Bilenkin550Week10_Term_Project_Milestones

May 17, 2025

1 DSC 550 Term Project - Milestone 1

1.0.1 Exploratory Data Analysis (EDA)

Finding Patterns in Credit Card Transactions to Detect Fraud

Today, credit cards have become an essential part of our daily lives, offering a convenient way to purchase goods and services. Instead of carrying large amounts of cash, consumers can simply use a single credit card to make transactions. Whether by swiping, inserting, or tapping against a contactless reader, making a payment has never been easier.

However, with the growing adoption of credit cards, fraudulent activities have also increased. Fraudsters can use stolen credit card information to make unauthorized purchases, often without the cardholder realizing it until it's too late. These fraudulent transactions lead to significant financial losses for banks and credit card issuers.

By leveraging big data from credit card transaction histories, banks can identify patterns and correlations associated with fraudulent activities. Machine learning models can analyze various features, such as transaction location, merchant category, purchase amounts, and unusual spending behaviors, to detect potential fraud. More importantly, predictive analytics can help banks assess the risk of issuing credit cards to individuals who may have a high likelihood of committing fraud.

Implementing machine learning-based fraud detection not only helps banks minimize financial losses but also enhances security for both consumers and merchants. A robust fraud prevention system ensures that legitimate transactions are processed smoothly while fraudulent attempts are blocked in real-time. As a result, customers can feel more secure using their credit cards, and merchants can conduct transactions with greater confidence.

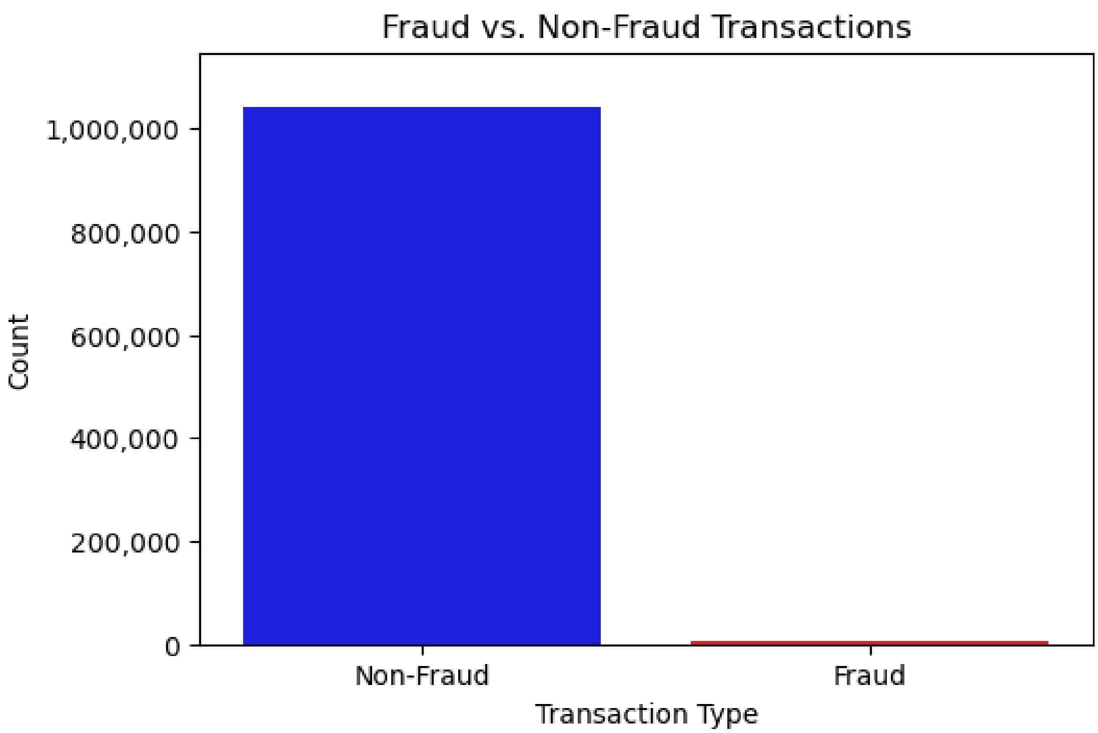
Banks can take preventive actions by freezing suspicious transactions, sending alert messages to cardholders, or implementing stricter verification processes.

[84]:
```
import pandas as pd

# Loading dataset
file_path = r"C:\Users\maxim\OneDrive\Desktop\BU\DSC 550\Term␣
↪Project\credit_card_transactions.csv"
df = pd.read_csv(file_path)
```

1. Fraud vs. Non-Fraud Transactions Count (Bar Chart)

[85]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter

# Counting fraud vs. non-fraud transactions
fraud_counts = df['is_fraud'].value_counts()

# Converting fraud labels to readable text
fraud_labels = {0: "Non-Fraud", 1: "Fraud"}

# Plotting the graph
plt.figure(figsize=(6, 4))
sns.barplot(x=fraud_counts.index.map(fraud_labels), y=fraud_counts.values,␣
 ↪palette=["blue", "red"], hue=fraud_counts.index, legend=False)

# Setting y-axis limits to make the fraud bar visible
plt.ylim(0, max(fraud_counts.values) * 1.1)  # Adjusting the upper limit to␣
 ↪make fraud visible

# Formating y-axis labels with commas for better readability
def comma_format(x, pos):
    return f'{int(x):,}'

plt.gca().yaxis.set_major_formatter(FuncFormatter(comma_format))

# Labeling and titling the graph
plt.xlabel("Transaction Type")
plt.ylabel("Count")
plt.title("Fraud vs. Non-Fraud Transactions")
plt.show()
```

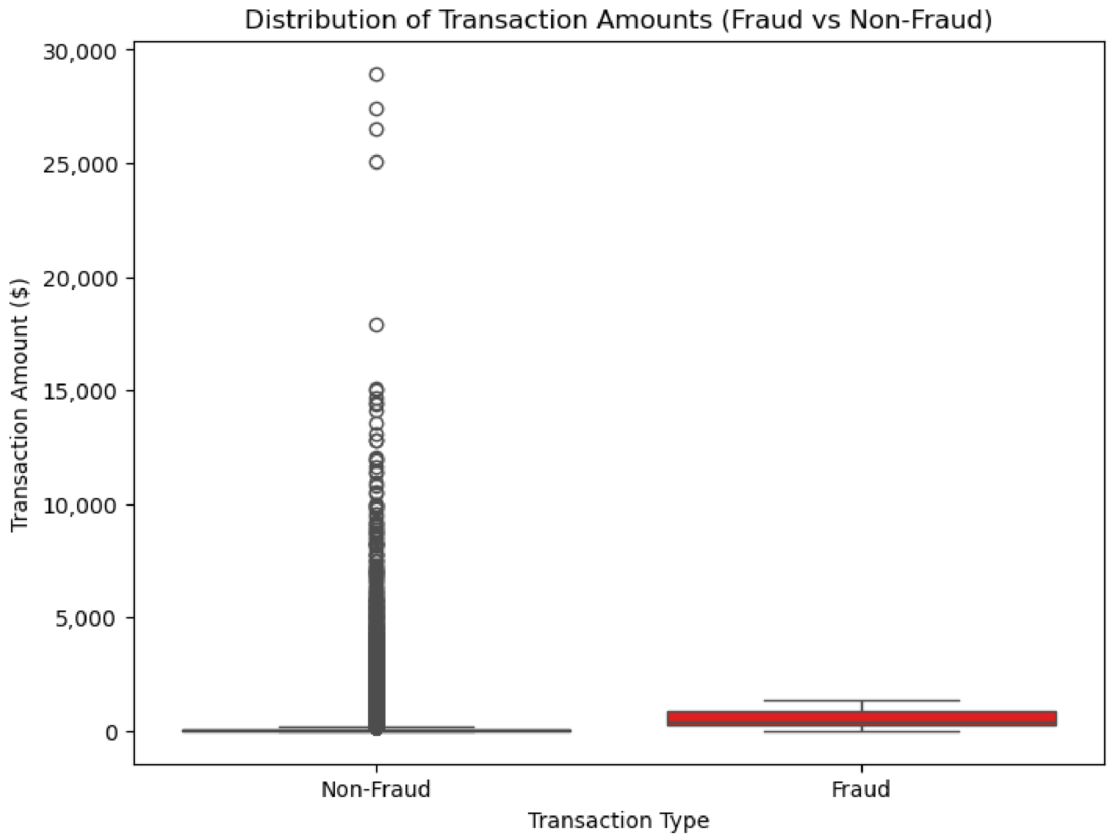


Explanation: "The Fraud vs. Non-Fraud Transactions" bar chart shows the number of Non-Fraud (higlighted in blue) and Fraud (highlighted in red) tranactions in the dataset, with count displayed on the left y-axis. As seen in the chart, the majority of transactions (over 1 million) are Non-Fraud, with a significantly smaller number being Fraud. This indicates that fraud is a relatively rare occurrence in the dataset.

2. Transaction Amounts by Fraud vs Non-Fraud (Box Plot):

[86]:
```
# Plotting Transaction Amounts by Fraud vs Non-Fraud
plt.figure(figsize=(8, 6))
sns.boxplot(x="is_fraud", y="amt", data=df, hue="is_fraud", palette=["blue",␣
↪"red"], legend=False)

# Converting 0 and 1 to "Non-Fraud" and "Fraud"
plt.xticks(ticks=[0, 1], labels=["Non-Fraud", "Fraud"])

plt.xlabel("Transaction Type")
plt.ylabel("Transaction Amount ($)")
plt.title("Distribution of Transaction Amounts (Fraud vs Non-Fraud)")

# Format the y-axis with commas for readability
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, loc: f'{x:,.
↪0f}'))
```

```
plt.show()
```



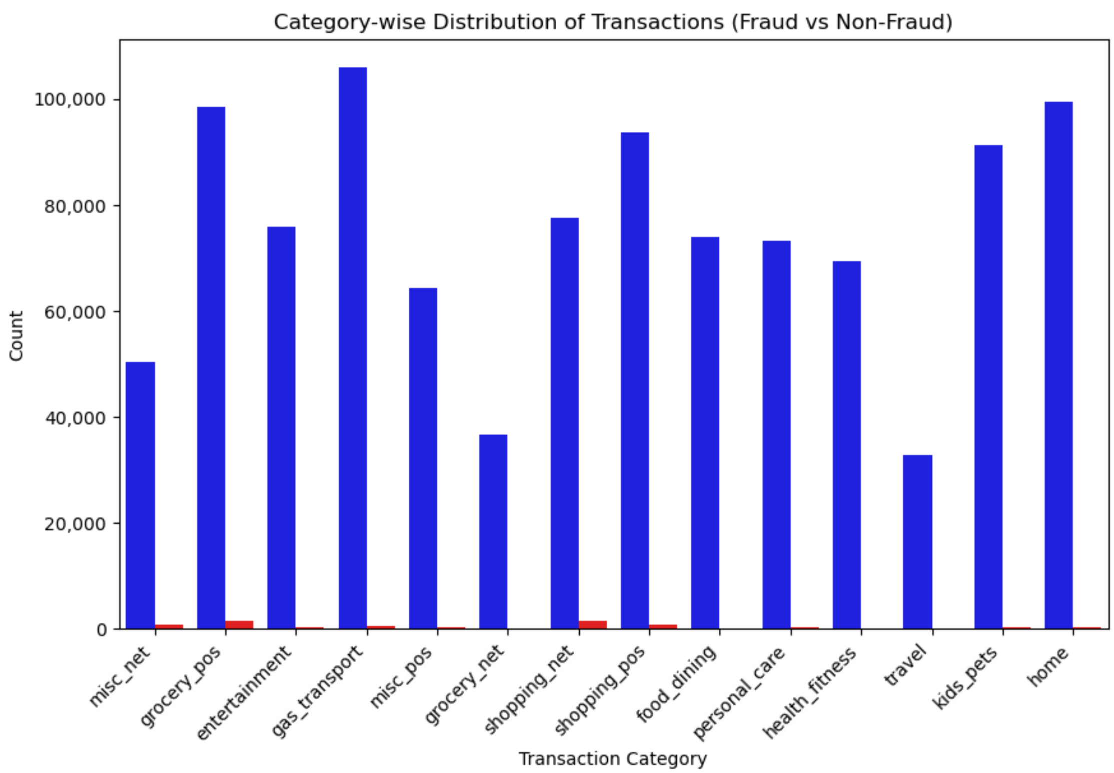
Explanation: The "Distribution of Transaction Amounts (Fraud vs Non-Fraud)" graph compares the transaction amounts of Non-Fraud and Fraud transactions in the dataset. The graph shows the transaction amounts on the y-axis and the transaction type (Non-Fraud or Fraud) on the x-axis. As shown, Non-Fraud transactions vary widely, ranging from 1 to 28,948.90 dollars. In contrast, Fraud transactions are generally smaller, ranging from 1.18 to 1,371.81 dollars. This suggests that fraudsters tend to make smaller credit card transactions, possibly hoping that small amounts will go unnoticed by banks.

Category-wise Distribution of Transactions

[87]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Plotting Category-wise Fraud vs Non-Fraud Distribution
plt.figure(figsize=(10, 6))
sns.countplot(x="category", hue="is_fraud", data=df, palette=["blue", "red"],␣
 ↪legend=False)

# Labeling and rotating the x-axis ticks
```

```
plt.xlabel("Transaction Category")
plt.ylabel("Count")
plt.title("Category-wise Distribution of Transactions (Fraud vs Non-Fraud)")
plt.xticks(rotation=45, ha='right')  # Adjusting the horizontal alignment for␣
 ↪better readability

# Formating the y-axis with commas for readability
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, loc: f'{int(x):
 ↪,}'))

plt.show()
```



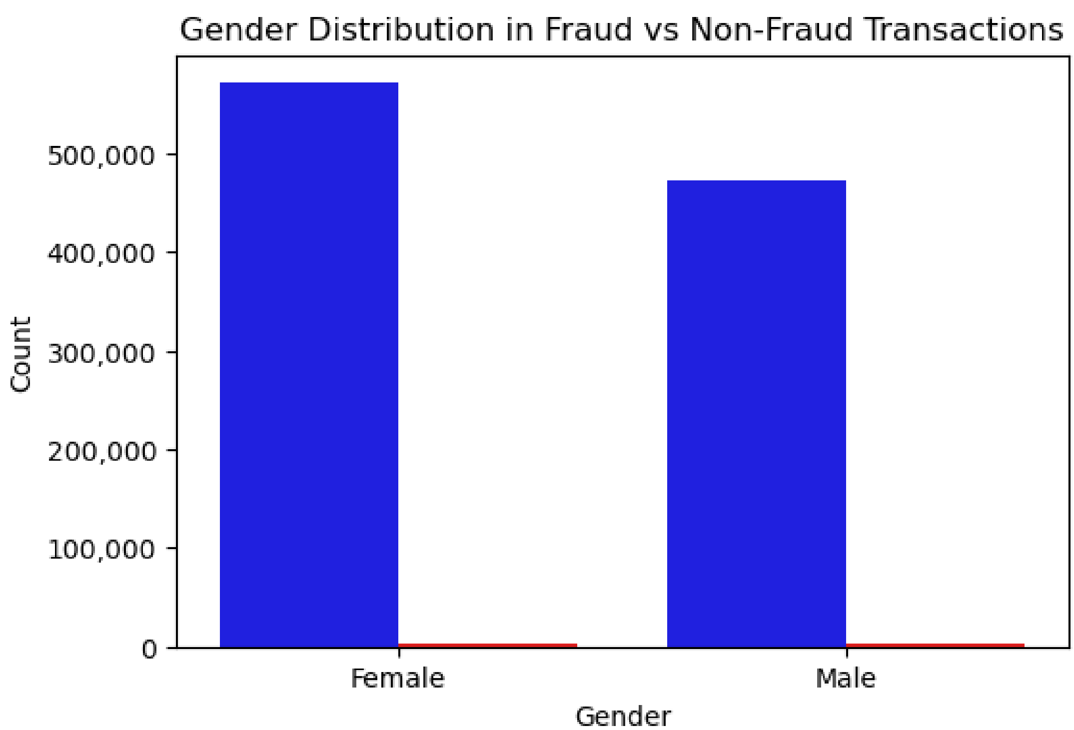
Explanation: The "Category-wise Distribution of Transactions (Fraud vs Non-Fraud)" graph shows transactions by category for both Non-Fraud and Fraud. It separates transactions by each category and indicates whether fraud occurred online or at the point of sale. For example, the red bar for misc_net shows online fraud transactions, while the red bar for misc_pos shows fraudulent transactions that occurred at the point of sale.

In line with the common belief that fraudulent credit card transactions mostly happen online, the graph partly validates this. We can see that for misc_net, fraudulent transactions (highlighted in red) are slightly higher than for misc_pos. The same trend is observed for shopping_net vs. shopping_pos, with the red bar for shopping_net being marginally higher than for shopping_pos.

However, the data for grocery_net contradicts this assumption. No fraud was detected online (grocery_net), while all fraudulent transactions occurred at the point of sale (grocery_pos). This is counterintuitive to the common belief that fraud mostly occurs online.

Gender Distribution in Fraud vs Non-Fraud Transactions

[88]:
```
# Plot: Gender Distribution in Fraud vs Non-Fraud Transactions
plt.figure(figsize=(6, 4))
sns.countplot(x="gender", hue="is_fraud", data=df, palette=["blue", "red"],␣
 ↪legend=False)

# Replace 'F' with 'Female' and 'M' with 'Male'
gender_labels = {'F': 'Female', 'M': 'Male'}
plt.xticks(ticks=[0, 1], labels=[gender_labels.get(x, x) for x in df['gender'].
 ↪unique()])

# Format the y-axis with commas for readability
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, loc: f'{int(x):
 ↪,}'))

# Labels and title
plt.xlabel("Gender")
plt.ylabel("Count")
plt.title("Gender Distribution in Fraud vs Non-Fraud Transactions")
plt.show()
```



Explanation: The “Gender Distribution in Fraud vs Non-Fraud Transactions” graph shows the number of fraudulent transactions made by females and males. On the y-axis, the graph counts the number of transactions made by each gender, while the x-axis shows the gender. An interesting insight from the dataset is that the number of fraudulent transactions is nearly the same for both genders. However, it is evident that a higher number of Non-Fraud transactions were made by females. Given that, one might expect more fraudulent transactions from females due to the higher overall transaction count. Despite this, the graph suggests that males are more prone to commit credit card fraud.

Overview/Conclusion:

By conducting graphical analysis, I’ve gained several insights from the dataset. For instance, I initially believed that there would be a much higher number of fraudulent credit card transactions, but the data revealed that fraud is actually quite minimal, amounting to only a few thousand dollars. Additionally, the analysis showed that males tend to commit more credit card fraud.

Furthermore, the data partially supports the common belief that more fraudulent transactions occur online than at the point of sale. From the visualizations, we can see that the highest credit card fraud occurred in the “grocery_pos” and “shopping_net” categories. This suggests that in the “grocery_pos” category, fraudsters went to physical stores and used stolen cards to make purchases, while in the “shopping_net” category, fraudsters made purchases online.

Finally, the transaction amount graph highlighted that fraudulent transactions tend to involve smaller amounts, with the highest being $1,371.81. This could suggest that fraudsters prefer to purchase cheaper items, possibly hoping that banks won’t notice the fraud because of the smaller transaction sizes.

2 DSC 550 Term Project - Milestone 2

2.0.1 Data Preparation for Modeling

In this section I will include all the necessary steps to completely prepare the credit card transactions dataset for model building.

This will include data transformation, feature engineering, removing duplicates, handling missing values, and addressing class imbalance.

2.0.2 Importing Necessary Libraries

In this step, I import the necessary libraries and load the dataset for data manipulation and analysis.

[89]:
```
import pandas as pd
import numpy as np

# Loading the dataset
file_path = r"C:\Users\maxim\OneDrive\Desktop\BU\DSC 550\Term␣
↪Project\credit_card_transactions.csv"
df = pd.read_csv(file_path)
```

2.0.3 Dropping Unnecessary Features

In this step, I am dropping columns that are not useful for modeling, such as 'unix_time', or any redundant identifiers.

[90]:
```python
# Dropping unnecessary columns/features not useful for modeling (e.g.,␣
↪'unix_time' or redundant identifiers)
df.drop(['unix_time'], axis=1, inplace=True)

# Displaying first two rows to confirm the unnecessary columns/features dropped
df.head(2)
```

[90]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0         1/1/2019 0:00  2.703190e+15
1           1         1/1/2019 0:00  6.304230e+11

                            merchant     category     amt      first   last  \
0         fraud_Rippin, Kub and Mann     misc_net    4.97   Jennifer  Banks
1  fraud_Heller, Gutmann and Zieme  grocery_pos  107.23  Stephanie   Gill

  gender                       street  …      lat      long  city_pop  \
0      F               561 Perry Cove  …  36.0788  -81.1781      3495
1      F  43039 Riley Greens Suite 393  …  48.8878 -118.2105       149

                                job        dob  \
0         Psychologist, counselling   3/9/1988
1  Special educational needs teacher  6/21/1978

                          trans_num  merch_lat  merch_long is_fraud  \
0  0b242abb623afc578575680df30655b9  36.011293  -82.048315        0
1  1f76529f8574734946361c461b024d99  49.159047 -118.186462        0

   merch_zipcode
0        28705.0
1            NaN

[2 rows x 23 columns]
```

2.0.4 Handling Missing Values

This step handles missing values in the dataset. I replace "?" with NaN and drop rows with missing data.

Alternatively, imputation can be used for missing data, but here I drop them.

[91]:
```python
# Checking and handling missing values appropriately
df.replace("?", np.nan, inplace=True)
df = df.dropna()
```

```python
# Displaying first two rows to confirm the missing values handled appropriately
df.head(2)
```

[91]:
```
   Unnamed: 0 trans_date_trans_time        cc_num                    merchant  \
0           0          1/1/2019 0:00  2.703190e+15  fraud_Rippin, Kub and Mann
2           2          1/1/2019 0:00  3.885950e+13        fraud_Lind-Buckridge

        category     amt     first     last gender                    street  \
0       misc_net    4.97  Jennifer    Banks      F            561 Perry Cove
2  entertainment  220.11    Edward  Sanchez      M  594 White Dale Suite 530

   …      lat      long  city_pop                          job        dob  \
0  …  36.0788  -81.1781      3495    Psychologist, counselling   3/9/1988
2  …  42.1808 -112.2620      4154  Nature conservation officer  1/19/1962

                          trans_num  merch_lat  merch_long is_fraud  \
0  0b242abb623afc578575680df30655b9  36.011293  -82.048315        0
2  a1a22d70485983eac12b5b88dad1cf95  43.150704 -112.154481        0

   merch_zipcode
0        28705.0
2        83236.0

[2 rows x 23 columns]
```

2.0.5 Data Type Conversion

I ensure that the data types of features are correct for modeling, specifically converting the 'amt' column to a float.

[92]:
```python
# Ensuring correct data types for modeling
df['amt'] = df['amt'].astype(float)

# Displaying the first two rows to confirm the 'amt' column converted to a float
df.head(2)
```

[92]:
```
   Unnamed: 0 trans_date_trans_time        cc_num                    merchant  \
0           0          1/1/2019 0:00  2.703190e+15  fraud_Rippin, Kub and Mann
2           2          1/1/2019 0:00  3.885950e+13        fraud_Lind-Buckridge

        category     amt     first     last gender                    street  \
0       misc_net    4.97  Jennifer    Banks      F            561 Perry Cove
2  entertainment  220.11    Edward  Sanchez      M  594 White Dale Suite 530

   …      lat      long  city_pop                          job        dob  \
0  …  36.0788  -81.1781      3495    Psychologist, counselling   3/9/1988
2  …  42.1808 -112.2620      4154  Nature conservation officer  1/19/1962
```

```
                          trans_num  merch_lat  merch_long is_fraud  \
0  0b242abb623afc578575680df30655b9  36.011293  -82.048315        0
2  a1a22d70485983eac12b5b88dad1cf95  43.150704 -112.154481        0

   merch_zipcode
0        28705.0
2        83236.0

[2 rows x 23 columns]
```

2.0.6 Feature Engineering

In this step, I create new features from existing ones. Here, I create a 'merchant_category' feature by combining 'merchant' and 'category'.

[93]:
```
# Creating a new feature from 'merchant' or 'category'
df['merchant_category'] = df['merchant'] + '_' + df['category']

# Displaying output anfter creating new feature
df.head(2)
```

[93]:
```
   Unnamed: 0 trans_date_trans_time        cc_num                  merchant  \
0           0         1/1/2019 0:00  2.703190e+15  fraud_Rippin, Kub and Mann
2           2         1/1/2019 0:00  3.885950e+13        fraud_Lind-Buckridge

        category     amt     first     last gender                    street  \
0       misc_net    4.97  Jennifer    Banks      F            561 Perry Cove
2  entertainment  220.11    Edward  Sanchez      M  594 White Dale Suite 530

   …      long city_pop                        job        dob  \
0  …  -81.1781     3495    Psychologist, counselling   3/9/1988
2  … -112.2620     4154  Nature conservation officer  1/19/1962

                          trans_num  merch_lat  merch_long is_fraud  \
0  0b242abb623afc578575680df30655b9  36.011293  -82.048315        0
2  a1a22d70485983eac12b5b88dad1cf95  43.150704 -112.154481        0

  merch_zipcode                   merchant_category
0       28705.0  fraud_Rippin, Kub and Mann_misc_net
2       83236.0   fraud_Lind-Buckridge_entertainment

[2 rows x 24 columns]
```

2.0.7 Encoding Categorical Variables

I convert categorical columns into dummy variables, which is necessary for many machine learning algorithms.

[94]:
```python
# Converting categorical columns to dummy variables
df = pd.get_dummies(df, columns=['gender', 'category'], drop_first=True)

# Displaying the first two rows to confirm the conversion
df.head(2)
```

[94]:
```
   Unnamed: 0 trans_date_trans_time        cc_num                      merchant  \
0           0          1/1/2019 0:00  2.703190e+15  fraud_Rippin, Kub and Mann
2           2          1/1/2019 0:00  3.885950e+13        fraud_Lind-Buckridge

      amt     first     last                      street            city state  \
0    4.97  Jennifer    Banks              561 Perry Cove  Moravian Falls    NC
2  220.11    Edward  Sanchez  594 White Dale Suite 530      Malad City    ID

   …  category_grocery_pos  category_health_fitness  category_home  \
0  …                 False                    False          False
2  …                 False                    False          False

   category_kids_pets category_misc_net category_misc_pos  \
0               False              True             False
2               False             False             False

  category_personal_care  category_shopping_net  category_shopping_pos  \
0                  False                  False                  False
2                  False                  False                  False

   category_travel
0            False
2            False

[2 rows x 36 columns]
```

2.0.8 Displaying the Cleaned and Transformed Dataset

Here I display the first few rows of the cleaned and transformed dataset to confirm all the changes.

[95]:
```python
# Printing the cleaned and transformed dataset
df.head()
```

[95]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0          1/1/2019 0:00  2.703190e+15
2           2          1/1/2019 0:00  3.885950e+13
4           4          1/1/2019 0:03  3.755340e+14
5           5          1/1/2019 0:04  4.767270e+15
7           7          1/1/2019 0:05  6.011360e+15

                     merchant     amt     first      last  \
0      fraud_Rippin, Kub and Mann    4.97  Jennifer     Banks
```

```
2             fraud_Lind-Buckridge  220.11    Edward   Sanchez
4              fraud_Keeling-Crist   41.96     Tyler    Garcia
5  fraud_Stroman, Hudson and Erdman   94.63  Jennifer    Conner
7             fraud_Corwin-Collins   71.65    Steven  Williams

                     street            city state  …  category_grocery_pos  \
0            561 Perry Cove  Moravian Falls    NC  …                 False
2   594 White Dale Suite 530      Malad City    ID  …                 False
4          408 Bradley Rest        Doe Hill    VA  …                 False
5         4655 David Island          Dublin    PA  …                 False
7  231 Flores Pass Suite 720        Edinburg    VA  …                 False

   category_health_fitness  category_home  category_kids_pets  \
0                    False          False               False
2                    False          False               False
4                    False          False               False
5                    False          False               False
7                    False          False               False

  category_misc_net category_misc_pos category_personal_care  \
0              True             False                  False
2             False             False                  False
4             False              True                  False
5             False             False                  False
7             False             False                  False

   category_shopping_net  category_shopping_pos  category_travel
0                  False                  False            False
2                  False                  False            False
4                  False                  False            False
5                  False                  False            False
7                  False                  False            False

[5 rows x 36 columns]
```

3 DSC 550 Term Project – Milestone 3

3.0.1 Model Building and Evaluation

In this milestone, I begin the process of building and evaluating machine learning models to detect fraudulent credit card transactions. Since the dataset contains a highly imbalanced target variable, special care was taken in selecting appropriate models and evaluation metrics. Building on the cleaned and engineered dataset from Milestone 2, this step focuses on preparing the data for modeling and evaluating classifiers that are well-suited for handling imbalanced classification problems such as fraud detection.

3.0.2 Step 1 & 2: Data Preparation — Encoding and Feature Engineering

Converted the trans_date_trans_time column into separate features such as hour, day, month, and weekday to help capture potential temporal patterns associated with fraud.

Dropped personally identifiable or redundant columns such as names and addresses to prevent data leakage and preserve privacy.

Applied frequency encoding to categorical variables including merchant, city, and state to handle high-cardinality features effectively.

Ensured the is_fraud binary target variable was present and removed cc_num, as it is a unique identifier with no predictive value.

Performed a stratified train-test split to maintain the same fraud ratio in both training and test sets.

[96]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split

# Step 1: Feature engineering on datetime and categorical columns
df['trans_date_trans_time'] = pd.to_datetime(df['trans_date_trans_time'])
df['trans_hour'] = df['trans_date_trans_time'].dt.hour
df['trans_day'] = df['trans_date_trans_time'].dt.day
df['trans_month'] = df['trans_date_trans_time'].dt.month
df['trans_weekday'] = df['trans_date_trans_time'].dt.weekday

# Step 2: Drop unnecessary or sensitive columns
cols_to_drop = ['Unnamed: 0', 'first', 'last', 'street',␣
 ↪'trans_date_trans_time', 'cc_num']
df.drop(columns=cols_to_drop, inplace=True)

# Step 3: Frequency encode high-cardinality categorical features
for col in ['merchant', 'city', 'state']:
    freq_encoding = df[col].value_counts(normalize=True)
    df[f'{col}_freq_enc'] = df[col].map(freq_encoding)
df.drop(columns=['merchant', 'city', 'state'], inplace=True)

# Step 4: Drop or encode remaining object-type columns
df.drop(columns=['job', 'dob', 'trans_num', 'merchant_category'], inplace=True)

# Step 5: Confirm target variable
if 'is_fraud' not in df.columns:
    raise ValueError("Target column 'is_fraud' not found in the dataset.")

# Step 6: Train-test split
X = df.drop(columns=['is_fraud'])
y = df['is_fraud']
X_train, X_test, y_train, y_test = train_test_split(
```

```
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Sanity check for any object columns
print("Remaining object columns in X_train:", X_train.
 ↪select_dtypes(include='object').columns.tolist())
```

```
Remaining object columns in X_train: []
```

3.0.3 Step 3: Encoding Categorical Features

I use `OrdinalEncoder` to convert any remaining object-type (categorical) features into a numeric format. The parameter `handle_unknown='use_encoded_value'` with `unknown_value=-1` ensures that unseen categories in the test set do not cause errors during prediction, which is especially useful when working with real-world datasets.

[97]:
```
from sklearn.preprocessing import OrdinalEncoder

# Identifying non-numeric (categorical) columns
non_numeric_cols = X_train.select_dtypes(include=['object']).columns.tolist()

if non_numeric_cols:
    # Initializing the encoder to handle unknown values in test set
    oe = OrdinalEncoder(handle_unknown='use_encoded_value', unknown_value=-1)

    # Fitting on training data and transforming both training and test data
    X_train.loc[:, non_numeric_cols] = oe.
 ↪fit_transform(X_train[non_numeric_cols])
    X_test.loc[:, non_numeric_cols] = oe.transform(X_test[non_numeric_cols])
```

3.0.4 Step 4: Model Training and Evaluation

I used a Random Forest Classifier, which is well-suited for tabular data and robust against class imbalance when `class_weight='balanced'` is applied.

Evaluation was performed using classification metrics appropriate for imbalanced datasets: **Precision, Recall, F1-score, Confusion Matrix**, and **ROC AUC Score**.

To enhance interpretability: - The **confusion matrix** is shown in both labeled tabular form and as a heatmap. - The **ROC Curve** is plotted to visualize the model's ability to distinguish between fraud and non-fraud across thresholds.

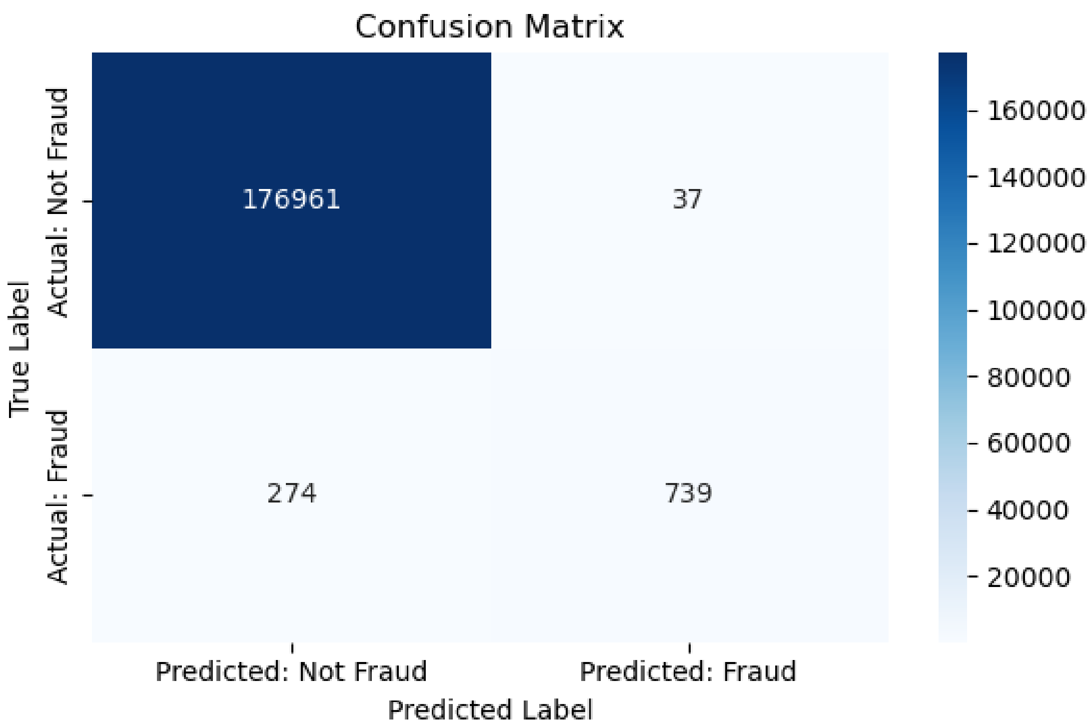
The primary objective is to **maximize Recall** (catch as many fraudulent transactions as possible) while maintaining **good Precision** (to reduce false positives).

[98]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪roc_auc_score, roc_curve
import pandas as pd
import seaborn as sns
```

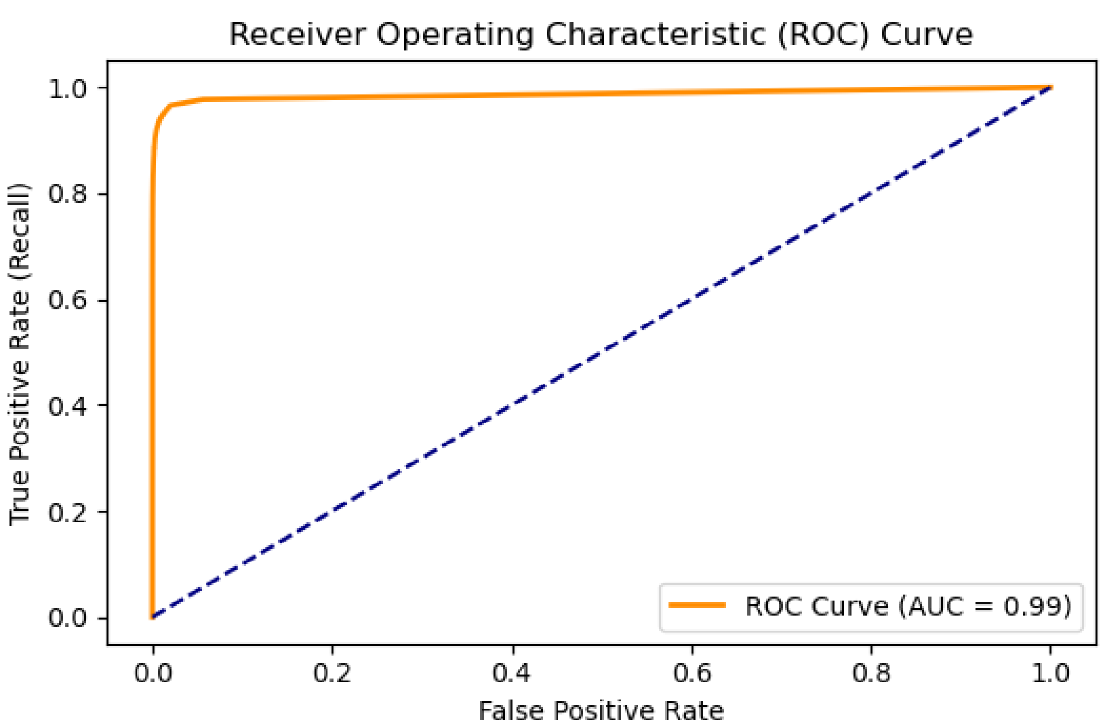
```python
import matplotlib.pyplot as plt

# Initialize the Random Forest classifier with balanced class weights and use␣
↪all CPU cores
rf = RandomForestClassifier(class_weight='balanced', random_state=42, n_jobs=-1)

# Train the model on the training set
rf.fit(X_train, y_train)

# Predict on the test set
y_pred = rf.predict(X_test)
y_pred_proba = rf.predict_proba(X_test)[:, 1]

# Classification Report with zero_division=0 to suppress warnings if needed
print("Classification Report:\n", classification_report(y_test, y_pred,␣
↪zero_division=0))

# Confusion Matrix as DataFrame for clear labeling
cm = confusion_matrix(y_test, y_pred)
cm_df = pd.DataFrame(cm, index=['Actual: Not Fraud', 'Actual: Fraud'],
                     columns=['Predicted: Not Fraud', 'Predicted: Fraud'])
print("\nConfusion Matrix:\n")
print(cm_df)

# Plotting Confusion Matrix as Heatmap
plt.figure(figsize=(6, 4))
sns.heatmap(cm_df, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# ROC AUC Score
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("\nROC AUC Score:", roc_auc)

# Plotting ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC Curve (AUC = {roc_auc:.
↪2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')  # Diagonal line
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate (Recall)')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
```

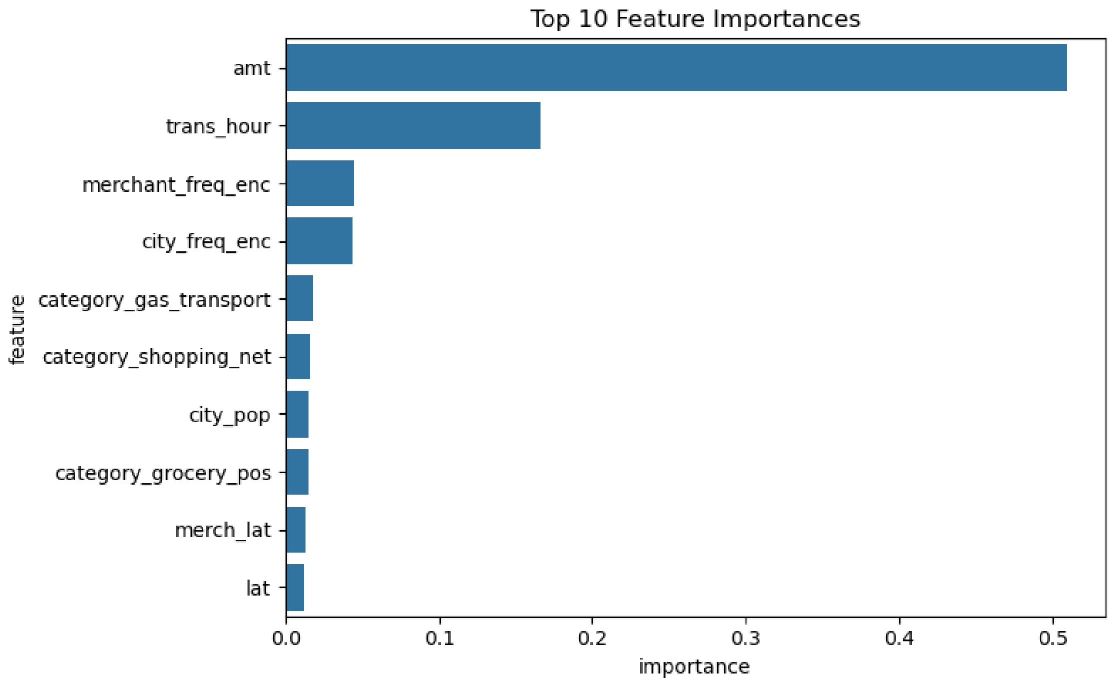
```python
plt.tight_layout()
plt.show()

# Plot Top 10 Feature Importances for interpretability
importances = rf.feature_importances_
features = X_train.columns
feat_imp_df = pd.DataFrame({'feature': features, 'importance': importances})
feat_imp_df = feat_imp_df.sort_values(by='importance', ascending=False).head(10)

plt.figure(figsize=(8, 5))
sns.barplot(x='importance', y='feature', data=feat_imp_df)
plt.title('Top 10 Feature Importances')
plt.tight_layout()
plt.show()
```

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

           0       1.00      1.00      1.00    176998
           1       0.95      0.73      0.83      1013

    accuracy                           1.00    178011
   macro avg       0.98      0.86      0.91    178011
weighted avg       1.00      1.00      1.00    178011


Confusion Matrix:

                   Predicted: Not Fraud  Predicted: Fraud
Actual: Not Fraud                176961                37
Actual: Fraud                       274               739
```



ROC AUC Score: 0.9868173952852625





Based on the model results, the classifier performed very well overall. The precision for fraud (class 1) is high at 0.95 (95%), meaning that when the model flags a transaction as fraudulent, it is correct 95% of the time. The recall for fraud is moderate at 0.73 (73%), indicating the model successfully identifies nearly three-quarters of all actual fraud cases. This suggests that while the model is quite accurate when predicting fraud, it still misses about one-quarter of fraudulent transactions.

The F1-score for fraud is 0.83, showing a good balance between precision and recall. The ROC AUC score of 0.987 further confirms that the model does an excellent job distinguishing between fraud and non-fraud cases across different classification thresholds. The ROC curve, which rises sharply toward the top-left corner, visually supports this strong discriminative performance.

Given the dataset's high class imbalance, additional metrics like the Precision-Recall curve and Average Precision Score (discussed earlier) provide a more focused evaluation of the minority class performance. These combined evaluations suggest the model is robust, but there remains room for improvement, especially in recall. Approaches such as threshold tuning, resampling techniques, or using more advanced algorithms could help enhance the model's ability to detect more fraudulent transactions without significantly sacrificing precision.

3.0.5 Precision-Recall Curve

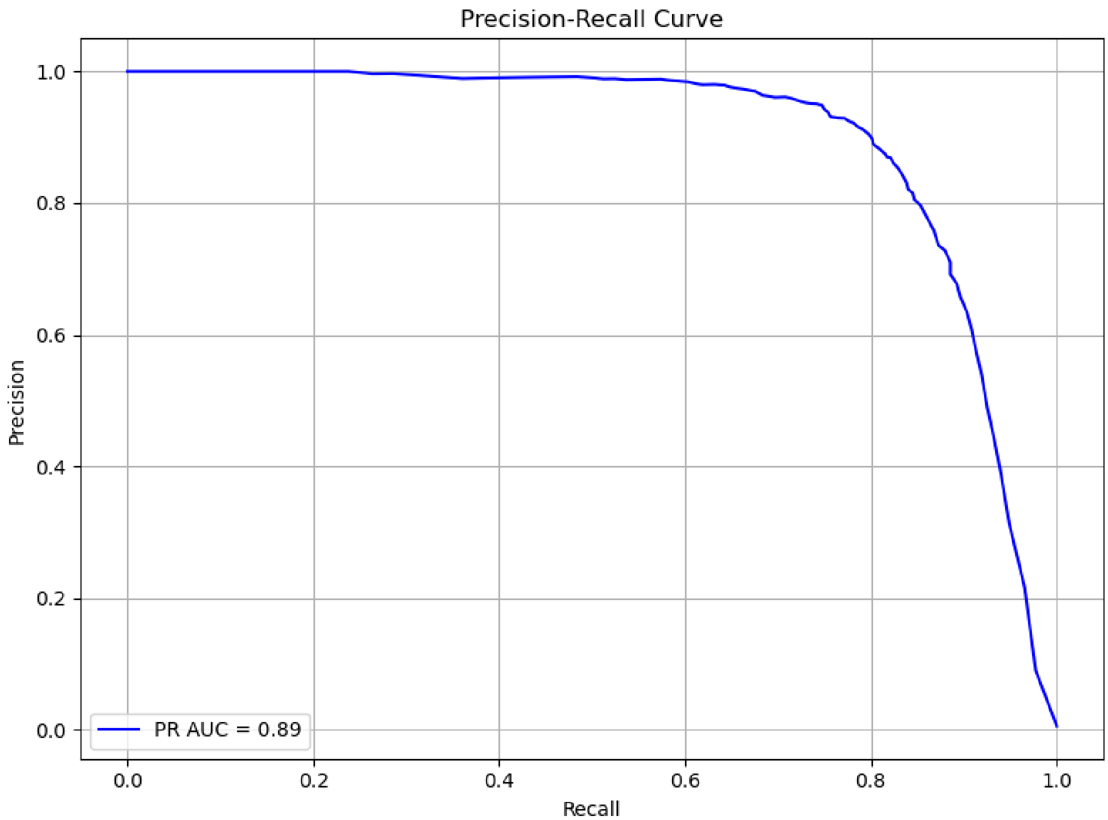
Given the significant class imbalance in the dataset—where the majority of transactions are non-fraudulent—metrics like accuracy and ROC AUC can sometimes be misleading. The Precision-Recall curve provides a more informative evaluation by focusing specifically on the model's performance with respect to the minority class (fraudulent transactions).

This curve highlights the crucial trade-off between precision (the accuracy of fraud predictions) and recall (the ability to detect all fraud cases). In fraud detection, maximizing recall is important to catch as many fraudulent transactions as possible, while maintaining high precision helps minimize false alarms.

The curve was generated using scikit-learn's precision_recall_curve function to visualize this balance and guide further model tuning.

[99]:
```python
from sklearn.metrics import precision_recall_curve, average_precision_score
import matplotlib.pyplot as plt

# Calculate the Average Precision Score (area under the Precision-Recall curve)
avg_precision = average_precision_score(y_test, y_pred_proba)
print(f"Precision-Recall AUC (Average Precision): {avg_precision:.4f}")

# Generate precision and recall values for different thresholds
precision, recall, _ = precision_recall_curve(y_test, y_pred_proba)

# Plot Precision-Recall curve
plt.figure(figsize=(8,6))
plt.plot(recall, precision, label=f'PR AUC = {avg_precision:.2f}', color='blue')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='lower left')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Precision-Recall AUC (Average Precision): 0.8943
```



3.0.6 Summary of the Precision-Recall Curve Result

The Precision-Recall AUC (also known as Average Precision) is approximately 0.89 (89%), indicating the model effectively balances precision and recall across various decision thresholds. This metric is particularly valuable for detecting credit card fraud in a highly imbalanced dataset, where traditional metrics like accuracy or ROC AUC can be misleading.

Examining the curve, precision remains very high — around 0.98 to 0.99 — through recall levels up to about 0.3. Beyond this point, the precision curve experiences a slight decline but stays near these high levels until recall reaches approximately 0.6. After recall passes 0.6, precision begins to decrease more noticeably, with an accelerated drop starting around 0.7 recall. By the time recall reaches 1.0, precision falls sharply toward zero, reflecting the increasing number of false positives as the model tries to identify every fraud case.

This trade-off between precision and recall is common in imbalanced classification problems. The Precision-Recall curve thus offers a focused evaluation of the model's performance on the minority (fraud) class, providing more insight than ROC AUC in this context.