In [3]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

if want to work in a single column then specify this thing and do operation on this thing df['Column name']

In [146]:
```python
file = 'Diwali Sales Data.csv'
df = pd.read_csv(file, encoding = 'unicode_escape')

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

In [148]:
```python
df.head()
```

Out[148]:

	User_ID	Cust_name	Product_ID	Gender	Age Group	Age	Marital_Status	State	Zone	Occupation	Product_Category	Orders	Amount
0	1002903	Sanskriti	P00125942	F	26-35	28	0	Maharashtra	Western	Healthcare	Auto	1	23952.0
1	1000732	Kartik	P00110942	F	26-35	35	1	Andhra Pradesh	Southern	Govt	Auto	3	23934.0
2	1001990	Bindu	P00118542	F	26-35	35	1	Uttar Pradesh	Central	Automobile	Auto	3	23924.0
3	1001425	Sudevi	P00237842	M	0-17	16	0	Karnataka	Southern	Construction	Auto	2	23912.0
4	1000588	Joni	P00057942	M	26-35	28	1	Gujarat	Western	Food Processing	Auto	2	23877.0

Know About The Data

In [149]:
```python
df.shape
# df.columns
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
```

Find Out the Null values

In [41]:
```python
# checking for the null values
print( df.isnull().sum() )

null = (df['Amount'].isnull())
print(null)
```

```
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
0        False
1        False
2        False
3        False
4        False
         ...
11246    False
11247    False
11248    False
11249    False
11250    False
Name: Amount, Length: 11251, dtype: bool
```

replace The Null Values with mean values

In [46]:
```python
Mean_amount = round(df['Amount'].mean())
print(Mean_amount)

df['Amount'] = df['Amount'].fillna(Mean_amount)
# same as this
# df['Amount'].fillna(df['Amount'].mean(), inplace=True)

# droping the null columns
# df.dropna(inplace = true)
```

```
9454
```

Changing Data Type of an Column

In [51]:
```python
df['Amount'] = df['Amount'].astype('int')
df[5:10]
```

Out[51]:

	User_ID	Cust_name	Product_ID	Gender	Age Group	Age	Marital_Status	State	Zone	Occupation	Product_Category	Orders	Amount
5	1000588	Joni	P00057942	M	26-35	28	1	Himachal Pradesh	Northern	Food Processing	Auto	1	23877
6	1001132	Balk	P00018042	F	18-25	25	1	Uttar Pradesh	Central	Lawyer	Auto	4	23841
7	1002092	Shivangi	P00273442	F	55+	61	0	Maharashtra	Western	IT Sector	Auto	1	9454
8	1003224	Kushal	P00205642	M	26-35	35	0	Uttar Pradesh	Central	Govt	Auto	2	23809
9	1003650	Ginny	P00031142	F	26-35	26	1	Andhra Pradesh	Southern	Media	Auto	4	23799

renaming Columns

In [59]:
```python
# columns = Dict{ Key: value
df.columns
df.rename(columns = {'Marital_Status':'Shadii'}, inplace = True)
df.columns
df.rename(columns = {'Shadii':'Marital_Status', 'Cust_name':'Coust_Name'}, inplace = True)
df.columns
```

Out[59]:
```
Index(['User_ID', 'Coust_Name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

Stat of the numeric Data

In [5]:
```python
df.describe()
df[['Age', 'Orders', 'Amount']].describe().round()
```

Out[5]:

	Age	Orders	Amount
count	11251.0	11251.0	11239.0
mean	35.0	2.0	9454.0
std	13.0	1.0	5222.0
min	12.0	1.0	188.0
25%	27.0	2.0	5443.0
50%	33.0	2.0	8109.0
75%	43.0	3.0	12675.0
max	92.0	4.0	23952.0

In [6]:
```python
df.columns
```

Out[6]:
```
Index(['User_ID', 'Cust_name', 'Product_ID', 'Gender', 'Age Group', 'Age',
       'Marital_Status', 'State', 'Zone', 'Occupation', 'Product_Category',
       'Orders', 'Amount'],
      dtype='object')
```

To see all the Data in Product Category

In [79]:
```python
df['Product_Category'].unique()
```

Out[79]:
```
array(['Auto', 'Hand & Power Tools', 'Stationery', 'Tupperware',
       'Footwear & Shoes', 'Furniture', 'Food', 'Games & Toys',
       'Sports Products', 'Books', 'Electronics & Gadgets', 'Decor',
       'Clothing & Apparel', 'Beauty', 'Household items', 'Pet Care',
       'Veterinary', 'Office'], dtype=object)
```

In [24]:
```python
df['Gender'].unique()
```

Out[24]:
```
array(['F', 'M'], dtype=object)
```

Exploratory data Analysis

Gender

countplot() and barplot()

are both used for visualizing categorical data in seaborn, but they serve slightly different purposes:

use **countplot()** when you want to show how many times each category appears like F , M

use **barplot()** when you want to show the summary statistics of a numeric variable across categories (for X , Y).

male & female diversion

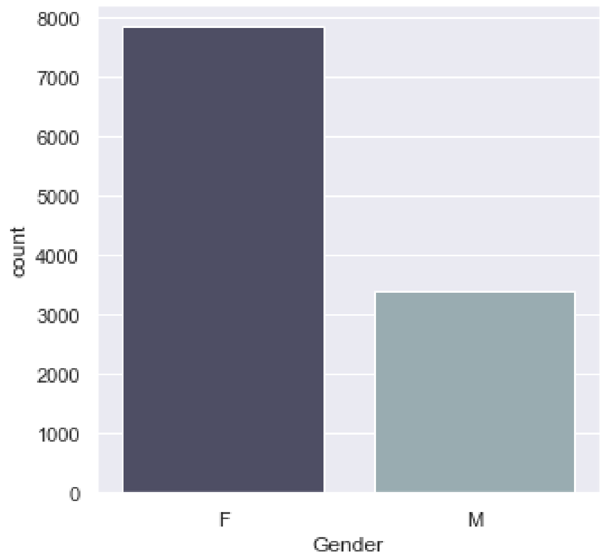
In [125]:

```
sale_gen = df.groupby(['Gender'] , as_index = False)['Gender'].count().sort_values(by = 'Gender')
print(sale_gen)

sns.countplot(data = df, x = 'Gender', palette = 'bone')
```

```
   Gender
1    3409
0    7842
```

Out[125]: <Axes: xlabel='Gender', ylabel='count'>



male & female contribution in sales

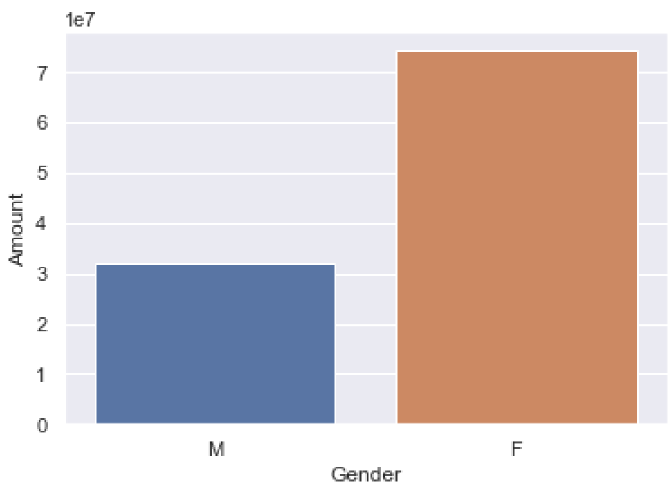
In [77]:

```
sale_gen = df.groupby(['Gender'] , as_index = False)['Amount'].sum().round().sort_values(by = 'Amount')
print(sale_gen)

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

```
  Gender      Amount
1      M  31913276.0
0      F  74335856.0
```

Out[77]: <AxesSubplot:xlabel='Gender', ylabel='Amount'>



[Females Tends to shop more than Mens]

df.groupby(['Gender'] , as_index = False)['Amount'] -- will return grouped Object so we have to use agg funs()

as_index=False: Ensures that the 'Gender' column is not used as the index in the resulting DataFrame, keeping it as a regular column.

Select the 'Amount' column from the grouped data to perform the aggregation.

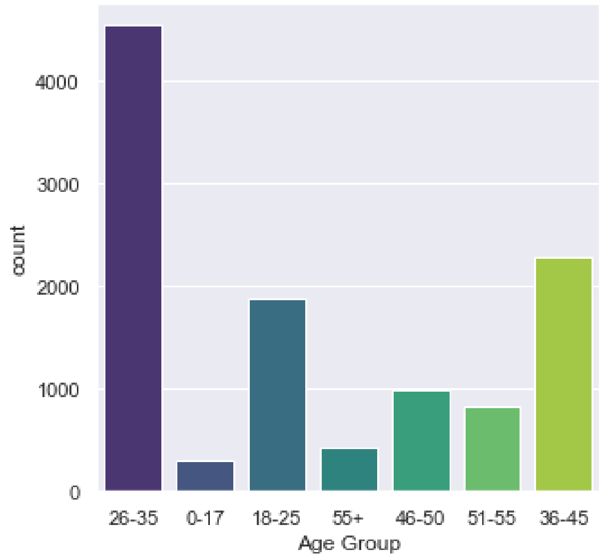
Age Group by Genders

Age Group Diversion

In [46]:
```python
# Only Show the Various Age Group plotted
# palette='viridis, 'plasma', 'Blues', 'husl', 'pastel
sns.set(rc ={ 'figure.figsize':(5,5)})

sns.countplot(data = df, x = 'Age Group', palette='viridis')
```

Out[46]: <Axes: xlabel='Age Group', ylabel='count'>

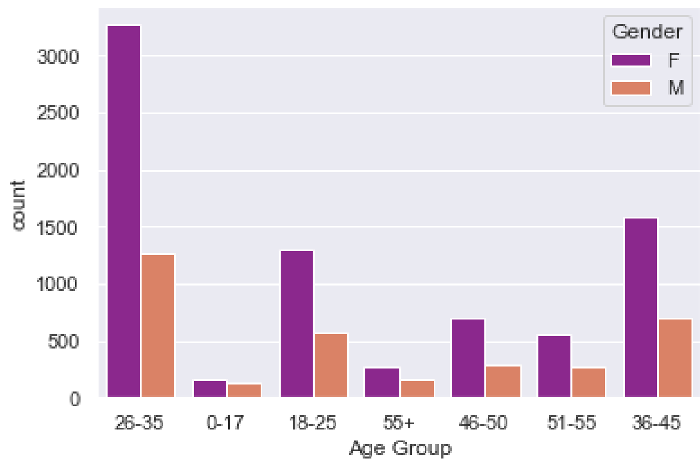


Male and Female diverion in Age Group

In [94]:
```python
# Devide each group with respect to Gender
# palette='viridis, 'plasma', 'Blues', 'husl', 'pastel
sns.set(rc ={ 'figure.figsize':(5,5)})


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

Out[94]: <AxesSubplot:xlabel='Age Group', ylabel='count'>



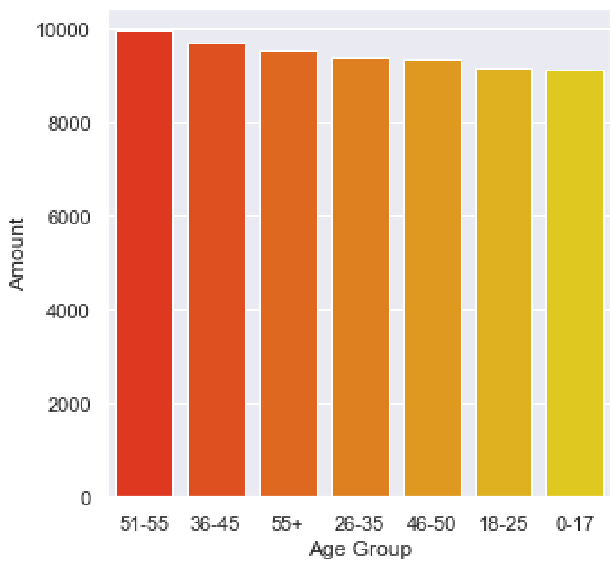
average amount spent by customers in each age group

In [121]:
```python
sns.set(rc ={ 'figure.figsize':(5,5)})

avg_amount_by_age = df.groupby(['Age Group'] , as_index = False)['Amount'].mean().round().sort_values(by = 'Amount', ascending =
# print(avg_amount_by_age)

sns.barplot(data  = avg_amount_by_age, x = 'Age Group', y = 'Amount', palette='autumn')
```

Out[121]: <Axes: xlabel='Age Group', ylabel='Amount'>



[Females between age group of 26-35 Tends to shop more than age group of 0-17]

[same for males between age group of 26-35 Tends to shop more than age group of 0-17]

State wise Order Quantity & it's Amount

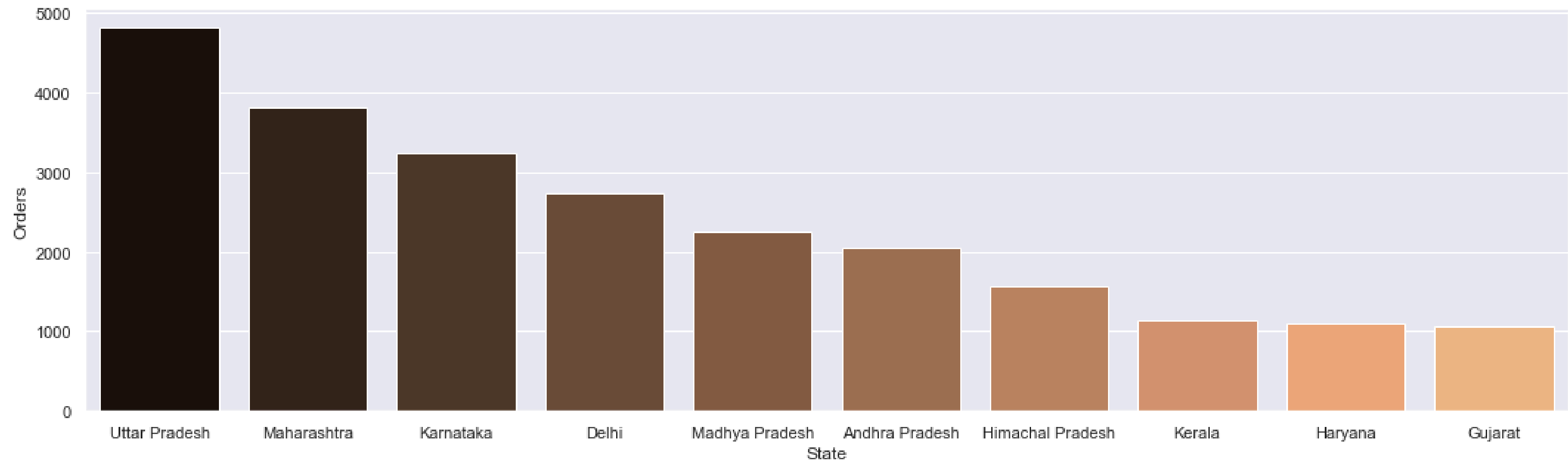
customer distribution across different states

In [120]:
```
# To streach the Data Visual Pic
sns.set(rc ={ 'figure.figsize':(18,5)})

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

sns.barplot(data = State_Order, x = 'State', y = 'Orders', palette = 'copper')
```

Out[120]: `<Axes: xlabel='State', ylabel='Orders'>`



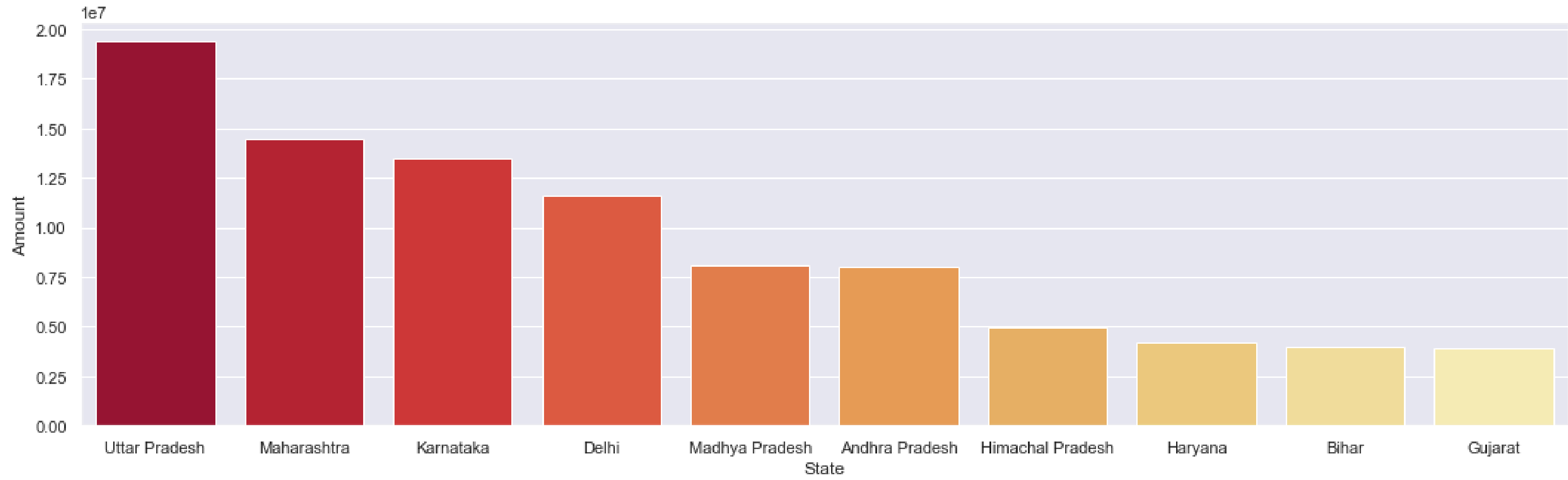
State wise Total Amount

In [118]:
```
# To streach the Data Visual Pic
sns.set(rc ={ 'figure.figsize':(18,5)})

state = df.groupby(['State'],as_index = False)['Amount'].sum().sort_values(by = 'Amount', ascending = False).round().head(10)
# print(state)

sns.barplot(data = state, x = 'State', y = 'Amount', palette= 'YlOrRd_r')
```

Out[118]: `<Axes: xlabel='State', ylabel='Amount'>`



[Most sales comes from UP, maharashtra, Karnataka while least order purchased from Kerala, Haryana, Gujrat]

Occupation

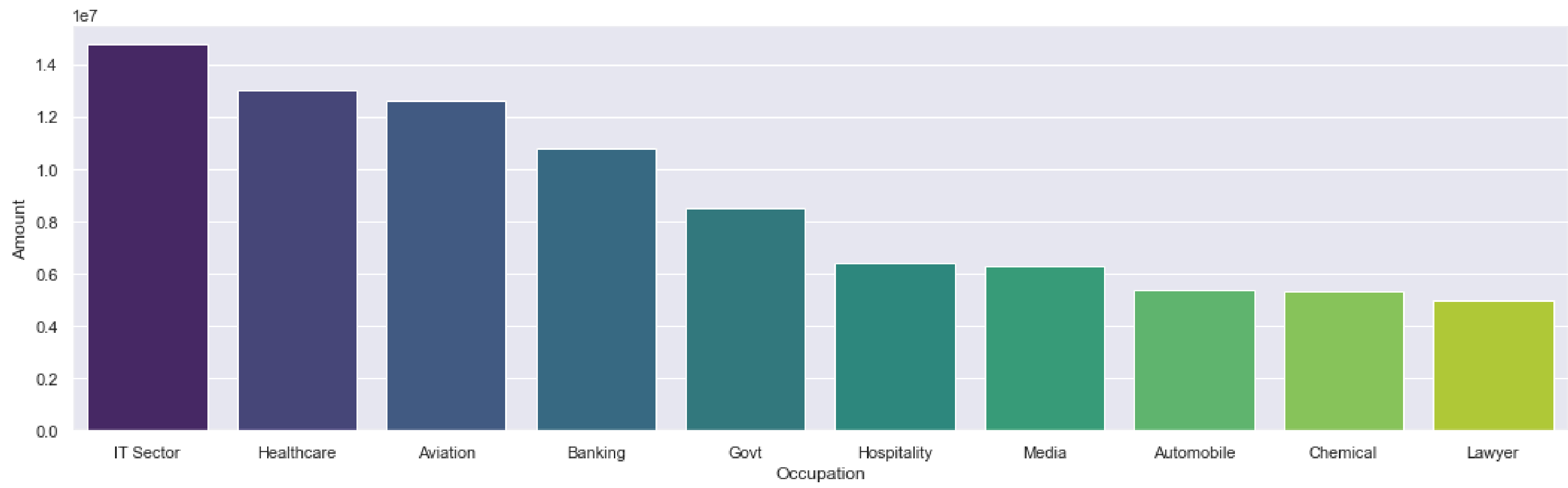
Occupation wise Order

In [61]:
```python
# To streach the Data Visual Pic
sns.set(rc ={ 'figure.figsize':(18,5)})

state = df.groupby(['Occupation'],as_index = False)['Amount'].sum().sort_values(by = 'Amount', ascending = False).round().head(10
# print(state)


sns.barplot(data = state, x = 'Occupation', y = 'Amount', palette='viridis')
```

Out[61]: <Axes: xlabel='Occupation', ylabel='Amount'>



[in Occupation wise order amount & Quantity Top Occupation is IT-sector & lowest Occupation is Lawer in top 10]

Maritial Status

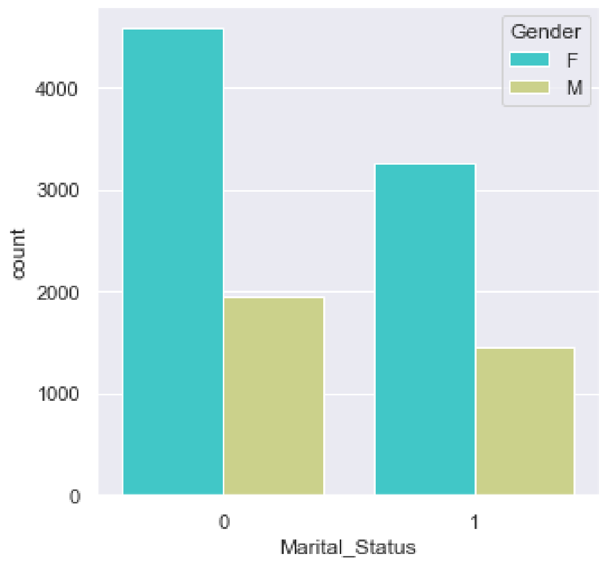
Gender By maritial status

In [150]:
```python
df['Gender'].count()         # 11251 'F' , 'M'
df['Marital_Status'].count() # 11251 [ married '1' 4,729] [unmarried '0' 6,522]

mapping = {0: 'unmarried', 1: 'married'}
df['Marital_Status_Details'] = df['Marital_Status'].map(mapping)

sns.countplot(data = df, x = 'Marital_Status', hue = 'Gender', palette = 'rainbow')
```

Out[150]: <Axes: xlabel='Marital_Status', ylabel='count'>



Sale analysis in married customers

In [152]:

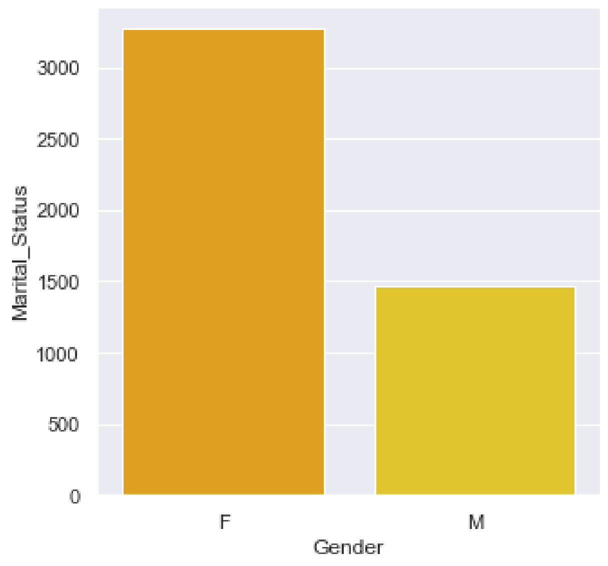
```
# To streach down the Data Visual Pic
sns.set(rc ={ 'figure.figsize':(5,5)})

gender_by_Married = df.groupby(['Gender'], as_index = False)['Marital_Status'].sum().sort_values('Marital_Status', ascending = Fa
print(gender_by_Married)

sns.barplot(x = 'Gender', y = 'Marital_Status', data = gender_by_Married, palette = 'Wistia_r')
```

```
  Gender  Marital_Status
0      F            3266
1      M            1463
```

Out[152]: <Axes: xlabel='Gender', ylabel='Marital_Status'>



[Unmarried Women Tends to buy more things than married women :) same as men too]

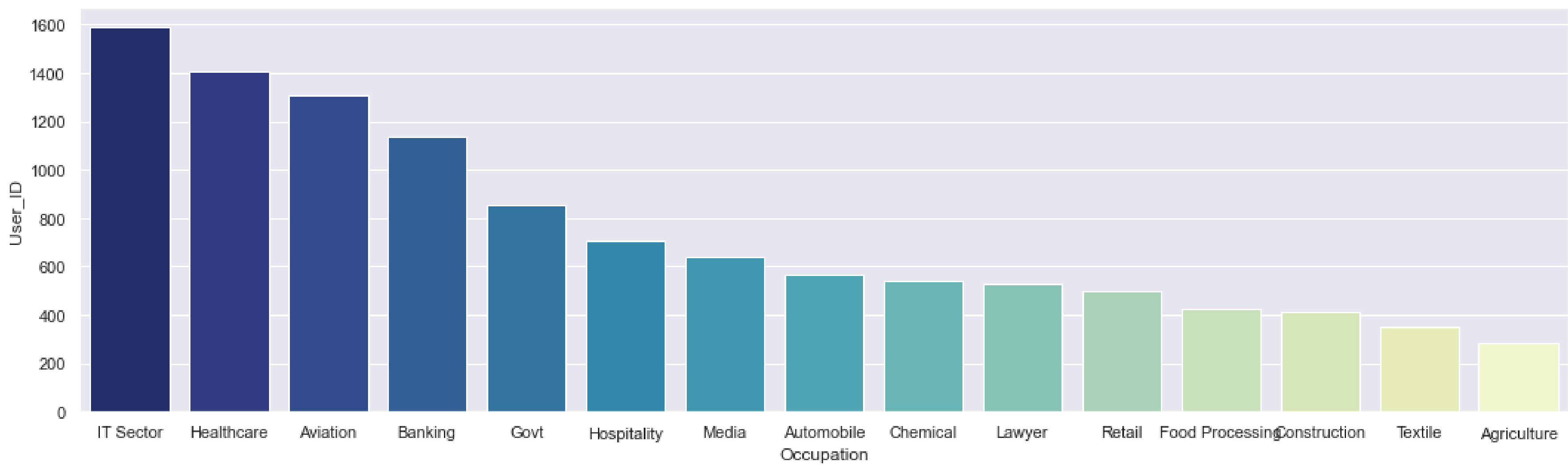
Occupation

In [114]:

```
sns.set(rc ={ 'figure.figsize':(18,5)})

Occu_by_ID = df.groupby(['Occupation'] , as_index = False)['User_ID'].count().sort_values('User_ID', ascending = False)
sns.barplot(data = Occu_by_ID, x = 'Occupation', y = 'User_ID', palette = 'YlGnBu_r')
```

Out[114]: <Axes: xlabel='Occupation', ylabel='User_ID'>



Occupation wise Marital_Status

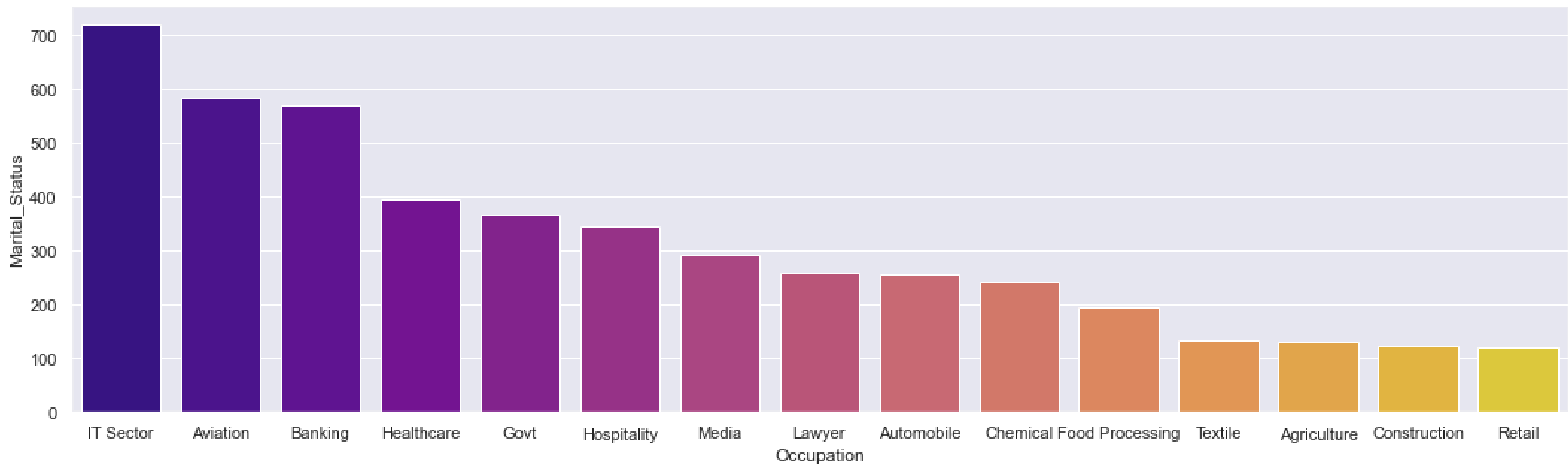
In [42]:

```
# To streach down the Data Visual Pic
sns.set(rc ={ 'figure.figsize':(18,5)})

gender_by_Married = df.groupby(['Occupation'], as_index = False)['Marital_Status'].sum().sort_values('Marital_Status', ascending
# print(gender_by_Married)

sns.barplot(x = 'Occupation', y = 'Marital_Status', data = gender_by_Married, palette = 'plasma')
```

Out[42]: <Axes: xlabel='Occupation', ylabel='Marital_Status'>



[It sector, Aviation, Banking sector Coustomer tends to shope more than Agriculture, Construction & Retails]

Purchase Behavior Analysis:

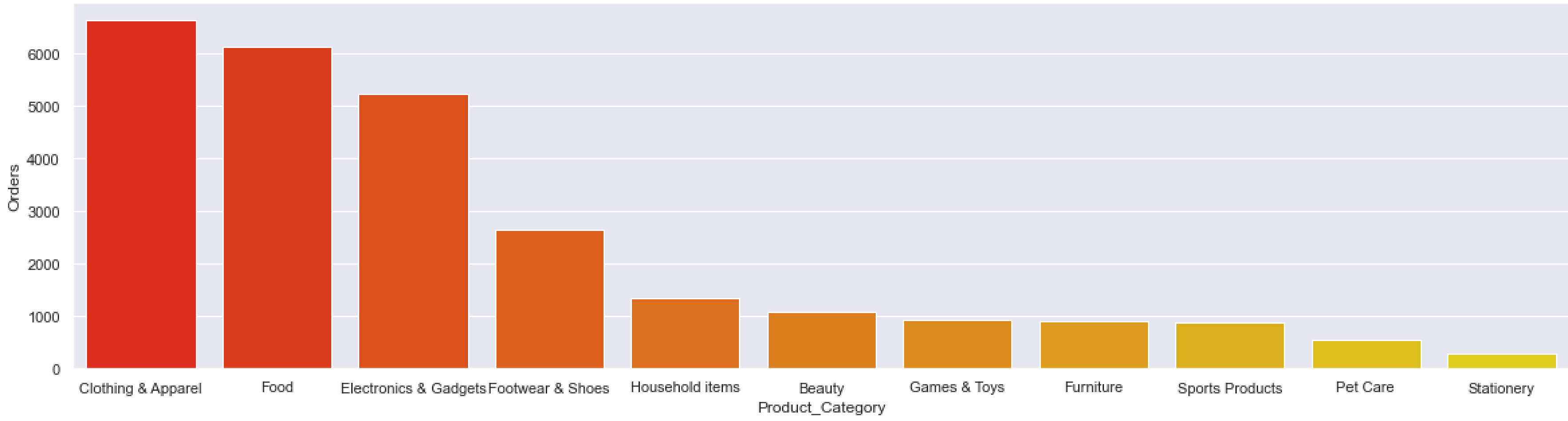
product categories have the highest number of orders.

In [100]:

```
#df[['Product_Category', 'Orders']]
sns.set(rc ={ 'figure.figsize':(20,5)})

Product_order = df.groupby(['Product_Category'], as_index = False)['Orders'].sum().sort_values(by='Orders', ascending = False).he
sns.barplot(data = Product_order, x = 'Product_Category', y = 'Orders', palette= 'autumn' )
```

Out[100]: `<Axes: xlabel='Product_Category', ylabel='Orders'>`



[Clothing & Apparel, Food, electronics id brought the most where stationary, furniture, pet care, sports brought the least]

Zone Wise Sale

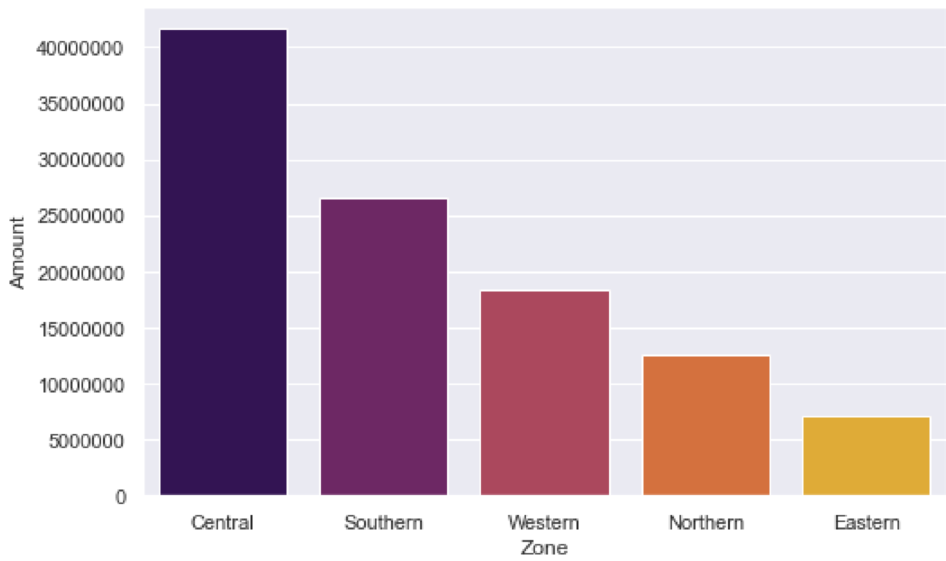
Zone wise sale Amount

In [112]:

```
sns.set(rc ={ 'figure.figsize':(8,5)})

Zone_sale = df.groupby(['Zone'], as_index = False)['Amount'].sum().round().sort_values(by = 'Amount', ascending = False)
# print(Zone_sale)

sns.barplot(data = Zone_sale, x = 'Zone', y = 'Amount', palette=  'inferno')
plt.ticklabel_format(style='plain', axis='y')
```

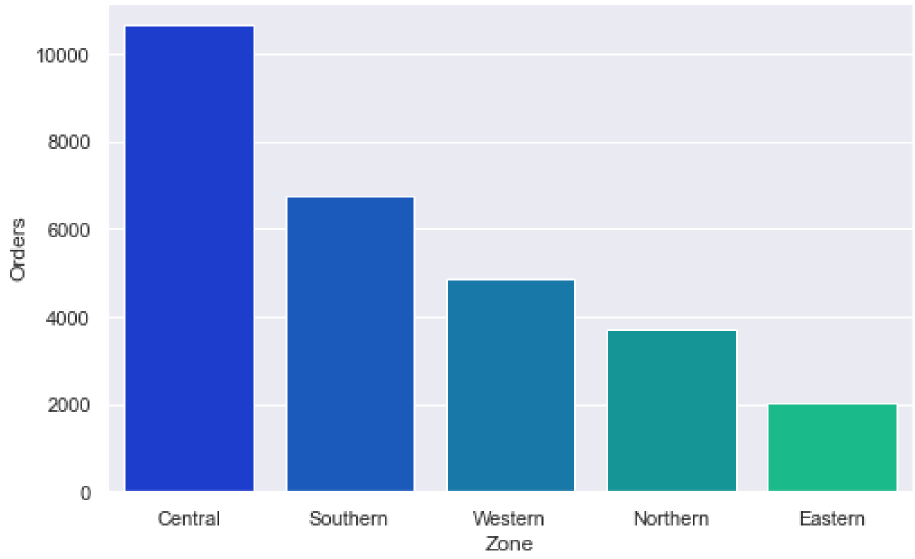


Zone wise sale Order

In [115]:
```
sns.set(rc ={ 'figure.figsize':(8,5)})
Zone_order = df.groupby(['Zone'], as_index = False)['Orders'].sum().round().sort_values(by = 'Orders', ascending = False)
# print(Zone_order)

sns.barplot(data = Zone_order, x = 'Zone', y = 'Orders', palette= 'winter')
```

Out[115]: <Axes: xlabel='Zone', ylabel='Orders'>



[Central region tends to order most than eastern]

Summary of the Insights

Gender Shopping Trends: Females tend to shop more than males.

Age Group Shopping Trends: Both females and males in the 26-35 age group shop more compared to the 0-17 age group.

Geographic Sales: The highest sales are from Uttar Pradesh, Maharashtra, and Karnataka, while Kerala, Haryana, and Gujarat have the lowest.

Occupation-based Shopping: IT-sector professionals have the highest order amounts and quantities, while lawyers rank lowest among the top 10 occupations.

Marital Status and Shopping: Unmarried women and men tend to buy more than their married counterparts.

Product Categories: Clothing & Apparel, Food, and Electronics are the most purchased, while Stationery, Furniture, Pet Care, and Sports items are the least.

Regional Sales: The Central region has the highest order volume, surpassing the Eastern region.