EXPLORATORY DATA ANALYSIS

- Number of Rows
- Number of Columns
- Shape of the data
- Numerical and Categorical Variable
- Missing Values
- Outliers(Skewed Data)
- Profiling the Data
- Statistical Analysis
- Graph Based Analysis
    1. Univariate Analysis
    2. Bivariate Analysis
    3. Multivariate Analysis

Black Friday

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data=pd.read_csv(r"blackFriday_train.csv")
```

In [3]:
```
data_copy=data
```

In [4]:
```
# I have made a Copy of the dataset so i can refer the original dataset whenever I neede
```

Profile of the data

In [5]:
```
data_copy.head()
```

Out[5]:

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

Feature Types

In [6]:
```
data_copy.dtypes
```

Out[6]:
```
User_ID                        int64
Product_ID                    object
Gender                        object
Age                           object
Occupation                     int64
City_Category                 object
Stay_In_Current_City_Years    object
Marital_Status                 int64
Product_Category_1             int64
Product_Category_2           float64
Product_Category_3           float64
Purchase                       int64
dtype: object
```

In [7]:
```
# Observation:
#      There are five features with object type,five features with int type and two featu
```

Shape of Data

In [8]:
```
data_copy.shape
```

Out[8]:
```
(550068, 12)
```

In [9]:
```
data_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     550068 non-null  int64  
 1   Product_ID                  550068 non-null  object 
 2   Gender                      550068 non-null  object 
 3   Age                         550068 non-null  object 
 4   Occupation                  550068 non-null  int64  
 5   City_Category               550068 non-null  object 
 6   Stay_In_Current_City_Years  550068 non-null  object 
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 50.4+ MB
```

Missing Values

In [10]:
```
data_copy.isnull().sum()
```

Out[10]:
```
User_ID                            0
Product_ID                         0
Gender                             0
Age                                0
Occupation                         0
City_Category                      0
Stay_In_Current_City_Years         0
Marital_Status                     0
Product_Category_1                 0
Product_Category_2            173638
Product_Category_3            383247
Purchase                           0
dtype: int64
```

In [11]:
```
# Observation:
#     There are 173638 null values in Product_Category_2 and 383247 null values in Produ
#     Which needs to be handled through Feature Engineering
```

In [12]:
```
data_col=data_copy[data_copy.dtypes[data_copy.dtypes=='object'].index]
```

In [13]:
```
data_num=data_copy[data_copy.dtypes[data_copy.dtypes!='object'].index]
```

Numerical Features

In [14]:
```
data_num.head()
```

Out[14]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purc
0	1000001	10	0	3	NaN	NaN	
1	1000001	10	0	1	6.0	14.0	
2	1000001	10	0	12	NaN	NaN	
3	1000001	10	0	12	14.0	NaN	
4	1000002	16	0	8	NaN	NaN	

Categorical Features

In [15]:
```
data_col.head()
```

Out[15]:

	Product_ID	Gender	Age	City_Category	Stay_In_Current_City_Years
0	P00069042	F	0-17	A	2
1	P00248942	F	0-17	A	2
2	P00087842	F	0-17	A	2
3	P00085442	F	0-17	A	2
4	P00285442	M	55+	C	4+

In [16]:
```
# Observation:
#     Some Features like Stay_In_Current_City_Years and Age should be preprocessed to i
#     as it belongs to int type
```

Unique Values in Stay In Current City Years

In [17]:
```
data_copy['Stay_In_Current_City_Years'].unique()
```

Out[17]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

In [18]:
```
# Observation:
#     There are five unique values in that '4+' should be handled so I can make this fea
```

In [19]:
```
data_copy['Stay_In_Current_City_Years']=data_copy['Stay_In_Current_City_Years'].str.rep
```

In [20]:
```
# Replacing all the records which has "+" with empty string
```

In [21]:
```
data_copy['Stay_In_Current_City_Years'].unique()
```

Out[21]:
```
array(['2', '4', '3', '1', '0'], dtype=object)
```

Changing the Stay_In_Current_City_Years type to int

In [22]:
```
data_copy['Stay_In_Current_City_Years']=data_copy['Stay_In_Current_City_Years'].astype(
```

In [23]:
```
data_copy['Stay_In_Current_City_Years'].dtype
```

Out[23]:
```
dtype('int32')
```

In [24]:
```
data_copy.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  int32  
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int32(1), int64(5), object(4)
memory usage: 48.3+ MB
```

Unique Records in Age Feature

In [25]:
```python
data_copy['Age'].unique()
```

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

In [26]:
```python
ls=['0-17', '26-35', '46-50', '51-55', '36-45', '18-25']
cols=['Age']
for item in ls:
    for i in cols:
        data_copy[i]=data_copy[i].str.replace(item,item[-2:])
```

In [27]:
```python
# Observation:
#       replacing all the records with last two character of the feature
```

In [28]:
```python
data_copy['Age'].unique()
```

Out[28]:
```
array(['17', '55+', '35', '50', '55', '45', '25'], dtype=object)
```

In [29]:
```python
data_copy['Age']=data_copy['Age'].str.replace("+","")
```

In [30]:
```python
# Observation:
#      replacing all the records which has '+' with empty string
```

In [31]:
```python
data_copy['Age'].unique()
```

Out[31]:
```
array(['17', '55', '35', '50', '45', '25'], dtype=object)
```

Changing Age Feature to int type

In [32]:
```python
data_copy['Age']=data_copy['Age'].astype("int")
```

In [33]:
```python
data_copy.head()
```

Out[33]:

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

In [34]:
```
data_copy.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  int32  
 4   Occupation                  550068 non-null  int64  
 5   City_Category               550068 non-null  object 
 6   Stay_In_Current_City_Years  550068 non-null  int32  
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int32(2), int64(5), object(3)
memory usage: 46.2+ MB
```

In [35]:
```
data_num=data_copy[data_copy.dtypes[data_copy.dtypes!='object'].index]
```

In [36]:
```
data_col=data_copy[data_copy.dtypes[data_copy.dtypes=='object'].index]
```

Statistical Analysis Of Numerical Features

In [37]:
```
data_num.describe().T
```

Out[37]:

	count	mean	std	min	25%	50%	75'
User_ID	550068.0	1.003029e+06	1727.591586	1000001.0	1001516.0	1003077.0	1004478.
Age	550068.0	3.812199e+01	9.979704	17.0	35.0	35.0	45.
Occupation	550068.0	8.076707e+00	6.522660	0.0	2.0	7.0	14.
Stay_In_Current_City_Years	550068.0	1.858418e+00	1.289443	0.0	1.0	2.0	3.
Marital_Status	550068.0	4.096530e-01	0.491770	0.0	0.0	0.0	1.
Product_Category_1	550068.0	5.404270e+00	3.936211	1.0	1.0	5.0	8.
Product_Category_2	376430.0	9.842329e+00	5.086590	2.0	5.0	9.0	15.
Product_Category_3	166821.0	1.266824e+01	4.125338	3.0	9.0	14.0	16.
Purchase	550068.0	9.263969e+03	5023.065394	12.0	5823.0	8047.0	12054.

In [38]:
```
# Observation:
#     It gives minimum,25,50,75,100 percentiles of the numerical records
#     Purchase feature is left skewed as minimum value and 25% varies a lot from 12.0->
#     It also have higher standard deviation so dispersion is larger
```

Statistical Analysis Of Categorical Features

In [39]:
```
data_col.describe()
```

Out[39]:

	Product_ID	Gender	City_Category
count	550068	550068	550068
unique	3631	2	3
top	P00265242	M	B
freq	1880	414259	231173

In [40]:
```
# Observation:
#     In Gender feature,The most frequent records are Male and has frequency of 414258
#     In City Category,There are three unique records where 'B' has most Frequent occur
```

Correlation of the Data

In [41]:
```
data_num.corr()
```

Out[41]:

	User_ID	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Pr
User_ID	1.000000	0.043190	-0.023971	-0.030737	0.020443	
Age	0.043190	1.000000	0.096812	-0.002128	0.312095	
Occupation	-0.023971	0.096812	1.000000	0.030005	0.024280	
Stay_In_Current_City_Years	-0.030737	-0.002128	0.030005	1.000000	-0.012819	
Marital_Status	0.020443	0.312095	0.024280	-0.012819	1.000000	
Product_Category_1	0.003825	0.059216	-0.007618	-0.004213	0.019888	
Product_Category_2	0.001529	0.055319	-0.000384	-0.001657	0.015138	
Product_Category_3	0.003419	0.057713	0.013263	0.002093	0.019473	
Purchase	0.004716	0.016670	0.020833	0.005422	-0.000463	

In [42]:
```
# Observation:
#     Purchase column is the dependent feature.User_ID and Marital_Status are less
#     Correlated with the purchase column
```

Covariance of the Data

In [43]:
```
data_num.cov()
```

Out[43]:

	User_ID	Age	Occupation	Stay_In_Current_City_Years	Marital_Statu
User_ID	2.984573e+06	744.632501	-270.113921	-68.470253	17.3676
Age	7.446325e+02	99.594494	6.301908	-0.027380	1.5316
Occupation	-2.701139e+02	6.301908	42.545100	0.252356	0.0778
Stay_In_Current_City_Years	-6.847025e+01	-0.027380	0.252356	1.662662	-0.0081
Marital_Status	1.736762e+01	1.531676	0.077882	-0.008129	0.2418
Product_Category_1	2.600801e+01	2.326150	-0.195578	-0.021384	0.0384
Product_Category_2	1.346196e+01	2.807842	-0.012700	-0.010846	0.0378
Product_Category_3	2.443929e+01	2.369118	0.354959	0.011092	0.0394
Purchase	4.092159e+04	835.660700	682.554656	35.119961	-1.1446

Memory Consumed

In [44]:
```
data_copy.memory_usage()
```

Out[44]:
```
Index                             128
User_ID                       4400544
Product_ID                    4400544
Gender                        4400544
Age                           2200272
Occupation                    4400544
City_Category                 4400544
Stay_In_Current_City_Years    2200272
Marital_Status                4400544
Product_Category_1            4400544
Product_Category_2            4400544
Product_Category_3            4400544
Purchase                      4400544
dtype: int64
```

Skewness Of the Data

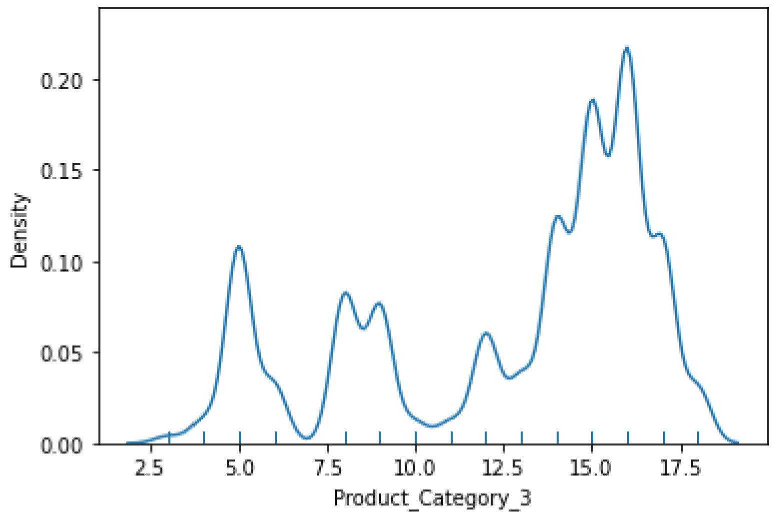
In [45]:
```
data_copy.skew()
```

Out[45]:
```
User_ID                       0.003066
Age                           0.048869
Occupation                    0.400140
Stay_In_Current_City_Years    0.317236
Marital_Status                0.367437
Product_Category_1            1.025735
Product_Category_2           -0.162758
Product_Category_3           -0.765446
Purchase                      0.600140
dtype: float64
```

In [46]:
```
# Observation:
#     It shows that the Product_Category_3 feature is left skewed distributed
#     and the purchase feature is right skewed distributed.
```

In [47]:
```
sns.distplot(data_copy['Product_Category_3'], rug=True, hist=False)
```

Out[47]: <AxesSubplot:xlabel='Product_Category_3', ylabel='Density'>



In [48]:
```
# Observation:
#     It Shows that the Product_Category_3 has left skewed distribution
#     It needs to be processed to manage the outliers
```

In [49]:
```
data_copy.head()
```

Out[49]:

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

Find out the number of Puchase made based on the Gender

In [50]:
```
data_copy.groupby("Gender").count()
```

Out[50]:

	User_ID	Product_ID	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Statu
Gender							
F	135809	135809	135809	135809	135809	135809	13580
M	414259	414259	414259	414259	414259	414259	41425

In [51]:
```
# Observation:
#     It seems that Male has purchase more items compared to Female
```

Which Gender made the highest average Purchase

In [52]:
```
data_copy.groupby("Gender").mean()['Purchase']
```

Out[52]:
```
Gender
F    8734.565765
M    9437.526040
Name: Purchase, dtype: float64
```

In [53]:
```
# Observation:
#     The Average Purchase of Male is greater than the Female purchase
```

In [54]:
```
data_copy['Marital_Status'].unique()
```

Out[54]:
```
array([0, 1], dtype=int64)
```

Display Average Purchase items based on gender with respect to their Marital Status

In [55]:
```
data_copy.groupby(["Marital_Status","Gender"]).mean()['Purchase']
```

Out[55]:
```
Marital_Status  Gender
0               F         8679.845815
                M         9453.756740
1               F         8810.249789
                M         9413.817605
Name: Purchase, dtype: float64
```

In [56]:
```
# Observation:
#     It seems that Male Gender with Unmarried status has the Maximum Average Purchase
#     and From the Female Gender Unmarried status has the maximum average purchase
```

Which City have the highest average Purchase among all

In [57]:
```
data_copy.groupby(["City_Category"]).mean()['Purchase']
```

Out[57]:
```
City_Category
A    8911.939216
B    9151.300563
C    9719.920993
Name: Purchase, dtype: float64
```

In [58]:
```
# Observation:
#     The Most Frequent Purchase are made from the City C group
```

Which City has the Highest Average Purchase Where the Order is from Male

In [59]:
```
data_copy[data_copy.Gender=='M'].groupby("City_Category").mean()['Purchase']
```

Out[59]:
```
City_Category
A    9017.834470
B    9354.854433
C    9913.567248
Name: Purchase, dtype: float64
```

In [60]:
```
# Observation:
#     It seems the City_Category C has more items ordered as a Male Candidate
```

Which City has the Highest Average Purchase Where the Order is from Female

In [61]:
```
data_copy[data_copy.Gender=='F'].groupby("City_Category").mean()['Purchase']
```

Out[61]:
```
City_Category
A    8579.708576
B    8540.677694
C    9130.107518
Name: Purchase, dtype: float64
```

In [62]:
```
# Observation:
#     It seems that the City_Category C has nore items ordered as a Female Candidate
```

Find out the Candidates Who made the Maximum Purchase Items

In [63]:
```
data_copy[data_copy['Purchase']==max(data_copy['Purchase'])]
```

Out[63]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_
87440	1001474	P00052842	M	35	4	A	2	
93016	1002272	P00052842	M	35	0	C	1	
370891	1003160	P00052842	M	35	17	C	3	

In [64]:
```
# Observation:
#     The maximum purchase items was 23961 which was made from three candidates
#     they are male having around 35 years old they are from A and C City Category
```

Find out the candidates Who made the Minimum Purchase Items

In [65]:
```
data_copy[data_copy['Purchase']==min(data_copy['Purchase'])]
```

Out[65]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_
545946	1000050	P00370293	F	35	2	A	1	
546016	1000155	P00370293	M	45	12	C	4	
546045	1000194	P00370853	F	17	10	C	3	
546046	1000195	P00370293	M	35	12	B	4	
546173	1000377	P00370293	M	35	17	B	2	
...	...	...	...	...	...	...	...	
549986	1005918	P00370853	M	35	12	A	3	
549989	1005922	P00370853	M	55	3	C	3	
550004	1005940	P00370853	M	55	12	C	1	
550024	1005973	P00370293	M	17	10	C	4	
550029	1005979	P00370853	M	35	1	B	1	

101 rows × 12 columns

In [66]:
```
# Description:
#     The Minimum Pruchase was around 12 which was made from around 101 candidates
```

In [67]:
```
data_copy.head()
```

Out[67]:

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

Find out the Average Purchase made thorugh Each City Category who has been Stayed in Current City for More than one year

In [68]:
```
data_copy[data_copy['Stay_In_Current_City_Years']>1].groupby('City_Category').mean()
```

Out[68]:

	User_ID	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Ca
City_Category						
A	1.002926e+06	36.616674	8.064456	2.935410	0.355658	
B	1.003004e+06	37.782881	8.123790	2.939852	0.408884	
C	1.003024e+06	39.247631	8.425248	2.941777	0.425033	

Find out the total Purchase items made thorugh Each City Category who has been Stayed in Current City for More than one year

In [69]:
```
data_copy[data_copy['Stay_In_Current_City_Years']>1].groupby('City_Category').sum()
```

Out[69]:

	User_ID	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Cate
City_Category						
A	74454232221	2718312	598681	217916	26403	
B	119430669886	4498921	967324	350057	48687	
C	88806777471	3474946	745963	260462	37632	

Find the maximum items sold by Product_Category_1

In [70]:
```
data_copy[data_copy["Product_Category_1"]==max(data_copy["Product_Category_1"])]['Produ
```

Out[70]: 20

Find the maximum items sold by Product_Category_1

In [71]:
```
data_copy[data_copy["Product_Category_1"]==min(data_copy["Product_Category_1"])]['Produ
```

Out[71]: 1

Find the maximum items sold by Product_Category_2

In [72]:
```
data_copy[data_copy["Product_Category_2"]==data_copy["Product_Category_2"].max()]['Produ
```

Out[72]: 18.0

Find the maximum items sold by Product_Category_2

In [73]:
```
data_copy[data_copy["Product_Category_2"]==data_copy["Product_Category_2"].min()]['Produ
```

Out[73]: 2.0

Find the maximum items sold by Product_Category_3

In [74]:
```
data_copy[data_copy["Product_Category_3"]==data_copy["Product_Category_3"].max()]['Produ
```

Out[74]: 18.0

Find the maximum items sold by Product_Category_3

In [75]:
```
data_copy[data_copy["Product_Category_3"]==data_copy["Product_Category_3"].min()]['Produ
```

Out[75]: 3.0

In [76]:
```
data_copy.head()
```

Out[76]:

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

In [77]:
```
data_num.head()
```

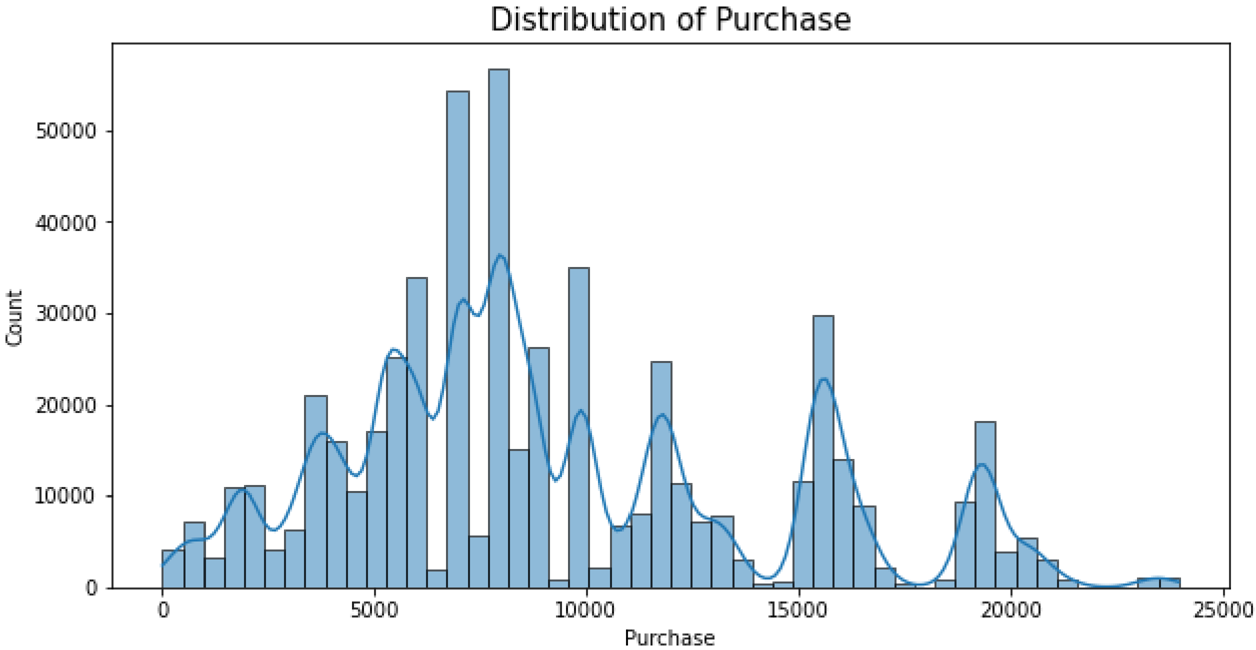
Out[77]:

	User_ID	Age	Occupation	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Cate
0	1000001	17	10	2	0	3	
1	1000001	17	10	2	0	1	
2	1000001	17	10	2	0	12	
3	1000001	17	10	2	0	12	
4	1000002	55	16	4	0	8	

Graph Analysis

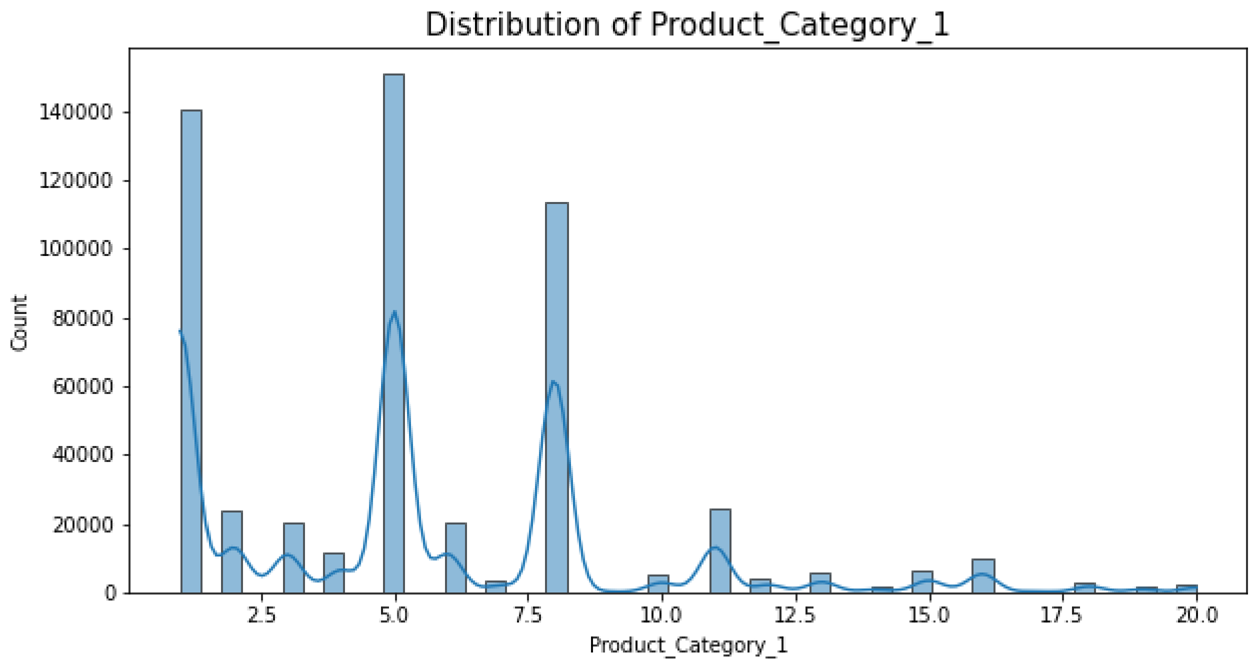
Univariate Analysis

In [78]:
```
sns.histplot(data=data_copy['Purchase'],kde=True,bins=50)
fig=plt.gcf()
fig.set_size_inches(10,5)
plt.title("Distribution of Purchase",color='black',size=15)
plt.show()
```



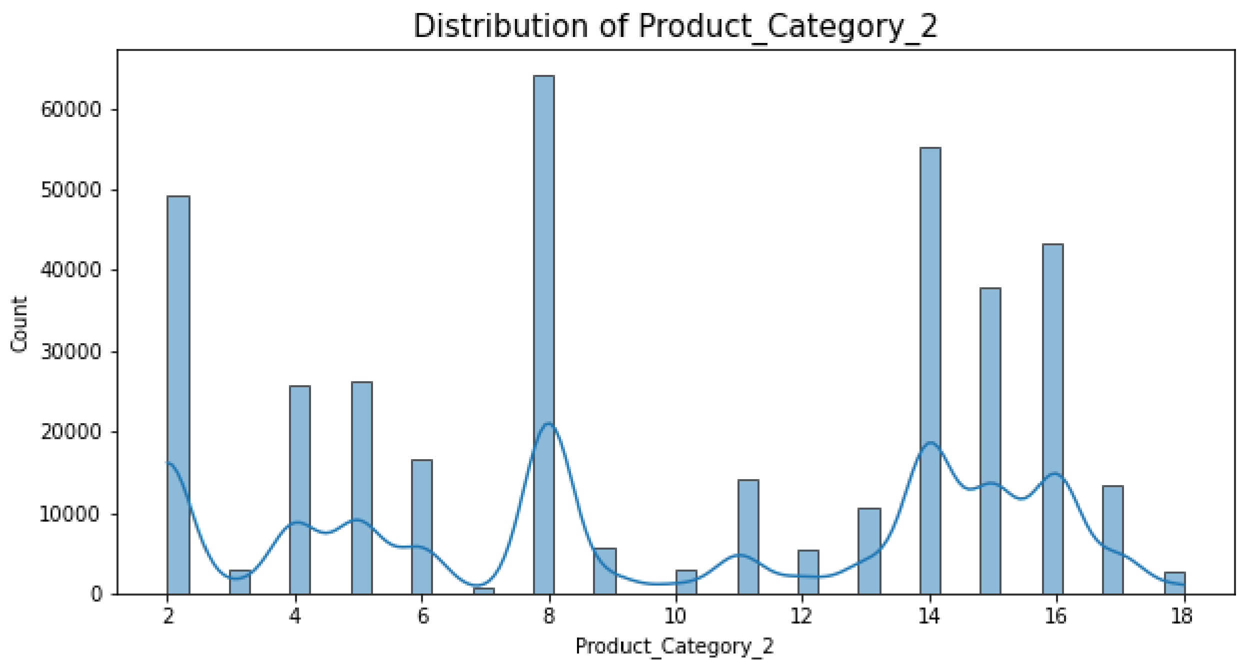
In [79]:
```
# Observation:
#     The Distribution of purchase is right skewed distribution
```

In [80]:
```
sns.histplot(data=data_copy['Product_Category_1'],kde=True,bins=50)
fig=plt.gcf()
fig.set_size_inches(10,5)
plt.title("Distribution of Product_Category_1",color='black',size=15)
plt.show()
```



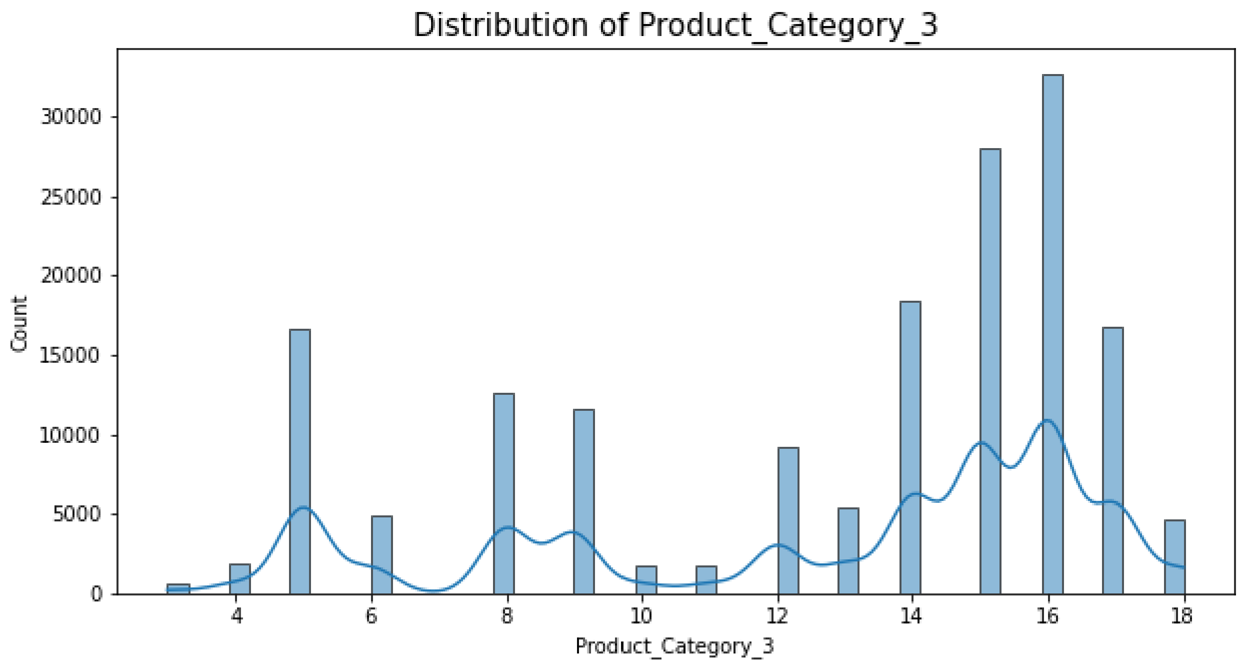
In [81]:
```
# Observation:
#     There are lot of null values and skewed data(outliers) which has to be handled
```

In [82]:
```
sns.histplot(data=data_copy['Product_Category_2'],kde=True,bins=50)
fig=plt.gcf()
fig.set_size_inches(10,5)
plt.title("Distribution of Product_Category_2",color='black',size=15)
plt.show()
```



In [83]:
```
# Observation:
#     There are lot of null values and skewed data(outliers) which has to be handled
```

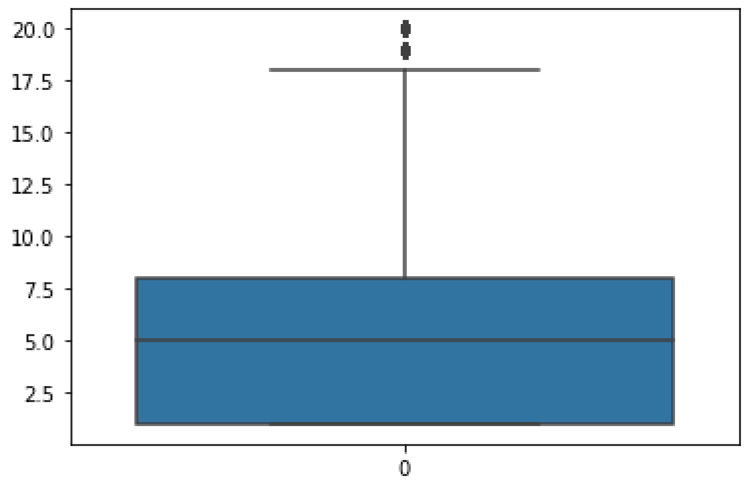
In [84]:
```
sns.histplot(data=data_copy['Product_Category_3'],kde=True,bins=50)
fig=plt.gcf()
fig.set_size_inches(10,5)
plt.title("Distribution of Product_Category_3",color='black',size=15)
plt.show()
```



In [85]:
```
# Observation:
#     There are lot of null values and skewed data(outliers) which has to be handled
#         It has left skewed distribution
```

In [86]:
```
sns.boxplot(data=data_copy['Product_Category_1'])
```

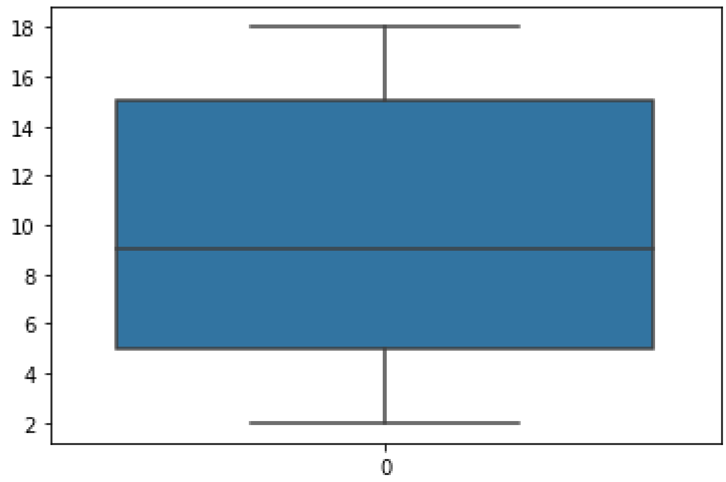
Out[86]: <AxesSubplot:>



In [87]:
```
# Observation:
#     The Product_Category_1 has right skewed data which has some outliers
#     Feature Engineering is required to handle the records
```

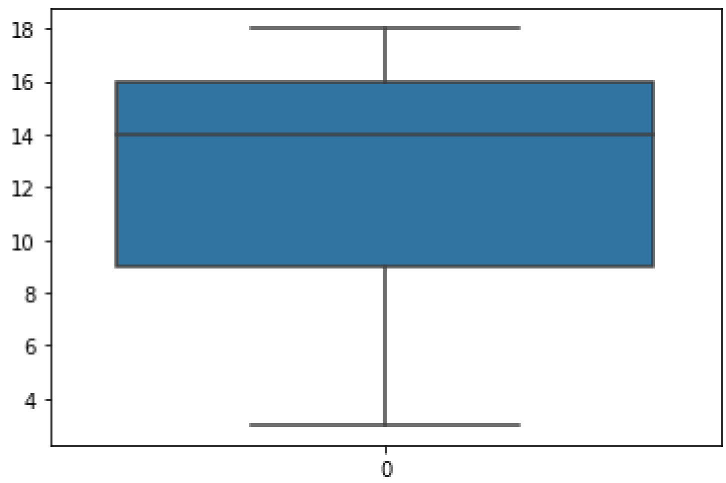
In [88]:
```
sns.boxplot(data=data_copy['Product_Category_2'])
```

Out[88]: <AxesSubplot:>



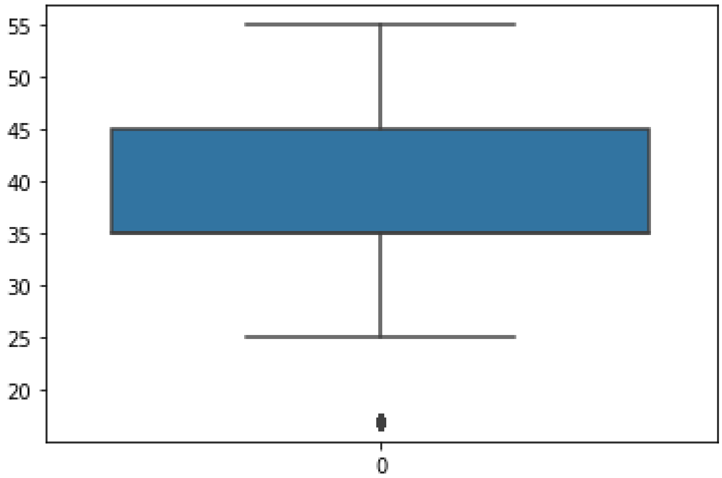
In [89]:
```
sns.boxplot(data=data_copy['Product_Category_3'])
```

Out[89]: <AxesSubplot:>



In [90]:
```
sns.boxplot(data=data_copy['Age'])
```

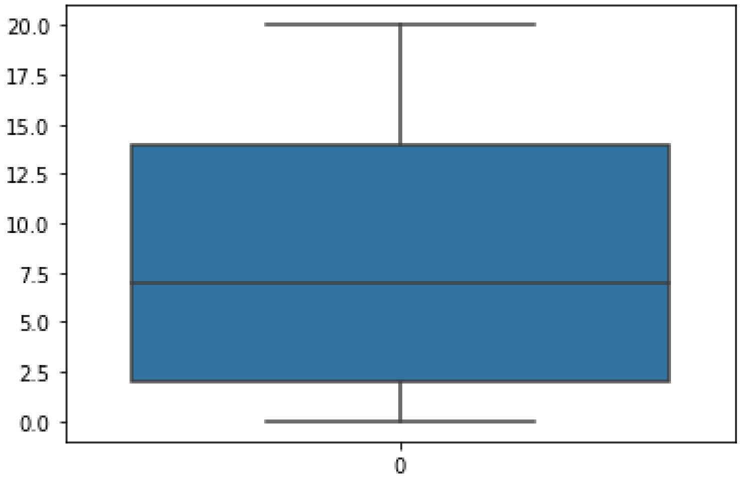
Out[90]: <AxesSubplot:>



In [91]:
```
# Observation:
#     The Age feature has outlier in the left distribution which has to be preprocessed
```

In [92]:
```
sns.boxplot(data=data_copy['Occupation'])
```

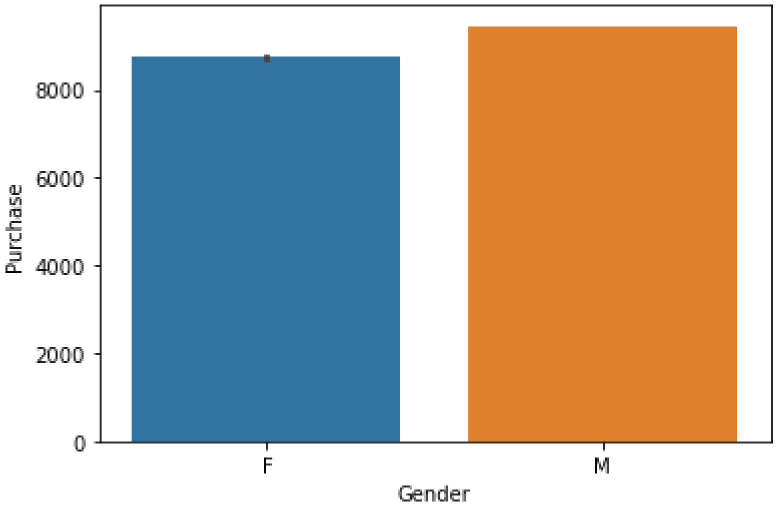
Out[92]: <AxesSubplot:>



Bivariate Analysis

In [93]:
```
sns.barplot(x='Gender',y='Purchase',data=data_copy)
```

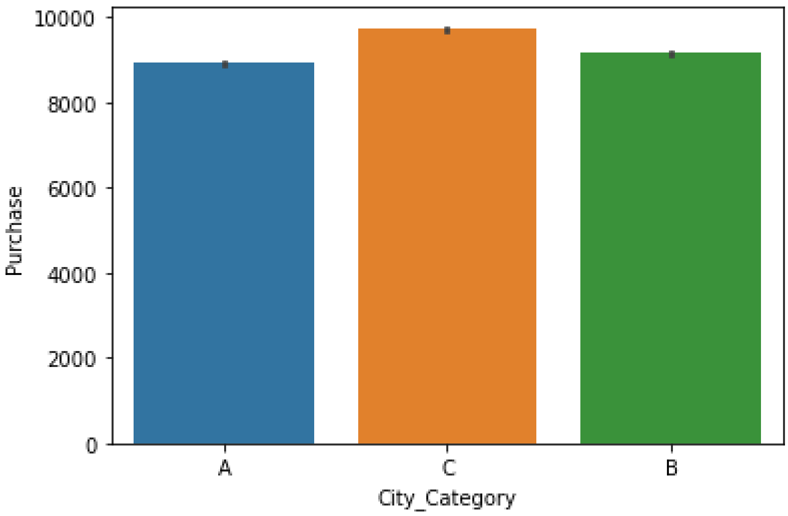
Out[93]: <AxesSubplot:xlabel='Gender', ylabel='Purchase'>



In [94]:
```
# Observation:
#     The Maximum number of purchase are made by male Candidates
```

In [95]:
```
sns.barplot(x='City_Category',y='Purchase',data=data_copy)
```

Out[95]: <AxesSubplot:xlabel='City_Category', ylabel='Purchase'>

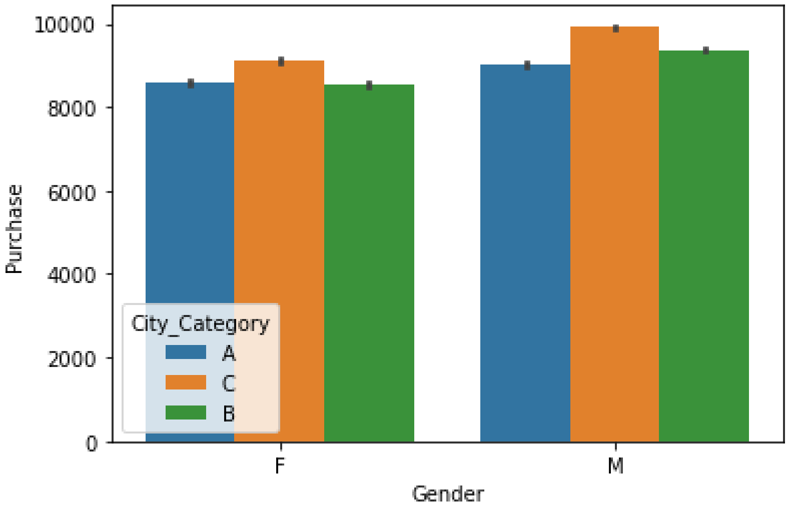


In [96]:
```
# Observation:
#     The Maximum Purchase of the items are transfered from the City Category 'C'
```

Multivariate Analvsis

In [97]:
```
sns.barplot(x='Gender',y='Purchase',hue='City_Category',data=data_copy)
```

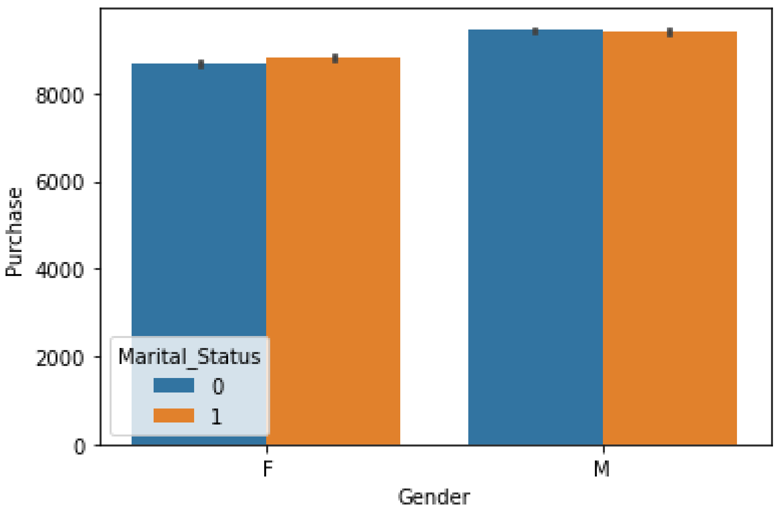
Out[97]: <AxesSubplot:xlabel='Gender', ylabel='Purchase'>



In [98]:
```
# Observation:
#     It displays the number of purchase of the items which each City Category with Gend
#     By Visvalizing the male with C category has the maximum items purchased
```

In [99]:
```
sns.barplot(x='Gender',y='Purchase',hue='Marital_Status',data=data_copy)
```

Out[99]: <AxesSubplot:xlabel='Gender', ylabel='Purchase'>

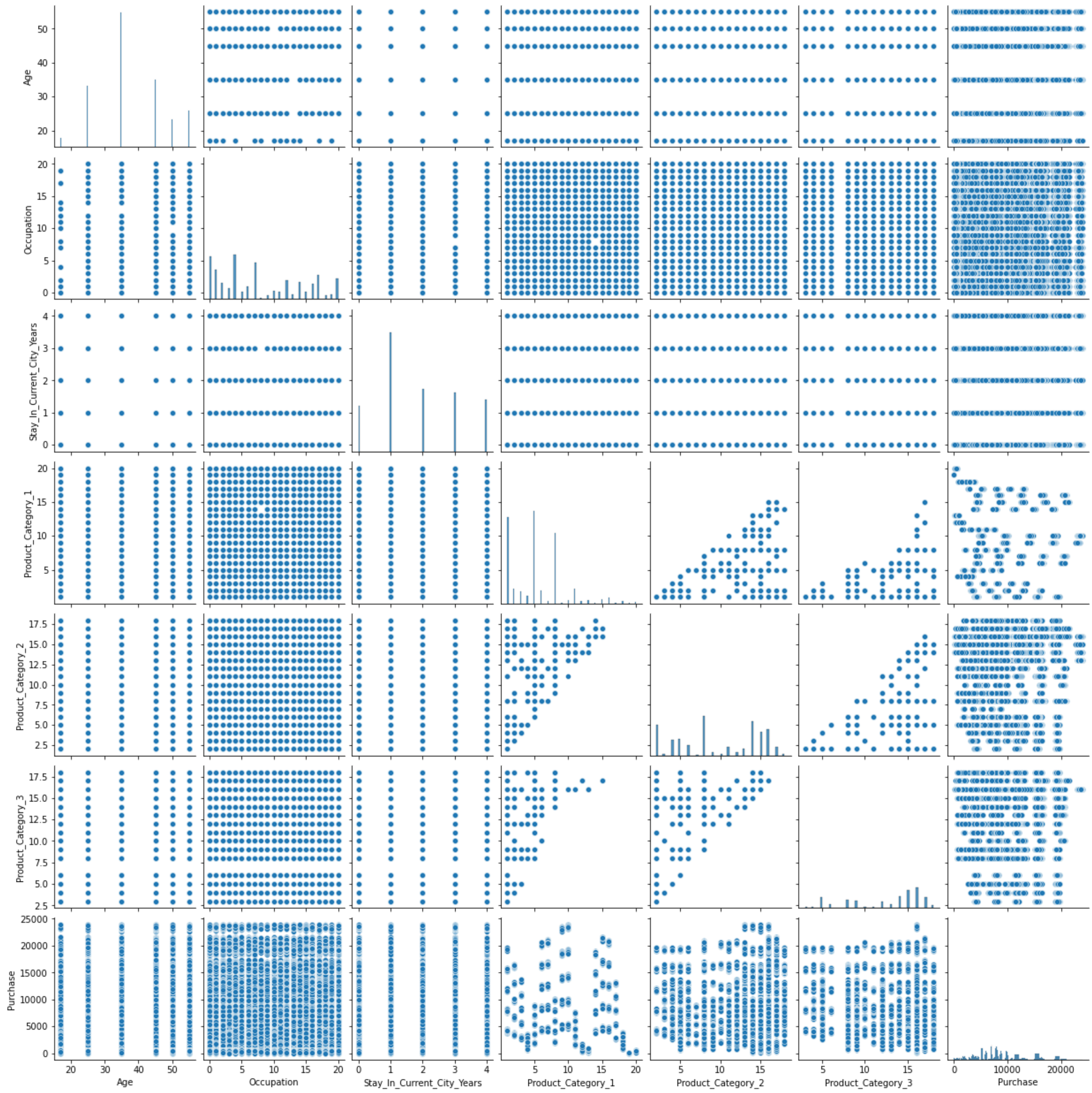


In [100]:
```
# Observation:
#     From the visvalization the Married Male has the maximum number of Pruchase
```

Distribution Between the Features

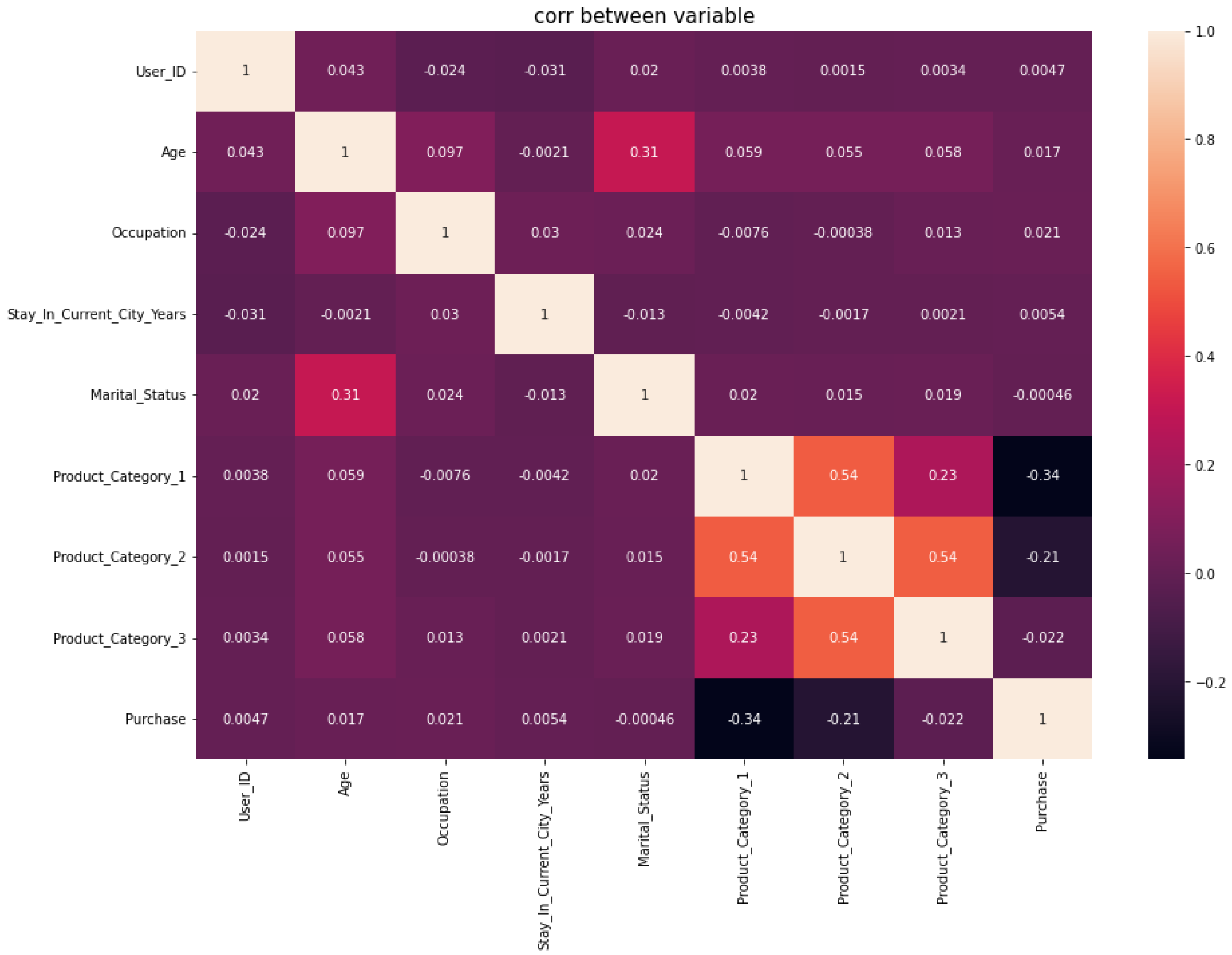
In [101]:
```
'Age','Occupation','Stay_In_Current_City_Years','Product_Category_1','Product_Category_2
```

Out[101]: <seaborn.axisgrid.PairGrid at 0x22972172ac0>



Correlation Between the Features

In [102]:
```
sns.heatmap(data_num.corr(),annot=True)
fig=plt.gcf()
fig.set_size_inches(15,10)
plt.title("corr between variable",color='black',size=15)
plt.show()
```



Distribution of the Features

In [103]:
```
sns.violinplot(data=data_num.corr(),orient="v")
fig=plt.gcf()
fig.set_size_inches(15,10)
plt.title("Distribution of the Features",color='black',size=15)
plt.show()
```