EDA and Feature Selection

June 20, 2024

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0.2 EDA and Feature Engineering

Cleaning the data and data preparation and Model Training

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

[83]:
```
df_train=pd.read_csv('train.csv')
df_test=pd.read_csv('dftest.csv')
```

[84]:
```
df_train.columns
```

[84]:
```
Index(['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'],
      dtype='object')
```

[85]:
```
df_test.columns
```

[85]:
```
Index(['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'],
      dtype='object')
```

[86]:
```
df_train.columns
```

[86]:
```
Index(['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'],
      dtype='object')
```

[87]:
```
df_test.columns
```

[87]:
```
Index(['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'],
      dtype='object')
```

[88]:
```
df= df_train.merge(df_test,how='left')
```

[89]:
```
df.head()
```

[89]:

	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

[90]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 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_1          550068 non-null  int64
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
```

```
 11  Purchase                    550068 non-null  int64
dtypes: float64(2), int64(5), object(5)
memory usage: 50.4+ MB
```

[91]:
```
df.describe()
```

[91]:

	User_ID	Occupation	Marital_Status	Product_Category_1	\
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	

	Product_Category_2	Product_Category_3	Purchase
count	376430.000000	166821.000000	550068.000000
mean	9.842329	12.668243	9263.968713
std	5.086590	4.125338	5023.065394
min	2.000000	3.000000	12.000000
25%	5.000000	9.000000	5823.000000
50%	9.000000	14.000000	8047.000000
75%	15.000000	16.000000	12054.000000
max	18.000000	18.000000	23961.000000

[92]:
```
# Droping unnecessasary columns
df.drop(['User_ID'],axis=1,inplace=True)
```

[93]:
```
# finding the null values
df.isnull().sum()
```

[93]:
```
Product_ID                         0
Gender                             0
Age                                0
Occupation                         0
City_Category                      0
Stay_In_Current_City_Years         0
Marital_Status                     0
Product_Category_1                 0
Product_Category_2            173638
Product_Category_3            383247
Purchase                           0
dtype: int64
```

[94]:
```
#converting categorical data to numerical data
pd.get_dummies(df['Gender'],drop_first=1)
```

[94]:
```
              M
0        False
1        False
2        False
3        False
4         True
…         …
550063    True
550064   False
550065   False
550066   False
550067   False

[550068 rows x 1 columns]
```

1 handling categorical data

[95]:
```
# handling Gender columns
df['Gender']=df['Gender'].map({'F':0,'M':1})
```

[96]:
```
df.head()
```

[96]:
```
   Product_ID  Gender   Age  Occupation City_Category  \
0  P00069042       0  0-17          10             A
1  P00248942       0  0-17          10             A
2  P00087842       0  0-17          10             A
3  P00085442       0  0-17          10             A
4  P00285442       1   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
4                         4+               0                   8

   Product_Category_2  Product_Category_3  Purchase
0                 NaN                 NaN      8370
1                 6.0                14.0     15200
2                 NaN                 NaN      1422
3                14.0                 NaN      1057
4                 NaN                 NaN      7969
```

[97]:
```
# handling categorical Age col
df['Age'].unique()
```

[97]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

[99]:
```
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})
```

[100]:
```
df.head()
```

[100]:

	Product_ID	Gender	Age	Occupation	City_Category	\
0	P00069042	0	1	10	A	
1	P00248942	0	1	10	A	
2	P00087842	0	1	10	A	
3	P00085442	0	1	10	A	
4	P00285442	1	7	16	C	

	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	\
0	2	0	3	
1	2	0	1	
2	2	0	12	
3	2	0	12	
4	4+	0	8	

	Product_Category_2	Product_Category_3	Purchase
0	NaN	NaN	8370
1	6.0	14.0	15200
2	NaN	NaN	1422
3	14.0	NaN	1057
4	NaN	NaN	7969

[101]:
```
df_city = pd.get_dummies(df['City_Category'], drop_first=True).astype(int)
```

[102]:
```
df_city.head()
```

[102]:

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

[103]:
```
df=pd.concat([df,df_city],axis=1)
```

[104]:
```
df.drop(['City_Category'],axis=1,inplace=True)
```

[105]:
```
df.head()
```

[105]:

	Product_ID	Gender	Age	Occupation	Stay_In_Current_City_Years	\
0	P00069042	0	1	10	2	

```
1  P00248942       0    1          10                          2
2  P00087842       0    1          10                          2
3  P00085442       0    1          10                          2
4  P00285442       1    7          16                         4+

   Marital_Status  Product_Category_1  Product_Category_2  Product_Category_3  \
0               0                   3                 NaN                 NaN
1               0                   1                 6.0                14.0
2               0                  12                 NaN                 NaN
3               0                  12                14.0                 NaN
4               0                   8                 NaN                 NaN

   Purchase  B  C
0      8370  0  0
1     15200  0  0
2      1422  0  0
3      1057  0  0
4      7969  0  1
```

2 Handling the Missing values

[106]:
```
nullval=df.isnull().sum()
```

[107]:
```
#Replacing Missing values
df['Product_Category_2'].unique()
```

[107]:
```
array([nan,  6., 14.,  2.,  8., 15., 16., 11.,  5.,  3.,  4., 12.,  9.,
       10., 17., 13.,  7., 18.])
```

[108]:
```
df['Product_Category_2'].value_counts()
```

[108]:
```
Product_Category_2
8.0     64088
14.0    55108
2.0     49217
16.0    43255
15.0    37855
5.0     26235
4.0     25677
6.0     16466
11.0    14134
17.0    13320
13.0    10531
9.0      5693
12.0     5528
10.0     3043
```

```
3.0      2884
18.0     2770
7.0       626
Name: count, dtype: int64
```

[109]:
```
# Rplacing the null values with mode
df['Product_Category_2']=df['Product_Category_2'].
 ↪fillna(df['Product_Category_2'].mode()[0])
```

[110]:
```
# checking the null values in col
df['Product_Category_2'].isnull().sum()
```

[110]:
```
0
```

[111]:
```
#Replacing the null Values in Product category 3
df['Product_Category_3'].value_counts()
```

[111]:
```
Product_Category_3
16.0    32636
15.0    28013
14.0    18428
17.0    16702
5.0     16658
8.0     12562
9.0     11579
12.0     9246
13.0     5459
6.0      4890
18.0     4629
4.0      1875
11.0     1805
10.0     1726
3.0       613
Name: count, dtype: int64
```

[112]:
```
#Replacing the missing values with mode
df['Product_Category_3']=df['Product_Category_3'].
 ↪fillna(df['Product_Category_3'].mode()[0])
```

[113]:
```
# checking the null values in Product category col 3
df['Product_Category_3'].isnull().sum()
```

[113]:
```
0
```

[114]:
```
df['Stay_In_Current_City_Years'].unique()
```

[114]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

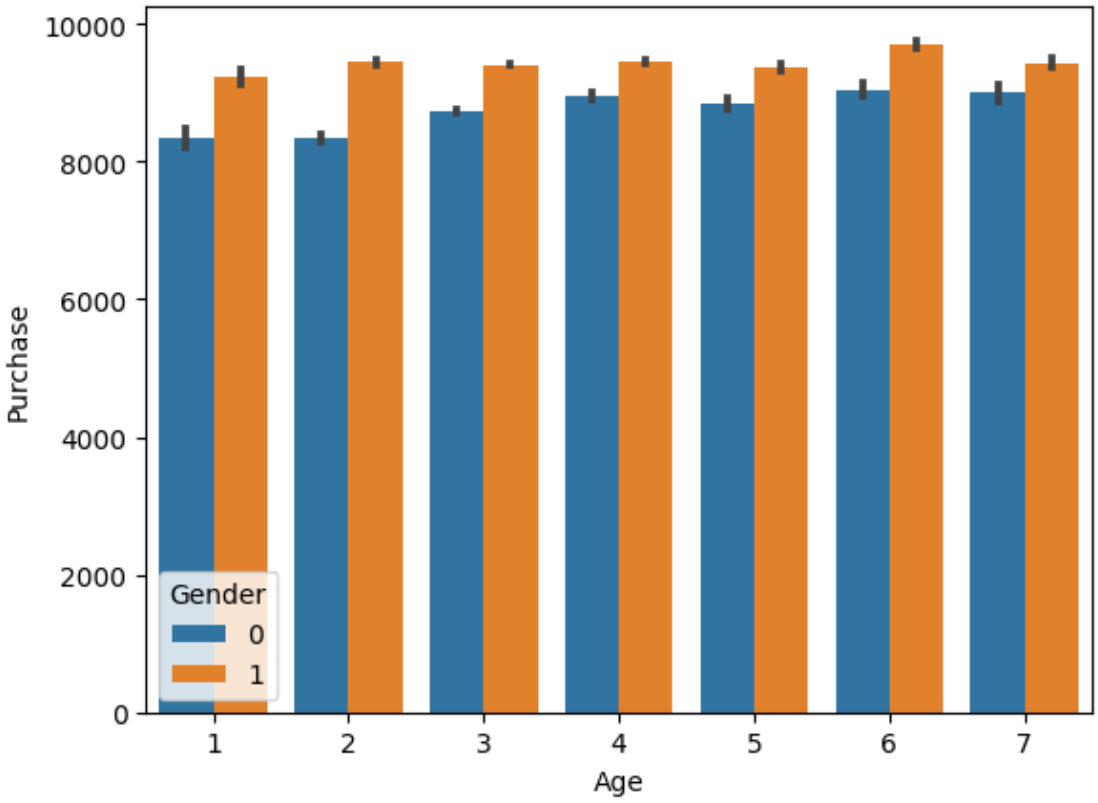
[115]:
```
#Replacing the 4+ with 4
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].str.
 ↪replace('+', '')
```

[116]:
```
#converting object to integer
df['Stay_In_Current_City_Years']=df['Stay_In_Current_City_Years'].astype(int)
```

3 Visualization

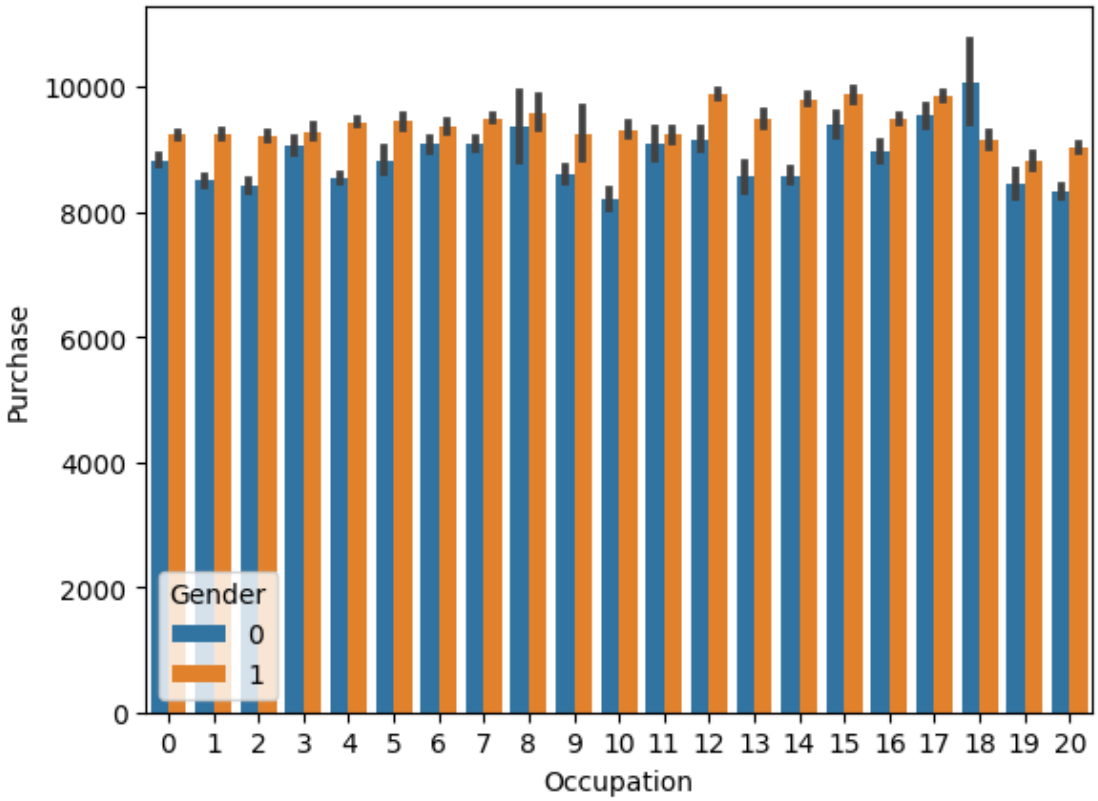
[117]:
```
#bar plot cmparing 'Age' and 'Purchase'
sns.barplot(x='Age', y='Purchase', hue='Gender', data=df)
```

[117]: <Axes: xlabel='Age', ylabel='Purchase'>



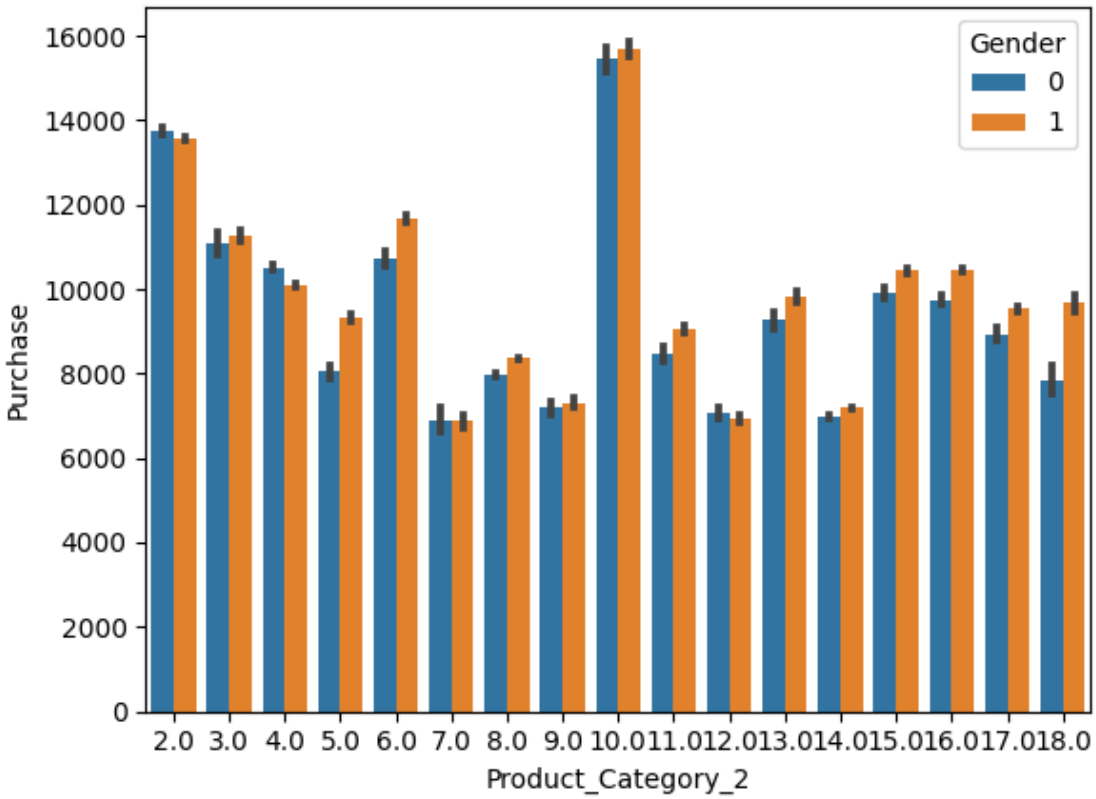
[118]:
```
#Visualization of purchase with occupation
sns.barplot(x='Occupation',y='Purchase',hue='Gender',data=df)
```

[118]: <Axes: xlabel='Occupation', ylabel='Purchase'>



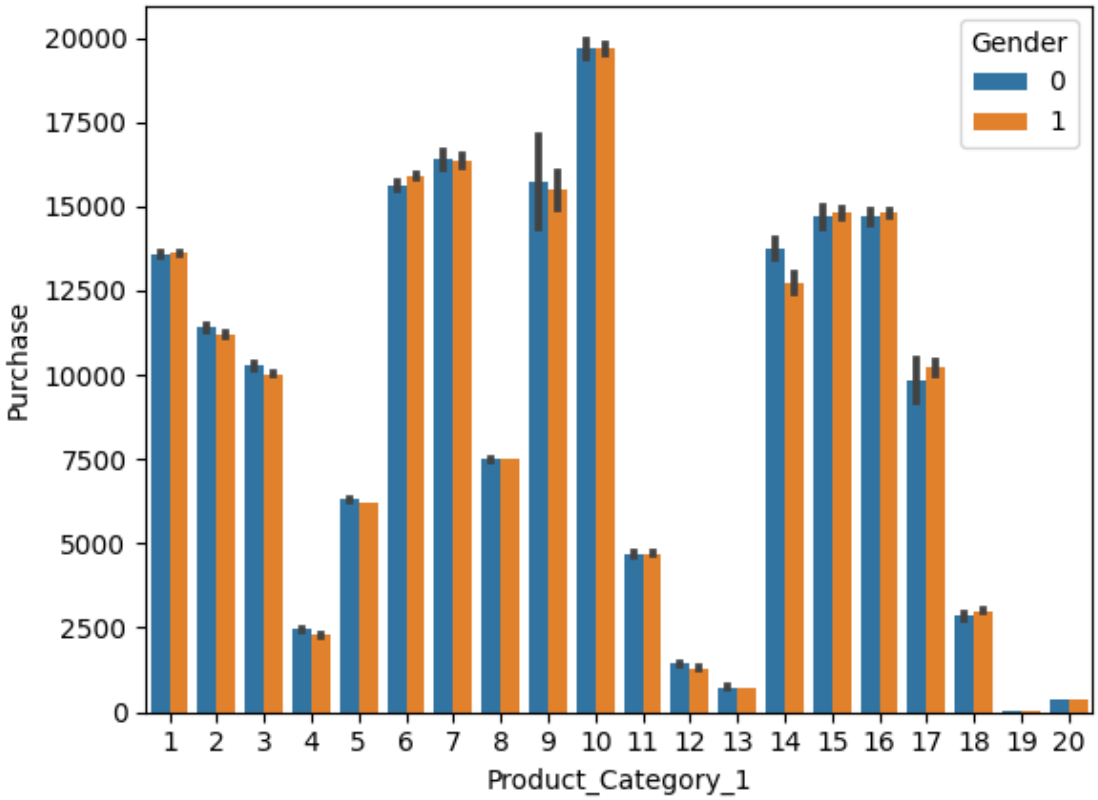
[119]:
```
sns.barplot(x='Product_Category_2',y='Purchase',hue='Gender',data=df)
```

[119]: <Axes: xlabel='Product_Category_2', ylabel='Purchase'>



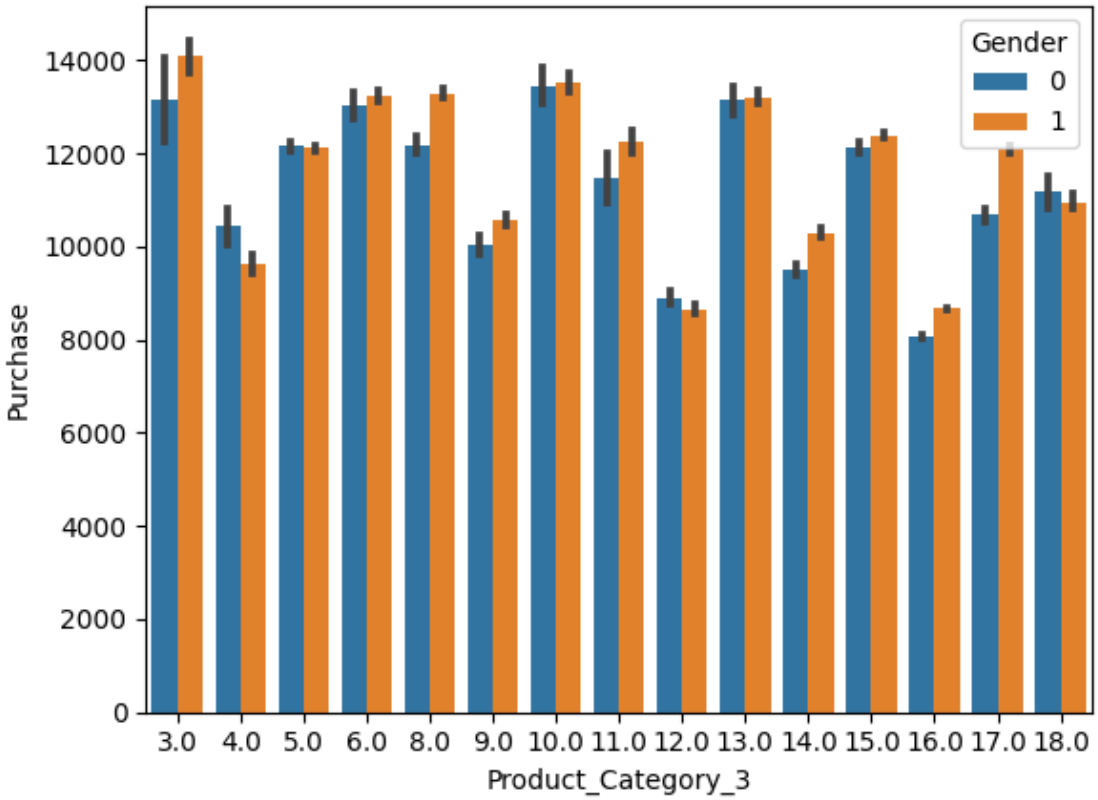
[120]:
```
sns.barplot(x='Product_Category_1',y='Purchase',hue='Gender',data=df)
```

[120]: <Axes: xlabel='Product_Category_1', ylabel='Purchase'>



[121]:
```
sns.barplot(x='Product_Category_3',y='Purchase',hue='Gender',data=df)
```

[121]:
```
<Axes: xlabel='Product_Category_3', ylabel='Purchase'>
```



4 Feature Scaling

[122]:
```
df_test=df[df['Purchase'].isnull()]
```

[123]:
```
df_train=df[~df['Purchase'].isnull()]
```

[129]:
```
X=df_train.drop('Purchase',axis=1)
X.head()
X.shape
```

[129]:
```
(550068, 11)
```

[132]:
```
Y=df_train['Purchase']
Y
```

[132]:
```
0          8370
1         15200
2          1422
3          1057
4          7969
```

```
…
550063      368
550064      371
550065      137
550066      365
550067      490
Name: Purchase, Length: 550068, dtype: int64
```

[133]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.
↪33,random_state=42)
```

[134]:
```
X_train.drop('Product_ID',axis=1,inplace=True)
X_test.drop('Product_ID',axis=1,inplace=True)
```

[136]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.fit_transform(X_test)
```

[137]:
```
print(X_train)
```

```
[[ 0.57141282 -1.10505734  0.90867822 …  0.36891877  1.17569512
  -0.67282374]
 [ 0.57141282  1.84716932 -1.23820419 …  0.36891877 -0.85056064
  -0.67282374]
 [ 0.57141282  0.37105599  1.36872445 … -1.09182956 -0.85056064
   1.48627336]
 …
 [-1.75004823 -1.10505734 -1.08485545 …  0.36891877  1.17569512
  -0.67282374]
 [-1.75004823 -1.10505734 -0.62480922 …  0.36891877  1.17569512
  -0.67282374]
 [-1.75004823 -1.10505734 -0.93150671 …  0.36891877 -0.85056064
  -0.67282374]]
```

[138]:
```
print(X_test)
```

```
[[ 0.57491817  1.85432241  1.67314502 …  0.36853635 -0.85317164
   1.490841  ]
 [-1.73937798  0.37396835  0.44724923 …  0.36853635  1.1720971
  -0.67076234]
 [-1.73937798  0.37396835 -1.23835749 …  0.36853635 -0.85317164
  -0.67076234]
 …
 [ 0.57491817 -1.10638572 -0.93188354 …  0.36853635 -0.85317164
   1.490841  ]
 [ 0.57491817  0.37396835 -0.16569867 …  0.00396261 -0.85317164
```

```
  1.490841  ]
[ 0.57491817 -1.10638572 -0.62540959 …  0.36853635  1.1720971
 -0.67076234]]
```

[ ]: