portfolio

July 21, 2025

1 Step 1: Import Libraries

[1199]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Step 2: Load and Explore the Dataset

1. Import the CSV file containing the New Year sales data.

[1200]:
```
df = pd.read_csv('New_Year_Sales_Data.csv', encoding='latin1')
df.head(4)      # Display the first 4 rows of the DataFrame
```

[1200]:
```
   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

             State      Zone    Occupation Product_Category  Orders   Amount  \
0      Maharashtra   Western    Healthcare             Auto       1  23952.0
1  AndhraÂ Pradesh  Southern          Govt             Auto       3  23934.0
2    Uttar Pradesh   Central    Automobile             Auto       3  23924.0
3        Karnataka  Southern  Construction             Auto       2  23912.0

   Status  unnamed1
0     NaN       NaN
1     NaN       NaN
2     NaN       NaN
3     NaN       NaN
```

3 Step 3: Data Cleaning

[1201]:
```
df.info()  # Display dataset information
```

```
<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
```

1. Check for null values.

[1202]:
```
df.isnull().sum(  )     # Check for missing values in each column
```

[1202]:
```
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
Status              11251
unnamed1            11251
dtype: int64
```

2. Drop unnecessary columns that do not contribute to analysis.

```
[1203]: df.drop (['Status','unnamed1'], axis=1, inplace=True)  # Drop unnecessary␣
          ↪columns
```

```
[1204]: df.head(2) # Display the first 2 rows after cleaning
```

```
[1204]:    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

                     State      Zone  Occupation Product_Category  Orders   Amount
        0      Maharashtra   Western  Healthcare             Auto       1  23952.0
        1  AndhraÂ Pradesh  Southern        Govt             Auto       3  23934.0
```

3. Drop rows with null values in other important columns.

```
[1205]: df.dropna(subset=['Amount'], inplace=True)  # Drop rows with missing 'Amount'␣
          ↪values
```

```
[1206]: df.isnull().sum() # Check for missing values again after cleaning
```

```
[1206]: 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
```

4. Convert the Amount column to an integer type for consistency in calculations.

```
[1207]: df['Amount'] = df['Amount'].astype(int)  # Convert 'Amount' column to integer␣
          ↪type
```

4 Step 4: Data Overview and Summary:

1. Get summary statistics.

```
[1208]: df.describe()  # Display summary statistics of the DataFrame
```

[1208]:
```
            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
```

2. Check for unique values in columns to understand the dataset better

[1209]:
```
df.nunique()
```

[1209]:
```
User_ID             3752
Cust_name           1250
Product_ID          2350
Gender                 2
Age Group              7
Age                   81
Marital_Status         2
State                 16
Zone                   5
Occupation            15
Product_Category      18
Orders                 4
Amount              6583
dtype: int64
```

5 Exploratory Data Analysis (EDA)

6 1. Gender Analysis

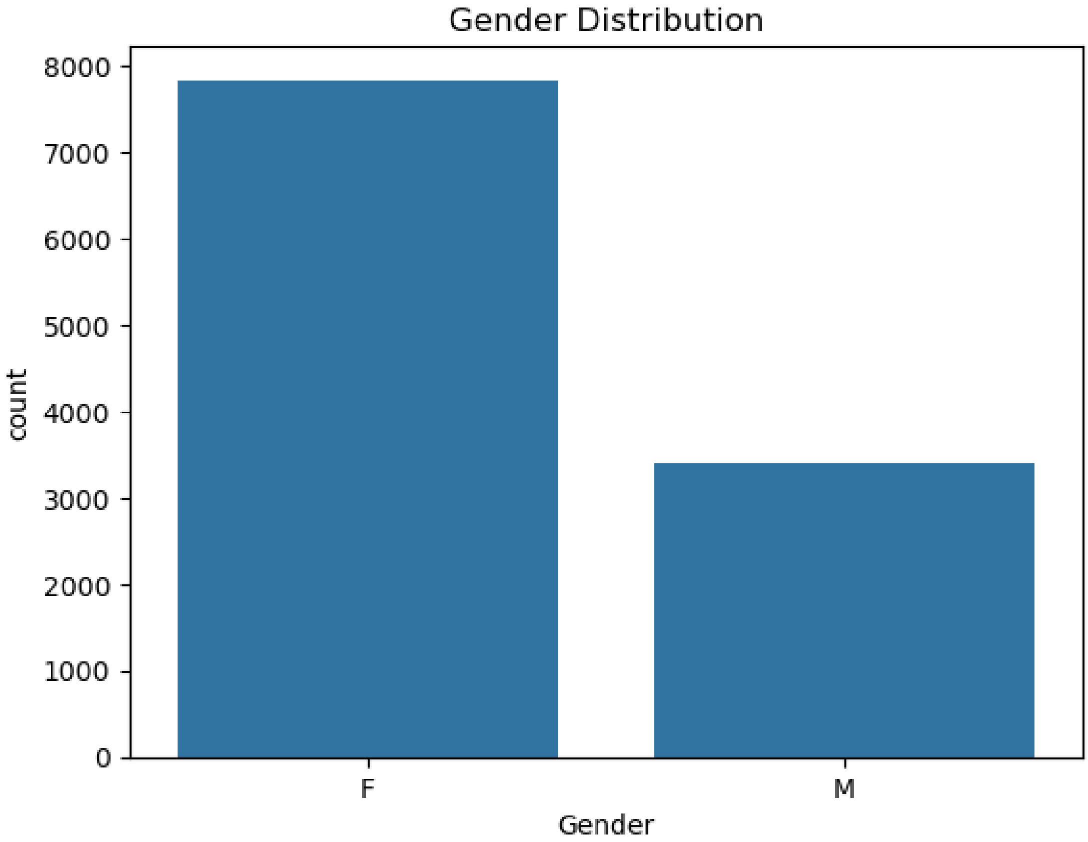
- Question: Which gender has a higher purchasing power?

[ ]:
```
df.groupby('Gender')['Amount'].sum()
```

[ ]:
```
Gender
F    74335853
M    31913276
Name: Amount, dtype: int32
```

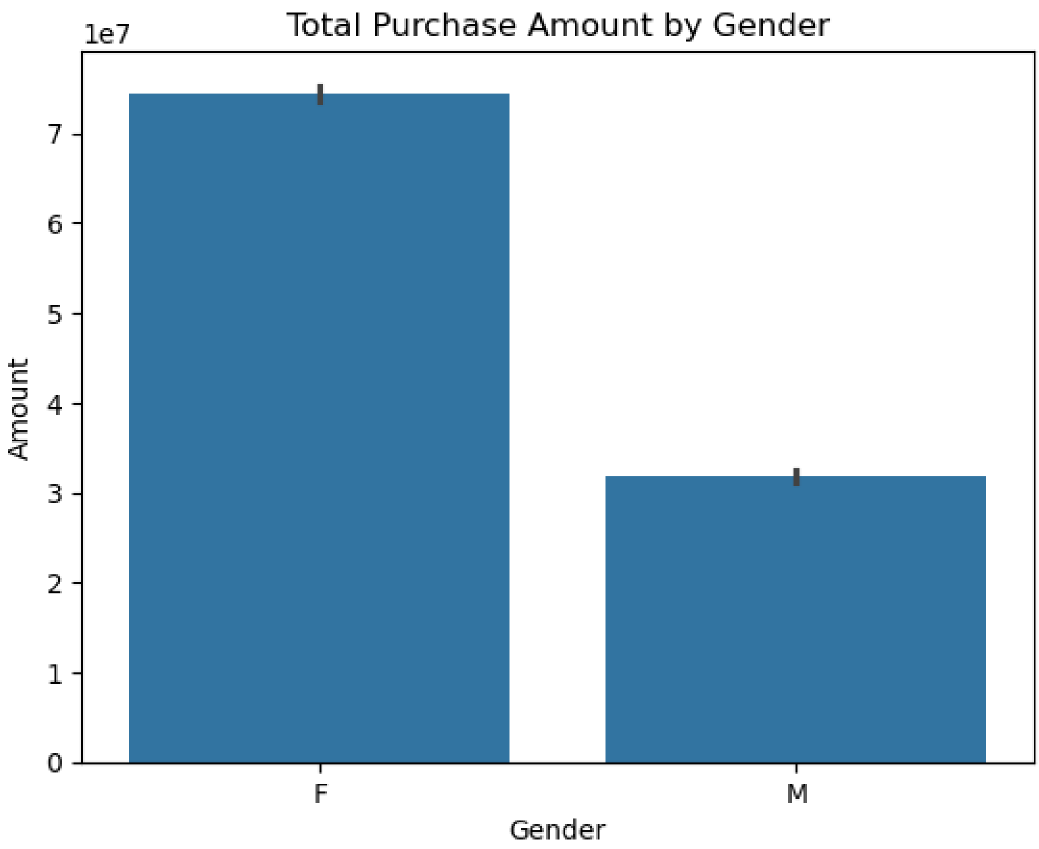
```
* Create a count plot for gender.
```

[1211]:
```
sns.countplot(x='Gender', data=df)
plt.title('Gender Distribution')
plt.show()
```



* Plot a bar chart to show the total purchase amount by gender.

```
[1212]: sns.barplot(x='Gender', y='Amount', data=df, estimator=sum)
plt.title('Total Purchase Amount by Gender')
plt.show()
```



7 2. Age Group Analysis

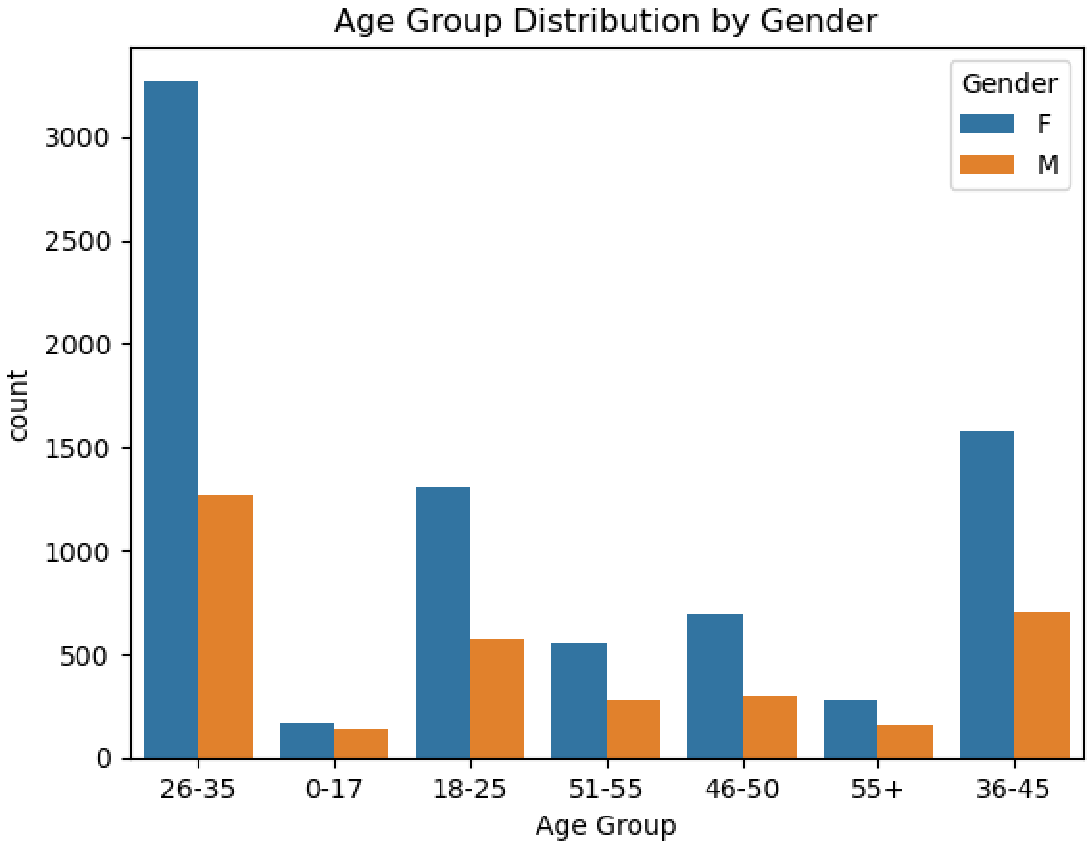
- Question: Which age group has the most purchases, and is there a trend in purchasing power by age?

```
[1213]: df.groupby('Age Group')['Amount'].sum()
```

```
[1213]: Age Group
        0-17      2699653
        18-25    17240732
        26-35    42613442
        36-45    22144994
        46-50     9207844
        51-55     8261477
        55+       4080987
        Name: Amount, dtype: int32
```

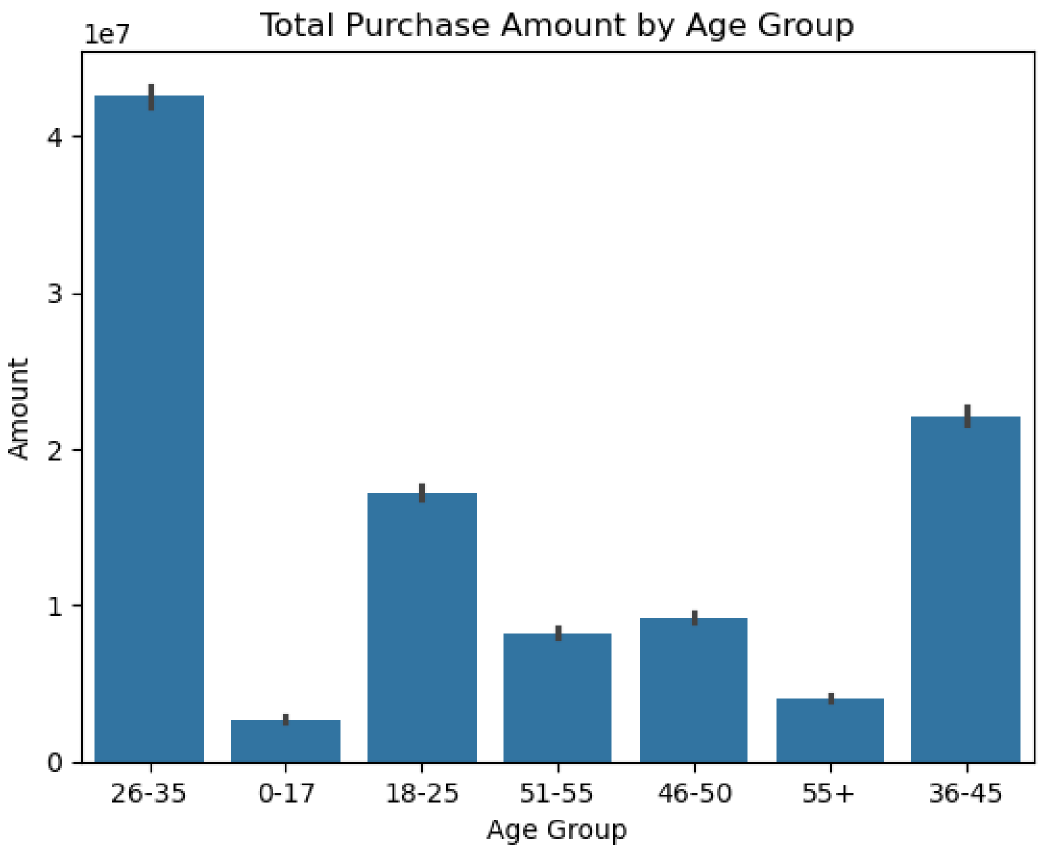
```
o Plot a count plot of age groups with hue as gender.
```

[1214]:
```
sns.countplot(x='Age Group', hue='Gender', data=df)
plt.title('Age Group Distribution by Gender')
plt.show()
```



Plot a bar chart showing total purchase amount by age group.

[1215]:
```
sns.barplot(x='Age Group', y='Amount', data=df, estimator=sum)
plt.title('Total Purchase Amount by Age Group')
plt.show()
```



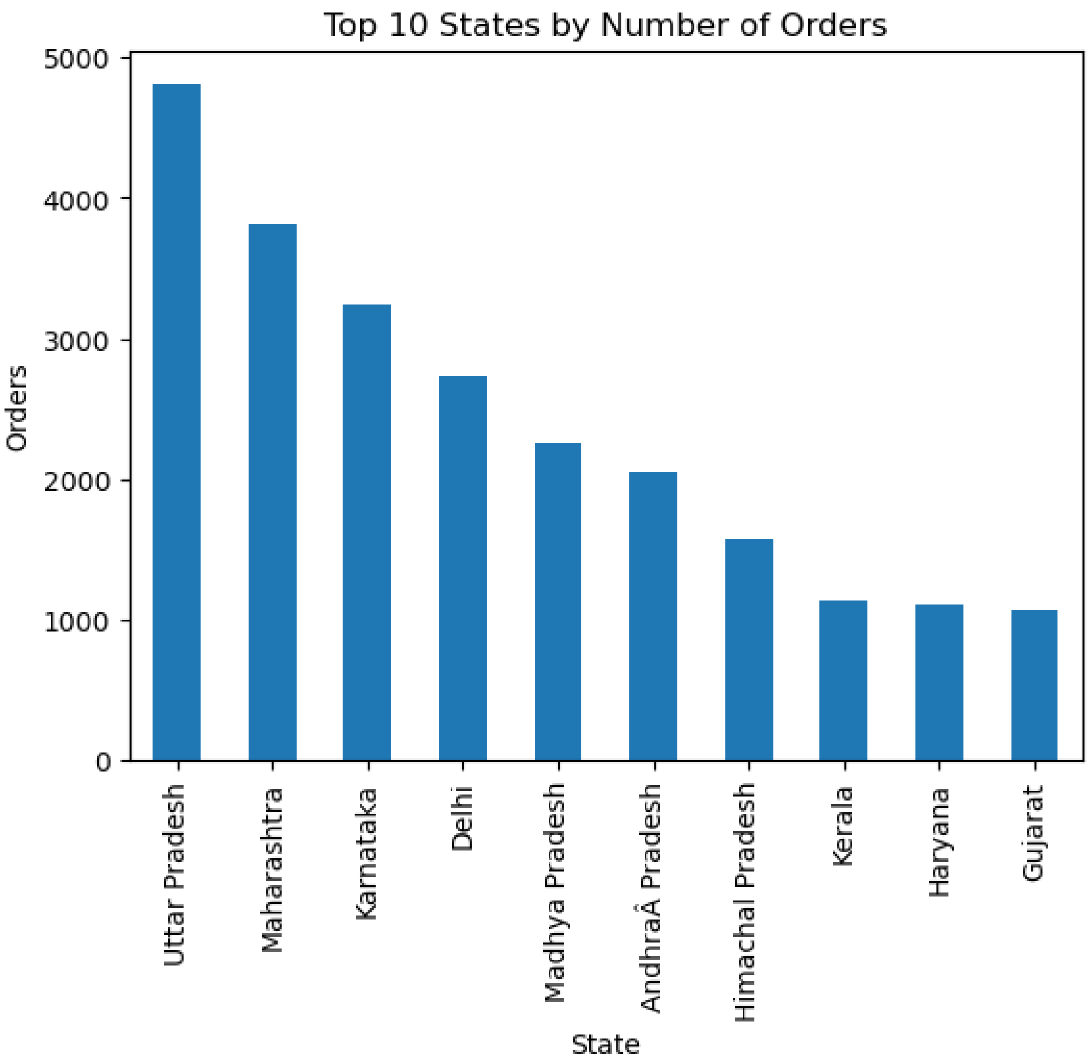
8 3. State Analysis

Question: Which states generate the highest number of orders and revenue?

```
* Plot bar charts for the number of orders and total amount by state, focusing on
the top 10 states.
```

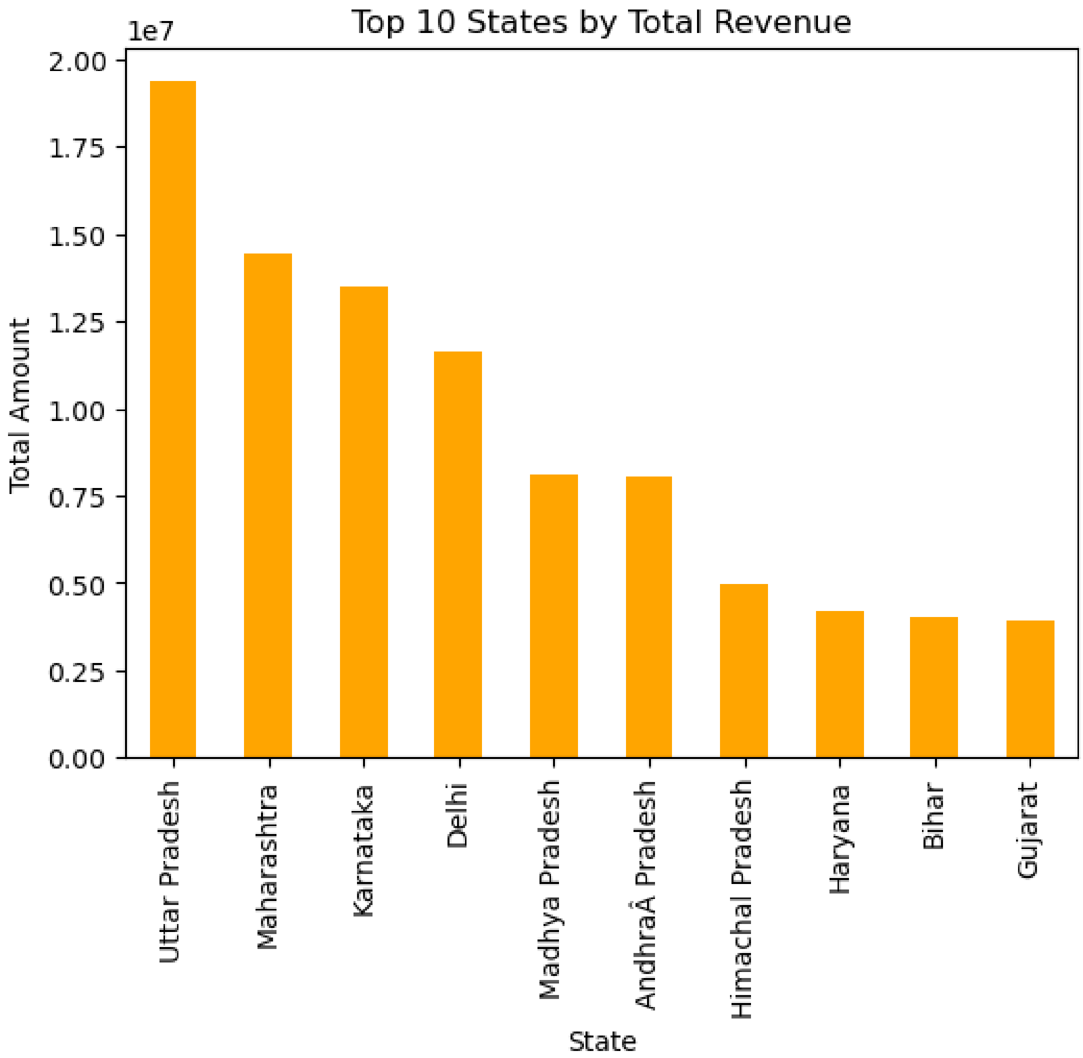
[1216]:

```
top_states_orders = df.groupby('State')['Orders'].sum().
 ↪sort_values(ascending=False).head(10)
top_states_orders.plot(kind='bar')
plt.title('Top 10 States by Number of Orders')
plt.ylabel('Orders')
plt.show()
```



[1217]:

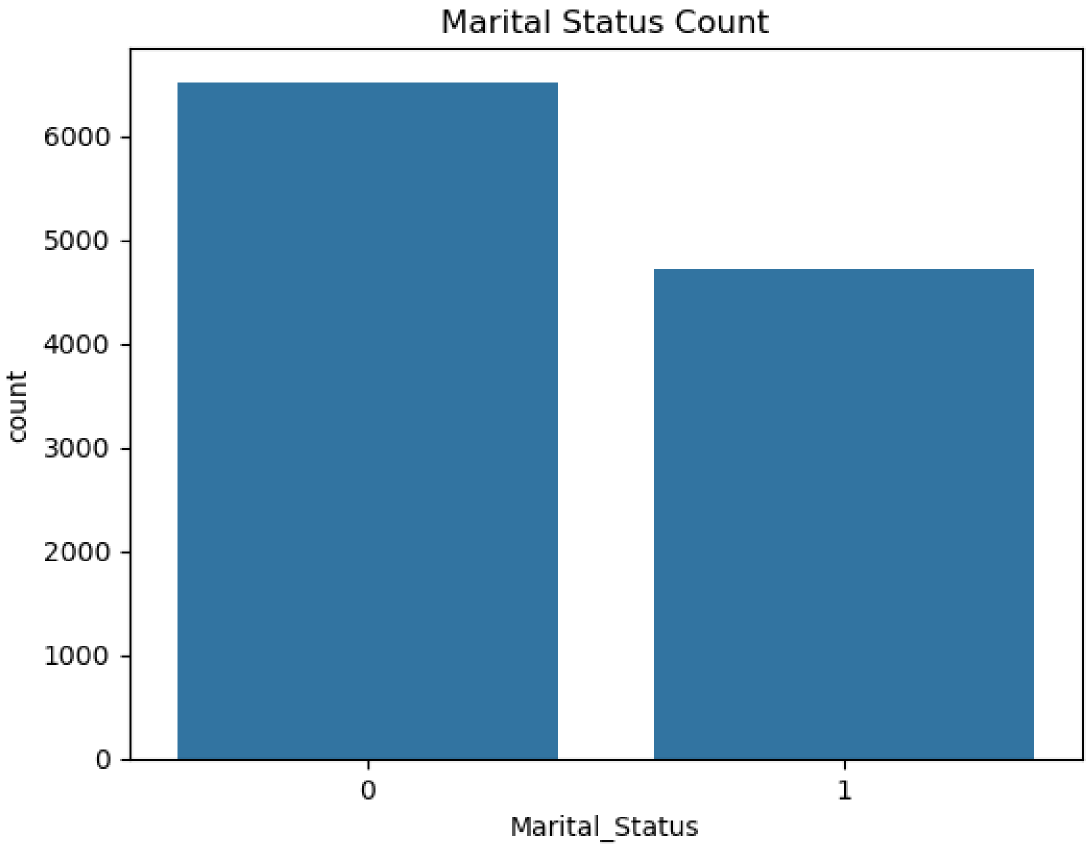
```
top_states_amount = df.groupby('State')['Amount'].sum().
 ↪sort_values(ascending=False).head(10)
top_states_amount.plot(kind='bar', color='orange')
plt.title('Top 10 States by Total Revenue')
plt.ylabel('Total Amount')
plt.show()
```



9 Marital Status Analysis

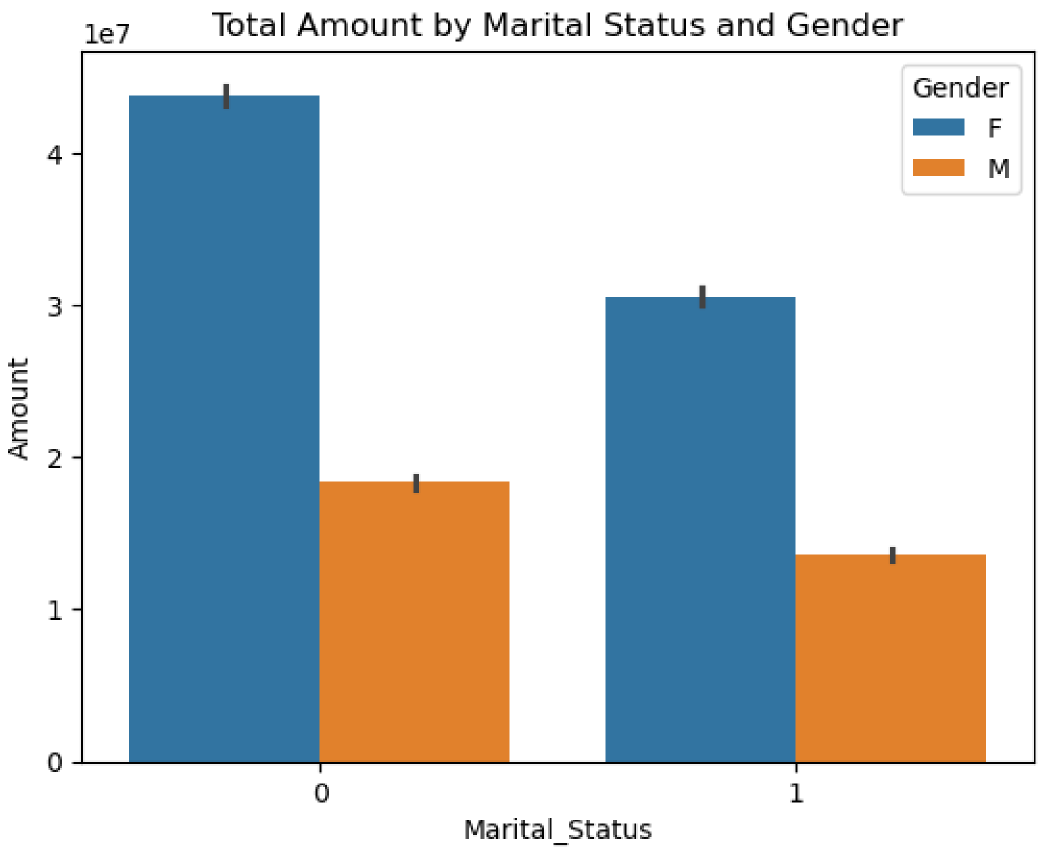
- Question: How does marital status affect purchasing behavior?

[1218]:
```
sns.countplot(x='Marital_Status', data=df)
plt.title('Marital Status Count')
plt.show()
```



- Plot a count plot for marital status and a bar chart showing total amount spent by marital status, with gender as a hue.

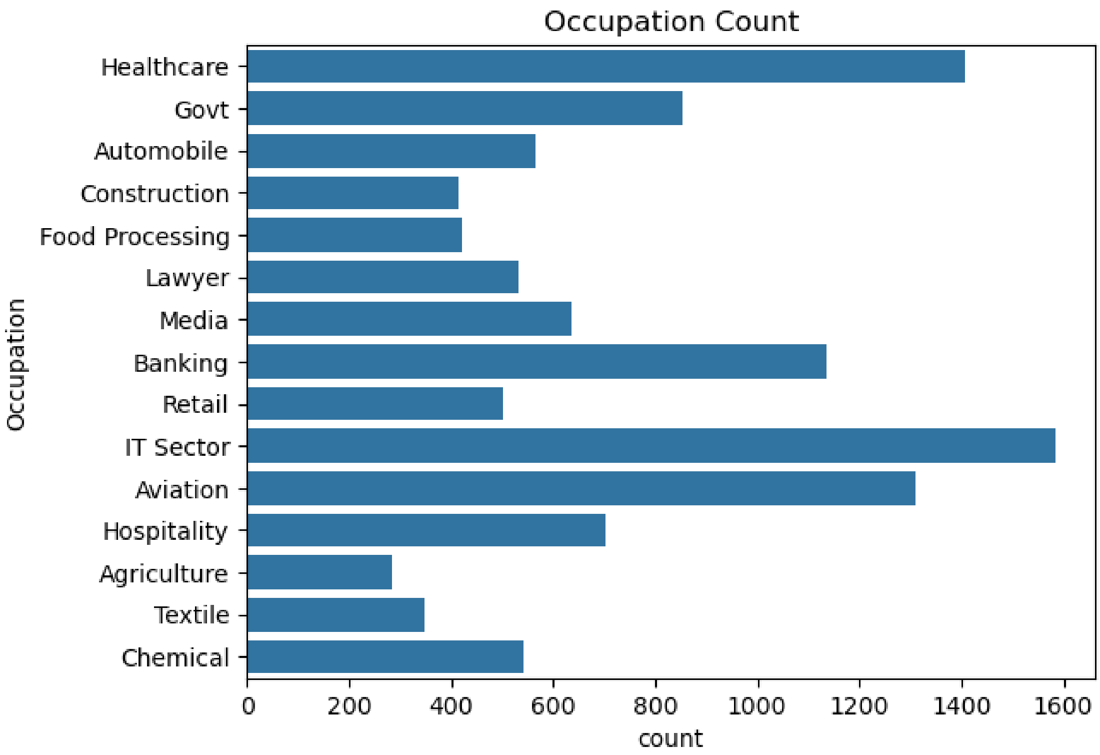
[1219]:
```
sns.barplot(x='Marital_Status', y='Amount', hue='Gender', data=df,␣
  ↪estimator=sum)
plt.title('Total Amount by Marital Status and Gender')
plt.show()
```



9.1 Occupation Analysis

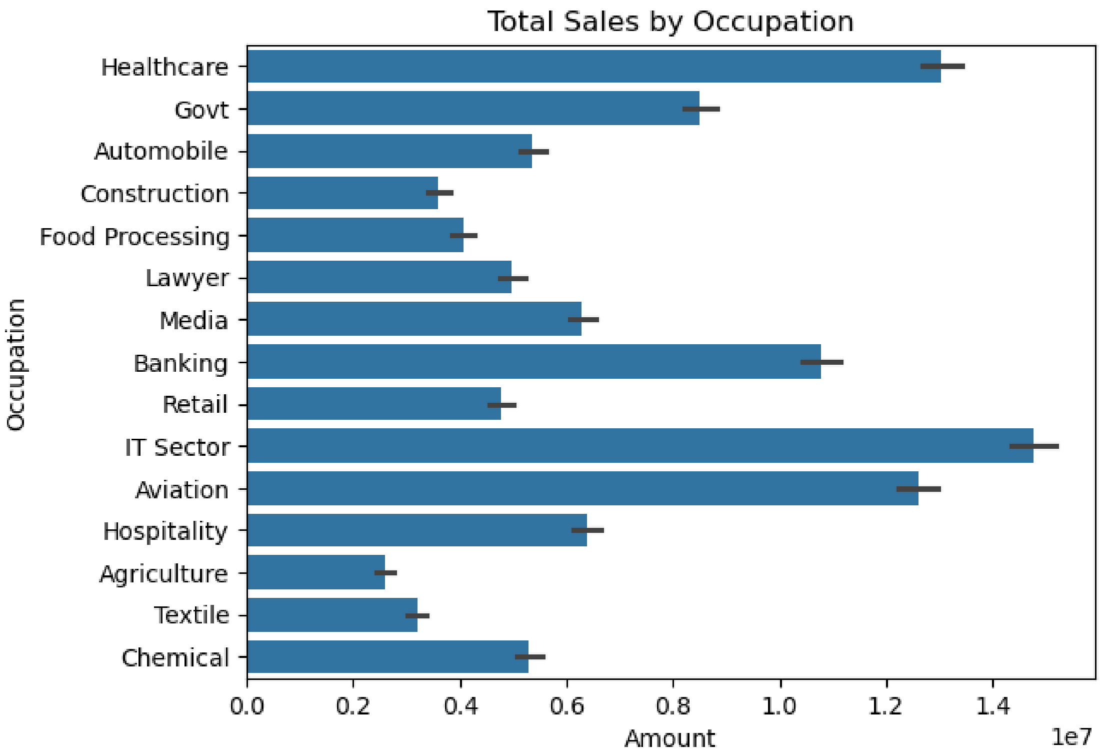
- Question: Which occupations contribute most to sales?

```
[1220]: sns.countplot(y='Occupation', data=df)
        plt.title('Occupation Count')
        plt.show()
```



- Create a count plot for occupation and a bar chart for total sales by occupation.

[1221]:
```
sns.barplot(y='Occupation', x='Amount', data=df, estimator=sum)
plt.title('Total Sales by Occupation')
plt.show()
```

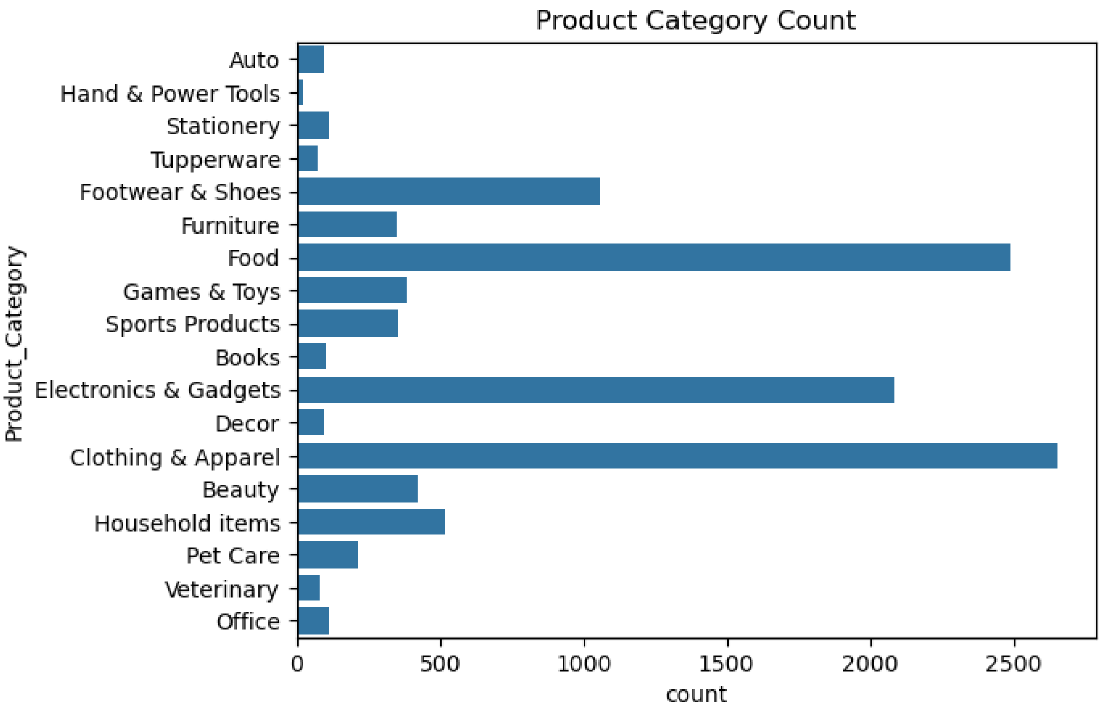


# 6. Product Category Analysis

- *Question:* What product categories are the most popular, and which ones generate the most revenue?

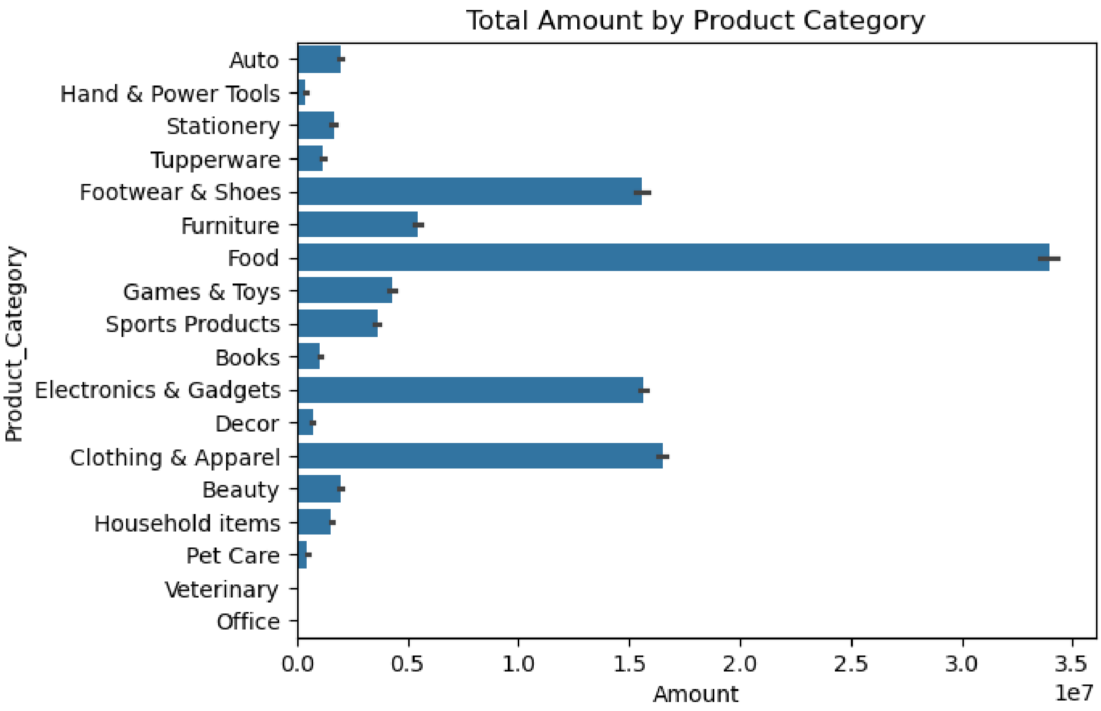
`* Create a count plot for product categories.`

[1222]:
```
sns.countplot(y='Product_Category', data=df)
plt.title('Product Category Count')
plt.show()
```



`* Create a bar chart to show the total amount by product category for the top` categories.

```
[1223]: sns.barplot(y='Product_Category', x='Amount', data=df, estimator=sum)
plt.title('Total Amount by Product Category')
plt.show()
```



# Additional Questions:

1. Which age group contributes the most to each product category, and does this vary by gender?

```
[1224]: df.groupby('Age Group')['Amount'].sum()
```

```
[1224]: Age Group
        0-17       2699653
        18-25     17240732
        26-35     42613442
        36-45     22144994
        46-50      9207844
        51-55      8261477
        55+        4080987
        Name: Amount, dtype: int32
```

2. How does the amount spent vary by marital status across different age groups?

```
[1225]: df.groupby('State')['Orders'].sum().sort_values(ascending=False).head(1)
```

```
[1225]: State
        Uttar Pradesh    4807
        Name: Orders, dtype: int64
```

```
3. Which states show the highest growth in orders and revenue, and are there seasonal
spikes in sales?
```

[1226]:
```
df.groupby('State')['Amount'].sum().sort_values(ascending=False).head(1)
```

[1226]:
```
State
Uttar Pradesh    19374968
Name: Amount, dtype: int32
```

```
4. Are there specific occupations that prefer particular product categories more than
others?
```

[1227]:
```
df.groupby('Occupation')['Amount'].sum().sort_values(ascending=False).head(1)
```

[1227]:
```
Occupation
IT Sector    14755079
Name: Amount, dtype: int32
```

[1228]:
```
df['Product_Category'].value_counts().head(1)
```

[1228]:
```
Product_Category
Clothing & Apparel    2655
Name: count, dtype: int64
```

```
5.What is the correlation between age and spending amount, and does this differ by
gender?
```

[1229]:
```
df.groupby('Product_Category')['Amount'].sum().sort_values(ascending=False).
  ↪head(1)
```

[1229]:
```
Product_Category
Food    33933883
Name: Amount, dtype: int32
```

10 Conclusion Summary

High-purchasing customers are likely married males aged 26–35 from Maharashtra or UP, working in IT or Healthcare, buying Clothing and Electronics.

[ ]:
```

```

[ ]:
```

```