

```
In [2]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OrdinalEncoder, PowerTransformer
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, roc_auc_score
from sklearn import metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVR, SVC

import warnings
warnings.filterwarnings('ignore')
```

```
In [3]: from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, accuracy_score
from sklearn.linear_model import Ridge, Lasso, RidgeCV, LassoCV

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
```

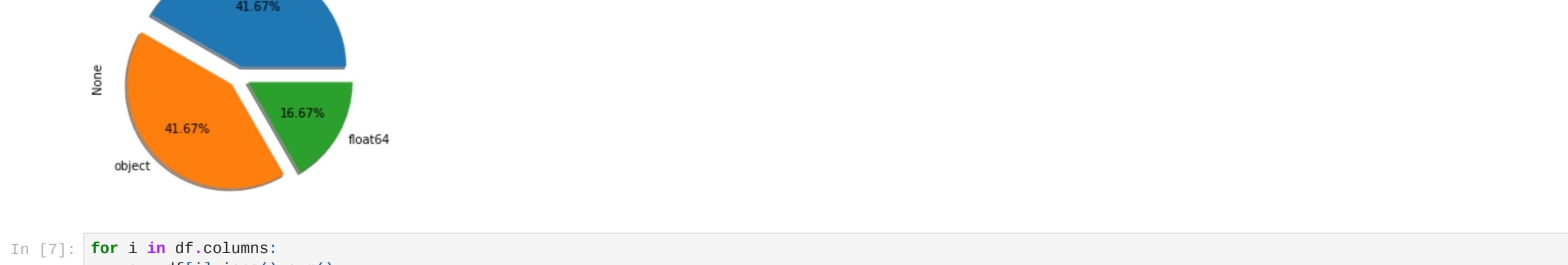
```
In [4]: df = pd.read_csv(r"C:\Users\Shrikant\OneDrive\Desktop\Black_Friday_Project\blackFriday_train.csv")
df.tail(6)
```

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
550062	1006032	P00372445	M	46-50	7	A	3	0	20	NaN	473
550063	1006033	P00372445	M	51-55	13	B	1	1	20	NaN	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	NaN	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	NaN	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	NaN	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	NaN	490

```
In [5]: 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  int64
 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  366821 non-null  float64
11   Purchase            550068 non-null  int64
dtypes: float64(2), int64(5), object(5)
memory usage: 56.4+ MB
```

```
In [6]: df.dtypes.value_counts().plot.pie(explode=[0.1,0.1,0.1],autopct='%1.2f%%',shadow=True)
plt.title('type of our data');
```



```
In [7]: for i in df.columns:
a = df[i].isna().sum()
if a > 0:
print(i, 'column has', a, 'NaN values')
```

```
Product_Category_2 column has 173638 NaN values
Product_Category_3 column has 383247 NaN values
```

```
In [8]: for i in df.columns:
and if i.value_counts()
bilen(a.index)
print(i, 'column has', b, 'categorical data counts')
```

User\_ID column has 5891 categorical data counts  
Product\_ID column has 3631 categorical data counts  
Gender column has 2 categorical data counts  
Age column has 7 categorical data counts  
Occupation column has 21 categorical data counts  
City\_Category column has 3 categorical data counts  
Stay\_In\_Current\_City\_Years column has 5 categorical data counts  
Marital\_Status column has 2 categorical data counts  
Product\_Category\_1 column has 20 categorical data counts  
Product\_Category\_2 column has 17 categorical data counts  
Product\_Category\_3 column has 15 categorical data counts  
Purchase column has 18195 categorical data counts

```
In [9]: df.describe(include='all')
```

	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
count	550068.00	550068	550068	550068	550068.000000	550068	550068	550068.000000	550068.000000	376430.000000	166821.000000	550068.000000
unique	NaN	3631	2	7	NaN	3	5	NaN	NaN	NaN	NaN	NaN
top	NaN	P00265242	M	26-35	NaN	B	1	NaN	NaN	NaN	NaN	NaN
freq	NaN	1890	414259	219587	NaN	211173	193821	NaN	NaN	NaN	NaN	NaN
mean	1.003027e+06	NaN	NaN	NaN	8.076707	NaN	NaN	0.409653	5.404270	9.842329	12.666243	9263.9687
std	1.727992e+03	NaN	NaN	NaN	6.522660	NaN	NaN	0.491770	3.936211	5.086590	4.125338	5023.0653
min	1.000910e+06	NaN	NaN	NaN	0.000000	NaN	NaN	0.000000	1.000000	2.000000	3.000000	12.0000
25%	1.001516e+06	NaN	NaN	NaN	2.000000	NaN	NaN	0.000000	1.000000	5.000000	9.000000	5823.0000
50%	1.003077e+06	NaN	NaN	NaN	7.000000	NaN	NaN	0.000000	5.000000	9.000000	14.000000	8047.0000
75%	1.004478e+06	NaN	NaN	NaN	14.000000	NaN	NaN	1.000000	8.000000	15.000000	16.000000	12054.0000
max	1.006040e+06	NaN	NaN	NaN	20.000000	NaN	NaN	1.000000	20.000000	18.000000	18.000000	23961.0000

A basic observation is that:  
Product P00265242 is the most popular product. Most of the transactions were made by men. Age group with most transactions was 26-35. City Category with most transactions was B

Their are lot amount of nan values present in columns (Product\_Category\_2 and Product\_Category\_3) need to replace it

```
In [10]: df

df.Product_Category_2.value_counts()
```

	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	P00089042	F	0-17	10	A	2	0	3	9.0	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	9.0	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	9.0	NaN	7969
...	...	...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	1	20	9.0	NaN	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	9.0	NaN	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	9.0	NaN	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	9.0	NaN	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	9.0	NaN	490

550068 rows × 12 columns

```
In [11]: df.Product_Category_3.value_counts()
```

	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	P00089042	F	0-17	10	A	2	0	3	9.0	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	9.0	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	9.0	NaN	7969
...	...	...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	1	20	9.0	NaN	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	9.0	NaN	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	9.0	NaN	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	9.0	NaN	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	9.0	NaN	490

550068 rows × 12 columns

```
In [14]: df.Product_Category_3.value_counts()
```

	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	P00089042	F	0-17	10	A	2	0	3	9.0	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	9.0	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	9.0	NaN	7969
...	...	...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	1	20	9.0	NaN	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	9.0	NaN	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	9.0	NaN	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	9.0	NaN	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	9.0	NaN	490

550068 rows × 12 columns

```
In [17]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 11 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  object
 5   City_Category       550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  int64
 7   Marital_Status      550068 non-null  int64
 8   Product_Category_1  550068 non-null  int64
 9   Product_Category_2  550068 non-null  float64
10   Purchase            550068 non-null  int64
dtypes: float64(1), int64(5), object(5)
memory usage: 46.2+ MB
```

All nan values have been replaced

we can drop user id and product id columns as it has no relation with target

```
In [18]: columns = []
for i in df.columns:
if df[i].dtypes=='object':
columns.append(i)
print('Below Columns have object datatype which needs to be converted to Int\\n\\n',columns)

Below Columns have object datatype which needs to be converted to Int

['Product_ID', 'Gender', 'Age', 'City_Category', 'Stay_In_Current_City_Years']
```

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 11 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  int64
 4   Occupation           550068 non-null  object
 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  550068 non-null  float64
10   Purchase            550068 non-null  int64
dtypes: float64(1), int64(5), object(5)
memory usage: 46.2+ MB
```

```
In [20]: df = df.drop(['Product_ID', 'User_ID'], axis=1)
```

```
In [21]: x = df.drop(['Purchase'], axis=1)
y = df[['Purchase']]
```

```
In [22]: df

df
```

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Purchase
0	F	0-17	10	A	2	0	3	9.0	8370
1	F	0-17	10	A	2	0	1	6.0	15200
2	F	0-17	10	A	2	0	12	9.0	1422
3	F	0-17	10	A	2	0	12	14.0	1057
4	M	55+	16	C	4+	0	8	9.0	7969
...	...	...	...	...	...	...	...	...	...
550063	M	51-55	13	B	1	1	20	9.0	368
550064	F	26-35	1	C	3	0	20	9.0	371
550065	F	26-35	15	B	4+	1	20	9.0	137
550066	F	55+	1	C	2	0	20	9.0	365
550067	F	46-50	0	B	4+	1	20	9.0	490

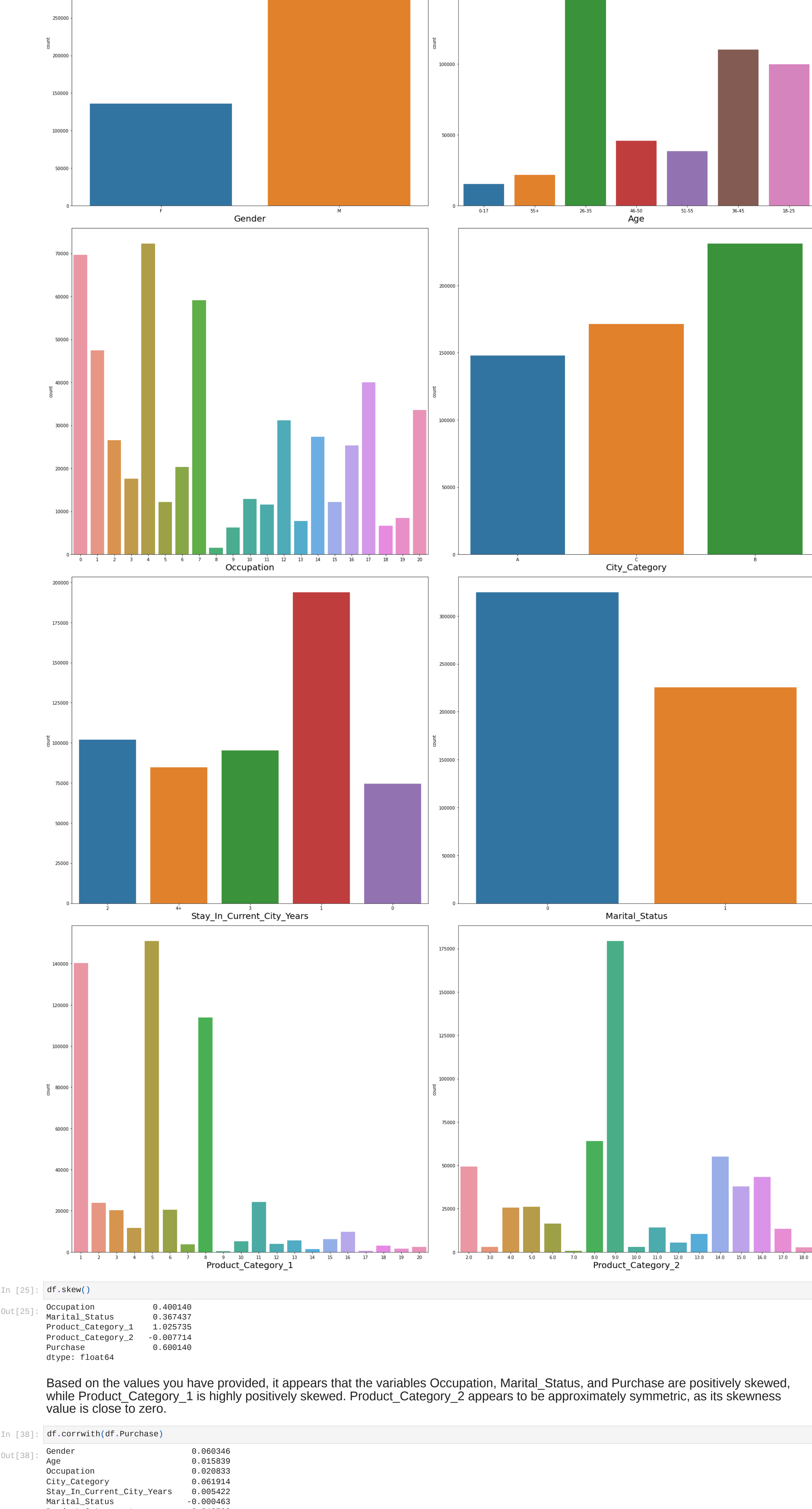
550068 rows × 9 columns

```
In [23]: plt.figure(figsize=(25,45), facecolor='white')

pltino = 1

for column in x:
if pltino <= 8:
ax = plt.subplot(4,2,pltino)
sns.countplot(x(column))
plt.xlabel(column, fontsize=20)

pltino+=1
plt.tight_layout()
```



```
In [25]: df.skew()

Marital_Status      0.367437
Product_Category_1  1.025735
Product_Category_2  -0.007714
Purchase            0.606140
dtype: float64
```

Based on the values you have provided, it appears that the variables Occupation, Marital\_Status, and Purchase are positively skewed, while Product\_Category\_1 is highly positively skewed. Product\_Category\_2 appears to be approximately symmetric, as its skewness value is close to zero.

```
In [38]: df.corrwith(df.Purchase)
```

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Purchase
Gender	0.060346	0.015309	0.028833	0.061914	0.050422	-0.000463	-0.343783	-0.166076	1.000000
Age	0.015309	0.028833	0.061914	0.050422	-0.000463	-0.343783	-0.166076	1.000000	0.060346
Occupation	0.028833	0.061914	0.050422	-0.000463	-0.343783	-0.166076	1.000000	0.015309	0.028833
City_Category	0.061914	0.050422	-0.000463	-0.343783	-0.166076	1.000000	0.015309	0.028833	0.061914
Stay_In_Current_City_Years	0.050422	-0.000463	-0.343783	-0.166076	1.000000	0.015309	0.028833	0.061914	0.050422
Marital_Status	-0.000463	-0.343783	-0.166076	1.000000	0.015309	0.028833	0.061914	0.050422	-0.000463
Product_Category_1	-0.343783	-0.166076	1.000000	0.015309	0.028833	0.061914	0.050422	-0.000463	-0.343783
Product_Category_2	-0.166076	1.000000	0.015309	0.028833	0.061914	0.050422	-0.000463	-0.343783	-0.166076
Purchase	1.000000	0.060346	0.015309	0.028833	0.061914	0.050422	-0.000463	-0.343783	1.000000
dtype	float64	float64	float64	float64	float64	float64	float64	float64	float64

Product\_Category\_1 and Product\_Category\_2

This indicates a moderate positive correlation between these two variables.

```
In [39]: for i in df.columns:
if df[i].dtypes=='object':
df[i]=enc.fit_transform(df[i].values.reshape(-1,1))
```

```
In [41]: df

df
```

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Purchase
0	0.00	0.13	0.03	1.00	0.03	0.04	0.01	0.01	0.06
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
42	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
83	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00