```
import pandas as pd

df = pd.read_csv('/kaggle/input/default-of-credit-card-clients-
dataset/UCI_Credit_Card.csv')
df.head()
```

```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3
PAY_4  \
0   1    20000.0    2          2         1   24      2      2     -1
-1
1   2   120000.0    2          2         2   26     -1      2      0
0
2   3    90000.0    2          2         2   34      0      0      0
0
3   4    50000.0    2          2         1   37      0      0      0
0
4   5    50000.0    1          2         1   57     -1      0     -1
0

   ...  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3
\
0  ...        0.0        0.0        0.0       0.0     689.0       0.0

1  ...     3272.0     3455.0     3261.0       0.0    1000.0    1000.0

2  ...    14331.0    14948.0    15549.0    1518.0    1500.0    1000.0

3  ...    28314.0    28959.0    29547.0    2000.0    2019.0    1200.0

4  ...    20940.0    19146.0    19131.0    2000.0   36681.0   10000.0


   PAY_AMT4  PAY_AMT5  PAY_AMT6  default.payment.next.month
0       0.0       0.0       0.0                           1
1    1000.0       0.0    2000.0                           1
2    1000.0    1000.0    5000.0                           0
3    1100.0    1069.0    1000.0                           0
4    9000.0     689.0     679.0                           0

[5 rows x 25 columns]
```

Data Cleaning

```
# Drop ID column
df.drop('ID', axis=1, inplace=True)

# Check missing values
print(df.isnull().sum())
```

```
# Check duplicates
df.duplicated().sum()
```

```
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default.payment.next.month    0
dtype: int64

35
```

Encoding Categorical Features

```
df.rename(columns={
    'default.payment.next.month': 'default',
    'PAY_0': 'PAY_1'
}, inplace=True)


df['SEX'] = df['SEX'].map({1: 'Male', 2: 'Female'})
df = pd.get_dummies(df, columns=['SEX', 'EDUCATION', 'MARRIAGE'],
drop_first=True)

df.head()
```

```
   LIMIT_BAL  AGE  PAY_1  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6  BILL_AMT1
\
0    20000.0   24      2      2     -1     -1     -2     -2     3913.0
```

```
1   120000.0   26     -1      2      0      0      0      2     2682.0
2    90000.0   34      0      0      0      0      0      0    29239.0
3    50000.0   37      0      0      0      0      0      0    46990.0
4    50000.0   57     -1      0     -1      0      0      0     8617.0

   BILL_AMT2  ...  SEX_Male  EDUCATION_1  EDUCATION_2  EDUCATION_3  \
0     3102.0  ...     False        False         True        False
1     1725.0  ...     False        False         True        False
2    14027.0  ...     False        False         True        False
3    48233.0  ...     False        False         True        False
4     5670.0  ...      True        False         True        False

   EDUCATION_4  EDUCATION_5  EDUCATION_6  MARRIAGE_1  MARRIAGE_2
MARRIAGE_3
0        False        False        False        True       False
False
1        False        False        False       False        True
False
2        False        False        False       False        True
False
3        False        False        False        True       False
False
4        False        False        False        True       False
False

[5 rows x 31 columns]
```

ℹ Categorical Variable Meanings

As per the original UCI source:

SEX: 1 = Male, 2 = Female

EDUCATION: 1 = Graduate school, 2 = University, 3 = High school, 4–6 = Others

MARRIAGE: 1 = Married, 2 = Single, 3 = Others

Normalize / Scale Numerical Features

```
from sklearn.preprocessing import StandardScaler

# Select numeric columns
num_cols = ['LIMIT_BAL', 'AGE'] + [col for col in df.columns if
```

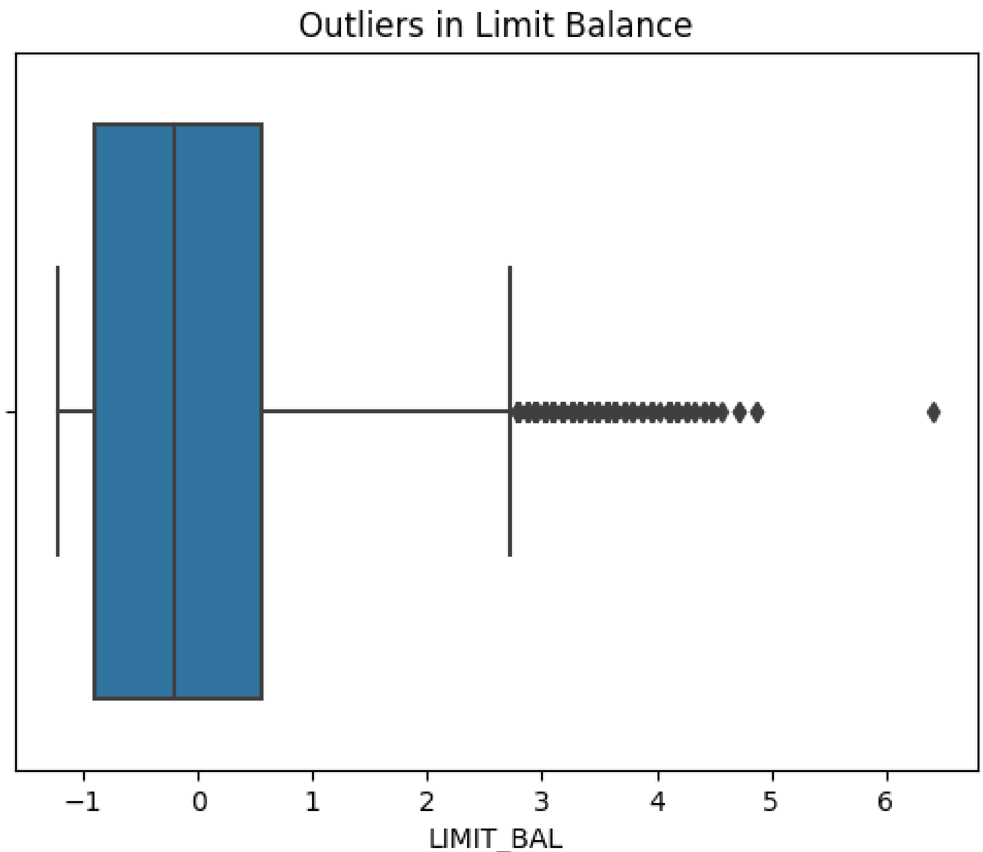
```
'BILL_AMT' in col or 'PAY_AMT' in col]

scaler = StandardScaler()
df[num_cols] = scaler.fit_transform(df[num_cols])
```

Feature Engineering

```
# Create new feature: average bill amount
df['avg_bill_amt'] = df[[f'BILL_AMT{i}' for i in range(1,
7)]].mean(axis=1)

# Ratio of payment to bill
df['pay_to_bill_ratio'] = df['PAY_AMT1'] / (df['BILL_AMT1'] + 1)  #
avoid divide by zero
```

Outlier Detection & Handling

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

# Boxplot to see outliers
sns.boxplot(x=df['LIMIT_BAL'])
plt.title("Outliers in Limit Balance")
plt.show()

# Use IQR to remove outliers in LIMIT_BAL
Q1 = df['LIMIT_BAL'].quantile(0.25)
Q3 = df['LIMIT_BAL'].quantile(0.75)
IQR = Q3 - Q1

df = df[(df['LIMIT_BAL'] >= Q1 - 1.5*IQR) & (df['LIMIT_BAL'] <= Q3 +
1.5*IQR)]
```



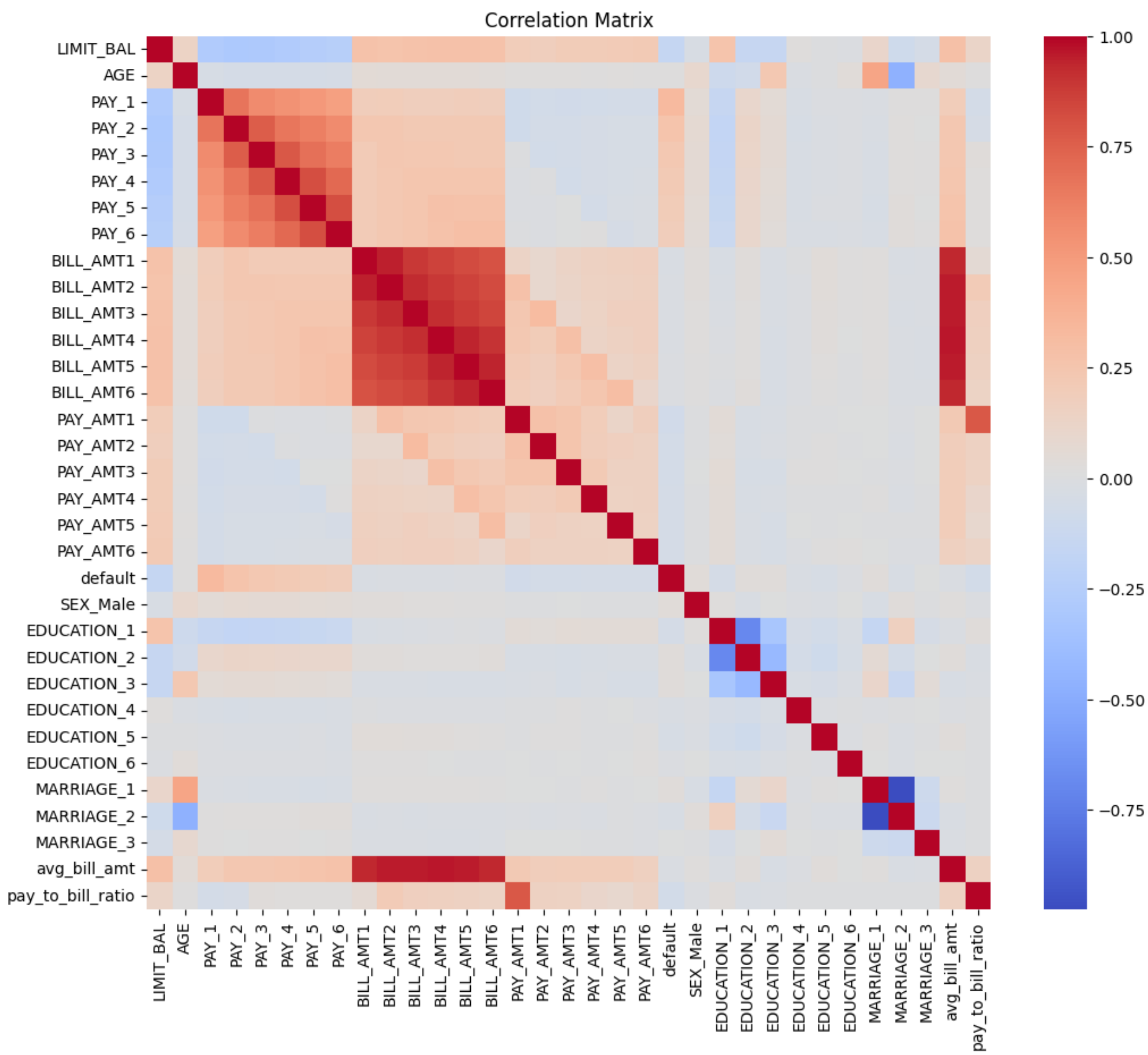
Explanation:

The boxplot visually shows outliers.

The IQR method statistically removes extreme values:

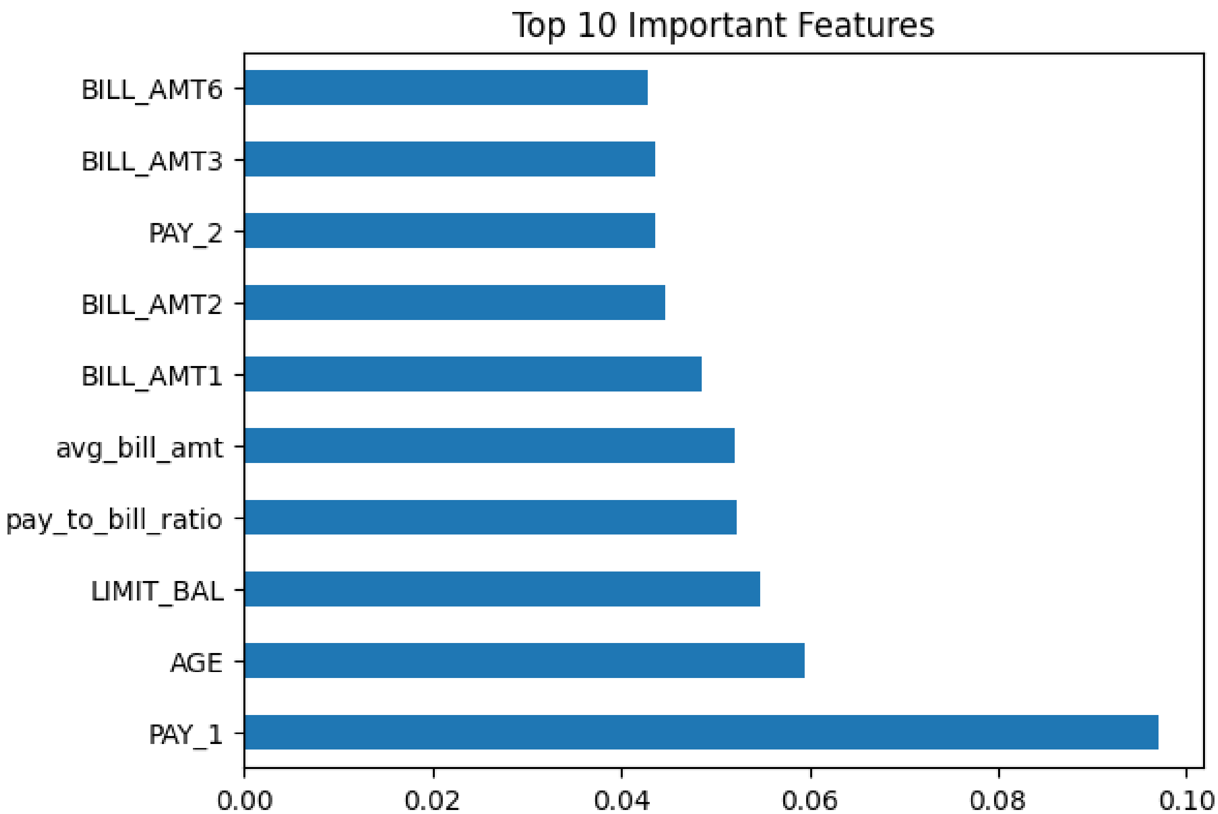
Data < Q1 – 1.5×IQR or > Q3 + 1.5×IQR is considered an outlier and removed.

```
# Correlation Heatmap
corr = df.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(corr, cmap='coolwarm', annot=False)
plt.title("Correlation Matrix")
plt.show()
```



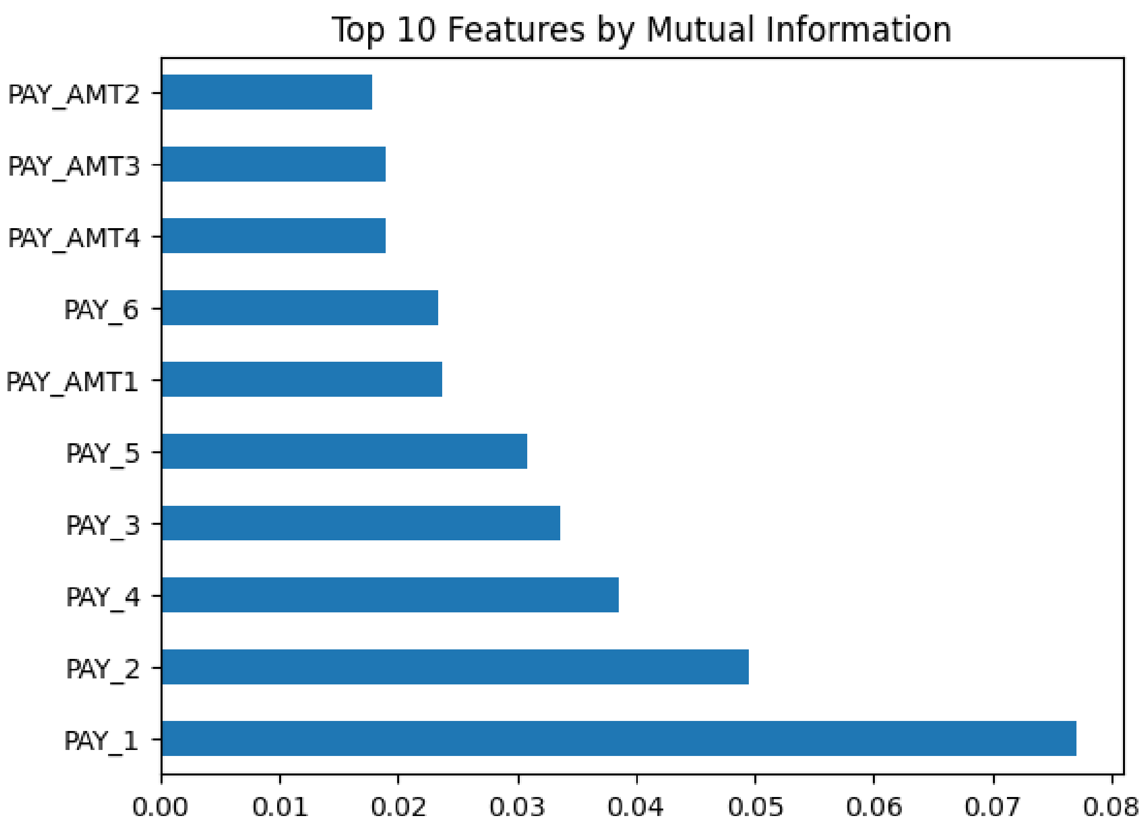
Feature Importance using Random Forest

```
from sklearn.ensemble import RandomForestClassifier

X = df.drop('default', axis=1)
y = df['default']

model = RandomForestClassifier()
model.fit(X, y)

# Get feature importances
importances = pd.Series(model.feature_importances_, index=X.columns)
importances.sort_values(ascending=False).head(10).plot(kind='barh')
plt.title('Top 10 Important Features')
plt.show()
```



Using Mutual Information

```
from sklearn.feature_selection import mutual_info_classif

mi = mutual_info_classif(X, y)
mi_series = pd.Series(mi, index=X.columns)
mi_series.sort_values(ascending=False).head(10).plot(kind='barh')
plt.title('Top 10 Features by Mutual Information')
plt.show()
```



A short explanation of what changes were made and why

Data Preprocessing & Feature Engineering – Summary

Here's a brief explanation of the changes made and why:

1. **Dropped Unnecessary Columns**
   - Removed the `ID` column as it does not provide predictive value for modeling.
2. **Handled Missing Values**
   - Checked for missing values using `.isnull().sum()` – the dataset had no missing values, so no imputation was required.
3. **Removed Duplicates**
   - Verified and confirmed there were no duplicate records using `.duplicated().sum()`.
4. **Encoded Categorical Variables**
   - Mapped numeric values in `SEX`, `EDUCATION`, and `MARRIAGE` columns to meaningful labels (e.g., 1 → Male).

- Applied one-hot encoding (`pd.get_dummies()`) to convert these categorical columns into numeric binary variables for machine learning compatibility.

5. **Normalized Numerical Features**
   - Used `StandardScaler` to standardize continuous features like `LIMIT_BAL`, `AGE`, `BILL_AMT1-6`, and `PAY_AMT1-6` to improve model performance and training stability.
6. **Feature Engineering**
   - Created new features:
     - `avg_bill_amt`: Average of all bill amounts to summarize monthly spending.
     - `pay_to_bill_ratio`: Ratio of first payment to first bill amount to estimate repayment behavior.
7. **Outlier Detection and Handling**
   - Used boxplots to identify outliers in `LIMIT_BAL`.
   - Applied the IQR method to remove extreme outliers and improve data quality.
8. **Feature Selection (Optional)**
   - Performed feature importance analysis using a Random Forest model to identify the most relevant features for prediction.

These steps helped clean and transform the data to make it suitable for training accurate and interpretable machine learning models.