In [12]: In [14]: Out[14]: In [20]:	<pre>import seaborn as sms import matplotlib.pyplot as plt  import os  #import data os.listdir (r"D:\Downloads\Python_Diwali_Sales_Analysis\Python_Diwali_Sales_Analysis ['Diwali Sales Data.csv',    'Diwali_Sales_Analysis.ipynb',    'DIWALI_SALES_PROJECT.ipynb']  sale_data = pd.read_csv (r"D:\Downloads\Python_Diwali_Sales_Analysis\Pyt</pre>
In [21]: Out[21]: In [22]: Out[22]:	sale_data.shape         (11251, 15)         sale_data.head(10)         User_ID Cust_name Product_ID Gender Group Age Group Age Marital_Status State Zone Occur         0 1002903 Sanskriti P00125942 F 26-35 28
	4       1000588       Joni       P00057942       M       26-35       28       1       Gujarat       Western       Processor         5       1000588       Joni       P00057942       M       26-35       28       1       Himachal Pradesh       Northern       Processor         6       1001132       Balk       P00018042       F       18-25       25       1       Uttar Pradesh       Central         7       1002092       Shivangi       P00273442       F       55+       61       0       Maharashtra       Western       IT         8       1003224       Kushal       P00205642       M       26-35       35       0       Uttar Pradesh       Central
In [23]:	9 1003650 Ginny P00031142 F 26-35 26 1 Andhra Pradesh Southern  sale_data.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 11251 entries, 0 to 11250 Data columns (total 15 columns): # Column Non-Null Count Dtype</class>
	0 User_ID 11251 non-null int64 1 Cust_name 11251 non-null object 2 Product_ID 11251 non-null object 3 Gender 11251 non-null object 4 Age Group 11251 non-null int64 6 Marital_Status 11251 non-null int64 7 State 11251 non-null object 8 Zone 11251 non-null object 9 Occupation 11251 non-null object 10 Product_Category 11251 non-null object 11 Orders 11251 non-null int64 12 Amount 11239 non-null float64 13 Status 0 non-null float64
In [25]:	<pre>14 unnamed1    0 non-null float64 dtypes: float64(3), int64(4), object(8) memory usage: 1.3+ MB  #drop blank columns sale_data.drop(['Status', 'unnamed1'], axis=1 , inplace=True)  sale_data.info()</pre>
	<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 11251 entries, 0 to 11250 Data columns (total 13 columns):     # Column</class></pre>
In [27]:	10 Product_Category 11251 non-null object 11 Orders 11251 non-null int64 12 Amount 11239 non-null float64 dtypes: float64(1), int64(4), object(8) memory usage: 1.1+ MB  #checking null values pd.isnull(sale_data)
Out[27]:	User_IDCust_nameProduct_IDGender GroupAge GroupAge GroupMarital_StatusStateZoneOccupation0FalseFalseFalseFalseFalseFalseFalseFalse1FalseFalseFalseFalseFalseFalseFalseFalse2FalseFalseFalseFalseFalseFalseFalseFalse
	3FalseFalseFalseFalseFalseFalseFalseFalseFalse4FalseFalseFalseFalseFalseFalseFalse11246FalseFalseFalseFalseFalseFalseFalseFalse11247FalseFalseFalseFalseFalseFalseFalseFalse11248FalseFalseFalseFalseFalseFalseFalseFalse
	11249FalseFalseFalseFalseFalseFalseFalseFalse11250FalseFalseFalseFalseFalseFalseFalseFalse11251 rows × 13 columns
n [28]:	<pre>pd.isnull(sale_data).sum()  User_ID</pre>
n [29]: n [30]: out[30]:	<pre>#drop null values sale_data.dropna(inplace= True)  sale_data.shape (11239, 13)</pre>
n [32]: n [34]: ut[34]:	<pre>#change dtype sale_data['Amount'] = sale_data ['Amount'].astype('int')  sale_data['Amount'].dtypes dtype('int32')</pre>
	EDA Gender
[39]: ht[39]: ht[45]:	<pre>sale_data.columns  Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',</pre>
	8000 - 7000 - 6000 -
	5000 - ting 4000 - 3000 -
	2000 - 1000 - 0
[46]:	<pre>f</pre>
	8000 - 7832 7000 - 6000 -
	5000 - til 4000 - 3000 -
	2000 -
[47]: :[47]:	<pre>Gender  sale_data.groupby(['Gender'], as_index = False)['Amount'].sum().sort_values(by= 'Amount</pre>
[48]:	<pre>0   F 74335853 1   M 31913276  sale_gender = sale_data.groupby(['Gender'], as_index = False)['Amount'].sum().sort_ From the above plots, we can conclude that the number of female buyers is greater</pre>
[56]:	Age
	<pre>for bars in ax.containers:     ax.bar_label(bars)</pre> Gender F
	2500 - 2000 -
	1000 -
[58]:	26-35
ıt[58]:	Age Group       Amount         2       26-35       42613442         3       36-45       22144994         1       18-25       17240732
. [50]	<pre>4     46-50     9207844 5     51-55     8261477 6     55+     4080987 0     0-17     2699653  sale_age = sale_data.groupby(['Age Group'], as_index = False)['Amount'].sum().sort_</pre>
[59]:	From the above plot, we can conclude that the maximum number of buyers belong to the age group between 26-35 female.  State
[62]: t[62]:	<pre>#Orders from top 5 states sale_state = sale_data.groupby(['State'], as_index = False)['Orders'].sum().sort_val sms.set(rc={'figure.figsize' : (15,5)}) sms.barplot(data = sale_state , x= 'State' , y= 'Orders') </pre> <pre><axes: ,="" xlabel="State" ylabel="Orders"></axes:></pre>
	5000 4000 3000 8.000
	1000 Uttar Pradesh Maharashtra Karnataka Delhi Madhya Pradesh Andhra PradeshHimachal Pradesh Kerala Haryana Gujarat State
[63]: t[63]:	<pre>#Total Amount from top 5 states sale_state = sale_data.groupby(['State'], as_index = False)['Amount'].sum().sort_value sms.set(rc={'figure.figsize' : (15,5)}) sms.barplot(data = sale_state , x= 'State' , y= 'Amount') </pre> <pre><axes: ,="" xlabel="State" ylabel="Amount"></axes:></pre>
	1.75 1.50 1.25 1.00
	0.75 0.50 0.25 0.00  Uttar Pradesh Maharashtra Karnataka Delhi Madhya Pradesh Andhra Pradesh Himachal Pradesh Haryana Bihar Gujarat State
	From the above plot, we can say that the maximum sale has been done in Uttar Pradesh. Also, we can notice that karela has made more orders compare to haryana and gujrat but amount spent is less.  Marital Status
n [ ]: [71]:	<pre>ms = sms.countplot(x= 'Marital_Status' , data = sale_data) sms.set(rc={'figure.figsize' : (6,5)}) for bars in ax.containers:     ax.bar_label(bars)</pre>
	6000
	4000 4000 3000
	2000
[74]:	0 0 1  Marital_Status  sale_ms = sale_data.groupby(['Marital_Status'], as_index = False)['Amount'].sum().s
[74]:	<pre>sms.set(rc={'figure.figsize' : (15,5)}) sms.barplot(data = sale_ms , x= 'Marital_Status' , y= 'Amount')  <axes: ,="" xlabel="Marital_Status" ylabel="Amount">  1e7 6</axes:></pre>
	5 4 THOUR 3 2
	Married People has the highest purchasing power
[75]:	<pre>Occupation  ms = sms.countplot(x= 'Occupation' , data = sale_data) sms.set(rc={'figure.figsize' : (25,5)})</pre>
	for bars in ms.containers:     ms.bar_label(bars)  1600 1400 1200 1137
	1000 854 600 400 200 0
[76]:	Healthcare Govt AutomobileConstructFound ProcessingLawyer Media Banking Occupation Retail IT Sector Aviation Hospitality Agriculture Textile Chemical Sale_ms = sale_data.groupby(['Occupation'], as_index = False)['Amount'].sum().sort_sms.set(rc={'figure.figsize' : (25,5)}) sms.barplot(data = sale_ms , x= 'Occupation' , y= 'Amount')
t[76]:	<pre><axes: ,="" xlabel="Occupation" ylabel="Amount"></axes:></pre>
	From the above graph we can notice that the most of the buyers are working in IT, Healthcare and Aviation.
[77]:	<pre>Product Category  ms = sms.countplot(x= 'Product_Category' , data = sale_data) sms.set(rc={'figure.figsize' : (25,5)})</pre>
	for bars in ms.containers: ms.bar_label(bars)  2655  2690  2000  2007
[78]:	1059
[78]:	<pre>sms.barplot(data = sale_ms , x= 'Product_Category' , y= 'Amount')  <axes: ,="" xlabel="Product_Category" ylabel="Amount">  35</axes:></pre>
	Conclusion  "It is possible that married women aged 26-35 from UP, Maharashtra, and Karnataka working in IT, Healthcare, and Aviation may prioritize purchasing food products
n [ ]:	working in IT, Healthcare, and Aviation may prioritize purchasing food products followed by clothing."

In [1]: **import** pandas **as** pd

import numpy as np