



## ✓ Credit Card Fraud Detection

### Import the Data Set

```
from google.colab import files
uploaded = files.upload()
```

 **Choose Files** No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.  
Saving archive (1) zip to archive (1) zip

```
from google.colab import drive
drive.mount('/content/drive')
```


 Mounted at /content/drive

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Load the dataset
data = pd.read_csv('/content/creditcard.csv') # Update the path as necessary
```

### Structure of the Dataset

```
data.info()
```

 `<class 'pandas.core.frame.DataFrame'>`  
RangeIndex: 107046 entries, 0 to 107045  
Data columns (total 31 columns):

#	Column	Non-Null Count	Dtype
0	Time	107046 non-null	int64
1	V1	107046 non-null	float64
2	V2	107046 non-null	float64
3	V3	107046 non-null	float64
4	V4	107046 non-null	float64
5	V5	107046 non-null	float64
6	V6	107046 non-null	float64
7	V7	107046 non-null	float64
8	V8	107046 non-null	float64
9	V9	107046 non-null	float64
10	V10	107046 non-null	float64
11	V11	107046 non-null	float64
12	V12	107046 non-null	float64
13	V13	107046 non-null	float64
14	V14	107046 non-null	float64
15	V15	107046 non-null	float64
16	V16	107046 non-null	float64
17	V17	107046 non-null	float64
18	V18	107046 non-null	float64
19	V19	107046 non-null	float64
20	V20	107046 non-null	float64
21	V21	107046 non-null	float64
22	V22	107046 non-null	float64
23	V23	107046 non-null	float64
24	V24	107046 non-null	float64
25	V25	107046 non-null	float64
26	V26	107046 non-null	float64
27	V27	107046 non-null	float64
28	V28	107045 non-null	float64
29	Amount	107045 non-null	float64
30	Class	107045 non-null	float64

dtypes: float64(30), int64(1)  
memory usage: 25.3 MB

```
# Summary statistics
data_description = data.describe()
print(data_description)
```

Time	count	107046.000000	107046.000000	107046.000000	107046.000000	\	
	mean	44163.193393	-0.257831	-0.026560	0.682250		
	std	17718.024713	1.853150	1.647586	1.317292		
	min	0.000000	-56.407510	-72.715728	-33.680984		
	25%	34238.000000	-1.023275	-0.595414	0.176950		
	50%	46023.000000	-0.260775	0.078063	0.757881		
	75%	58413.750000	1.154981	0.738193	1.383324		
	max	70256.000000	1.960497	18.902453	4.226108		
	V4	count	107046.000000	107046.000000	107046.000000		107046.000000
mean		0.157009	-0.283548	0.098077	-0.116249		
std		1.344114	1.348799	1.299593	1.208427		
min		-5.172595	-42.147898	-26.160506	-31.764946		
25%		-0.712661	-0.906588	-0.645561	-0.605549		
50%		0.184854	-0.318181	-0.154784	-0.071994		
75%		1.024500	0.244910	0.493216	0.409485		
max		16.715537	34.801666	22.529298	36.677268		
V8		count	107046.000000	107046.000000	...	107046.000000	107046.000000
	mean	0.058826	-0.054332	...	-0.030490	-0.106799	
	std	1.232005	1.110405	...	0.741472	0.639652	
	min	-73.216718	-9.283925	...	-34.830382	-10.933144	
	25%	-0.134727	-0.697239	...	-0.224126	-0.533261	
	50%	0.077532	-0.121239	...	-0.056729	-0.082983	
	75%	0.369074	0.542787	...	0.120478	0.314211	
	max	20.007208	10.392889	...	27.202839	10.503090	
	V23	count	107046.000000	107046.000000	107046.000000	107046.000000	\
mean		-0.037448	0.010167	0.133350	0.025764		
std		0.623527	0.595680	0.440034	0.491594		
min		-44.807735	-2.836627	-10.295397	-2.534330		
25%		-0.176768	-0.323162	-0.130802	-0.323569		
50%		-0.049385	0.066011	0.171578	-0.069111		
75%		0.080706	0.407201	0.421048	0.294199		
max		19.002942	4.016342	5.541598	3.517346		
V27		count	107046.000000	107045.000000	107045.000000	107045.000000	
	mean	0.001604	0.001640	96.201778	0.002195		
	std	0.391995	0.320114	261.083669	0.046803		
	min	-9.390980	-9.617915	0.000000	0.000000		
	25%	-0.061142	-0.005091	7.050000	0.000000		
	50%	0.010696	0.023365	25.150000	0.000000		
	75%	0.084614	0.076725	87.000000	0.000000		
	max	12.152401	33.847808	19656.530000	1.000000		

[8 rows x 31 columns]

```
# Correlation matrix
data_correlation = data.corr()
print(data_correlation)
```



```

V0      -0.000091  0.040999  0.000040 -0.000000 -0.010000  0.000000 -0.000000
V7      0.001811 -0.095439 -0.032614 -0.093095 -0.046591  0.385821 -0.245636
V8      0.003615  0.013440  0.006673  0.003476  0.020038 -0.094854  0.059624
V9      0.012819  0.120192  0.109231 -0.032188 -0.026413 -0.019445 -0.114625
V10     0.004346  0.016112 -0.022666 -0.075493 -0.020344 -0.134181 -0.264604
V11     0.036859 -0.103081 -0.004226  0.007644  0.004513 -0.010298  0.181361
V12     0.011362  0.011422  0.024001 -0.022224 -0.005584  0.021705 -0.291451
V13     -0.015258  0.040377  0.000849 -0.001750 -0.004817 -0.005640 -0.002931
V14     0.025787 -0.070869  0.020707 -0.024153  0.013479  0.014753 -0.368841
V15     -0.001174 -0.093143 -0.014780  0.008115 -0.006544 -0.034282  0.001143
V16     -0.005177  0.106066  0.020579 -0.005525 -0.021017 -0.013158 -0.249897
V17     -0.007457 -0.078437 -0.070094 -0.011900 -0.012963  0.017496 -0.404573
V18     -0.019184  0.018809  0.018182 -0.014404 -0.000888  0.048608 -0.154981
V19     -0.011815 -0.008452 -0.002260  0.003989 -0.010012 -0.057533  0.044073
V20     -0.006610 -0.030547  0.002778 -0.027855  0.108452  0.427260  0.012235
V21     -0.000216 -0.012366 -0.026530 -0.015192  0.054282  0.131681  0.088744
V22     0.000614 -0.009072  0.008906 -0.010555 -0.034442 -0.078011 -0.018004
V23     0.004199  0.106387  0.036862 -0.016658  0.027209 -0.138558 -0.005879
V24     1.000000 -0.039003 -0.008761 -0.004799 -0.008779  0.019995 -0.009851
V25     -0.039003  1.000000 -0.112737  0.048402  0.056925 -0.065504  0.008701
V26     -0.008761 -0.112737  1.000000  0.000181  0.001912  0.002163  0.006176
V27     -0.004799  0.048402  0.000181  1.000000 -0.005604  0.012196  0.063883
V28     -0.008779  0.056925  0.001912 -0.005604  1.000000  0.010710  0.009220
Amount  0.019995 -0.065504  0.002163  0.012196  0.010710  1.000000  0.003383
Class   -0.009851  0.008701  0.006176  0.063883  0.009220  0.003383  1.000000

```

[31 rows x 31 columns]

```

# Filter the dataset to only include fraudulent transactions
fraudulent_count = data[data['Class'] == 1]

```

```

# Filter the dataset for fraudulent transactions
fraudulent_data = data[data['Class'] == 1]

```

```

# summary statistics for fraudulent transactions
fraudulent_stats = fraudulent_data['Amount'].describe()
print("Summary Statistics for Fraudulent Transactions:")
print(fraudulent_stats)

```

Summary Statistics for Fraudulent Transactions:

```

count      235.000000
mean       115.033362
std        252.411933
min         0.000000
25%        1.000000
50%         7.580000
75%        99.990000
max       1809.680000
Name: Amount, dtype: float64

```

```

# Checking how many fraudulent transactions there are
fraudulent_count = data['Class'].value_counts()
print(f'Number of Legitimate Transactions: {fraudulent_count[0]}')
print(f'Number of Fraudulent Transactions: {fraudulent_count[1]}')

```

Number of Legitimate Transactions: 106810  
Number of Fraudulent Transactions: 235

```

# Convert 'Time' column to 24-hour format as a string in a new column
fraudulent_data = fraudulent_data.copy() # Create a copy
fraudulent_data['Time_24hr'] = pd.to_datetime(fraudulent_data['Time'], unit='s').dt.strftime('%H:%M:%S')

```

```

# Convert 'Time' to minutes
fraudulent_data['Time_in_minutes'] = fraudulent_data['Time'] / 60 # Retain minutes for plotting

```

```

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set(style='whitegrid')

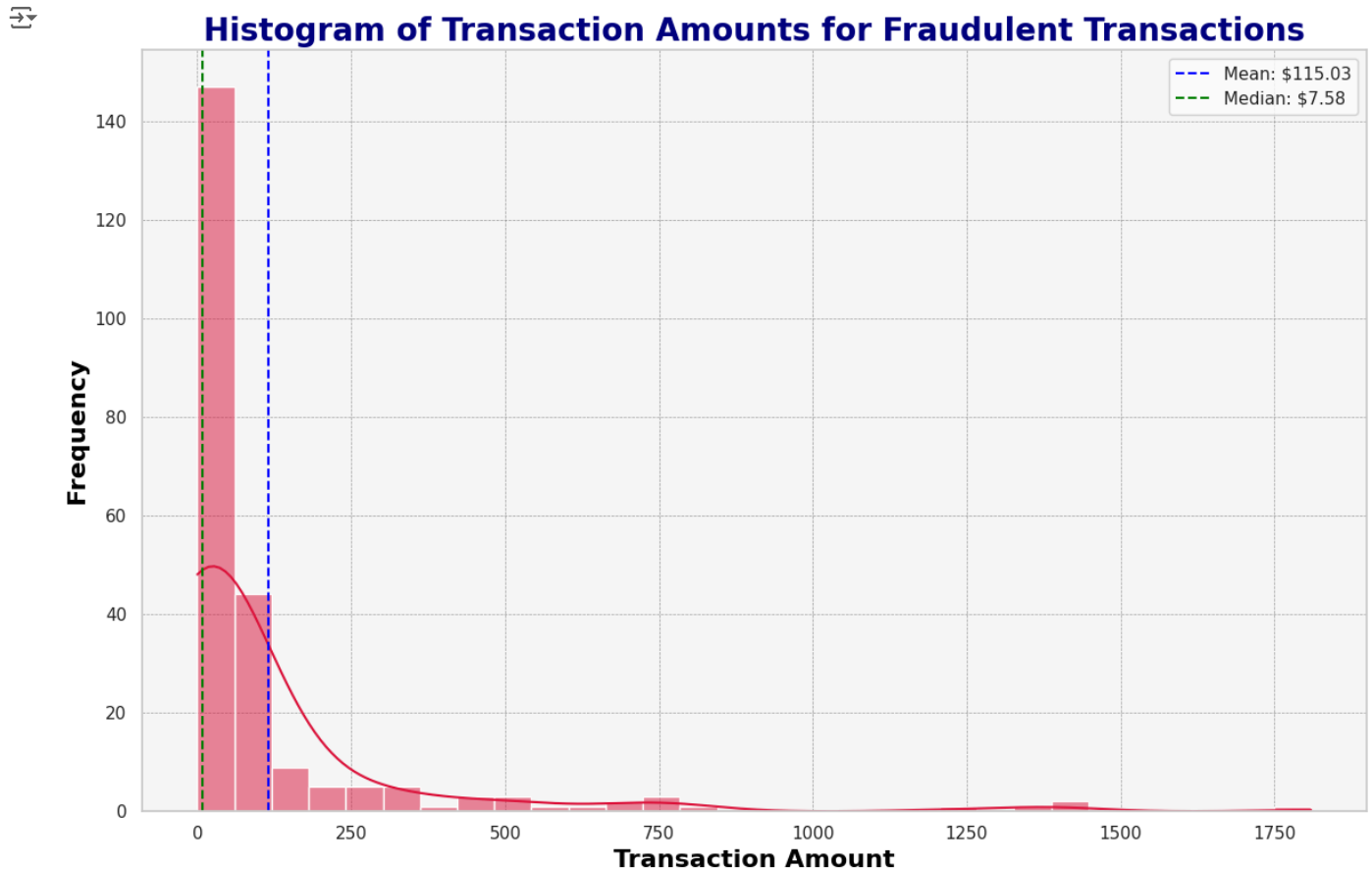
```

```

# Creating the histogram
plt.figure(figsize=(12, 8))
sns.histplot(fraudulent_data['Amount'], bins=30, color='crimson', kde=True)
mean_amount = fraudulent_data['Amount'].mean()
median_amount = fraudulent_data['Amount'].median()
plt.axvline(mean_amount, color='blue', linestyle='--', label=f'Mean: ${mean_amount:.2f}')
plt.axvline(median_amount, color='green', linestyle='--', label=f'Median: ${median_amount:.2f}')
plt.title('Histogram of Transaction Amounts for Fraudulent Transactions', fontsize=20, fontweight='bold', color='navy')

```

```
plt.xlabel('Transaction Amount', fontsize=16, fontweight='bold', color='black')
plt.ylabel('Frequency', fontsize=16, fontweight='bold', color='black')
plt.legend()
plt.grid(color='gray', linestyle='--', linewidth=0.5, alpha=0.7)
plt.gca().set_facecolor('whitesmoke')
plt.tight_layout()
plt.show()
```



*Observation: Most fraudulent transactions are relatively small, with 75% under 105.89. This pattern suggests that fraudsters may opt for smaller amounts to avoid detection. However, there is a broad range in amounts, from \$0 up to 2,125.87, showing that while larger fraud attempts are less frequent, they do occur.*

```
# Convert Time from seconds to 24-hour clock format (HH:MM:SS)
fraudulent_data['Time_24hr'] = pd.to_datetime(fraudulent_data['Time'], unit='s').dt.strftime('%H:%M:%S')
```

```
# Creating hour Column
# Converting tie to hours
data['Hour'] = (data['Time'] // 3600) % 24 # Get the hour in a 24-hour format
```

```
# Filter for fraudulent transactions
fraudulent_data = data[data['Class'] == 1]
```

```
# Count fraudulent transactions by hour
hourly_counts = fraudulent_data['Hour'].value_counts().sort_index()
```

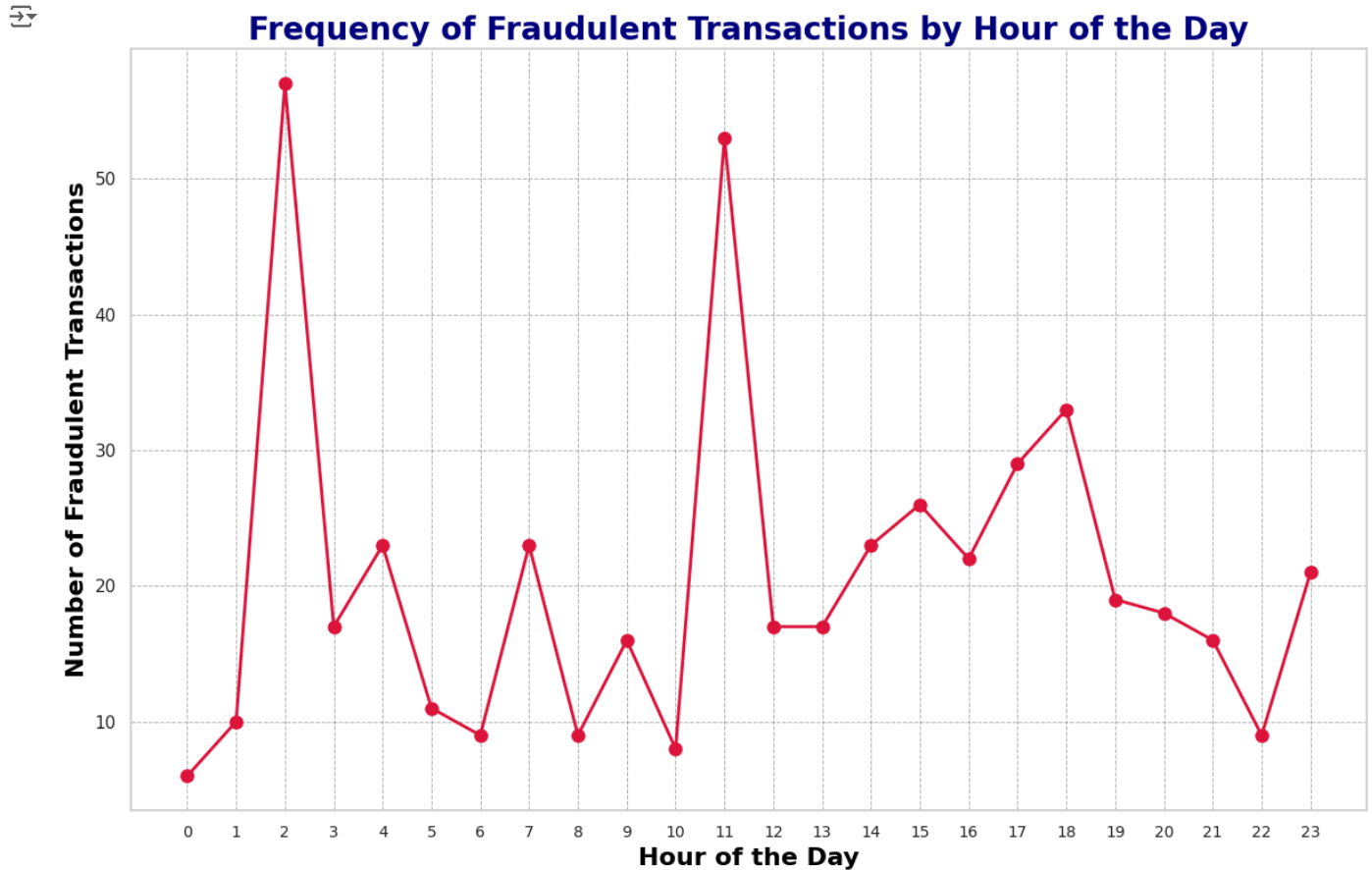
```
# hour with the highest and lowest number of transactions
highest_hour = hourly_counts.idxmax()
highest_count = hourly_counts.max()
lowest_hour = hourly_counts.idxmin()
lowest_count = hourly_counts.min()
```

```
print(f"The hour with the most fraudulent transactions is {highest_hour}:00 with {highest_count} transactions.")
```

```
print(f"The hour with the least fraudulent transactions is {lowest_hour}:00 with {lowest_count} transactions.")
```

```
↗ The hour with the most fraudulent transactions is 11:00 with 43 transactions.  
The hour with the least fraudulent transactions is 0:00 with 2 transactions.
```

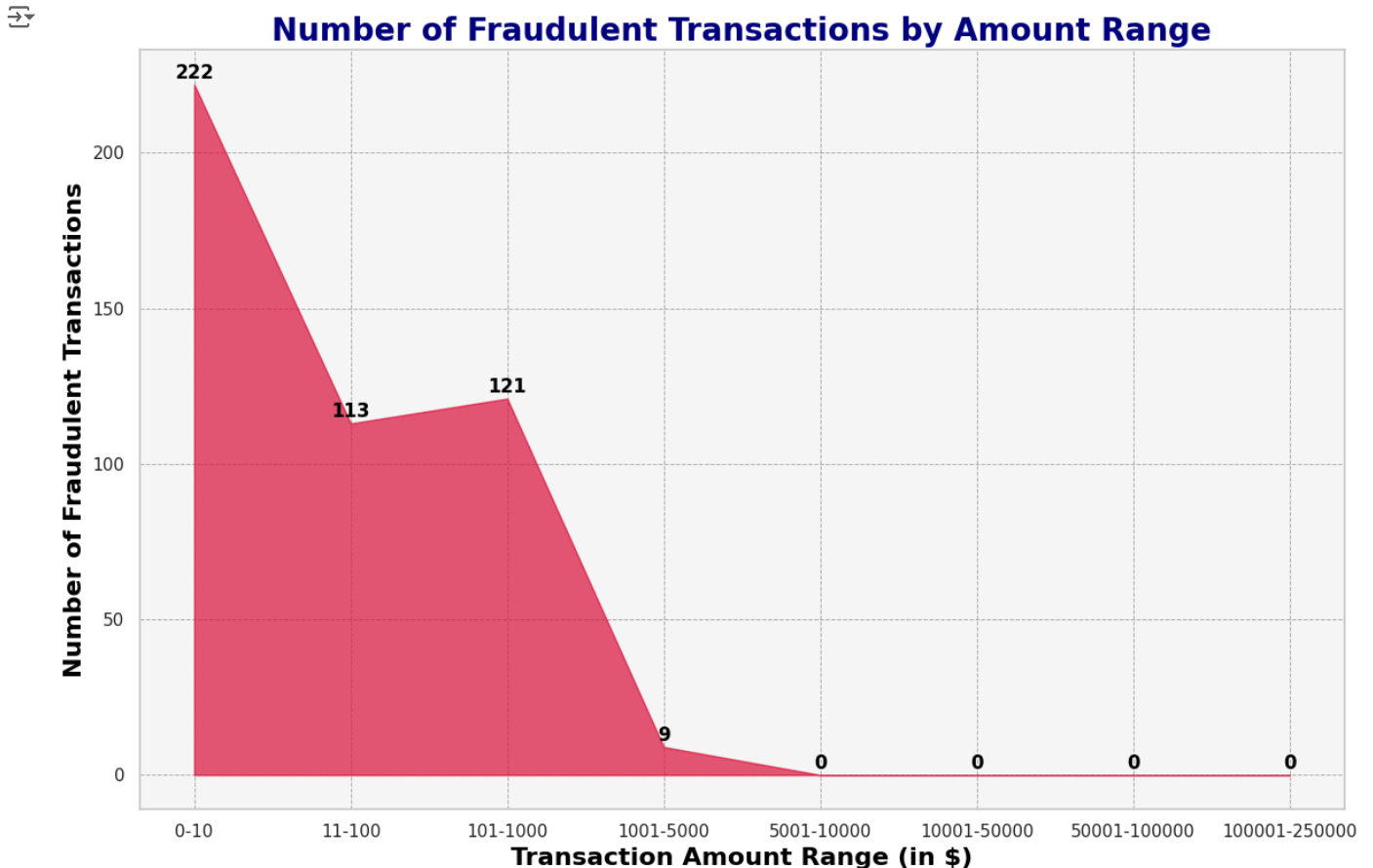
```
import pandas as pd  
import matplotlib.pyplot as plt  
hourly_fraud_counts = fraudulent_data[fraudulent_data['Class'] == 1]['Hour'].value_counts().sort_index()  
plt.figure(figsize=(12, 8), facecolor='white')  
plt.plot(hourly_fraud_counts.index, hourly_fraud_counts.values, marker='o', color='crimson', linewidth=2, markersize=8)  
plt.title('Frequency of Fraudulent Transactions by Hour of the Day', fontsize=20, fontweight='bold', color='navy')  
plt.xlabel('Hour of the Day', fontsize=16, fontweight='bold', color='black')  
plt.ylabel('Number of Fraudulent Transactions', fontsize=16, fontweight='bold', color='black')  
plt.grid(color='gray', linestyle='--', linewidth=0.7, alpha=0.6)  
plt.xticks(hourly_fraud_counts.index, fontsize=10)  
plt.tight_layout()  
plt.show()
```



*Observations: Fraudulent activity peaks in the early morning hours, suggesting fraudsters may take advantage of lower oversight during this time. Midnight has the least activity, indicating a potential preference for times when fewer transactions occur.*

```
# Area Plot for fraudulent transactions by amount range
plt.figure(figsize=(12, 8), facecolor='white')

# Creating an area plot
plt.fill_between(amount_range_counts.index, amount_range_counts.values, color='crimson', alpha=0.7)
for i, value in enumerate(amount_range_counts.values):
    plt.text(i, value + 2, str(value), ha='center', fontsize=12, fontweight='bold', color='black')
plt.title('Number of Fraudulent Transactions by Amount Range', fontsize=20, fontweight='bold', color='navy')
plt.xlabel('Transaction Amount Range (in $)', fontsize=16, fontweight='bold', color='black')
plt.ylabel('Number of Fraudulent Transactions', fontsize=16, fontweight='bold', color='black')
plt.grid(color='gray', linestyle='--', linewidth=0.7, alpha=0.6)
plt.gca().set_facecolor('whitesmoke')
plt.tight_layout()
plt.show()
```



```
Check for missing values in the dataset
print("Missing values before handling:")
print(data.isnull().sum())
drop rows with any NaN values
data = data.dropna()
# Verify that there are no missing values left
print("Missing values after handling:")
print(data.isnull().sum())
# splitting and modeling
X = data.drop(columns=['Class']) # Features
y = data['Class'] # Target
# Train-test split and model training as before
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
plot_confusion_matrix_heatmap(y_test, y_pred)
```

```
Missing values before handling:
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       1
Amount    1
Class     1
Hour      0
dtype: int64
Missing values after handling:
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
Hour      0
dtype: int64
```

