CREDIT CARD FRAUD DETECTION

- Data Exploration
- Data Preprocesssing
- Exploratory Data Analysis
- Feature Selection

credit-card-fraud

August 2, 2025

1 CREDIT CARD FRAUD DETECTION

Step 1: Import Libraries

[15]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split   # Data splitting
from sklearn.preprocessing import StandardScaler   # Feature scaling
from sklearn.ensemble import RandomForestClassifier # Random Forest model
from sklearn.metrics import classification_report, confusion_matrix   # Model␣
 ↪evaluation metrics
from imblearn.over_sampling import SMOTE   # Handling class imbalance
```

Step 2: Load Dataset

[2]:
```
df = pd.read_csv('creditcard.csv')  # Download from Kaggle & put it in same␣
 ↪folder
print("Dataset Loaded Successfully!")
```

```
Dataset Loaded Successfully!
```

Step 3: Basic Exploration

[3]:
```
print("Shape of data:", df.shape)
print("Fraudulent Transactions (%):", round((df['Class'].value_counts()[1]/
 ↪len(df))*100, 2), "%")
```

```
Shape of data: (284807, 31)
Fraudulent Transactions (%): 0.17 %
```

Step 4: Check for Missing Values

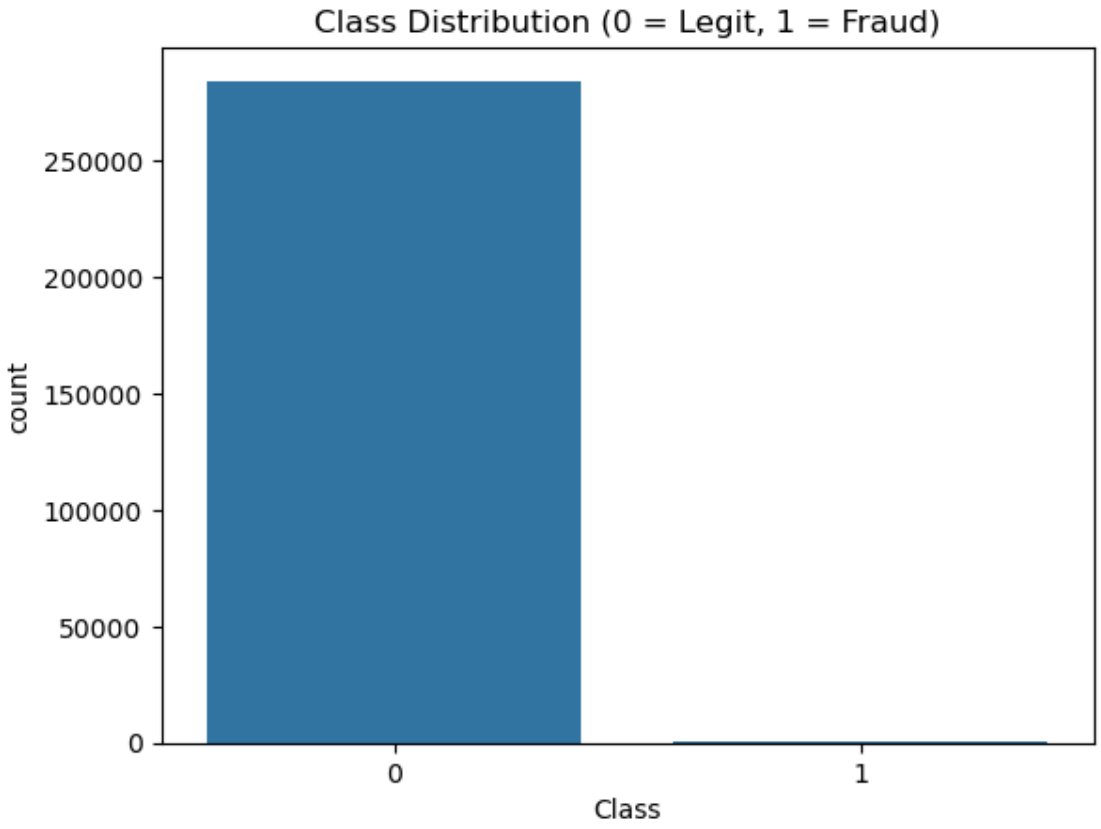
[ ]:
```
print(df.isnull().sum())   # Check for missing values
```

```
Time      0
V1        0
V2        0
```

```
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

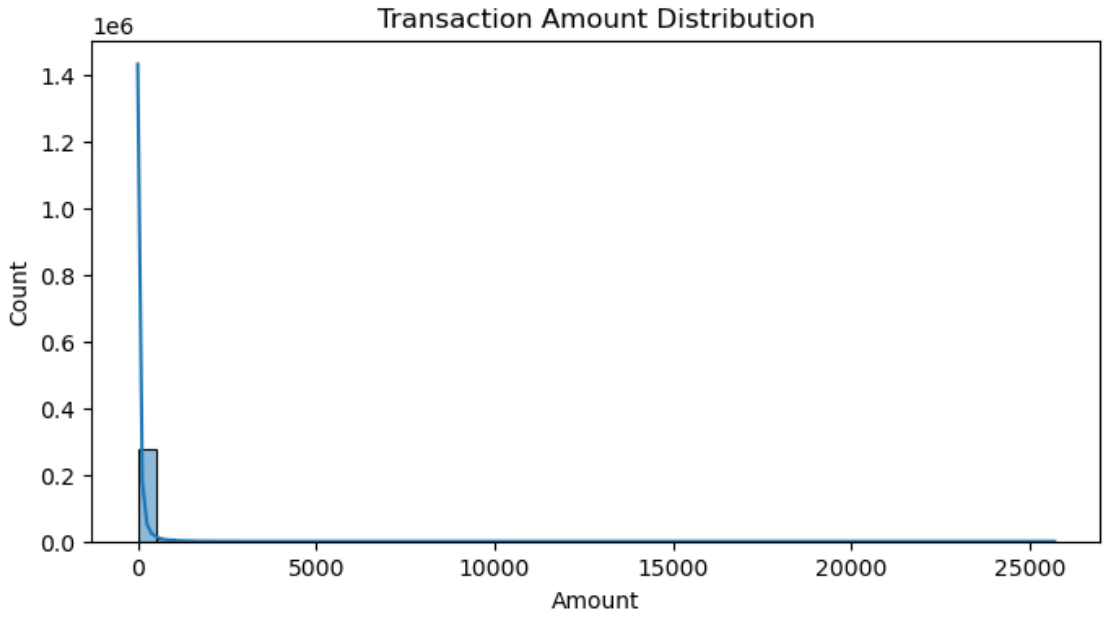
Step 5: Visualizing Class Imbalance

[ ]:
```
sns.countplot(x='Class', data=df)    # Visualizing class distribution
plt.title("Class Distribution (0 = Legit, 1 = Fraud)")
plt.show()
```



Step 6: Transaction Amount Distribution

[ ]:
```
plt.figure(figsize=(8,4))
sns.histplot(df['Amount'], bins=50, kde=True)  # Visualizing transaction amount␣
↪distribution
plt.title("Transaction Amount Distribution")
plt.show()
```



Step 7: Normalize 'Amount' Feature

```
[ ]: scaler = StandardScaler()  # Feature scaling
df['NormalizedAmount'] = scaler.fit_transform(df['Amount'].values.reshape(-1,␣
  ↪1))  # Normalizing the 'Amount' feature
df.drop(['Amount', 'Time'], axis=1, inplace=True)  # Dropping 'Amount' and␣
  ↪'Time' columns
```

Step 8: Prepare Data for Training

```
[ ]: X = df.drop('Class', axis=1)  # Features
y = df['Class']
```

Step 9: Handle Imbalanced Dataset Using SMOTE

```
[ ]: print("Before SMOTE:", y.value_counts())              # Checking class␣
  ↪distribution
sm = SMOTE(random_state=42)                               # Applying SMOTE to handle␣
  ↪class imbalance
X_res, y_res = sm.fit_resample(X, y)
print("After SMOTE:", y_res.value_counts())
```

```
Before SMOTE: Class
0    284315
1       492
Name: count, dtype: int64
After SMOTE: Class
```

```
0    284315
1    284315
Name: count, dtype: int64
```

Step 10: Train/Test Split

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.
     ↪2, random_state=42)       # Splitting the dataset into training and testing␣
     ↪sets
```

Step 11: Train Model

```
[ ]: model = RandomForestClassifier(n_estimators=100, random_state=42)  #␣
     ↪Initializing the Random Forest model
     model.fit(X_train, y_train)
```

```
[ ]: RandomForestClassifier(random_state=42)
```

Step 12: Evaluate Model

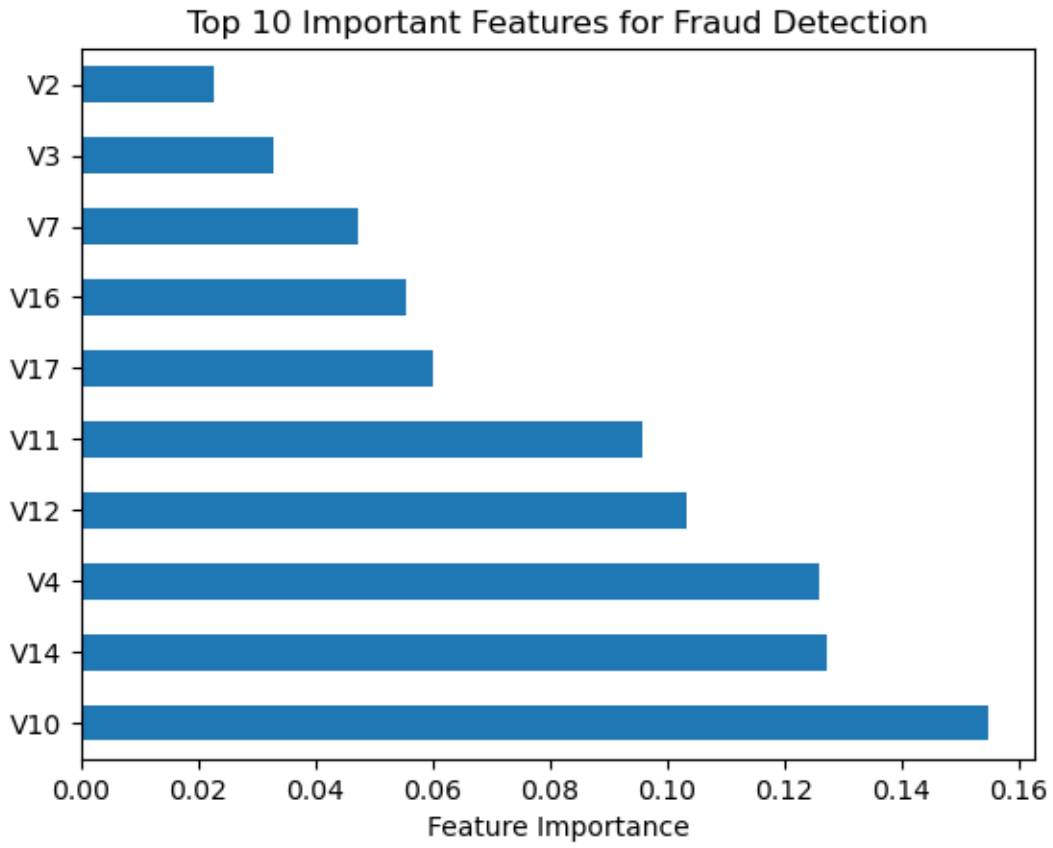
```
[ ]: y_pred = model.predict(X_test)  # Making predictions on the test set
     print("\nClassification Report:\n", classification_report(y_test, y_pred))  #␣
     ↪Evaluating the model performance
     print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))   # Displaying␣
     ↪the confusion matrix
```

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

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726


Confusion Matrix:
 [[56738    12]
 [    0 56976]]
```

Step 13: Feature Importance

```
[14]: importances = pd.Series(model.feature_importances_, index=X.columns)
      importances.nlargest(10).plot(kind='barh')   # Plotting top 10 important␣
      ↪features
      plt.xlabel("Feature Importance")
      plt.title("Top 10 Important Features for Fraud Detection")
```

```
plt.show()
```


Top 10 Important Features for Fraud Detection
V2
V3
V7
V16
V17
V11
V12
V4
V14
V10
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
Feature Importance

[ ]: