black

August 6, 2024

0.0.1 Black Friday Dataset EDA And Feature Enaineering

0.0.2 Cleaning and preparing the data for model Training

1 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.

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

[ ]:
```python
df_train = pd.read_csv('/content/train.csv')
```

[ ]:
```python
df_train
```

[ ]:
```
        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_1  \
```

```
0                                   2           0                3
1                                   2           0                1
2                                   2           0               12
3                                   2           0               12
4                                  4+           0                8
…                                …           …                 …
550063                              1           1               20
550064                              3           0               20
550065                             4+           1               20
550066                              2           0               20
550067                             4+           1               20

        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
…                    …                 …       …
550063                 NaN                 NaN       368
550064                 NaN                 NaN       371
550065                 NaN                 NaN       137
550066                 NaN                 NaN       365
550067                 NaN                 NaN       490

[550068 rows x 12 columns]
```

[ ]:
```
df_test = pd.read_csv('/content/test.csv')
```

[ ]:
```
## apend is not working
##df = df_train.append(df_test)
```

[ ]:
```
#The error message "'DataFrame' object has no attribute 'append'" occurs
# because the append() method was deprecated in pandas 2.0.
# Instead, you should use the concat() function to append data frames.
df = pd.concat([df_train, df_test], ignore_index=True)
```

[ ]:
```
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_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    8370.0
1                 6.0                14.0   15200.0
2                 NaN                 NaN    1422.0
3                14.0                 NaN    1057.0
4                 NaN                 NaN    7969.0
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 783667 entries, 0 to 783666
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: 71.7+ MB
```

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

[ ]:
```
            User_ID     Occupation  Marital_Status  Product_Category_1  \
count  7.836670e+05  783667.000000   783667.000000       783667.000000
mean   1.003029e+06       8.079300        0.409777            5.366196
std    1.727267e+03       6.522206        0.491793            3.878160
min    1.000001e+06       0.000000        0.000000            1.000000
25%    1.001519e+06       2.000000        0.000000            1.000000
50%    1.003075e+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       537685.000000       237858.000000  550068.000000
mean             9.844506           12.668605    9263.968713
std              5.089093            4.125510    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
```

2 Drop the unwanted columns

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

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

[ ]:
```
  Product_ID Gender   Age  Occupation City_Category  \
0  P00069042      F  0-17          10             A
1  P00248942      F  0-17          10             A
2  P00087842      F  0-17          10             A
3  P00085442      F  0-17          10             A
4  P00285442      M   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    8370.0
1                 6.0                14.0   15200.0
2                 NaN                 NaN    1422.0
3                14.0                 NaN    1057.0
4                 NaN                 NaN    7969.0
```

2.0.1 Convert the categorical into numerical

[ ]:
```
## Converting the gender to the numerical variable
# first is to create the dummy dataset for the gender and then assigning it to␣
↪the dataset
#df['Gender']=pd.get_dummies(df['Gender'],drop_first=1)
# The next is to directly map to the gendeer column
df['Gender']=df['Gender'].map({'F':0,'M':1})
df.head()
```

[ ]:
```
  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    8370.0
1                 6.0                14.0   15200.0
2                 NaN                 NaN    1422.0
3                14.0                 NaN    1057.0
4                 NaN                 NaN    7969.0
```

[ ]:
```
df['Age'].unique()
```

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

For Age column

[ ]:
```
#pd.get_dummies(df['Age'],drop_first=True)
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})
```

Label encoding can also be performed for this task ##second technqiue from sklearn import preprocessing

2.0.2 label_encoder object knows how to understand word labels.

label_encoder = preprocessing.LabelEncoder()

2.0.3 Encode labels in column 'Age'.

df['Age']= label_encoder.fit_transform(df['Age'])

df['Age'].unique()

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

[ ]:
```
  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    8370.0
1                 6.0                14.0   15200.0
2                 NaN                 NaN    1422.0
3                14.0                 NaN    1057.0
4                 NaN                 NaN    7969.0
```

[ ]:
```
##fixing categorical City_category
## As like earlier we discussed we are creating the dummies
# and adding it to the dataset
df_city=pd.get_dummies(df['City_Category'],drop_first=True)
# as the previous code is resulting in the true and false added the dtype as␣
↪INT.
df_city=pd.get_dummies(df['City_Category'],drop_first=True, dtype=int)
```

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

[ ]:
```
   B  C
0  0  0
1  0  0
2  0  0
3  0  0
4  0  1
```

[ ]:
```
df=pd.concat([df,df_city],axis=1)
df = df.drop('City_Category', axis =1)
```

```
df.head()
```

[ ]:

```
  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  0
1   15200.0  0  0
2    1422.0  0  0
3    1057.0  0  0
4    7969.0  0  1
```

[ ]:

```
df.head()
```

[ ]:

```
  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  0
1   15200.0  0  0
2    1422.0  0  0
3    1057.0  0  0
4    7969.0  0  1
```

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

[ ]:
```
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
```

[ ]:
```
## Focus on replacing missing values
df['Product_Category_2'].unique()
```

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

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

[ ]:
```
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
```

[ ]:
```
# For the categorical variables and discrete variables
# the Mode is used to relpace the misssing values.
```

```
df['Product_Category_2'].mode()[0]
#here the indexing is used to get the mode alone in the result.
```

[ ]: 8.0

[ ]:
```
## Replace the missing values with mode using the fillna
df['Product_Category_2']=df['Product_Category_2'].
↪fillna(df['Product_Category_2'].mode()[0])
```

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

[ ]: 0

[ ]:
```
## Product_category 3 replace missing values
df['Product_Category_3'].unique()
```

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

[ ]:
```
df['Product_Category_3'].value_counts()
```

[ ]:
```
Product_Category_3
16.0    46469
15.0    39968
14.0    26283
17.0    23818
5.0     23799
8.0     17861
9.0     16532
12.0    13115
13.0     7849
6.0      6888
18.0     6621
4.0      2691
11.0     2585
10.0     2501
3.0       878
Name: count, dtype: int64
```

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

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

[ ]:
```
  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                 8.0                16.0
1               0                   1                 6.0                14.0
2               0                  12                 8.0                16.0
3               0                  12                14.0                16.0
4               0                   8                 8.0                16.0

   Purchase  B  C
0    8370.0  0  0
1   15200.0  0  0
2    1422.0  0  0
3    1057.0  0  0
4    7969.0  0  1
```

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

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

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

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

[ ]:
```
  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                 8.0                16.0
1               0                   1                 6.0                14.0
2               0                  12                 8.0                16.0
3               0                  12                14.0                16.0
4               0                   8                 8.0                16.0

   Purchase  B  C
0    8370.0  0  0
1   15200.0  0  0
2    1422.0  0  0
3    1057.0  0  0
```

```
4    7969.0  0  1
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 783667 entries, 0 to 783666
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  int64
 11  C                           783667 non-null  int64
dtypes: float64(3), int64(7), object(2)
memory usage: 71.7+ MB
```

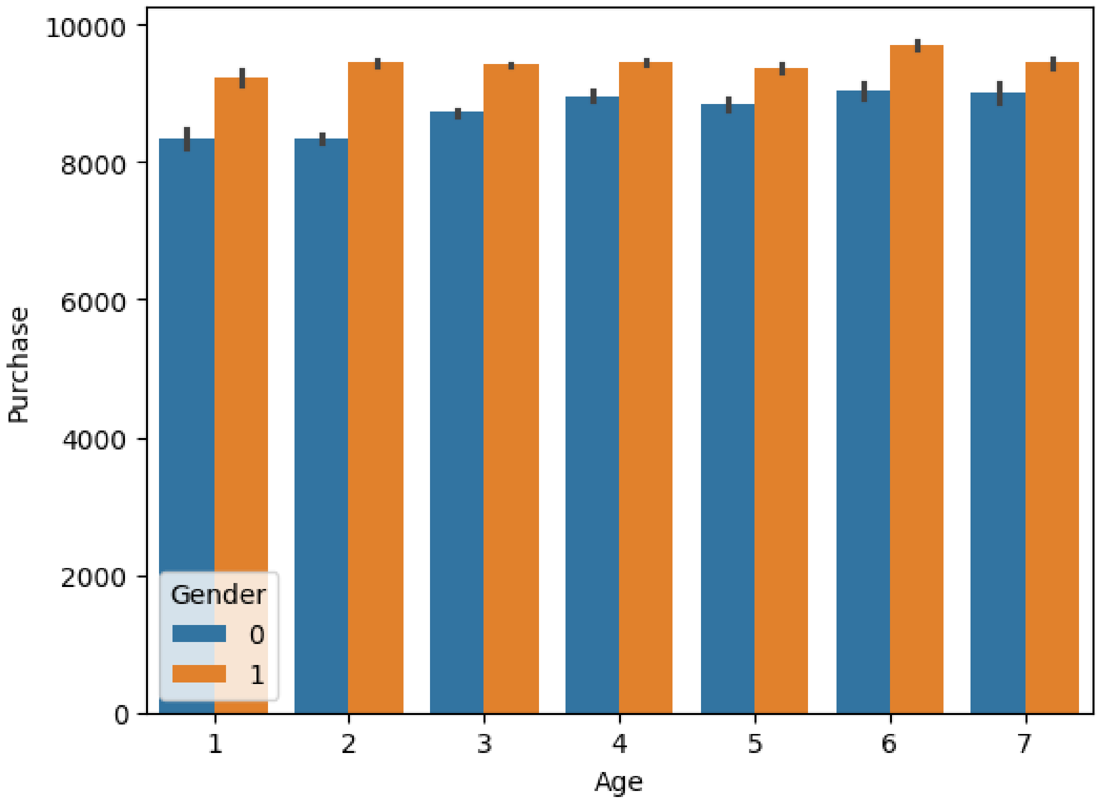
[ ]:
```python
##convert object into integers
df['Stay_In_Current_City_Years']=df['Stay_In_Current_City_Years'].
 ↪astype('int64')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 783667 entries, 0 to 783666
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  int64
 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  int64
 11  C                           783667 non-null  int64
dtypes: float64(3), int64(8), object(1)
```

```
memory usage: 71.7+ MB
```

[ ]:
```
##Visualisation Age vs Purchased
sns.barplot(x = 'Age',y = 'Purchase',hue='Gender',data=df)
```

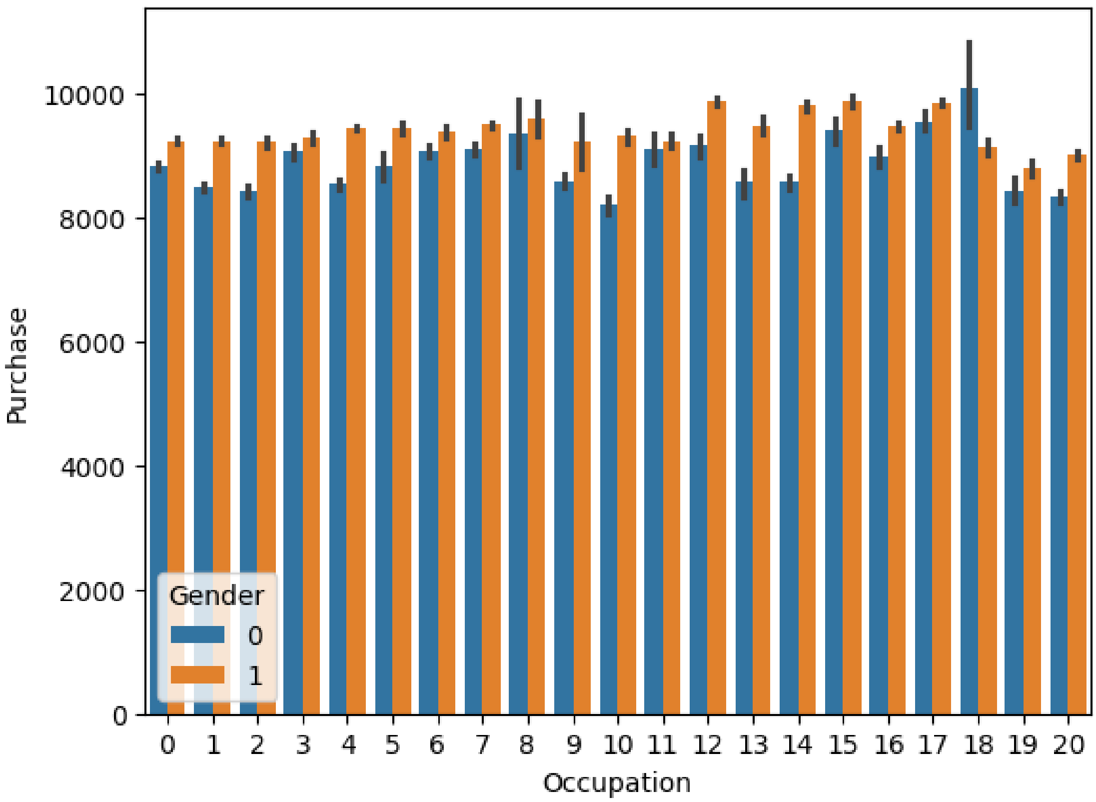
[ ]:
```
<Axes: xlabel='Age', ylabel='Purchase'>
```



2.1 Purchasing of men is high then women

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

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

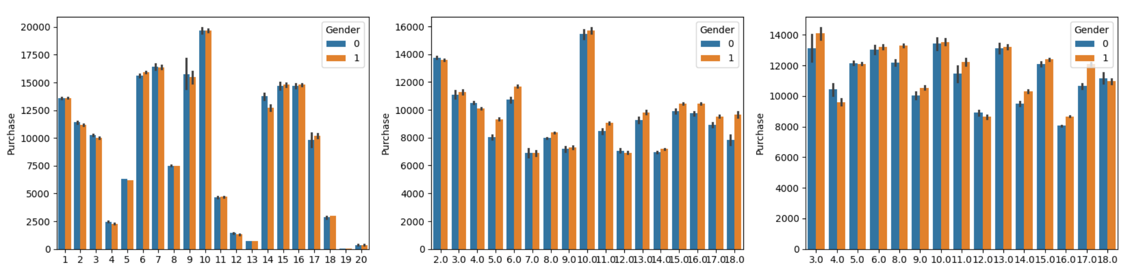


[ ]:
```
plt.figure(figsize= (20,15))

plt.subplot(3,3,1)
sns.barplot(x = 'Product_Category_1',y = 'Purchase',hue='Gender',data=df)

plt.subplot(3,3,2)
sns.barplot(x = 'Product_Category_2',y = 'Purchase',hue='Gender',data=df)

plt.subplot(3,3,3)
sns.barplot(x = 'Product_Category_3',y = 'Purchase',hue='Gender',data=df)
plt.savefig('product-wise purchasing.jpg')
```



[ ]:
```
#sns.pairplot(df, hue = 'Product_ID', diag_kind = 'kde')
#plt.savefig('pairplot.jpg')
```

[ ]:
```
##Feature Scaling
# test data is taken where the purchase is null as we compbined before
# train is taken with purchase which are not Nan
df_test=df[df['Purchase'].isnull()]
```

[ ]:
```
df_test.head(5)
```

[ ]:
```
        Product_ID  Gender  Age  Occupation  Stay_In_Current_City_Years  \
550068   P00128942       1    5           7                           2
550069   P00113442       1    3          17                           0
550070   P00288442       0    4           1                           4
550071   P00145342       0    4           1                           4
550072   P00053842       0    3           1                           1

        Marital_Status  Product_Category_1  Product_Category_2  \
550068               1                   1                11.0
550069               0                   3                 5.0
550070               1                   5                14.0
550071               1                   4                 9.0
550072               0                   4                 5.0

        Product_Category_3  Purchase  B  C
550068                16.0       NaN  1  0
550069                16.0       NaN  0  1
550070                16.0       NaN  1  0
550071                16.0       NaN  1  0
550072                12.0       NaN  0  1
```

[ ]:
```
df_train=df[~df['Purchase'].isnull()] # ~ not having
df_train.head(5)
```

[ ]:
```
  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                 8.0                16.0
1               0                   1                 6.0                14.0
2               0                  12                 8.0                16.0
3               0                  12                14.0                16.0
```

```
4             0                   8                 8.0                16.0

   Purchase  B  C
0    8370.0  0  0
1   15200.0  0  0
2    1422.0  0  0
3    1057.0  0  0
4    7969.0  0  1
```

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

[ ]:
```
   Gender  Age  Occupation  Stay_In_Current_City_Years  Marital_Status  \
0       0    1          10                           2               0
1       0    1          10                           2               0
2       0    1          10                           2               0
3       0    1          10                           2               0
4       1    7          16                           4               0

   Product_Category_1  Product_Category_2  Product_Category_3  B  C
0                   3                 8.0                16.0  0  0
1                   1                 6.0                14.0  0  0
2                  12                 8.0                16.0  0  0
3                  12                14.0                16.0  0  0
4                   8                 8.0                16.0  0  1
```

[ ]:
```
X.shape
```

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

[ ]:
```
y=df_train['Purchase']
```

[ ]:
```
y.shape
```

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

[ ]:
```
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)
```

[ ]:
```
X_train.head()
```

[ ]:
```
        Gender  Age  Occupation  Stay_In_Current_City_Years  Marital_Status  \
396876       1    2          14                           3               0
433826       1    6           0                           0               1
516298       1    4          17                           0               0
193380       1    3           4                           1               0
```

```
273542       0    4          20                            3                1

        Product_Category_1  Product_Category_2  Product_Category_3  B  C
396876                   1                 2.0                16.0  1  0
433826                   8                16.0                16.0  0  0
516298                   3                 4.0                12.0  0  1
193380                   8                16.0                16.0  1  0
273542                   3                 4.0                12.0  1  0
```

[ ]:
```
## feature Scaling
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train =sc.fit_transform(X_train)
X_test =sc.transform(X_test)
```

[ ]:
```
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
```

[ ]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)
lr.score(X_train, y_train)*100, lr.score(X_test,y_test)*100
```

[ ]:
```
(13.210555628187514, 12.948768560712399)
```

[ ]:
```
dt = DecisionTreeRegressor()
dt.fit(X_train, y_train)
dt.score(X_train, y_train)*100, dt.score(X_test,y_test)*100
```

[ ]:
```
(79.83631647792538, 55.82640534204286)
```

[ ]:
```
#lr3 = Lasso()
#lr3.fit(X_train, y_train)
#lr3.score(X_train, y_train)*100, lr3.score(X_test,y_test)*100
```

[ ]:
```
lr4 = Ridge()
lr4.fit(X_train, y_train)
lr4.score(X_train, y_train)*100, lr4.score(X_test,y_test)*100
```

[ ]:
```
(13.210555628099762, 12.948769558874373)
```

[ ]:
```
rfr = RandomForestRegressor()
rfr.fit(X_train, y_train)
rfr.score(X_train, y_train)*100, rfr.score(X_test,y_test)*100
```

[ ]: (78.75051863025938, 62.922348370441014)

[ ]:
```
knr = KNeighborsRegressor()
knr.fit(X_train, y_train)
knr.score(X_train, y_train)*100, knr.score(X_test,y_test)*100
```

[ ]: (64.73951731332154, 50.659057532616615)

[ ]:
```
from sklearn.metrics import r2_score
```

[ ]:
```
print(r2_score(y_test,rfr.predict(X_test)))
```

0.6292234837044102

[ ]:
```
from sklearn.metrics import classification_report
```

[ ]:
```
from sklearn.ensemble import GradientBoostingRegressor
```

[ ]:
```
gbr = GradientBoostingRegressor()
```

[ ]:
```
gbr.fit(X_train, y_train)
print(r2_score(y_test, gbr.predict(X_test)))
```

0.6444959838731033

[ ]:
```
gbr.score(X_train, y_train)*100, gbr.score(X_test,y_test)*100
```

[ ]: (64.96087814238759, 64.44959838731033)

[ ]:
```
from xgboost import XGBRegressor, XGBRFRegressor
xgb = XGBRegressor()
xgbr = XGBRFRegressor()
```

[ ]:
```
xgb.fit(X_train, y_train)
print(r2_score(y_test, xgb.predict(X_test)))

xgbr.fit(X_train, y_train)
print(r2_score(y_test, xgbr.predict(X_test)))
```

0.6668955124144831
0.5845697344685554

[ ]:
```
xgb.score(X_train, y_train)*100, xgb.score(X_test,y_test)*100
```

[ ]: (67.99197211448806, 66.68955124144831)

[ ]:
```
xgbr.score(X_train, y_train)*100, xgbr.score(X_test,y_test)*100
```

[ ]: (58.9592269938375, 58.45697344685554)

[ ]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

[ ]:
```
def evaluate_model(true, predicted):
    mae = mean_absolute_error(true, predicted)
    mse = mean_squared_error(true, predicted)
    rmse = np.sqrt(mean_squared_error(true, predicted))
    r2_square = r2_score(true, predicted)
    return mae, mse, rmse, r2_square
```

[ ]:
```
from sklearn.ensemble import AdaBoostRegressor
```

[ ]:
```
models = {
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "XGBRegressor": XGBRegressor(),
    "AdaBoost Regressor": AdaBoostRegressor()
}
```

[ ]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import make_scorer

# Define hyperparameter ranges for each model
param_grid = {
    "K-Neighbors Regressor": {"n_neighbors": [3, 5, 7],},
    "Random Forest Regressor": {'n_estimators': [8,16,32,64,128,256],␣
↪"max_depth": [3, 5, 7]},
    "XGBRegressor": {'depth': [6,8,10],'learning_rate': [0.01, 0.05, 0.
↪1],'iterations': [30, 50, 100]},
    "AdaBoost Regressor": {'learning_rate':[.1,.01,0.5,.001],'n_estimators':␣
↪[8,16,32,64,128,256]}
}

model_list = []
r2_list =[]

for model_name, model in models.items():
    # Create a scorer object to use in grid search
    scorer = make_scorer(r2_score)

    # Perform grid search to find the best hyperparameters
    grid_search = GridSearchCV(
        model,
        param_grid[model_name],
        scoring=scorer,
        cv=5,
```

```
        n_jobs=-1
    )

    grid_search.fit(X_train, y_train) # Make predictions

    y_train_pred = grid_search.predict(X_train)

    y_test_pred = grid_search.predict(X_test)

    # Evaluate Train and Test dataset
    model_train_mae, model_train_mse, model_train_rmse, model_train_r2 =␣
↪evaluate_model(y_train, y_train_pred)

    model_test_mae, model_test_mse, model_test_rmse, model_test_r2 =␣
↪evaluate_model(y_test, y_test_pred)

    print(model_name)

    model_list.append(model_name)

    print('Best hyperparameters:', grid_search.best_params_)
    print('Model performance for Training set')
    print("- Root Mean Squared Error: {:.4f}".format(model_train_rmse))
    print("- Mean Squared Error: {:.4f}".format(model_train_mse))
    print("- Mean Absolute Error: {:.4f}".format(model_train_mae))
    print("- R2 Score: {:.4f}".format(model_train_r2))
    print('----------------------------------')
    print('Model performance for Test set')
    print("- Root Mean Squared Error: {:.4f}".format(model_test_rmse))
    print("- Mean Squared Error: {:.4f}".format(model_test_rmse))
    print("- Mean Absolute Error: {:.4f}".format(model_test_mae))
    print("- R2 Score: {:.4f}".format(model_test_r2))
    r2_list.append(model_test_r2)
    print('='*35)
    print('\n')
```

```
K-Neighbors Regressor
Best hyperparameters: {'n_neighbors': 5}
Model performance for Training set
- Root Mean Squared Error: 2983.5495
- Mean Squared Error: 8901567.7598
- Mean Absolute Error: 2192.1820
- R2 Score: 0.6474
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 3526.3571
- Mean Squared Error: 3526.3571
```

```
- Mean Absolute Error: 2564.8292
- R2 Score: 0.5066
===================================


Random Forest Regressor
Best hyperparameters: {'max_depth': 7, 'n_estimators': 128}
Model performance for Training set
- Root Mean Squared Error: 2964.1804
- Mean Squared Error: 8786365.4030
- Mean Absolute Error: 2236.1604
- R2 Score: 0.6520
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 2987.6687
- Mean Squared Error: 2987.6687
- Mean Absolute Error: 2251.5360
- R2 Score: 0.6458
===================================



/usr/local/lib/python3.10/dist-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning:
[11:26:33] WARNING: /workspace/src/learner.cc:740:
Parameters: { "depth", "iterations" } are not used.

  warnings.warn(smsg, UserWarning)

XGBRegressor
Best hyperparameters: {'depth': 6, 'iterations': 30, 'learning_rate': 0.1}
Model performance for Training set
- Root Mean Squared Error: 2895.8257
- Mean Squared Error: 8385806.4002
- Mean Absolute Error: 2178.0139
- R2 Score: 0.6678
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 2928.4398
- Mean Squared Error: 2928.4398
- Mean Absolute Error: 2199.5659
- R2 Score: 0.6597
===================================
```

[ ]:

```
```