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 [11]:

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

In [12]:

```
df.shape
```

Out[12]:

```
(11251, 15)
```

In [13]:

```
df.head()
```

Out[13]:

| | User_ID | Cust_name | Product_ID | Gender | Age Group | Age | Marital_Status | State | Z |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1002903 | Sanskriti | P00125942 | F | 26-35 | 28 | 0 | Maharashtra | Wes |
| **1** | 1000732 | Kartik | P00110942 | F | 26-35 | 35 | 1 | Andhra Pradesh | Sout |
| **2** | 1001990 | Bindu | P00118542 | F | 26-35 | 35 | 1 | Uttar Pradesh | Ce |
| **3** | 1001425 | Sudevi | P00237842 | M | 0-17 | 16 | 0 | Karnataka | Sout |
| **4** | 1000588 | Joni | P00057942 | M | 26-35 | 28 | 1 | Gujarat | Wes |

In [14]:

```
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 [15]:

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

In [16]:

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

Out[16]:

```
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 [17]:

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

In [18]:
```python
# change data type
df['Amount'] = df['Amount'].astype('int')
```

In [19]:
```python
df['Amount'].dtypes
```

Out[19]:
```
dtype('int32')
```

In [20]:
```python
df.columns
```

Out[20]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

In [21]:
```python
#rename column
df.rename(columns= {'Marital_Status':'Shaadi'})
```

Out[21]:

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

11239 rows × 13 columns

In [22]:

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

Out[22]:

| | 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 [23]:

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

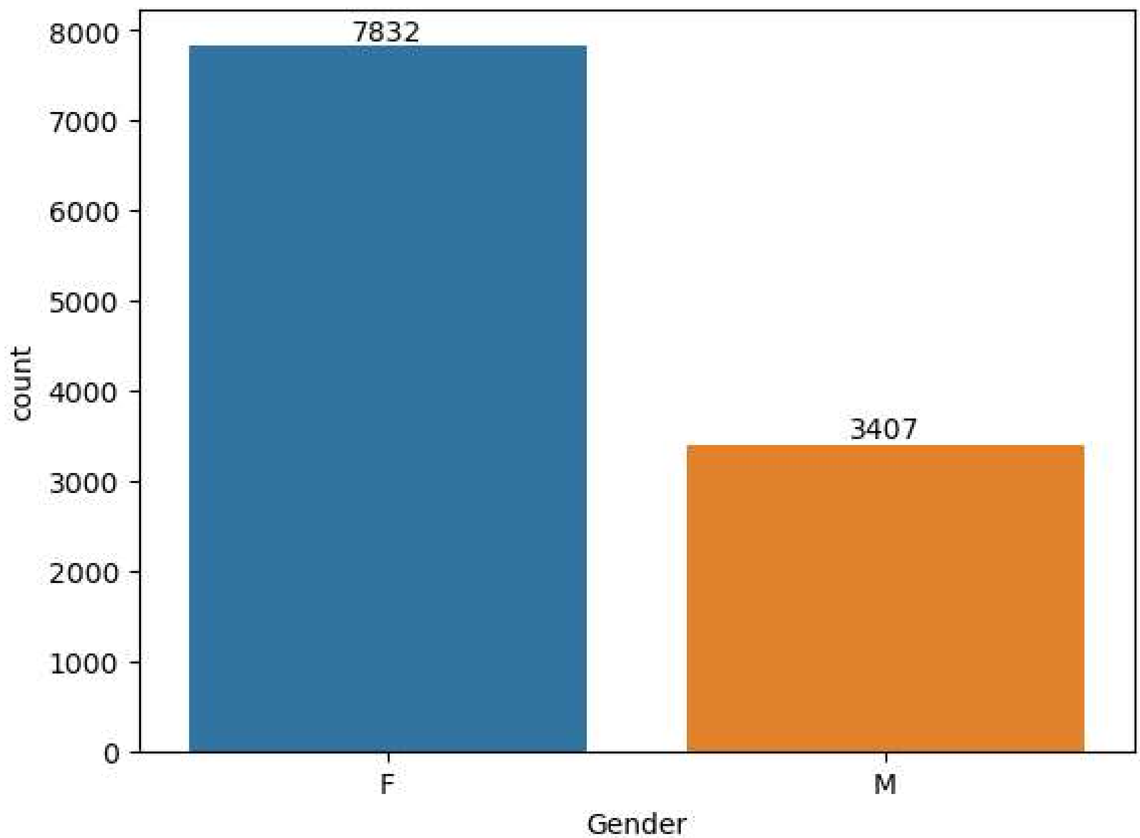
Out[23]:

| | 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

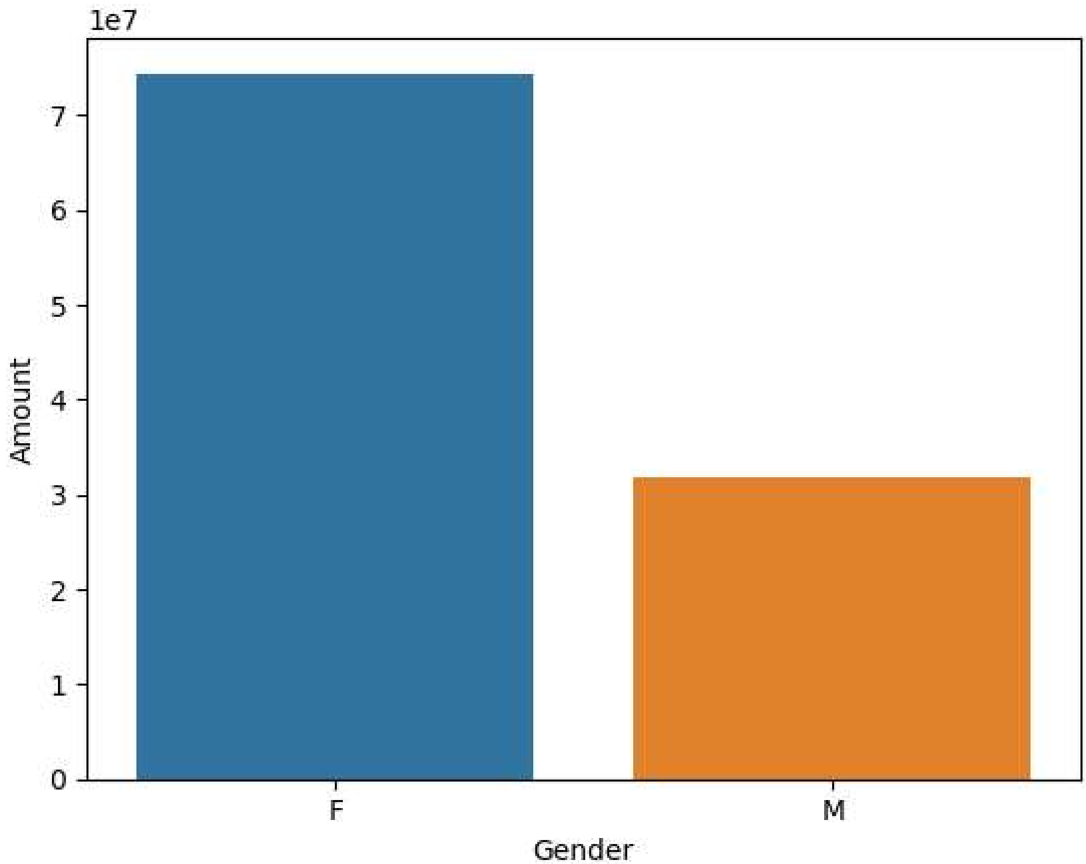
In [24]:
```
# plotting a bar chart for Gender and it's count

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

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



In [25]:

```
# plotting a bar chart for gender vs total amount

sales_gen = df.groupby(['Gender'], as_index=False)['Amount'].sum().sort_v

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

Out[25]: <Axes: xlabel='Gender', ylabel='Amount'>

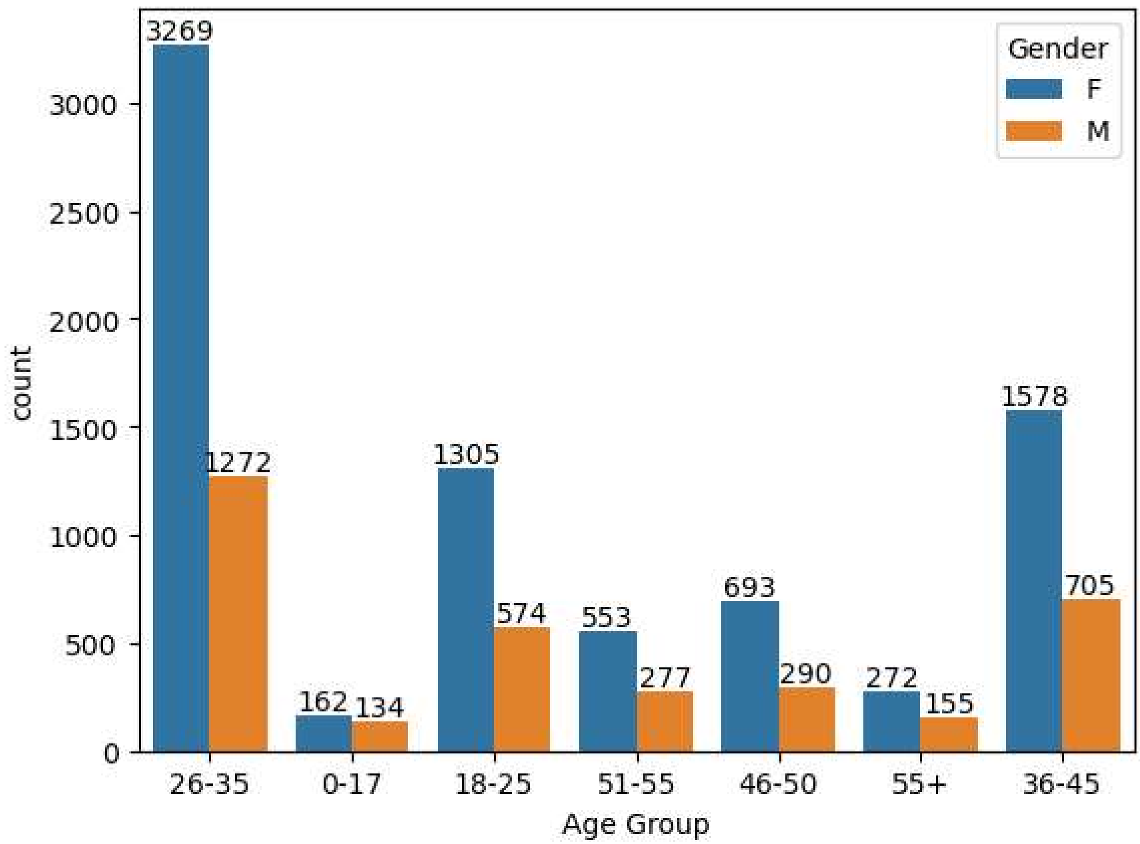



*From above graphs we can see that most of the buyers are females and even the purchasing power of females are greater than men*

## Age

In [26]:

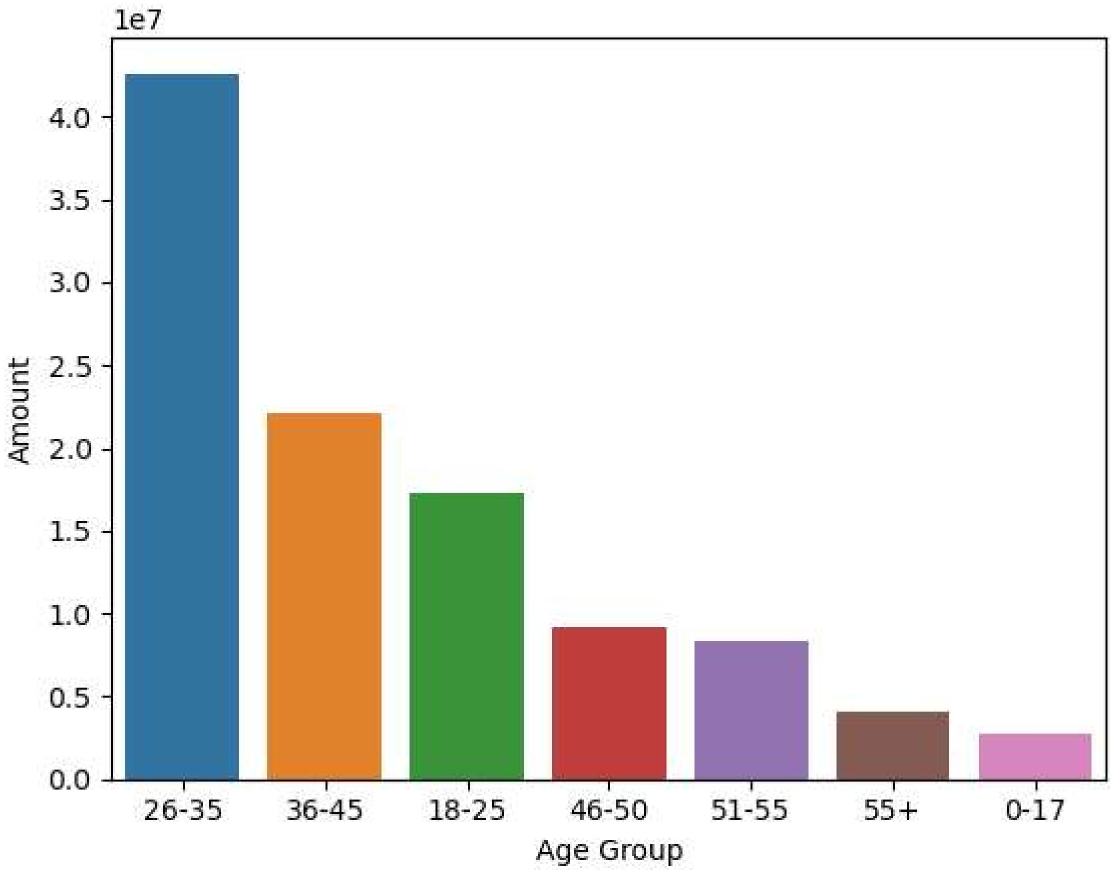
```
ax = sns.countplot(data = df, x = 'Age Group', hue = 'Gender')

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



In [27]:

```
# Total Amount vs Age Group
sales_age = df.groupby(['Age Group'], as_index=False)['Amount'].sum().sor

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

Out[27]: <Axes: xlabel='Age Group', ylabel='Amount'>

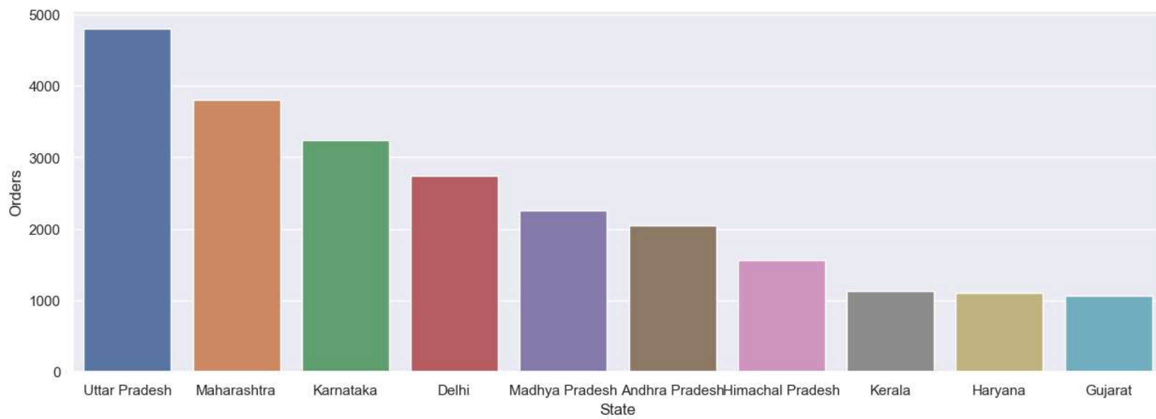



*From above graphs we can see that most of the buyers are of age group between 26-35 yrs female*

## State

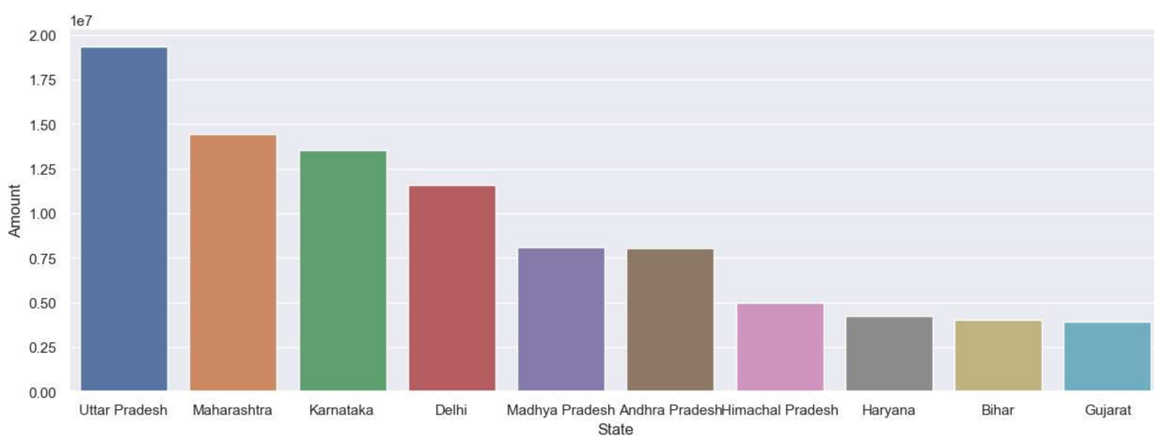
In [28]:
```
# total number of orders from top 10 states

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

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

Out[28]: <Axes: xlabel='State', ylabel='Orders'>




In [29]:
```
# total amount/sales from top 10 states

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

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

Out[29]: <Axes: xlabel='State', ylabel='Amount'>

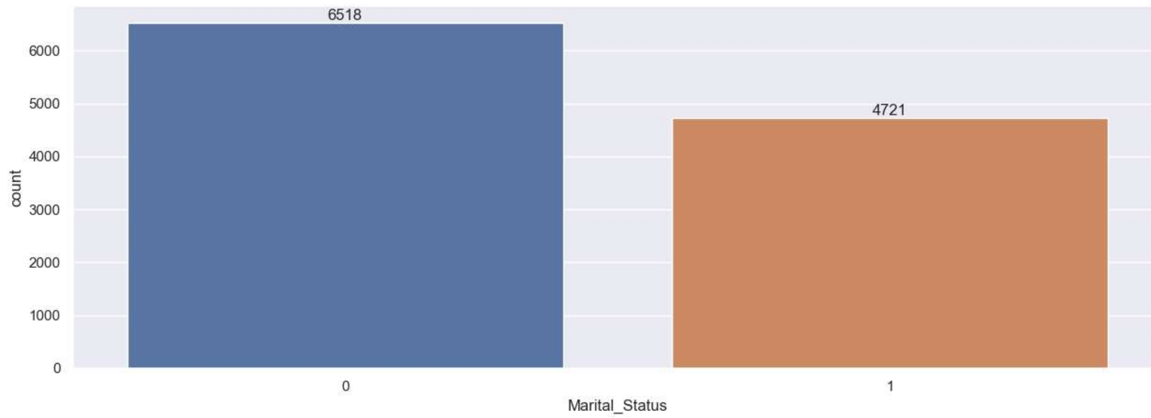



*From above graphs we can see that most of the orders & total sales/amount are from Uttar Pradesh, Maharashtra and Karnataka respectively*

## Marital Status

In [30]:

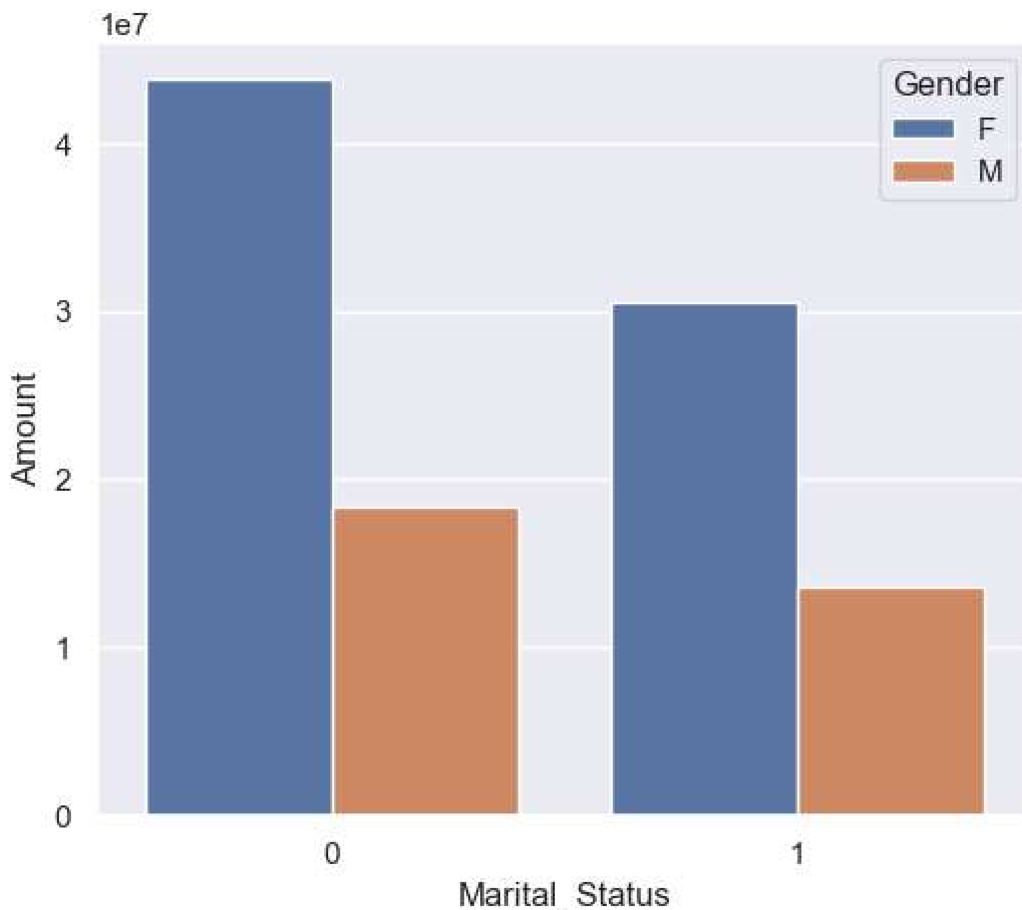
```
ax = sns.countplot(data = df, x = 'Marital_Status')

sns.set(rc={'figure.figsize':(7,5)})
for bars in ax.containers:
    ax.bar_label(bars)
```



In [31]:

```
sales_state = df.groupby(['Marital_Status', 'Gender'], as_index=False)['A
sns.set(rc={'figure.figsize':(6,5)})
sns.barplot(data = sales_state, x = 'Marital_Status',y= 'Amount', hue='G
```

Out[31]: <Axes: xlabel='Marital_Status', ylabel='Amount'>

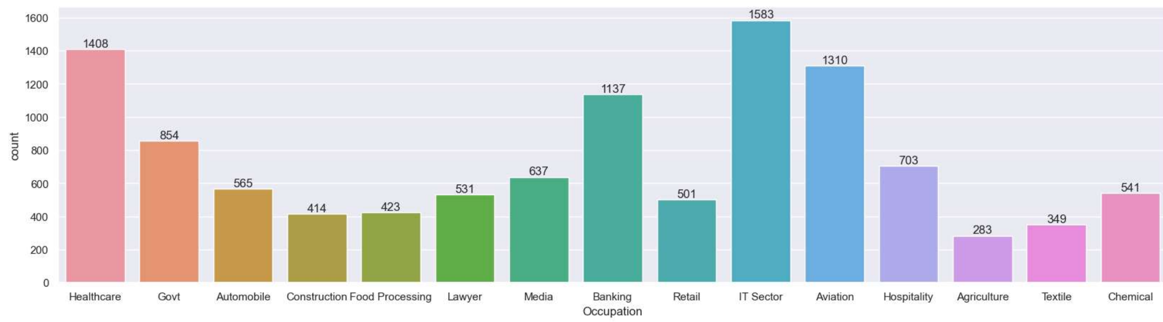



*From above graphs we can see that most of the buyers are married (women) and they have high purchasing power*

## Occupation

In [32]:

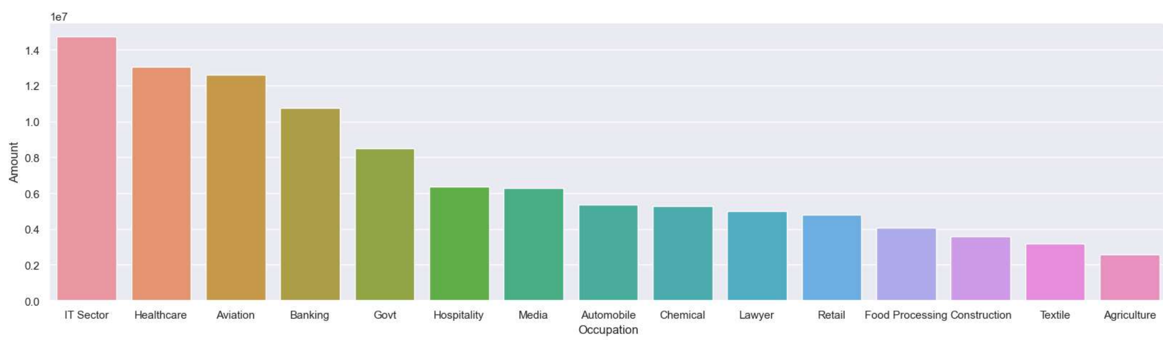
```
sns.set(rc={'figure.figsize':(20,5)})
ax = sns.countplot(data = df, x = 'Occupation')

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




In [33]:

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

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

Out[33]: <Axes: xlabel='Occupation', ylabel='Amount'>

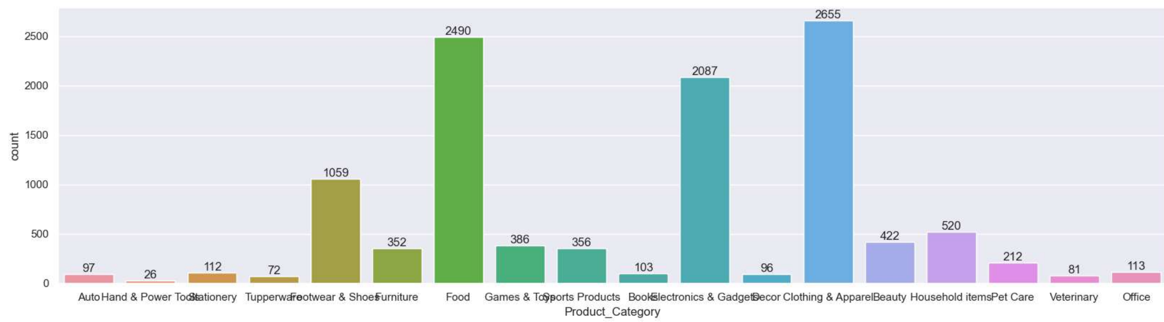



*From above graphs we can see that most of the buyers are working in IT, Healthcare and Aviation sector*

## Product Category

In [34]:

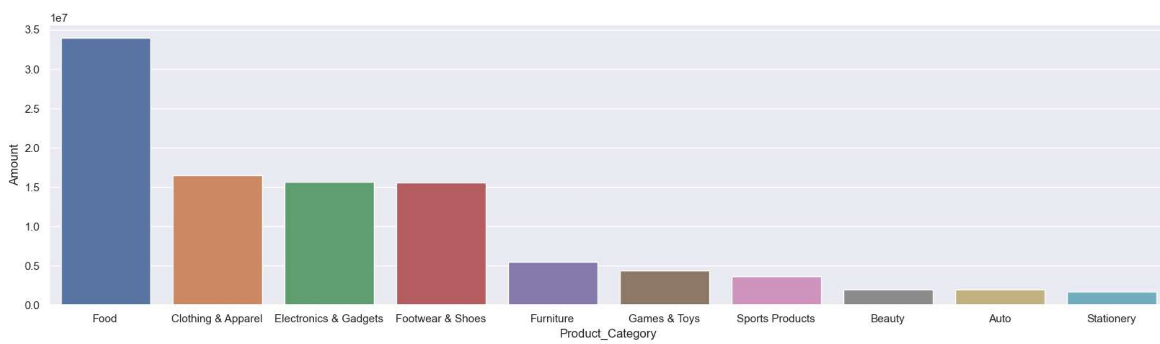
```python
sns.set(rc={'figure.figsize':(20,5)})
ax = sns.countplot(data = df, x = 'Product_Category')

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




In [35]:

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

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

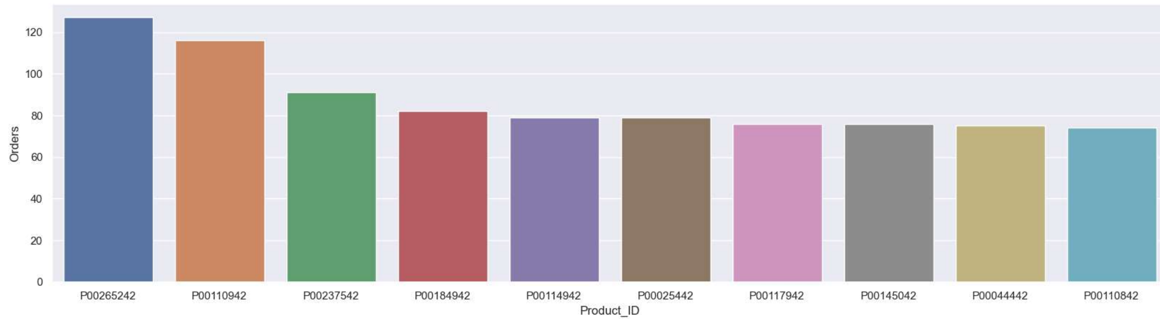
Out[35]: <Axes: xlabel='Product_Category', ylabel='Amount'>




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

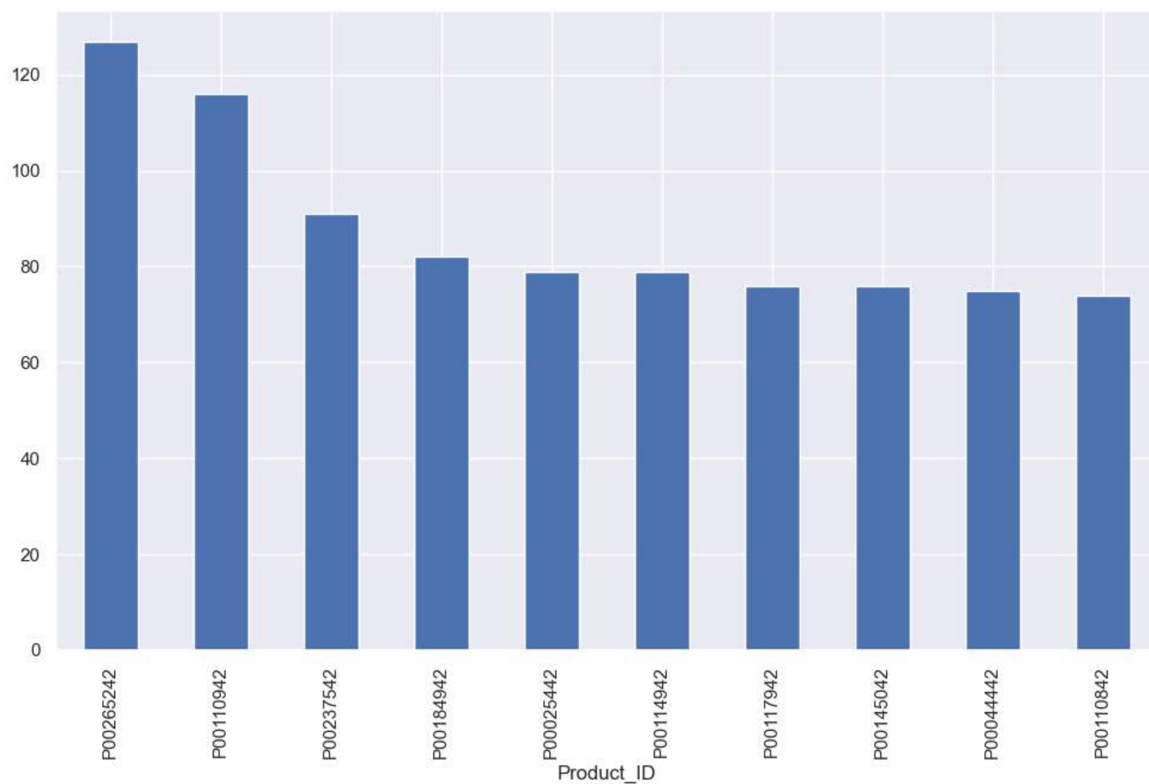
In [36]:
```
sales_state = df.groupby(['Product_ID'], as_index=False)['Orders'].sum()

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

Out[36]: <Axes: xlabel='Product_ID', ylabel='Orders'>




In [37]:
```
# 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(ascend
```

Out[37]: <Axes: 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*

Thank you!