In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df=pd.read_csv('C:/Users/ADMIN/FIREBLAZE/FIREBLAZE ML/Black Friday Sales.csv')
df.head()
```

Out[2]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Catego
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	
3	1000001	P00085442	F	0-17	10	A	2	0	12	
4	1000002	P00285442	M	55+	16	C	4+	0	8	

In [3]:
```
df.shape
```

Out[3]: (550068, 12)

In [4]:
```
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  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
```

In [5]:
```
df.describe()
```

Out[5]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	376430.000000	166821.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9.842329	12.668243	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5.086590	4.125338	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	2.000000	3.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5.000000	9.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	9.000000	14.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	15.000000	16.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	18.000000	18.000000	23961.000000

Checking Distribution

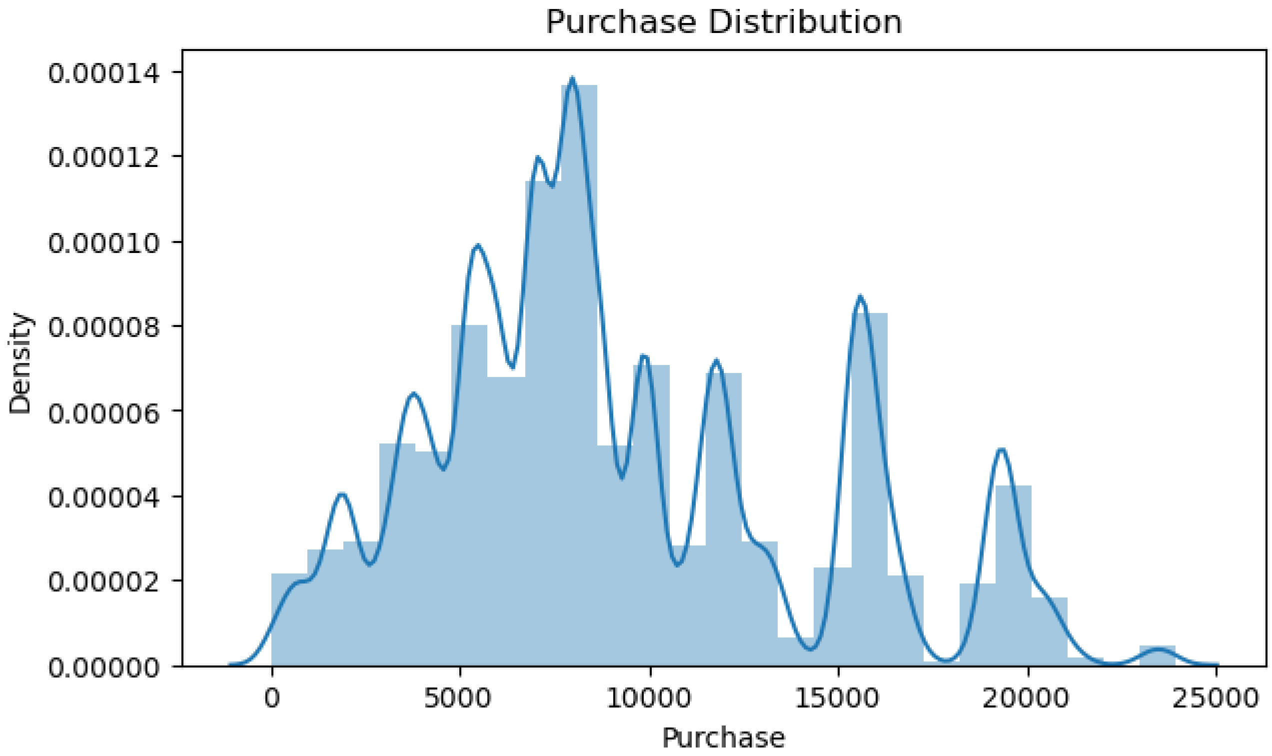
In [6]:

```
plt.figure(figsize=(7,4))
plt.title("Purchase Distribution")
sns.distplot(df['Purchase'],bins=25)

#First part of the graph has a normal distribution and later forming some peaks in the graph
#Evaluating the whole graph,it has a normal distribution
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_3368\370290696.py:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  sns.distplot(df['Purchase'],bins=25)
```

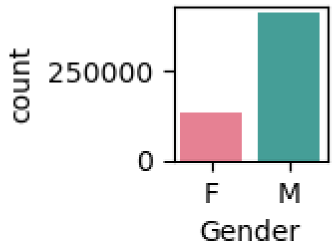
Out[6]:

```
<Axes: title={'center': 'Purchase Distribution'}, xlabel='Purchase', ylabel='Density'>
```



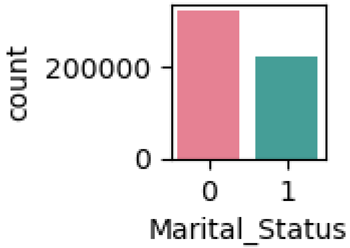
In [7]:

```
df['Gender'].value_counts()
plt.figure(figsize=(1,1))
sns.countplot(x ='Gender', data = df, palette ='husl')
plt.show()
#We observe that male customers have done more transactions than female during Black Friday sales.
```



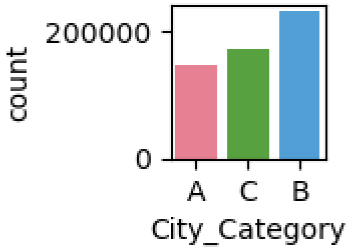
In [8]:

```
plt.figure(figsize=(1,1))
sns.countplot(x='Marital_Status',data=df,palette='husl')
plt.show()
#There are more unmarried customers in the dataset who purchase more during Black Friday sales.
#Majority of the buyers are single
```



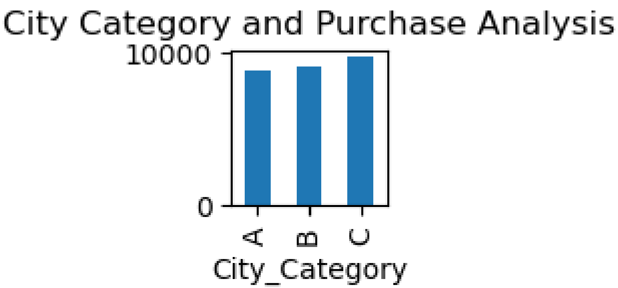
In [9]:

```
plt.figure(figsize=(1,1))
sns.countplot(x='City_Category',data=df,palette='husl')
plt.show()

#If we group by City_Category to see the variation with purchase
#We can see that city category B has made the most number of purchases followed by C.


```

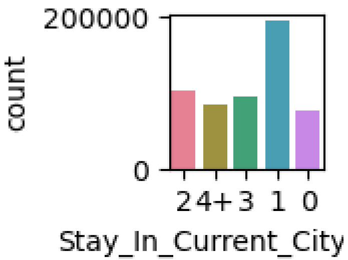


In [10]:
```
plt.figure(figsize=(1,1))
df.groupby("City_Category").mean()["Purchase"].plot(kind='bar')
plt.title("City Category and Purchase Analysis")
plt.show()
#We then observe that the customers from city C spends the most
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_3368\4088996167.py:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  df.groupby("City_Category").mean()["Purchase"].plot(kind='bar')
```

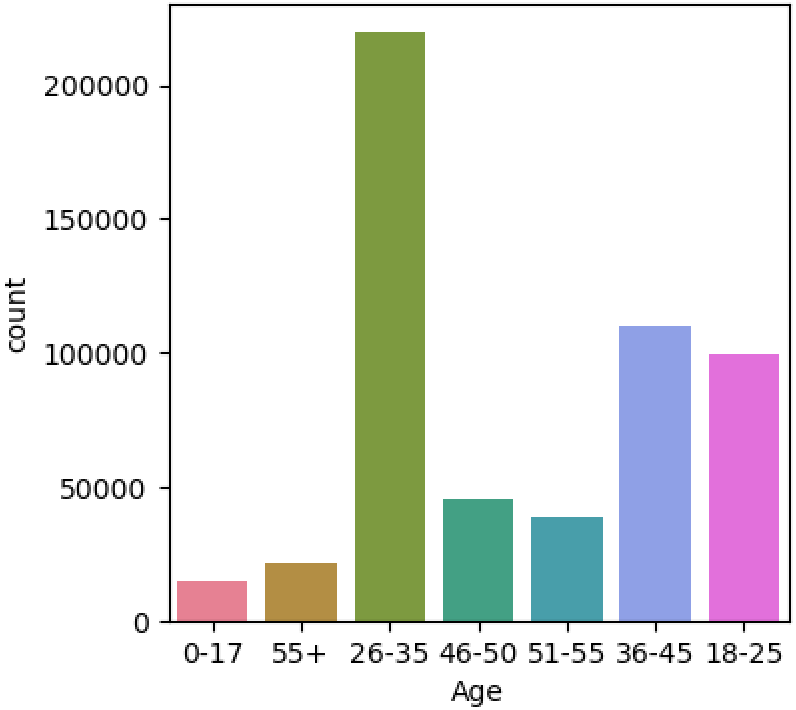


In [11]:
```
plt.figure(figsize=(1,1))
sns.countplot(x ='Stay_In_Current_City_Years',data=df,palette='husl')
plt.show()
#It looks like the longest customer is living in that city are less prone to buy new things
#whereas Customers which are new in town are more likely to take advantage of the low prices in Black Friday Sales
```



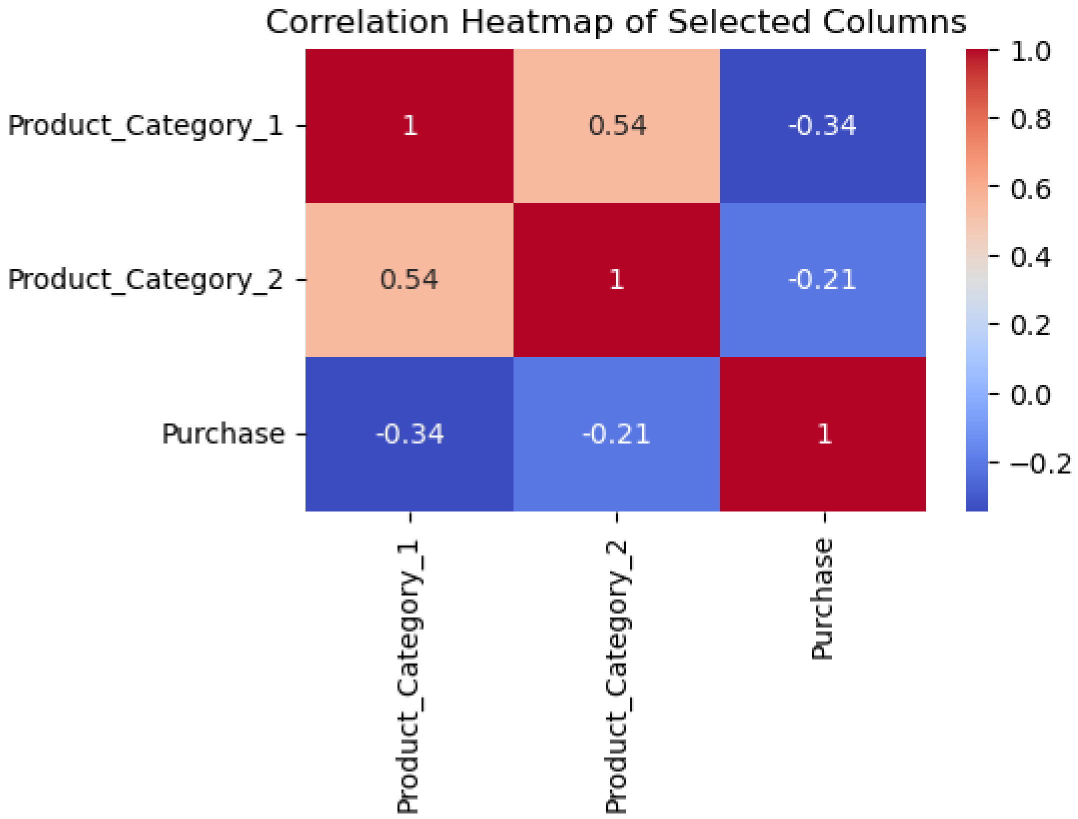
In [12]:

```
plt.figure(figsize=(4,4))
sns.countplot(x='Age',data=df,palette='husl')
plt.show()
#We can see that the Age group (26-35) makes the most no. of purchases during Black Friday Sales.
```



In [13]:

```
df1=df[["Product_Category_1","Product_Category_2","Purchase"]]
correlation=df1.corr()
plt.figure(figsize=(5,3))
sns.heatmap(correlation,annot=True,cmap="coolwarm")
plt.title("Correlation Heatmap of Selected Columns")
plt.show()

```



Preprocessing dataset

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
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 [15]:
```
Product_Category_3=(df["Product_Category_3"].isnull().sum()/len(df["Product_Category_3"]))*100
Product_Category_3
#the mentioned column has null values more than 50%
```

Out[15]:
```
69.67265865311198
```

In [16]:
```
df=df.drop(columns=["Product_Category_3"])
```

In [17]:
```
df['Product_Category_2'].fillna(df['Product_Category_2'].mean(),inplace=True)
```

In [18]:
```
df.nunique()
```

Out[18]:
```
User_ID                        5891
Product_ID                     3631
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
Purchase                      18105
dtype: int64
```

In [19]:
```
df=df.drop(["User_ID","Product_ID"],axis=1)

#We can drop User_ID and Product_ID for model prediction as it has more unique values Or
#if not the results will be biased to User_ID or Product_ID

```

Converting categorical data into numerical

In [20]:
```
from sklearn.preprocessing import LabelEncoder
```

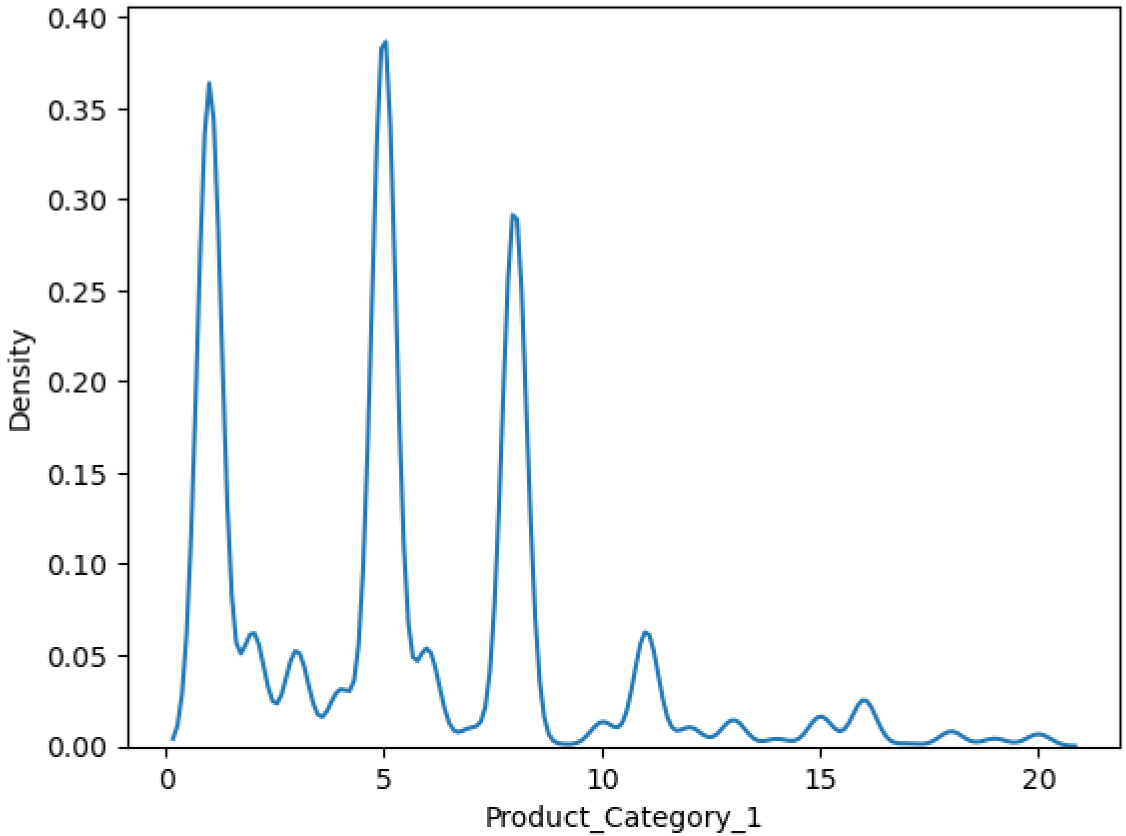
In [21]:
```
LE=LabelEncoder()
```

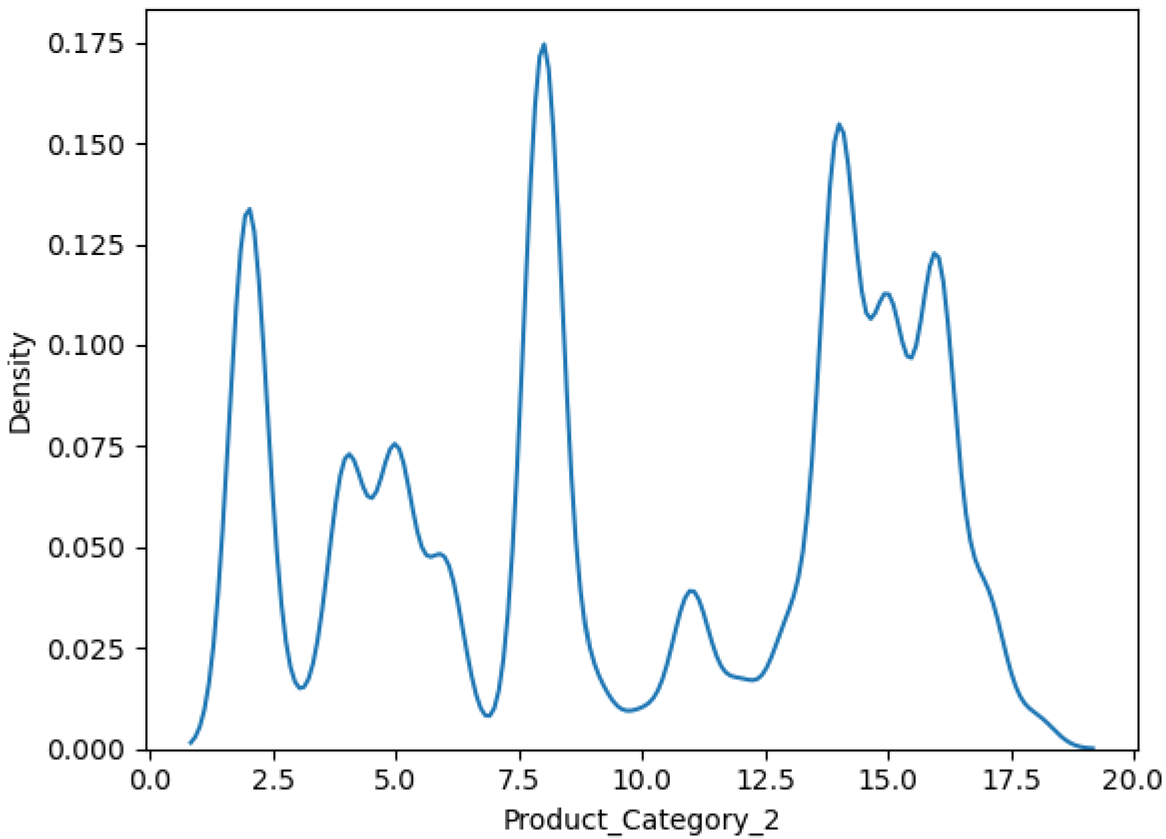
In [22]:
```
categorical_columns=['Gender','Age','City_Category','Stay_In_Current_City_Years']
```

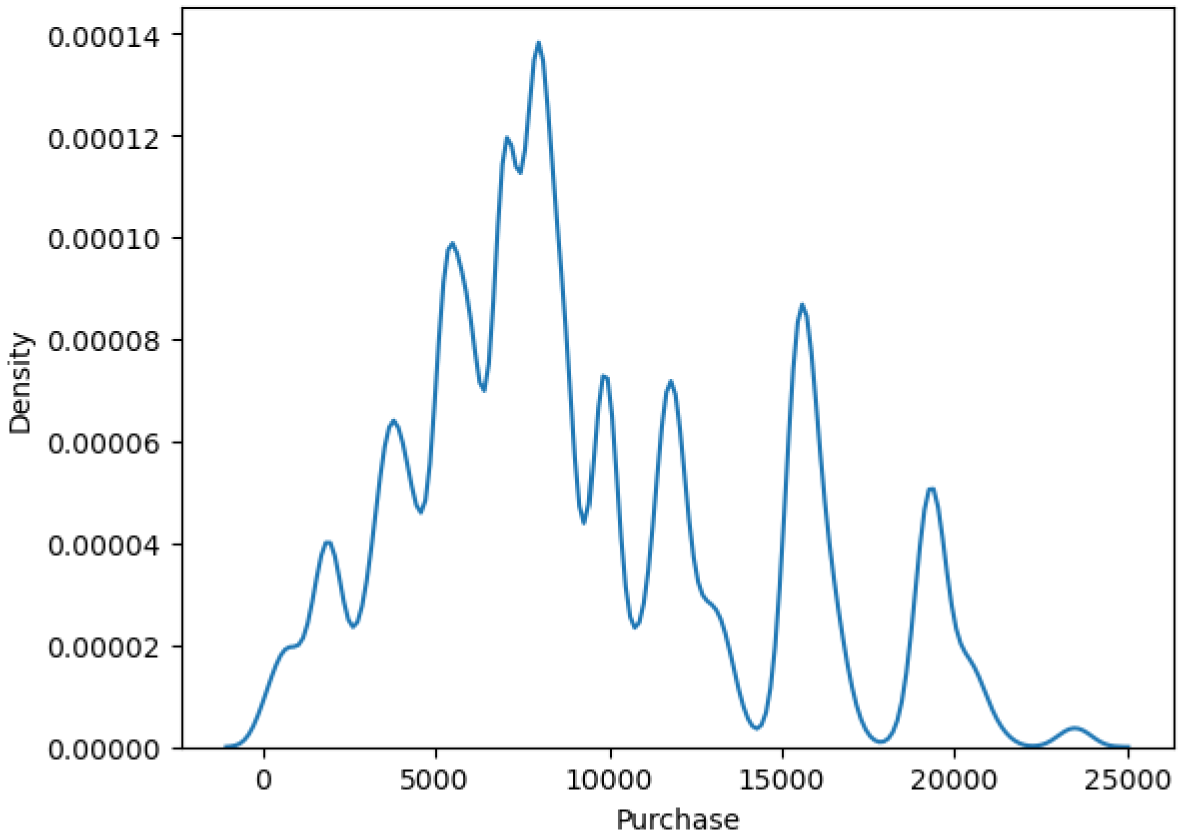
In [23]:
```
for column in categorical_columns:
    df[column] = LE.fit_transform(df[column])

```

Checking skewness

In [24]:
```
for i in df1:
    sns.kdeplot(data=df1,x=i)
    plt.show()

#from this we can see Product_Category_1 is rightly skewed
```




0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
Density
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Product_Category_2



Treating skewness of column with PowerTransformer

In [25]:
```
from sklearn.preprocessing import PowerTransformer
```

In [26]:
```
PT=PowerTransformer()
```

In [27]:

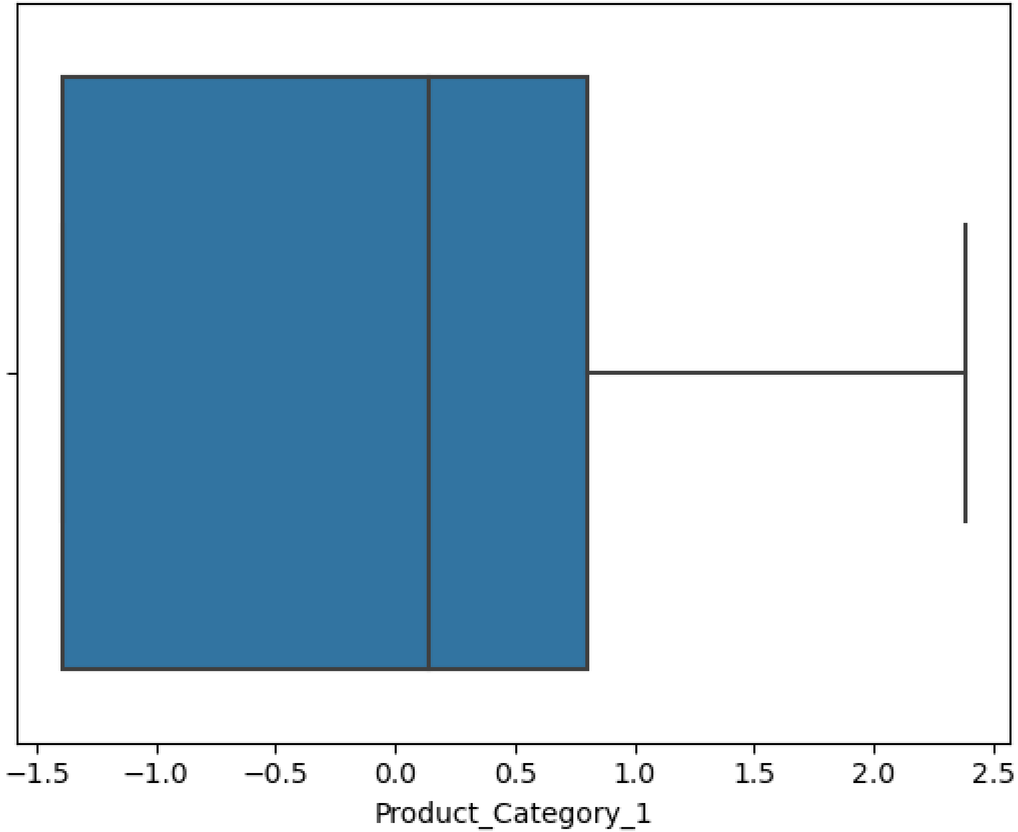
```
columns_to_scale=['Product_Category_1','Product_Category_2','Purchase']
for column in columns_to_scale:
    df[column] = PT.fit_transform(df[[column]])
```

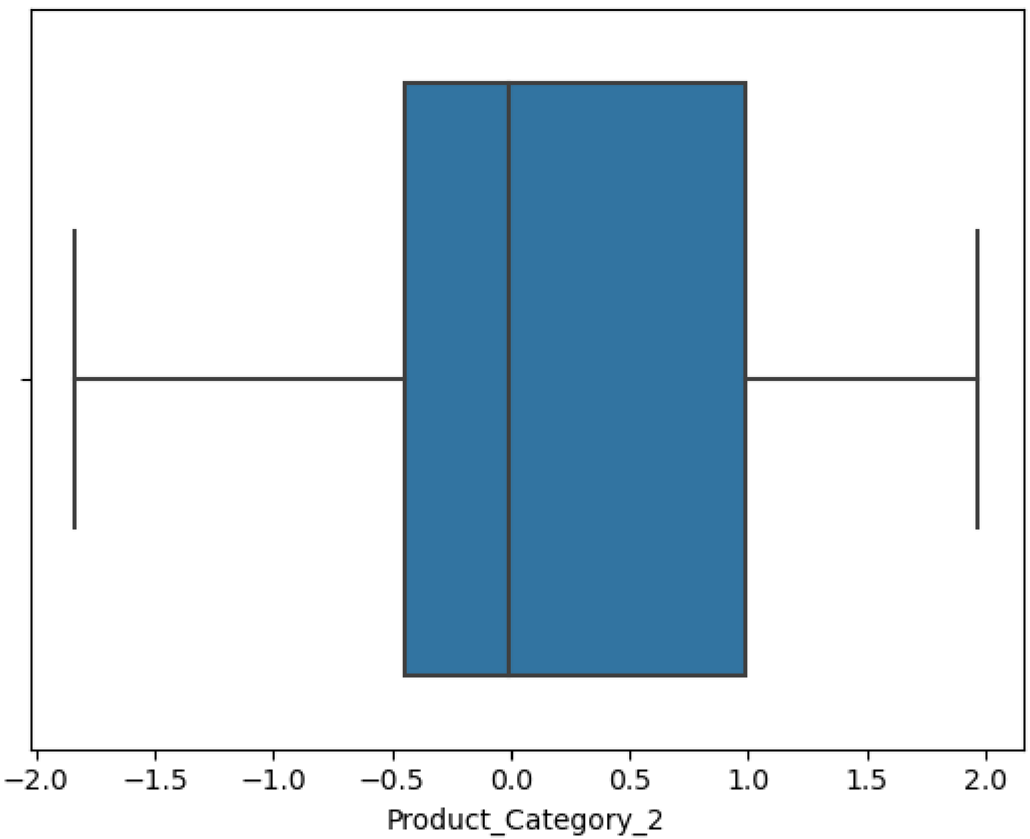
Checking & Treating outliers

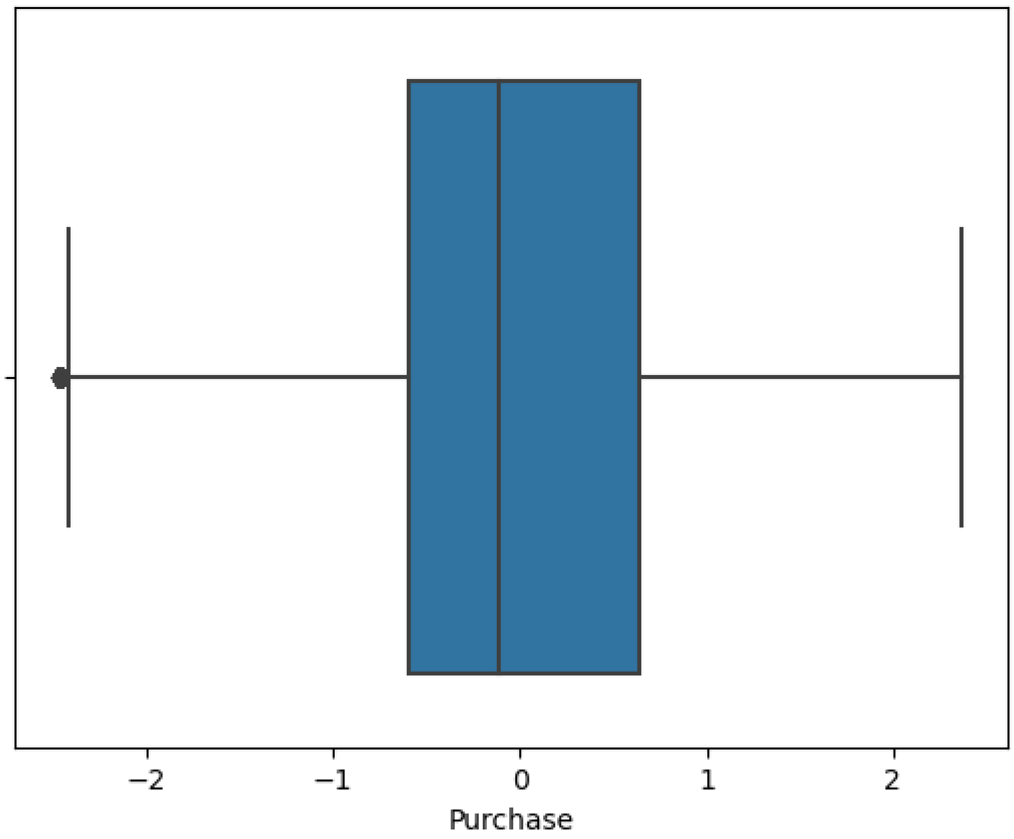
In [28]:

```
lst=df[['Product_Category_1','Purchase']]
for col in lst:
    Q3=df[col].quantile(0.75)
    Q1=df[col].quantile(0.25)
    IQR=Q3-Q1
    uw=Q3+1.5*IQR
    lw=Q1-1.5*IQR
df=df[(df[col]>=lw)&(df[col]<=uw)]
```

In [29]:
```
for i in df1:
    sns.boxplot(data=df,x=i)
    plt.show()
```




−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Product_Category_2



Split the data for training & testing

In [30]:
```
from sklearn.model_selection import train_test_split
```

In [31]:
```
x=df.drop('Purchase',axis=1)
y=df['Purchase']
```

In [32]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)
```

LinearRegression

In [33]:
```
from sklearn.linear_model import LinearRegression,Lasso
```

In [34]:
```
LR=LinearRegression().fit(x_train,y_train)
```

In [35]:
```
LR.score(x_train,y_train)
```

Out[35]: 0.18770518525090651

In [36]:
```
y_pred=LR.predict(x_test)
```

In [37]:
```
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
```

In [38]:
```
mse=mean_squared_error(y_test,y_pred)
mae=mean_absolute_error(y_test,y_pred)
r2_score(y_test,y_pred)

print("r2_score:            ",(r2_score(y_test,y_pred)))
print("mean_squared_error:  ",(mean_squared_error(y_test,y_pred)))
print("mean_absolute_error: ",(mean_absolute_error(y_test,y_pred)))
```

```
r2_score:             0.1815723738838485
mean_squared_error:   0.7774466714826213
mean_absolute_error:  0.6637134352307733
```

In [39]:
```
residual=y_test-y_pred #Residuals are the differences between the observed values and the values predicted by mode
```

DecisionTreeRegressor

In [40]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [41]:
```
DTR=DecisionTreeRegressor(random_state=0).fit(x_train,y_train)
```

In [42]:
```
DTR.score(x_train,y_train)
```

Out[42]:
```
0.7484293563655522
```

In [43]:
```
y_pred=DTR.predict(x_test)
```

In [44]:
```
r2_score(y_test,y_pred)
```

Out[44]:
```
0.6053220765476833
```

In [45]:
```
print("r2_score:            ",(r2_score(y_test,y_pred)))
print("mean_squared_error:  ",(mean_squared_error(y_test,y_pred)))
print("mean_absolute_error: ",(mean_absolute_error(y_test,y_pred)))
```

```
r2_score:            0.6053220765476833
mean_squared_error:  0.3749152986829032
mean_absolute_error: 0.45428613008948127
```

RandomForestRegressor

In [46]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [47]:
```
RFR=RandomForestRegressor(n_estimators=100,max_depth=15,random_state=0).fit(x_train,y_train)
```

In [48]:
```
DTR.score(x_train,y_train)
```

Out[48]: 0.7484293563655522

In [49]:
```
y_pred=RFR.predict(x_test)
```

In [50]:
```
print("r2_score:             ",(r2_score(y_test,y_pred)))
print("mean_squared_error:   ",(mean_squared_error(y_test,y_pred)))
print("mean_absolute_error: ",(mean_absolute_error(y_test,y_pred)))
```

```
r2_score:              0.6593111530508973
mean_squared_error:    0.3236296058684633
mean_absolute_error:   0.4357836320832321
```

KNeighborsRegressor

In [51]:
```
from sklearn.neighbors import KNeighborsRegressor
```

In [52]:
```
KNR=KNeighborsRegressor(n_neighbors=15).fit(x_train,y_train)
```

In [53]:
```
KNR.score(x_train,y_train)
```

Out[53]: 0.48710993328704766

In [54]:
```
y_pred=KNR.predict(x_test)
```

In [55]:
```
print("r2_score:             ",(r2_score(y_test,y_pred)))
print("mean_squared_error:   ",(mean_squared_error(y_test,y_pred)))
print("mean_absolute_error: ",(mean_absolute_error(y_test,y_pred)))
```

```
r2_score:              0.41852151822054695
mean_squared_error:    0.5523622318854204
mean_absolute_error:   0.5494539115276138
```

In [ ]:

```
```