walmart-casestudy

July 4, 2023

[120]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
```

[121]:
```
!gdown "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/
↪original/walmart_data.csv?1641285094"
```

```
Downloading…
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/ori
ginal/walmart_data.csv?1641285094
To: /content/walmart_data.csv?1641285094
100% 23.0M/23.0M [00:00<00:00, 417MB/s]
```

Objective: The management of Walmart has obtained transactional data from customers and seeks to analyze the purchasing behavior of customers during the Black Friday sale. The dataset includes various columns such as User_ID, Product_ID, Gender, Age, Occupation, City_Category, Stay_IN_Current_City_Tears, Marital_Status, Product_Category, and Purchase. The primary objective is to determine the purchasing patterns based on gender, specifically identifying whether males or females spend more during the Black Friday sale.

[122]:
```
df = pd.read_csv("/content/walmart_data.csv?1641285094")
df
```

[122]:
```
        User_ID Product_ID Gender   Age  Occupation City_Category  \
0       1000001  P00069042      F  0-17          10             A
1       1000001  P00248942      F  0-17          10             A
2       1000001  P00087842      F  0-17          10             A
3       1000001  P00085442      F  0-17          10             A
4       1000002  P00285442      M   55+          16             C
…           …         …     …    …           …
550063  1006033  P00372445      M 51-55          13             B
550064  1006035  P00375436      F 26-35           1             C
550065  1006036  P00375436      F 26-35          15             B
550066  1006038  P00375436      F   55+           1             C
```

```
550067  1006039  P00371644      F  46-50          0             B

       Stay_In_Current_City_Years  Marital_Status  Product_Category  Purchase
0                               2               0                 3      8370
1                               2               0                 1     15200
2                               2               0                12      1422
3                               2               0                12      1057
4                              4+               0                 8      7969
…                             …           …                …       …
550063                          1               1                20       368
550064                          3               0                20       371
550065                         4+               1                20       137
550066                          2               0                20       365
550067                         4+               1                20       490

[550068 rows x 10 columns]
```

[123]:
```
df.shape
```

[123]:
```
(550068, 10)
```

The dataset comprises approximately 550k rows of data and 10 columns.

[124]:
```
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
```

The dataset is devoid of any null values.

An additional categorical column has been created to indicate the marital status of users. The value 0 represents unmarried users, while the value 1 indicates married users.

[125]:
```
def Marital_Status_Category(val):
    if val == 0 :
        return "Unmarried"
    else:
        return "Married"
df["Marital_Status_category"] = df["Marital_Status"].
 ↪apply(Marital_Status_Category)
##Sample space = ("Married, Unmarried")
```

[126]:
```
df.describe().T
```

[126]:
```
                     count          mean          std        min        25%  \
User_ID           550068.0  1.003029e+06  1727.591586  1000001.0  1001516.0
Occupation        550068.0  8.076707e+00     6.522660        0.0        2.0
Marital_Status    550068.0  4.096530e-01     0.491770        0.0        0.0
Product_Category  550068.0  5.404270e+00     3.936211        1.0        1.0
Purchase          550068.0  9.263969e+03  5023.065394       12.0     5823.0

                        50%        75%        max
User_ID           1003077.0  1004478.0  1006040.0
Occupation              7.0       14.0       20.0
Marital_Status          0.0        1.0        1.0
Product_Category        5.0        8.0       20.0
Purchase             8047.0    12054.0    23961.0
```

[127]:
```
df.describe(include= "object").T
```

[127]:
```
                            count unique        top    freq
Product_ID                 550068   3631  P00265242    1880
Gender                     550068      2          M  414259
Age                        550068      7      26-35  219587
City_Category              550068      3          B  231173
Stay_In_Current_City_Years 550068      5          1  193821
Marital_Status_category    550068      2  Unmarried  324731
```

Based on the information presented in the aforementioned table, we can deduce that :

Based on the data, it can be determined that the product with the highest popularity is P00265242.
The Black Friday Sale sees a higher contribution from unmarried individuals.
Specifically, unmarried males are the top contributors.

converting Stay_In_Current_City_Years into category

[128]:
```
#Replace '4+' to 4
df['Stay_In_Current_City_Years']=df['Stay_In_Current_City_Years'].
 ↪replace('4+',4)
```

```
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].
 ↪astype("category")
```

[129]:
```
#changing it from object dtype to category  to save memory
df["Age"]=df["Age"].astype("category")
df["Gender"]=df["Gender"].astype("category")
df["City_Category"]=df["City_Category"].astype("category")
df["Product_Category"]=df["Product_Category"].astype("category")
```

Retrieving the list of the top 10 products sold during the sale.

[130]:
```
temp=df['Product_ID'].value_counts().reset_index()
temp.columns=['Product_ID','Count']
temp=temp.sort_values(by='Count', ascending=False)
temp.head(10)
```

[130]:

	Product_ID	Count
0	P00265242	1880
1	P00025442	1615
2	P00110742	1612
3	P00112142	1562
4	P00057642	1470
5	P00184942	1440
6	P00046742	1438
7	P00058042	1422
8	P00059442	1406
9	P00145042	1406

The aforementioned product IDs represent the top 10 sold items, accompanied by their respective total sales count. Notably, P00265242 emerges as the highest-selling product.

[131]:
```
temp=df.groupby(['Product_ID'])['Purchase'].sum().reset_index().
 ↪sort_values(by='Purchase', ascending=False)
temp.head(10)
```

[131]:

	Product_ID	Purchase
249	P00025442	27995166
1016	P00110742	26722309
2443	P00255842	25168963
582	P00059442	24338343
1745	P00184942	24334887
1030	P00112142	24216006
1018	P00110942	23639564
2263	P00237542	23425576
565	P00057642	23102780
104	P00010742	22164153

The table above presents the total sum of each product's sales during the Black Friday sale. These products represent the top 10 contributors to our revenue.

[132]:
```
temp=df.groupby(['User_ID'])['Purchase'].sum().reset_index().
 ↪sort_values(by='Purchase', ascending=False)
temp.head(10)
```

[132]:

	User_ID	Purchase
4166	1004277	10536909
1634	1001680	8699596
2831	1002909	7577756
1885	1001941	6817493
416	1000424	6573609
4335	1004448	6566245
5683	1005831	6512433
981	1001015	6511314
3297	1003391	6477160
1142	1001181	6387961

The aforementioned customers, who are among the top 10 contributors to the Black Friday sale, warrant recognition and consideration for additional rewards or exclusive offers. Implementing such measures can potentially enhance the revenue of our company.

Non graphical Analysis(Unique Values and Value Counts)

[133]:
```
for i in df.columns:
    print(f'{i} has {df[i].nunique()} unique values')
    print(""*20)
```

```
User_ID has 5891 unique values

Product_ID has 3631 unique values

Gender has 2 unique values

Age has 7 unique values

Occupation has 21 unique values

City_Category has 3 unique values

Stay_In_Current_City_Years has 5 unique values

Marital_Status has 2 unique values

Product_Category has 20 unique values

Purchase has 18105 unique values

Marital_Status_category has 2 unique values
```

[134]:

```
for i in range(df.shape[1]):
    print(df.columns[i])
    print("~"*22)
    print(df.iloc[:,i].value_counts())
    print("-"*58)
    print()
```

```
User_ID
~~~~~~~~~~~~~~~~~~~~~~
1001680    1026
1004277     979
1001941     898
1001181     862
1000889     823
           …
1002690       7
1002111       7
1005810       7
1004991       7
1000708       6
Name: User_ID, Length: 5891, dtype: int64
----------------------------------------------------------

Product_ID
~~~~~~~~~~~~~~~~~~~~~~
P00265242    1880
P00025442    1615
P00110742    1612
P00112142    1562
P00057642    1470
             …
P00314842       1
P00298842       1
P00231642       1
P00204442       1
P00066342       1
Name: Product_ID, Length: 3631, dtype: int64
----------------------------------------------------------

Gender
~~~~~~~~~~~~~~~~~~~~~~
M    414259
F    135809
Name: Gender, dtype: int64
----------------------------------------------------------
```

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

Occupation
~~~~~~~~~~~~~~~~~~~~~~
4     72308
0     69638
7     59133
1     47426
17    40043
20    33562
12    31179
14    27309
2     26588
16    25371
6     20355
3     17650
10    12930
5     12177
15    12165
11    11586
19     8461
13     7728
18     6622
9      6291
8      1546
Name: Occupation, dtype: int64
----------------------------------------------------------

City_Category
~~~~~~~~~~~~~~~~~~~~~~
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
----------------------------------------------------------

Stay_In_Current_City_Years
~~~~~~~~~~~~~~~~~~~~~~
```

```
1    193821
2    101838
3     95285
4     84726
0     74398
Name: Stay_In_Current_City_Years, dtype: int64
-----------------------------------------------------------

Marital_Status
~~~~~~~~~~~~~~~~~~~~~~
0    324731
1    225337
Name: Marital_Status, dtype: int64
-----------------------------------------------------------

Product_Category
~~~~~~~~~~~~~~~~~~~~~~
5     150933
1     140378
8     113925
11     24287
2      23864
6      20466
3      20213
4      11753
16      9828
15      6290
13      5549
10      5125
12      3947
7       3721
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64
-----------------------------------------------------------

Purchase
~~~~~~~~~~~~~~~~~~~~~~
7011     191
7193     188
6855     187
6891     184
7012     183
        …
```

```
23491      1
18345      1
3372       1
855        1
21489      1
Name: Purchase, Length: 18105, dtype: int64
----------------------------------------------------------

Marital_Status_category
~~~~~~~~~~~~~~~~~~~~~~
Unmarried    324731
Married      225337
Name: Marital_Status_category, dtype: int64
----------------------------------------------------------
```

[135]:
```
df.nunique()
```

[135]:
```
User_ID                        5891
Product_ID                     3631
Gender                            2
Age                               7
Occupation                       21
City_Category                     3
Stay_In_Current_City_Years        5
Marital_Status                    2
Product_Category                 20
Purchase                      18105
Marital_Status_category           2
dtype: int64
```

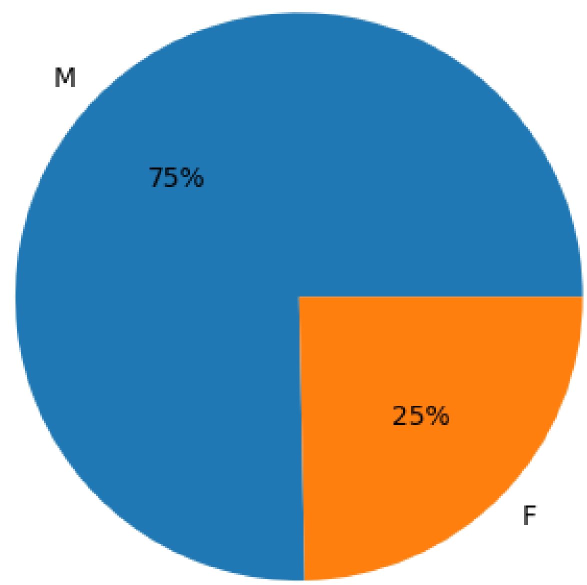
The variable "Purchase" represents the amount spent on purchases and is considered a continuous variable.

The variables "User_ID" and "Product_ID" serve the purpose of identification.

On the other hand, the variables "Gender," "Age," "Occupation," "City_Category," "Stay_In_Current_City_Years," "Marital_Status," and "Product_Category" are categorical variables.

Visual Analysis

[136]:
```
data = df["Gender"].value_counts(normalize = True)*100
plt.pie(x = data.values, labels=data.index, autopct='%.0f%%')
plt.show()
```



Based on the data provided, it can be deduced that 75% of the population in the given dataset is male, while the female population accounts for 25%.

Among the total number of customers, specifically 5.5L (550,000), the male users constitute more than 4.2L (420,000+), while the female users account for more than 1.4L (140,000+). Hence, it can be concluded that the distribution of male and female customers is in a ratio of 3:1.

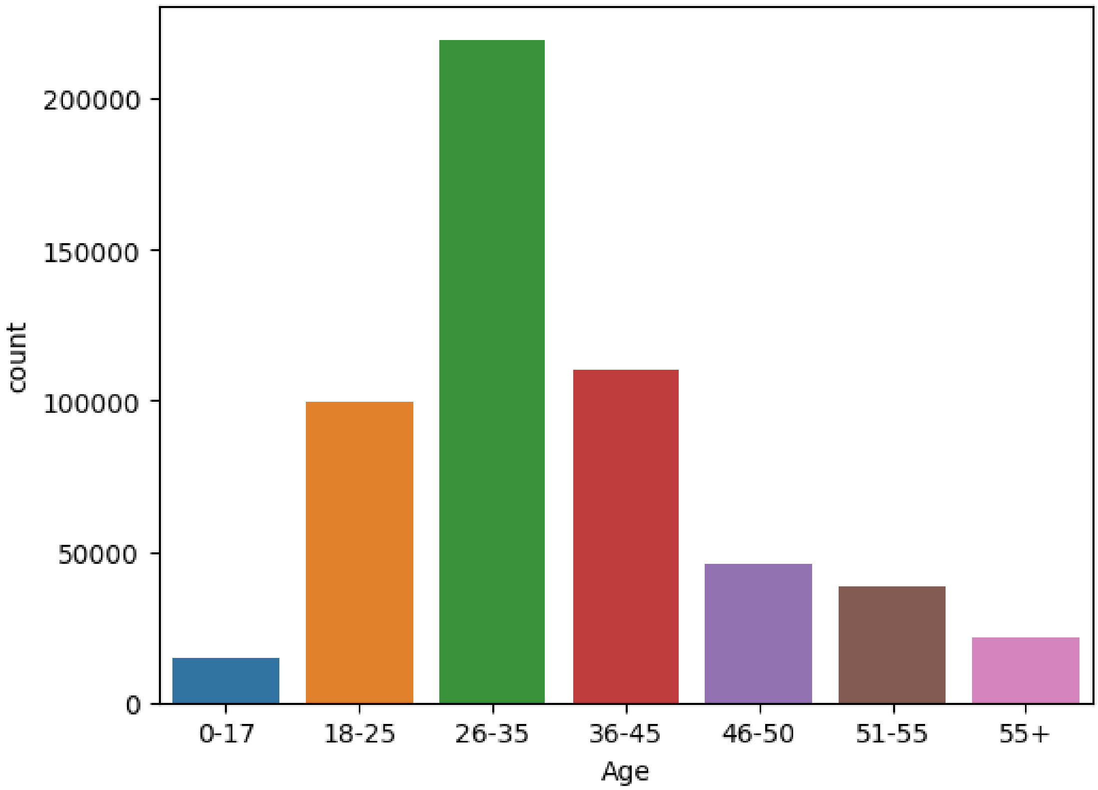
[137]:
```
df["Age"].value_counts()
```

[137]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

The highest-ranking category corresponds to individuals aged between 26 and 35. It is noteworthy that users within this age range make the most significant contribution to the sale. Subsequently, the age range of 36-45 follows closely in terms of contribution.

[138]:
```
df["Age"] = df["Age"].astype("category")
sns.countplot(data=df, x="Age")
```

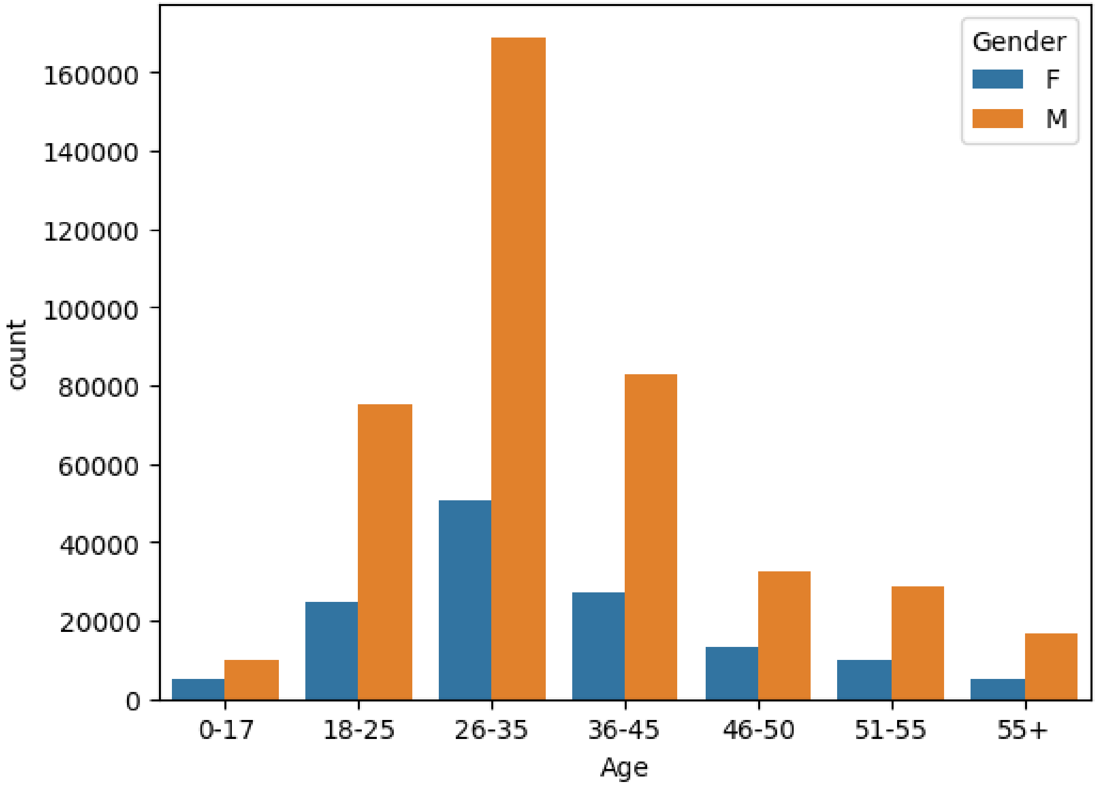
[138]: <Axes: xlabel='Age', ylabel='count'>



The age group between 26 and 35 exhibits the highest level of engagement during the Black Friday sale.

[139]:
```
df["Age"] = df["Age"].astype("category")

sns.countplot(x="Age", hue="Gender", data=df)
```

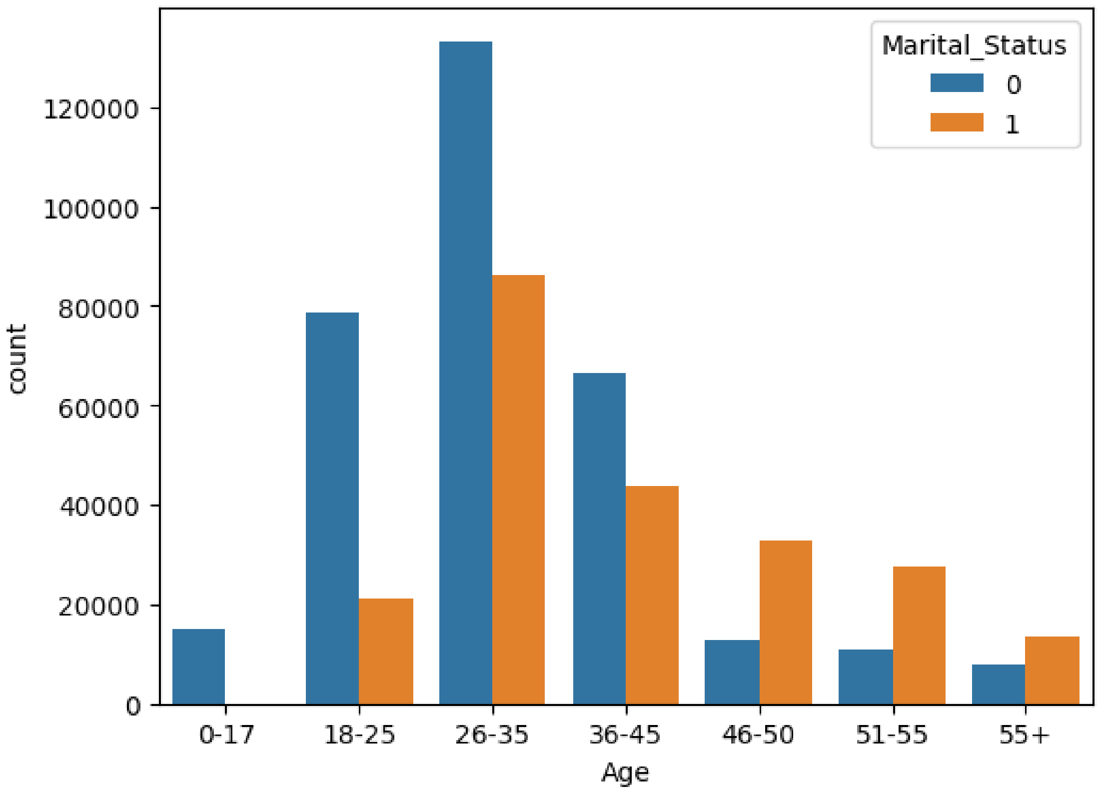
[139]: <Axes: xlabel='Age', ylabel='count'>



Males within the age range of 26 to 35 demonstrate greater participation in Black Friday sales compared to other age groups. Additionally, males aged 18 to 25 and 36 to 45 exhibit higher levels of activity in the sales compared to females within the age range of 26 to 35.

[140]:
```
df["Age"] = df["Age"].astype("category")

sns.countplot(x="Age", hue="Marital_Status", data=df)
```

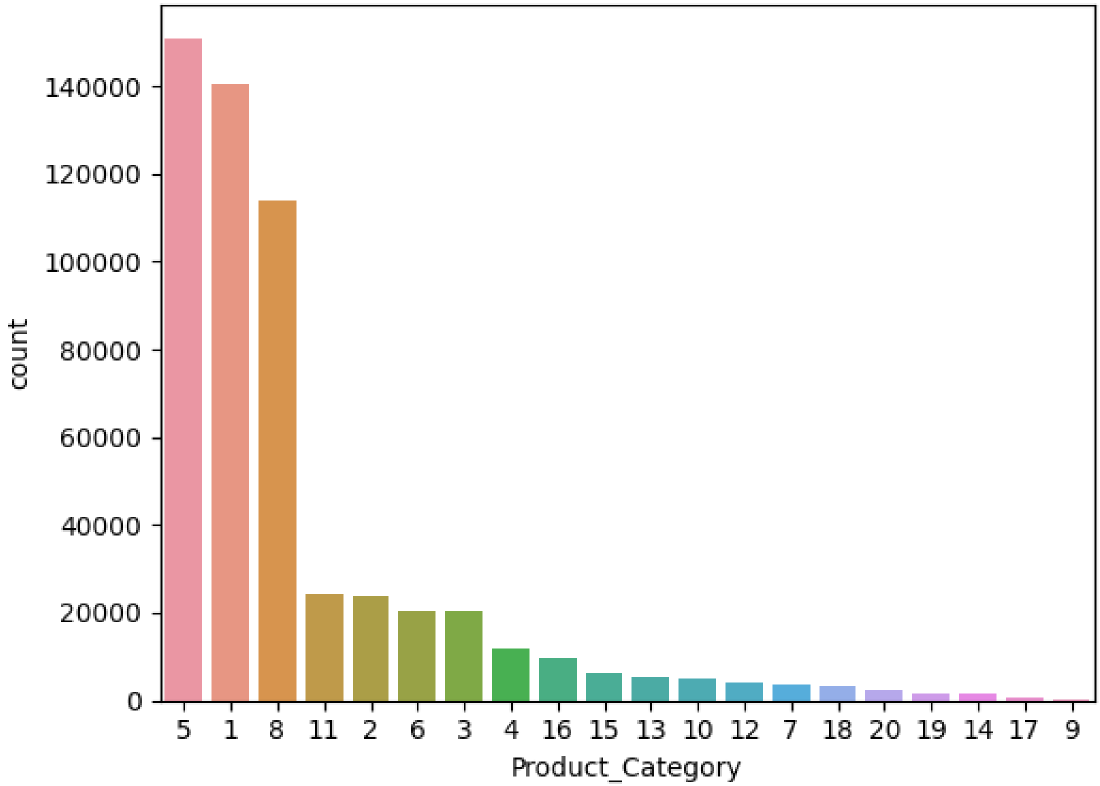
[140]: <Axes: xlabel='Age', ylabel='count'>



Based on the available information, it can be deduced that unmarried individuals between the ages of 18 and 25 to 36 and 45 display greater engagement during Black Friday sales. Conversely, married individuals within the age range of 26 to 45 demonstrate increased activity in the sales. This suggests that married men may potentially be responsible for the purchases made by their spouses.

[141]:
```
order = df["Product_Category"].value_counts().index  #Order based on value␣
 ↪counts
sns.countplot(x="Product_Category", data=df, order=order)
```

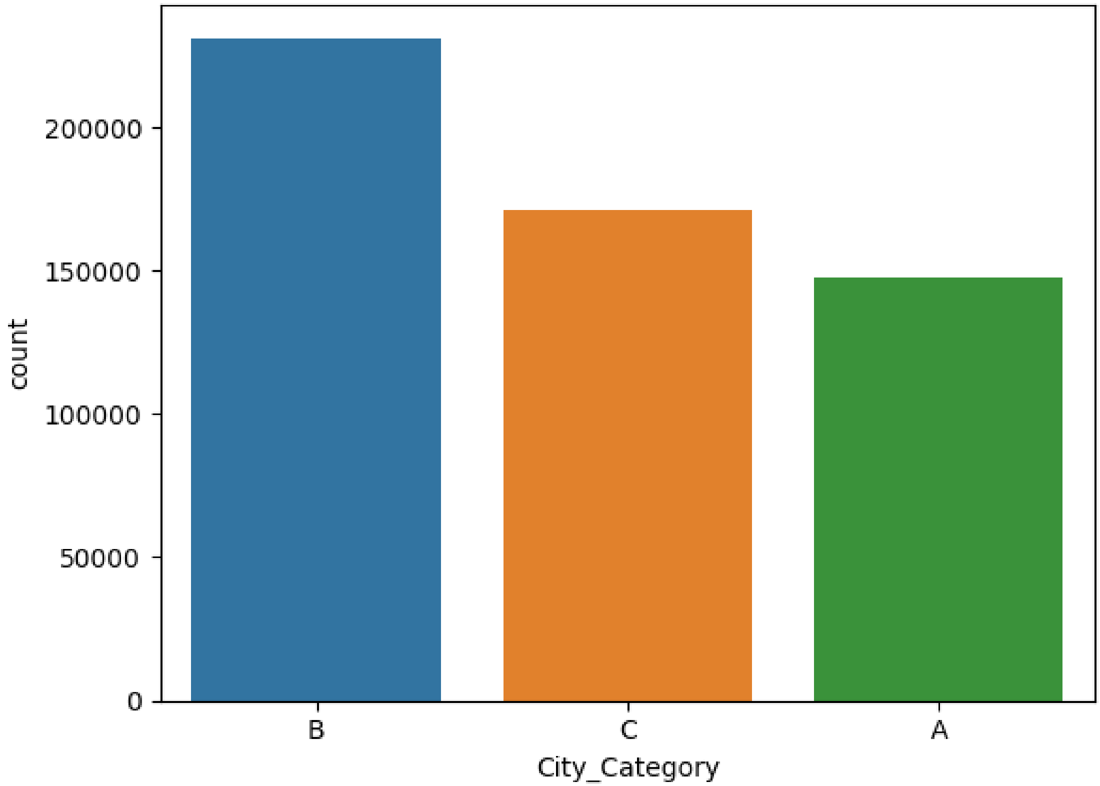
[141]: <Axes: xlabel='Product_Category', ylabel='count'>



Among the 20 products, Product 5,1 and 8 stand out as the top-selling items.

[142]:
```
order = df["City_Category"].value_counts().index
sns.countplot(x="City_Category", data=df, order=order)
```

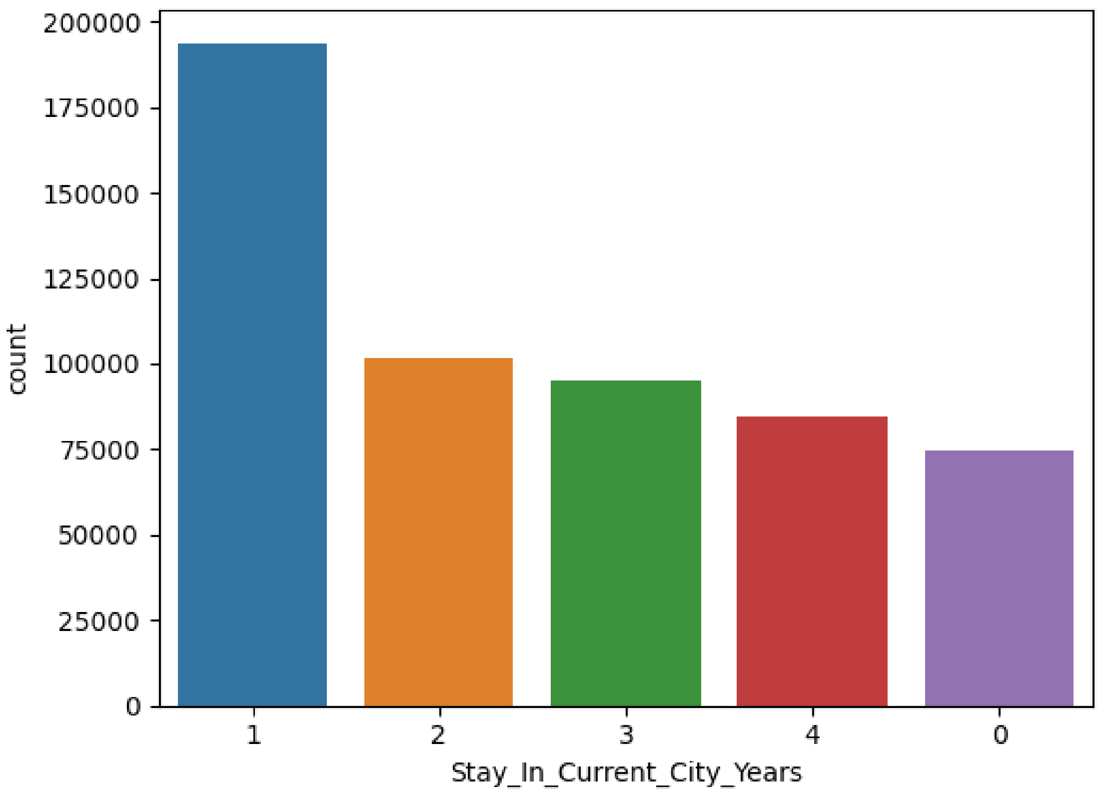
[142]: <Axes: xlabel='City_Category', ylabel='count'>



The majority of users originate from City B.

[143]:
```
order = df["Stay_In_Current_City_Years"].value_counts().index
sns.countplot(x="Stay_In_Current_City_Years", data=df, order=order)
```

[143]: `<Axes: xlabel='Stay_In_Current_City_Years', ylabel='count'>`



Individuals who have resided within a specific country for a duration exceeding one year exhibit a heightened propensity for increased purchasing and spending during sales events.

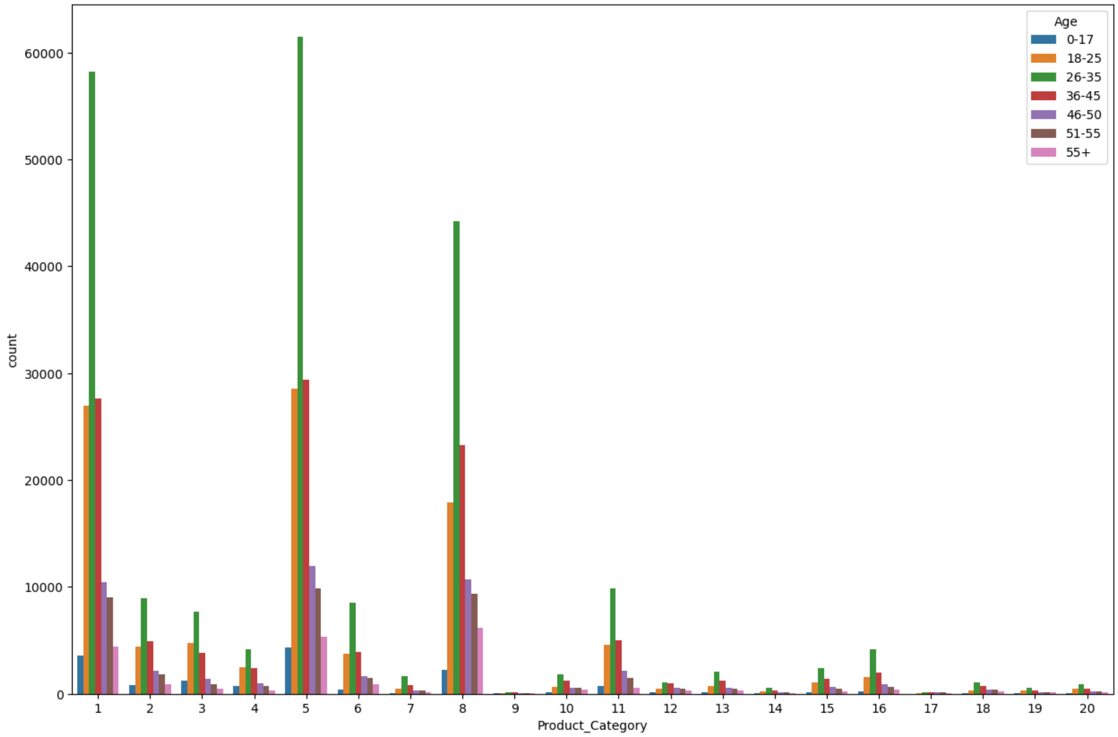
[144]:
```
df["Married_Gender"] = df.apply(lambda x: (x["Gender"], x["Marital_Status"]),␣
↪axis = 1)
df
```

[144]:
```
        User_ID Product_ID Gender   Age  Occupation City_Category  \
0       1000001  P00069042      F  0-17          10             A
1       1000001  P00248942      F  0-17          10             A
2       1000001  P00087842      F  0-17          10             A
3       1000001  P00085442      F  0-17          10             A
4       1000002  P00285442      M   55+          16             C
…           …         …     …    …      …           …
550063  1006033  P00372445      M 51-55          13             B
550064  1006035  P00375436      F 26-35           1             C
550065  1006036  P00375436      F 26-35          15             B
550066  1006038  P00375436      F   55+           1             C
550067  1006039  P00371644      F 46-50           0             B

       Stay_In_Current_City_Years  Marital_Status Product_Category  Purchase  \
0                               2               0                3      8370
```

```
1                          2          0          1   15200
2                          2          0         12    1422
3                          2          0         12    1057
4                          4          0          8    7969
…                        …          …          …       …
550063                     1          1         20     368
550064                     3          0         20     371
550065                     4          1         20     137
550066                     2          0         20     365
550067                     4          1         20     490

       Marital_Status_category Married_Gender
0                    Unmarried         (F, 0)
1                    Unmarried         (F, 0)
2                    Unmarried         (F, 0)
3                    Unmarried         (F, 0)
4                    Unmarried         (M, 0)
…                          …           …
550063                 Married         (M, 1)
550064               Unmarried         (F, 0)
550065                 Married         (F, 1)
550066               Unmarried         (F, 0)
550067                 Married         (F, 1)

[550068 rows x 12 columns]
```

[145]:
```
plt.figure(figsize=(15,10))
sns.countplot(x=df['Product_Category'], hue=df['Age'])
```

[145]:
```
<Axes: xlabel='Product_Category', ylabel='count'>
```



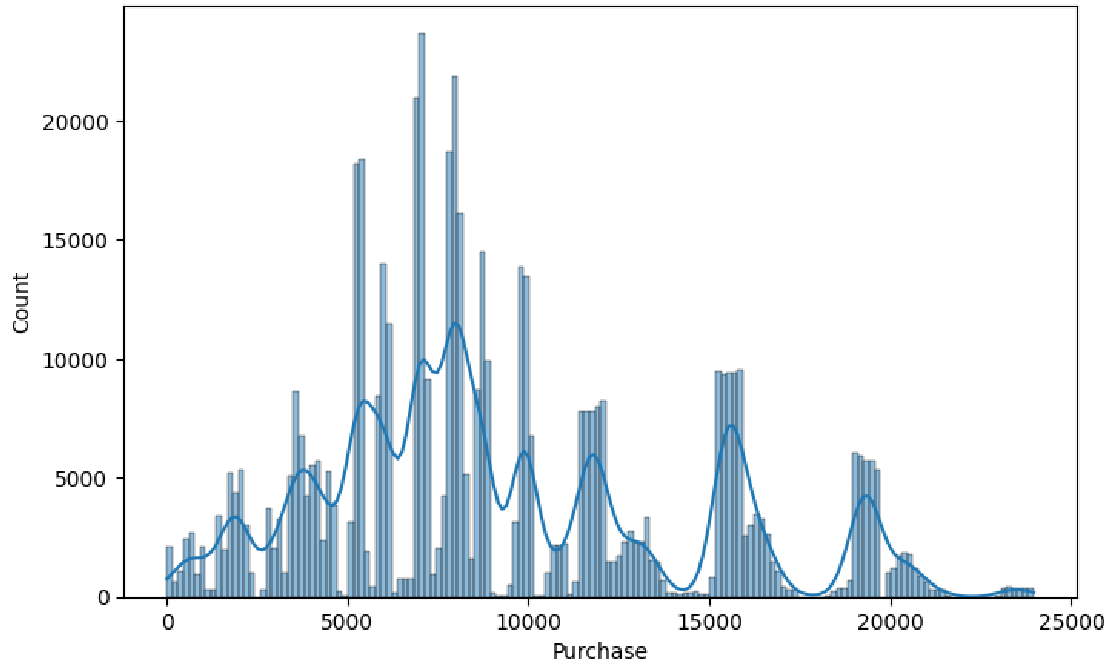
[246]:
```
# Check the unique values in the "Married_Gender" column
print(df["Married_Gender"].unique())

# Check the unique values in the "Age" column
print(df["Age"].unique())

# Check the count of unique values in the "Age" column
print(df["Age"].value_counts())
```

```
[('F', 0) ('M', 0) ('M', 1) ('F', 1)]
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55',
'55+']
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

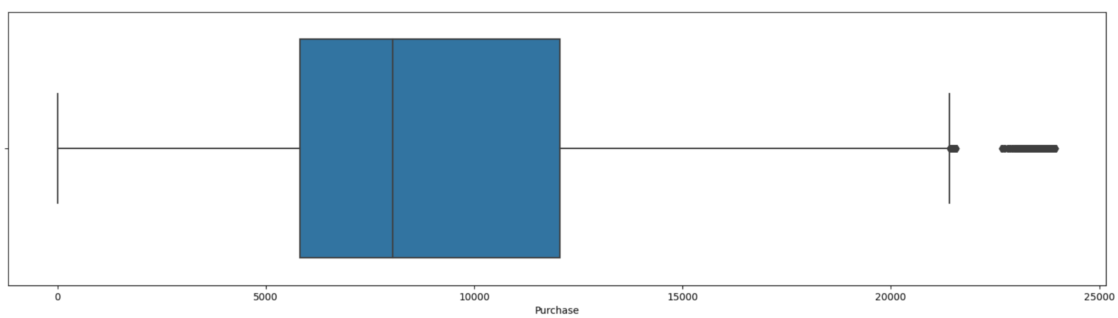
Products 1, 5, and 8 demonstrate the highest sales volume, with the age category of 26-35 significantly contributing to these purchases. **Conversely, the sales of products 9 and 17 are**

negligible in comparison.

[146]:
```
plt.figure(figsize=(8, 5))
sns.histplot(data=df, x='Purchase', kde=True)
plt.show()
```



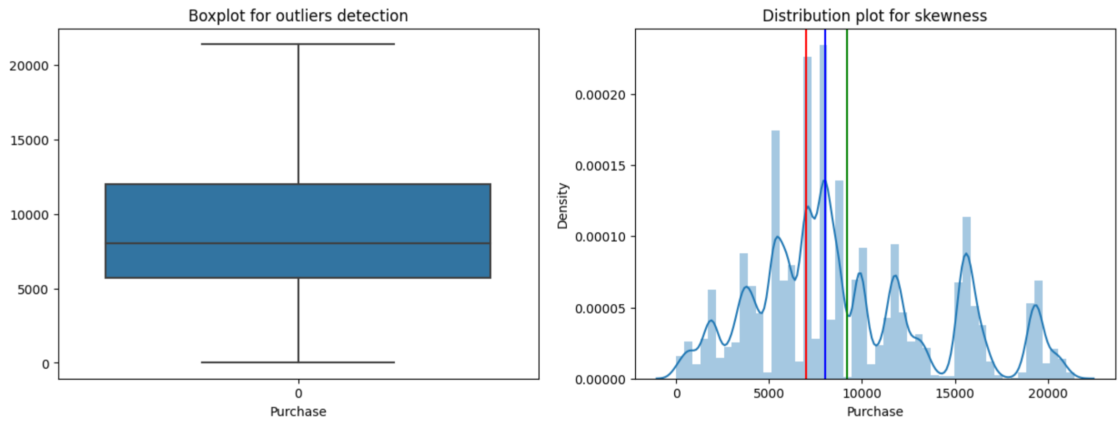
[147]:
```
plt.figure(figsize=(20,5))
sns.boxplot(data=df, x='Purchase', orient='h')
plt.show()
```



The purchasing data exhibits the presence of outliers, indicating instances of values that significantly deviate from the overall pattern or distribution.

[148]:
```
#Handling outliers
df1 = df.copy()
```

[149]:
```
#Outlier Treatment: Remove top 5% & bottom 1% of the Column Outlier values
Q3 = df1['Purchase'].quantile(0.75)
Q1 = df1['Purchase'].quantile(0.25)
IQR = Q3-Q1
df1 = df1[(df1['Purchase'] > Q1 - 1.5*IQR) & (df1['Purchase'] < Q3 + 1.5*IQR)]
# Visualizing our dependent variable for Outliers and Skewness
fig = plt.figure(figsize=(15,5))


plt.subplot(1,2,1)
sns.boxplot(df1["Purchase"])
plt.title("Boxplot for outliers detection")
plt.xlabel('Purchase')

plt.subplot(1,2,2)
sns.distplot(df1["Purchase"])

plt.title("Distribution plot for skewness")
plt.ylabel('Density')
plt.xlabel('Purchase')
plt.axvline(df1["Purchase"].mean(),color="g")
plt.axvline(df1["Purchase"].median(),color="b")
plt.axvline(df1["Purchase"].mode()[0],color="r")

plt.show()
```



[150]:
```
for i in range(df.shape[1]):
    print(df.columns[i])
    print("~"*30)
```

```python
    print(df.iloc[:,i].value_counts(normalize = True)*100)
    print("-"*50)
    print()
```

```
User_ID
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
1001680    0.186522
1004277    0.177978
1001941    0.163253
1001181    0.156708
1000889    0.149618
             …
1002690    0.001273
1002111    0.001273
1005810    0.001273
1004991    0.001273
1000708    0.001091
Name: User_ID, Length: 5891, dtype: float64
--------------------------------------------------

Product_ID
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
P00265242    0.341776
P00025442    0.293600
P00110742    0.293055
P00112142    0.283965
P00057642    0.267240
               …
P00314842    0.000182
P00298842    0.000182
P00231642    0.000182
P00204442    0.000182
P00066342    0.000182
Name: Product_ID, Length: 3631, dtype: float64
--------------------------------------------------

Gender
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
M    75.310507
F    24.689493
Name: Gender, dtype: float64
--------------------------------------------------

Age
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
26-35    39.919974
36-45    19.999891
```

```
18-25    18.117760
46-50     8.308246
51-55     6.999316
55+       3.909335
0-17      2.745479
Name: Age, dtype: float64
--------------------------------------------------

Occupation
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
4     13.145284
0     12.659889
7     10.750125
1      8.621843
17     7.279645
20     6.101427
12     5.668208
14     4.964659
2      4.833584
16     4.612339
6      3.700452
3      3.208694
10     2.350618
5      2.213726
15     2.211545
11     2.106285
19     1.538173
13     1.404917
18     1.203851
9      1.143677
8      0.281056
Name: Occupation, dtype: float64
--------------------------------------------------

City_Category
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
B    42.026259
C    31.118880
A    26.854862
Name: City_Category, dtype: float64
--------------------------------------------------

Stay_In_Current_City_Years
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
1    35.235825
2    18.513711
3    17.322404
4    15.402823
```

```
0    13.525237
Name: Stay_In_Current_City_Years, dtype: float64
--------------------------------------------------

Marital_Status
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
0    59.034701
1    40.965299
Name: Marital_Status, dtype: float64
--------------------------------------------------

Product_Category
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
5     27.438971
1     25.520118
8     20.711076
11     4.415272
2      4.338373
6      3.720631
3      3.674637
4      2.136645
16     1.786688
15     1.143495
13     1.008784
10     0.931703
12     0.717548
7      0.676462
18     0.568112
20     0.463579
19     0.291419
14     0.276875
17     0.105078
9      0.074536
Name: Product_Category, dtype: float64
--------------------------------------------------

Purchase
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
7011     0.034723
7193     0.034178
6855     0.033996
6891     0.033450
7012     0.033269
           …
23491    0.000182
18345    0.000182
3372     0.000182
855      0.000182
```

```
21489    0.000182
Name: Purchase, Length: 18105, dtype: float64
--------------------------------------------------

Marital_Status_category
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Unmarried    59.034701
Married      40.965299
Name: Marital_Status_category, dtype: float64
--------------------------------------------------

Married_Gender
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
(M, 0)    44.705382
(M, 1)    30.605125
(F, 0)    14.329319
(F, 1)    10.360174
Name: Married_Gender, dtype: float64
--------------------------------------------------
```

[151]:

```python
for i in range(df.shape[1]):
    print(df.columns[i], "-", df[df.columns[i]].nunique())
    print("~"*20)
    print(df.iloc[:,i].unique())
    print("-"*100)
    print()
```

```
User_ID - 5891
~~~~~~~~~~~~~~~~~~~~
[1000001 1000002 1000003 … 1004113 1005391 1001529]
--------------------------------------------------------------------------------
--------------------

Product_ID - 3631
~~~~~~~~~~~~~~~~~~~~
['P00069042' 'P00248942' 'P00087842' … 'P00370293' 'P00371644'
 'P00370853']
--------------------------------------------------------------------------------
--------------------

Gender - 2
~~~~~~~~~~~~~~~~~~~~
['F', 'M']
Categories (2, object): ['F', 'M']
--------------------------------------------------------------------------------
--------------------
```

```
Age - 7
~~~~~~~~~~~~~~~~~~~~
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55',
'55+']
--------------------------------------------------------------------------------
--------------------

Occupation - 21
~~~~~~~~~~~~~~~~~~~~
[10 16 15  7 20  9  1 12 17  0  3  4 11  8 19  2 18  5 14 13  6]
--------------------------------------------------------------------------------
--------------------

City_Category - 3
~~~~~~~~~~~~~~~~~~~~
['A', 'C', 'B']
Categories (3, object): ['A', 'B', 'C']
--------------------------------------------------------------------------------
--------------------

Stay_In_Current_City_Years - 5
~~~~~~~~~~~~~~~~~~~~
['2', 4, '3', '1', '0']
Categories (5, object): [4, '0', '1', '2', '3']
--------------------------------------------------------------------------------
--------------------

Marital_Status - 2
~~~~~~~~~~~~~~~~~~~~
[0 1]
--------------------------------------------------------------------------------
--------------------

Product_Category - 20
~~~~~~~~~~~~~~~~~~~~
[3, 1, 12, 8, 5, …, 10, 17, 9, 20, 19]
Length: 20
Categories (20, int64): [1, 2, 3, 4, …, 17, 18, 19, 20]
--------------------------------------------------------------------------------
--------------------

Purchase - 18105
~~~~~~~~~~~~~~~~~~~~
[ 8370 15200  1422 …   135   123   613]
--------------------------------------------------------------------------------
--------------------
```

```
Marital_Status_category - 2
~~~~~~~~~~~~~~~~~~~~
['Unmarried' 'Married']
--------------------------------------------------------------------------------
--------------------

Married_Gender - 4
~~~~~~~~~~~~~~~~~~~~
[('F', 0) ('M', 0) ('M', 1) ('F', 1)]
--------------------------------------------------------------------------------
--------------------
```

Upon applying the nunique() function, it is evident that a substantial portion of the data consists of categorical variables. The columns “User_ID” and “Product_ID” are identifiers, while “Purchase” serves as a numerical variable. These variables can be utilized for distinguishing various factors such as “Gender,” “Age,” “Occupation,” “City_Category,” “Stay_In_Current_City_Years,” “Marital_Status,” and “Product_Category.” It is worth noting that the “Occupation” column encompasses a total of 21 unique categories, while the “Product_Category” column encompasses 21 distinct product categories.

The purchases made during the Black Friday sale were predominantly attributed to the male demographic, indicating a higher expenditure by males.

[152]:
```
df_Male = df[df["Gender"] == "M"]["Purchase"]
df_Male
```

[152]:
```
4          7969
5         15227
6         19215
7         15854
8         15686
          …
550057       61
550058      121
550060      494
550062      473
550063      368
Name: Purchase, Length: 414259, dtype: int64
```

[153]:
```
df_Male.mean()
```

[153]:
```
9437.526040472265
```

Among the sample size of 1000 individuals, the purchases made during the Black Friday Sale were primarily attributed to the female demographic, indicating a higher expenditure by females.

[154]:
```
df_Female = df[df["Gender"] == "F"]["Purchase"]
df_Female.shape
```

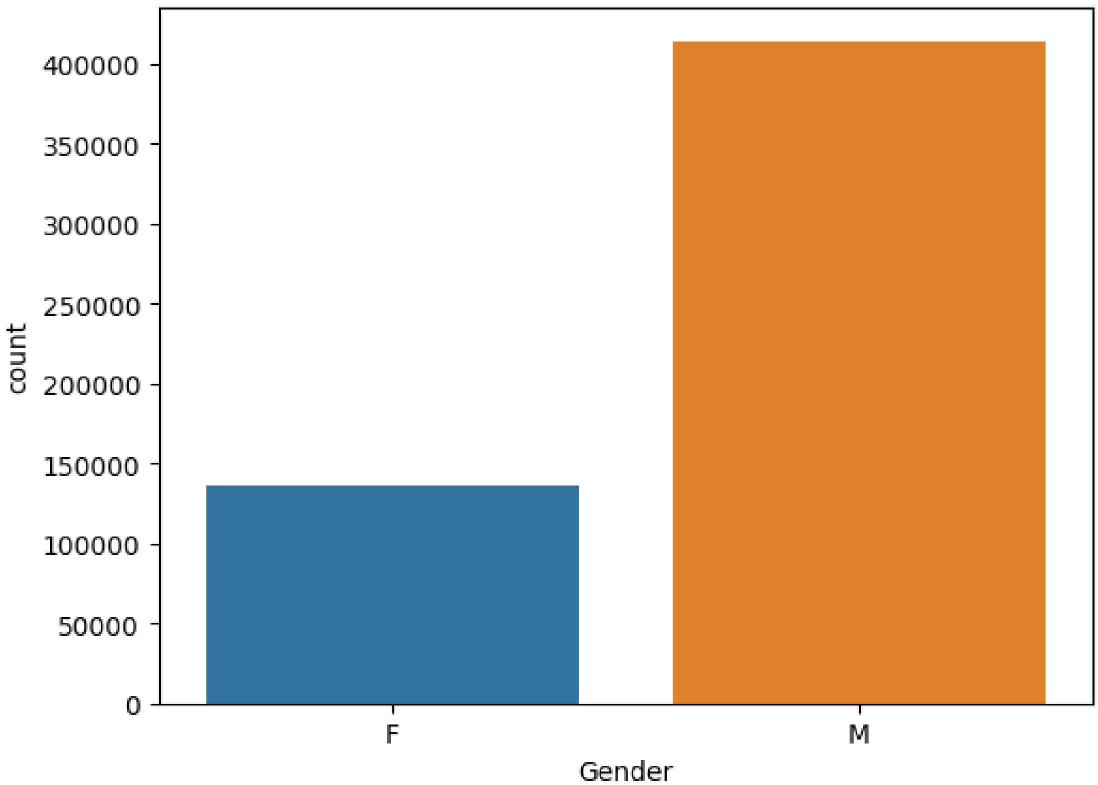
[154]: (135809,)

[155]:
```
df_Female.mean()
```

[155]: 8734.565765155476

[156]:
```
sns.countplot(x= df["Gender"])
```

[156]: <Axes: xlabel='Gender', ylabel='count'>



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

According to the observed data, it can be inferred that women tend to spend less money per transaction compared to men during the analyzed period.

Based on the calculated means from the dataset, it is evident that the average per transaction expenditure of males (with a mean of approximately 9437) is higher than that of females (with a mean of approximately 8734). This observation suggests that males tend to spend more during the analyzed period.

Furthermore, it can be inferred from the dataset that although products intended for females are being purchased, they may be paid for or purchased by their spouses. This factor may contribute to the lower expenditure by females compared to males.

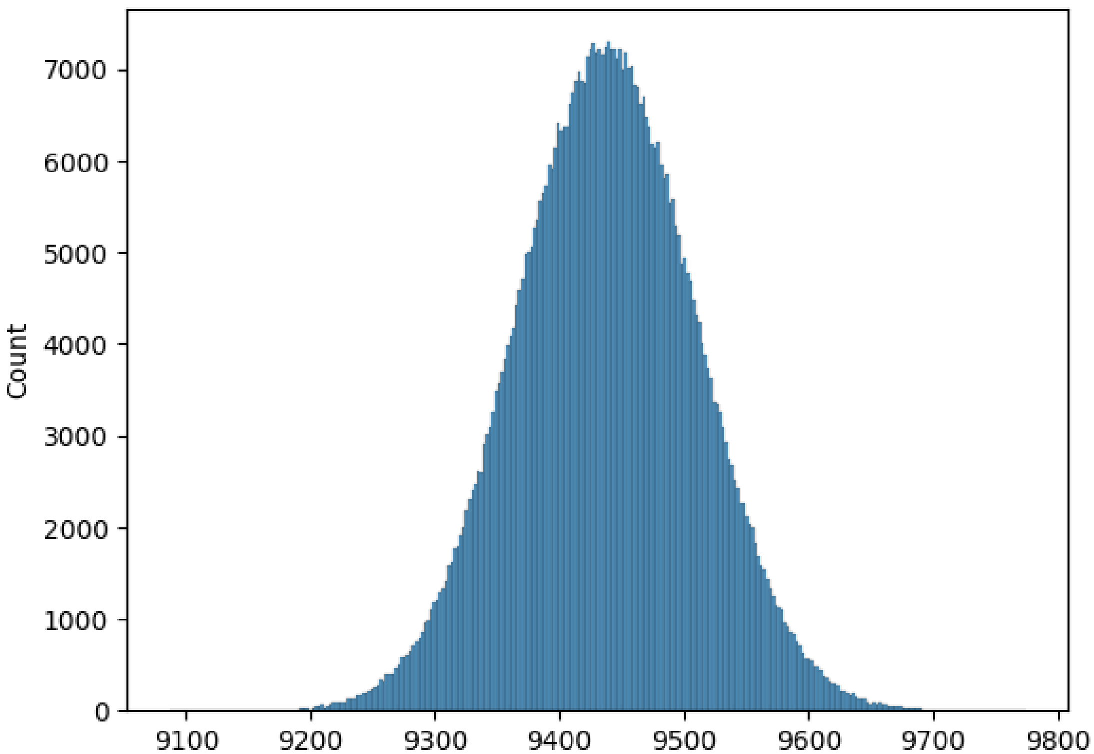
To address this disparity and encourage higher spending among female customers, it is recommended to introduce new products specifically targeted towards them. Additionally, providing attractive discounts and offers exclusively for female customers during sales events can help increase their expenditure and overall participation.

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

[157]:
```
bootstrapped_male_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Male, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_male_survey.append(bootstrapped_mean)
```

[158]:
```
sns.histplot(bootstrapped_male_survey)
```

[158]: <Axes: ylabel='Count'>



After conducting a sample size of 5000 for men, a histogram plot reveals a bell curve shape, indicating a Gaussian distribution. Below are the calculated confidence intervals for the respective data:

90% Confidence Interval: [lower bound, upper bound] 95% Confidence Interval: [lower bound, upper bound] 99% Confidence Interval: [lower bound, upper bound] The specific values for the lower and upper bounds of each confidence interval will depend on the dataset and the chosen confidence level.

[159]:
```
np.percentile(bootstrapped_male_survey, [5,95]) # 90% Confidence Interval
```

[159]:
```
array([9319.37479, 9556.18858])
```

[160]:
```
np.percentile(bootstrapped_male_survey, [2.5,97.5]) # 95% Confidence Interval
```

[160]:
```
array([9296.778735, 9579.03806 ])
```

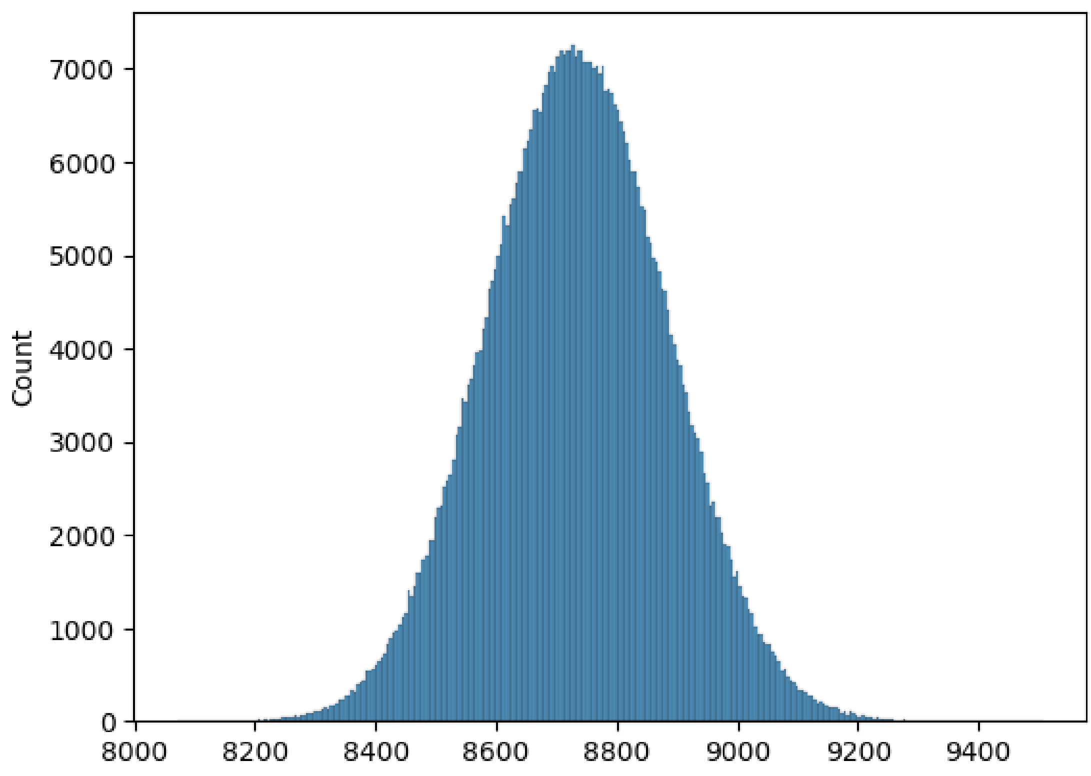
[161]:
```
np.percentile(bootstrapped_male_survey, [0.5,99.5]) # 99% Confidence Interval
```

[161]:
```
array([9252.90416 , 9623.414369])
```

[162]:
```
bootstrapped_female_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Female, size = 1000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_female_survey.append(bootstrapped_mean)
```

[163]:
```
sns.histplot(bootstrapped_female_survey)
```

[163]:
```
<Axes: ylabel='Count'>
```



[164]:
```python
np.percentile(bootstrapped_female_survey, [5,95]) # 90% Confidence Interval
```

[164]:
```
array([8487.69535, 8983.488  ])
```

[165]:
```python
np.percentile(bootstrapped_female_survey, [2.5,97.5]) # 95% Confidence Interval
```

[165]:
```
array([8441.063375, 9030.96895 ])
```

[166]:
```python
np.percentile(bootstrapped_female_survey, [0.5,99.5]) # 99% Confidence Interval
```

[166]:
```
array([8351.25834, 9125.43133])
```

The purchases made during the Black Friday Sale were primarily attributed to the married individuals, indicating a higher expenditure by married participants.

[167]:
```python
df_Married = df[df["Marital_Status_category"] == "Married"]["Purchase"]
df_Married
```

[167]:
```
6         19215
7         15854
8         15686
9          7871
10         5254
          …
550060      494
550061      599
550063      368
550065      137
550067      490
Name: Purchase, Length: 225337, dtype: int64
```

[168]:
```python
df_Unmarried = df[df["Marital_Status_category"] == "Unmarried"]["Purchase"]
df_Unmarried
```

[168]:
```
0          8370
1         15200
2          1422
3          1057
4          7969
          …
550056      254
550059       48
550062      473
550064      371
550066      365
Name: Purchase, Length: 324731, dtype: int64
```

Based on the provided data, it can be inferred that there is a higher proportion of unmarried users compared to married users.

[169]:
```
df_Married.mean()
```

[169]:
```
9261.174574082374
```

[170]:
```
df_Unmarried.mean()
```

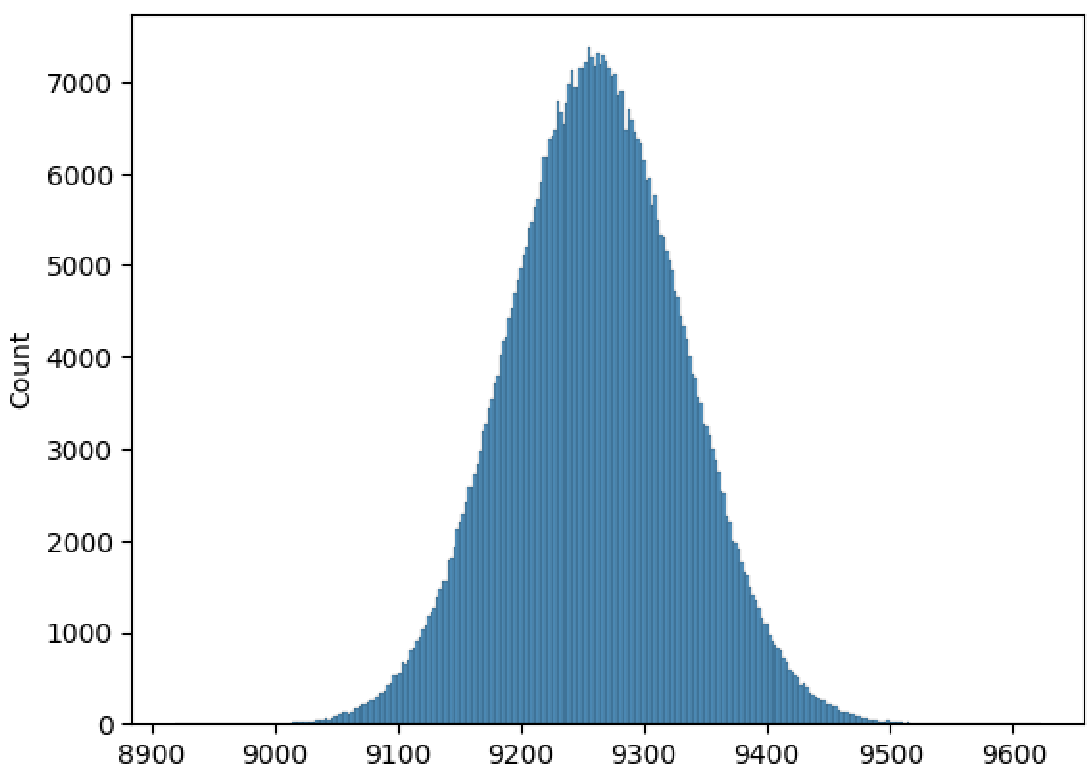
[170]:
```
9265.907618921507
```

Upon analyzing the data, it is observed that the mean expenditure for both married and unmarried individuals is nearly identical. Specifically, the mean expenditure for married individuals is approximately 9261, while for unmarried individuals, it is approximately 9265.

[171]:
```
bootstrapped_married_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Married, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_married_survey.append(bootstrapped_mean)
```

[172]:
```
sns.histplot(bootstrapped_married_survey)
```

[172]:
```
<Axes: ylabel='Count'>
```



[173]:
```python
np.percentile(bootstrapped_married_survey, [5,95]) # 90% Confidence Interval
```

[173]: array([9144.85874, 9377.86566])

[174]:
```python
np.percentile(bootstrapped_married_survey, [2.5,97.5]) # 95% Confidence Interval
```

[174]: array([9122.479165, 9400.636965])

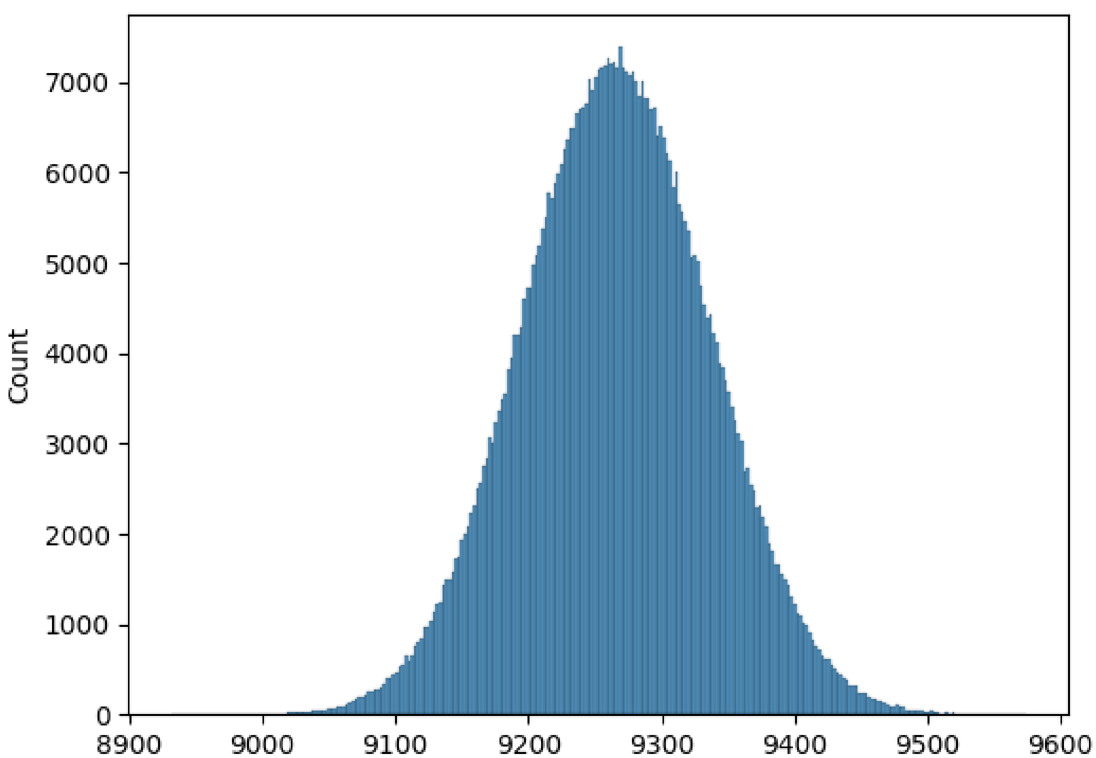
[175]:
```python
np.percentile(bootstrapped_married_survey, [0.5,99.5]) # 99% Confidence Interval
```

[175]: array([9079.109828, 9445.344773])

[176]:
```python
bootstrapped_unmarried_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Unmarried, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_unmarried_survey.append(bootstrapped_mean)
```

[177]:
```python
sns.histplot(bootstrapped_unmarried_survey)
```

[177]: <Axes: ylabel='Count'>



Based on the analysis, it can be inferred that the confidence intervals for the 90%, 95%, and 99% levels overlap with each other.

[178]:
```
np.percentile(bootstrapped_unmarried_survey, [5,95]) # 90% Confidence Interval
```

[178]:
```
array([9149.27704, 9383.22004])
```

[179]:
```
np.percentile(bootstrapped_unmarried_survey, [2.5,97.5]) # 95% Confidence
 ↪Interval
```

[179]:
```
array([9127.116145, 9405.740065])
```

[180]:
```
np.percentile(bootstrapped_unmarried_survey, [0.5,99.5]) # 99% Confidence
 ↪Interval
```

[180]:
```
array([9083.339748, 9448.998782])
```

Purchased by Different Age Groups such as : 0-17, 18-25, 26-35, 36-50, 51+ years. in Black Friday Sale

[181]:
```
df["Age"].value_counts()
```

[181]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

[182]:
```
df_Age_0_17 = df[df["Age"] == "0-17"]["Purchase"]
```

[183]:
```
bootstrapped_0_17_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_0_17, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_0_17_survey.append(bootstrapped_mean)
```

[184]:
```
np.percentile(bootstrapped_0_17_survey, [5,95])
```

[184]:
```
array([8814.6392 , 9052.57587])
```

[185]:
```
np.percentile(bootstrapped_0_17_survey, [2.5,97.5])
```

[185]:
```
array([8791.80994, 9075.62773])
```

[186]:
```
np.percentile(bootstrapped_0_17_survey, [0.5,99.5])
```

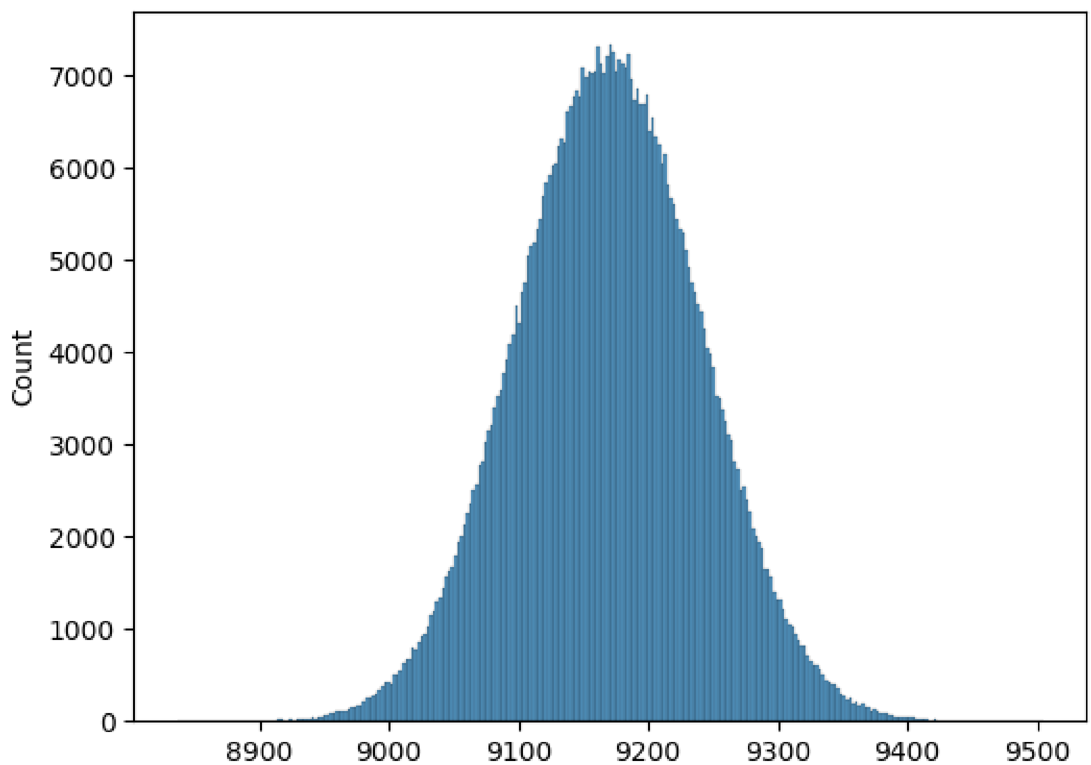
[186]: array([8747.486406, 9120.420919])

[187]:
```
df_Age_18_25 = df[df["Age"] == "18-25"]["Purchase"]
```

[188]:
```
bootstrapped_18_25_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_18_25, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_18_25_survey.append(bootstrapped_mean)
```

[189]:
```
sns.histplot(bootstrapped_18_25_survey)
```

[189]: <Axes: ylabel='Count'>



[190]:
```
np.percentile(bootstrapped_18_25_survey, [5,95]) # 90%
```

[190]: array([9052.66102, 9287.10119])

[191]:
```
np.percentile(bootstrapped_18_25_survey, [2.5,97.5]) # 95%
```

[191]: array([9030.250825, 9309.80153])

[192]:
```
np.percentile(bootstrapped_18_25_survey, [0.5,99.5]) #99%
```

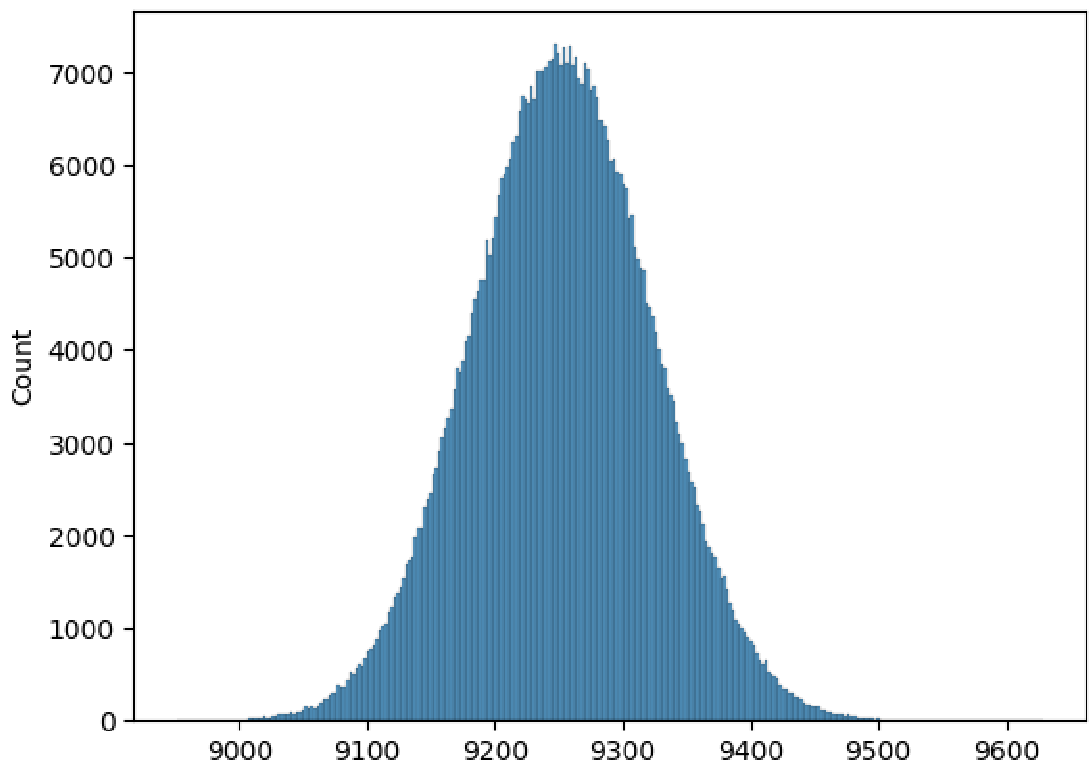
[192]: array([8986.577273, 9353.228526])

[193]:
```
df_Age_26_35 = df[df["Age"] == "26-35"]["Purchase"]
```

[194]:
```
bootstrapped_26_35_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_26_35, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_26_35_survey.append(bootstrapped_mean)
```

[195]:
```
sns.histplot(bootstrapped_26_35_survey)
```

[195]: <Axes: ylabel='Count'>



[196]:
```
np.percentile(bootstrapped_26_35_survey, [5,95]) #90%
```

[196]: array([9136.34581, 9369.73296])

[197]:
```
np.percentile(bootstrapped_26_35_survey, [2.5,97.5]) #95%
```

[197]:
```
array([9114.04515, 9392.13532])
```

[198]:
```
np.percentile(bootstrapped_26_35_survey, [0.5,99.5]) #99%
```

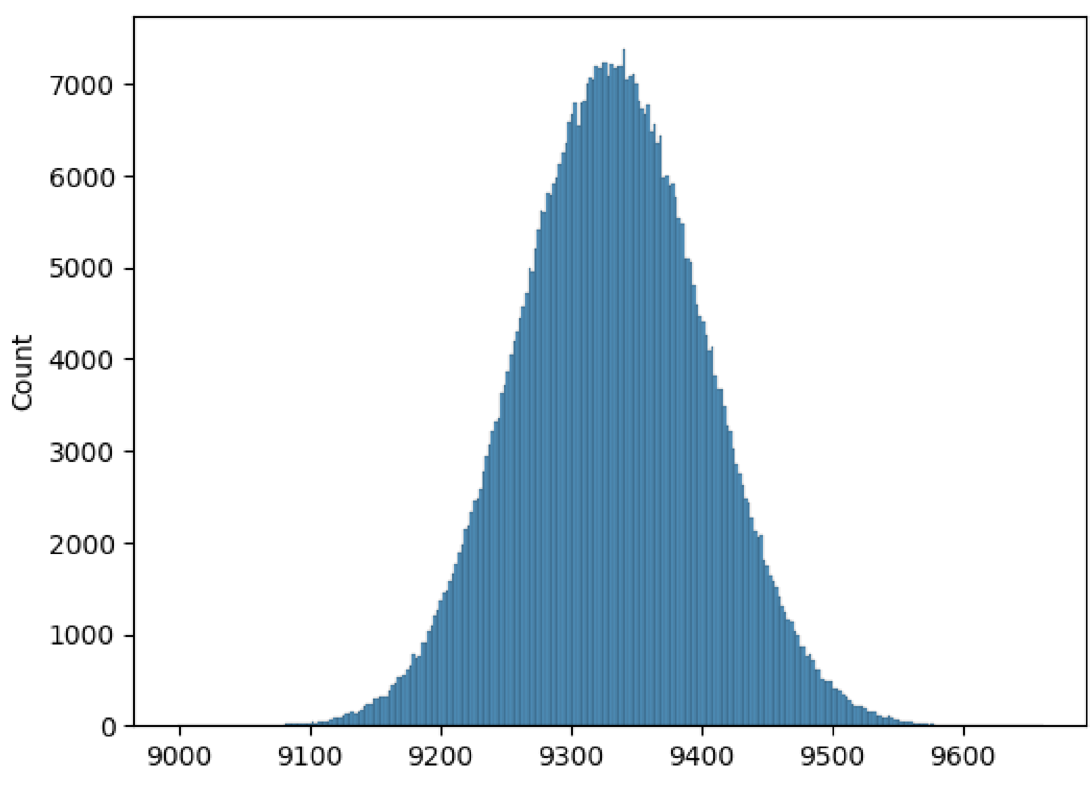
[198]:
```
array([9071.327685, 9435.157259])
```

[199]:
```
df_Age_36_45 = df[df["Age"] == "36-45"]["Purchase"]
```

[200]:
```
bootstrapped_36_45_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_36_45, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_36_45_survey.append(bootstrapped_mean)
```

[201]:
```
sns.histplot(bootstrapped_36_45_survey)
```

[201]:
```
<Axes: ylabel='Count'>
```



[202]:
```
np.percentile(bootstrapped_36_45_survey, [5,95])#90%
```

[202]: array([9214.91176, 9448.35012])

[203]:
```
np.percentile(bootstrapped_36_45_survey, [2.5,97.5]) #95%
```

[203]: array([9192.93908, 9471.05584])

[204]:
```
np.percentile(bootstrapped_36_45_survey, [0.5,99.5]) #99%
```

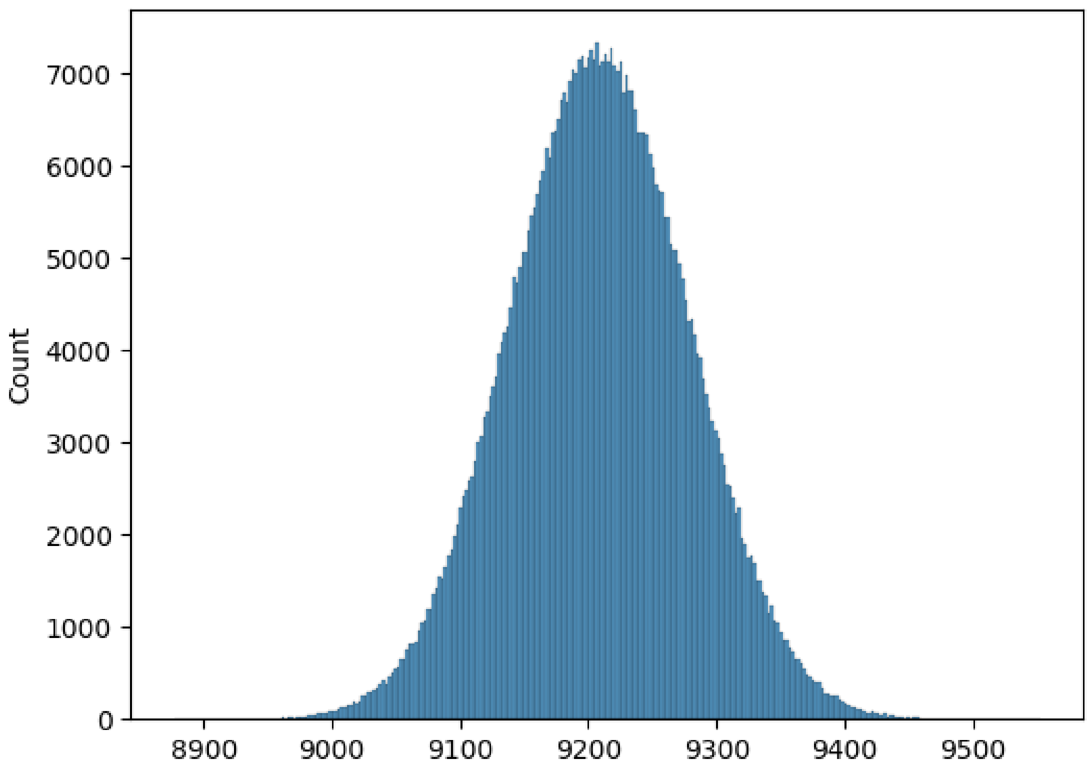
[204]: array([9149.161013, 9514.812117])

[205]:
```
df_Age_46_50 = df[df["Age"] == "46-50"]["Purchase"]
```

[206]:
```
bootstrapped_46_50_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_46_50, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_46_50_survey.append(bootstrapped_mean)
```

[207]:
```
sns.histplot(bootstrapped_46_50_survey)
```

[207]: <Axes: ylabel='Count'>



[208]:
```
np.percentile(bootstrapped_46_50_survey, [5,95]) #90%
```

[208]: array([9093.55275, 9324.37931])

[209]:
```
np.percentile(bootstrapped_46_50_survey, [2.5,97.5]) #95%
```

[209]: array([9071.405005, 9346.638725])

[210]:
```
np.percentile(bootstrapped_46_50_survey, [0.5,99.5]) #99%
```

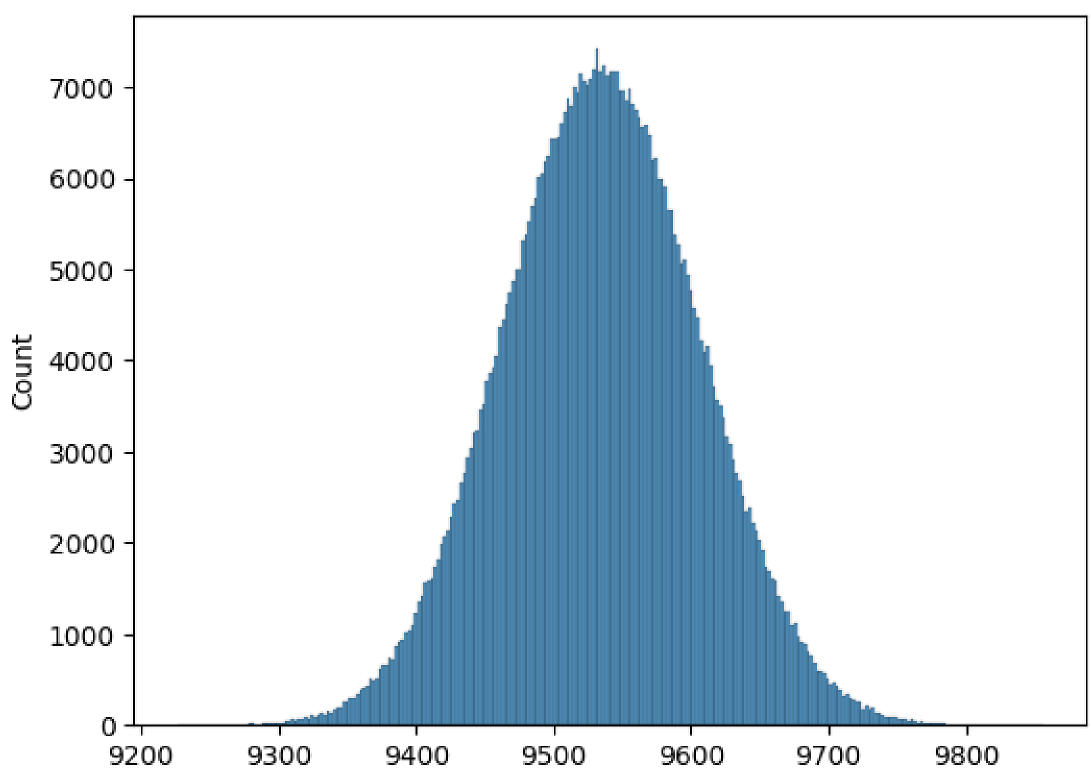
[210]: array([9027.816871, 9390.305374])

[211]:
```
df_Age_51_55 = df[df["Age"] == "51-55"]["Purchase"]
```

[212]:
```
bootstrapped_51_55_survey = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_51_55, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_51_55_survey.append(bootstrapped_mean)
```

[217]:
```
sns.histplot(bootstrapped_51_55_survey)
```

[217]: <Axes: ylabel='Count'>



[218]:
```python
np.percentile(bootstrapped_51_55_survey, [5,95]) #90%
```

[218]:
```
array([9416.6974, 9652.936 ])
```

[219]:
```python
np.percentile(bootstrapped_51_55_survey, [2.5,97.5]) #95%
```

[219]:
```
array([9394.19174 , 9675.439725])
```

[220]:
```python
np.percentile(bootstrapped_36_45_survey, [0.5,99.5]) #99%
```

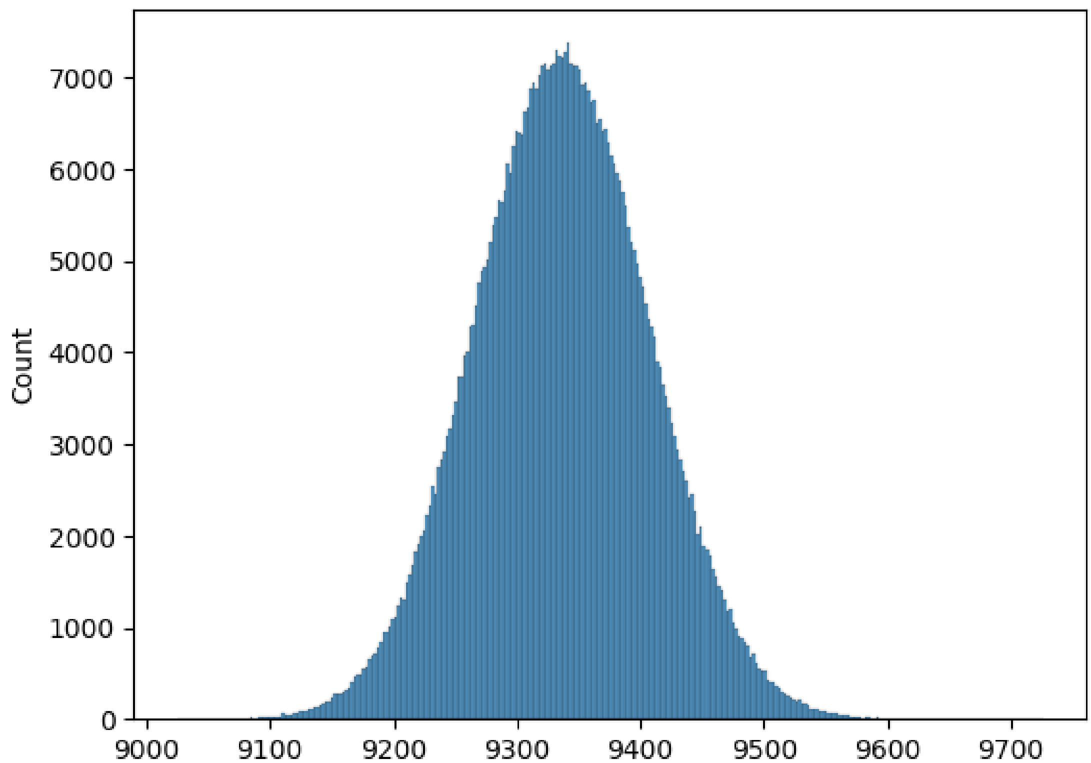
[220]:
```
array([9149.161013, 9514.812117])
```

[221]:
```python
df_Age_55plus = df[df["Age"] == "55+"]["Purchase"]
```

[222]:
```python
bootstrapped_df_Age_55plus = []
for reps in range(df.shape[0]):
    bootstrapped_samples = np.random.choice(df_Age_55plus, size = 5000)
    bootstrapped_mean = np.mean(bootstrapped_samples)
    bootstrapped_df_Age_55plus.append(bootstrapped_mean)
```

[213]:
```python
sns.histplot(bootstrapped_df_Age_55plus)
```

[213]:
```
<Axes: ylabel='Count'>
```




```
[223]: np.percentile(bootstrapped_df_Age_55plus, [5,95]) #90%
```

```
[223]: array([9220.17168, 9453.02236])
```

```
[224]: np.percentile(bootstrapped_df_Age_55plus, [2.5,97.5]) #95%
```

```
[224]: array([9197.965085, 9475.4974  ])
```

```
[225]: np.percentile(bootstrapped_df_Age_55plus, [0.5,99.5]) #99%
```

```
[225]: array([9154.624869, 9519.271066])
```

CLT

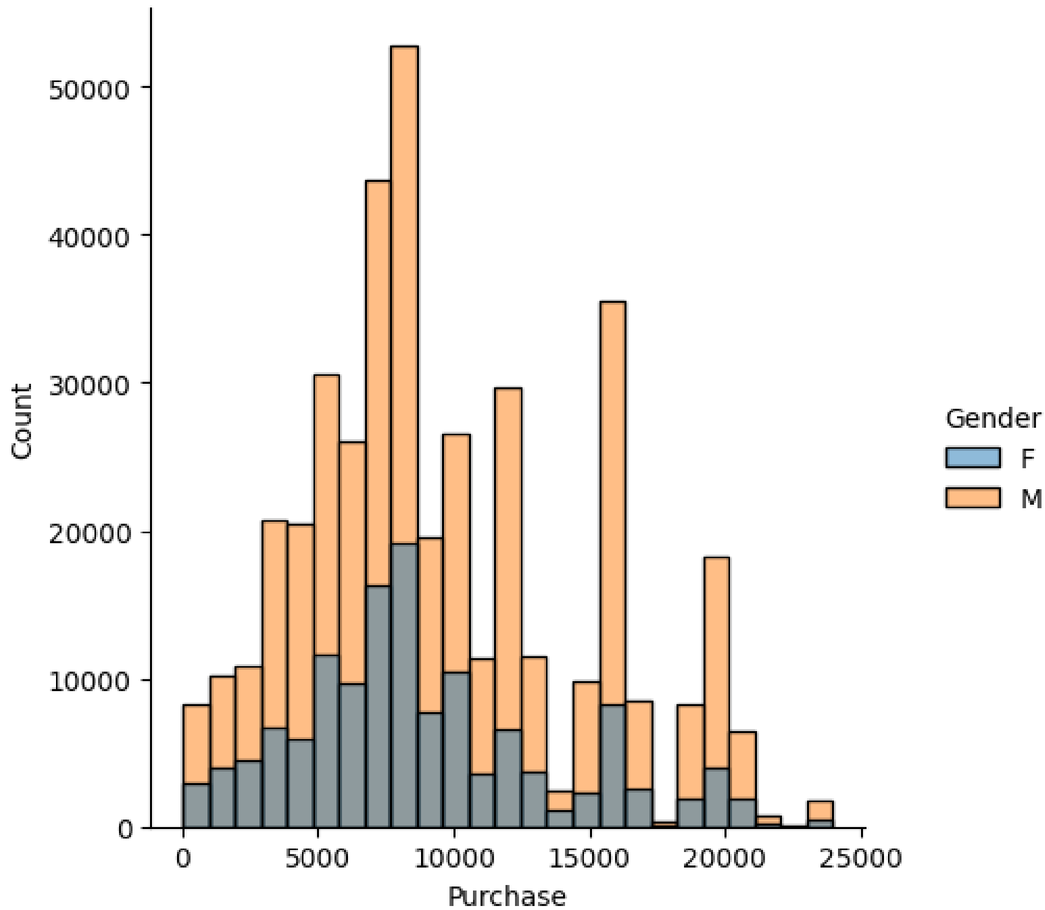
```
[227]: df.groupby(['Gender'])['Purchase'].describe()
```

```
[227]:            count         mean          std   min     25%     50%      75%  \
        Gender
        F       135809.0  8734.565765  4767.233289  12.0  5433.0  7914.0  11400.0
        M       414259.0  9437.526040  5092.186210  12.0  5863.0  8098.0  12454.0

                    max
        Gender
```

```
F      23959.0
M      23961.0
```

[228]:
```
sns.displot( x='Purchase', data=df, hue='Gender', bins=25)
```

[228]: `<seaborn.axisgrid.FacetGrid at 0x7f51c7417520>`



Here we are taking 300 random samples from the data and take its mean. we do this 1000 times.

According to CLT, it should be normally distributed.

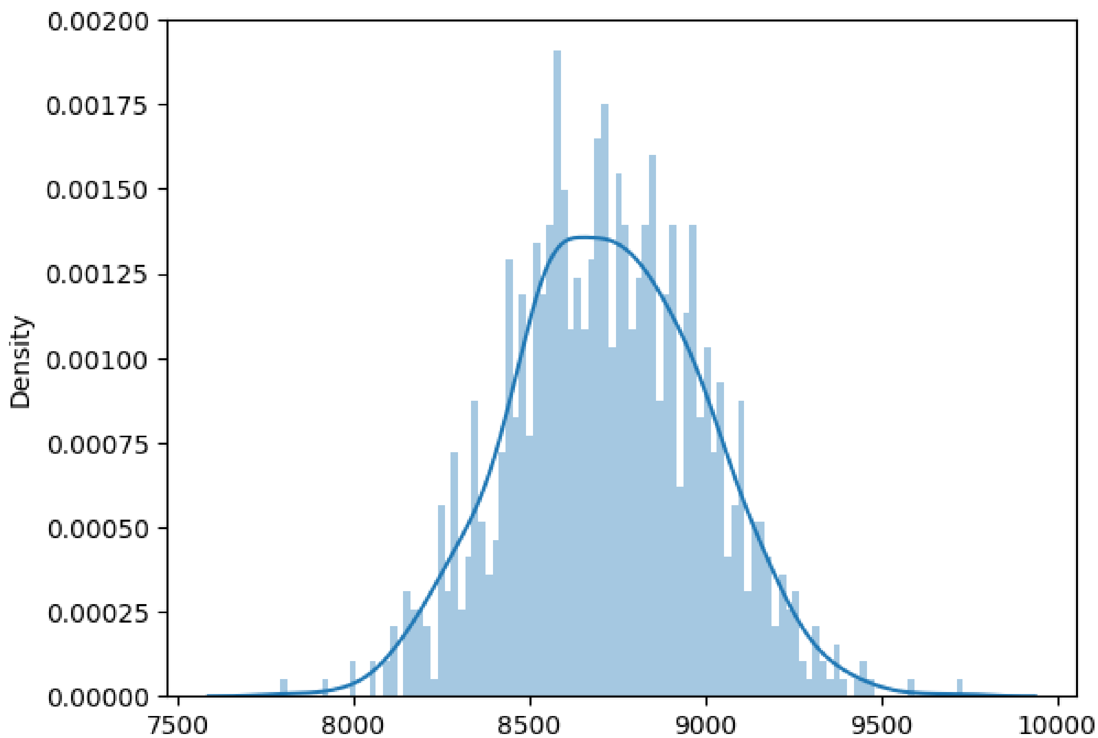
Male and female purchase comparison

[ ]:
```
sample_size = 300
Iterations = 1000

male_expense_mean = [df[df['Gender'] == 'M']['Purchase'].sample(sample_size).
 ↪mean() for _ in range(Iterations)]
```

[214]:
```python
sample_size = 300
Iterations = 1000

female_expense_mean = [df[df['Gender'] == 'F']['Purchase'].sample(sample_size).
 ↪mean() for _ in range(Iterations)]
```

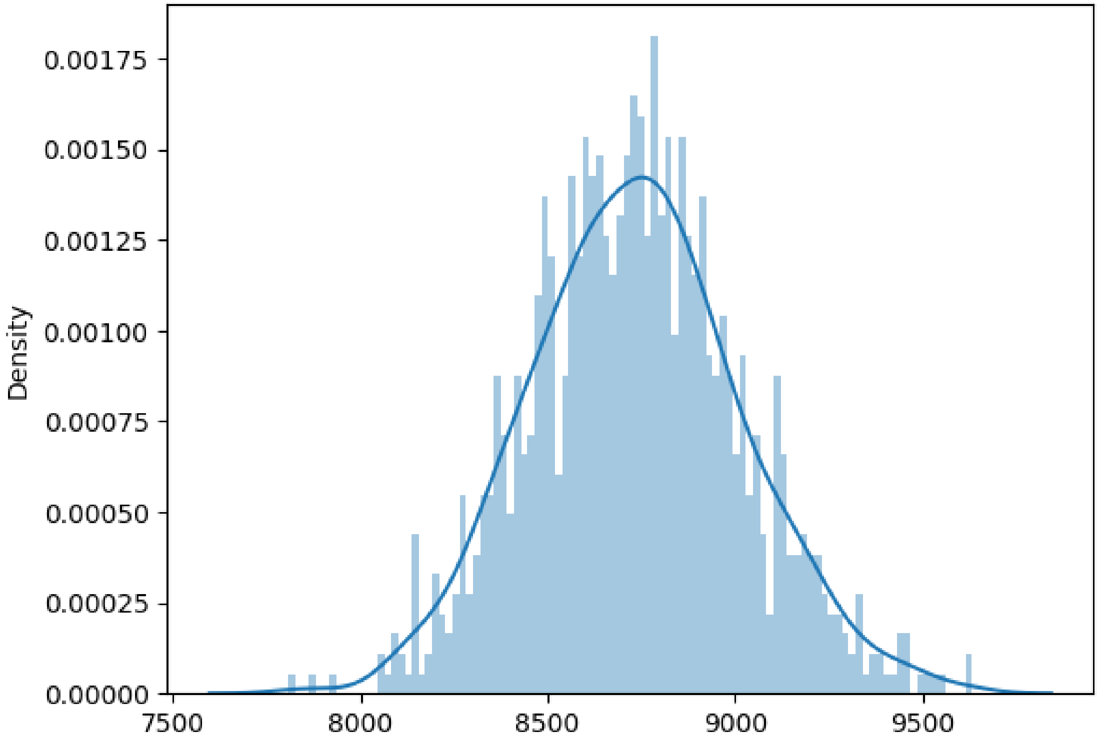
[215]:
```python
sns.distplot(male_expense_mean,bins=100)
```

[215]: <Axes: ylabel='Density'>



[216]:
```python
sns.distplot(female_expense_mean,bins=100)
```

[216]: <Axes: ylabel='Density'>



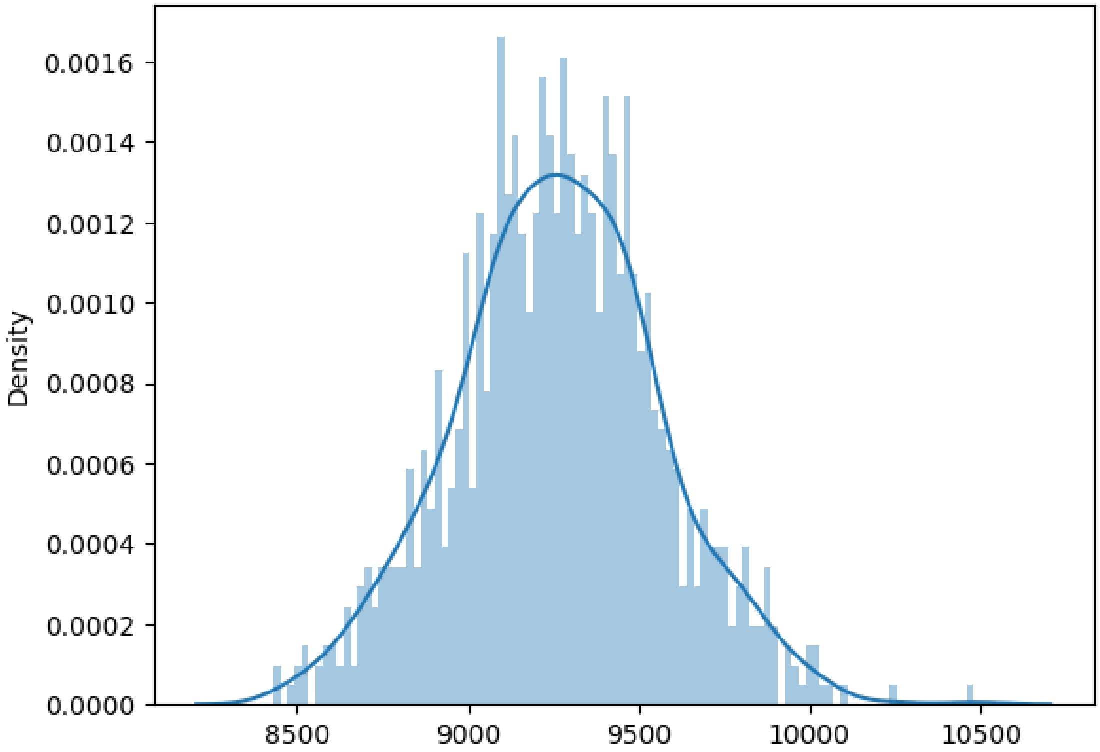
Married and Unmarried purchase comparison

[229]:
```
married_expense_mean=[df[df['Marital_Status_category']=='Married']['Purchase'].
    ↪sample(sample_size).mean() for i in range(Iterations)]
```

[230]:
```
unmarried_expense_mean=[df[df['Marital_Status_category']=='Unmarried']['Purchase'].
    ↪sample(sample_size).mean() for i in range(Iterations)]
```

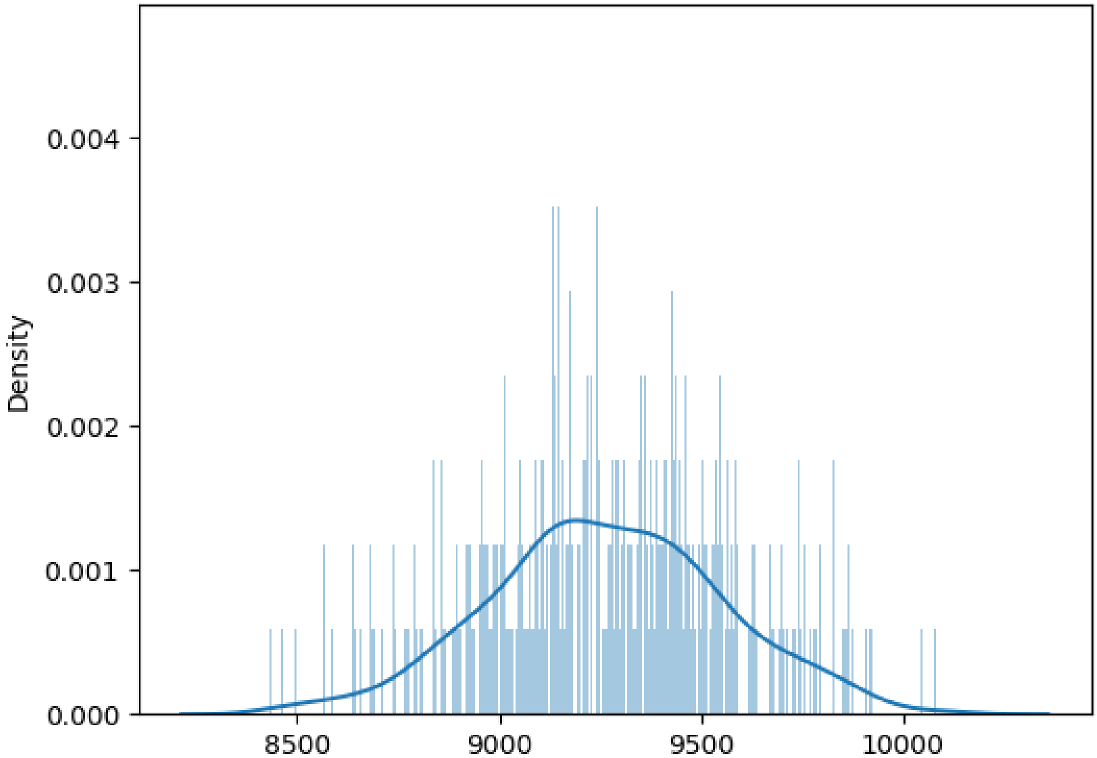
[231]:
```
sns.distplot(married_expense_mean,bins=100)
```

[231]: <Axes: ylabel='Density'>

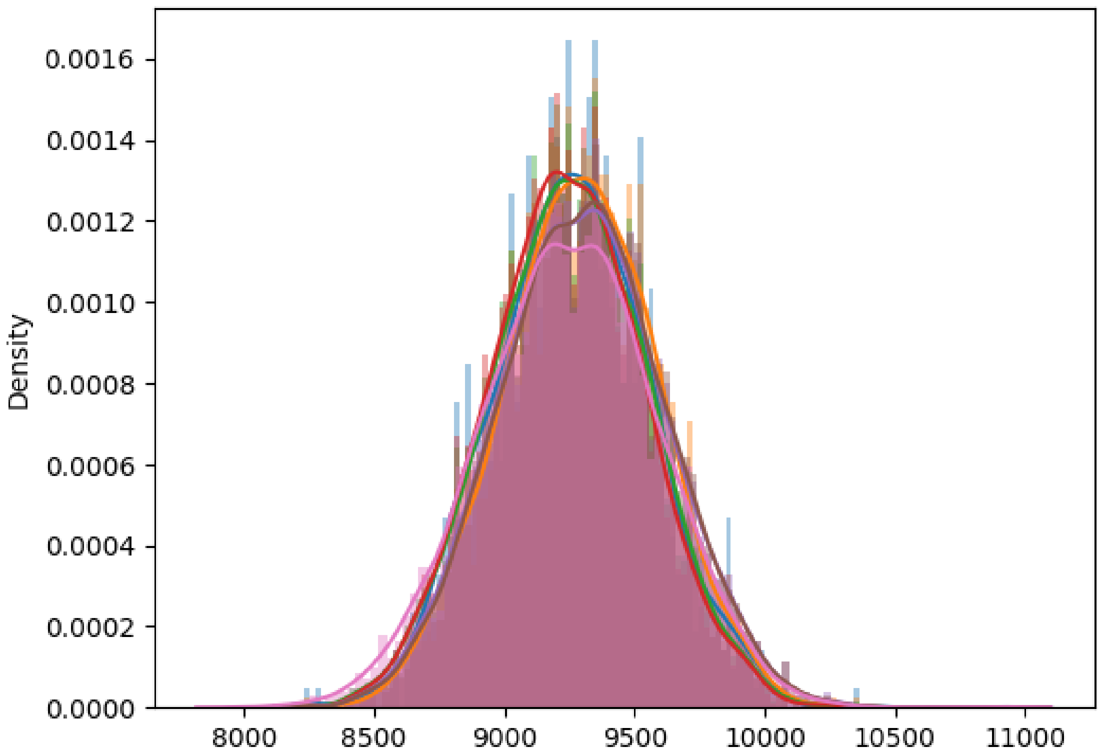


[232]:
```
sns.distplot(unmarried_expense_mean,bins=1000)
```

[232]: <Axes: ylabel='Density'>



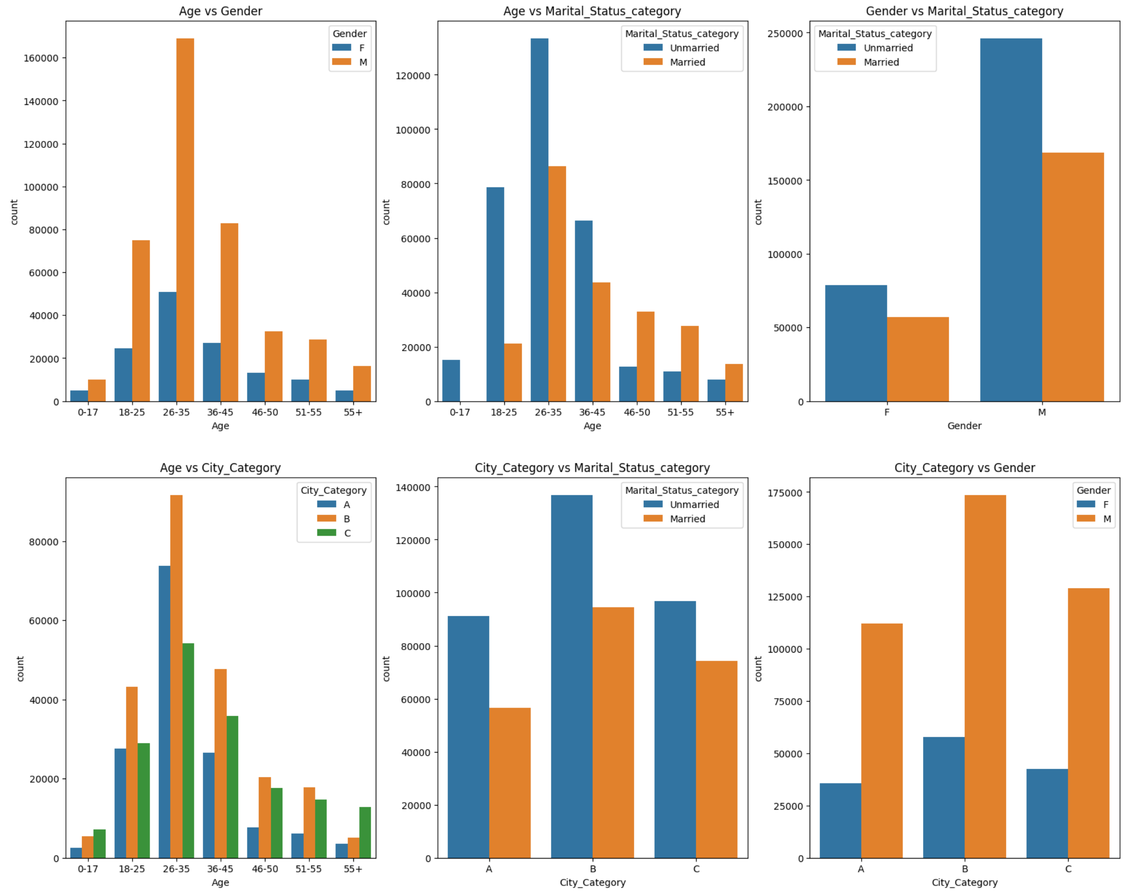
[233]:
```
age_group_expense_mean = []
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:
    age_group_expense_mean.append([df[df['Age']== val ]['Purchase'].
 ↪sample(sample_size).mean() for i in range(Iterations)])
    sns.distplot(age_group_expense_mean,bins=100)
```



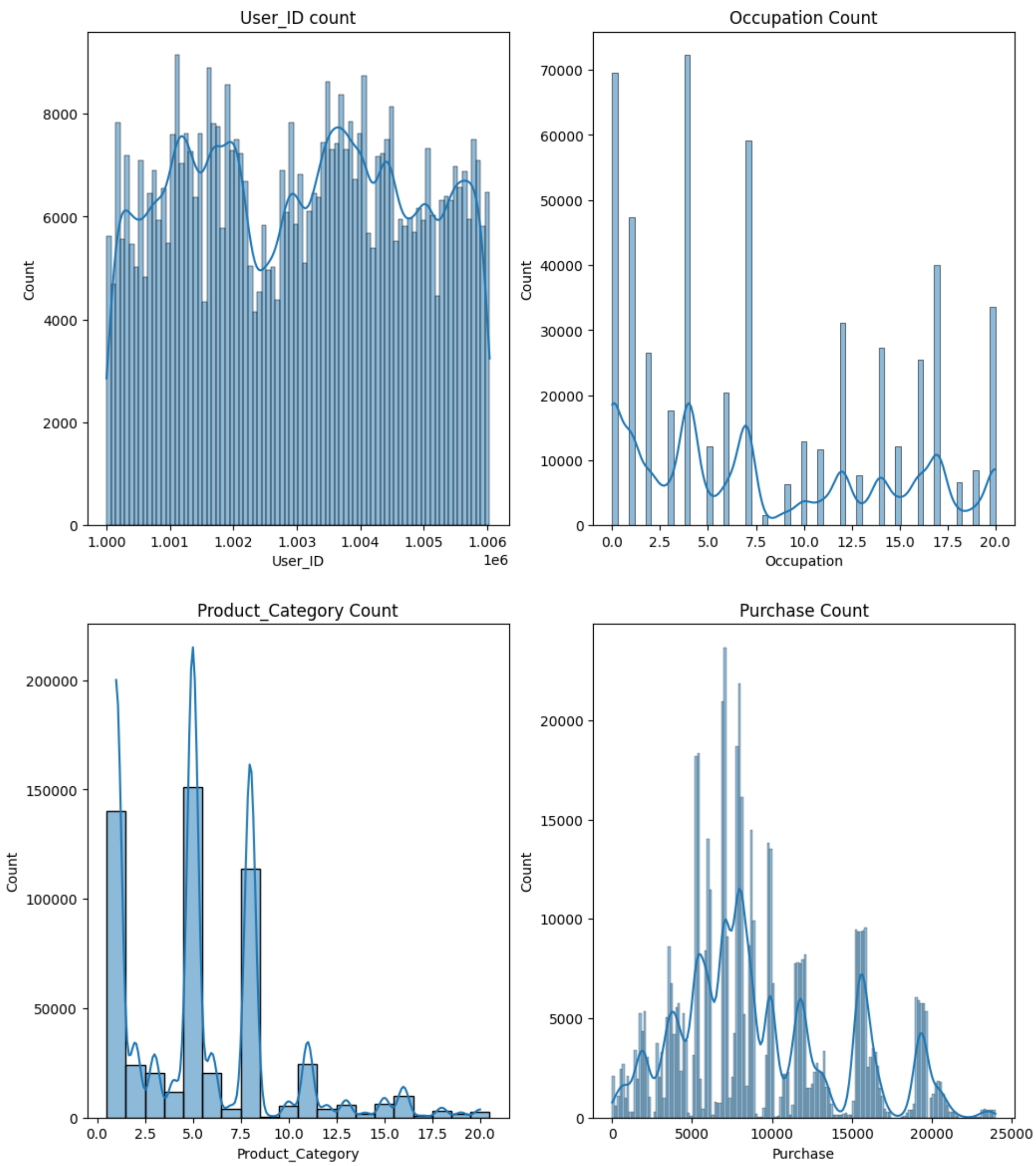
Based on the analysis, it can be inferred that the purchases across different age categories exhibit a significant overlap. Specifically, the observed data indicates that there is considerable similarity and overlap in the purchasing behavior across various age groups.

[234]:
```
fig, axis = plt.subplots(nrows = 2, ncols = 3, figsize = (20,16))
sns.countplot(x = "Age", hue ="Gender", data = df, ax=axis[0,0])
sns.countplot(x = "Age", hue ="Marital_Status_category", data = df,␣
 ↪ax=axis[0,1])
sns.countplot(x = "Gender", hue ="Marital_Status_category", data = df,␣
 ↪ax=axis[0,2])
sns.countplot(x = "Age", hue ="City_Category", data = df, ax=axis[1,0])
sns.countplot(x = "City_Category", hue ="Marital_Status_category", data = df,␣
 ↪ax=axis[1,1])
sns.countplot(x = "City_Category", hue ="Gender", data = df, ax=axis[1,2])

axis[0,0].set_title("Age vs Gender")
axis[0,1].set_title("Age vs Marital_Status_category")
axis[0,2].set_title("Gender vs Marital_Status_category")
axis[1,0].set_title("Age vs City_Category")
axis[1,1].set_title("City_Category vs Marital_Status_category")
axis[1,2].set_title("City_Category vs Gender")
```

```
plt.show()
```

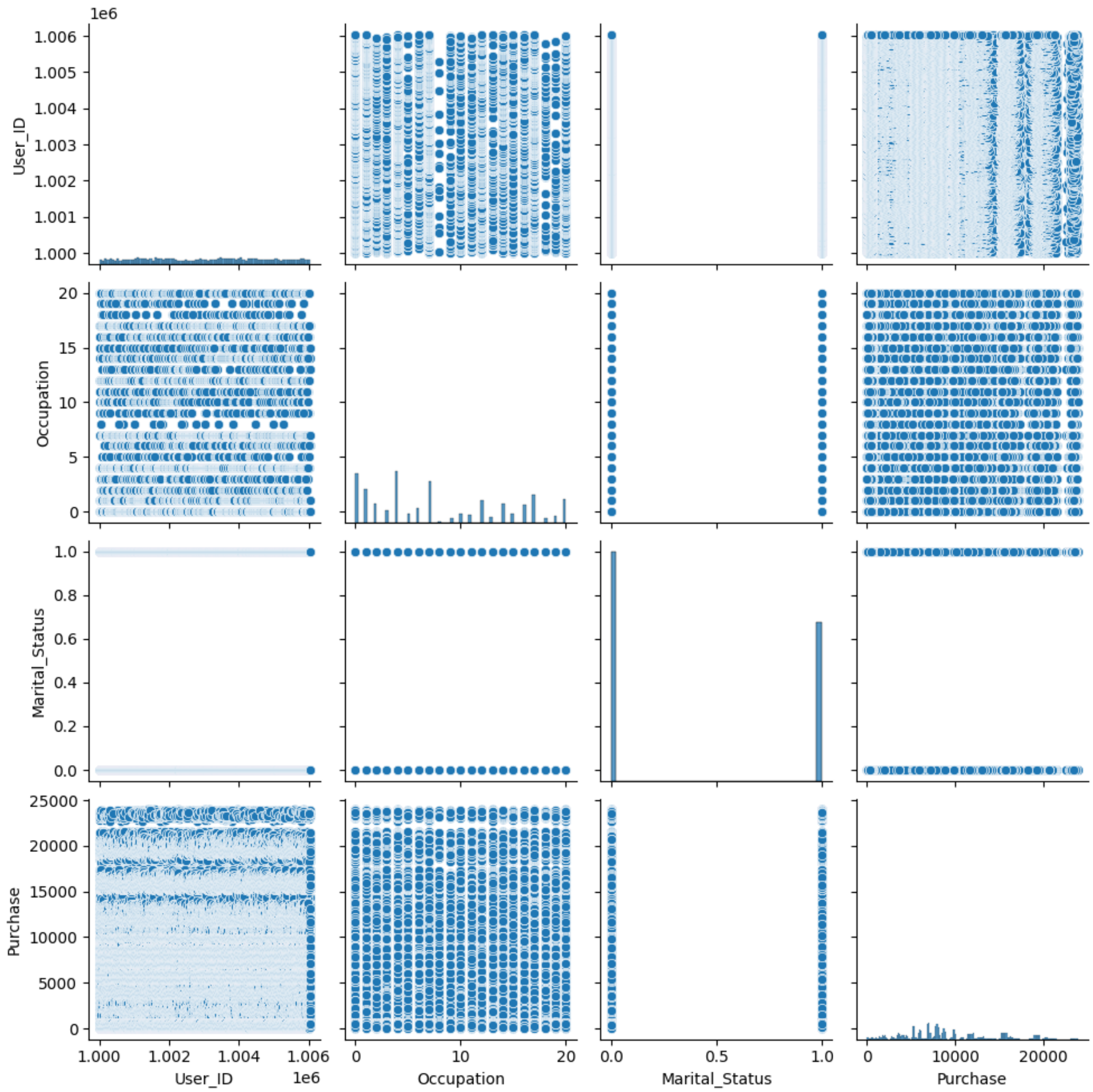


[235]:
```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.histplot(data=df, x="User_ID", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Occupation", kde=True, ax=axis[0,1])
sns.histplot(data=df, x="Product_Category", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Purchase", kde=True, ax=axis[1,1])
axis[0,0].set_title("User_ID count")
axis[0,1].set_title("Occupation Count")
axis[1,0].set_title("Product_Category Count")
axis[1,1].set_title("Purchase Count")

plt.show()
```



[236]:
```
sns.pairplot(df)
```

[236]: <seaborn.axisgrid.PairGrid at 0x7f51c4f7a950>



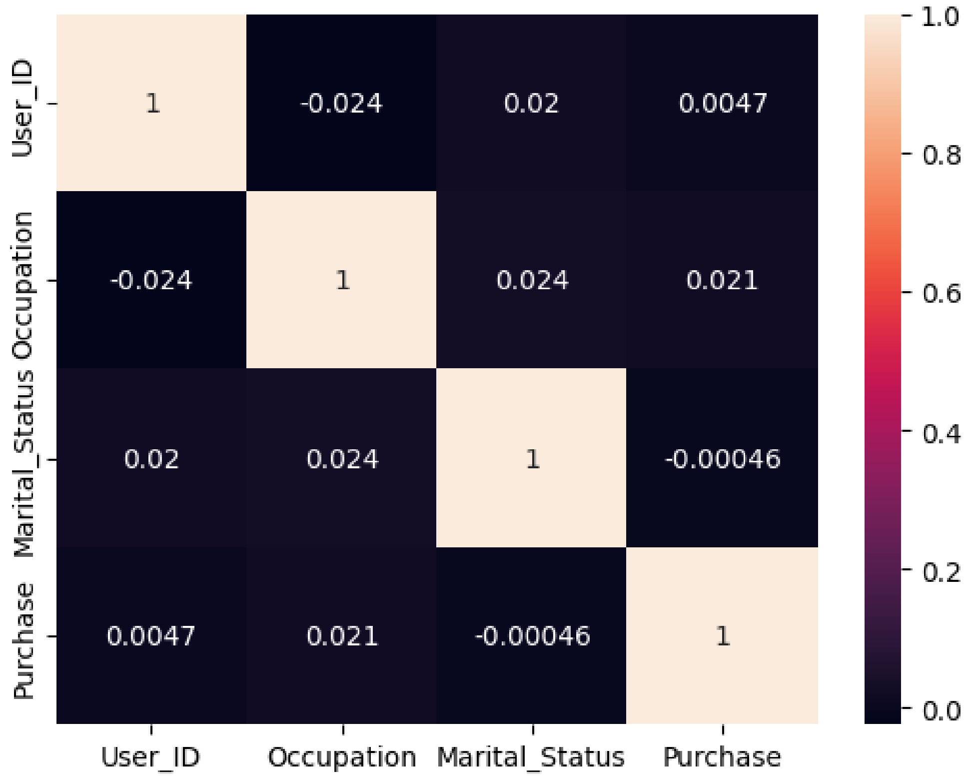
[237]:
```
df.corr()
```

[237]:

	User_ID	Occupation	Marital_Status	Purchase
User_ID	1.000000	-0.023971	0.020443	0.004716
Occupation	-0.023971	1.000000	0.024280	0.020833
Marital_Status	0.020443	0.024280	1.000000	-0.000463
Purchase	0.004716	0.020833	-0.000463	1.000000

[238]:
```
#plt.figure(figsize=(15,10))
sns.heatmap(df.corr(), annot = True)
```

[238]: <Axes: >



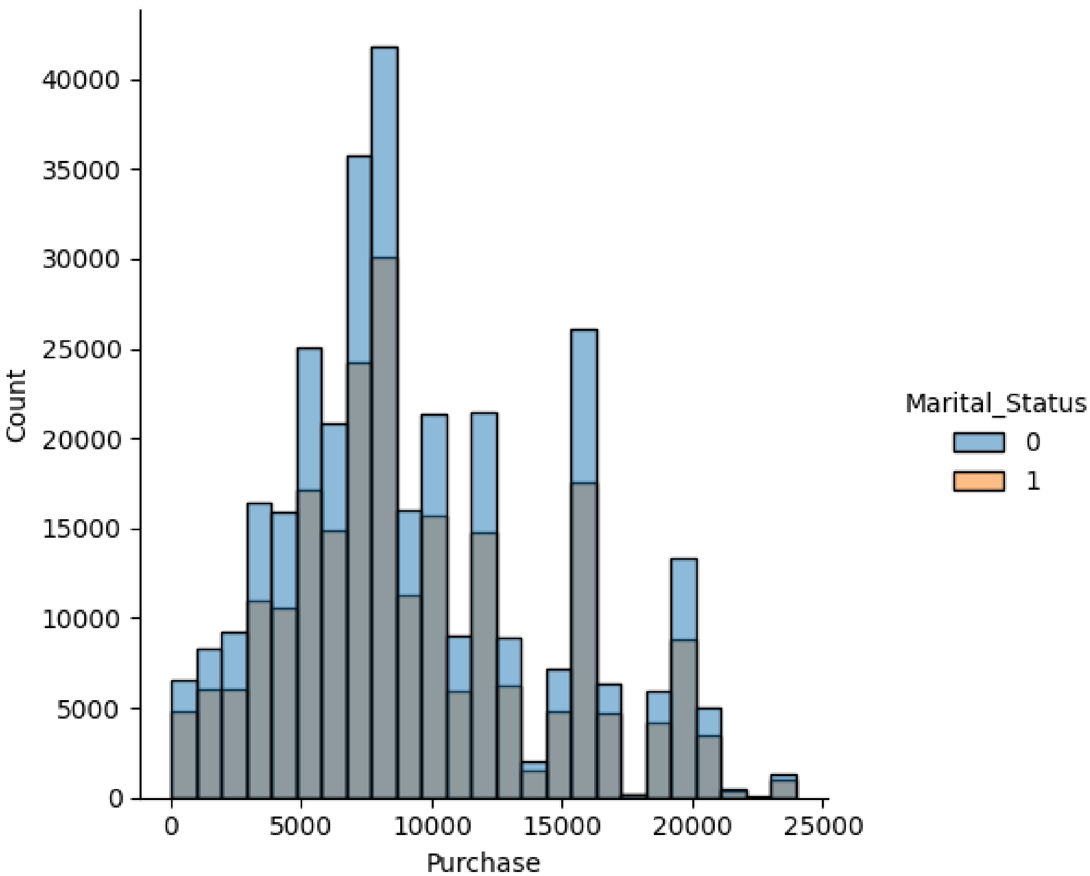
Performing the same activity for Married vs Unmarried and Age For Age, you can try bins based on life stages: 0-17, 18-25, 26-35, 36-50, 51+ years.

[239]:
```
df.groupby(['Marital_Status'])['Purchase'].describe()
```

[239]:
```
                   count         mean          std   min     25%     50%  \
Marital_Status
0               324731.0  9265.907619  5027.347859  12.0  5605.0  8044.0
1               225337.0  9261.174574  5016.897378  12.0  5843.0  8051.0

                    75%      max
Marital_Status
0               12061.0  23961.0
1               12042.0  23961.0
```

[240]:
```
sns.displot( x='Purchase', data=df, hue='Marital_Status', bins=25)
```

[240]:
```
<seaborn.axisgrid.FacetGrid at 0x7f51bf9b5ba0>
```



[241]:
```
df.groupby(['Age'])['Purchase'].describe()
```

[241]:

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

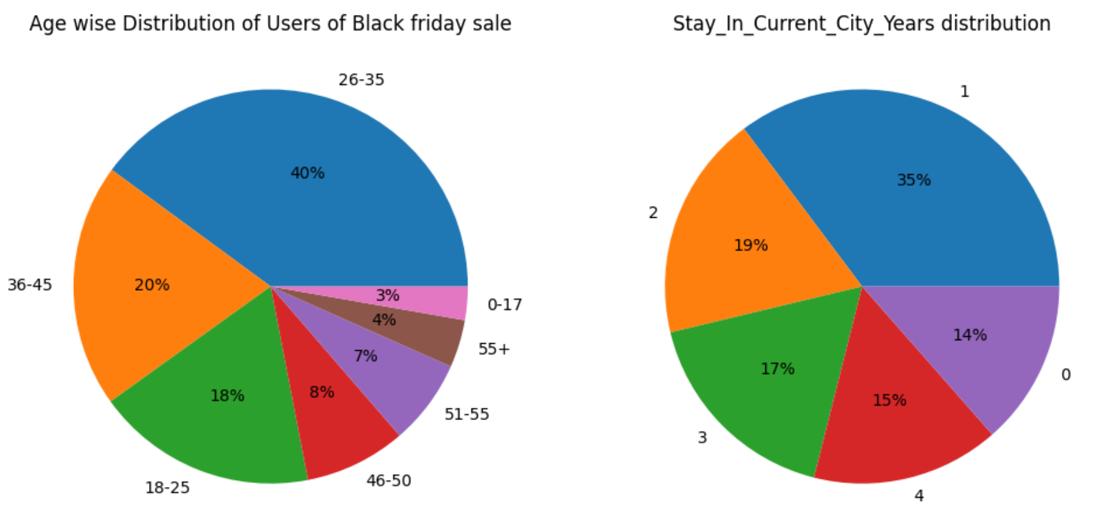
\

Age	max
0-17	23955.0
18-25	23958.0
26-35	23961.0
36-45	23960.0
46-50	23960.0

```
51-55   23960.0
55+     23960.0
```

[242]:
```python
data = df['Age'].value_counts(normalize=True)*100
```

[243]:
```python
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 8))

data = df['Age'].value_counts(normalize=True)*100
#palette_color = sns.color_palette('BrBG_r')
axs[0].pie(x=data.values, labels=data.index, autopct='%.0f%%') #␣
 ↪colors=palette_color)
axs[0].set_title("Age wise Distribution of Users of Black friday sale")

data = df['Stay_In_Current_City_Years'].value_counts(normalize=True)*100
#palette_color = sns.color_palette('YlOrRd_r')
axs[1].pie(x=data.values, labels=data.index, autopct='%.0f%%')#␣
 ↪colors=palette_color)
axs[1].set_title("Stay_In_Current_City_Years distribution")
plt.show()
```



1 Insights:

The majority, approximately 75%, of the population is male, while only around 25% are female. The most active age group in terms of involvement and participation is the 26-35 age bracket. Product categories 1, 5, and 8 demonstrate the highest demand among customers. The largest proportion of users originates from Country B. When considering the flow of purchase value, the order is as follows: Unmarried males > Married males > Unmarried females > Married females. Individuals who have resided in a particular city for at least one year engage in more shopping activities compared to other groups.

2 Recommendations:

In order to increase female participation in the sale, it is recommended to introduce different new items specifically targeted towards them. Creating attractive offers and discounts can also help in attracting more female customers.

To encourage participation from the age groups of 0-17 and 55+, it is advisable to offer a wider range of products that cater to their preferences. Increasing discounts and offers specifically targeting these age categories can help in boosting their engagement. It is important to acknowledge that age plays a crucial role in purchasing power, and addressing the needs of older individuals with appealing products can be a strategic opportunity.

Maintaining a sufficient stock of the most demanded products, such as those falling under categories 1, 5, and 8, is crucial to meet customer demands and ensure customer satisfaction.

Given that the majority of users belong to Country B, it is recommended to maintain adequate stock levels of all the required products in this country to cater to the demand effectively.

To increase women's involvement and overall revenue, more products, offers, and discounts specifically tailored to attract and tempt female customers should be implemented.

Although there is no significant difference in spending patterns between married and unmarried individuals, there are notable differences in product preferences. Targeting those products that appeal to the preferences of married and unmarried individuals can be an effective strategy to enhance their engagement and boost sales.

It is essential to create awareness about the products sold at the supermarket, as there is potential for growth in an unsaturated market. Implementing marketing strategies to increase awareness and reach out to a wider customer base can yield positive results.

The data analysis aligns with the Central Limit Theorem (CLT), where even for sampled data, the mean and median remain approximately the same. This indicates the reliability of the data and supports decision-making based on statistical measures.

By implementing these recommendations, it is anticipated that customer engagement, sales, and overall revenue can be positively influenced, leading to a more successful and prosperous business.**- VRM**