In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
df=pd.read_csv(r"C:\Users\Sanath\Desktop\Diwali Sales Data.csv",encoding = 'unicode_escape')
df.head()
```

Out[1]:

| | User_ID | Cust_name | Product_ID | Gender | Age Group | Age | Marital_Status | State | Zone | Occupation | Product_Category | Orders | An |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1002903 | Sanskriti | P00125942 | F | 26-35 | 28 | 0 | Maharashtra | Western | Healthcare | Auto | 1 | 23 |
| 1 | 1000732 | Kartik | P00110942 | F | 26-35 | 35 | 1 | Andhra Pradesh | Southern | Govt | Auto | 3 | 23 |
| 2 | 1001990 | Bindu | P00118542 | F | 26-35 | 35 | 1 | Uttar Pradesh | Central | Automobile | Auto | 3 | 23 |
| 3 | 1001425 | Sudevi | P00237842 | M | 0-17 | 16 | 0 | Karnataka | Southern | Construction | Auto | 2 | 23 |
| 4 | 1000588 | Joni | P00057942 | M | 26-35 | 28 | 1 | Gujarat | Western | Food Processing | Auto | 2 | 23 |

In [2]:
```
df.shape
```

Out[2]:
```
(11251, 15)
```

In [3]:
```
#data cleaning
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 [4]:
```
#1dropping unwanted data
df.drop(['Status','unnamed1'],axis=1,inplace=True)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11251 entries, 0 to 11250
Data columns (total 13 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
dtypes: float64(1), int64(4), object(8)
memory usage: 1.1+ MB
```

In [6]:
```
#checking null
pd.isnull(df).sum()
```

Out[6]:
```
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 [7]:
```
#drop null values in amount col
df.dropna(inplace=True)
```

In [8]:
```
#12 rows having null value are dropped i.e 11251->11239
df.shape
```

Out[8]:
```
(11239, 13)
```

In [9]:
```
pd.isnull(df).sum()
```

Out[9]:
```
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              0
dtype: int64
```

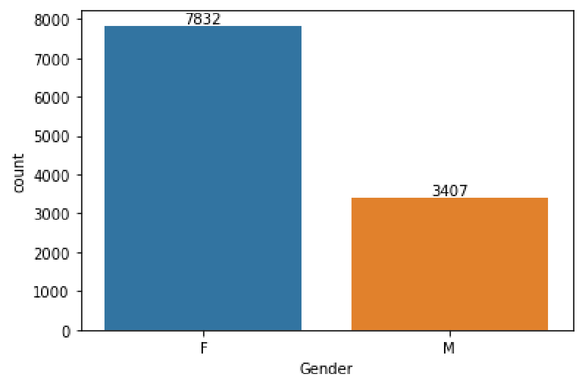
In [10]:
```
df.describe()
```

Out[10]:

| | 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 | 9453.610858 |
| **std** | 1.716039e+03 | 12.753866 | 0.493589 | 1.114967 | 5222.355869 |
| **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 |

# EDA(Exploratory Data Analysis)

In [11]:
```
#No.of Males and Females
a=sns.countplot(x='Gender',data=df)
for bars in a.containers:
    a.bar_label(bars)
```



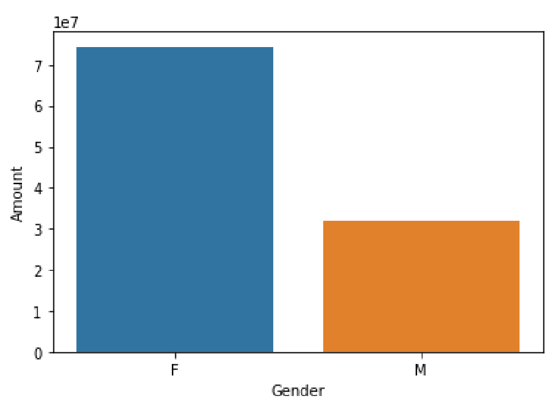

In [12]:
```
#Amount generated by female/male
df.groupby(['Gender'],as_index=False)['Amount'].sum()
```

Out[12]:

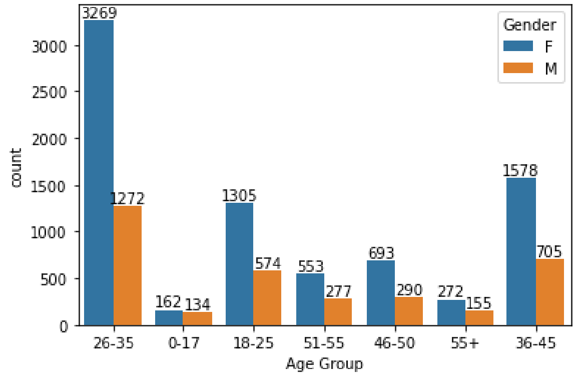
| | Gender | Amount |
|---|---|---|
| **0** | F | 74335856.43 |
| **1** | M | 31913276.00 |

In [13]:
```
#Amount generated by female/male
a1=df.groupby(['Gender'],as_index=False)['Amount'].sum()
sns.barplot(x='Gender',y='Amount',data=a1)
```

Out[13]: <AxesSubplot:xlabel='Gender', ylabel='Amount'>

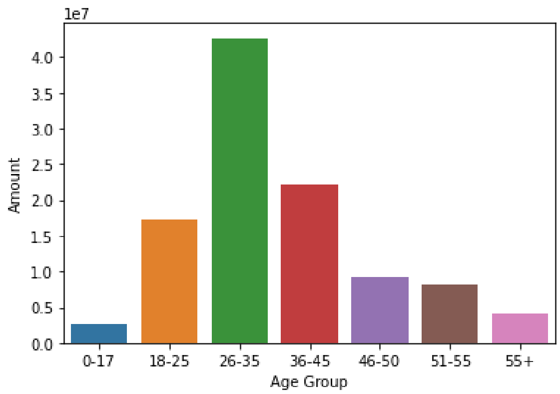


In [14]:
```
#agegroup
a3=sns.countplot(data=df,x='Age Group',hue='Gender')
for bars in a3.containers:
    a3.bar_label(bars)
```



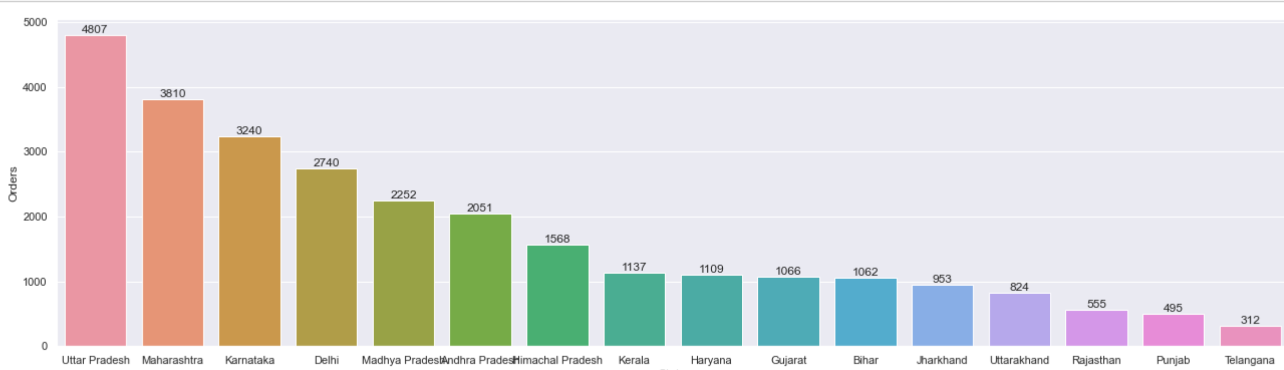

In [15]:
```
#Total amount spend by age group
a4=df.groupby(['Age Group'],as_index=False)['Amount'].sum()
sns.barplot(x='Age Group',y='Amount',data=a4)
```

Out[15]: <AxesSubplot:xlabel='Age Group', ylabel='Amount'>




# From above graph we can see that most of the buyers are females of age group of 26-35

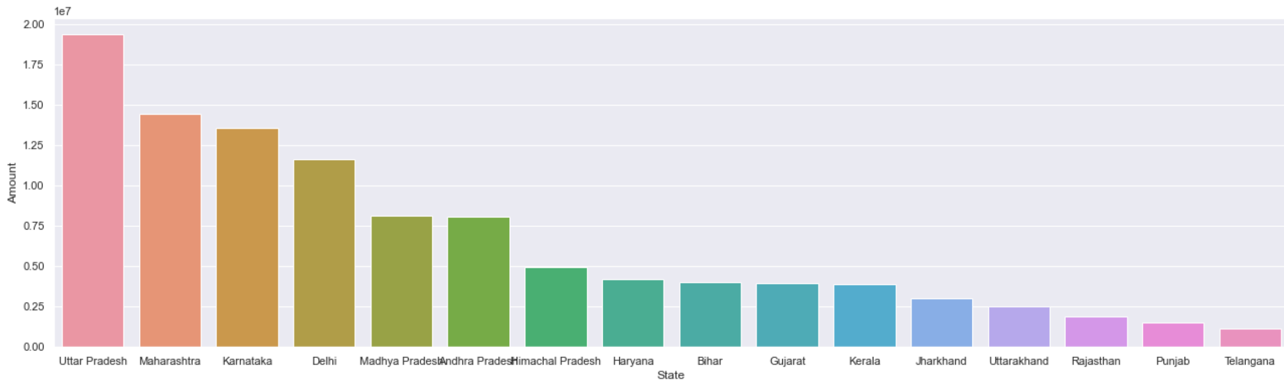
In [16]:
```
#State VS Orders
a5=df.groupby(['State'],as_index=False)['Orders'].sum().sort_values(by='Orders',ascending=False)
sns.set(rc={'figure.figsize':(22,6)})
a6=sns.barplot(x='State',y='Orders',data=a5)
for bars in a6.containers:
    a6.bar_label(bars)
```




# From the above graph we can see that UP has the highest order count

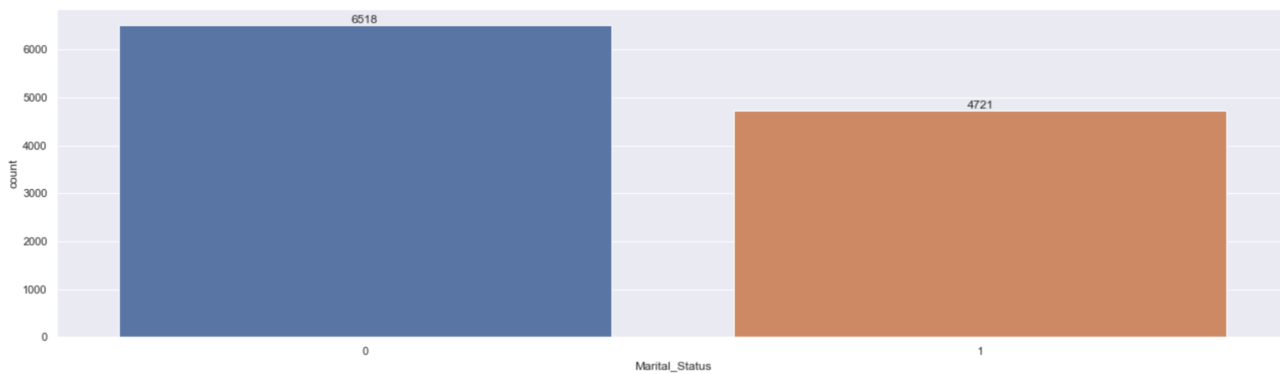
In [17]:
```
#Total amount spend by State
a4=df.groupby(['State'],as_index=False)['Amount'].sum().sort_values(by='Amount',ascending=False)
sns.barplot(x='State',y='Amount',data=a4)
```

Out[17]: <AxesSubplot:xlabel='State', ylabel='Amount'>

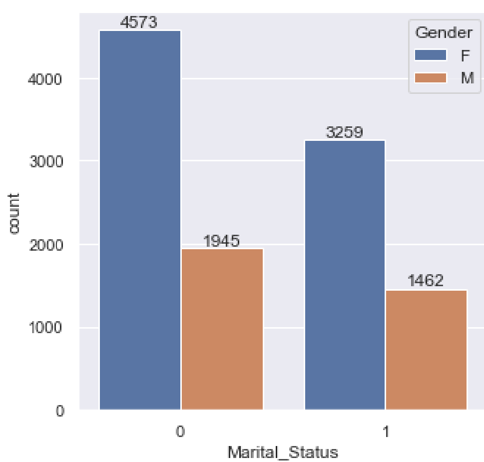



# Here we can see that Haryana has the purchasing power more than Kerala which has more order count than Haryana

In [18]:
```
#Martial Status i.e unmarried and married
a7=sns.countplot(x='Marital_Status',data=df)
sns.set(rc={'figure.figsize':(5,5)})
for bars in a7.containers:
    a7.bar_label(bars)
```

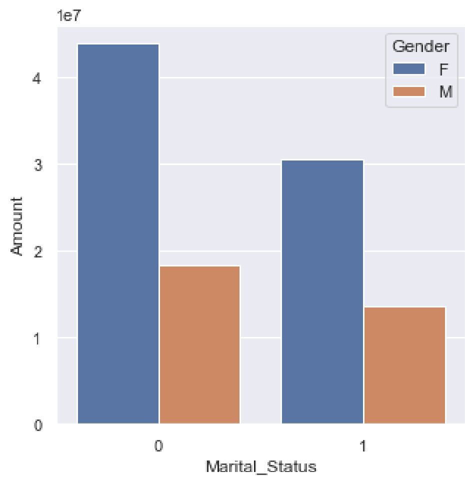



In [19]:
```
a3=sns.countplot(data=df,x='Marital_Status',hue='Gender')
for bars in a3.containers:
    a3.bar_label(bars)
```

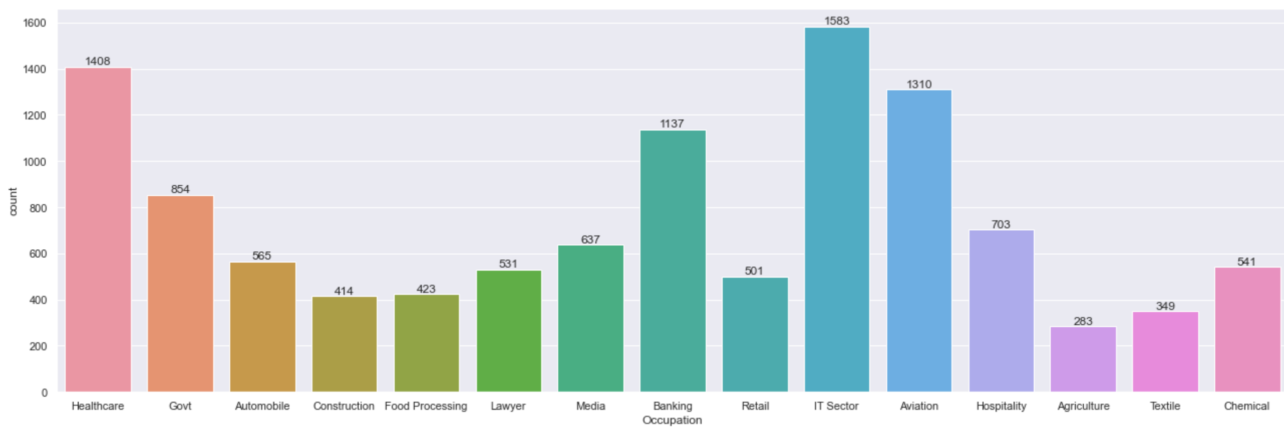


In [20]:
```
a8=df.groupby(['Marital_Status','Gender'],as_index=False)['Amount'].sum()
sns.barplot(x='Marital_Status',y='Amount',data=a8,hue='Gender')
```

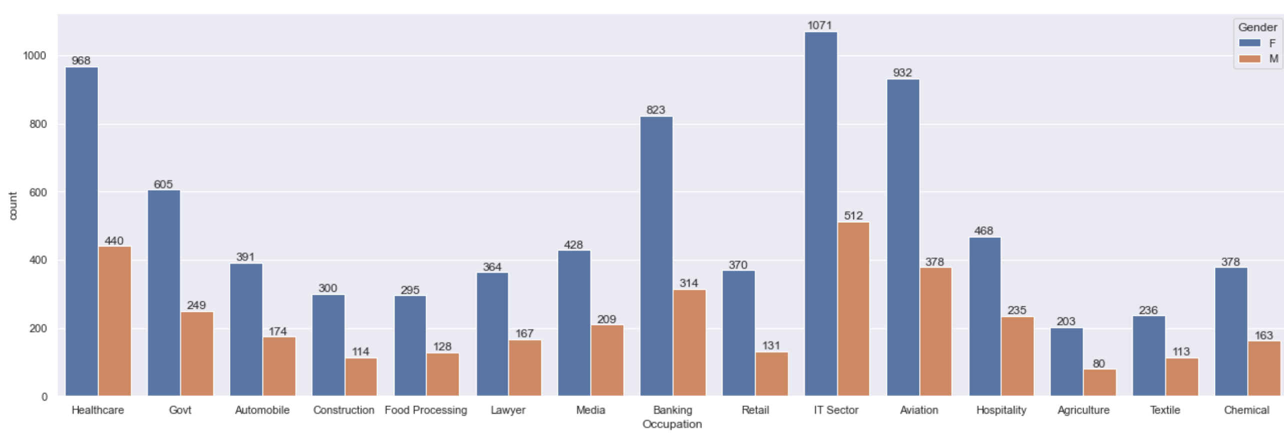
Out[20]: <AxesSubplot:xlabel='Marital_Status', ylabel='Amount'>




In [21]:
```
#Occupation
sns.set(rc={'figure.figsize':(22,7)})
a9=sns.countplot(data=df,x='Occupation')
for bars in a9.containers:
    a9.bar_label(bars)
```

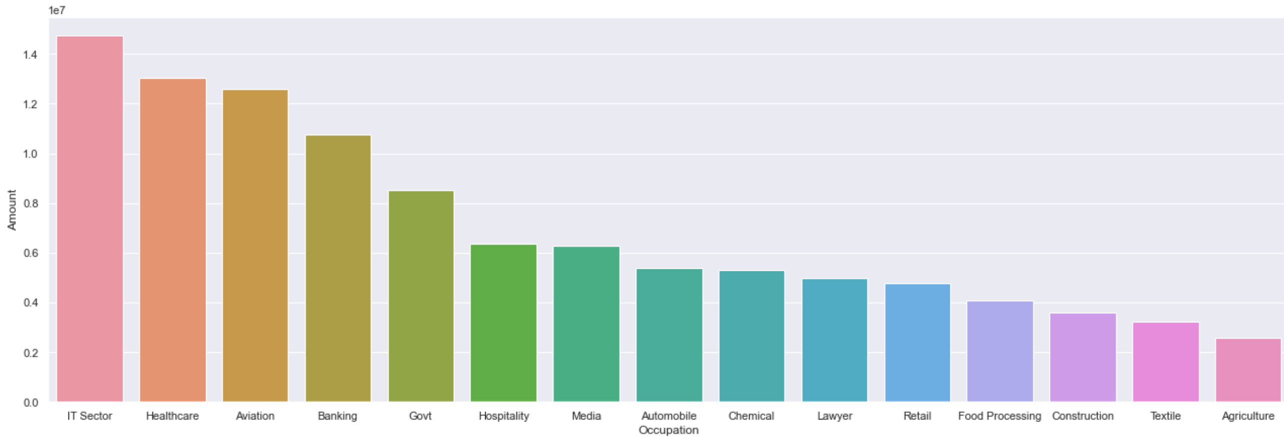



In [22]:
```
sns.set(rc={'figure.figsize':(22,7)})
a9=sns.countplot(data=df,x='Occupation',hue='Gender')
for bars in a9.containers:
    a9.bar_label(bars)
```



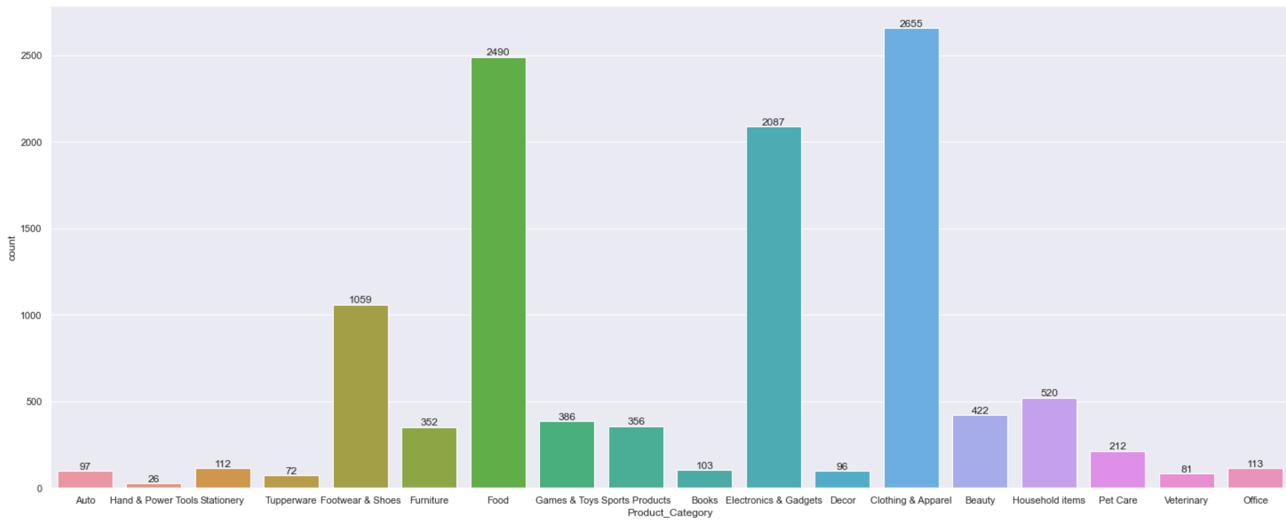
In [23]:
```
a10=df.groupby(['Occupation'],as_index=False)['Amount'].sum().sort_values(by='Amount',ascending=False)
sns.barplot(x='Occupation',y='Amount',data=a10)
```

Out[23]: <AxesSubplot:xlabel='Occupation', ylabel='Amount'>



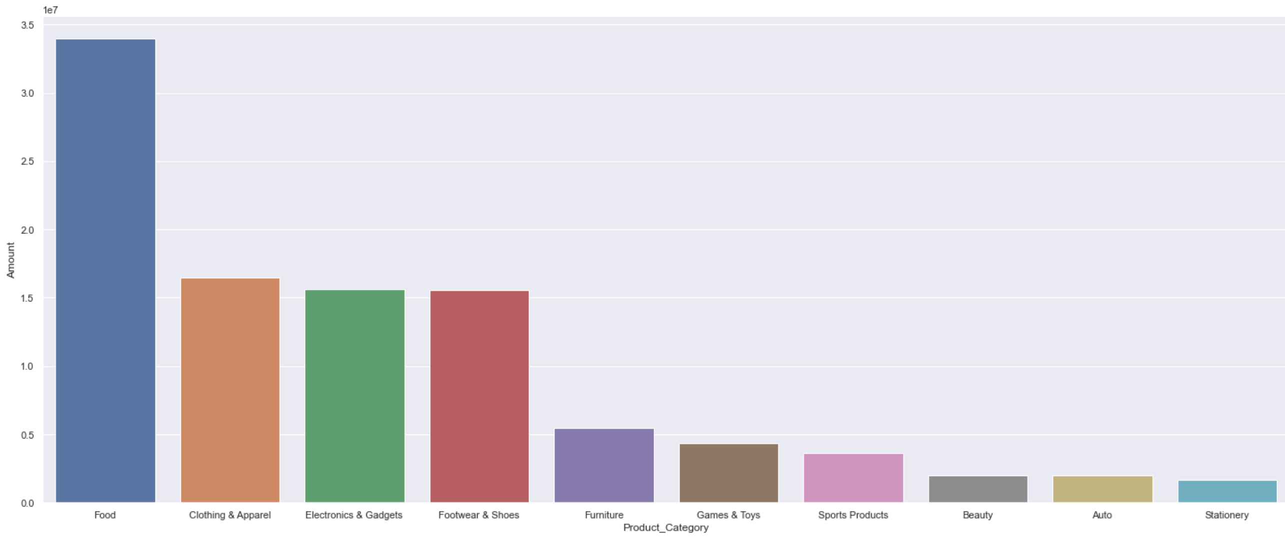

# Here we can see IT sector has highest Purchasing Power

In [24]:
```
#Product Category
sns.set(rc={'figure.figsize':(25,10)})
a11=sns.countplot(x='Product_Category',data=df)
for bars in a11.containers:
    a11.bar_label(bars)
```



In [28]:
```
sns.set(rc={'figure.figsize':(25,10)})
a12=df.groupby(['Product_Category'],as_index=False)['Amount'].sum().sort_values(by='Amount',ascending=False).head(1(
sns.barplot(x='Product_Category',y='Amount',data=a12)
```

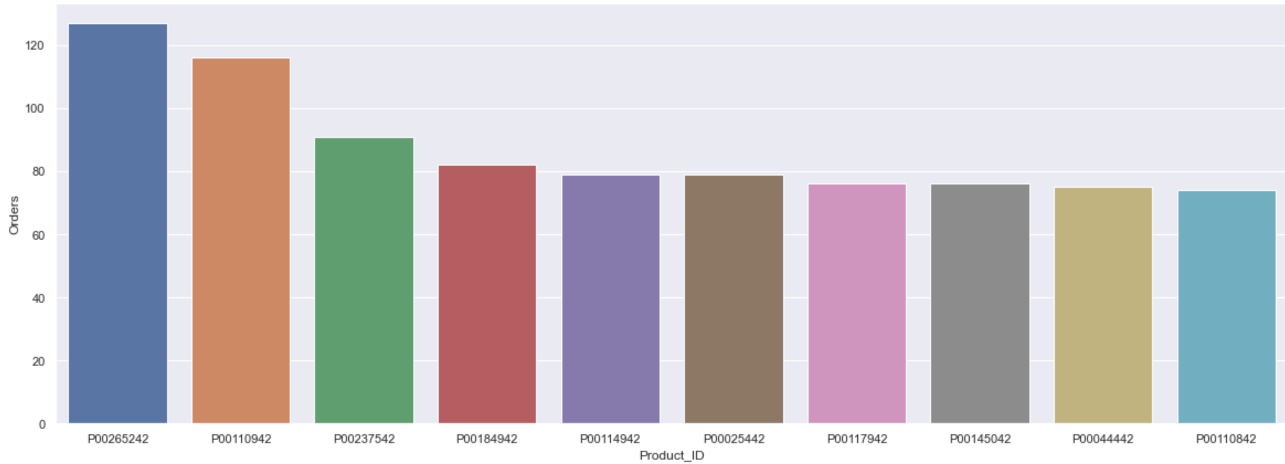
Out[28]: <AxesSubplot:xlabel='Product_Category', ylabel='Amount'>




## Here we can see food category has the highest sales

In [27]:
```
#Product ID
a13=df.groupby(['Product_ID'],as_index=False)['Orders'].sum().sort_values(by='Orders',ascending=False).head(10)
sns.set(rc={'figure.figsize':(20,7)})
sns.barplot(x='Product_ID',y='Orders',data=a13)
```

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




## Conclusion:

Unmarried woman of age group 26-35 yrs from UP, Maharashtra and Karnataka working in IT,Healthcare and Aviation are most likely to buy products from Food,Clothing and Electronics category

## Thank you!