```
# Install required libraries
!pip install pandas numpy matplotlib seaborn scikit-learn imbalanced-learn
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.26.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.8.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.10/dist-packages (0.12.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.55.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
```

```
# Import libraries
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
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
```

```
# Step 3: Load the Dataset from GitHub Repository
url = "https://raw.githubusercontent.com/IndulekhaKP/credit-card-fraud-detection/main/data/creditcard.csv"
data = pd.read_csv(url)
print(f"Dataset shape: {data.shape}")
data.head(100)
```

```
Dataset shape: (284807, 31)
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
95	64.0	-0.658305	0.406791	2.037461	-0.291298	0.147910	-0.350857	0.945373	-0.172560	0.025133	...	-0.156096	-0.238805	0.089877
96	64.0	0.959602	0.370711	0.888613	2.343244	0.352491	1.365515	-0.277771	0.516053	-0.700929	...	-0.155547	-0.403239	0.356504
97	67.0	-0.653445	0.160225	1.592256	1.296832	0.997175	-0.343000	0.469937	-0.132470	-0.197794	...	0.038363	0.336449	-0.014883
98	67.0	-1.494668	0.837241	2.628211	3.145414	-0.609098	0.258495	-0.012189	0.102136	-0.286164	...	-0.140047	0.355044	0.332720
99	68.0	1.232996	0.189454	0.491040	0.633673	-0.511574	-0.990609	0.066240	-0.196940	0.075921	...	-0.251566	-0.770139	0.125998

100 rows × 31 columns

```
# Count the number of instances for each class
print(data['Class'].value_counts())
```

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

```
# Filter the rows where Class is 1
fraudulent_transactions = data[data['Class'] == 1]
```

```
# Display the fraudulent transactions
fraudulent_transactions
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	
541	406.0	-2.312227	1.951992	-1.609851	3.997906	-0.522188	-1.426545	-2.537387	1.391657	-2.770089	...	0.517232	-0.035049	-0.4
623	472.0	-3.043541	-3.157307	1.088463	2.288644	1.359805	-1.064823	0.325574	-0.067794	-0.270953	...	0.661696	0.435477	1.3
4920	4462.0	-2.303350	1.759247	-0.359745	2.330243	-0.821628	-0.075788	0.562320	-0.399147	-0.238253	...	-0.294166	-0.932391	0.1
6108	6986.0	-4.397974	1.358367	-2.592844	2.679787	-1.128131	-1.706536	-3.496197	-0.248778	-0.247768	...	0.573574	0.176968	
6329	7519.0	1.234235	3.019740	-4.304597	4.732795	3.624201	-1.357746	1.713445	-0.496358	-1.282858	...	-0.379068	-0.704181	-0.6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	0.697211	-2.064945	...	0.778584	-0.319189	0.6
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	0.248525	-1.127396	...	0.370612	0.028234	-0.1
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	1.210158	-0.652250	...	0.751826	0.834108	0.1
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	1.058733	-1.632333	...	0.583276	-0.269209	-0.4
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-0.068384	0.577829	...	-0.164350	-0.295135	-0.0

492 rows × 31 columns

```
data.info()
data.describe()
```

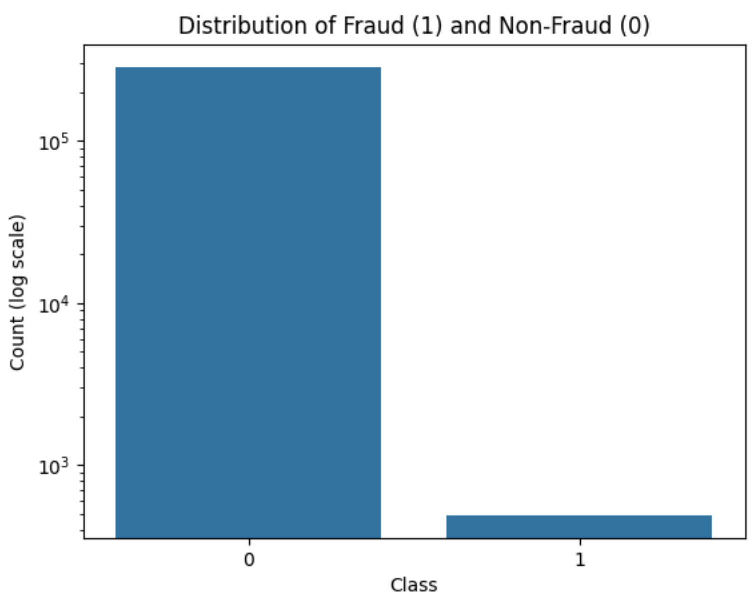
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	1.759061e-12	-8.251130e-13	-9.654937e-13	8.321385e-13	1.649999e-13	4.248366e-13	-3.054600e-13	8.777971e-14
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+01
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-02
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-01
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+01

8 rows × 31 columns

```
sns.countplot(x='Class', data=data)
plt.title("Distribution of Fraud (1) and Non-Fraud (0)")
plt.show()
```

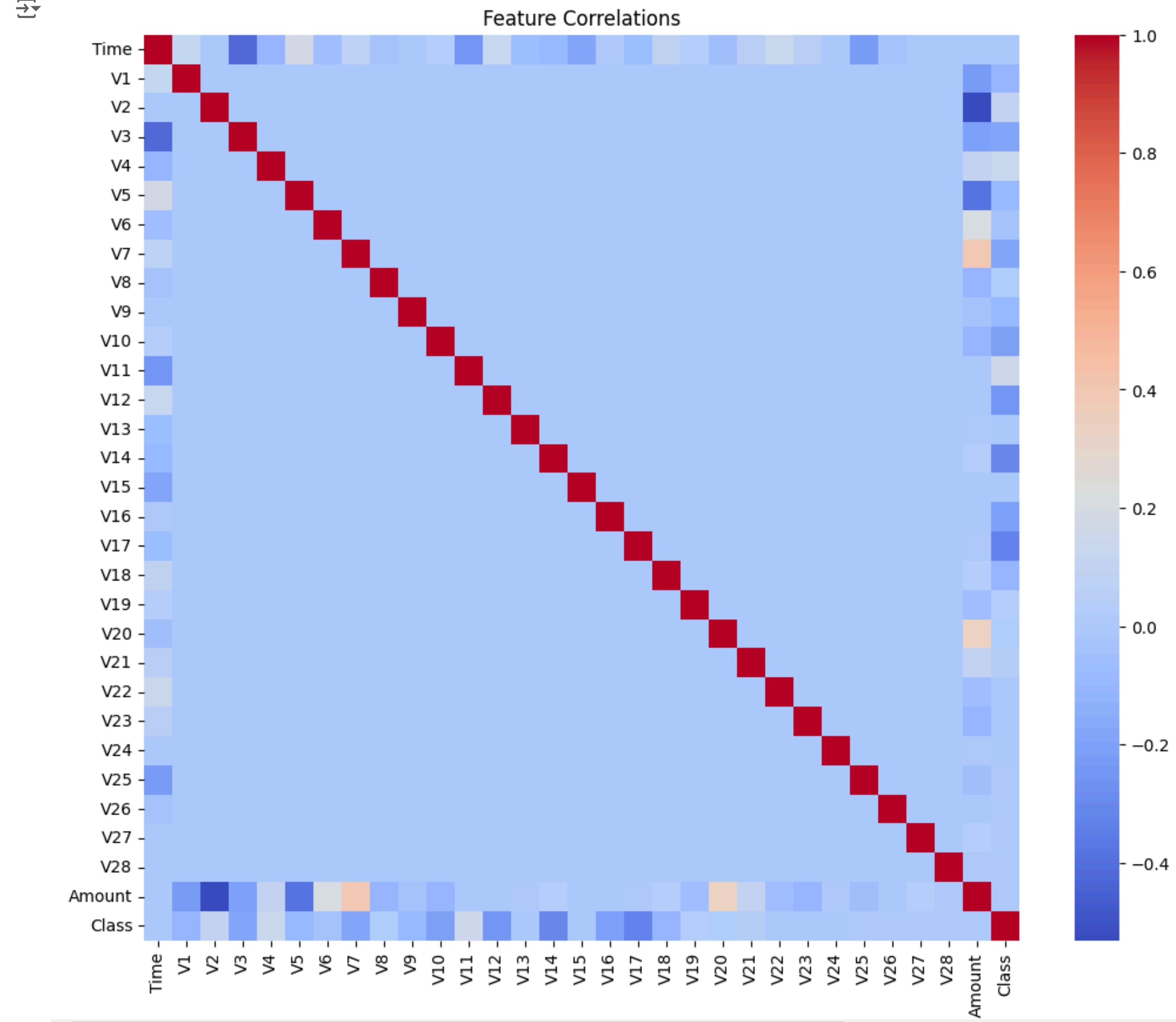

```
sns.countplot(x='Class', data=data)
plt.yscale('log')  # Apply logarithmic scale to the y-axis
plt.title("Distribution of Fraud (1) and Non-Fraud (0)")
plt.xlabel("Class")
plt.ylabel("Count (log scale)")
plt.show()
```




```
print(data['Class'].value_counts())
```

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

```
plt.figure(figsize=(12, 10))
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, cmap="coolwarm")
plt.title("Feature Correlations")
plt.show()
```




```
X = data.drop(columns=['Class'])
y = data['Class']
```

```
# Check for missing values in the features (X) and target (y)
print("Missing values in features (X):\n", X.isnull().sum())
print("Missing values in target (y):\n", y.isnull().sum())
```

```
Missing values in features (X):
 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
dtype: int64
Missing values in target (y):
 0
```

```
# Drop rows with NaN values in either X or y
X = X.dropna()
y = y[X.index]  # Ensures X and y are aligned after dropping NaNs
```

```
# Resample the data using SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)
```

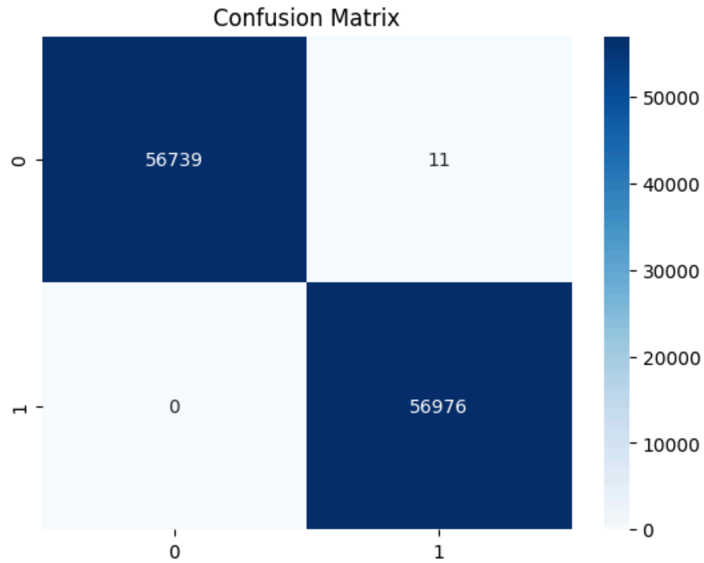
```
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
y_pred = model.predict(X_test)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
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
```

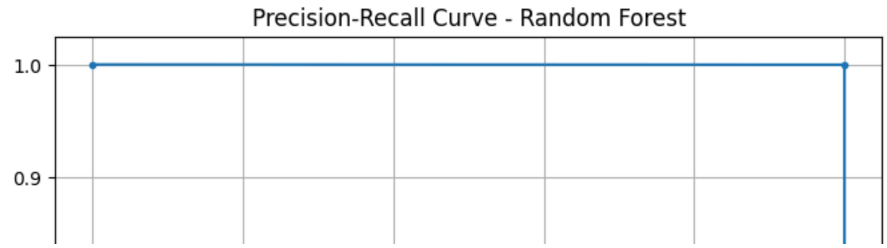
```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix")
plt.show()
```




```
from sklearn.metrics import classification_report, accuracy_score

print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.999903276295658
              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
```

```
# Plot Precision-Recall Curve for Random Forest
from sklearn.metrics import precision_recall_curve

y_pred_rf = model.predict(X_test)  # Predictions for test data
precision_rf, recall_rf, _ = precision_recall_curve(y_test, y_pred_rf)

plt.figure(figsize=(8, 6))
plt.plot(recall_rf, precision_rf, marker='.', label='Random Forest')
plt.title("Precision-Recall Curve - Random Forest")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.legend()
plt.grid()
plt.show()
```




```
# Plot ROC Curve for Random Forest
from sklearn.metrics import roc_curve, auc

y_pred_prob_rf = model.predict_proba(X_test)[:, 1]  # Get probabilities for class 1
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_prob_rf)
roc_auc_rf = auc(fpr_rf, tpr_rf)
```