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


```

Table of Contents

6. Recommendations

LEGEND

Analysis Steps in Red color

Sub Headings in orange color

These are insights got from analysing the data, in Blue color

" " code sections are notes to self, some quick code snippets, or some notes while doing analysis

```
''' Notes to Self
my markdown templates
<span style="font-size:50px; font-family:Arial;color:red">Use this for heading/span><li>
<span style="font-size:30px; font-family:Arial;color:orange">Sub Headings in orange color</span><li>
<span style="font-size:25px; font-family:Arial;color:#8DDBF2">Use this for insight </span><li>
'''
```

```
' Notes to Self\nmy markdown templates\n<span style="font-size:50px; font-family:Arial;color:red">Use this for heading/span>
<li>\n<span style="font-size:30px; font-family:Arial;color:orange">Sub Headings in orange color</span><li>\n<span style="font-
size:25px; font-family:Arial;color:#8DDBF2">Use this for insight </span><li>\n'
```

1.0

Step 1: Understanding the Problem and the Data

About 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.

Business Problem

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

Key points:

1. WHAT: Analyse customer purchase behavior, focussing on the purchase amount wrt gender and other factors
2. WHY: Identify the spending habits of Men and Women to see if we can gain any insights out of the analysis

Dataset The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday.

The dataset has the following features: Dataset link: Walmart_data.csv

- User_ID: User ID
- Product_ID: Product ID
- Gender: Sex of User
- Age: Age in bins
- Occupation: Occupation(Masked)
- City_Category: Category of the City (A,B,C)
- StayInCurrentCityYears: Number of years stay in current city
- Marital_Status: Marital Status
- ProductCategory: Product Category (Masked)
- Purchase: Purchase Amount

2.0

Step 2: Import and Inspect the Data

```
'''
Notes to Self
During this step, looking into the statistics is critical to gain initial know-how of its structure, variable kinds, and capabi

'''
```

```
' \nNotes to Self\nDuring this step, looking into the statistics is critical to gain initial know-how of its structure, variable kinds, and capability issues.\n\n'
```

```
df =pd.read_csv("walmart_data.csv")
df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Pu
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	

```
df.columns
```

```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

2.1

Statistical summary for numerical columns and Unique values for categorical data

```
#Instead of manually creating tables and collecting values
#lets automate it.
#We will generate a table of all columns in Markdown format
#We will paste this table into a markdown cell and then we may add additional analysis
#!pip install tabulate
from tabulate import tabulate
def generate_markdown_table_with_details(df):
    column_details = []
    for col in df.columns:
        dtype = str(df[col].dtype)
        if df[col].dtype == 'object':
            cat_or_num = 'Categorical'
            details = df[col].unique().tolist()
            if(len(details)>10):
                details= f'{df[col].nunique()} unique values'
        else:
            cat_or_num = 'Numerical'
            details = f"Min: {df[col].min()}, Max: {df[col].max()}"
        column_details.append([col, dtype, cat_or_num, details, ''])

    # Create a DataFrame for the table
    table_df = pd.DataFrame(column_details, columns=['Column Name', 'Data Type', 'Categorical or Numerical', 'Details', 'Busine

    # Convert DataFrame to Markdown
    markdown_table = tabulate(table_df, headers='keys', tablefmt='pipe', showindex=False)
    return markdown_table

markdown_table = generate_markdown_table_with_details(df)
print(f'There are a total of {df.shape[0]} rows and {df.shape[1]} columns')
print(markdown_table)

```

```
There are a total of 550068 rows and 10 columns
| Column Name                | Data Type   | Categorical or Numerical   | Details
|:---------------------------|:------------|:---------------------------|:-------------------------------------------------
```

```
| User_ID                    | int64      | Numerical                | Min: 1000001, Max: 1006040
| Product_ID                 | object     | Categorical              | 3631 unique values
| Gender                     | object     | Categorical              | ['F', 'M']
| Age                        | object     | Categorical              | ['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '
| Occupation                 | int64      | Numerical                | Min: 0, Max: 20
| City_Category              | object     | Categorical              | ['A', 'C', 'B']
| Stay_In_Current_City_Years | object     | Categorical              | ['2', '4+', '3', '1', '0']
| Marital_Status             | int64      | Numerical                | Min: 0, Max: 1
| Product_Category           | int64      | Numerical                | Min: 1, Max: 20
| Purchase                   | int64      | Numerical                | Min: 12, Max: 23961
```

```
'''
Notes to Self
Adding insights about columns and data size.
We identify which columns are numerical, which are categorical
Within categorical, we identify if it is nominal or ordinal data.  This helps us to decide best graph to use
Also ordinal data can be converted into numeric using codes thereby making it available for some kind of graphs.
'''
```

```
' \nNotes to Self\nAdding insights about columns and data size.  \nWe identify which columns are numerical, which are categorical\nWithin categorical, we identify if it is nominal or ordinal data.  This helps us to decide best graph to use \nAlso ordinal data can be converted into numeric using codes thereby making it available for some kind of graphs.\n'
```

There are a total of 550068 rows and 10 columns

Column Name	Data Type	Categorical or Numerical	Details	Business Description(fill manually)
User_ID	int64	Cat(Nominal)	Min: 1000001, Max: 1006040	
Product_ID	object	Cat(Nominal)	3631 unique values	
Gender	object	Cat(Nominal)	['F', 'M']	
Age	object	Cat(Ordinal)	['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']	Age in Bins
Occupation	int64	Cat(Nominal)	Min: 0, Max: 20	Has been encoded into numerical values
City_Category	object	Cat(Nominal)	['A', 'C', 'B']	Category of the City (A,B,C)
Stay_In_Current_City_Years	object	Cat(Ordinal)	['2', '4+', '3', '1', '0']	Number of years stay in current city
Marital_Status	int64	Cat(Nominal)	Min: 0, Max: 1	Has been encoded into numerical values
Product_Category	int64	Cat(Nominal)	Min: 1, Max: 20	Has been encoded into numerical values
Purchase	int64	Numerical	Min: 12, Max: 23961	

There is only ONE column that has real numerical data, the purchase column, rest all columns are categorical in nature

```
'''
Notes to Self
Let's get a quick summary of the dataset using the pandas describe() method.
The describe() function applies basic statistical computations on the dataset like extreme values, count of data points standar
Any missing value or NaN value is automatically skipped. describe() function gives a good picture of the distribution of data.
'''
df.describe(include ='all')
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Prod
count	5.500680e+05	550068	550068	550068	550068.000000	550068	550068	550068.000000	5
unique	NaN	3631	2	7	NaN	3	5	NaN	
top	NaN	P00265242	M	26-35	NaN	B	1	NaN	
freq	NaN	1880	414259	219587	NaN	231173	193821	NaN	
mean	1.003029e+06	NaN	NaN	NaN	8.076707	NaN	NaN	0.409653	
std	1.727592e+03	NaN	NaN	NaN	6.522660	NaN	NaN	0.491770	
min	1.000001e+06	NaN	NaN	NaN	0.000000	NaN	NaN	0.000000	
25%	1.001516e+06	NaN	NaN	NaN	2.000000	NaN	NaN	0.000000	
50%	1.003077e+06	NaN	NaN	NaN	7.000000	NaN	NaN	0.000000	
75%	1.004478e+06	NaN	NaN	NaN	14.000000	NaN	NaN	1.000000	
max	1.006040e+06	NaN	NaN	NaN	20.000000	NaN	NaN	1.000000	

2.2

Step 3: Handling Missing Values

```
'''
Notes to Self
Missing Data can also refer to as NA(Not Available) values in pandas. There are several useful functions for detecting, removin

isnull()
notnull()
dropna()
fillna()
replace()
interpolate()
'''
```

```
' \nNotes to Self\nMissing Data can also refer to as NA(Not Available) values in pandas. There are several useful functions
for detecting, removing, and replacing null values in Pandas DataFrame
:\n\nisnull()\nnotnull()\ndropna()\nfillna()\nreplace()\ninterpolate()\n'
```

```
#Now let's check if there are any missing values in our dataset or not.
df.isnull().sum()
```

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

Awesome! the data does not have any missing values

Lets add some columns for analysing the categorical and numerical data better

- For categorical data- we will add some codes
- For numerical data -we will add some labels after binning the data

```
#REMOVE IF NOT NEEDED

# Create a new column with the binned values
```

```
# df['IncomeGroup'] = pd.cut(df['Income'], bins=income_bin_edges, labels=["Less than 60k","More than 60K"])
# df['AgeGroup'] = pd.cut(df['Age'], bins=age_bin_edges, labels=["Less than 24","24-35","36 and above"])
```

3.0

Step 4: Explore Data Characteristics

```
'''
Notes to self
By exploring the characteristics of your information very well, you can gain treasured insights into its structure, pick out ca
Let's start by exploring the data according to the dataset.

for categorical columns, use
--------------------------------
sns.countplot(data=df, x='Product')
df.Product.value_counts().plot.bar()
df['Product'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90, colors=sns.color_palette('pastel'))



for numerical columns use
---------------------------
df.hist() # Quickly create histograms for all numeric columns
sns.histplot(data=df["Age"], kde=True)
df.Age.plot.hist() #hist for Specific column
df.Age.plot.kde()
df.Age.plot.box()

df.plot.box()#Print boxplots of all numerical columns in one go

sns.violinplot(data=df , x='Age')




'''
```

```
' \nNotes to self\nBy exploring the characteristics of your information very well, you can gain treasured insights into its structure, pick out capability problems or anomalies, and inform your subsequent evaluation and modeling choices. Documenting any findings or observations from this step is critical, as they may be relevant for destiny reference or communication with stakeholders.\nLet\'s start by exploring the data according to the dataset.\n\nfor categorical columns, use\n--------------------------------\nsns.countplot(data=df, x=\'Product\')\ndf.Product.value_counts().plot.bar()\ndf[\'Product\'].value_counts().plot.pie(autopct=\'%1.1f%%\', startangle=90, colors=sns.color_palette(\'pastel\'))\n\n\n\nfor numerical columns use\n---------------------------\ndf.hist() # Quickly create histograms for all numeric columns\nsns.histplot(data=df["Age"], kde=True)\ndf.Age.plot.hist() #hist for Specific column\ndf.Age.plot.kde()\ndf.Age.plot.box()\n\ndf.plot.box()#Print boxplots of all numerical columns in one go\n\nsns.violinplot(data=df , x=\'Age\')\n\n\n\n\n'
```

3.1

Univariate and Bivariate Analysis (Analysis of one attribute at a time.)

3.1.1

Analysis of User_ID and Purchase column

```
frequentUsers = df.groupby('User_ID').Purchase.count().reset_index()
frequentUsers.describe()


```

	User_ID	Purchase
count	5.891000e+03	5891.000000
mean	1.003025e+06	93.374300
std	1.743379e+03	107.190049
min	1.000001e+06	6.000000
25%	1.001518e+06	26.000000
50%	1.003026e+06	54.000000
75%	1.004532e+06	117.000000
max	1.006040e+06	1026.000000

We have data of 5891 customers

- Each user has shopped multiple times, from a minimum of 6 to a maximum of 1026 times
- On average, each user has shopped for 93 times.
- This is a very decent number to be able to quantify some individual user's buying habit

```
# The user data in the original dataset can be separated out as a separate dataframe so that we can run analysis on users indep
users = df[['User_ID','Gender', 'Age', 'Occupation', 'City_Category','Stay_In_Current_City_Years', 'Marital_Status','Purchase']
users
```

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Purchase		
								count	sum	mean
0	1000001	F	0-17	10	A	2	0	35	334093	9545.514286
1	1000002	M	55+	16	C	4+	0	77	810472	10525.610390
2	1000003	M	26-35	15	A	3	0	29	341635	11780.517241
3	1000004	M	46-50	7	B	2	1	14	206468	14747.714286
4	1000005	M	26-35	20	A	1	1	106	821001	7745.292453
...	...	...	...	...	...	...	...	...	...	...
5886	1006036	F	26-35	15	B	4+	1	514	4116058	8007.894942
5887	1006037	F	46-50	1	C	4+	0	122	1119538	9176.540984

```
# Flatten the column names
users.columns = [''.join(col).strip() for col in users.columns]
users
```

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Purchasecount	Purchasesum
0	1000001	F	0-17	10	A	2	0	35	334093
1	1000002	M	55+	16	C	4+	0	77	810472
2	1000003	M	26-35	15	A	3	0	29	341635
3	1000004	M	46-50	7	B	2	1	14	206468
4	1000005	M	26-35	20	A	1	1	106	821001
...	...	...	...	...	...	...	...	...	...
5886	1006036	F	26-35	15	B	4+	1	514	4116058
5887	1006037	F	46-50	1	C	4+	0	122	1119538
5888	1006038	F	55+	1	C	2	0	12	90034
5889	1006039	F	46-50	0	B	4+	1	74	590319
5890	1006040	M	26-35	6	B	2	0	180	1653299

5891 rows × 10 columns

```
users.describe()
```

	User_ID	Occupation	Marital_Status	Purchasecount	Purchasesum	Purchasemean
count	5.891000e+03	5891.000000	5891.000000	5891.000000	5.891000e+03	5891.000000
mean	1.003025e+06	8.153285	0.419963	93.374300	8.650166e+05	9568.839914
std	1.743379e+03	6.323140	0.493594	107.190049	9.436445e+05	1890.087105
min	1.000001e+06	0.000000	0.000000	6.000000	4.668100e+04	2318.733333
25%	1.001518e+06	3.000000	0.000000	26.000000	2.376780e+05	8287.212366
50%	1.003026e+06	7.000000	0.000000	54.000000	5.212130e+05	9386.208333
75%	1.004532e+06	14.000000	1.000000	117.000000	1.119250e+06	10654.633199
max	1.006040e+06	20.000000	1.000000	1026.000000	1.053691e+07	18577.893617

Average spend per user is 9568, with maximum spend at 18577 and minimum at 2318

3.1.2

Analysis of Product_ID column

```
products = df.groupby(['Product_Category','Product_ID'],as_index=False).agg(
    Revenue=('Purchase', 'sum'),
    Quantity=('Purchase', 'count'),
    Male_count=('Gender', lambda x: (x == 'M').sum()),
    Female_count=('Gender', lambda x: (x == 'F').sum()),
    Married_count=('Marital_Status', lambda x: (x == 1).sum()),
    Unmarried_count=('Marital_Status', lambda x: (x == 0).sum())
)
products
```

	Product_Category	Product_ID	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count
0	1	P00000642	7635578	512	441	71	203	309
1	1	P00000942	581125	55	48	7	17	38
2	1	P00001042	6922380	503	427	76	193	310
3	1	P00001542	640313	69	58	11	35	34
4	1	P00002042	889731	93	86	7	33	60
...	...	...	...	...	...	...	...	...
3626	19	P00370293	28790	785	543	242	331	454
3627	19	P00370853	30588	818	609	209	326	492
3628	20	P00371644	326257	899	643	256	375	524
3629	20	P00372445	313817	837	603	234	345	492
3630	20	P00375436	304653	814	581	233	350	464

3631 rows × 8 columns

```
Start coding or generate with AI.
```

```
products['Price'] = round(products.Revenue/products.Quantity,0)
products['MalePercentage'] = round(products.Male_count*100/(products.Male_count+products.Female_count),0)
products['UnmarriedPercentage'] = round(products.Unmarried_count*100/(products.Unmarried_count+products.Married_count),0)
products
```

	Product_Category	Product_ID	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count	Price	MalePe
0	1	P00000642	7635578	512	441	71	203	309	14913.0	
1	1	P00000942	581125	55	48	7	17	38	10566.0	
2	1	P00001042	6922380	503	427	76	193	310	13762.0	
3	1	P00001542	640313	69	58	11	35	34	9280.0	
4	1	P00002042	889731	93	86	7	33	60	9567.0	
...	...	...	...	...	...	...	...	...	...	
3626	19	P00370293	28790	785	543	242	331	454	37.0	
3627	19	P00370853	30588	818	609	209	326	492	37.0	
3628	20	P00371644	326257	899	643	256	375	524	363.0	
3629	20	P00372445	313817	837	603	234	345	492	375.0	
3630	20	P00375436	304653	814	581	233	350	464	374.0	

3631 rows × 11 columns

```
products.sort_values(by='Revenue', ascending=False)
```

	Product_Category	Product_ID	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count	Price	MaleP
31	1	P00025442	27995166	1615	1267	348	652	963	17334.0	
129	1	P00110742	26722309	1612	1247	365	648	964	16577.0	
3545	16	P00255842	25168963	1383	1008	375	535	848	18199.0	
1807	6	P00059442	24338343	1406	1048	358	577	829	17310.0	
253	1	P00184942	24334887	1440	1141	299	597	843	16899.0	
...	...	...	...	...	...	...	...	...	...	
853	5	P00012942	1717	1	1	0	0	1	1717.0	
3287	11	P00325342	1656	1	1	0	1	0	1656.0	
3312	11	P00353042	1545	1	1	0	1	0	1545.0	
3355	12	P00309042	726	1	0	1	1	0	726.0	
3375	13	P00091742	405	1	1	0	0	1	405.0	

3631 rows × 11 columns

```
products.describe()
```

	Product_Category	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count	Price	Male
count	3631.000000	3.631000e+03	3631.000000	3631.000000	3631.000000	3631.000000	3631.000000	3631.000000	3
mean	6.484164	1.403419e+06	151.492151	114.089507	37.402644	62.059212	89.432939	7874.911319	
std	3.801726	2.647138e+06	212.852932	163.547026	53.307847	86.409797	127.347006	3873.754005	
min	1.000000	4.050000e+02	1.000000	0.000000	0.000000	0.000000	0.000000	37.000000	
25%	5.000000	1.152100e+05	19.500000	13.000000	5.000000	9.000000	11.000000	5386.000000	
50%	6.000000	4.378210e+05	71.000000	51.000000	17.000000	29.000000	41.000000	6943.000000	
75%	8.000000	1.517297e+06	194.000000	142.000000	49.000000	81.000000	113.000000	10154.500000	
max	20.000000	2.799517e+07	1880.000000	1372.000000	508.000000	793.000000	1087.000000	21257.000000	

- There are 3631 products
- Average product price is $7874, withmaximumat$21257 and minimum at $37

```

top1PercentProducts = products[:int(round(len(products)*0.01,0))]
top1PercentProducts
```

	Product_Category	Product_ID	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count	Price	MaleF
0	1	P00000642	7635578	512	441	71	203	309	14913.0	
1	1	P00000942	581125	55	48	7	17	38	10566.0	
2	1	P00001042	6922380	503	427	76	193	310	13762.0	
3	1	P00001542	640313	69	58	11	35	34	9280.0	
4	1	P00002042	889731	93	86	7	33	60	9567.0	
5	1	P00002142	10424160	735	578	157	315	420	14183.0	
6	1	P00004242	1269862	113	95	18	38	75	11238.0	
7	1	P00004442	1632933	147	127	20	53	94	11108.0	
8	1	P00006942	6165491	498	425	73	167	331	12381.0	
9	1	P00007042	351139	44	40	4	20	24	7980.0	
10	1	P00008842	1299569	109	93	16	38	71	11923.0	
11	1	P00009342	3964157	351	288	63	127	224	11294.0	
12	1	P00009642	24539	3	3	0	1	2	8180.0	
13	1	P00010742	22164153	1350	1069	281	574	776	16418.0	
14	1	P00010942	4073491	305	265	40	110	195	13356.0	
15	1	P00013542	15836	1	0	1	0	1	15836.0	
16	1	P00014042	2471491	194	175	19	75	119	12740.0	
17	1	P00014842	4255327	412	329	83	138	274	10328.0	
18	1	P00015542	2644080	295	247	48	107	188	8963.0	
19	1	P00015842	3579328	267	225	42	100	167	13406.0	
20	1	P00016042	6406520	447	384	63	168	279	14332.0	
21	1	P00016342	2168552	191	138	53	79	112	11354.0	
22	1	P00016542	1883681	159	132	27	52	107	11847.0	
23	1	P00016742	2710920	266	232	34	101	165	10191.0	
24	1	P00016842	2902550	315	280	35	122	193	9214.0	
25	1	P00017642	333018	51	42	9	17	34	6530.0	
26	1	P00019342	4330757	330	284	46	120	210	13124.0	
27	1	P00019942	1224440	107	95	12	42	65	11443.0	
28	1	P00020342	3649188	358	289	69	130	228	10193.0	
29	1	P00022142	785570	75	69	6	27	48	10474.0	
30	1	P00024542	136554	10	8	2	6	4	13655.0	
31	1	P00025442	27995166	1615	1267	348	652	963	17334.0	
32	1	P00027842	12128	1	0	1	1	0	12128.0	
33	1	P00028042	4597211	376	314	62	141	235	12227.0	
34	1	P00028442	5332834	418	335	83	159	259	12758.0	
35	1	P00029542	2545638	218	198	20	85	133	11677.0	

- The highest grossing Top 1% products are all from Product_Category 1.

3.1.3

Bivariate analysis of Product and Gender

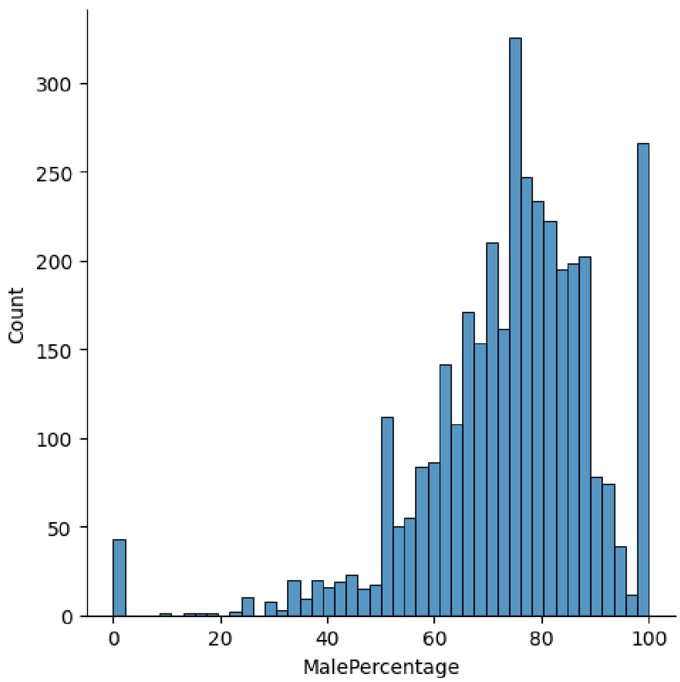
```
1 top1MalePreferredProducts = products.sort_values(by='MalePercentage', ascending=False)
2 top1MalePreferredProducts
```

	Product_Category	Product_ID	Revenue	Quantity	Male_count	Female_count	Married_count	Unmarried_count	Price	MalePe
2734	8	P00262742	11882	2	2	0	1	1	5941.0	
1954	7	P00135942	16954	1	1	0	1	0	16954.0	
1966	7	P00194942	55208	4	4	0	3	1	13802.0	
1965	7	P00188142	25185	2	2	0	0	2	12592.0	
1964	7	P00172242	54146	3	3	0	2	1	18049.0	
...	...	...	...	...	...	...	...	...	...	
1400	5	P00231642	7181	1	0	1	0	1	7181.0	
3419	14	P00152042	52338	4	0	4	1	3	13084.0	
1726	5	P00350742	6989	1	0	1	0	1	6989.0	
90	1	P00060842	15737	1	0	1	0	1	15737.0	
1583	5	P00301942	7147	1	0	1	1	0	7147.0	

3631 rows × 11 columns

```
1 sns.displot(data=top1MalePreferredProducts.MalePercentage)
```

```
<seaborn.axisgrid.FacetGrid at 0x1a4570c2ab0>
```



The breakup in percentages per product for male-females largely is in line with the overall count of 75%-25% across all products

```
1 top1MalePreferredProducts.query('MalePercentage>90').Product_ID.count()
```

```
429
```

```
1 top1MalePreferredProducts.query('MalePercentage>99').Product_ID.count()
```

```
264
```

There are 264 products bought exclusively by males

```
top1MalePreferredProducts.query('MalePercentage<1').Product_ID.count()
```

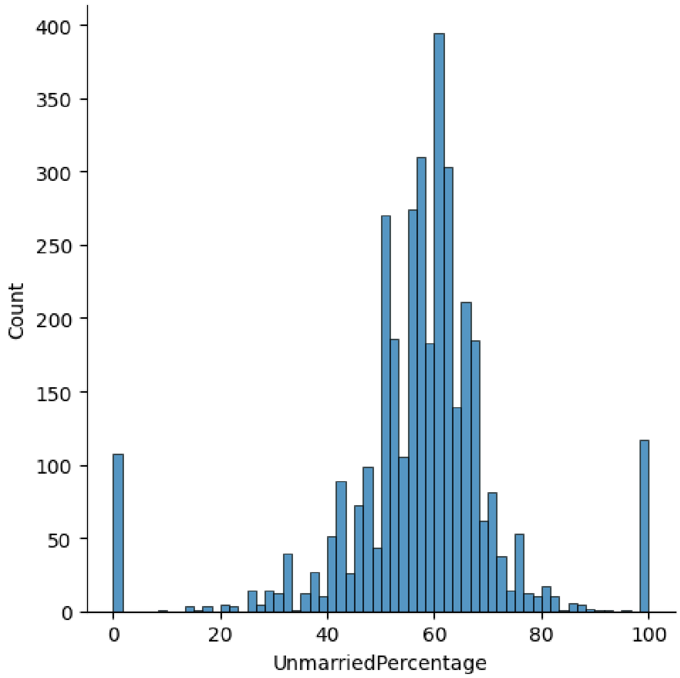
```
43
```

There are 43 products bought exclusively by females

analysis

```
sns.displot(data=products.UnmarriedPercentage)
```

```
<seaborn.axisgrid.FacetGrid at 0x1a471f1a870>
```



3.1.4

Bivariate analysis of Product and Marital Status

```
products.query('UnmarriedPercentage>99').Product_ID.count()
```

```
117
```

There are 117 products bought exclusively by Unmarried customers

```
products.query('UnmarriedPercentage<1').Product_ID.count()
```

```
107
```

There are 107 products bought exclusively by Married customers

3.1.5

Bivariate analysis of Product Category and Gender. Purchase

```
product_categories = products.groupby('Product_Category', as_index=False).agg(
    Revenue=('Revenue','sum'),
    Male_count=('Male_count', 'sum'),
    Female_count=('Female_count', 'sum'),
    Married_count=('Married_count', 'sum'),
    Unmarried_count=('Unmarried_count', 'sum')
```

```
    )
product_categories.sort_values(by='Revenue', ascending=False, inplace=True)
product_categories

```

	Product_Category	Revenue	Male_count	Female_count	Married_count	Unmarried_count
0	1	1910013754	115547	24831	56003	84375
4	5	941835229	108972	41961	61277	89656
7	8	854318799	80367	33558	48514	65411
5	6	324150302	15907	4559	8327	12139
1	2	268516186	18206	5658	9726	14138
2	3	204084713	14207	6006	7854	12359
15	16	145120612	7426	2402	4115	5713
10	11	113791115	19548	4739	9619	14668
9	10	100837301	3963	1162	2347	2778
14	15	92969042	5244	1046	2667	3623
6	7	60896731	2778	943	1681	2040
3	4	27380488	8114	3639	4576	7177
13	14	20014696	900	623	677	846
17	18	9290201	2743	382	1484	1641
8	9	6370324	340	70	163	247
16	17	5878699	516	62	280	298
11	12	5331844	2415	1532	1913	2034
12	13	4008601	4087	1462	2387	3162
19	20	944727	1827	723	1070	1480
18	19	59378	1152	451	657	946

```
product_categories['MalePercentage'] = round(product_categories.Male_count*100/(product_categories.Male_count+product_categorie
product_categories['UnmarriedPercentage'] = round(product_categories.Unmarried_count*100/(product_categories.Unmarried_count+pr
product_categories
```

	Product_Category	Revenue	Male_count	Female_count	Married_count	Unmarried_count	MalePercentage	UnmarriedPercentage
0	1	1910013754	115547	24831	56003	84375	82.0	60.0
4	5	941835229	108972	41961	61277	89656	72.0	59.0
7	8	854318799	80367	33558	48514	65411	71.0	57.0
5	6	324150302	15907	4559	8327	12139	78.0	59.0
1	2	268516186	18206	5658	9726	14138	76.0	59.0
2	3	204084713	14207	6006	7854	12359	70.0	61.0
15	16	145120612	7426	2402	4115	5713	76.0	58.0
10	11	113791115	19548	4739	9619	14668	80.0	60.0
9	10	100837301	3963	1162	2347	2778	77.0	54.0
14	15	92969042	5244	1046	2667	3623	83.0	58.0
6	7	60896731	2778	943	1681	2040	75.0	55.0
3	4	27380488	8114	3639	4576	7177	69.0	61.0
13	14	20014696	900	623	677	846	59.0	56.0
17	18	9290201	2743	382	1484	1641	88.0	53.0
8	9	6370324	340	70	163	247	83.0	60.0
16	17	5878699	516	62	280	298	89.0	52.0
11	12	5331844	2415	1532	1913	2034	61.0	52.0
12	13	4008601	4087	1462	2387	3162	74.0	57.0
19	20	944727	1827	723	1070	1480	72.0	58.0
18	19	59378	1152	451	657	946	72.0	59.0

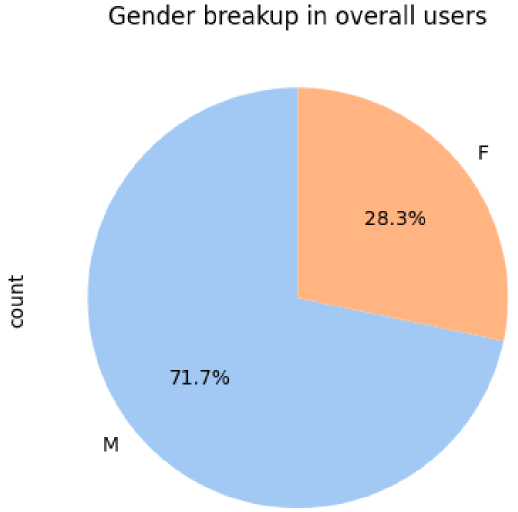
- Product Category 1 is the highest grossing category with USD 1.91 Billion in revenue
- For this category, 82% buyers are male. However, as overall we have 75% male customers for Walmart, it would be prudent to check if the 82% is statistically significantly different from the average.
- This category contains ALL the Top 1% revenue-grossing products for Walmart
- Categories 5,8,6,2,3,16,11,10 are the other 1 Billion plus categories
- Category 19 is the lowest grossing category with just $59378 revenue

3.1.6

Univariate analysis of Gender column

```
users['Gender'].value_counts().plot.pie(
autopct='%1.1f%%',
startangle=90, colors=sns.color_palette('pastel'))
plt.title("Gender breakup in overall users")
```

```
Text(0.5, 1.0, 'Gender breakup in overall users')
```




```
users['Gender'].value_counts()
```

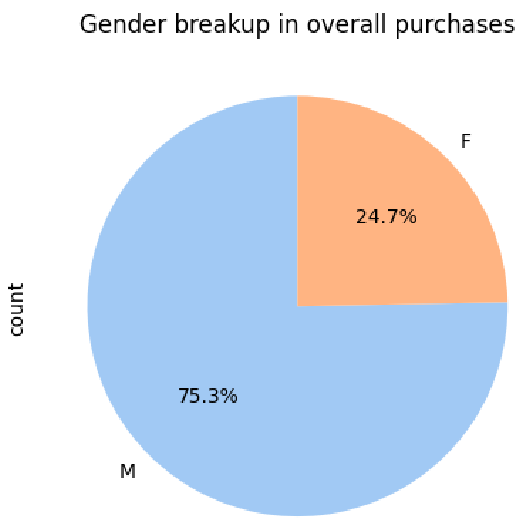
```
Gender
M    4225
F    1666
Name: count, dtype: int64
```

3.1.7

Bivariate analysis of Gender and Purchase column

```
df['Gender'].value_counts().plot.pie(
autopct='%1.1f%%',
startangle=90, colors=sns.color_palette('pastel'))
plt.title("Gender breakup in overall purchases")
```

```
Text(0.5, 1.0, 'Gender breakup in overall purchases')
```

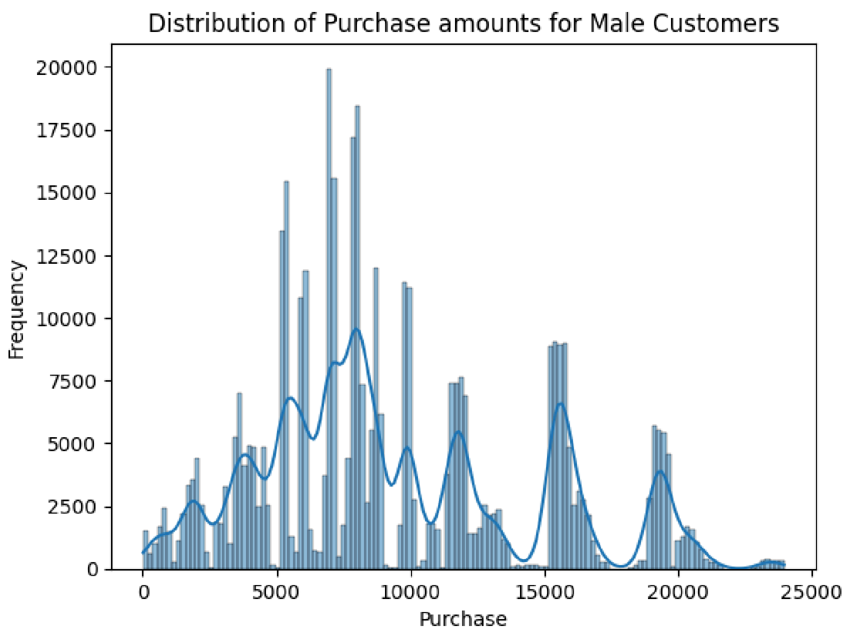


- There are 5891 unique users
- Out of these 4225(72%) are males, 1666 (28%) are females
- In terms of purchases too, 75% of purchases are by males and 25% are by females

```
males= df[df.Gender=='M']
females = df[df.Gender=='F']

PopMeanFemales = females.Purchase.mean()
PopMeanMales = males.Purchase.mean()
print(f'Population Mean purchase amount for females is ${PopMeanFemales:.2f}')
print(f'Population Mean purchase amount for males is ${PopMeanMales:.2f}')
```

```
Population Mean purchase amount for females is $8734.57
Population Mean purchase amount for males is $9437.53
```

```
# plot the sample_means_male to see the distribution
sns.histplot(males.Purchase, kde=True)
plt.xlabel('Purchase')
plt.ylabel('Frequency')
plt.title('Distribution of Purchase amounts for Male Customers')
plt.show()
```



- The distribution of purchase amounts for males is not really normal. However we can use CLT to estimate the mean value with some confidence.
- Instead of giving exact average, it is better to give an interval for the mean purchase amount.
- We can do this by using the Central limit theorem
- We will select a sample, and use the sample mean to calculate an interval

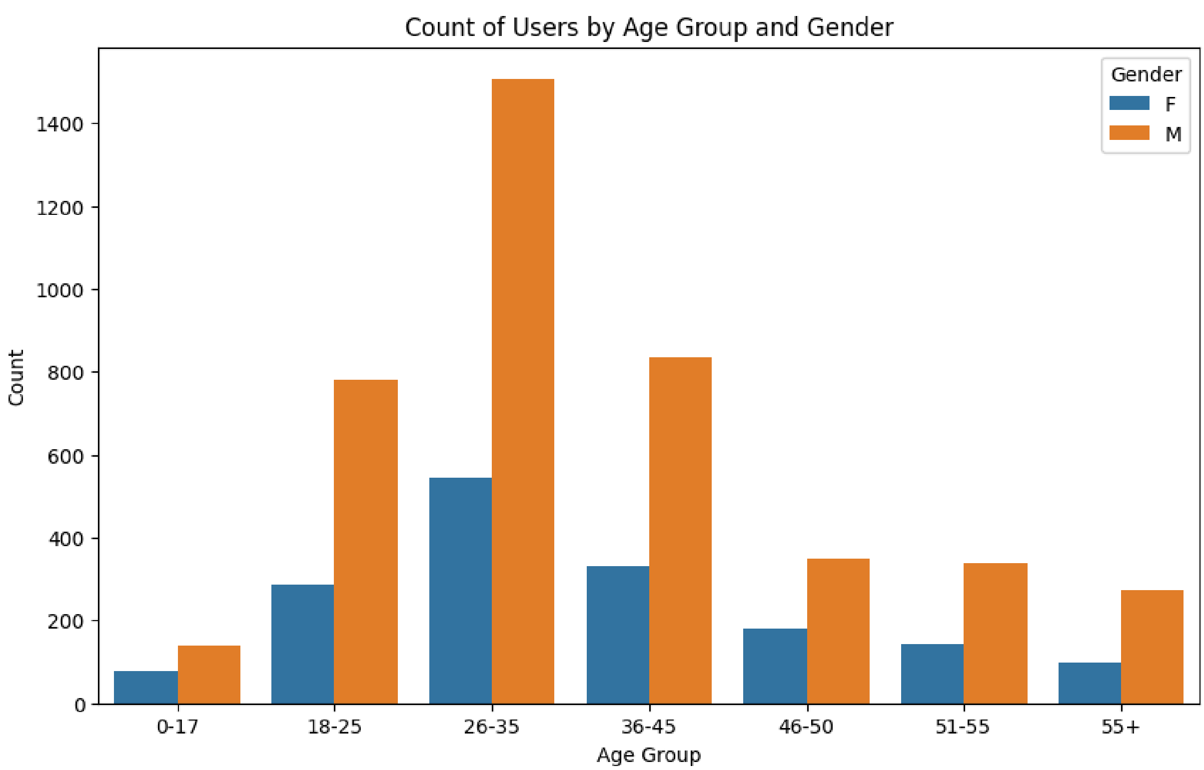
3.1.8

Univariate analysis of Age column

```
age = users.groupby(['Age','Gender'],as_index=False).size().sort_values(by="Age")
age
```

	Age	Gender	size
0	0-17	F	78
1	0-17	M	140
2	18-25	F	287
3	18-25	M	782
4	26-35	F	545
5	26-35	M	1508
6	36-45	F	333
7	36-45	M	834
8	46-50	F	182
9	46-50	M	349
10	51-55	F	142
11	51-55	M	339
12	55+	F	99
13	55+	M	273

```
# Univariate Analysis

plt.figure(figsize=(10, 6))
sns.barplot(data=age, x='Age', y='size', hue='Gender')
plt.title('Count of Users by Age Group and Gender')
plt.xlabel('Age Group')
plt.ylabel('Count')
plt.show()
```



3.1.9

Bivariate analysis of Age and Gender column

```
#select all records where gender is M

male_users = age[age['Gender'] == 'M']
male_users

# Insights from the age distribution plot
total_users = age['size'].sum()
male_users_count = male_users['size'].sum()
female_users_count = total_users - male_users_count

print(f"Total Users: {total_users}")
print(f"Male Users: {male_users_count} ({(male_users_count / total_users) * 100:.2f}%)")
print(f"Female Users: {female_users_count} ({(female_users_count / total_users) * 100:.2f}%)")

# Age group distribution
age_groups = age.groupby('Age')['size'].sum().reset_index()
age_groups['percentage'] = (age_groups['size'] / total_users) * 100
print("\nAge Group Distribution:")
print(age_groups)

# Gender distribution within each age group
age_gender_distribution = age.pivot(index='Age', columns='Gender', values='size').fillna(0)
age_gender_distribution['Total'] = age_gender_distribution.sum(axis=1)
age_gender_distribution['Male_Percentage'] = (age_gender_distribution['M'] / age_gender_distribution['Total']) * 100
age_gender_distribution['Female_Percentage'] = (age_gender_distribution['F'] / age_gender_distribution['Total']) * 100
print("\nAge and Gender Distribution:")
print(age_gender_distribution)
```

```
Total Users: 5891
Male Users: 4225 (71.72%)
Female Users: 1666 (28.28%)

Age Group Distribution:
     Age  size  percentage
0   0-17   218    3.700560
1  18-25  1069   18.146325
2  26-35  2053   34.849771
3  36-45  1167   19.809879
4  46-50   531    9.013750
5  51-55   481    8.164997
6    55+   372    6.314717

Age and Gender Distribution:
Gender    F     M  Total  Male_Percentage  Female_Percentage
Age
0-17     78   140    218        64.220183          35.779817
18-25   287   782   1069        73.152479          26.847521
26-35   545  1508   2053        73.453483          26.546517
36-45   333   834   1167        71.465296          28.534704
46-50   182   349    531        65.725047          34.274953
51-55   142   339    481        70.478170          29.521830
55+      99   273    372        73.387097          26.612903
```

- The highest number of users are in 26-35 age category and comprise 34% of overall users
- 19% users are in 36-45 age group and 18% of users belong to 18-25 age group
- In the 0-17 age group, while only 3.7% of users lie, 35% of them are females, which is highest female ratio in any age group.

3.1.10

Bivariate Analysis of Occupation and Gender

```
occ = users.groupby(['Occupation','Gender'],as_index=False).size().sort_values(by="Occupation")
occ
```

	Occupation	Gender	size
0	0	F	226
1	0	M	462
2	1	F	203
3	1	M	314
4	2	F	88
5	2	M	168
6	3	F	98
7	3	M	72
8	4	F	228
9	4	M	512
11	5	M	80
10	5	F	31
12	6	F	99
13	6	M	129
14	7	F	137
15	7	M	532
16	8	F	3
17	8	M	14
18	9	F	85
19	9	M	3
21	10	M	126
20	10	F	66
22	11	F	22
23	11	M	106
24	12	F	46
25	12	M	330
26	13	F	33
27	13	M	107
28	14	F	78
29	14	M	216
31	15	M	112
30	15	F	28
32	16	F	49
33	16	M	186
34	17	F	50
35	17	M	441
36	18	F	4
37	18	M	63
38	19	F	15
39	19	M	56
40	20	F	77
41	20	M	196

3.1.11

Univariate Analysis of Occupation

```
# Insights from the occupation distribution plot
occ_groups = occ.groupby('Occupation')['size'].sum().reset_index()
occ_groups['percentage'] = (occ_groups['size'] / total_users) * 100
print("Occupation Distribution:")
print(occ_groups)
```

```
Occupation Distribution:
    Occupation  size  percentage
0            0   688   11.678832
1            1   517    8.776099
2            2   256    4.345612
3            3   170    2.885758
4            4   740   12.561535
5            5   111    1.884230
6            6   228    3.870311
7            7   669   11.356306
8            8    17    0.288576
9            9    88    1.493804
10          10   192    3.259209
11          11   128    2.172806
12          12   376    6.382618
13          13   140    2.376507
14          14   294    4.990664
15          15   140    2.376507
16          16   235    3.989136
17          17   491    8.334748
18          18    67    1.137328
19          19    71    1.205228
20          20   273    4.634188
```

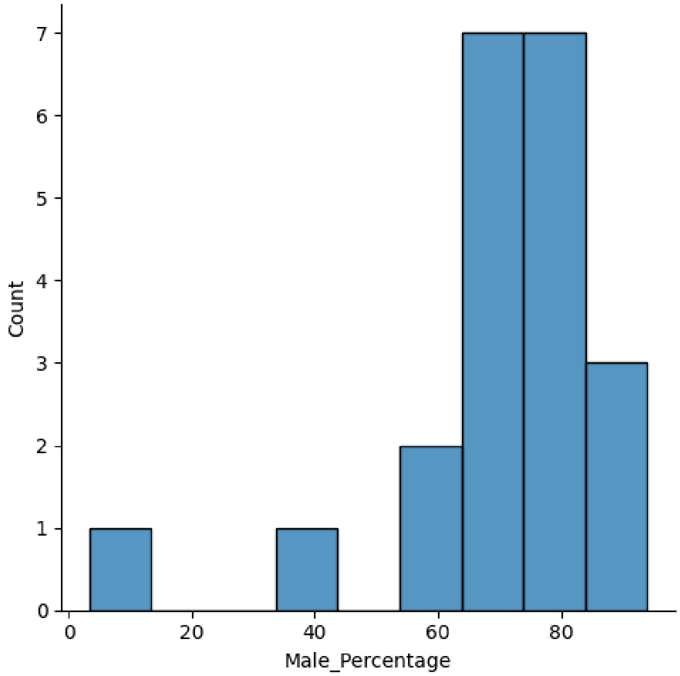
Occupations 0,4 and 7 have the maximum number of users, each have 11-12% users

```
# Gender distribution within each Occupation
occ_gender_distribution = occ.pivot(index='Occupation', columns='Gender', values='size').fillna(0)
occ_gender_distribution['Total'] = occ_gender_distribution.sum(axis=1)
occ_gender_distribution['Male_Percentage'] = (occ_gender_distribution['M'] / occ_gender_distribution['Total']) * 100
occ_gender_distribution['Female_Percentage'] = (occ_gender_distribution['F'] / occ_gender_distribution['Total']) * 100
print("\Occupation and Gender Distribution:")
print(occ_gender_distribution)
```

```
\Occupation and Gender Distribution:
Gender        F    M  Total  Male_Percentage  Female_Percentage
Occupation
0           226  462    688        67.151163          32.848837
1           203  314    517        60.735010          39.264990
2            88  168    256        65.625000          34.375000
3            98   72    170        42.352941          57.647059
4           228  512    740        69.189189          30.810811
5            31   80    111        72.072072          27.927928
6            99  129    228        56.578947          43.421053
7           137  532    669        79.521674          20.478326
8             3   14     17        82.352941          17.647059
9            85    3     88         3.409091          96.590909
10           66  126    192        65.625000          34.375000
11           22  106    128        82.812500          17.187500
12           46  330    376        87.765957          12.234043
13           33  107    140        76.428571          23.571429
14           78  216    294        73.469388          26.530612
15           28  112    140        80.000000          20.000000
16           49  186    235        79.148936          20.851064
17           50  441    491        89.816701          10.183299
18            4   63     67        94.029851           5.970149
19           15   56     71        78.873239          21.126761
20           77  196    273        71.794872          28.205128
<>:6: SyntaxWarning: invalid escape sequence '\O'
<>:6: SyntaxWarning: invalid escape sequence '\O'
C:\Users\Admin\AppData\Local\Temp\ipykernel_37668\2747592413.py:6: SyntaxWarning: invalid escape sequence '\O'
  print("\Occupation and Gender Distribution:")
```

```
sns.displot(data=occ_gender_distribution['Male_Percentage'] )
```

```
<seaborn.axisgrid.FacetGrid at 0x1a455b648c0>
```



The gender wise breakup for occupation is similar to overall gender breakup. One Way ANOVA on Occupation and Male Percentage column can be used to confirm this further Occupation 9 is a occupation where 96.5% of users are males Occupation 18 is a occupation where 94% of users are females

3.1.12

Bivariate Analysis of Occupation and Age Group

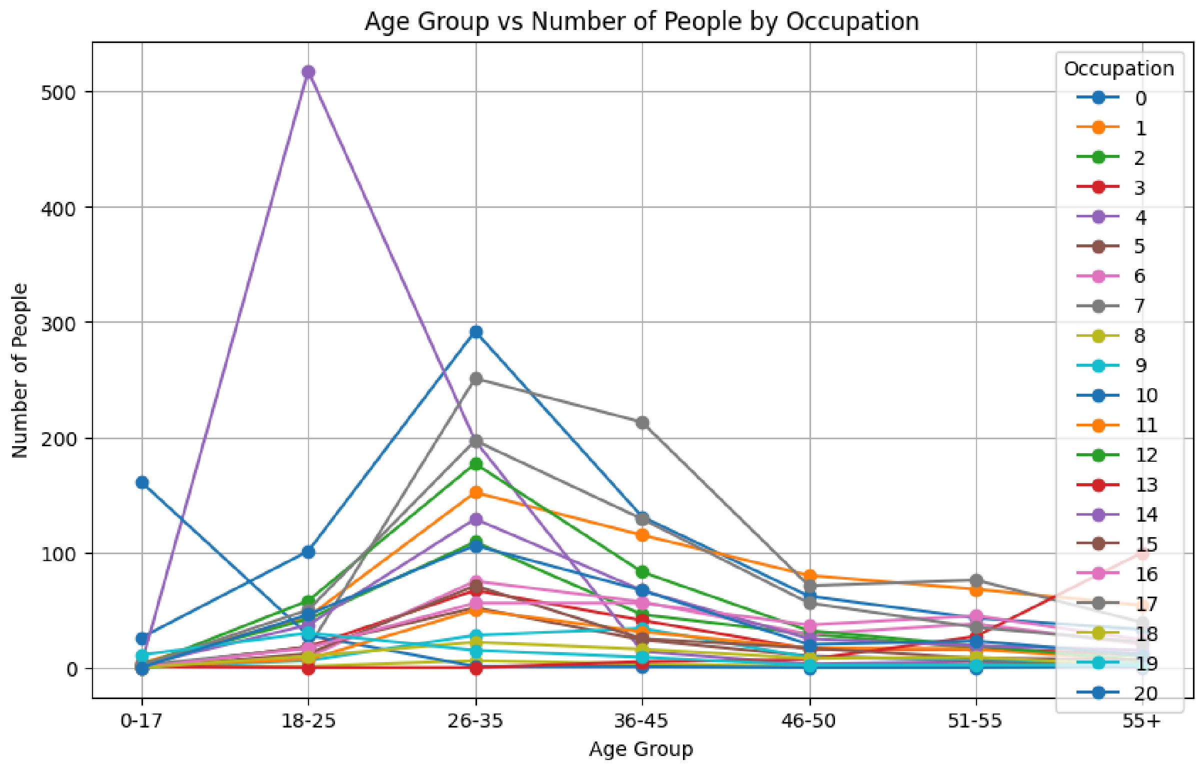
```
occAge = pd.crosstab(users.Age, users.Occupation)
occAge
```

Occupation	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	16	17	18	19	20
Age																					
0-17	26	4	3	0	3	0	0	2	1	0	...	1	1	1	2	0	0	2	0	11	0
18-25	101	44	42	18	518	18	9	17	1	6	...	7	58	0	37	12	17	50	10	30	46
26-35	292	152	109	67	197	52	75	251	6	28	...	50	177	0	129	71	56	197	22	15	106
36-45	131	115	46	41	14	24	57	213	3	34	...	31	83	5	67	25	56	129	16	9	67
46-50	62	80	29	16	3	10	29	71	1	9	...	17	32	7	25	17	37	56	8	2	20
51-55	43	68	17	16	5	6	38	76	2	7	...	16	19	27	19	8	45	35	9	2	23
55+	33	54	10	12	0	1	20	39	3	4	...	6	6	100	15	7	24	22	2	2	11

7 rows × 21 columns

```
# Plot the line chart
plt.figure(figsize=(10, 6))

for column in occAge.columns:
    plt.plot(occAge.index, occAge[column], marker='o', label=column)

# Customize the plot
plt.title('Age Group vs Number of People by Occupation')
plt.xlabel('Age Group')
plt.ylabel('Number of People')
```

```
plt.legend(title='Occupation')
plt.grid(True)
plt.show()
```

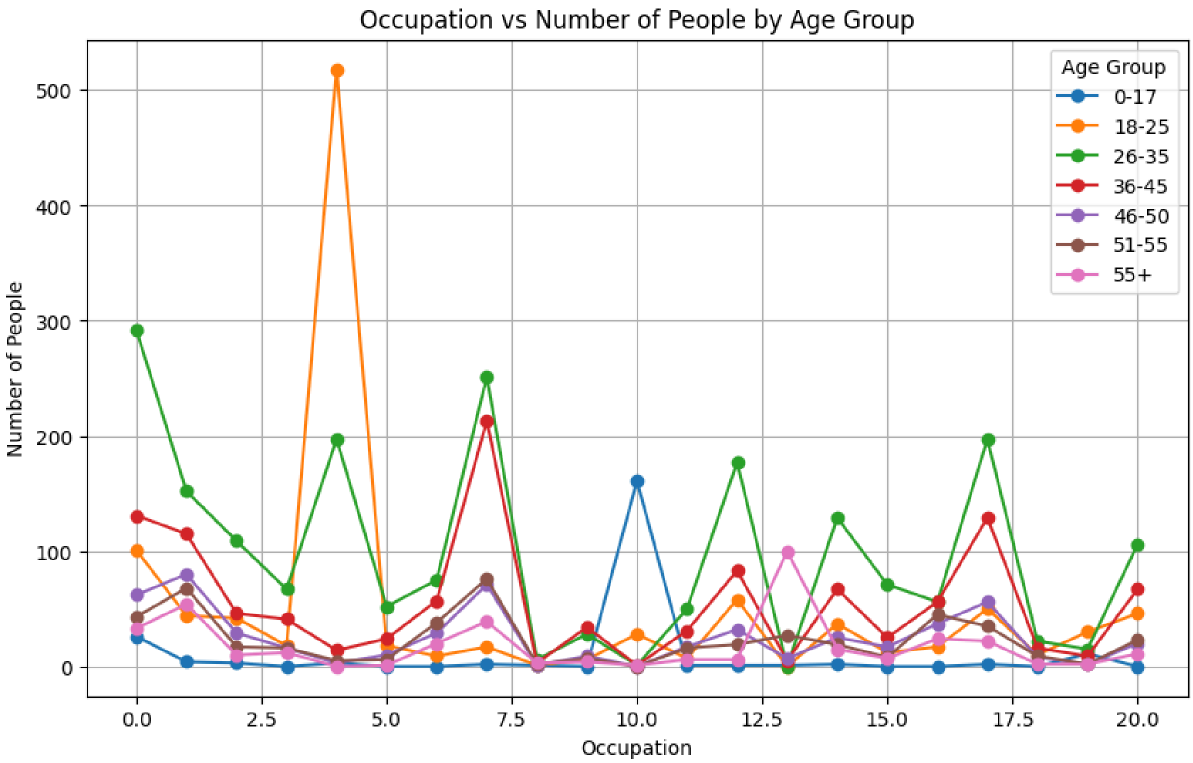



```
1 #find which occupation has maximum value for 26-35 age group
2 # Total number of users in the 26-35 age group
3
4 def age_group_top3_occupations(age_group):
5     total_users_in_age_group = cTrans[age_group].sum()
6
7     top_3 = cTrans.nlargest(3, age_group)[age_group]
8     print(f'{age_group} occupations {top_3.index.values}')
9     print(f'Total users in {age_group} = {(top_3/total_users_26_35).sum()*100}')
10
11
12 age_group_top3_occupations('18-25')
13 age_group_top3_occupations('26-35')
14 age_group_top3_occupations('36-45')
15
```

```
18-25 occupations [ 4  0 12]
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[181], line 12
      8     print(f'{age_group} occupations {top_3.index.values}')
      9     print(f'Total users in {age_group} = {(top_3/total_users_26_35).sum()*100}')
---> 12 age_group_top3_occupations('18-25')
     13 age_group_top3_occupations('26-35')
     14 age_group_top3_occupations('36-45')

Cell In[181], line 9, in age_group_top3_occupations(age_group)
      7 top_3 = cTrans.nlargest(3, age_group)[age_group]
      8 print(f'{age_group} occupations {top_3.index.values}')
----> 9 print(f'Total users in {age_group} = {(top_3/total_users_26_35).sum()*100}')

NameError: name 'total_users_26_35' is not defined
```

- For 26-35 age group, 36% of users are from occupations 0,4,7
- For 18-25 age group, 32% of users are from occupations 0,4,12
- For 36-45 age group, 23% of users are from occupations 0,7,17

```
# Plot the line chart
plt.figure(figsize=(10, 6))
cTrans = occAge.T
for column in cTrans.columns:
    plt.plot(cTrans.index, cTrans[column], marker='o', label=column)

# Customize the plot
plt.title('Occupation vs Number of People by Age Group')
plt.xlabel('Occupation')
plt.ylabel('Number of People')
plt.legend(title='Age Group')
plt.grid(True)
plt.show()
```



3.1.13

Bivariate Analysis of City_Category and Purchase

```
city = df.groupby('City_Category',as_index=False).size().sort_values(by="City_Category")
city['percent'] = round(city['size']*100/len(df),0)
city
```

	City_Category	size	percent
0	A	147720	27.0
1	B	231173	42.0
2	C	171175	31.0

42% of purchases are from City B, 31% from city C

3.1.14

Bivariate Analysis of City_Category and User_ID

```
cityUser = users.groupby('City_Category',as_index=False).size().sort_values(by="City_Category")
cityUser['percent'] = round(cityUser['size']*100/len(users),0)
```

```
cityUser
```

	City_Category	size	percent
0	A	1045	18.0
1	B	1707	29.0
2	C	3139	53.0

53% of users are from City C, 29% from City B

3.1.15

Bivariate Analysis of City_Category and Gender

```
cityGender = pd.crosstab(users.City_Category, users.Gender, margins=True)
cityGender['percent'] = cityGender.M*100/cityGender.All
cityGender
```

Gender	F	M	All	percent
City_Category				
A	295	750	1045	71.770335
B	503	1204	1707	70.533099
C	868	2271	3139	72.347881
All	1666	4225	5891	71.719572

The gender distribution across the three cities is same.

3.1.16

Bivariate Analysis of City_Category and Age Group

```
cityAge= pd.crosstab(users.City_Category, users.Age,margins=True)

#cityAge['percent'] = cityAge.M*100/cityGender.All
cityAge
```

Age	0-17	18-25	26-35	36-45	46-50	51-55	55+	All
City_Category								
A	25	214	461	176	53	67	49	1045
B	50	331	652	335	146	135	58	1707
C	143	524	940	656	332	279	265	3139
All	218	1069	2053	1167	531	481	372	5891

```
cityAge= pd.crosstab(users.City_Category, users.Age,normalize = 'index')
cityAge*100
```

Age	0-17	18-25	26-35	36-45	46-50	51-55	55+
City_Category							
A	2.392344	20.478469	44.114833	16.842105	5.071770	6.411483	4.688995
B	2.929115	19.390744	38.195665	19.625073	8.553017	7.908612	3.397774
C	4.555591	16.693214	29.945843	20.898375	10.576617	8.888181	8.442179

```
cityAge= pd.crosstab(users.City_Category, users.Age,normalize = 'columns',margins= True)
round(cityAge*100,0)
```

Age City_Category	0-17	18-25	26-35	36-45	46-50	51-55	55+	All
A	11.0	20.0	22.0	15.0	10.0	14.0	13.0	18.0
B	23.0	31.0	32.0	29.0	27.0	28.0	16.0	29.0
C	66.0	49.0	46.0	56.0	63.0	58.0	71.0	53.0

- In City A, 44% of users are from 26-35 age group
- While 53% of users are from City C, it has 71% of all 55+ aged users

3.1.17

Bivariate Analysis of City_Category and Occupation

```
cityOcc= pd.crosstab(users.City_Category, users.Occupation,margins=True)

#cityAge['percent'] = cityAge.M*100/cityGender.All
cityOcc
```

Occupation City_Category	0	1	2	3	4	5	6	7	8	9	...	12	13	14	15	16	17	18	19	20	All
A	129	94	68	34	172	14	24	113	4	7	...	77	12	53	25	35	62	7	14	59	1045
B	203	140	80	47	236	40	74	170	2	25	...	113	30	83	43	61	136	12	18	106	1707
C	356	283	108	89	332	57	130	386	11	56	...	186	98	158	72	139	293	48	39	108	3139
All	688	517	256	170	740	111	228	669	17	88	...	376	140	294	140	235	491	67	71	273	5891

4 rows × 22 columns

```
cityOcc= pd.crosstab(users.City_Category, users.Occupation,normalize = 'index')

round(cityOcc*100,0)

```

Occupation City_Category	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	16	17	18	19	20
A	12.0	9.0	7.0	3.0	16.0	1.0	2.0	11.0	0.0	1.0	...	2.0	7.0	1.0	5.0	2.0	3.0	6.0	1.0	1.0	6.0
B	12.0	8.0	5.0	3.0	14.0	2.0	4.0	10.0	0.0	1.0	...	3.0	7.0	2.0	5.0	3.0	4.0	8.0	1.0	1.0	6.0
C	11.0	9.0	3.0	3.0	11.0	2.0	4.0	12.0	0.0	2.0	...	2.0	6.0	3.0	5.0	2.0	4.0	9.0	2.0	1.0	3.0

3 rows × 21 columns

```
cityOcc.loc['A'].sum()
```

```
0.9999999999999999
```

```
cityOccTrans= cityOcc.T
def city_group_top3_occupations(city_group):
    top_3 = cityOccTrans.nlargest(3, city_group)[city_group]
    print(f'{city_group} occupations {top_3.index.values}')
    print(f'% users in top 3 occupations for {city_group} = {(top_3).sum()*100}')


city_group_top3_occupations('A')
city_group_top3_occupations('B')
city_group_top3_occupations('C')

```

```
A occupations [4 0 7]
% users in top 3 occupations for A = 39.61722488038278
B occupations [4 0 7]
% users in top 3 occupations for B = 35.67662565905097
C occupations [7 0 4]
% users in top 3 occupations for C = 34.21471806307741
```

3.1.18

Bivariate Analysis of City_Category and Product Category

```
cityProdCat= pd.crosstab(df.City_Category, df.Product_Category,margins=True)
cityProdCat
```

Product_Category	1	2	3	4	5	6	7	8	9	10	...	12	13	14	15	16	17	
City_Category																		
A	35081	6141	4943	3050	42211	5507	1226	32179	110	1333	...	1063	1614	481	1717	2848	121	7
B	58253	10444	8587	5226	64138	8526	1599	47553	174	2063	...	1675	2271	632	2638	4038	267	13
C	47044	7279	6683	3477	44584	6433	896	34193	126	1729	...	1209	1664	410	1935	2942	190	9
All	140378	23864	20213	11753	150933	20466	3721	113925	410	5125	...	3947	5549	1523	6290	9828	578	31

4 rows × 21 columns

3.1.19

Bivariate Analysis of Stay_In_Current_City_Years and UserID

```
stayDuration= users.groupby('Stay_In_Current_City_Years',as_index=False).size().sort_values('Stay_In_Current_City_Years')
stayDuration['percent'] = round(stayDuration['size']*100/stayDuration['size'].sum(),0)
stayDuration

```

	Stay_In_Current_City_Years	size	percent
0	0	772	13.0
1	1	2086	35.0
2	2	1145	19.0
3	3	979	17.0
4	4+	909	15.0

35% of users have stayed in same city for 1-2 yrs

3.1.20

Bivariate Analysis of Stay_In_Current_City_Years and Stay Duration

```
cityStayDuration = pd.crosstab(users.City_Category,users.Stay_In_Current_City_Years, normalize='index')
cityStayDuration
```

Stay_In_Current_City_Years	0	1	2	3	4+
City_Category					
A	0.140670	0.354067	0.175120	0.172249	0.157895
B	0.123609	0.356180	0.200351	0.172818	0.147042
C	0.131889	0.352979	0.197515	0.160561	0.157056

The duration of stay in the city is similar in all three cities across various duration categories.

```
genderStayDuration = pd.crosstab(users.Gender,users.Stay_In_Current_City_Years, normalize='index')
genderStayDuration
```

Stay_In_Current_City_Years	0	1	2	3	4+
Gender					
F	0.128451	0.362545	0.196879	0.171669	0.140456
M	0.132071	0.350769	0.193373	0.164024	0.159763

3.1.21

Bivariate Analysis of Marital_Status and Gender

```
maritalStatusGender= pd.crosstab(users.Marital_Status, users.Gender,margins=True)
maritalStatusGender
```

Gender	F	M	All
Marital_Status			
0	947	2470	3417
1	719	1755	2474
All	1666	4225	5891

```
print('Unmarried % = ',round(100*maritalStatusGender.at[0,'All'] /maritalStatusGender.at['All','All'],1))
print('Unmarried male% = ',round(100*maritalStatusGender.at[0,'M'] /maritalStatusGender.at['All','M'],1))
print('Unmarried female% = ',round(100*maritalStatusGender.at[0,'F'] /maritalStatusGender.at['All','F'],1))
```

```
Unmarried % =  58.0
Unmarried male% =  58.5
Unmarried female% =  56.8
```

58% of users are unmarried Ratio of unmarried users is same across genders

3.1.22

Bivariate Analysis of Marital_Status and Age Category

```
maritalStatusAge= pd.crosstab(users.Marital_Status, users.Age,margins=True)
maritalStatusAge
```

Age	0-17	18-25	26-35	36-45	46-50	51-55	55+	All
Marital_Status								
0	218	825	1244	705	156	136	133	3417
1	0	244	809	462	375	345	239	2474
All	218	1069	2053	1167	531	481	372	5891

```
# Calculate percentages
maritalStatusAge_percent = maritalStatusAge.div(maritalStatusAge['All'], axis=0) * 100
maritalStatusAge_percent


```

Age	0-17	18-25	26-35	36-45	46-50	51-55	55+	All
Marital_Status								
0	6.379865	24.143986	36.406204	20.632133	4.565408	3.980100	3.892303	100.0
1	0.000000	9.862571	32.700081	18.674212	15.157639	13.945028	9.660469	100.0
All	3.700560	18.146325	34.849771	19.809879	9.013750	8.164997	6.314717	100.0

```
print(24/(9+24))
print(36.4/(36.4+32))
print(20.6/(20.6+18.6))
```

```
0.7272727272727273
0.5321637426900584
0.5255102040816326
```

- 72% of users in 18-25 age group are unmarried
- 53% of users in 26-35 age group are unmarried
- 52% of users in 36-45 age group are unmarried

3.1.23

Bivariate Analysis of Marital_Status and Occupation

```
maritalStatusOcc= pd.crosstab(users.Marital_Status, users.Occupation,margins=True)
maritalStatusOcc
```

Occupation	0	1	2	3	4	5	6	7	8	9	...	12	13	14	15	16	17	18	19	20	All
Marital_Status																					
0	402	279	144	90	544	65	102	355	11	41	...	219	50	151	73	110	288	35	57	144	3417
1	286	238	112	80	196	46	126	314	6	47	...	157	90	143	67	125	203	32	14	129	2474
All	688	517	256	170	740	111	228	669	17	88	...	376	140	294	140	235	491	67	71	273	5891

3 rows × 22 columns

```
#Calculate the breakup of the married unmarried group acorss occupations
maritalStatusOcc_percent = maritalStatusOcc.div(maritalStatusOcc['All'], axis=0) * 100
maritalStatusOcc_percent
```

Occupation	0	1	2	3	4	5	6	7	8	9	...	12
Marital_Status												
0	11.764706	8.165057	4.214223	2.633889	15.920398	1.902253	2.985075	10.389230	0.321920	1.199883	...	6.409131
1	11.560226	9.620049	4.527082	3.233630	7.922393	1.859337	5.092967	12.691997	0.242522	1.899757	...	6.345998
All	11.678832	8.776099	4.345612	2.885758	12.561535	1.884230	3.870311	11.356306	0.288576	1.493804	...	6.382618

3 rows × 22 columns

```
#Calculate the breakup of the married unmarried group within each occupation
sum_first_two   = maritalStatusOcc_percent.iloc[0:2].sum()
# Calculate the percentages for each column
percentage_row = round((maritalStatusOcc_percent.iloc[0:1] / sum_first_two) * 100,1)

# Add the percentage row to the DataFrame
maritalStatusOcc_percent = pd.concat([maritalStatusOcc_percent,percentage_row])
maritalStatusOcc_percent
```

```
Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
       20, 'All'],
      dtype='object', name='Occupation')
Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
       20, 'All'],
      dtype='object', name='Occupation')
```

Occupation	0	1	2	3	4	5	6	7	8	9	...	
Marital_Status												
0	11.764706	8.165057	4.214223	2.633889	15.920398	1.902253	2.985075	10.389230	0.321920	1.199883	...	
1	11.560226	9.620049	4.527082	3.233630	7.922393	1.859337	5.092967	12.691997	0.242522	1.899757	...	
All	11.678832	8.776099	4.345612	2.885758	12.561535	1.884230	3.870311	11.356306	0.288576	1.493804	...	
0	50.400000	45.900000	48.200000	44.900000	66.800000	50.600000	37.000000	45.000000	57.000000	38.700000	...	5

4 rows × 22 columns

- 66% of users in Occupation 4 are unmarried
- 50% of users in Occupation 0 are unmarried
- 45% of users in Occupation 7 are unmarried
- 75% of users in Occupation 19 are unmarried

3.1.24

Bivariate Analysis of Marital_Status and City

```
maritalStatusCity= pd.crosstab(users.Marital_Status, users.City_Category,margins=True)
maritalStatusCity
```

City_Category	A	B	C	All
Marital_Status				
0	652	1004	1761	3417
1	393	703	1378	2474
All	1045	1707	3139	5891

```
#Calculate the breakup of the married unmarried group across each city
maritalStatusCity_percent = maritalStatusCity.div(maritalStatusCity['All'], axis=0) * 100
maritalStatusCity_percent
```

City_Category	A	B	C	All
Marital_Status				
0	19.081065	29.382499	51.536435	100.0
1	15.885206	28.415521	55.699272	100.0
All	17.738924	28.976405	53.284672	100.0

- The breakup of married-unmarried users is same as the general breakup of users across the cities

```
#Calculate the breakup of the married unmarried group within each city
sum_first_two   = maritalStatusCity_percent.iloc[0:2].sum()
# Calculate the percentages for each column
percentage_row = round((maritalStatusCity_percent.iloc[0:1] / sum_first_two) * 100,1)

# Add the percentage row to the DataFrame
maritalStatusCity_percent = pd.concat([maritalStatusCity_percent,percentage_row])
maritalStatusCity_percent
```

City_Category	A	B	C	All
Marital_Status				
0	19.081065	29.382499	51.536435	100.0
1	15.885206	28.415521	55.699272	100.0
All	17.738924	28.976405	53.284672	100.0
0	54.600000	50.800000	48.100000	50.0

- While overall we have 58% unmarried users, in City C we have only 48% of unmarried users

3.1.25

Bivariate Analysis of Marital_Status and Stay Duration

```
maritalStatusStayDuration= pd.crosstab(users.Marital_Status, users.Stay_In_Current_City_Years,margins=True)
maritalStatusStayDuration

#Calculate the breakup of the married unmarried group across each city
maritalStatusStayDuration_percent = maritalStatusStayDuration.div(maritalStatusStayDuration['All'], axis=0) * 100
maritalStatusStayDuration_percent



```

Stay_In_Current_City_Years	0	1	2	3	4+	All
Marital_Status						
0	13.666959	34.182031	19.402985	16.944688	15.803336	100.0
1	12.328213	37.105901	19.482619	16.168149	14.915117	100.0
All	13.104736	35.409947	19.436428	16.618571	15.430317	100.0

- The breakup of married-unmarried users is same as the general breakup of duration of stay of users irrespective of marital status. So marital status does not have any impact on duration of stay in a city for a user

3.1.26

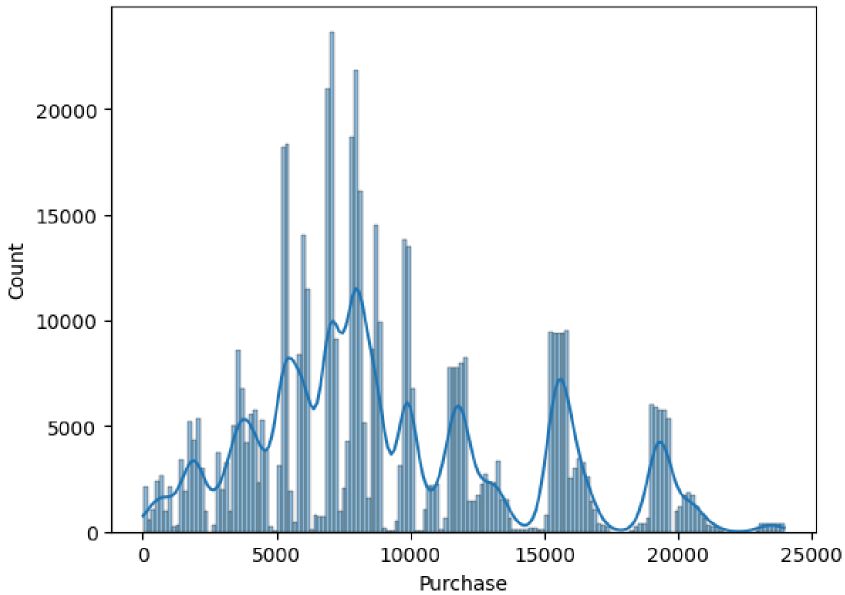
Univariate Analysis of Purchase column

```
df.Purchase.mean()
```

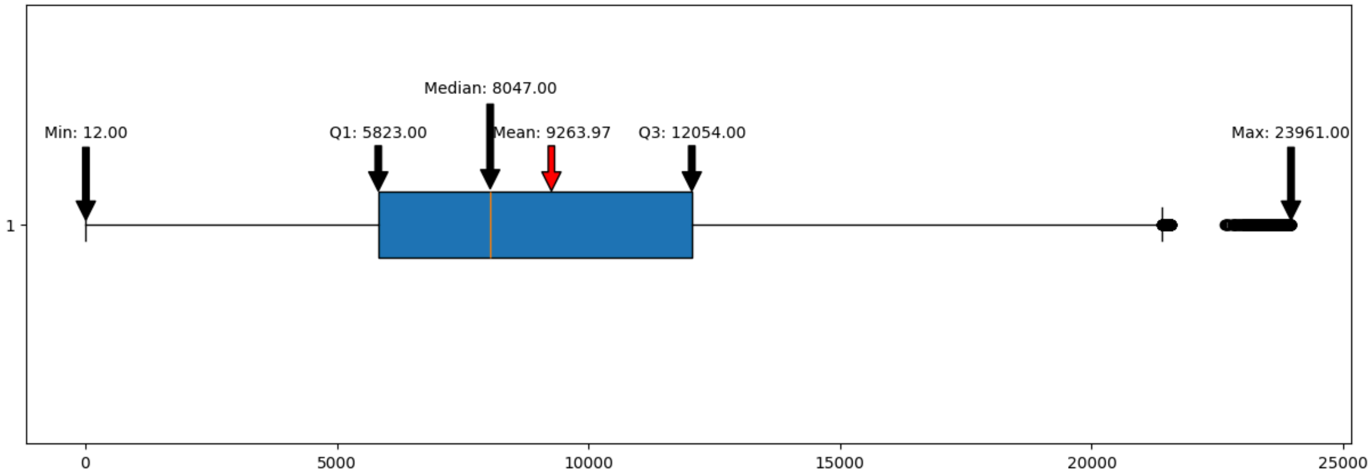
```
9263.968712959126
```

```
sns.histplot(data=df["Purchase"], kde=True)
```

```
<Axes: xlabel='Purchase', ylabel='Count'>
```




```python
data=df.Purchase #Only this one line is to be updated

fig, ax = plt.subplots(figsize=(15, 5))
# Create boxplot
boxplot = ax.boxplot(data, vert=False, patch_artist=True)

# Calculate the five-number summary + mean
mean = np.mean(data)
min_val = np.min(data)
q1 = np.percentile(data, 25)
median = np.median(data)
q3 = np.percentile(data, 75)
max_val = np.max(data)

# Annotate the five-number summary on the boxplot
ax.annotate(f'Min: {min_val:.2f}', xy=(min_val, 1), xytext=(min_val, 1.2),
            arrowprops=dict(facecolor='black', shrink=0.05), ha='center')

ax.annotate(f'Q1: {q1:.2f}', xy=(q1, 1.07), xytext=(q1, 1.2),
            arrowprops=dict(facecolor='black', shrink=0.05), ha='center')

ax.annotate(f'Median: {median:.2f}', xy=(median, 1.07), xytext=(median, 1.3),
            arrowprops=dict(facecolor='black', shrink=0.05), ha='center')

ax.annotate(f'Q3: {q3:.2f}', xy=(q3, 1.07), xytext=(q3, 1.2),
            arrowprops=dict(facecolor='black', shrink=0.05), ha='center')

ax.annotate(f'Max: {max_val:.2f}', xy=(max_val, 1), xytext=(max_val, 1.2),
            arrowprops=dict(facecolor='black', shrink=0.05), ha='center')

ax.annotate(f'Mean: {mean:.2f}', xy=(mean, 1.07), xytext=(mean, 1.2),
            arrowprops=dict(facecolor='red', shrink=0.05), ha='center')


# Display plot
plt.show()


```



- 50% of customers shop between $5823and$12054
- Overall range of purchase amount is from $12to$23961

4.0

Answering Questions asked in Case Study

4.1

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

We have already established that Mean purchase amount for males is $9437.53 Mean purchase amount for females is$8734.57

So women are not spending more money per transaction than men as per this data. Later we have statistically established that the spending habits of the two groups is different

Why are women spending less?

We observe that only 25% of customers are women as per given data.

Possible reasons

- Walmart's marketing strategies might be more appealing to men, leading to higher male foot traffic and spending
- Cultural norms and societal expectations might influence shopping behaviors. For example, women might be more likely to shop for groceries and household items, while men might shop for higher-ticket items
- Gender Roles: Traditional gender roles might play a part in determining who does the shopping and what they buy.

It could indicate that shopping experience of women needs improvement

This can be done by

- keeping more items relevant to women. The product mix at Walmart might cater more to male preferences, such as electronics and automotive products, which could result in higher spending by men
- making it easier to reach
- helpful and women friendly staff
- ensuring women safety
- Women are more likely to use coupons and look for discounts, which might lead them to shop at stores that offer better deals

4.2

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

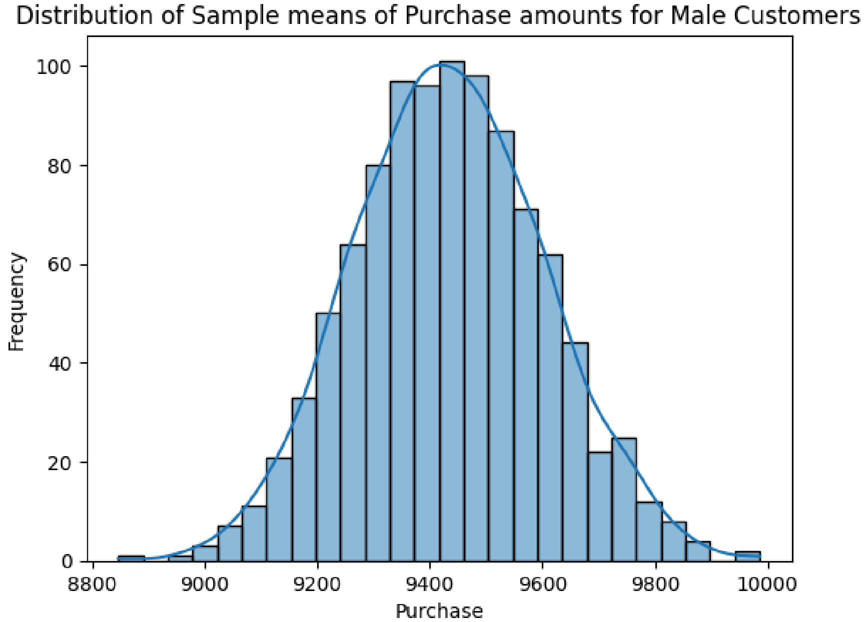
```
# select a random sample of 1000 rows for each gender
sample_males = males.sample(n=1000)
sample_females = females.sample(n=1000)

# identify confidence interval for the mean of the purchase
from scipy import stats

def my_decorator(func):
    def wrapper(data, confidence=0.95, text="Mean"):
        mean, lower,upper = func(data, confidence)
        return  f'Using CLT and single sample of {len(data)} rows, {text} = {mean:.2f}, CI = [{lower:.2f}, {upper:.2f}] with {c
    return wrapper

#We want to decorate the function mean_confidence_interval to add some text to the output
@my_decorator
def mean_confidence_interval_decorated(data, confidence=0.95):
    return mean_confidence_interval(data, confidence)

#Function to calculate the confidence interval for the mean of the purchase amount
def mean_confidence_interval(data, confidence=0.95):
    a = 1.0 * np.array(data)
    n = len(a)
    m, se = np.mean(a), stats.sem(a)
    h = se * stats.t.ppf((1 + confidence) / 2., n-1) #dof is n-1
    return m,m-h,m+h



print(f'Using actual population of {len(males)} rows, Population Mean purchase amount for males is ${PopMeanMales:.2f}')
print(f'{mean_confidence_interval_decorated(sample_males.Purchase, confidence=0.95, text="Mean Purchase amount for Males")}')
print()
print(f'Using actual population of {len(females)} rows,Population Mean purchase amount for females is ${PopMeanFemales:.2f}')
print(f'{mean_confidence_interval_decorated(sample_females.Purchase, confidence=0.95, text="Mean Purchase amount for Females")}
```

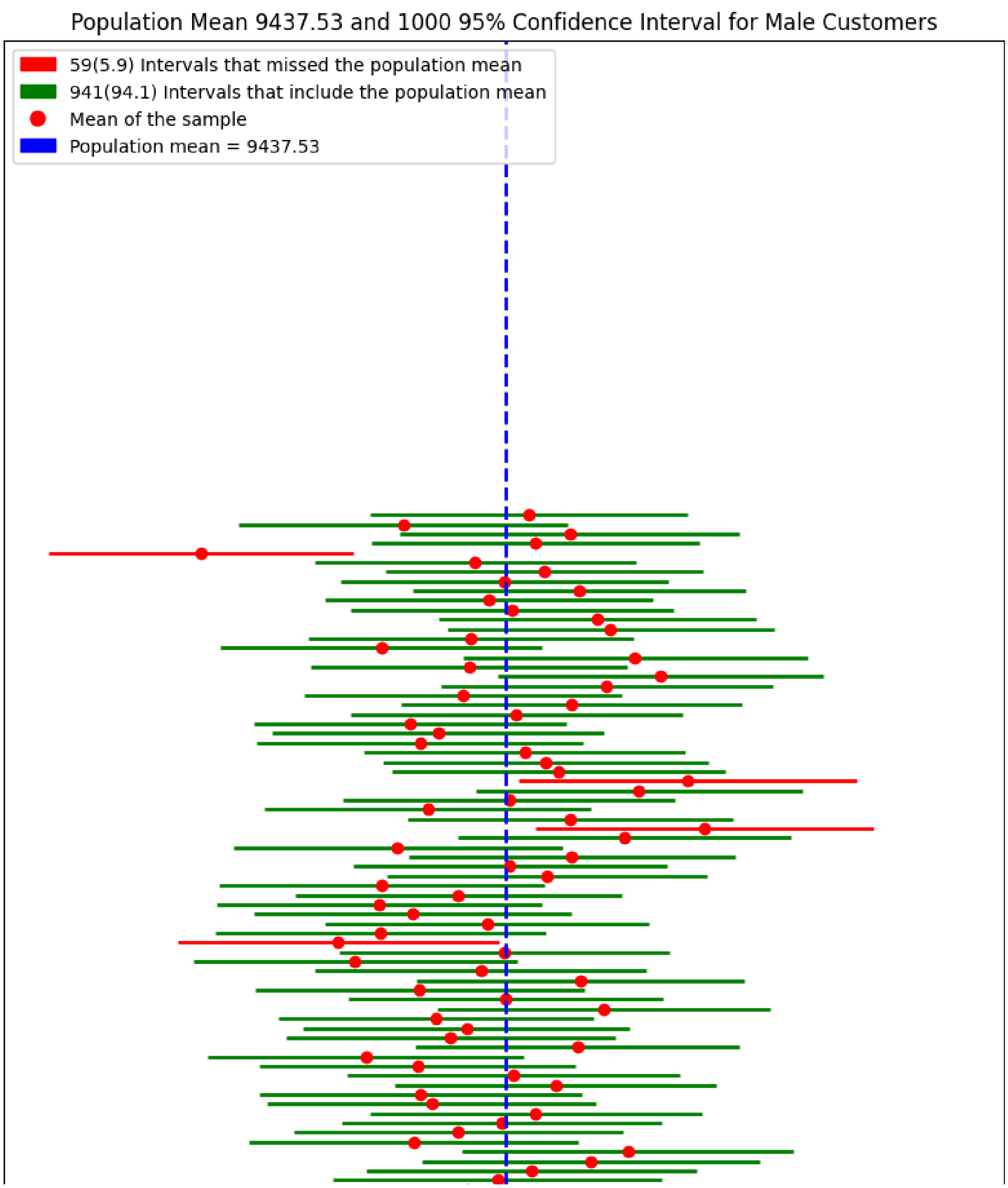
```
Using actual population of 414259 rows, Population Mean purchase amount for males is $9437.53
Using CLT and single sample of 1000 rows, Mean Purchase amount for Males = 9191.12, CI = [8889.37, 9492.87] with 95.0% confiden

Using actual population of 135809 rows,Population Mean purchase amount for females is $8734.57
Using CLT and single sample of 1000 rows, Mean Purchase amount for Females = 8811.79, CI = [8514.98, 9108.60] with 95.0% confid
```

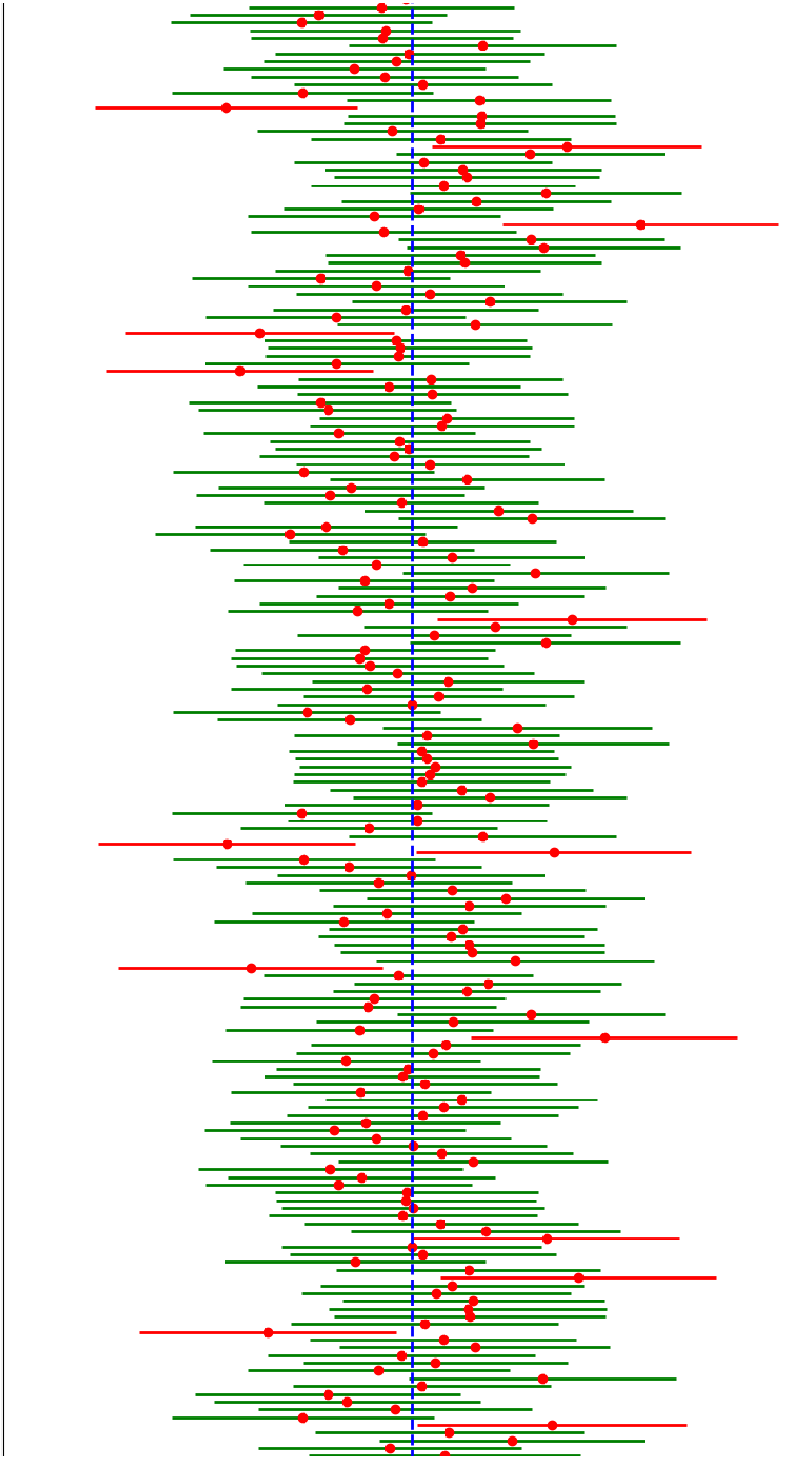
```
#Utility function to plot sample means distribution and confidence interval

import matplotlib.patches as mpatches

def plotConfidenceIntervals(sample_means,pop_mean,text,xlabel):
        #Plot the second and third colummns of sample_means which are the lower and upper bounds of the confidence interval

    totalIntervalCount = len(sample_means)
    plt.figure(figsize=(10, 5+round(totalIntervalCount/10,0)))
    missed=0

    #Plot 1000 confidence intervals to see how many contain the population mean
    for i in range(totalIntervalCount):
        # Plot the horizontal line for the confidence interval
        mean, lower,upper = sample_means[i]
        #Plot the confidence interval that miss the population mean in red
        if(lower<=pop_mean<=upper):
            plt.hlines(i*4, lower,upper, color='g', linewidth=2, label=f'95% CI for {mean:.2f}')
        else:
            missed=missed+1
            plt.hlines(i*4, lower,upper, color='r', linewidth=2, label=f'95% CI for {mean:.2f}')
        # Plot the sample mean as a dot
        plt.plot(mean, i*4, 'ro', label='Mean')

```

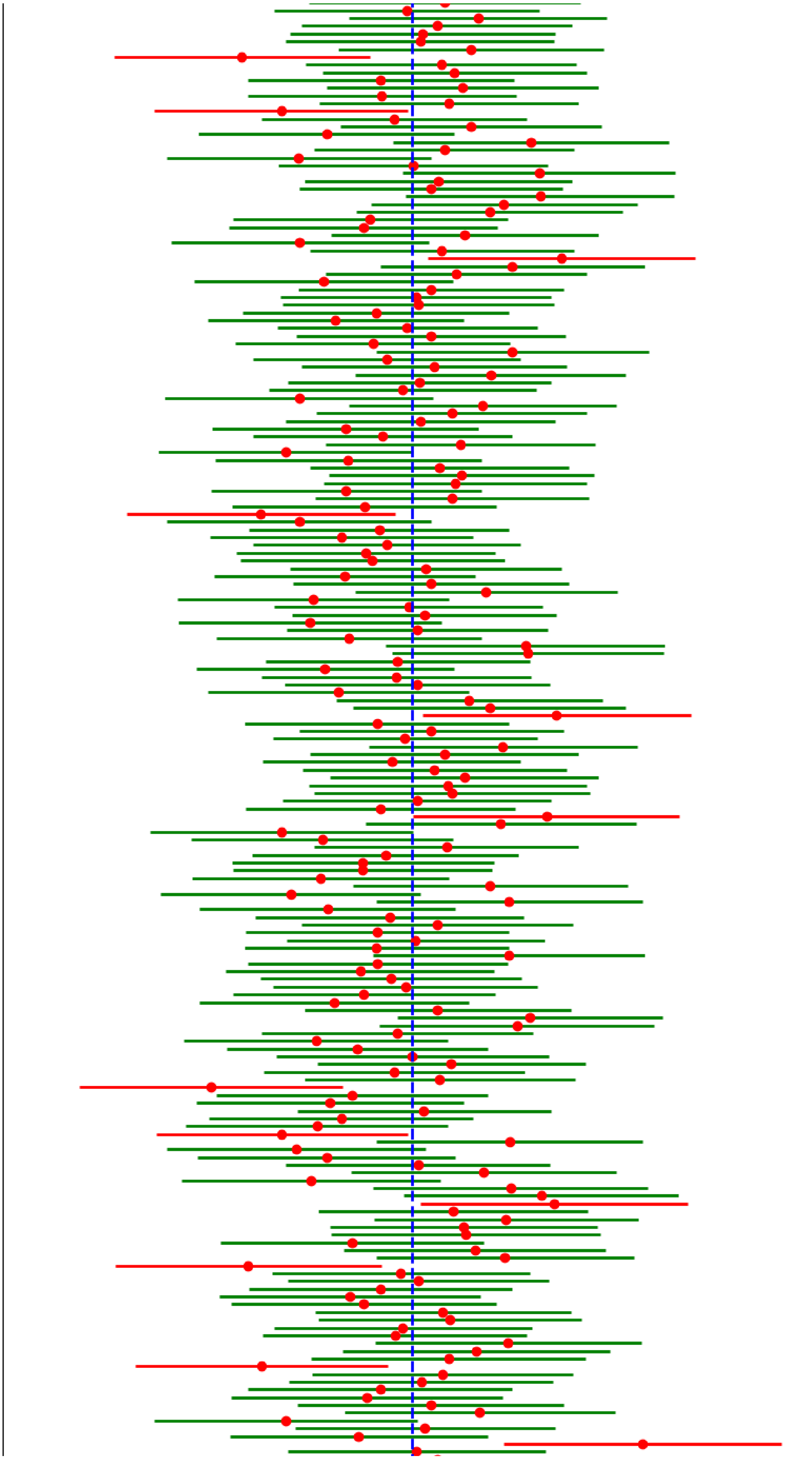
```
    # Plot the population mean
    plt.axvline(pop_mean, color='b', linestyle='dashed', linewidth=2, label='Mean')

    # Add custom legend
    red_line = mpatches.Patch(color='red', label=f'{missed}({missed*100/totalIntervalCount}) Intervals that missed the populati
    green_line = mpatches.Patch(color='green', label=f'{totalIntervalCount-missed}({(totalIntervalCount-missed)*100/totalInterv
    blue_line = mpatches.Patch(color='blue', label=f'Population mean = {pop_mean:.2f}')
    red_dot = plt.Line2D([0], [0], marker='o', color='w', label='Mean of the sample', markerfacecolor='red', markersize=10)

    plt.legend(handles=[red_line, green_line, red_dot,blue_line], loc='upper left')


    plt.title(f'Population Mean {pop_mean:.2f} and {totalIntervalCount} 95% Confidence Interval {text}')
    plt.xlabel(xlabel)
    plt.yticks([])  # Remove y-axis ticks


def plotSampleMeanDistributionAndConfidenceIntervals(data,
                            sample_size,
                            pop_mean,
                            confidence=0.95,
                            text="for"):

    sample_means=[]
    for _ in range(1000):
        sample  = data.sample(n=sample_size)
        m,l,u = mean_confidence_interval(sample, confidence)
        sample_means.append([m,l,u])
    #select first column of the sample_means_male, whcih is the mean
    sample_means = np.array(sample_means)
    # plot the sample_means_male to see the distribution
    sns.histplot(sample_means[:,0], kde=True)
    plt.xlabel(data.name)
    plt.ylabel('Frequency')
    plt.title(f'Distribution of Sample means of {data.name} amounts {text}')
    plt.show()

    plotConfidenceIntervals(sample_means,pop_mean,text,data.name)
    return sample_means
```

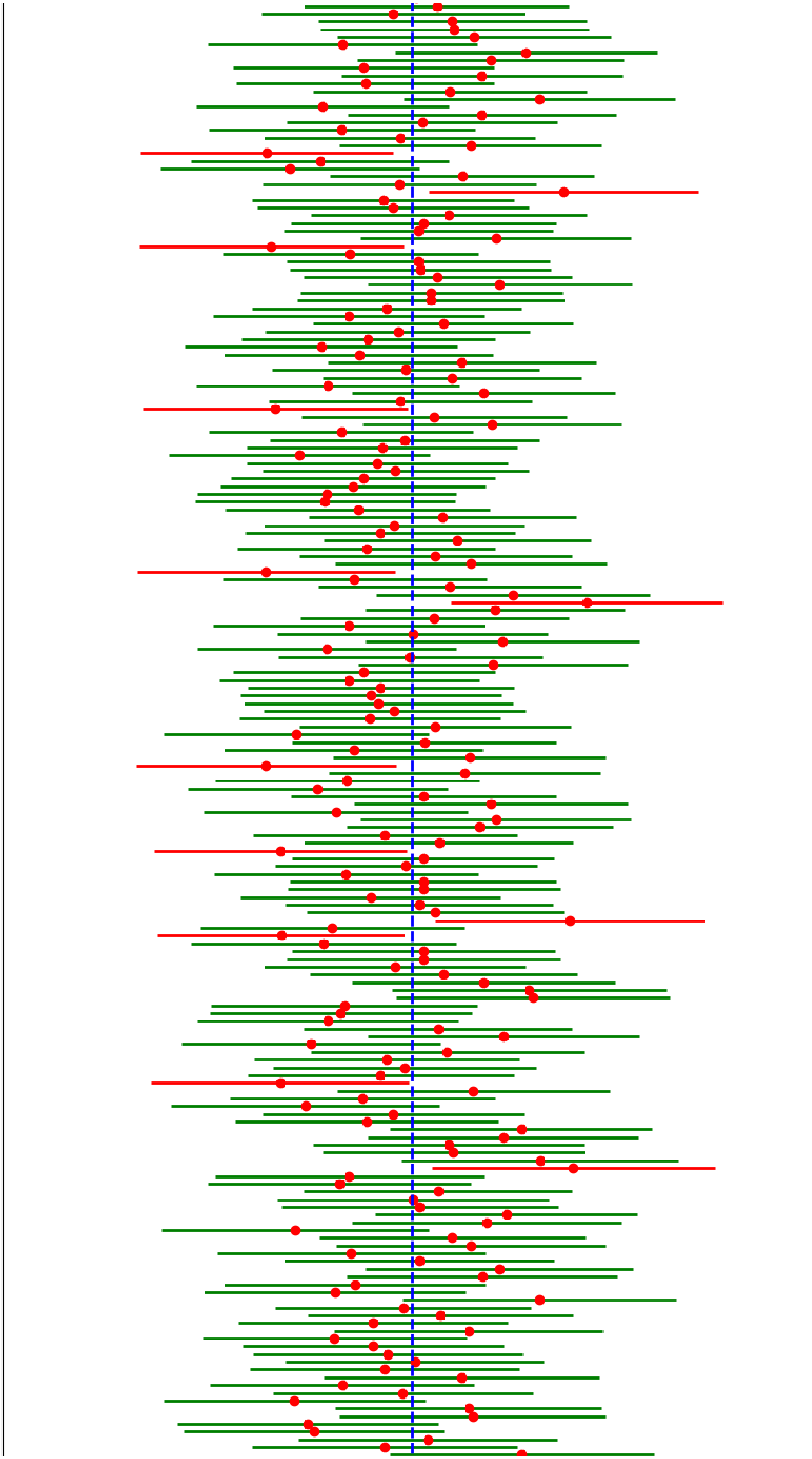
```
male_sample_means = plotSampleMeanDistributionAndConfidenceIntervals(males.Purchase, 1000, PopMeanMales, confidence=0.95, text=
```

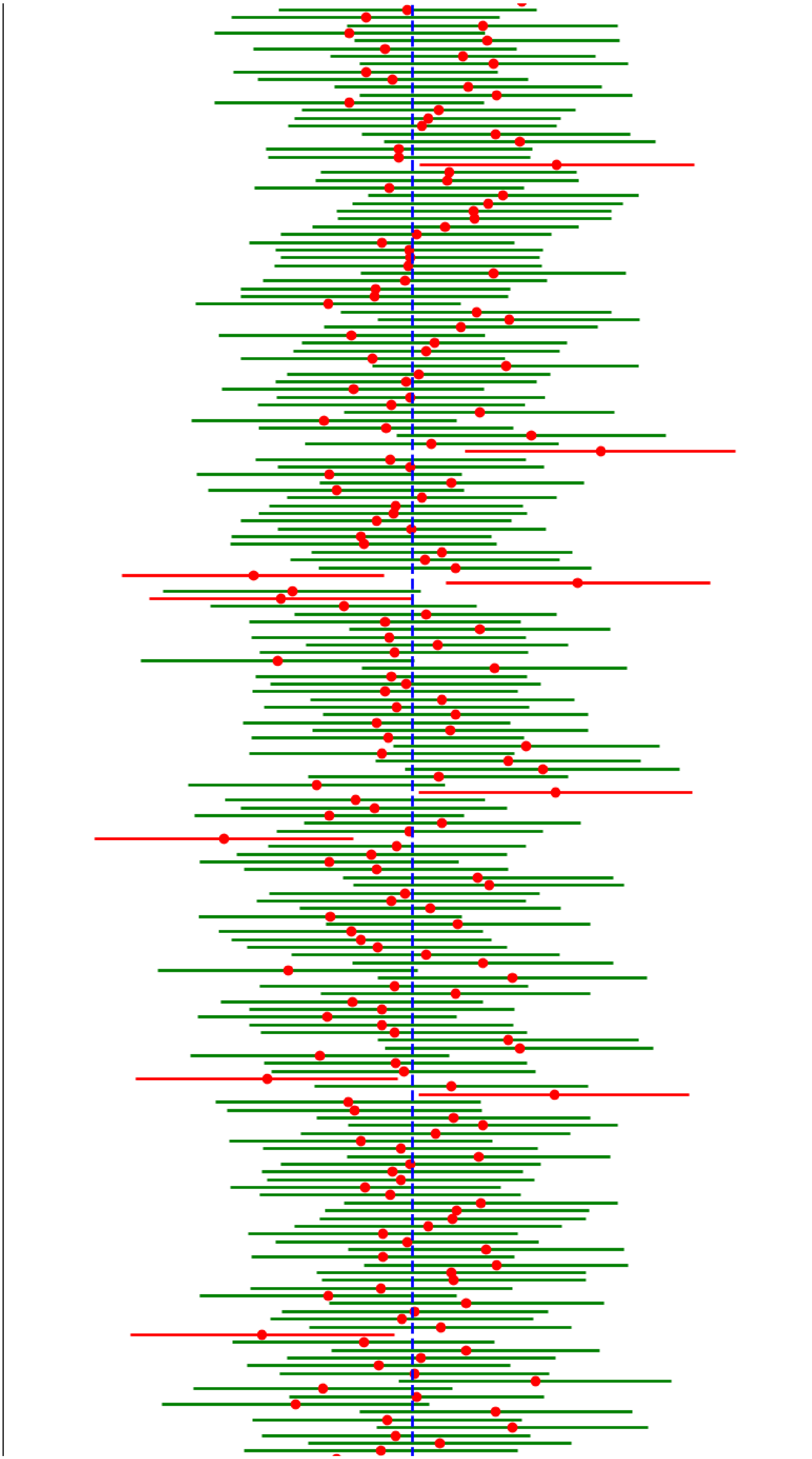

Distribution of Sample means of Purchase amounts for Male Customers
Frequency
Purchase
0
20
40
60
80
100
8800
9000
9200
9400
9600
9800
10000

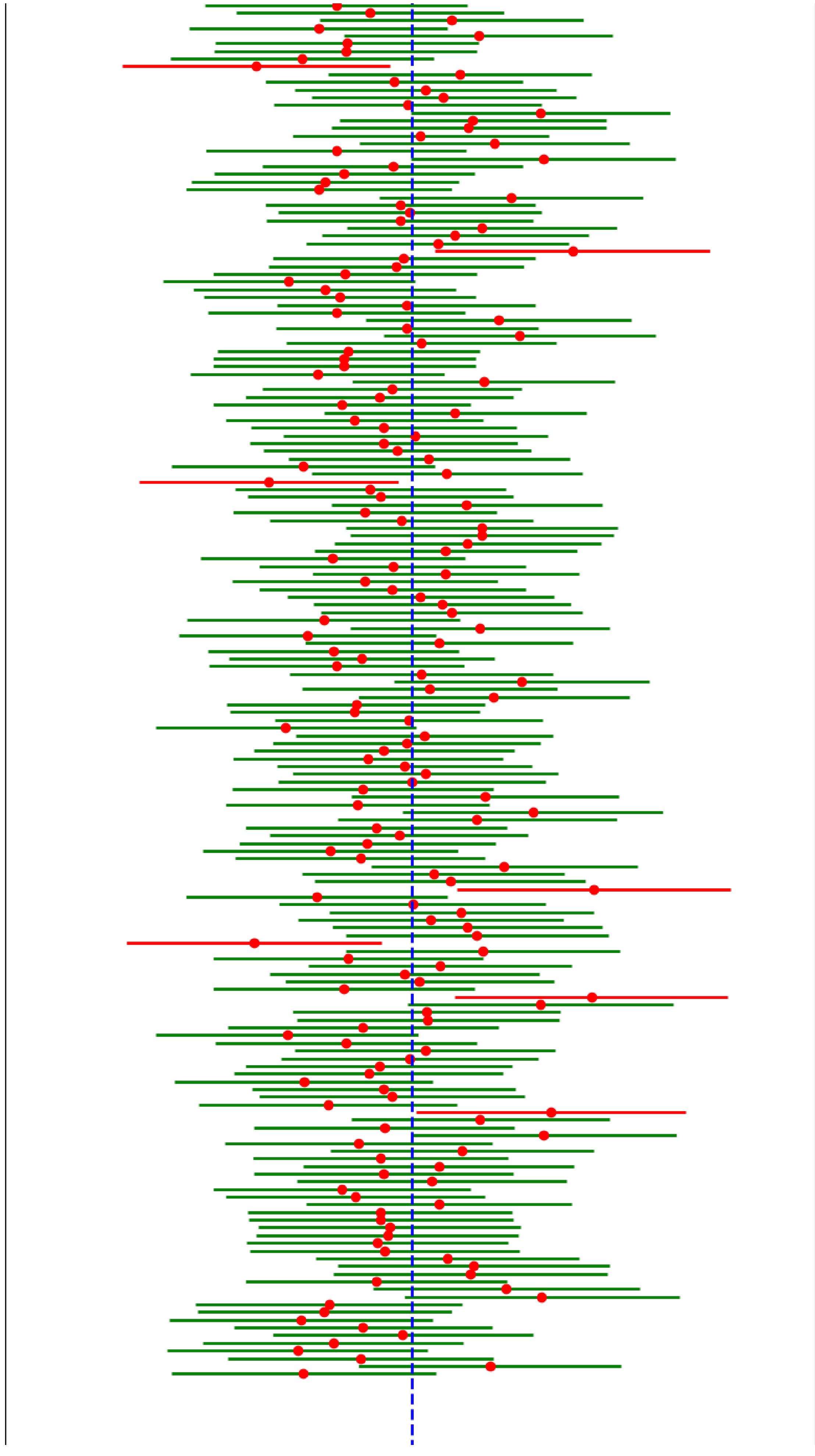

Population Mean 9437.53 and 1000 95% Confidence Interval for Male Customers
59(5.9) Intervals that missed the population mean
941(94.1) Intervals that include the population mean
Mean of the sample
Population mean = 9437.53

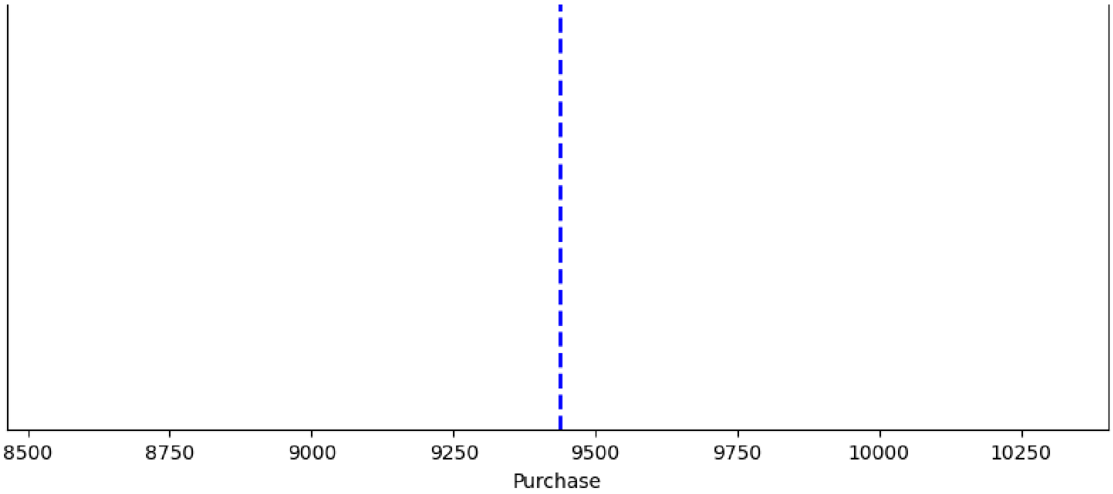




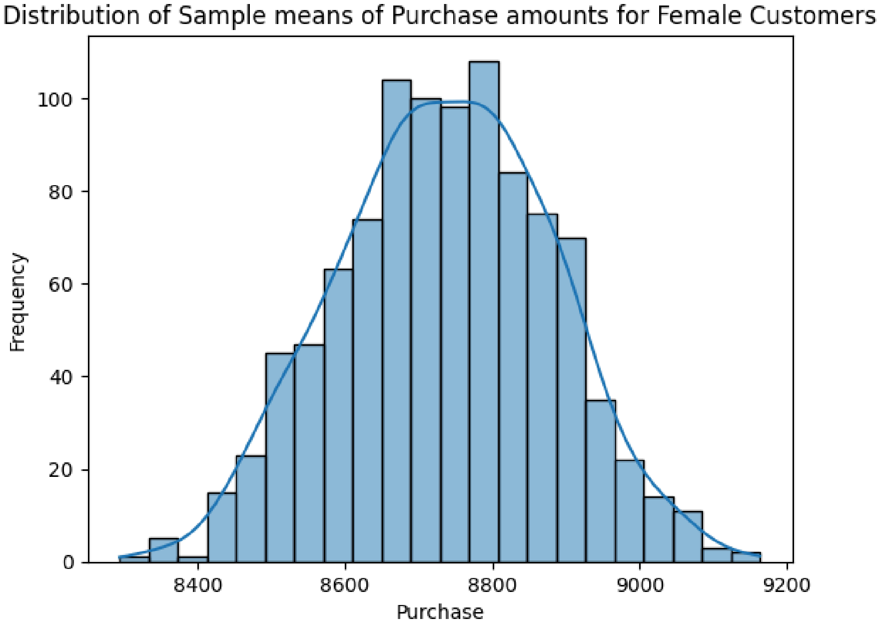




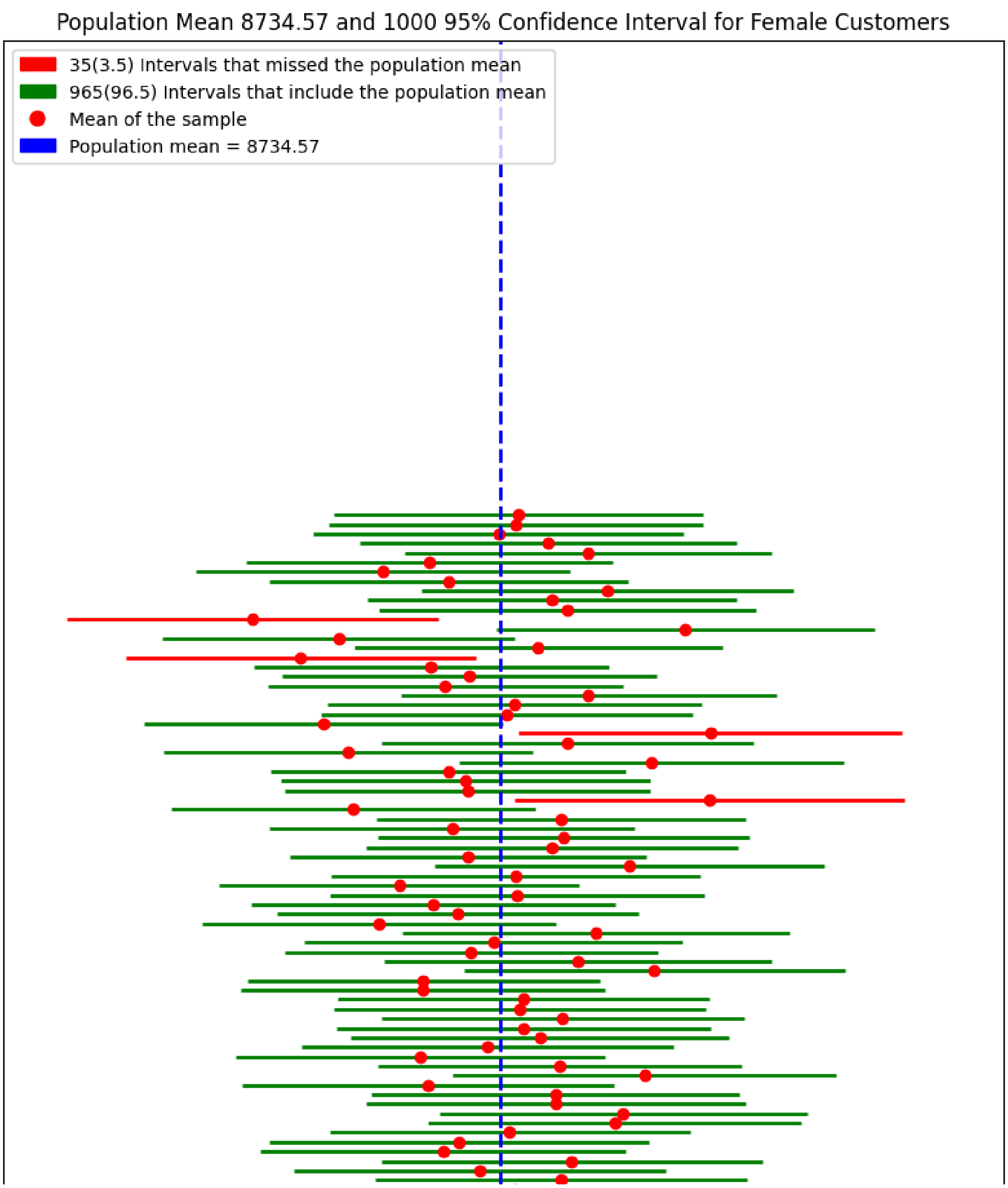



8500
8750
9000
9250
9500
9750
10000
10250
Purchase

```
female_sample_means = plotSampleMeanDistributionAndConfidenceIntervals(females.Purchase, 1000, PopMeanFemales, confidence=0.95,

```



Distribution of Sample means of Purchase amounts for Female Customers
Frequency
0
20
40
60
80
100
8400
8600
8800
9000
9200
Purchase



Population Mean 8734.57 and 1000 95% Confidence Interval for Female Customers
35(3.5) Intervals that missed the population mean
965(96.5) Intervals that include the population mean
Mean of the sample
Population mean = 8734.57