['User_ID'].nunique().
       ↪reset_index().rename(columns = {'User_ID' : 'unique_customers'}).
       ↪sort_values(by = 'unique_customers', ascending = False)
      age_dist['percent_share'] =  np.round(age_dist['unique_customers'] /␣
       ↪age_dist['unique_customers'].sum() * 100, 2)
      age_dist['cumulative_percent'] =  age_dist['percent_share'].cumsum()
      age_dist
```

[36]:

	Age	unique_customers	percent_share	cumulative_percent
2	26-35	2053	34.85	34.85
3	36-45	1167	19.81	54.66
1	18-25	1069	18.15	72.81
4	46-50	531	9.01	81.82
5	51-55	481	8.16	89.98
6	55+	372	6.31	96.29
0	0-17	218	3.70	99.99

```
[37]: plt.figure(figsize = (8, 5))
```

```
plt.title('Share of Unique customers based on their age group', fontdict =␣
↪{'fontsize' : 20,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 600} )
plt.pie(x = age_dist['percent_share'], labels = age_dist['Age'], explode = [0.
↪1] + [0] * 6, autopct = '%.2f%%',
       textprops = {'fontsize' : 10,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500})
plt.show()
```



[38]:
```
walmart_data['Age'].value_counts()
```

[38]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

[39]:
```
age_revenue = pd.DataFrame(walmart_data.groupby(by = 'Age', as_index =␣
↪False)['Purchase'].sum().sort_values(by = 'Purchase', ascending = False)).
↪reset_index()
```

```
age_revenue['percent_share'] = np.round((age_revenue['Purchase'] /␣
 ↪age_revenue['Purchase'].sum()) * 100, 2)
age_revenue['cumulative_percent_share'] = age_revenue['percent_share'].cumsum()
age_revenue
```

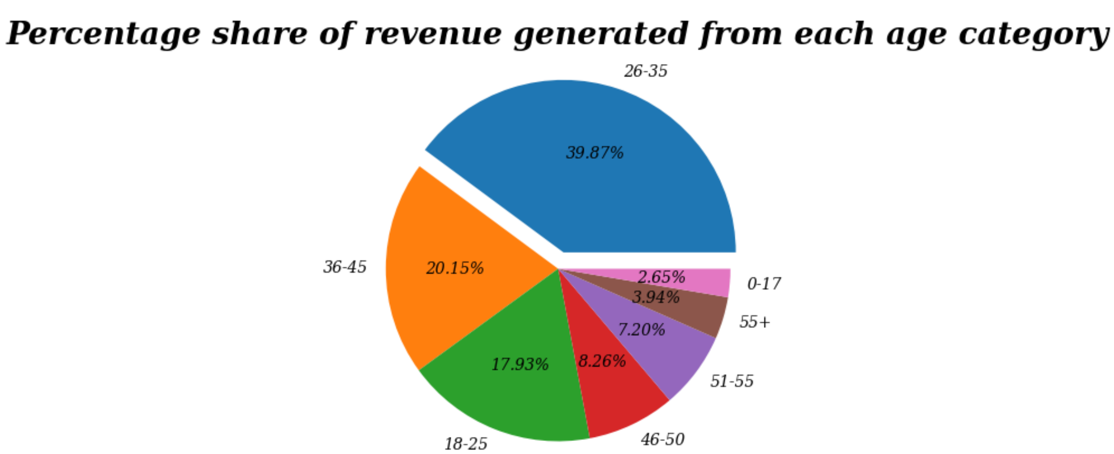
[39]:

	index	Age	Purchase	percent_share	cumulative_percent_share
0	2	26-35	2031770578	39.87	39.87
1	3	36-45	1026569884	20.15	60.02
2	1	18-25	913848675	17.93	77.95
3	4	46-50	420843403	8.26	86.21
4	5	51-55	367099644	7.20	93.41
5	6	55+	200767375	3.94	97.35
6	0	0-17	134913183	2.65	100.00

Users aged 26-35 represent the largest age group,constituting approximately 40% of the dataset.

The 0-17 age group and the 55+ age group each contribute to about 3% of the dataset.

[40]:
```
plt.figure(figsize = (8, 5))
plt.title('Percentage share of revenue generated from each age category',␣
 ↪fontdict = {'fontsize' : 20,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 600} )
plt.pie(x = age_revenue['percent_share'], labels = age_revenue['Age'],
        explode = [0.1] + [0] * 6, autopct = '%.2f%%',
       textprops = {'fontsize' : 10,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500})
plt.show()
```



[41]:
```
city_dist = walmart_data.groupby(by = ['City_Category'])['User_ID'].nunique().
    ↪reset_index().rename(columns = {'User_ID' : 'unique_customers'})
city_dist['percent_share'] = np.round((city_dist['unique_customers'] /
    ↪city_dist['unique_customers'].sum()) * 100, 2)
city_dist['cumulative_percent_share'] = city_dist['percent_share'].cumsum()
city_dist
```

[41]:

	City_Category	unique_customers	percent_share	cumulative_percent_share
0	A	1045	17.74	17.74
1	B	1707	28.98	46.72
2	C	3139	53.28	100.00

[42]:
```
walmart_data['City_Category'].value_counts()
```

[42]:
```
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

What is the revenue generated from different cities ?

[43]:
```
cities_revenue = walmart_data.groupby('City_Category')['Purchase'].sum().
    ↪reset_index().rename(columns={'Purchase' : 'Revenue from Cities'})
cities_revenue.sort_values(by ='Revenue from Cities',ascending=False)
```

[43]:

	City_Category	Revenue from Cities
1	B	2115533605
2	C	1663807476
0	A	1316471661

[44]:
```
walmart_data.groupby(by = ['Product_Category'])['Product_ID'].nunique().
    ↪sort_values(ascending=False)
```

[44]:
```
Product_Category
8     1047
5      967
1      493
11     254
2      152
6      119
7      102
16      98
3       90
4       88
14      44
15      44
```

```
13      35
18      30
10      25
12      25
17      11
20       3
9        2
19       2
Name: Product_ID, dtype: int64
```

What is the revenue generated from different product categories ?

[45]:
```
products_revenue = pd.DataFrame(walmart_data.
    ↪groupby('Product_Category')['Purchase'].sum().sort_values(ascending=False)).
    ↪reset_index()
products_revenue
```

[45]:
```
    Product_Category    Purchase
0                  1  1910013754
1                  5   941835229
2                  8   854318799
3                  6   324150302
4                  2   268516186
5                  3   204084713
6                 16   145120612
7                 11   113791115
8                 10   100837301
9                 15    92969042
10                 7    60896731
11                 4    27380488
12                14    20014696
13                18     9290201
14                 9     6370324
15                17     5878699
16                12     5331844
17                13     4008601
18                20      944727
19                19       59378
```

[46]:
```
top5 =  np.round(products_revenue.iloc[:5].sum()/products_revenue['Purchase'].
    ↪sum()* 100, 2)
print(f'Top 5 product categories from which Walmart makes {top5} % of total␣
    ↪revenue are :{list(products_revenue["Product_Category"].iloc[:5])}')
```

```
Top 5 product categories from which Walmart makes Product_Category     0.00
Purchase            84.36
dtype: float64 % of total revenue are :[1, 5, 8, 6, 2]
```

What is the total Revenue generated by Walmart from each Gender ?

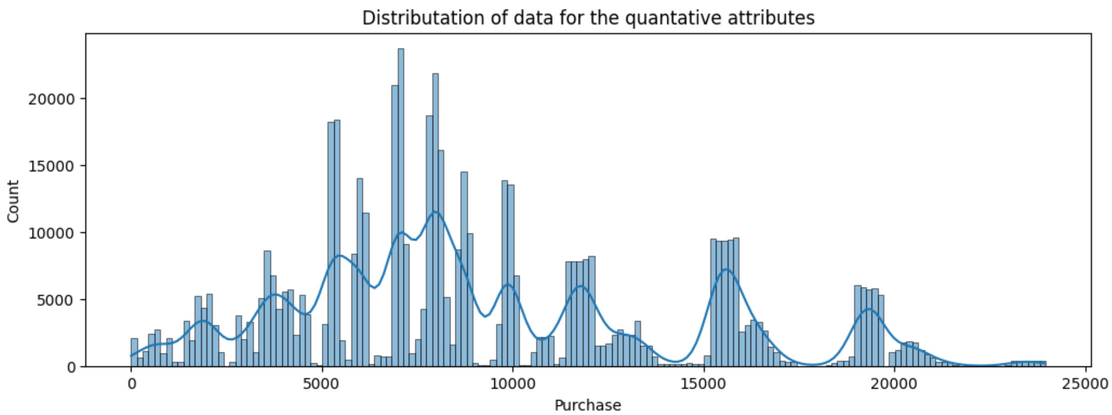
[47]:
```
gender_revenue = pd.DataFrame(walmart_data.groupby('Gender')['Purchase'].sum().
↪sort_values(ascending=False)).reset_index()
gender_revenue['Percentage_share'] = np.round( gender_revenue['Purchase']/
↪gender_revenue['Purchase'].sum()* 100, 2)
gender_revenue
```

[47]:

	Gender	Purchase	Percentage_share
0	M	3909580100	76.72
1	F	1186232642	23.28

1.7 Univariate Analysis

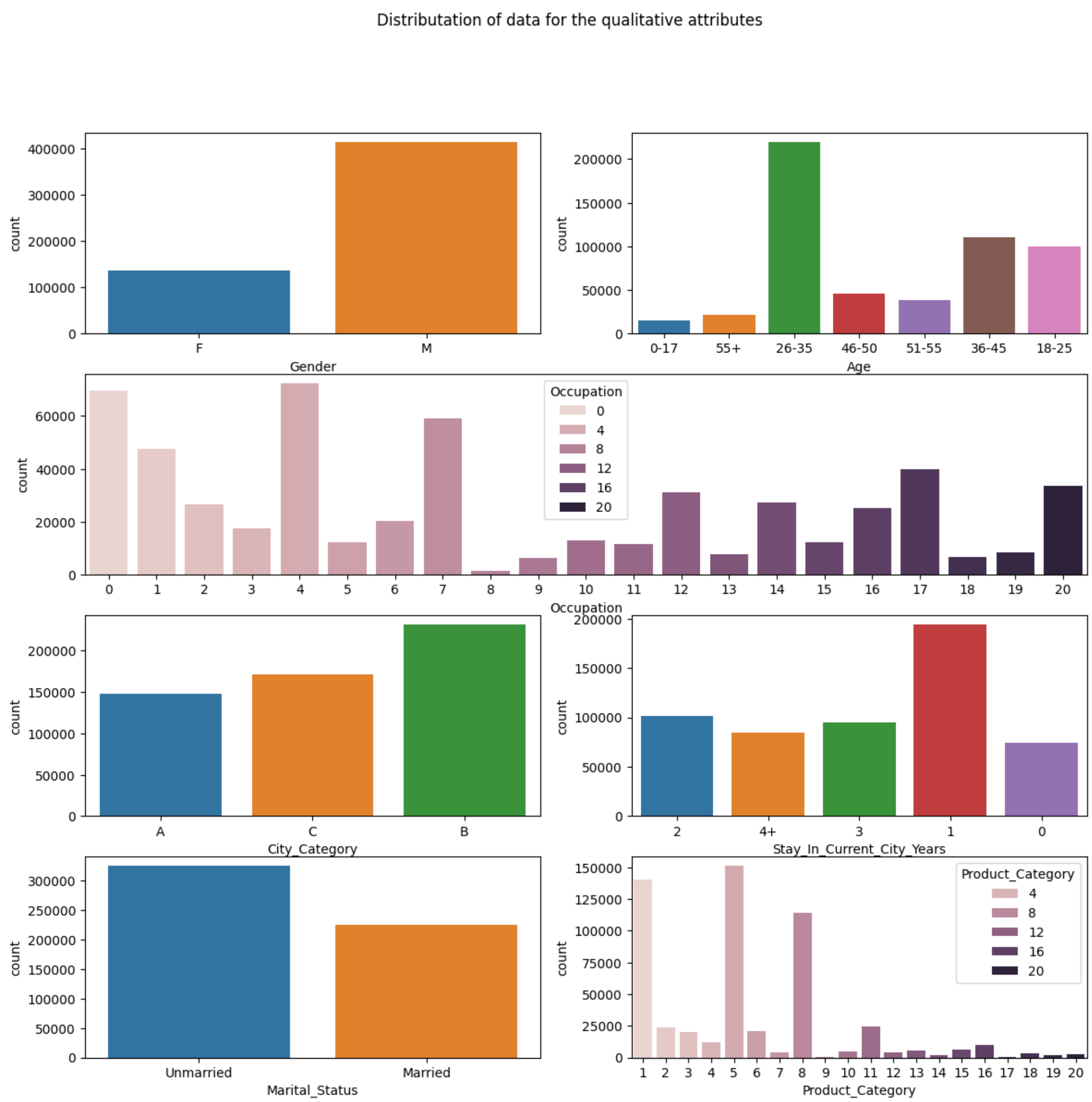
[48]:
```
#Distributation of data for the quantative attributes
plt.figure(figsize=(12,4))
plt.title("Distributation of data for the quantative attributes")
sns.histplot(data=walmart_data,x="Purchase",kde=True)
plt.show()
```



[49]:
```
#Distributation of data for the qualitative attribute
fig,ax=plt.subplots(4,2,figsize=(14,13))
fig.suptitle("Distributation of data for the qualitative attributes")
plt.subplot(4,2,1)
sns.countplot(data=walmart_data,x="Gender", hue='Gender')
plt.subplot(4,2,2)
sns.countplot(data=walmart_data,x="Age", hue="Age")
plt.subplot(4,2,(3,4))
sns.countplot(data=walmart_data,x="Occupation", hue="Occupation")
plt.subplot(4,2,5)
sns.countplot(data=walmart_data,x="City_Category", hue="City_Category")
plt.subplot(4,2,6)
```

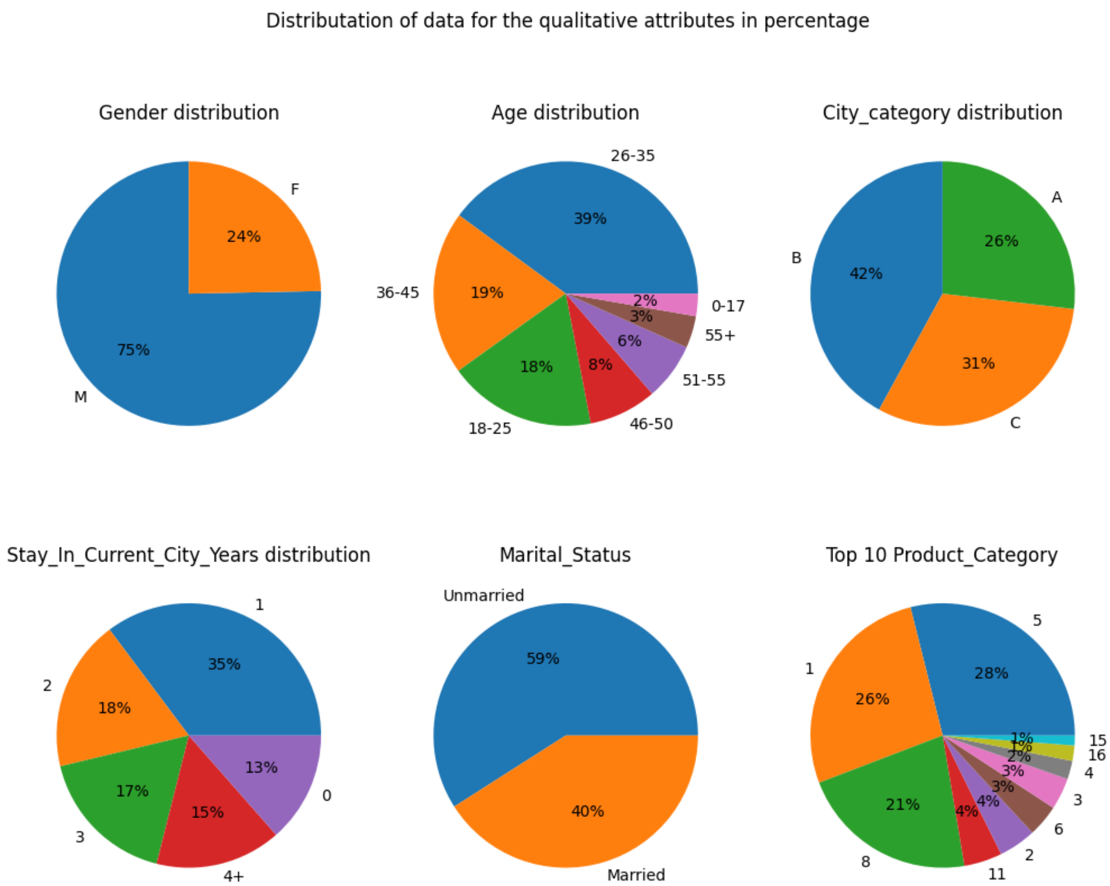
```
sns.countplot(data=walmart_data,x="Stay_In_Current_City_Years", hue="Stay_In_Current_City_Years")

plt.subplot(4,2,7)
sns.countplot(data=walmart_data,x="Marital_Status", hue="Marital_Status")
plt.subplot(4,2,8)
sns.countplot(data=walmart_data,x="Product_Category", hue="Product_Category")

plt.show()
```

```
<ipython-input-49-d5793114de09>:8: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.
  plt.subplot(4,2,(3,4))
```



[50]:

```
fig,ax=plt.subplots(2,3,figsize=(10,9))
fig.suptitle("Distributation of data for the qualitative attributes in␣
↪percentage")
plt.subplot(2,3,1)
data_Gender=walmart_data['Gender'].value_counts(normalize=True)*100
plt.pie(data_Gender, labels=data_Gender.index, autopct='%d%%', startangle=90)
plt.title("Gender distribution")

plt.subplot(2,3,2)
data_Age=walmart_data['Age'].value_counts(normalize=True)*100
plt.pie(data_Age, labels=data_Age.index,autopct='%d%%', startangle=0)
plt.title("Age distribution")

plt.subplot(2,3,3)
data_City_Category=walmart_data['City_Category'].
↪value_counts(normalize=True)*100
plt.pie(data_City_Category, labels=data_City_Category.index, autopct='%d%%',␣
↪startangle=90)
plt.title("City_category distribution")

plt.subplot(2,3,4)
data_Stay_In_Current_City_Years=walmart_data['Stay_In_Current_City_Years'].
↪value_counts(normalize=True)*100
plt.pie(data_Stay_In_Current_City_Years, labels=data_Stay_In_Current_City_Years.
↪index, autopct='%d%%', startangle=0)
plt.title("Stay_In_Current_City_Years distribution")

plt.subplot(2,3,5)
data_Marital_Status=walmart_data["Marital_Status"].
↪value_counts(normalize=True)*100
plt.pie(data_Marital_Status, labels=data_Marital_Status.index, autopct='%d%%',␣
↪startangle=0)
plt.title("Marital_Status")

plt.subplot(2,3,6)
data_Product_Category=(walmart_data["Product_Category"].
↪value_counts(normalize=True)*100).sort_values(ascending=False).head(10)

plt.pie(data_Product_Category, labels=data_Product_Category.index,␣
↪autopct='%d%%', startangle=0)
plt.title("Top 10 Product_Category")

plt.tight_layout()

plt.show()
```



Insights

1. Gender Distribution:

   The data suggests a significant majority of male users, indicating a potential gender based trend in shopping behavior.

2. **Age Group Preferences:**

   Users aged between 26 and 35 are the most prominent age group in the dataset, with a focus on users aged 18 to 45.

3. Occupation Trends:

   Occupations labeled as 0, 4, and 7 appear frequently among the 20 occupation types.

4. City Residence:

   City category labeled as 'B' has the highest number of users, while categories 'A' and 'C' show a more evenly distributed user population.

5. Length of Residence:

A majority of users have resided in their current city for more than one year, indicating stability in their place of residence.

6. Marital Status:

   Unmarried users outnumber married users in the dataset.

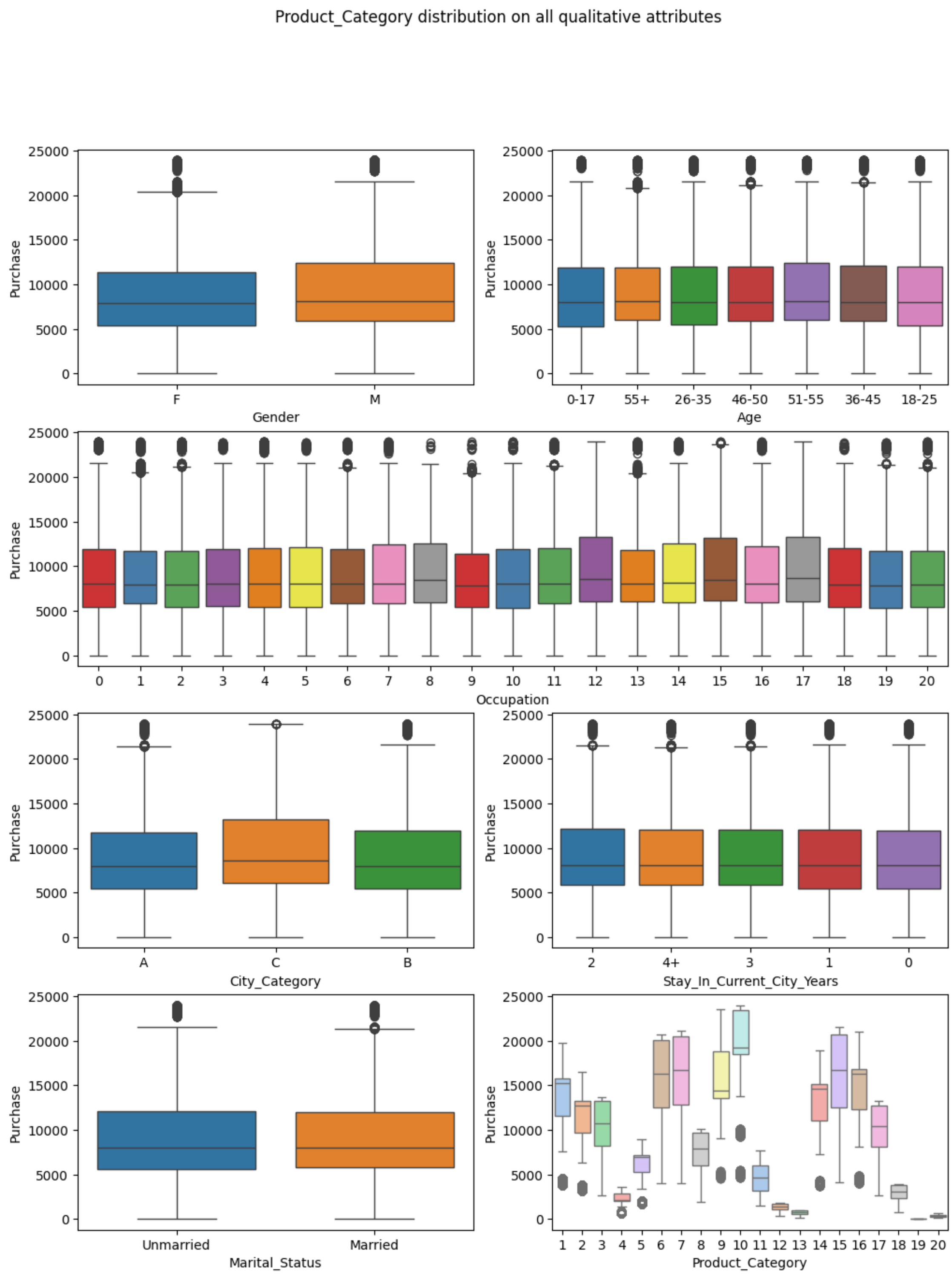
7. Product Category Preferences:

   Users predominantly purchase products from categories 5, 1, and 8.

1.8 Bivariate Analysis

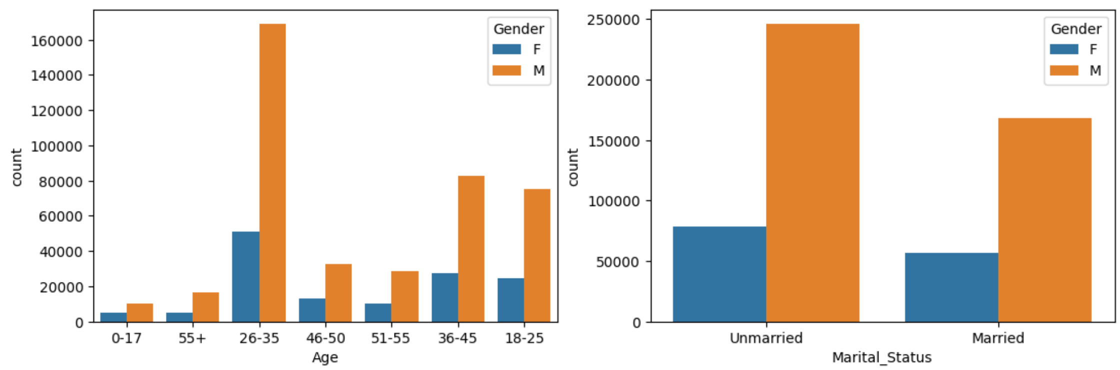
[51]:
```
fig,ax=plt.subplots(4,2,figsize=(12,15))
fig.suptitle("Product_Category distribution on all qualitative attributes")

plt.subplot(4,2,1)
sns.boxplot(data=walmart_data,x="Gender",y="Purchase", hue="Gender",␣
 ↪legend=False)
plt.subplot(4,2,2)
sns.boxplot(data=walmart_data,x="Age",y="Purchase", hue="Age", legend=False)
plt.subplot(4,2,(3,4))
sns.boxplot(data=walmart_data,x="Occupation",y="Purchase", hue="Occupation",␣
 ↪legend=False, palette='Set1')
plt.subplot(4,2,5)
sns.boxplot(data=walmart_data,x="City_Category",y="Purchase",␣
 ↪hue="City_Category", legend=False)
plt.subplot(4,2,6)
sns.boxplot(data=walmart_data,x="Stay_In_Current_City_Years",y="Purchase",␣
 ↪hue="Stay_In_Current_City_Years", legend=False)
plt.subplot(4,2,7)
sns.boxplot(data=walmart_data,x="Marital_Status",y="Purchase",␣
 ↪hue="Marital_Status", legend=False)
plt.subplot(4,2,8)
sns.boxplot(data=walmart_data,x="Product_Category",y="Purchase",␣
 ↪hue="Product_Category", legend=False, palette='pastel')
plt.show()
```

```
<ipython-input-51-90099fdcd5a6>:8: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.
  plt.subplot(4,2,(3,4))
```



[52]:
```
plt.subplots(1,2,figsize=(13,4))
fig.suptitle("Gender distribution on age and marital_status")
```

```python
plt.subplot(1,2,1)
sns.countplot(data=walmart_data,x="Age",hue="Gender")
plt.subplot(1,2,2)
sns.countplot(data=walmart_data,x="Marital_Status",hue="Gender")
plt.show()
```



[53]:
```python
walmart_revised_Data =walmart_data.drop(["User_ID","Product_ID"],axis=1)
```

[54]:
```python
walmart_revised_Data.head()
```

[54]:

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	\
0	F	0-17	10	A	2	
1	F	0-17	10	A	2	
2	F	0-17	10	A	2	
3	F	0-17	10	A	2	
4	M	55+	16	C	4+	

	Marital_Status	Product_Category	Purchase
0	Unmarried	3	8370
1	Unmarried	1	15200
2	Unmarried	12	1422
3	Unmarried	12	1057
4	Unmarried	8	7969

[55]:
```python
sample1=walmart_revised_Data.sample(n=300)
sample1
```

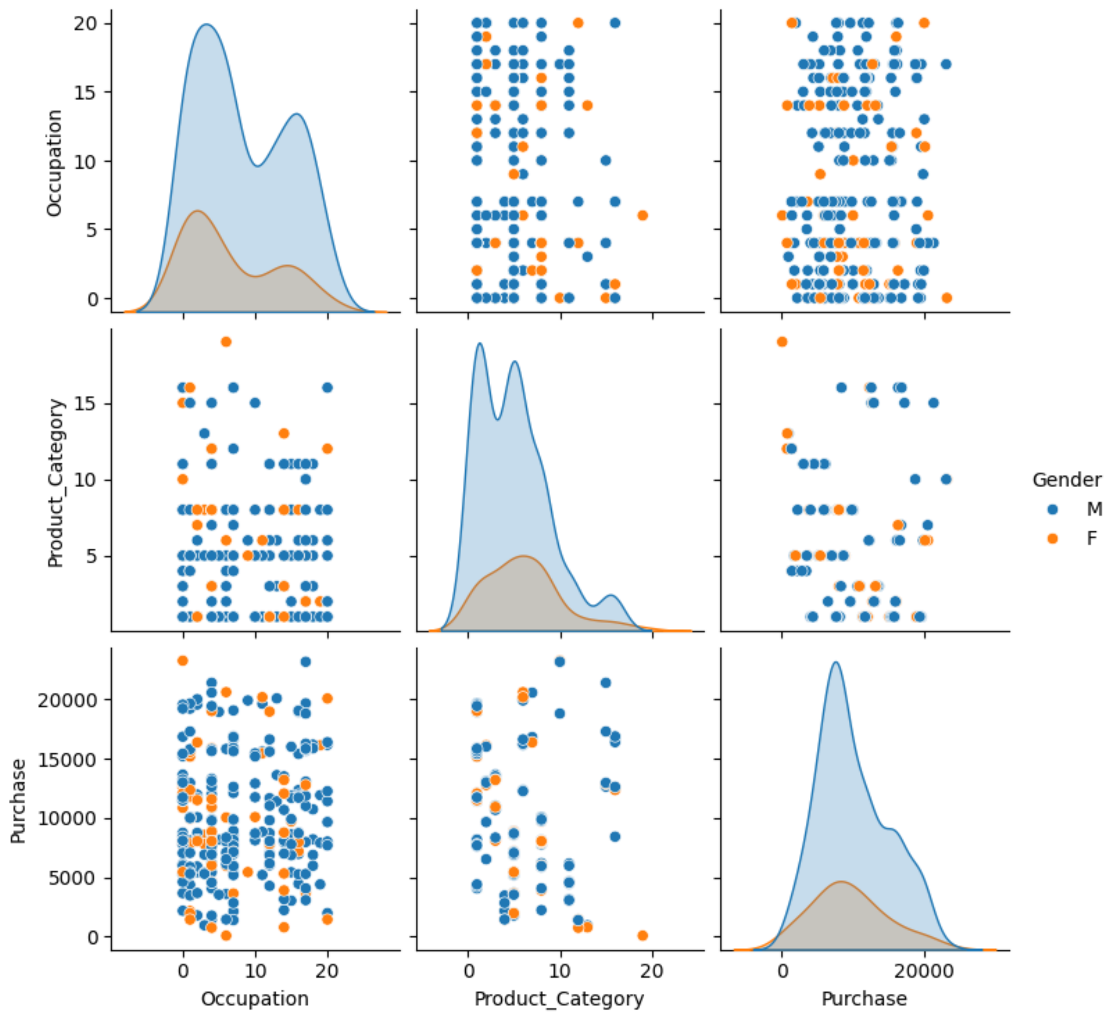
[55]:

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	\
311305	M	36-45	1	B	2	
539263	F	26-35	15	C	1	
347582	M	26-35	16	B	2	
186401	M	46-50	16	B	3	
207198	M	26-35	15	A	4+	

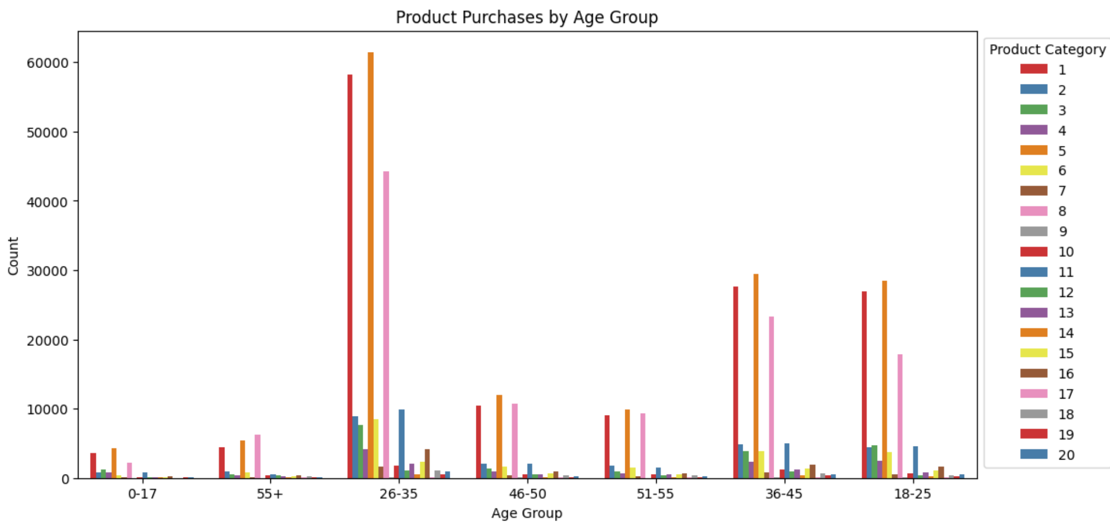
```
…          …     …         …             …                          …
3761           M   18-25          0             A                          3
266602         M   51-55          7             C                         4+
270776         M   26-35          4             B                          2
380879         M   36-45         17             C                          1
210293         F   36-45          9             B                          3

       Marital_Status Product_Category  Purchase
311305      Unmarried                1     19231
539263        Married                8      9705
347582        Married                6     12352
186401      Unmarried                5      8763
207198      Unmarried               11      3012
…                …              …       …
3761        Unmarried                1     11734
266602      Unmarried               16     12626
270776      Unmarried                1     19451
380879      Unmarried               11      3058
210293        Married                5      5424

[300 rows x 8 columns]
```

[56]:

```
sns.pairplot(data=sample1,hue="Gender")
plt.show()
```



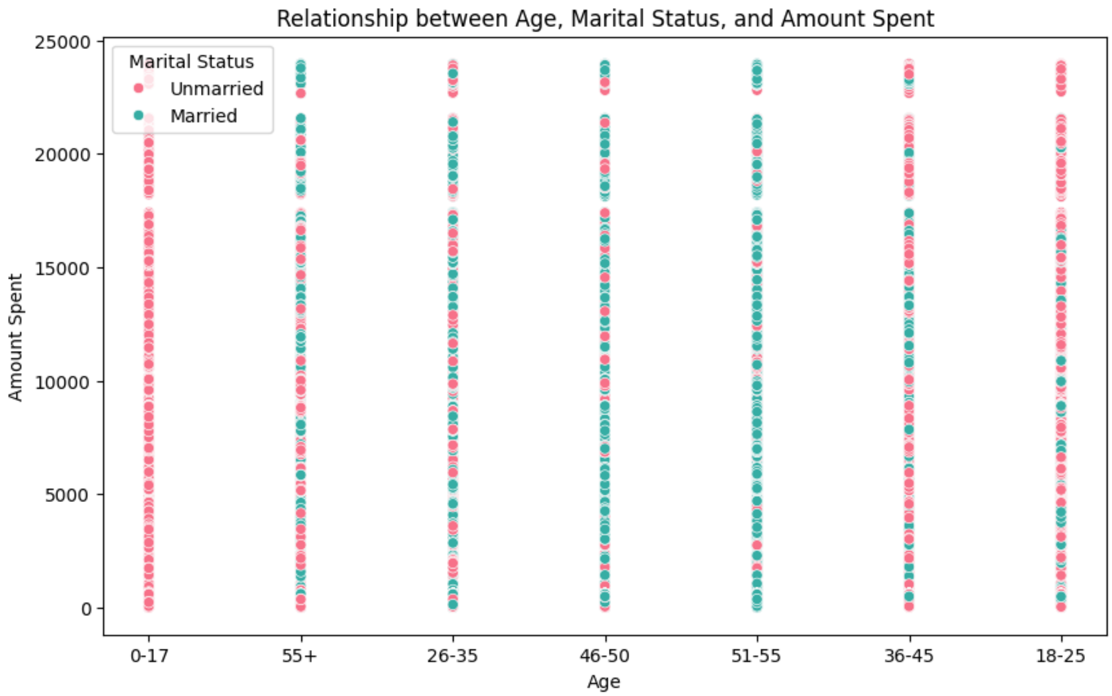
[57]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=walmart_data, x="Age", hue="Product_Category",␣
 ↪palette='Set1')
plt.title("Product Purchases by Age Group")
plt.xlabel("Age Group")
plt.ylabel("Count")
plt.legend(title="Product Category", bbox_to_anchor=(1, 1), loc='upper left')
plt.show()
```



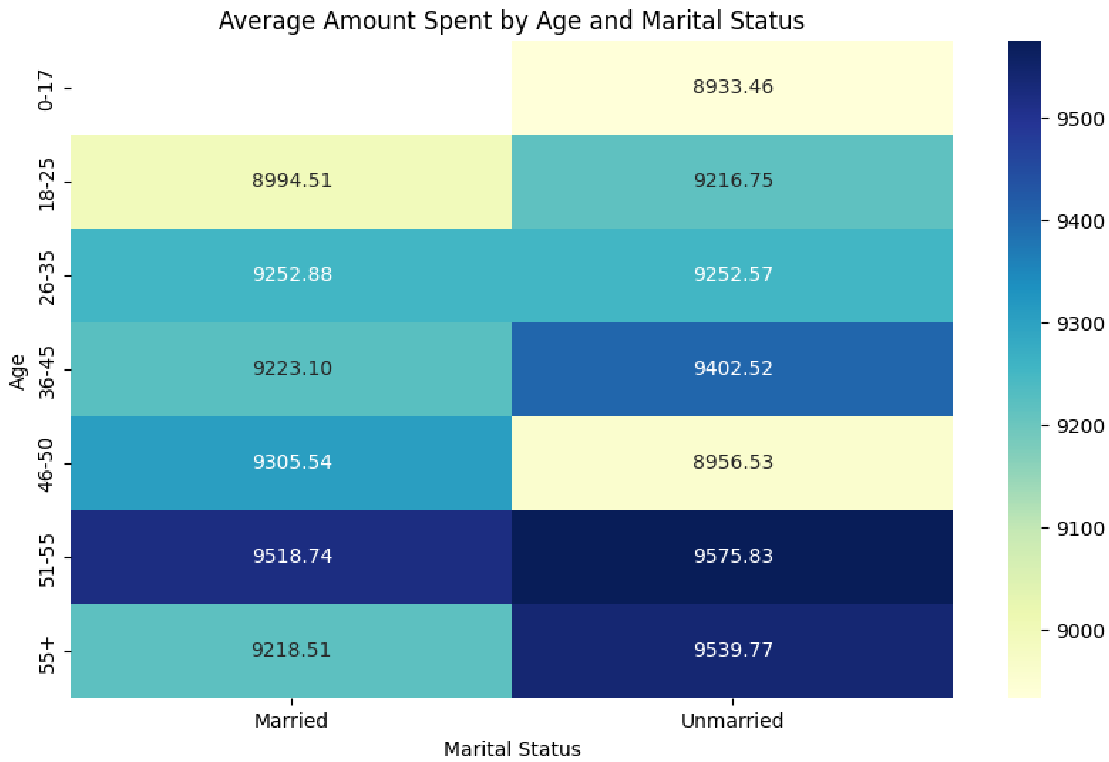
##Multivariate Analysis

[58]:
```
# Scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(data=walmart_data, x="Age", y="Purchase", hue="Marital_Status",␣
↪palette='husl')
plt.title("Relationship between Age, Marital Status, and Amount Spent")
plt.xlabel("Age")
plt.ylabel("Amount Spent")
plt.legend(title="Marital Status")
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/IPython/core/pylabtools.py:151:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  fig.canvas.print_figure(bytes_io, **kw)
```



[59]:
```
# Heatmap
plt.figure(figsize=(10, 6))
pivot_table = walmart_data.pivot_table(index="Age", columns="Marital_Status",␣
↪values="Purchase", aggfunc="mean")
sns.heatmap(pivot_table, cmap="YlGnBu", annot=True, fmt=".2f")
plt.title("Average Amount Spent by Age and Marital Status")
plt.xlabel("Marital Status")
plt.ylabel("Age")
plt.show()
```



Scatter Plot Insights:

There doesn't seem to be a clear, discernible pattern or trend in the relationship between age, marital status, and the amount spent based on the scatter plot. The distribution of data points across different ages and marital status categories appears to be relatively scattered, indicating that there may not be a strong linear relationship between these variables.

Heatmap Insights:

The heatmap provides a clearer visualization of the average amount spent across different age groups and marital status categories. There doesn't appear to be a strong correlation between age, marital status, and the average amount spent, as indicated by the lack of significant variation in the average spending amounts across different age and marital status categories.

Overall, based on these visualizations, it seems that there may not be a strong relationship between age, marital status, and the amount spent. However, these insights are based on the provided visualizations, and further analysis, such as statistical testing or additional data exploration, may be necessary to confirm these findings.

1.9 Answering questions:

1. Are women spending more money per transaction than men? Why or Why not?
2. Confidence intervals and distribution of the mean of the expenses by female and male customers.

3. Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?
4. Results when the same activity is performed for Married vs Unmarried.
5. Results when the same activity is performed for Age.

[60]:
```
walmart_data.head()
```

[60]:
```
   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      Unmarried                3      8370
1                          2      Unmarried                1     15200
2                          2      Unmarried               12      1422
3                          2      Unmarried               12      1057
4                         4+      Unmarried                8      7969
```

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

[61]:
```
#creating a walmart_data for purchase amount vs gender
money_spend = walmart_data.groupby('Gender')['Purchase'].agg(['sum','count']).
 ↪reset_index()

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

#calculationg percentage distribution of purchase amount
money_spend['%sum'] = round(money_spend['sum']/money_spend['sum'].sum(),2)

#calculationg per purchase amount
money_spend['per_purchase'] = round(money_spend['sum']/money_spend['count'],2)

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

money_spend
```

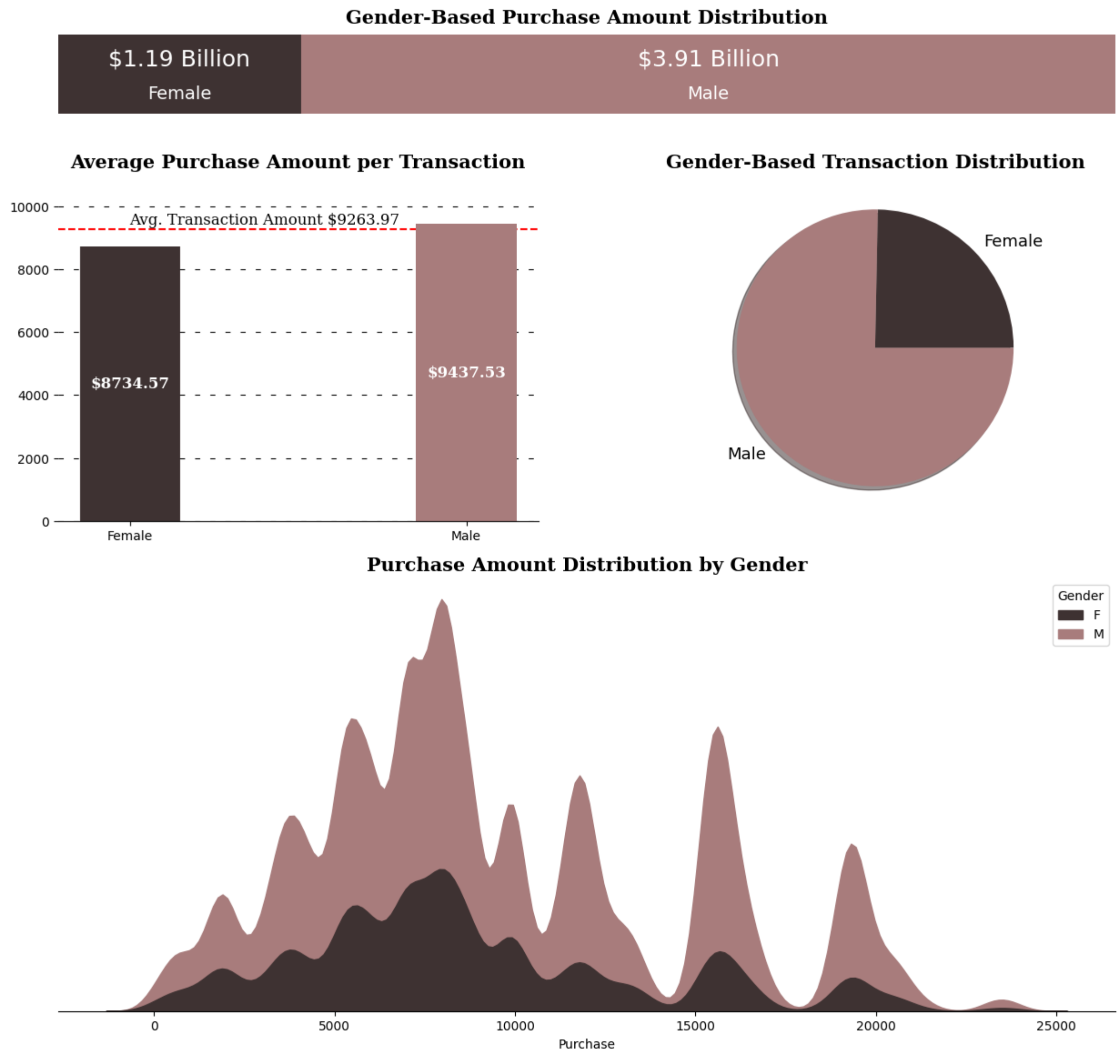
[61]:
```
   Gender         sum   count  sum_in_billions  %sum  per_purchase
0  Female  1186232642  135809             1.19  0.23       8734.57
1    Male  3909580100  414259             3.91  0.77       9437.53
```

[62]:
```
#setting the plot style
fig = plt.figure(figsize = (15,14))
gs = fig.add_gridspec(3,2,height_ratios =[0.10,0.4,0.5])
```

```
color_map = ["#3E3232", "#A87C7C"]

                                        #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0,:])

#plotting the visual
ax.barh(money_spend.loc[0,'Gender'],width = money_spend.loc[0,'%sum'],color =␣
↪color_map[0],label = 'Female')
ax.barh(money_spend.loc[0,'Gender'],width = money_spend.loc[1,'%sum'],left␣
↪=money_spend.loc[0,'%sum'], color =  color_map[1],label = 'Male' )

#inserting the text
txt = [0.0] #for left parameter in ax.text()

for i in money_spend.index:
    #for amount
    ax.text(money_spend.loc[i,'%sum']/2 + txt[0],0.15,f"${money_spend.
↪loc[i,'sum_in_billions']} Billion", va = 'center', ha='center',fontsize=18,
            color='white')

    #for gender
    ax.text(money_spend.loc[i,'%sum']/2 + txt[0],- 0.20 ,f"{money_spend.
↪loc[i,'Gender']}", va = 'center', ha='center',fontsize=14, color='white')

    txt += money_spend.loc[i,'%sum']

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

#customizing ticks
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0,1)

#plot title
ax.set_title('Gender-Based Purchase Amount Distribution',{'font':'serif',␣
↪'size':15,'weight':'bold'})


                                            #Distribution of Purchase Amount␣
↪per Transaction
ax1 = fig.add_subplot(gs[1,0])

#plotting the visual
```

```
ax1.bar(money_spend['Gender'],money_spend['per_purchase'],color =␣
 ↪color_map,zorder = 2,width = 0.3)

#adding average transaction line
avg = round(walmart_data['Purchase'].mean(),2)

ax1.axhline(y = avg, color ='red', zorder = 0,linestyle = '--')

#adding text for the line
ax1.text(0.4,avg +300, f"Avg. Transaction Amount ${avg:}", {'font':
 ↪'serif','size' : 12},ha = 'center',va = 'center')

#adjusting the ylimits
ax1.set_ylim(0,11000)

#adding the value_counts
for i in money_spend.index:
    ax1.text(money_spend.loc[i,'Gender'],money_spend.loc[i,'per_purchase']/
 ↪2,f"${money_spend.loc[i,'per_purchase']}",
             {'font':'serif','size' : 12,'color':'white','weight':'bold' },ha =␣
 ↪'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#setting title for visual
ax1.set_title('Average Purchase Amount per Transaction',{'font':'serif', 'size':
 ↪15,'weight':'bold'})

                                        # creating pie chart for gender␣
 ↪disribution
ax2 = fig.add_subplot(gs[1,1])

ax2.pie(money_spend['count'],labels = money_spend['Gender'], shadow =␣
 ↪True,colors = color_map, textprops={'fontsize': 13, 'color': 'black'})

#setting title for visual
ax2.set_title('Gender-Based Transaction Distribution',{'font':'serif', 'size':
 ↪15,'weight':'bold'})

                                        # creating kdeplot for purchase amount␣
 ↪distribution

ax3 = fig.add_subplot(gs[2,:])
```

```
#plotting the kdeplot
sns.kdeplot(data = walmart_data, x = 'Purchase', hue = 'Gender', palette =␣
↪color_map,fill = True, alpha = 1,ax = ax3)

#removing the axis lines
for axislines in ['top','left','right']:
    ax1.spines[axislines].set_visible(False)
    ax3.spines[axislines].set_visible(False)

# adjusting axis labels
ax3.set_yticks([])
ax3.set_ylabel('')

#setting title for visual
ax3.set_title('Purchase Amount Distribution by Gender',{'font':'serif', 'size':
↪15,'weight':'bold'})

plt.show()
```



Insights 1. 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. 2. Average Transaction Value

The average purchase amount per transaction was slightly higher for male customers than female customers ($9438 vs $8735). 3. Distribution of Purchase Amount

As seen above, the purchase amount for both the genders is not normally distributed.

Comparing the average purchase amounts:

Women (F) spend an average of 8,734.57 per transaction. Men (M) spend an average of 9,437.53 per transaction. No, women are not spending more money per transaction than men.

Analyzing the reasons why females are spending less money per transaction than men.

The key reasons why females are spending less money per transaction than men in the provided dataset:-

1. Gender Distribution: There are significantly more male customers (414,259 than female customers (135,809) in the dataset. This difference in sample size can influence the average spending per transaction, as larger sample sizes tend to have more stable and higher averages.
2. Occupation Distribution: The dataset shows that the gender distribution varies across different occupations. Some occupations have a higher representation of females, while others have more males. These variations in occupation choices can affect the overall spending patterns.
3. Product Category Preferences: In most product categories, male customers make more purchases than female customers, resulting in higher counts for males. This suggests that males might be buying more expensive products or spending more in certain product categories.
4. Income Disparities: Income disparities between genders, which are not directly reflected in the dataset, can influence spending behavior. If males, on average, have higher incomes,they may be more willing to spend more per transaction.
5. Sample Size Impact: The difference in the number of males and females in the dataset can impact the overall average spending calculation. With a larger number of males, even small differences in spending can lead to variations in the average.

1.9.1 Confidence Interval Construction: Estimating Average Purchase Amount per Transaction by Female and Male

1. Step 1 - Building CLT Curve

   As seen above, the purchase amount distribution is not Normal. So we need to use Central Limit Theorem. It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution

2. Step 2 - Building Confidence Interval

   After building CLT curve, we will create a confidence interval predicting population mean at 99%,95% and 90% Confidence level.

Note - I am using different sample sizes of **`[300, 3000, and 30000]`**

---

[63]:
```
#Creating a function to calculate confidence interval

def confidence_interval(data,ci):
    #Converting the list to series
    lower_ci = (100-ci)/2
    upper_ci = (100+ci)/2

    #Calculating lower limit and upper limit of confidence interval
    interval = np.percentile(data,[lower_ci,upper_ci]).round(0)

    return interval
```

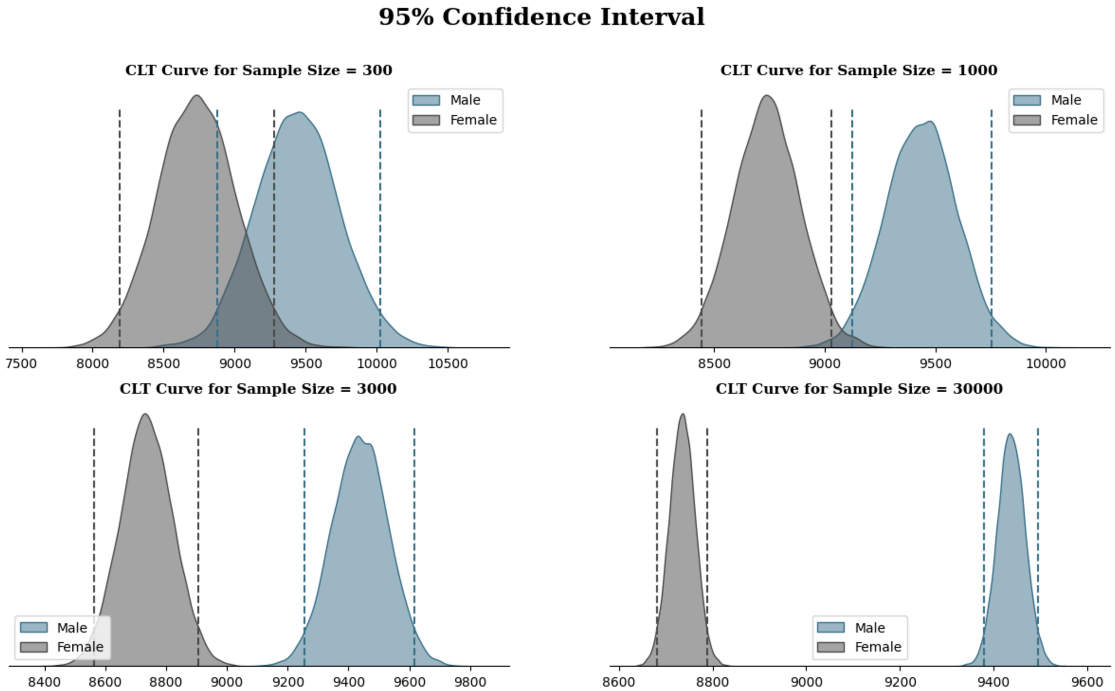
[64]:

```
def plot(ci):

    #setting the plot style
    fig = plt.figure(figsize = (15,8))
    gs = fig.add_gridspec(2,2)

    #creating separate data frames for each gender
    walmart_data_male = walmart_data.loc[walmart_data['Gender'] ==␣
↪'M','Purchase']
    walmart_data_female = walmart_data.loc[walmart_data['Gender'] ==␣
↪'F','Purchase']

    #sample sizes and corresponding plot positions
    sample_sizes = [(300,0,0),(1000,0,1),(3000,1,0),(30000,1,1)]

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

    male_samples = {}
    female_samples = {}

    # In each iteration of the loop, "i", "x", "y" will hold the "sample size",␣
↪"row position", "column position" respectively for plotting purposes
    # This allows iterate over different sample sizes and correspondingly place␣
↪the resulting plots in different positions within a grid of subplots
    for i,x,y in sample_sizes:
        male_means = [] #list for collecting the means of male sample
        female_means = [] #list for collecting the means of female sample

        for j in range(bootstrap_samples):
            #creating random 5000 samples of i (sample size)
            male_bootstrapped_samples = np.random.choice(walmart_data_male,size␣
↪= i)
            female_bootstrapped_samples = np.random.
↪choice(walmart_data_female,size = i)

            #calculating mean of those samples
            male_sample_mean = np.mean(male_bootstrapped_samples)
            female_sample_mean = np.mean(female_bootstrapped_samples)

            #appending the mean to the list
            male_means.append(male_sample_mean)
            female_means.append(female_sample_mean)

        #storing the above sample generated
        male_samples[f'{ci}%_{i}'] = male_means
        female_samples[f'{ci}%_{i}'] = female_means
```

```
        #creating a temporary dataframe for creating kdeplot
        temp_walmart_data = pd.DataFrame(data = {'male_means':
↪male_means,'female_means':female_means})

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

        #plots for male and female
        sns.kdeplot(data = temp_walmart_data,x = 'male_means',color ="#3A7089"␣
↪,fill = True, alpha = 0.5,ax = ax,label = 'Male')
        sns.kdeplot(data = temp_walmart_data,x = 'female_means',color␣
↪="#4b4b4c" ,fill = True, alpha = 0.5,ax = ax,label = 'Female')

        #calculating confidence intervals for given confidence level(ci)
        m_range = confidence_interval(male_means,ci)
        f_range = confidence_interval(female_means,ci)

        #plotting confidence interval on the distribution
        for k in m_range:
            ax.axvline(x = k,ymax = 0.9, color ="#3A7089",linestyle = '--')

        for k in f_range:
            ax.axvline(x = k,ymax = 0.9, color ="#4b4b4c",linestyle = '--')


        #removing the axis lines
        for axislines in ['top','left','right']:
            ax.spines[axislines].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,'weight':'bold'})

        plt.legend()

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

    plt.show()
```

```
    return male_samples,female_samples
```

[65]:
```
m_samp_95,f_samp_95 = plot(95)
```



[66]:
```
fig = plt.figure(figsize = (20,10))
gs = fig.add_gridspec(3,1)

for i,j,k,l in [(m_samp_95,f_samp_95,95,1)]:
    #list for collecting ci for given cl
    m_ci = ['Male']
    f_ci = ['Female']

    #finding ci for each sample size (males)
    for m in i:
        m_range = confidence_interval(i[m],k)
        m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f}, Range =␣
 ↪{(m_range[1] - m_range[0]):.0f}")

    #finding ci for each sample size (females)
    for f in j:
        f_range = confidence_interval(j[f],k)
        f_ci.append(f"CI = ${f_range[0]:.0f} - ${f_range[1]:.0f}, Range =␣
 ↪{(f_range[1] - f_range[0]):.0f}")
```

```
                                    #plotting the summary
    ax = fig.add_subplot(gs[1])

    #contents of the table
    ci_info = [m_ci,f_ci]

    #plotting the table
    table = ax.table(cellText = ci_info, cellLoc='center',
                     colLabels =['Gender','Sample Size = 300','Sample Size = 1000','Sample Size = 3000','Sample Size = 30000'],
                     colLoc = 'center',colWidths = [0.05,0.2375,0.2375,0.2375,0.2375],bbox =[0, 0, 1, 1])

    table.set_fontsize(13)

    #removing axis
    ax.axis('off')

    #setting title
    ax.set_title(f"{k}% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'bold'})
```

95% Confidence Interval Summary

Gender	Sample Size = 300	Sample Size = 1000	Sample Size = 3000	Sample Size = 30000
Male	CI = 8876 – 10025, Range = 1149	CI = 9124 – 9754, Range = 630	CI = 9256 – 9618, Range = 362	CI = 9380 – 9496, Range = 116
Female	CI = 8192 – 9278, Range = 1086	CI = 8442 – 9031, Range = 589	CI = 8564 – 8906, Range = 342	CI = 8681 – 8788, Range = 107

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.

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. Company can use this finding to better understand how men and women shop differently. They can then adjust their marketing and product offerings to make shopping more appealing to achieve group, potentially boosting sales and customer satisfaction.

3. Population Average

It is concluding that at 95% confidence interval, the true population average for males falls between `$9,393` and `$9,483`, and for females, it falls between `$8,692` and `$8,777`.

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.

1.9.2 Are confidence intervals of average male and female spending overlapping?

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. Company can use this finding to better understand how men and women shop differently. They can then adjust their marketing and product offerings to make shopping more appealing to achieve group, potentially boosting sales and customer satisfaction.

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

- 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.

1.9.3 Are Married spending more money per transaction than Unmarried? Why or Why not?

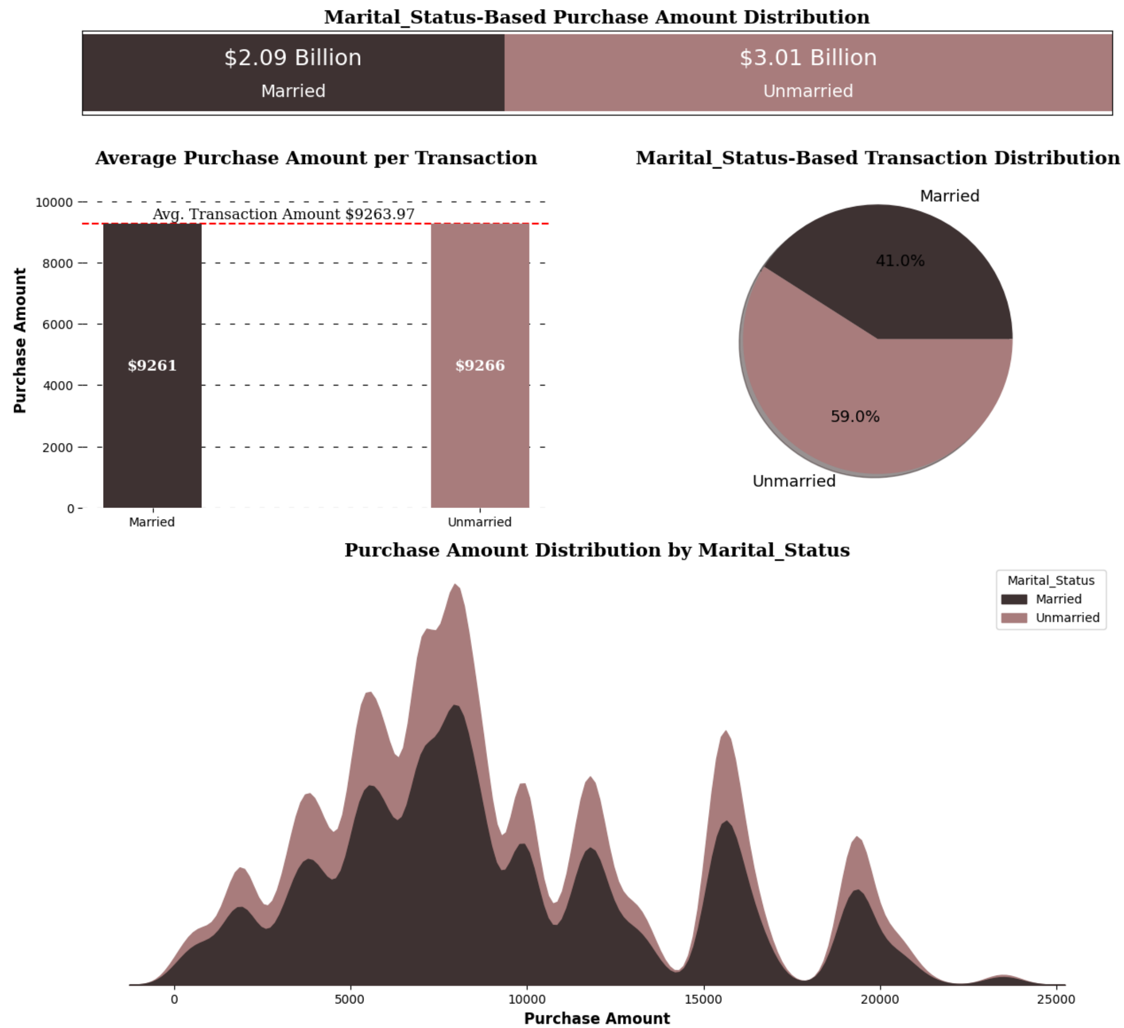
[67]:
```
#creating a walmart_data for purchase amount vs marital status
expenses = walmart_data.groupby('Marital_Status')['Purchase'].
 ↪agg(['sum','count']).reset_index()

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

#calculationg percentage distribution of purchase amount
expenses['%sum'] = round(expenses['sum']/expenses['sum'].sum(),2)

#calculationg per purchase amount
expenses['per_purchase'] = round(expenses['sum']/expenses['count'],2)
expenses.reset_index(drop=True)
```

```
[67]:   Marital_Status         sum   count  sum_in_billions  %sum  per_purchase
      0        Married  2086885295  225337             2.09  0.41       9261.17
      1      Unmarried  3008927447  324731             3.01  0.59       9265.91
```

```
[68]: #setting the plot style
fig = plt.figure(figsize = (15,14))
gs = fig.add_gridspec(3,2,height_ratios =[0.10,0.4,0.5])

                                        #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0,:])
color_map = ["#3E3232", "#A87C7C"]

#plotting the visual
ax.barh(expenses.loc[0,'Marital_Status'],width = expenses.loc[0,'%sum'],color␣
 ↪=color_map[0],label = 'Unmarried')
ax.barh(expenses.loc[0,'Marital_Status'],width = expenses.loc[1,'%sum'],left␣
 ↪=expenses.loc[0,'%sum'], color = color_map[1] ,label = 'Married')

#inserting the text
txt = [0.0] #for left parameter in ax.text()

for i in expenses.index:
    #for amount
    ax.text(expenses.loc[i,'%sum']/2 + txt[0],0.15,f"${expenses.
 ↪loc[i,'sum_in_billions']} Billion",
           va = 'center', ha='center',fontsize=18, color='white')

    #for marital status
    ax.text(expenses.loc[i,'%sum']/2 + txt[0],- 0.20 ,f"{expenses.
 ↪loc[i,'Marital_Status']}",
           va = 'center', ha='center',fontsize=14, color='white')

    txt += expenses.loc[i,'%sum']

#customizing ticks
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0,1)

#plot title
ax.set_title('Marital_Status-Based Purchase Amount Distribution',{'font':
 ↪'serif', 'size':15,'weight':'bold'})


                                            #Distribution of Purchase Amount␣
 ↪per Transaction
```

```
ax1 = fig.add_subplot(gs[1,0])

color_map = ["#3E3232", "#A87C7C"]

#plotting the visual
ax1.bar(expenses['Marital_Status'],expenses['per_purchase'],color =␣
 ↪color_map,zorder = 2,width = 0.3)

#adding average transaction line
avg = round(walmart_data['Purchase'].mean(),2)

ax1.axhline(y = avg, color ='red', zorder = 0,linestyle = '--')

#adding text for the line
ax1.text(0.4,avg + 300, f"Avg. Transaction Amount ${avg}",
         {'font':'serif','size' : 12},ha = 'center',va = 'center')

#adjusting the ylimits
ax1.set_ylim(0,11000)

#adding the value_counts
for i in expenses.index:
    ax1.text(expenses.loc[i,'Marital_Status'],expenses.loc[i,'per_purchase']/
 ↪2,f"${expenses.loc[i,'per_purchase']:.0f}",
             {'font':'serif','size' : 12,'color':'white','weight':'bold' },ha =␣
 ↪'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#adding axis label
ax1.set_ylabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax1.set_title('Average Purchase Amount per Transaction',{'font':'serif', 'size':
 ↪15,'weight':'bold'})

                                        # creating pie chart for Marital_Status␣
 ↪disribution
ax2 = fig.add_subplot(gs[1,1])

color_map = ["#3E3232", "#A87C7C"]
ax2.pie(expenses['count'],labels = expenses['Marital_Status'],autopct = '%.
 ↪1f%%',shadow = True,colors = color_map,textprops={'fontsize': 13, 'color':␣
 ↪'black'})
```

```
#setting title for visual
ax2.set_title('Marital_Status-Based Transaction Distribution',{'font':'serif',␣
↪'size':15,'weight':'bold'})

                                        # creating kdeplot for purchase amount␣
↪distribution

ax3 = fig.add_subplot(gs[2,:])
color_map = ["#3E3232", "#A87C7C"]

#plotting the kdeplot
sns.kdeplot(data = walmart_data, x = 'Purchase', hue = 'Marital_Status',␣
↪palette = color_map,fill = True, alpha = 1,
            ax = ax3,hue_order = ['Married','Unmarried'])

#removing the axis lines
for axislines in ['top','left','right', 'bottom']:
    ax1.spines[axislines].set_visible(False)
    ax2.spines[axislines].set_visible(False)
    ax3.spines[axislines].set_visible(False)

# adjusting axis labels
ax3.set_yticks([])
ax3.set_ylabel('')
ax3.set_xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax3.set_title('Purchase Amount Distribution by Marital_Status',{'font':'serif',␣
↪'size':15,'weight':'bold'})

plt.show()
```



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. 2. Average Transaction Value

The average purchase amount per transaction was almost similar for married and unmarried customers (`$9261` vs `$9266`). 3. Distribution of Purchase Amount

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

1.9.4 Confidence Interval Construction: Estimating Average Purchase Amount per Transaction by Marital Status

1. Step 1 - Building CLT Curve

As seen above, the purchase amount distribution is not Normal. So we need to use Central Limit Theorem. It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution

2. Step 2 - Building Confidence Interval

   After building CLT curve, we will create a confidence interval predicting population mean at 95% Confidence level.

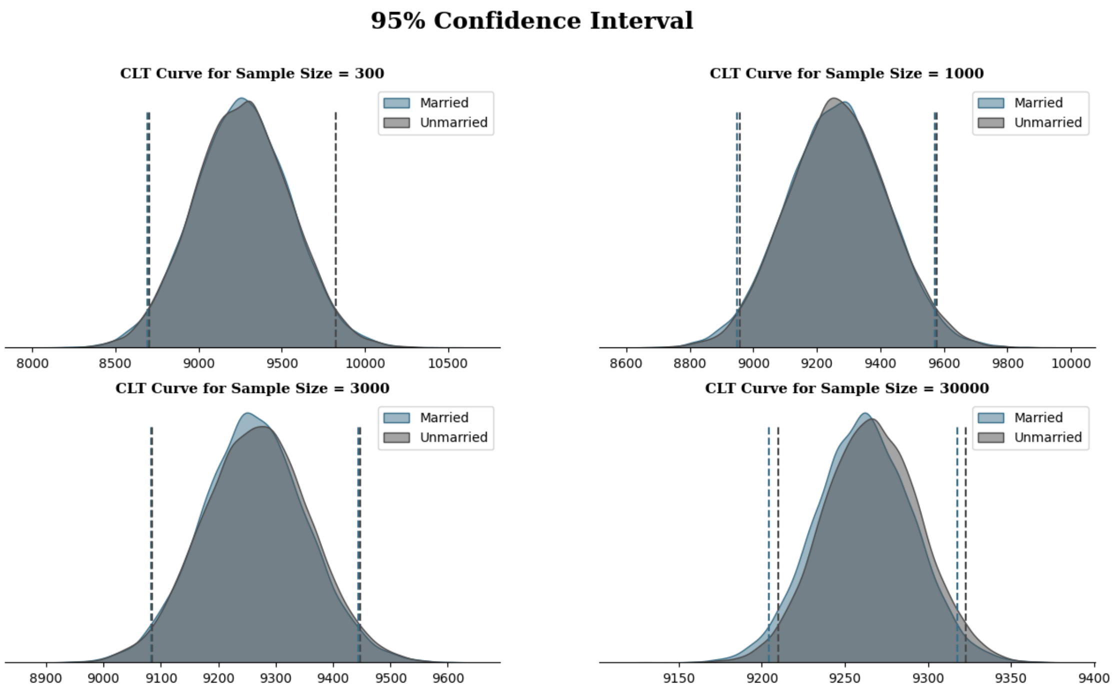
Note - We will use different sample sizes of `[300,1000,3000,30000]`

[69]:
```
#defining a function for plotting the visual for given confidence interval

def plot(ci):
    #setting the plot style
    fig = plt.figure(figsize = (15,8))
    gs = fig.add_gridspec(2,2)

    #creating separate data frames
    df_married = walmart_data.loc[walmart_data['Marital_Status'] ==␣
↪'Married','Purchase']
    df_unmarried = walmart_data.loc[walmart_data['Marital_Status'] ==␣
↪'Unmarried','Purchase']

    #sample sizes and corresponding plot positions
    sample_sizes = [(300,0,0),(1000,0,1),(3000,1,0),(30000,1,1)]

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

    married_samples = {}
    unmarried_samples = {}

    for i,x,y in sample_sizes:
        married_means = [] #list for collecting the means of married sample
        unmarried_means = [] #list for collecting the means of unmarried sample

        for j in range(bootstrap_samples):

            #creating random 5000 samples of i sample size
            married_bootstrapped_samples = np.random.choice(df_married,size = i)
            unmarried_bootstrapped_samples = np.random.choice(df_unmarried,size␣
↪= i)

            #calculating mean of those samples
            married_sample_mean = np.mean(married_bootstrapped_samples)
            unmarried_sample_mean = np.mean(unmarried_bootstrapped_samples)

            #appending the mean to the list
```

```
            married_means.append(married_sample_mean)
            unmarried_means.append(unmarried_sample_mean)

        #storing the above sample generated
        married_samples[f'{ci}%_{i}'] = married_means
        unmarried_samples[f'{ci}%_{i}'] = unmarried_means

        #creating a temporary dataframe for creating kdeplot
        temp_df = pd.DataFrame(data = {'married_means':
↪married_means,'unmarried_means':unmarried_means})

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

        #plots for married and unmarried
        sns.kdeplot(data = temp_df,x = 'married_means',color ="#3A7089" ,fill =␣
↪True, alpha = 0.5,ax = ax,label = 'Married')
        sns.kdeplot(data = temp_df,x = 'unmarried_means',color ="#4b4b4c" ,fill␣
↪= True, alpha = 0.5,ax = ax,label = 'Unmarried')

        #calculating confidence intervals for given confidence level(ci)
        m_range = confidence_interval(married_means,ci)
        u_range = confidence_interval(unmarried_means,ci)

        #plotting confidence interval on the distribution
        for k in m_range:
            ax.axvline(x = k,ymax = 0.9, color ="#3A7089",linestyle = '--')

        for k in u_range:
            ax.axvline(x = k,ymax = 0.9, color ="#4b4b4c",linestyle = '--')


        #removing the axis lines
        for axislines in ['top','left','right']:
            ax.spines[axislines].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,'weight':'bold'})

        plt.legend()
```

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

    plt.show()

    return married_samples,unmarried_samples
```

[70]:
```
m_samp_95,u_samp_95 = plot(95)
```



[71]:
```
#setting the plot style
fig,ax = plt.subplots(figsize = (20,3))

#list for collecting ci for given cl
m_ci = ['Married']
u_ci = ['Unmarried']

#finding ci for each sample size (married)
for m in m_samp_95:
    m_range = confidence_interval(m_samp_95[m],95)
    m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f}, Range =␣
 ↪{(m_range[1] - m_range[0]):.0f}")
```

```
#finding ci for each sample size (unmarried)
for u in u_samp_95:
    u_range = confidence_interval(u_samp_95[u],95)
    u_ci.append(f"CI = ${u_range[0]:.0f} - ${u_range[1]:.0f}, Range = {(u_range[1] - u_range[0]):.0f}")

                                    #plotting the summary
#contents of the table
ci_info = [m_ci,u_ci]

#plotting the table
table = ax.table(cellText = ci_info, cellLoc='center',
             colLabels =['Marital_Status','Sample Size = 300','Sample Size = 1000','Sample Size = 3000','Sample Size = 30000'],
             colLoc = 'center',colWidths = [0.1,0.225,0.225,0.225,0.225],bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax.axis('off')

#setting title
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'bold'})

plt.show()
```

95% Confidence Interval Summary

Marital_Status	Sample Size = 300	Sample Size = 1000	Sample Size = 3000	Sample Size = 30000
Married	CI = 8691 – 9827, Range = 1136	CI = 8948 – 9571, Range = 623	CI = 9083 – 9444, Range = 361	CI = 9204 – 9318, Range = 114
Unmarried	CI = 8700 – 9827, Range = 1127	CI = 8959 – 9578, Range = 619	CI = 9085 – 9448, Range = 363	CI = 9210 – 9323, Range = 113

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.

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 married customers falls between `$9,217` and `$9,305`, and for unmarried customers, it falls between `$9,222` and `$9,311`.

4. 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. The confidence intervals of average spending for married and unmarried customers overlap, indicating that there is no statistically significant difference in spending between these two groups.

1.9.5 Are confidence intervals of average married and unmarried customer spending overlapping?

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.

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

- 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.

To leverage this conclusion, The retail company can focus on providing a consistent shopping experience for both married and unmarried customers. They can continue to offer a diverse range of products and promotions that appeal to a broad customer base, ensuring that both groups feel valued and catered to.

###Are youngers spending more money per transaction than olders? Why or Why not?

[72]:
```python
#creating a walmart_data for purchase amount vs age group
money_byAge = walmart_data.groupby('Age')['Purchase'].agg(['sum','count']).
 ↪reset_index()

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

#calculationg percentage distribution of purchase amount
money_byAge['%sum'] = round(money_byAge['sum']/money_byAge['sum'].sum(),2)

#calculationg per purchase amount
money_byAge['per_purchase'] = round(money_byAge['sum']/money_byAge['count'],2)
```

```
money_byAge.reset_index(drop=True)
```

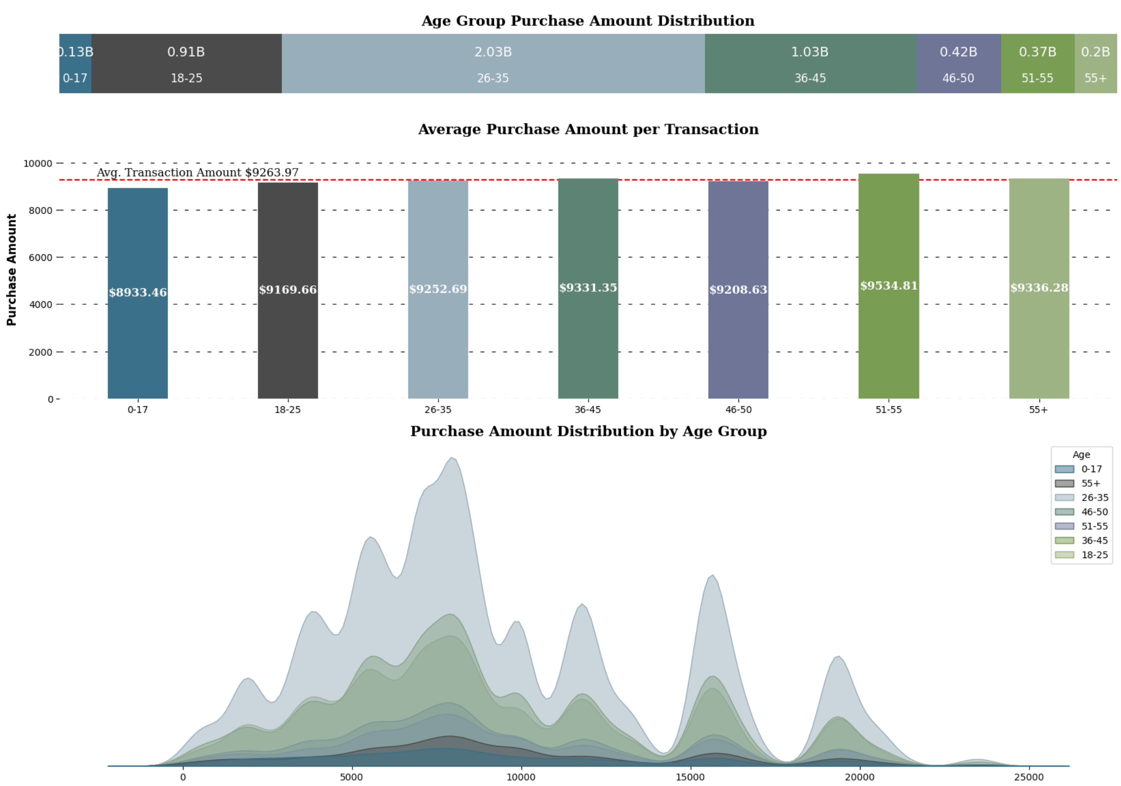
[72]:

	Age	sum	count	sum_in_billions	%sum	per_purchase
0	0-17	134913183	15102	0.13	0.03	8933.46
1	18-25	913848675	99660	0.91	0.18	9169.66
2	26-35	2031770578	219587	2.03	0.40	9252.69
3	36-45	1026569884	110013	1.03	0.20	9331.35
4	46-50	420843403	45701	0.42	0.08	9208.63
5	51-55	367099644	38501	0.37	0.07	9534.81
6	55+	200767375	21504	0.20	0.04	9336.28

[73]:
```
#setting the plot style
fig = plt.figure(figsize = (20,14))
gs = fig.add_gridspec(3,1,height_ratios =[0.10,0.4,0.5])

                                        #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0])
color_map = ["#3A7089",␣
↪"#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384']

#plotting the visual
left = 0

for i in money_byAge.index:
    ax.barh(money_byAge.loc[0,'Age'],width = money_byAge.loc[i,'%sum'],left =␣
↪left,color = color_map[i],label = money_byAge.loc[i,'Age'])
    left += money_byAge.loc[i,'%sum']

#inserting the text
txt = 0.0 #for left parameter in ax.text()

for i in money_byAge.index:
    #for amount
    ax.text(money_byAge.loc[i,'%sum']/2 + txt,0.15,f"{money_byAge.
↪loc[i,'sum_in_billions']}B", va = 'center', ha='center',fontsize=14,␣
↪color='white')

    #for age grp
    ax.text(money_byAge.loc[i,'%sum']/2 + txt,- 0.20 ,f"{money_byAge.
↪loc[i,'Age']}", va = 'center', ha='center',fontsize=12, color='white')

    txt += money_byAge.loc[i,'%sum']

#customizing ticks
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0,1)
```

```
#plot title
ax.set_title('Age Group Purchase Amount Distribution',{'font':'serif', 'size':
↪15,'weight':'bold'})

                                            #Distribution of Purchase Amount␣
↪per Transaction

ax1 = fig.add_subplot(gs[1])

#plotting the visual
ax1.bar(money_byAge['Age'],money_byAge['per_purchase'],color = color_map,zorder␣
↪= 2,width = 0.4)

#adding average transaction line
avg = round(walmart_data['Purchase'].mean(),2)

ax1.axhline(y = avg, color ='red', zorder = 0,linestyle = '--')

#adding text for the line
ax1.text(0.4,avg + 300, f"Avg. Transaction Amount ${avg}", {'font':
↪'serif','size' : 12},ha = 'center',va = 'center')

#adjusting the ylimits
ax1.set_ylim(0,11000)

#adding the value_counts
for i in money_byAge.index:
    ax1.text(money_byAge.loc[i,'Age'],money_byAge.loc[i,'per_purchase']/
↪2,f"${money_byAge.loc[i,'per_purchase']}",
             {'font':'serif','size' : 12,'color':'white','weight':'bold' },ha =␣
↪'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#adding axis label
ax1.set_ylabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax1.set_title('Average Purchase Amount per Transaction',{'font':'serif', 'size':
↪15,'weight':'bold'})

                                        # creating kdeplot for purchase amount␣
↪distribution
```

```
ax2 = fig.add_subplot(gs[2,:])

#plotting the kdeplot
sns.kdeplot(data = walmart_data, x = 'Purchase', hue = 'Age', palette =␣
↪color_map, fill = True, alpha = 0.5, ax = ax2)

#removing the axis lines
for axislines in ['top','left','right', 'bottom']:
  ax.spines[axislines].set_visible(False)
  ax1.spines[axislines].set_visible(False)
  ax2.spines[axislines].set_visible(False)

# adjusting axis labels
ax2.set_yticks([])
ax2.set_ylabel('')
ax2.set_xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax2.set_title('Purchase Amount Distribution by Age Group',{'font':'serif',␣
↪'size':15,'weight':'bold'})

plt.show()
```



Insights

1. Total Sales Comparison

   Age group between **26 - 45** accounts to almost 60% of the total sales suggesting that Walmart's Black Friday sales are most popular among these age groups.

   The age group 0-17 has the lowest sales percentage (2.6%), which is expected as they may not have as much purchasing power. Understanding their preferences and providing special offers could be beneficial, especially considering the potential for building customer loyalty as they age.

2. Average Transaction Value

   While there is not a significant difference in per purchase spending among the age groups, the 51-55 age group has a relatively low sales percentage (7.2%)but they have the highest per purchase spending at 9535. Walmart could consider strategies to attract and retain this high-spending demographic.

3. Distribution of Purchase Amount

   As seen above, the purchase amount for all age groups is not normally distributed.

1.9.6 Confidence Interval Construction: Estimating Average Purchase Amount per Transaction

1. Step 1 - Building CLT Curve

   As seen above, the purchase amount distribution is not Normal. So we need to use Central Limit Theorem. It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution

2. Step 2 - Building Confidence Interval

   After building CLT curve, we will create a confidence interval predicting population mean at 95% Confidence level.

Note - We will use different sample sizes of `[300,1000,3000,30000]`

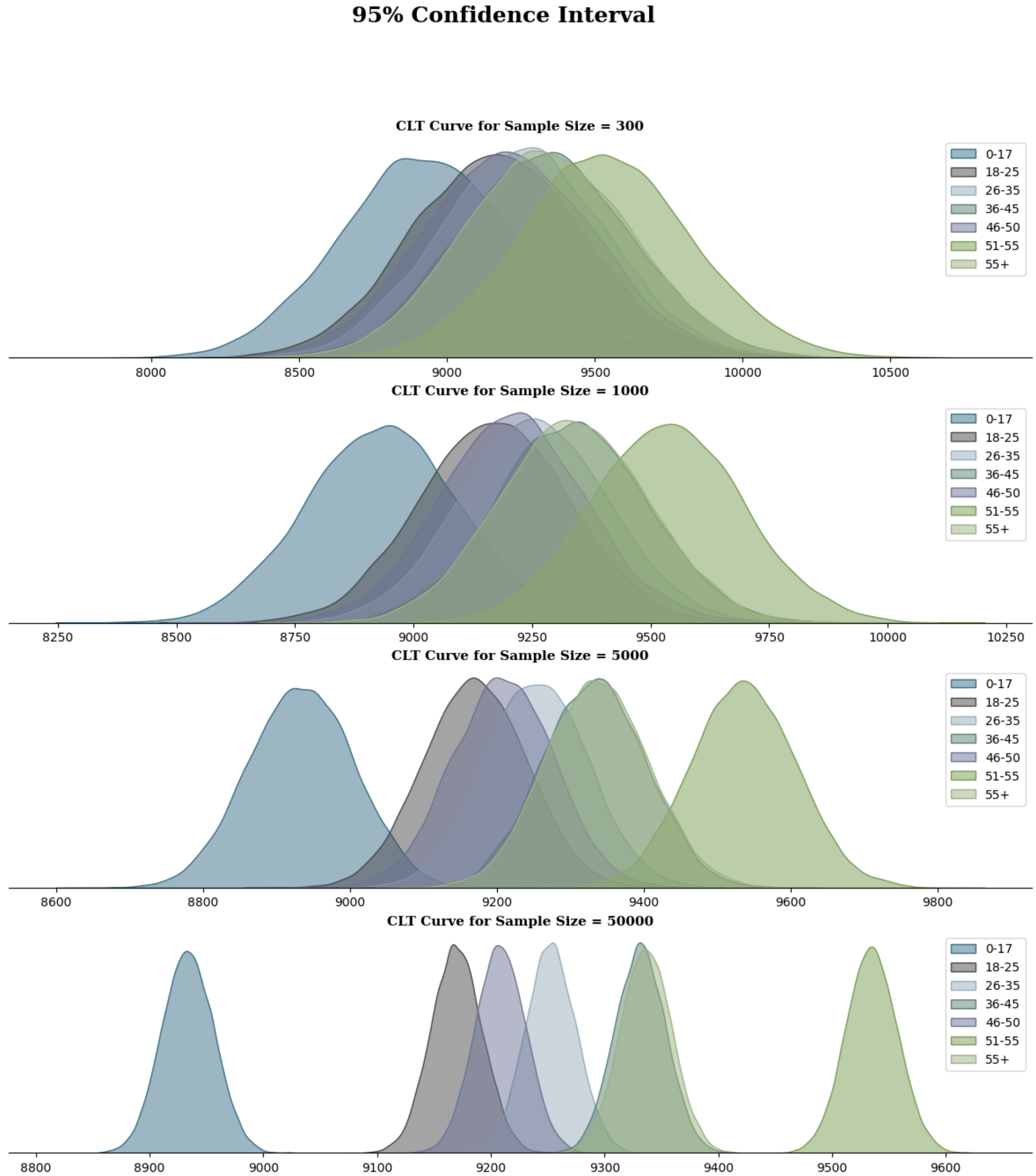
[74]:
```
#defining a function for plotting the visual for given confidence interval

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_data.loc[walmart_data['Age'] == '0-17','Purchase']
    df_2 = walmart_data.loc[walmart_data['Age'] == '18-25','Purchase']
    df_3 = walmart_data.loc[walmart_data['Age'] == '26-35','Purchase']
```

```
df_4 = walmart_data.loc[walmart_data['Age'] == '36-45','Purchase']
df_5 = walmart_data.loc[walmart_data['Age'] == '46-50','Purchase']
df_6 = walmart_data.loc[walmart_data['Age'] == '51-55','Purchase']
df_7 = walmart_data.loc[walmart_data['Age'] == '55+','Purchase']


#sample sizes and corresponding plot positions
sample_sizes = [(300,0),(1000,1),(5000,2),(50000,3)]

#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,'46-50':l5,'51-55':l6,'55+':l7})

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

        #plots
        for p,q in [('#3A7089', '0-17'),('#4b4b4c', '18-25'),('#99AEBB',␣
↪'26-35'),('#5C8374', '36-45'),('#6F7597', '46-50'),
                  ('#7A9D54', '51-55'),('#9EB384', '55+')]:

            sns.kdeplot(data = temp_df,x = q,color =p ,fill = True, alpha = 0.
↪5,ax = ax,label = q)

        #removing the axis lines
        for axislines in ['top','left','right']:
            ax.spines[axislines].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,'weight':'bold'})

        plt.legend()

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

    plt.show()

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

[75]:

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



[76]:

```
#setting the plot style
fig,ax = plt.subplots(figsize = (20,5))

#list for collecting ci for given cl
ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7 =␣
 ↪['0-17'],['18-25'],['26-35'],['36-45'],['46-50'],['51-55'],['55+']
```

```python
#finding ci for each sample size
#samples = [samples1,samples2,samples3,samples4,samples5,samples6,samples7]

samples = [(samples1,ci_1),(samples2,ci_2),(samples3,ci_3),(samples4,ci_4),(samples5,ci_5),(samples6,

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] - s_range[0]):.0f}")



                                    #plotting the summary
#contents of the table
ci_info = [ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7]

#plotting the table
table = ax.table(cellText = ci_info, cellLoc='center',
             colLabels =['Age Group','Sample Size = 100','Sample Size = 1000','Sample Size = 5000','Sample Size = 50000'],
             colLoc = 'center',colWidths = [0.1,0.225,0.225,0.225,0.225],bbox=[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax.axis('off')

#setting title
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'bold'})

plt.show()
```

95% Confidence Interval Summary

Age Group	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
0-17	CI = 8364 – 9517, Range = 1153	CI = 8619 – 9258, Range = 639	CI = 8793 – 9075, Range = 282	CI = 8889 – 8978, Range = 89
18-25	CI = 8610 – 9745, Range = 1135	CI = 8859 – 9478, Range = 619	CI = 9032 – 9309, Range = 277	CI = 9126 – 9214, Range = 88
26-35	CI = 8700 – 9822, Range = 1122	CI = 8944 – 9562, Range = 618	CI = 9113 – 9391, Range = 278	CI = 9209 – 9297, Range = 88
36-45	CI = 8776 – 9905, Range = 1129	CI = 9016 – 9644, Range = 628	CI = 9195 – 9469, Range = 274	CI = 9287 – 9375, Range = 88
46-50	CI = 8646 – 9781, Range = 1135	CI = 8901 – 9524, Range = 623	CI = 9069 – 9344, Range = 275	CI = 9165 – 9252, Range = 87
51-55	CI = 8959 – 10121, Range = 1162	CI = 9222 – 9856, Range = 634	CI = 9395 – 9676, Range = 281	CI = 9490 – 9580, Range = 90
55+	CI = 8782 – 9903, Range = 1121	CI = 9027 – 9643, Range = 616	CI = 9199 – 9478, Range = 279	CI = 9292 – 9381, Range = 89

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.

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 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`

1.9.7 Are confidence intervals of customer's age-group spending overlapping?

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

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.

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.

7. Targeted Marketing

   Company can create advertisements and promotions that specifically appeal to men and women. By understanding what each group likes, it can make its advertising more effective.

8. Product Choices

   Company can look at which types of products are popular with men and women and make sure those products are easy to find and buy in the store.

9. Different Groups

   Company can also look at other factors, like how old customers are, where they live, and if they're married or not. This can help to figure out how to make shopping better for different types of customers.

10. Consistent Shopping

    While Company is making shopping better for different groups, it's important to make sure that everyone has a good shopping experience, no matter who they are.

11. Keep Learning

    Company should always pay attention to what customers are doing and keep trying to make things better. This way, they can keep up with what customers like and make shopping even better.