analysis-code-file

June 29, 2024

[4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt # Visualizing Data
%matplotlib inline
import seaborn as sns
```

[8]:
```
df = pd.read_csv('Diwali Sales Data.csv', encoding ='unicode_escape')
```

[9]:
```
df.shape
```

[9]:
```
(11251, 15)
```

[10]:
```
df.head()
```

[10]:
```
   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
```

[11]:
```
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
```

[12]:
```
df.drop(['Status','unnamed1'], axis=1, inplace=True)
# Removed Status unnamed1 column
```

[15]:
```
pd.isnull(df).sum()
```

[15]:
```
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
```

[16]:
```
df.shape
```

[16]:
```
(11251, 13)
```

[20]:
```
df.dropna(inplace=True)
# Removed Null Values
```

[21]:
```
df.shape
```

[21]: (11239, 13)

[22]:
```
# Initialize List of Lists
data_test = [['madhav', 11], ['Gopi', 15], ['Keshav', ], ['Lalita', 16]]

# Creating Pandas DataFrame using List
df_test = pd.DataFrame(data_test, columns=['Name', 'Age'])

df_test
```

[22]:

	Name	Age
0	madhav	11.0
1	Gopi	15.0
2	Keshav	NaN
3	Lalita	16.0

[25]:
```
df_test.dropna(inplace = True) # Saving Changes
```

[24]:
```
df_test
```

[24]:

	Name	Age
0	madhav	11.0
1	Gopi	15.0
3	Lalita	16.0

[26]:
```
# Changing Data Type
df['Amount'] = df['Amount'].astype('int')
```

[29]:
```
df[['Age','Orders','Amount']].describe()
```

[29]:

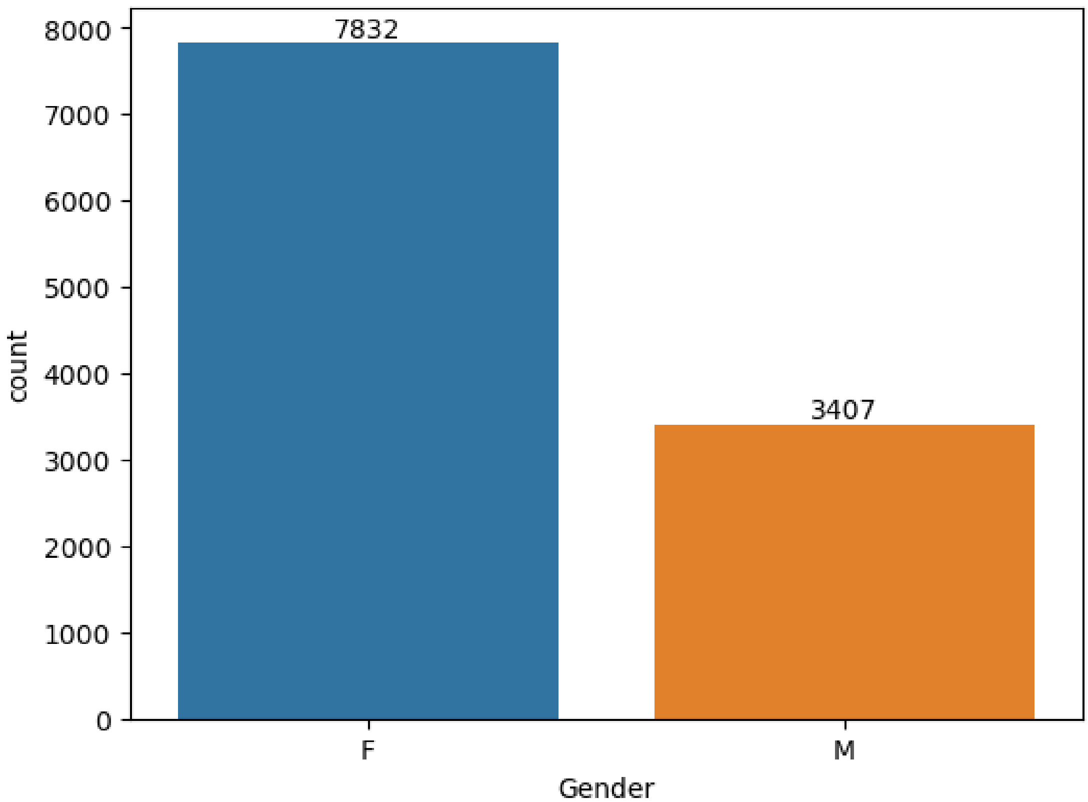
	Age	Orders	Amount
count	11239.000000	11239.000000	11239.000000
mean	35.410357	2.489634	9453.610553
std	12.753866	1.114967	5222.355168
min	12.000000	1.000000	188.000000
25%	27.000000	2.000000	5443.000000
50%	33.000000	2.000000	8109.000000
75%	43.000000	3.000000	12675.000000
max	92.000000	4.000000	23952.000000

1 Exploratory Data Analysis (EDA)

[30]:
```
df.columns
```

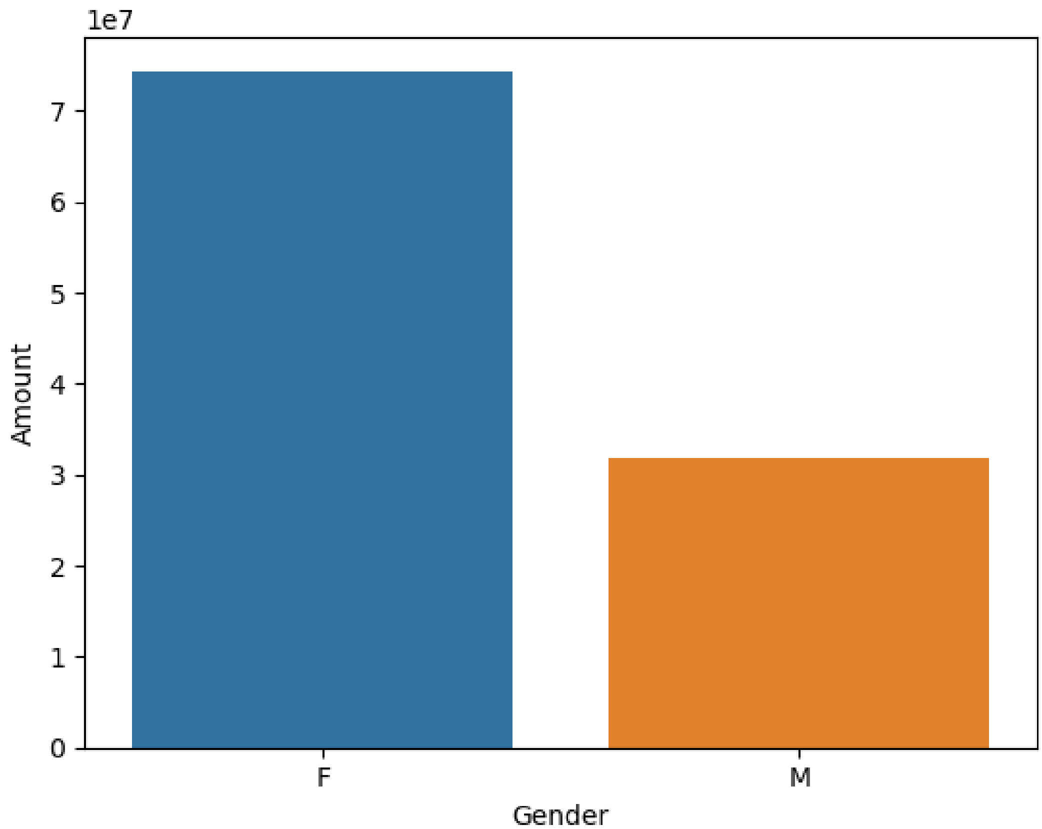
[30]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

[33]:
```
ax = sns.countplot(x = 'Gender', data = df)

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



[36]:
```
# Grouped the 'Gender' Column, Grouped by Amount and took SUM and sorted the␣
↪Vales.
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)
```

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



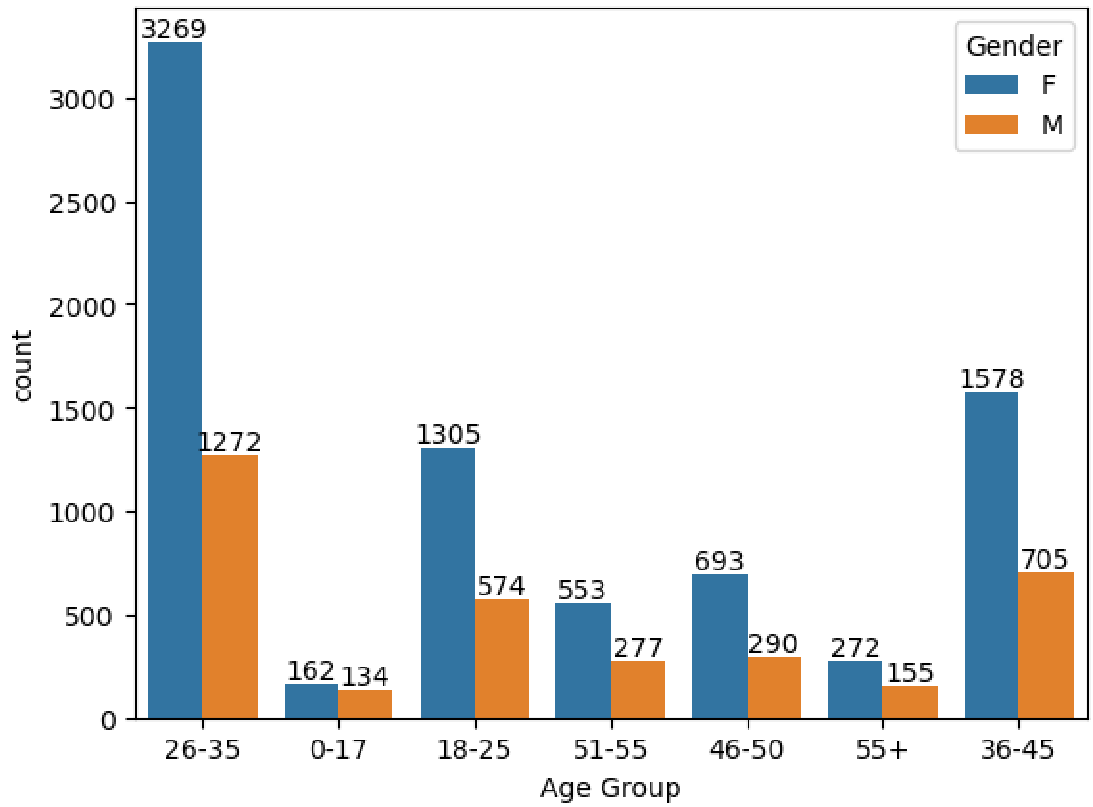
From the above graphs we can see that most of the buyers are females and even the purchasing power of females is greater than men

1.0.1 Age

[37]:
```
df.columns
```

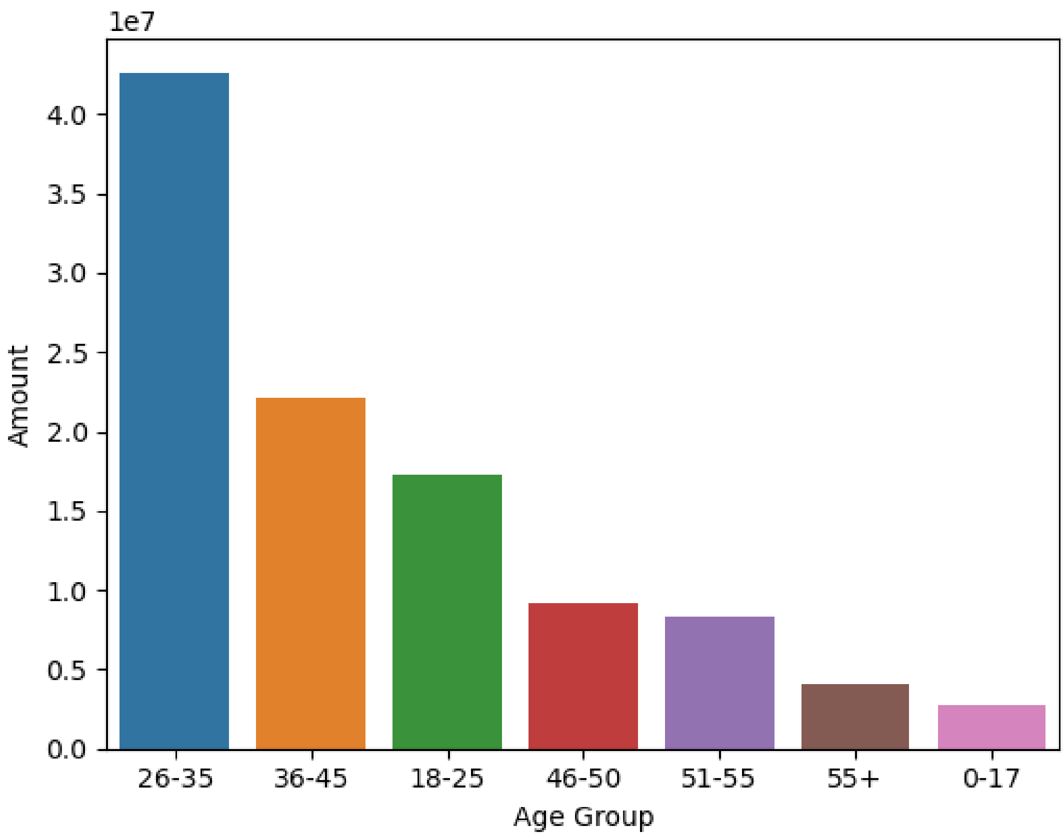
[37]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

[40]:
```
ax = sns.countplot(data = df, x = 'Age Group', hue = 'Gender')

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



[41]:
```
# Grouped the 'Age' Column, Grouped by Amount and took SUM and sorted the Vales.
↪
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)
```

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



By seeing the above graphs we can say that most of the buyers are of age group between 26-35 years and are Females.

1.0.2 State

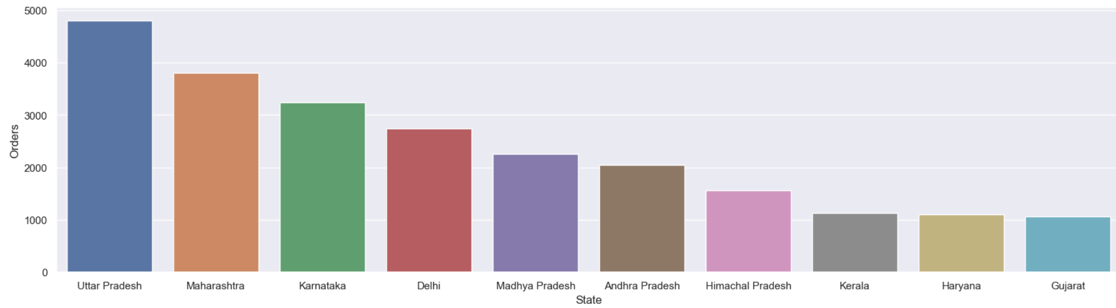
[42]:
```
df.columns
```

[42]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

[55]:
```
# Total number of Orders from Top 10 states

# Grouped the 'State' Column, Grouped by Orders and took SUM and sorted the␣
↪Vales.
sales_state = df.groupby(['State'], as_index = False) ['Orders'].sum().
↪sort_values(by = ['Orders'], ascending = False).head(10)

sns.set(rc = {'figure.figsize':(20,5)}) # setting plot size
```

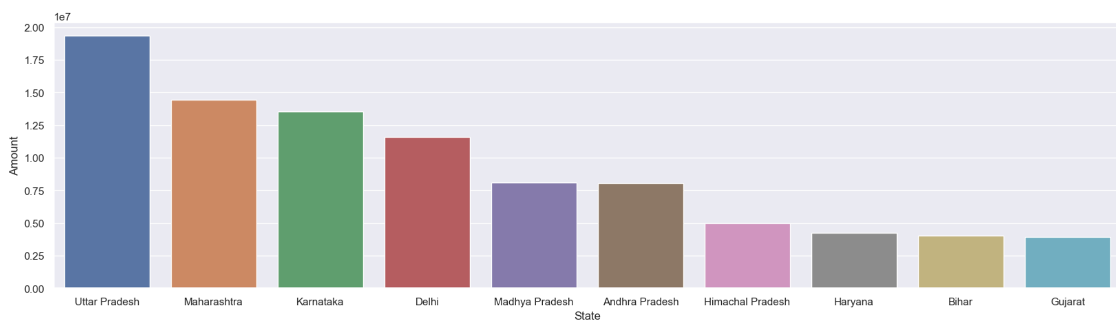
```
sns.barplot(x = 'State', y = 'Orders', data = sales_state)
```

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



[56]:
```
# Total Amount/Sales from Top 10 states

# Grouped the 'State' Column, Grouped by Amount and took SUM and sorted the␣
↪Vales.
sales_state = df.groupby(['State'], as_index = False) ['Amount'].sum().
↪sort_values(by = ['Amount'], ascending = False).head(10)

sns.set(rc = {'figure.figsize':(20,5)}) # setting plot size

sns.barplot(x = 'State', y = 'Amount', data = sales_state)
```

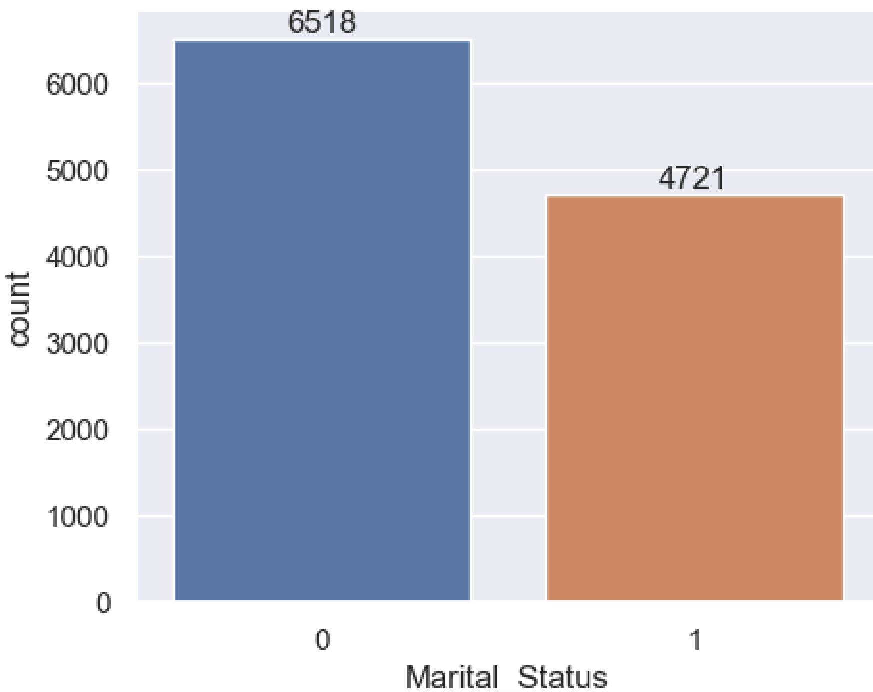
[56]: <Axes: xlabel='State', ylabel='Amount'>



From the above graphs we can see that unexpectedly most of the orders are from Uttar Pradesh, Maharashtra and Karnataka respectively.

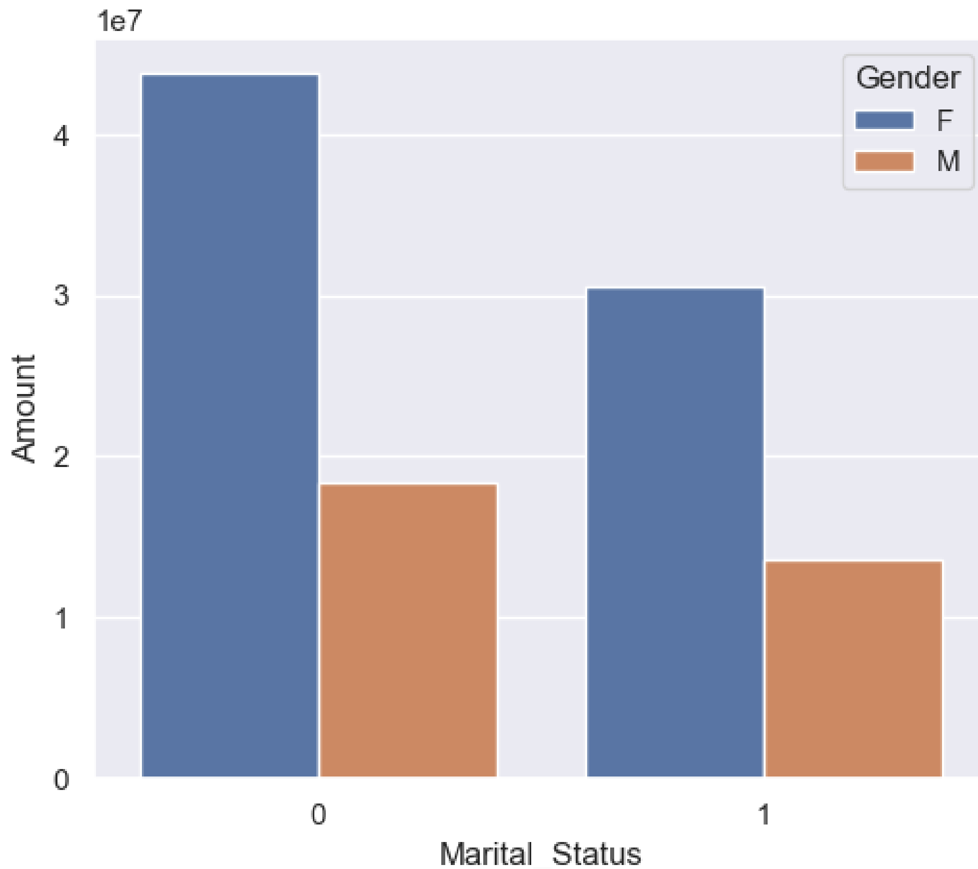
1.0.3 Marital Status

[63]:
```
ax = sns.countplot(x = 'Marital_Status', data = df)

sns.set(rc = {'figure.figsize':(6,4)})

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



[69]:
```
# Grouped the 'Marital Status' Column, Grouped by Amount and took SUM and
↪sorted the Vales.
sales_mar = 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(x = 'Marital_Status', y = 'Amount', data = sales_mar, hue =
↪'Gender')
```

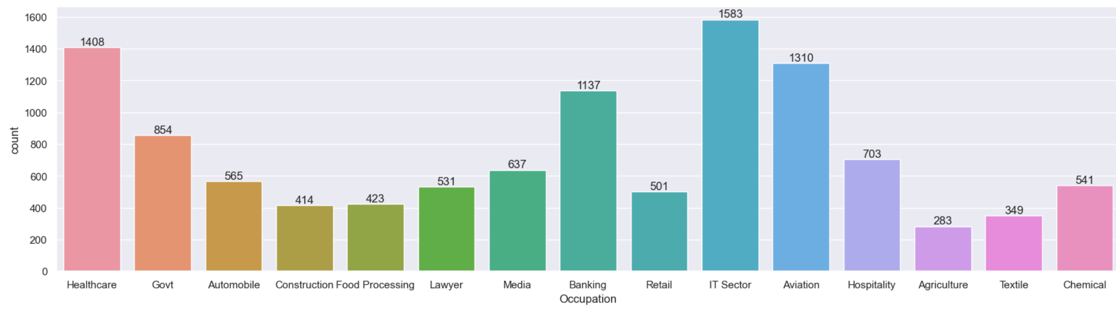
[69]:
```
<Axes: xlabel='Marital_Status', ylabel='Amount'>
```



From the above graphs we can say that most of the buyers are married [women] and they have high purchasing power.

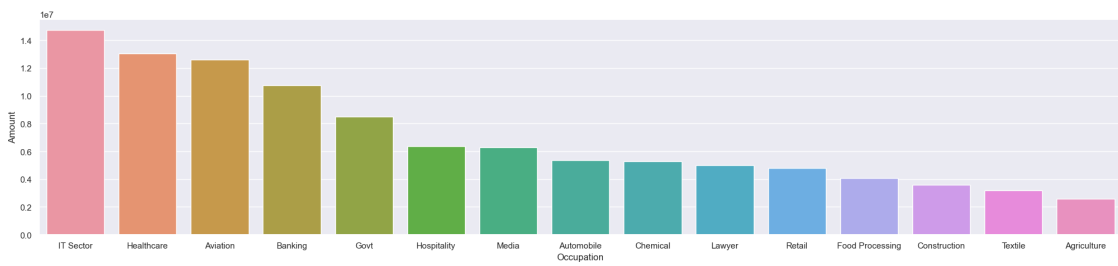
1.0.4 Occupation

[73]:
```
ax = sns.countplot(x = 'Occupation', data = df)

sns.set(rc = {'figure.figsize':(25,5)})

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




```
[78]: # Grouped the 'Occupation' Column, Grouped by Amount and took SUM and sorted␣
      ↪the Vales.
      sales_occ = df.groupby(['Occupation'], as_index = False) ['Amount'].sum().
      ↪sort_values(by = ['Amount'], ascending = False)

      sns.set(rc = {'figure.figsize':(25,5)})

      sns.barplot(x = 'Occupation', y = 'Amount', data = sales_occ)
```

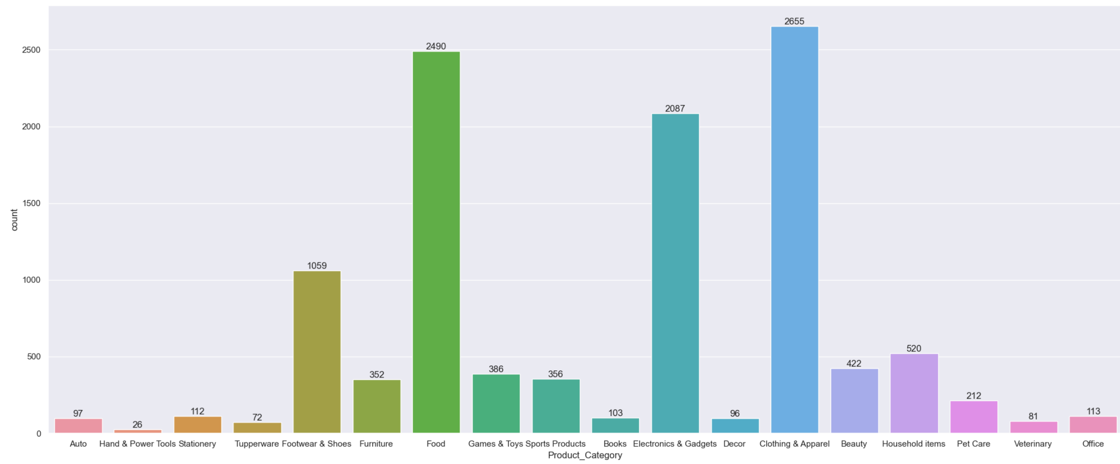
```
[78]: <Axes: xlabel='Occupation', ylabel='Amount'>
```



From the above graph we can say that most of the buyers are working in IT Sector, Aviation and Helthcare Sector.

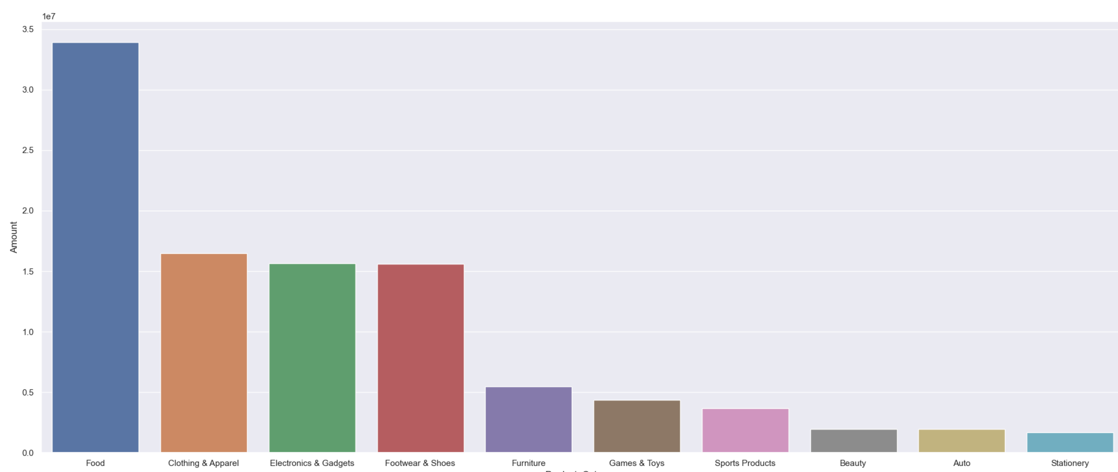
1.0.5 Product Category

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

      sns.set(rc = {'figure.figsize':(25,10)})

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



[87]:
```python
# Grouped the 'Product Category' Column, Grouped by Amount and took SUM and sorted the Vales.
sales_pc = df.groupby(['Product_Category'], as_index = False) ['Amount'].sum().sort_values(by = ['Amount'], ascending = False).head(10)

sns.set(rc = {'figure.figsize':(25,10)})

sns.barplot(x = 'Product_Category', y = 'Amount', data = sales_pc)
```

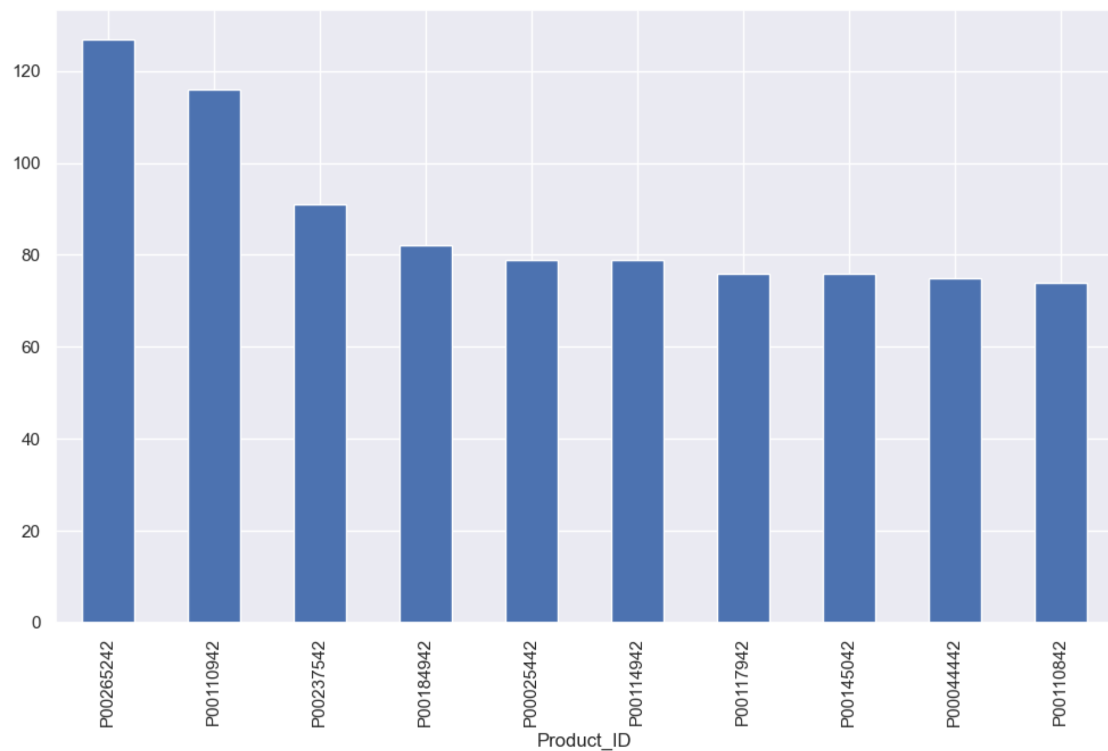
[87]: `<Axes: xlabel='Product_Category', ylabel='Amount'>`



From the above graph we see that the most sold product category are: Food, Clothing and Electronics Category.

[89]:
```
# Top 10 Most sold products

fig1, ax1 = plt.subplots(figsize=(12,7))

df.groupby('Product_ID')['Orders'].sum().nlargest(10).sort_values(ascending =
 ↪False).plot(kind = 'bar')
```

[89]:
```
<Axes: xlabel='Product_ID'>
```



2 Conclusion on the basis of Analysis:

–> Married women age group between 26-35 from Uttar Pradesh.

–> Maharashtra & Karnataka working in IT sector.

–> people are more likely to buy products from Clothing & Electronics Category.