In [1]:
```python
# import the necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from matplotlib import gridspec
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, roc_auc_score, auc
```

Loading the Data

In [2]:
```python
# Load the dataset from the csv file using pandas
# best way is to mount the drive on colab and
# copy the path for the csv file
data = pd.read_csv("creditcard.csv")
```

In [3]:
```python
# Grab a peek at the data
data.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
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	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0
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	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0
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	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0
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	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0
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	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0

5 rows × 31 columns

Exploitary Data Analysis

In [4]:
```python
# Print the shape of the data
# data = data.sample(frac = 0.1, random_state = 48)
print(data.shape)
print(data.describe())
```

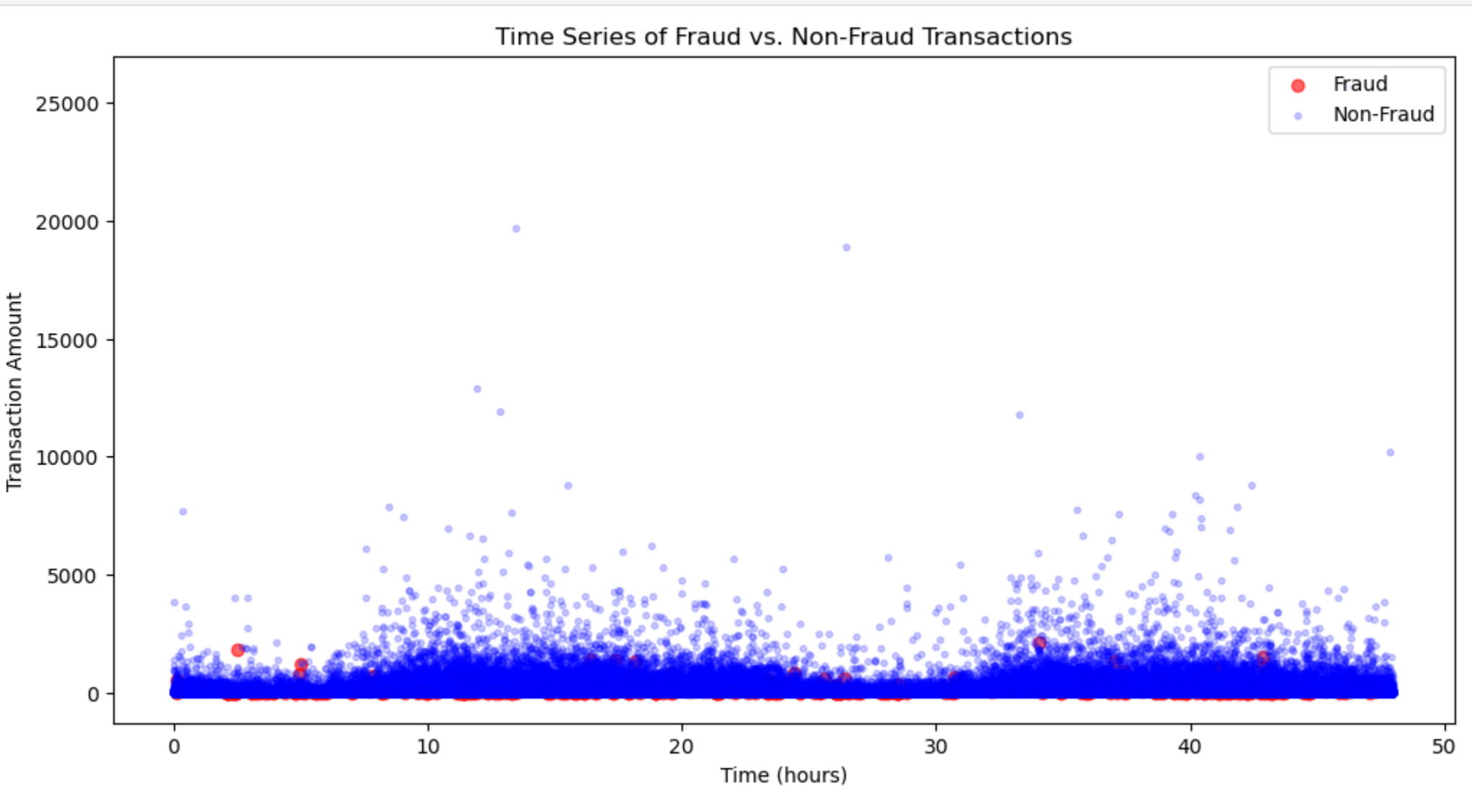
```
(284807, 31)
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15  2.074095e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -2.406331e-15
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean   5.340915e-16  1.683437e-15 -3.660091e-16 -1.227390e-16      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000

               Class
count  284807.000000
mean        0.001727
std         0.041527
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

In [5]:
```python
# Determine number of fraud cases in dataset
data['Time'] = data['Time'] / 3600
fraud = data[data['Class'] == 1]
valid = data[data['Class'] == 0]
outlierFraction = len(fraud)/float(len(valid))
print(outlierFraction)
print('Fraud Cases: {}'.format(len(data[data['Class'] == 1])))
print('Valid Transactions: {}'.format(len(data[data['Class'] == 0])))
```

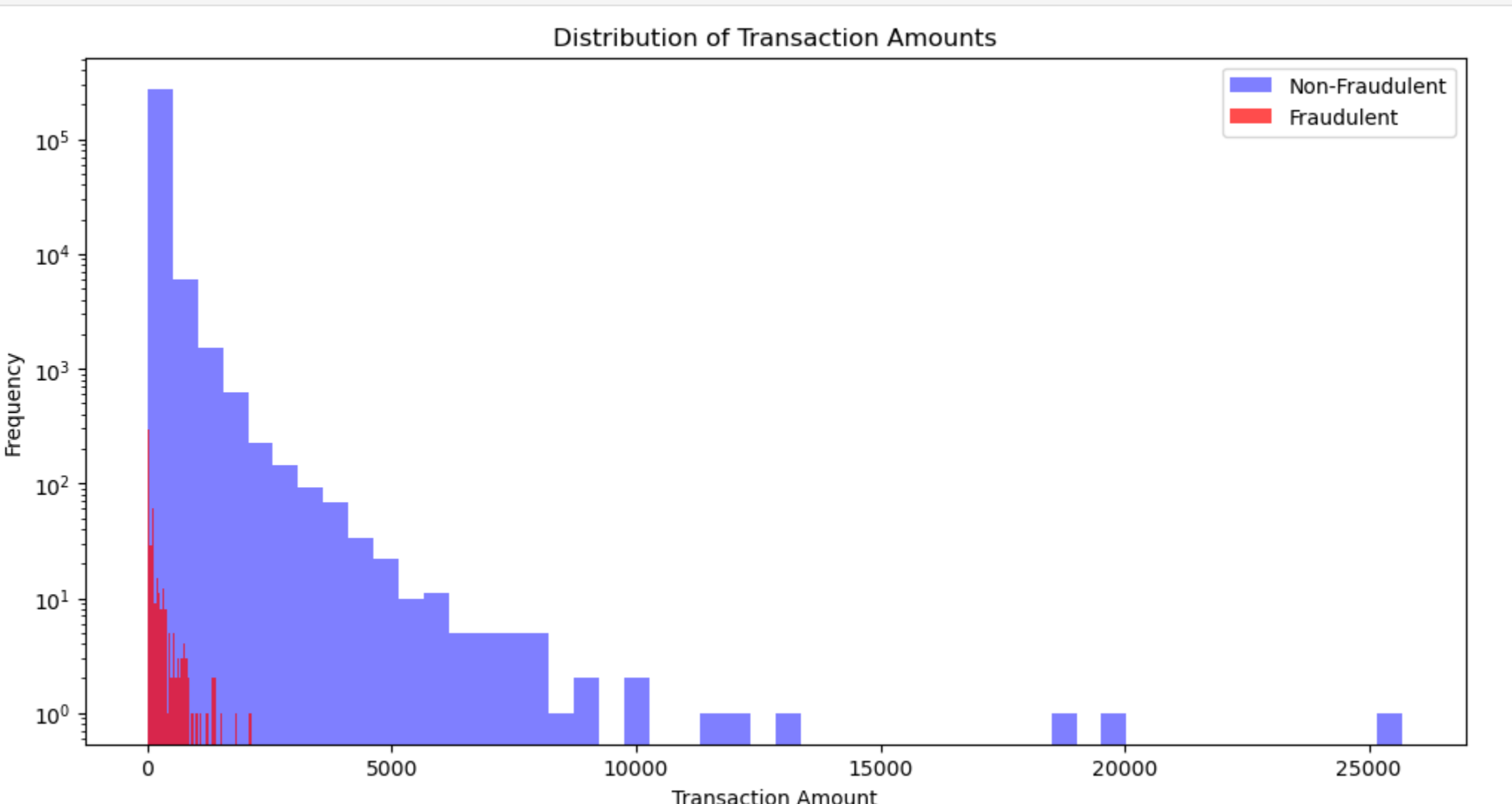
```
0.0017304750013189597
Fraud Cases: 492
Valid Transactions: 284315
```

Visualization

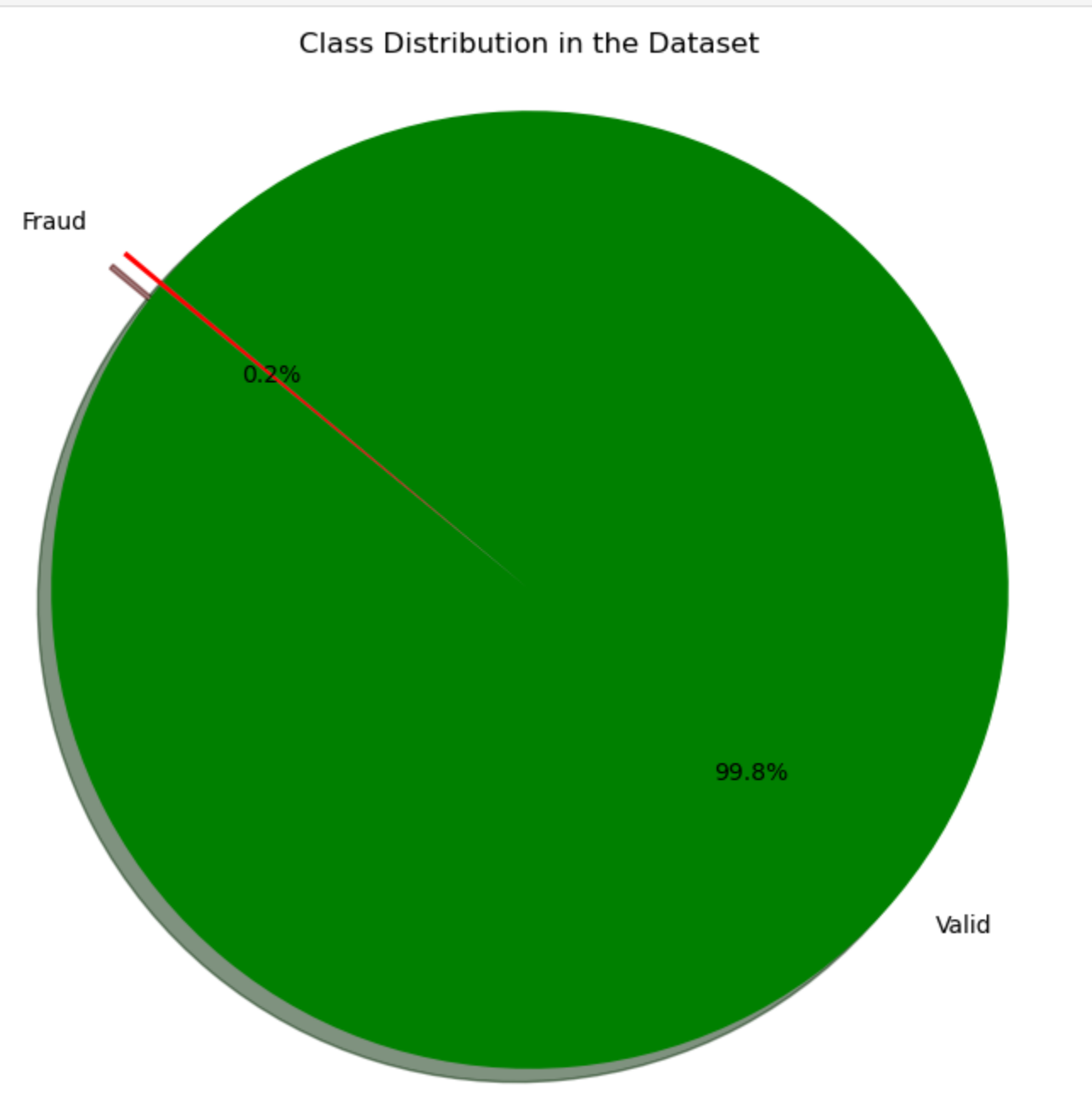
In [6]:
```python
plt.figure(figsize=(12, 6))
plt.scatter(fraud['Time'], fraud['Amount'], color='red', marker='o', label='Fraud', alpha=0.6)
plt.scatter(valid['Time'], valid['Amount'], color='blue', marker='.', label='Non-Fraud', alpha=0.2)

plt.title('Time Series of Fraud vs. Non-Fraud Transactions')
plt.xlabel('Time (hours)')
plt.ylabel('Transaction Amount')
plt.legend(loc='upper right')
plt.show()
```



In [7]:
```python
# Create a figure with subplots
plt.figure(figsize=(12, 6))

# Plot histograms for transaction amounts
plt.hist(valid['Amount'], bins=50, alpha=0.5, label='Non-Fraudulent', color='blue')
plt.hist(fraud['Amount'], bins=50, alpha=0.7, label='Fraudulent', color='red')

plt.title('Distribution of Transaction Amounts')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.legend(loc='upper right')
plt.yscale('log')  # Use a logarithmic scale on the y-axis for better visualization

plt.show()
```

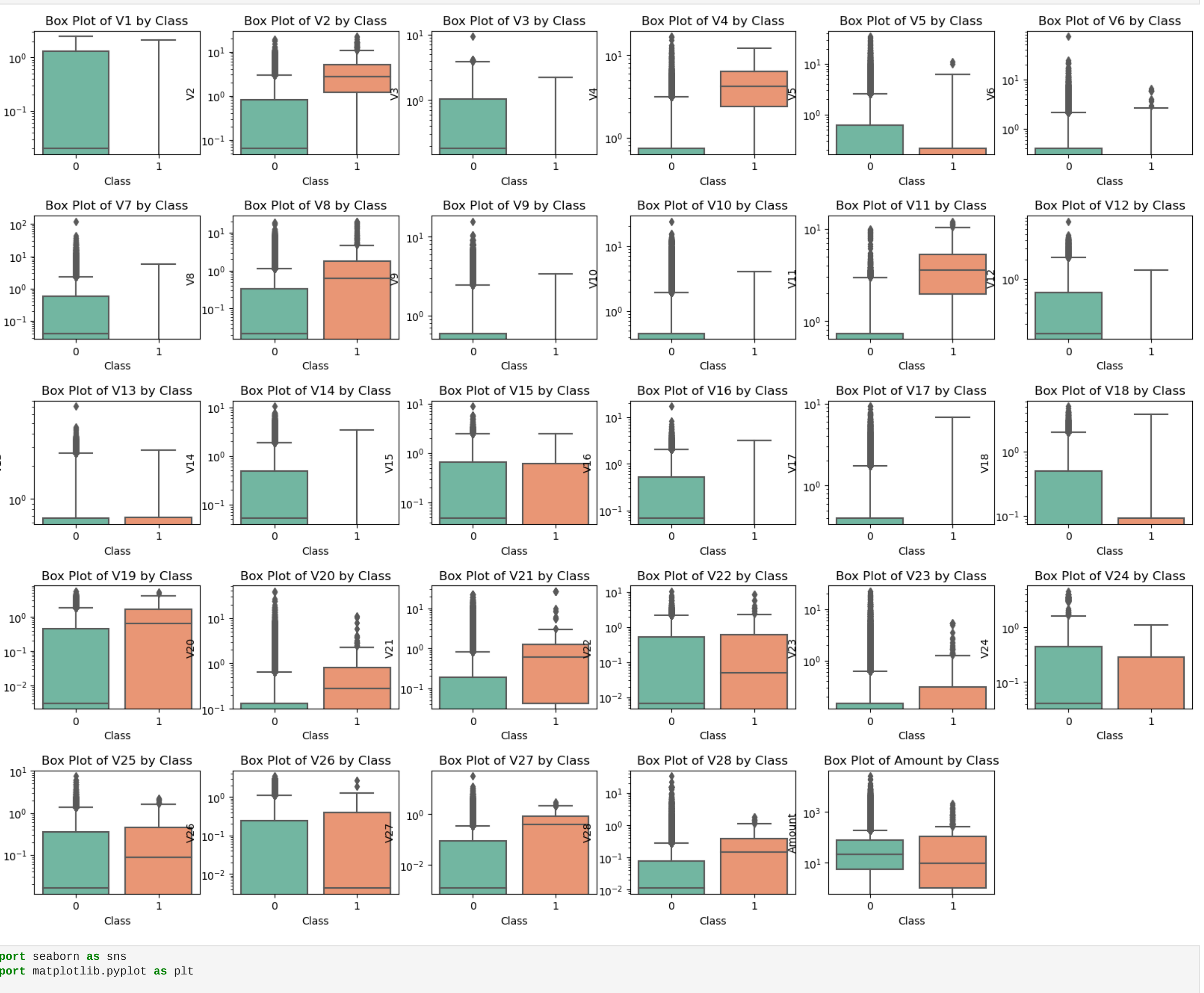


In [8]:
```python
import matplotlib.pyplot as plt

# Count the number of fraud and valid transactions
fraud_count = len(data[data['Class'] == 1])
valid_count = len(data[data['Class'] == 0])

# Create data for the pie chart
labels = 'Fraud', 'Valid'
sizes = [fraud_count, valid_count]
colors = ['red', 'green']
explode = (0.1, 0)  # Explode the 'Fraud' slice for emphasis (optional)

# Create the pie chart
plt.figure(figsize=(8, 8))
plt.pie(sizes, explode=explode, labels=labels, colors=colors, autopct='%1.1f%%', shadow=True, startangle=140)
plt.axis('equal')  # Equal aspect ratio ensures that the pie chart is circular.

# Add a title
plt.title("Class Distribution in the Dataset")

# Display the pie chart
plt.show()
```

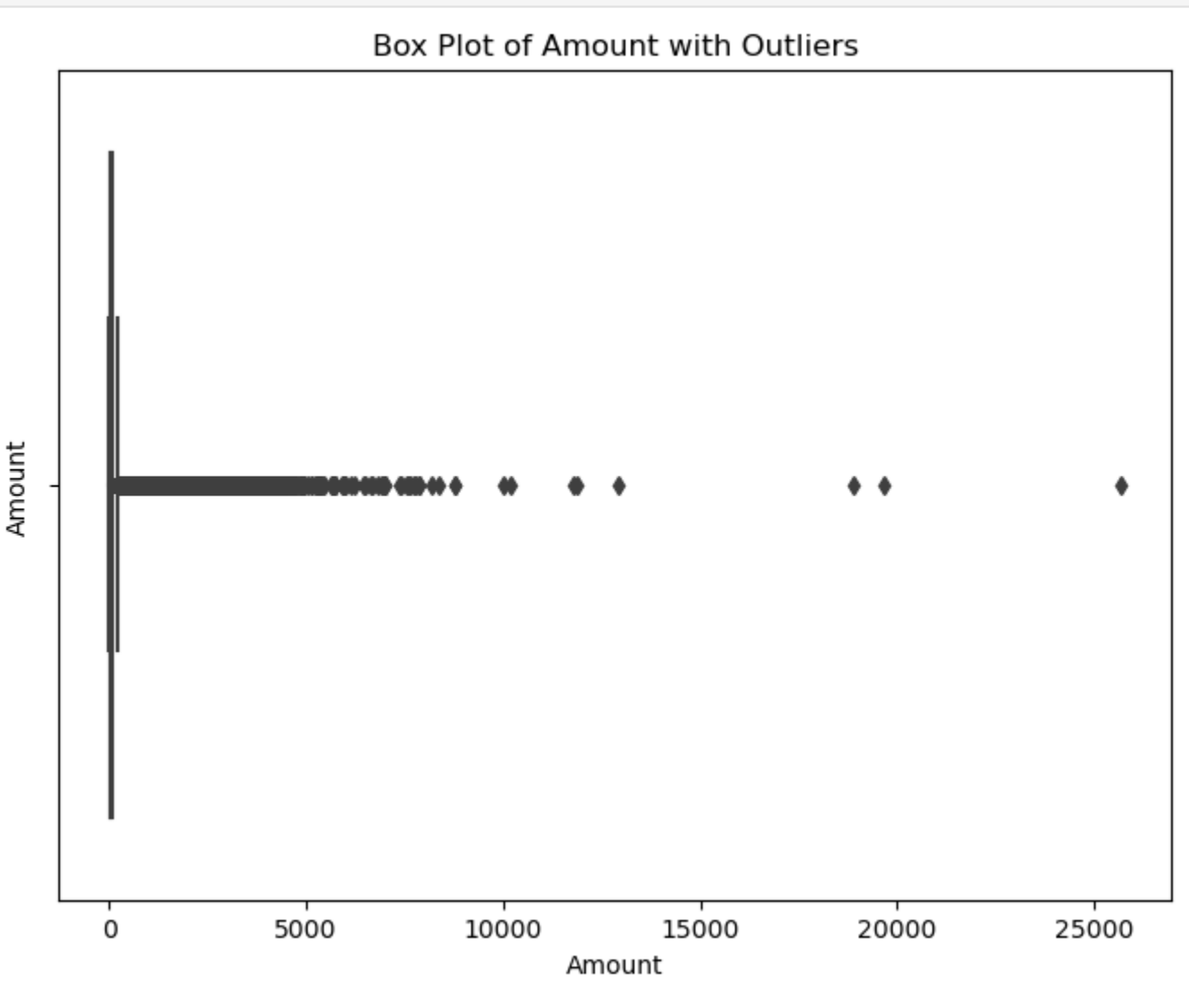


From the above information we came to know that dataset is imbalanced

In [18]:
```python
# Create a figure with subplots
plt.figure(figsize=(20, 15))
plt.subplots_adjust(hspace=0.5)

# List of features you want to create box plots for
features = ['V1', 'V2', 'V3','V4','V5','V6','V7','V8','V9','V10','V11','V12','V13','V14','V15','V16','V17',
            'V18','V19','V20','V21','V22','V23','V24','V25','V26','V27','V28', 'Amount']  # Add more features as needed

# Create box plots for each feature
for i, feature in enumerate(features):
    plt.subplot(5, 6, i + 1)
    sns.boxplot(x='Class', y=feature, data=data, palette="Set2")
    plt.title(f'Box Plot of {feature} by Class')
    plt.yscale('log')  # Use a logarithmic scale on the y-axis for better visualization

plt.show()
```



In [10]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Create a boxplot for the 'Amount' column with outliers displayed
plt.figure(figsize=(8, 6))
sns.boxplot(x=data['Amount'], showfliers=True)
plt.title('Box Plot of Amount with Outliers')
plt.ylabel('Amount')
plt.show()
```



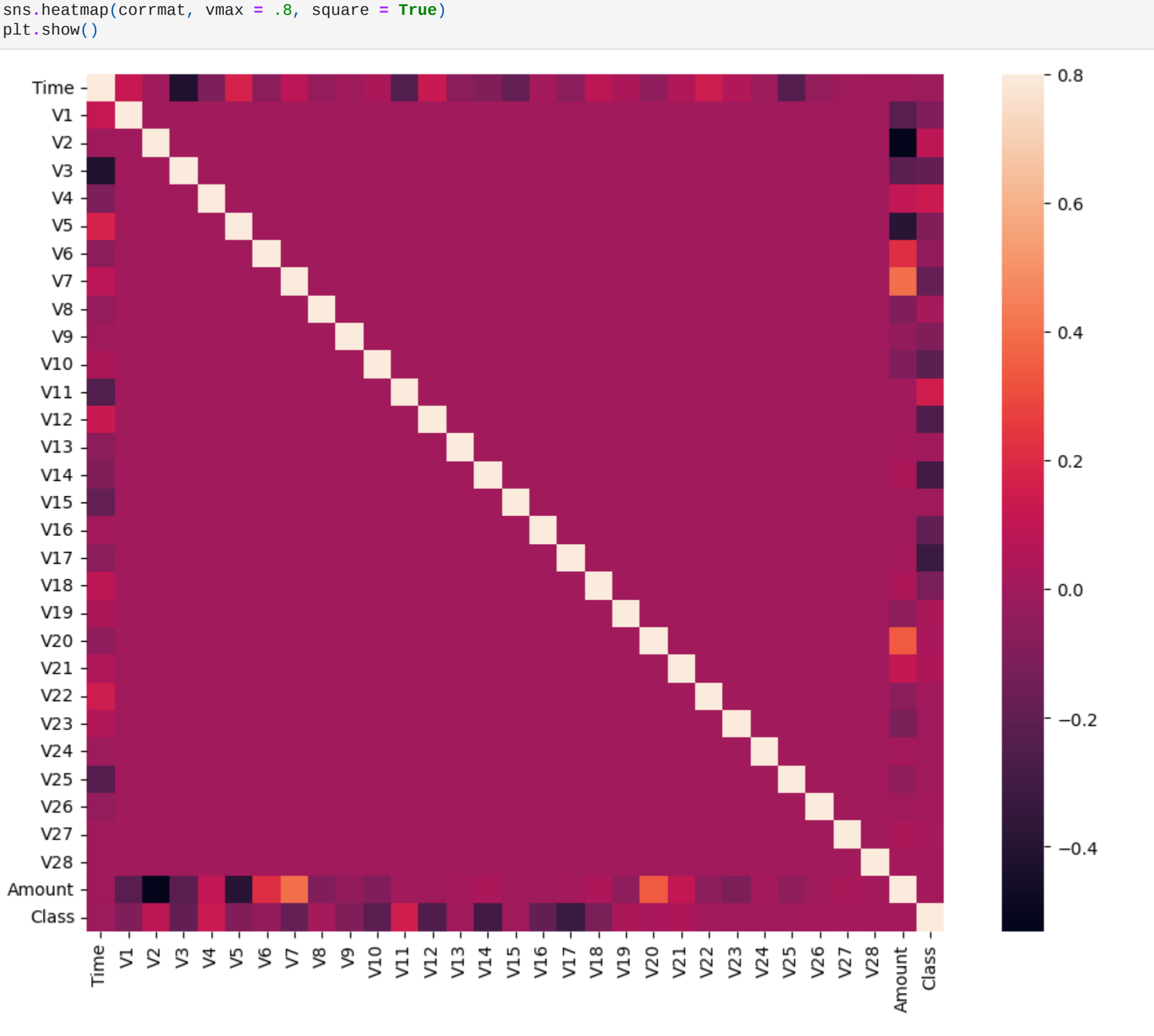
In [11]:
```python
#Fraudulant transaction
print("Amount details of the fraudulent transaction")
fraud.Amount.describe()
```

Out[11]:
```
Amount details of the fraudulent transaction
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

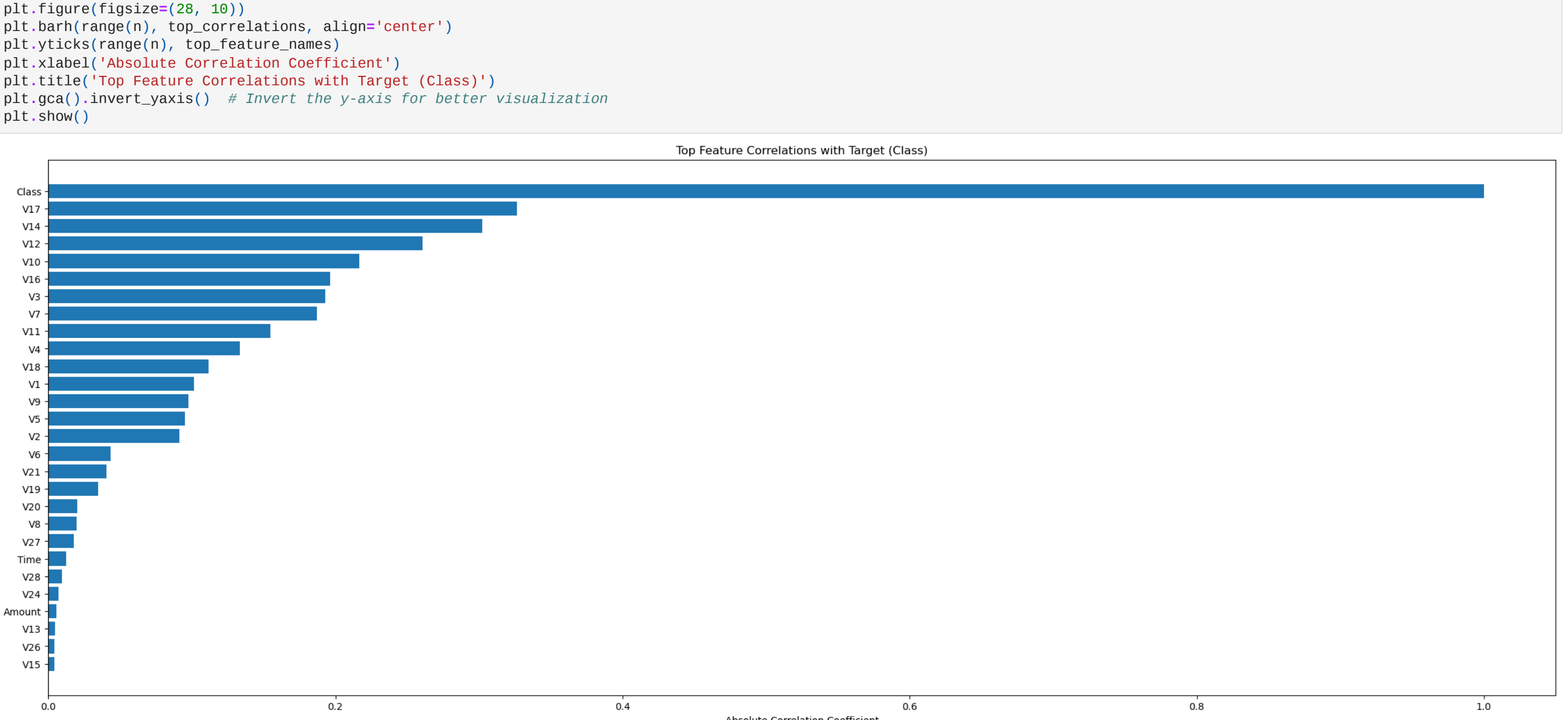
In [12]:
```python
#Normal Transaction
print("details of valid transaction")
valid.Amount.describe()
```

Out[12]:
```
details of valid transaction
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

In [13]:
```python
# Correlation matrix
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



In [14]:
```python
# Calculate the absolute Pearson correlation coefficient between features and the target variable
correlations = data.corrwith(data['Class']).abs()

# Sort feature importances in descending order
sorted_correlations = correlations.sort_values(ascending=False)

# Get the top n important features (e.g., top 10)
n = 28
top_correlations = sorted_correlations[:n]
top_feature_names = top_correlations.index

# Create a bar chart to visualize feature importance
plt.figure(figsize=(28, 10))
plt.barh(range(n), top_correlations, align='center')
plt.yticks(range(n), top_feature_names)
plt.xlabel('Absolute Correlation Coefficient')
plt.title('Top Feature Correlations with Target (Class)')
plt.gca().invert_yaxis()  # Invert the y-axis for better visualization
plt.show()
```



In [15]:
```python
# dividing the X and the Y from the dataset
X = data.drop(['Class'], axis = 1)
Y = data["Class"]
print(X.shape)
print(Y.shape)
# getting just the values for the sake of processing
# (its a numpy array with no columns)
xData = X.values
yData = Y.values
```

```
(284807, 30)
(284807,)
```

In [16]:
```python
# Split the data into training and testing sets
xTrain, xTest, yTrain, yTest = train_test_split(xData, yData, test_size = 0.2, random_state = 42)
```

In [ ]: