Importing the data

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

Loading the data

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

Basic analysis of data

```
df.shape
```

```
(550068, 10)
```

```
df.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
```

```
df.isnull()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_C
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
550063	False	False	False	False	False	False	
550064	False	False	False	False	False	False	
550065	False	False	False	False	False	False	
550066	False	False	False	False	False	False	
550067	False	False	False	False	False	False	

550068 rows × 10 columns

```
df.isnull().sum()
```

	0
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

For statistical analysis

```
df.describe()
```

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

```
df.describe(include="object")
```

	Product_ID	Gender	Age	City_Category	Stay_In_Current_City_Years
count	550068	550068	550068	550068	550068
unique	3631	2	7	3	5
top	P00265242	M	26-35	B	1
freq	1880	414259	219587	231173	193821

exploratory data analysis. (EDA)

```
df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current
0	1000001	P00069042	F	0-17	10	A	
1	1000001	P00248942	F	0-17	10	A	
2	1000001	P00087842	F	0-17	10	A	

```
df.duplicated()
```

	0
0	False
1	False
2	False
3	False
4	False
...	...
550063	False
550064	False
550065	False
550066	False
550067	False

550068 rows × 1 columns

dtype: bool

```
df[df.duplicated()]
```

User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_

```
df["Gender"].value_counts()
```

Gender	count
M	414259
F	135809

dtype: int64

```
df["Gender"].value_counts(normalize=True)
```

Gender	proportion
M	0.753105
F	0.246895

dtype: float64

Double-click (or enter) to edit

```
df["Purchase"].describe()
```

	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

dtype: float64

```
df["Age"].value_counts()
```

Age	count
26-35	219587
36-45	110013
18-25	99660
46-50	45701
51-55	38501
55+	21504
0-17	15102

dtype: int64

```
df.groupby(by = "Gender")["User_ID"].nunique()
```

Gender	User_ID
F	1666
M	4225

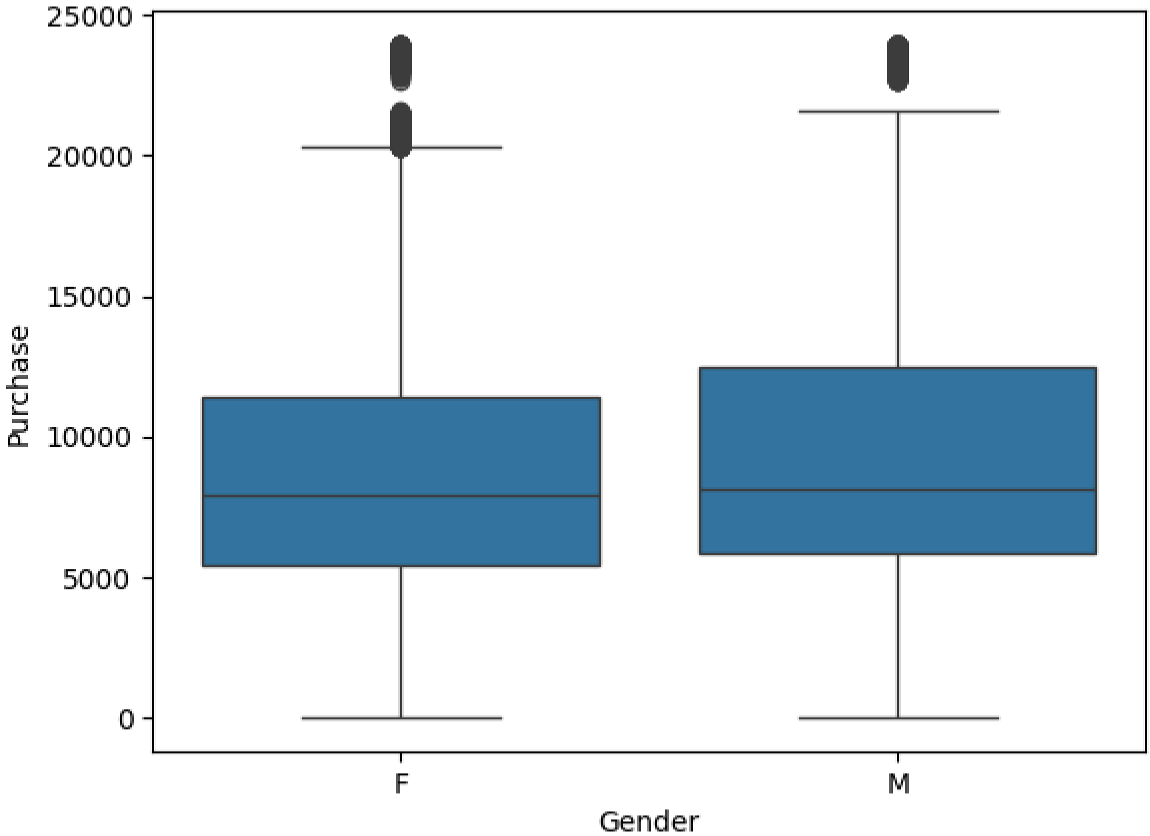
dtype: int64

```
df.groupby(by = "Gender")["Purchase"].describe().T
```

Gender	F	M
count	135809.000000	414259.00000
mean	8734.565765	9437.52604
std	4767.233289	5092.18621
min	12.000000	12.00000
25%	5433.000000	5863.00000
50%	7914.000000	8098.00000
75%	11400.000000	12454.00000
max	23959.000000	23961.00000

```
sns.boxplot(x = "Gender" , y= "Purchase" , data = df)
```

<Axes: xlabel='Gender', ylabel='Purchase'>



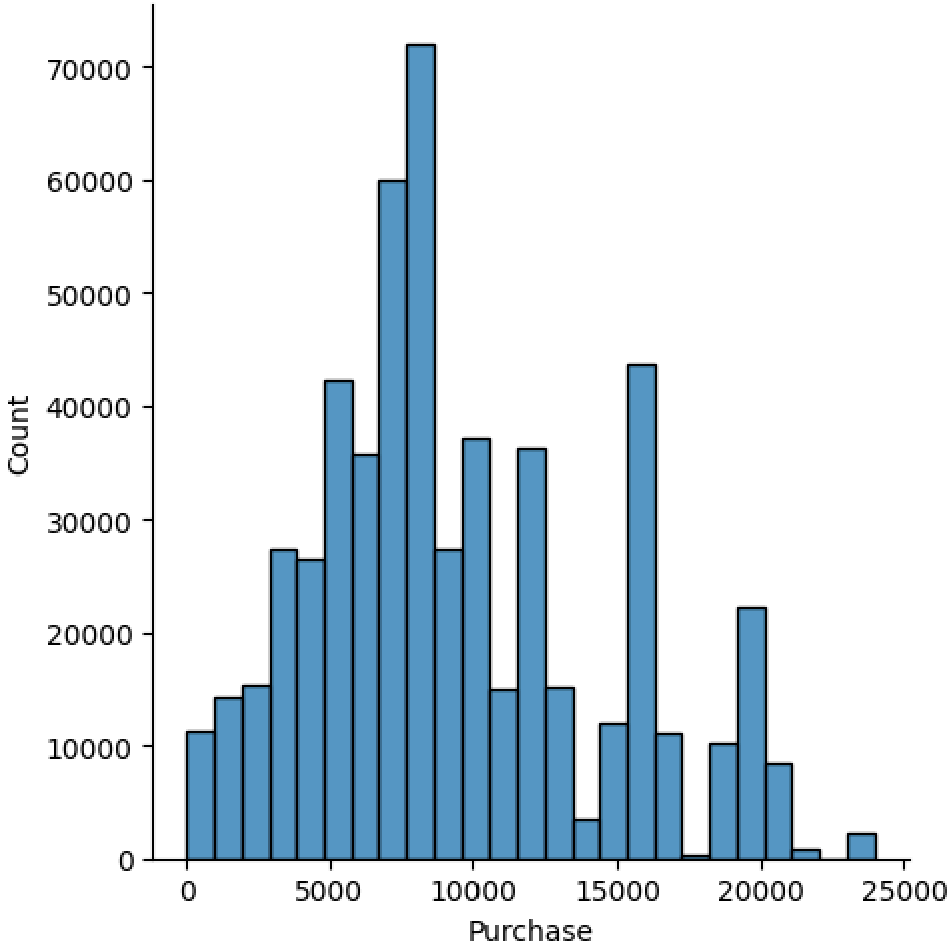
The boxplot illustrated.

- The purchases of both the genders.

- More outlier in female.
- Median is almost same.
- Male spread is slightly more than femail.

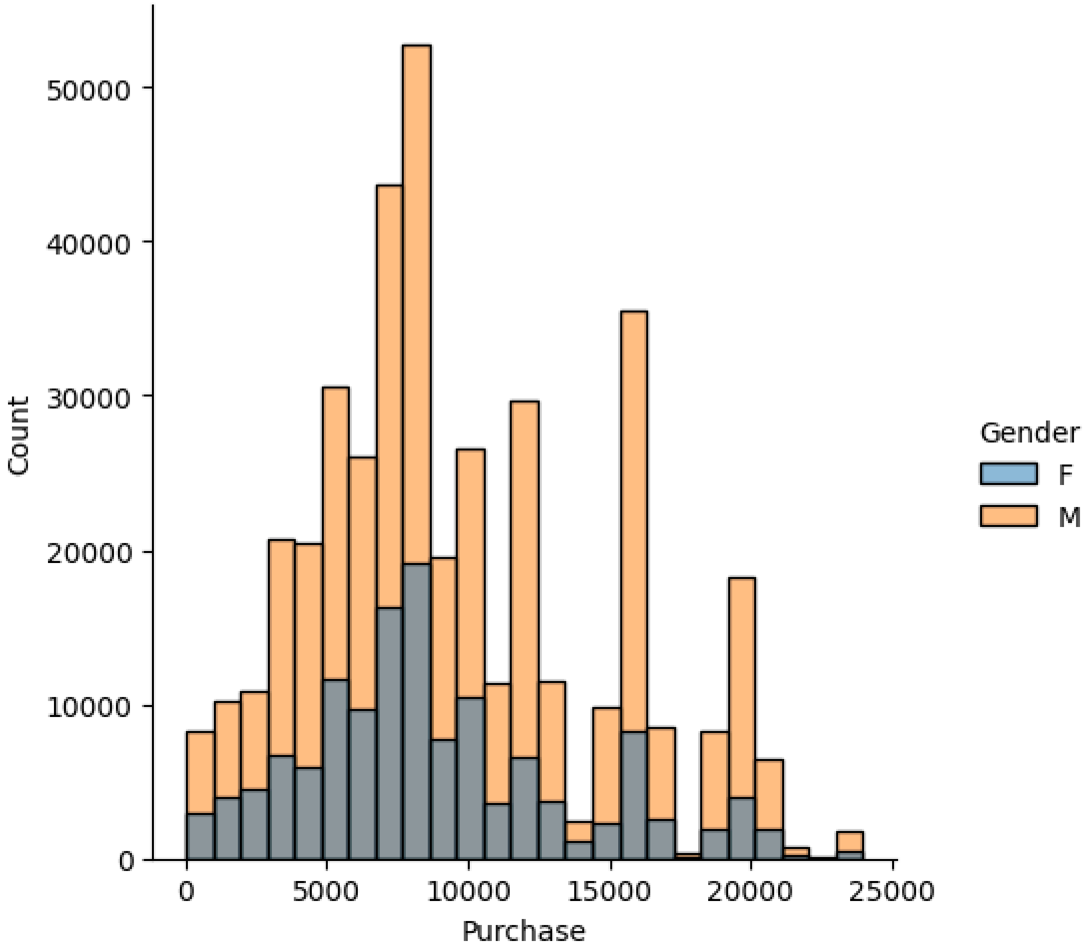
```
sns.displot(df, x="Purchase", bins=25)
```

<seaborn.axisgrid.FacetGrid at 0x7fced1925510>




```
sns.displot(df, x="Purchase" , hue = "Gender" , bins=25)
```

<seaborn.axisgrid.FacetGrid at 0x7fcec517c3d0>




```
df.groupby("Gender")['Purchase'].describe()
```

Gender	count	mean	std	min	25%	50%	75%	max
F	135809.0	8734.565765	4767.233289	12.0	5433.0	7914.0	11400.0	23959.0
M	414259.0	9437.526040	5092.186210	12.0	5863.0	8098.0	12454.0	23961.0

```
df.sample(300).groupby("Gender")['Purchase'].describe()
```

Gender	count	mean	std	min	25%	50%	75%	max
F	73.0	8409.931507	4574.871526	237.0	5270.0	8010.0	10009.0	19547.0
M	227.0	9093.171806	4905.738674	14.0	5358.0	8035.0	11830.5	23508.0

```
df.sample(300).groupby("Gender")['Purchase'].describe()
```

Gender	count	mean	std	min	25%	50%	75%	max
F	82.0	8805.878049	4334.845808	1485.0	6031.0	8173.5	9950.25	20300.0
M	218.0	9608.605505	5189.321947	50.0	5942.0	7991.0	12658.75	23928.0

```
sample_size = 300
n = 1500
```

```
male_sample_means = [df[df["Gender"] == "M"]["Purchase"].sample(sample_size).mean
```

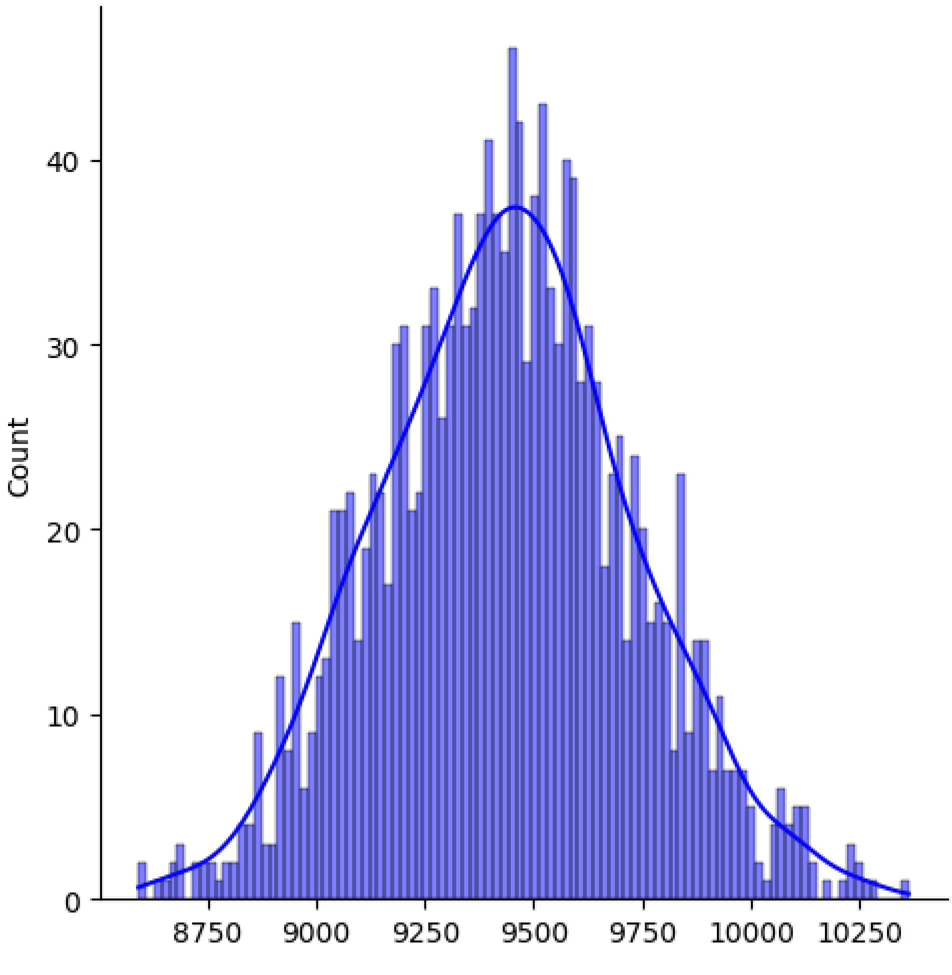
```
female_sample_means = [df[df["Gender"] == "F"]["Purchase"].sample(sample_size).me
```

```
np.mean(male_sample_means) , np.mean(female_sample_means)
```

```
(np.float64(9437.052102222222), np.float64(8736.558242222221))
```

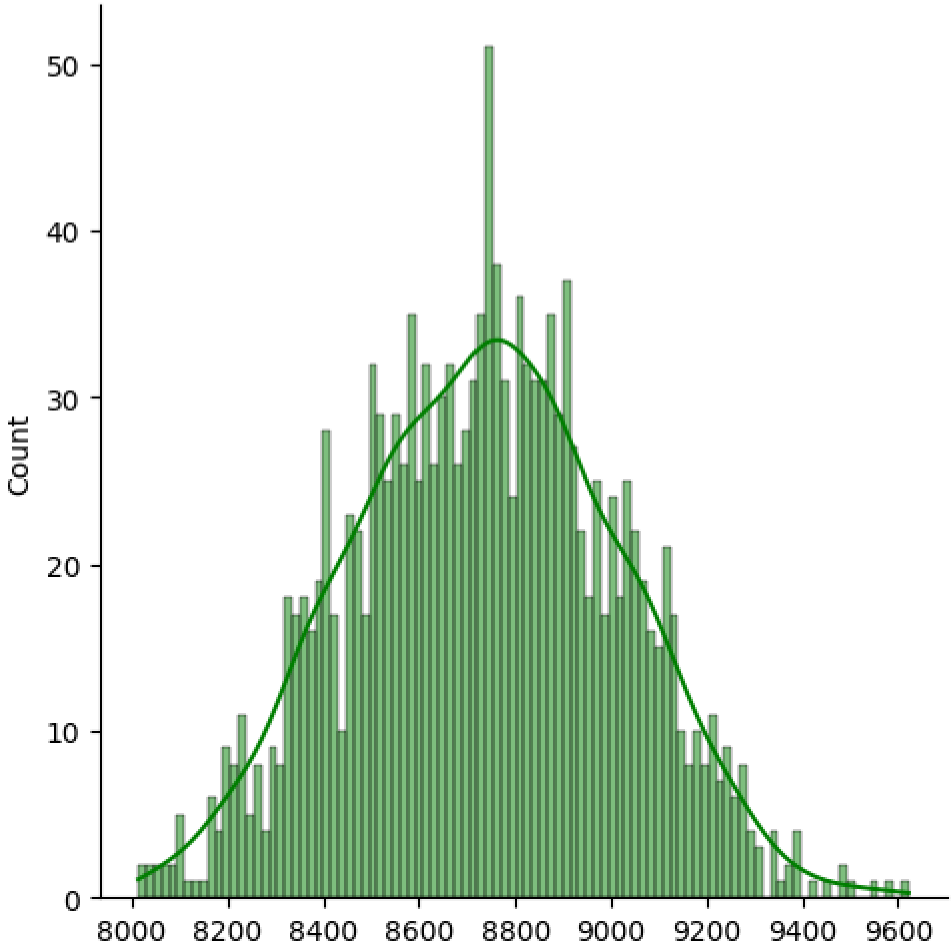
```
sns.displot(male_sample_means, kde=True, bins=100, color='blue')
```

```
<seaborn.axisgrid.FacetGrid at 0x7fcec4ef1250>
```




```
sns.displot(female_sample_means, kde=True, bins=100, color='green')
```

<seaborn.axisgrid.FacetGrid at 0x7fcec2993690>




```
#95% CI
z = 1.96

lower_limit_male = np.mean(male_sample_means) - z * np.std(male_sample_means) / n
upper_limit_male = np.mean(male_sample_means) + z * np.std(male_sample_means) / n
```

```
lower_limit_male , upper_limit_male
```

(np.float64(9422.406557444936), np.float64(9451.697646999508))

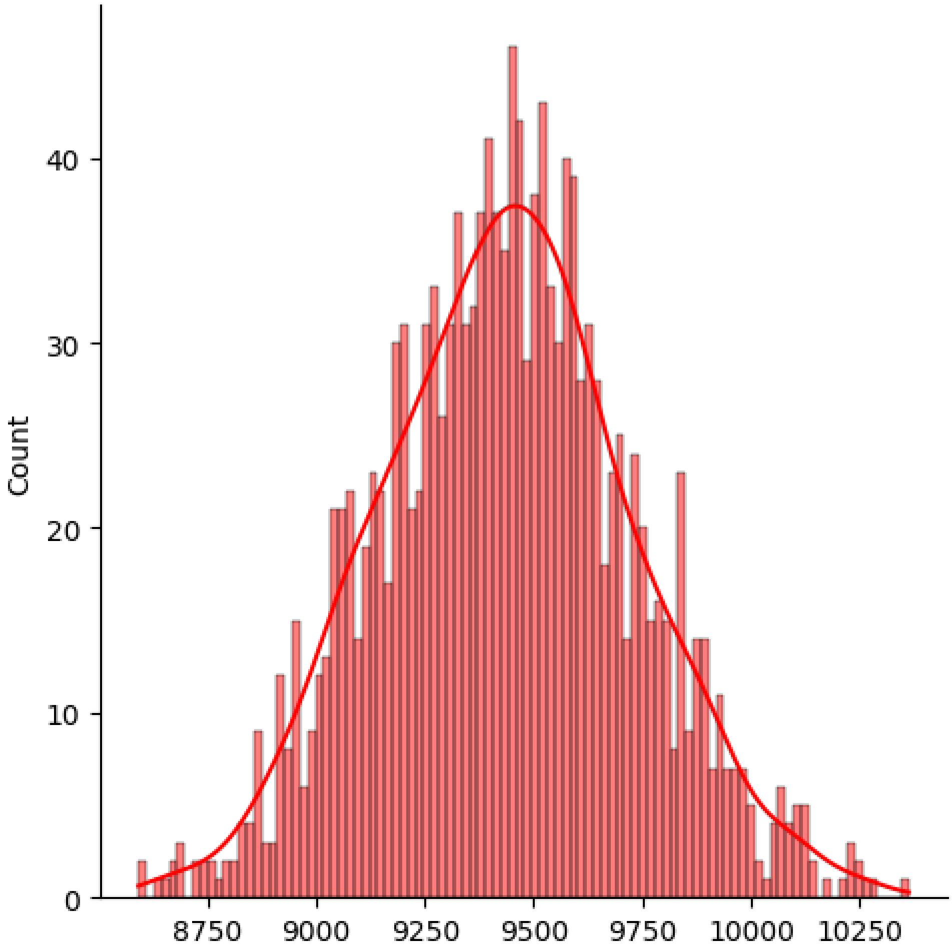
```
lower_limit_female = np.mean(female_sample_means) - z * np.std(female_sample_mean
upper_limit_female = np.mean(female_sample_means) + z * np.std(female_sample_mean
```

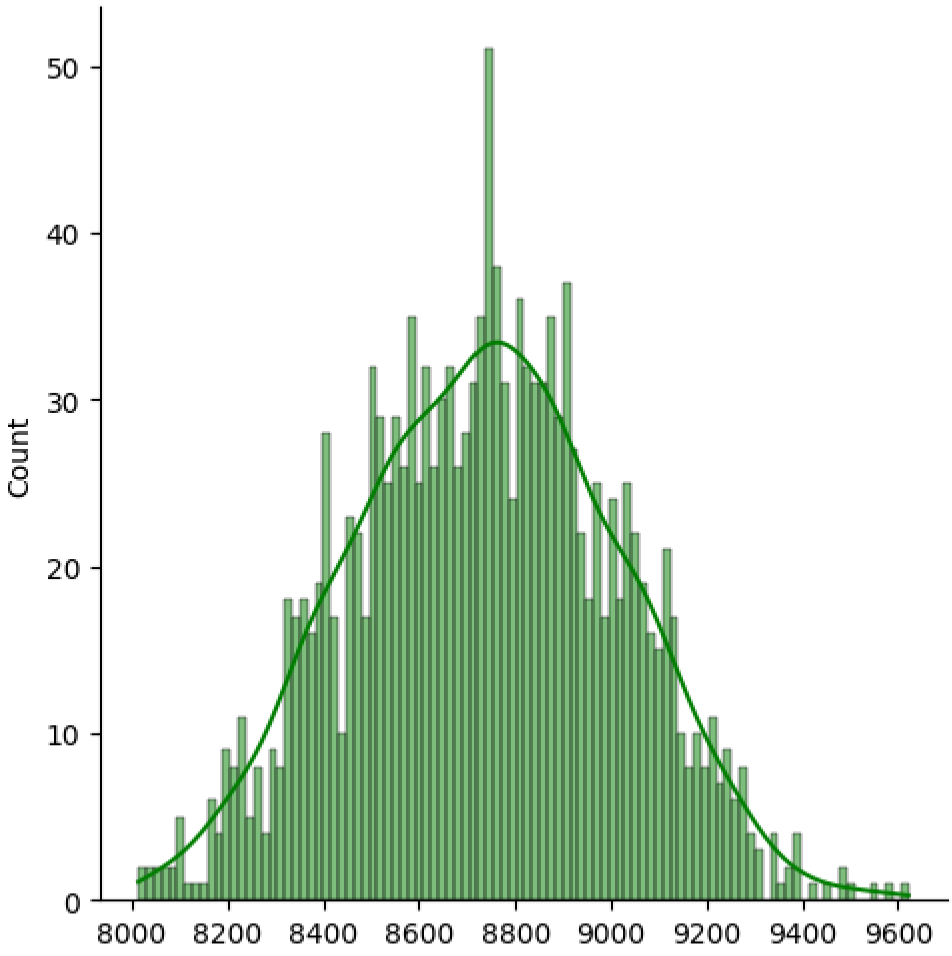
```
lower_limit_female , upper_limit_female
```

(np.float64(8722.649901325763), np.float64(8750.46658311868))

```
sns.displot(male_sample_means, kde=True, bins=100, color='r')
sns.displot(female_sample_means, kde=True, bins=100, color='g')
```

```
<seaborn.axisgrid.FacetGrid at 0x7fcec272e550>
```





The overlaping is creating difficulty to understand if there is any pattern or trend for each gender.

1. This column has no Eliminatory factor. Need to try other columns.
2. Increase the sample size to check if there is any better result.

Question 5 - confidence intervals of average male and female spends are overlapping or not overlapping. How can Walmart leverage this conclusion to make changes or improvements?

Solution -- Confidence Interval Analysis Male Customers' 95% Confidence Interval: [9422.4, 9451.6]

Female Customers' 95% Confidence Interval: [8722.6, 8750.4]

No, the confidence intervals do not overlap.

The upper bound for females (8750.4) is less than the lower bound for males (9422.4).

This means that, with 95% confidence, we can conclude that male customers spend more on average than female customers.

The fact that the confidence intervals do not overlap indicates a statistically significant difference in the average spending between genders. This is not due to random chance — there is real evidence that males spend more than females.

According to my observatuion Walmart can

*Increase average transaction values.

*Enhance customer satisfaction with personalized experiences.

*Improve inventory planning and sales conversion.

Question -7 Give recommendations and action items to Walmart.

Recommendations & Action Items for Walmart

Leverage Higher Spending Among Male Customers:

targete on products popular with men (electronics, tools, sports gear).

Implement upselling and cross-selling strategies focused on male shopping habits.

come-up with exciting offers with increase and repeat the purchases for male customers.

Boost Female Customer Spending:

Conduct surveys or focus groups to understand female spending drivers and barriers.

Give more recommendations and discounts tailored for women.

Expand and optimize product assortment to better meet female customers’ preferences.

Optimize Inventory and Merchandising:

Adjust stock levels based on higher demand from male customers in key categories.

Use data to refine product placement and promotional displays for different genders.

Enhance Customer Experience Through Personalization:

Implement product recommendations based on gender and purchase history.

Send targeted communications with gender-specific promotions and product updates.

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