diwali-sales-analysis-using-python

July 19, 2024

1 DIWALI SALES ANALYSIS

1.0.1 Import python libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt # visualizing data
%matplotlib inline
import seaborn as sns
```

1.0.2 Import csv file

[2]:
```
df = pd.read_csv('Diwali Sales Data.csv', encoding= 'unicode_escape')
```

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

[3]:
```
(11251, 15)
```

[4]:
```
df.head()
```

[4]:
```
   User_ID  Cust_name Product_ID Gender Age Group  Age  Marital_Status  \
0  1002903  Sanskriti  P00125942      F     26-35   28               0
1  1000732     Kartik  P00110942      F     26-35   35               1
2  1001990      Bindu  P00118542      F     26-35   35               1
3  1001425     Sudevi  P00237842      M      0-17   16               0
4  1000588       Joni  P00057942      M     26-35   28               1

            State      Zone       Occupation Product_Category  Orders  \
0     Maharashtra   Western       Healthcare             Auto       1
1  Andhra Pradesh  Southern             Govt             Auto       3
2   Uttar Pradesh   Central       Automobile             Auto       3
3       Karnataka  Southern     Construction             Auto       2
4         Gujarat   Western  Food Processing             Auto       2

    Amount  Status  unnamed1
0  23952.0     NaN       NaN
1  23934.0     NaN       NaN
```

```
2  23924.0      NaN        NaN
3  23912.0      NaN        NaN
4  23877.0      NaN        NaN
```

[5]:
```
df.head(15)
```

[5]:
```
    User_ID   Cust_name Product_ID Gender Age Group  Age  Marital_Status  \
0   1002903  Sanskriti  P00125942      F     26-35   28               0
1   1000732     Kartik  P00110942      F     26-35   35               1
2   1001990      Bindu  P00118542      F     26-35   35               1
3   1001425     Sudevi  P00237842      M      0-17   16               0
4   1000588       Joni  P00057942      M     26-35   28               1
5   1000588       Joni  P00057942      M     26-35   28               1
6   1001132       Balk  P00018042      F     18-25   25               1
7   1002092   Shivangi  P00273442      F       55+   61               0
8   1003224     Kushal  P00205642      M     26-35   35               0
9   1003650      Ginny  P00031142      F     26-35   26               1
10  1003829   Harshita  P00200842      M     26-35   34               0
11  1000214   Kargatis  P00119142      F     18-25   20               0
12  1004035     Elijah  P00080342      F     18-25   20               1
13  1001680    Vasudev  P00324942      M     26-35   26               1
14  1003858       Cano  P00293742      M     46-50   46               1

              State      Zone       Occupation Product_Category  Orders  \
0       Maharashtra   Western       Healthcare             Auto       1
1    Andhra Pradesh  Southern             Govt             Auto       3
2     Uttar Pradesh   Central       Automobile             Auto       3
3         Karnataka  Southern     Construction             Auto       2
4           Gujarat   Western  Food Processing             Auto       2
5  Himachal Pradesh  Northern  Food Processing             Auto       1
6     Uttar Pradesh   Central           Lawyer             Auto       4
7       Maharashtra   Western        IT Sector             Auto       1
8     Uttar Pradesh   Central             Govt             Auto       2
9    Andhra Pradesh  Southern            Media             Auto       4
10            Delhi   Central          Banking             Auto       1
11   Andhra Pradesh  Southern           Retail             Auto       2
12   Andhra Pradesh  Southern        IT Sector             Auto       2
13   Andhra Pradesh  Southern       Automobile             Auto       4
14   Madhya Pradesh   Central      Hospitality             Auto       3

      Amount  Status  unnamed1
0   23952.00     NaN       NaN
1   23934.00     NaN       NaN
2   23924.00     NaN       NaN
3   23912.00     NaN       NaN
4   23877.00     NaN       NaN
5   23877.00     NaN       NaN
```

```
6   23841.00      NaN        NaN
7        NaN      NaN        NaN
8   23809.00      NaN        NaN
9   23799.99      NaN        NaN
10  23770.00      NaN        NaN
11  23752.00      NaN        NaN
12  23730.00      NaN        NaN
13  23718.00      NaN        NaN
14       NaN      NaN        NaN
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11251 entries, 0 to 11250
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 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  object
 5   Age               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
 14  unnamed1          0 non-null      float64
dtypes: float64(3), int64(4), object(8)
memory usage: 1.3+ MB
```

1.0.3 Drop unrelated/blank columns

[7]:
```
df.drop(['Status', 'unnamed1'], axis=1, inplace=True)
```

1.0.4 Check for null values

[8]:
```
pd.isnull(df).sum()
```

[8]:
```
User_ID              0
Cust_name            0
Product_ID           0
Gender               0
```

```
Age Group            0
Age                  0
Marital_Status       0
State                0
Zone                 0
Occupation           0
Product_Category     0
Orders               0
Amount              12
dtype: int64
```

1.0.5 Drop null values

[9]:
```
df.dropna(inplace=True)
```

1.0.6 Change data type

[10]:
```
df['Amount'] = df['Amount'].astype('int')
```

[11]:
```
df['Amount'].dtypes
```

[11]:
```
dtype('int32')
```

[12]:
```
df.columns
```

[12]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

[13]:
```
# describe() method returns description of the data in the DataFrame (i.e.␣
↪count, mean, std, etc)
df.describe()
```

[13]:

	User_ID	Age	Marital_Status	Orders	Amount
count	1.123900e+04	11239.000000	11239.000000	11239.000000	11239.000000
mean	1.003004e+06	35.410357	0.420055	2.489634	9453.610553
std	1.716039e+03	12.753866	0.493589	1.114967	5222.355168
min	1.000001e+06	12.000000	0.000000	1.000000	188.000000
25%	1.001492e+06	27.000000	0.000000	2.000000	5443.000000
50%	1.003064e+06	33.000000	0.000000	2.000000	8109.000000
75%	1.004426e+06	43.000000	1.000000	3.000000	12675.000000
max	1.006040e+06	92.000000	1.000000	4.000000	23952.000000

[14]:
```
# use describe() for specific columns
df[['Age', 'Orders', 'Amount']].describe()
```

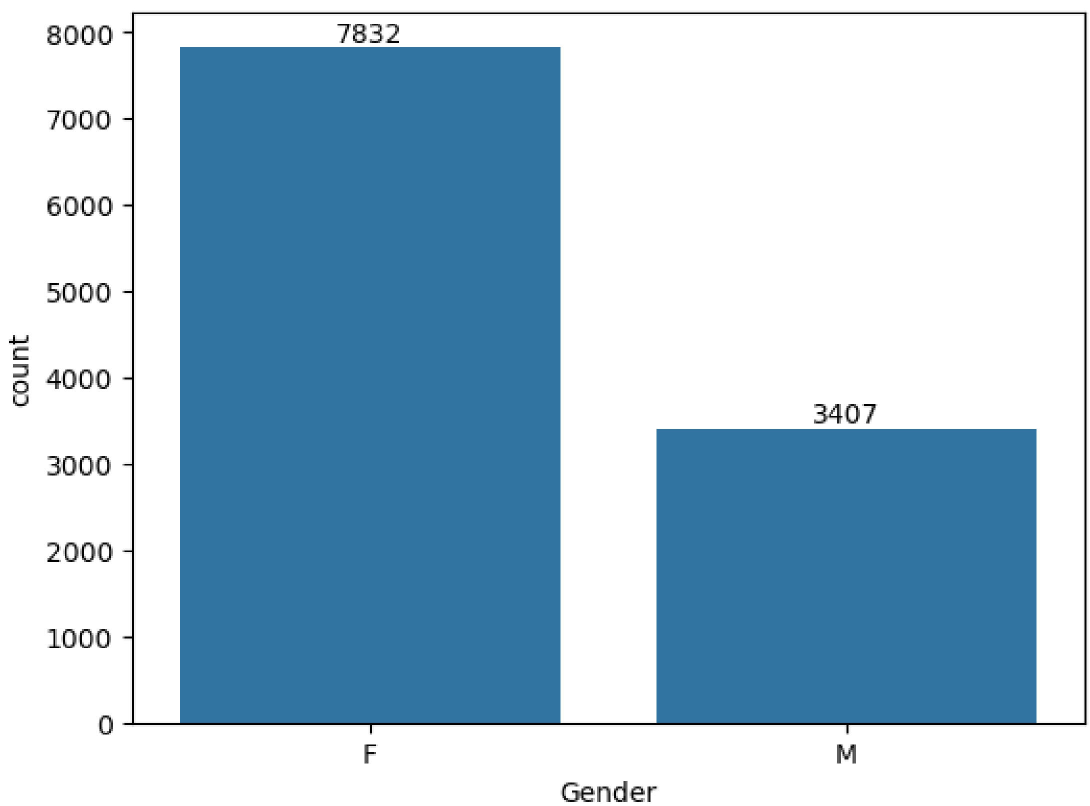
[14]:

	Age	Orders	Amount
count	11239.000000	11239.000000	11239.000000
mean	35.410357	2.489634	9453.610553
std	12.753866	1.114967	5222.355168
min	12.000000	1.000000	188.000000
25%	27.000000	2.000000	5443.000000
50%	33.000000	2.000000	8109.000000
75%	43.000000	3.000000	12675.000000
max	92.000000	4.000000	23952.000000

2 Exploratory Data Analysis

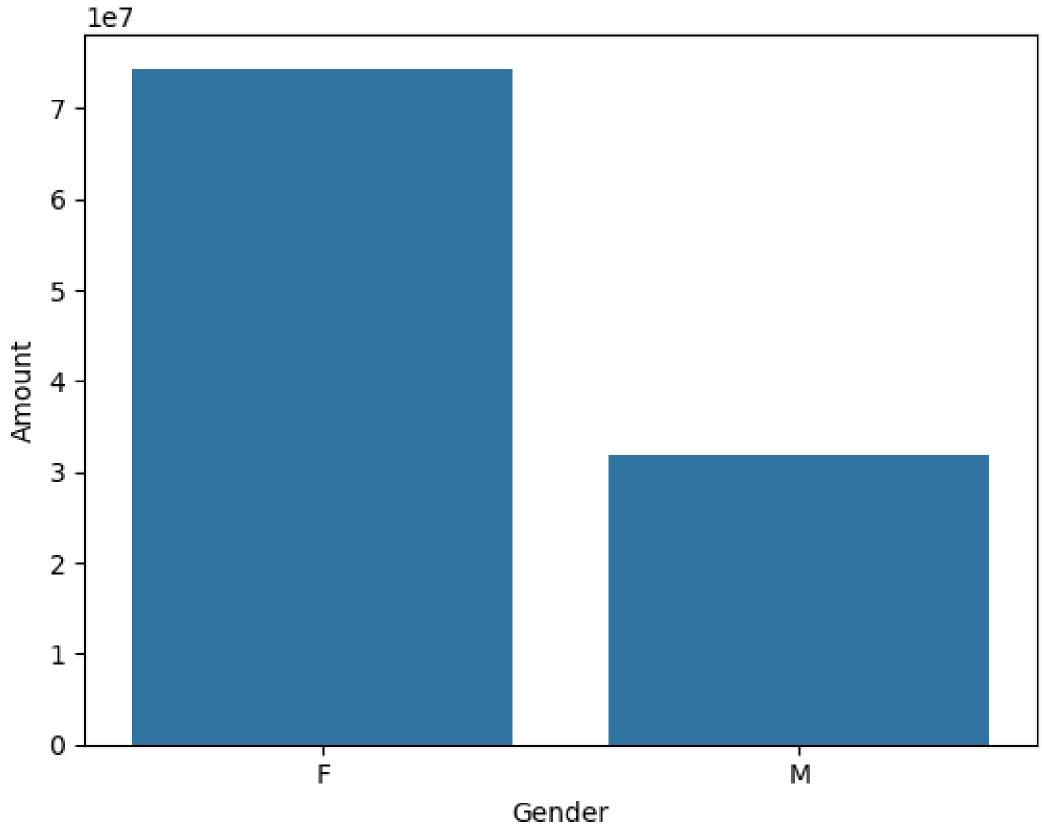
2.0.1 Gender

[15]:
```
# plotting a bar chart for Gender and it's count

ax = sns.countplot(x = 'Gender',data = df)

for bars in ax.containers:
    ax.bar_label(bars)
```



[16]:
```
# plotting a bar chart for gender vs total amount

sales_gen = df.groupby(['Gender'], as_index=False)['Amount'].sum().
 ↪sort_values(by='Amount', ascending=False)

sns.barplot(x = 'Gender',y= 'Amount' ,data = sales_gen)
```

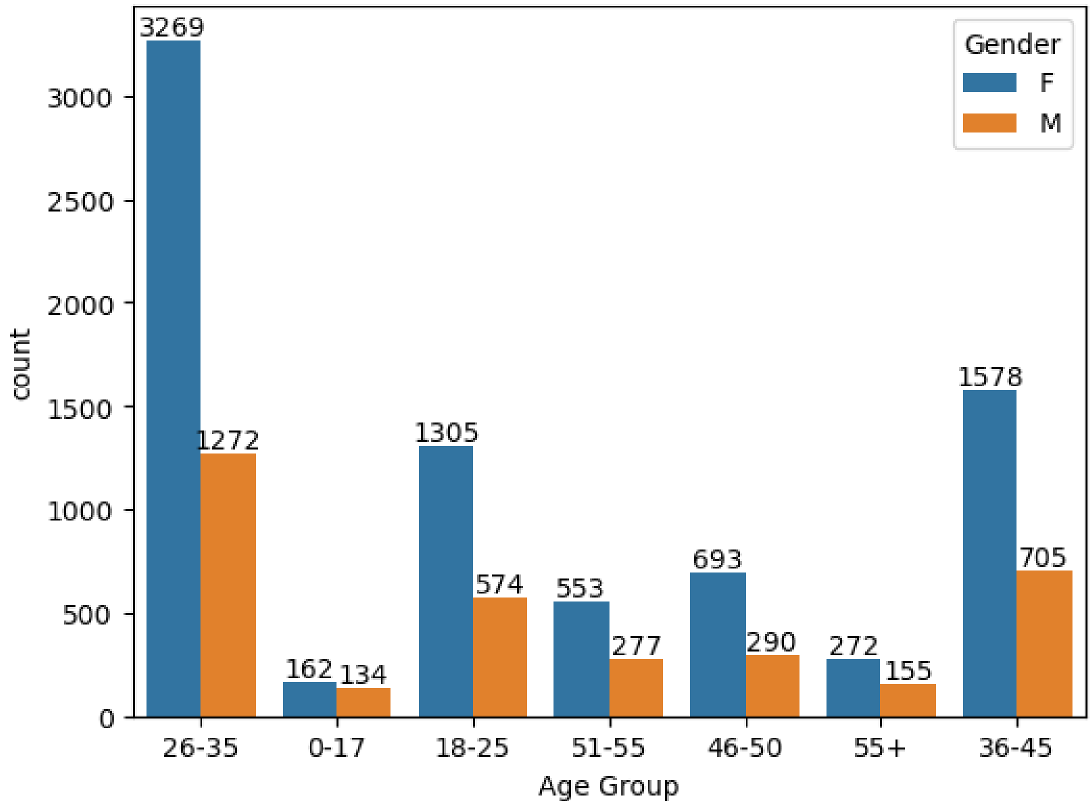
[16]: <Axes: xlabel='Gender', ylabel='Amount'>



From above graphs we can see that most of the buyers are females and even the purchasing power of females are greater than men

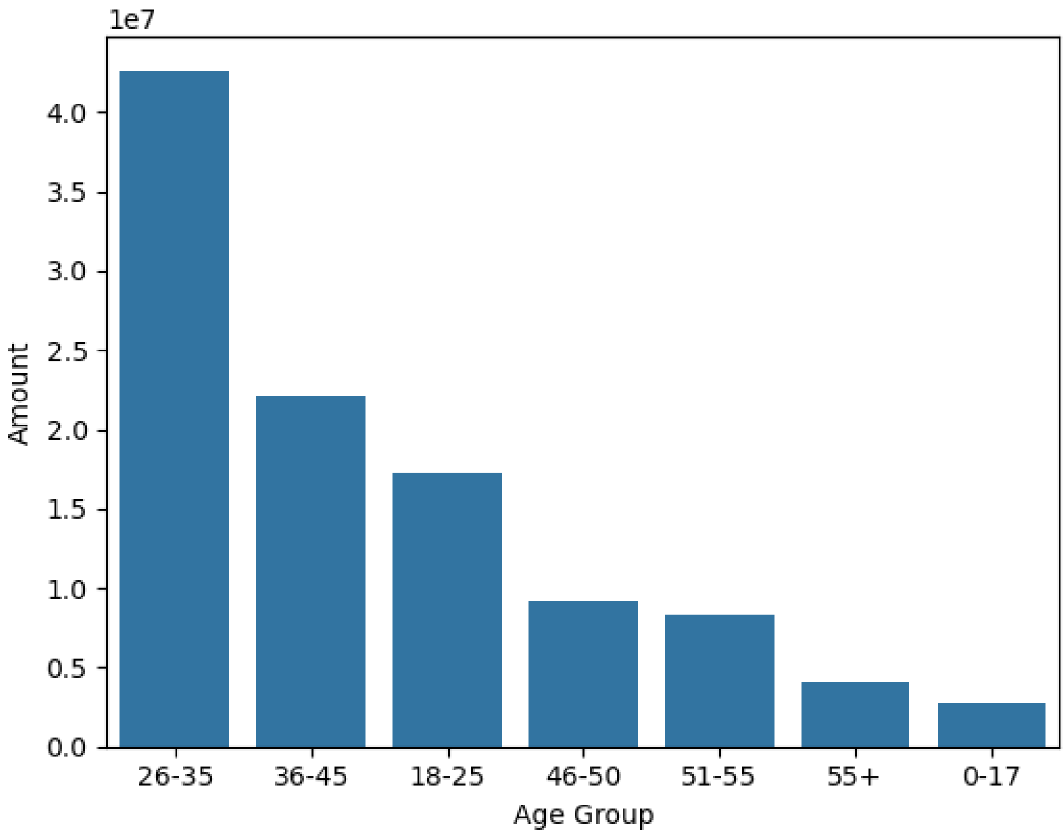
2.0.2 Age

[17]:
```
ax = sns.countplot(data = df, x = 'Age Group', hue = 'Gender')

for bars in ax.containers:
    ax.bar_label(bars)
```




```
[18]: # Total Amount vs Age Group
sales_age = df.groupby(['Age Group'], as_index=False)['Amount'].sum().
 ↪sort_values(by='Amount', ascending=False)

sns.barplot(x = 'Age Group',y= 'Amount' ,data = sales_age)
```

```
[18]: <Axes: xlabel='Age Group', ylabel='Amount'>
```

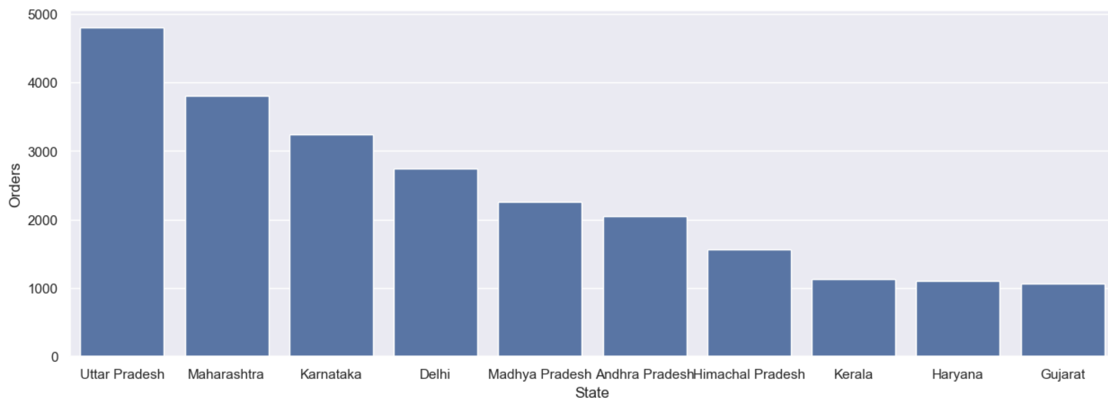


From above graphs we can see that most of the buyers are of age group between 26-35 yrs female

2.0.3 State

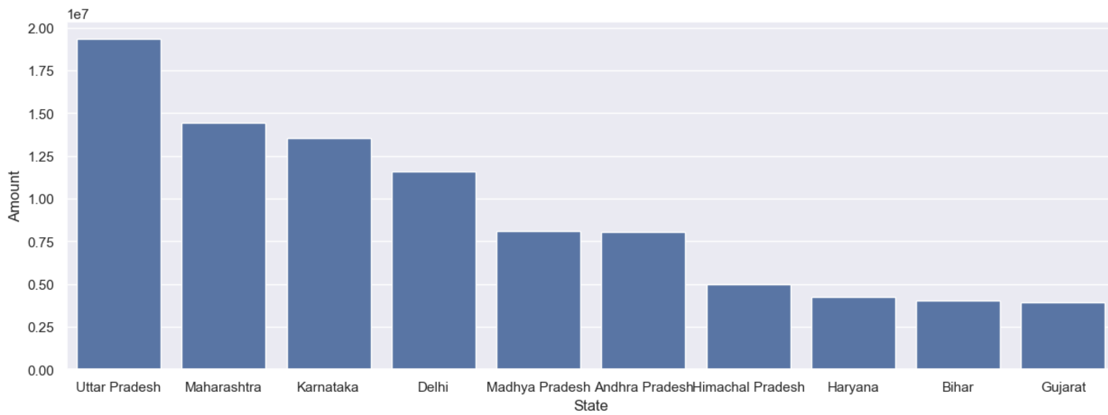
[19]:
```
# total number of orders from top 10 states

sales_state = df.groupby(['State'], as_index=False)['Orders'].sum().
 ↪sort_values(by='Orders', ascending=False).head(10)

sns.set(rc={'figure.figsize':(15,5)})
sns.barplot(data = sales_state, x = 'State',y= 'Orders')
```

[19]: <Axes: xlabel='State', ylabel='Orders'>



[20]:
```
# total amount/sales from top 10 states

sales_state = df.groupby(['State'], as_index=False)['Amount'].sum().
↪sort_values(by='Amount', ascending=False).head(10)

sns.set(rc={'figure.figsize':(15,5)})
sns.barplot(data = sales_state, x = 'State',y= 'Amount')
```

[20]:
```
<Axes: xlabel='State', ylabel='Amount'>
```

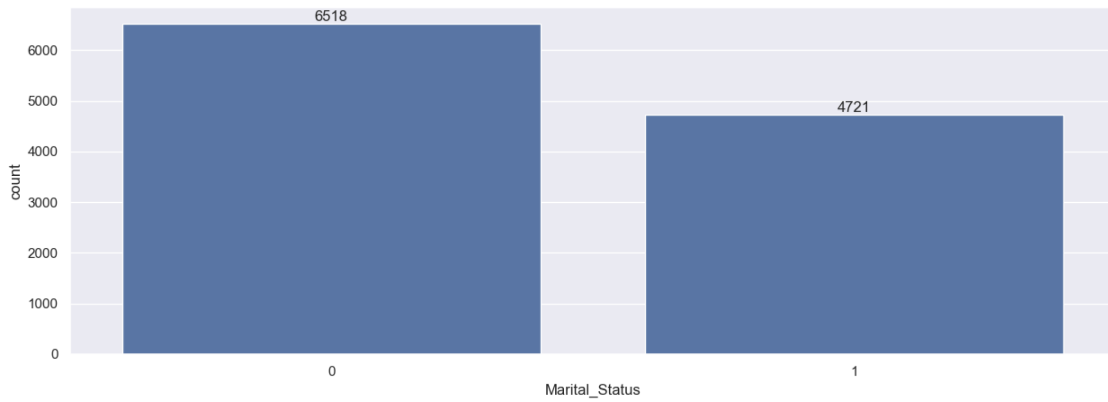


From above graphs we can see that most of the orders & total sales/amount are from Uttar Pradesh, Maharashtra and Karnataka respectively

2.0.4 Marital Status

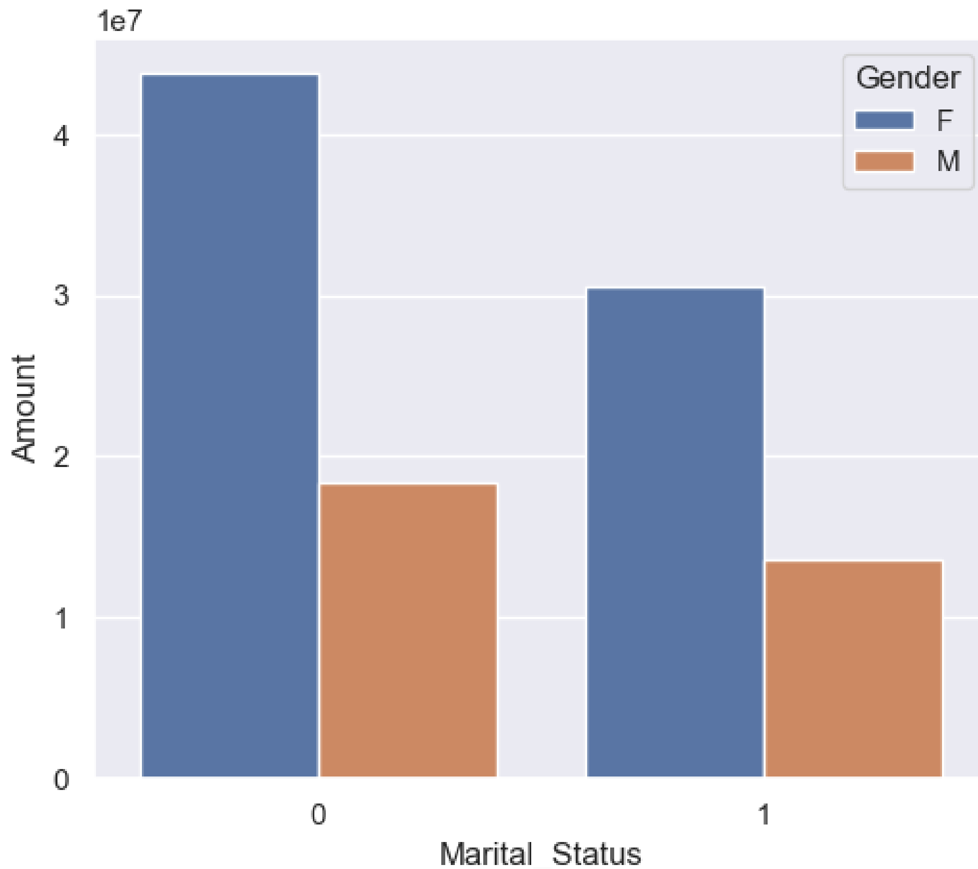
[21]:
```
ax = sns.countplot(data = df, x = 'Marital_Status')

sns.set(rc={'figure.figsize':(7,5)})
```

```
for bars in ax.containers:
    ax.bar_label(bars)
```



[22]:
```
sales_state = df.groupby(['Marital_Status', 'Gender'],␣
↪as_index=False)['Amount'].sum().sort_values(by='Amount', ascending=False)

sns.set(rc={'figure.figsize':(6,5)})
sns.barplot(data = sales_state, x = 'Marital_Status',y= 'Amount', hue='Gender')
```

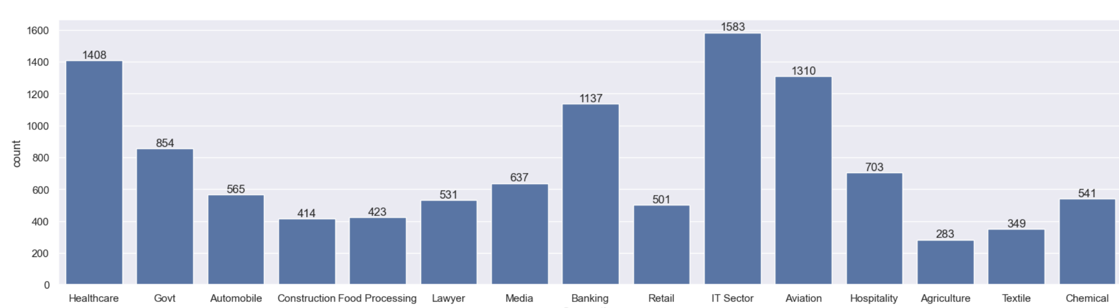
[22]: <Axes: xlabel='Marital_Status', ylabel='Amount'>



From above graphs we can see that most of the buyers are married (women) and they have high purchasing power

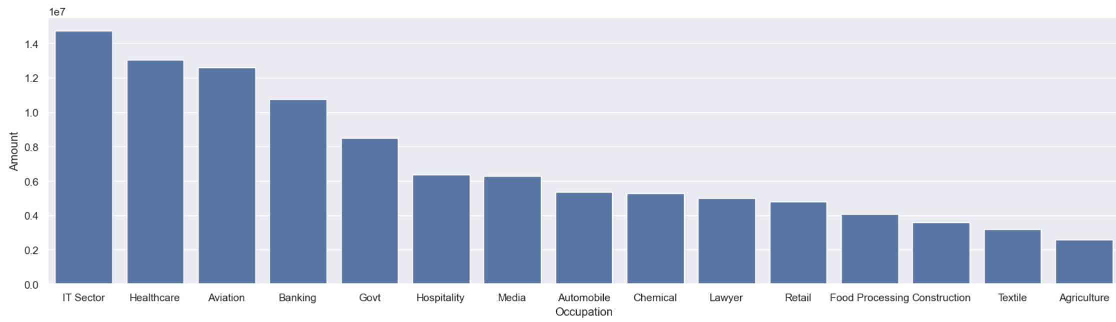
2.0.5 Occupation

[23]:
```
sns.set(rc={'figure.figsize':(20,5)})
ax = sns.countplot(data = df, x = 'Occupation')

for bars in ax.containers:
    ax.bar_label(bars)
```



```python
[24]: sales_state = df.groupby(['Occupation'], as_index=False)['Amount'].sum().
      ↪sort_values(by='Amount', ascending=False)

      sns.set(rc={'figure.figsize':(20,5)})
      sns.barplot(data = sales_state, x = 'Occupation',y= 'Amount')
```

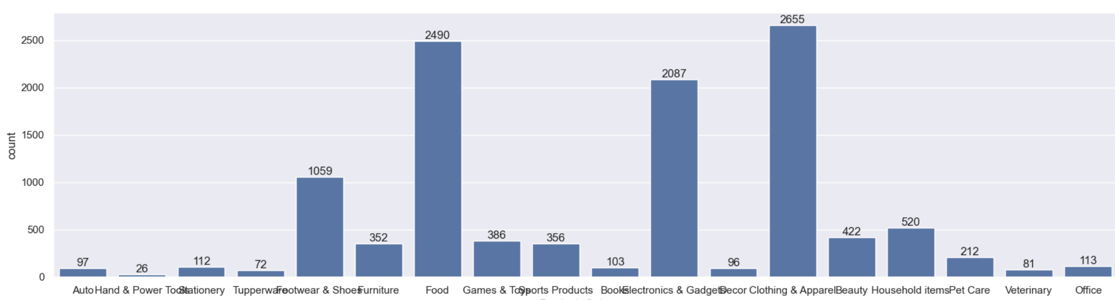
[24]: <Axes: xlabel='Occupation', ylabel='Amount'>



From above graphs we can see that most of the buyers are working in IT, Healthcare and Aviation sector

2.0.6 Product Category

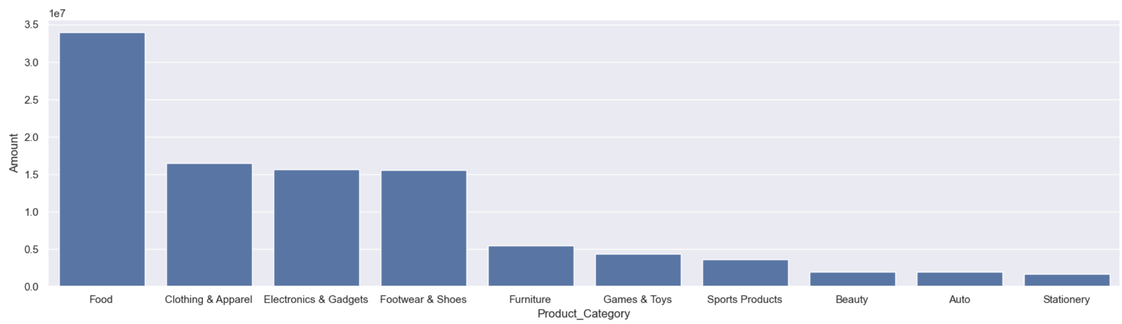
```python
[25]: sns.set(rc={'figure.figsize':(20,5)})
      ax = sns.countplot(data = df, x = 'Product_Category')

      for bars in ax.containers:
          ax.bar_label(bars)
```




```python
[26]: sales_state = df.groupby(['Product_Category'], as_index=False)['Amount'].sum().
      ↪sort_values(by='Amount', ascending=False).head(10)
```

```
sns.set(rc={'figure.figsize':(20,5)})
sns.barplot(data = sales_state, x = 'Product_Category',y= 'Amount')
```

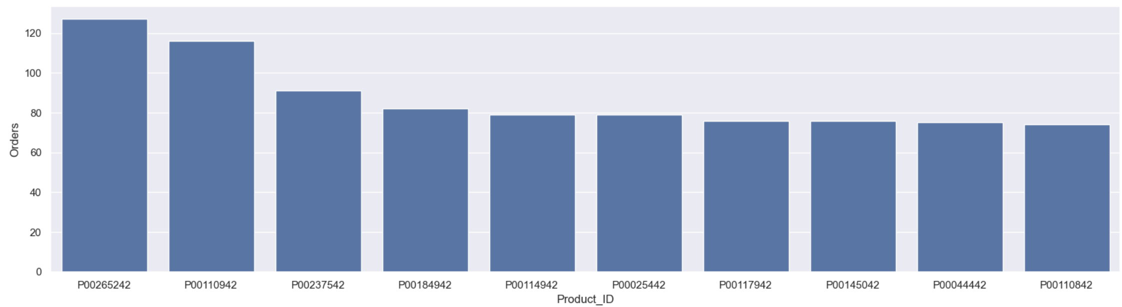
[26]: <Axes: xlabel='Product_Category', ylabel='Amount'>



From above graphs we can see that most of the sold products are from Food, Clothing and Electronics category

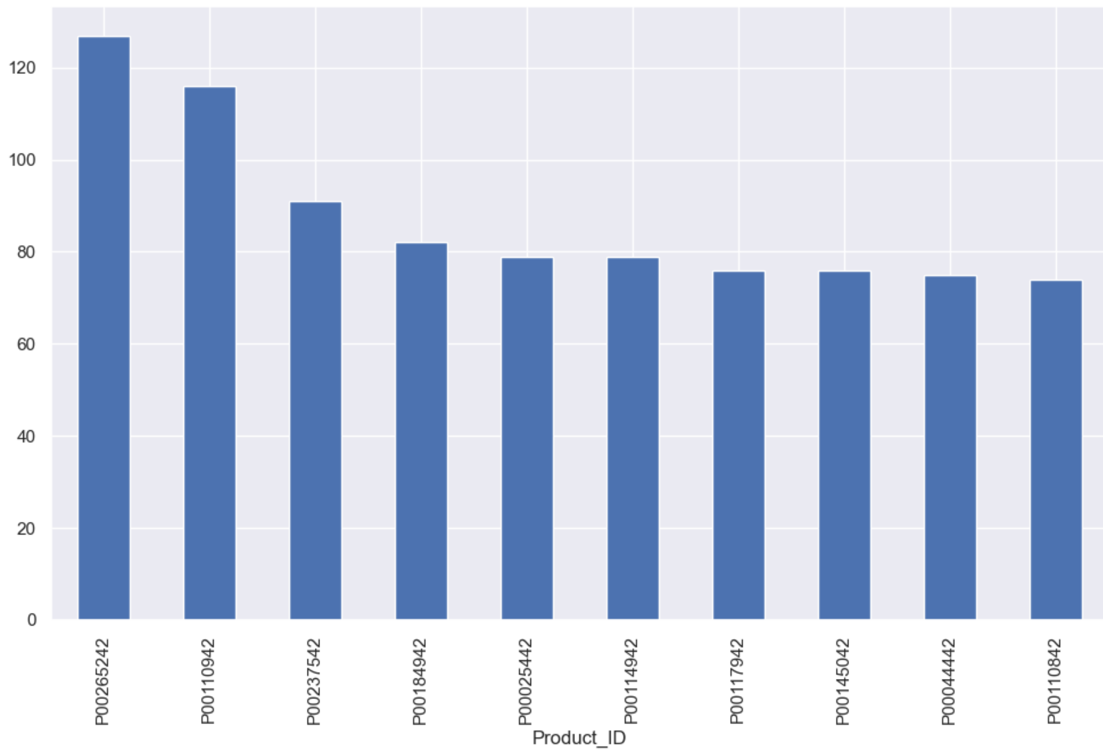
[27]:
```
sales_state = df.groupby(['Product_ID'], as_index=False)['Orders'].sum().
  ↪sort_values(by='Orders', ascending=False).head(10)

sns.set(rc={'figure.figsize':(20,5)})
sns.barplot(data = sales_state, x = 'Product_ID',y= 'Orders')
```

[27]: <Axes: xlabel='Product_ID', ylabel='Orders'>



[28]:
```
# top 10 most sold products (same thing as above)

fig1, ax1 = plt.subplots(figsize=(12,7))
df.groupby('Product_ID')['Orders'].sum().nlargest(10).
  ↪sort_values(ascending=False).plot(kind='bar')
```

[28]: <Axes: xlabel='Product_ID'>



120
100
80
60
40
20
0
P00265242
P00110942
P00237542
P00184942
P00025442
P00114942
P00117942
P00145042
P00044442
P00110842
Product_ID