

In [1]:

```
# import python libraries

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

In [2]:

```
# import csv file
df = pd.read_csv('Diwali Sales Data.csv', encoding= 'unicode_escape')
```

In [3]:

```
df.shape
```

Out[3]:

(11251, 15)

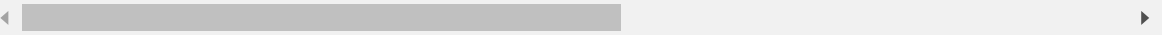
In [5]:

```
df
```

Out[5]:

	User_ID	Cust_name	Product_ID	Gender	Age Group	Age	Marital_Status	State
0	1002903	Sanskriti	P00125942	F	26-35	28	0	Maharashtra
1	1000732	Kartik	P00110942	F	26-35	35	1	Andhra Pradesh
2	1001990	Bindu	P00118542	F	26-35	35	1	Uttar Pradesh
3	1001425	Sudevi	P00237842	M	0-17	16	0	Karnataka
4	1000588	Joni	P00057942	M	26-35	28	1	Gujarat
...
11246	1000695	Manning	P00296942	M	18-25	19	1	Maharashtra
11247	1004089	Reichenbach	P00171342	M	26-35	33	0	Haryana
11248	1001209	Oshin	P00201342	F	36-45	40	0	Madhya Pradesh
11249	1004023	Noonan	P00059442	M	36-45	37	0	Karnataka
11250	1002744	Brumley	P00281742	F	18-25	19	0	Maharashtra

11251 rows × 15 columns



In [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
```

In [7]:

```
#drop unrelated/blank columns
df.drop(['Status', 'unnamed1'], axis=1, inplace=True)
```

In [8]:

```
#check for null values
pd.isnull(df).sum()
```

Out[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
```

In [9]:

```
# drop null values
df.dropna(inplace=True)
```

In [10]:

```
# change data type
df['Amount'] = df['Amount'].astype('int')
```

In [11]:

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

Out[11]:

```
dtype('int32')
```

In [12]:

```
df.columns
```

Out[12]:

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

In [13]:

```
#rename column
df.rename(columns= {'Marital_Status':'Shaadi'})
```

Out[13]:

	User_ID	Cust_name	Product_ID	Gender	Age Group	Age	Shaadi	State	Z
0	1002903	Sanskriti	P00125942	F	26-35	28	0	Maharashtra	Wes
1	1000732	Kartik	P00110942	F	26-35	35	1	Andhra Pradesh	Soutl
2	1001990	Bindu	P00118542	F	26-35	35	1	Uttar Pradesh	Ce
3	1001425	Sudevi	P00237842	M	0-17	16	0	Karnataka	Soutl
4	1000588	Joni	P00057942	M	26-35	28	1	Gujarat	Wes
...
11246	1000695	Manning	P00296942	M	18-25	19	1	Maharashtra	Wes
11247	1004089	Reichenbach	P00171342	M	26-35	33	0	Haryana	Nortl
11248	1001209	Oshin	P00201342	F	36-45	40	0	Madhya Pradesh	Ce
11249	1004023	Noonan	P00059442	M	36-45	37	0	Karnataka	Soutl
11250	1002744	Brumley	P00281742	F	18-25	19	0	Maharashtra	Wes

11239 rows × 13 columns

In [14]:

```
# describe() method returns description of the data in the DataFrame (i.e. count, mean, s
df.describe()
```

Out[14]:

	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

In [15]:

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

Out[15]:

	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

Exploratory Data Analysis

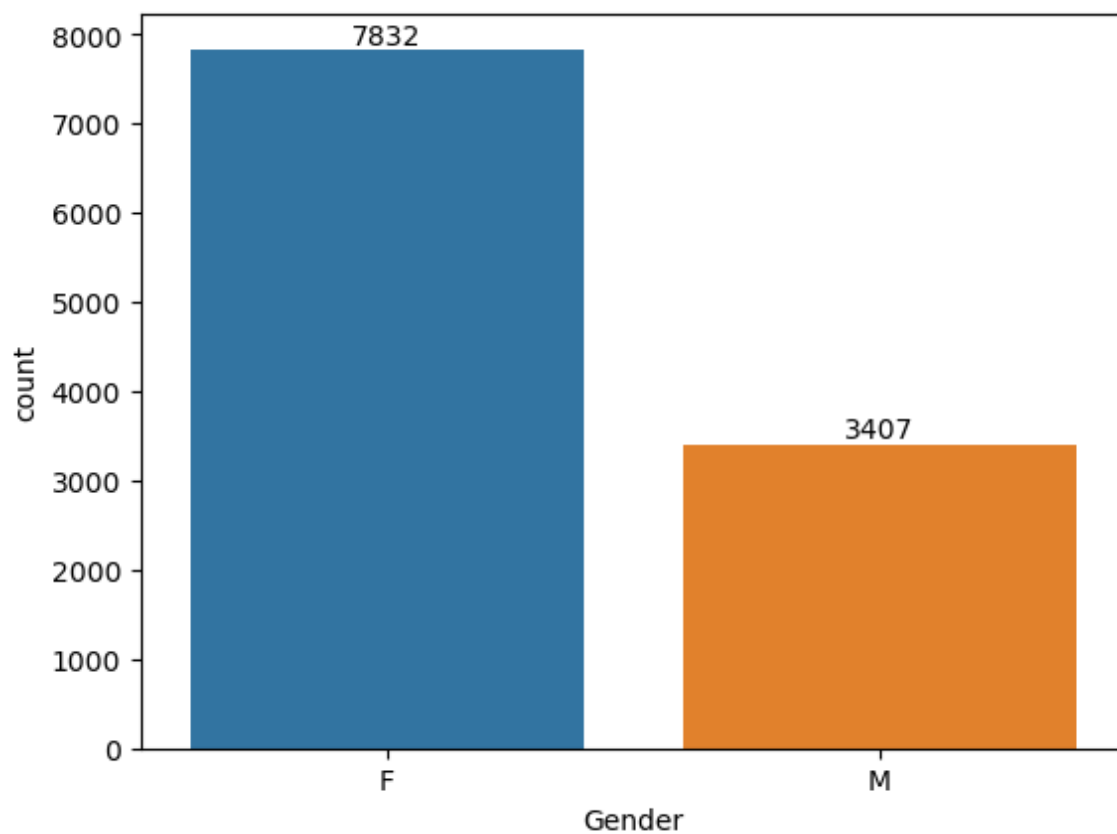
Gender

In [16]:

```
# 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)
```

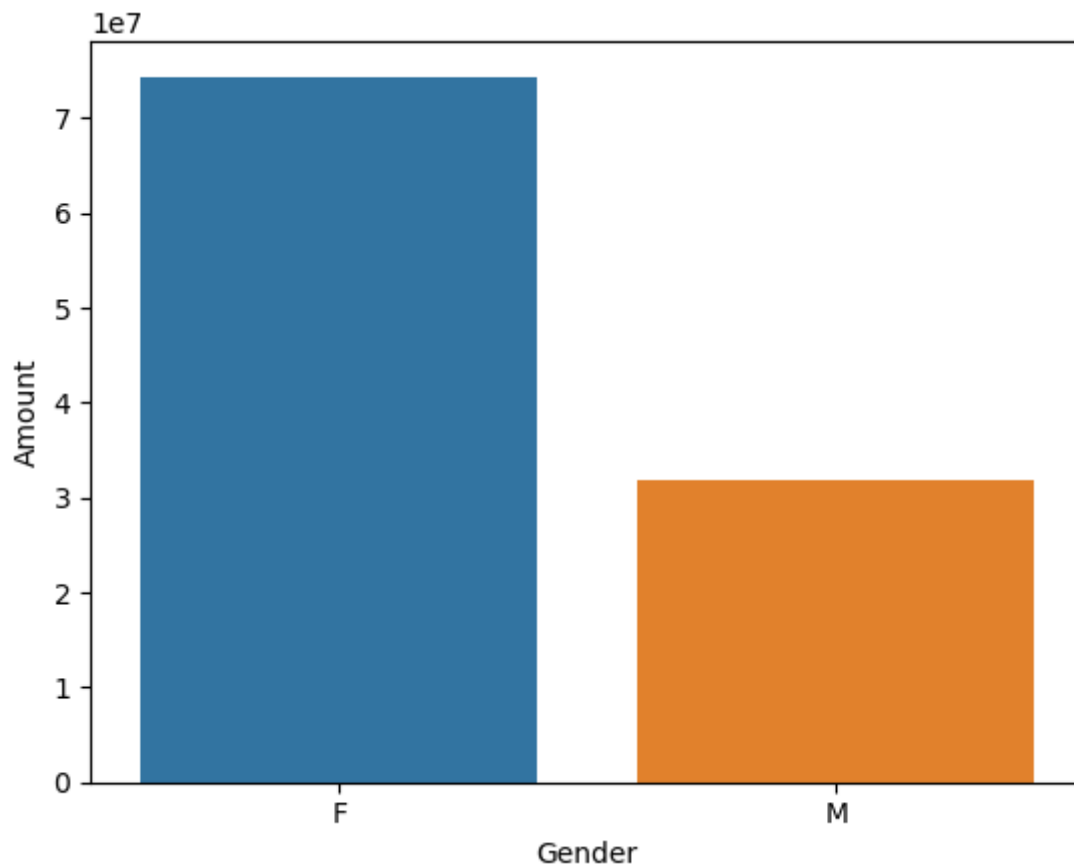


In [17]:

```
# plotting a bar chart for gender vs total amount  
sales_gen = df.groupby(['Gender'], as_index=False)['Amount'].sum().sort_values(by='Amount')  
sns.barplot(x = 'Gender',y= 'Amount' ,data = sales_gen)
```

Out[17]:

<AxesSubplot:xlabel='Gender', ylabel='Amount'>

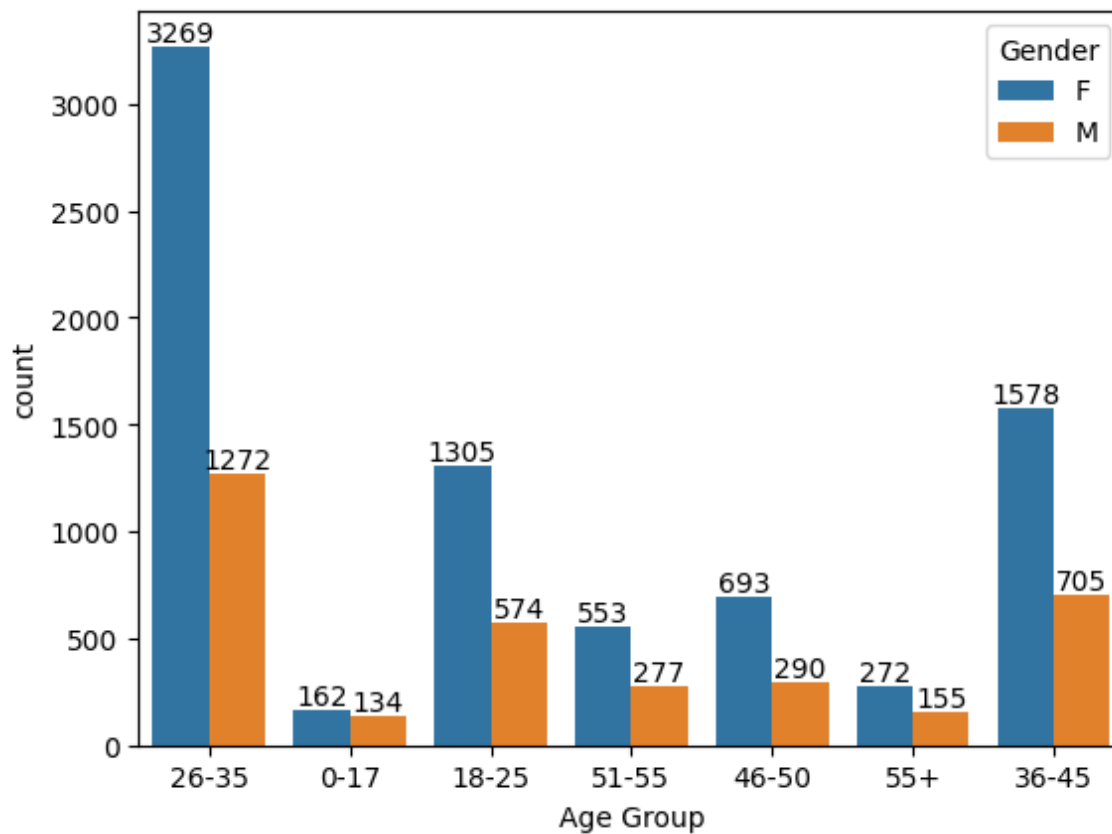


From above graphs we can see that most of the buyers are females and even the purchasing power of females are greater than men

Age

In [17]:

```
ax = sns.countplot(data = df, x = 'Age Group', hue = 'Gender')  
  
for bars in ax.containers:  
    ax.bar_label(bars)
```

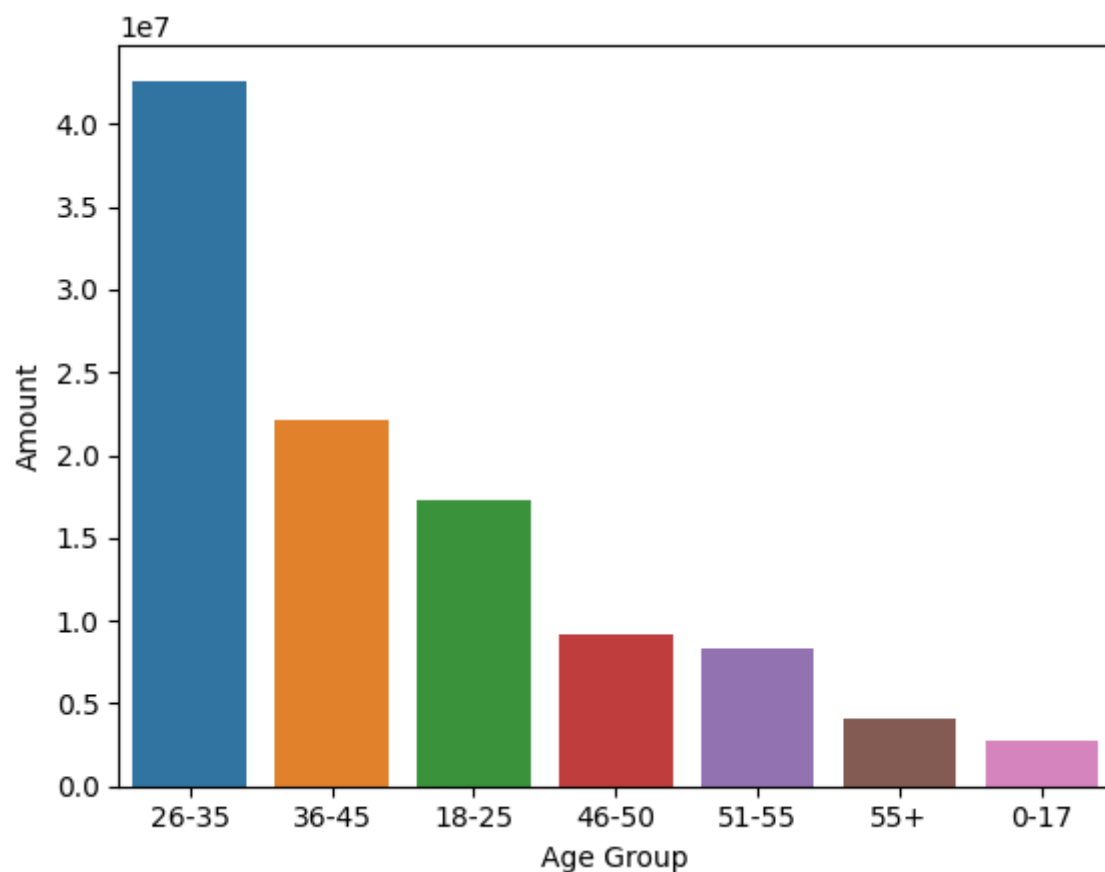


In [18]:

```
# 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)
```

Out[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

State

In [19]:

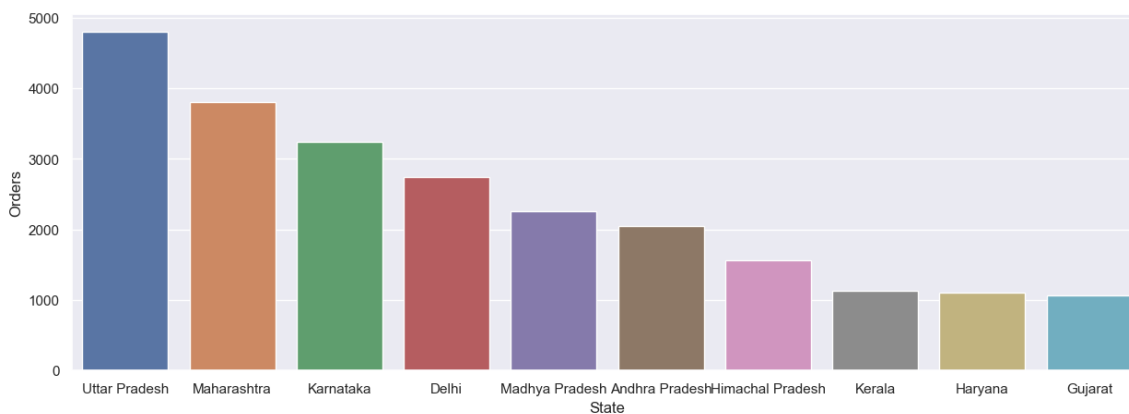
```
# total number of orders from top 10 states

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

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

Out[19]:

<AxesSubplot:xlabel='State', ylabel='Orders'>



In [20]:

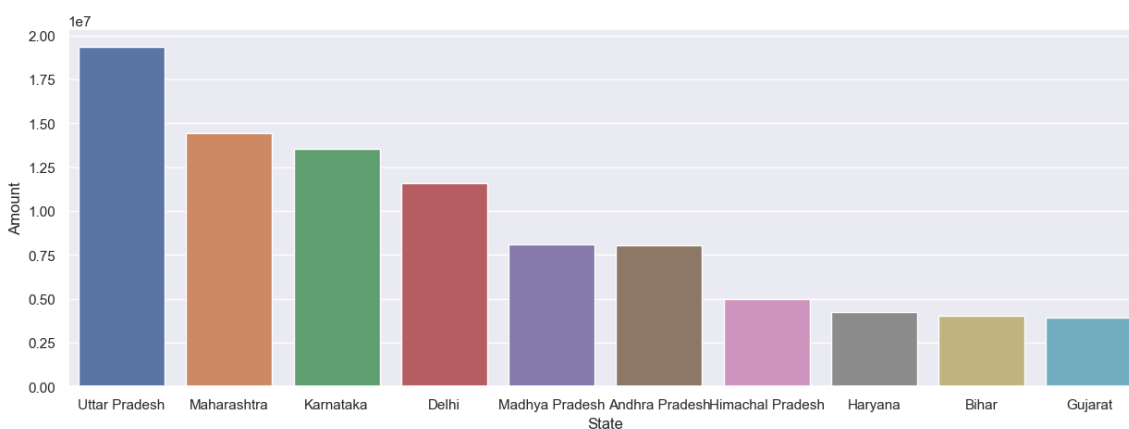
```
# total amount/sales from top 10 states

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

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

Out[20]:

<AxesSubplot:xlabel='State', ylabel='Amount'>

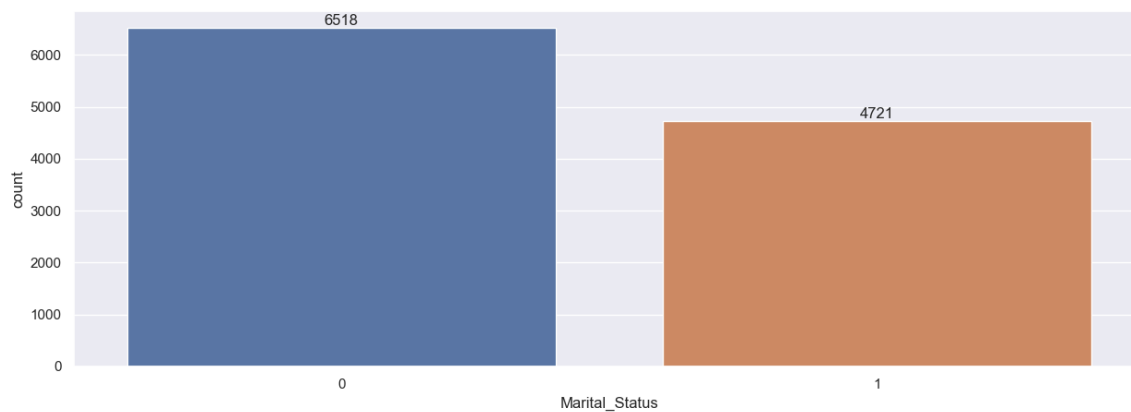


From above graphs we can see that most of the orders & total sales/amount are from Uttar Pradesh, Maharashtra and Karnataka respectively

Marital Status

In [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)
```



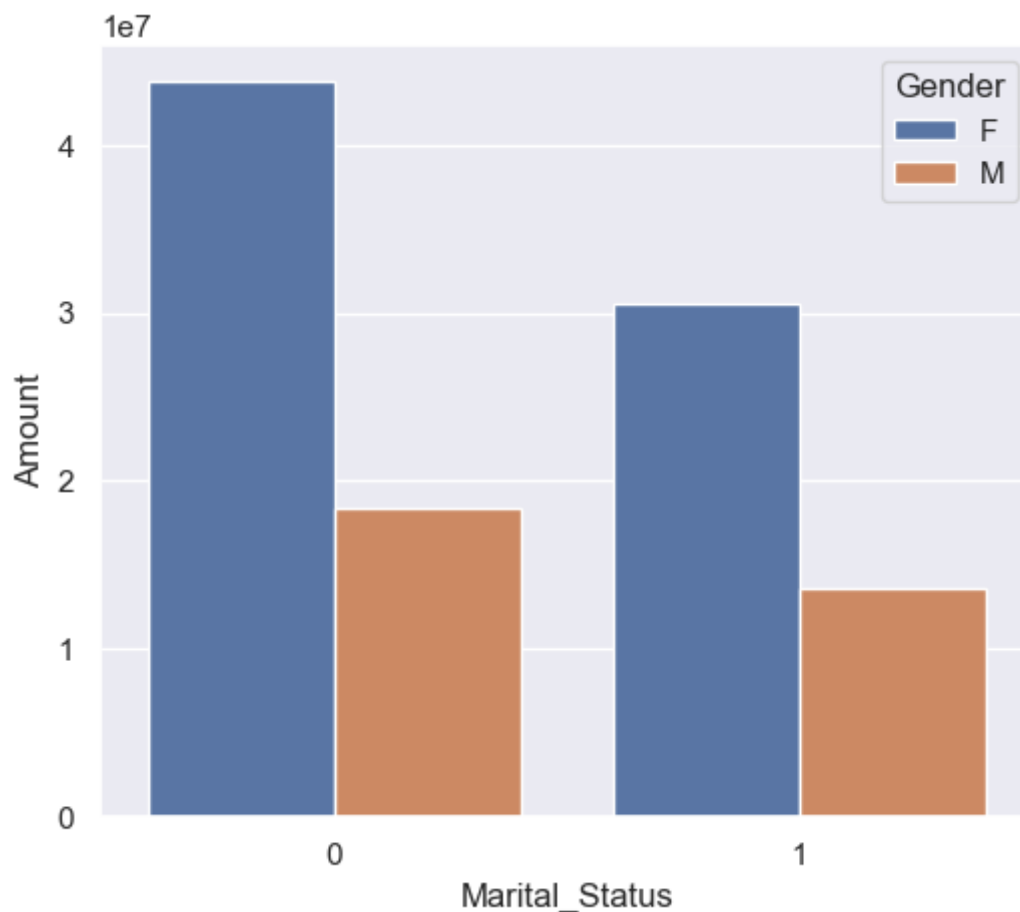
In [22]:

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

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

Out[22]:

<AxesSubplot:xlabel='Marital_Status', ylabel='Amount'>



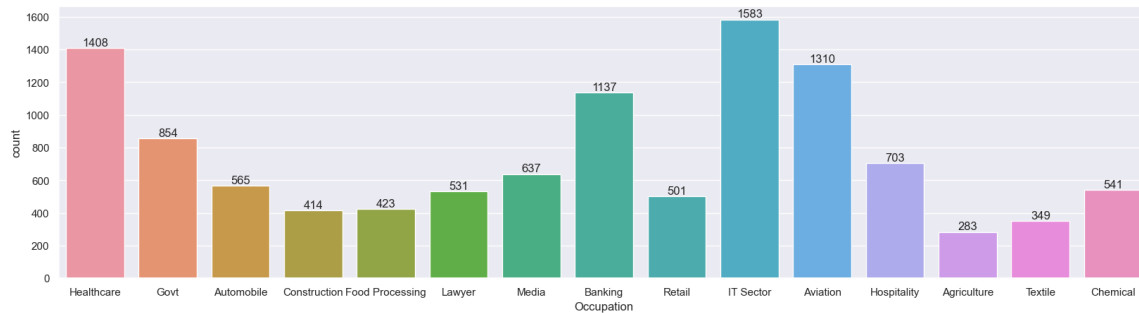
From above graphs we can see that most of the buyers are married (women) and they have high purchasing power

Occupation

In [23]:

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

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



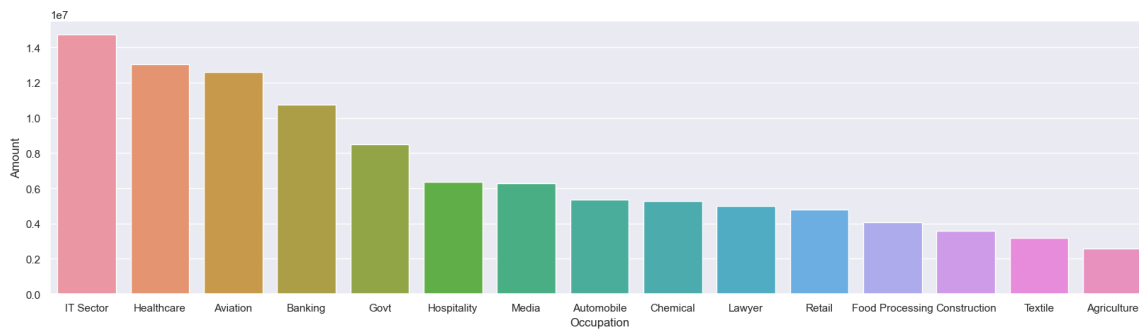
In [26]:

```
sales_state = df.groupby(['Occupation'], as_index=False)['Amount'].sum().sort_values(by='Amount')
```

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

Out[26]:

<AxesSubplot:xlabel='Occupation', ylabel='Amount'>



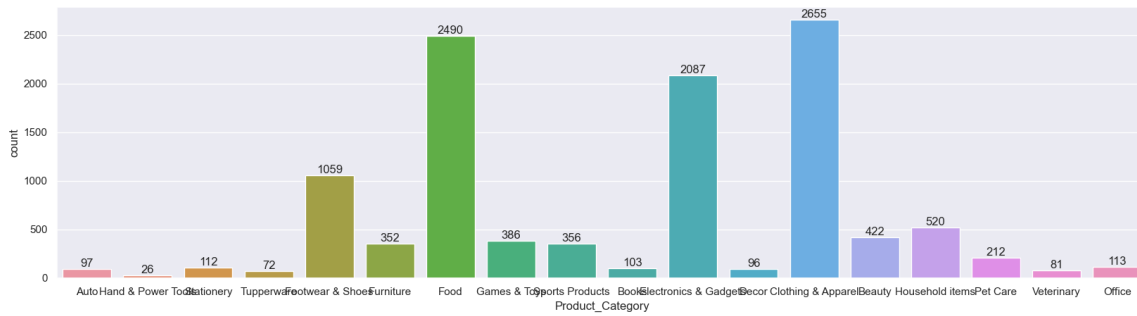
From above graphs we can see that most of the buyers are working in IT, Healthcare and Aviation sector

Product Category

In [27]:

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

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



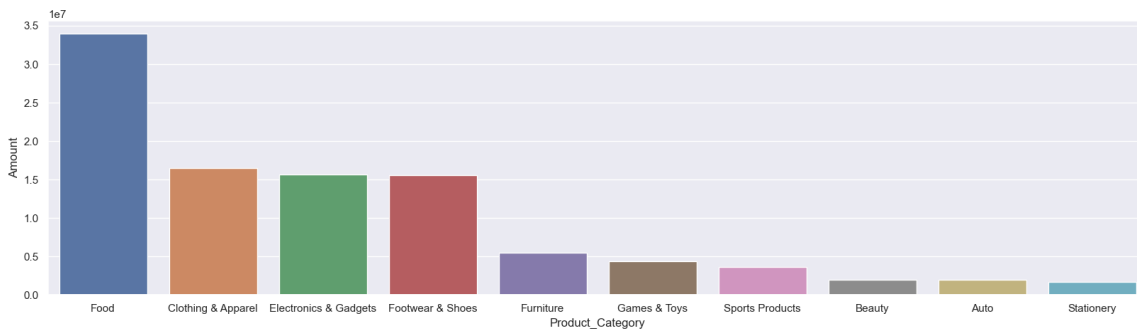
In [28]:

```
sales_state = df.groupby(['Product_Category'], as_index=False)['Amount'].sum().sort_values

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

Out[28]:

<AxesSubplot:xlabel='Product_Category', ylabel='Amount'>



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

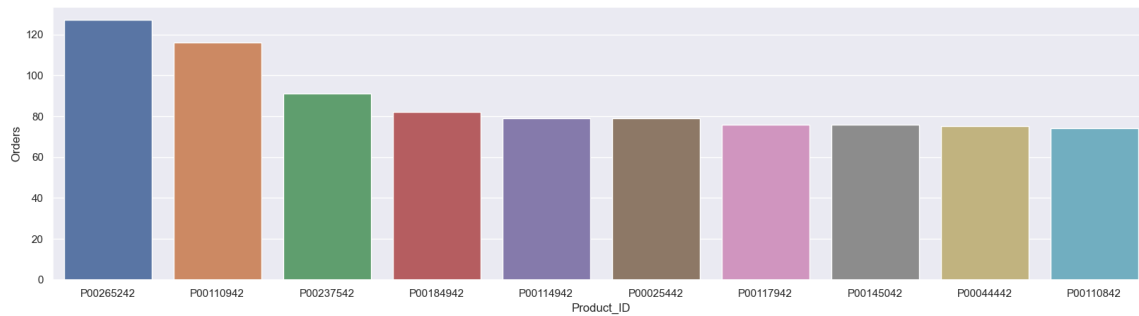
In [29]:

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

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

Out[29]:

<AxesSubplot:xlabel='Product_ID', ylabel='Orders'>



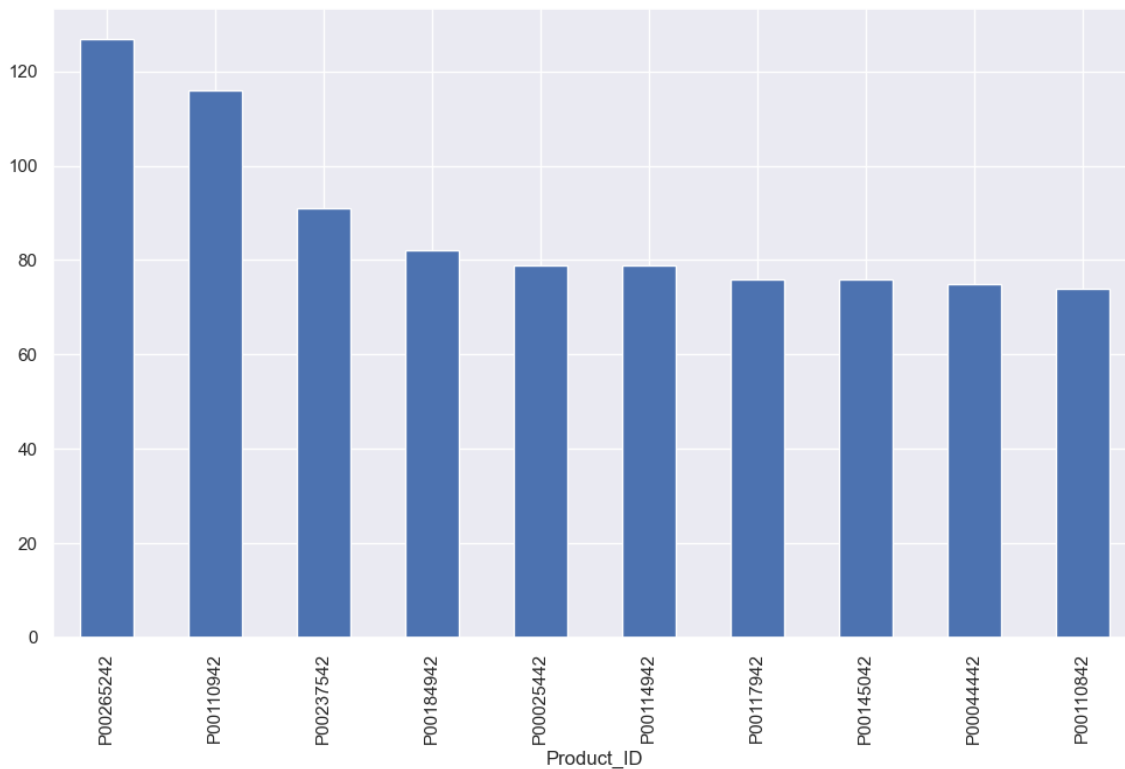
In [30]:

```
# 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', ax=ax1)
```

Out[30]:

<AxesSubplot:xlabel='Product_ID'>



Conclusion:

Married women age group 26-35 yrs from UP, Maharastra and Karnataka working in IT, Healthcare and Aviation are more likely to buy products from Food, Clothing and Electronics category

In []: