Predicting Customer Purchase In this assignment we are going to classify the customer according to his purchasing pattern. We will study the customer behaviour patterns and will categorize them into categories based on within how many days they make their purchases. Then we will train a classification model that will classify which customer belongs to which category. In [41]: #loading the required packages import pandas as pd import matplotlib.pyplot as plt import seaborn as sb import numpy as np from sklearn.tree import DecisionTreeClassifier from sklearn.model_selection import train_test_split from sklearn.metrics import classification report, accuracy score from sklearn.preprocessing import LabelEncoder from sklearn.impute import SimpleImputer # Load the datasets In [2]: online sales = pd.read csv('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Online customer data = pd.read excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Cus discount coupons = pd.read csv('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Di marketing spend= pd.read csv('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Mark tax amount = pd.read excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Tax am In [3]: # Merging datasets using 'CustomerID' and 'Product Category as the common key merged data = pd.merge(online sales, customer data, on='CustomerID', how='left') merged data = pd.merge(merged data, discount coupons, on='Product Category', how='left') merged data = pd.merge(merged data, tax amount, on='Product Category', how='left') # Convert 'Date' column in the marketing spend DataFrame to datetime data type In [4]: marketing spend['Date'] = pd.to datetime(marketing spend['Date']) merged_data['Transaction_Date'] = pd.to_datetime(merged_data['Transaction_Date'], format='%Y%m%d') # Merge datasets using 'Transaction Date' as the common key merged data = pd.merge(merged data, marketing spend, left on='Transaction Date', right on='Date', how='left') # Dropping the duplicate 'Date' column if needed merged data.drop(columns=['Date'], inplace=True) # Calculating Invoice Value for each transaction in the merged dataset In [5]: merged data['Invoice Value'] = ((merged data['Quantity'] * merged data['Avg Price']) * (1 - merged data['Discount pct']) * (1 + merged data['GST']) + merged data['Delivery Charges']) .abs() #examining the merged dataset merged data.head() CustomerID Transaction_ID Transaction_Date Out[6]: Product_SKU Product_name Product_Category Quantity Avg_Price Delivery_Charges Cc **Nest Learning** Thermostat 0 17850 16679 2019-01-01 GGOENEBJ079499 Nest-USA 153.71 6.5 1 3rd Gen-USA -Stainle... **Nest Learning** Thermostat 1 17850 16679 2019-01-01 GGOENEBJ079499 Nest-USA 1 153.71 6.5 3rd Gen-USA -Stainle... **Nest Learning** Thermostat 17850 16679 2019-01-01 GGOENEBJ079499 Nest-USA 153.71 6.5 3rd Gen-USA -Stainle **Nest Learning** Thermostat 3 17850 2019-01-01 GGOENEBJ079499 6.5 16679 Nest-USA 153.71 3rd Gen-USA -Stainle... **Nest Learning** Thermostat Nest-USA 17850 16679 2019-01-01 GGOENEBJ079499 153.71 6.5 3rd Gen-USA -Stainle... 5 rows × 21 columns #correcting the format In [7]: merged_data['Transaction_Date'] = pd.to_datetime(merged_data['Transaction_Date']) merged_data['Transaction_Date'] 2019-01-01 Out[7]: 2019-01-01 2019-01-01 3 2019-01-01 2019-01-01 2019-12-31 630683 630684 2019-12-31 630685 2019-12-31 630686 2019-12-31 630687 2019-12-31 Name: Transaction Date, Length: 630688, dtype: datetime64[ns] In [18]: # Calculating Recency for Each Transaction merged data['Transaction Date'] = pd.to datetime(merged data['Transaction Date']) merged data['Recency'] = merged data.groupby('CustomerID')['Transaction Date'].diff().dt.days merged data['Recency'] = merged data['Recency'].fillna(0).astype(int) merged data['Recency'] 1057 0 Out[18]: 2393 0 3281 0 4866 0 4926 1 . . . 628492 163 629152 1 629224 0 629884 0 629920 12 Name: Recency, Length: 1740, dtype: int32 In [19]: # Dropping rows where Recency is less than 1 merged data = merged data[merged data['Recency'] > 0] In [20]: #Identify Repeat Customers repeat customers = merged data.groupby('CustomerID')['Transaction ID'].count() > 1 merged_data['IsRepeatCustomer'] = merged_data['CustomerID'].map(repeat customers) merged_data['IsRepeatCustomer'] C:\Users\sujoydutta\AppData\Local\Temp\ipykernel_14228\2896614341.py:3: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row indexer,col indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy merged data['IsRepeatCustomer'] = merged data['CustomerID'].map(repeat customers) 4926 Out[20]: 23505 True 23601 True 27156 True 31550 True 627160 False 628348 True 628492 True 629152 True 629920 True Name: IsRepeatCustomer, Length: 1006, dtype: bool In [21]: #seeing how many repeat customers merged data['IsRepeatCustomer'].value counts() True 845 Out[21]: False 161 Name: IsRepeatCustomer, dtype: int64 In [22]: | #Calculate Average Days per Transaction for Repeat Customers avg_days_per_transaction = merged_data[merged_data['IsRepeatCustomer']].groupby('CustomerID')['Recency'].mean() avg_days_per_transaction CustomerID Out[22]: 12383 35.500000 12431 107.333333 26.44444 12471 12474 15.750000 56.000000 12481 18092 27.000000 34.500000 18109 19.750000 18116 70.666667 18118 18223 28.333333 Name: Recency, Length: 209, dtype: float64 In [23]: # Creating Categorical Labels (0-30 days, 30-60 days, 60-90 days, 90+ days) bins = [0, 30, 60, 90, np.inf]labels = ['0-30 days', '30-60 days', '60-90 days', '90+ days'] AvgDaysPerTransactionCategory = pd.cut(avg_days_per_transaction, bins=bins, labels=labels) In [24]: #viewing the new variable AvgDaysPerTransactionCategory.value counts() 30-60 days Out[24]: 0-30 days 55 60-90 days 48 20 90+ days Name: Recency, dtype: int64 In [25]: # Create a new variable 'RecencyCategory' based on Recency merged data['RecencyCategory'] = pd.cut(merged data['Recency'], bins=bins, labels=labels, right=False) merged data['RecencyCategory'] C:\Users\sujoydutta\AppData\Local\Temp\ipykernel 14228\3764021990.py:2: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#ret urning-a-view-versus-a-copy merged data['RecencyCategory'] = pd.cut(merged data['Recency'], bins=bins, labels=labels, right=False) 4926 0-30 days Out[25]: 23505 0-30 days 23601 0-30 days 27156 0-30 days 31550 0-30 days . . . 90+ days 627160 628348 0-30 days 628492 90+ days 629152 0-30 days 629920 0-30 days Name: RecencyCategory, Length: 1006, dtype: category Categories (4, object): ['0-30 days' < '30-60 days' < '60-90 days' < '90+ days'] In [26]: #examining the new dataset merged data.head() Out[26]: CustomerID Transaction_ID Transaction_Date Product_SKU Product_name Product_Category Quantity Avg_Price Delivery_Charge **Nest Learning** Thermostat 4926 17850 16984 2019-01-04 GGOENEBJ079499 Nest-USA 153.71 3rd Gen-USA -Stainle... Android Men's 3/4 Sleeve 23505 17850 18017 2019-01-16 GGOEAAEB031614 Apparel 20.62 6 Raglan Henley Black **Nest Learning** Thermostat 23601 17850 18021 GGOENEBJ079499 153.71 6 2019-01-17 Nest-USA 3rd Gen-USA -Stainle... **Red Spiral** 27156 17850 18208 2019-01-18 GGOEGOCT019199 9.97 6 Google Office 155 Notebook **Nest Protect** Smoke + CO 31550 17850 18492 2019-01-21 GGOENEBQ079099 81.50 Nest-USA White Battery Alarm-USA 5 rows × 25 columns merged data.info() In [27]: <class 'pandas.core.frame.DataFrame'> Int64Index: 1006 entries, 4926 to 629920 Data columns (total 25 columns): Column Non-Null Count Dtvpe 0 CustomerID 1006 non-null int64 Transaction ID 1 1006 non-null int64 2 Transaction Date 1006 non-null datetime64[ns] 1006 non-null 3 Product SKU object Product name 4 1006 non-null object 5 Product_Category 1006 non-null object int64 6 Quantity 1006 non-null 7 Avg Price 1006 non-null float64 8 Delivery_Charges 1006 non-null float64 9 Coupon Status 1006 non-null object 10 Gender 1006 non-null object 1006 non-null 11 Location object 1006 non-null 12 Tenure Months int64 13 Month 1002 non-null object Coupon_Code 14 1002 non-null object 15 Discount pct 1002 non-null float64 1006 non-null float64 16 GST Offline Spend 1006 non-null 17 int64 18 Online Spend 1006 non-null float64 1006 non-null 19 Total float64 20 Invoice Value 1002 non-null float64 21 Recency 1006 non-null int32 1006 non-null 22 IsRepeatCustomer bool 23 AvgDaysPerTransactionCategory 0 non-null category RecencyCategory 1006 non-null category dtypes: bool(1), category(2), datetime64[ns](1), float64(7), int32(1), int64(5), object(8) memory usage: 180.2+ KB #dropping useless columns In [28]: subset=merged_data.drop(['Product_SKU','Coupon_Status','Month','Total','AvgDaysPerTransactionCategory','Product subset Out[28]: CustomerID Transaction_ID Transaction_Date Product_Category Quantity Avg_Price Delivery_Charges Gender Location Tenure_Mo 2019-01-04 4926 17850 16984 Nest-USA 153.71 6.5 Μ Chicago 23505 17850 18017 Chicago 2019-01-16 **Apparel** 20.62 6.5 M 23601 17850 18021 2019-01-17 Nest-USA 1 153.71 6.5 Chicago M 27156 17850 18208 2019-01-18 Office 155 9.97 6.5 Chicago 31550 17850 18492 2019-01-21 Nest-USA 81.50 6.5 Chicago M California 627160 14810 48258 2019-12-28 Nest-USA 151.88 6.5 628348 16525 48340 2019-12-29 Apparel 61.15 F California 628492 48349 Nest-USA F California 15808 2019-12-29 121.30 6.5 629152 15808 48393 2019-12-30 49.95 F California Nest 629920 14606 48447 6.5 F Chicago 2019-12-31 Drinkware 10.59 1006 rows × 18 columns # Creating an instance of LabelEncoder In [37]: label encoder = LabelEncoder() # List of categorical columns to encode categorical_columns = ['Product_Category', 'Gender', 'Location'] # Apply Label Encoding to each categorical column for col in categorical columns: subset[col] = label encoder.fit transform(subset[col]) In [42]: # Selecting Features and Target Variable features = ['CustomerID', 'Transaction ID', 'Product Category', 'Quantity', 'Avg Price', 'Delivery Charges', 'G X = subset[features] y = subset['RecencyCategory'] In [43]: # Creating an imputer instance imputer = SimpleImputer(strategy='mean') # Fit and transform the imputer on your feature data X = imputer.fit transform(X) In [44]: #Splitting the Data into Training and Testing Sets X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42) In [45]: # Training the Decision Tree Classifier clf = DecisionTreeClassifier(random state=42) clf.fit(X_train, y_train) Out[45]: DecisionTreeClassifier DecisionTreeClassifier(random_state=42) #Making the Predictions In [46]: y pred = clf.predict(X test) array(['0-30 days', '30-60 days', '30-60 days', '0-30 days', '30-60 days', '90+ days', '0-30 days', '60-90 days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '0-30 days', '90+ days', '0-30 days', '0-30 days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '30-60 days', '0-30 days', '0-30 days', '60-90 days', '90+ days', '0-30 days', '0-30 days', '60-90 days', '0-30 days', '30-60 days', '30-60 days', '0-30 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '90+ days', '0-30 days', '90+ days', '30-60 days', '0-30 days', '0-30 days', '90+ days', '90+ days', '30-60 days', '90+ days', '30-60 days', '90+ days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '90+ days', '60-90 days', '0-30 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '60-90 days', '0-30 days', '30-60 days', '90+ days', '30-60 days', '90+ days', '0-30 days', '60-90 days', '60-90 days', '0-30 days', '90+ days', '60-90 days', '0-30 days', '90+ days', '90+ days', '30-60 days', '0-30 days', '0-30 days', '90+ days', '90+ days', '0-30 days', '90+ days', '60-90 days', '0-30 days', '90+ days', '60-90 days', '0-30 days', '0-30 days', '30-60 days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '60-90 days', '90+ days', '60-90 days', '0-30 days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '90+ days', '60-90 days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '60-90 days', '0-30 days', '30-60 days', '30-60 days', '30-60 days', '0-30 days', '90+ days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '90+ days', '30-60 days', '0-30 days', '0-30 days', '90+ days', '0-30 days', '60-90 days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '60-90 days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '90+ days', '90+ days', '0-30 days', '30-60 days', '0-30 days', '0-30 days', '30-60 days', '90+ days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '30-60 days', '0-30 days', '0-30 days', '60-90 days', '30-60 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '0-30 days', '90+ days', '0-30 days', '30-60 days', '60-90 days', '90+ days', '60-90 days', '30-60 days', '90+ days', '0-30 days', '0-30 days', '0-30 days', '60-90 days', '0-30 days', '60-90 days', '0-30 days', '90+ days', '30-60 days', '60-90 days', '0-30 days', '0-30 days', '60-90 days', '0-30 days', '30-60 days', '0-30 days', '30-60 days', '0-30 days', '60-90 days', '0-30 days'], dtype=object) In [47]: # Model Performance Evaluation accuracy = accuracy score(y test, y pred) classification report result = classification report(y test, y pred) # Printing the evaluation metrics print("Accuracy:", accuracy) print("\nClassification Report:\n", classification_report result) Accuracy: 1.0 Classification Report: recall f1-score support precision 0-30 days 1.00 1.00 1.00 100 30-60 days 1.00 1.00 1.00 40 1.00 1.00 60-90 days 1.00 24 1.00 90+ days 1.00 1.00 38 1.00 202 accuracy macro avg 1.00 1.00 1.00 202 weighted avg 1.00 1.00 1.00 202 **Remark:** The model is 100% accurate and we can say that it can classify customers into recency categories perfectly.