BLACK FRIDAY SALES ANALYSIS

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Abstract:

This study helps to analyze the black Friday sales dataset and would give an insight into the shopping trends of customers using a dataset containing attributes such as User_ID, Product_ID, Gender, Age, Occupation, product_catergory_1, product_category_2, product_category_3 and Purchase. The analysis evaluates how buying behaviors can vary by category of products, physical locations, age, gender, occupation and depending on different features. The analysis aims to figure out key factors impacting sales numbers and potential correlations among variables, how one feature is dependent on the other feature and some other empirical analysis using the application of mathematical and statistical techniques and the models.

Goals and Objectives:

The main objective and goal are to understand consumer trends, tendencies, and purchasing patterns, to identify the primary driving factors and features influencing consumer expenditures and quantity of sales. For the creation of predictive models that, using characteristics and product categories as a foundation, to examine how purchases spread among multiple groups—such as age, gender, and occupation and understand how these different factors affect the choices that customers make, to find connections between attributes, product categories, and expenditures by using regression analysis and identifying correlations between components.

- **Motivation:**
  The motivation behind Black Friday sales analysis is to gain insight into customer purchasing patterns based on gender, age and their occupation, analyze the effectiveness of marketing, to get to know which attributes contribute most of the analysis i.e. important features and which features effect sales the most.

- **Significance**:
  Black Friday sales analysis is highly significant because it helps us to know the shopping trend, learn about client behavior, to retrieve the crucial features to improve the model performance and accuracy, to analyze the purchasing trends based on different attributes age, gender, occupation etc.

- **Objectives:**
  The main objective of analyzing Black Friday sales is to know the purchase trends, which age group buys what products and which gender buys what products taking into the consideration the attributes such as occupation, city, age, gender etc. which product sales drive most of the overall sales by using different techniques and analysis methods such as bivariate analysis, univariate analysis, exploratory data analysis, tree based models and classification metrics.

- **Features:**
  Attributes like User_ID, Product_ID, Gender, Age, Occupation, City_Category, Stay_In_Current_City_Years, Marital status, Product_Category_1, Product_Category_2, and Product_Category_3 is included in Black Friday sales analysis features. These resources simplify the analysis of product categories, purchase patterns, and buyer characteristics.

Related work (Background):

The practical tutorials and scholar papers available on platforms like Kaggle and blogs of Ali Ahmad delve into the implementation of Decision tree classifier, XGBoost models for sales analysis. The Kaggle tutorial on Decision tree classifier by Prashant presents a step-by-step guide for employing the model to provide insights into customer purchasing decisions.

In addition to theoretical aspects, Kaggle competitions and real-world applications serve as valuable resources for understanding the practical implementation of these models in sales analysis scenarios. Competitions like "Analysis of Store Sales" on Kaggle provide insights into the diverse approaches and methodologies applied by practitioners to effectively analyze sales trends.

In summary, these sources collectively offer a broad understanding of how models like Decision tree classifier, Decision tree regressor and XGBoost are employed, both theoretically and practically, to analyze and predict sales data, enabling businesses to make informed decisions and optimize their operations

Dataset:

We have taken our dataset from Kaggle (https://www.kaggle.com/datasets/pranavuikey/black-friday-sales-eda/data). The dataset comprises of 12 columns and 550069 rows. Data plays a major role in defining the efficiency of our model. Quality data refers to better identification of trends and patterns, which is vital for predicting future sales based on the resemblances drawn in the data.

To improve the quality of the dataset we have handled the missing values by replacing them with mode and removing outlier data. We need to drop the duplicate rows as they lead to biasing in model. The attributes of the dataset are described below to understand and get more insights into the data.

- Attributes in the Dataset:

a. User_ID: A unique number allocated to user.
b. Product_ID: A unique number allotted to the products.
c. Gender: Describes the user as male or female.
d. Age: Provides the range of age of the user.
e. Occupation: Represents occupation code of user.
f. City_Category: Provides the city where user lives.
g. Stay_In_Current_City_Years: Gives number of years the user has been living in current city.
h. Marital Status: Describes whether the user is married or unmarried.
i. Product_Category_1: The year when the outlet was established.
j. Product_Category_2: Type of location where the outlet is situated.
k. Product_Category_3: Unique identifier for the item.
l. Purchase: target variable - the sales figure for the item at the outlet.

- Dataset Structure:

a. Predictor Variables: features like User_ID, Product_ID, Gender, Age, Occupation, City_Category, Stay_In_Current_City_Years, Marital Status, and Product_Category_1, Product_Category_2, and Product_Category_3 serve as predictor variables influencing the prediction of response variable.
b. Response Variable: purchase is the target variable that needs to be predicted based on the predictor variables.

These predictor variables provide a comprehensive insight into product details, purchasing patterns and customer characteristics. This dataset is used for training machine learning models such as Decision trees and XGBoost to analyze sales based on identified patterns.

Detail design of features:

Features are the input variables or attributes which are used in making predictions. Initially we explored the data by removing the irrelevant columns and converting categorical variables to numerical variables by label encoder as the algorithms cannot handle categorical data. Visualize a correlation matrix using a heat map to identify the correlation between features. We have split the dataset in 70-30 ratio to train, test datasets for evaluating the model performance on unseen data.

We have used 'SelectKBest' function imported from sklearn for feature selection. It will select the most relevant features related to target variable from the dataset. It identifies the important features based on the univariate analysis which is a statistical method that analyzes the distribution of single variable at a time. We have identified the top 7 most relevant features that are Age, occupation, City_Category, Marital_Status, Product_Category_1, Product_Category_2, Purchase.

Analysis:

Analysis was done on Black Friday Sales data using different techniques. Data preprocessing was the first step that was performed after the dataset was extracted from Kaggle. Data preprocessing has gone through many cleaning methods such as dropping the irrelevant columns that are not useful for analysis. Dropping duplicate rows, finding the missing values, and replacing those

values with the numeric, replacing the valueless categorical values with some mapping values, removing the null valued rows was done as a part of data cleaning and making it ready for some training and analysis.

The cleaned data was then analyzed using various techniques and methods, such as Exploratory data analysis, univariate analysis, bivariate analysis using different display of plots, correlation analysis and feature selection to find the relations between the attributes and to retrieve the vital feature of the data which would help in drawing the analysis more accurately.

Training the model is done using the decision tree classifier on 70 percent of the data and the other 30 percent of the data went through the testing.

Then the evaluation of the model is done to make some predictions after the data is reshaped. The data that went through the testing after the training was then tested to find how accurate the results that were given are. We have used confusion matrix techniques, precision, recall, f1 score and support techniques to find the accuracy of the data.

Exploratory data analysis:

EDA facilitates the determination of values that are unavailable, outliers, or gaps in the data as well as offers an early evaluation of links and structures within the data. It further helps in figuring out the structure and concentrations of many different attributes. It offers fundamental knowledge about correlations.

With in the Exploratory data analysis, we have dropped all the irrelevant columns from the dataset.

After dropping the irrelevant columns this is how the data looks:

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3
0	1000001	F	0-17	10	A	2	0	3	NaN	NaN
1	1000001	F	0-17	10	A	2	0	1	6.0	14.0
2	1000001	F	0-17	10	A	2	0	12	NaN	NaN
3	1000001	F	0-17	10	A	2	0	12	14.0	NaN
4	1000002	M	55+	16	C	4+	0	8	NaN	NaN

Dropped the duplicate rows (present a number of times in the data) and then found out the total number of rows present in the data.

Counting the total number of rows first

```
#Here i am counting the number of rows.
Sales.count()
```

```
User_ID                     550068
Gender                      550068
Age                         550068
Occupation                  550068
City_Category               550068
Stay_In_Current_City_Years  550068
Marital_Status              550068
Product_Category_1          550068
Product_Category_2          376430
Product_Category_3          166821
Purchase                    550068
dtype: int64
```

Getting the number of duplicate rows present in the data.

```
[ ] # @title Dropping The Duplicate Rows
    # Here we are finding the duplicate rows using the duplicated() command.
    rows_duplicate = Sales[Sales.duplicated()]
    # Printing the duplicate rows.
    print("Number of duplicate rows: ", rows_duplicate.shape)
```

```
Number of duplicate rows:  (2543, 11)
```

Dropping these duplicate rows and counting the number of total rows present in the data

```
# After dropping the duplicate rows again i am counting the number of rows.
Sales.count()
```

```
User_ID                       547525
Gender                        547525
Age                           547525
Occupation                    547525
City_Category                 547525
Stay_In_Current_City_Years    547525
Marital_Status                547525
Product_Category_1            547525
Product_Category_2            375825
Product_Category_3            166734
Purchase                      547525
dtype: int64
```

Then as a part of exploratory data analysis, we have replaced the missing values with the numeric values

Where after that the data looks like:

```
# @title Replacing The Missing Data With Numeric Values
# In the 'Gender' column we are Replacing 'F' with 0 and 'no' with 1 using replace command.
Sales['Gender'] = Sales['Gender'].replace({'F': 0, 'M': 1})

# Here we are displaying the dataFrame with the replaced values of 'Gender' column.
print(Sales)
```

```
        User_ID  Gender    Age  Occupation City_Category  \
0       1000001       0   0-17          10             A
1       1000001       0   0-17          10             A
2       1000001       0   0-17          10             A
3       1000001       0   0-17          10             A
4       1000002       1    55+          16             C
...         ...     ...    ...         ...           ...
550063  1006033       1  51-55          13             B
550064  1006035       0  26-35           1             C
550065  1006036       0  26-35          15             B
550066  1006038       0    55+           1             C
550067  1006039       0  46-50           0             B

       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
```

```
        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
...                    ...                 ...       ...
550063                 NaN                 NaN       368
550064                 NaN                 NaN       371
550065                 NaN                 NaN       137
550066                 NaN                 NaN       365
550067                 NaN                 NaN       490

[547525 rows x 11 columns]
```

For the analysis part, we had replaced the missing values with the numeric values

First finding the missing values from the dataset goes as:

```
# @title Filling The Missing Values
# Using the isnull() command i am checking the missing values in the dataset
print(Sales.isnull().sum())
```

For the analysis part, we had replaced the missing values in product category_2 with the numeric values

```
[ ] # We are filling the missing values in Product_Category_2 with the mode value of Product_Category_2.
    Sales["Product_Category_2"].fillna(Sales["Product_Category_2"].mode()[0],inplace=True)
    # Here we are displaying the dataFrame after filling the missing values of 'Product_Category_2' column.
    print(Sales)
```

Filling the missing values in the product category_3

```
# We are filling the missing values in Product_Category_3 with the mode value of Product_Category_3.
Sales["Product_Category_3"].fillna(Sales["Product_Category_3"].mode()[0],inplace=True)
# Here we are displaying the dataFrame after filling the missing values of 'Product_Category_3' column.
print(Sales)
```

Here is the display for the dataset statistics

```
[ ] <class 'pandas.core.frame.DataFrame'>
    Int64Index: 547525 entries, 0 to 550067
    Data columns (total 11 columns):
     #   Column                      Non-Null Count   Dtype
    ---  ------                      --------------   -----
     0   User_ID                     547525 non-null  int64
     1   Gender                      547525 non-null  int64
     2   Age                         547525 non-null  int64
     3   Occupation                  547525 non-null  int64
     4   City_Category               547525 non-null  object
     5   Stay_In_Current_City_Years  547525 non-null  object
     6   Marital_Status              547525 non-null  int64
     7   Product_Category_1          547525 non-null  int64
     8   Product_Category_2          547525 non-null  float64
     9   Product_Category_3          547525 non-null  float64
     10  Purchase                    547525 non-null  int64
    dtypes: float64(2), int64(7), object(2)
    memory usage: 50.1+ MB
```

	User_ID	Gender	Age	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_C
count	5.475250e+05	547525.000000	547525.000000	547525.000000	547525.000000	547525.000000	547525.000000	547
mean	1.003029e+06	0.753186	3.496251	8.078466	0.409563	5.398765	9.263243	
std	1.727581e+03	0.431158	1.353850	6.521839	0.491754	3.940801	4.300364	
min	1.000001e+06	0.000000	1.000000	0.000000	0.000000	1.000000	2.000000	
25%	1.001516e+06	1.000000	3.000000	2.000000	0.000000	1.000000	8.000000	

As a part of the exploratory data analysis, we have detected the outliners for gender, age, occupation, purchase, product_category_1, product_category_2, product_category3 as follows:

Detecting Outliners for Gender attribute:

```
# Using the boxplot we are checking outliers for the Gender
# Creating a boxplot for gender
sns.boxplot(x=Sales['Gender'])
# For the plot we are adding a title
plt.title('Boxplot of Gender')
# Displaying the plot
plt.show()
```

Detecting Outliners for age:

```
# Using the boxplot we are checking outliers for the Age
# Creating a boxplot for Age
sns.boxplot(x=Sales['Age'])
# For the plot we are adding a title
plt.title('Boxplot of Age')
# Displaying the plot
plt.show()
```

Implementation:

After the data had been cleansed, it was analyzed using a variety of approaches and implements, including Exploratory data analysis, detecting the outliners for age, detecting outliners for gender, detecting outliners for occupation, checking outliners for marital status, checking outliners for product categories and purchase was done through a boxplot display to point out any disparities or abnormalities in the data.

We have performed univariate analysis to get the early insight into the characteristics of the data and the distribution of each variable independently, discovering patterns and unusual values, to

support in recognizing the features and actions of specific elements using the histogram representation.

Performed bivariate analysis using the bar plot visualization and scatter plot visualization to understand the relation between two variables such as how age feature effects the purchase trends, how occupation adds for the purchase, how a particular gender or product is affecting the purchase.

Implemented the co relation analysis using heat maps for all the attributes of the data set to find the to select the model's strongest determinants can be assisted by knowing how alterations to one variable relate to modifications in another.

To select the vital features, label conder was imported to encode the categorical values which helps in converting the categorical values to the numerical values which would help us to analyze the data more accurately to share the crucial features.

Feature selection is done using the installation of selectKBest function which would help to find the most impacting element/feature in the data.

For Model selection and model training, we have imported all the libraries such as train_test_split, DecisionTreeClassifier, metrics, confusion_matrix, classification_report and accuracy_score. Next, the training the test cases were created by splitting the data into training_size which comprises of 70 percent of the data and testing size as 30 percent of the data.

Training the model is done using the decision tree classifier technique. But the training data set is in 1D array form, but to perform decision tree classifier the data must be in 2d array format. So, we applied the reshaping technique first and then fitted the decision tree model using the training data which would help us coordinate with the model selected by altering the parameters to reduce errors to promote performance. In the following phase, the model gathers up on patterns and connections seen in the initial training data.

To Evaluate the data that was trained, testing of the data is done on the 30 percent of the data. So, we applied the reshaping technique first and then fitted the decision tree model using the testing data.

To find the accuracy of the data which was tested we have evaluated the model creating a confusion matrix which helps to evaluate the effectiveness of the model and it improves evaluating a model's expected accuracy.

Next to that we have applied precision, f1 score, recall and support in the classification report to determine the efficiency of the classifying model. F1-score optimizes recall and precision by prioritizing precise predictions of positives over actual positive identifications. Support is the dispersion of groups.

The model training and testing goes as follows:

Model selection and training:

Creating the train class and test data

Creating The Train And Test Cases

```
# @title Creating The Train And Test Cases
# Here we are Ssplitting the varaibles as training_size as 70 and testing_size as 30
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7,
                                                    test_size = 0.3, random_state = 100)
```

Training the model decision Tree classifier

Training The Model-Decision Tree Classifier

```
[ ] # @title Training The Model-Decision Tree Classifier
    # Here X_train data is 1D array to perform the decision tree classifier data should be in 2D array. So we are reshaping the X_train data using values.reshape() command
    X_train = X_train.values.reshape(-1, 1)
    # Here we are creating Decision Tree model
    dtree_model = DecisionTreeClassifier()
    # We are fitting the Decision Tree model Using training data
    dtree_model.fit(X_train, y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier()
```

Model Evaluation:

```
[ ] # @title Evaluating The Model
    # Here X_test data is 1D array to perform the decision tree classifier data should be in 2D array. So we are reshaping the x_test data using values.reshape() command
    X_test = X_test.values.reshape(-1, 1)
    # Here we are using the decision tree model to make the predictions on the data which is reshaped
    y_pred = dtree_model.predict(X_test)
    # Here we are printing the y_predicted values
    print(y_pred)
```

```
[2 1 8 ... 8 8 1]
```

Finding the accuracy of the model:

```
# @title Finding The Accuracy
# Here we are comparing y_test,y_pred using accuracy_score()
accuracy = accuracy_score(y_test, y_pred)*100
# Here we are printing the accuracy of the testing data
print(f"Accuracy: {accuracy}")
```

```
Accuracy: 86.4118331814961
```

Creating a confusion matrix

```
[92] # @title Creating A Confusion Matrix
     # Here we are comparing y_test,y_pred using confusion_matrix()
     conf_matrix = confusion_matrix(y_test, y_pred)
     # Here we are displaying the confusion matrix
     print("Confusion Matrix:")
     print(conf_matrix)
```

Decision Tree classifier results:

Decision Tree Classifier Results

```
# @title Decision Tree Classifier Results
# Here we are printing the classification report
print("Classification Report:")
# Here we are comparing y_test,y_pred using classification_report()
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           1       0.93      0.88      0.91     14940
           2       0.58      0.50      0.54      1529
           3       0.86      0.68      0.76      1614
           4       0.72      0.68      0.70      1104
           5       0.97      1.00      0.98     25184
           6       0.58      0.68      0.62      3012
           7       0.28      0.18      0.22       731
           8       0.84      0.97      0.90     19306
           9       0.21      0.17      0.19        64
          10       0.81      0.58      0.67       563
          11       0.83      0.67      0.74      5201
          12       0.71      0.60      0.65       534
          13       0.93      0.99      0.96      1003
          14       0.75      0.40      0.52       236
          15       0.58      0.39      0.47      1273
          16       0.37      0.22      0.27      1969
          17       0.71      0.36      0.48       112
          18       0.58      0.31      0.40       657

    accuracy                           0.86     79032
   macro avg       0.68      0.57      0.61     79032
weighted avg       0.85      0.86      0.86     79032
```

Creating other model and training and testing the data for that:

```
# @title Creating The Train And Test Cases
# Here we are Ssplitting the varaibles as training_size as 70 and testing_size as 30
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7,
                                                    test_size = 0.3, random_state = 100)
```

Training the data:

```
# @title Training Data
# To verify the split we are printing the shapes
print(X_train)
print(y_train)
```

Testing the data:

```
[98] # @title Testing Data
     # To verify the split we are printing the shapes
     print(X_test)
     print(y_test)
```

This is how training the model decision classifier happens:

Training The Model-Guassian Model

```
[ ] # @title Training The Model-Guassian Model
    # Here X_train data is 1D array to perform the Gaussian Modle data should be in 2D array. So we are reshaping the X_train data using values.reshape() command
    X_train = X_train.values.reshape(-1, 1)
    # Here we are creating Gaussian model
    Gaussian_model = GaussianNB()
    # We are fitting the Guassian model Using training data
    Gaussian_model.fit(X_train, y_train)
```

```
GaussianNB
GaussianNB()
```

Coming to the evaluation of the model we are transforming the testing data which is in 1D array to 2D array

Evaluating The Model

```
[ ] # @title Evaluating The Model
    # Here X_test data is 1D array to perform the Gaussian Model data should be in 2D array. So we are reshaping the x_test data using values.reshape() command
    X_test = X_test.values.reshape(-1, 1)
    # Here we are using the Gaussian model to make the predictions on the data which is reshaped
    y_pred = Gaussian_model.predict(X_test)
    # Here we are printing the y_predicted values
    print(y_pred)
```

```
[1 1 5 ... 8 8 1]
```

Now we had found the accuracy of the testing data with the predicted data:

Finding The Accuracy

```
# @title Finding The Accuracy
# Here we are comparing y_test,y_pred using accuracy_score()
accuracy = accuracy_score(y_test, y_pred)*100
# Here we are printing the accuracy of the testing data
print(f"Accuracy: {accuracy}")
```

```
Accuracy: 54.43870837129264
```

Then we have compared the testing data and predicted data using the confusion matrix:

```
# @title Creating A Confusion Matrix
# Here we are comparing y_test,y_pred using confusion_matrix()
conf_matrix = confusion_matrix(y_test, y_pred)
# Here we are displaying the confusion matrix
print("Confusion Matrix:")
print(conf_matrix)
```

Preliminary Results:

This section contains all the results of the analysis on Black Friday sales which goes from data preprocessing to the evaluation of the model.

Starting with the exploratory data analysis, we first read the dataset.

Reading The Black Friday Sales Dataset.

```
# @title Reading The Black Friday Sales Dataset.
# Reading the csv file
Sales = pd.read_csv("Black Friday Sales.csv")
# Here we are displaying the top 5 rows.
Sales.head(5)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Prc
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	
3	1000001	P00085442	F	0-17	10	A	2	0	12	
4	1000002	P00285442	M	55+	16	C	4+	0	8	

Dropping of the duplicate rows and irrelevant columns is done.

Dropping The Irrelevant Columns

```
# @title Dropping The Irrelevant Columns
#Here we are dropping the irrelevant columns, In my case i am dropping the Product_ID
Sales = Sales.drop(['Product_ID'], axis=1)
# Here we are displaying the top 5 rows
Sales.head(5)
```

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Categor
0	1000001	F	0-17	10	A	2	0	3	
1	1000001	F	0-17	10	A	2	0	1	
2	1000001	F	0-17	10	A	2	0	12	
3	1000001	F	0-17	10	A	2	0	12	
4	1000002	M	55+	16	C	4+	0	8	

Dropping The Duplicate Rows

```
[ ] # @title Dropping The Duplicate Rows
    # Here we are finding the duplicate rows using the duplicated() command.
    rows_duplicate = Sales[Sales.duplicated()]
    # Printing the duplicate rows.
    print("Number of duplicate rows: ", rows_duplicate.shape)
```

```
Number of duplicate rows:  (2543, 11)
```

```
[ ] #Here i am counting the number of rows.
    Sales.count()
```

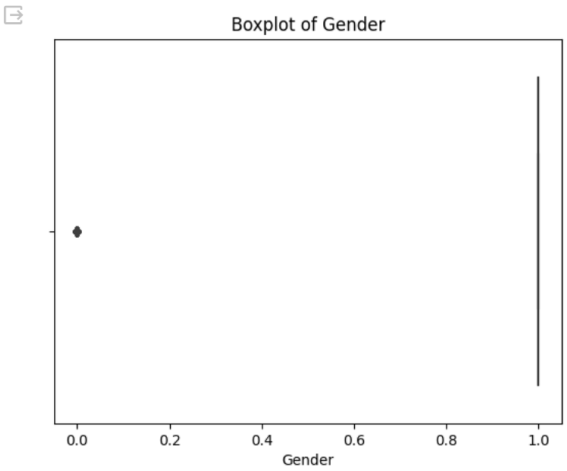
```
User_ID                     550068
Gender                      550068
Age                         550068
Occupation                  550068
City_Category               550068
Stay_In_Current_City_Years  550068
Marital_Status              550068
Product_Category_1          550068
Product_Category_2          376430
Product_Category_3          166821
Purchase                    550068
dtype: int64
```

After dropping the duplicate rows and irrelevant columns we got the data count.

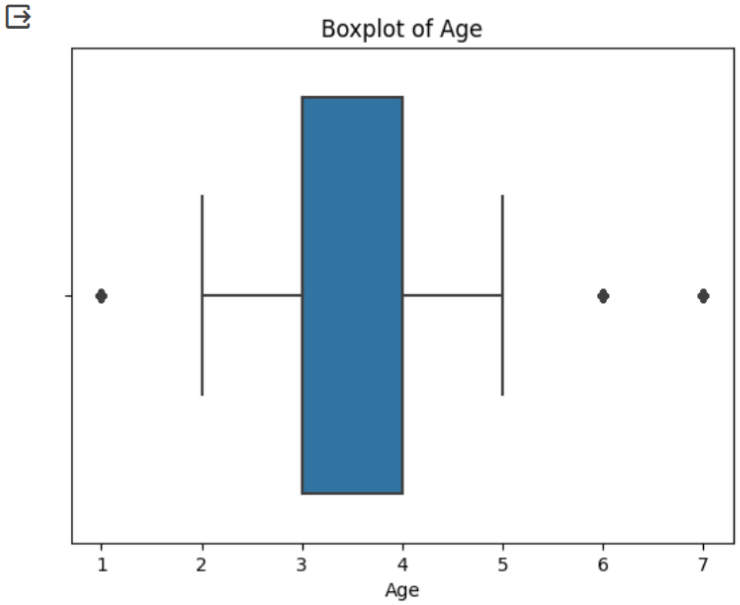
```
# After dropping the duplicate rows again i am counting the number of rows.
Sales.count()
```

```
User_ID                     547525
Gender                      547525
Age                         547525
Occupation                  547525
City_Category               547525
Stay_In_Current_City_Years  547525
Marital_Status              547525
Product_Category_1          547525
Product_Category_2          375825
Product_Category_3          166734
Purchase                    547525
dtype: int64
```

Outlier’s detection for Gender.

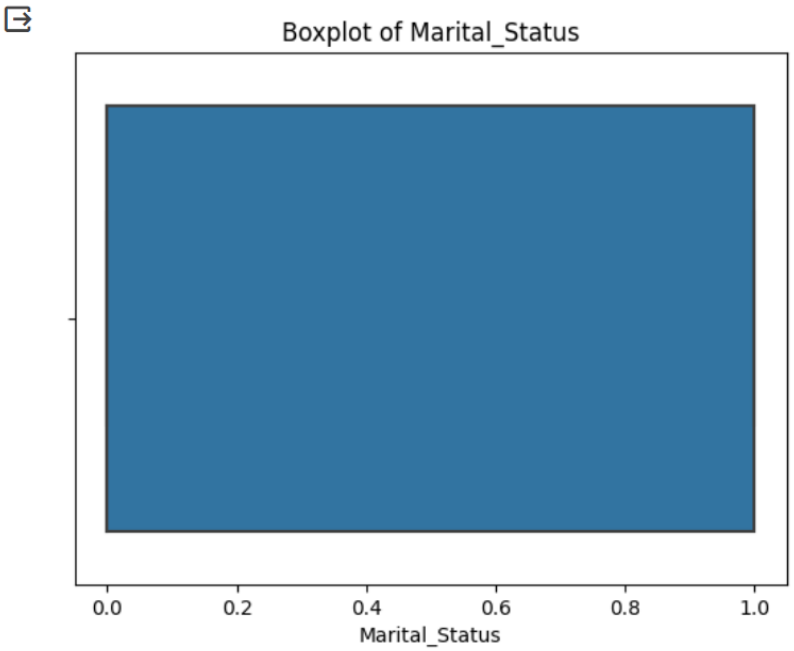


Outlier’s detection for Age using the boxplot.

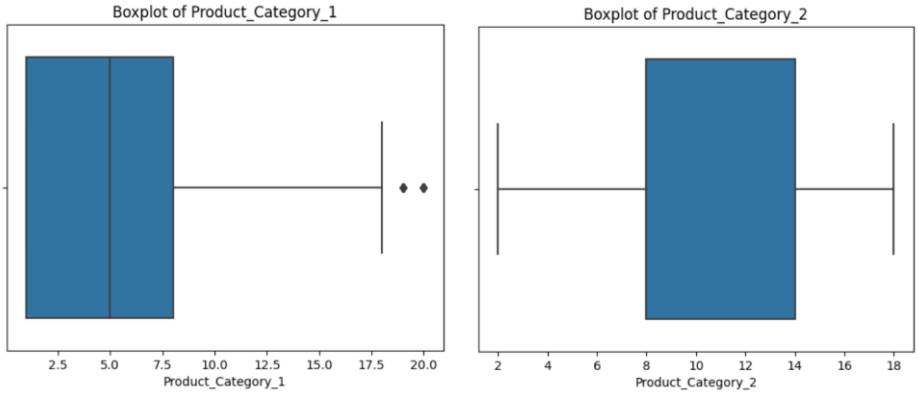


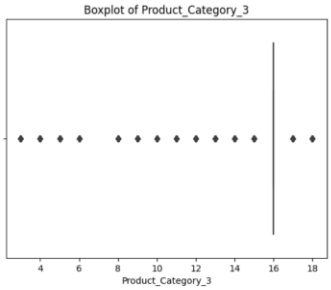
Outlier’s detection for Occupation

Outlier’s detection for Marital_status attribute using the box plot.

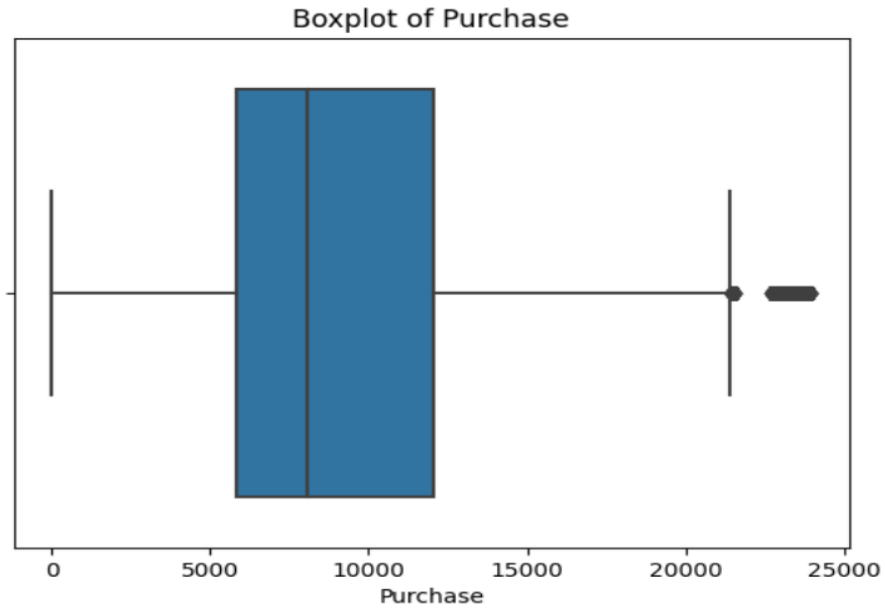


Outliers for product_category1, product_category2, product_category3.

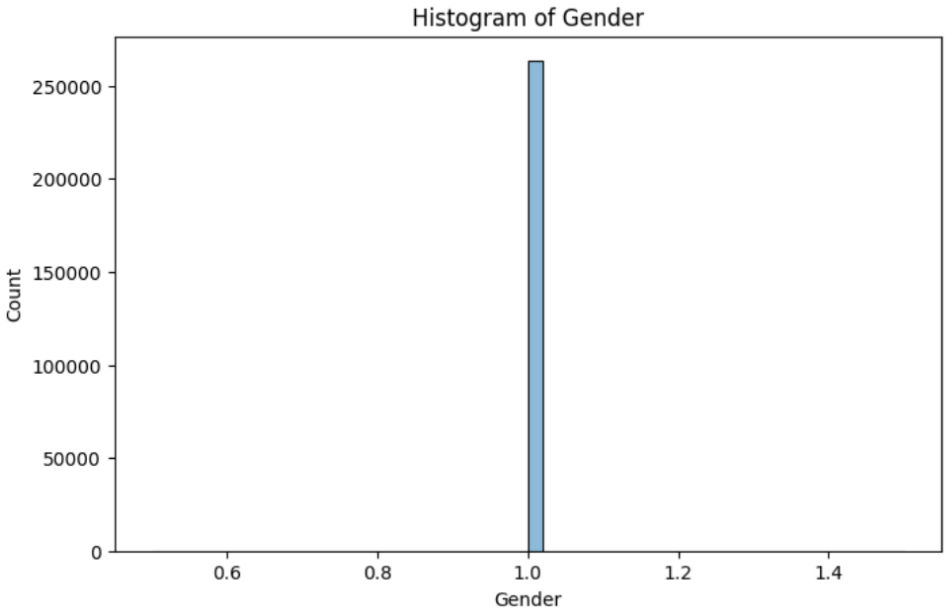




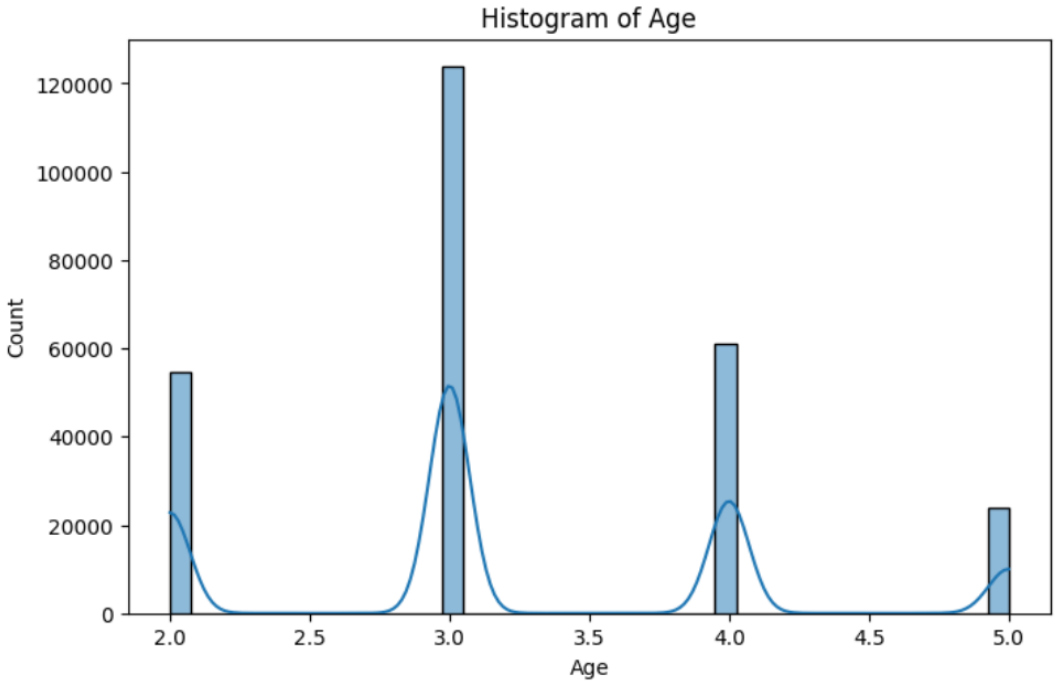
Visualization of the outliers for purchase attribute.



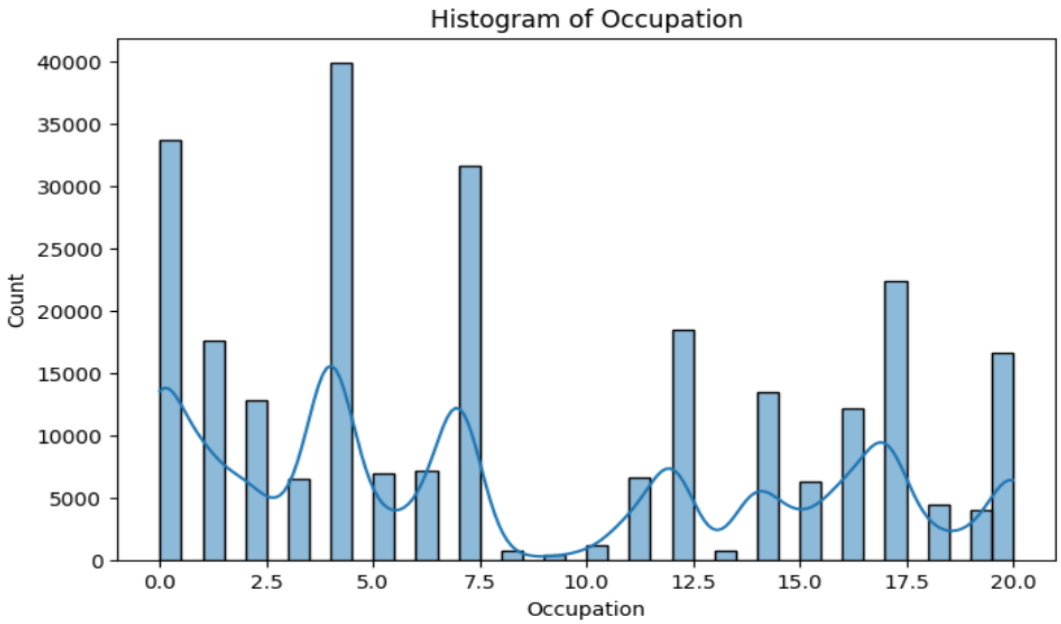
Pictorial result of the univariate analysis for Gender attribute using histogram.



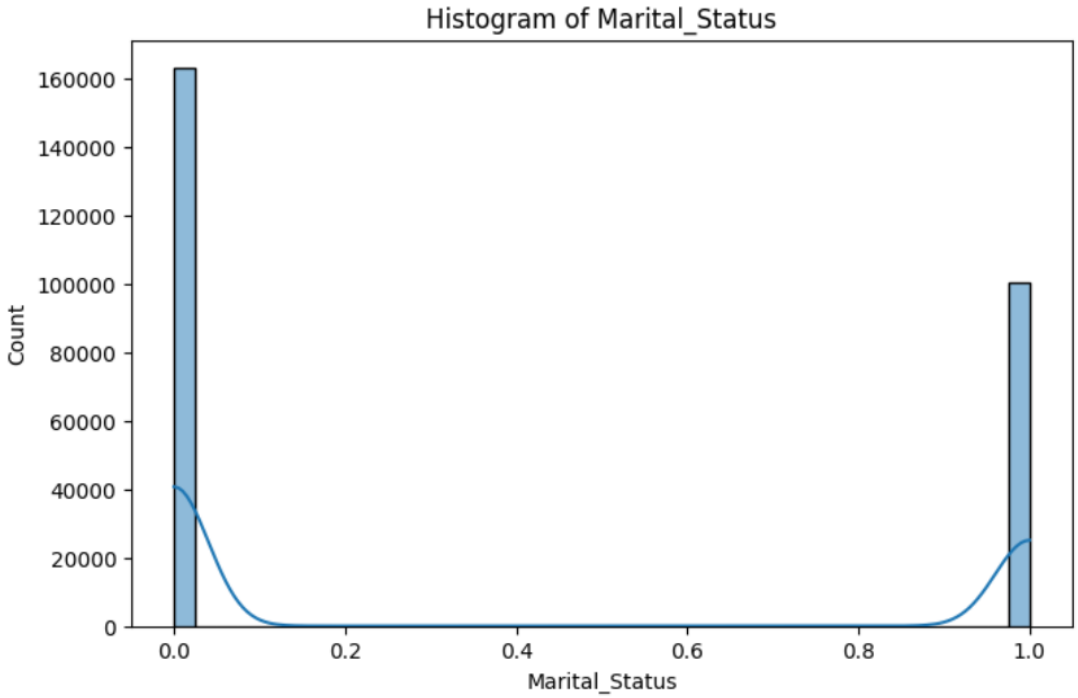
Pictorial result of the univariate analysis for Age attribute using histogram.



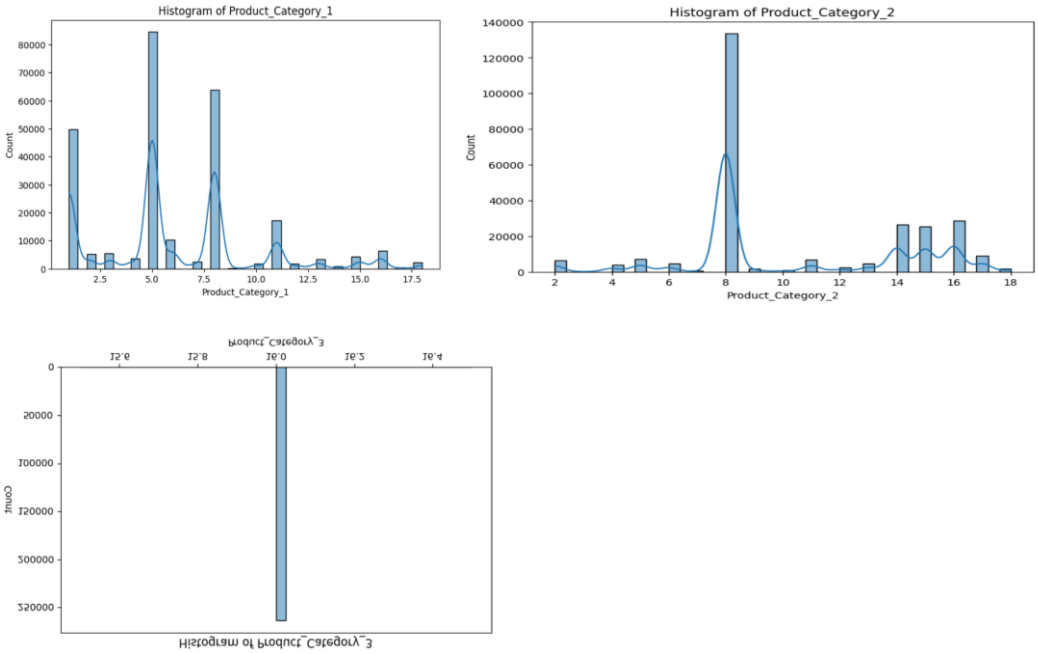
Pictorial result of the univariate analysis for Occupation attribute using histogram.



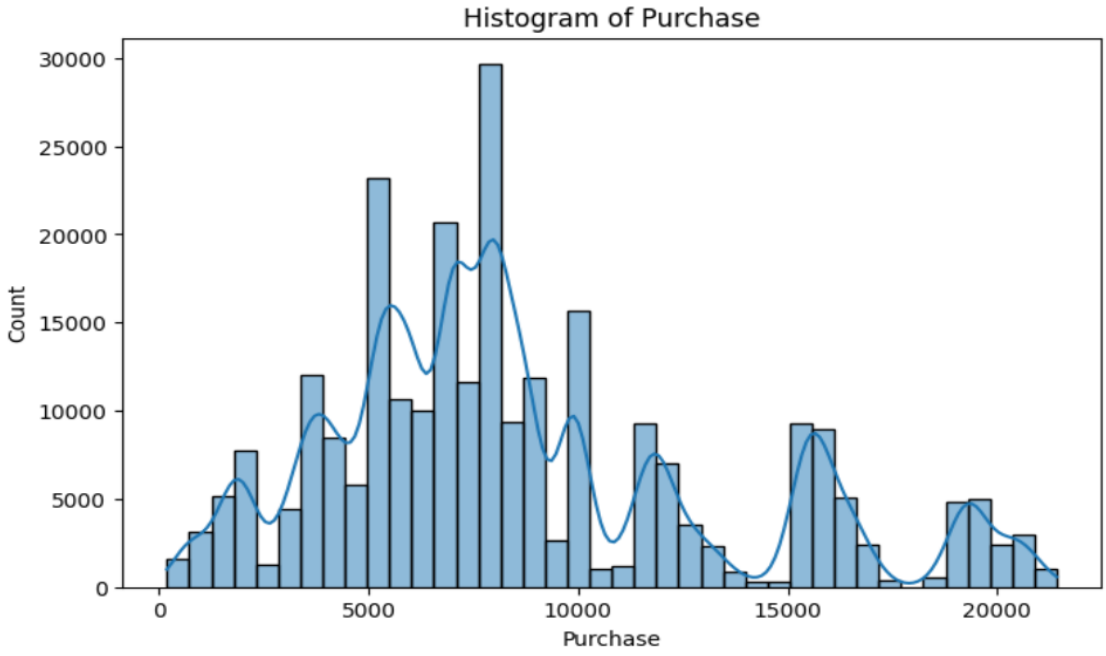
Pictorial result of the univariate analysis for Marital_status attribute using histogram.



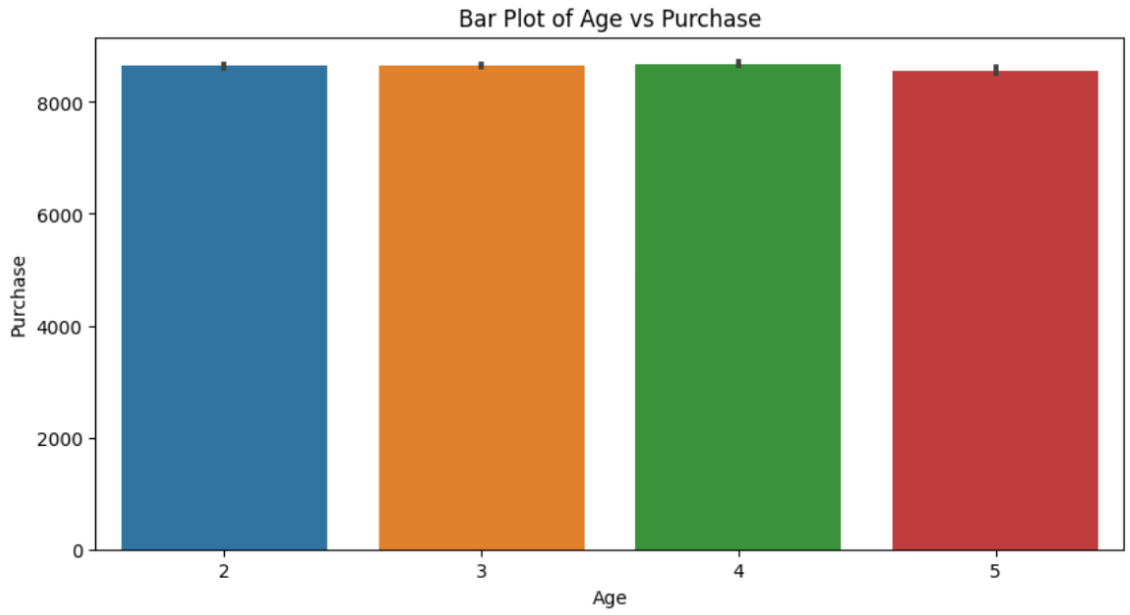
Pictorial result of the univariate analysis for Product_category_1, product_category_2, product_category_3 attribute using histogram.



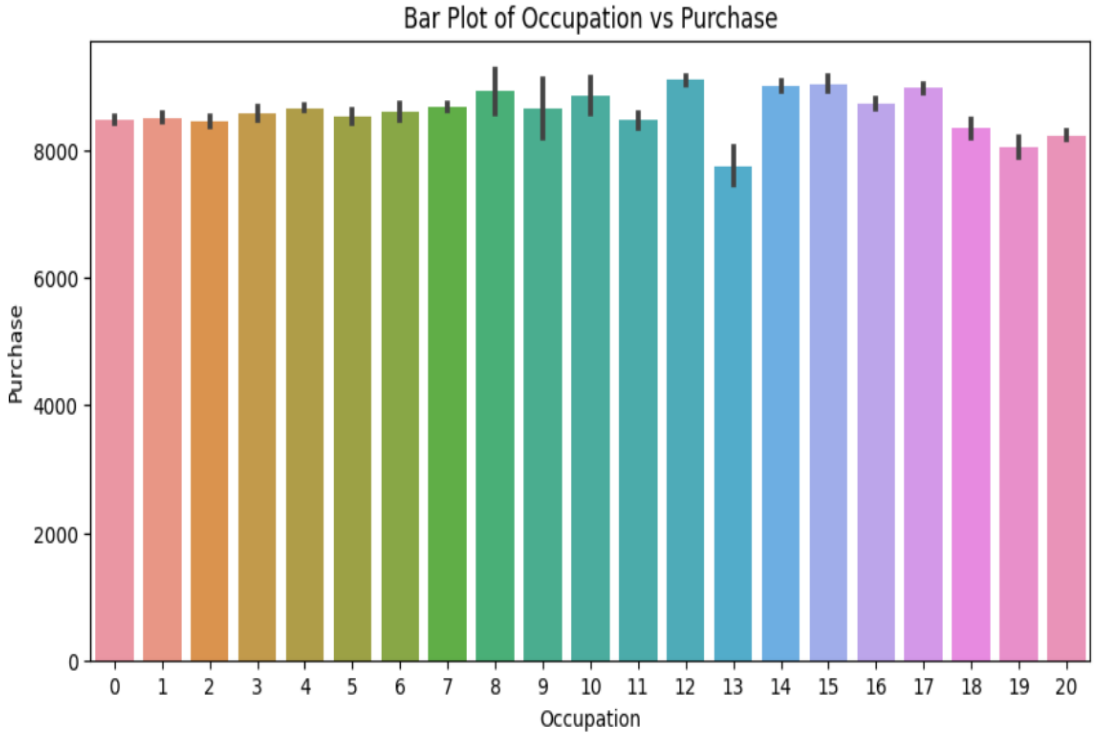
Pictorial result of the univariate analysis for purchase attribute using histogram.



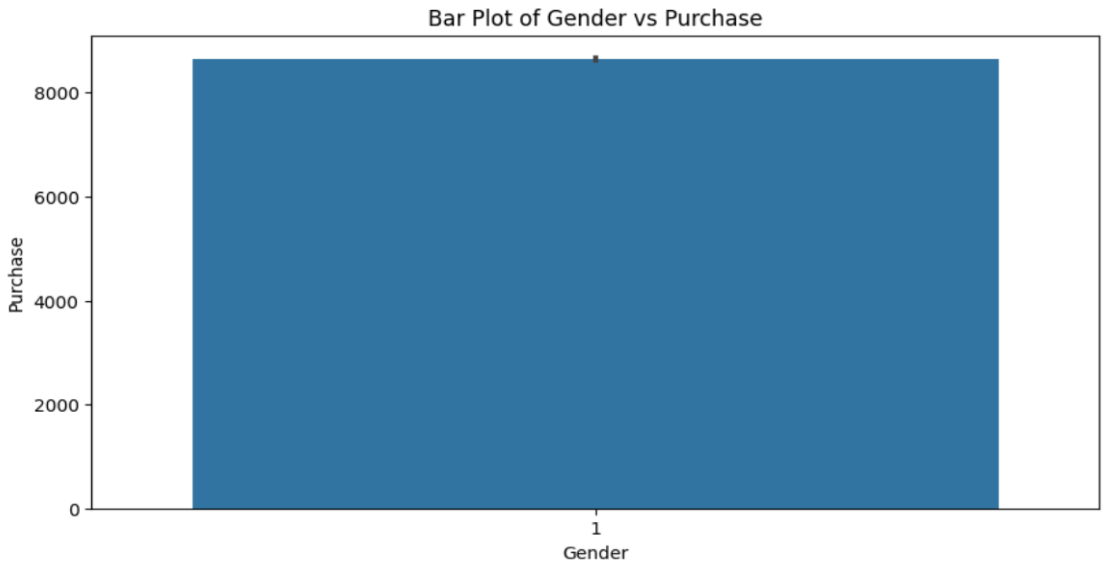
Pictorial representation for bivariate analysis of age and purchase features.



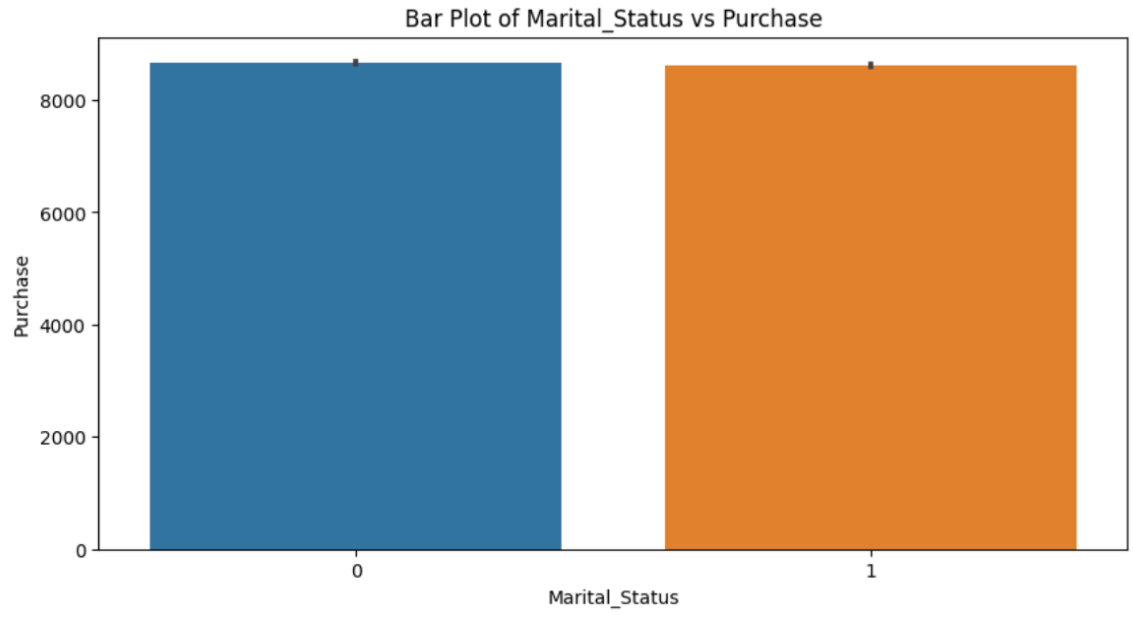
Pictorial representation for bivariate analysis of occupation and purchase features.



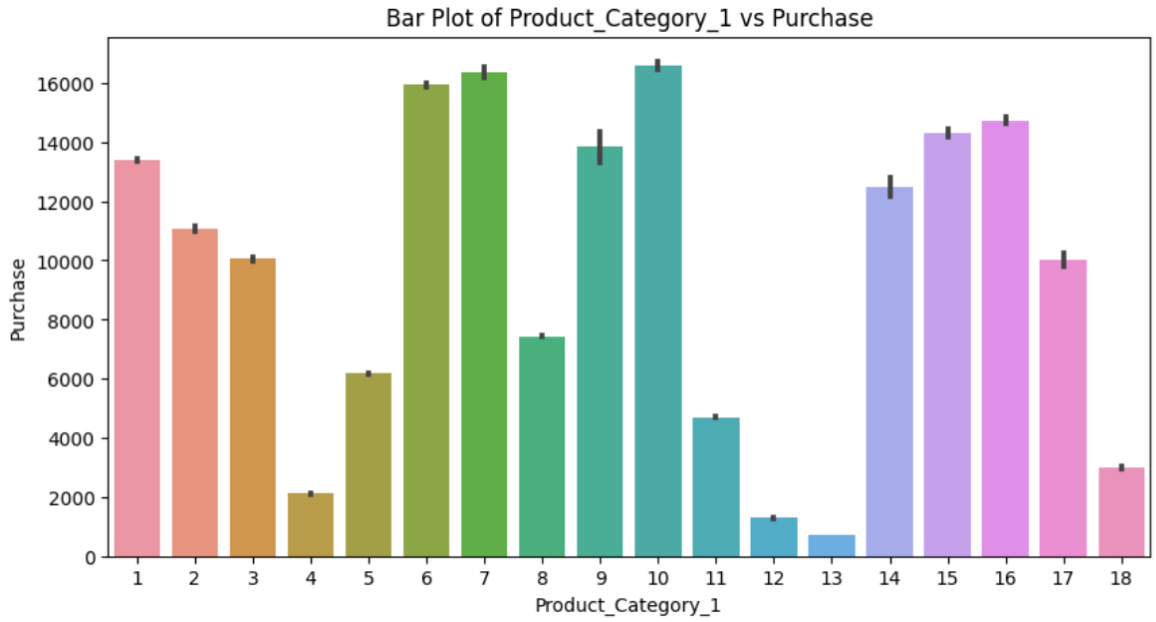
Pictorial representation for bivariate analysis of gender and purchase features using Bar plot.



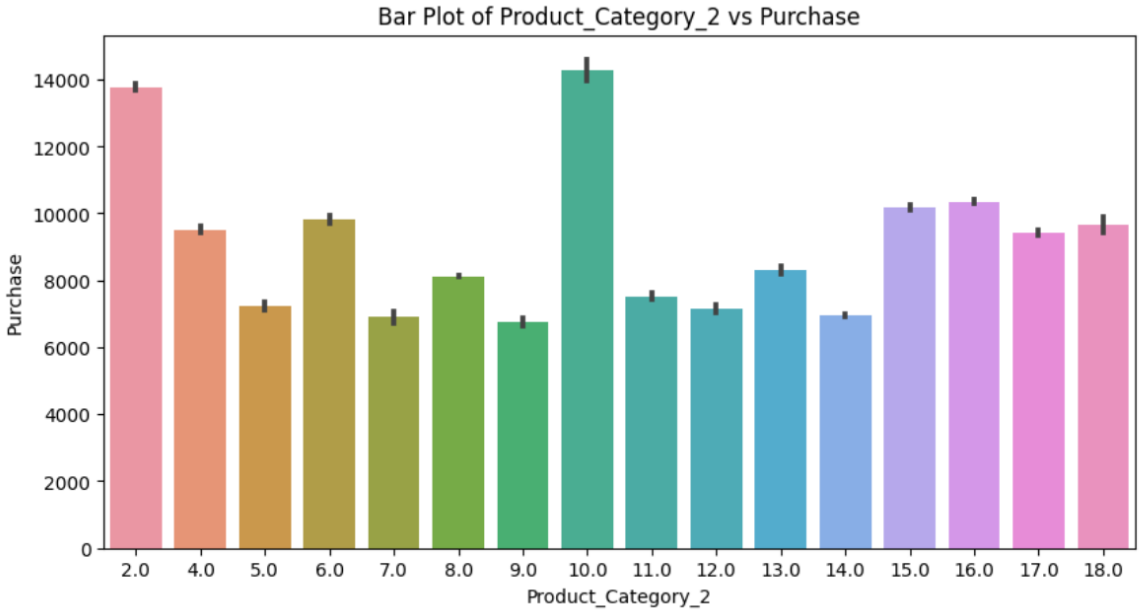
Pictorial representation for bivariate analysis of Marital_status and purchase features using Bar plot.



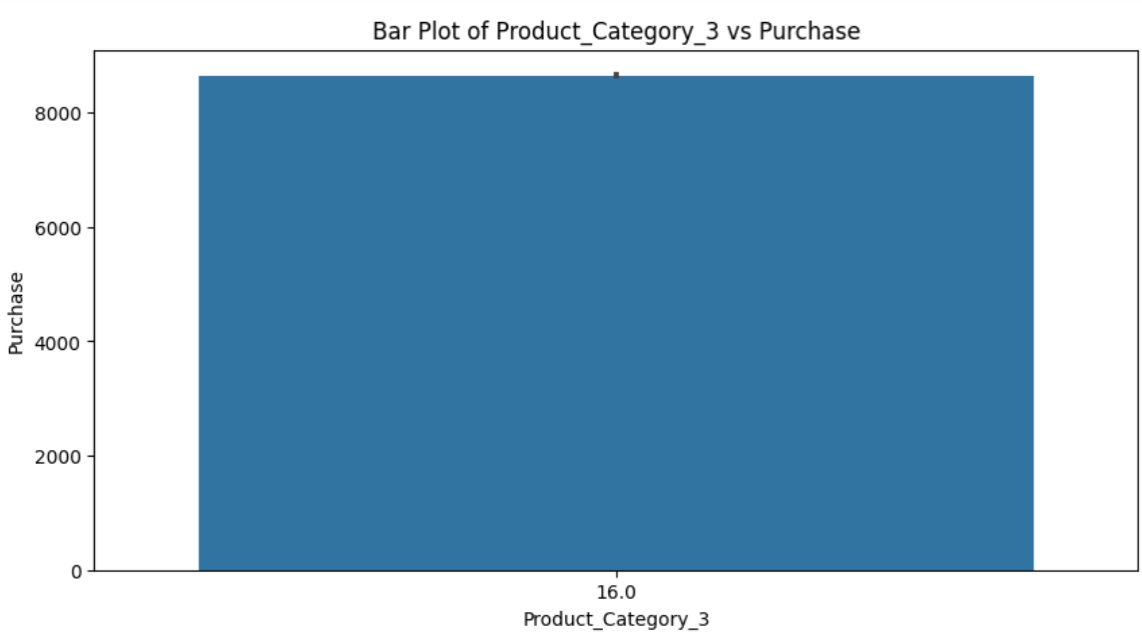
Pictorial representation for bivariate analysis of product_category_1 and purchase features using Bar plot.



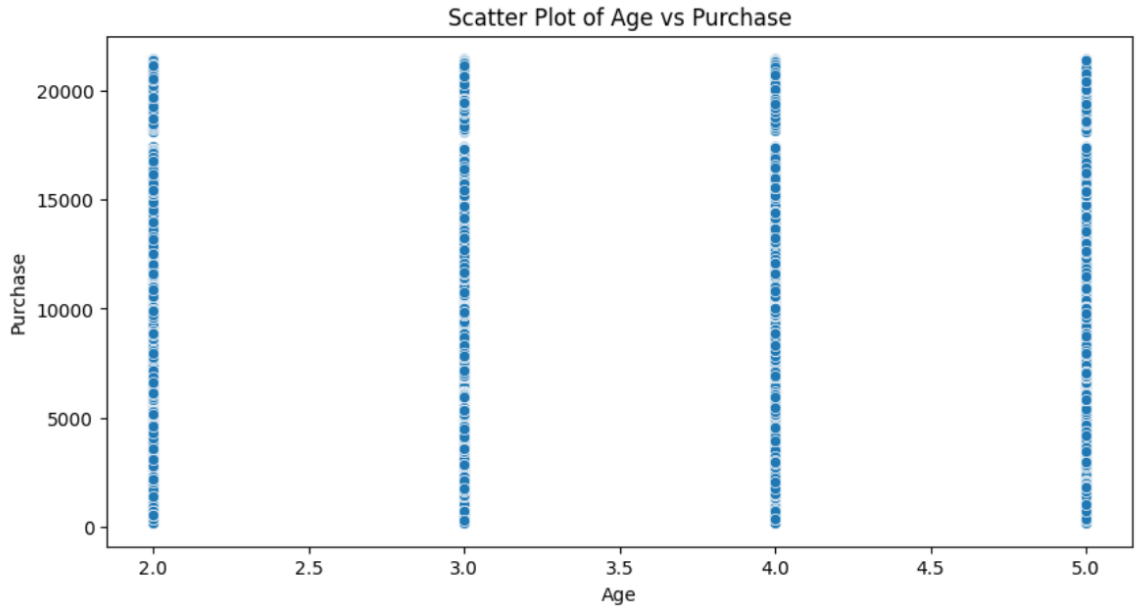
Pictorial representation for bivariate analysis of product_category_2 and purchase features using Bar plot.



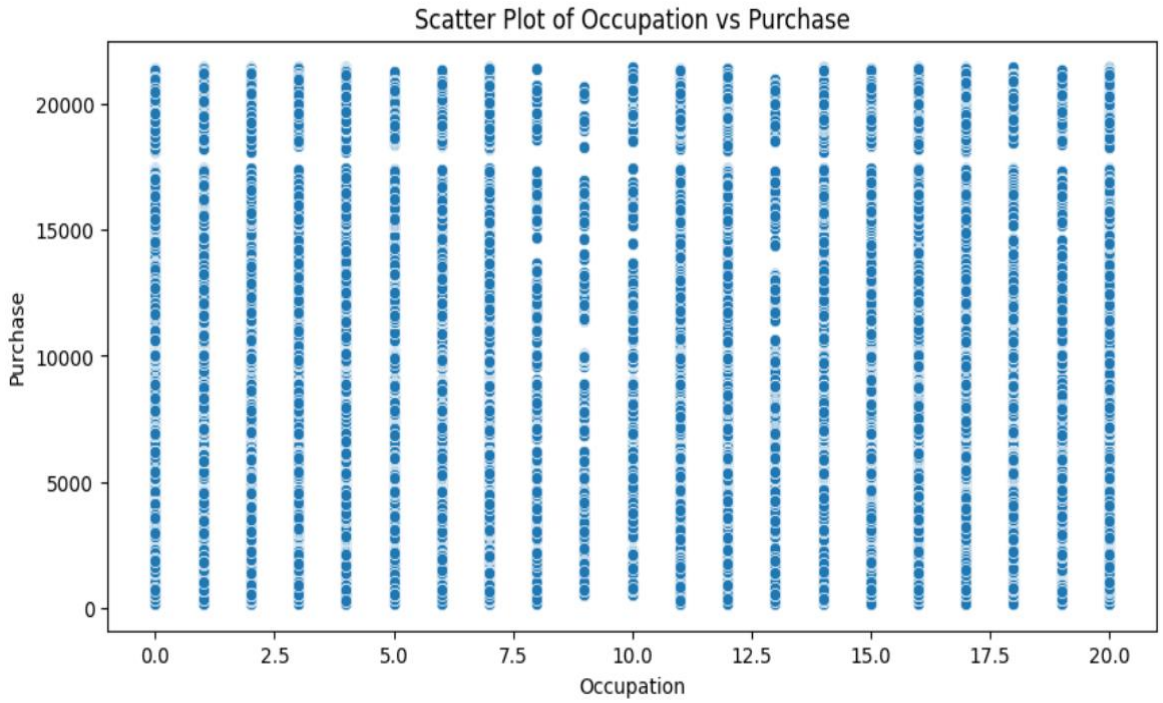
representation for bivariate analysis of product_category_3 and purchase features using Bar plot.



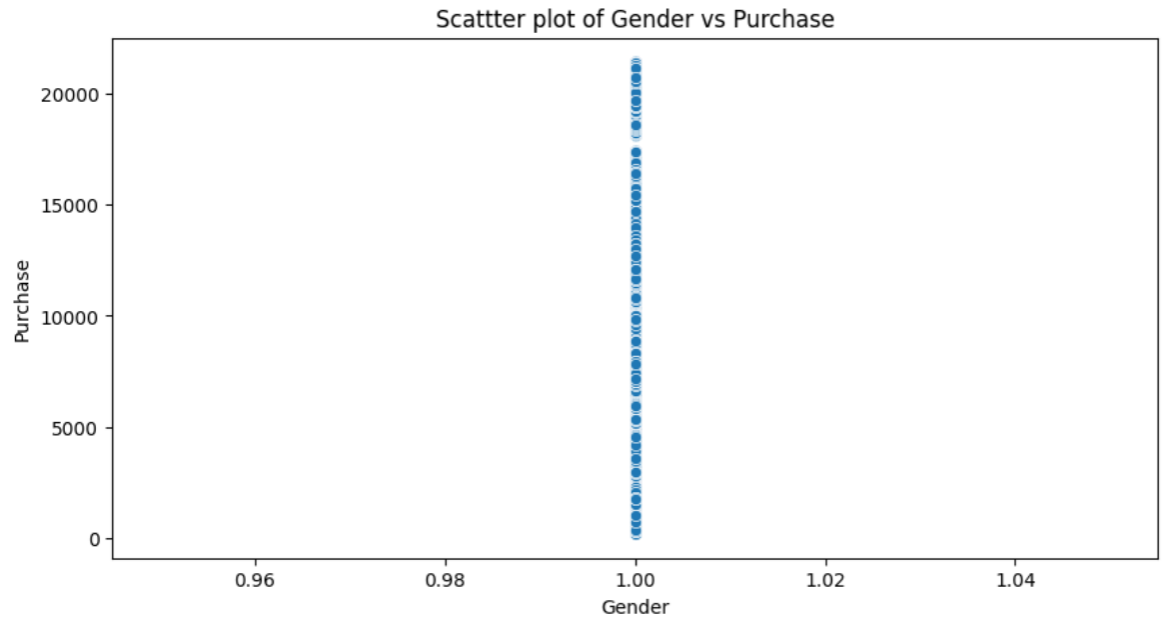
Pictorial representation for bivariate analysis of age and purchase features using scatter plot.



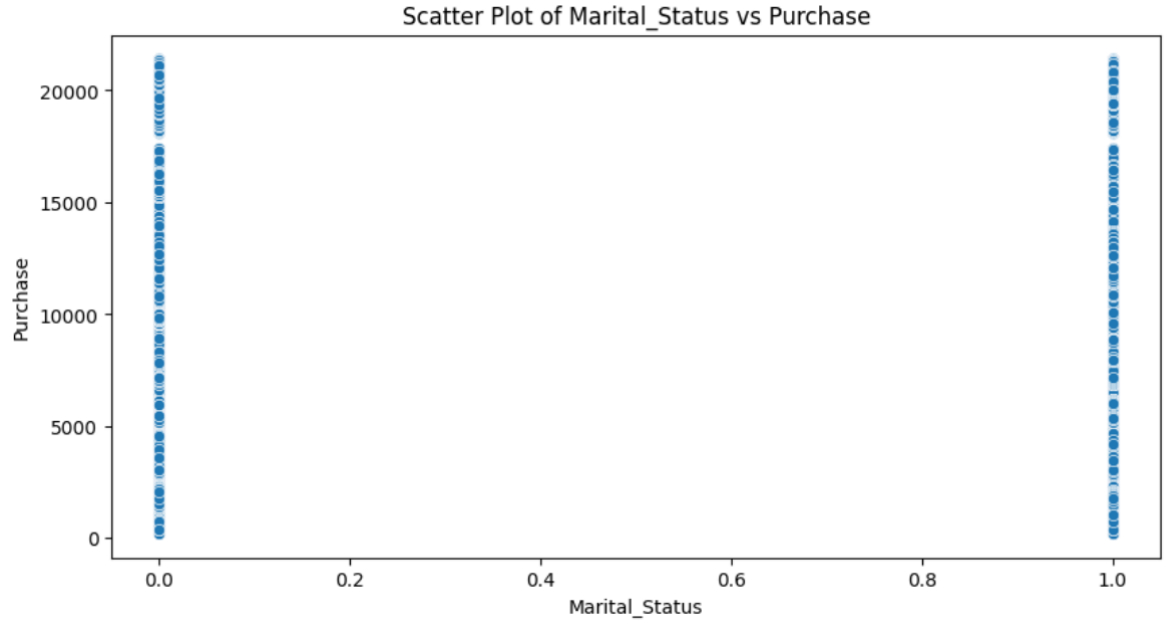
Pictorial representation for bivariate analysis of occupation and purchase features using scatter plot.



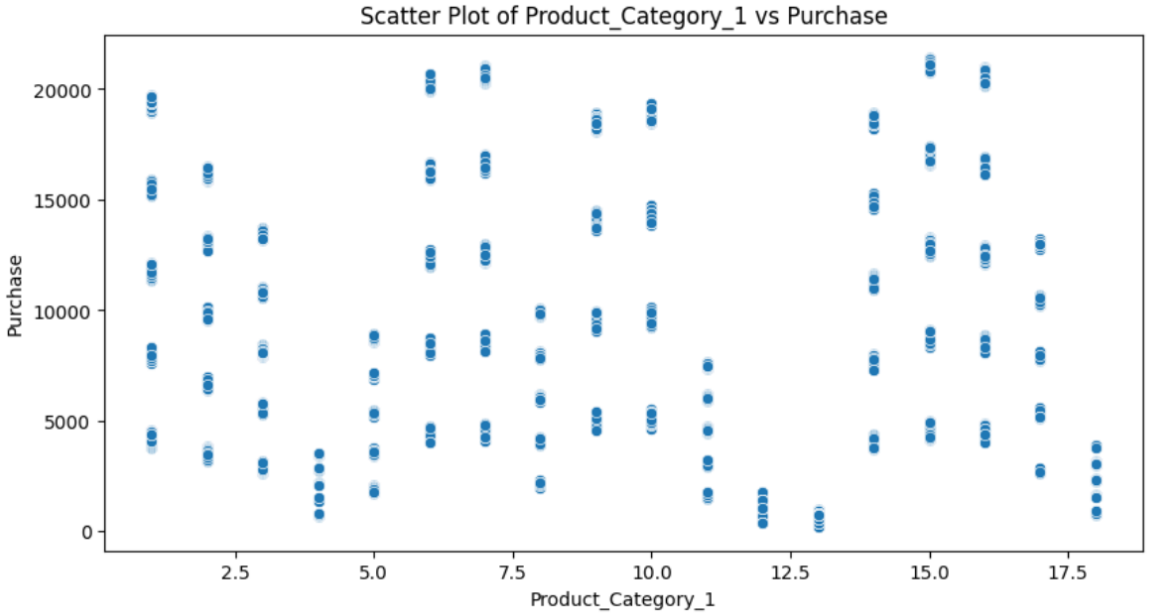
Pictorial representation for bivariate analysis of gender and purchase features using scatter plot.



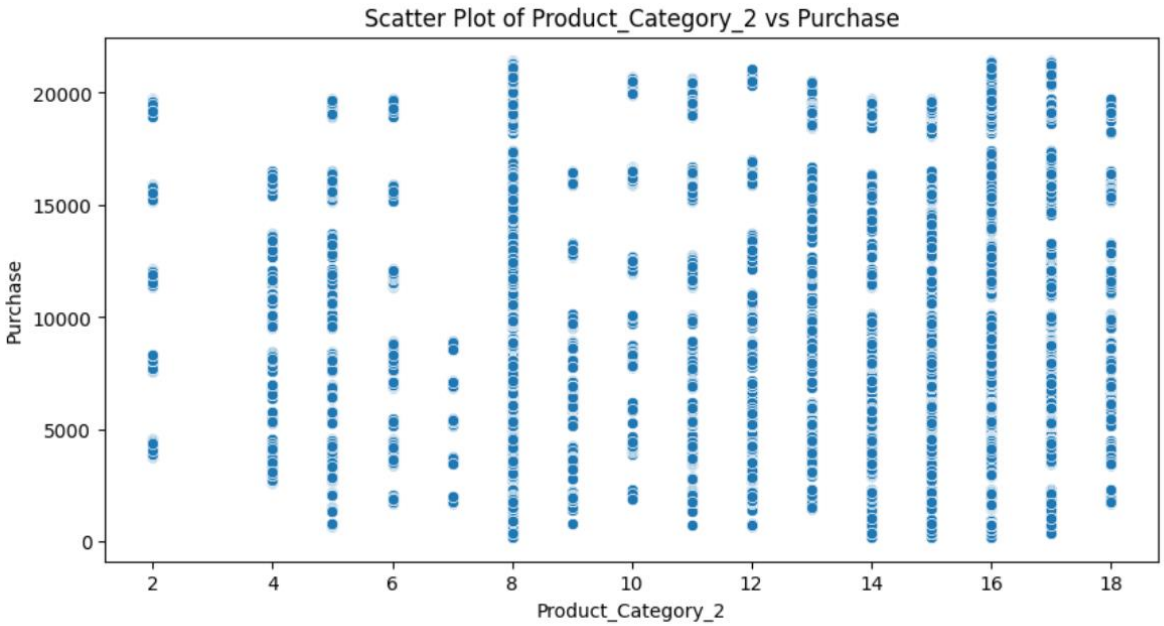
Pictorial representation for bivariate analysis of marital_status and purchase features using scatter plot.



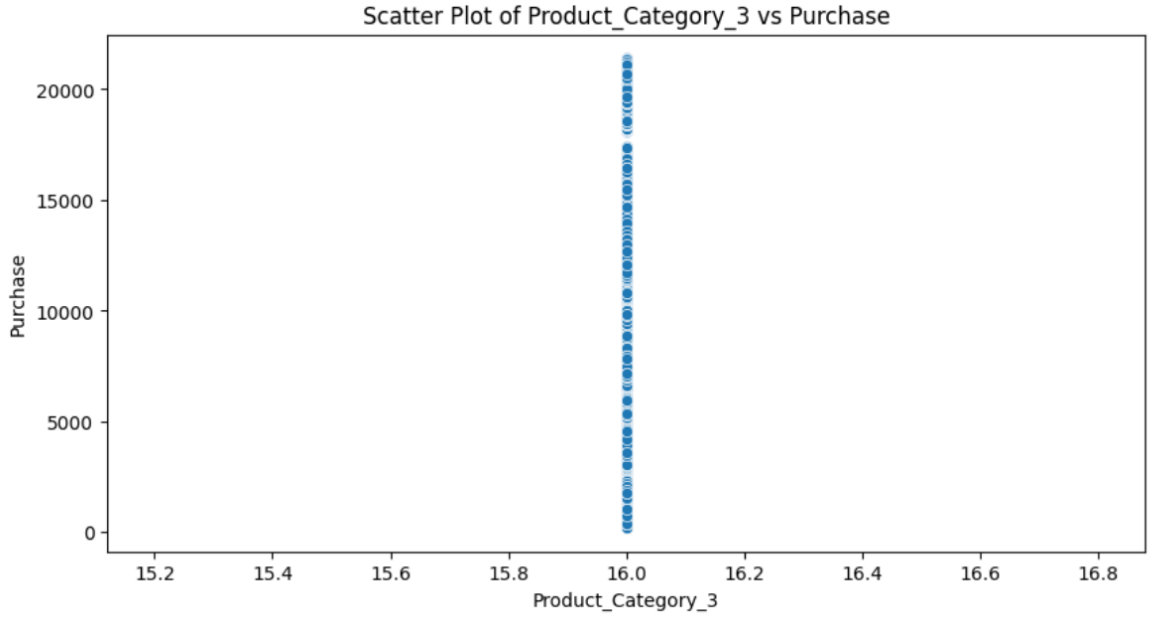
Pictorial representation for bivariate analysis of product_category_1 and purchase features using scatter plot.



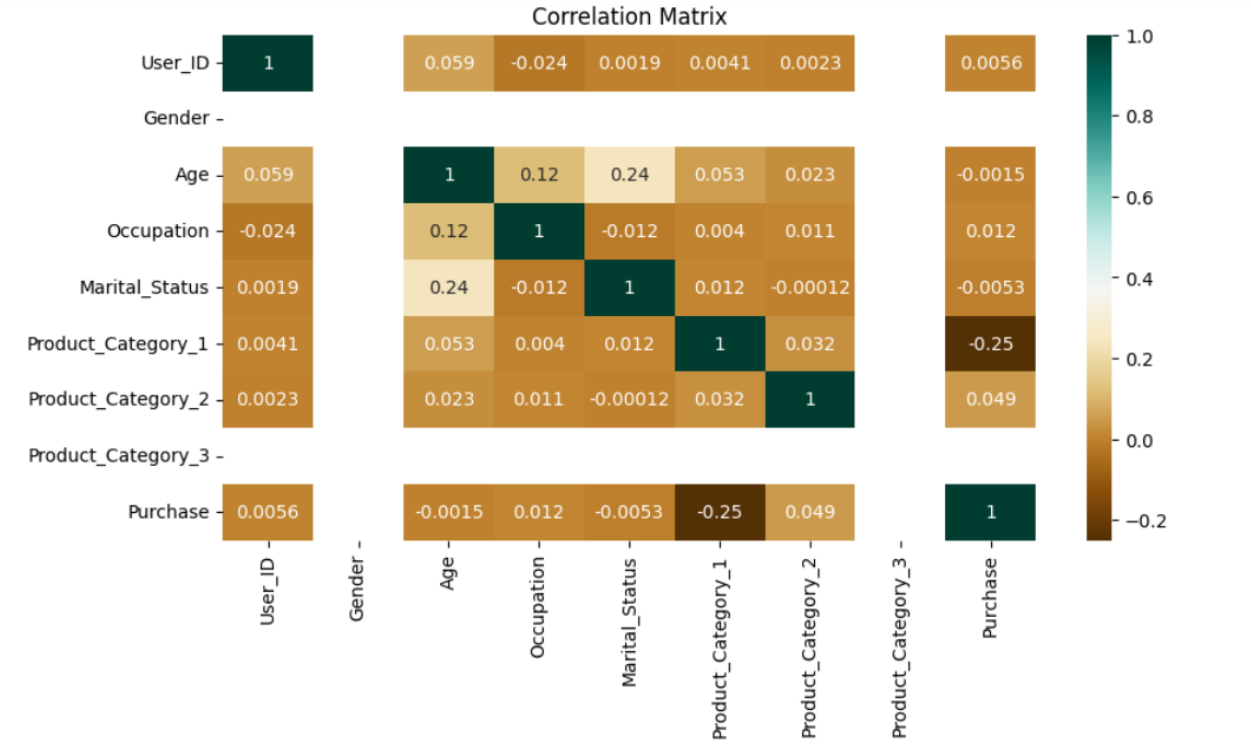
Pictorial representation for bivariate analysis of product_category_2 and purchase features using scatter plot.



Pictorial representation for bivariate analysis of product_category_3 and purchase features using scatter plot.



Correlation analysis using Heatmaps.



Feature selection:

Most important features were retrieved using the selectkbest function.

```
Most Important Features: Index(['Age', 'Occupation', 'City_Category', 'Marital_Status',
       'Product_Category_1', 'Product_Category_2', 'Purchase'],
      dtype='object')
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0 6 8] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: divide by zero encountered in divide
  f = msb / msw
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid value encountered in divide
  f = msb / msw
```

Project Management:

Work Completed:

- **Description:**
  Chosen a Black Friday sales dataset from Kaggle and have observed the key features and quality of the data. Preprocessed the dataset by dropping irrelevant columns, removing the null values, duplicate values and replacing valueless categorical values with some mapping values. Later, Exploratory Data Analysis was performed using Univariate, Bivariate analyses and outlier detection to find the relations between the attributes and to retrieve the most vital feature of the data. For Feature selection SelectKBest is used as it selects the most relevant features. Selected Decision Tree classifier as model and trained 70% of the dataset and evaluated the trained model with accuracy, confusion matrix, classification report.

- **Responsibility:**
  Praharsha Mutyala - Exploratory Data Analysis, Detecting Outliers.
  Murali Manobhiram Penumutchu - Model Selection, Model Training and Model Evaluation.
  Likhitha - Univariate, Bivariate and Correlation Analysis.
  Amarnadh Kari- Feature Selection.

- **Contributions:**
  Praharsha - 25%
  Murali Manobhiram - 25%
  Likhitha Chandanati - 25%
  Amarnadh Kari - 25%

Work To Be Completed:

- **Description:**

  After the first draft we plan on implementing a few more models such as Linear Regression, Random Forest classifier and try to improve the accuracy of the decision tree model and perform dimensionality reduction

- **Responsibility:**
  Praharsha Mutyala - Building K-Nearest Neighbours (KNN) model and try improving the accuracy
  Murali Manobhiram Penumutchu - Building Random Forest model and try improving the accuracy
  Likhitha Chandanati - Qualitative and Quantitative Analysis
  Amarnadh Kari - Resampling Techniques

- **Issues/Concerns:**

1. Handling the missing values in the black Friday sales dataset.
2. Handling categorical values such as age, gender and converting them into numerical values.
3. The analysis results are impacted by identifying the outliers.
4. Whether the Model is robust to new data.

References:

1.(https://www.kaggle.com/code/prashant111/decision-tree-classifier-tutorial) : Kaggle tutorial by prashant for reference

2.(https://medium.com/@1512aliahmad/black-friday-sales-prediction-cd477ebae018) : publication by Ali Ahmad for reference

3. XGBoost, Decision Tree, and Random Forest Tutorials:

a. Towards DataScience: "Complete Guide to Parameter Tuning in XGBoost" - Available at: https://towardsdatascience.com/complete-guide-to-parameter-tuning-in-xgboost-w ith-codes-in-python-7f94d34bc058

b.Scikit learn Documentation: "Decision Trees" - Available at:

https://scikit-learn.org/stable/modules/tree.html.

4.(https://www.kaggle.com/datasets/pranavuikey/black-friday-sales-eda/data): This is the dataset taken from Kaggle.

GitHub Repository Link- https://github.com/MuraliManobhiRam/Methods-in-Empirical-Analysis-Project-Group13.git