Black Friday Dataset EDA And Feature Engineering

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Problem Statement

A retail company “ABC Private Limited” wants to understand the customer purchase behaviour (specifically, purchase amount) against various products of different categories. They have shared purchase summary of various customers for selected high volume products from last month. The data set also contains customer demographics (age, gender, marital status, city_type, stay_in_current_city), product details (product_id and product category) and Total purchase_amount from last month.

Now, they want to build a model to predict the purchase amount of customer against various products which will help them to create personalized offer for customers against different products.

In [2]:
```
## importing the data
df_train = pd.read_csv("E:/My Python Projects/3. Python Projects/EDA/2. Black Friday Dataset/Raw/train.csv")
df_test = pd.read_csv("E:/My Python Projects/3. Python Projects/EDA/2. Black Friday Dataset/Raw/test.csv")
```

Analyzing the data

In [3]:
```
df_train.head()
```

Out[3]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	NaN	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	14.0	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	NaN	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	NaN	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	NaN	7969

In [4]:
```
df_test.head()
```

Out[4]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3
0	1000004	P00128942	M	46-50	7	B	2	1	1	11.0	NaN
1	1000009	P00113442	M	26-35	17	C	0	0	3	5.0	NaN
2	1000010	P00288442	F	36-45	1	B	4+	1	5	14.0	NaN
3	1000010	P00145342	F	36-45	1	B	4+	1	4	9.0	NaN
4	1000011	P00053842	F	26-35	1	C	1	0	4	5.0	12.0

In [5]:
```
## Merging the train and test data

df = pd.concat([df_train, df_test])
df.head()
```

Out[5]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	NaN	8370.0
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	14.0	15200.0
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	NaN	1422.0
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	NaN	1057.0
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	NaN	7969.0

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 783667 entries, 0 to 233598
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     783667 non-null  int64  
 1   Product_ID                  783667 non-null  object 
 2   Gender                      783667 non-null  object 
 3   Age                         783667 non-null  object 
 4   Occupation                  783667 non-null  int64  
 5   City_Category               783667 non-null  object 
 6   Stay_In_Current_City_Years  783667 non-null  object 
 7   Marital_Status              783667 non-null  int64  
 8   Product_Category_1          783667 non-null  int64  
 9   Product_Category_2          537685 non-null  float64
 10  Product_Category_3          237858 non-null  float64
 11  Purchase                    550068 non-null  float64
dtypes: float64(3), int64(4), object(5)
memory usage: 77.7+ MB
```

In [8]:
```
df.describe()
```

Out[8]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
count	7.836670e+05	783667.000000	783667.000000	783667.000000	537685.000000	237858.000000	550068.000000
mean	1.003029e+06	8.079300	0.409777	5.366196	9.844506	12.668605	9263.968713
std	1.727267e+03	6.522206	0.491793	3.878160	5.089093	4.125510	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	2.000000	3.000000	12.000000
25%	1.001519e+06	2.000000	0.000000	1.000000	5.000000	9.000000	5823.000000
50%	1.003075e+06	7.000000	0.000000	5.000000	9.000000	14.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	15.000000	16.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	18.000000	18.000000	23961.000000

In [9]:
```
## droping the User_ID column
df.drop(['User_ID'], axis = 1, inplace = True)
```

In [10]:
```
df.head()
```

Out[10]:

	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	P00069042	F	0-17	10	A	2	0	3	NaN	NaN	8370.0
1	P00248942	F	0-17	10	A	2	0	1	6.0	14.0	15200.0
2	P00087842	F	0-17	10	A	2	0	12	NaN	NaN	1422.0
3	P00085442	F	0-17	10	A	2	0	12	14.0	NaN	1057.0
4	P00285442	M	55+	16	C	4+	0	8	NaN	NaN	7969.0

In [11]:
```
pd.get_dummies(df['Gender'], dtype = int)
```

Out[11]:

	F	M
0	1	0
1	1	0
2	1	0
3	1	0
4	0	1
...	...	...
233594	1	0
233595	1	0
233596	1	0
233597	1	0
233598	1	0

783667 rows × 2 columns

In [12]:
```
## Handling Categorical Feature Gender
df['Gender'] = df['Gender'].map({'F':0, 'M':1})
df.head()
```

Out[12]:

	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	P00069042	0	0-17	10	A	2	0	3	NaN	NaN	8370.0
1	P00248942	0	0-17	10	A	2	0	1	6.0	14.0	15200.0
2	P00087842	0	0-17	10	A	2	0	12	NaN	NaN	1422.0
3	P00085442	0	0-17	10	A	2	0	12	14.0	NaN	1057.0
4	P00285442	1	55+	16	C	4+	0	8	NaN	NaN	7969.0

In [13]:
```
## Handling Categorical Feature Age
df.Age.unique()
```

Out[13]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

In [14]:
```
df['Age'] = df['Age'].map({'0-17':1, '18-25':2, '26-35':3, '36-45':4, '46-50':5, '51-55':6, '55+':7})
df.head()
```

Out[14]:

	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	P00069042	0	1	10	A	2	0	3	NaN	NaN	8370.0
1	P00248942	0	1	10	A	2	0	1	6.0	14.0	15200.0
2	P00087842	0	1	10	A	2	0	12	NaN	NaN	1422.0
3	P00085442	0	1	10	A	2	0	12	14.0	NaN	1057.0
4	P00285442	1	7	16	C	4+	0	8	NaN	NaN	7969.0

In [15]:
```
## Handling Categorical Feature City_category
df_city = pd.get_dummies(df['City_Category'], drop_first = True, dtype = int)
```

In [16]:
```
df_city.head()
```

Out[16]:

	B	C
0	0	0
1	0	0
2	0	0
3	0	0
4	0	1

In [17]:
```
df = pd.concat([df,df_city], axis = 1)
df.head()
```

Out[17]:

	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	B	C
0	P00069042	0	1	10	A	2	0	3	NaN	NaN	8370.0	0	0
1	P00248942	0	1	10	A	2	0	1	6.0	14.0	15200.0	0	0
2	P00087842	0	1	10	A	2	0	12	NaN	NaN	1422.0	0	0
3	P00085442	0	1	10	A	2	0	12	14.0	NaN	1057.0	0	0
4	P00285442	1	7	16	C	4+	0	8	NaN	NaN	7969.0	0	1

In [18]:
```
## Droping City_Category column
df.drop('City_Category', axis = 1, inplace = True)
```

In [19]:
```
df.head()
```

Out[19]:

	Product_ID	Gender	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	B	C
0	P00069042	0	1	10	2	0	3	NaN	NaN	8370.0	0	0
1	P00248942	0	1	10	2	0	1	6.0	14.0	15200.0	0	0
2	P00087842	0	1	10	2	0	12	NaN	NaN	1422.0	0	0
3	P00085442	0	1	10	2	0	12	14.0	NaN	1057.0	0	0
4	P00285442	1	7	16	4+	0	8	NaN	NaN	7969.0	0	1

Fixing Missing Values

In [20]:
```
## Missing Values
df.isnull().sum()
```

Out[20]:
```
Product_ID                        0
Gender                            0
Age                               0
Occupation                        0
Stay_In_Current_City_Years        0
Marital_Status                    0
Product_Category_1                0
Product_Category_2           245982
Product_Category_3           545809
Purchase                     233599
B                                 0
C                                 0
dtype: int64
```

In [21]:
```
## Replacing missing values
df['Product_Category_2'].unique()
```

Out[21]:
```
array([nan,  6., 14.,  2.,  8., 15., 16., 11.,  5.,  3.,  4., 12.,  9.,
       10., 17., 13.,  7., 18.])
```

In [22]:
```
df['Product_Category_2'].value_counts()
```

Out[22]:
```
Product_Category_2
8.0     91317
14.0    78834
2.0     70498
16.0    61687
15.0    54114
5.0     37165
4.0     36705
6.0     23575
11.0    20230
17.0    19104
13.0    15054
9.0      8177
12.0     7801
10.0     4420
3.0      4123
18.0     4027
7.0       854
Name: count, dtype: int64
```

In [23]:
```
## Replacing missing values with mode
df['Product_Category_2'].mode()[0]
```

Out[23]:
```
8.0
```

In [24]:
```
## For Product_Category_2
df['Product_Category_2'] = df['Product_Category_2'].fillna(df['Product_Category_2'].mode()[0])
```

In [25]:
```
df['Product_Category_2'].isnull().sum()
```

Out[25]:
```
0
```

In [26]:
```
## For Product_Category_3
df['Product_Category_3'] = df['Product_Category_3'].fillna(df['Product_Category_3'].mode()[0])
```

In [27]:
```
df['Product_Category_3'].isnull().sum()
```

Out[27]:
```
0
```

In [28]:
```
df.head()
```

Out[28]:

	Product_ID	Gender	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	B	C
0	P00069042	0	1	10	2	0	3	8.0	16.0	8370.0	0	0
1	P00248942	0	1	10	2	0	1	6.0	14.0	15200.0	0	0
2	P00087842	0	1	10	2	0	12	8.0	16.0	1422.0	0	0
3	P00085442	0	1	10	2	0	12	14.0	16.0	1057.0	0	0
4	P00285442	1	7	16	4+	0	8	8.0	16.0	7969.0	0	1

In [30]:
```
df['Stay_In_Current_City_Years'].unique()
```

Out[30]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

In [31]:
```
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].str.replace('+','')
```

In [32]:
```
df['Stay_In_Current_City_Years'].unique()
```

Out[32]:
```
array(['2', '4', '3', '1', '0'], dtype=object)
```

In [33]:
```
df.head()
```

Out[33]:

	Product_ID	Gender	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	B	C
0	P00069042	0	1	10	2	0	3	8.0	16.0	8370.0	0	0
1	P00248942	0	1	10	2	0	1	6.0	14.0	15200.0	0	0
2	P00087842	0	1	10	2	0	12	8.0	16.0	1422.0	0	0
3	P00085442	0	1	10	2	0	12	14.0	16.0	1057.0	0	0
4	P00285442	1	7	16	4	0	8	8.0	16.0	7969.0	0	1

In [34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 783667 entries, 0 to 233598
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   Product_ID                  783667 non-null  object 
 1   Gender                      783667 non-null  int64  
 2   Age                         783667 non-null  int64  
 3   Occupation                  783667 non-null  int64  
 4   Stay_In_Current_City_Years  783667 non-null  object 
 5   Marital_Status              783667 non-null  int64  
 6   Product_Category_1          783667 non-null  int64  
 7   Product_Category_2          783667 non-null  float64
 8   Product_Category_3          783667 non-null  float64
 9   Purchase                    550068 non-null  float64
 10  B                           783667 non-null  int32  
 11  C                           783667 non-null  int32  
dtypes: float64(3), int32(2), int64(5), object(2)
memory usage: 71.7+ MB
```

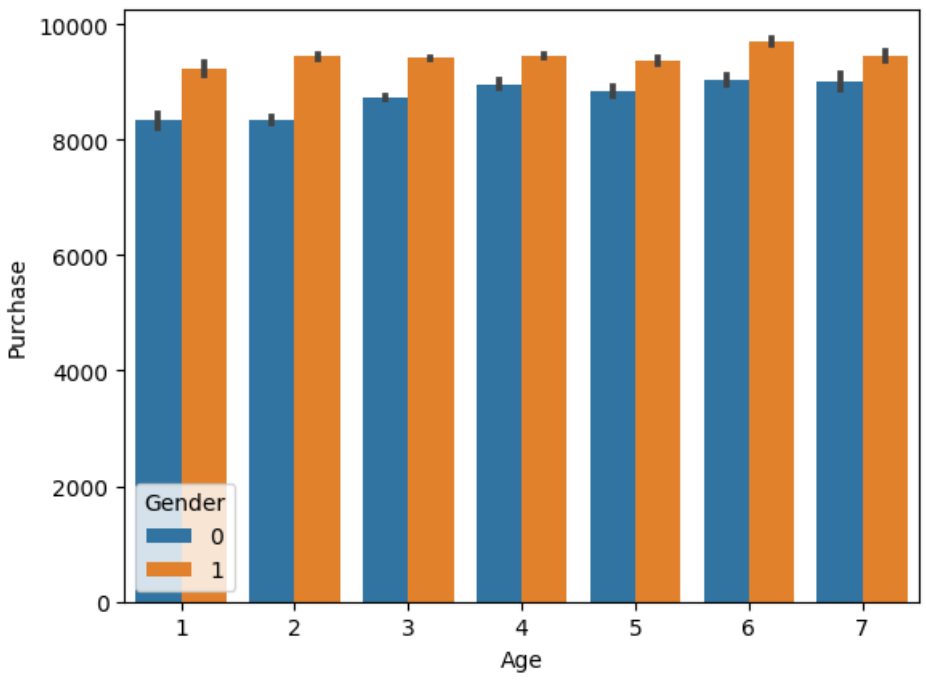
In [35]:
```
## Convert object into integer
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].astype(int)
```

In [36]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 783667 entries, 0 to 233598
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   Product_ID                  783667 non-null  object 
 1   Gender                      783667 non-null  int64  
 2   Age                         783667 non-null  int64  
 3   Occupation                  783667 non-null  int64  
 4   Stay_In_Current_City_Years  783667 non-null  int32  
 5   Marital_Status              783667 non-null  int64  
 6   Product_Category_1          783667 non-null  int64  
 7   Product_Category_2          783667 non-null  float64
 8   Product_Category_3          783667 non-null  float64
 9   Purchase                    550068 non-null  float64
 10  B                           783667 non-null  int32  
 11  C                           783667 non-null  int32  
dtypes: float64(3), int32(3), int64(5), object(1)
memory usage: 68.8+ MB
```

Visualization

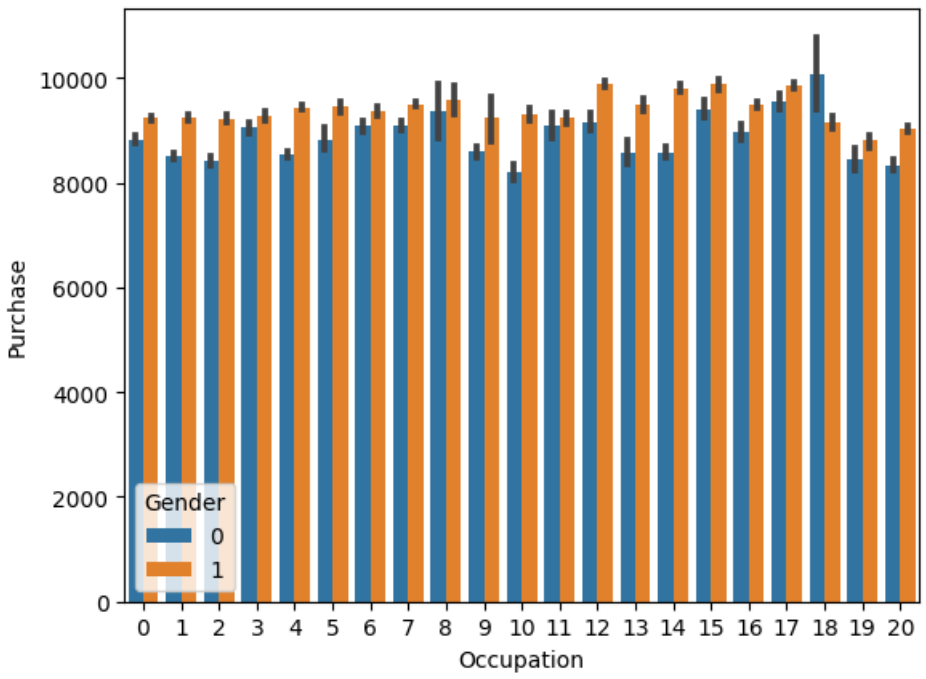
In [37]:
```
## Visualization of Purchase with Age
sns.barplot(data = df, x='Age', y='Purchase', hue='Gender')
plt.show()
```



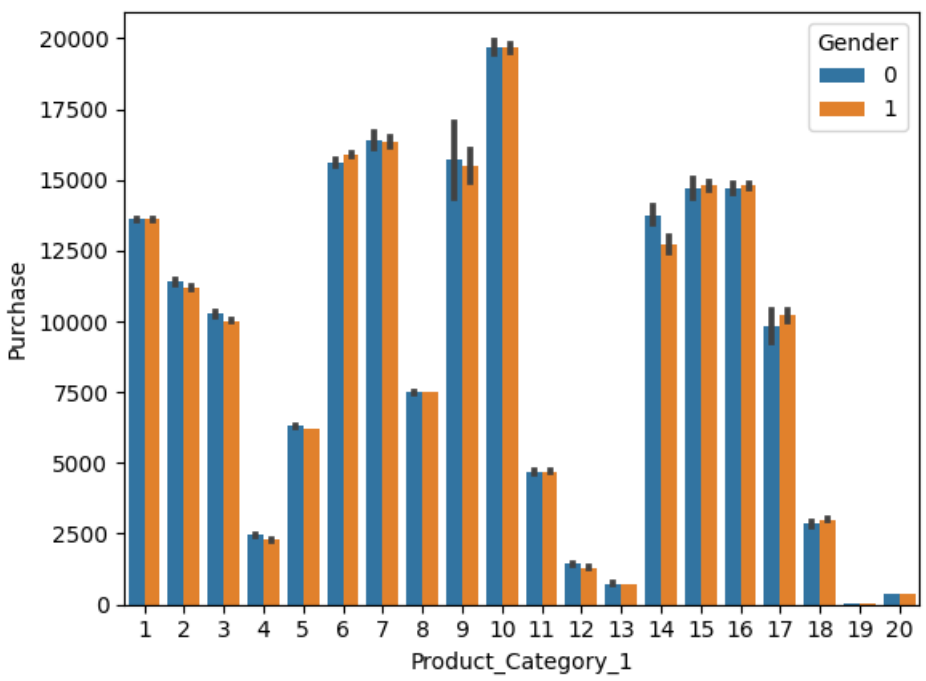
Observation

Purchasing of men is high then women

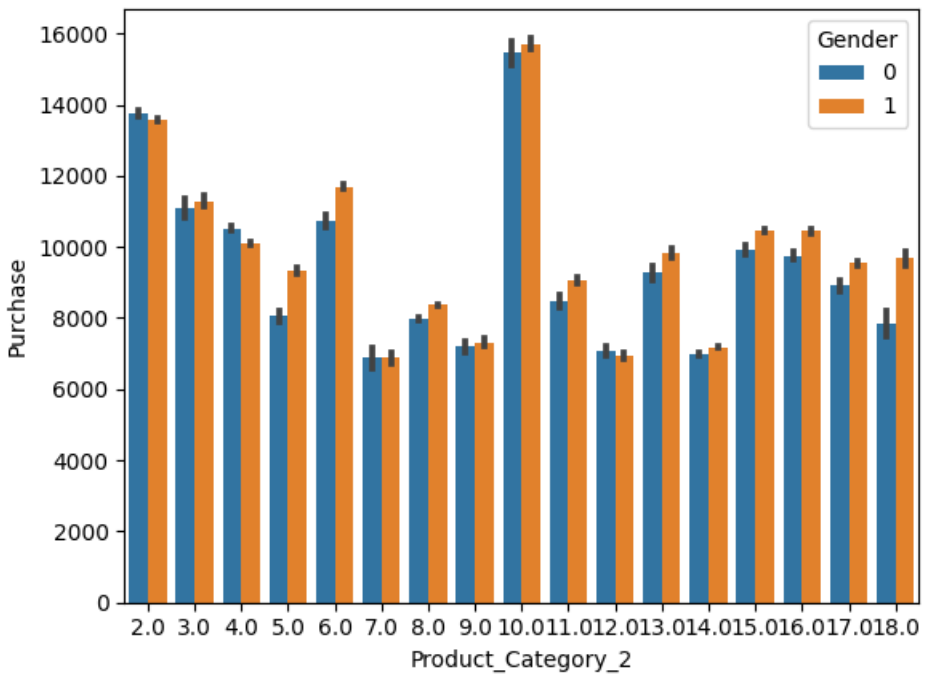
In [36]:
```
## Visualization of Purchase with Occupation
sns.barplot(data = df, x='Occupation', y='Purchase', hue='Gender')
plt.show()
```



In [38]:
```
## Visualization of Purchase with Product_Category_1
sns.barplot(data = df, x='Product_Category_1', y='Purchase', hue='Gender')
plt.show()
```



In [39]:
```
## Visualization of Purchase with Product_Category_2
sns.barplot(data = df, x='Product_Category_2', y='Purchase', hue='Gender')
plt.show()
```



In [40]:
```
## Visualization of Purchase with Product_Category_3
sns.barplot(data = df, x='Product_Category_3', y='Purchase', hue='Gender')
plt.show()
```