CSCI - 6409 - The Process of Data Science - Fall 2022
</center>

Group 3
</center>

Black Friday Sales Prediction
</center>

Anmol Sidhu - B00923820 Fenil Milankumar Parmar - B00895684 Kalpit Machhi - B00911364 Omid Amini - B00942240 Amankumar Manojkumar Patel - B00888136

Initialization of project

Importing required basic libraries

In [ ]:

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Importing required basic libraries

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
df_train=pd.read_csv('/content/drive/MyDrive/black friday dataset/train.csv')
```

In [ ]:

```
df_train['set']='train'
```

In [ ]:

```
df_test=pd.read_csv('/content/drive/MyDrive/black friday dataset/test.csv')
```

In [ ]:

```
df_test['set']='test'
```

In [ ]:

```
#merging into one dataframe
df=pd.concat([df_train,df_test])
df_bak=df
```

Data Exploration and EDA

In [ ]:

```
df.head()
```

Out[ ]:

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

In [ ]:

```
#Total records and columns
df.shape
```

Out[ ]:

```
(783667, 13)
```

In [ ]:

```
df.columns
```

Out[ ]:

```
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', 'set'],
      dtype='object')
```

Performing EDA on data to understand the data

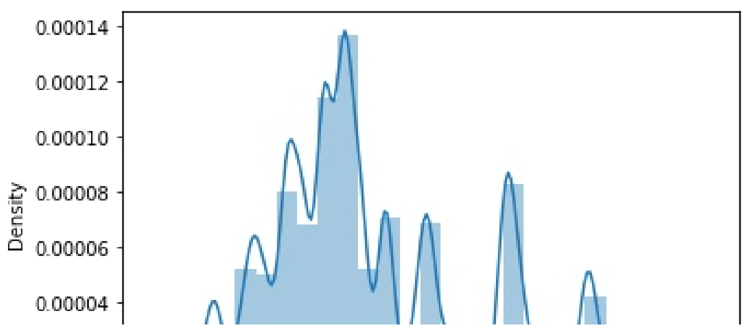
In [ ]:

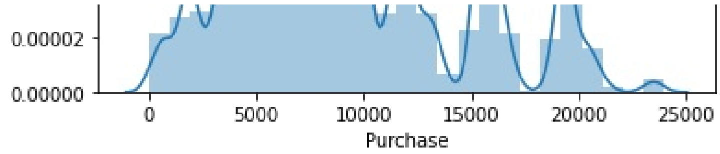
```
#distribution of purchase
sns.distplot(df["Purchase"],bins=25)
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt you
r code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3ceb1ce50>
```





The dataset shows a normal distribution

Plots to see the distribution of various features in our dataset

In [ ]:

```
#plots to see the distribution of various features in our dataset
fig,ax=plt.subplots(1,6,figsize=(30,5))
sns.countplot(df['Gender'],ax=ax[0])
sns.countplot(df['Age'],ax=ax[1])
sns.countplot(df['Occupation'],ax=ax[2])
sns.countplot(df['Marital_Status'],ax=ax[3])
sns.countplot(df['City_Category'],ax=ax[4])
sns.countplot(df['Stay_In_Current_City_Years'],ax=ax[5])
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
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in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
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in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
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ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
```
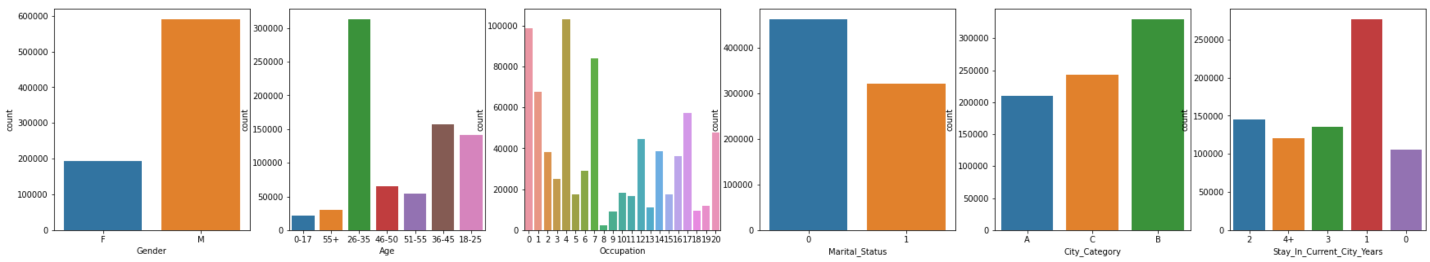

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3deb08a90>
```



1. **We have more males in the dataset than females.**
2. **Out of all the orders placed , the age category (26-35) had the highest number of orders .**
3. **Occupation 3 has the highest number of people purchasing during the black friday sale.**
   4.Unmarried people have purchased more as compared to married people.

5.City Category B had the most number of purchases.
6.People who have moved in the city and living from 1 year have purchased the most.

In [ ]:

```
df['Product_ID'].value_counts().sort_values(ascending=False)
```

Out[ ]:

```
P00265242    2709
P00025442    2310
P00110742    2292
P00112142    2279
P00046742    2084
             ...
P00100242       1
P00156942       1
P00359842       1
P0099542        1
P00253842       1
Name: Product_ID, Length: 3677, dtype: int64
```

Product P00265242 was purchased the most

Product P00265242 was purchased the most

In [ ]:

```
product_df=df.groupby(['Product_ID']).Purchase.agg('mean').to_frame('Mean_Puchase').rese
t_index()
product_df
```

Out[ ]:

	Product_ID	Mean_Puchase
0	P00000142	11143.642361
1	P00000242	10551.851064
2	P00000342	5313.422131
3	P00000442	4795.358696
4	P00000542	5417.530201
...	...	...
3672	P0099542	NaN
3673	P0099642	6439.230769
3674	P0099742	7872.603175
3675	P0099842	7228.549020
3676	P0099942	5572.785714

3677 rows × 2 columns

distribution of each product category w.r.t purchase

In [ ]:

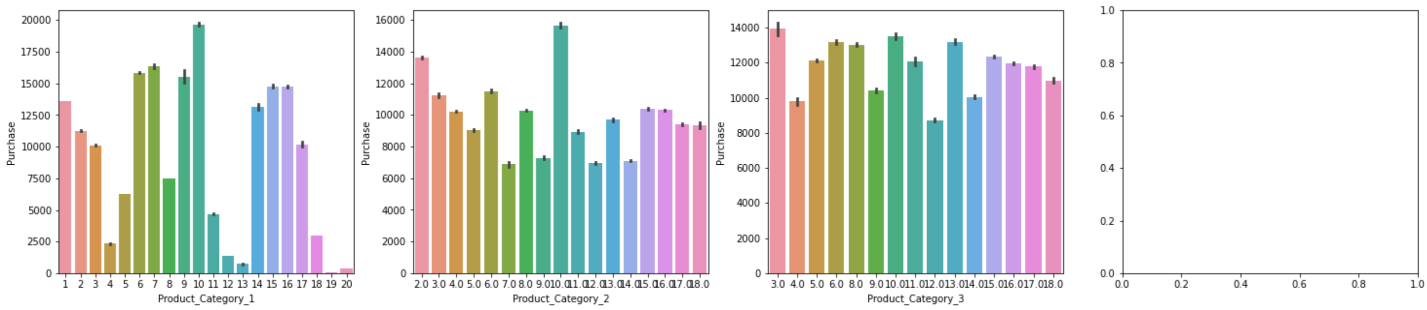
```
#distribution of each product category w.r.t purchase
fig,ax=plt.subplots(1,4,figsize=(25,5))
sns.barplot('Product_Category_1','Purchase',data=df,ax=ax[0])
sns.barplot('Product_Category_2','Purchase',data=df,ax=ax[1])
sns.barplot('Product_Category_3','Purchase',data=df,ax=ax[2])
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
```

```
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3de95ea30>
```



1. **In Prodcut_Category_1 , category 10 adds up to highest amount of purchases.**
   2.In Prodcut_Category_2 , category 10 adds up to highest amount of purchases.
   3.In Prodcut_Category_3 , category 3 adds up to highest amount of purchases.

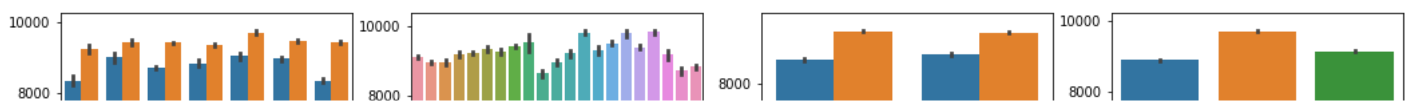
In [ ]:

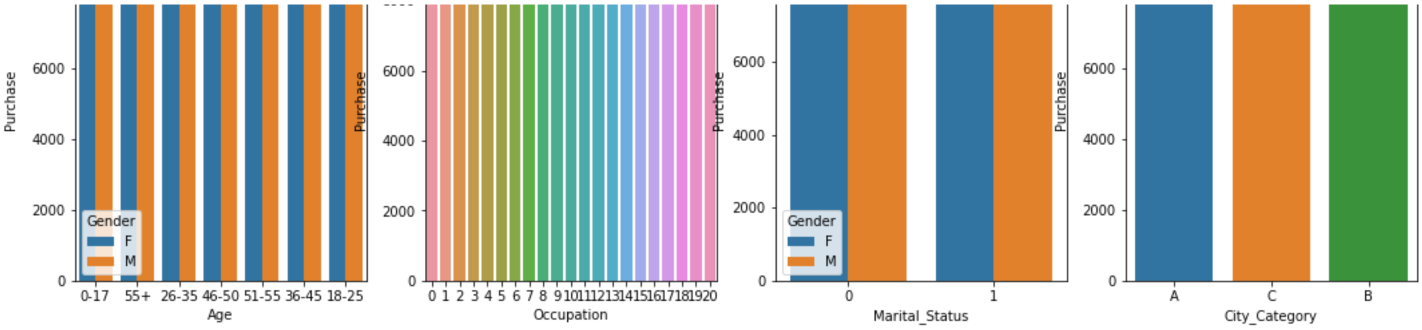
```
fig,ax=plt.subplots(1,4,figsize=(18,5))
sns.barplot('Age','Purchase',hue='Gender',data=df,ax=ax[0])

sns.barplot('Occupation','Purchase',data=df,ax=ax[1])

sns.barplot('Marital_Status','Purchase',hue='Gender',data=df,ax=ax[2])
sns.barplot('City_Category','Purchase',data=df,ax=ax[3])
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  warnings.warn(
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3de65e040>
```





1.Males and females from the age category (51-55) had the highest amount of pruchases even though age category 6 had very less people.
2.Mostly all of the occupations have similar purchasing trends.
3.Married females have purchased more than unmarried females, whereas married and unmarried men have similar purchases. Overall, men have purchased more than females in both the cases.

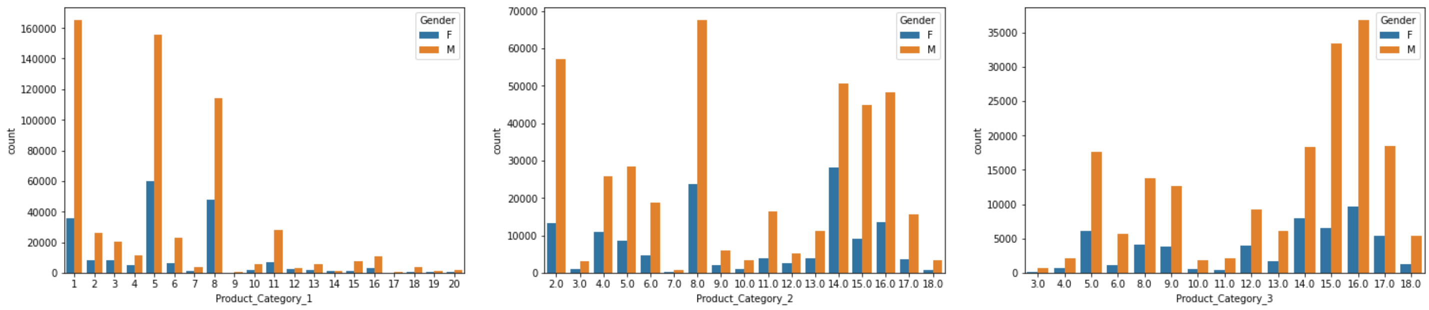
In [ ]:

```
fig,ax=plt.subplots(1,3,figsize=(25,5))

sns.countplot(df['Product_Category_1'],hue=df['Gender'],data=df,ax=ax[0])

sns.countplot(df['Product_Category_2'],hue=df['Gender'],data=df,ax=ax[1])

sns.countplot(df['Product_Category_3'],hue=df['Gender'],data=df,ax=ax[2])
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c4e1a92e0>
```



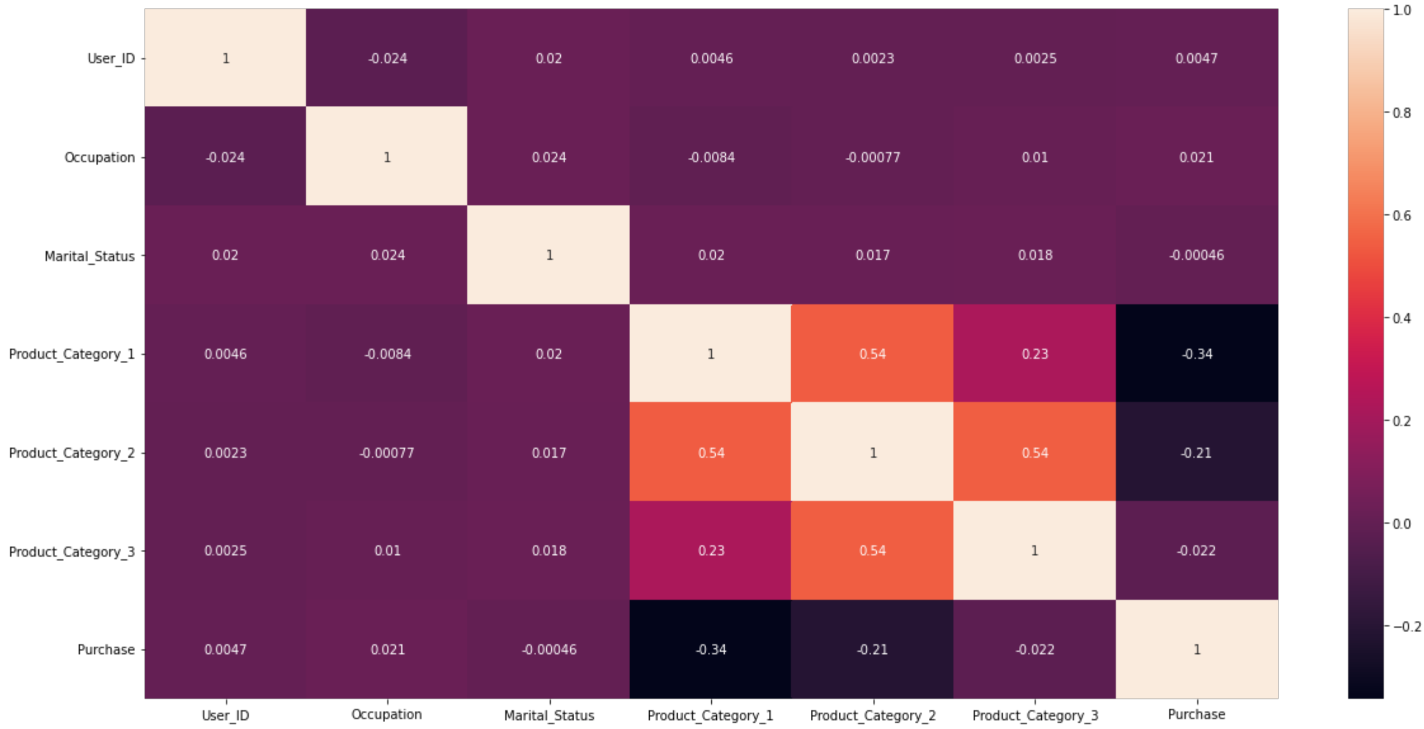
Initial Correlation Matrix

In [ ]:

```
#heatmap
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(),annot=True)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6bb5e7f0>
```



Data Preprocessing

In [ ]:

```
df.head()
```

Out[ ]:

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

In [ ]:

```
df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
User_ID	783667.0	1.003029e+06	1727.266668	1000001.0	1001519.0	1003075.0	1004478.0	1006040.0
Occupation	783667.0	8.079300e+00	6.522206	0.0	2.0	7.0	14.0	20.0
Marital_Status	783667.0	4.097774e-01	0.491793	0.0	0.0	0.0	1.0	1.0
Product_Category_1	783667.0	5.366196e+00	3.878160	1.0	1.0	5.0	8.0	20.0
Product_Category_2	537685.0	9.844506e+00	5.089093	2.0	5.0	9.0	15.0	18.0
Product_Category_3	237858.0	1.266860e+01	4.125510	3.0	9.0	14.0	16.0	18.0
Purchase	550068.0	9.263969e+03	5023.065394	12.0	5823.0	8047.0	12054.0	23961.0

Product ID and User ID are of no use to us. But we can use Product ID and User_ID to create other meaningful features and later drop them

We will create:
1.Product_Popularity_Count
2.Category_Count
3.Purchasing_Power

In [ ]:

```
df_new=df.groupby(['Product_ID']).Product_ID.agg('count').to_frame('Product_count').rese
t_index()
df_new.sort_values('Product_count',ascending=False)
```

Out[ ]:

	Product_ID	Product_count
2568	P00265242	2709
251	P00025442	2310
1036	P00110742	2292
1050	P00112142	2279
464	P00046742	2084
...	...	...
991	P00106242	1
992	P00106342	1
803	P00081342	1
806	P00081642	1
1423	P00149742	1

3677 rows × 2 columns

Preprocessing of MinMaxScaler

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
df_new['Popularity_score']=scaler.fit_transform(df_new[['Product_count']])
```

In [ ]:

```
df_new.drop(['Product_count'],axis=1,inplace=True)
```

In [ ]:

```
df_new
```

Out[ ]:

	Product_ID	Popularity_score
0	P00000142	0.603767
1	P00000242	0.201256
2	P00000342	0.128508
3	P00000442	0.046160
4	P00000542	0.084195

...	Product_ID	Popularity_score
3672	P0099542	0.000000
3673	P0099642	0.007016
3674	P0099742	0.062408
3675	P0099842	0.049483
3676	P0099942	0.006278

3677 rows × 2 columns

In [ ]:

```
product_dict=dict(zip(df_new.Product_ID,df_new.Popularity_score))
df['Product_popularity_score']=df['Product_ID'].map(product_dict)
df.head()
```

Out[ ]:

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

Some products were not present in df_train but were present in df_test

In [ ]:

```
#some products were not present in df_train but were present in df_test
df['Product_popularity_score'].isnull().sum()
```

Out[ ]:

0

replacing nulls in Product_Popularity_Count with mean

In [ ]:

```
#replacing nulls with mean
df['Product_popularity_score']=df['Product_popularity_score'].fillna(df['Product_popular
ity_score'].mean())
```

In [ ]:

```
df_new=df.groupby(['User_ID']).Purchase.agg('sum').to_frame("Purchasing_Power_Total").res
et_index()
df_new['Purchasing_Power']=scaler.fit_transform(df_new[['Purchasing_Power_Total']])
```

In [ ]:

```
df_new.drop(['Purchasing_Power_Total'],axis=1,inplace=True)
df_new
```

Out[ ]:

	User_ID	Purchasing_Power
0	1000001	0.027398
1	1000002	0.072810
2	1000003	0.028117
3	1000004	0.015232
4	1000005	0.073813
...	...	...
5886	1006036	0.387921
5887	1006037	0.102272
5888	1006038	0.004133
5889	1006039	0.051823
5890	1006040	0.153154

5891 rows × 2 columns

In [ ]:

```
Purchase_power_dict=dict(zip(df_new.User_ID,df_new.Purchasing_Power))
df['Purchasing_Power']=df['User_ID'].map(Purchase_power_dict)
df.head()
```

Out[ ]:

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

In [ ]:

```
df['Category_count'] = np.where(pd.notna(df['Purchase']), 3 - df.isnull().sum(axis=1), 4
- df.isnull().sum(axis=1))
```

In [ ]:

```
df
```

Out[ ]:

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

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_C
233594	1006036	P00118942	F	26-35	15	B	4+	1	
233595	1006036	P00254642	F	26-35	15	B	4+	1	
233596	1006036	P00031842	F	26-35	15	B	4+	1	
233597	1006037	P00124742	F	46-50	1	C	4+	0	
233598	1006039	P00316642	F	46-50	0	B	4+	1	

783667 rows × 16 columns

We created a new feature using Product_ID and since User_ID and Product_ID are of no use we can drop them now

In [ ]:

```
#We created a new feature using Product_ID and since User_ID and Product_ID are of no use
we can drop them now
df=df.drop(['User_ID','Product_ID'],axis=1)
```

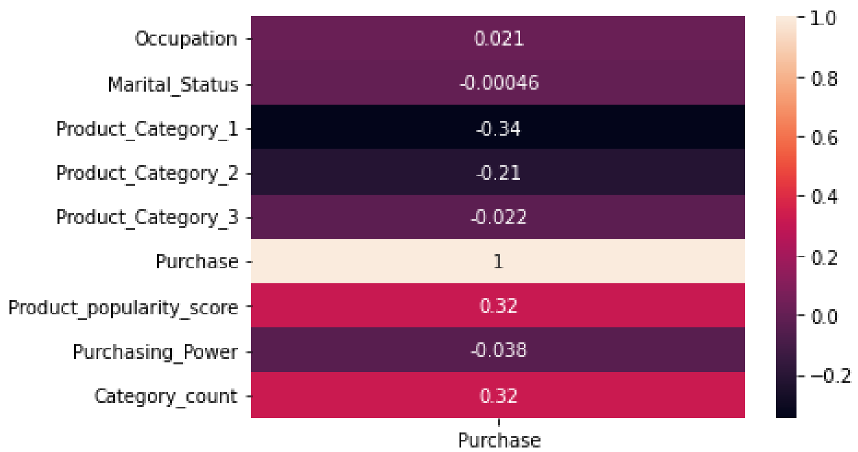
Checking Corelation of our new features

In [ ]:

```
sns.heatmap(df.corr()[['Purchase']],annot=True)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3ce7b2400>
```



Checking Null Values

In [ ]:

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

Out[ ]:

```
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          245982
Product_Category_3          545809
Purchase                    233599
set                              0
Product_popularity_score         0
Purchasing_Power                 0
Category_count                   0
dtype: int64
```

Checking value distribution of Product_Category_2 Column

In [ ]:

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

Out[ ]:

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

Replacing null in Product_Category_2 with -ve value so the model understands these are null

In [ ]:

```
df['Product_Category_2']=df['Product_Category_2'].fillna(-1).astype(int)
```

Replacing null in Product_Category_3 with -ve value

In [ ]:

```
cat_3_mode=df['Product_Category_3'].mode()[0]
df['Product_Category_3']=df['Product_Category_3'].fillna(-1).astype(int)
```

Checking Null values again for confirmation

In [ ]:

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

Out[ ]:

```
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               0
```

```
Product_Category_2                 0
Product_Category_3                 0
Purchase                      233599
set                                0
Product_popularity_score           0
Purchasing_Power                   0
Category_count                     0
dtype: int64
```

Unique values distribution

In [ ]:

```
df.apply(lambda x:len(x.unique()))
```

Out[ ]:

```
Gender                           2
Age                              7
Occupation                      21
City_Category                    3
Stay_In_Current_City_Years       5
Marital_Status                   2
Product_Category_1              20
Product_Category_2              18
Product_Category_3              16
Purchase                     18106
set                              2
Product_popularity_score       803
Purchasing_Power              5876
Category_count                   3
dtype: int64
```

Checking for Categorical Variables

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 783667 entries, 0 to 233598
Data columns (total 14 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   Gender                      783667 non-null  object 
 1   Age                         783667 non-null  object 
 2   Occupation                  783667 non-null  int64  
 3   City_Category               783667 non-null  object 
 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  int64  
 8   Product_Category_3          783667 non-null  int64  
 9   Purchase                    550068 non-null  float64
 10  set                         783667 non-null  object 
 11  Product_popularity_score    783667 non-null  float64
 12  Purchasing_Power            783667 non-null  float64
 13  Category_count              783667 non-null  int64  
dtypes: float64(3), int64(6), object(5)
memory usage: 105.8+ MB
```

In [ ]:

```
df.head()
```

Out[ ]:

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Categor

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Categor
0	F	0-17	10	A	2	0	3	
1	F	0-17	10	A	2	0	1	
2	F	0-17	10	A	2	0	12	
3	F	0-17	10	A	2	0	12	
4	M	55+	16	C	4+	0	8	

In [ ]:

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

Out[ ]:

```
26-35    313015
36-45    156724
18-25    141953
46-50     65278
51-55     54784
55+       30579
0-17      21334
Name: Age, dtype: int64
```

Converting Age

In [ ]:

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

In [ ]:

```
df['Age'].value_counts().sort_index()
```

Out[ ]:

```
1     21334
2    141953
3    313015
4    156724
5     65278
6     54784
7     30579
Name: Age, dtype: int64
```

Converting City_Category into One hot encoding

In [ ]:

```
city_cat=pd.get_dummies(df['City_Category'],drop_first=True)
```

In [ ]:

```
city_cat
```

Out[ ]:

	B	C
0	0	0
1	0	0
2	0	0

	B	C
3	0	0
4	0	1
...	...	...
233594	1	0
233595	1	0
233596	1	0
233597	0	1
233598	1	0

783667 rows × 2 columns

In [ ]:

```
df=pd.concat([df,city_cat],axis=1)
```

In [ ]:

```
df.drop('City_Category',axis=1,inplace=True)
```

In [ ]:

```
df.head()
```

Out[ ]:

	Gender	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Ca
0	F	1	10	2	0	3	-1	
1	F	1	10	2	0	1	6	
2	F	1	10	2	0	12	-1	
3	F	1	10	2	0	12	14	
4	M	7	16	4+	0	8	-1	

Converting Gender

In [ ]:

```
df["Gender"]=df['Gender'].map({'M':0,'F':1})
```

In [ ]:

```
df.head()
```

Out[ ]:

	Gender	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Ca
0	1	1	10	2	0	3	-1	
1	1	1	10	2	0	1	6	
2	1	1	10	2	0	12	-1	
3	1	1	10	2	0	12	14	
4	0	7	16	4+	0	8	-1	

In [ ]:

```
df["Stay_In_Current_City_Years"].value_counts()
```

Out[ ]:

```
1     276425
2     145427
3     135428
4+    120671
0     105716
Name: Stay_In_Current_City_Years, dtype: int64
```

Converting Stay_In_Current_City_Years

In [ ]:

```
df["Stay_In_Current_City_Years"]=df["Stay_In_Current_City_Years"].str.replace('+','').ast
ype(int)
```

```
<ipython-input-132-323548bbe965>:1: FutureWarning: The default value of regex will change
from True to False in a future version. In addition, single character regular expressions
will *not* be treated as literal strings when regex=True.
  df["Stay_In_Current_City_Years"]=df["Stay_In_Current_City_Years"].str.replace('+','').a
stype(int)
```

In [ ]:

```
df.columns
```

Out[ ]:

```
Index(['Gender', 'Age', 'Occupation', 'Stay_In_Current_City_Years',
       'Marital_Status', 'Product_Category_1', 'Product_Category_2',
       'Product_Category_3', 'Purchase', 'set', 'Product_popularity_score',
       'Purchasing_Power', 'Category_count', 'B', 'C'],
      dtype='object')
```

In [ ]:

```
df=df.loc[:,[ 'Gender', 'Age', 'Occupation','B', 'C',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
              'Product_Category_2', 'Product_Category_3','Category_count','Product_popul
arity_score','Purchasing_Power','Purchase','set']]
```

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 783667 entries, 0 to 233598
Data columns (total 15 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   Gender                      783667 non-null  int64  
 1   Age                         783667 non-null  int64  
 2   Occupation                  783667 non-null  int64  
 3   B                           783667 non-null  uint8  
 4   C                           783667 non-null  uint8  
 5   Stay_In_Current_City_Years  783667 non-null  int64  
 6   Marital_Status              783667 non-null  int64  
 7   Product_Category_1          783667 non-null  int64  
 8   Product_Category_2          783667 non-null  int64  
 9   Product_Category_3          783667 non-null  int64  
 10  Category_count              783667 non-null  int64  
 11  Product_popularity_score    783667 non-null  float64
 12  Purchasing_Power            783667 non-null  float64
 13  Purchase                    550068 non-null  float64
 14  set                         783667 non-null  object 
dtypes: float64(3), int64(9), object(1), uint8(2)
memory usage: 85.2+ MB
```

Cleaned dataset

In [ ]:

```
df.head()
```

Out[ ]:

	Gender	Age	Occupation	B	C	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Proc
0	1	1	10	0	0	2	0	3	-1	
1	1	1	10	0	0	2	0	1	6	
2	1	1	10	0	0	2	0	12	-1	
3	1	1	10	0	0	2	0	12	14	
4	0	7	16	0	1	4	0	8	-1	

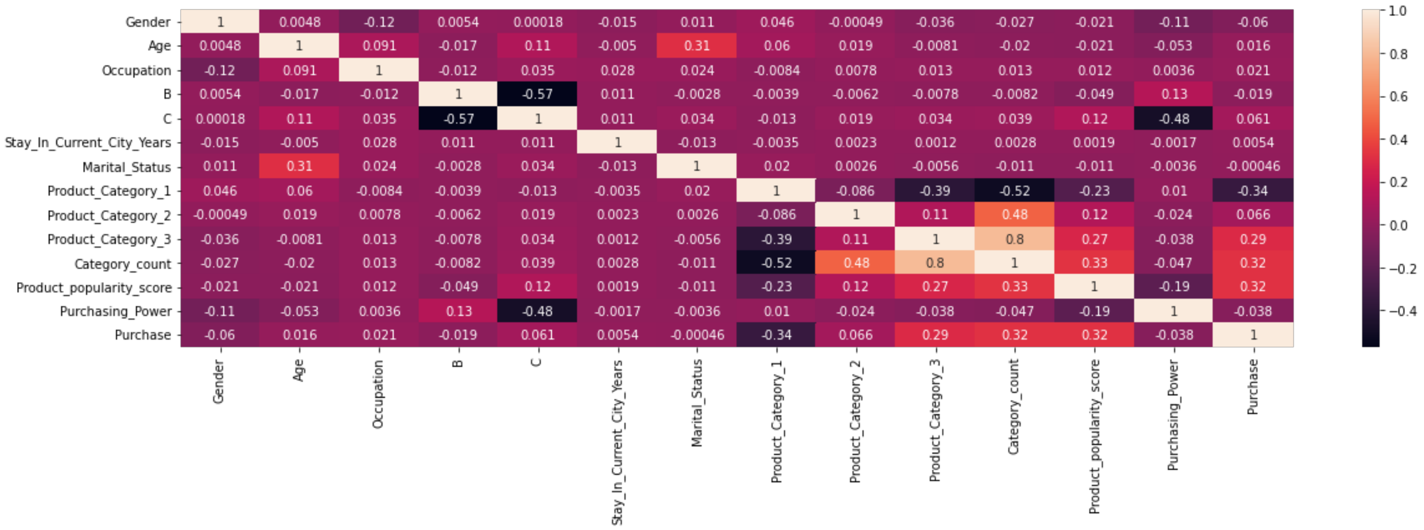
Final Correlation Matrix

In [ ]:

```
plt.figure(figsize=(20,5))
sns.heatmap(df.corr(),annot=True)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3cf1952e0>
```



Normalizing purchase feature for better modelling

In [ ]:

```
#normalizing purchase feature for better modelling
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
df['Purchase']=scaler.fit_transform(df[['Purchase']])
```

In [ ]:

```
df['Purchase'].sort_values(ascending=False)
```

Out[ ]:

```
370891    1.000000
93016     1.000000
87440     1.000000
503697    0.999958
321782    0.999958
            ...
233594         NaN
```

```
233595         NaN
233596         NaN
233597         NaN
233598         NaN
Name: Purchase, Length: 783667, dtype: float64
```

In [ ]:

```
df_bak2=df
```

Modelling

In [ ]:

```
from sklearn.feature_selection import SelectKBest, mutual_info_classif
from sklearn.model_selection import train_test_split
```

Dividing data into train and test on the basis of the flag set

In [ ]:

```
#dividing data into train and test on the basis of the flag set
df_train=df[df['set']=='train']
df_test=df[df['set']=='test']
```

In [ ]:

```
df_train.drop('set',axis=1,inplace=True)
df_test.drop('set',axis=1,inplace=True)
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:4906: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

In [ ]:

```
target=df_train['Purchase']
```

In [ ]:

```
df_train.drop('Purchase',axis=1,inplace=True)
```

In [ ]:

```
X_train,X_test,y_train,y_test=train_test_split(df_train,target,test_size=0.2,random_stat
e=42)
```

Checking importance of features

In [ ]:

```
#checking importance of features
from sklearn.feature_selection import SelectKBest, mutual_info_regression

K_features = 'all'
ft_scorer = SelectKBest(score_func=mutual_info_regression, k=K_features)
print(X_train.shape)
print(y_train.shape)
X = ft_scorer.fit_transform(X_train, y_train)
```

```
(440054, 13)
(440054,)
```

In [ ]:

```
pd.Series(ft_scorer.scores_*1000, index=df_train.columns).sort_values(ascending=False)
```

Out[ ]:

```
Product_Category_1            1669.641452
Product_popularity_score      1070.421238
Product_Category_2             529.360141
Product_Category_3             234.620595
Category_count                 171.956953
Purchasing_Power                70.651576
Occupation                       9.624324
Gender                           6.898495
Age                              5.438610
C                                3.390445
B                                1.198837
Stay_In_Current_City_Years       0.750075
Marital_Status                   0.000000
dtype: float64
```

Decision Tree Regressor

Applying GridSearchCV hyperparameter tuning on Decision Tree Regressor

In [ ]:

```
from sklearn.model_selection import GridSearchCV
params=[{'max_depth':range(1,10)}]
dt_grid = GridSearchCV(DecisionTreeRegressor(), params, refit = True)
```

In [ ]:

```
dt_grid.fit(X_train,y_train)
```

Out[ ]:

```
GridSearchCV(estimator=DecisionTreeRegressor(),
             param_grid=[{'max_depth': range(1, 10)}])
```

Linear Regression

In [ ]:

```
from sklearn.linear_model import LinearRegression
reg=LinearRegression()
reg.fit(X_train,y_train)
y_pred=reg.predict(X_test)
```

In [ ]:

```
from sklearn.metrics import mean_squared_error, r2_score
print(np.sqrt(mean_squared_error(y_test,y_pred)))
r2_score(y_test,y_pred)
```

```
0.18733191911620875
```

Out[ ]:

```
0.1989274194272881
```

Best Parameters for Decision Tree Regressor

In [ ]:

```
print(dt_grid.best_params_)
print(dt_grid.best_estimator_)
```

```
{'max_depth': 9}
DecisionTreeRegressor(max_depth=9)
```

In [ ]:

```
from sklearn.tree import DecisionTreeRegressor
model=DecisionTreeRegressor(max_depth=9)
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
print(np.sqrt(mean_squared_error(y_test,y_pred)))
print(r2_score(y_test,y_pred))
```

```
0.11737424108918598
0.6855193729461644
```

XGBRegressor

XGBRegressor hyperparameter tuning

In [ ]:

```
from sklearn.model_selection import GridSearchCV
import xgboost as xgb
params=[{
        'eta':range(0,1),
        'max-depth':range(1,20),
         'tree_method':['auto', 'exact', 'approx', 'hist', 'gpu_hist'],
         'grow_policy':['depthwise', 'lossguide'],
         'max_leaves':range(1,10)}]


xgb_grid =GridSearchCV(xgb.XGBRegressor(), params, refit = True)
```

With 100,000 instances.

In [ ]:

```
xgb_grid.fit(X_train[:100000],y_train[:100000])
xgb_grid.best_params_
```

With 15,000 instances.

In [ ]:

```
xgb_grid.fit(X_train[:15000],y_train[:15000])
xgb_grid.best_params_
```

XGBRegressor best params

In [ ]:

```
xgb_grid.best_params_
```

Out[ ]:

```
{'eta': 0,
 'grow_policy': 'lossguide',
 'max-depth': 1,
 'max_leaves': 7,
 'tree_method': 'hist'}
```

These calculated paramters are not giving best results since we used only of chunk of dataset to tune the hyperparamters due to lower computance

In [ ]:

```
import xgboost as xgb
model=xgb.XGBRegressor(max_depth=13)
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
print(np.sqrt(mean_squared_error(y_test,y_pred)))
print(r2_score(y_test,y_pred))
```

```
[03:04:10] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
0.1064946434014973
0.7411168230251325
```

Random Forest Regressor

Hyperparameter tuning for Random Forest Regressor

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
params = [{'max_depth': [10,20,30, 60, 80, 90, 100],
           'min_samples_leaf': [1, 3, 4, 5],
          'min_samples_split': [2, 8, 10, 12],
          'n_estimators': [100, 200,300]}]

rf_grid = GridSearchCV(RandomForestRegressor(n_jobs=10), params, refit = True, verbose =
3)
```

Best Parameters for Random Forest Regressor

In [ ]:

```
rf_grid.fit(X_train[0:5000],y_train[0:5000])
rf_grid.best_params_
```

Parameters

{'max_depth': 10,

'min_samples_leaf': 3,

'min_samples_split': 10,

'n_estimators': 200}

Due to low computation accessibility we were only able to perform hyperparamter tuning for a small chunk of the dataset .

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
model=RandomForestRegressor(n_estimators=200,n_jobs=4)
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
print(np.sqrt(mean_squared_error(y_test,y_pred)))
print(r2_score(y_test,y_pred))
```

```
0.11342680238837338
0.7063164099661337
```

We get best results for XGBoost Regressor, therefore, we will use it as our model.

Results and Learning Curve

Results and Learning Curvs

In the above steps, we have performed EDA and pre-processed the data accordingly. Missing values are taken care of, and the texual data is also handled by performing one-hot encoding.

Here, our target is to predict the purchase amount an individual is likely to make on the black friday sale using information such as their gender, age, occupation, marital status, purchasing power, etc.

It is a supervised learning problem as we have purchase amount for the data instances. And specifically, it is a Regression problem since we are trying to predict a continuous value (purchasing amount).

We trained three different regression model and evaluate their performance by plotting their learning curves. R^2 value is used to analyze the performance of models. The following models were trained as seen in the above sections:

(1) Linear Regressor

(2) Random Forest Regressor (Bagging Technique)

(3) XGBoost (Boosting Technique)

The dataset that we have used has over 3,00,000 instances. Plotting Training curves for models on the complete dataset is a time-comsuming task. And sometimes training fails at the very end of many hours of training. So, we have used a subset of 25,000 data instances for our training plots. More data can be used for training to get more accurate models.

In [ ]:

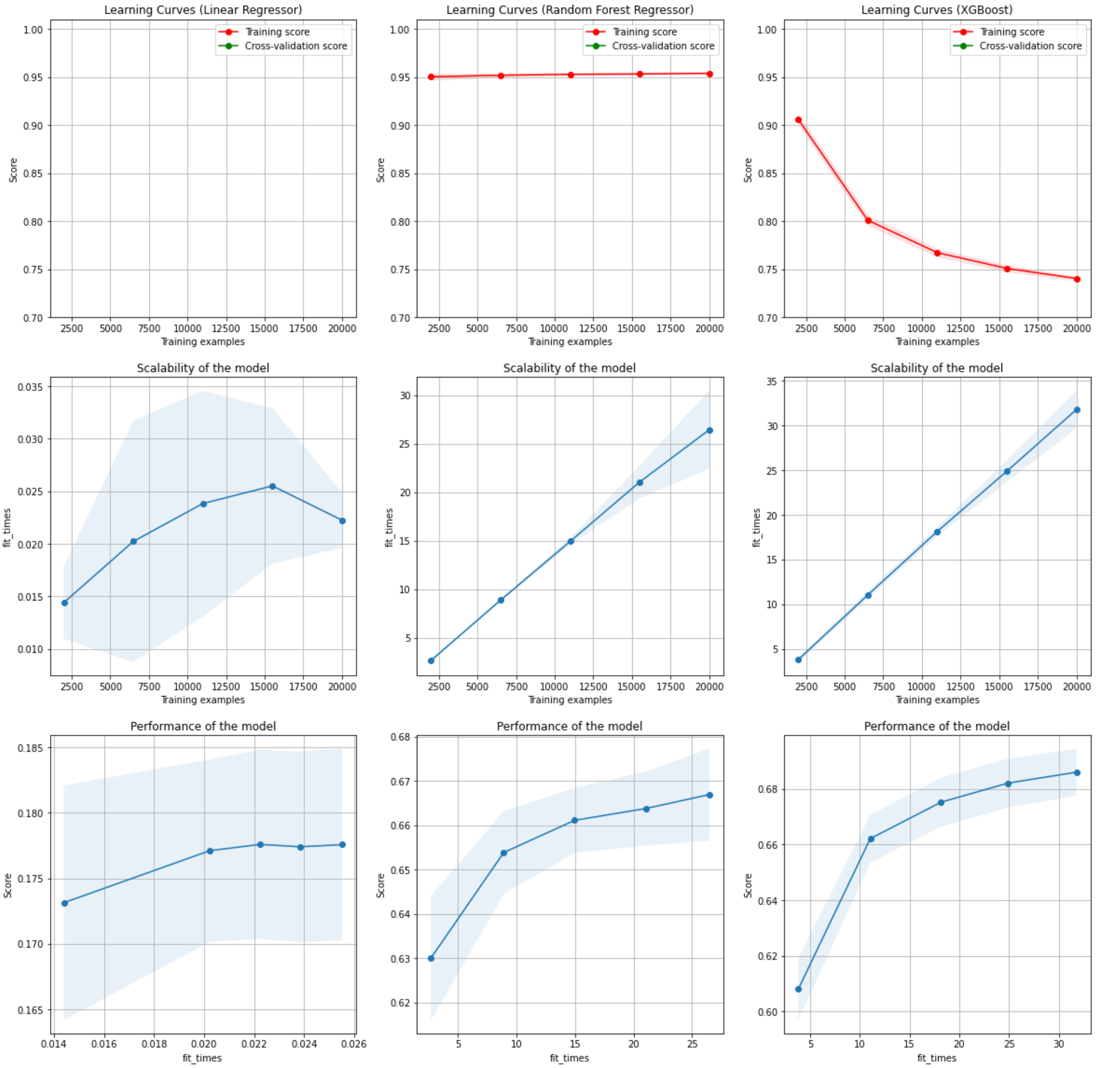
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVC
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from sklearn.datasets import load_digits
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
from xgboost import XGBRegressor
import time

training_time = []


def plot_learning_curve(
    estimator,
    title,
    X,
    y,
    axes=None,
    ylim=None,
    cv=None,
    n_jobs=None,
    scoring=None,
    train_sizes=np.linspace(0.1, 1.0, 5),
    model_name=None
):

    print("\nTraining : ", model_name)
    start_time = time.time()
    if axes is None:
        _, axes = plt.subplots(1, 3, figsize=(20, 5))

    axes[0].set_title(title)
    if ylim is not None:
        axes[0].set_ylim(*ylim)
    axes[0].set_xlabel("Training examples")
    axes[0].set_ylabel("Score")
```

```
    train_sizes, train_scores, test_scores, fit_times, _ = learning_curve(
        estimator,
        X,
        y,
        scoring=scoring,
        cv=cv,
        n_jobs=n_jobs,
        train_sizes=train_sizes,
        return_times=True,
    )

    training_time.append({"Model Name": model_name, "n_jobs": n_jobs, "Time": time.time(
) - start_time})

    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    fit_times_mean = np.mean(fit_times, axis=1)
    fit_times_std = np.std(fit_times, axis=1)

    # Plot learning curve
    axes[0].grid()
    axes[0].fill_between(
        train_sizes,
        train_scores_mean - train_scores_std,
        train_scores_mean + train_scores_std,
        alpha=0.1,
        color="r",
    )
    axes[0].fill_between(
        train_sizes,
        test_scores_mean - test_scores_std,
        test_scores_mean + test_scores_std,
        alpha=0.1,
        color="g",
    )
    axes[0].plot(
        train_sizes, train_scores_mean, "o-", color="r", label="Training score"
    )
    axes[0].plot(
        train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation score"
    )
    axes[0].legend(loc="best")

    # Plot n_samples vs fit_times
    axes[1].grid()
    axes[1].plot(train_sizes, fit_times_mean, "o-")
    axes[1].fill_between(
        train_sizes,
        fit_times_mean - fit_times_std,
        fit_times_mean + fit_times_std,
        alpha=0.1,
    )
    axes[1].set_xlabel("Training examples")
    axes[1].set_ylabel("fit_times")
    axes[1].set_title("Scalability of the model")

    # Plot fit_time vs score
    fit_time_argsort = fit_times_mean.argsort()
    fit_time_sorted = fit_times_mean[fit_time_argsort]
    test_scores_mean_sorted = test_scores_mean[fit_time_argsort]
    test_scores_std_sorted = test_scores_std[fit_time_argsort]
    axes[2].grid()
    axes[2].plot(fit_time_sorted, test_scores_mean_sorted, "o-")
    axes[2].fill_between(
        fit_time_sorted,
        test_scores_mean_sorted - test_scores_std_sorted,
        test_scores_mean_sorted + test_scores_std_sorted,
        alpha=0.1,
    )
    axes[2].set_xlabel("fit_times")
```

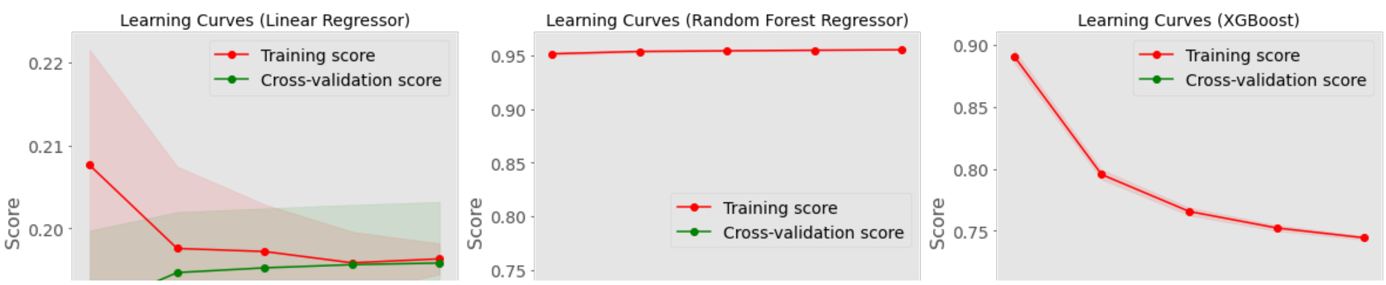
```
    axes[2].set_ylabel("Score")
    axes[2].set_title("Performance of the model")

    print(model_name, " is trained.")
    print("Time taken : ", time.time() - start_time)

    return plt


fig, axes = plt.subplots(3, 3, figsize=(20, 20))

# X, y = load_digits(return_X_y=True)

title = r"Learning Curves (Linear Regressor)"
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
estimator = LinearRegression()
plot_learning_curve(
    estimator,
    title,
    X_train[:25000],
    y_train[:25000],
    axes=axes[:, 0],
    ylim=(0.7, 1.01),
    cv=cv,
    n_jobs=4,
    scoring="r2",
    model_name="Linear Regression"
)

title = r"Learning Curves (Random Forest Regressor)"
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
estimator = RandomForestRegressor(n_estimators=100)
plot_learning_curve(
    estimator,
    title,
    X_train[:25000],
    y_train[:25000],
    axes=axes[:, 1],
    ylim=(0.7, 1.01),
    cv=cv,
    n_jobs=4,
    scoring="r2",
    model_name="RandomForest"
)

title = "Learning Curves (XGBoost)"
# Cross validation with 50 iterations to get smoother mean test and train
# score curves, each time with 20% data randomly selected as a validation set.
cv = ShuffleSplit(n_splits=50, test_size=0.2, random_state=0)
estimator = XGBRegressor(n_estimators=1000)
plot_learning_curve(
    estimator,
    title,
    X_train[:25000],
    y_train[:25000],
    axes=axes[:, 2],
    ylim=(0.7, 1.01),
    cv=cv,
    n_jobs=4,
    scoring="r2",
    model_name="XGBoost"
)



plt.show()
```

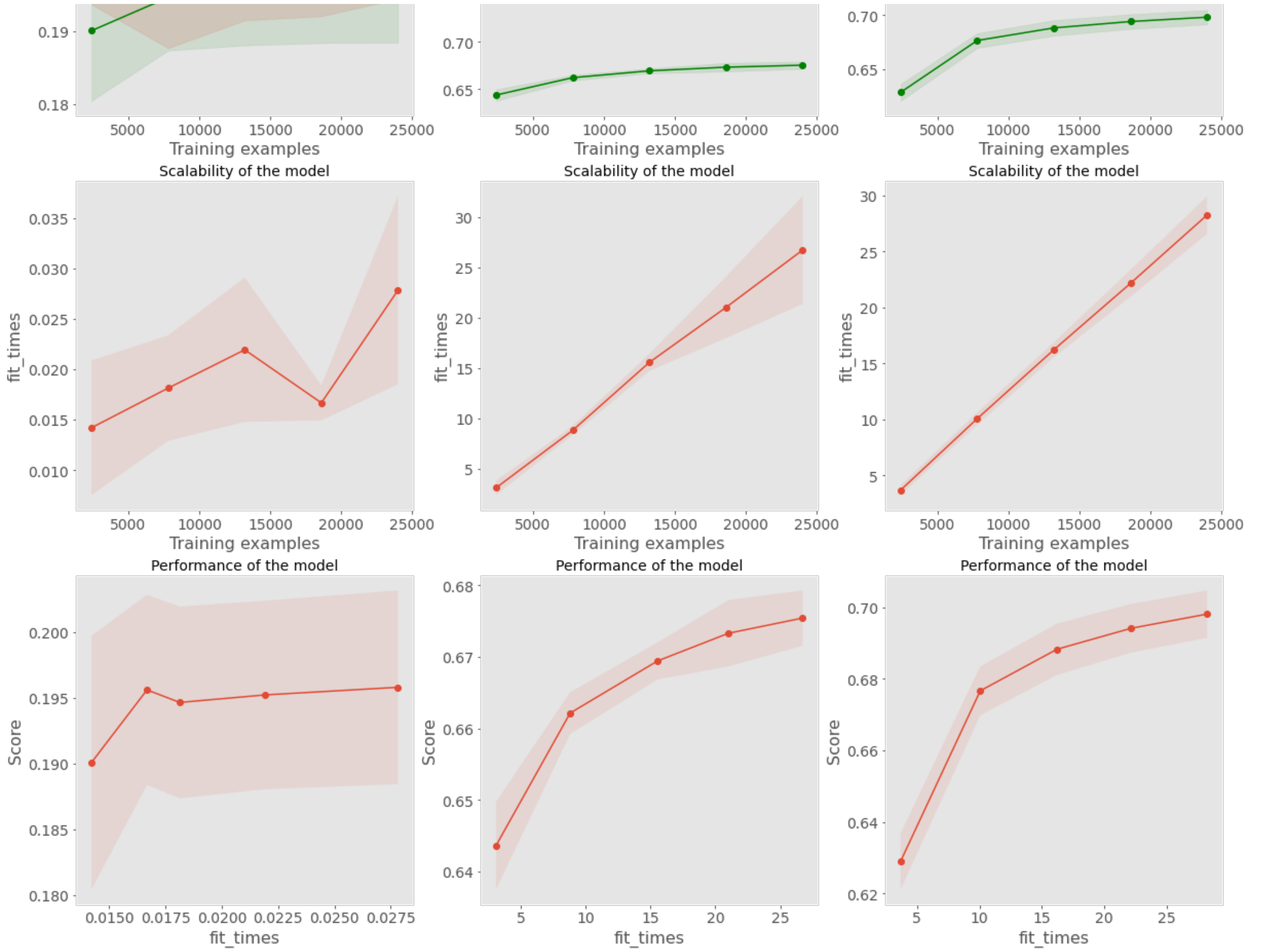
```
Training :  Linear Regression
Linear Regression  is trained.
Time taken :  0.647869348526001

Training :  RandomForest
```

```
RandomForest  is trained.
Time taken :  106.59112644195557

Training :  XGBoost
XGBoost  is trained.
Time taken :  1220.5953707695007
```



In the above graphs, the learning curves, the scalability and the performance of the models are plotted.
We use Linear Regression as our baseline model and compare other models with its curve.
The Training learning curve for the XGBoost algorithm is going down as well as the Validation scores goes up shows us the model is getting better. The XGBoost algorithm can score more in terms of predicting the purchase amount. Therefore, it turns out to be the best algorithm if we compare the learning curves.
The RandomForestRegressor , shows it may be able to learn with the increase of training data. Its training score does not change much.





Predicting values for test data provided by kaggle

In [ ]:

```
df_test.drop(['Purchase'],axis=1,inplace=True)
df_test.head()
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:4906: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

Out[ ]:

	Gender	Age	Occupation	B	C	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Proc
0	0	5	7	1	0	2	1	1	11	
1	0	3	17	0	1	0	0	3	5	
2	1	4	1	1	0	4	1	5	14	
3	1	4	1	1	0	4	1	4	9	
4	1	3	1	0	1	1	0	4	5	

In [ ]:

```
y_pred=model.predict(df_test)
```

In [ ]:

```
df_pred=pd.DataFrame(y_pred,columns={'Predicted Purchase'})
```

In [ ]:

```
df_pred['Purchase']=scaler.inverse_transform(df_pred[['Predicted Purchase']])
```

Our Final Output. This model can be used by businesses to predict customer behaviour during Black Friday.

In [ ]:

```
df_pred
```

Out[ ]:

	Predicted Purchase	Purchase
0	0.628084	15053.994141
1	0.432533	10370.739258
2	0.271535	6514.979980
3	0.118789	2856.878174
4	0.104091	2504.869385
...	...	...
233594	0.285133	6840.656250
233595	0.237353	5696.363281
233596	0.396020	9496.286133
233597	0.742370	17791.007812
233598	0.122676	2949.972168

233599 rows × 2 columns

References

[1] https://www.kaggle.com/datasets/sdolezel/black-friday

[2] https://scikit-learn.org/stable/modules/learning_curve.html

[3] https://seaborn.pydata.org/generated/seaborn.heatmap.html

[4] https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

[5] https://xgboost.readthedocs.io/en/stable/

[6] https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html

[7] https://www.investopedia.com/terms/r/r-squared.asp#:~:text=R%2Dsquared%20values%20range%20from,)%20you%20are%20interested%20in).

[8] https://medium.com/analytics-vidhya/sales-prediction-on-black-friday-using-ml-regression-technique-380af62c181e