Walmart Business Case - Confidence Interval and CLT

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.

Problem Statement:

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).

Column Profiling

- 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

Importing Libraries and Dataset

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import gdown
from scipy.stats import norm
!gdown 1lcjtmvtSjco6cnWaJvgJNTGjGJoKieh1
```

```
Downloading...
From: https://drive.google.com/uc?id=1lcjtmvtSjco6cnWaJvgJNTGjGJoKieh1
To: /content/walmart-data.csv
100% 23.0M/23.0M [00:00<00:00, 180MB/s]
```

```
# Loading the dataset -
data = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094')
data.sample(10)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	P
97760	1003169	P00274042	M	51-55	0	C	2	0	1	
378227	1004183	P00171742	M	26-35	1	B	4+	0	5	
244745	1001694	P00028842	M	26-35	12	B	3	1	6	
87270	1001451	P00109242	M	36-45	20	B	0	0	6	
320160	1001320	P00289242	M	26-35	4	A	2	0	1	
357959	1001150	P00051542	F	26-35	20	A	1	0	8	

```
data.shape
```

```
(550068, 10)
```

```
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
```

```
data.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

```
data.isnull().sum().sum()
```

```
0
```

Unique Attributes and Value Counts

```
data.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purcha
0	1000001	P00069042	F	0-17	10	A	2	0	3	83
1	1000001	P00248942	F	0-17	10	A	2	0	1	152
2	1000001	P00087842	F	0-17	10	A	2	0	12	14

```
data['User_ID'].value_counts()
```

User_ID	count
1001680	1026
1004277	979
1001941	898
1001181	862
1000889	823
...	...
1002690	7
1002111	7
1005810	7
1004991	7
1000708	6

5891 rows × 1 columns

dtype: int64

```
data['User_ID'].nunique()
```

```
5891
```

```
data['Product_ID'].value_counts()
```

Product_ID	count
P00265242	1880
P00025442	1615
P00110742	1612
P00112142	1562
P00057642	1470
...	...
P00314842	1
P00298842	1
P00231642	1
P00204442	1
P00066342	1

3631 rows × 1 columns

dtype: int64

```
data['Product_ID'].nunique()
```

```
3631
```

Visualizing the data

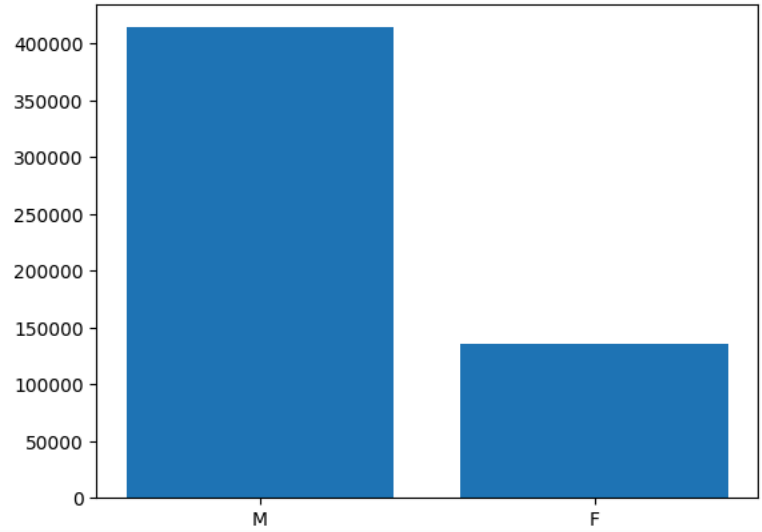
```
gender=data['Gender'].value_counts()
gender
```

Gender	count
M	414259
F	135809

dtype: int64

```
x_bar=gender.index
y_bar=gender
plt.bar(x_bar,y_bar)
```

```
<BarContainer object of 2 artists>
```

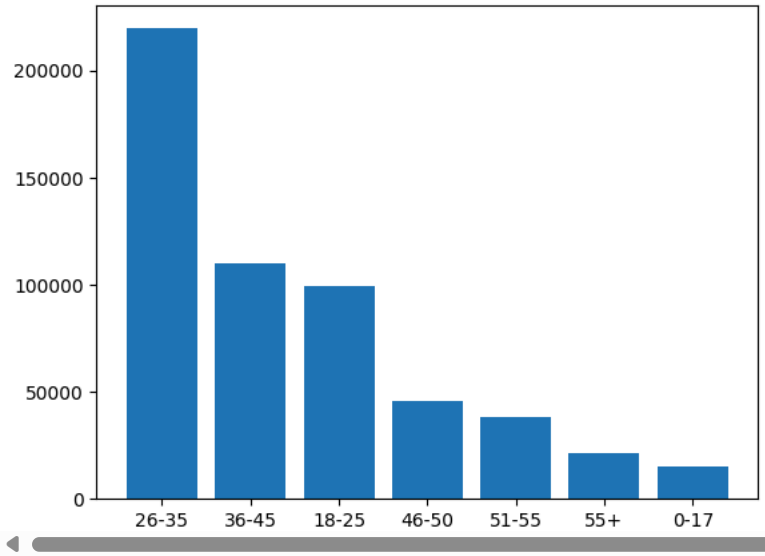


On the whole from the given data, 75% are males and rest are females.

```
age=data['Age'].value_counts()
```

```
x_bar=age.index
y_bar=age
plt.bar(x_bar,y_bar)
```

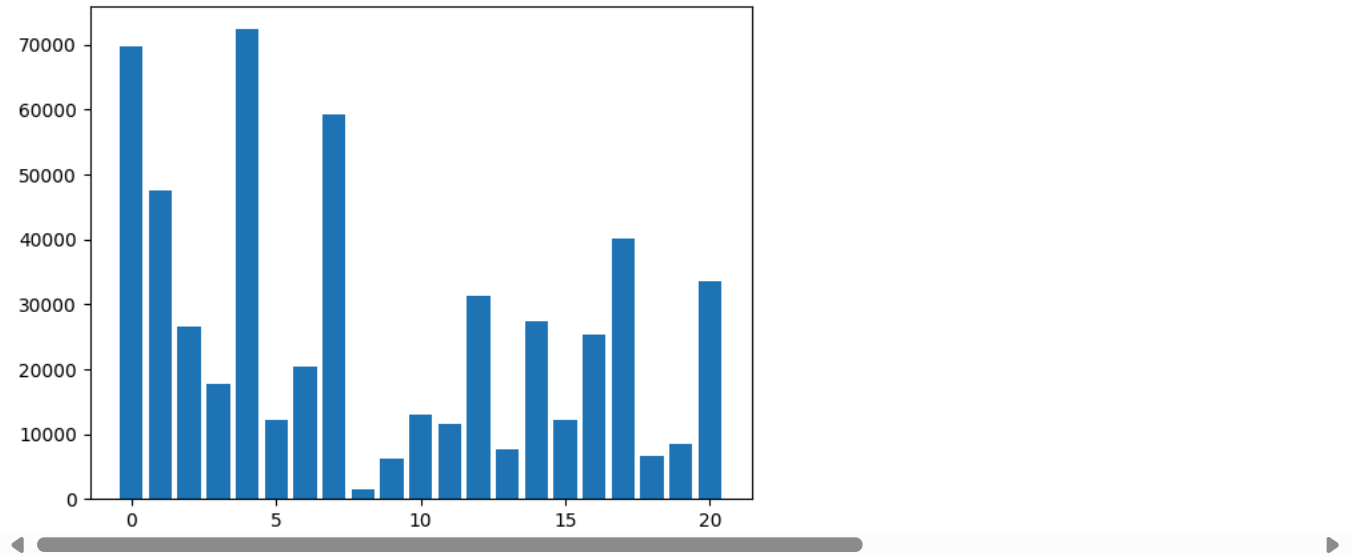
```
<BarContainer object of 7 artists>
```



Most of the Walmart customers are from the age range between 26 and 35.

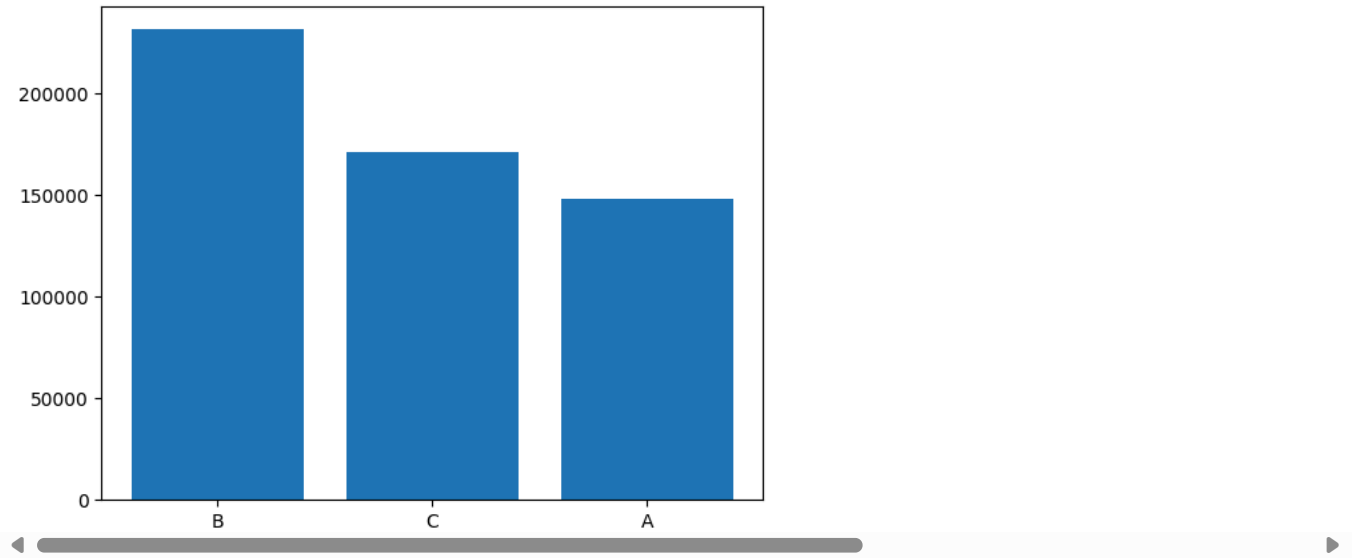
```
occ=data['Occupation'].value_counts()
x_bar=occ.index
y_bar=occ
plt.bar(x_bar,y_bar)
```

```
<BarContainer object of 21 artists>
```




```
city_cat=data['City_Category'].value_counts()
x_bar=city_cat.index
y_bar=city_cat
plt.bar(x_bar,y_bar)
```

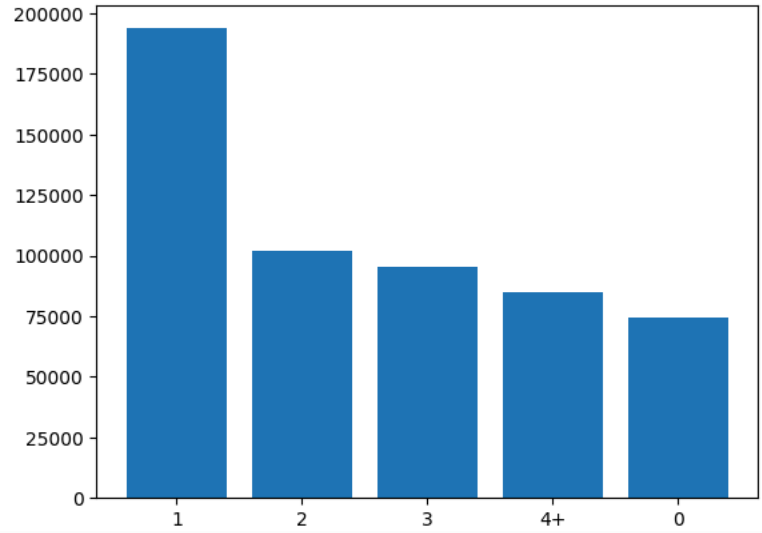
```
<BarContainer object of 3 artists>
```



The Customers from B category cities are more followed C and A.

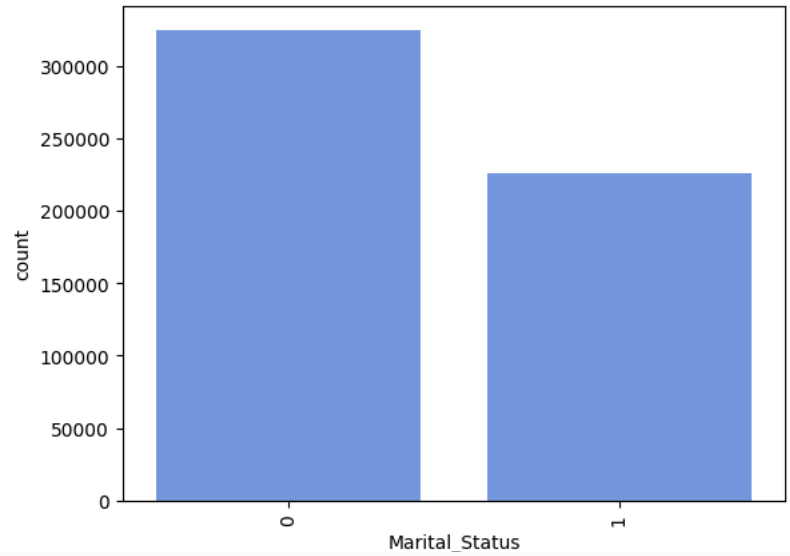
```
city_stay=data['Stay_In_Current_City_Years'].value_counts()
x_bar=city_stay.index
y_bar=city_stay
plt.bar(x_bar,y_bar)
```

```
<BarContainer object of 5 artists>
```



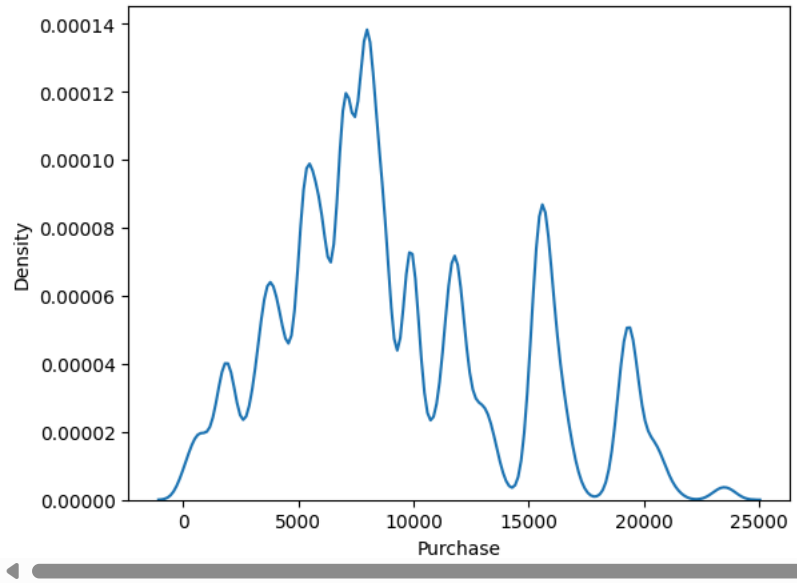

```
sns.countplot(x='Marital_Status', data=data, color='cornflowerblue')
plt.xticks(rotation=90)
```

```
([0, 1], [Text(0, 0, '0'), Text(1, 0, '1')])
```




```
sns.kdeplot(data['Purchase'])
```

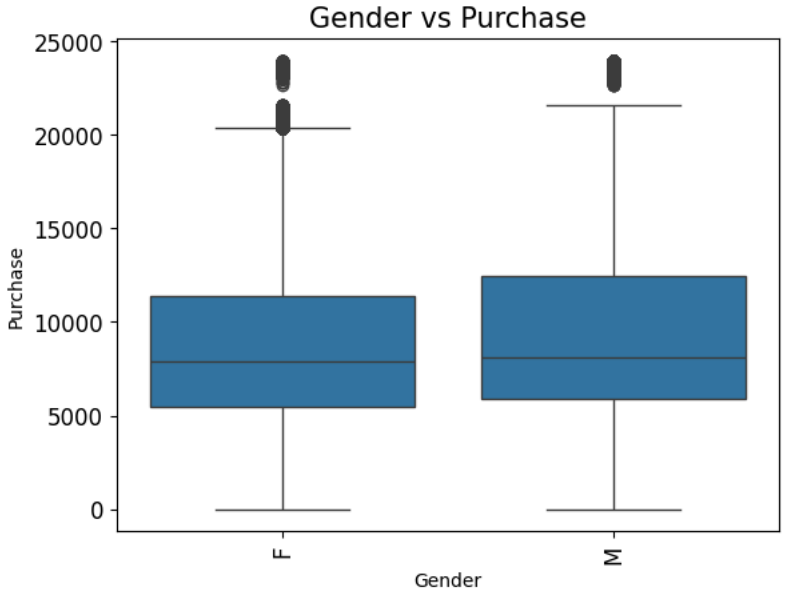
```
<Axes: xlabel='Purchase', ylabel='Density'>
```

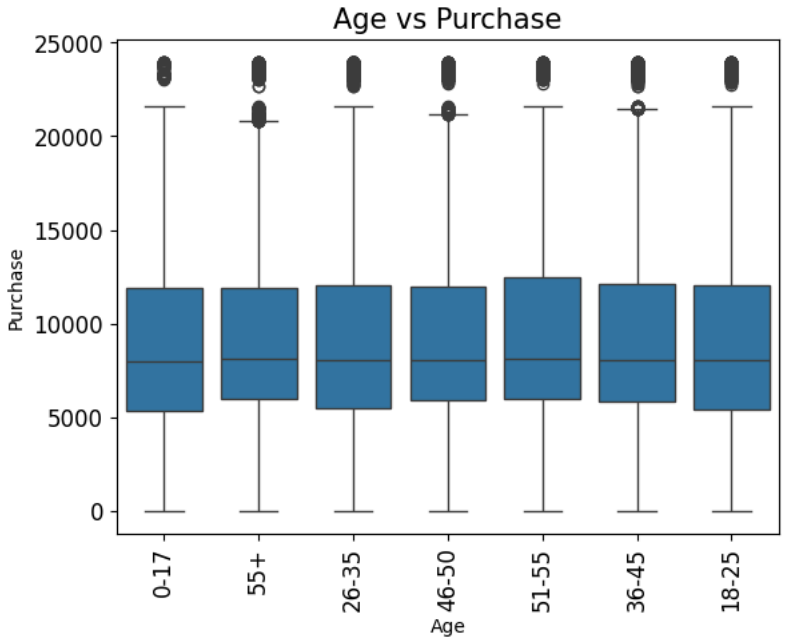


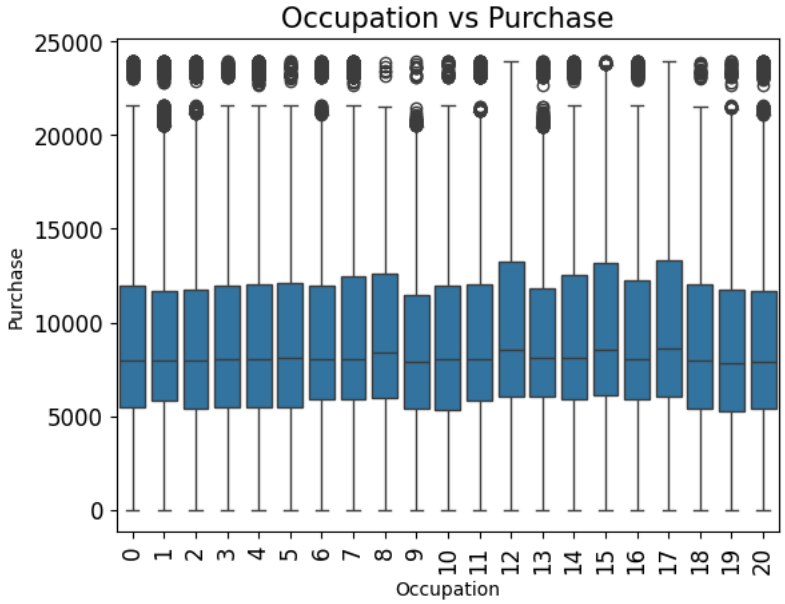
Bivariate Analysis

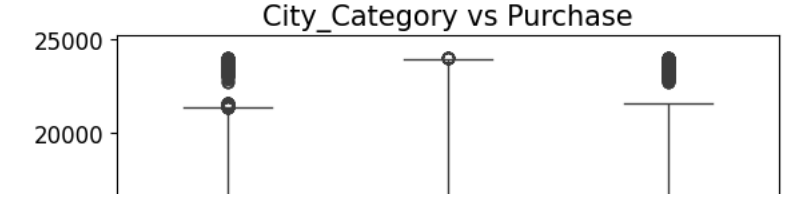
```
col = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status']

for i in col:
  sns.boxplot(x=i, y='Purchase', data=data)
  plt.xticks(rotation=90,fontsize=12)
  plt.yticks(fontsize=12)
  plt.title(f'{i} vs Purchase', fontsize=15)
  plt.show()
```

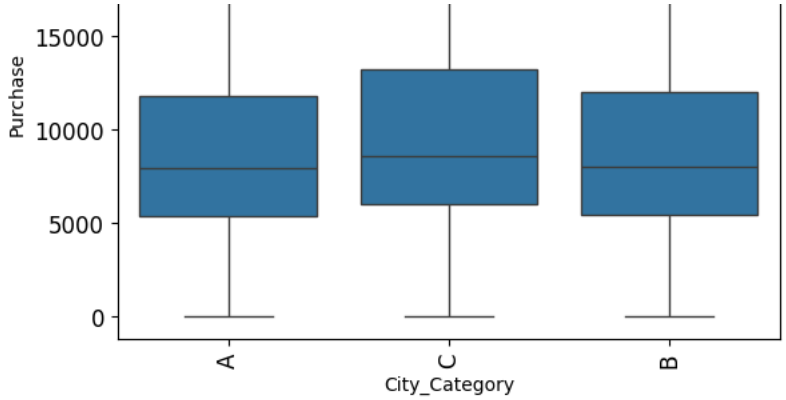
[4]

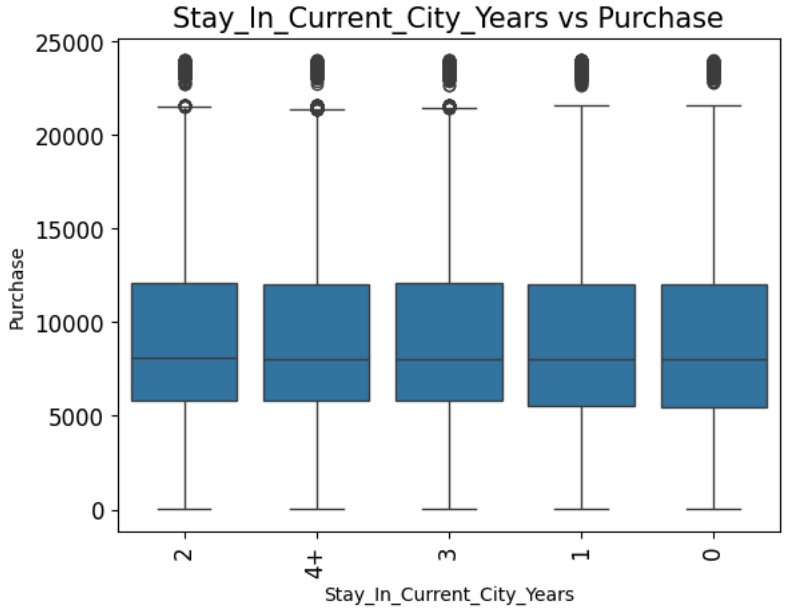

Gender vs Purchase
Purchase
Gender
F
M
0
5000
10000
15000
20000
25000

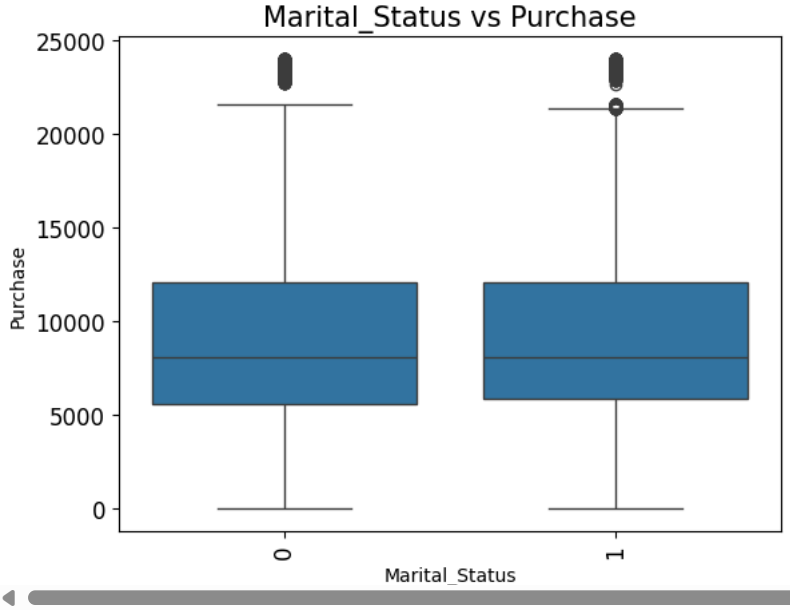

Age vs Purchase
Purchase
Age
0-17
55+
26-35
46-50
51-55
36-45
18-25
0
5000
10000
15000
20000
25000


Occupation vs Purchase
Purchase
Occupation
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
0
5000
10000
15000
20000
25000

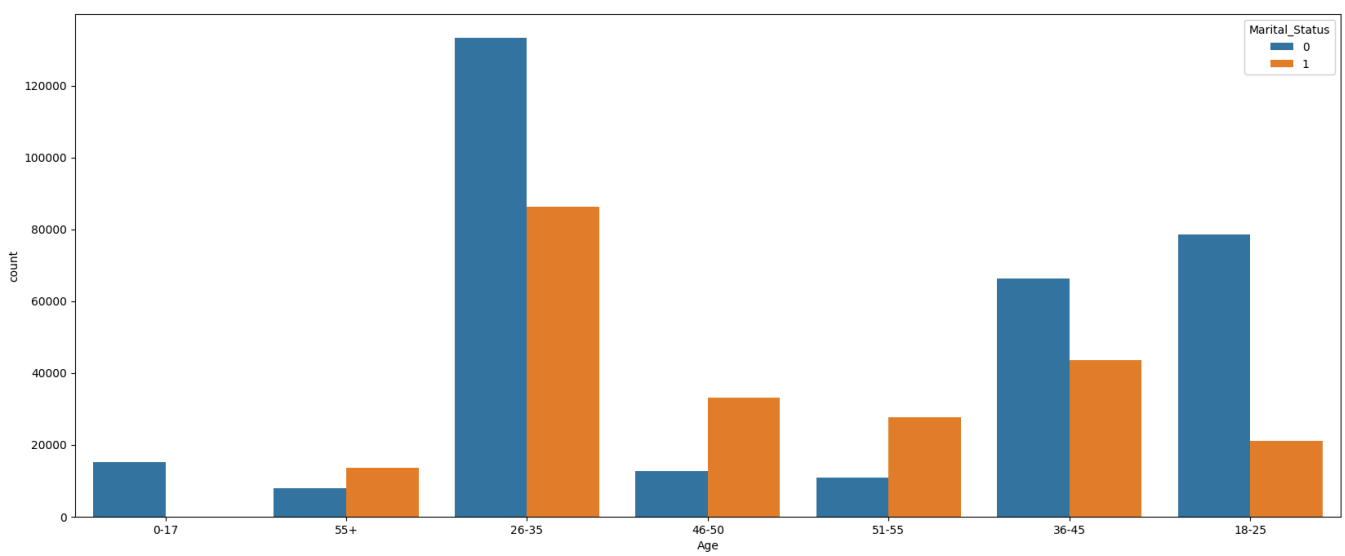

City_Category vs Purchase
20000
25000


15000
10000
5000
0
Purchase
A
C
B
City_Category

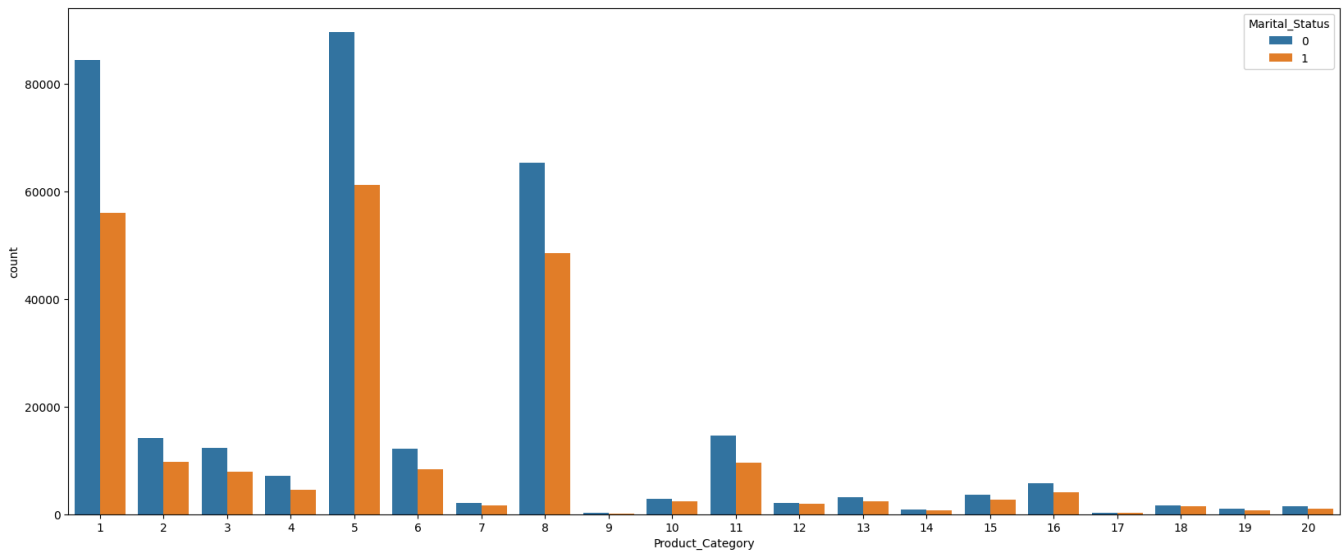

Stay_In_Current_City_Years vs Purchase
25000
20000
15000
10000
5000
0
Purchase
2
4+
3
1
0
Stay_In_Current_City_Years


Marital_Status vs Purchase
25000
20000
15000
10000
5000
0
Purchase
0
1
Marital_Status

```
plt.figure(figsize=(20, 8))
sns.countplot(data=data, x='Age',hue='Marital_Status')
plt.show()
```

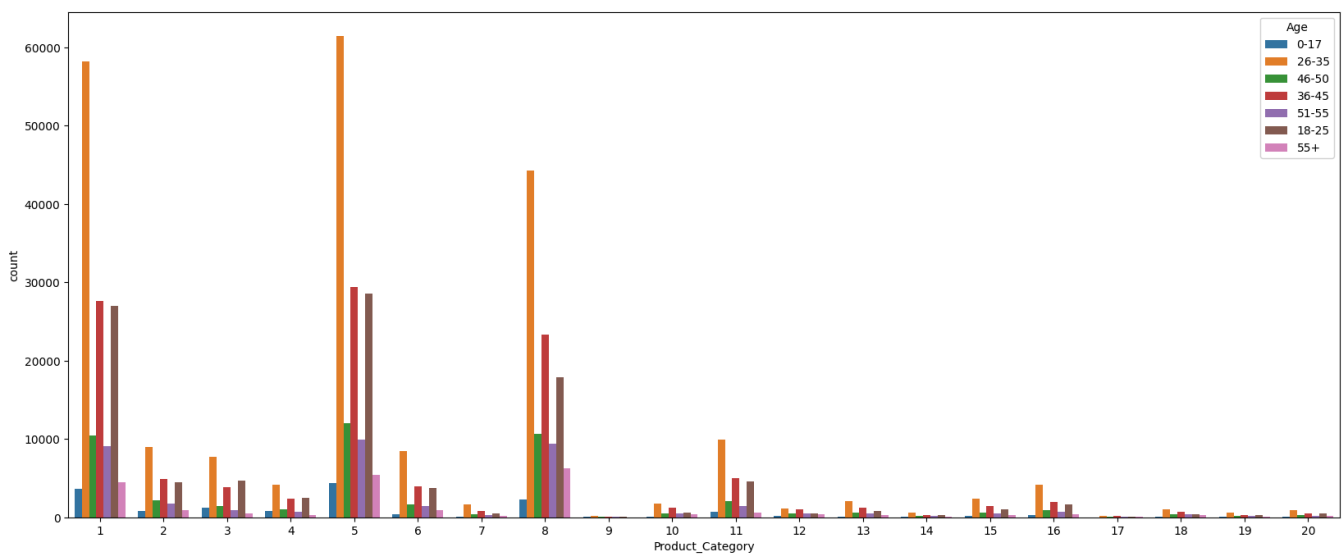



```
plt.figure(figsize=(20, 8))
sns.countplot(data=data, x='Product_Category',hue='Marital_Status')
plt.show()
```



Most of the purchases are done by males

```
plt.figure(figsize=(20, 8))
sns.countplot(data=data, x='Product_Category',hue='Age')
plt.show()
```



1, 5 and 8 were the most purchased product_category sold in Walmart.

```
data[col].melt().groupby(['variable', 'value'])['value'].count()*100/len(data)
```

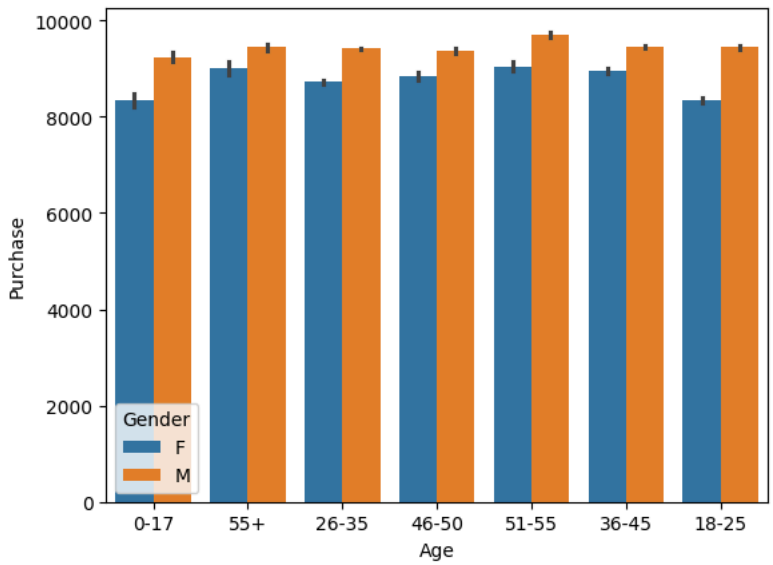
variable	value	value
Age	0-17	2.745479
	18-25	18.117760
	26-35	39.919974
	36-45	19.999891
	46-50	8.308246
	51-55	6.999316
	55+	3.909335
City_Category	A	26.854862
	B	42.026259
	C	31.118880
Gender	F	24.689493
	M	75.310507
Marital_Status	0	59.034701
	1	40.965299
Occupation	0	12.659889
	1	8.621843
	2	4.833584
	3	3.208694
	4	13.145284
	5	2.213726
	6	3.700452
	7	10.750125
	8	0.281056
	9	1.143677
	10	2.350618
	11	2.106285
	12	5.668208
	13	1.404917
	14	4.964659
	15	2.211545
	16	4.612339
	17	7.279645
	18	1.203851
	19	1.538173
	20	6.101427
Stay_In_Current_City_Years	0	13.525237
	1	35.235825
	2	18.513711
	3	17.322404
	4+	15.402823

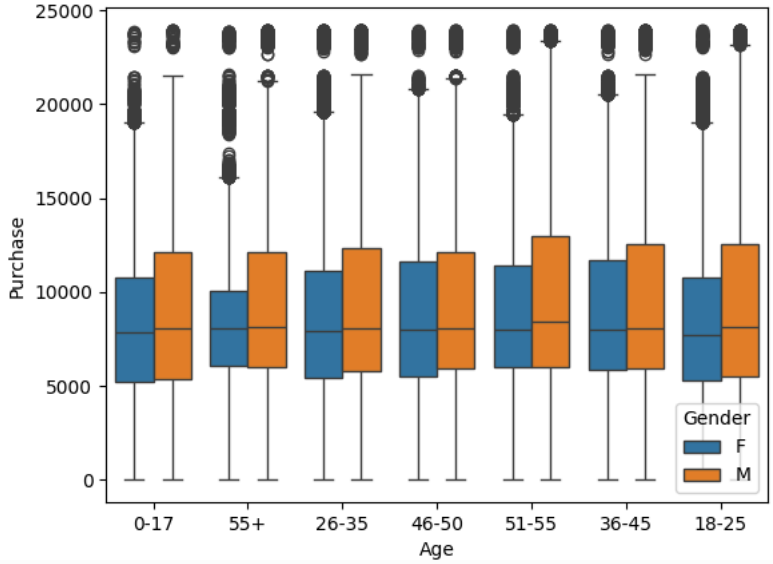
dtype: float64

Multi-variate Analysis

```
sns.barplot(data=data, x='Age', y='Purchase',hue="Gender")
plt.show()
```

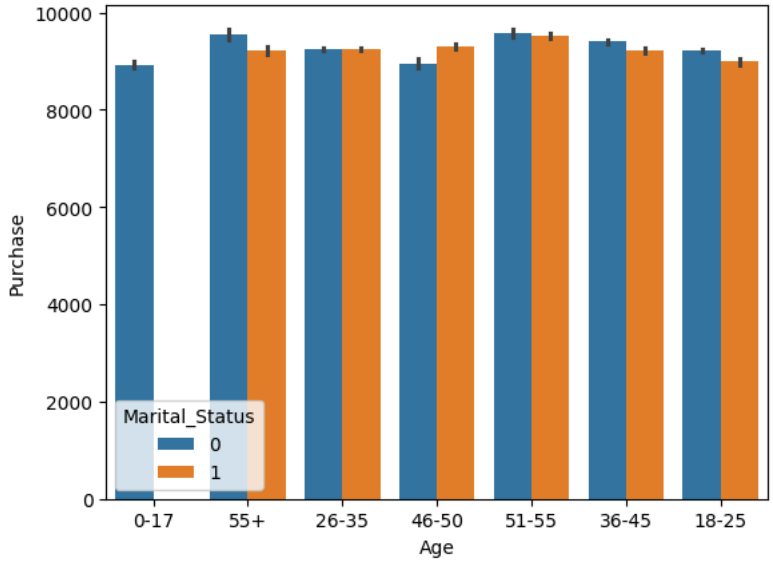
```
sns.boxplot(x='Age',y='Purchase',hue='Gender',data=data)
plt.show()
```

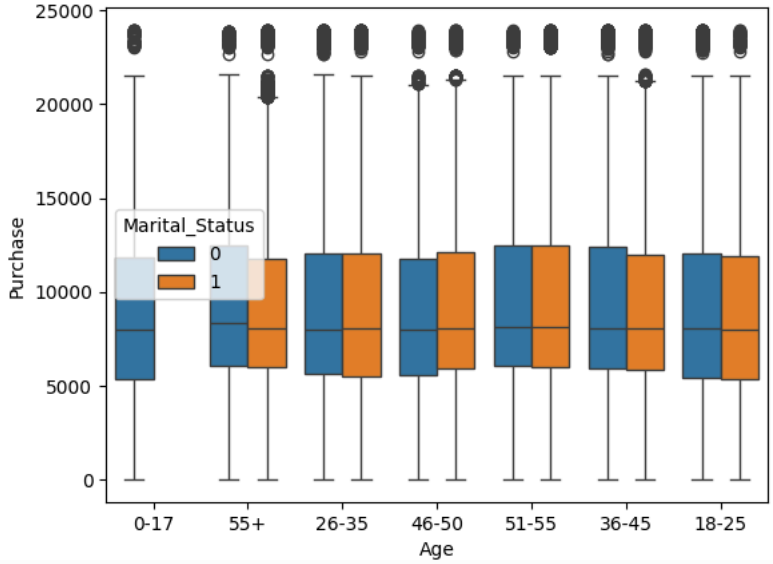





```
sns.barplot(data=data, x='Age', y='Purchase',hue="Marital_Status")
plt.show()
```

```
sns.boxplot(x='Age',y='Purchase',hue='Marital_Status',data=data)
plt.show()
```






```
data.describe(include='all').T
```

	count	unique	top	freq	mean	std	min	25%	50%	75%
User_ID	550068.0	NaN	NaN	NaN	1003028.842401	1727.591586	1000001.0	1001516.0	1003077.0	1004478.0
Product_ID	550068	3631	P00265242	1880	NaN	NaN	NaN	NaN	NaN	NaN
Gender	550068	2	M	414259	NaN	NaN	NaN	NaN	NaN	NaN
Age	550068	7	26-35	219587	NaN	NaN	NaN	NaN	NaN	NaN
Occupation	550068.0	NaN	NaN	NaN	8.076707	6.52266	0.0	2.0	7.0	14.0
City_Category	550068	3	B	231173	NaN	NaN	NaN	NaN	NaN	NaN
Stay_In_Current_City_Years	550068	5	1	193821	NaN	NaN	NaN	NaN	NaN	NaN
Marital_Status	550068.0	NaN	NaN	NaN	0.409653	0.49177	0.0	0.0	0.0	1.0
Product_Category	550068.0	NaN	NaN	NaN	5.40427	3.936211	1.0	1.0	5.0	8.0
Purchase	550068.0	NaN	NaN	NaN	9263.968713	5023.065394	12.0	5823.0	8047.0	12054.0

Distribution of Expenses based on Gender

```
data.groupby('Gender').describe()
```

	User_ID								Occupation		...	Product_Cate	
	count	mean	std	min	25%	50%	75%	max	count	mean	...	75%	max
Gender													
F	135809.0	1.003130e+06	1786.630589	1000001.0	1001569.0	1003159.0	1004765.0	1006039.0	135809.0	6.74054	...	8.0	
M	414259.0	1.002996e+06	1706.493873	1000002.0	1001505.0	1003041.0	1004411.0	1006040.0	414259.0	8.51475	...	8.0	

2 rows × 40 columns

```
data.groupby('Gender')['Purchase'].describe()
```

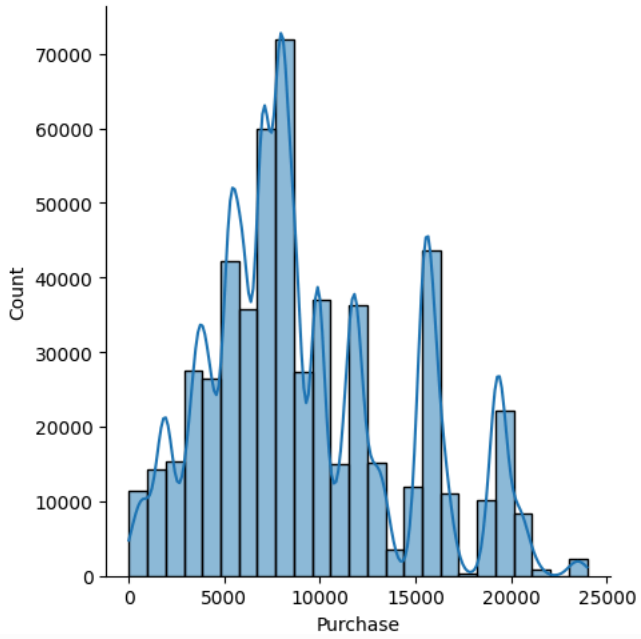
	count	mean	std	min	25%	50%	75%	max
Gender								
F	135809.0	8734.565765	4767.233289	12.0	5433.0	7914.0	11400.0	23959.0
M	414259.0	9437.526040	5092.186210	12.0	5863.0	8098.0	12454.0	23961.0

```
# Female Purchases
Female_data = data[data["Gender"]=="F"]
print("Female Purchase amount Mean:"+ str(Female_data["Purchase"].mean()))
print("Female Purchase amount SD:"+ str(Female_data["Purchase"].std()))

# Male Purchases
Male_data = data[data["Gender"]=="M"]
print("Male Purchase amount Mean:"+ str(Male_data["Purchase"].mean()))
print("Male Purchase amount SD:"+ str(Male_data["Purchase"].std()))
```

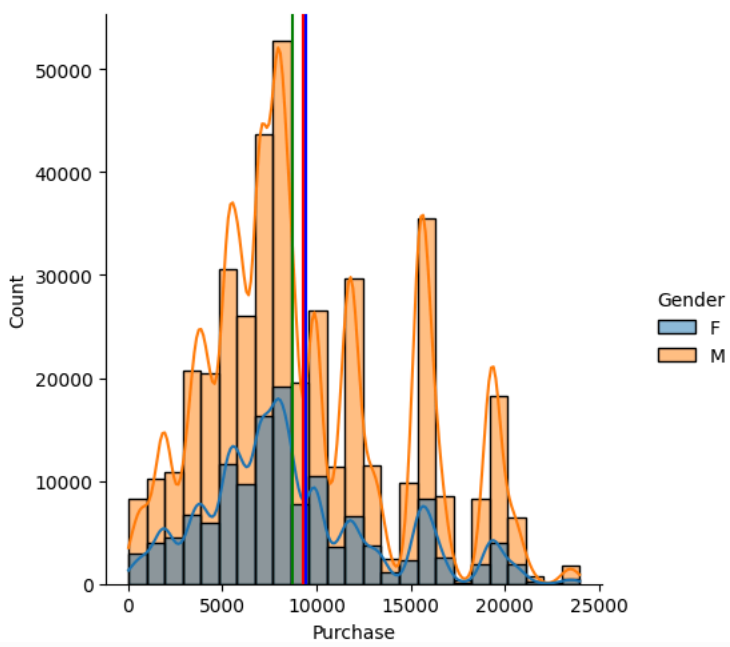
```
Female Purchase amount Mean:8734.565765155476
Female Purchase amount SD:4767.233289291444
Male Purchase amount Mean:9437.526040472265
Male Purchase amount SD:5092.186209777949
```

```
sns.displot(x='Purchase', bins=25, kde=True, data=data )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e0734de3880>
```




```
sns.displot(x='Purchase', bins=25, kde=True, hue='Gender', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Gender']=='M']['Purchase'].mean(), color='b')
plt.axvline(x=data[data['Gender']=='F']['Purchase'].mean(), color='g')
plt.show()
```



Almost male and female means coincide with overall means.

Exploring data using CLT.

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

Gender	count	mean	std	min	25%	50%	75%	max
F	69.0	8855.246377	5568.838694	480.0	5438.0	7985.0	10699.0	23365.0
M	231.0	9372.939394	5257.901485	12.0	5652.5	8008.0	12303.0	23775.0

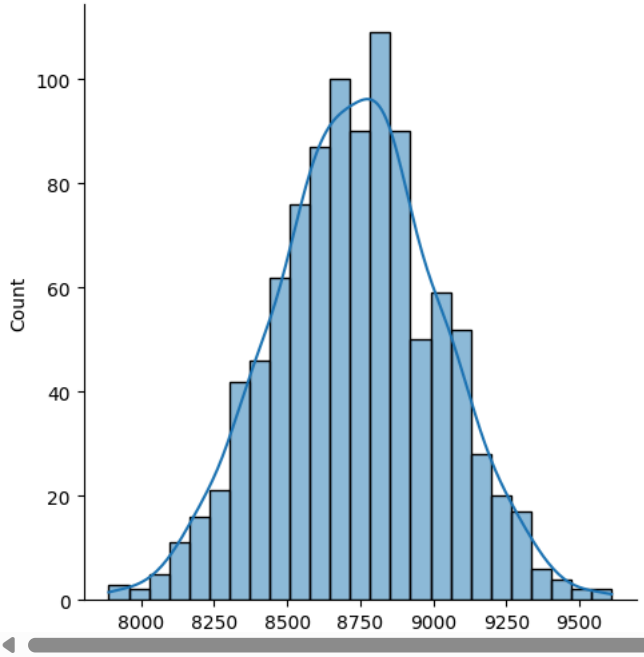
```
data.sample(00).groupby('Gender')['Purchase'].describe()
```

count	mean	std	min	25%	50%	75%	max

```
female_sample_means_for_300=[Female_data.sample(300, replace=True)['Purchase'].mean() for i in range(1000)]
```

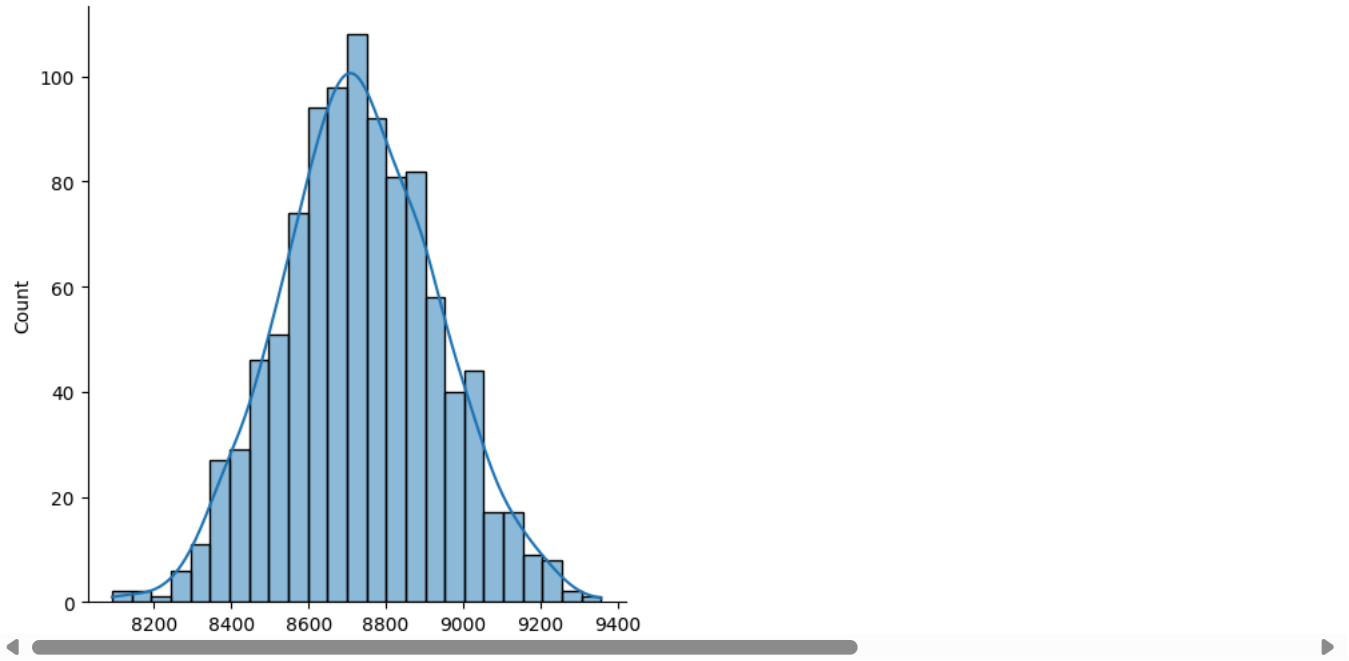
```
sns.displot( bins=25, kde=True,  data=female_sample_means_for_300 )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e07321e9840>
```



```
female_sample_means_for_600=[Female_data.sample(600, replace=True)['Purchase'].mean() for i in range(1000)]
sns.displot( bins=25, kde=True,  data=female_sample_means_for_600 )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e073618c6a0>
```

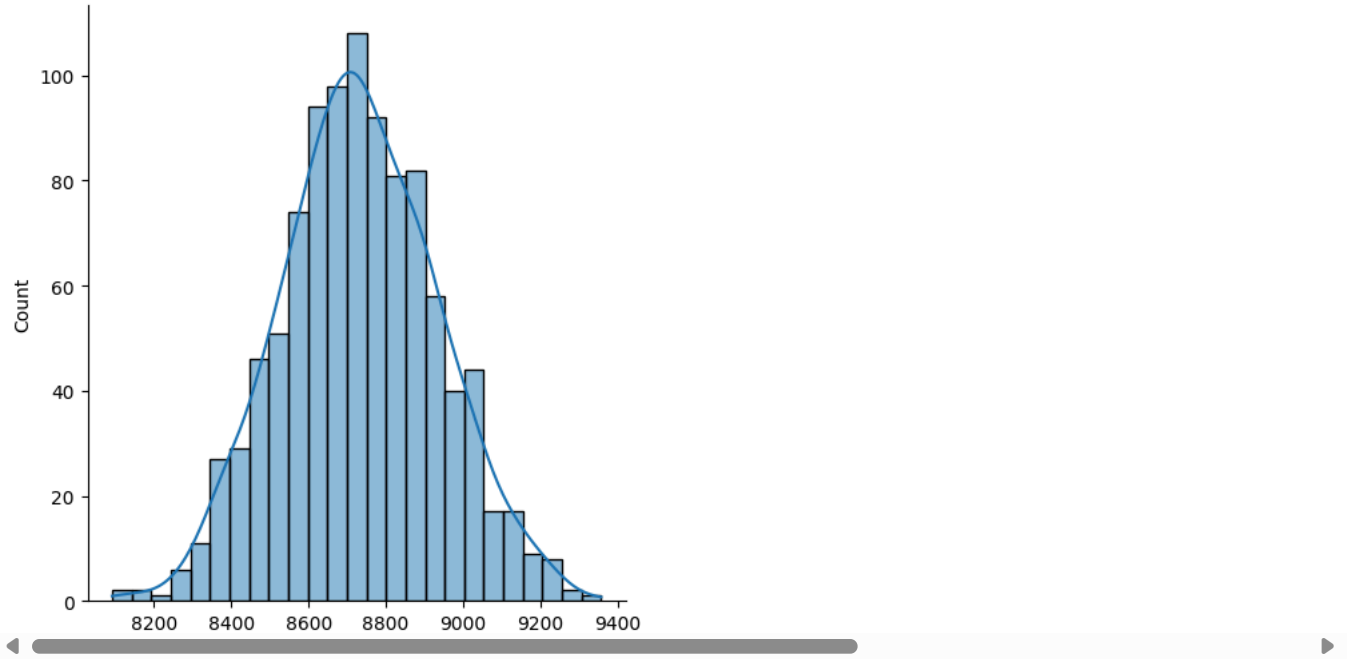



```
np.mean(female_sample_means_for_600)
```

```
8732.294033333334
```

```
male_sample_means_for_600=[Male_data.sample(600, replace=True)['Purchase'].mean() for i in range(1000)]
sns.displot( bins=25, kde=True,  data=female_sample_means_for_600 )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e07361a0850>
```




```
np.mean(male_sample_means_for_600)
```

```
9443.043593333334
```

```
f_stderror=np.std(female_sample_means_for_600)/np.sqrt(1000)
```

```
m_stderror=np.std(male_sample_means_for_600)/np.sqrt(1000)
```

```
norm.interval(confidence=.95,loc=np.mean(female_sample_means_for_600),scale=f_stderror)
```

```
(8719.866794165076, 8744.72127250159)
```

```
norm.interval(confidence=.95,loc=np.mean(male_sample_means_for_600),scale=m_stderror)
```

```
(9430.085888350462, 9456.001298316205)
```

The confidence interval of the sample average of male and female does not coincide.

Distribution of Expenses based on Maritial Status

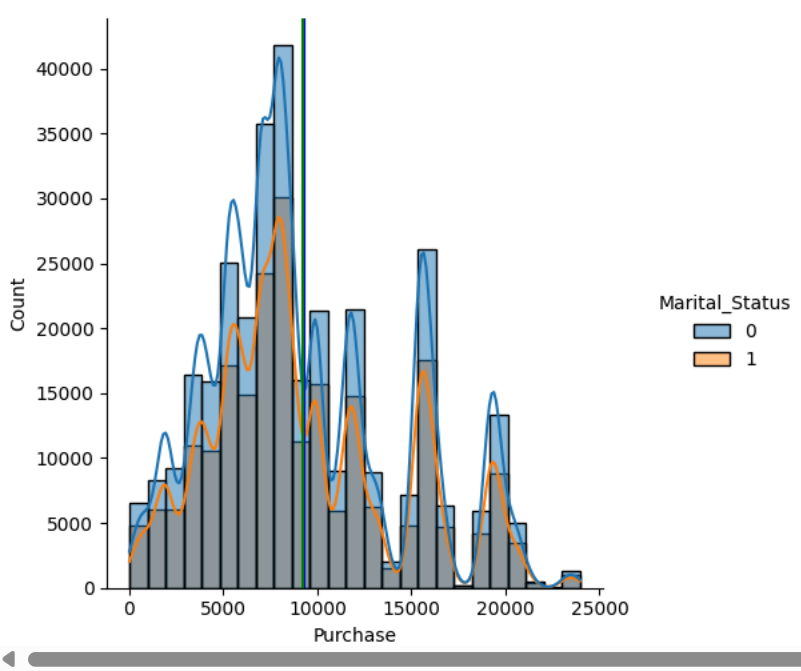
```
data.groupby('Marital_Status')['Purchase'].describe()
```

Marital_Status	count	mean	std	min	25%	50%	75%	max
0	324731.0	9265.907619	5027.347859	12.0	5605.0	8044.0	12061.0	23961.0
1	225337.0	9261.174574	5016.897378	12.0	5843.0	8051.0	12042.0	23961.0

```
# Single Purchases
Single_data = data[data["Marital_Status"]==0]
print("Single Purchase amount Mean:"+ str(Single_data["Purchase"].mean()))
print("Single Purchase amount SD:"+ str(Single_data["Purchase"].std()))

# Married Purchases
Married_data = data[data["Marital_Status"]==1]
print("Married Purchase amount Mean:"+ str(Married_data["Purchase"].mean()))
print("Married Purchase amount SD:"+ str(Married_data["Purchase"].std()))
```

```
Single Purchase amount Mean:9265.907618921507
Single Purchase amount SD:5027.347858674457
Married Purchase amount Mean:9261.174574082374
Married Purchase amount SD:5016.89737779313
```

```
sns.displot(x='Purchase', bins=25, kde=True, hue='Marital_Status', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Marital_Status']==0]['Purchase'].mean(), color='b')
plt.axvline(x=data[data['Marital_Status']==1]['Purchase'].mean(), color='g')
plt.show()
```

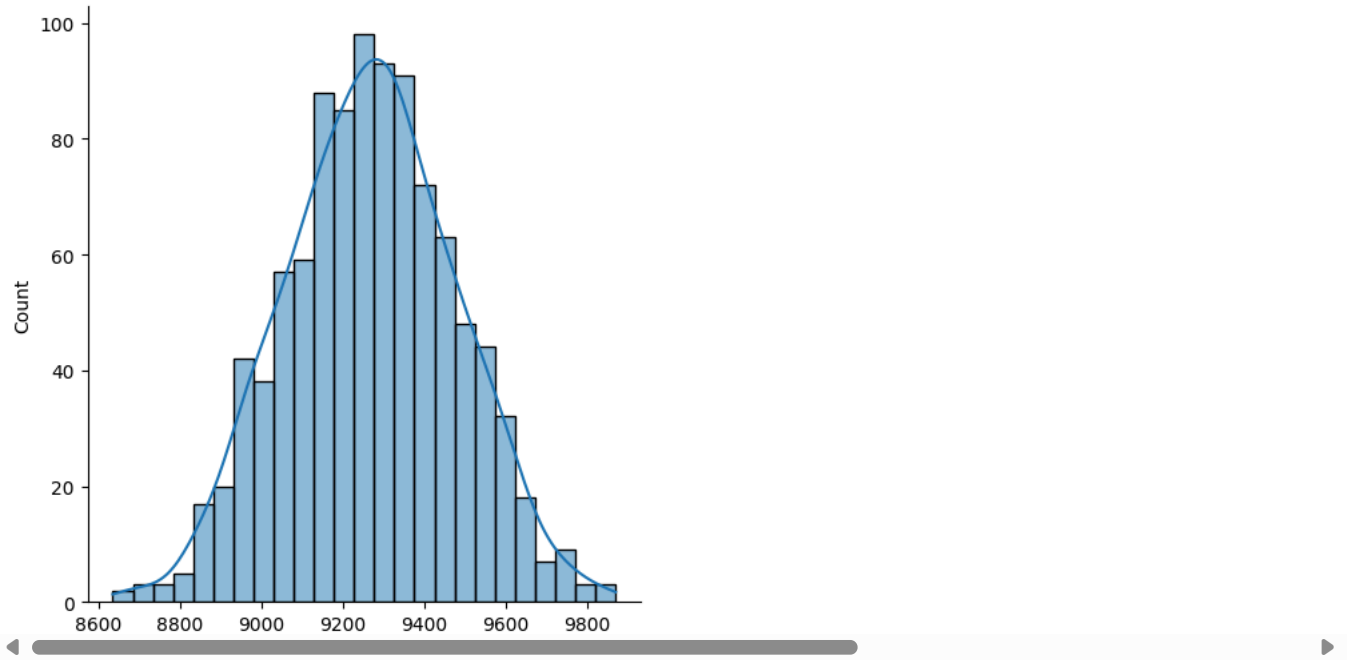



```
data.sample(600).groupby('Marital_Status')['Purchase'].describe()
```

Marital_Status	count	mean	std	min	25%	50%	75%	max
0	346.0	9375.910405	4965.922135	191.0	5942.25	8615.5	11903.75	23809.0
1	254.0	9423.377953	4878.291733	566.0	5977.75	8138.0	12064.25	23262.0

```
single_sample_means_for_600=[Single_data.sample(600, replace=True)['Purchase'].mean() for i in range(1000)]
sns.displot( bins=25, kde=True,  data=single_sample_means_for_600 )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e07338154e0>
```

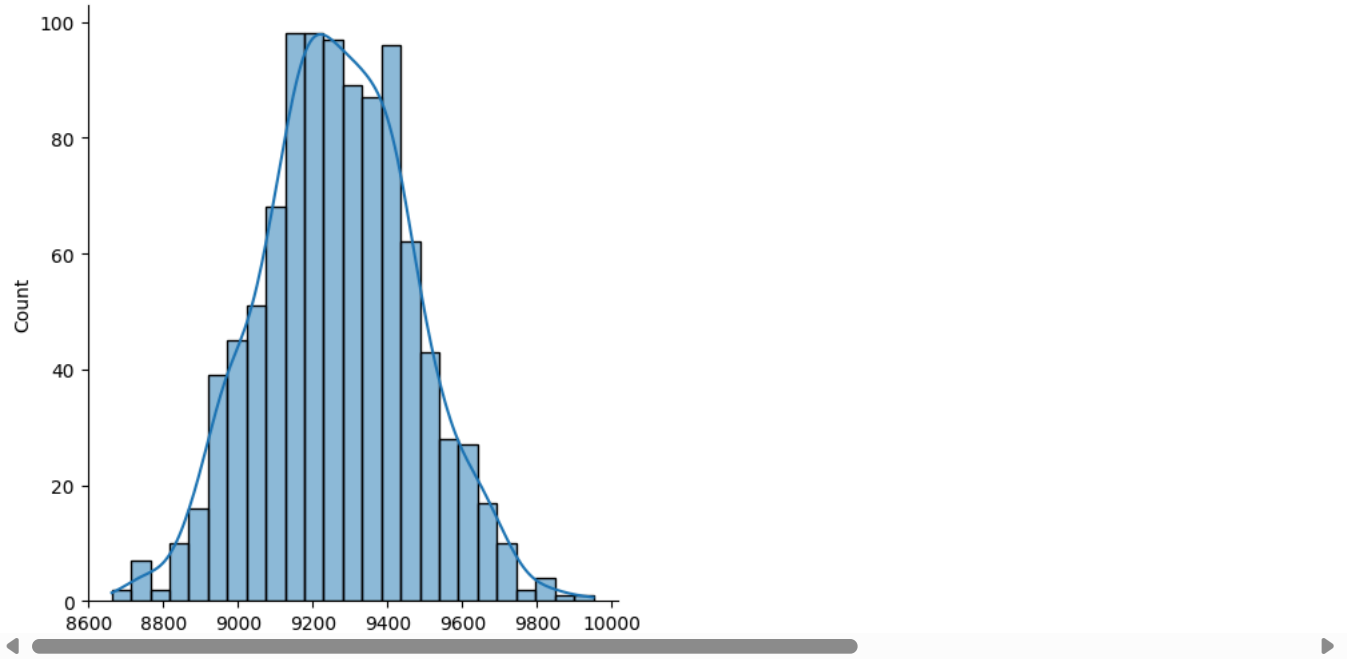



```
np.mean(single_sample_means_for_600)
```

```
9268.45226
```

```
married_sample_means_for_600=[Married_data.sample(600, replace=True)['Purchase'].mean() for i in range(1000)]
sns.displot( bins=25, kde=True,  data=married_sample_means_for_600 )
```

```
<seaborn.axisgrid.FacetGrid at 0x7e072f6001c0>
```




```
np.mean(married_sample_means_for_600)
```

```
9266.183008333335
```

```
s_stderror=np.std(single_sample_means_for_600)/np.sqrt(1000)
```

```
m_stderror=np.std(married_sample_means_for_600)/np.sqrt(1000)
```

```
norm.interval(confidence=.95,loc=np.mean(single_sample_means_for_600),scale=s_stderror)
```

```
(9255.62389375113, 9281.28062624887)
```

```
norm.interval(confidence=.95,loc=np.mean(married_sample_means_for_600),scale=m_stderror)
```

```
(9253.660797812818, 9278.705218853853)
```

Average of both sample means taking Maritial Status as a account coincides each other.

Distribution of Expenses based on Age

```
data.groupby('Age')['Purchase'].describe()
```

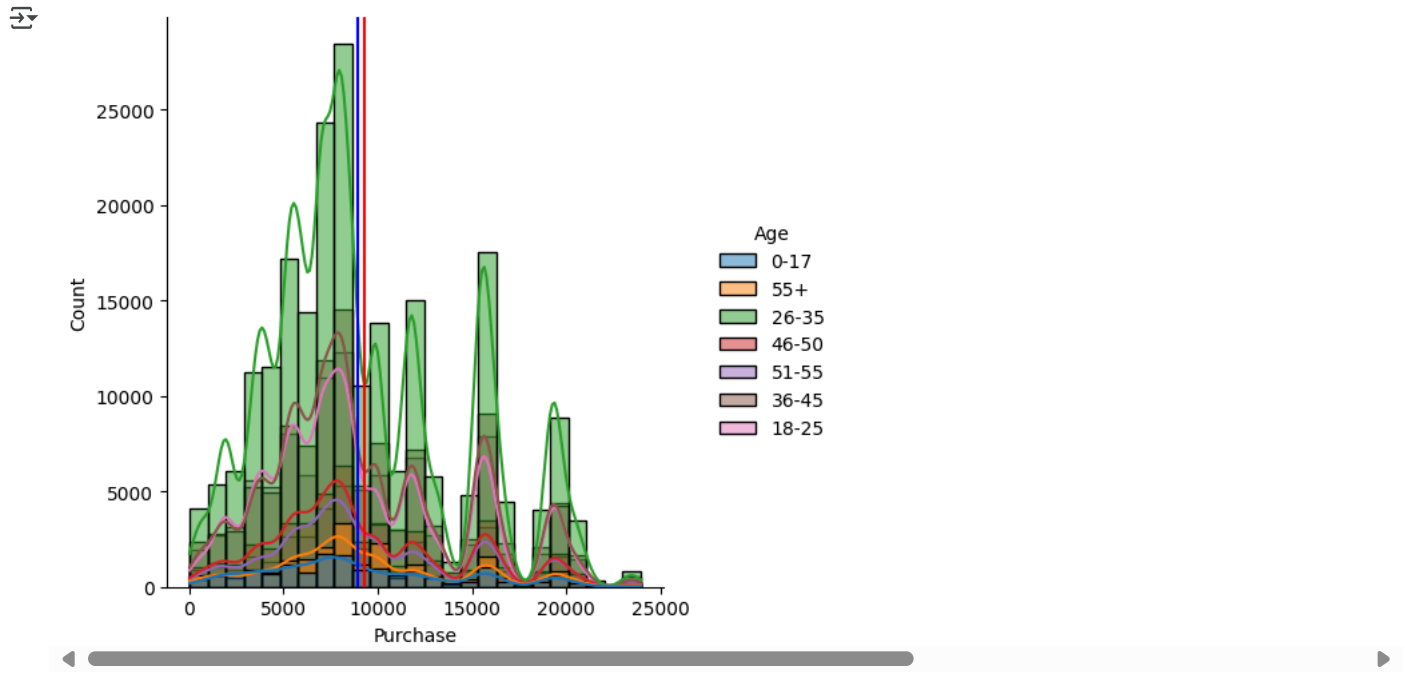
Age	count	mean	std	min	25%	50%	75%	max
0-17	15102.0	8933.464640	5111.114046	12.0	5328.0	7986.0	11874.0	23955.0
18-25	99660.0	9169.663606	5034.321997	12.0	5415.0	8027.0	12028.0	23958.0
26-35	219587.0	9252.690633	5010.527303	12.0	5475.0	8030.0	12047.0	23961.0
36-45	110013.0	9331.350695	5022.923879	12.0	5876.0	8061.0	12107.0	23960.0
46-50	45701.0	9208.625697	4967.216367	12.0	5888.0	8036.0	11997.0	23960.0
51-55	38501.0	9534.808031	5087.368080	12.0	6017.0	8130.0	12462.0	23960.0
55+	21504.0	9336.280459	5011.493996	12.0	6018.0	8105.5	11932.0	23960.0

```
# Single Purchases
Age_grp1 = data[data["Age"]=='0-17']
print("Age_grp1 Purchase amount Mean:"+ str(Age_grp1["Purchase"].mean()))
print("Age_grp1 Purchase amount SD:"+ str(Age_grp1["Purchase"].std()))

# Married Purchases
Age_grp2 = data[data["Age"]=='18-25']
print("Age_grp2 Purchase amount Mean:"+ str(Age_grp2["Purchase"].mean()))
print("Age_grp2 Purchase amount SD:"+ str(Age_grp2["Purchase"].std()))

# Married Purchases
Age_grp3 = data[data["Age"]=='26-35']
print("Age_grp3 Purchase amount Mean:"+ str(Age_grp3["Purchase"].mean()))
print("Age_grp3 Purchase amount SD:"+ str(Age_grp3["Purchase"].std()))

# Married Purchases
Age_grp4 = data[data["Age"]=='36-45']
print("Age_grp4 Purchase amount Mean:"+ str(Age_grp4["Purchase"].mean()))
print("Age_grp4 Purchase amount SD:"+ str(Age_grp4["Purchase"].std()))

# Married Purchases
Age_grp5 = data[data["Age"]=='46-50']
print("Age_grp5 Purchase amount Mean:"+ str(Age_grp5["Purchase"].mean()))
print("Age_grp5 Purchase amount SD:"+ str(Age_grp5["Purchase"].std()))

# Married Purchases
Age_grp6 = data[data["Age"]=='51-55']
print("Age_grp6 Purchase amount Mean:"+ str(Age_grp6["Purchase"].mean()))
print("Age_grp6 Purchase amount SD:"+ str(Age_grp6["Purchase"].std()))

# Married Purchases
Age_grp7 = data[data["Age"]=='55+']
print("Age_grp7 Purchase amount Mean:"+ str(Age_grp7["Purchase"].mean()))
print("Age_grp7 Purchase amount SD:"+ str(Age_grp7["Purchase"].std()))
```

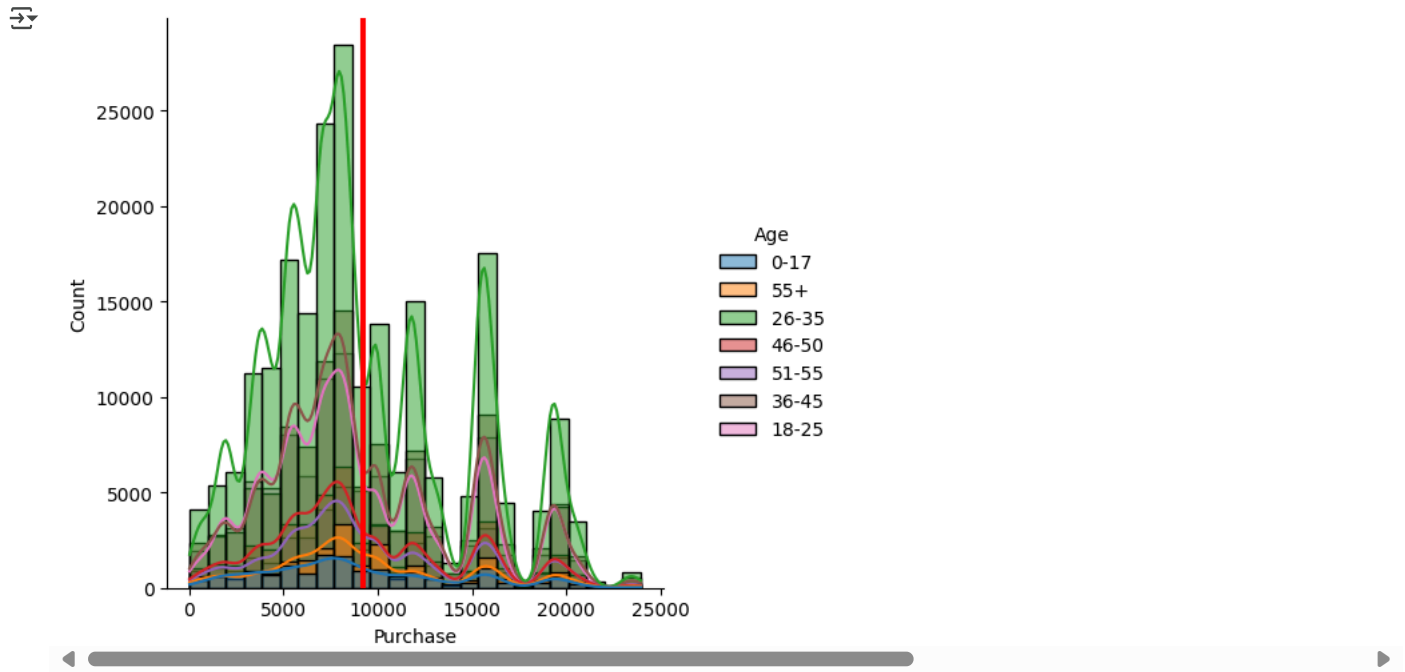
```
Age_grp1 Purchase amount Mean:8933.464640444974
Age_grp1 Purchase amount SD:5111.11404600277
Age_grp2 Purchase amount Mean:9169.663606261289
Age_grp2 Purchase amount SD:5034.321997176577
Age_grp3 Purchase amount Mean:9252.690632869888
Age_grp3 Purchase amount SD:5010.527303002927
Age_grp4 Purchase amount Mean:9331.350694917874
Age_grp4 Purchase amount SD:5022.923879204652
Age_grp5 Purchase amount Mean:9208.625697468327
Age_grp5 Purchase amount SD:4967.216367142921
Age_grp6 Purchase amount Mean:9534.808030960236
Age_grp6 Purchase amount SD:5087.368079602116
Age_grp7 Purchase amount Mean:9336.280459449405
Age_grp7 Purchase amount SD:5011.493995603418
```

```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
```

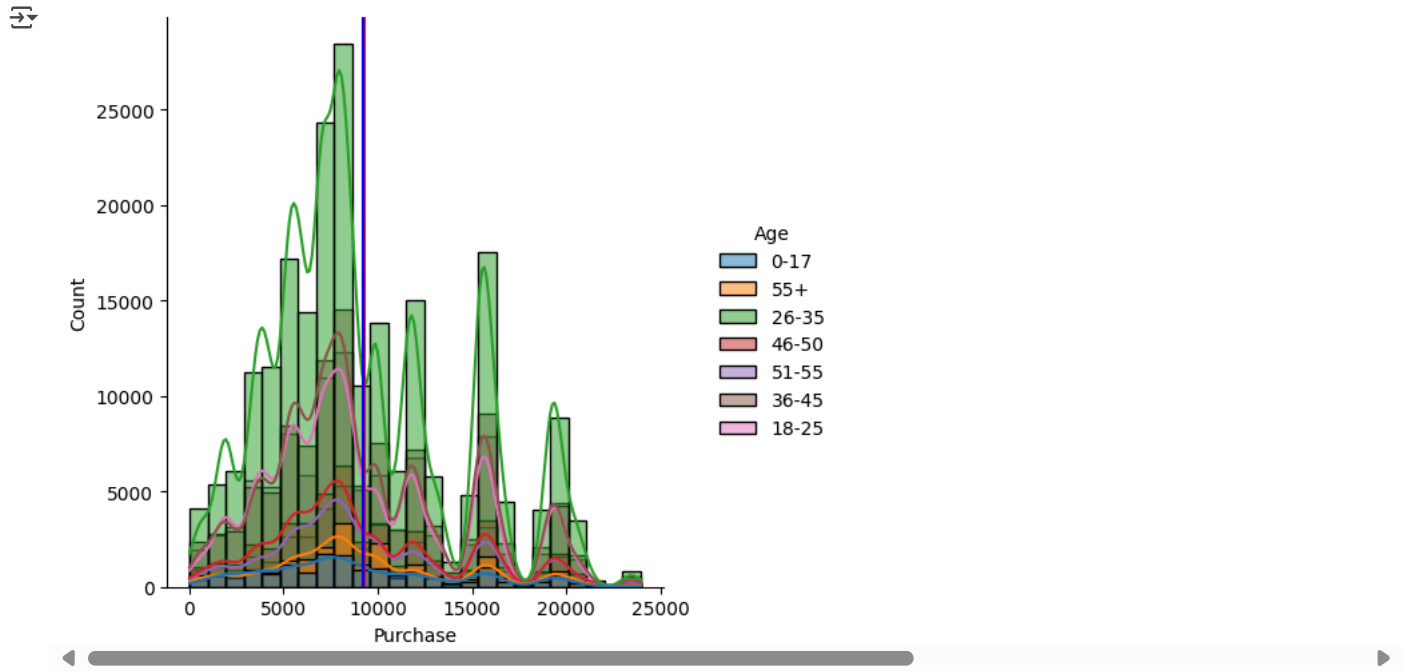
```
plt.axvline(x=data[data['Age']=='0-17']['Purchase'].mean(), color='b')
plt.show()
```



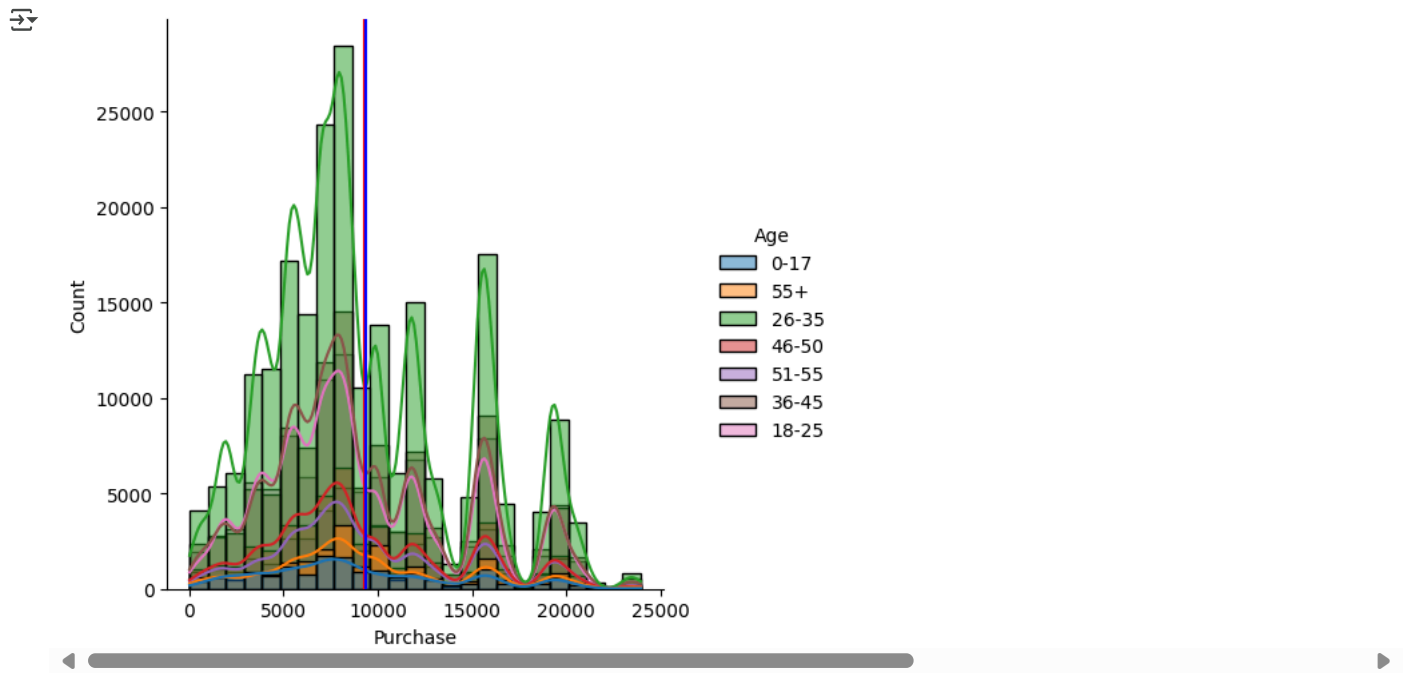

```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Age']=='18-25']['Purchase'].mean(), color='r')
plt.show()
```



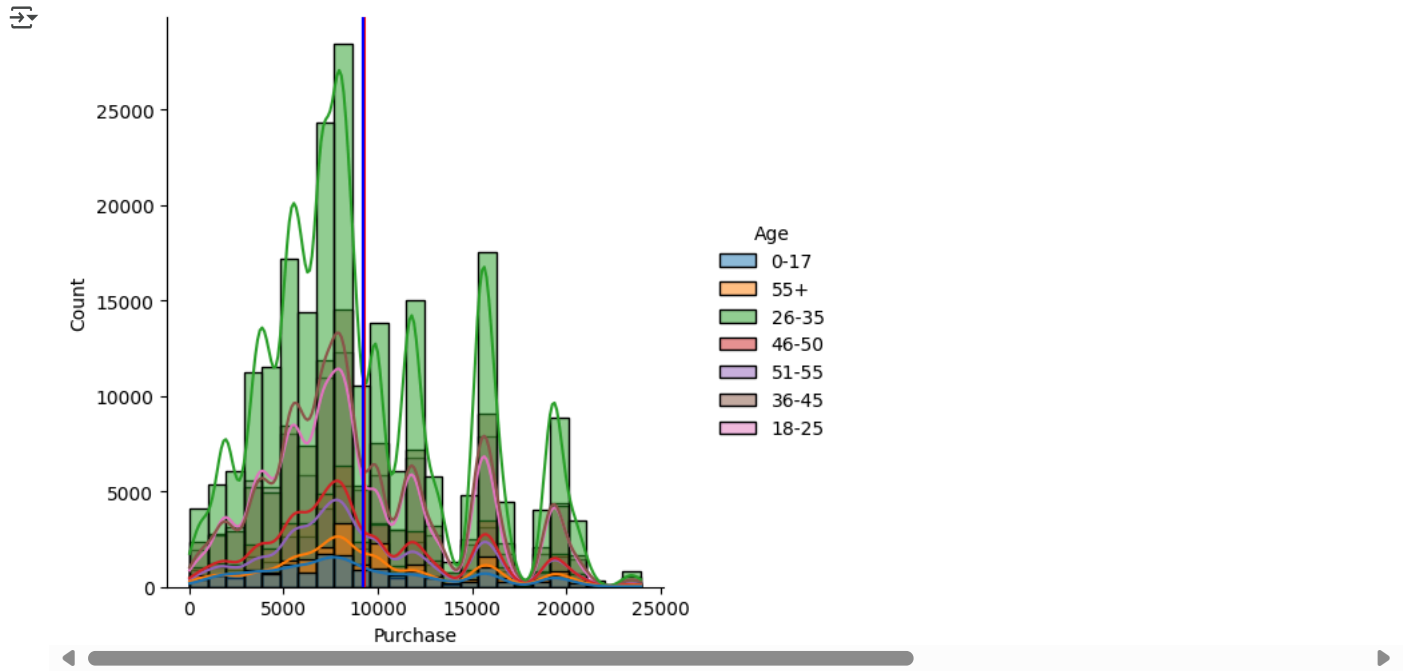

```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Age']=='26-35']['Purchase'].mean(), color='b')
plt.show()
```



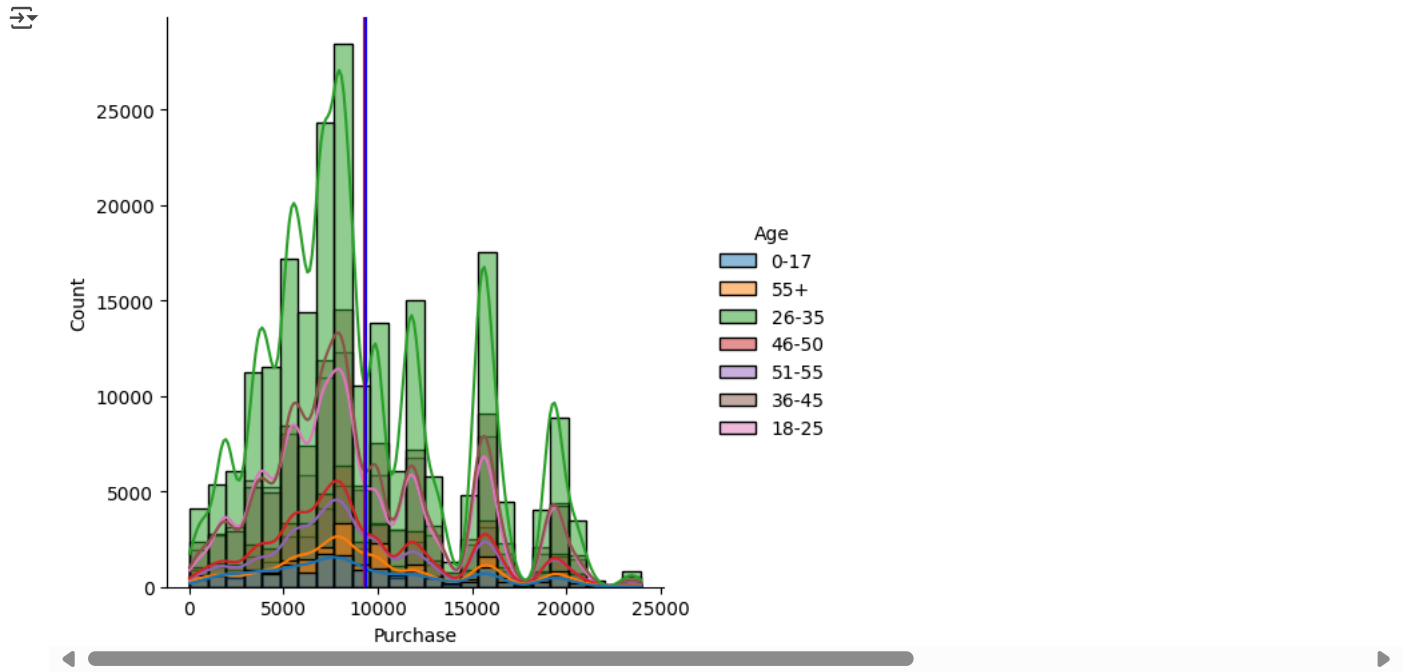

```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Age']=='36-45']['Purchase'].mean(), color='b')
plt.show()
```




```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Age']=='46-50']['Purchase'].mean(), color='b')
plt.show()
```




```
sns.displot(x='Purchase', bins=25, kde=True, hue='Age', data=data )
plt.axvline(x=data['Purchase'].mean(), color='r')
plt.axvline(x=data[data['Age']=='55+']['Purchase'].mean(), color='b')
plt.show()
```




```
Age_grp1_means_for_600=[Age_grp1.sample(600, replace=True)['Purchase'].mean() for i in range(1000)]
sns.displot( bins=25, kde=True,  data=married_sample_means_for_600 )
```