Black_Friday_V2

March 27, 2023

Read & Import packages.

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error,␣
↪r2_score

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost.sklearn import XGBRegressor
```

Master Dataset contains total of 7,83,667 records.

We divided the data in the ratio of 70-30%

[5]:
```
df_train = pd.read_csv('https://raw.githubusercontent.com/commonemail270/EDA/
↪main/Balck_friday_dataset/train.csv')
df_test = pd.read_csv('https://raw.githubusercontent.com/commonemail270/EDA/
↪main/Balck_friday_dataset/test.csv')
df_train.head()
```

[5]:
```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
```

```
4                        4+               0                   8

   Product_Category_2  Product_Category_3  Purchase
0                 NaN                 NaN      8370
1                 6.0                14.0     15200
2                 NaN                 NaN      1422
3                14.0                 NaN      1057
4                 NaN                 NaN      7969
```

[6]:
```python
df_test.head()
```

[6]:
```
   User_ID Product_ID Gender    Age  Occupation City_Category  \
0  1000004  P00128942      M  46-50           7             B
1  1000009  P00113442      M  26-35          17             C
2  1000010  P00288442      F  36-45           1             B
3  1000010  P00145342      F  36-45           1             B
4  1000011  P00053842      F  26-35           1             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               1                   1
1                          0               0                   3
2                         4+               1                   5
3                         4+               1                   4
4                          1               0                   4

   Product_Category_2  Product_Category_3
0                11.0                 NaN
1                 5.0                 NaN
2                14.0                 NaN
3                 9.0                 NaN
4                 5.0                12.0
```

Data Analysis

[7]:
```python
df_train.isnull().sum().sort_values(ascending=False) * 100 / len(df_train)
```

[7]:
```
Product_Category_3            69.672659
Product_Category_2            31.566643
User_ID                        0.000000
Product_ID                     0.000000
Gender                         0.000000
Age                            0.000000
Occupation                     0.000000
City_Category                  0.000000
Stay_In_Current_City_Years     0.000000
Marital_Status                 0.000000
Product_Category_1             0.000000
```

```
Purchase                       0.000000
dtype: float64
```

[170]:
```
df_test.isnull().sum().sort_values(ascending=False) * 100 / len(df_test)
```

[170]:
```
Product_Category_3            69.590195
Product_Category_2            30.969311
Product_Category_1             0.000000
Marital_Status                 0.000000
Stay_In_Current_City_Years     0.000000
City_Category                  0.000000
Occupation                     0.000000
Age                            0.000000
Gender                         0.000000
Product_ID                     0.000000
User_ID                        0.000000
dtype: float64
```

[10]:
```

```

[10]:
```
233599
```

[171]:
```
df_train.describe().T
```

[171]:
```
                       count          mean          std        min        25%  \
User_ID             550068.0  1.003029e+06  1727.591586  1000001.0  1001516.0
Occupation          550068.0  8.076707e+00     6.522660        0.0        2.0
Marital_Status      550068.0  4.096530e-01     0.491770        0.0        0.0
Product_Category_1  550068.0  5.404270e+00     3.936211        1.0        1.0
Product_Category_2  376430.0  9.842329e+00     5.086590        2.0        5.0
Product_Category_3  166821.0  1.266824e+01     4.125338        3.0        9.0
Purchase            550068.0  9.263969e+03  5023.065394       12.0     5823.0

                          50%        75%        max
User_ID             1003077.0  1004478.0  1006040.0
Occupation                7.0       14.0       20.0
Marital_Status            0.0        1.0        1.0
Product_Category_1        5.0        8.0       20.0
Product_Category_2        9.0       15.0       18.0
Product_Category_3       14.0       16.0       18.0
Purchase               8047.0    12054.0    23961.0
```

We will impute the missing values of Product Category 2 with mean value as Mean and Median of feature is close to 9.

[172]:
```
df_train['Product_Category_2'] = df_train['Product_Category_2'].
    ↪fillna(df_train['Product_Category_2'].mean())
```

[173]:
```
df_test['Product_Category_2'] = df_test['Product_Category_2'].
 ↪fillna(df_test['Product_Category_2'].mean())
```

[174]:
```
df_train['Stay_In_Current_City_Years'].unique()
```

[174]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

[175]:
```
df_train['Age'].unique()
```

[175]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

[176]:
```
df_train['Gender'].unique()
```

[176]:
```
array(['F', 'M'], dtype=object)
```

[177]:
```
df_train['City_Category'].unique()
```

[177]:
```
array(['A', 'C', 'B'], dtype=object)
```

**Data Cleaning.

[178]:
```
train_df = df_train.copy()
train_df.Stay_In_Current_City_Years.replace({'0':0,
                                            '1':1,
                                            '2':2,
                                            '3':3,
                                            '4+':4},inplace=True)
train_df.Age.replace({"55+":"55 & above"},inplace=True)
train_df.Gender.replace({'M':1,'F':0},inplace=True)
train_df.City_Category.replace({'A':1,'B':2,'C':3},inplace=True)
```

[179]:
```
train_df = train_df.rename(columns={'Age':'Age_Groups'})
train_df.head()
```

[179]:
```
   User_ID Product_ID  Gender  Age_Groups  Occupation  City_Category  \
0  1000001  P00069042       0        0-17          10              1
1  1000001  P00248942       0        0-17          10              1
2  1000001  P00087842       0        0-17          10              1
3  1000001  P00085442       0        0-17          10              1
4  1000002  P00285442       1  55 & above          16              3

   Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                           2               0                   3
1                           2               0                   1
2                           2               0                  12
3                           2               0                  12
```

```
4                           4               0                   8

   Product_Category_2  Product_Category_3  Purchase
0            9.842329                 NaN      8370
1            6.000000                14.0     15200
2            9.842329                 NaN      1422
3           14.000000                 NaN      1057
4            9.842329                 NaN      7969
```

[180]:
```
test_df = df_test.copy()
test_df.Stay_In_Current_City_Years.replace({'0':0,
                                            '1':1,
                                            '2':2,
                                            '3':3,
                                            '4+':4},inplace=True)
test_df.Age.replace({"55+":"55 & above"},inplace=True)
test_df.Gender.replace({'M':1,'F':0},inplace=True)
test_df.City_Category.replace({'A':1,'B':2,'C':3},inplace=True)
```

[181]:
```
test_df = test_df.rename(columns={'Age':'Age_Groups'})
test_df.head(1)
```

[181]:
```
   User_ID Product_ID  Gender Age_Groups  Occupation  City_Category  \
0  1000004  P00128942       1      46-50           7              2

   Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                           2               1                   1

   Product_Category_2  Product_Category_3
0                11.0                 NaN
```

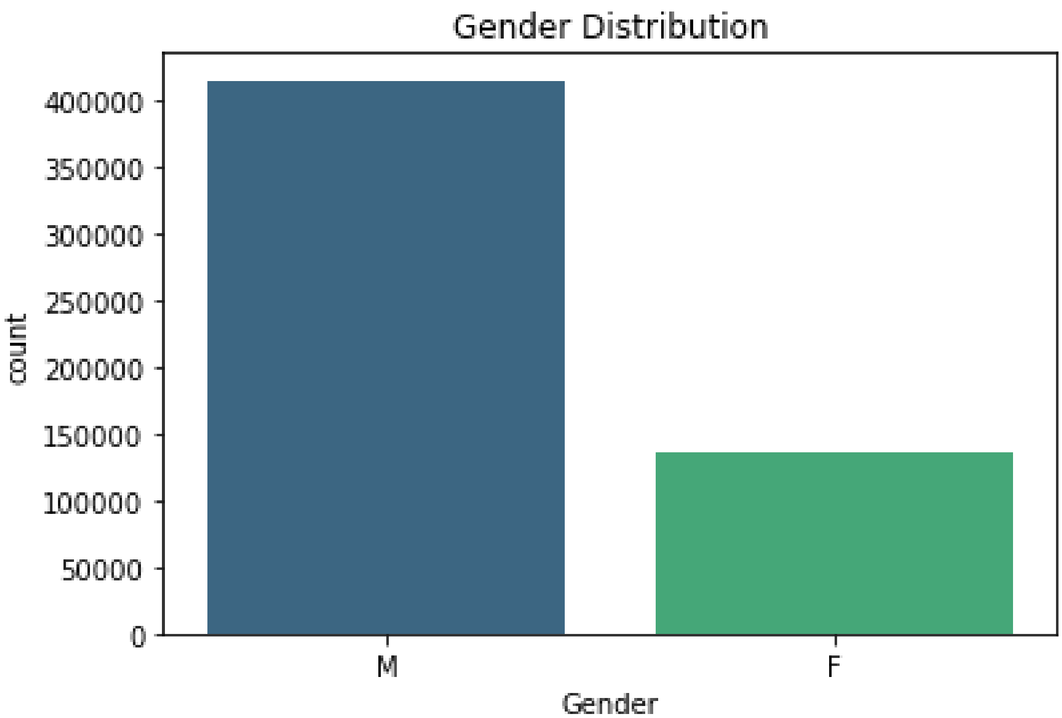
**Exploratory Data Analysis.

[182]:
```
df_train.head(2)
```

[182]:
```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1

   Product_Category_2  Product_Category_3  Purchase
0            9.842329                 NaN      8370
1            6.000000                14.0     15200
```

Univariate Analysis.

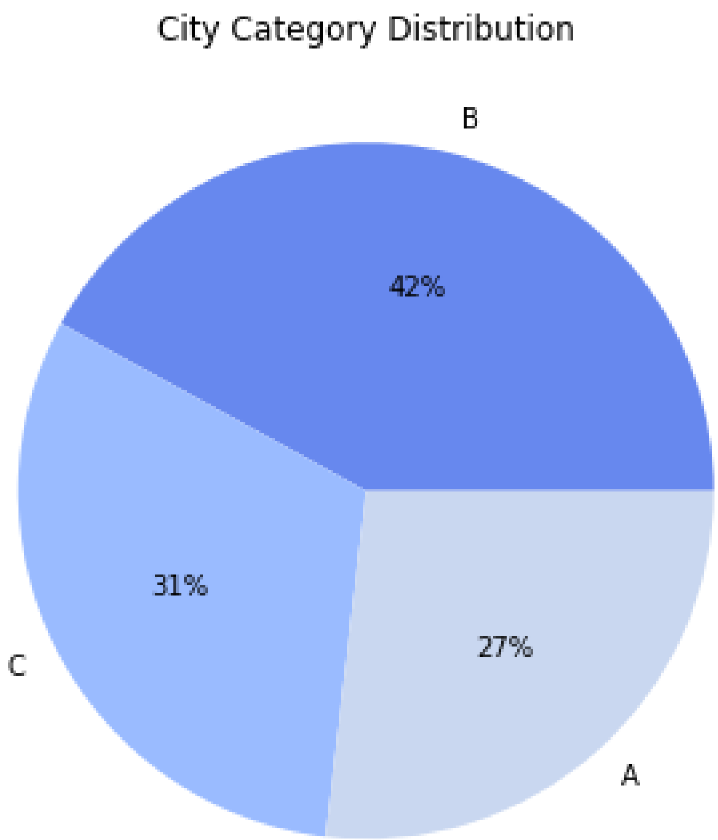
[183]:
```
plt.title("Gender Distribution")
sns.countplot(df_train['Gender'], palette='viridis',order = df_train['Gender'].
 ↪value_counts().index)
plt.show()
```



Insights:

1. The Gender feature has high data imbalance. The ratio of count of female customers is very less compared to male customers.
2. Need to handle this class imbalance using SMOTE/Oversampling techniques.

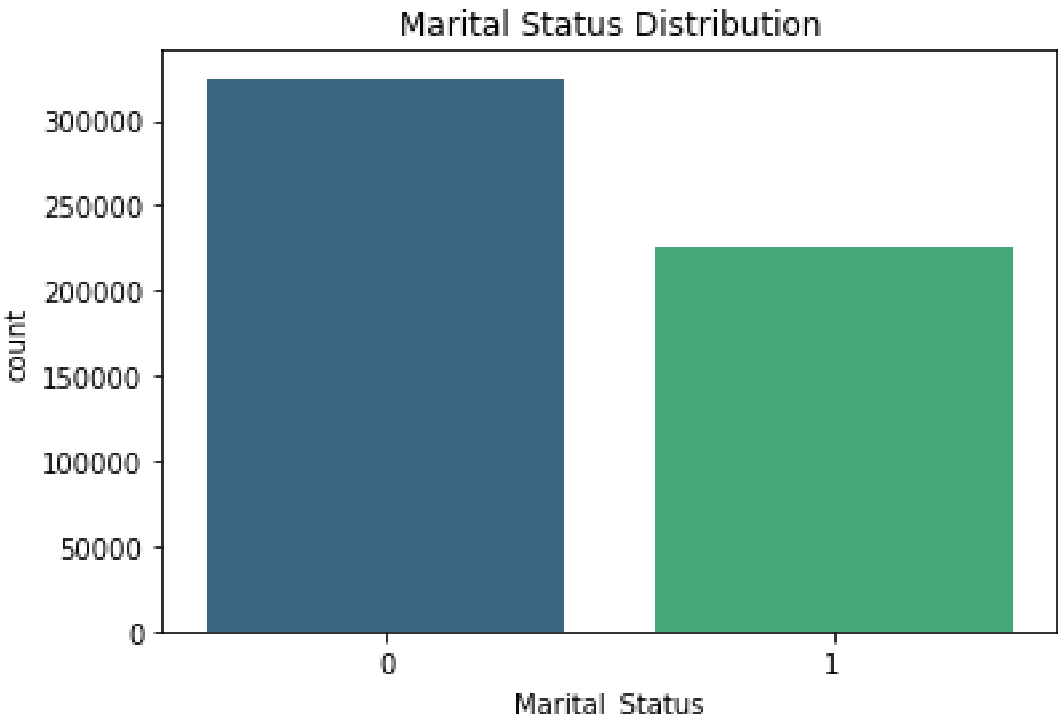
[184]:
```
plt.figure(figsize = (10,6))
plt.title("City Category Distribution")
palette_color = sns.color_palette('coolwarm')

# plotting data on chart
plt.pie(df_train['City_Category'].value_counts(normalize=True),␣
 ↪colors=palette_color, autopct='%.0f%%', labels =␣
 ↪list(df_train['City_Category'].value_counts().index))

# displaying chart
plt.show()
```



Insight:

1. City category B has observed to be having highest percentage of customers who have purchased in Black Friday Sale i.e 42% compared to A and C.

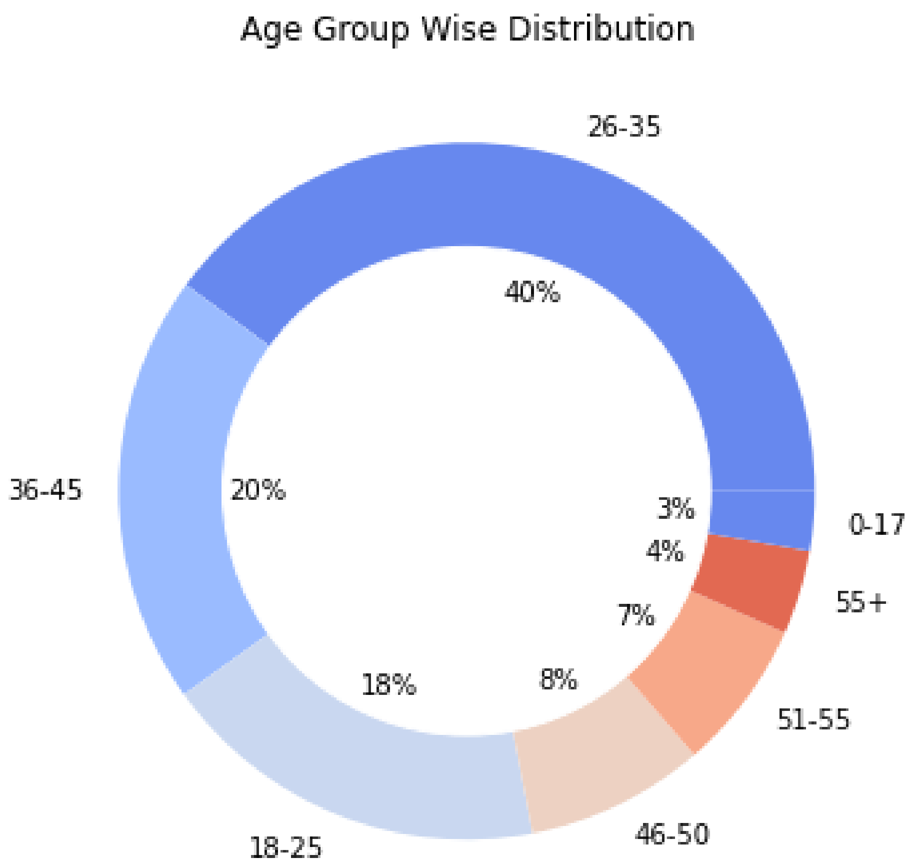
[185]:
```
plt.title("Marital Status Distribution")
sns.countplot(df_train['Marital_Status'], palette='viridis')
plt.show()
```



Insight:

1. Data shows unmarried customers have spent on Black Friday sale more than married customers.

[186]:
```
plt.figure(figsize = (10,6))
plt.title("Age Group Wise Distribution")

my_circle = plt.Circle((0, 0), 0.7, color='white')
palette_color = sns.color_palette('coolwarm')

# plotting data on chart
plt.pie(df_train['Age'].value_counts(normalize=True), colors=palette_color,␣
↪autopct='%.0f%%', labels = list(df_train['Age'].value_counts().index))

p = plt.gcf()
p.gca().add_artist(my_circle)

# displaying chart
plt.show()
```

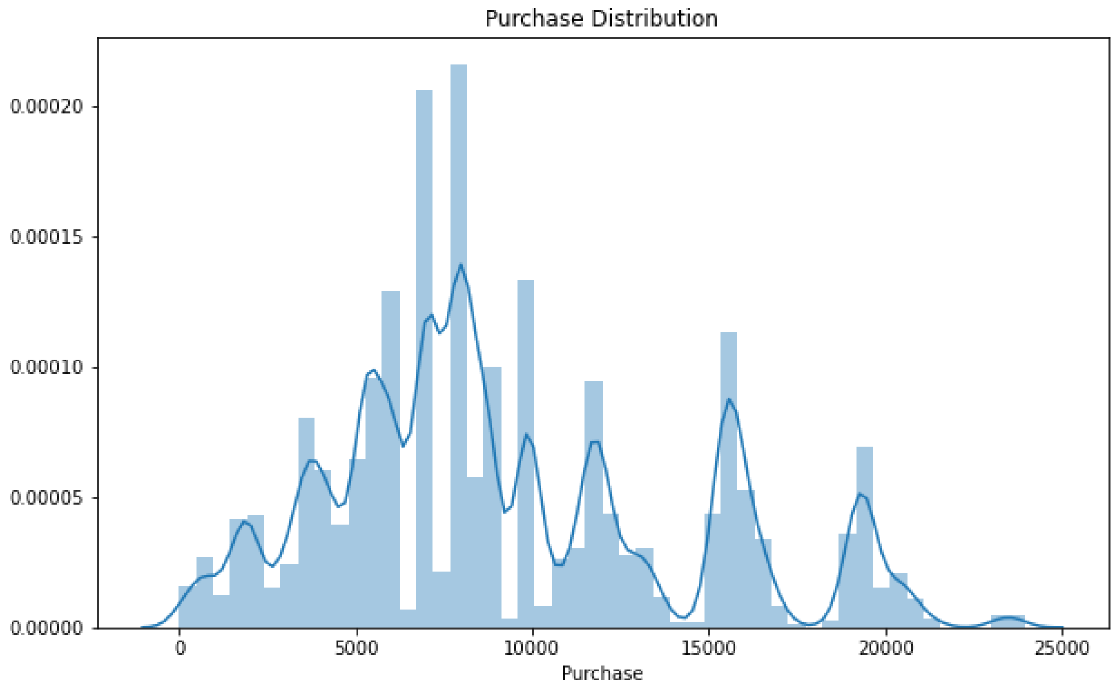


Insights:

1. Age group 26-35 years has highest percentage of customers who have spent on Black Friday sale i.e almost around 40%.
2. Age group 0-17 years has lowest percentage of customers who have spent (3%). And it is reasonable as teenage customers are less probable to have income.
3. Age group 18-25 & 36-45 years has average percentage of customers who spent on sale (around 20%).
4. Customers with Age above 45 years has observed to have decreasing percentage of customers as trend.

[187]:
```
plt.figure(figsize = (10,6))
plt.title("Purchase Distribution")
sns.distplot(df_train['Purchase'])
```

[187]: <matplotlib.axes._subplots.AxesSubplot at 0x17656552c10>

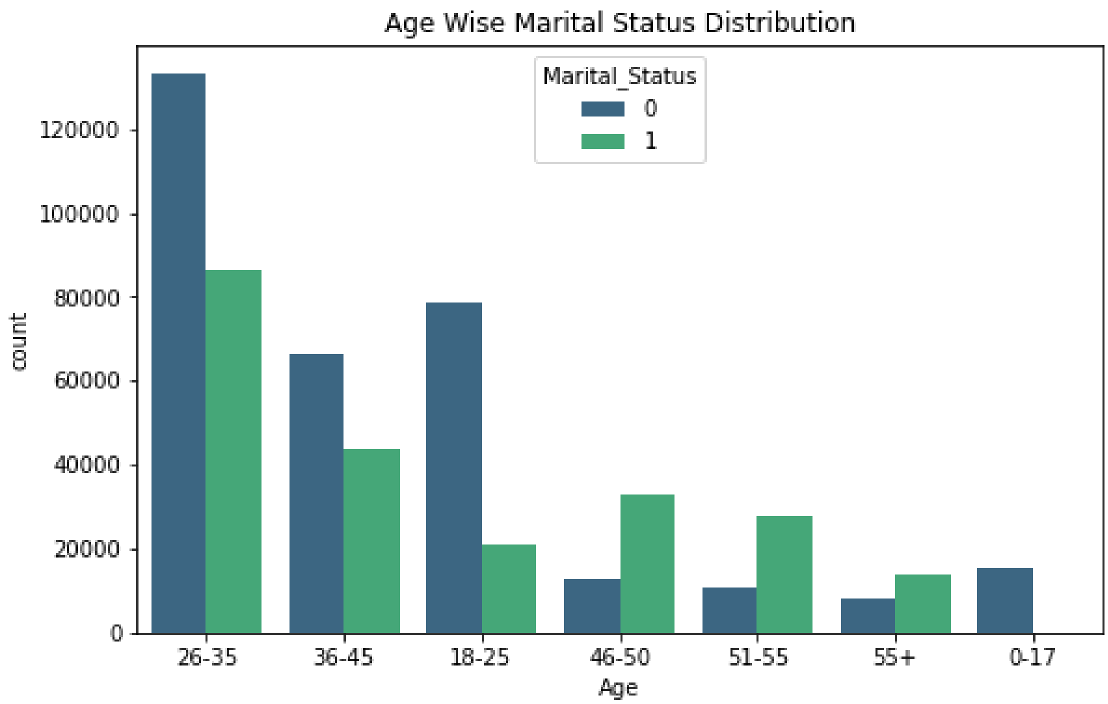


Insights:

1. The important observation form the above visualisation can be made that there are some outliers present in the dependent/target feature "Purchase".
2. According to distplot data is nearly normally distributed.

Bivariate Analysis.

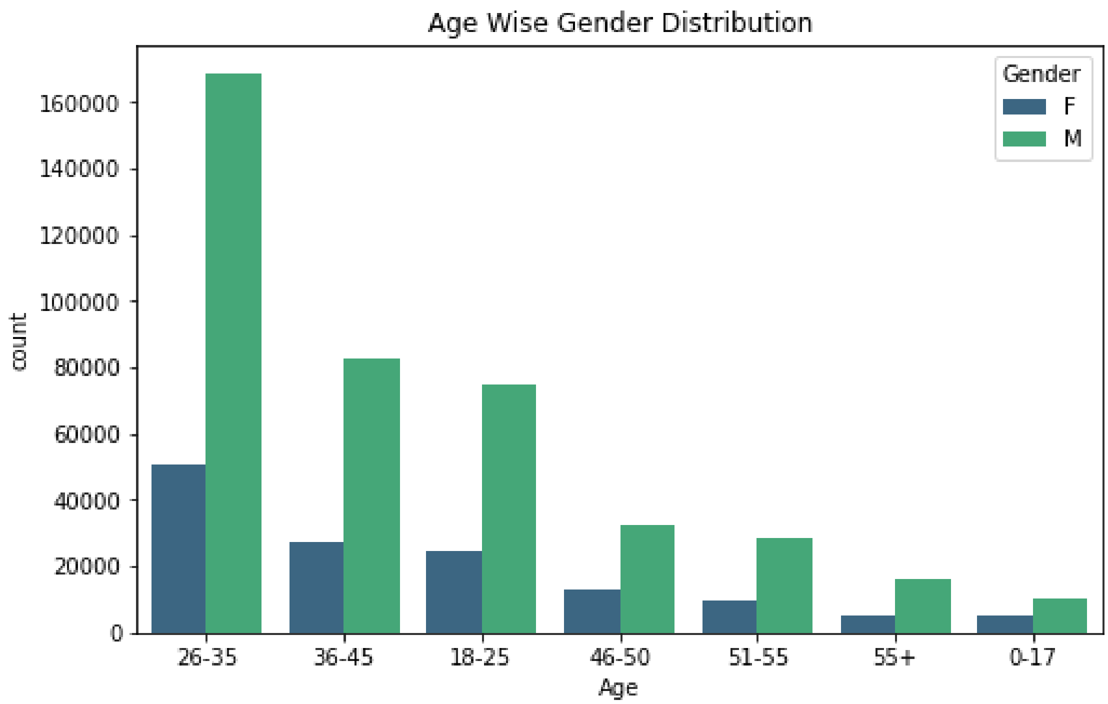
[188]:
```
plt.figure(figsize = (8,5))
plt.title("Age Wise Marital Status Distribution")
sns.countplot(df_train['Age'], hue=df_train['Marital_Status'],␣
  ↪palette='viridis', order = df_train['Age'].value_counts().index)
plt.show()
```



Insights:

1. Age group 0-17 years has all the single customers.
2. Age group 18-25 & 36-45 years has high single ratio than married.
3. Age group 26-35 years has highest ratio of both being single and married customers.
4. As age group is getting increased the ratio of being single is reduced. For example, 46-50, 51-55 & 55+, etc.

[189]:
```
plt.figure(figsize = (8,5))
plt.title("Age Wise Gender Distribution")
sns.countplot(df_train['Age'], hue=df_train['Gender'], palette='viridis', order␣
 ↪= df_train['Age'].value_counts().index)
plt.show()
```

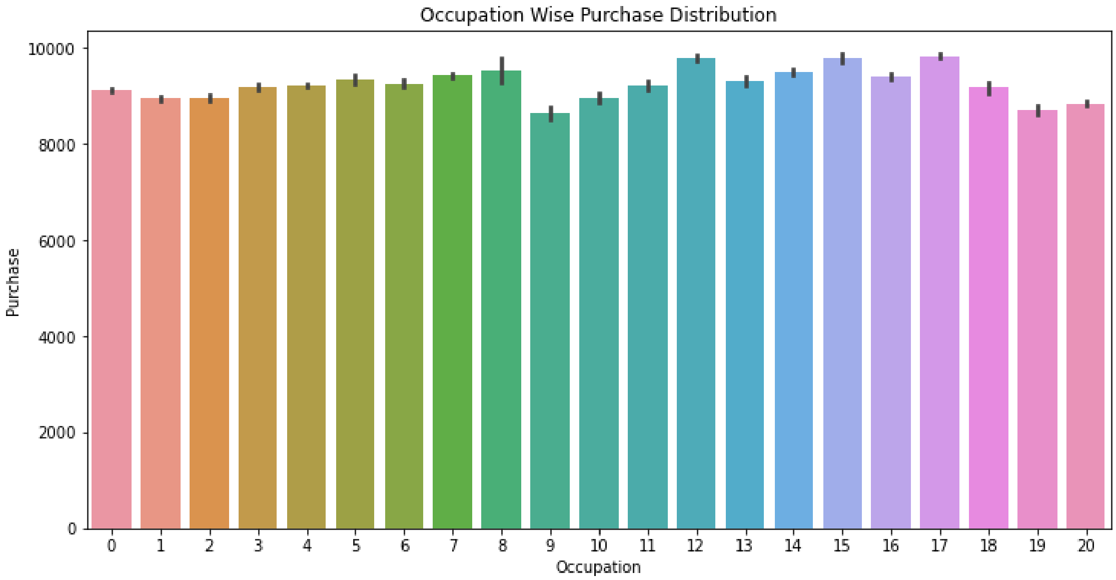


Insights:

1. In each Age group Male customers are dominating in spending/purchase in Black Friday Sale.
2. Age group 26-35 years has highest number of customers, whereas group 18-25 & 36-45 years has average number of customers.
3. Age groups 0-17 & 55+ years has lowest number of customers.
4. Less number of customers are witnessed in age groups 46-50 & 51-55 years to purchase in Sale.

[190]:
```
plt.figure(figsize = (12,6))
plt.title("Occupation Wise Purchase Distribution")
sns.barplot(x='Occupation', y='Purchase', data=df_train)
```

[190]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x17656e6ce50>
```

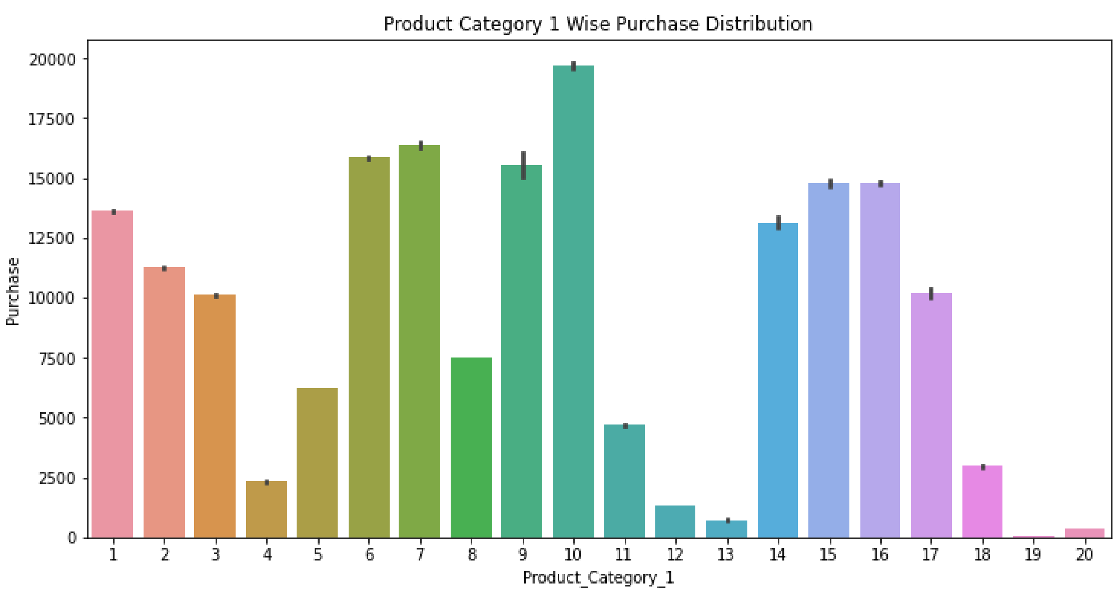


Insight:

1. Almost all of the Occupation categories have spent 8000-10000 in Black Friday sale

[191]:
```
plt.figure(figsize = (12,6))
plt.title("Product Category 1 Wise Purchase Distribution")
sns.barplot(x='Product_Category_1', y='Purchase', data=df_train)
```

[191]: <matplotlib.axes._subplots.AxesSubplot at 0x1765ecfe1c0>

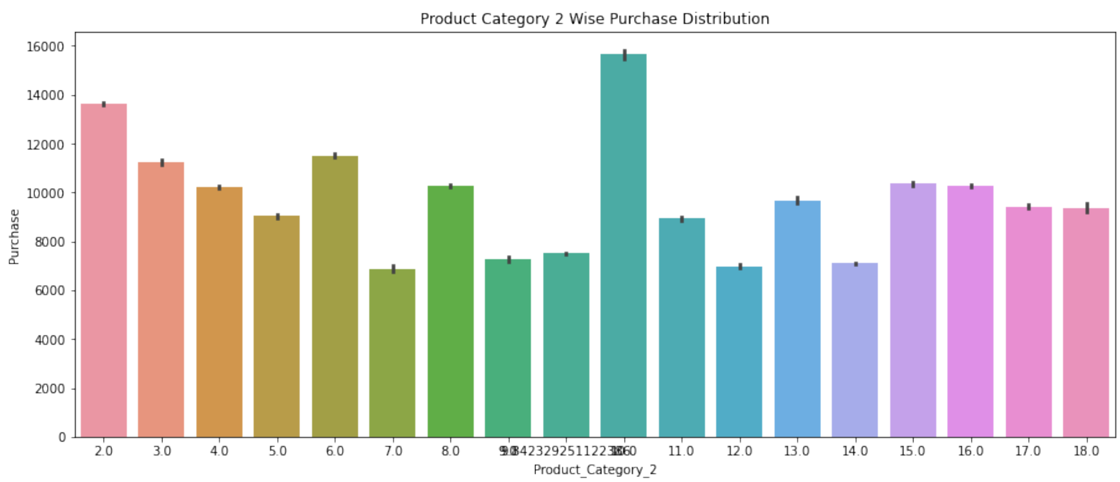


Insights:

1. Product category 10 has highest Purchase happened in Black Friday Sale.
2. Other Categories has a dispersed sales.

[192]:
```python
plt.figure(figsize = (15,6))
plt.title("Product Category 2 Wise Purchase Distribution")
sns.barplot(x='Product_Category_2', y='Purchase', data=df_train)
```

[192]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x17663548d00>
```



Insights:

1. Product category 10 has highest Purchase happened in Black Friday Sale.
2. Other Categories has a dispersed sales.
3. We can't make any solid statement from above visualizations.

Multivariate Analysis.

[193]:
```python
pd.crosstab([df_train['Gender']], [df_train['Marital_Status'],␣
↪df_train['Age']], normalize=True)*100
```

[193]:
```
Marital_Status         0                                                          \
Age                 0-17      18-25      26-35     36-45     46-50     51-55
Gender
F               0.924068   3.337224   5.468051  3.026717  0.575565  0.650829
M               1.821411  10.941738  18.764589  9.040337  1.731422  1.319655

Marital_Status                   1                                             \
Age                  55+     18-25      26-35     36-45     46-50     51-55
```

```
Gender
F                0.346866  1.140041   3.758444  1.912673  1.823956  1.147858
M                1.086229  2.698757  11.928889  6.020165  4.177302  3.880975

Marital_Status
Age                   55+
Gender
F                0.577201
M                1.899038
```

Insights:

1. In all unmarried customers, Age groups 18-25 & 26-35 years has highest percentage of customers in both genders Male & Female.
2. In all Male married customers, Age groups 18-25 & 26-35 years has highest percentage of customers.
3. In all Female married customers, Age groups 26-35 & 36-45 years has highest purchase customers.

[194]:
```
pd.crosstab([df_train['City_Category'],df_train['Marital_Status']],
 ↪[df_train['Gender'], df_train['Age']], normalize=True)*100
```

[194]:
```
Gender                              F                                      \
Age                              0-17     18-25     26-35     36-45
City_Category Marital_Status
A             0              0.263058  0.861348  1.816866  0.853894
              1              0.000000  0.278329  1.362922  0.437764
B             0              0.284510  1.557989  2.550594  1.209305
              1              0.000000  0.566475  1.346561  0.810445
C             0              0.376499  0.917887  1.100591  0.963517
              1              0.000000  0.295236  1.048961  0.664463

Gender                                                                M   \
Age                             46-50     51-55       55+      0-17
City_Category Marital_Status
A             0              0.048358  0.085989  0.038541  0.199430
              1              0.178887  0.237243  0.027633  0.000000
B             0              0.269421  0.327778  0.077263  0.703549
              1              0.894798  0.443582  0.168343  0.000000
C             0              0.257786  0.237062  0.231062  0.918432
              1              0.750271  0.467033  0.381226  0.000000

Gender                                                                     \
Age                             18-25     26-35     36-45     46-50
City_Category Marital_Status
A             0              3.100526  6.613728  1.822684  0.394497
              1              0.765542  3.613008  1.724514  0.761179
```

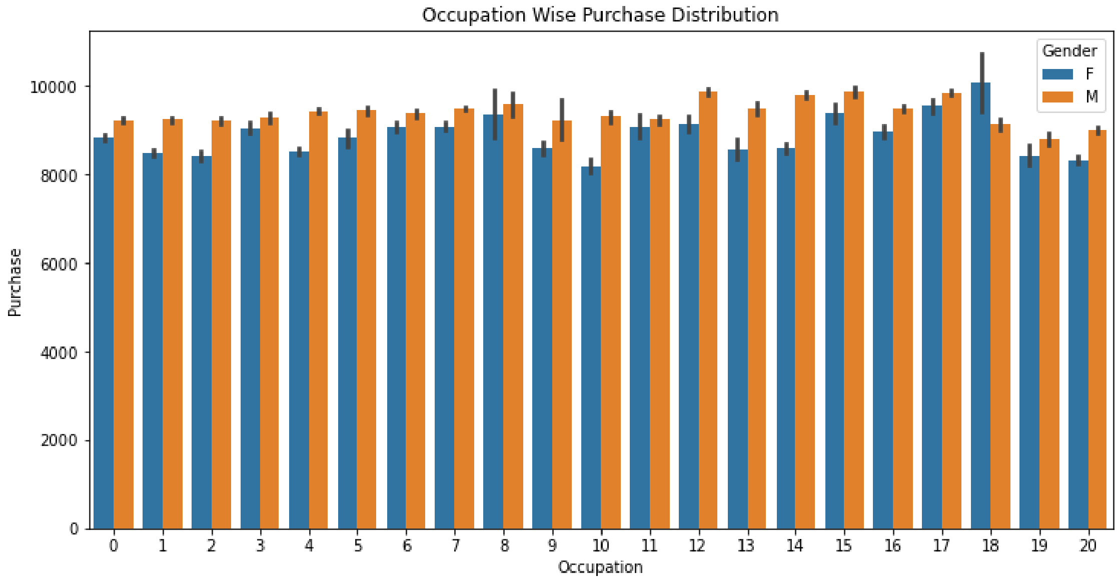
```
B             0                4.561800  7.664689  4.268200  0.612833
              1                1.175855  5.087735  2.365162  1.932670
C             0                3.279413  4.486173  2.949454  0.724092
              1                0.757361  3.228146  1.930489  1.483453

Gender
Age                               51-55       55+
City_Category Marital_Status
A             0                0.237243  0.238698
              1                0.548296  0.344685
B             0                0.539751  0.227608
              1                1.914127  0.465215
C             0                0.542660  0.619923
              1                1.418552  1.089138
```

Insights:

1. City B has highest percentage of Female customers in Age group 26-35 years in both Married and Unmarried marital status.
2. City B has highest percentage of Male customers in Age group 26-35 years in both Married and Unmarried marital status.
3. The above tabular representation shows that, in all the city categories A, B & C, the customers who have purchased/spent on Black Friday Sale always have high percentage of Unmarried customers irrespective of their Gender, Age groups.
4. Hence, we can say that Unmarried customers are more tend to spend in Black Friday sale.

[195]:
```
plt.figure(figsize = (12,6))
plt.title("Occupation Wise Purchase Distribution")
sns.barplot(x='Occupation', y='Purchase', hue = 'Gender',data=df_train)
```

[195]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1765f1214c0>
```

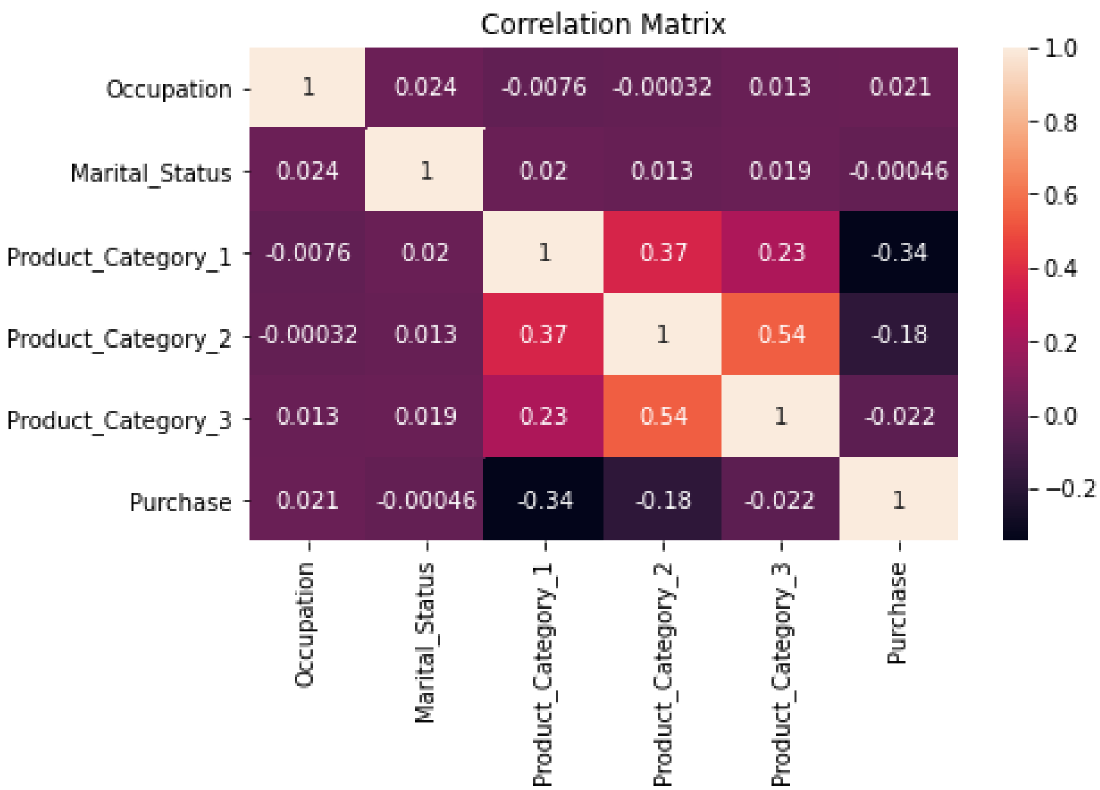


Insights:

1. In the Occupation level 18, Female customers has high purchase amount compared to Male customers.
2. The purchase amount of all the Occupation levels is almost in the range of 8000-10000, which indicates Occupation levels has no greater impact on the purchase in Black Friday..

[196]:
```
plt.figure(figsize = (7,4))
plt.title("Correlation Matrix")
feats = ['Gender', 'City_Category', 'Occupation','Stay_In_Current_City_Years',␣
↪'Marital_Status', 'Product_Category_1', 'Product_Category_2',␣
↪'Product_Category_3', 'Purchase']
sns.heatmap(df_train[feats].corr(), annot = True)
```

[196]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x17656e03f10>
```



Insights:

1. Occupation levels has no impact/correlation on independent as well as dependent features.Occupation feature can be dropped based on the various performance comparisons of the Model.
2. Product Category 3 has no correlation with target feature (Purchase).Also it has 70% of missing values, Hence, Product Category 3 feature can be dropped
3. Product Category 1 & Product Category 2 has strong negative correlation with target feature(Purchase). Which means the change of value in one feature varies with change of value in other feature. This is called as Inverse correlation. In other words, If the value of Purchase Category 1 increases, that will result in reduction in Purchase Value.

**Feature Engineering & Extraction

Transforming categorical feature into numeric using dummy encoding technique(One hot encoding).

[197]:
```
one_hot=pd.
 ↪get_dummies(data=train_df['Age_Groups'],prefix='Age_Group',drop_first=True)
one_hot
```

[197]:
```
   Age_Group_18-25  Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  \
0                0                0                0                0
1                0                0                0                0
```

```
2                    0                0                0                0
3                    0                0                0                0
4                    0                0                0                0
…                 …             …             …             …
550063               0                0                0                0
550064               0                1                0                0
550065               0                1                0                0
550066               0                0                0                0
550067               0                0                0                1

        Age_Group_51-55  Age_Group_55 & above
0                     0                     0
1                     0                     0
2                     0                     0
3                     0                     0
4                     0                     1
…                  …                   …
550063                1                     0
550064                0                     0
550065                0                     0
550066                0                     1
550067                0                     0

[550068 rows x 6 columns]
```

[198]:
```
train_df = pd.concat([train_df,one_hot],axis = 1).drop('Age_Groups',axis = 1)
train_df
```

[198]:
```
        User_ID Product_ID  Gender  Occupation  City_Category  \
0       1000001  P00069042       0          10              1
1       1000001  P00248942       0          10              1
2       1000001  P00087842       0          10              1
3       1000001  P00085442       0          10              1
4       1000002  P00285442       1          16              3
…         …        …      …       …          …
550063  1006033  P00372445       1          13              2
550064  1006035  P00375436       0           1              3
550065  1006036  P00375436       0          15              2
550066  1006038  P00375436       0           1              3
550067  1006039  P00371644       0           0              2

        Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                                2               0                   3
1                                2               0                   1
2                                2               0                  12
3                                2               0                  12
4                                4               0                   8
```

```
…                             …             …                 …
550063                         1                1                   20
550064                         3                0                   20
550065                         4                1                   20
550066                         2                0                   20
550067                         4                1                   20

        Product_Category_2  Product_Category_3  Purchase  Age_Group_18-25  \
0                 9.842329                 NaN      8370                0
1                 6.000000                14.0     15200                0
2                 9.842329                 NaN      1422                0
3                14.000000                 NaN      1057                0
4                 9.842329                 NaN      7969                0
…                      …                   …        …               …
550063            9.842329                 NaN       368                0
550064            9.842329                 NaN       371                0
550065            9.842329                 NaN       137                0
550066            9.842329                 NaN       365                0
550067            9.842329                 NaN       490                0

        Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  \
0                     0                0                0                0
1                     0                0                0                0
2                     0                0                0                0
3                     0                0                0                0
4                     0                0                0                0
…                  …               …               …               …
550063                0                0                0                1
550064                1                0                0                0
550065                1                0                0                0
550066                0                0                0                0
550067                0                0                1                0

        Age_Group_55 & above
0                          0
1                          0
2                          0
3                          0
4                          1
…                      …
550063                     0
550064                     0
550065                     0
550066                     1
550067                     0

[550068 rows x 17 columns]
```

[199]:
```
one_hot_test = pd.
 ↪get_dummies(data=test_df['Age_Groups'],prefix='Age_Group',drop_first=True)
one_hot_test
```

[199]:
```
        Age_Group_18-25  Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  \
0                     0                0                0                1
1                     0                1                0                0
2                     0                0                1                0
3                     0                0                1                0
4                     0                1                0                0
…                   …              …              …              …
233594                0                1                0                0
233595                0                1                0                0
233596                0                1                0                0
233597                0                0                0                1
233598                0                0                0                1

        Age_Group_51-55  Age_Group_55 & above
0                     0                     0
1                     0                     0
2                     0                     0
3                     0                     0
4                     0                     0
…                   …                   …
233594                0                     0
233595                0                     0
233596                0                     0
233597                0                     0
233598                0                     0

[233599 rows x 6 columns]
```

[200]:
```
test_df = pd.concat([test_df,one_hot_test],axis = 1).drop('Age_Groups',axis = 1)
test_df.head()
```

[200]:
```
   User_ID Product_ID  Gender  Occupation  City_Category  \
0  1000004  P00128942       1           7              2
1  1000009  P00113442       1          17              3
2  1000010  P00288442       0           1              2
3  1000010  P00145342       0           1              2
4  1000011  P00053842       0           1              3

   Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                           2               1                   1
1                           0               0                   3
2                           4               1                   5
3                           4               1                   4
```

```
4                             1               0                   4

   Product_Category_2  Product_Category_3  Age_Group_18-25  Age_Group_26-35  \
0                11.0                 NaN                0                0
1                 5.0                 NaN                0                1
2                14.0                 NaN                0                0
3                 9.0                 NaN                0                0
4                 5.0                12.0                0                1

   Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  Age_Group_55 & above
0                0                1                0                     0
1                0                0                0                     0
2                1                0                0                     0
3                1                0                0                     0
4                0                0                0                     0
```

Drop unwanted features.

Dropping Product_Category_3 as it has 70% of the data missing..

[201]:
```
train_df.drop(columns = ['User_ID','Product_ID','Product_Category_3',␣
 ↪'Occupation'],axis = 1,inplace=True)
train_df
```

[201]:
```
        Gender  City_Category  Stay_In_Current_City_Years  Marital_Status  \
0            0              1                           2               0
1            0              1                           2               0
2            0              1                           2               0
3            0              1                           2               0
4            1              3                           4               0
…          …            …                          …             …
550063       1              2                           1               1
550064       0              3                           3               0
550065       0              2                           4               1
550066       0              3                           2               0
550067       0              2                           4               1

        Product_Category_1  Product_Category_2  Purchase  Age_Group_18-25  \
0                        3            9.842329      8370                0
1                        1            6.000000     15200                0
2                       12            9.842329      1422                0
3                       12           14.000000      1057                0
4                        8            9.842329      7969                0
…                      …                 …       …             …
550063                  20            9.842329       368                0
550064                  20            9.842329       371                0
550065                  20            9.842329       137                0
550066                  20            9.842329       365                0
```

```
550067                    20          9.842329      490                 0

        Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  \
0                     0                0                0                0
1                     0                0                0                0
2                     0                0                0                0
3                     0                0                0                0
4                     0                0                0                0
…                   …                …                …                …
550063                0                0                0                1
550064                1                0                0                0
550065                1                0                0                0
550066                0                0                0                0
550067                0                0                1                0

        Age_Group_55 & above
0                          0
1                          0
2                          0
3                          0
4                          1
…                        …
550063                     0
550064                     0
550065                     0
550066                     1
550067                     0

[550068 rows x 13 columns]
```

[202]:
```python
test_df.drop(columns = ['User_ID','Product_ID','Product_Category_3',␣
 ↪'Occupation'],axis = 1,inplace=True)
test_df
```

[202]:
```
        Gender  City_Category  Stay_In_Current_City_Years  Marital_Status  \
0            1              2                           2               1
1            1              3                           0               0
2            0              2                           4               1
3            0              2                           4               1
4            0              3                           1               0
…          …            …                         …             …
233594       0              2                           4               1
233595       0              2                           4               1
233596       0              2                           4               1
233597       0              3                           4               0
233598       0              2                           4               1
```

```
        Product_Category_1  Product_Category_2  Age_Group_18-25  \
0                        1           11.000000                0
1                        3            5.000000                0
2                        5           14.000000                0
3                        4            9.000000                0
4                        4            5.000000                0
…                      …                 …               …
233594                   8            9.849586                0
233595                   5            8.000000                0
233596                   1            5.000000                0
233597                  10           16.000000                0
233598                   4            5.000000                0

        Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  \
0                     0                0                1                0
1                     1                0                0                0
2                     0                1                0                0
3                     0                1                0                0
4                     1                0                0                0
…                   …              …              …              …
233594                1                0                0                0
233595                1                0                0                0
233596                1                0                0                0
233597                0                0                1                0
233598                0                0                1                0

        Age_Group_55 & above
0                          0
1                          0
2                          0
3                          0
4                          0
…                        …
233594                     0
233595                     0
233596                     0
233597                     0
233598                     0

[233599 rows x 12 columns]
```

**Outlier treatment on train dataset.

[203]:
```python
import scipy.stats as stats

train_df['zscore'] = stats.zscore(train_df['Purchase'])
```

```
print("The Minimum zscore of feature Purchase is:", np.round(train_df['zscore'].
↪min()))
print("The Maximum zscore of feature Purchase is:", np.round(train_df['zscore'].
↪max()))
train_df.drop('zscore',axis = 1, inplace = True)
```

```
The Minimum zscore of feature Purchase is: -2.0
The Maximum zscore of feature Purchase is: 3.0
```

As per Z_score method to detect and remove outliers, the threshold value of lambda(the decision parameter) should be +3 & -3. And as our mimimum and maximum z_score is below the threshold, we can say that there are no outliers.

**Separate Independent and dependent features & Split the data in train and test sets.

[205]:
```
X = train_df.drop("Purchase",axis = True)
y = train_df["Purchase"]

x_train, x_test, y_train, y_test=train_test_split(X,y, test_size=0.2,␣
↪random_state=101)
```

**Modeling.

Linear Regression.

[206]:
```
lr = LinearRegression()
lr.fit(x_train, y_train)

y_pred_lr = lr.predict(x_test)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_lr)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_test, y_pred_lr))
print('R2 Score:',metrics.r2_score(y_test,y_pred_lr)*100)
```

```
RMSE: 4694.569599682641
MAPE: 1.1134022216354589
R2 Score: 12.631382780679578
```

[207]:
```
y_pred_train_lr = lr.predict(x_train)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_train, y_pred_train_lr)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_train, y_pred_train_lr))
print('R2 Score:',metrics.r2_score(y_train,y_pred_train_lr)*100)
```

```
RMSE: 4690.693640109924
MAPE: 1.1247366725912407
R2 Score: 12.800269305429568
```

Random Forest Regressor.

[208]:
```
rfr=RandomForestRegressor(random_state=0)
rfr.fit(x_train, y_train)

y_pred_rfr=rfr.predict(x_test)

print("RMSE:", np.sqrt(metrics.mean_squared_error(y_test, y_pred_rfr)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_test, y_pred_rfr))
print("R2 Score:",round(metrics.r2_score(y_test,y_pred_rfr)*100,2))
```

```
RMSE: 3015.3225343046383
MAPE: 0.3408985831052717
R2 Score: 63.96
```

[209]:
```
y_pred_train_rfr = rfr.predict(x_train)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_train, y_pred_train_rfr)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_train,␣
 ↪y_pred_train_rfr))
print('R2 Score:',metrics.r2_score(y_train,y_pred_train_rfr)*100)
```

```
RMSE: 2853.0580891810814
MAPE: 0.32484695245946726
R2 Score: 67.74015817141503
```

XGBoost Regressor.

[210]:
```
xgb_reg=XGBRegressor()
xgb_reg.fit(x_train,y_train)
y_pred_xgb = xgb_reg.predict(x_test)
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test, y_pred_xgb)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_test, y_pred_xgb))
print("R2 Score:",round(metrics.r2_score(y_test,y_pred_xgb)*100,2))
```

```
RMSE: 2972.3568267550327
MAPE: 0.3567527385887654
R2 Score: 64.98
```

[211]:
```
y_pred_train_xgb = xgb_reg.predict(x_train)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_train, y_pred_train_xgb)))
print('MAPE:', metrics.mean_absolute_percentage_error(y_train,␣
 ↪y_pred_train_xgb))
print('R2 Score:',metrics.r2_score(y_train,y_pred_train_xgb)*100)
```

```
RMSE: 2935.1009550901113
MAPE: 0.3530069512521715
R2 Score: 65.85814662280279
```

Performance Metrics Comparison:

RMSE: 4694.56 MAPE: 1.11 R2 Score: 12.63

RMSE: 3015.32 MAPE: 0.34 R2 Score: 63.96

RMSE: 2972.35 MAPE: 0.35 R2 Score: 64.98

Clearly, XGBoost Regressor is performing well as we are getting lowest RSME, low MAPE and high R-squared errors as compared to other models.

**Merge outputs with x_test and comapre Actual and Predicted Values.

[212]:
```
output_df = df_train[df_train.index.isin(x_test.index)]
output_df.head(2)
```

[212]:
```
    User_ID Product_ID Gender   Age  Occupation City_Category  \
2   1000001  P00087842      F  0-17          10             A
12  1000005  P00031342      M 26-35          20             A

   Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
2                           2               0                  12
12                          1               1                   8

    Product_Category_2  Product_Category_3  Purchase
2             9.842329                 NaN      1422
12            9.842329                 NaN      6073
```

[213]:
```
preds = pd.DataFrame(y_pred_xgb).rename(columns={0:'Predictions'}).
  ↪set_index(x_test.index)
preds.head(2)
```

[213]:
```
        Predictions
24033   8125.541016
301904  7806.015137
```

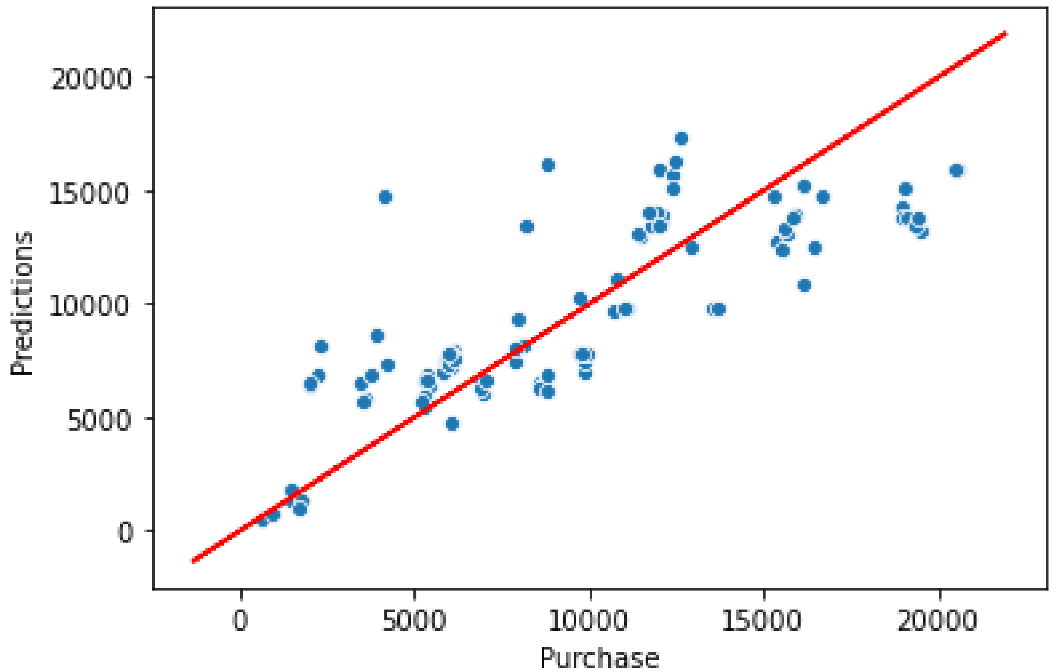
[214]:
```
output_df= output_df.merge(preds, how = 'left' ,left_index=True,␣
  ↪right_index=True)
output_df
```

[214]:
```
        User_ID Product_ID Gender   Age  Occupation City_Category  \
2       1000001  P00087842      F  0-17          10             A
12      1000005  P00031342      M 26-35          20             A
14      1000006  P00231342      F 51-55           9             A
22      1000008  P00213742      M 26-35          12             C
23      1000008  P00214442      M 26-35          12             C
…          …          …       …    …         …           …
550044  1006004  P00370853      F 26-35          15             C
550047  1006009  P00372445      F 26-35          12             C
550048  1006010  P00371644      M 36-45           0             C
550051  1006013  P00375436      F 26-35          20             C
```

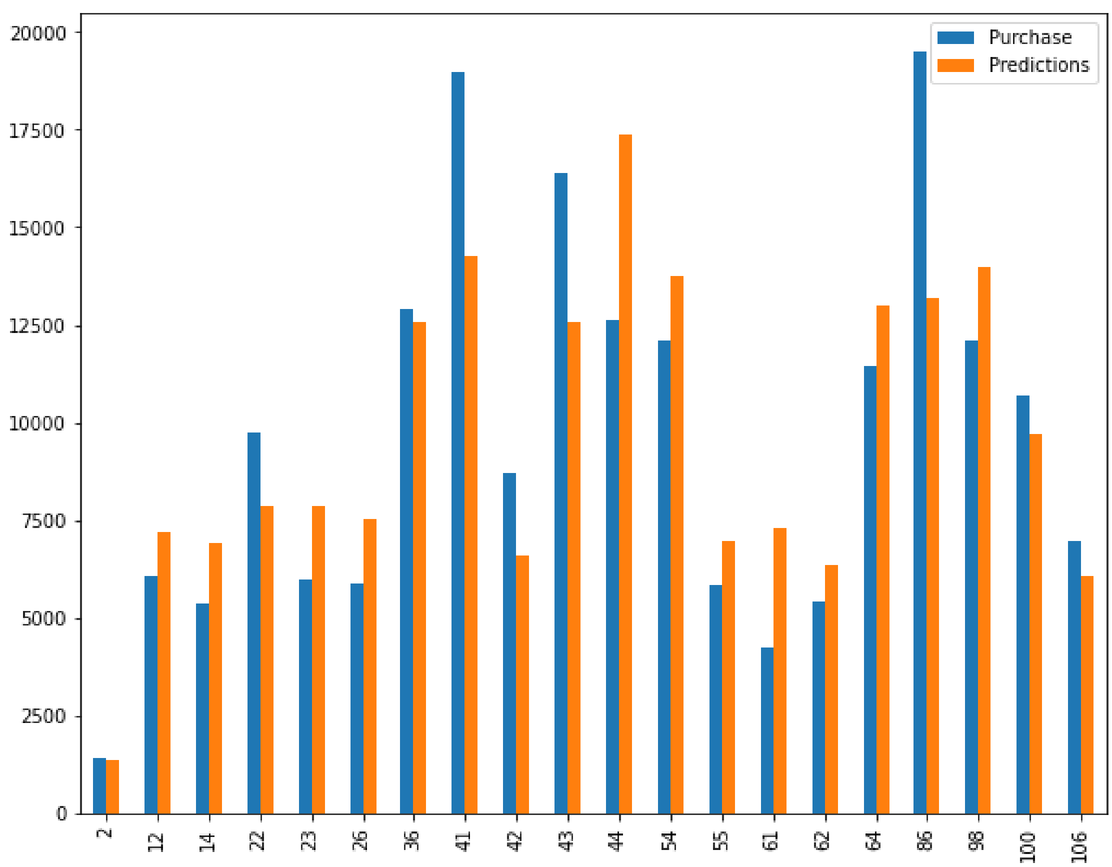
```
550064   1006035   P00375436       F   26-35           1             C

       Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
2                               2               0                  12
12                              1               1                   8
14                              1               0                   5
22                             4+               1                   8
23                             4+               1                   8
…                             …              …                 …
550044                          2               0                  19
550047                          3               0                  20
550048                          1               0                  20
550051                          3               0                  20
550064                          3               0                  20

        Product_Category_2  Product_Category_3  Purchase  Predictions
2                 9.842329                 NaN      1422  1348.173950
12                9.842329                 NaN      6073  7207.742676
14                8.000000                14.0      5378  6909.993164
22                9.842329                 NaN      9743  7862.944824
23                9.842329                 NaN      5982  7862.944824
…                      …                 …       …          …
550044            9.842329                 NaN        62   245.385040
550047            9.842329                 NaN       244   381.417999
550048            9.842329                 NaN       591   420.123199
550051            9.842329                 NaN       489   381.417999
550064            9.842329                 NaN       371   381.417999

[110014 rows x 13 columns]
```

Let's visualize the predicted results.

[228]:
```
sns.scatterplot(data=output_df.head(100), x='Purchase',y='Predictions')
plt.plot(y_pred_xgb,y_pred_xgb,'r')
plt.show()
output_df[['Purchase','Predictions']].head(20).plot(kind='bar',figsize=(10,8))
plt.show()
```



20000
15000
10000
5000
0
Predictions
0
5000
10000
15000
20000
Purchase



Purchase
Predictions
20000
17500
15000
12500
10000
7500
5000
2500
0
2
12
14
22
23
26
36
41
42
43
44
54
55
61
62
64
86
98
100
106

The Blue bar represents Actual purchase value and Orange bar represents Predicted purchase value. We can see that most of the Actual and predicted valuesare close. And model is Performing well and not overfitting.

[ ]:
```

```

**Predict on Unseen data.

[215]:
```
test_df.head(2)
```

[215]:
```
   Gender  City_Category  Stay_In_Current_City_Years  Marital_Status  \
0       1              2                           2               1
1       1              3                           0               0

   Product_Category_1  Product_Category_2  Age_Group_18-25  Age_Group_26-35  \
0                   1                11.0                0                0
1                   3                 5.0                0                1

   Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  Age_Group_55 & above
0                0                1                0                     0
1                0                0                0                     0
```

[217]:
```
pred_xgb = xgb_reg.predict(test_df)
test_preds = pd.DataFrame(pred_xgb).rename(columns={0:'Predicted Purchase'})
test_preds.head()
```

[217]:
```
   Predicted Purchase
0        14242.577148
1        10929.032227
2         7042.043945
3         2967.486816
4         2478.158936
```

[218]:
```
test_df.merge(test_preds, how = 'left', left_index = True, right_index = True)
```

[218]:
```
        Gender  City_Category  Stay_In_Current_City_Years  Marital_Status  \
0            1              2                           2               1
1            1              3                           0               0
2            0              2                           4               1
3            0              2                           4               1
4            0              3                           1               0
…           …              …                           …               …
233594       0              2                           4               1
233595       0              2                           4               1
233596       0              2                           4               1
```

```
233597       0             3                          4               0
233598       0             2                          4               1

        Product_Category_1  Product_Category_2  Age_Group_18-25  \
0                        1           11.000000                0
1                        3            5.000000                0
2                        5           14.000000                0
3                        4            9.000000                0
4                        4            5.000000                0
…                      …                  …                 …
233594                   8            9.849586                0
233595                   5            8.000000                0
233596                   1            5.000000                0
233597                  10           16.000000                0
233598                   4            5.000000                0

        Age_Group_26-35  Age_Group_36-45  Age_Group_46-50  Age_Group_51-55  \
0                     0                0                1                0
1                     1                0                0                0
2                     0                1                0                0
3                     0                1                0                0
4                     1                0                0                0
…                   …                …                …                …
233594                1                0                0                0
233595                1                0                0                0
233596                1                0                0                0
233597                0                0                1                0
233598                0                0                1                0

        Age_Group_55 & above  Predicted Purchase
0                          0        14242.577148
1                          0        10929.032227
2                          0         7042.043945
3                          0         2967.486816
4                          0         2478.158936
…                        …                  …
233594                     0         7344.817871
233595                     0         6442.360352
233596                     0        12347.626953
233597                     0        19883.351562
233598                     0         2308.947021

[233599 rows x 13 columns]
```