CREDIT CARD FRAUD DETECTION

DATA COLLECTION AND DATA PREPARATION

Import Libraries

In [1]:
```
#import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sqlalchemy import create_engine
from sklearn.preprocessing import StandardScaler
```

Database connection and load data

In [2]:
```
#create SQLAlchemy engine
engine = create_engine('postgresql+psycopg2://postgres:admin@localhost:5432/fraud_detectionDB')
```

✅ Deliverable: Data successfully stored in PostgreSQL, schema applied

In [3]:
```
# read data into pandas
df = pd.read_sql_query("SELECT * FROM cc_data", engine)
```

In [4]:
```
# View top rows
print(df.head())
```

```
   time        v1        v2        v3        v4        v5        v6        v7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599   
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803   
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461   
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609   
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941   

         v8        v9  ...       v21       v22       v23       v24       v25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928  0.128539   
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846  0.167170   
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -0.327642   
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575  0.647376   
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -0.206010   

        v26       v27       v28  amount  class  
0 -0.189115  0.133558 -0.021053  149.62      0  
1  0.125895 -0.008983  0.014724    2.69      0  
2 -0.139097 -0.055353 -0.059752  378.66      0  
3 -0.221929  0.062723  0.061458  123.50      0  
4  0.502292  0.219422  0.215153   69.99      0  

[5 rows x 31 columns]
```

Data Profiling

In [5]:

```
print("Dataset Information")
print(df.info())
```

```
Dataset Information
<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
None
```

In [6]:
```
# List all columns in the dataset.
print("Columns in Dataset")
print(df.columns)
```

```
Columns in Dataset
Index(['time', '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',
       'class'],
      dtype='object')
```

In [7]:
```
print("\nData shape:", df.shape)
```

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

In [8]:
```
# Count and print missing values per column
print(df.isnull().sum())
```

```
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
```

Data Cleaning

In [9]:

```
# Check unique values & class balance

print("\nUnique values in 'Class':", df['class'].unique())
print("\nClass distribution (counts):")
```

```python
print(df['class'].value_counts())
print("\nClass distribution (percentage):")
print(df['class'].value_counts(normalize=True) * 100)
```

```
Unique values in 'Class': [0 1]

Class distribution (counts):
class
0    284315
1       492
Name: count, dtype: int64

Class distribution (percentage):
class
0    99.827251
1     0.172749
Name: proportion, dtype: float64
```

RESULT

So there are 284,315 normal transactions and 492 fraud transaction. The dataset is heavily imbalanced.

In [44]:
```python
# Simple textual report
# ---------------------------
fraud_count = df['class'].value_counts()[1]
normal_count = df['class'].value_counts()[0]

print("Quick Report Summary:")
print(f"Total transactions: {len(df)}")
print(f"Normal transactions: {normal_count}")
print(f"Fraud transactions: {fraud_count}")
print(f"Fraud Rate: {100 * fraud_count / len(df):.4f}%")

print("\nData is ready for modeling or deeper insights ")
```

```
Quick Report Summary:
Total transactions: 284807
Normal transactions: 284315
Fraud transactions: 492
Fraud Rate: 0.1727%

Data is ready for modeling or deeper insights
```

Data Validation

In [45]:
```
# Data validation on SQL and Python
df = pd.read_sql("SELECT COUNT(*) FROM cc_data", engine)
print("SQL:", df)
print(f"✅ Row count validation passed: {df.shape[0]} rows match SQL.")
```

```
SQL:      count
0  284807
✅ Row count validation passed: 1 rows match SQL.
```

Report Genration

1. Dataset Identification ✅
2. Data Import into SQL ✅
3. Normalization into relational tables : our table is flat table. No normalization. As data didn’t require normalization as each row is an independent transaction. ✅
4. Initial SQL Profiling (SQL+Python) ✅
5. Data Cleaning & Transformation (Python): Nulls (none found), Duplicates (kept fraud class and non-fraud duplicates), Cleaning on Task 3 ✅
6. Data Validation ✅
7. Final Deliverable : Cleaned dataset on task 3 ✅

EXPLORATORY DATA ANALYSIS AND VISUALIZATION

Summary Statistics

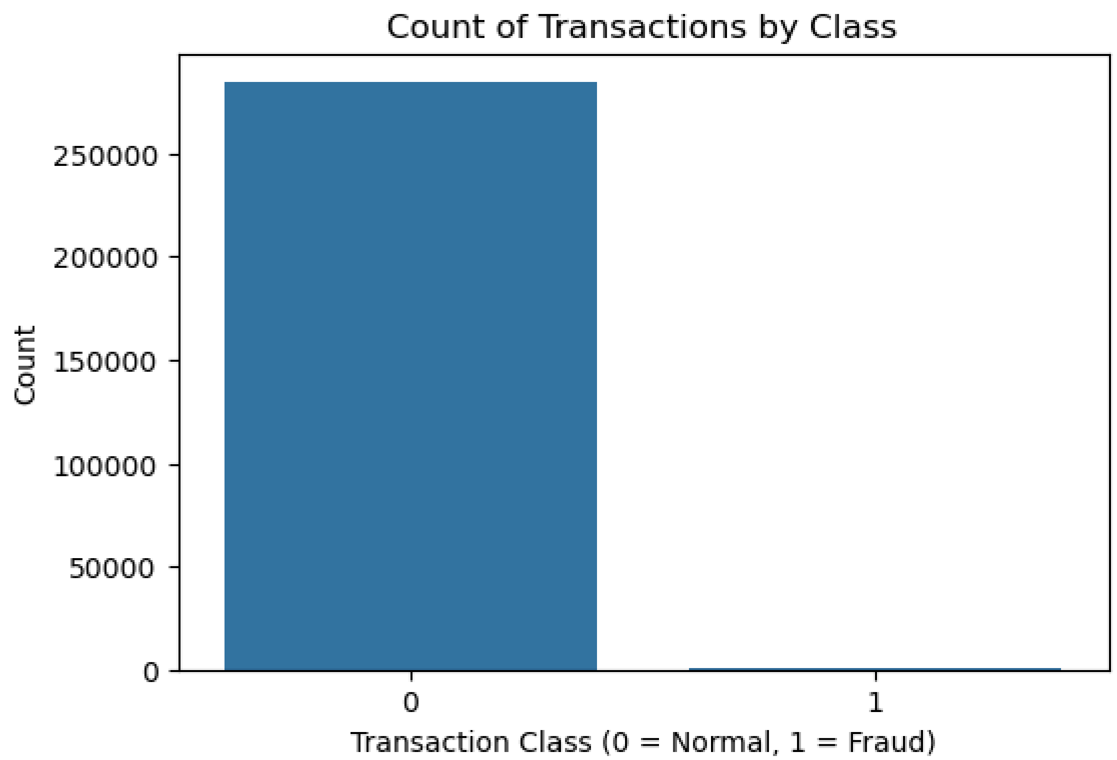
In [10]:
```
# Explorartory data analysis

print("\nStatistical summary:")
print(df.describe())
```

```
Statistical summary:
                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  1.205498e-16 -2.406306e-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   ...  1.656562e-16 -3.568593e-16  2.610582e-16  4.473066e-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   5.213180e-16  1.683537e-15 -3.659966e-16 -1.223710e-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]
```

Univariate Analysis

In [11]:
```python
# Distribution of normal transaction and fraud transaction

plt.figure(figsize=(6, 4))
sns.countplot(x='class', data=df)
plt.title('Count of Transactions by Class')
plt.xlabel('Transaction Class (0 = Normal, 1 = Fraud)')
plt.ylabel('Count')
plt.show()
```



In [12]:
```
# Count and print unique transaction amounts
print(df["amount"].value_counts())
```

```
amount
1.00      13688
1.98       6044
0.89       4872
9.99       4747
15.00      3280
          ...
202.24        1
252.85        1
615.52        1
180.93        1
807.48        1
Name: count, Length: 32767, dtype: int64
```

In [13]:

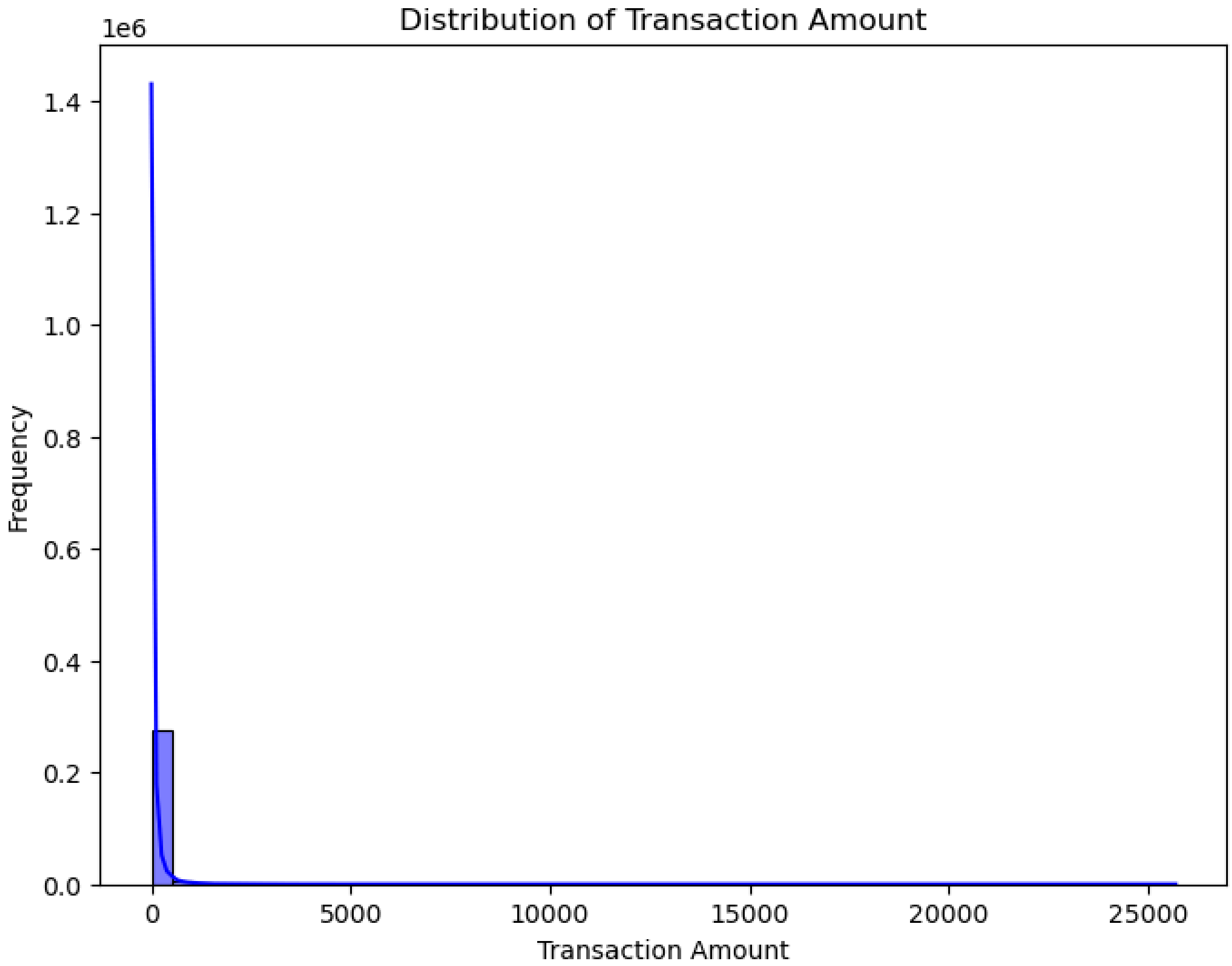
```
# Show percentage distribution of transaction amounts
df["amount"].value_counts(normalize=True)
```

Out[13]:

```
amount
1.00      0.048061
1.98      0.021221
0.89      0.017106
9.99      0.016667
15.00     0.011517
            ...
202.24    0.000004
252.85    0.000004
615.52    0.000004
180.93    0.000004
807.48    0.000004
Name: proportion, Length: 32767, dtype: float64
```

In [14]:

```
# Distribution of transaction Amount

plt.figure(figsize=(8, 6))
sns.histplot(df['amount'], bins=50, kde=True, color='blue')
plt.title('Distribution of Transaction Amount')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.show()
```



In [15]:
```
# Count and print unique transaction times (duration)
print(df["time"].value_counts())
```

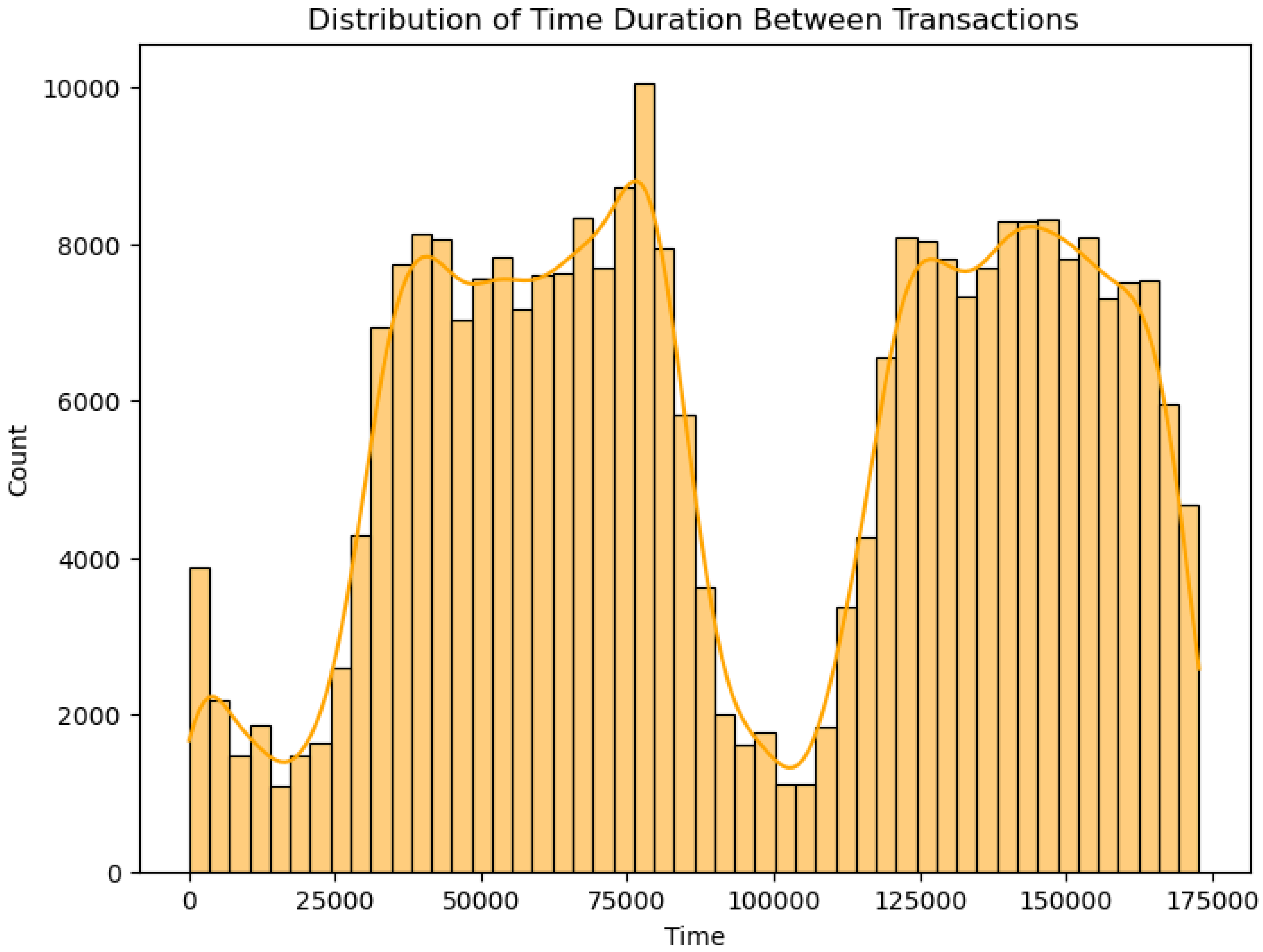
```
time
163152.0    36
64947.0     26
68780.0     25
3767.0      21
3770.0      20
            ..
172760.0     1
172758.0     1
172757.0     1
172756.0     1
172754.0     1
Name: count, Length: 124592, dtype: int64
```

In [16]:
```
# Show percentage distribution of transaction times (duration)
df["time"].value_counts(normalize=True)
```

Out[16]:
```
time
163152.0    0.000126
64947.0     0.000091
68780.0     0.000088
3767.0      0.000074
3770.0      0.000070
              ...
172760.0    0.000004
172758.0    0.000004
172757.0    0.000004
172756.0    0.000004
172754.0    0.000004
Name: proportion, Length: 124592, dtype: float64
```

In [17]:
```
# Distribution of Time duration between transactions

plt.figure(figsize=(8,6))
sns.histplot(df["time"], bins=50, kde=True, color="orange")
plt.title("Distribution of Time Duration Between Transactions")
plt.xlabel("Time")
plt.ylabel("Count")
```

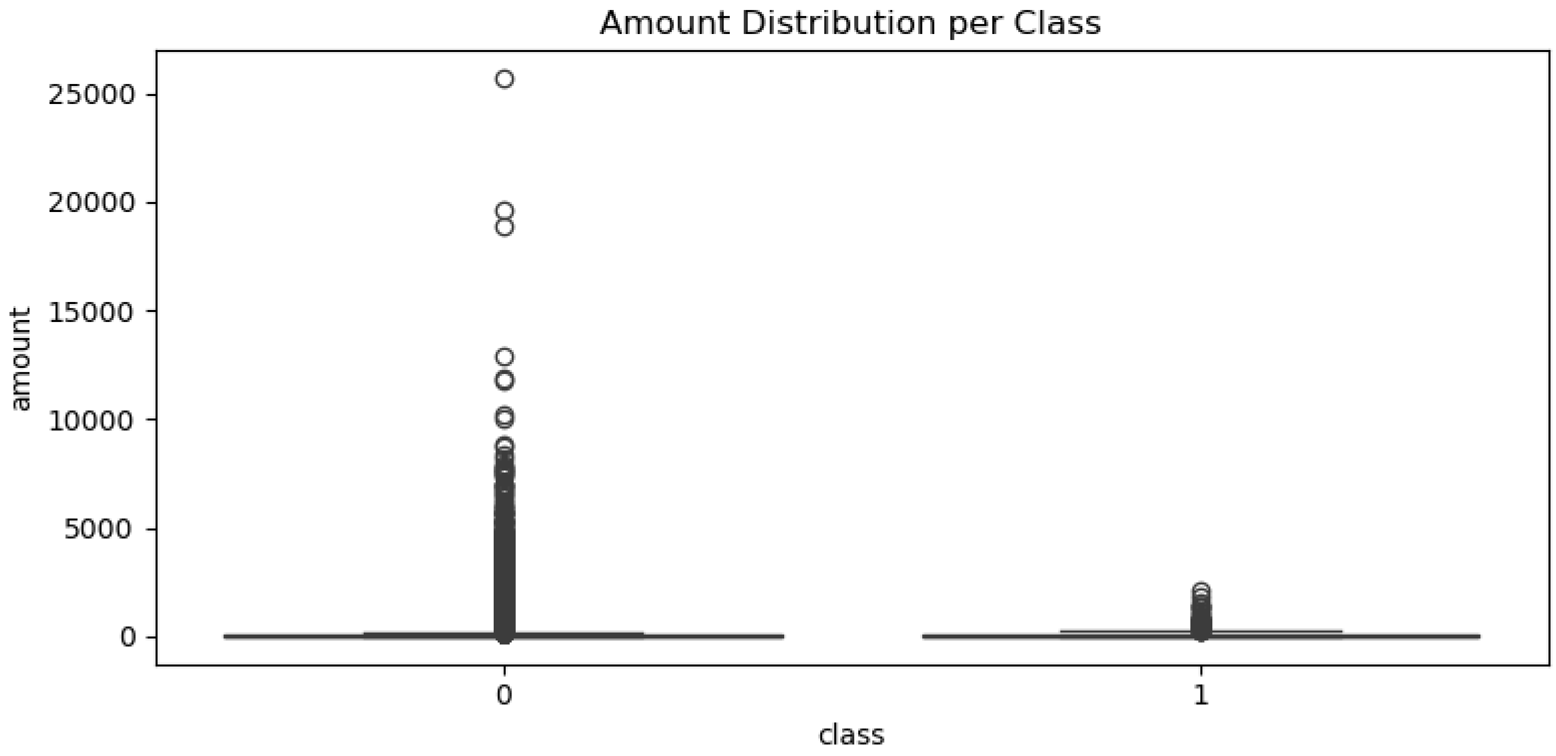
Out[17]:
```
Text(0, 0.5, 'Count')
```

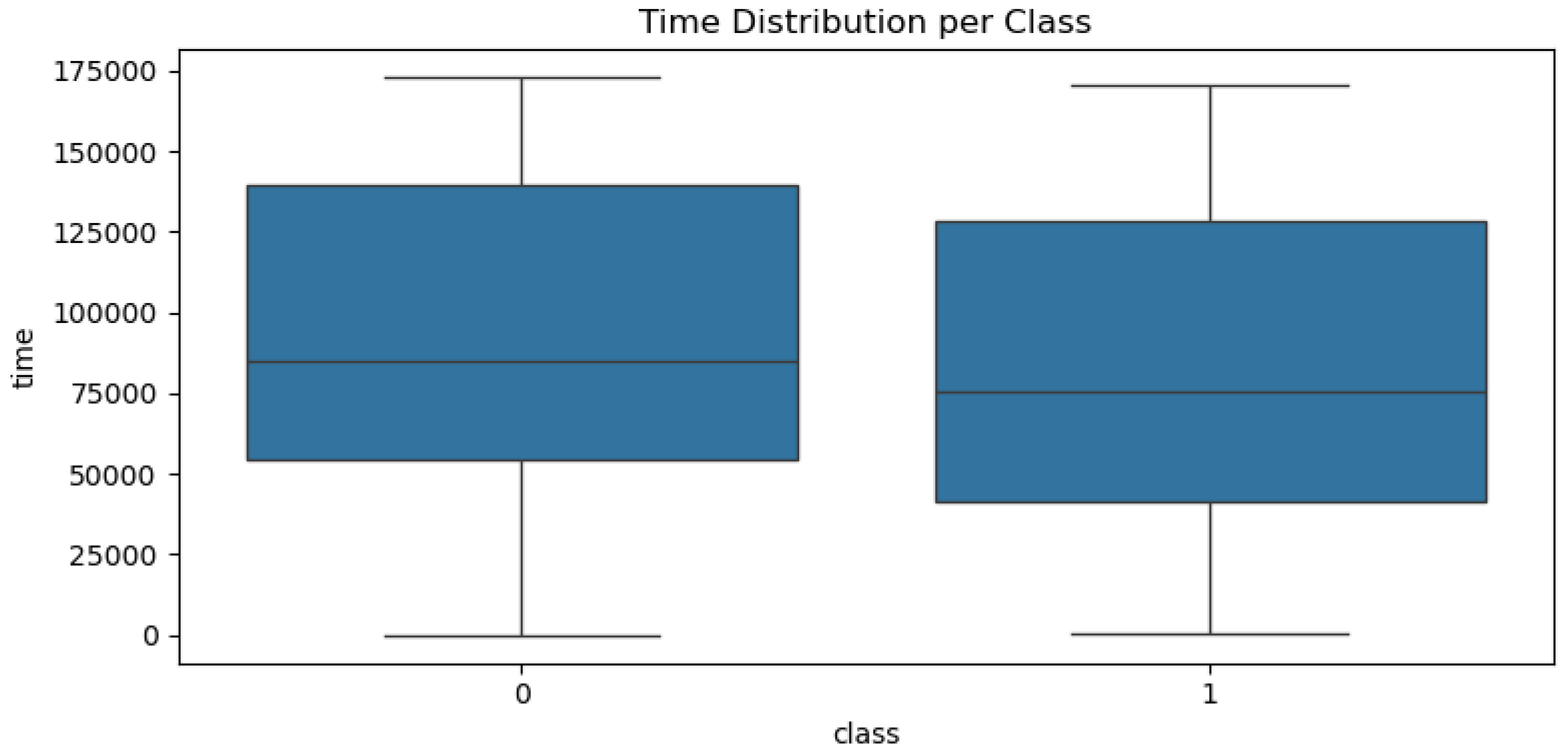


Bivariate/ Multivariate Analysis

In [18]:
```
# Distribution of Time and Amount per Class (0=non-fraud, 1=fraud case)

# Boxplot Figure 1: Amount vs Class
```

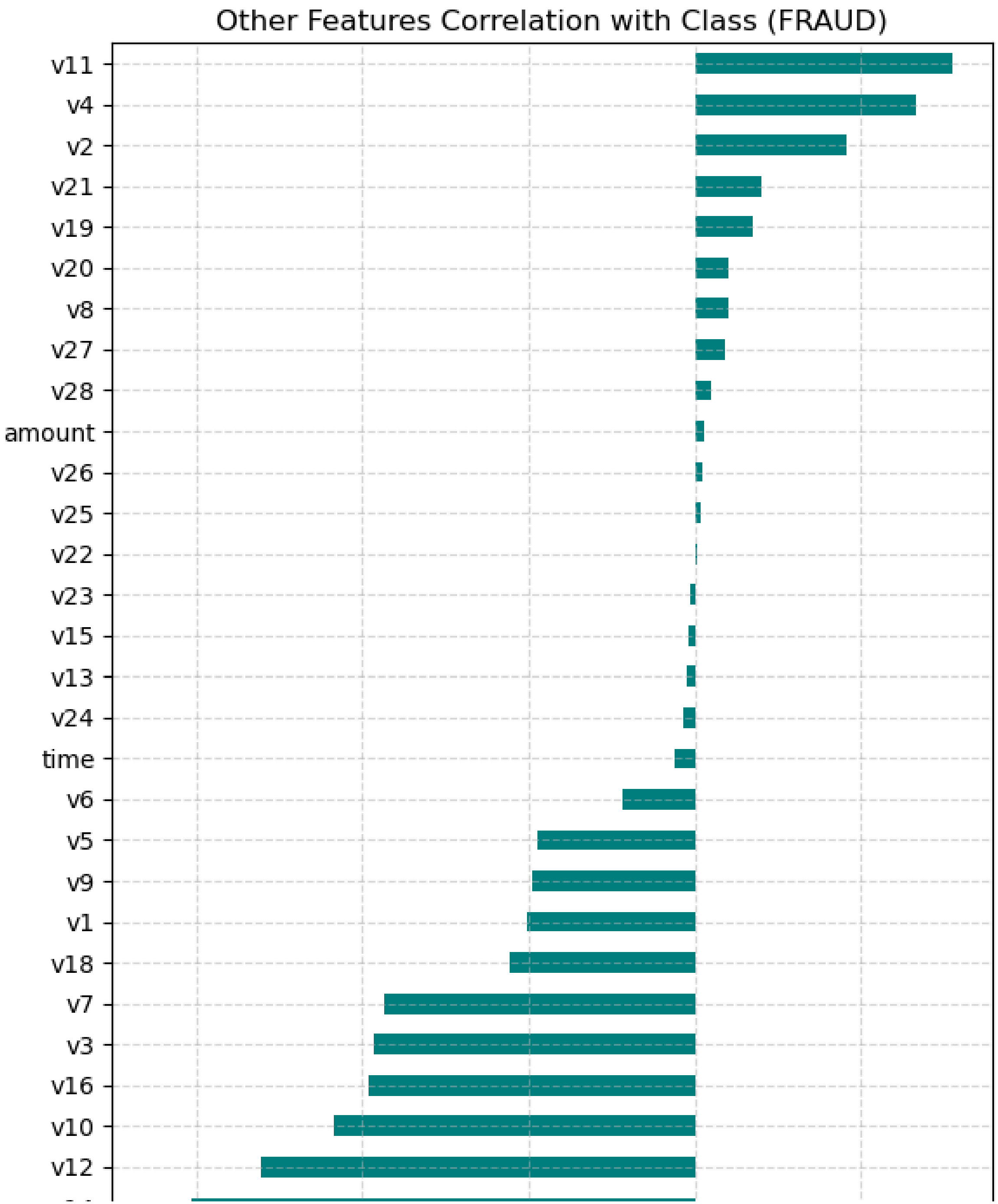
```
plt.figure(figsize=(8,4))
sns.boxplot(x="class", y="amount", data=df)
plt.title("Amount Distribution per Class")
plt.tight_layout()
plt.show()

# Boxplot Figure 2: Time vs Class

plt.figure(figsize=(8,4))
sns.boxplot(x="class", y="time", data=df)
plt.title("Time Distribution per Class")
plt.tight_layout()
plt.show()
```



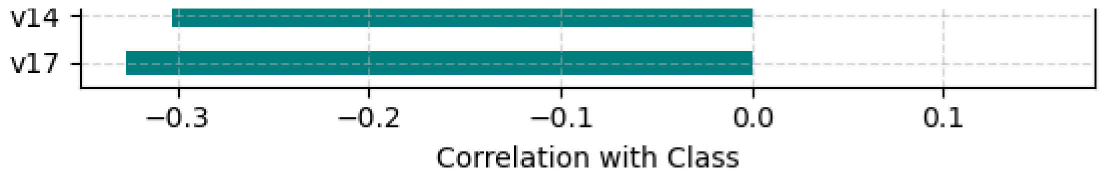


In [19]:

```
# Correlation between Features and Class 1 (Fraud)

correlations = df.corr()["class"].drop("class").sort_values()

plt.figure(figsize=(6, 8))
correlations.plot(kind="barh", color="teal")

plt.title("Other Features Correlation with Class (FRAUD)")
plt.xlabel("Correlation with Class")
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```



Other Features Correlation with Class (FRAUD)
v11
v4
v2
v21
v19
v20
v8
v27
v28
amount
v26
v25
v22
v23
v15
v13
v24
time
v6
v5
v9
v1
v18
v7
v3
v16
v10
v12



DATA PREPARATION

In [20]:
```
# 1.Handling missing values.
df.isnull().sum()
```

Out[20]:

```
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
```

In [21]:

```
# 2.Handling duplicated values.

# Show all rows that are duplicates (keeping and showing all occurrences)
df[df.duplicated(keep=False)]
```

Out[21]:

	time	v1	v2	v3	v4	v5	v6	v7	v8	v9	...	v21	v22
32	26.0	-0.529912	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.286717	...	0.046949	0.208105
33	26.0	-0.529912	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.286717	...	0.046949	0.208105
34	26.0	-0.535388	0.865268	1.351076	0.147575	0.433680	0.086983	0.693039	0.179742	-0.285642	...	0.049526	0.206537
35	26.0	-0.535388	0.865268	1.351076	0.147575	0.433680	0.086983	0.693039	0.179742	-0.285642	...	0.049526	0.206537
112	74.0	1.038370	0.127486	0.184456	1.109950	0.441699	0.945283	-0.036715	0.350995	0.118950	...	0.102520	0.605089
...	...	...	...	...	...	...	...	...	...	...	...	...	...
283485	171627.0	-1.457978	1.378203	0.811515	-0.603760	-0.711883	-0.471672	-0.282535	0.880654	0.052808	...	0.284205	0.949659
284190	172233.0	-2.667936	3.160505	-3.355984	1.007845	-0.377397	-0.109730	-0.667233	2.309700	-1.639306	...	0.391483	0.266536
284191	172233.0	-2.667936	3.160505	-3.355984	1.007845	-0.377397	-0.109730	-0.667233	2.309700	-1.639306	...	0.391483	0.266536
284192	172233.0	-2.691642	3.123168	-3.339407	1.017018	-0.293095	-0.167054	-0.745886	2.325616	-1.634651	...	0.402639	0.259746
284193	172233.0	-2.691642	3.123168	-3.339407	1.017018	-0.293095	-0.167054	-0.745886	2.325616	-1.634651	...	0.402639	0.259746

1854 rows × 31 columns

In [22]:

```
# Show duplicates based only on Time, Amount, and Class features
df[df.duplicated(subset=["time", "amount", "class"], keep=False)]
```

Out[22]:

	time	v1	v2	v3	v4	v5	v6	v7	v8	v9	...	v21	v2
32	26.0	-0.529912	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.286717	...	0.046949	0.20810
33	26.0	-0.529912	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.286717	...	0.046949	0.20810
34	26.0	-0.535388	0.865268	1.351076	0.147575	0.433680	0.086983	0.693039	0.179742	-0.285642	...	0.049526	0.20653
35	26.0	-0.535388	0.865268	1.351076	0.147575	0.433680	0.086983	0.693039	0.179742	-0.285642	...	0.049526	0.20653
108	73.0	1.162281	1.248178	-1.581317	1.475024	1.138357	-1.020373	0.638387	-0.136762	-0.805505	...	-0.124012	-0.22715
...	...	...	...	...	...	...	...	...	...	...	...	...	...
284193	172233.0	-2.691642	3.123168	-3.339407	1.017018	-0.293095	-0.167054	-0.745886	2.325616	-1.634651	...	0.402639	0.25974
284248	172273.0	-0.765414	1.343887	-0.306101	-0.645545	-0.067358	-1.172196	0.516073	0.342927	0.368227	...	-0.289752	-0.70988
284251	172273.0	2.061056	-0.077031	-1.068720	0.422266	-0.181192	-1.227747	0.160285	-0.314824	0.596385	...	-0.292782	-0.72755
284328	172348.0	2.064806	0.008284	-2.226901	0.926502	1.119908	0.178604	0.349210	-0.010441	0.262333	...	0.006761	0.08782
284329	172348.0	-1.351689	1.969541	-2.145252	-0.866654	0.438384	-0.124297	-0.245481	1.404284	-0.342847	...	-0.296305	-1.00713

8736 rows × 31 columns

DATA CLEANING

In [23]:

```
# Count the total number of duplicated rows (keeping the first occurrence as non-duplicate)
df.duplicated().sum()
```

Out[23]: np.int64(1081)

In [24]:

```
# Count the total number of duplicated rows (marking all duplicates as True)
df.duplicated(keep=False).sum()
```

Out[24]: np.int64(1854)

In [25]:
```
# Count the number of unique duplicated rows (after dropping exact duplicates)
df[df.duplicated(keep=False)].drop_duplicates().shape[0]
```

Out[25]:
```
773
```

In [26]:
```
# Show the distribution of Class values among duplicated rows
df[df.duplicated(keep=False)]["class"].value_counts()
```

Out[26]:
```
class
0    1822
1      32
Name: count, dtype: int64
```

Observation

There are 1,822 duplicats on Class 0 (normal) and 32 duplicats on Class 1 (fraud).

Since Class 1 has few duplicats, I decided not too drop the duplicats.

I will only drop the duplicats from Class 0.

In [30]:
```
# Separating Class between 0 and 1
fraud = df[df["class"] == 1]
normal = df[df["class"] == 0]

# Drop duplicated values from Class 0 only
normal_cleaned = normal.drop_duplicates()

# Combined both Classes and renamed the dataset as df_cleaned

# Duplicated values of Class 0 have been dropped from the dataset
df_cleaned = pd.concat([fraud, normal_cleaned], ignore_index=True)
```

In [31]:
```
# Count duplicates in the cleaned dataset (df_cleaned)
df_cleaned.duplicated().sum()
```

Out[31]:
```
np.int64(19)
```

In [32]:
```python
# Check Class distribution in duplicates of the cleaned dataset
df_cleaned[df_cleaned.duplicated(keep=False)]["class"].value_counts()
```

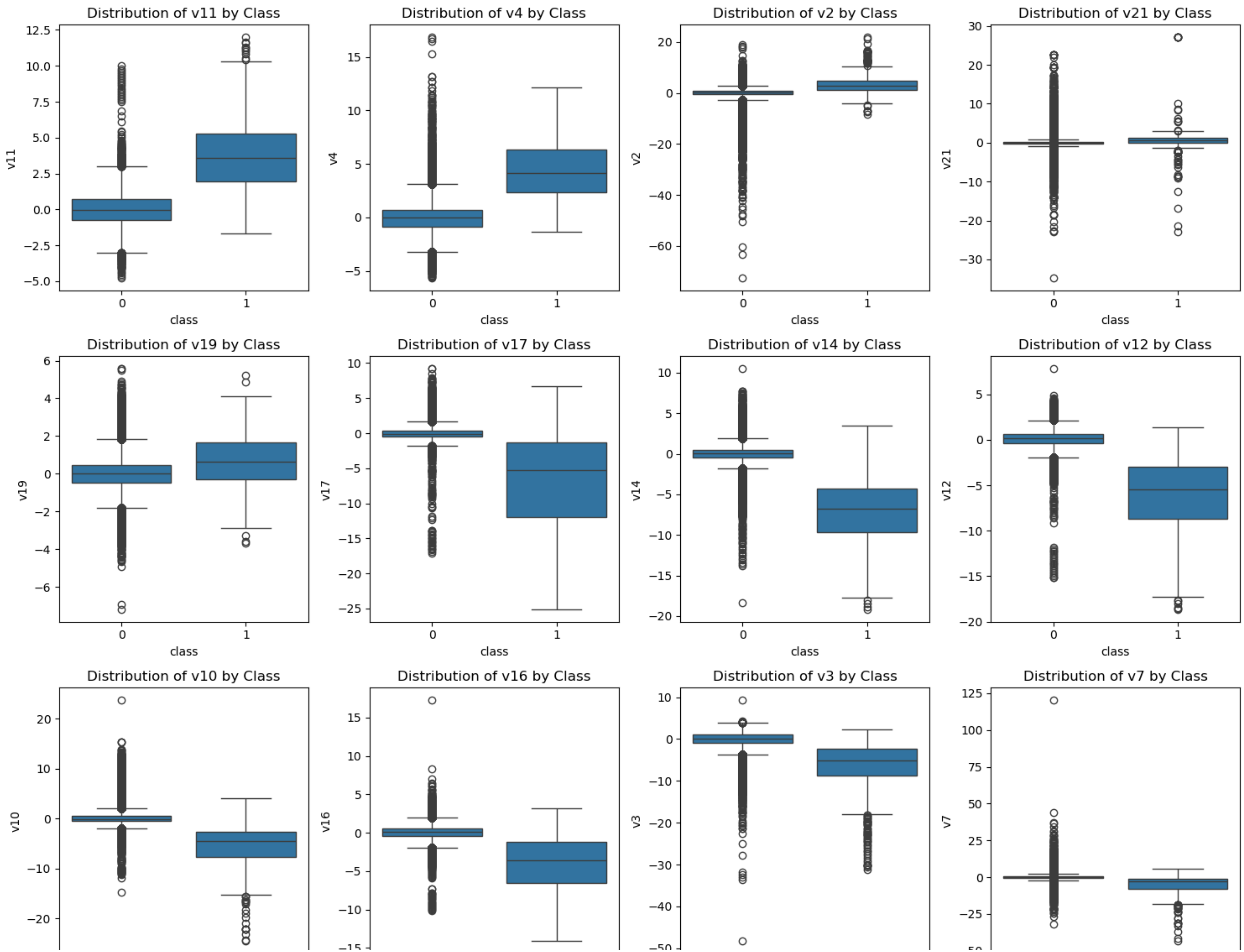
Out[32]:
```
class
1    32
Name: count, dtype: int64
```

In [33]:
```python
# Show the percentage distribution of unique values in the Class feature
df_cleaned["class"].value_counts(normalize=True) * 100
```

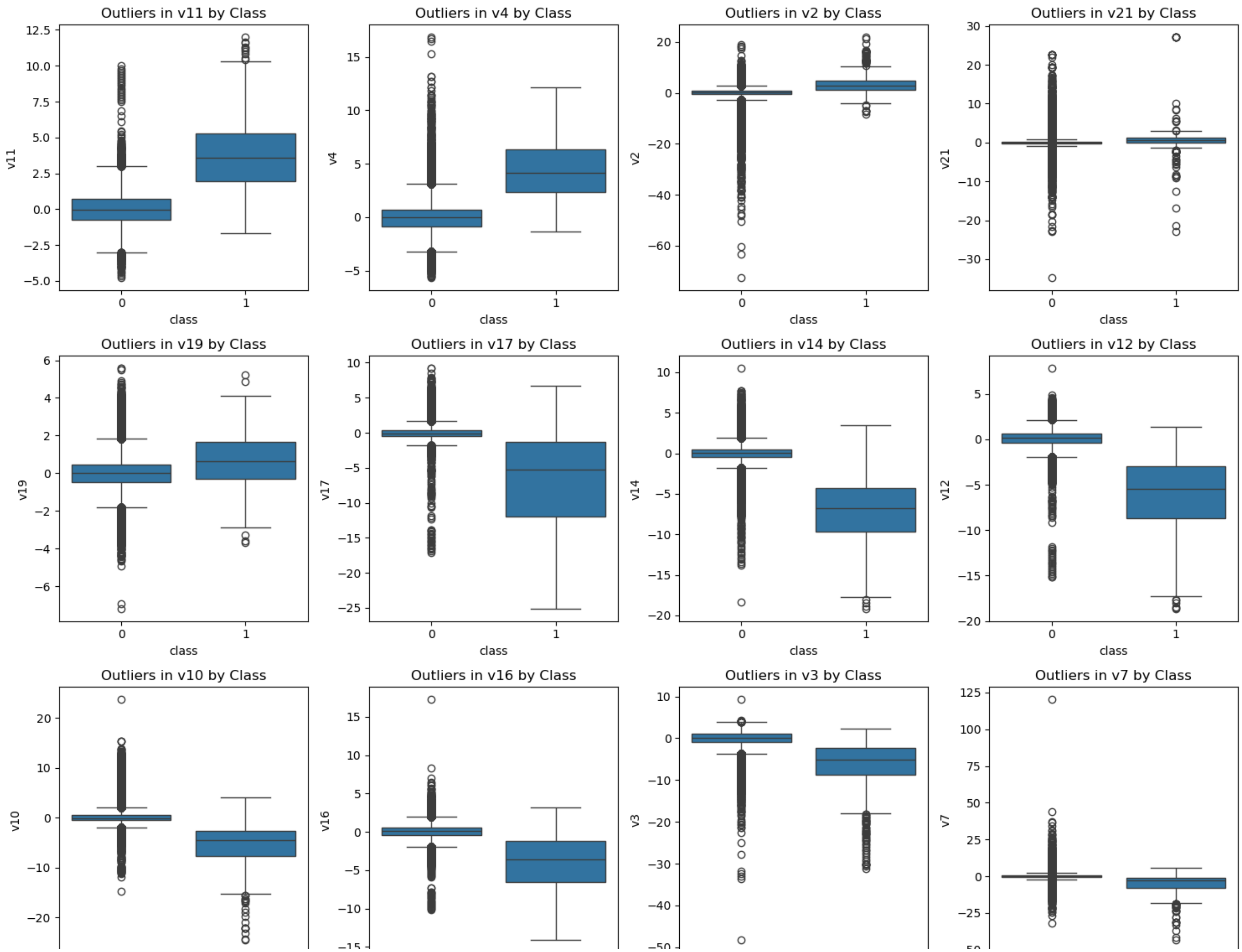
Out[33]:
```
class
0    99.826605
1     0.173395
Name: proportion, dtype: float64
```

Outliers and Anomaly Detection

In [39]:
```python
#CHECKING CLASS DISTRIBUTION:

# A. Feature Distribution between Fraud and Non-fraud Transactions

# Selected features based on Strongest Positive and Strongest Negative correlations with Class

selected_features = ['v11', 'v4', 'v2', 'v21', 'v19', # Strong Positive
                     'v17', 'v14', 'v12', 'v10', 'v16', 'v3', 'v7']  # Strong Negative

plt.figure(figsize=(15, 12))
for i, feature in enumerate(selected_features, 1):
    plt.subplot(3, 4, i)
    sns.boxplot(data=df_cleaned, x='class', y=feature)
    plt.title(f'Distribution of {feature} by Class')
plt.tight_layout()
plt.show()
```

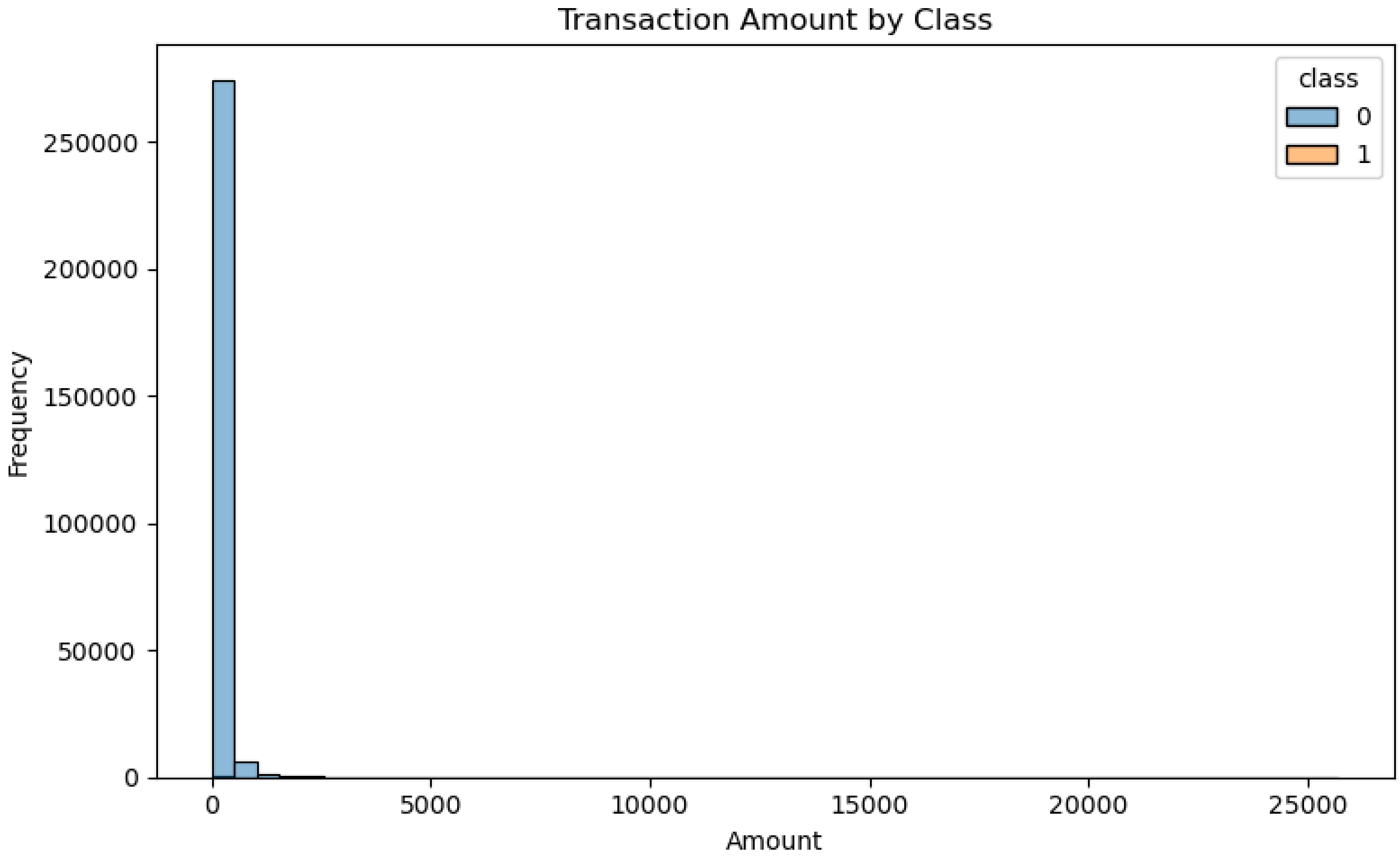

Distribution of v11 by Class
Distribution of v4 by Class
Distribution of v2 by Class
Distribution of v21 by Class
Distribution of v19 by Class
Distribution of v17 by Class
Distribution of v14 by Class
Distribution of v12 by Class
Distribution of v10 by Class
Distribution of v16 by Class
Distribution of v3 by Class
Distribution of v7 by Class
class

In [40]:
```
# B. Outlier Visualization with Boxplots

plt.figure(figsize=(15, 12))
for i, feature in enumerate(selected_features, 1):
    plt.subplot(3, 4, i)
    sns.boxplot(data=df_cleaned, x='class', y=feature)
    plt.title(f'Outliers in {feature} by Class')
plt.tight_layout()
plt.show()
```


Outliers in v11 by Class
v11
class
Outliers in v4 by Class
v4
class
Outliers in v2 by Class
v2
class
Outliers in v21 by Class
v21
class
Outliers in v19 by Class
v19
class
Outliers in v17 by Class
v17
class
Outliers in v14 by Class
v14
class
Outliers in v12 by Class
v12
class
Outliers in v10 by Class
v10
Outliers in v16 by Class
v16
Outliers in v3 by Class
v3
Outliers in v7 by Class
v7

In [41]:

```
# C. Histogram for Transaction Amount

plt.figure(figsize=(8, 5))
sns.histplot(df_cleaned, x='amount', hue='class', bins=50)
plt.title('Transaction Amount by Class', fontsize=12)
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



RESULT

- I have decided not to drop any outliers.
- Outliers were retained because they may represent real fraudulent behavior, which is inherently anomalous.
- Removing them could reduce the model's ability to detect rare but significant fraud patterns.

PowerBI Visulization

In [42]:
```
# Find all duplicates (marking all occurrences, not just subsequent ones)
duplicates_df = df[df.duplicated(keep=False)]

# KPIs for duplicates
total_duplicates = duplicates_df.shape[0]          # All duplicates found
duplicate_class_counts = duplicates_df['class'].value_counts()

# Breakdown
duplicate_normal = duplicate_class_counts.get(0, 0)
duplicate_fraud  = duplicate_class_counts.get(1, 0)

# After cleaning
total_after_cleaning = df_cleaned.shape[0]

print(f"Total duplicate records found: {total_duplicates}")
print(f"Duplicates in Normal class: {duplicate_normal}")
print(f"Duplicates in Fraud class: {duplicate_fraud}")
print(f"Total records after cleaning: {total_after_cleaning}")
```

```
Total duplicate records found: 1854
Duplicates in Normal class: 1822
Duplicates in Fraud class: 32
Total records after cleaning: 283745
```

In [43]:
```
# Export to CSV
df_cleaned.to_csv("cleaned_creditcard_data.csv", index=False)
```

POWER BI DATA VISUALIZATION

- Total Transactions - 284,807
- Total Fraud Cases - 492
- Fraud Rate (%) - 0.1727%
- Total Normal Transactions - 284,315
- Average Transaction Amount - 88.35 (currency units)

- Max Transaction Amount -25,691.16
- Min Transaction Amount - 0.00
- ✅ No missing values in dataset.
- ✅ Duplicates found:
- Total Duplicate Records - 1854
- Duplicates in Normal Class - 1822
- Duplicates in Fraud Class - 32
- Total Records After Cleaning - 283746

Final Clean Dataset

- Total Records (after cleaning) 283746
- Fraud Rate (after cleaning) ~0.17% unchanged