[174]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
from scipy.stats import zscore
from sklearn.model_selection import train_test_split
```

[175]:
```
df = pd.read_csv(r"C:\Users\user\Downloads\train.csv")
df # data
```

[175]:

luct_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category
069042	F	0-17	10	A	2	0	3	NaN	N
248942	F	0-17	10	A	2	0	1	6.0	1
087842	F	0-17	10	A	2	0	12	NaN	N
085442	F	0-17	10	A	2	0	12	14.0	N
285442	M	55+	16	C	4+	0	8	NaN	N
...	...	...	...	...	...	...	...	...	
372445	M	51-55	13	B	1	1	20	NaN	N
375436	F	26-35	1	C	3	0	20	NaN	N
375436	F	26-35	15	B	4+	1	20	NaN	N

[176]:
```
df = df.head(10000)
df
```

[176]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Produ
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	
...	...	...	...	...	...	...	...	...	...	...	
9995	1001530	P00151742	M	26-35	4	A	1	1	8	15.0	
9996	1001530	P00119742	M	26-35	4	A	1	1	5	8.0	
9997	1001530	P00178842	M	26-35	4	A	1	1	2	4.0	
9998	1001530	P00124842	M	26-35	4	A	1	1	11	NaN	
9999	1001530	P00343042	M	26-35	4	A	1	1	5	18.0	

10000 rows × 12 columns

[177]:
```
df.shape
```

[177]:
```
(10000, 12)
```

[178]:
```
df.size
```

[178]:
```
120000
```

[179]:
```
df.info() # information of data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   User_ID                     10000 non-null  int64  
 1   Product_ID                  10000 non-null  object 
 2   Gender                      10000 non-null  object 
 3   Age                         10000 non-null  object 
 4   Occupation                  10000 non-null  int64  
 5   City_Category               10000 non-null  object 
 6   Stay_In_Current_City_Years  10000 non-null  object 
 7   Marital_Status              10000 non-null  int64  
 8   Product_Category_1          10000 non-null  int64  
 9   Product_Category_2          6757 non-null   float64
 10  Product_Category_3          2997 non-null   float64
 11  Purchase                    10000 non-null  int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 937.6+ KB
```

[180]:
```
df.describe()
```

[180]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
count	1.000000e+04	10000.000000	10000.000000	10000.000000	6757.000000	2997.000000	10000.000000
mean	1.000791e+06	8.433700	0.405300	5.292800	9.796359	12.811144	9152.487700
std	4.402229e+02	6.660333	0.490975	3.660739	5.055550	4.057049	4881.543001
min	1.000001e+06	0.000000	0.000000	1.000000	2.000000	3.000000	186.000000
25%	1.000403e+06	3.000000	0.000000	2.000000	5.000000	9.000000	5831.750000
50%	1.000817e+06	7.000000	0.000000	5.000000	9.000000	14.000000	8021.500000
75%	1.001172e+06	15.000000	1.000000	8.000000	14.000000	16.000000	11922.250000
max	1.001530e+06	20.000000	1.000000	18.000000	18.000000	18.000000	23958.000000

[181]:
```
df.dtypes # data type of each column
```

[181]:
```
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
```

[182]:
```
df.isna().sum() # cheking null values
```

[182]:
```
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            3243
Product_Category_3            7003
Purchase                         0
dtype: int64
```

[183]:
```
df.axes
```

[183]:
```
[RangeIndex(start=0, stop=10000, step=1),
 Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
        'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
        'Product_Category_2', 'Product_Category_3', 'Purchase'],
       dtype='object')]
```

Allthe columns except Product_Category_2 , Product_Category_3 dosentnt contain null values

[184]:
```
# most of the roes in both column are empty then there is point of filling them because it will dissrupt the data trend so delete the useless col
```

[277]:

[277]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Purchase
0	1000001	446	0	0	10	0	2	0	3	8370
1	1000001	1545	0	0	10	0	2	0	1	15200
2	1000001	549	0	0	10	0	2	0	12	1422
3	1000001	530	0	0	10	0	2	0	12	1057
4	1000002	1772	1	6	16	2	4	0	8	7969
...	...	...	...	...	...	...	...	...	...	...
9995	1001530	923	1	2	4	0	1	1	8	7967
9996	1001530	733	1	2	4	0	1	1	5	8590
9997	1001530	1082	1	2	4	0	1	1	2	13147
9998	1001530	767	1	2	4	0	1	1	11	5975
9999	1001530	2102	1	2	4	0	1	1	5	8653

10000 rows × 10 columns

[186]:
```
df.isna().sum() # cheking null values
```

[186]:
```
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
Purchase                      0
dtype: int64
```

[187]:
```
df["Product_Category_1"].unique()
```

[187]:
```
array([ 3,  1, 12,  8,  5,  4,  2,  6, 14, 11, 13, 15,  7, 16, 18, 10, 17,
        9], dtype=int64)
```

[278]:
```
df.dtypes
```

[278]:
```
User_ID                       int64
Product_ID                    int32
Gender                        int64
Age                           int32
Occupation                    int64
City_Category                 int32
Stay_In_Current_City_Years    int32
Marital_Status                int64
Product_Category_1            int64
Purchase                      int64
dtype: object
```

[189]:
```
df.axes
```

[189]:
```
[RangeIndex(start=0, stop=10000, step=1),
 Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
        'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
        'Purchase'],
       dtype='object')]
```

''' numericals column are User_ID', 'Product_ID', 'Age' , 'Purchase' '''

their are only 1 numericals columns

[264]:
```
def numerical_parameter_check (col) :
    print(f"mean of {col} : {df[col].mean()}")
    print(f"mode of {col} : {df[col].mode()[0]}")
    print(f"median of {col} : {df[col].median()}")
    print(f"var of {col} : {df[col].var()}")
    print(f"std of {col} : {df[col].std()}")
    print(f"median of {col} : {df[col].median()}")
    print(f"skew of {col} : {df[col].skew()}")
    print(f"\nzscore of {col} : {zscore(df[col])}")
```

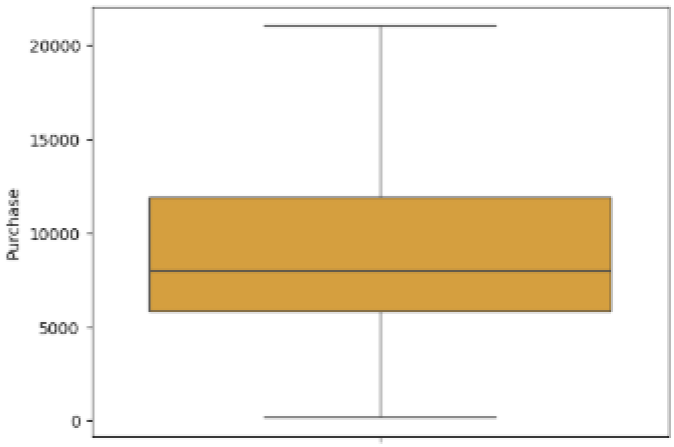
[267]:
```
numerical_parameter_check('Purchase')
```

```
mean of Purchase : 9142.3088
mode of Purchase : 21058
median of Purchase : 8021.5
var of Purchase : 23562693.54519693
std of Purchase : 4854.141895865523
median of Purchase : 8021.5
skew of Purchase : 0.6218016348244392

zscore of Purchase : 0      -0.159111
1       1.248005
2      -1.590538
3      -1.665735
4      -0.241725
          ...
9995   -0.242137
9996   -0.113787
9997    0.825046
9998   -0.652529
9999   -0.100807
Name: Purchase, Length: 10000, dtype: float64
```

[192]:
```
def graph_numerical(col):
    print(f"{col} : Outliers Checking")
    sns.boxplot(df[col], color = "orange")
    plt.show()

    q1 = df[col].quantile(0.25)
    q3 = df[col].quantile(0.75)

    iqr  = q3 - q1

    LowerTail = q1 - 1.5 * iqr
    UpperTail = q3 + 1.5 * iqr

    print(f"IQR = {iqr}")
    print(f"Lower Tail = {LowerTail}")
    print(f"Upper Tail = {UpperTail}")
```

•[268]:
```
graph_numerical('Purchase')
```

```
Purchase : Outliers Checking
```



```
IQR = 6090.5
Lower Tail = -3304.0
Upper Tail = 21058.0
```

we have to handle otlier from purchase

[194]:
```
# here we see that bmi contain outlier now we have to handle them
def outlier_handling (col) :
    q1 = df[col].quantile(0.25)
    q3 = df[col].quantile(0.75)

    iqr  = q3 - q1

    LowerTail = q1 - 1.5 * iqr
    UpperTail = q3 + 1.5 * iqr

    print(f"IQR = {iqr}")
    print(f"Lower Tail = {LowerTail}")
    print(f"Upper Tail = {UpperTail}")
    print("-"*80)


    Outliers = df[(df[col] < LowerTail) | (df[col] > UpperTail)]
    print(f"\nOutliers of {col}")

    df.loc[(df[col] < LowerTail), col] = LowerTail
    df.loc[(df[col] > UpperTail), col] = UpperTail
```

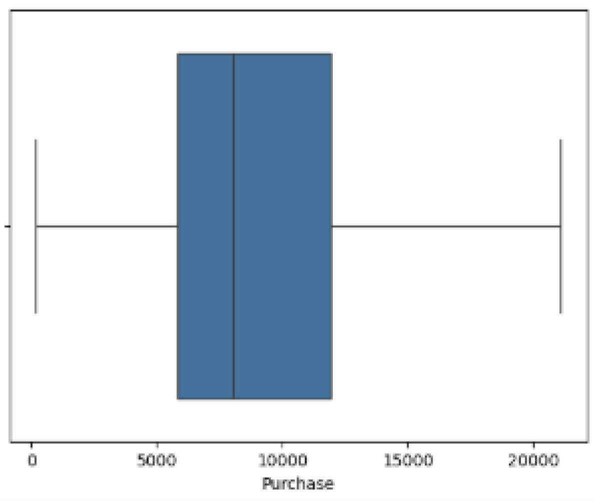
[195]:
```
outlier_handling('Purchase')
```

```
IQR = 6090.5
Lower Tail = -3304.0
Upper Tail = 21058.0
--------------------------------------------------------------------------------

Outliers of Purchase
```

```
[195]: outlier_handling('Purchase')

IQR = 6090.5
Lower Tail = -3304.0
Upper Tail = 21058.0
--------------------------------------------------------------------------------

Outliers of Purchase
```

```
[196]: sns.boxplot( df , x = 'Purchase') #@ outlier are deleted now
```

```
[196]: <Axes: xlabel='Purchase'>
```

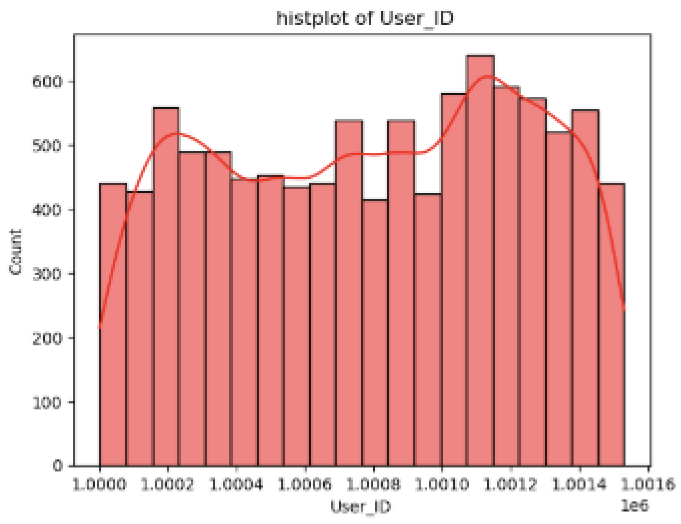


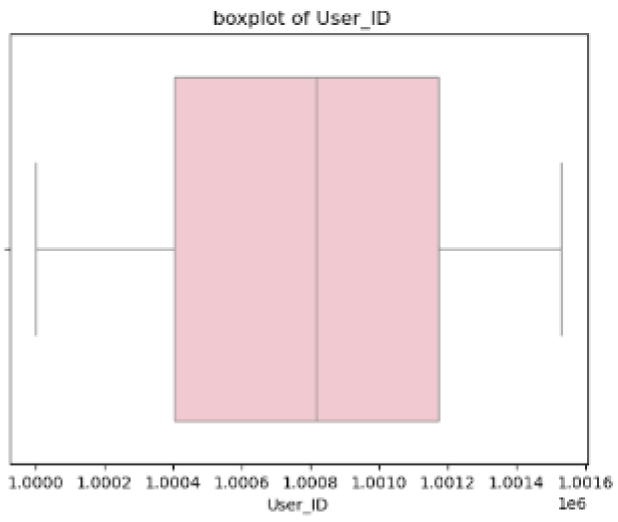
Univariant Analysis

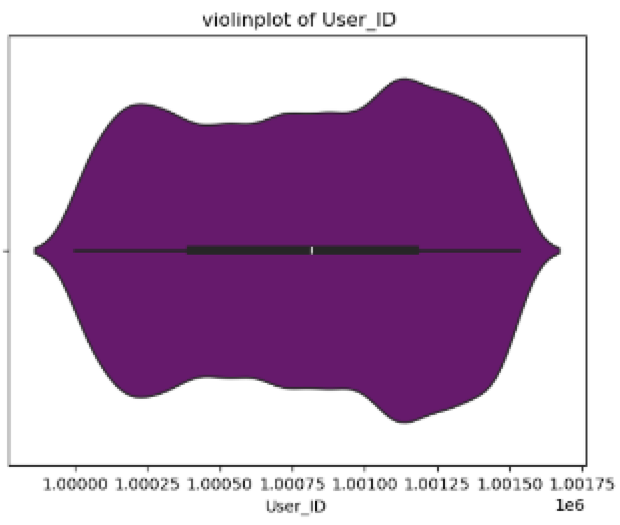
```
[259]: def Univarinat_plot(col): # here we done univariant analysis by plotting histplot , boxplot , violinplot , kdeplot
    sns.histplot(df[col], bins=20, kde=True, color = "red")
    plt.title(f" histplot of {col}")
    plt.show()
    sns.boxplot(x=df[col], color = "pink")
    plt.title(f" boxplot of {col}")
    plt.show()
    sns.violinplot(x=df[col],color = "purple")
    plt.title(f" violinplot of {col}")
    plt.show()

    sns.kdeplot( data = df , x = df[col], fill=True, color="black")
    plt.title(f" kdeplot of {col}")
    plt.show()
```

```
[260]: column = ('User_ID', 'Purchase')
for col in column :
    print(col)
    Univarinat_plot(col)
    print("#"*149)
```

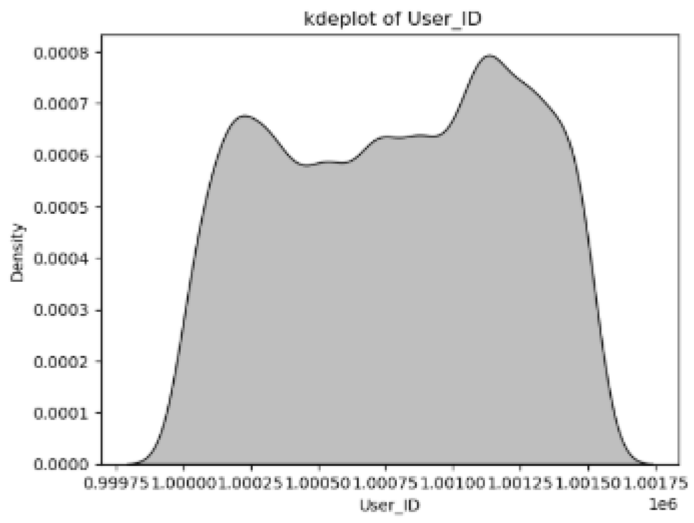
```
User_ID
```





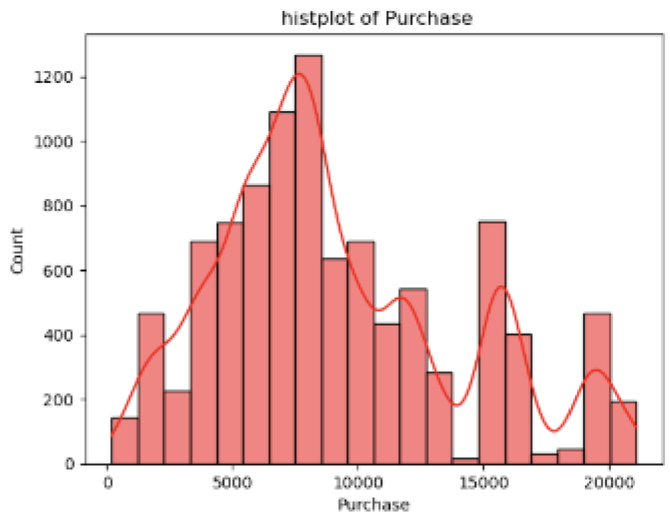


violinplot of User_ID
1.00000
1.00025
1.00050
1.00075
1.00100
1.00125
1.00150
1.00175
User_ID
1e6

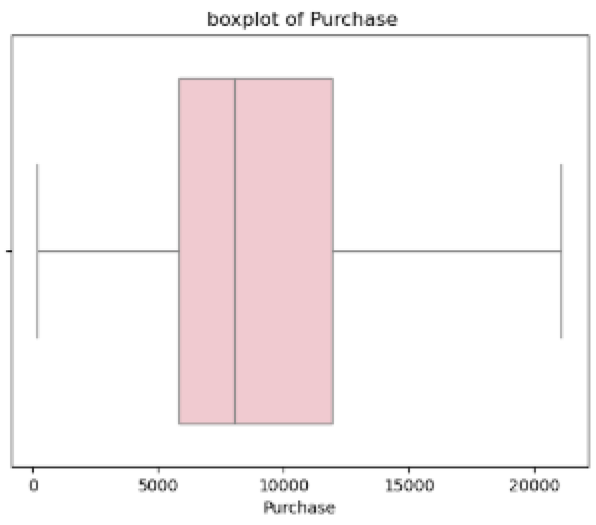


kdeplot of User_ID
Density
0.0008
0.0007
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
0.99975
1.00000
1.00025
1.00050
1.00075
1.00100
1.00125
1.00150
1.00175
User_ID
1e6

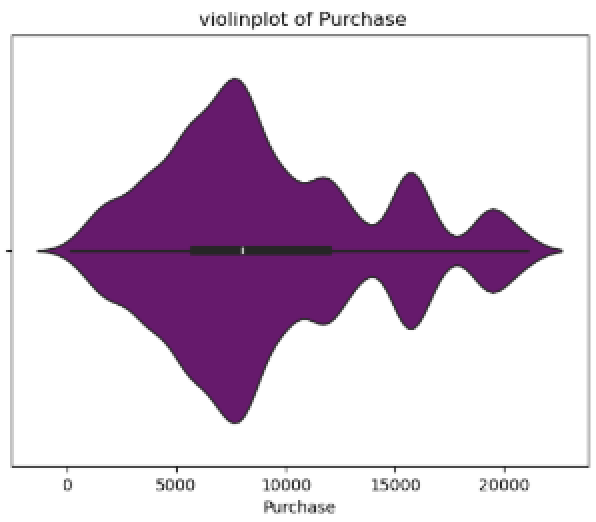
```
#################################################################################################################################################
#############
Purchase
```



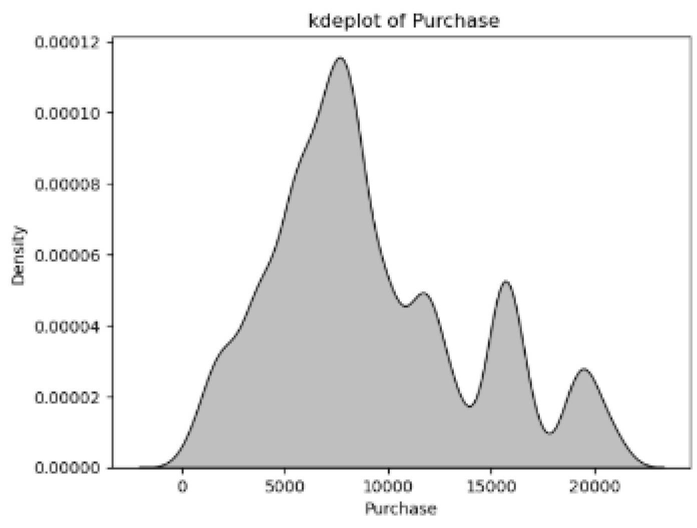
histplot of Purchase
Count
1200
1000
800
600
400
200
0
0
5000
10000
15000
20000
Purchase



boxplot of Purchase
0
5000
10000
15000
20000
Purchase



violinplot of Purchase
0
5000
10000
15000
20000
Purchase



```
##############################################################################################################################
############
```

categorical columns

```
[199]: # categorical column  'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category','Stay_In_Current_City_Years', 'Marital_Status', 'Product_Catego
```

```
[200]: # Product_ID column
```

```
[201]: df['Product_ID'].unique()
```

```
[201]: array(['P00069042', 'P00248942', 'P00087842', ..., 'P00163542',
              'P00182842', 'P00293542'], dtype=object)
```

```
[202]: df['Product_ID'].nunique()
```

```
[202]: 2303
```

```
[203]: df['Product_ID'].value_counts()
```

```
[203]: Product_ID
       P00025442    35
       P00112142    34
       P00110742    31
       P00265242    31
       P00110942    30
                    ..
       P00333842     1
       P00249342     1
       P00354542     1
       P00122342     1
       P00293542     1
       Name: count, Length: 2303, dtype: int64
```

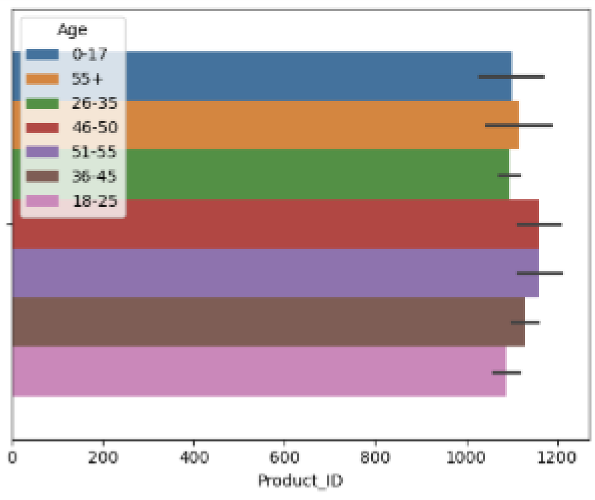
```
[204]: # converting the categorical column to numerical

       le = LabelEncoder()


       df['Product_ID'] = le.fit_transform(df['Product_ID'])
```

```
[205]: df['Product_ID'].unique()
```

```
[205]: array([ 446, 1545,  549, ...,  994, 1115, 1818])
```

1.products purchase according to age groups

```
[206]: sns.barplot(data=df, x="Product_ID", hue="Age")
       plt.show()
```



```
[207]: # Gender column
```

```
[208]: df['Gender'].unique()
```

```
[208]: array(['F', 'M'], dtype=object)
```

```
[209]: df['Gender'].nunique()
```

```
[209]: 2
```

```
[210]: df['Gender'].value_counts()
```

```
[210]: Gender
       M    7636
       F    2364
       Name: count, dtype: int64
```

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

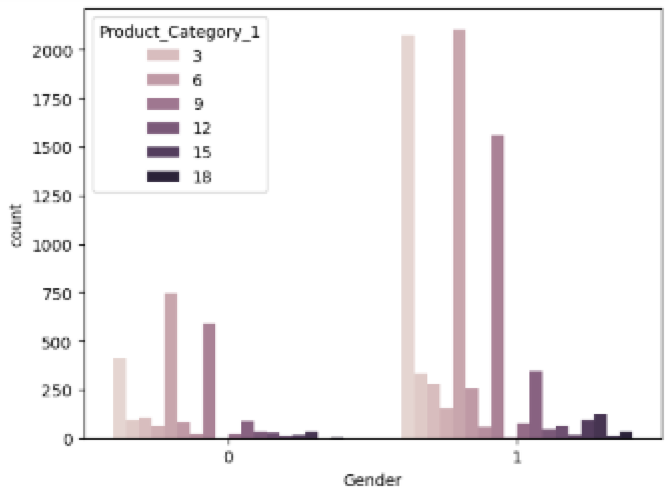
```
C:\Users\user\AppData\Local\Temp\ipykernel_7212\2748739240.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be remo
d in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `po
et_option('future.no_silent_downcasting', True)`
  df['Gender'] = df['Gender'].replace({"M":1 , "F":0} )
```

```
[212]: df['Gender'].value_counts()
```

```
[212]: Gender
       1    7636
       0    2364
       Name: count, dtype: int64
```

Genderwise Count of buying product_category_1 product according to gender

```
[257]: sns.countplot( df , x = 'Gender' , hue = 'Product_Category_1')
       plt.show()
```



```
[214]: # Age column
```

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

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

```
[216]: df['Age'].nunique()
```

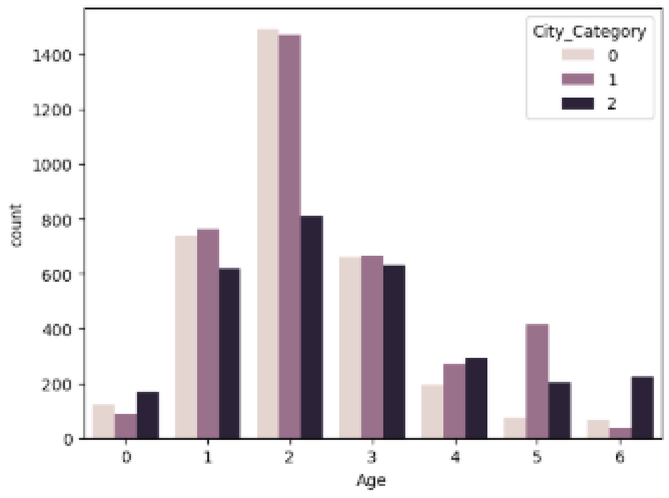
```
[216]: 7
```

```
[217]: df['Age'].value_counts()
```

```
[217]: Age
       26-35    3776
       18-25    2118
       36-45    1961
       46-50     752
       51-55     690
       0-17      378
       55+       325
       Name: count, dtype: int64
```

Age group purchase according to city_category

```
[258]: sns.countplot( df , x = 'Age' , hue = "City_Category"  )
       plt.show()
```

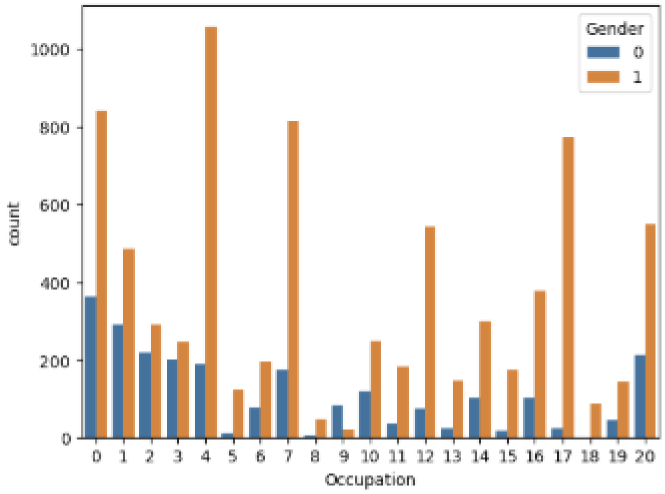


```
[219]: # converting the categorical column to numerical

       le = LabelEncoder()

       df['Age'] = le.fit_transform(df['Age'])
```

```
[220]: # 'Occupation'

[221]: df['Occupation'].unique()

[221]: array([10, 16, 15,  7, 20,  9,  1, 12, 17,  0,  3,  4, 11,  8, 19,  2, 18,
               5, 14, 13,  6], dtype=int64)

[222]: df['Occupation'].nunique()

[222]: 21

[223]: df['Occupation'].value_counts()

       1      777
       20     764
       12     618
       2      510
       16     480
       3      447
       14     399
       10     370
       6      271
       11     216
       15     192
       19     187
       13     167
       5      131
       9      104
       18      85
       8       51
       Name: count, dtype: int64
```

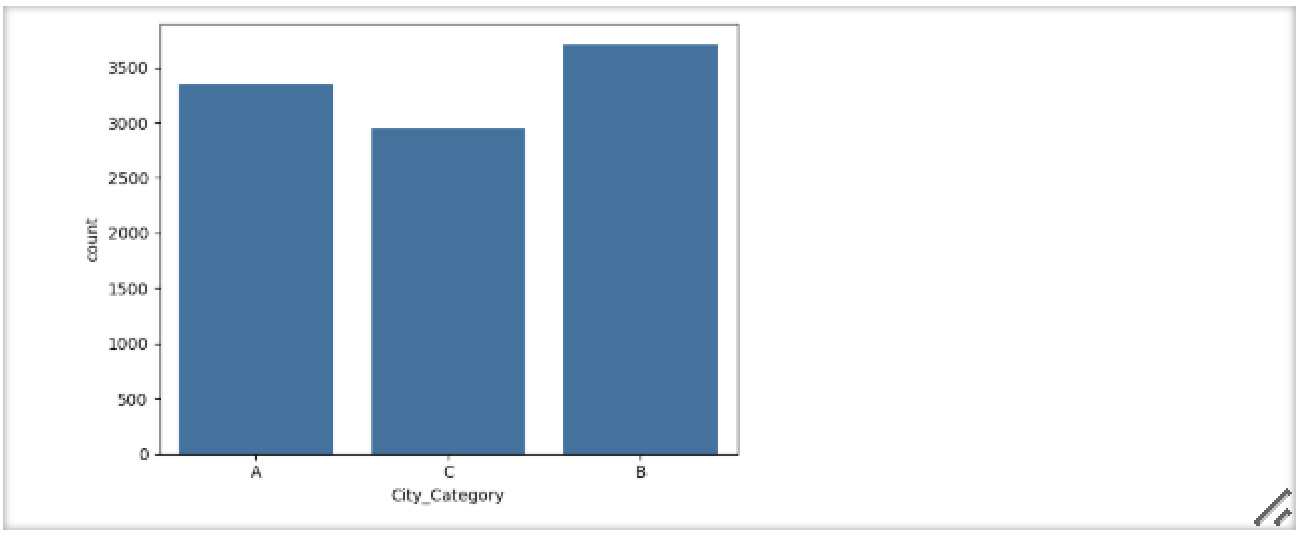
Genderwise occupation of buyers

```
[224]: sns.countplot( df , x = 'Occupation' , hue = "Gender"  )

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



```
[225]: # City_Category column

[226]: df.columns

[226]: Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
              'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
              'Purchase'],
             dtype='object')

[227]: df["City_Category"].unique()

[227]: array(['A', 'C', 'B'], dtype=object)

[228]: df["City_Category"].nunique()

[228]: 3

[229]: df["City_Category"].value_counts()

[229]: City_Category
       B    3711
       A    3346
       C    2943
       Name: count, dtype: int64

[230]: sns.countplot(df  , x = "City_Category")
       plt.show()
```

[230]:
```
sns.countplot(df  , x = "City_Category")
plt.show()
```



[231]:
```
# converting the categorical column to numerical

le = LabelEncoder()

df['City_Category'] = le.fit_transform(df['City_Category'])
```

[232]:
```
#  column Stay_In_Current_City_Years
```

[233]:
```
df["Stay_In_Current_City_Years"].unique()
```

[233]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

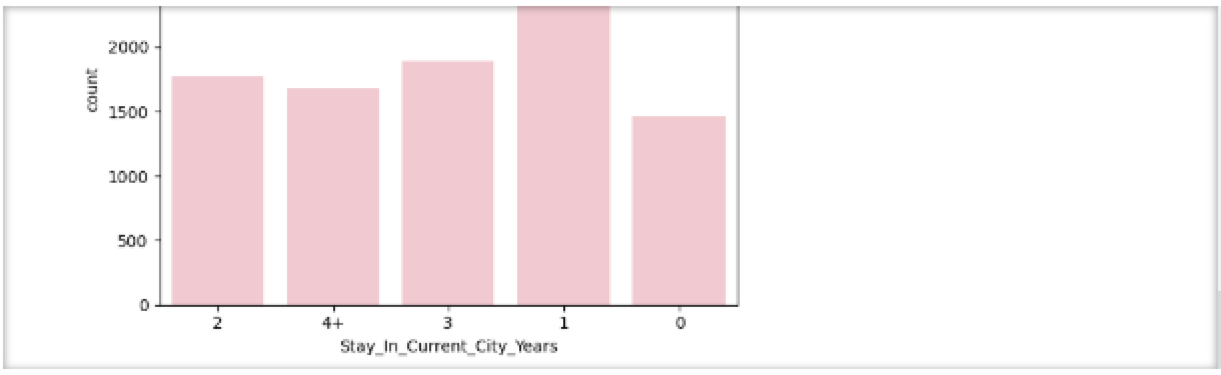
[234]:
```
df["Stay_In_Current_City_Years"].nunique()
```

[234]:
```
5
```

[235]:
```
df["Stay_In_Current_City_Years"].value_counts()
```

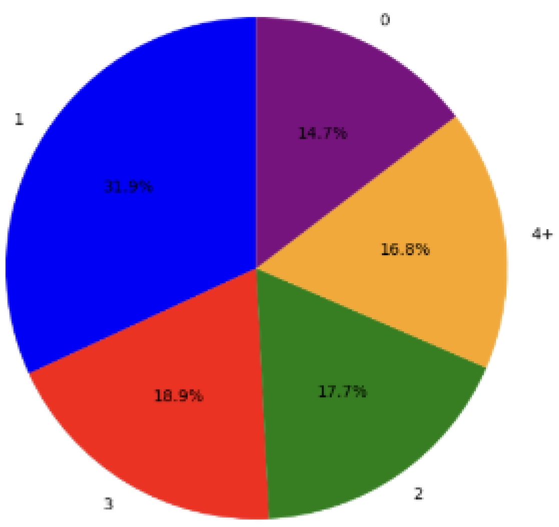
[235]:
```
Stay_In_Current_City_Years
1     3198
3     1891
2     1770
4+    1684
0     1465
Name: count, dtype: int64
```

[236]:
```
sns.countplot(df  , x = "Stay_In_Current_City_Years" ,  color = "pink")
plt.show()
```



Division of buyers with Stay_In_Current_City_Years

[237]:
```
stay_counts = df["Stay_In_Current_City_Years"].value_counts()
plt.figure(figsize=(7, 7))
plt.pie(stay_counts, labels=stay_counts.index, autopct="%1.1f%%", startangle=90, colors=['blue', 'red', 'green', 'orange', 'purple'])
plt.show()
```



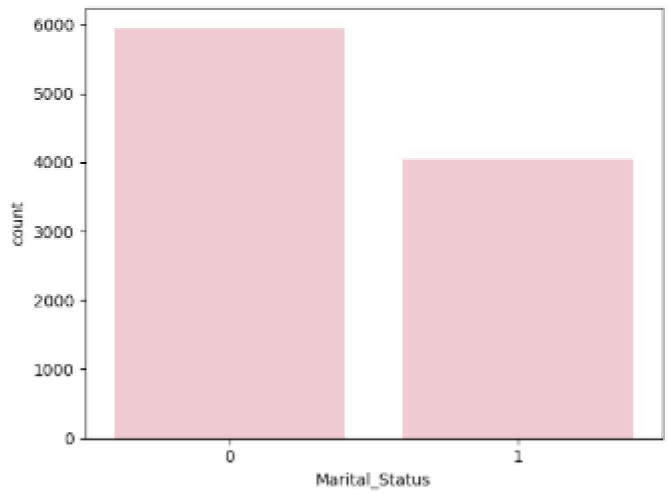
[238]:
```
# converting the categorical column to numerical

le = LabelEncoder()


df['Stay_In_Current_City_Years'] = le.fit_transform(df['Stay_In_Current_City_Years'])
```

[239]:
```
# Marital_Status column
```

[240]:
```
df["Marital_Status"].unique()
```

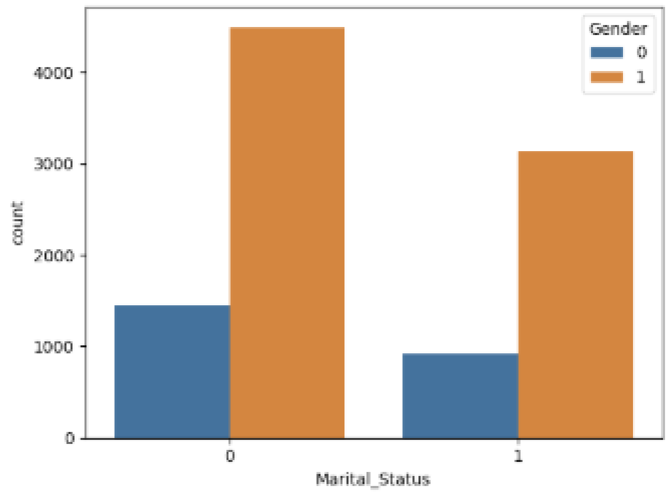
[240]:
```
array([0, 1], dtype=int64)
```

```
[241]: df["Marital_Status"].nunique()

[241]: 2

[242]: df["Marital_Status"].value_counts()

[242]: Marital_Status
       0    5947
       1    4053
       Name: count, dtype: int64

[243]: sns.countplot(df  , x = "Marital_Status" ,  color = "pink")
       plt.show()
```

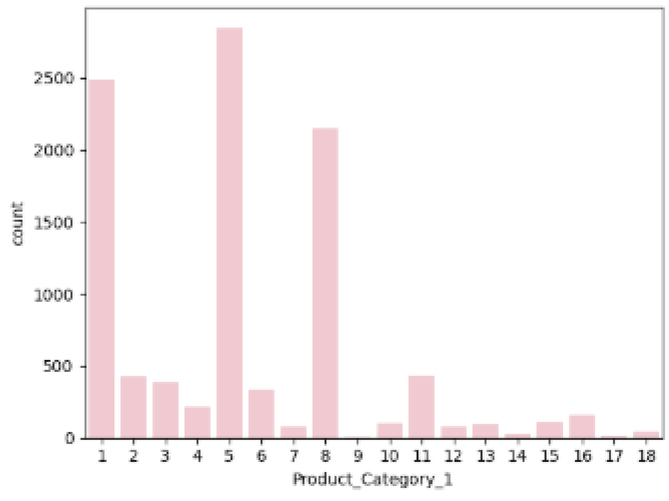


Maritial status of buyers gender wise

```
[244]: sns.countplot(df  , x = "Marital_Status"  , hue = "Gender")
       plt.show()
```

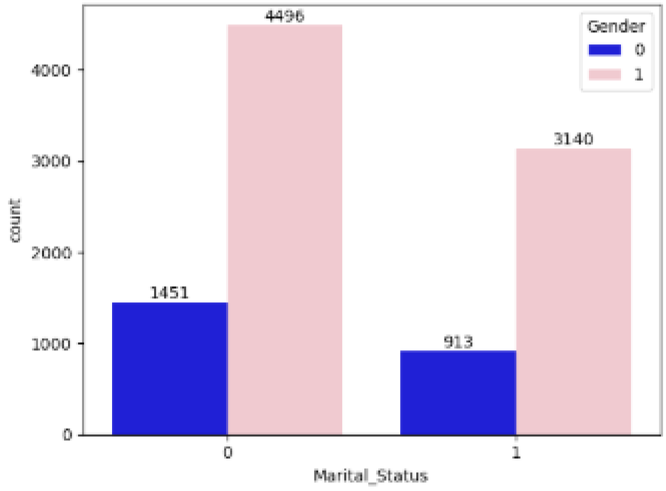


```
[245]: # Product_Category_1 column

[246]: df["Product_Category_1"].unique()

[246]: array([ 3,  1, 12,  8,  5,  4,  2,  6, 14, 11, 13, 15,  7, 16, 18, 10, 17,
                9], dtype=int64)

[247]: df["Product_Category_1"].nunique()

[247]: 18

[248]: df["Product_Category_1"].value_counts()

[248]: Product_Category_1
       5     2851
       1     2489
       8     2149
       11     438
       2     426
       3     389
       6     340
       4     217
       16    158
       15    110
       10     98
       13     90
       12     80
       7      76
       18     43
       14     27
       17     13
       9       6
       Name: count, dtype: int64

[249]: sns.countplot(df  , x = "Product_Category_1" ,  color = "pink")
       plt.show()
```



Product_Category_1 wise buyers according to gender

[250]:
```python
a = sns.countplot(data=df, x="Marital_Status", hue="Gender", palette=["blue", "pink"])
for bar in a.containers:
    ax.bar_label(bar)
```



[253]:
```python
df.corr()
```

[253]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1
User_ID	1.000000	0.009598	-0.005759	-0.018767	0.011987	-0.062634	0.014731	0.019161	0.020092
Product_ID	0.009598	1.000000	0.021914	0.031332	0.008506	0.015248	-0.001963	0.010395	0.020830
Gender	-0.005759	0.021914	1.000000	-0.004614	0.132995	-0.014939	0.091974	0.021635	-0.054706
Age	-0.018767	0.031332	-0.004614	1.000000	0.116024	0.126883	0.025146	0.335784	0.069731
Occupation	0.011987	0.008506	0.132995	0.116024	1.000000	0.042955	0.094785	-0.020515	-0.002038
City_Category	-0.062634	0.015248	-0.014939	0.126883	0.042955	1.000000	0.035716	0.022975	-0.041322
Stay_In_Current_City_Years	0.014731	-0.001963	0.091974	0.025146	0.094785	0.035716	1.000000	0.043902	-0.000389
Marital_Status	0.019161	0.010395	0.021635	0.335784	-0.020515	0.022975	0.043902	1.000000	0.013426
Product_Category_1	0.020092	0.020830	-0.054706	0.069731	-0.002038	-0.041322	-0.000389	0.013426	1.000000
Purchase	-0.039901	-0.089751	0.068921	0.004549	0.003229	0.086723	0.011884	-0.000242	-0.323908

[254]:
```python
df.cov()
```

[254]:

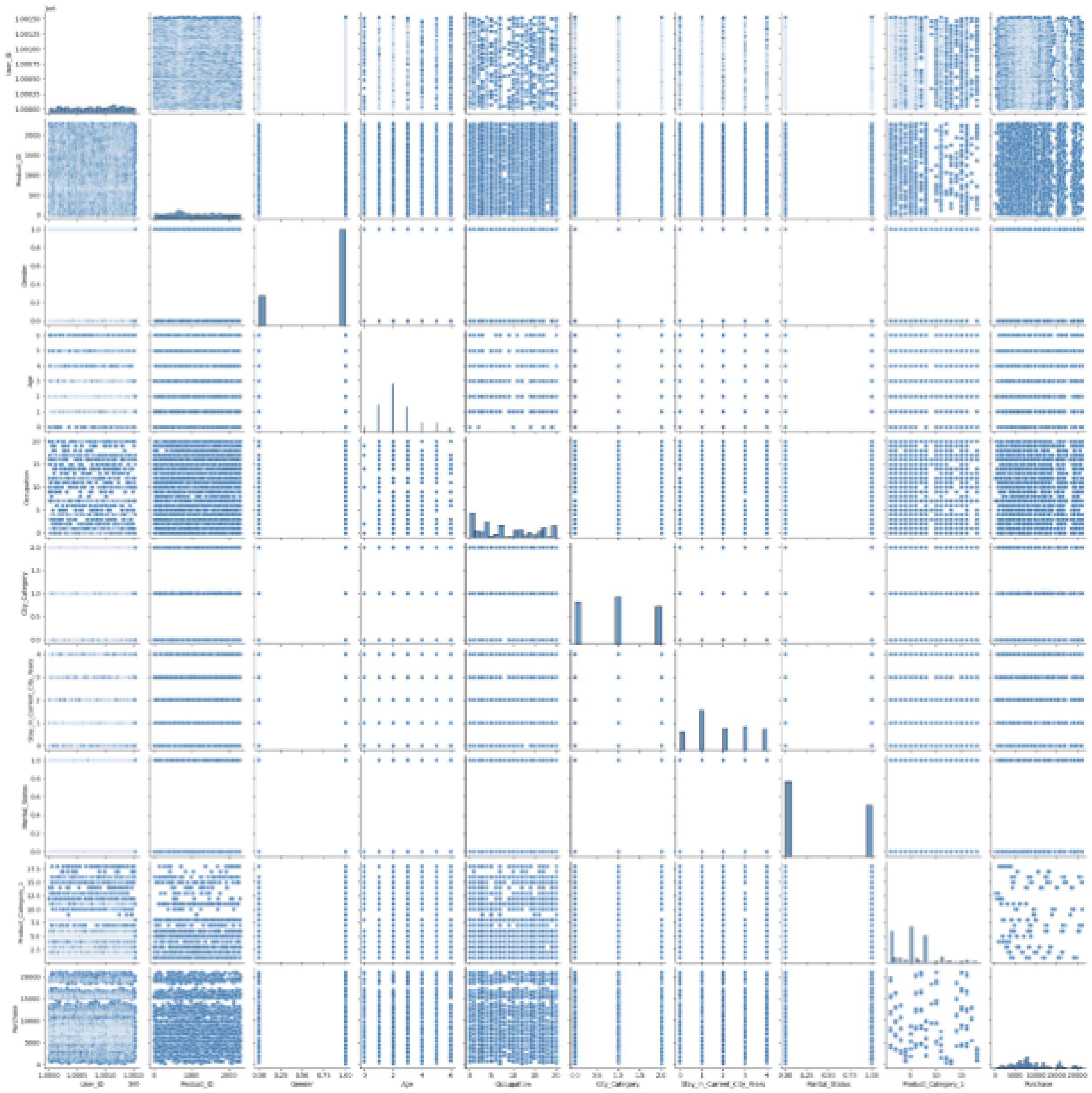
	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_
User_ID	193796.197147	2746.957379	-1.077167	-11.219168	35.147189	-21.838889	8.604191	4.141497	
Product_ID	2746.957379	422677.838167	6.053352	27.662969	36.831092	7.851575	-1.693324	3.318034	
Gender	-1.077167	6.053352	0.180533	-0.002662	0.376364	-0.005027	0.051851	0.004513	
Age	-11.219168	27.662969	-0.002662	1.844189	1.049416	0.136476	0.045309	0.223883	
Occupation	35.147189	36.831092	0.376364	1.049416	44.360040	0.226601	0.837625	-0.067085	
City_Category	-21.838889	7.851575	-0.005027	0.136476	0.226601	0.627339	0.037534	0.008934	
Stay_In_Current_City_Years	8.604191	-1.693324	0.051851	0.045309	0.837625	0.037534	1.760463	0.028599	
Marital_Status	4.141497	3.318034	0.004513	0.223883	-0.067085	0.008934	0.028599	0.241056	
Product_Category_1	32.379027	49.574520	-0.085091	0.346657	-0.049692	-0.119812	-0.001890	0.024131	
Purchase	-85264.241699	-283240.368402	142.149415	29.987183	104.405114	333.426087	76.540642	-0.576914	-5

Multivarient Analysis

Multivarient Analysis

[255]:
```
print(sns.pairplot(data = df))
```

```
<seaborn.axisgrid.PairGrid object at 0x000002D3FB2F2120>
```



*[256]:
```
X = df.drop(columns=["Purchase"])
Y = df['Purchase']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state = 10)

print("Training Data Shape (X_train):", X_train.shape)
print("Testing Data Shape (X_test):", X_test.shape)
print("Training Labels Shape (Y_train):", Y_train.shape)
print("Testing Labels Shape (Y_test):", Y_test.shape)
```

```
Training Data Shape (X_train): (8000, 9)
Testing Data Shape (X_test): (2000, 9)
Training Labels Shape (Y_train): (8000,)
Testing Labels Shape (Y_test): (2000,)
```