Machine Learning Model On Black Friday Sales

Contents

Description:

In this project, we will first explore the dataset using NumPy and Pandas to perform data cleaning and preprocessing tasks. We will then use Seaborn and Matplotlib to create visualizations that help us gain insights into customer behavior and preferences. The visualizations will include histograms, bar charts, and heatmaps, among others.

After exploring the data, we will use Scikit-Learn to develop a machine learning model that predicts the purchase amount based on customer demographics. We will split the dataset into training and testing sets and evaluate the performance of different algorithms, such as linear regression, decision trees, and random forests. We will then select the best algorithm and use it to make predictions on the test dataset.

Finally, we will summarize our findings and provide recommendations for retailers based on our analysis. This project will help us develop skills in data analysis using NumPy, Pandas, Seaborn, and Matplotlib, as well as machine learning using Scikit-Learn.

Problem Statement.

The Black Friday Sale dataset contains information about customer demographics, purchase behavior, and product categories. The goal of this project is to analyze the dataset to gain insights into customer behavior and preferences. This analysis will help retailers better understand their customers and improve their marketing strategies. In addition, a machine learning model will be developed to predict the purchase amount based on customer demographics.

Import Libraries And Data

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import ydata_profiling
%matplotlib inline

plt.style.use('bmh')
```

Data Loading and Description

In [2]:
```
data = pd.read_csv('Black Friday Sales.csv')
```

In [3]:
```
data.sample(3)
```

Out[3]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Yea
516279	1001505	P00272542	M	51-55	11	C	
328357	1002581	P00313642	M	26-35	11	A	
123914	1001146	P00324442	F	18-25	16	B	

The Black Friday Sales dataset is a dataset containing the transactions occurring in a retail store during Black Friday. The dataset contains the following columns:

Features	Description
'User_ID'	A unique identifier for each user
'Product_ID'	A unique identifier for each product
'Gender'	Gender of the user (Male or Female)
'Age'	Age of the user
'Occupation'	Occupation of the user
'City_Category'	Category of the city where the user lives (A, B or C)
'Stay_In_Current_City_Years'	Number of years the user has lived in the current city
'Marital_Status'	Marital status of the user
'Product_Category_1'	Category of the product
'Product_Category_2'	Category of the product
'Product_Category_3'	Category of the product
'Purchase'	Purchase amount in dollars

The dataset includes various features such as age, gender, marital status, product categories, and purchase amount. The dataset can be used for various machine learning tasks, including regression, clustering, and association rule mining. This dataset can be used to predict the purchase amount or product categories based on customer demographics or to perform customer segmentation analysis.

Basic Data Exploration

In [4]:
```
data.shape
```

Out[4]:
```
(550068, 12)
```

In [5]:
```
data.columns
```

Out[5]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Categor
y',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
       'Product_Category_2', 'Product_Category_3', 'Purchase'],
      dtype='object')
```

In [6]:
```
data.head()
```

Out[6]:

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

In [7]:
```
data.tail()
```

Out[7]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Yea
550063	1006033	P00372445	M	51-55	13	B	
550064	1006035	P00375436	F	26-35	1	C	
550065	1006036	P00375436	F	26-35	15	B	4
550066	1006038	P00375436	F	55+	1	C	
550067	1006039	P00371644	F	46-50	0	B	4

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     550068 non-null  int64  
 1   Product_ID                  550068 non-null  object 
 2   Gender                      550068 non-null  object 
 3   Age                         550068 non-null  object 
 4   Occupation                  550068 non-null  int64  
 5   City_Category               550068 non-null  object 
 6   Stay_In_Current_City_Years  550068 non-null  object 
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 50.4+ MB
```

In [9]:
```
data.describe()
```

Out[9]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Pr
count	5.500680e+05	550068.000000	550068.000000	550068.000000	376430.000000	
mean	1.003029e+06	8.076707	0.409653	5.404270	9.842329	
std	1.727592e+03	6.522660	0.491770	3.936211	5.086590	
min	1.000001e+06	0.000000	0.000000	1.000000	2.000000	
25%	1.001516e+06	2.000000	0.000000	1.000000	5.000000	
50%	1.003077e+06	7.000000	0.000000	5.000000	9.000000	
75%	1.004478e+06	14.000000	1.000000	8.000000	15.000000	
max	1.006040e+06	20.000000	1.000000	20.000000	18.000000	

Profiling Report

In [10]:
```
from ydata_profiling import ProfileReport
profile = ProfileReport(data, explorative = True, dark_mode = True)
profile.to_file(output_file="Black_Friday_Sale_Data_Report.html")
```

Summarize dataset: 100% 58/58 [00:38<00:00, 1.55it/s, Completed]

Generate report structure: 100% 1/1 [00:05<00:00, 5.46s/it]

Render HTML: 100% 1/1 [00:03<00:00, 3.63s/it]

Export report to file: 100% 1/1 [00:00<00:00, 13.96it/s]

-- You can find the report in the repository as "Black_Friday_Sale_Data_Report.html"

Checking for missing values

Checking Null Values

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
User_ID                            0
Product_ID                         0
Gender                             0
Age                                0
Occupation                         0
City_Category                      0
Stay_In_Current_City_Years         0
Marital_Status                     0
Product_Category_1                 0
Product_Category_2            173638
Product_Category_3            383247
Purchase                           0
dtype: int64
```

Null Value in percentage

In [12]:
```
data.isnull().sum()/data.shape[0]*100
```

Out[12]:
```
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
Product_Category_2            31.566643
Product_Category_3            69.672659
Purchase                       0.000000
dtype: float64
```

Analysing And Handling Null Values

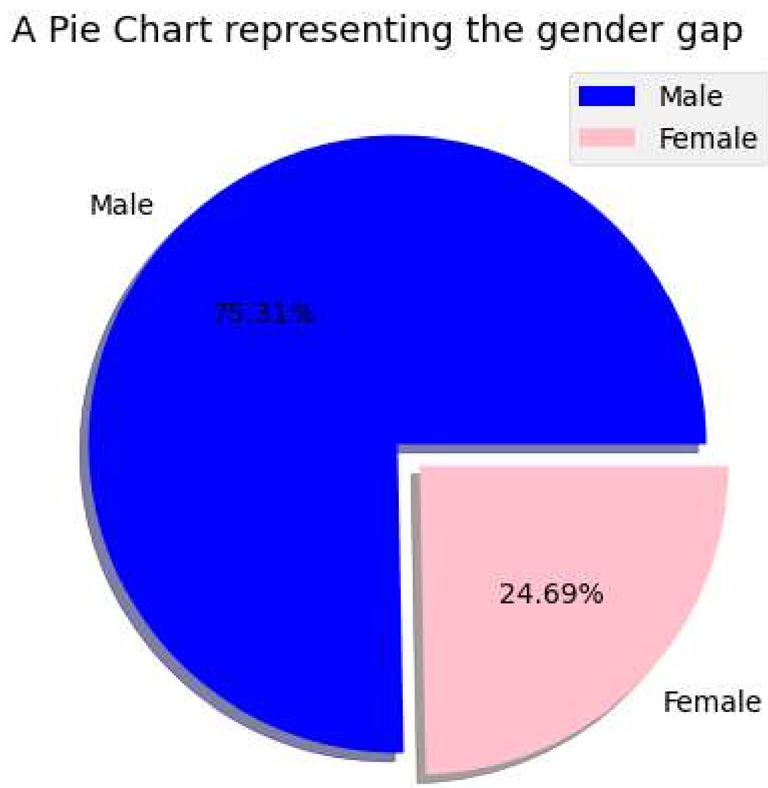
In [13]:
```
data['Product_Category_2'] = data['Product_Category_2'].fillna(0)
```

In [14]:
```
data['Product_Category_3'] = data['Product_Category_3'].fillna(0)
```

Exploratory Data Analysis

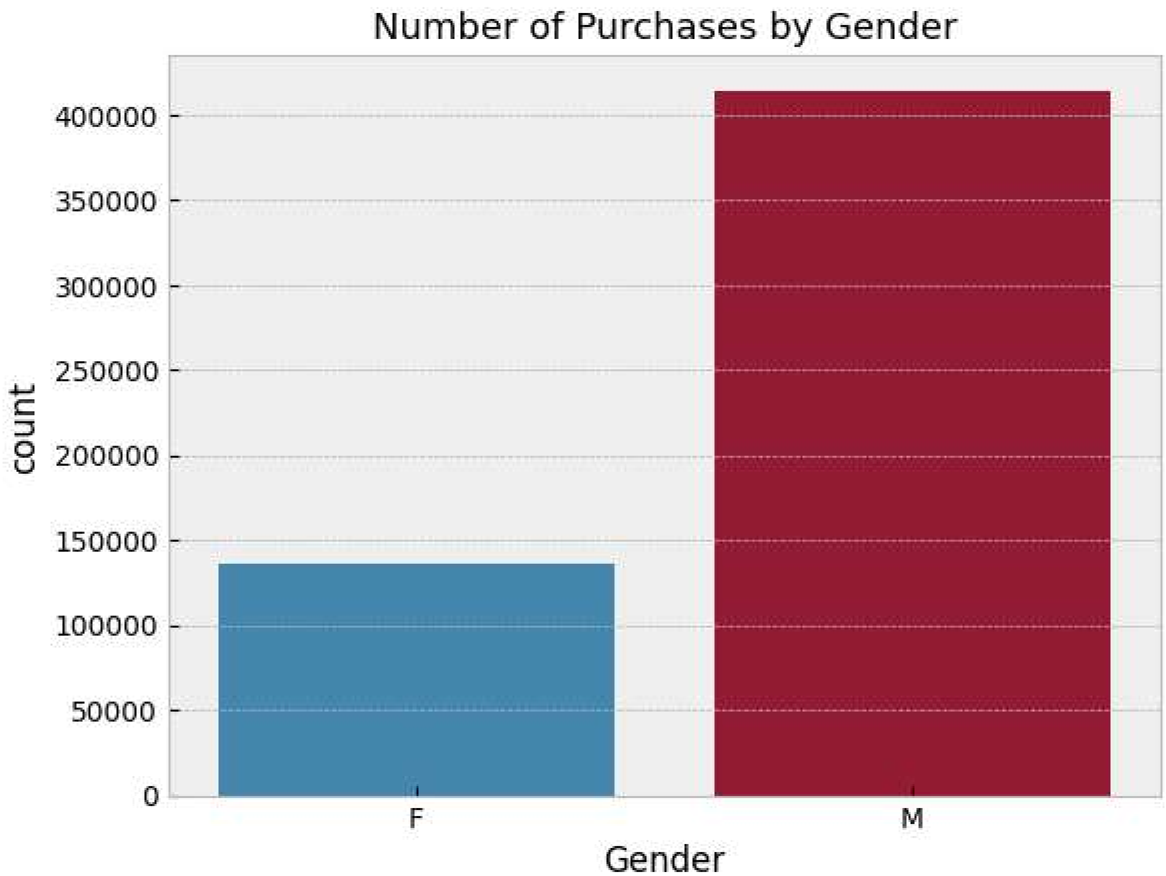
1. A Pie Chart Representing The Gender Gap

In [15]:
```
plt.figure(figsize = (8, 5))
plt.pie(data['Gender'].value_counts(),
        colors = ['blue', 'pink'],
        labels = ['Male', 'Female'],
        shadow = True,
        explode = [0, 0.1],
        autopct = '%.2f%%')
plt.title('A Pie Chart representing the gender gap', fontsize = 13, loc = 'lef
plt.legend()
plt.show()
```



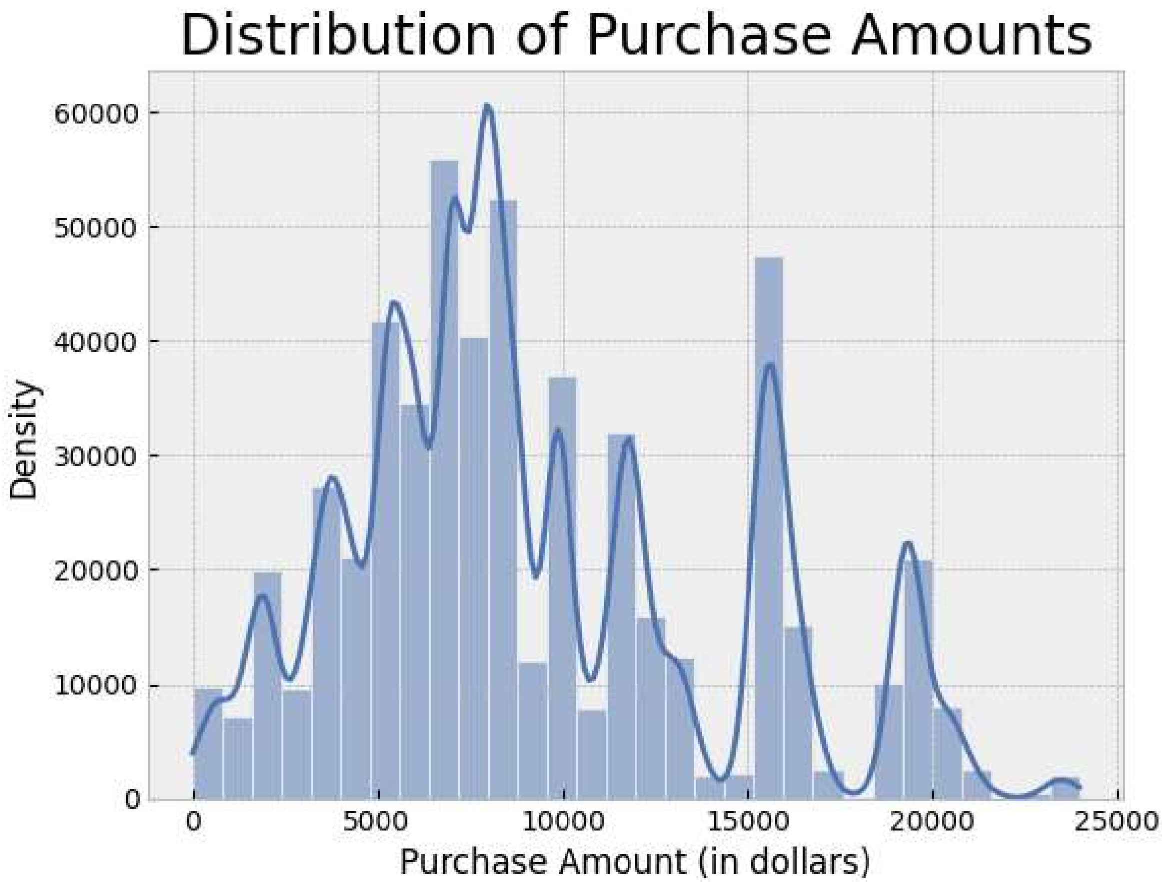
2. Number of Purchases by Gender

In [16]:
```
sns.countplot(x='Gender', data=data)
plt.title('Number of Purchases by Gender', fontsize = 13)
plt.show()
```



3. Distribution of Purchase Amounts

In [17]:
```
sns.histplot(data['Purchase'], kde=True, bins=30, color='#4C72B0')
plt.title('Distribution of Purchase Amounts', fontsize = 20)
plt.xlabel('Purchase Amount (in dollars)')
plt.ylabel('Density')
plt.show()
```



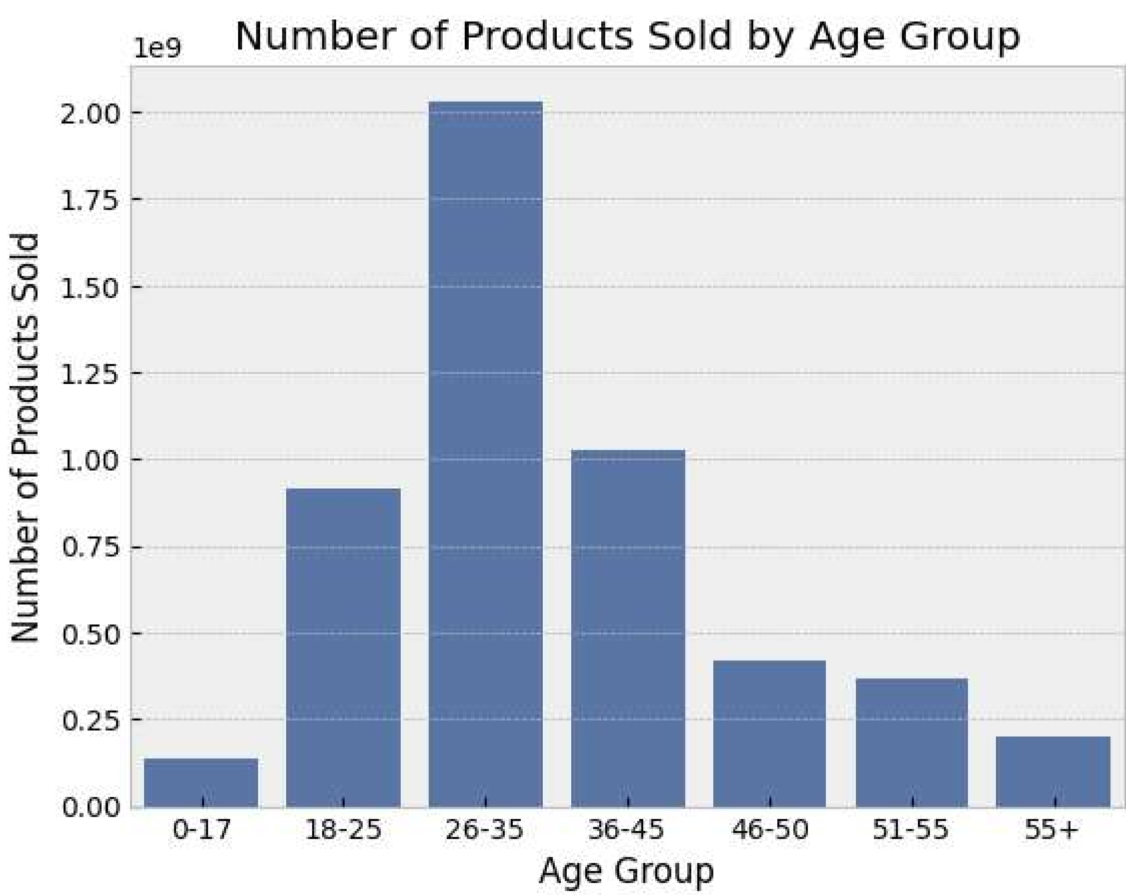
4. Number of Products Sold by Age Group

In [18]:
```
DF1 = pd.DataFrame(data.groupby('Age')['Purchase'].sum())
DF1.reset_index(inplace = True)
DF1
```

Out[18]:

	Age	Purchase
0	0-17	134913183
1	18-25	913848675
2	26-35	2031770578
3	36-45	1026569884
4	46-50	420843403
5	51-55	367099644
6	55+	200767375

In [19]:
```
sns.barplot(data = DF1, x='Age', y='Purchase', color='#4C72B0')
plt.title('Number of Products Sold by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Number of Products Sold')
plt.show()
```

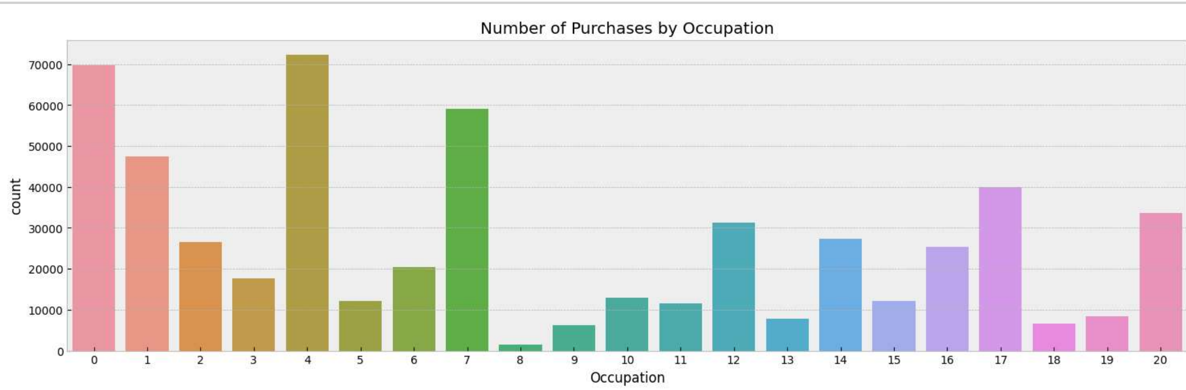


5. Purchase Amount by City Category

In [20]:
```
sns.boxplot(x='City_Category', y='Purchase', data=data)
plt.title('Purchase Amount by City Category')
plt.show()
```

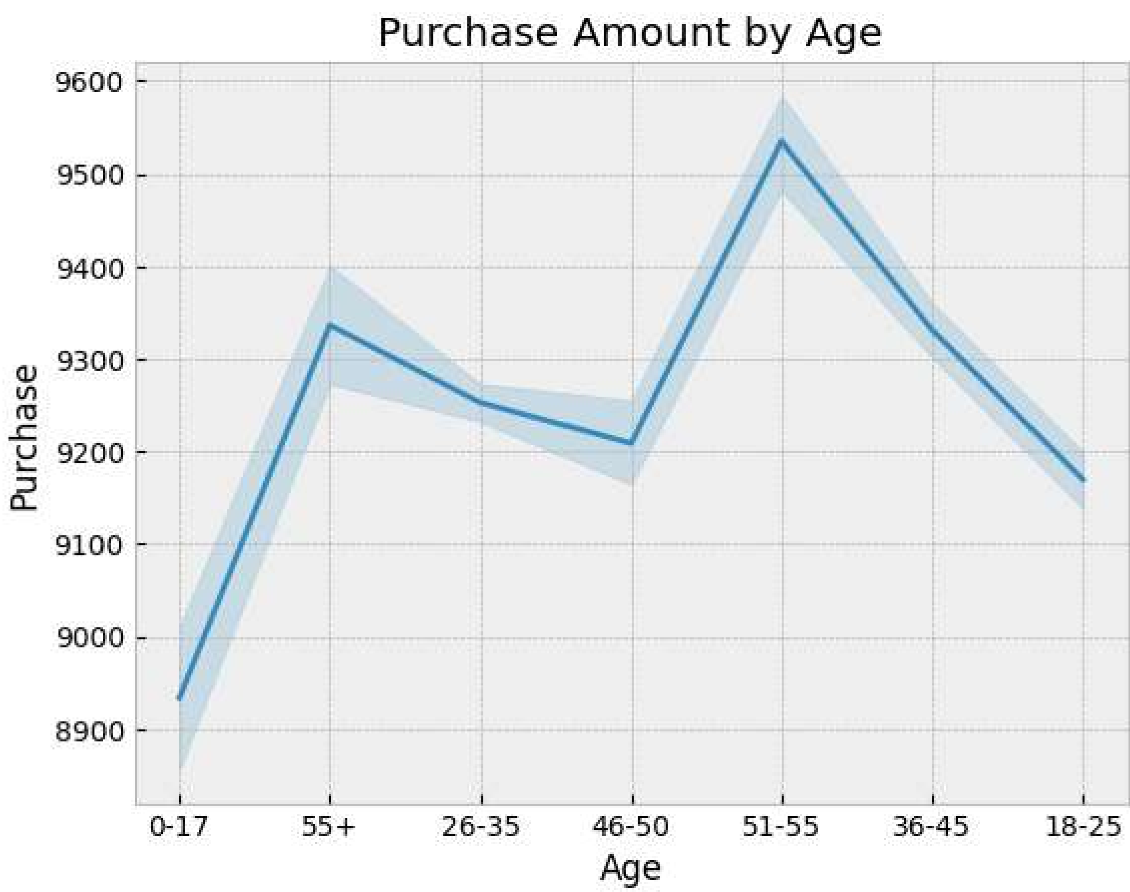
6. Number of Purchases by Occupation

In [21]:
```
plt.figure(figsize=(18,5))
sns.countplot(x='Occupation', data=data)
plt.title('Number of Purchases by Occupation')
plt.show()
```



7. Purchase Amount by Age

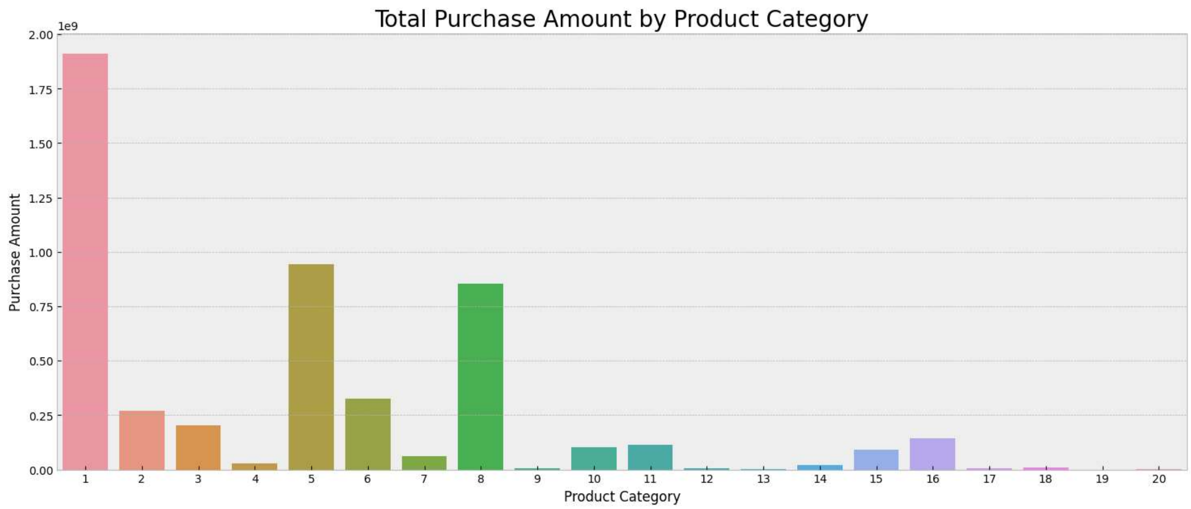
In [22]:
```
sns.lineplot(x='Age', y='Purchase', data=data)
plt.title('Purchase Amount by Age')
plt.show()
```



8. Bar chart showing the total purchase amount by product category

In [23]:
```
purchase_by_category = data.groupby('Product_Category_1')['Purchase'].sum()
```

In [24]:
```
plt.figure(figsize=(18,7))
sns.barplot(data=data, x=purchase_by_category.index, y=purchase_by_category.va
plt.title('Total Purchase Amount by Product Category', fontsize = 20)
plt.xlabel('Product Category')
plt.ylabel('Purchase Amount')
plt.show()
```

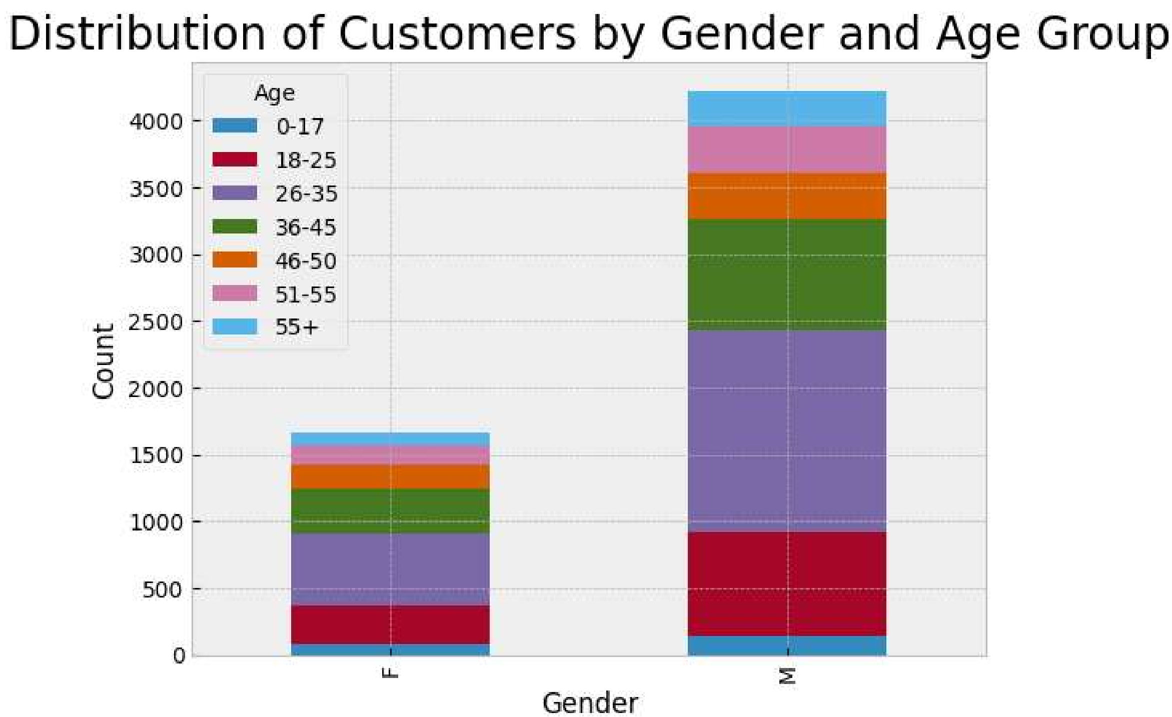


9. Stacked bar chart showing the distribution of customers by gender and age group

In [25]:
```
# Calculate the number of customers by gender and age group
customers_by_gender_age = data.groupby(['Gender', 'Age'])['User_ID'].nunique()
```

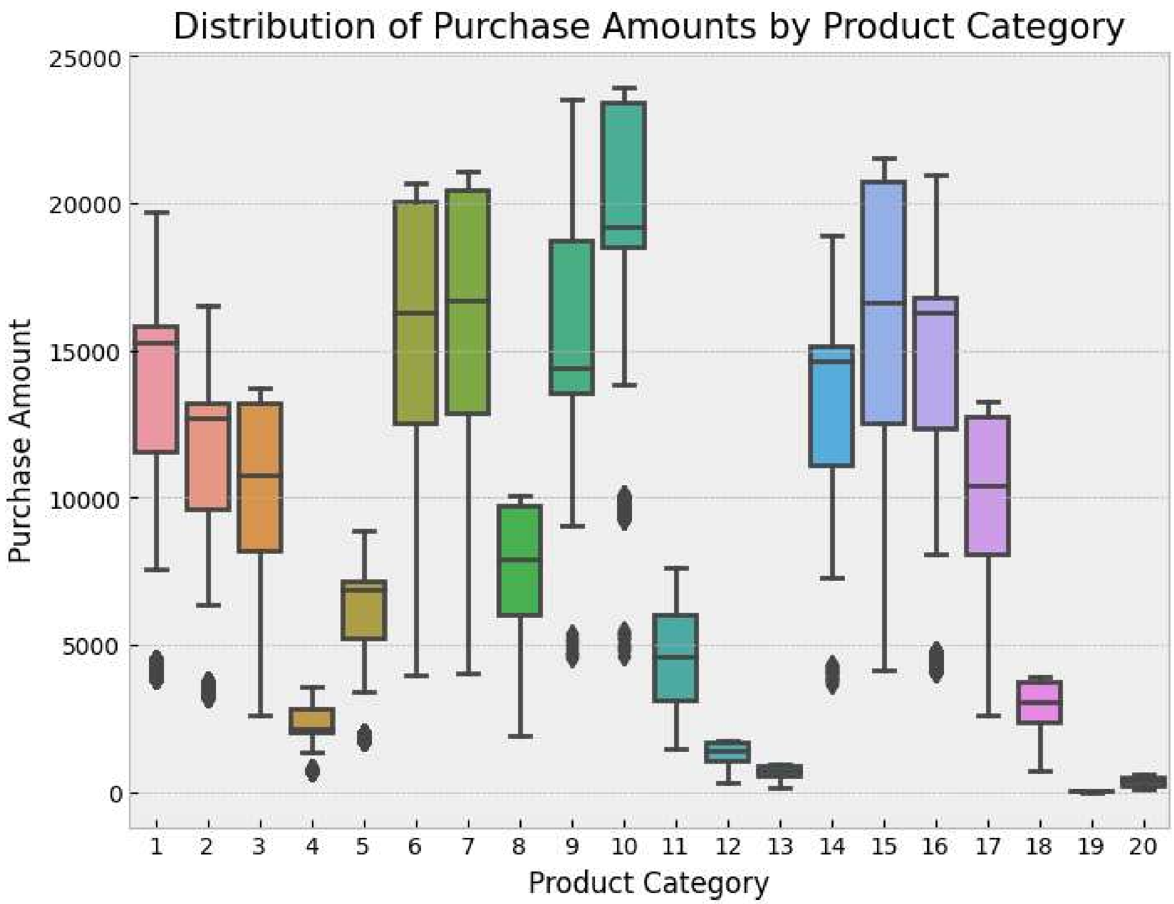
In [26]:
```
plt.figure(figsize=(8,6))
customers_by_gender_age.plot(kind='bar', stacked=True)
plt.title('Distribution of Customers by Gender and Age Group', fontsize = 20)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



10. Box plot showing the distribution of purchase amounts by product category

In [27]:
```
plt.figure(figsize=(8,6))
sns.boxplot(data=data, x='Product_Category_1', y='Purchase')
plt.title('Distribution of Purchase Amounts by Product Category', fontsize = 1!
plt.xlabel('Product Category')
plt.ylabel('Purchase Amount')
plt.show()
```

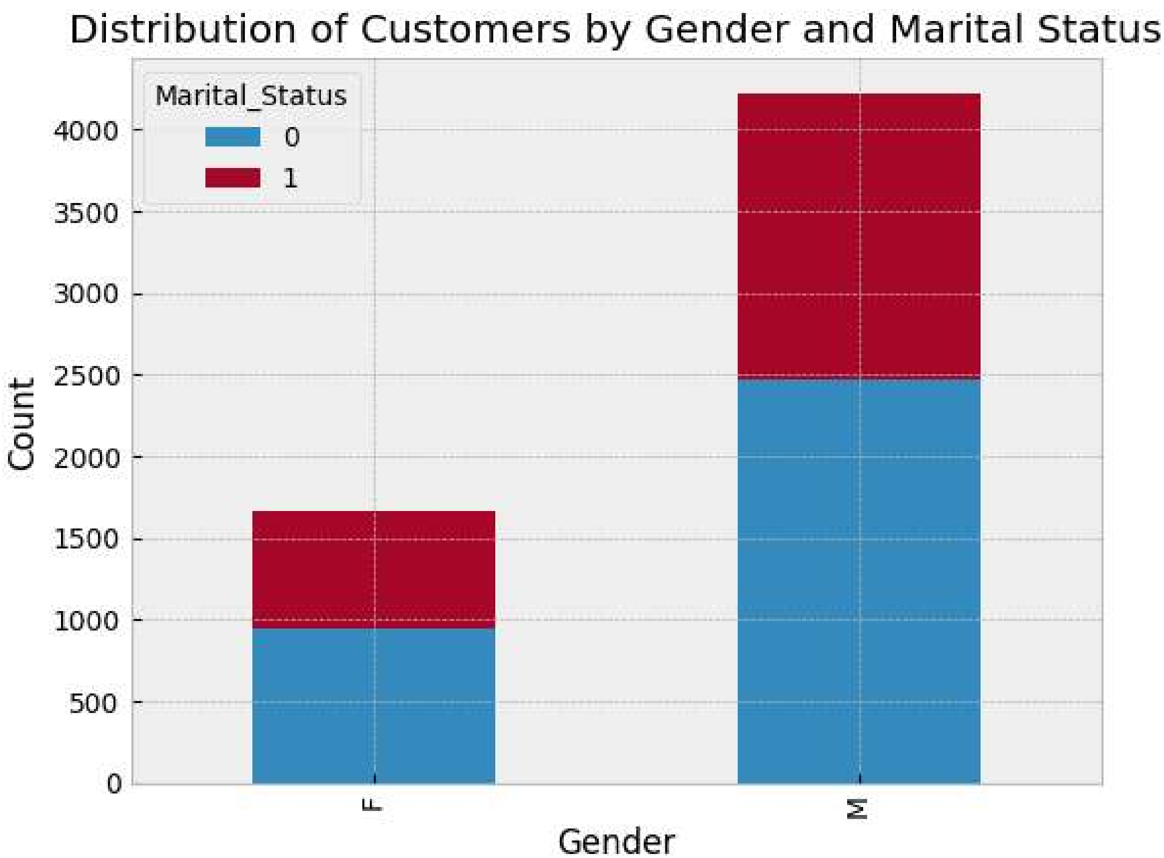


11. Distribution of Customers by Gender and Marital Status

In [28]:
```
# Calculate the number of customers by gender and marital status
customers_by_gender_marital = data.groupby(['Gender', 'Marital_Status'])['User_
```

In [29]:
```
plt.figure(figsize=(8,6))
customers_by_gender_marital.plot(kind='bar', stacked=True)
plt.title('Distribution of Customers by Gender and Marital Status')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



12. Distribution of Purchase Amounts by Gender and City Category

In [30]:
```
# Create a box plot of the distribution of purchase amounts by gender and city
plt.figure(figsize=(8,6))
sns.boxplot(data=data, x='City_Category', y='Purchase', hue='Gender')
plt.title('Distribution of Purchase Amounts by Gender and City Category')
plt.xlabel('City Category')
plt.ylabel('Purchase Amount')
plt.legend(loc='upper right')
plt.show()
```

Feature Engineering for Model building

Drop unwanted columns

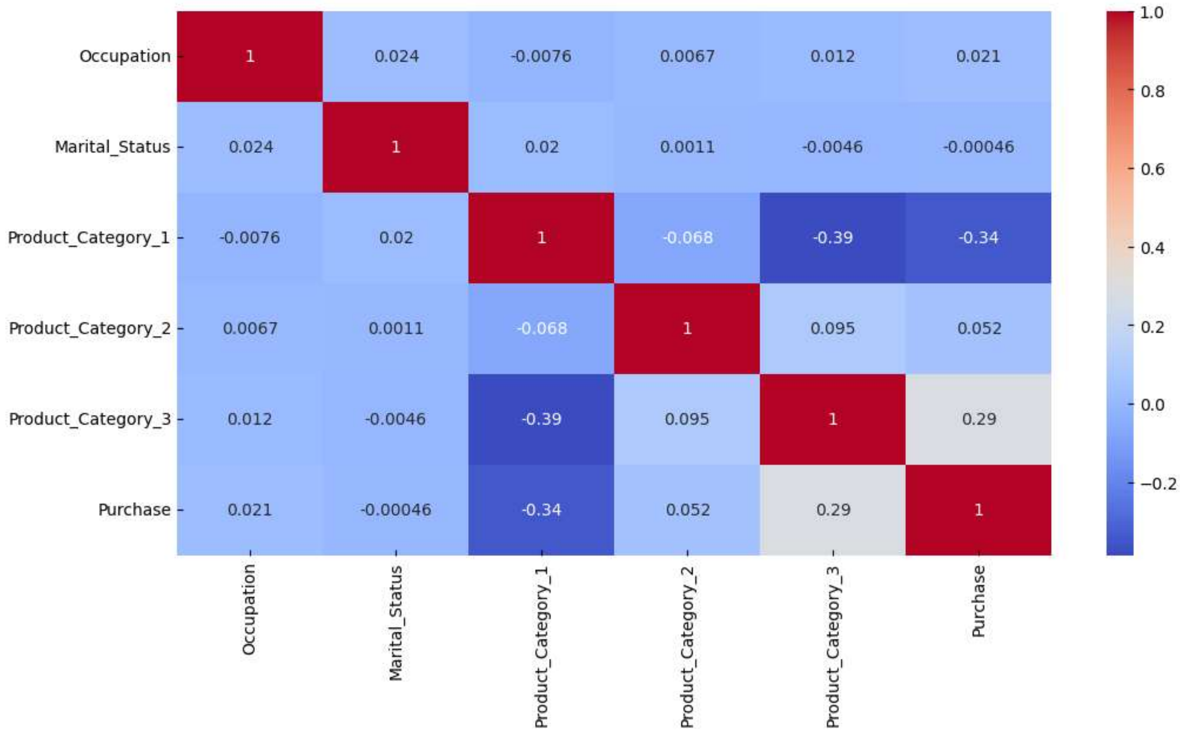
In [31]:
```
data = data.drop(["User_ID","Product_ID"],axis=1)
```

Correlation Between Numerical Features Using Heatmap

In [32]:
```
num_cols = data.select_dtypes(include='number').columns.tolist()

plt.figure(figsize=(12,6))
sns.heatmap(data[num_cols].corr(),annot=True,cmap='coolwarm')
```

Out[32]:
```
<AxesSubplot: >
```



- As we can see from the heatmap above, all the Features are not correleted with the **Purchase**, instead most of them are correlated with each other.

Convert Categorical variable into Numerical

In [33]:
```
data['Stay_In_Current_City_Years'] = data['Stay_In_Current_City_Years'].replac
```

In [34]:
```
#Dummy Variables:
data = pd.get_dummies(data, columns=['Stay_In_Current_City_Years'])
```

In [35]:
```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()
```

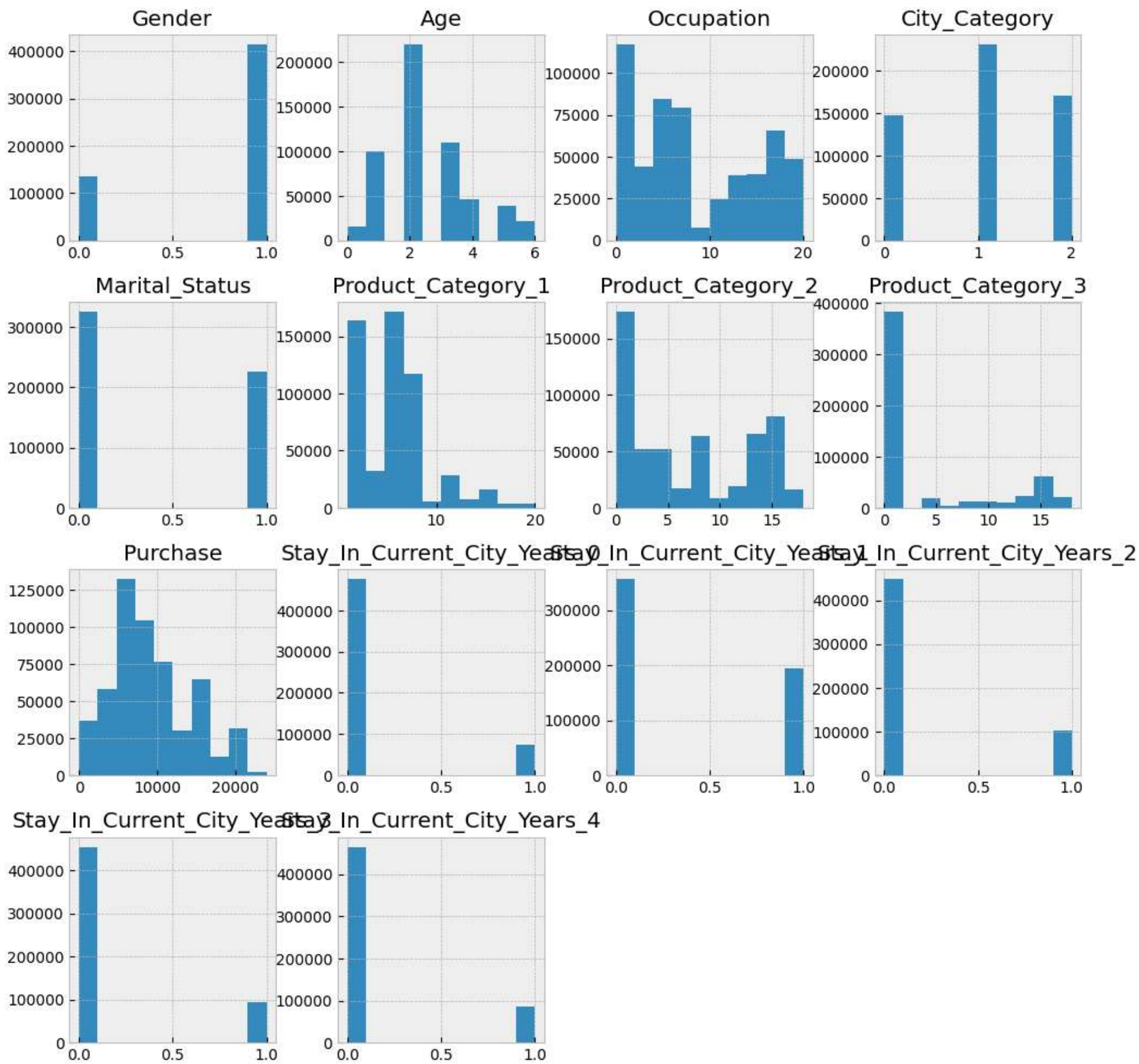
In [36]:
```
data['Gender'] = LE.fit_transform(data['Gender'])
```

In [37]:
```
data['Age'] = LE.fit_transform(data['Age'])
```

In [38]:
```
data['City_Category'] = LE.fit_transform(data['City_Category'])
```

In [39]:
```
data['Marital_Status'] = LE.fit_transform(data['Marital_Status'])
```

In [40]:
```
data.hist(figsize = (12,12))
plt.show()
```



- **--**

Scaling And Transformation

In [41]:
```
from sklearn.preprocessing import RobustScaler
```

In [42]:
```
RS = RobustScaler()
```

In [43]:
```
data[['Age','Occupation']] = RS.fit_transform(data[['Age','Occupation']])
```

Splitting Data Into Independent And Dependent Variables

In [44]:
```
X = data.drop("Purchase",axis=1)
```

In [45]:
```
y=data['Purchase']
```

In [46]:
```
from sklearn.model_selection import train_test_split
```

In [47]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, rand
```

Model Selection/Predictions

1. Linear Regression

In [48]:
```
from sklearn.linear_model import LinearRegression
```

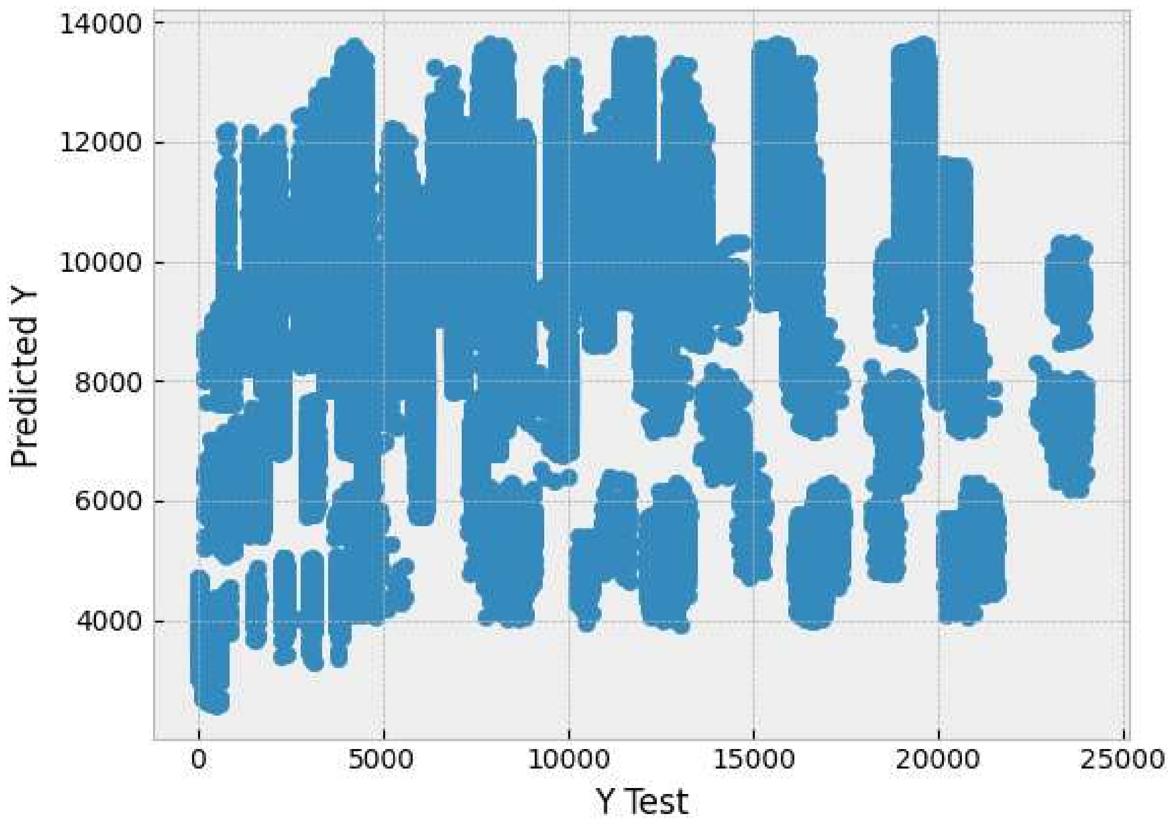
In [49]:
```
LR = LinearRegression()
```

In [50]:
```
LR.fit(X_train,y_train)
```

Out[50]:
```
▾ LinearRegression
LinearRegression()
```

In [51]:
```
LR_y_pred = LR.predict(X_test)
```

In [52]:
```
plt.scatter(x=y_test,y=LR_y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
plt.show()
```



In [53]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
```

In [54]:
```
mean_absolute_error(y_test, LR_y_pred)
```

Out[54]: 3529.2817093165413

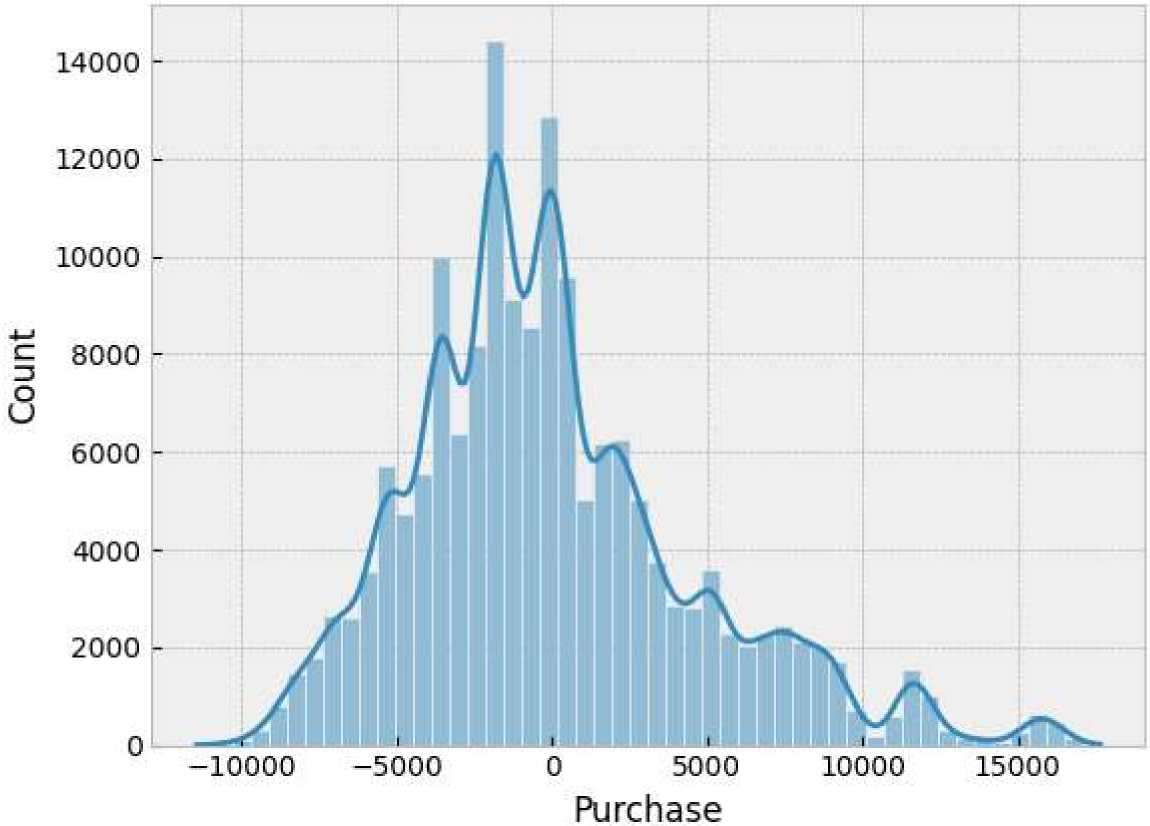
In [55]:
```
mean_squared_error(y_test, LR_y_pred)
```

Out[55]: 21416007.8989785

In [56]:
```
r2_score(y_test, LR_y_pred)
```

Out[56]: 0.15023513815129363

In [57]:
```
sns.histplot((y_test-LR_y_pred),bins=50,kde=True)
plt.show()
```



2. Decision Tree Regressor

In [58]:
```
from sklearn.tree import DecisionTreeRegressor
```

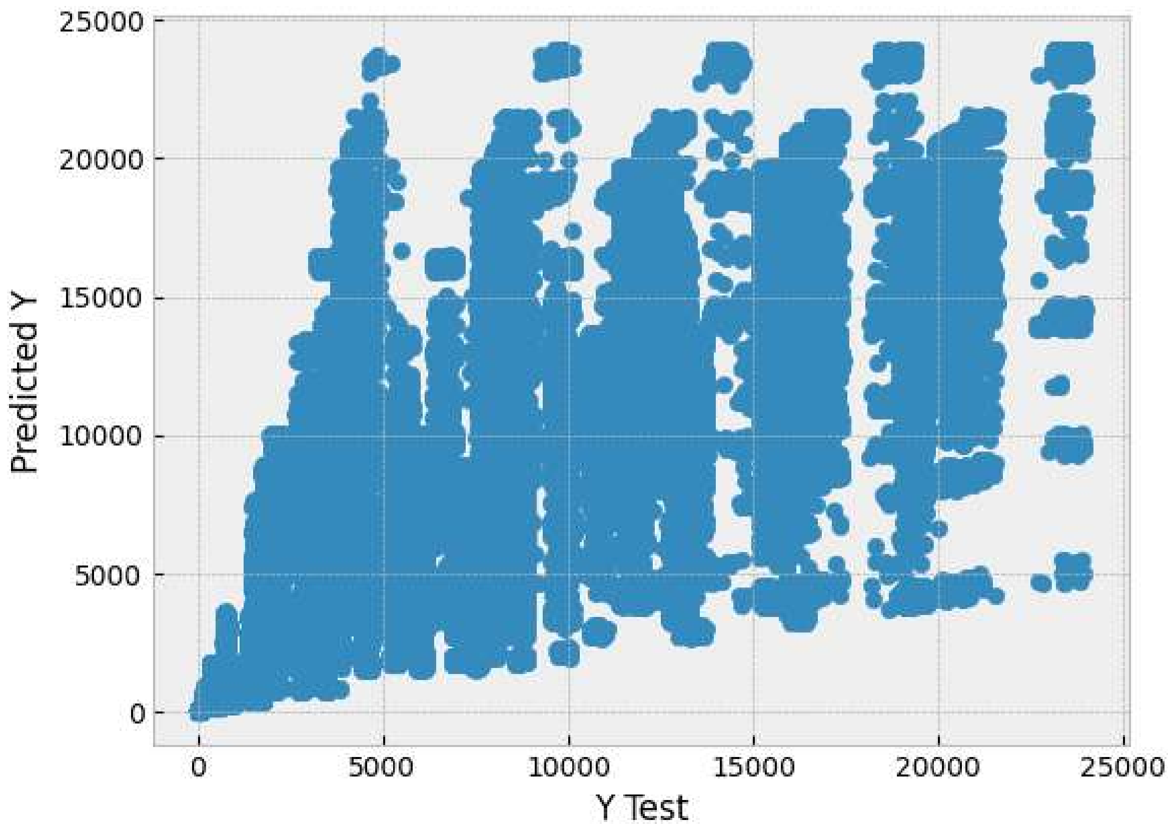
In [59]:
```
DTR = DecisionTreeRegressor(random_state = 42)
```

In [60]:
```
DTR.fit(X_train, y_train)
```

Out[60]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

In [61]:
```
DTR_y_pred = DTR.predict(X_test)
```

In [62]:
```
plt.scatter(x=y_test,y=DTR_y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
plt.show()
```



In [63]:
```
mean_absolute_error(y_test, DTR_y_pred)
```

Out[63]: 2381.2563346644984

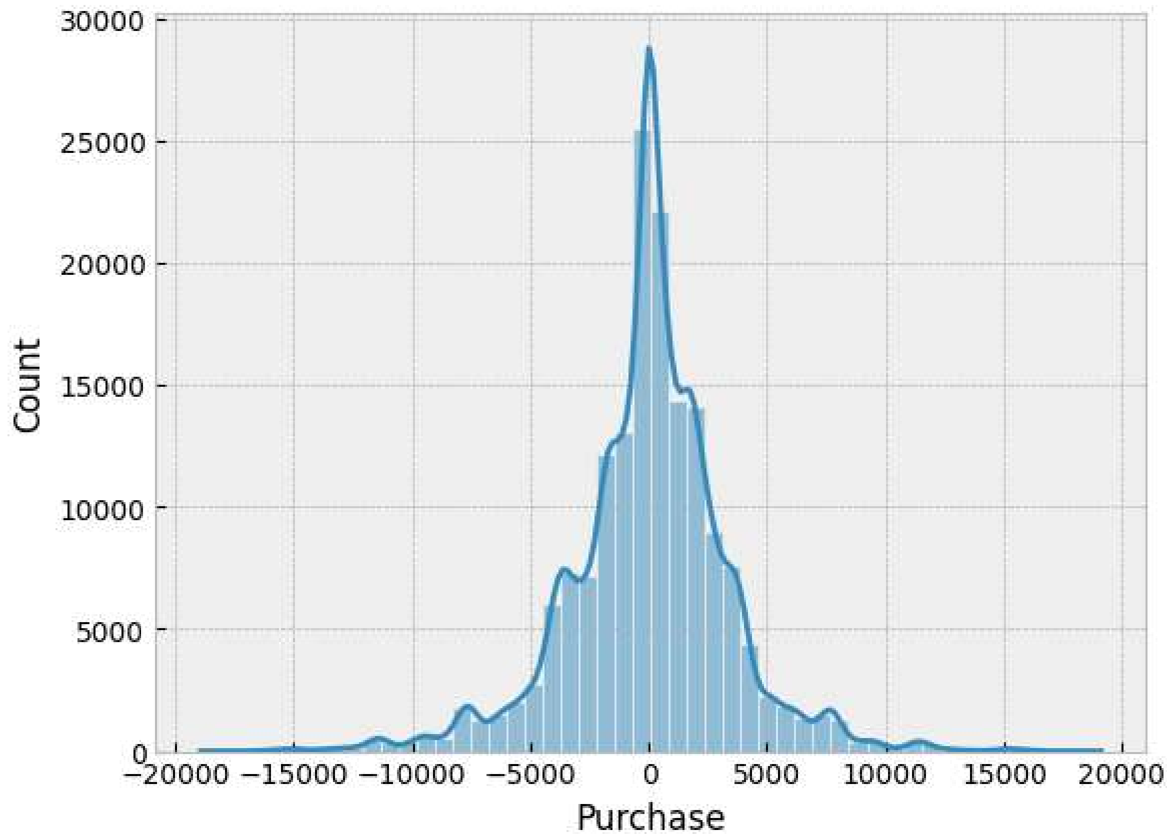
In [64]:
```
mean_squared_error(y_test, DTR_y_pred)
```

Out[64]: 11410205.130702421

In [65]:
```
r2_score(y_test, DTR_y_pred)
```

Out[65]: 0.5472549584267186

In [66]:
```
sns.histplot((y_test-DTR_y_pred),bins=50,kde=True)
plt.show()
```



3. Random Forest Regressor

In [67]:
```
from sklearn.ensemble import RandomForestRegressor
```

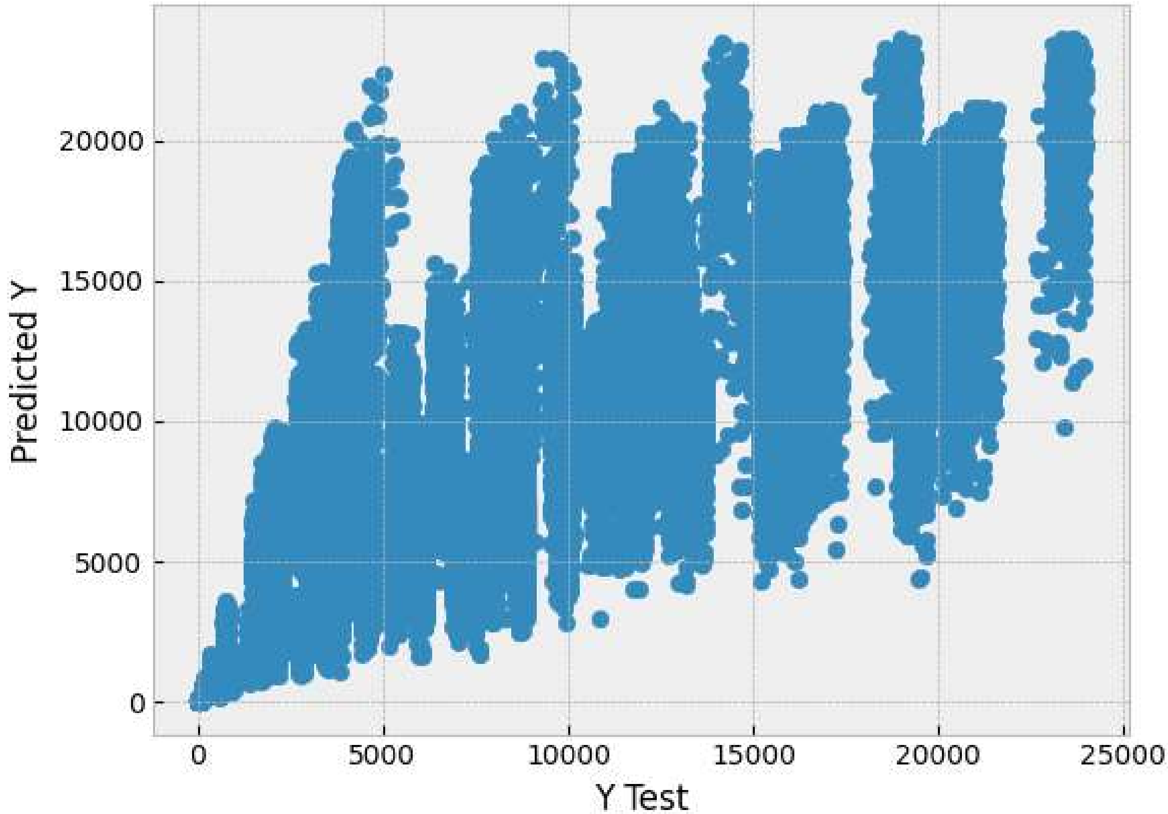
In [68]:
```
RFR = RandomForestRegressor(random_state = 0)
```

In [69]:
```
RFR.fit(X_train, y_train)
```

Out[69]:
```
RandomForestRegressor
RandomForestRegressor(random_state=0)
```

In [70]:
```
RFR_y_pred = RFR.predict(X_test)
```

In [71]:
```
plt.scatter(x=y_test,y=RFR_y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
plt.show()
```



In [72]:
```
mean_absolute_error(y_test, RFR_y_pred)
```

Out[72]: 2227.16366988596

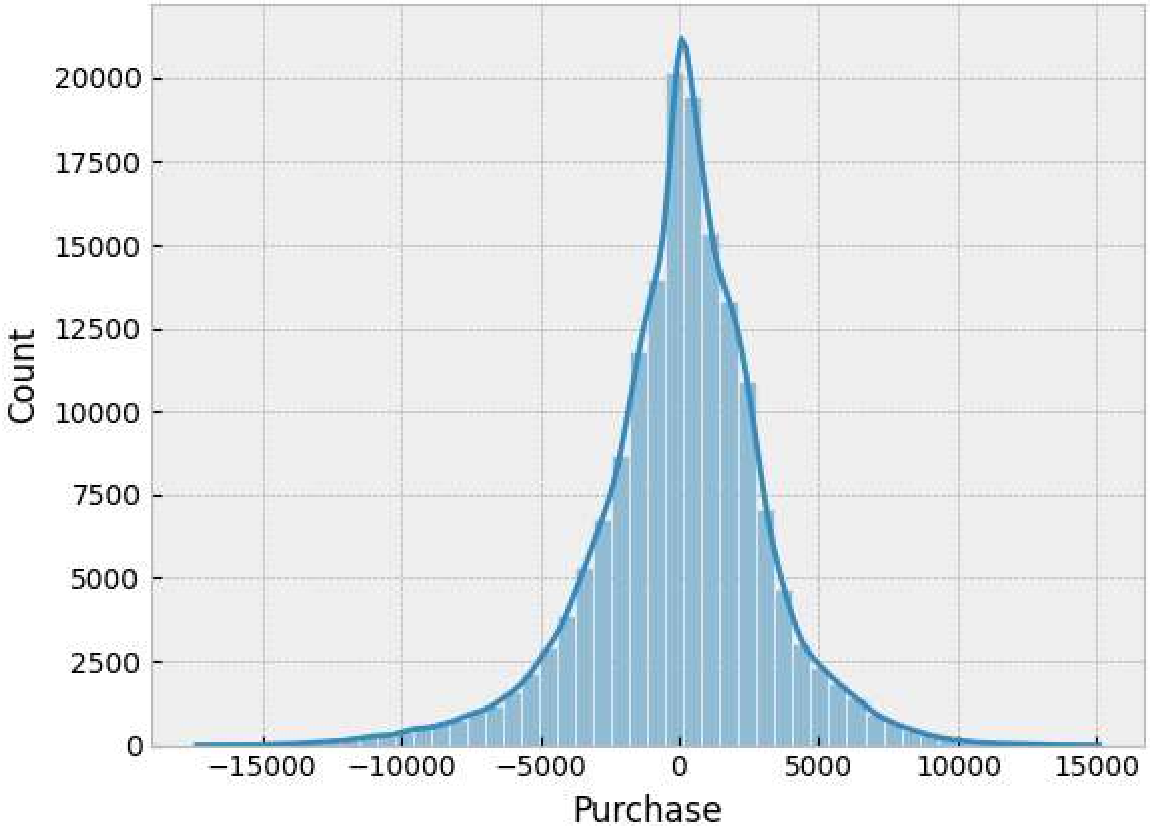
In [73]:
```
mean_squared_error(y_test, RFR_y_pred)
```

Out[73]: 9371638.76895137

In [74]:
```
r2_score(y_test, RFR_y_pred)
```

Out[74]: 0.6281431459420692

In [75]:
```
sns.histplot((y_test-RFR_y_pred),bins=50,kde=True)
plt.show()
```



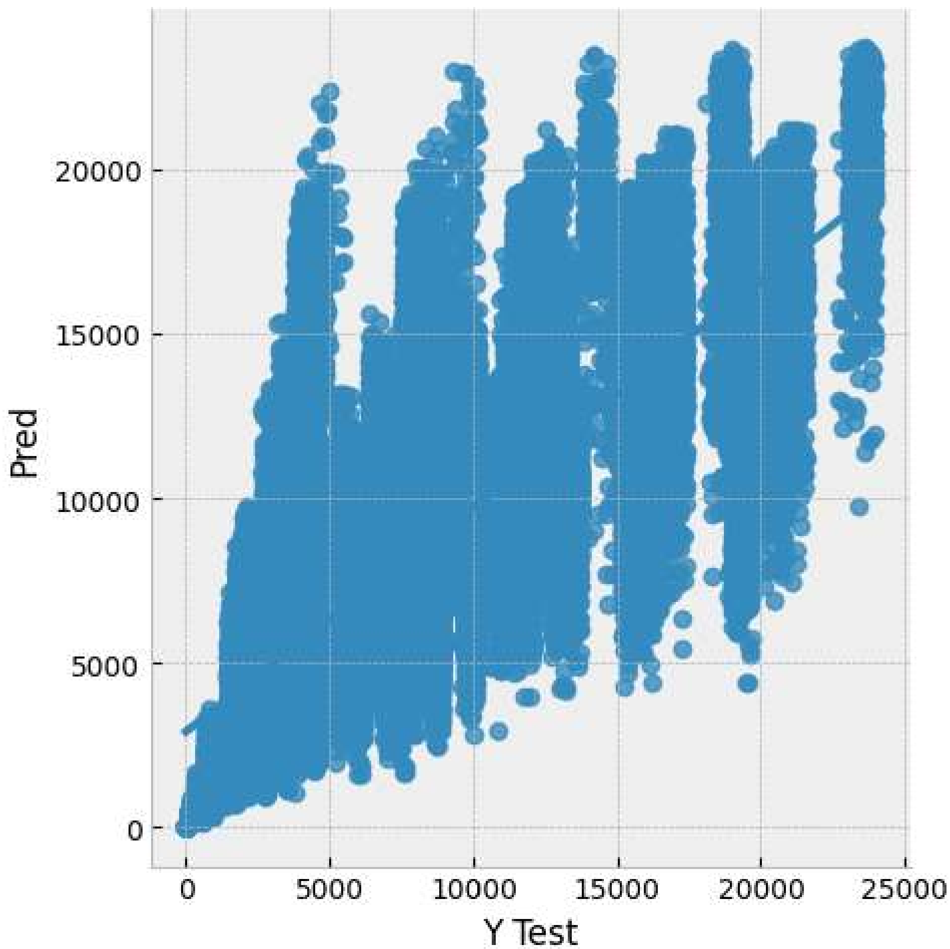
- Notice here that our **residuals looked to be normally distributed** and that's really a **good sign which means that our model was a correct choice for the data.**

Actual Vs Predicted sample.

In [76]:
```
data1 = pd.DataFrame({'Y Test':y_test , 'Pred':RFR_y_pred},columns=['Y Test','
sns.lmplot(x='Y Test',y='Pred',data=data1,palette='rainbow')
data.head()
```

Out[76]:

	Gender	Age	Occupation	City_Category	Marital_Status	Product_Category_1	Product_Categor
0	0	-2.0	0.25	0	0	3	
1	0	-2.0	0.25	0	0	1	
2	0	-2.0	0.25	0	0	12	
3	0	-2.0	0.25	0	0	12	
4	1	4.0	0.75	2	0	8	



Conclusions

- In this project, we explored the Black Friday dataset and performed exploratory data analysis using Pandas, Matplotlib, and Seaborn. We also learned how to handle missing values and preprocess the data to create new features that can improve our predictions.
- Using Pandas profiling, we generated an HTML report containing all the information about the various features present in the dataset. From our analysis, we found that the type and date/year columns have a significant impact on the average price increase/decrease rate.

- Moreover, we identified the features that are highly positively and negatively correlated with price, which can help us better predict the price of products during the next Black Friday sale.
- We also experimented with various machine learning models, including Linear Regression, Decision Tree Regression, and Random Forest Regression, to predict the purchase amount based on the available features. We evaluated the models using the RMSE and residual score, and found that the Random Forest model performed the best with an accuracy score of 62%.
- Overall, this project provided valuable insights into how to perform data analysis, preprocess data, and build machine learning models to make accurate predictions.