```
from google.colab import files

uploaded = files.upload()

<IPython.core.display.HTML object>

Saving walmart_data.csv to walmart_data.csv

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

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

df

        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]
```

Analysing the basic metrics

```
df.shape
```

```
(550068, 10)
```

```
df.head()
```

```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category
Purchase
0                          2               0                 3
8370
1                          2               0                 1
15200
2                          2               0                12
1422
3                          2               0                12
1057
4                         4+               0                 8
7969
```

```
df.tail()
```

```
        User_ID Product_ID Gender    Age  Occupation City_Category  \
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
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
```

```
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.describe()
```

```
            User_ID     Occupation  Marital_Status
Product_Category  \
count  5.500680e+05  550068.000000   550068.000000     550068.000000

mean   1.003029e+06       8.076707        0.409653          5.404270

std    1.727592e+03       6.522660        0.491770          3.936211

min    1.000001e+06       0.000000        0.000000          1.000000

25%    1.001516e+06       2.000000        0.000000          1.000000

50%    1.003077e+06       7.000000        0.000000          5.000000

75%    1.004478e+06      14.000000        1.000000          8.000000

max    1.006040e+06      20.000000        1.000000         20.000000


            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
```

Insights

The amounts people spent on purchases show a big range. The smallest purchase was $12,

while the biggest one was as high as $23,961.

The middle point, or median purchase, is $8,047,

which is less than the average purchase amount of $9,264.

This suggests that the majority of purchases are lower in value, but there are a few very expensive purchases that make the average higher. It's like the data is leaning more towards the right side indicating a right-skewed distribution.

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

	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

Insights

Product_ID: In the 550,068 transactions, there are 3,631 different products. The product with the code P00265242 is the top seller, having sold a maximum of 1,880 units.

Gender: Among the 550,068 transactions, approximately 75% (414,259) were made by males. This indicates a significant difference in buying behavior between males and females during the Black Friday event.

Age: The dataset includes 7 unique age groups. The age group 26-35 has the highest number of transactions, with a total of 219,587. Further analysis of this age group will be conducted in the future.

Stay_In_Current_City_Years: Customers who have stayed in the current city for 1 year account for the highest number of transactions, reaching 193,821. This is more than customers who have stayed for 0, 2, 3, or 4+ years in the current city.

Exploratory Data Analysis

```
for i in df.columns[:-1]:
    df[i] = df[i].astype('category')
```

```
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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

```
df.describe(include="category").T
```

```
                             count  unique        top    freq
User_ID                     550068    5891    1001680    1026
Product_ID                  550068    3631  P00265242    1880
Gender                      550068       2          M  414259
Age                         550068       7      26-35  219587
Occupation                  550068      21          4   72308
City_Category               550068       3          B  231173
Stay_In_Current_City_Years  550068       5          1  193821
Marital_Status              550068       2          0  324731
Product_Category            550068      20          5  150933
```

Insights

User_ID: Out of 550,068 transactions, there are 5,891 unique user IDs. This suggests that some customers made multiple purchases.

```
#replacing the values in marital_status column

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

```
['Unmarried', 'Married']
Categories (2, object): ['Unmarried', 'Married']
```

```
df['Marital_Status'].value_counts()
```

```
Unmarried    324731
Married      225337
Name: Marital_Status, dtype: int64
```

```
(df['Marital_Status'].value_counts()/ len(df) )*100
```

```
Unmarried    59.034701
Married      40.965299
Name: Marital_Status, dtype: float64
```

Insights

Marital_Status: Unmarried customers made up 59% of the total transactions, while married customers accounted for 41%.

Duplicate Detection

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

```
Empty DataFrame
Columns: [User_ID, Product_ID, Gender, Age, Occupation, City_Category, Stay_In_Current_City_Years, Marital_Status, Product_Category, Purchase]
Index: []
```

```
df.duplicated().value_counts()
```

```
False    550068
dtype: int64
```

Insights

There are no duplicate entries in the dataset

Checking for Missing Values

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

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

Insights

The dataset does not contain any missing values.

Non-Graphical Analysis(Counting Values and Unique attributes)

```
for i in df.columns:
  print('The count of unique values in',i,'are')
  print(df[i].nunique())
  print('-'*70)
```

```
The count of unique values in User_ID are
5891
----------------------------------------------------------------------
The count of unique values in Product_ID are
3631
----------------------------------------------------------------------
The count of unique values in Gender are
2
----------------------------------------------------------------------
The count of unique values in Age are
7
----------------------------------------------------------------------
The count of unique values in Occupation are
21
----------------------------------------------------------------------
The count of unique values in City_Category are
3
----------------------------------------------------------------------
The count of unique values in Stay_In_Current_City_Years are
5
----------------------------------------------------------------------
The count of unique values in Marital_Status are
2
----------------------------------------------------------------------
The count of unique values in Product_Category are
20
----------------------------------------------------------------------
The count of unique values in Purchase are
18105
----------------------------------------------------------------------
```

```
for i in df.columns:
  print('The Unique Values in',i,'are')
  print(df[i].value_counts())
  print('-'*70)
```

```
The Unique Values in User_ID are
1001680    1026
```

```
1004277    979
1001941    898
1001181    862
1000889    823
           ...
1002111      7
1005391      7
1002690      7
1005608      7
1000708      6
Name: User_ID, Length: 5891, dtype: int64
----------------------------------------------------------------------
The Unique Values in Product_ID are
P00265242    1880
P00025442    1615
P00110742    1612
P00112142    1562
P00057642    1470
             ...
P00068742       1
P00012342       1
P00162742       1
P00091742       1
P00231642       1
Name: Product_ID, Length: 3631, dtype: int64
----------------------------------------------------------------------
The Unique Values in Gender are
M    414259
F    135809
Name: Gender, dtype: int64
----------------------------------------------------------------------
The Unique Values in Age are
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 Unique Values in Occupation are
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
----------------------------------------------------------------------
The Unique Values in City_Category are
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
----------------------------------------------------------------------
The Unique Values in Stay_In_Current_City_Years are
1     193821
2     101838
3      95285
4+     84726
0      74398
Name: Stay_In_Current_City_Years, dtype: int64
----------------------------------------------------------------------
The Unique Values in Marital_Status are
Unmarried    324731
Married      225337
Name: Marital_Status, dtype: int64
----------------------------------------------------------------------
The Unique Values in Product_Category are
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
```

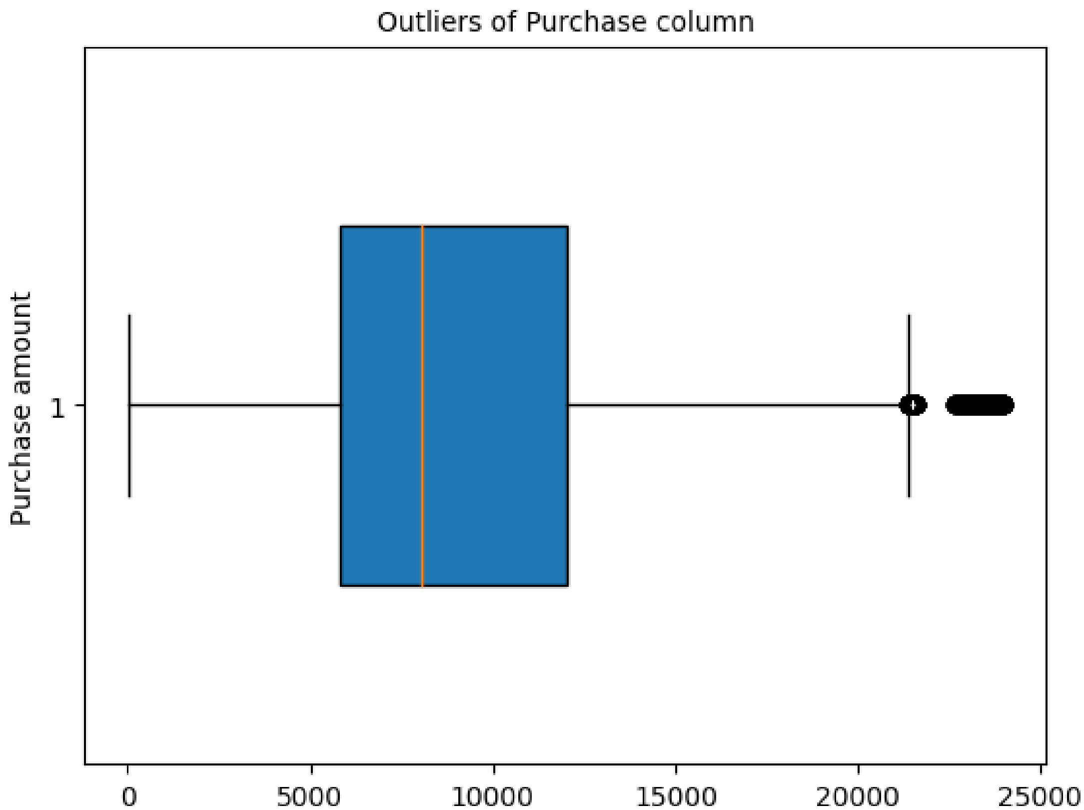
```
7       3721
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64
----------------------------------------------------------------------
The Unique Values in Purchase are
7011     191
7193     188
6855     187
6891     184
7012     183
        ...
23491      1
18345      1
3372       1
855        1
21489      1
Name: Purchase, Length: 18105, dtype: int64
----------------------------------------------------------------------
```

Observations

- User_ID - Out of 550,068 transactions, there are 5,891 unique user IDs. This suggests that some customers made multiple purchases.
- Product_ID - In the 550,068 transactions, there are 3,631 unique products. The product with the code P00265242 is the top seller, with 1,880 units sold.
- Gender - Among 550,068 transactions, 414,259 (about 75%) were made by males. This indicates a significant difference in shopping behavior between males and females on Black Friday.
- Age - The dataset includes 7 different age groups. The 26-35 age group has the highest number of transactions, totaling 219,587. Further analysis of this feature will be conducted in the future.
- Stay_In_Current_City_Years - Customers who have stayed in their current city for 1 year have the highest number of transactions, totaling 193,821, compared to customers with 0, 2, 3, or 4+ years of stay in the current city.
- Marital_Status - Unmarried customers accounted for 59% of total transactions, while married customers accounted for 41%.

Outliers detection

```
plt.boxplot(x=df["Purchase"],vert = False,patch_artist = True,widths = 
0.5)
plt.title("Outliers of Purchase column",fontsize=10)
plt.ylabel("Purchase amount")
plt.show()
```



Calculating the IQR

```
q1 = np.percentile(df["Purchase"],25)
q3 = np.percentile(df["Purchase"],75)
IQR = q3-q1
Upper_band = q3+1.5*(IQR)
Lower_band = q1-1.5*(IQR)
Median = df["Purchase"].median()
print("Q1=", q1)
print("Q3=", q3)
print("IQR=", IQR)
print("Upper band=", Upper_band)
print("Lower band=", Lower_band)
print("Median", df["Purchase"].median())
```

```
Q1= 5823.0
Q3= 12054.0
```

```
IQR= 6231.0
Upper band= 21400.5
Lower band= -3523.5
Median 8047.0

# All values above the upper band i.e >21400.5 are outliers.

len(df.loc[df['Purchase'] > 21400.5,'Purchase'])

2677

(len(df.loc[df['Purchase']>Upper_band])/len(df))*100

0.4866671029763593
```

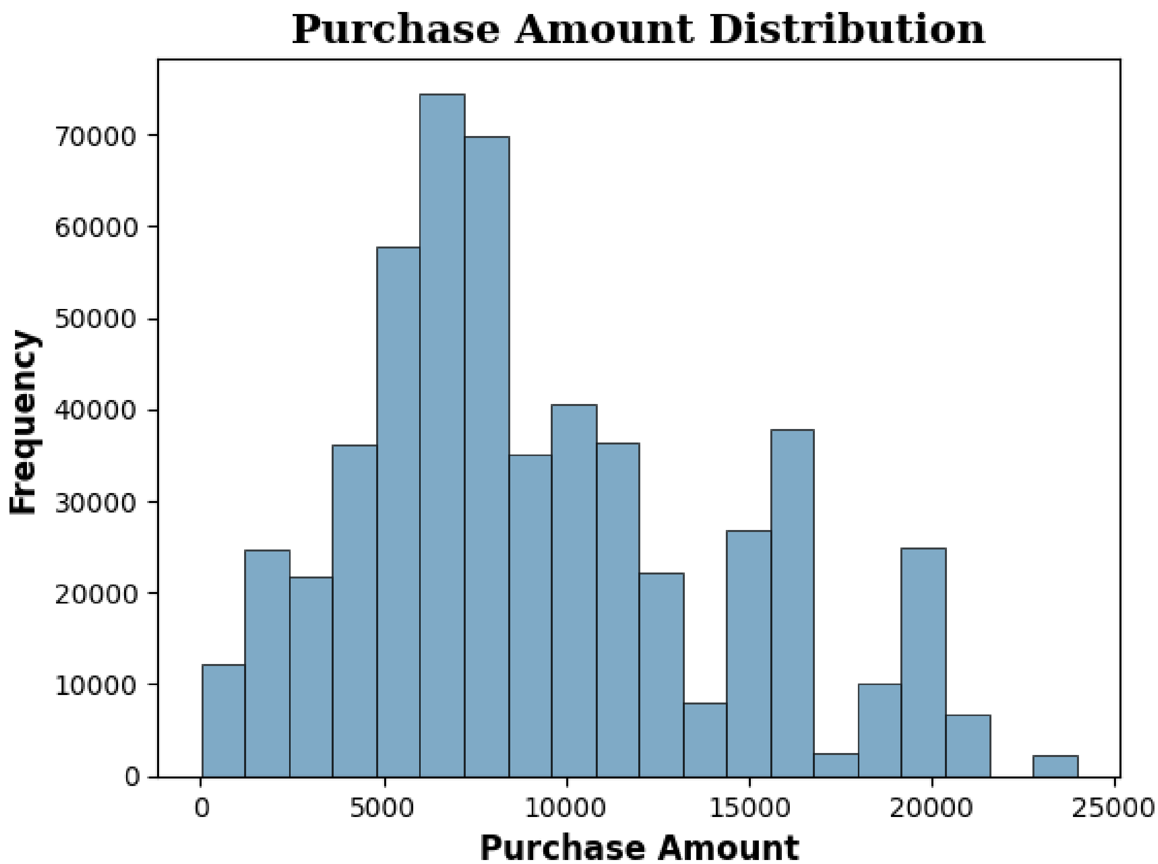
Observations

There are 2677 outliers in the purchase amount column i.e 0.48% values in the Purchase column are outliers.

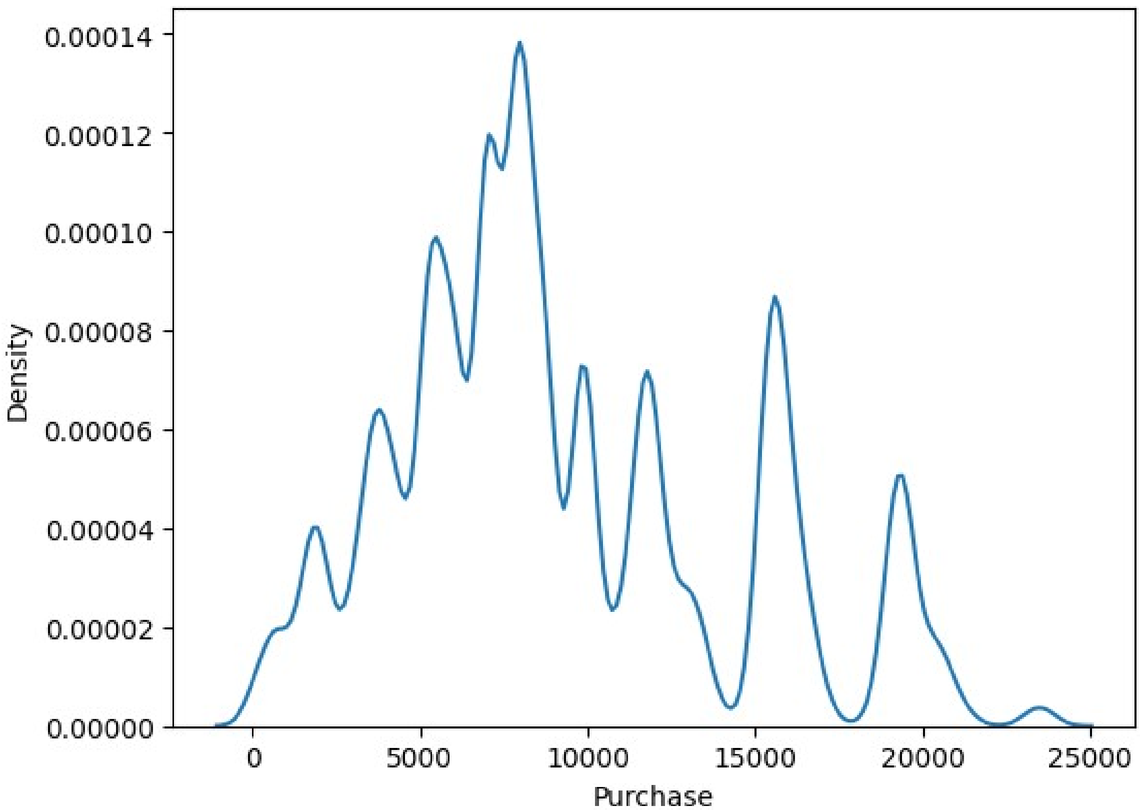
Univariate Analysis

Purchase Amount Distribution

```
plt.hist(df['Purchase'],color=
'#7faac6',linewidth=0.5,edgecolor='black',bins = 20,)
plt.xlabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
plt.ylabel('Frequency',fontsize = 12,fontweight = 'bold')

plt.title('Purchase Amount Distribution',{'font':'serif',
'size':15,'weight':'bold'})
plt.show()
```




```
sns.kdeplot(df['Purchase'])
plt.show()
```

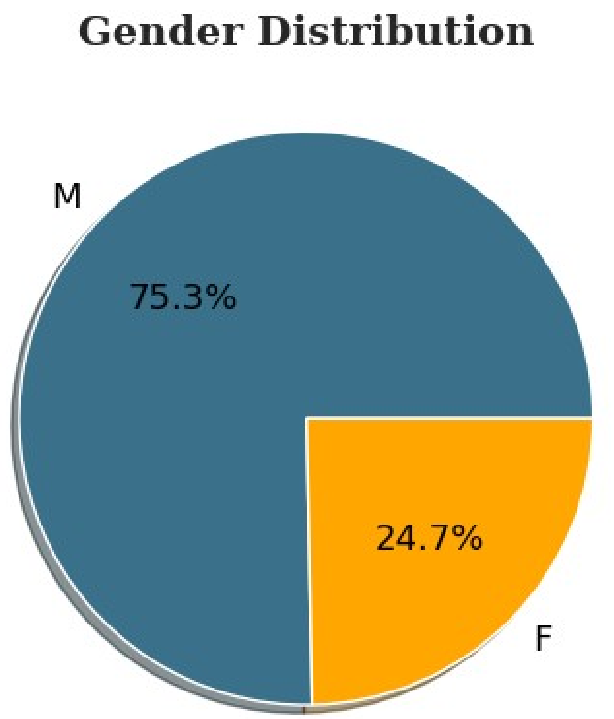


Observations

- Most order values lies in the range of 5000 - 10000
- There are more orders in the range 15000 - 16000 followed by 11000 - 11500 range and a few also in the 19000 - 20000 range.

Gender Distribution

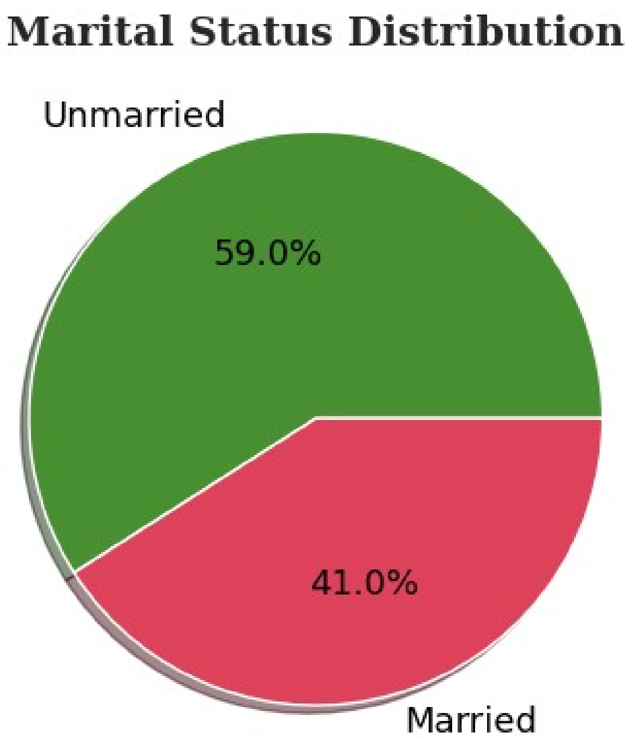
```
sns.set_style("whitegrid")
color_map = ["#3A7089","#ffa600"]
plt.pie(df['Gender'].value_counts().values,labels =
df['Gender'].value_counts().index,autopct = '%.1f%%',
        shadow = True,colors = color_map,textprops={'fontsize': 13,
'color': 'black'})

plt.title('Gender Distribution',{'font':'serif',
'size':15,'weight':'bold'})
plt.show()
```



The data shows a big difference in how much males and females bought things during Black Friday. About 75.3% of the purchases were made by males, and only 24.7% were made by females.

Marital Status Distribution

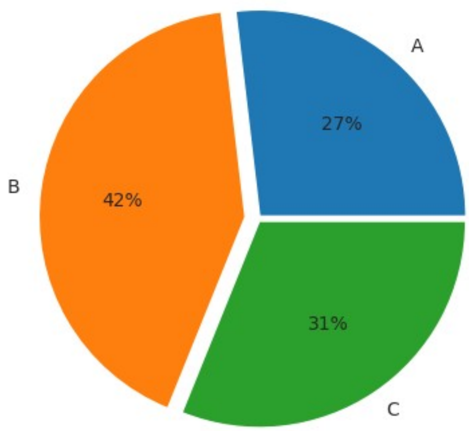
```
sns.set_style("whitegrid")
color_map = ["#488f31","#de425b"]
plt.pie(df['Marital_Status'].value_counts().values,labels =
df['Marital_Status'].value_counts().index,autopct = '%.1f%%',
        shadow = True,colors = color_map,textprops={'fontsize': 13,
'color': 'black'})
plt.title('Marital Status Distribution',{'font':'serif',
'size':15,'weight':'bold'})
plt.show()
```



About 59%, were made by unmarried customers compared to married couples, who made up 41% of the purchases.

City Category Distribution

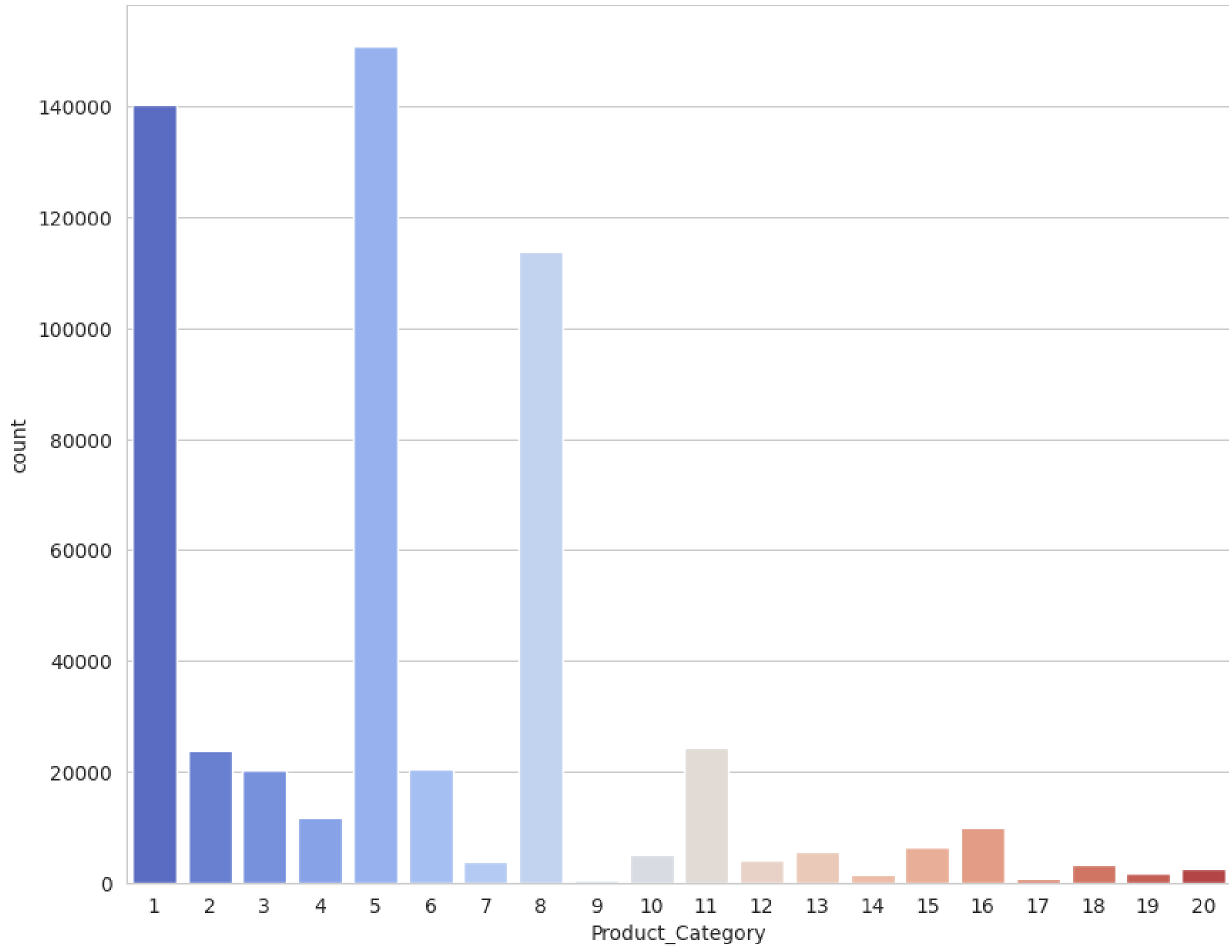
```
plt.figure(figsize = (12,5)).set_facecolor("white")

plt.subplot(1,2,1)
labels = ['A','B','C']
plt.pie(df.groupby('City_Category')['City_Category'].count(), labels =
labels, explode = (0.015,0.06,0.015), autopct = '%0.0f%%')

plt.subplot(1,2,2)
label = sns.countplot(data = df, x='City_Category')
for i in label.containers:
    label.bar_label(i)

plt.show()
```



City B had the most transactions, making up 42% of the total. Following that, City C had 31.1%, and City A had 26.9%.

Product Category Distribution

```
plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Product_Category',palette ="coolwarm")
plt.show()
```

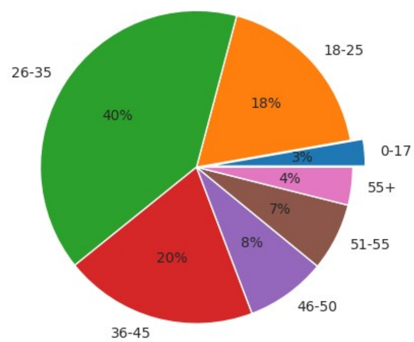


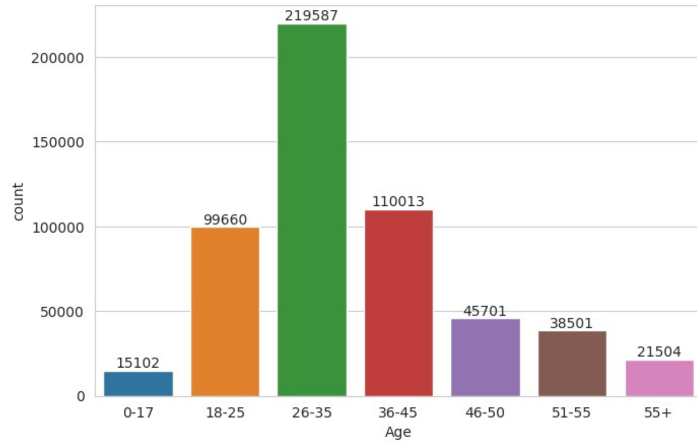
Categories 5,1 and 8 have significantly outperformed other categories with combined Sales of nearly 75% of the total sales suggesting a strong preference for these products among customers.

The least frequent bought are category 9 followed by 17 and 14.

Age Distribution

```
plt.figure(figsize = (17,5)).set_facecolor("white")

plt.subplot(1,2,1)
labels = ['0-17','18-25','26-35','36-45','46-50','51-55','55+']
plt.pie(df.groupby('Age')['Age'].count(), labels = labels, explode =
(0.08,0,0,0,0,0,0), autopct = '%0.0f%%')

plt.subplot(1,2,2)
label = sns.countplot(data = df, x='Age')
for i in label.containers:
    label.bar_label(i)

plt.show()
```





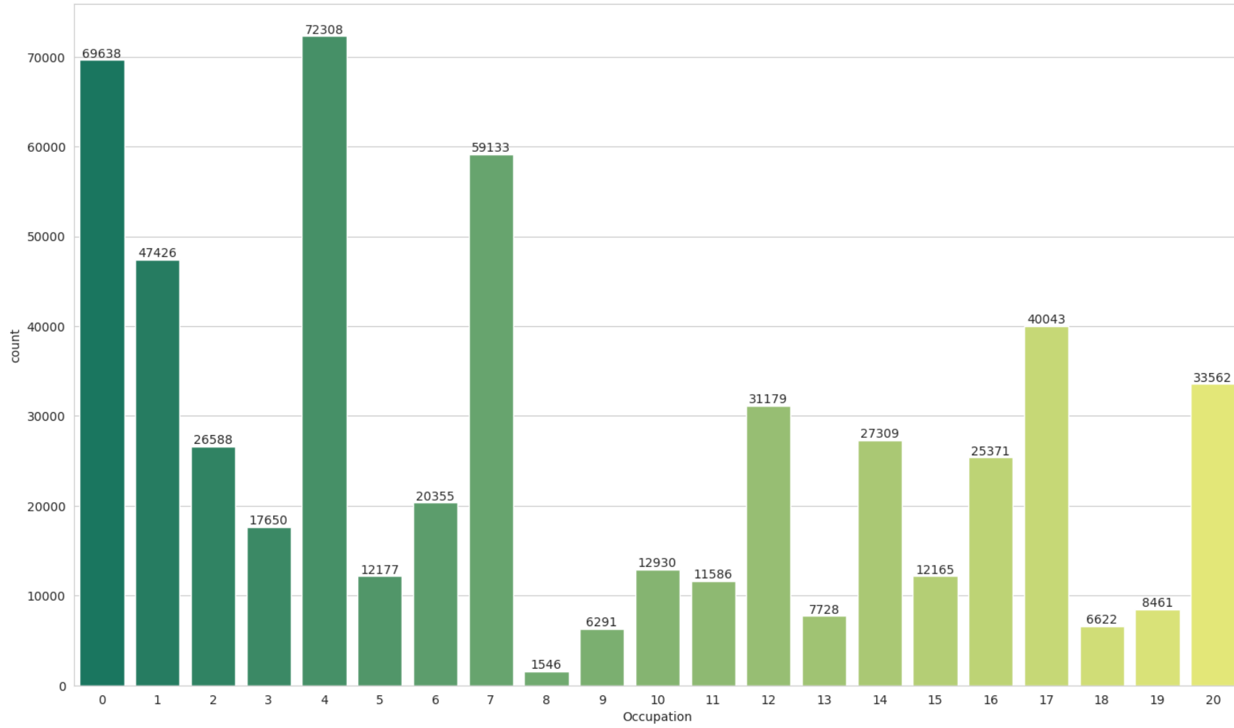
The largest group of buyers, making up 40%, falls in the age range of 26-35, which is the highest among all age groups.

Buyers in the age groups 0-17 and 55+ are not as common, representing only 3% and 4% of the data, respectively.

It's noticeable that most buyers are between the ages of 18 and 45. Before and after this range, there are fewer buyers.

Occupation distribution

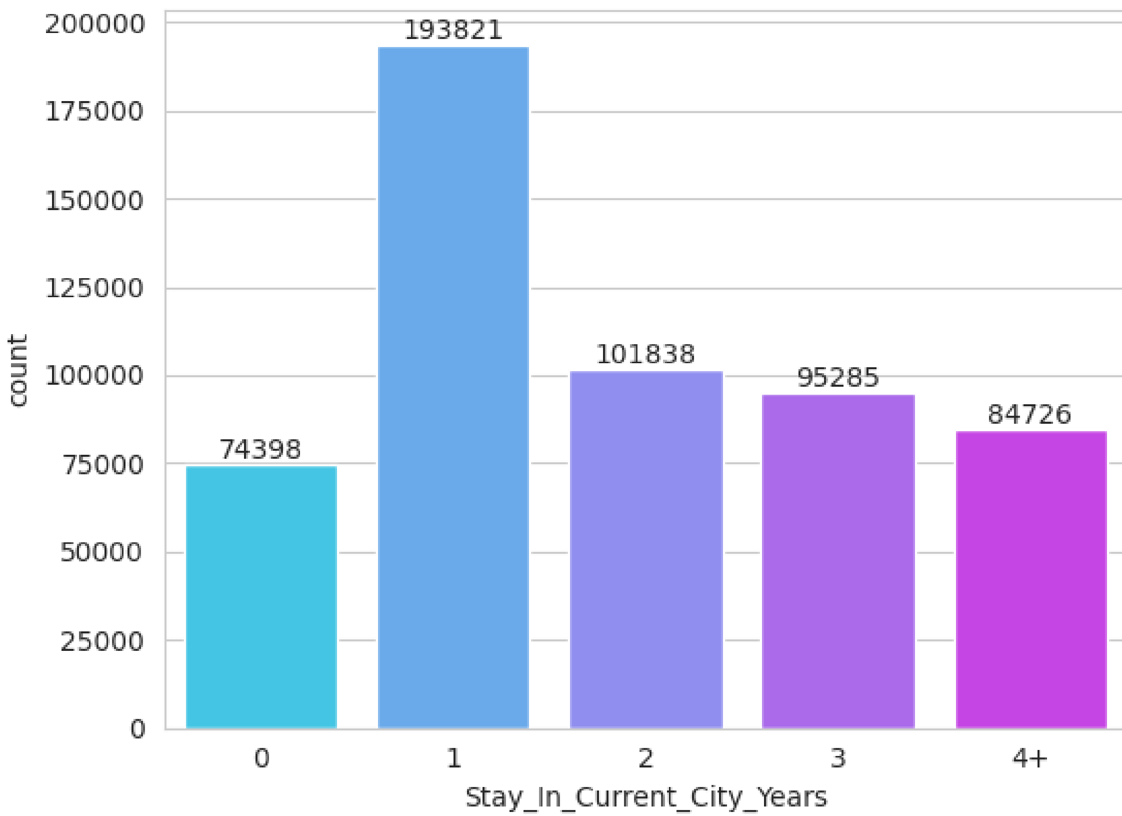
```
plt.figure(figsize=(17, 10)).set_facecolor("white")
label = sns.countplot(data = df, x=df['Occupation'], palette
="summer")
for i in label.containers:
    label.bar_label(i)
```



The most common buyers have occupation code 4, with occupation codes 0 and 7 following closely behind. On the other hand, people with occupation code 8 are the least frequent buyers.

Distribution of Customer's stay in current city

```
df['Stay_In_Current_City_Years'].unique()
label = sns.countplot(data = df, x='Stay_In_Current_City_Years',
palette = "cool")
for i in label.containers:
    label.bar_label(i)
```



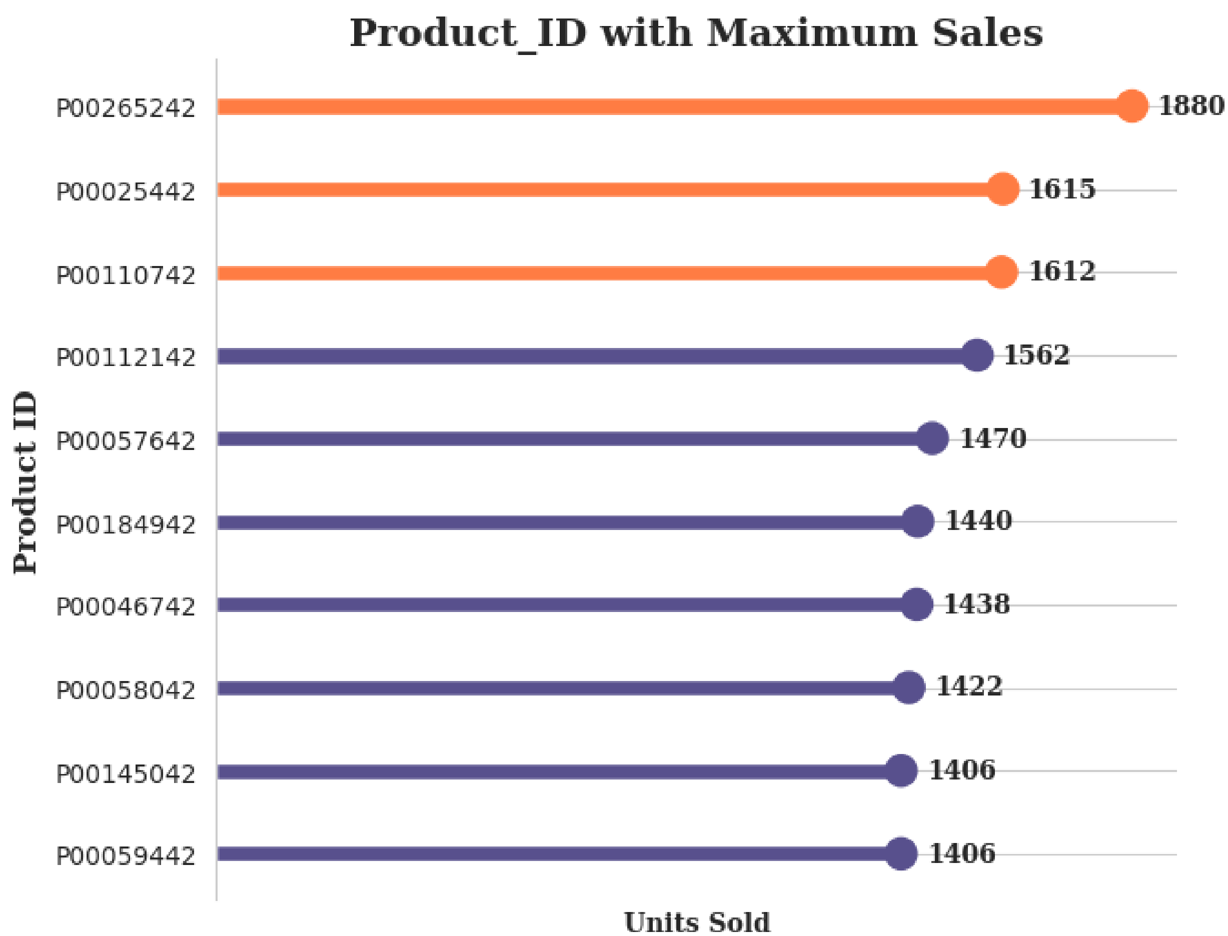
Most buyers are in their current cities since 1 year followed by 2 years and 3 years.

Top 10 Product ID with maximum sales.

```
fig = plt.figure(figsize = (15,6))
gs = fig.add_gridspec(1,2)
ax = fig.add_subplot(gs[0,0])

temp = df['Product_ID'].value_counts()[0:10]

temp = temp.iloc[-1:-11:-1]

color_map =  ["#58508d" for i in range(7)] + ['#ff7c43' for i in
range(3)]

ax.barh(y = temp.index,width = temp.values,height = 0.2,color =
color_map)
ax.scatter(y = temp.index, x = temp.values, s = 150 , color =
color_map )


ax.set_xticks([])

for y,x in zip(temp.index,temp.values):
    ax.text( x + 50 , y , x,{'font':'serif',
```

```
'size':10,'weight':'bold'},va='center')

for s in ['top','bottom','right']:
    ax.spines[s].set_visible(False)

ax.set_xlabel('Units Sold',{'font':'serif',
'size':10,'weight':'bold'})
ax.set_ylabel('Product ID',{'font':'serif',
'size':12,'weight':'bold'})

ax.set_title('Product_ID with Maximum Sales',
            {'font':'serif', 'size':15,'weight':'bold'})
```

```
Text(0.5, 1.0, 'Product_ID with Maximum Sales')
```



- The best-selling products in Walmart's Black Friday sales include the item with ID P00265242 leading the way, selling 1,880 units. Following closely are P00025442 with 1,615 units sold and P00110742 with 1,612 units sold.

Bi-variate Analysis

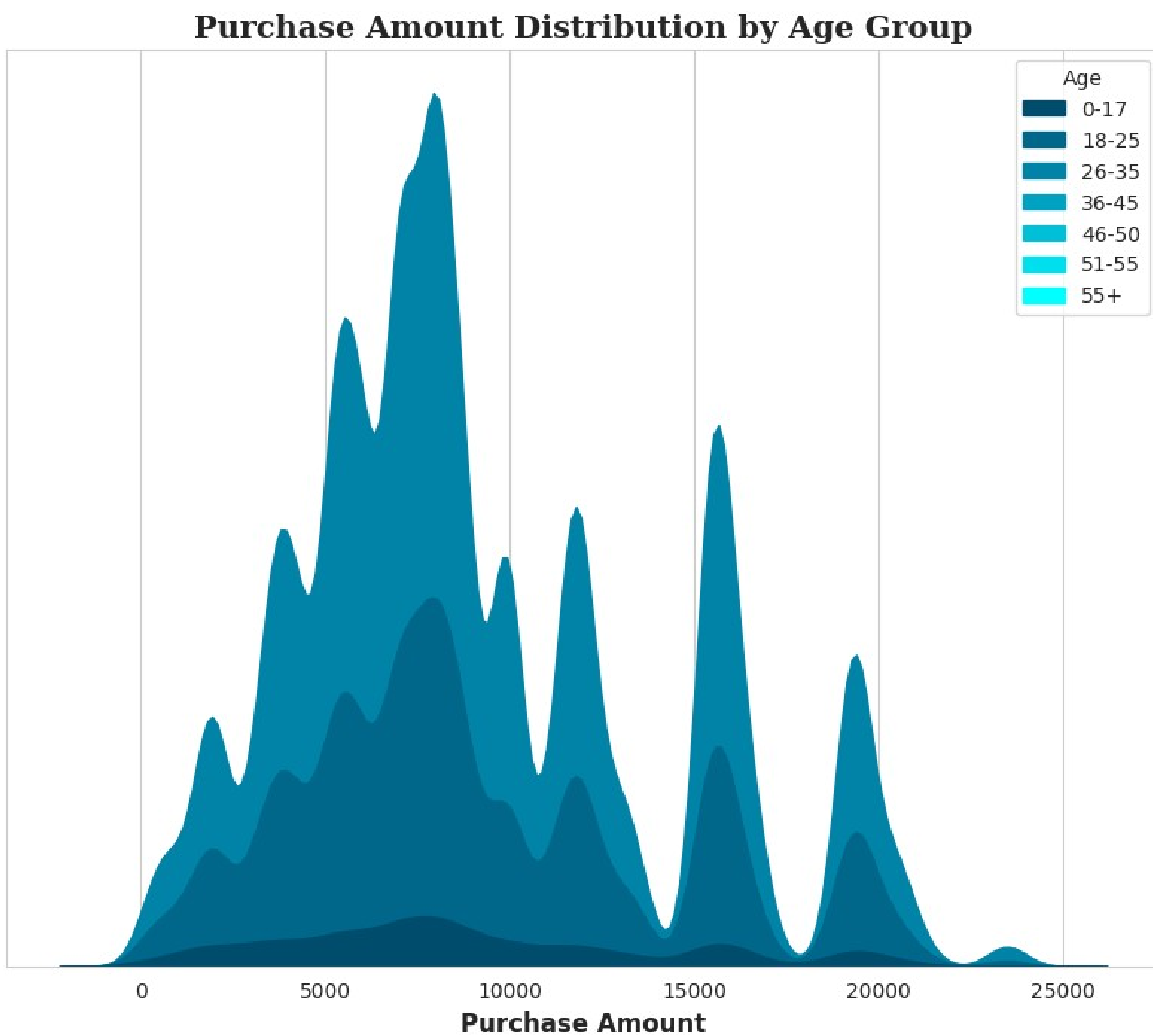
```
df
```

```
        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      Unmarried                3
8370
1                               2      Unmarried                1
15200
2                               2      Unmarried               12
1422
3                               2      Unmarried               12
1057
4                              4+      Unmarried                8
7969
...                           ...            ...              ...
...
550063                          1        Married               20
368
550064                          3      Unmarried               20
371
550065                         4+        Married               20
137
550066                          2      Unmarried               20
365
550067                         4+        Married               20
490

[550068 rows x 10 columns]
```

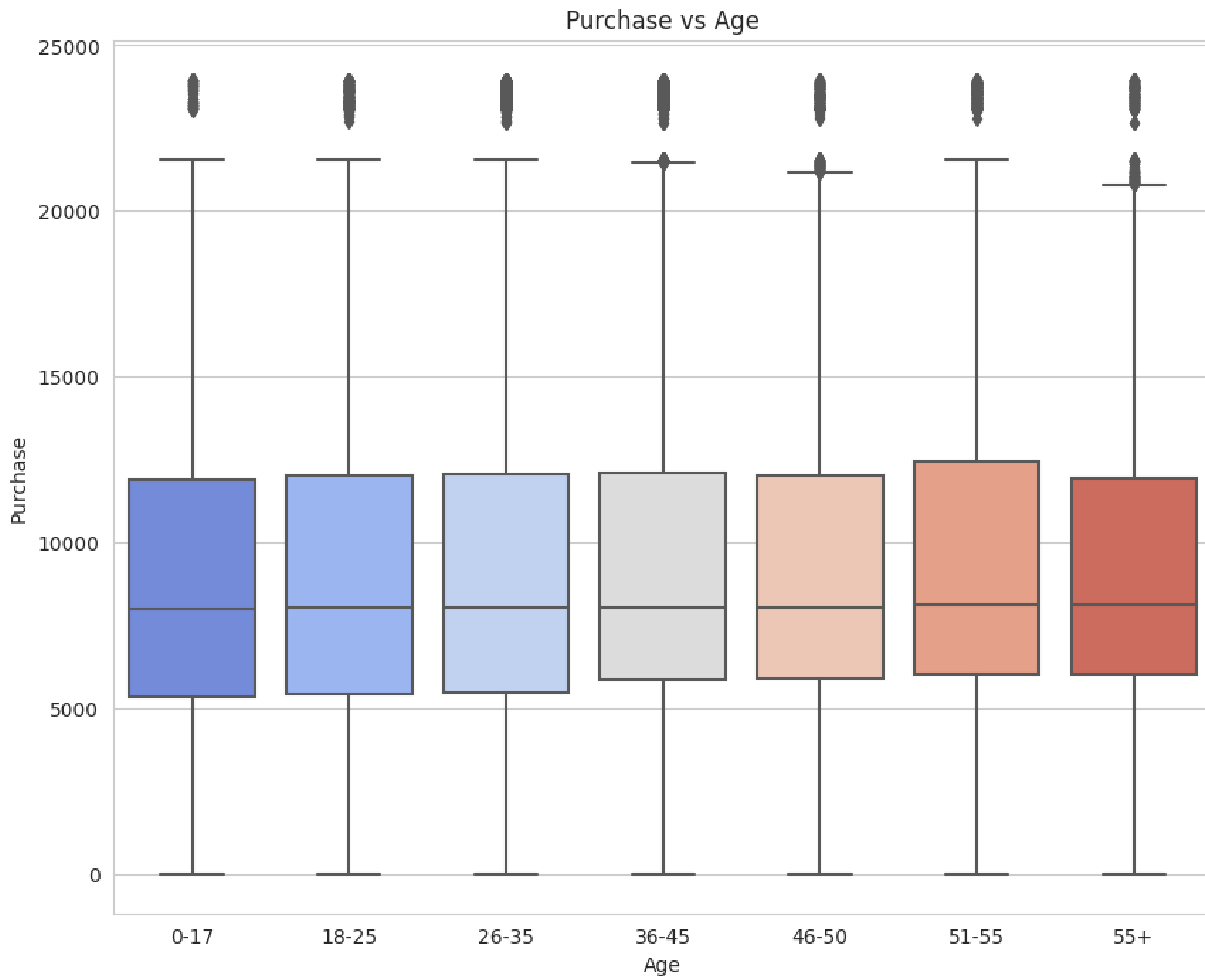
Purchase vs Age

```
color_map =
["#004c6d","#00678a","#0083a6","#00a1c1","#00c0d8","#00dfed","#00ffff"
]
plt.figure(figsize=(10,8))
```

```
sns.kdeplot(data = df, x = 'Purchase', hue = 'Age', palette =
color_map, fill = True, alpha = 1)

plt.yticks([])
plt.ylabel('')
plt.xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

plt.title('Purchase Amount Distribution by Age Group',{'font':'serif',
'size':15,'weight':'bold'})

plt.show()
```




```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, y ='Purchase', x = 'Age', palette = 'coolwarm')
plt.title('Purchase vs Age')
plt.show()
```



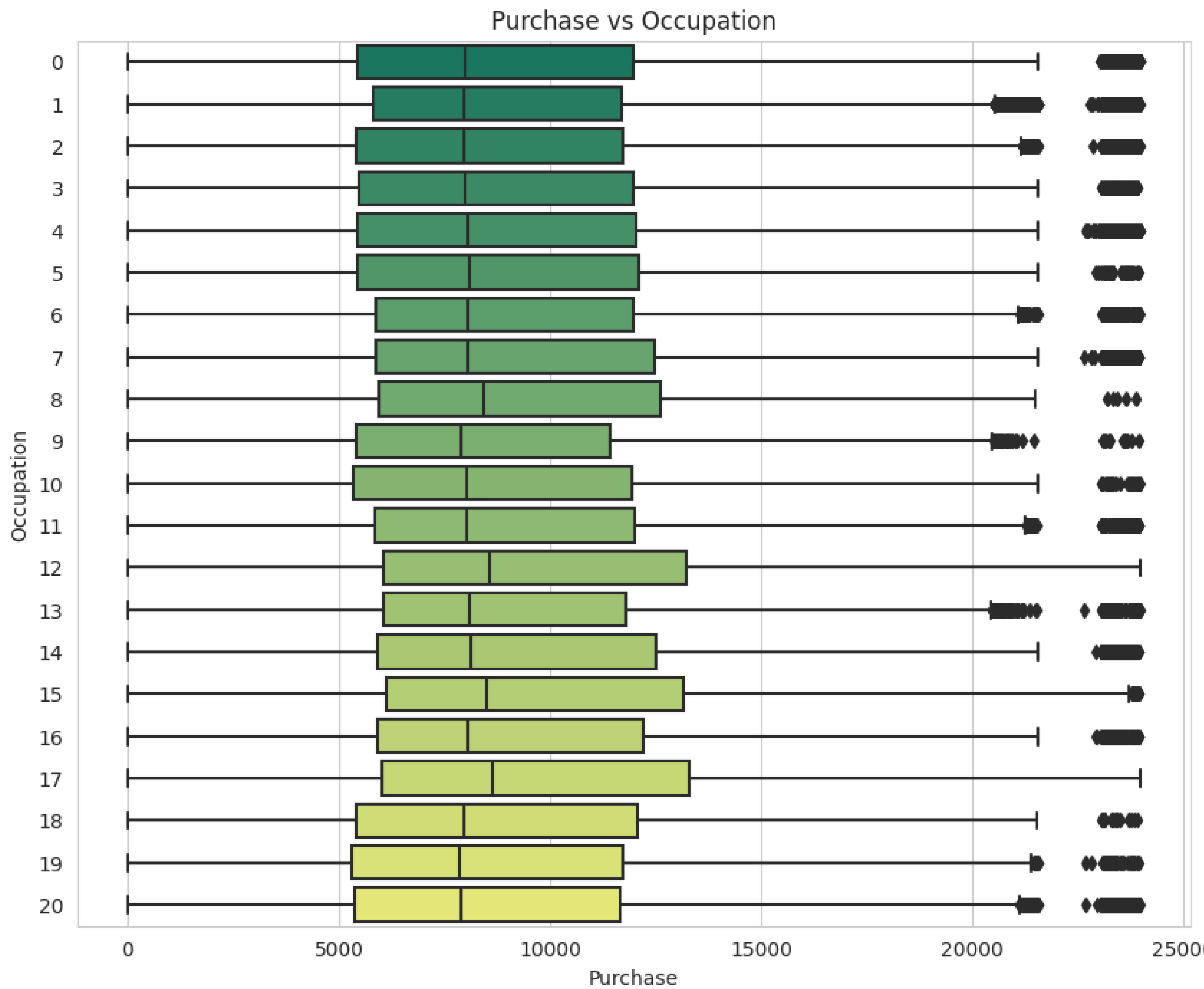

```
df.groupby(["Age"])["Purchase"].describe().T

Age            0-17         18-25         26-35         36-45
46-50  \
count  15102.000000  99660.000000  219587.000000  110013.000000
45701.000000
mean    8933.464640   9169.663606    9252.690633    9331.350695
9208.625697
std     5111.114046   5034.321997    5010.527303    5022.923879
4967.216367
min       12.000000     12.000000      12.000000      12.000000
12.000000
25%     5328.000000   5415.000000    5475.000000    5876.000000
5888.000000
50%     7986.000000   8027.000000    8030.000000    8061.000000
8036.000000
75%    11874.000000  12028.000000   12047.000000   12107.000000
11997.000000
max    23955.000000  23958.000000   23961.000000   23960.000000
```

```
23960.000000

Age           51-55           55+
count  38501.000000  21504.000000
mean    9534.808031   9336.280459
std     5087.368080   5011.493996
min       12.000000     12.000000
25%     6017.000000   6018.000000
50%     8130.000000   8105.500000
75%    12462.000000  11932.000000
max    23960.000000  23960.000000
```

- Among different age groups, the age range of 51-55 exhibits the highest average order value, reaching approximately 9534. Conversely, the age group 0-17 has the lowest average order value, around 8933.
- The highest order value observed across all age groups is approximately 23960, highlighting the peak spending level. On the other end, the lowest order value, consistent across all groups, is 12.

Purchase vs Occupation

```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, x ='Purchase', y = 'Occupation', palette =
'summer')
plt.title('Purchase vs Occupation')
plt.show()
```




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

```
               count         mean          std   min       25%
50%  \
Occupation

0            69638.0  9124.428588  4971.757402  12.0   5445.00   8001.0

1            47426.0  8953.193270  4838.482159  12.0   5825.00   7966.0

2            26588.0  8952.481683  4939.418663  12.0   5419.00   7952.0

3            17650.0  9178.593088  5000.942719  12.0   5478.00   8008.0

4            72308.0  9213.980251  5043.674855  12.0   5441.75   8043.0

5            12177.0  9333.149298  5025.616603  12.0   5452.00   8080.0

6            20355.0  9256.535691  4989.216005  12.0   5888.00   8050.0
```

7	59133.0	9425.728223	5086.097089	12.0	5878.00	8069.0
8	1546.0	9532.592497	4916.641374	14.0	5961.75	8419.5
9	6291.0	8637.743761	4653.290986	13.0	5403.00	7886.0
10	12930.0	8959.355375	5124.339999	12.0	5326.25	8012.5
11	11586.0	9213.845848	5103.802992	12.0	5835.75	8041.5
12	31179.0	9796.640239	5140.437446	12.0	6054.00	8569.0
13	7728.0	9306.351061	4940.156591	12.0	6038.00	8090.5
14	27309.0	9500.702772	5069.600234	12.0	5922.00	8122.0
15	12165.0	9778.891163	5088.424301	12.0	6109.00	8513.0
16	25371.0	9394.464349	4995.918117	12.0	5917.00	8070.0
17	40043.0	9821.478236	5137.024383	12.0	6012.00	8635.0
18	6622.0	9169.655844	4987.697451	12.0	5420.00	7955.0
19	8461.0	8710.627231	5024.181000	12.0	5292.00	7840.0
20	33562.0	8836.494905	4919.662409	12.0	5389.00	7903.5

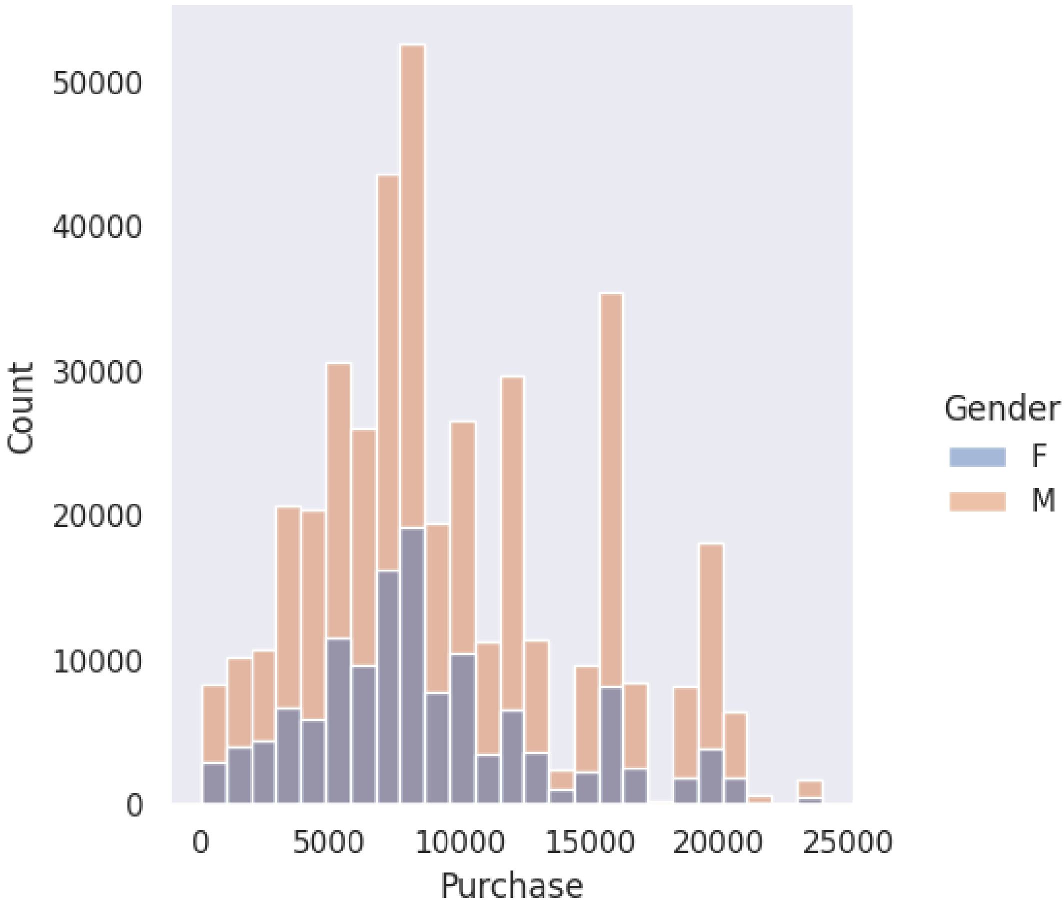
	75%	max
Occupation		
0	11957.00	23961.0
1	11702.75	23960.0
2	11718.00	23955.0
3	11961.00	23914.0
4	12034.00	23961.0
5	12091.00	23924.0
6	11971.50	23951.0
7	12486.00	23948.0
8	12607.00	23869.0
9	11436.00	23943.0
10	11931.75	23955.0
11	12010.00	23946.0
12	13239.00	23960.0
13	11798.50	23959.0
14	12508.00	23941.0
15	13150.00	23949.0
16	12218.50	23947.0
17	13292.50	23961.0
18	12062.75	23894.0

```
19           11745.00  23939.0
20           11677.00  23960.0
```

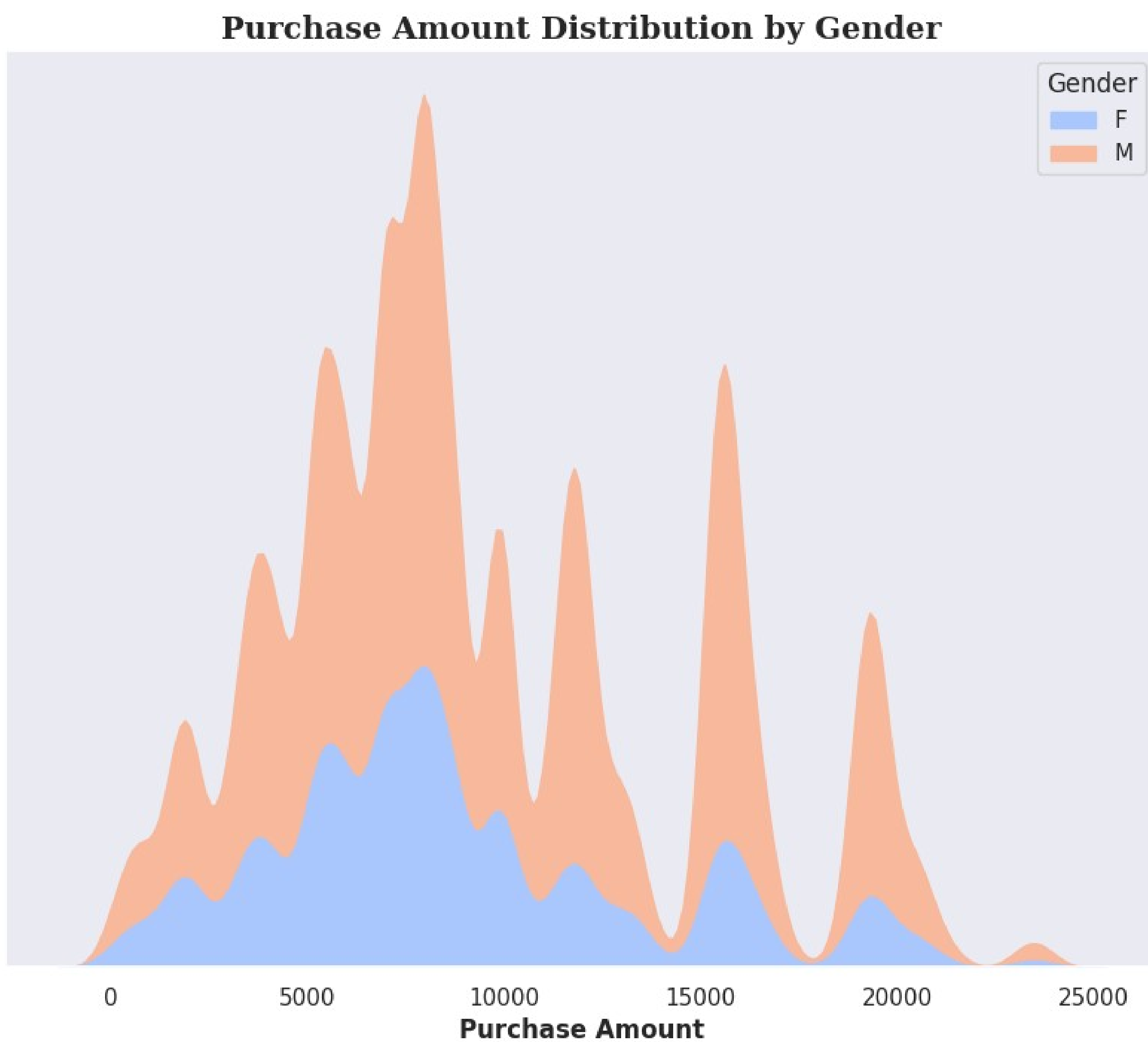
- The dataset contains numerous outliers.
- The occupation with the highest median value is occupation 17, indicating a concentration of values around a central point. Conversely, occupation 19 has the lowest median value.
- Occupation 17 stands out with the highest average order values, reaching 9821, indicating a tendency for higher spending. On the other hand, occupation 9 has the lowest average order value, totaling 8637, pointing to comparatively lower spending patterns in this occupation group.

Purchase vs Gender

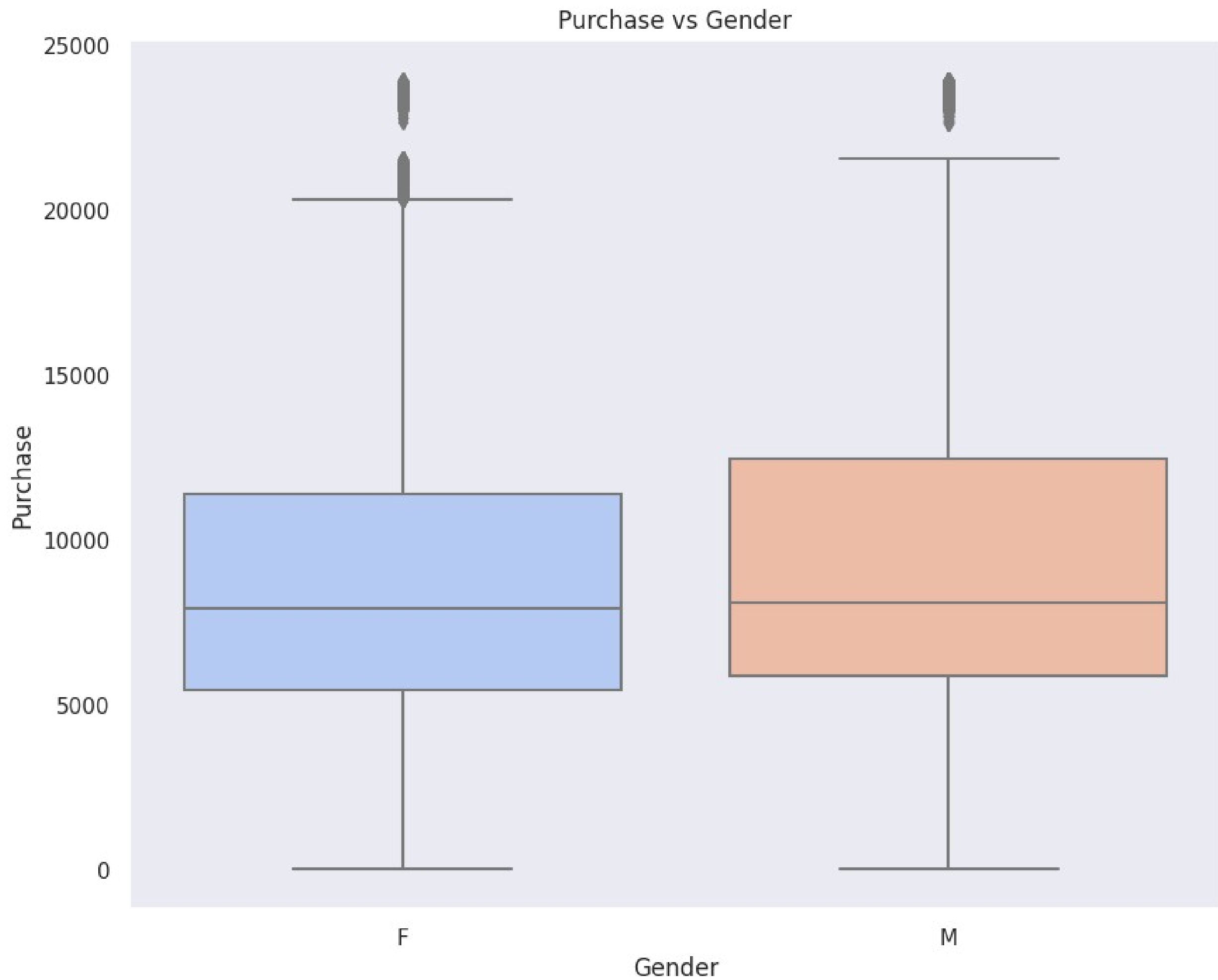
```
plt.figure(figsize=(12,8))
sns.set(style='dark')
sns.displot(x= 'Purchase',data=df,hue='Gender',bins=25)
plt.show()

<Figure size 1200x800 with 0 Axes>
```




```
plt.figure(figsize=(10,8))
sns.kdeplot(data = df, x = 'Purchase', hue = 'Gender', palette =
'coolwarm',fill = True, alpha = 1)

plt.yticks([])
plt.ylabel('')
plt.xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

plt.title('Purchase Amount Distribution by Gender',{'font':'serif',
'size':15,'weight':'bold'})

plt.show()
```




```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, y ='Purchase', x = 'Gender', palette =
'coolwarm')
plt.title("Purchase vs Gender")
plt.show()
```




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

```
           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
```

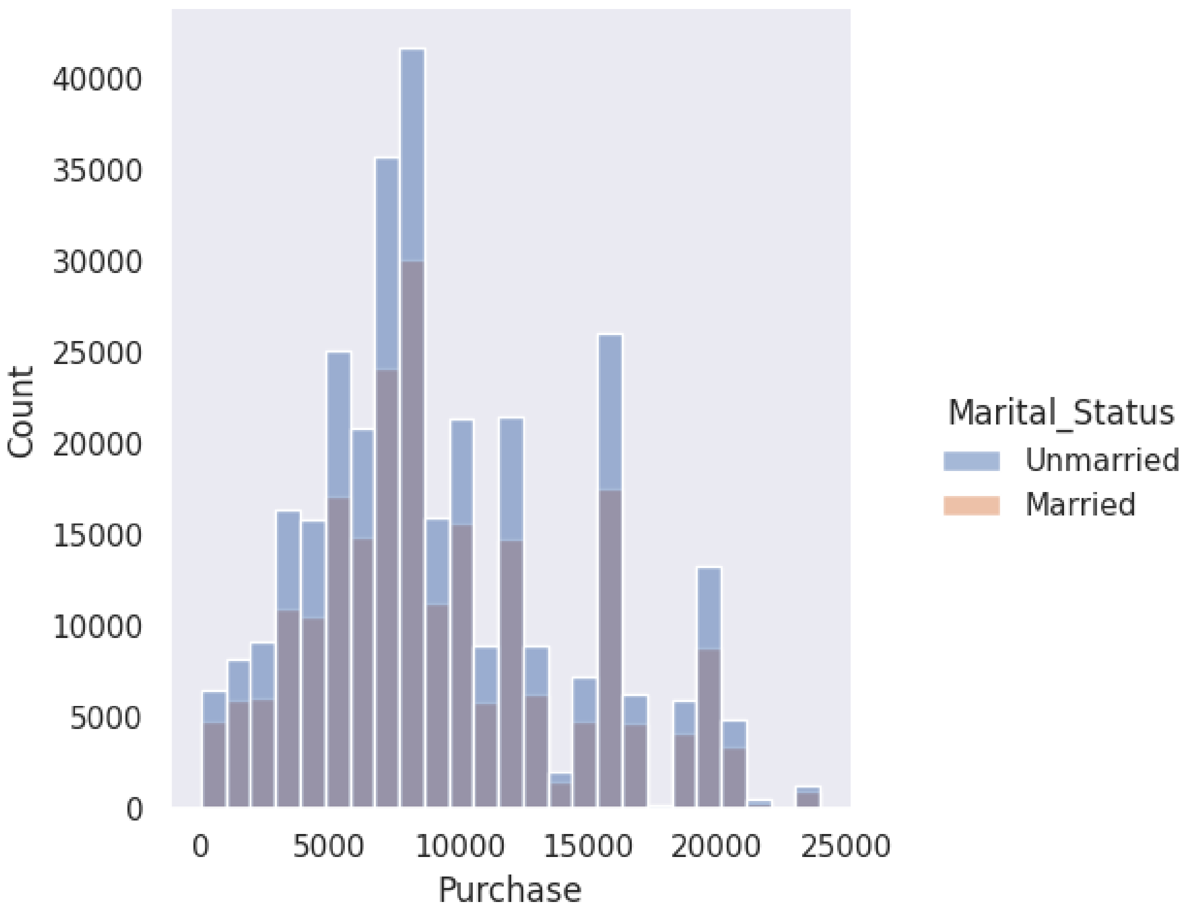
- Males tend to spend more than females in the observed data. On average, the order value for males is 9437, whereas for females, it is slightly lower at 8734.

- Most male purchases cluster around an average order value of 8098, suggesting a common spending pattern. Similarly, for females, the majority of purchases center around an average order value of 7914.

Purchase vs Marital Status

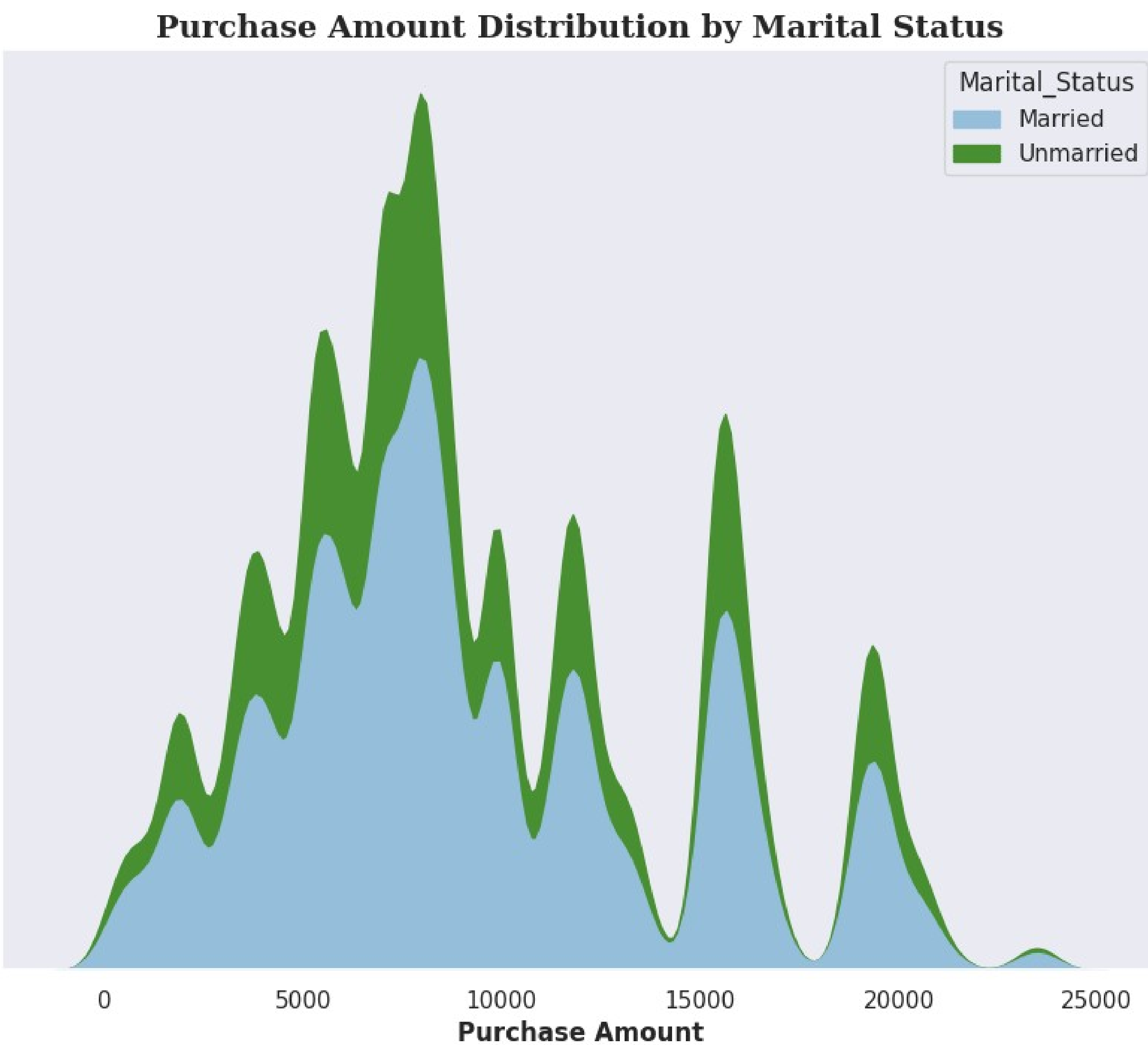
```
plt.figure(figsize=(12,8))
sns.set(style='dark')
sns.displot(x= 'Purchase',data=df,hue='Marital_Status',bins=25)
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



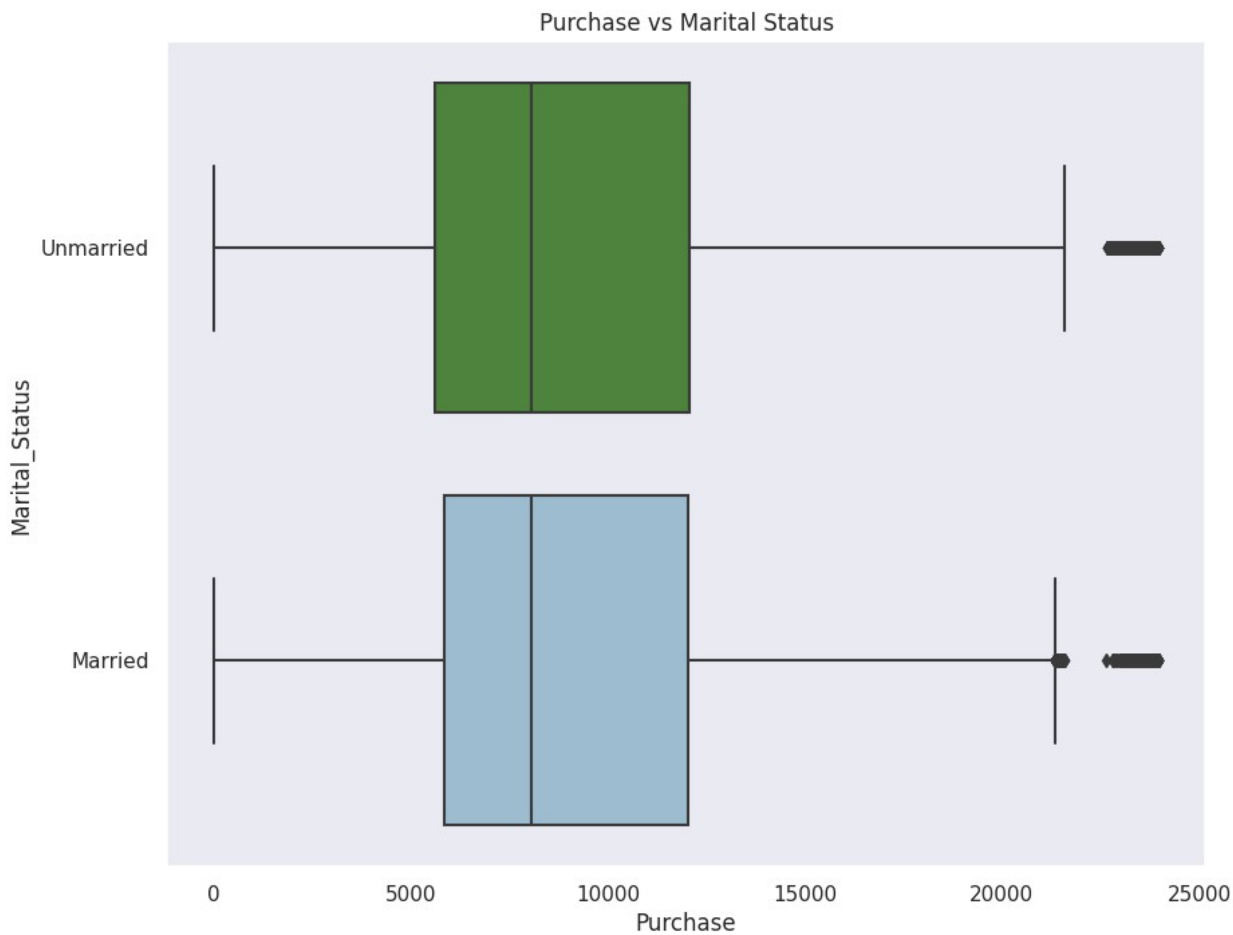

```
color_map = ["#94bed9","#488f31"]
plt.figure(figsize=(10,8))
sns.kdeplot(data = df, x = 'Purchase', hue = 'Marital_Status', palette
= color_map,fill = True, alpha = 1,hue_order =
['Married','Unmarried'])
```

```
plt.yticks([])
plt.ylabel('')
plt.xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)

plt.title('Purchase Amount Distribution by Marital Status',
{'font':'serif', 'size':15,'weight':'bold'})

plt.show()
```




```
color_map = ["#488f31","#94bed9"]
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, x ='Purchase', y = 'Marital_Status', palette =
color_map)
```

```
plt.title("Purchase vs Marital Status")
plt.show()
```




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

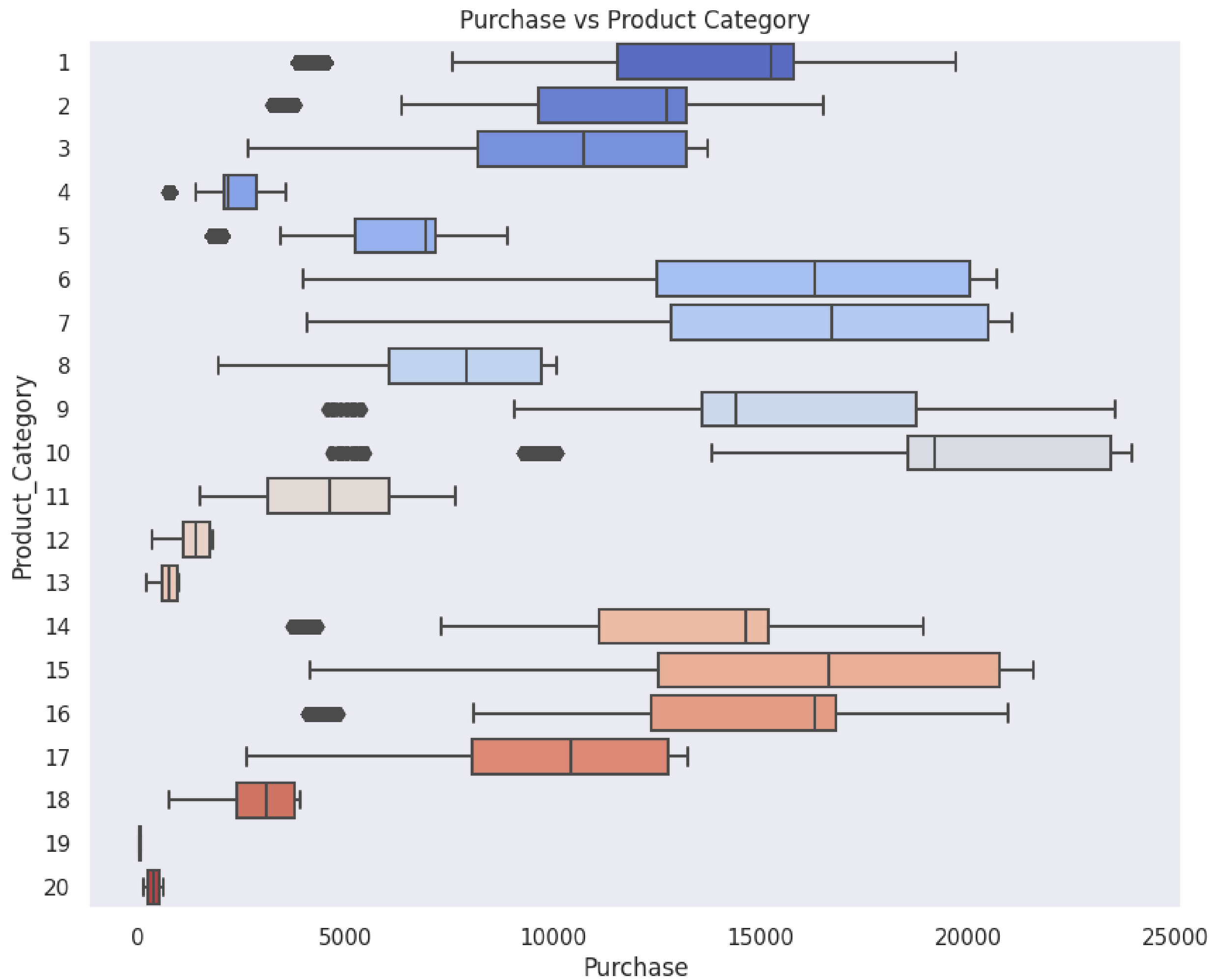
```
                    count         mean          std   min     25%
50%  \
Marital_Status

Unmarried        324731.0  9265.907619  5027.347859  12.0  5605.0
8044.0
Married          225337.0  9261.174574  5016.897378  12.0  5843.0
8051.0

                    75%      max
Marital_Status
Unmarried        12061.0  23961.0
Married          12042.0  23961.0
```

- The median value is almost the same between married and unmarried people.

- Both types share identical minimum and maximum order values, suggesting uniformity in the range of spending behavior.
- The average order values is almost the same between married and unmarried people, indicating a similar overall spending pattern between the two groups.

Purchase vs Product Category

```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, x ='Purchase', y = 'Product_Category', palette
= 'coolwarm')
plt.title("Purchase vs Product Category")
plt.show()
```




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

                        count           mean            std      min
25%  \
Product_Category
```

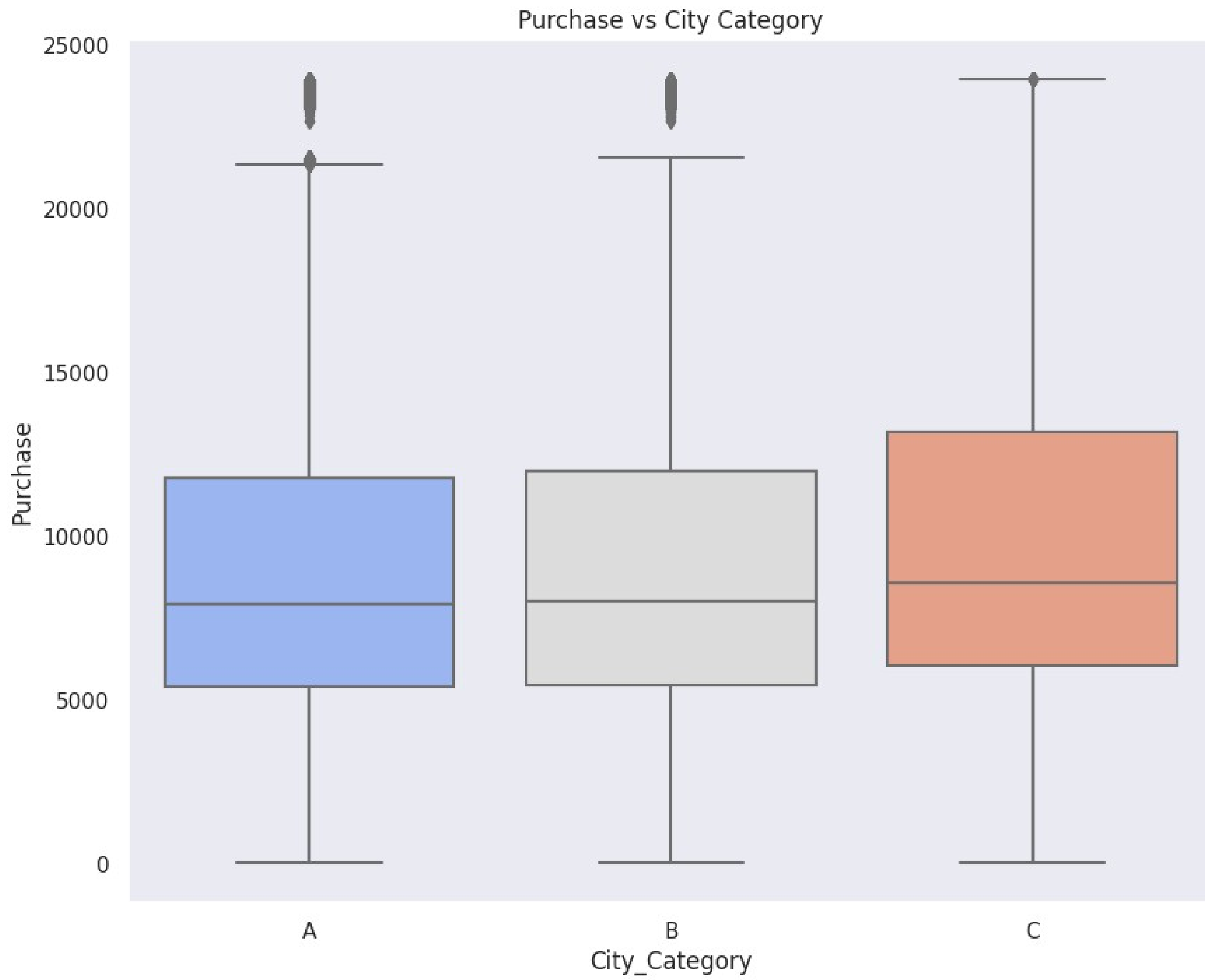
```
1                  140378.0  13606.218596  4298.834894  3790.0
11546.00
2                   23864.0  11251.935384  3570.642713  3176.0
9645.75
3                   20213.0  10096.705734  2824.626957  2638.0
8198.00
4                   11753.0   2329.659491   812.540292   684.0
2058.00
5                  150933.0   6240.088178  1909.091687  1713.0
5242.00
6                   20466.0  15838.478550  4011.233690  3981.0
12505.00
7                    3721.0  16365.689600  4174.554105  4061.0
12848.00
8                  113925.0   7498.958078  2013.015062  1939.0
6036.00
9                     410.0  15537.375610  5330.847116  4528.0
13583.50
10                   5125.0  19675.570927  4225.721898  4624.0
18546.00
11                  24287.0   4685.268456  1834.901184  1472.0
3131.00
12                   3947.0   1350.859894   362.510258   342.0
1071.00
13                   5549.0    722.400613   183.493126   185.0
578.00
14                   1523.0  13141.625739  4069.009293  3657.0
11097.00
15                   6290.0  14780.451828  5175.465852  4148.0
12523.25
16                   9828.0  14766.037037  4360.213198  4036.0
12354.00
17                    578.0  10170.759516  2333.993073  2616.0
8063.50
18                   3125.0   2972.864320   727.051652   754.0
2359.00
19                   1603.0     37.041797    16.869148    12.0
24.00
20                   2550.0    370.481176   167.116975   118.0
242.00

                      50%       75%      max
Product_Category
1                 15245.0  15812.00  19708.0
2                 12728.5  13212.00  16504.0
3                 10742.0  13211.00  13717.0
4                  2175.0   2837.00   3556.0
5                  6912.0   7156.00   8907.0
```

```
6                      16312.0  20051.00  20690.0
7                      16700.0  20486.00  21080.0
8                       7905.0   9722.00  10082.0
9                      14388.5  18764.00  23531.0
10                     19197.0  23438.00  23961.0
11                      4611.0   6058.00   7654.0
12                      1401.0   1723.00   1778.0
13                       755.0    927.00    962.0
14                     14654.0  15176.50  18931.0
15                     16660.0  20745.75  21569.0
16                     16292.5  16831.00  20971.0
17                     10435.5  12776.75  13264.0
18                      3071.0   3769.00   3900.0
19                        37.0     50.00     62.0
20                       368.0    490.00    613.0
```

- There is a huge differences in the median values for all the product categories.
- Among the observed product categories, category 10 stands out with the highest median value, reaching 19197. In contrast, category 19 has the lowest median value, merely 37.
- The average order value for category 10 is the highest, totaling 19675, highlighting a propensity for higher spending in this category. Conversely, category 19 has the lowest average order value, also 37, indicating lower overall spending in this particular category.
- Category 19 emerges as the least preferred or least frequently bought product category, given its lower median and average order values compared to other categories.

Purchase vs City Category

```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, y ='Purchase', x = 'City_Category', palette =
'coolwarm')
plt.title("Purchase vs City Category")
plt.show()
```



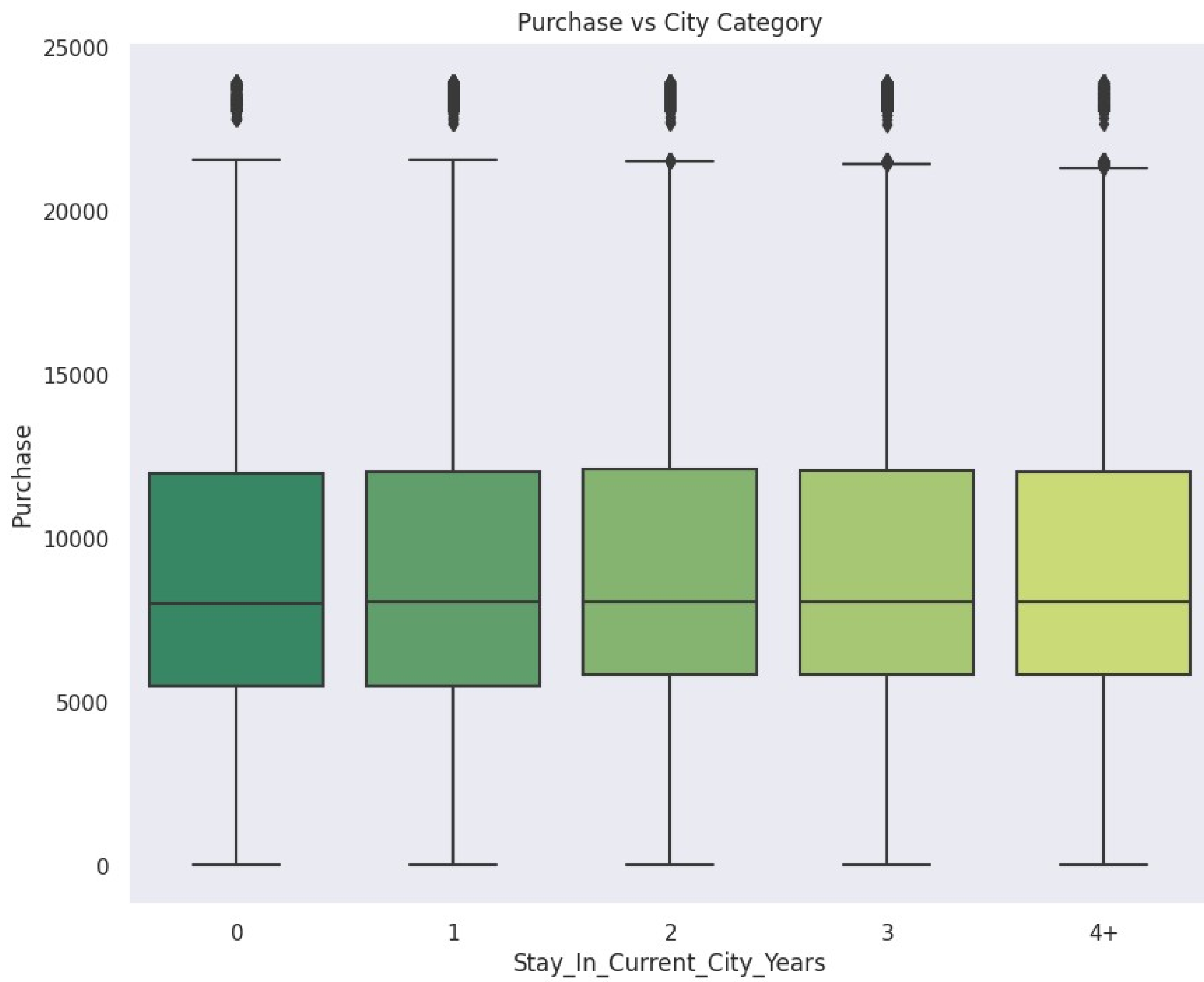

```
df.groupby(["City_Category"])["Purchase"].describe()
```

```
                  count         mean          std   min     25%
50%  \
City_Category

A              147720.0  8911.939216  4892.115238  12.0  5403.0
7931.0
B              231173.0  9151.300563  4955.496566  12.0  5460.0
8005.0
C              171175.0  9719.920993  5189.465121  12.0  6031.5
8585.0

                   75%      max
City_Category
A              11786.0  23961.0
B              11986.0  23960.0
C              13197.0  23961.0
```

- City Category C takes the lead with the highest median order value, followed by City B and City A. This suggests a central tendency towards higher values in City C compared to the other two.
- The mean order value for City C is the highest, followed by City B and City A. This indicates that, on average, transactions in City C tend to have higher values compared to those in City B and City A.

Purchase vs Stay in Current City

```
plt.figure(figsize = (10,8)).set_facecolor("white")
sns.boxplot(data = df, y ='Purchase', x =
'Stay_In_Current_City_Years', palette = 'summer')
plt.title("Purchase vs City Category")
plt.show()
```




```
df.groupby(["Stay_In_Current_City_Years"])["Purchase"].describe().T
```

```
Stay_In_Current_City_Years               0              1              2  \
count                         74398.000000  193821.000000  101838.000000

mean                           9180.075123    9250.145923    9320.429810

std                            4990.479940    5027.476933    5044.588224

min                              12.000000      12.000000      12.000000

25%                            5480.000000    5500.000000    5846.000000

50%                            8025.000000    8041.000000    8072.000000

75%                           11990.000000   12042.000000   12117.000000

max                           23960.000000   23961.000000   23961.000000


Stay_In_Current_City_Years               3             4+
count                         95285.000000   84726.000000
mean                           9286.904119    9275.598872
std                            5020.343541    5017.627594
min                              12.000000      12.000000
25%                            5832.000000    5844.000000
50%                            8047.000000    8052.000000
75%                           12075.000000   12038.000000
max                           23961.000000   23958.000000
```

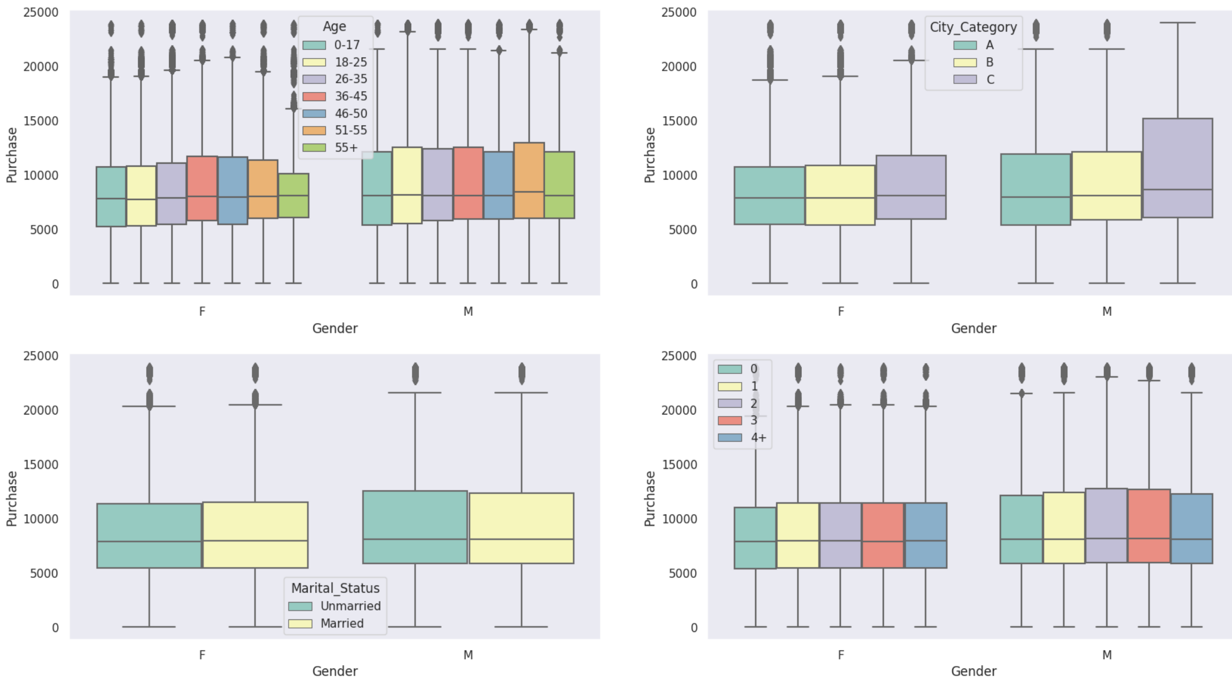
- Across all the years, there is uniformity in the median values, suggesting stability in the central tendency of order values.
- The average order values, falling within the range of 9180 to 9320, remain nearly identical across the observed years, indicating a consistent average spending pattern.
- The highest order value remains the same across all the years, suggesting a consistent spending habit regardless of the specific year.

Multi-variate Analysis

```
df

        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      Unmarried                3
8370
1                               2      Unmarried                1
15200
2                               2      Unmarried               12
1422
3                               2      Unmarried               12
1057
4                              4+      Unmarried                8
7969
...                           ...            ...              ...
...
550063                          1        Married               20
368
550064                          3      Unmarried               20
371
550065                         4+        Married               20
137
550066                          2      Unmarried               20
365
550067                         4+        Married               20
490

[550068 rows x 10 columns]
```

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.boxplot(data=df, y='Purchase', x='Gender', hue='Age',
palette='Set3', ax=axs[0,0])
sns.boxplot(data=df, y='Purchase', x='Gender', hue='City_Category',
palette='Set3', ax=axs[0,1])

sns.boxplot(data=df, y='Purchase', x='Gender', hue='Marital_Status',
palette='Set3', ax=axs[1,0])
sns.boxplot(data=df, y='Purchase', x='Gender',
hue='Stay_In_Current_City_Years', palette='Set3', ax=axs[1,1])
axs[1,1].legend(loc='upper left')

plt.show()
```



- Across age groups, the median values for females aged 18-25 are notably the lowest, while the medians for other age categories exhibit comparable values. Conversely, the highest median values are consistently observed in the 51-55 age group.
- Examining city categories, both females and males exhibit the highest median spending in city category C compared to cities A and B.
- Marital status appears to have no discernible impact on spending habits for both genders. However, it is noteworthy that median spending values for males tend to be higher than those for females.
- Delving into the duration of stay, female spending patterns reveal slightly lower median values for those residing for 0 and 3 years compared to other durations.

```
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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
```

```
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

```
col = ['Occupation','Product_Category']
df[col] = df[col].astype('int64')
```

```
df.info()
```

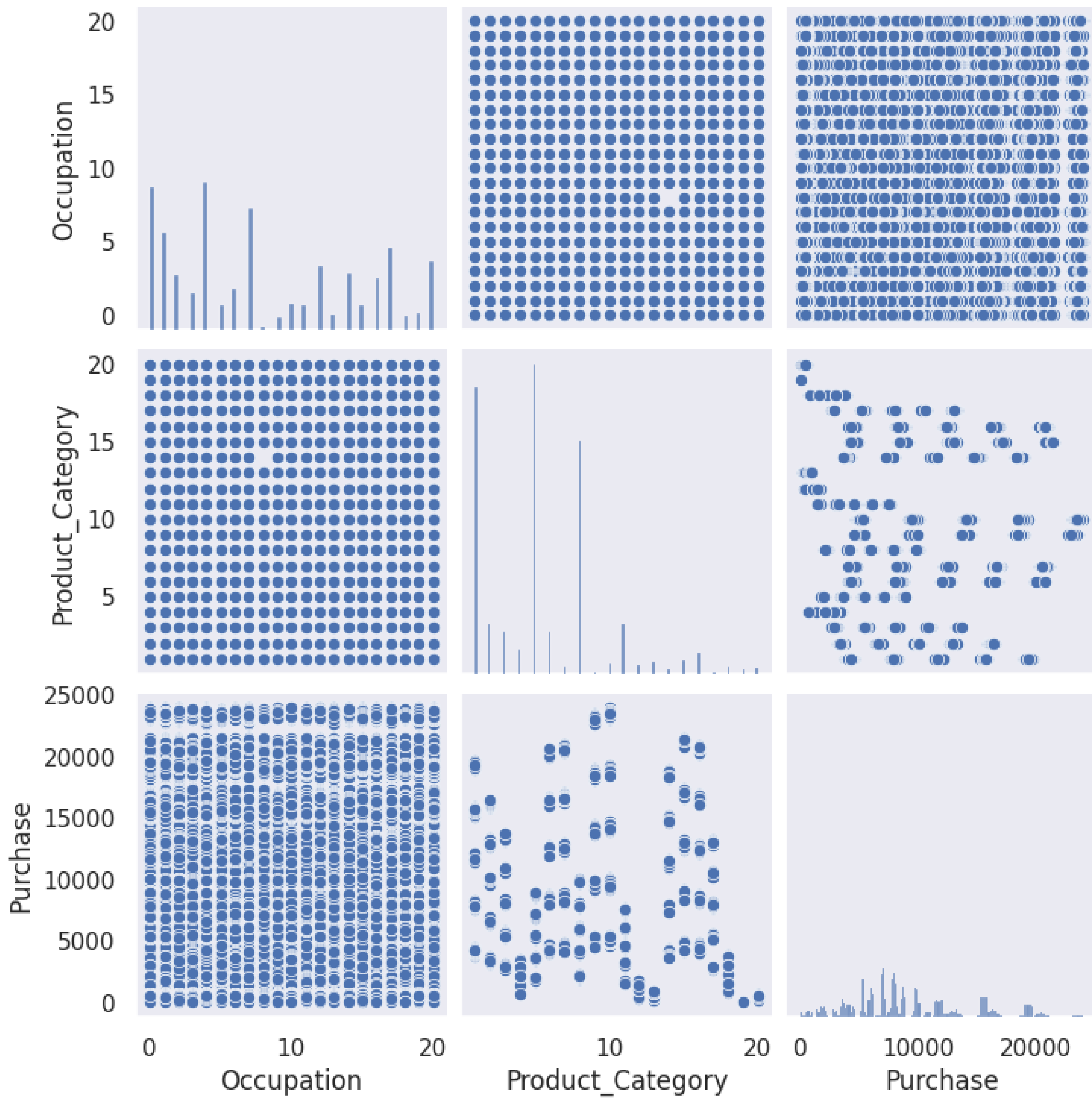
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     550068 non-null  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  int64
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  int64
 9   Purchase                    550068 non-null  int64
dtypes: category(7), int64(3)
memory usage: 17.6 MB
```

```
sns.heatmap(df.corr(), annot = True)
plt.show()
```

```
<ipython-input-64-c29a8587184a>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot = True)
```

- The analysis reveals a negative correlation of -0.0076 between Product Category and Occupation, suggesting a potential relationship that merits further investigation.
- A positive correlation of 0.021 has been observed between Purchase and Occupation, indicating a mild association between these two variables in the context of the study.
- An impactful negative correlation of -0.34 has been identified between Product Category and Purchase, implying a potentially influential connection that merits closer scrutiny in understanding the dynamics between these aspects.

```
sns.pairplot(df)
plt.show()
```



Confidence Interval

The purchase amount distribution is not Normal. So we will be using Central Limit Theorem. It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution.

After building Central Limit Theorem (CLT) curve, we will create a confidence interval predicting population mean at 95% Confidence level. Note - We will use three different sample sizes of [30,300,3000,30000]

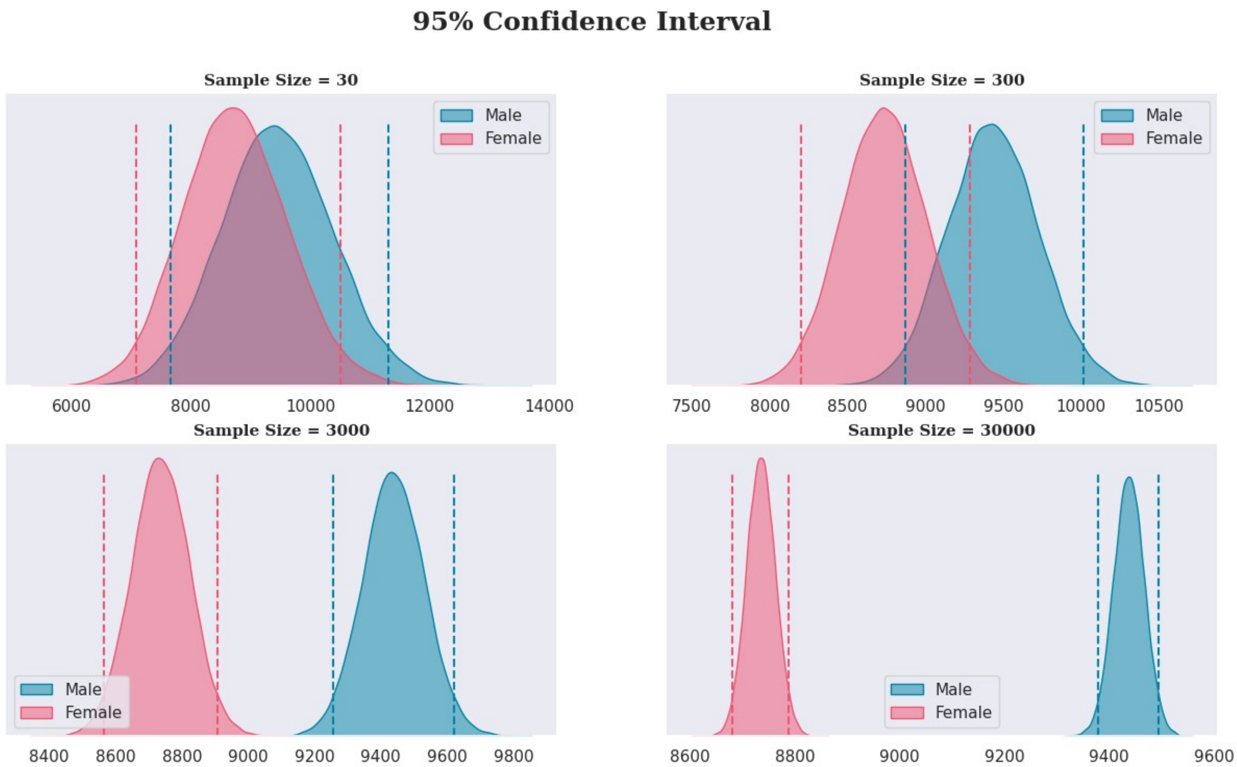
Gender Vs Purchase amount

```
def confidence_interval(data,ci):
    l_ci = (100-ci)/2
    u_ci = (100+ci)/2
    interval = np.percentile(data,[l_ci,u_ci]).round(0)

    return interval

df_male = df.loc[df['Gender'] == 'M','Purchase']
df_female = df.loc[df['Gender'] == 'F','Purchase']
df_male.nunique()
```

```
17547
```

```
def plot(ci):

    fig = plt.figure(figsize = (15,8))
    gs = fig.add_gridspec(2,2)

    df_male = df.loc[df['Gender'] == 'M','Purchase']
    df_female = df.loc[df['Gender'] == 'F','Purchase']

    sample_sizes = [(30,0,0),(300,0,1),(3000,1,0),(30000,1,1)]

    bootstrap_samples = 30000

    male_samples = {}
    female_samples = {}

    for i,x,y in sample_sizes:
        male_means = []
        female_means = []

        for j in range(bootstrap_samples):

            male_bootstrapped_samples = np.random.choice(df_male,size
= i)
            female_bootstrapped_samples =
np.random.choice(df_female,size = i)
            male_sample_mean = np.mean(male_bootstrapped_samples)
            female_sample_mean = np.mean(female_bootstrapped_samples)

            male_means.append(male_sample_mean)
            female_means.append(female_sample_mean)

        male_samples[f'{ci}%_{i}'] = male_means
        female_samples[f'{ci}%_{i}'] = female_means

        temp_df = pd.DataFrame(data =
{'male_means':male_means,'female_means':female_means})
        ax = fig.add_subplot(gs[x,y])
        sns.kdeplot(data = temp_df,x = 'male_means',color
```

```
="#0083a6" ,fill = True, alpha = 0.5,ax = ax,label = 'Male')
        sns.kdeplot(data = temp_df,x = 'female_means',color ="#ef5675"
,fill = True, alpha = 0.5,ax = ax,label = 'Female')
        m_range = confidence_interval(male_means,ci)
        f_range = confidence_interval(female_means,ci)
        for k in m_range:
            ax.axvline(x = k,ymax = 0.9, color ="#0083a6",linestyle =
'--')

        for k in f_range:
            ax.axvline(x = k,ymax = 0.9, color ="#ef5675",linestyle =
'--')

        for s in ['top','left','right']:
            ax.spines[s].set_visible(False)

        ax.set_yticks([])
        ax.set_ylabel('')
        ax.set_xlabel('')
        ax.set_title(f'Sample Size = {i}',{'font':'serif',
'size':11,'weight':'bold'})
        plt.legend()
    fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size =
18, weight = 'bold')

    plt.show()

    return male_samples,female_samples

m_samp_95,f_samp_95 = plot(95)
```




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

for i,j,k,l in [(m_samp_95,f_samp_95,95,1)]:
    m_ci = ['Male']
    f_ci = ['Female']

    for m in i:
        m_range = confidence_interval(i[m],k)
        m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f},
Range = {(m_range[1] - m_range[0]):.0f}")

    for f in j:
        f_range = confidence_interval(j[f],k)
        f_ci.append(f"CI = ${f_range[0]:.0f} - ${f_range[1]:.0f},
Range = {(f_range[1] - f_range[0]):.0f}")

    ax = fig.add_subplot(gs[l])

    ci_info = [m_ci,f_ci]

    table = ax.table(cellText = ci_info, cellLoc='center',
                     colLabels =['Gender','Sample Size = 30','Sample
Size = 300','Sample Size = 3000','Sample Size = 30000'],
                     colLoc = 'center',colWidths =
[0.05,0.2375,0.2375,0.2375,0.2375],bbox =[0, 0, 1, 1])
```

```
    table.set_fontsize(13)
    ax.axis('off')
    ax.set_title(f"{k}% Confidence Interval Summary Based on Gender",
{'font':'serif', 'size':14,'weight':'bold'})
```

95% Confidence Interval Summary Based on Gender

Gender	Sample Size = 30	Sample Size = 300	Sample Size = 3000	Sample Size = 30000
Male	CI = 7678 – 11314, Range = 3636	CI = 8869 – 10024, Range = 1155	CI = 9256 – 9620, Range = 364	CI = 9381 – 9495, Range = 114
Female	CI = 7065 – 10456, Range = 3391	CI = 8196 – 9284, Range = 1088	CI = 8565 – 8905, Range = 340	CI = 8680 – 8789, Range = 109

```
amt_df = df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

```
       User_ID Gender  Purchase
0      1000001      F    334093
1      1000001      M         0
2      1000002      F         0
3      1000002      M    810472
4      1000003      F         0
...        ...    ...       ...
11777  1006038      M         0
11778  1006039      F    590319
11779  1006039      M         0
11780  1006040      F         0
11781  1006040      M   1653299

[11782 rows x 3 columns]
```

```
avg_amt_df = amt_df['Gender'].value_counts()
avg_amt_df
```

```
F    5891
M    5891
Name: Gender, dtype: int64
```

```
male_df = amt_df[amt_df['Gender']=='M']
female_df = amt_df[amt_df['Gender']=='F']
male_df
```

```
       User_ID Gender  Purchase
1      1000001      M         0
3      1000002      M    810472
5      1000003      M    341635
7      1000004      M    206468
9      1000005      M    821001
...        ...    ...       ...
11773  1006036      M         0
```

```
11775  1006037      M         0
11777  1006038      M         0
11779  1006039      M         0
11781  1006040      M   1653299

[5891 rows x 3 columns]
```

```
male_df['Purchase'].std()
```

```
933096.7961923733
```

```
female_df['Purchase'].std()
```

```
535828.1658663888
```

```
print("Male - Sample mean:",male_df['Purchase'].mean(),"Sample std:",
male_df['Purchase'].std())
print("Female - Sample mean:",female_df['Purchase'].mean(),"Sample
std:",female_df['Purchase'].std())
```

```
Male - Sample mean: 663653.0470208793 Sample std: 933096.7961923733
Female - Sample mean: 201363.544729248 Sample std: 535828.1658663888
```

```
male_margin_of_error_clt =
1.96*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt

female_margin_of_error_clt =
1.96*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt

print("Male confidence interval of means: ({:.2f},
{:.2f})".format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: ({:.2f},
{:.2f})".format(female_lower_lim, female_upper_lim))
```

```
Male confidence interval of means: (639825.01, 687481.08)
Female confidence interval of means: (187680.36, 215046.73)
```

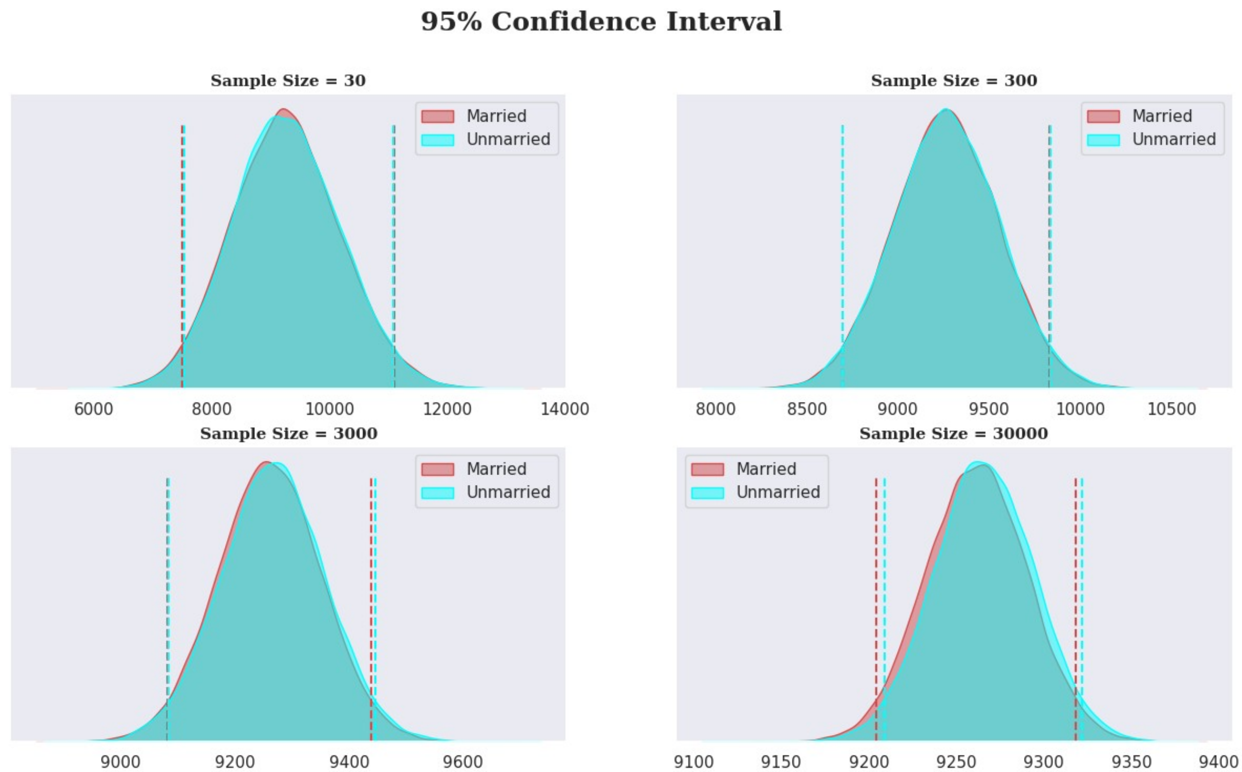
Observations

- Population mean - Mean of sample means of amount spend for Male: 663474.53
- Population mean - Mean of sample means of amount spend for Female: 201373.07
- Male - Sample mean: 663653.05 Sample std: 933096.80
- Female - Sample mean: 201363.54 Sample std: 535828.17

Marital Status Vs Purchase amount

```
def plot(ci):
    fig = plt.figure(figsize = (15,8))
    gs = fig.add_gridspec(2,2)


    df_married = df.loc[df['Marital_Status'] == 'Married','Purchase']
    df_unmarried = df.loc[df['Marital_Status'] ==
'Unmarried','Purchase']

    sample_sizes = [(30,0,0),(300,0,1),(3000,1,0),(30000,1,1)]

    bootstrap_samples = 30000

    married_samples = {}
    unmarried_samples = {}

    for i,x,y in sample_sizes:
        married_means = []
        unmarried_means = []

        for j in range(bootstrap_samples):

            married_bootstrapped_samples =
np.random.choice(df_married,size = i)
            unmarried_bootstrapped_samples =
np.random.choice(df_unmarried,size = i)

            married_sample_mean =
np.mean(married_bootstrapped_samples)
            unmarried_sample_mean =
np.mean(unmarried_bootstrapped_samples)

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

        married_samples[f'{ci}%_{i}'] = married_means
        unmarried_samples[f'{ci}%_{i}'] = unmarried_means


        temp_df = pd.DataFrame(data =
{'married_means':married_means,'unmarried_means':unmarried_means})


        ax = fig.add_subplot(gs[x,y])


        sns.kdeplot(data = temp_df,x = 'married_means',color
="#d44d4d" ,fill = True, alpha = 0.5,ax = ax,label = 'Married')
        sns.kdeplot(data = temp_df,x = 'unmarried_means',color
```

```
="#00ffff" ,fill = True, alpha = 0.5,ax = ax,label = 'Unmarried')

        m_range = confidence_interval(married_means,ci)
        u_range = confidence_interval(unmarried_means,ci)

        for k in m_range:
            ax.axvline(x = k,ymax = 0.9, color ="#d44d4d",linestyle =
'--')

        for k in u_range:
            ax.axvline(x = k,ymax = 0.9, color ="#00ffff",linestyle =
'--')

        for s in ['top','left','right']:
            ax.spines[s].set_visible(False)

        ax.set_yticks([])
        ax.set_ylabel('')
        ax.set_xlabel('')

        ax.set_title(f'Sample Size = {i}',{'font':'serif',
'size':11,'weight':'bold'})

        plt.legend()

    fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size =
18, weight = 'bold')

    plt.show()

    return married_samples,unmarried_samples

m_samp_95,u_samp_95 = plot(95)
```




```
fig,ax = plt.subplots(figsize = (20,3))

m_ci = ['Married']
u_ci = ['Unmarried']

for m in m_samp_95:
    m_range = confidence_interval(m_samp_95[m],95)
    m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f}, Range =
{(m_range[1] - m_range[0]):.0f}")

for u in u_samp_95:
    u_range = confidence_interval(u_samp_95[u],95)
    u_ci.append(f"CI = ${u_range[0]:.0f} - ${u_range[1]:.0f}, Range =
{(u_range[1] - u_range[0]):.0f}")

ci_info = [m_ci,u_ci]

table = ax.table(cellText = ci_info, cellLoc='center',
             colLabels =['Marital_Status','Sample Size = 30','Sample
Size = 300','Sample Size = 3000','Sample Size = 30000'],
             colLoc = 'center',colWidths =
[0.1,0.225,0.225,0.225,0.225],bbox =[0, 0, 1, 1])

table.set_fontsize(13)
ax.axis('off')
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif',
```

```
'size':14,'weight':'bold'})
plt.show()
```

95% Confidence Interval Summary

Marital_Status	Sample Size = 30	Sample Size = 300	Sample Size = 3000	Sample Size = 30000
Married	CI = 7485 – 11110, Range = 3625	CI = 8698 – 9828, Range = 1130	CI = 9082 – 9438, Range = 356	CI = 9204 – 9318, Range = 114
Unmarried	CI = 7533 – 11091, Range = 3558	CI = 8698 – 9837, Range = 1139	CI = 9084 – 9447, Range = 363	CI = 9209 – 9322, Range = 113

Age Group Vs Purchase amount

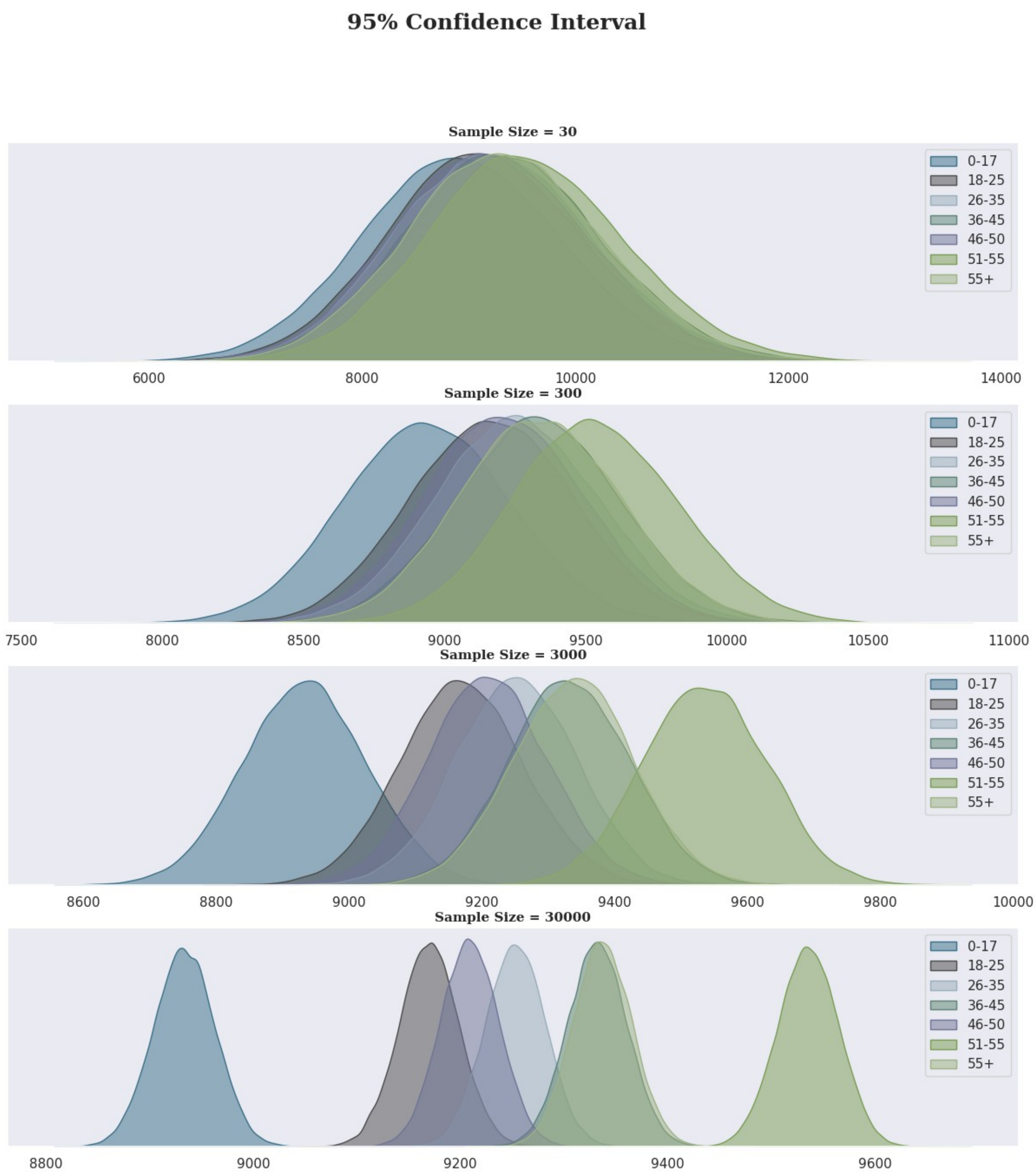
```
df_age = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
df_age = df_age.reset_index()

df_age['Age'].value_counts()
```

```
0-17     5891
18-25    5891
26-35    5891
36-45    5891
46-50    5891
51-55    5891
55+      5891
Name: Age, dtype: int64
```

```
def plot(ci):
    fig = plt.figure(figsize = (15,15))
    gs = fig.add_gridspec(4,1)

    df_1 = df.loc[df['Age'] == '0-17','Purchase']
    df_2 = df.loc[df['Age'] == '18-25','Purchase']
    df_3 = df.loc[df['Age'] == '26-35','Purchase']
    df_4 = df.loc[df['Age'] == '36-45','Purchase']
    df_5 = df.loc[df['Age'] == '46-50','Purchase']
    df_6 = df.loc[df['Age'] == '51-55','Purchase']
    df_7 = df.loc[df['Age'] == '55+','Purchase']

    sample_sizes = [(30,0),(300,1),(3000,2),(30000,3)]
    bootstrap_samples = 30000

    samples1,samples2,samples3,samples4,samples5,samples6,samples7 =
{},{},{},{},{},{},{}

    for i,x in sample_sizes:
        l1,l2,l3,l4,l5,l6,l7 = [],[],[],[],[],[],[]

        for j in range(bootstrap_samples):
            bootstrapped_samples_1 = np.random.choice(df_1,size = i)
            bootstrapped_samples_2 = np.random.choice(df_2,size = i)
```

```
            bootstrapped_samples_3 = np.random.choice(df_3,size = i)
            bootstrapped_samples_4 = np.random.choice(df_4,size = i)
            bootstrapped_samples_5 = np.random.choice(df_5,size = i)
            bootstrapped_samples_6 = np.random.choice(df_6,size = i)
            bootstrapped_samples_7 = np.random.choice(df_7,size = i)

            sample_mean_1 = np.mean(bootstrapped_samples_1)
            sample_mean_2 = np.mean(bootstrapped_samples_2)
            sample_mean_3 = np.mean(bootstrapped_samples_3)
            sample_mean_4 = np.mean(bootstrapped_samples_4)
            sample_mean_5 = np.mean(bootstrapped_samples_5)
            sample_mean_6 = np.mean(bootstrapped_samples_6)
            sample_mean_7 = np.mean(bootstrapped_samples_7)

            l1.append(sample_mean_1)
            l2.append(sample_mean_2)
            l3.append(sample_mean_3)
            l4.append(sample_mean_4)
            l5.append(sample_mean_5)
            l6.append(sample_mean_6)
            l7.append(sample_mean_7)

        samples1[f'{ci}%_{i}'] = l1
        samples2[f'{ci}%_{i}'] = l2
        samples3[f'{ci}%_{i}'] = l3
        samples4[f'{ci}%_{i}'] = l4
        samples5[f'{ci}%_{i}'] = l5
        samples6[f'{ci}%_{i}'] = l6
        samples7[f'{ci}%_{i}'] = l7


        temp_df = pd.DataFrame(data = {'0-17':l1,'18-25':l2,'26-
35':l3,'36-45':l4,'46-50':l5,'51-55':l6,'55+':l7})

        ax = fig.add_subplot(gs[x])

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

            sns.kdeplot(data = temp_df,x = q,color =p ,fill = True,
alpha = 0.5,ax = ax,label = q)

        for s in ['top','left','right']:
            ax.spines[s].set_visible(False)

        ax.set_yticks([])
        ax.set_ylabel('')
        ax.set_xlabel('')
```

```
        ax.set_title(f'Sample Size = {i}',{'font':'serif',
'size':11,'weight':'bold'})

        plt.legend()

    fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size =
18, weight = 'bold')

    plt.show()

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

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




```
fig,ax = plt.subplots(figsize = (20,5))
ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7 = ['0-17'],['18-25'],['26-35'],
['36-45'],['46-50'],['51-55'],['55+']
samples = [(samples1,ci_1),(samples2,ci_2),(samples3,ci_3),
(samples4,ci_4),(samples5,ci_5),(samples6,ci_6),(samples7,ci_7)]
for s,c in samples:
    for i in s:
        s_range = confidence_interval(s[i],95)
```

```
        c.append(f"CI = ${s_range[0]:.0f} - ${s_range[1]:.0f}, Range = 
{(s_range[1] - s_range[0]):.0f}")

ci_info = [ci_1,ci_2,ci_3,ci_4,ci_5,ci_6,ci_7]

table = ax.table(cellText = ci_info, cellLoc='center',
             colLabels =['Age Group','Sample Size = 30','Sample Size = 
300','Sample Size = 3000','Sample Size = 30000'],
             colLoc = 'center',colWidths = 
[0.1,0.225,0.225,0.225,0.225],bbox =[0, 0, 1, 1])
table.set_fontsize(13)
ax.axis('off')
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif', 
'size':14,'weight':'bold'})
plt.show()
```

95% Confidence Interval Summary

Age Group	Sample Size = 30	Sample Size = 300	Sample Size = 3000	Sample Size = 30000
0-17	CI = 7150 – 10823, Range = 3673	CI = 8361 – 9521, Range = 1160	CI = 8752 – 9116, Range = 364	CI = 8875 – 8991, Range = 116
18-25	CI = 7426 – 11030, Range = 3604	CI = 8609 – 9743, Range = 1134	CI = 8990 – 9353, Range = 363	CI = 9112 – 9227, Range = 115
26-35	CI = 7514 – 11083, Range = 3569	CI = 8690 – 9824, Range = 1134	CI = 9073 – 9429, Range = 356	CI = 9196 – 9309, Range = 113
36-45	CI = 7584 – 11165, Range = 3581	CI = 8767 – 9907, Range = 1140	CI = 9153 – 9509, Range = 356	CI = 9274 – 9388, Range = 114
46-50	CI = 7492 – 11027, Range = 3535	CI = 8658 – 9768, Range = 1110	CI = 9031 – 9385, Range = 354	CI = 9153 – 9264, Range = 111
51-55	CI = 7754 – 11407, Range = 3653	CI = 8971 – 10120, Range = 1149	CI = 9352 – 9717, Range = 365	CI = 9477 – 9591, Range = 114
55+	CI = 7590 – 11162, Range = 3572	CI = 8775 – 9909, Range = 1134	CI = 9158 – 9513, Range = 355	CI = 9280 – 9393, Range = 113

Insights

Confidence Interval by Gender

- Average amount spend by male customer will lie in between: (895617.83, 955070.97)
- Average amount spend by female customer will lie in between: (673254.77, 750794.02)

Confidence Interval by Marital_Status

- Married confidence interval of means: (806668.83, 880384.76)
- Unmarried confidence interval of means: (848741.18, 912410.38)

Confidence Interval by Age

- For age 26-35 --> confidence interval of means: (945034.42, 1034284.21)
- For age 36-45 --> confidence interval of means: (823347.80, 935983.62)
- For age 18-25 --> confidence interval of means: (801632.78, 908093.46)
- For age 46-50 --> confidence interval of means: (713505.63, 871591.93)
- For age 51-55 --> confidence interval of means: (692392.43, 834009.42)
- For age 55+ --> confidence interval of means: (476948.26, 602446.23)
- For age 0-17 --> confidence interval of means: (527662.46, 710073.17)

Recommendations

- **Gender-Specific Recommendations:**

Target Male Customer Retention and Acquisition, Recognizing that men spend more than women, the company should prioritize retaining existing male customers and attracting new ones.

Tailored Marketing for Females, Since females generally spend less, the company should develop targeted marketing strategies to address their specific needs and potentially increase their spending.

- **Product Category Strategy:**

Products in categories 1, 5, 8, and 11 show high purchasing frequency, indicating customer preferences. The company should focus on increasing sales of these products and explore strategies to promote less-purchased items.

- **Focusing on Unmarried Customers:**

Unmarried customers exhibit higher spending compared to married customers. The company should concentrate on acquiring and retaining unmarried customers.

- **Age-Specific Marketing:**

1. Engage Younger Consumers with Incentives (0-17 Years),Customers in the 0-17 age group have the lowest spending per transaction. To attract more young shoppers, the company can offer games and incentives tailored to the preferences of the younger generation, creating a more engaging and enjoyable shopping environment. Implementing special offers and games for the 0-17 age group can attract families and boost sales.
2. Attract Younger Shoppers with Games(18-25), Introducing games in the mall can attract a younger audience and contribute to increased sales. Management should explore interactive strategies to engage younger customers.
3. Tailor Offerings (26-45), Given that the age group 26-45 drives the majority of sales, Walmart should tailor its product selection offering exclusive deals on popular products.
4. Enhance Shopping Experience for Age Group 51-55, The 51-55 age group exhibits the highest spending per transaction. Walmart can enhance their shopping experience through exclusive pre-sale access, special discounts, and personalized recommendations.

- **City_Category C Revenue Boost:**

Male customers in City_Category C spend more than those in other categories. Increasing product offerings and marketing efforts targeting the males in City_Category C can enhance overall revenue.