Detect credit card fraud transactions using Logistic Regression

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About the dataset

- The dataset contains transactions made by credit cards in September 2013 by European cardholders.This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions

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

import warnings
warnings.filterwarnings('ignore')

# Model selection and training
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import
classification_report,accuracy_score,confusion_matrix
#Threshold
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

# importing dataset
df = pd.read_csv('creditcard.csv')

df.shape

(284807, 31)

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]
```

```
df.info() # no need to deal with null values
```

```
<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
```

```
df.describe()
```

```
                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]

# Checking for duplicate records
df.duplicated().sum()
```

```
1081
```

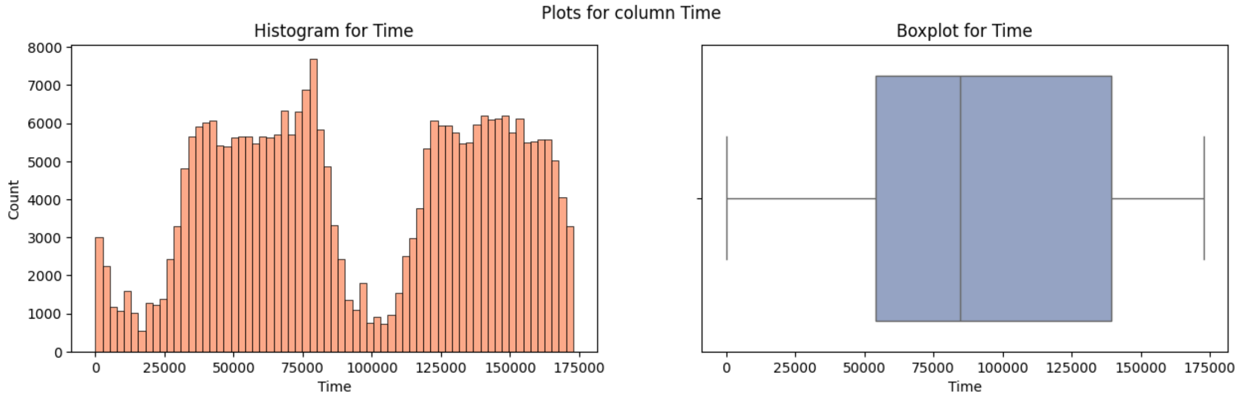
```python
# we found 1081 duplicate records and now we are dropping those
df.drop_duplicates(inplace=True)
print(f'New dataset without duplicates contains {df.shape[0]} rows and
{df.shape[1]} columns')
```

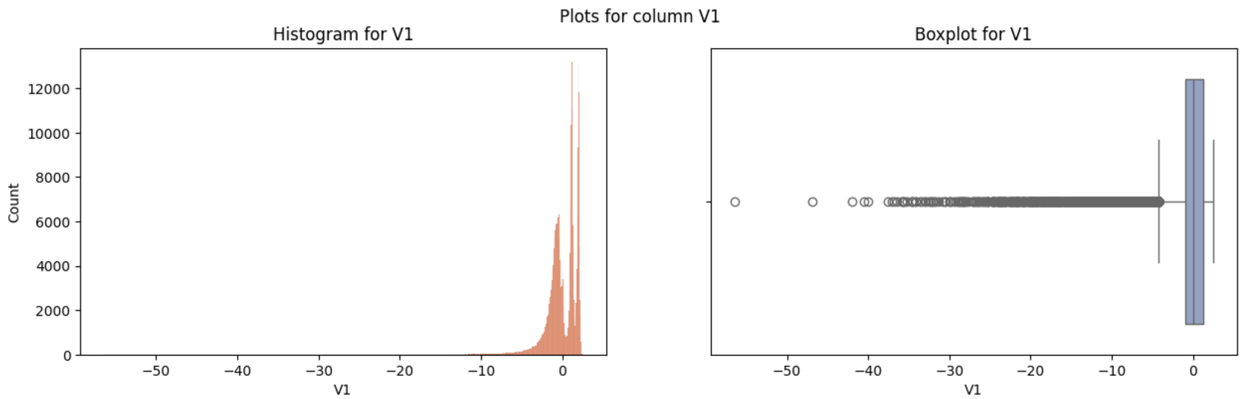
```
New dataset without duplicates contains 283726 rows and 31 columns
```

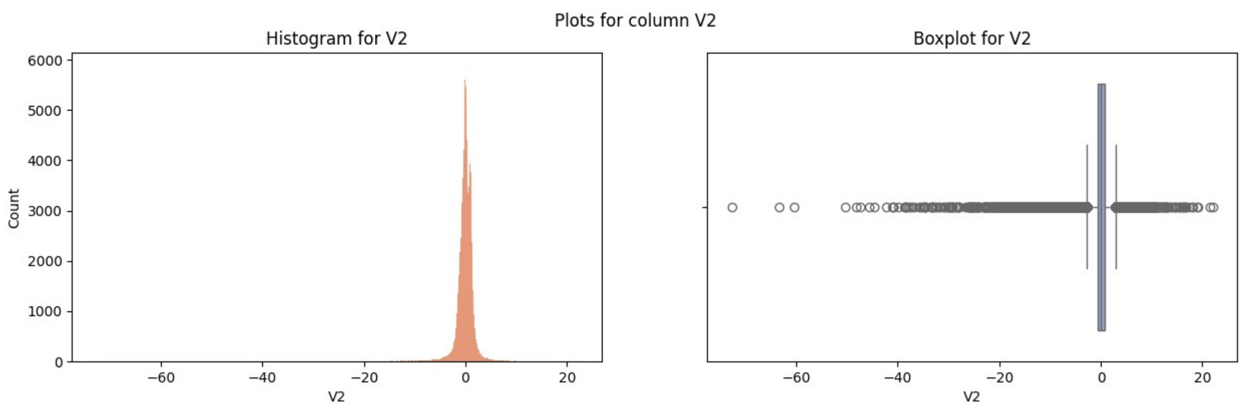
```python
# defining colours
colors = sns.color_palette("Set2")
colors
```

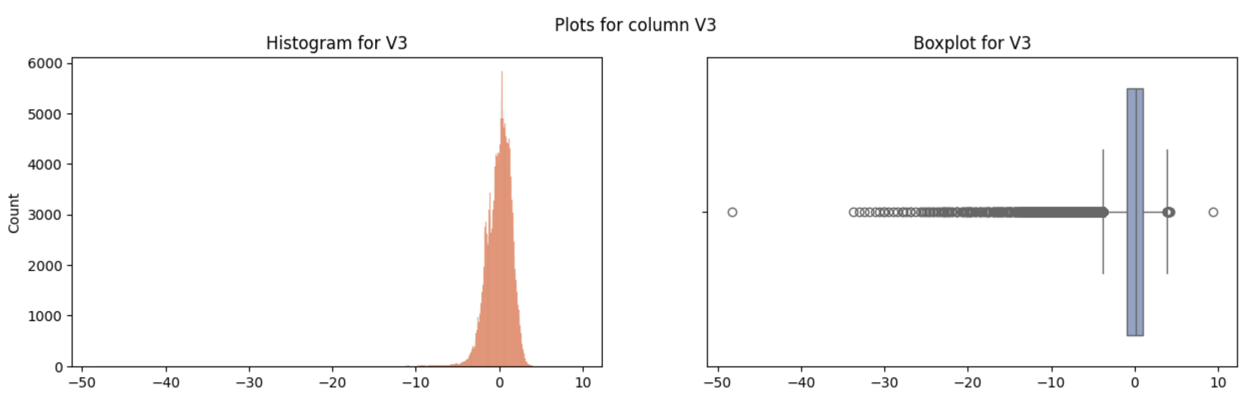
```
[(0.4, 0.7607843137254902, 0.6470588235294118),
 (0.9882352941176471, 0.5529411764705883, 0.3843137254901961),
 (0.5529411764705883, 0.6274509803921569, 0.796078431372549),
 (0.9058823529411765, 0.5411764705882353, 0.7647058823529411),
 (0.6509803921568628, 0.8470588235294118, 0.32941176470588235),
 (1.0, 0.8509803921568627, 0.1843137254901961),
 (0.8980392156862745, 0.7686274509803922, 0.5803921568627451),
 (0.7019607843137254, 0.7019607843137254, 0.7019607843137254)]
```

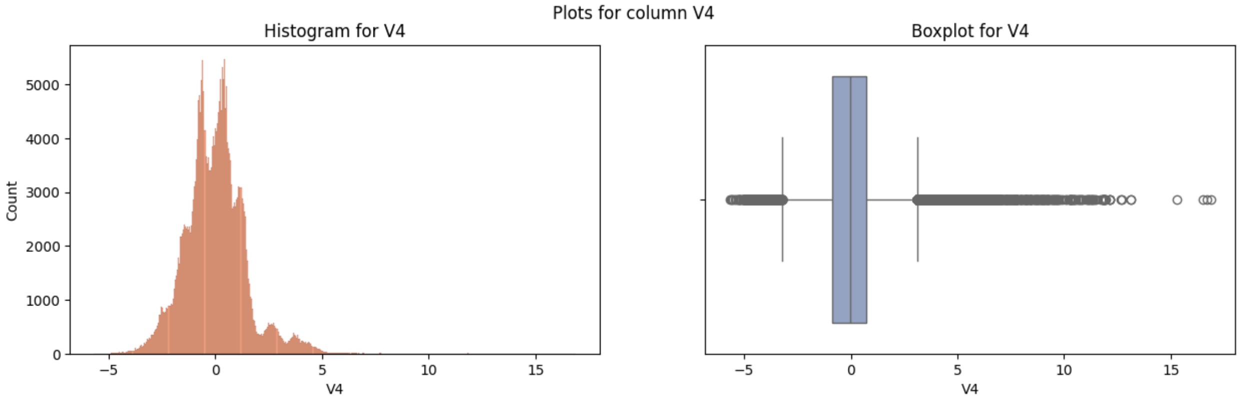
```python
# Here all columns are numerical columns so we can directly plot
countplot,boxplot,distplot etc
# Defining a function for representing numerical columns
def numerical_plots(column_name):
    fig,axes = plt.subplots(1,2,figsize = (15,4))
    fig.suptitle(f'Plots for column {column_name}')
    # Histogram
    sns.histplot(data=df,x=column_name,ax=axes[0],color=colors[1])
    axes[0].set_title(f'Histogram for {column_name}')
    # Boxplot
    sns.boxplot(data=df,x=column_name,ax=axes[1],color=colors[2])
    axes[1].set_title(f'Boxplot for {column_name}')

    plt.show()

# Plotting histogram and boxplot for all numerical columns
for i in df.columns:
    numerical_plots(i)
```

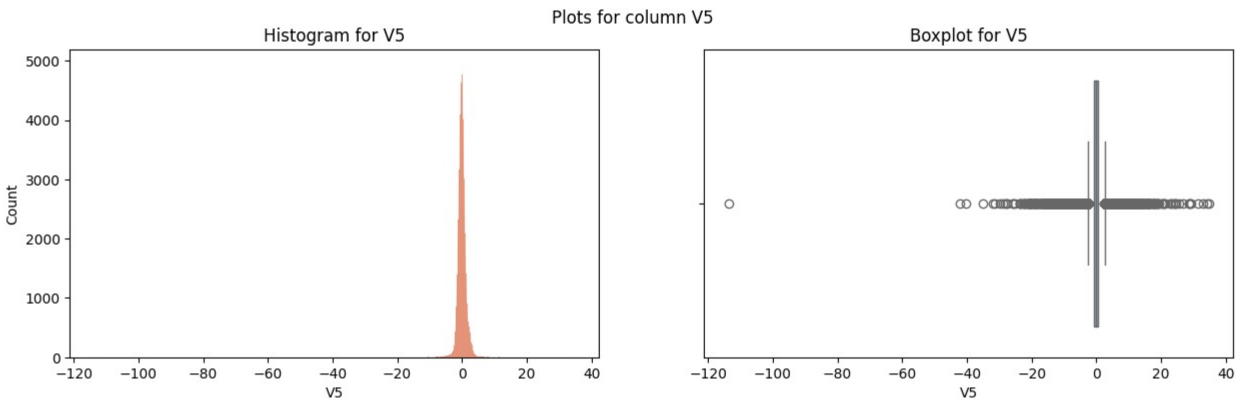

Plots for column Time
Histogram for Time
Boxplot for Time
Count
Time
Time

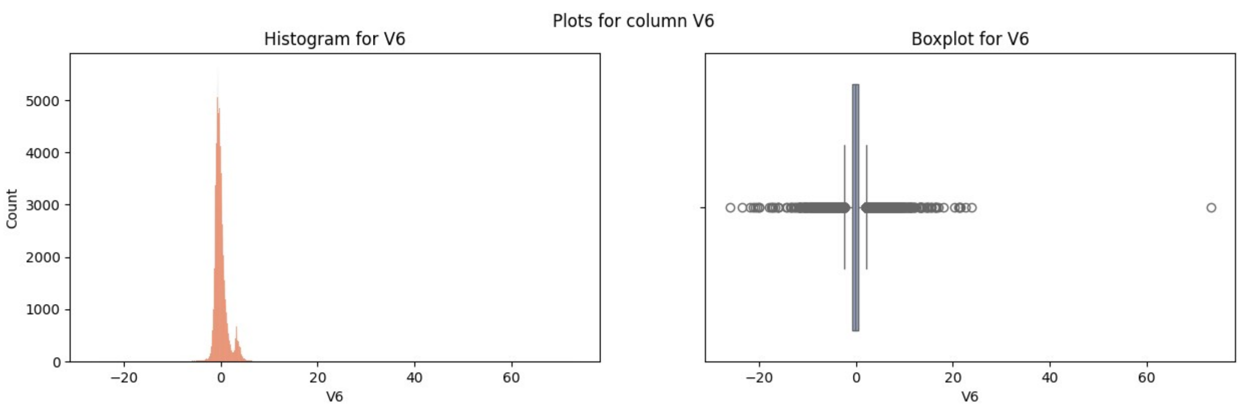

Plots for column V1
Histogram for V1
Boxplot for V1
Count
V1
V1

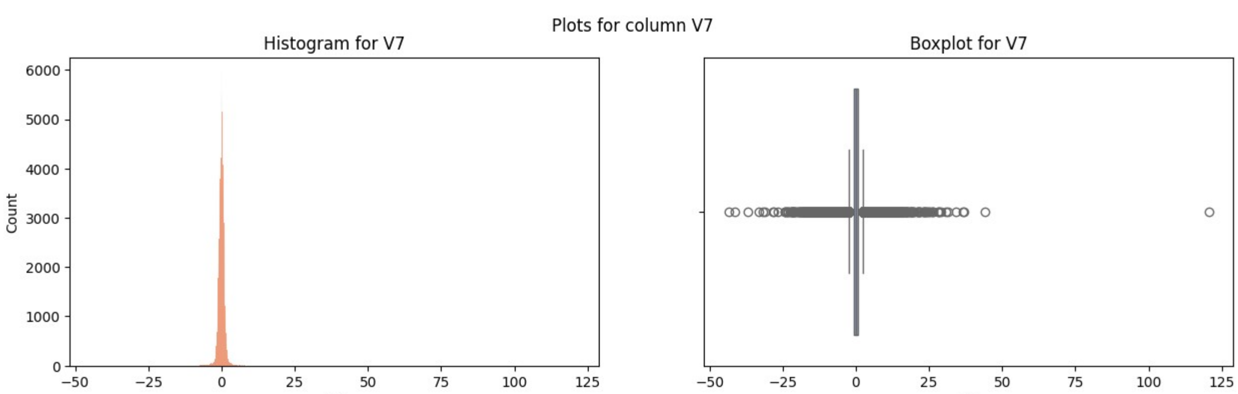

Plots for column V2
Histogram for V2
Boxplot for V2
Count
V2
V2

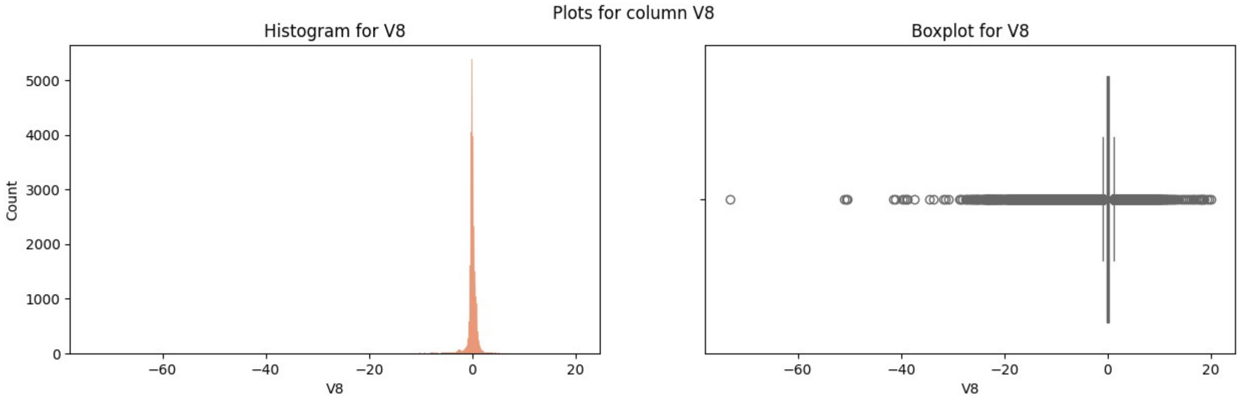

Plots for column V3
Histogram for V3
Boxplot for V3
Count
V3
V3

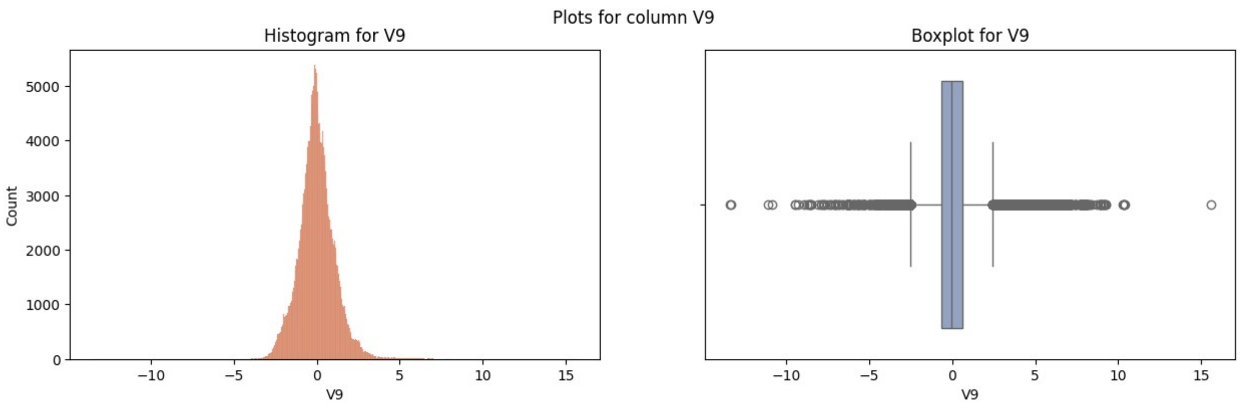

Plots for column V4
Histogram for V4
Count
V4
Boxplot for V4
V4

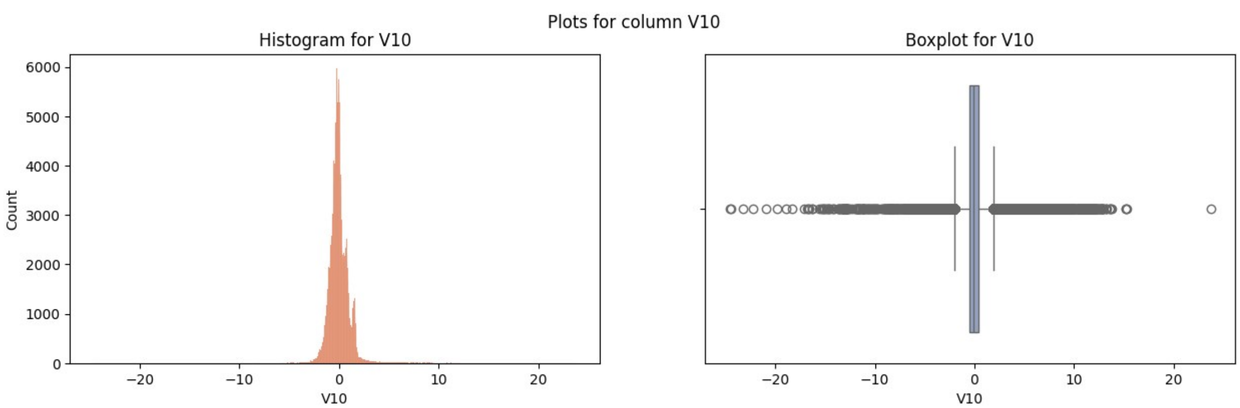

Plots for column V5
Histogram for V5
Count
V5
Boxplot for V5
V5

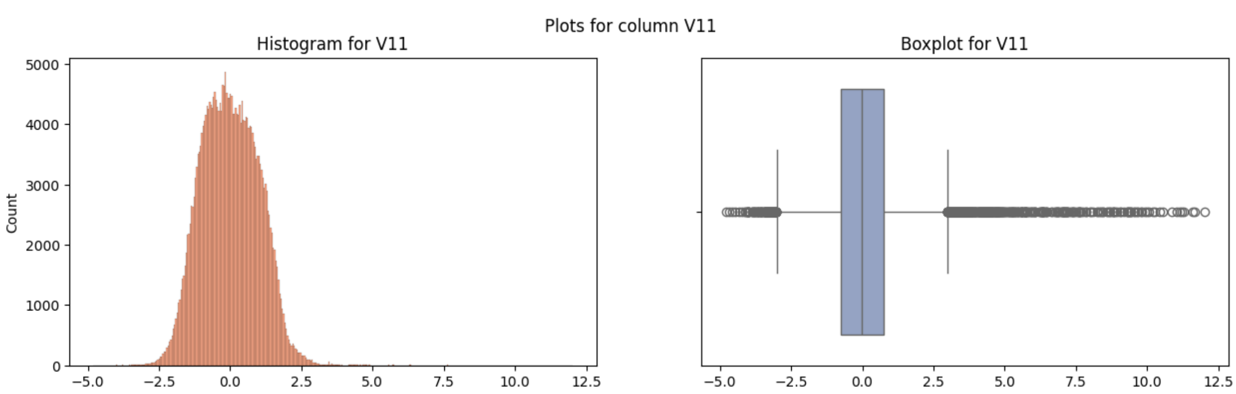

Plots for column V6
Histogram for V6
Count
V6
Boxplot for V6
V6

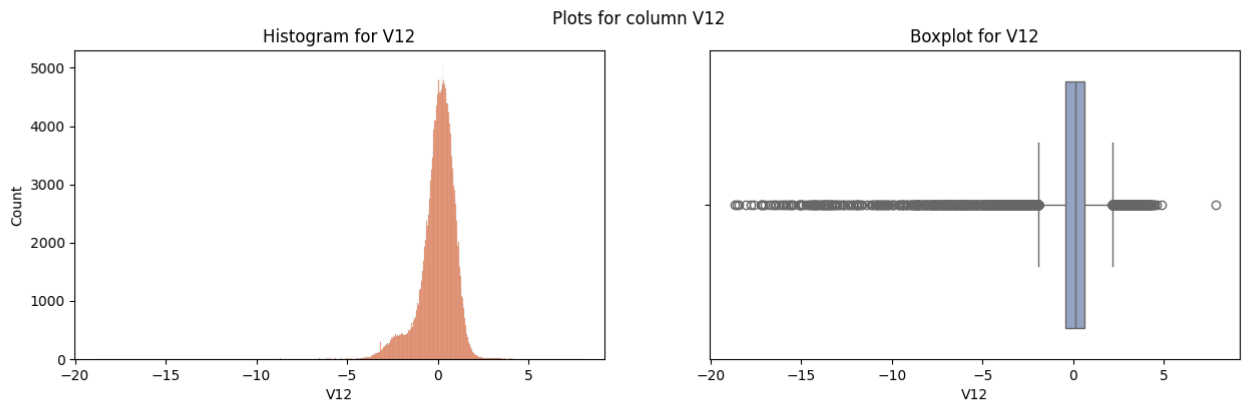

Plots for column V7
Histogram for V7
Count
V7
Boxplot for V7
V7

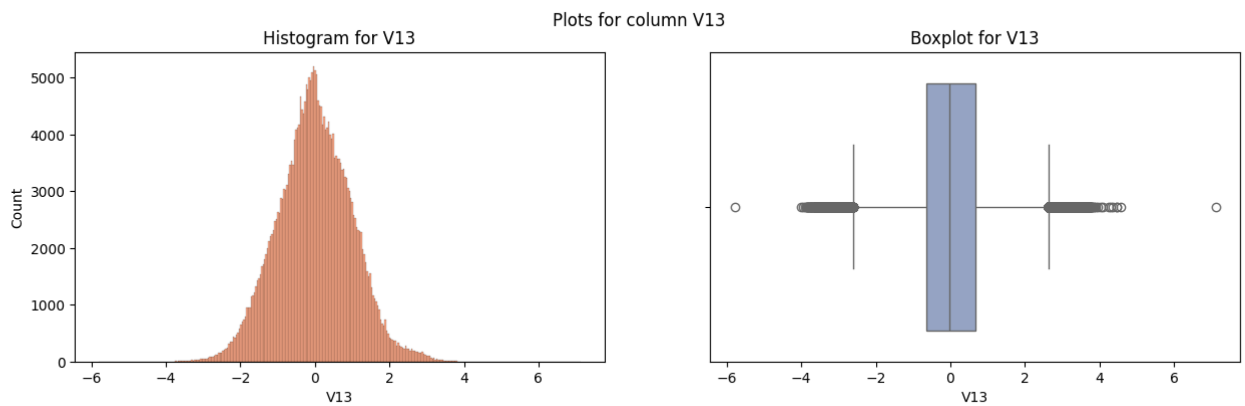

Plots for column V8
Histogram for V8
Count
V8
Boxplot for V8
V8

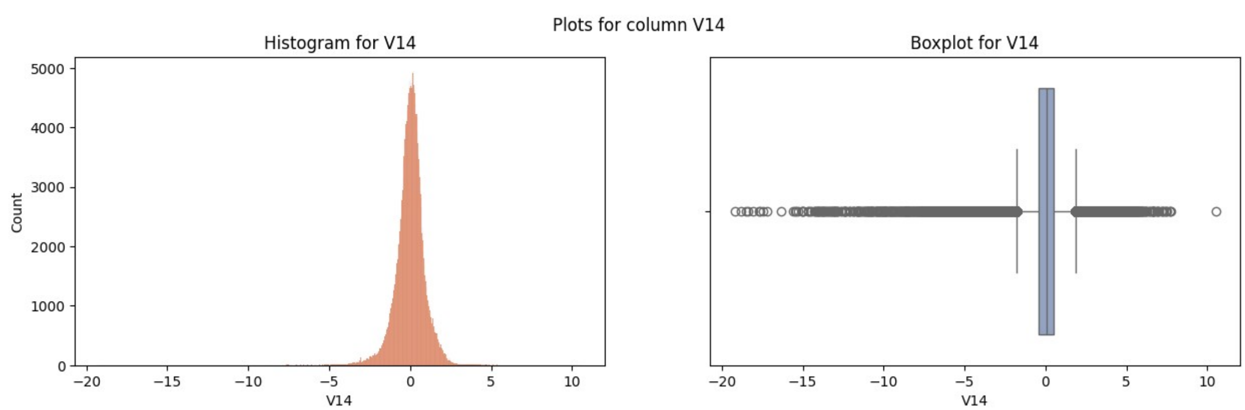

Plots for column V9
Histogram for V9
Count
V9
Boxplot for V9
V9

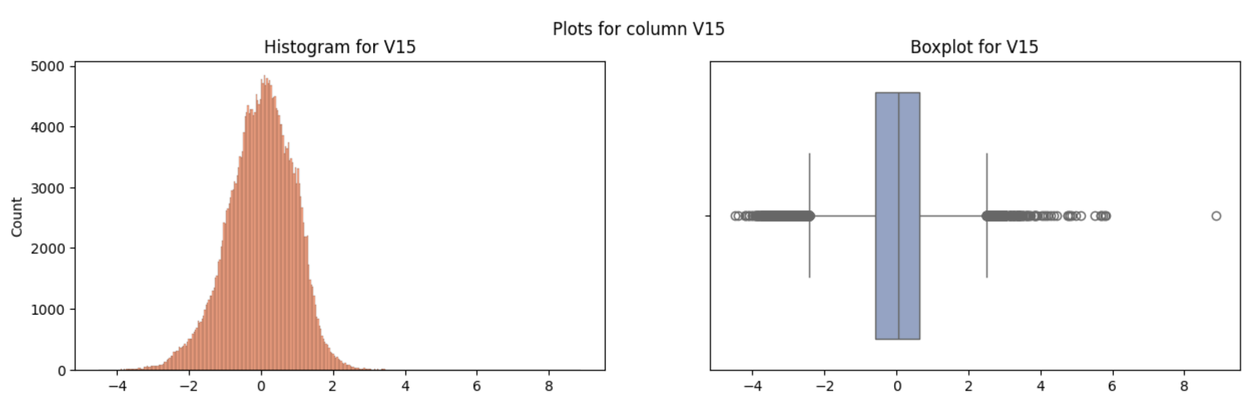

Plots for column V10
Histogram for V10
Count
V10
Boxplot for V10
V10

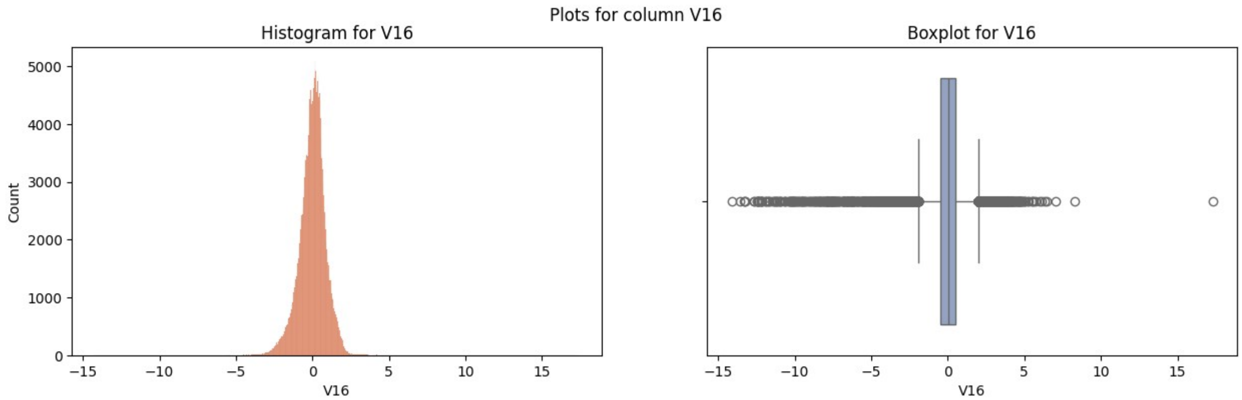

Plots for column V11
Histogram for V11
Count
V11
Boxplot for V11
V11

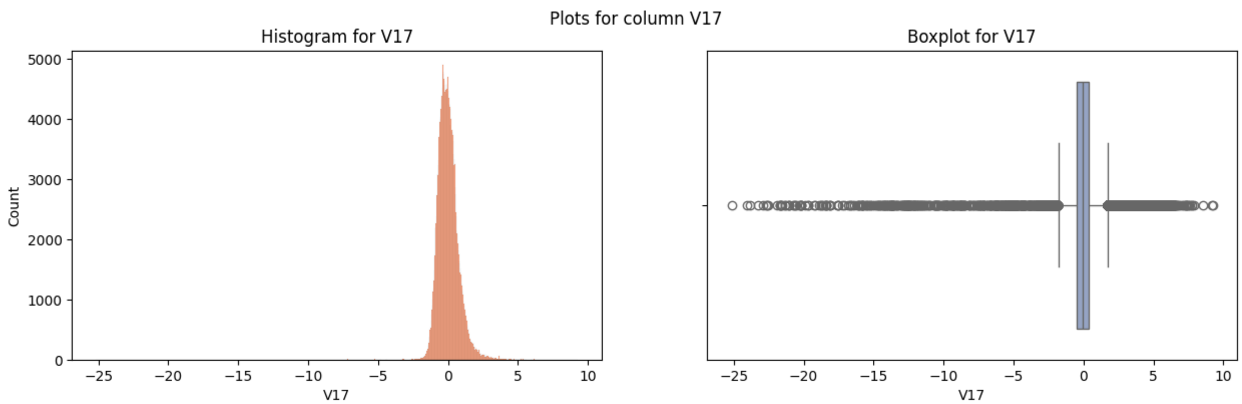

Plots for column V12
Histogram for V12
Boxplot for V12
Count
5000
4000
3000
2000
1000
0
−20
−15
−10
−5
0
5
V12

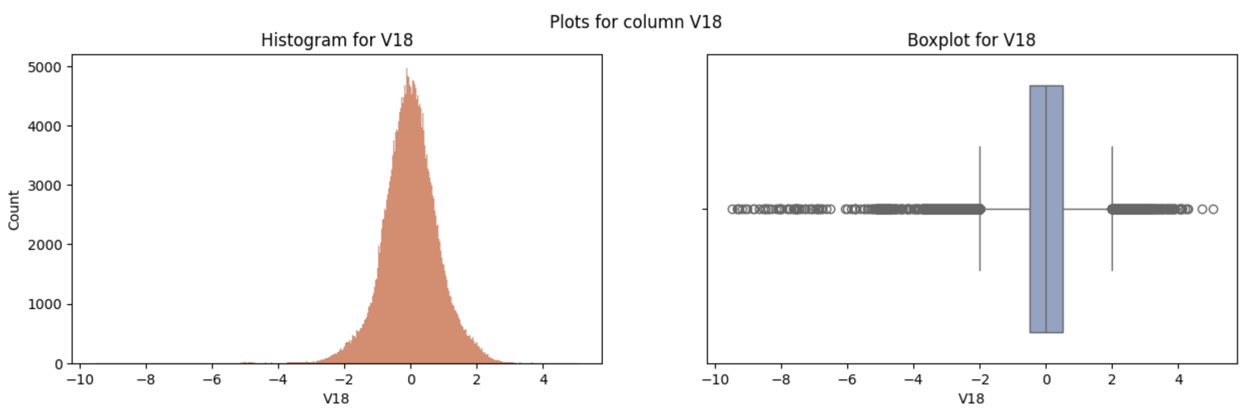

Plots for column V13
Histogram for V13
Boxplot for V13
Count
5000
4000
3000
2000
1000
0
−6
−4
−2
0
2
4
6
V13

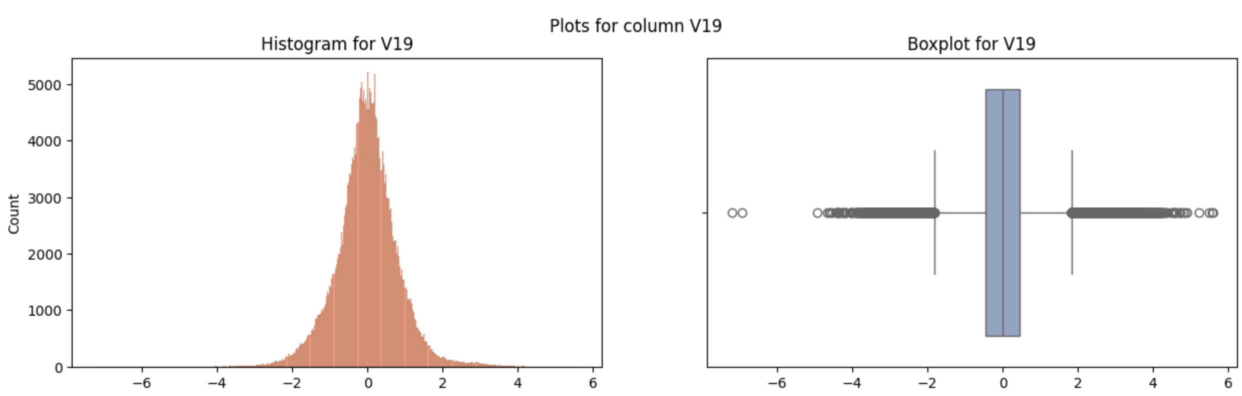

Plots for column V14
Histogram for V14
Boxplot for V14
Count
5000
4000
3000
2000
1000
0
−20
−15
−10
−5
0
5
10
V14

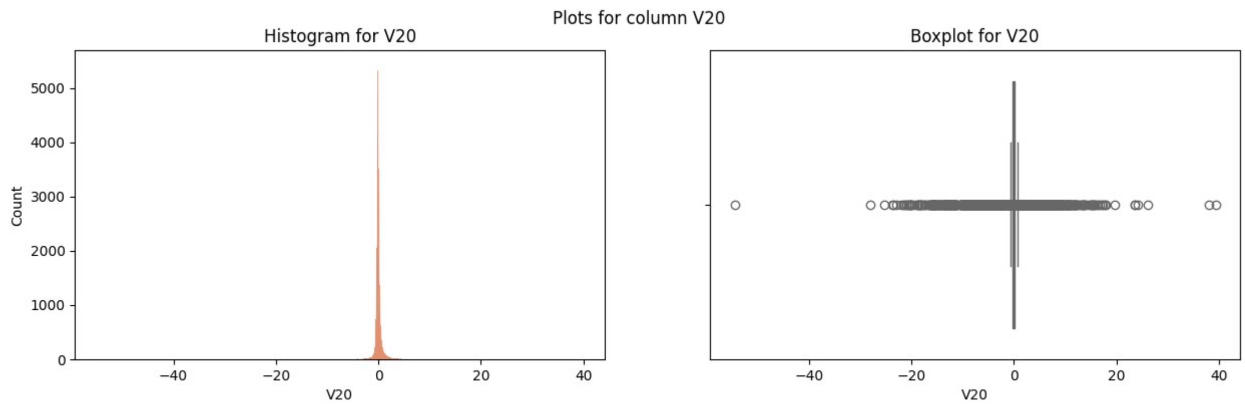

Plots for column V15
Histogram for V15
Boxplot for V15
Count
5000
4000
3000
2000
1000
0
−4
−2
0
2
4
6
8
V15

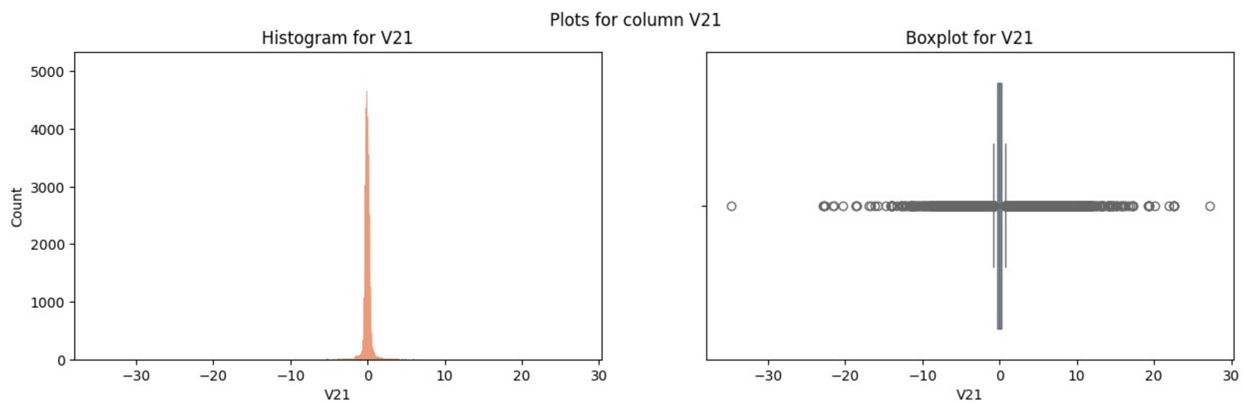

Plots for column V16
Histogram for V16
Boxplot for V16
Count
V16

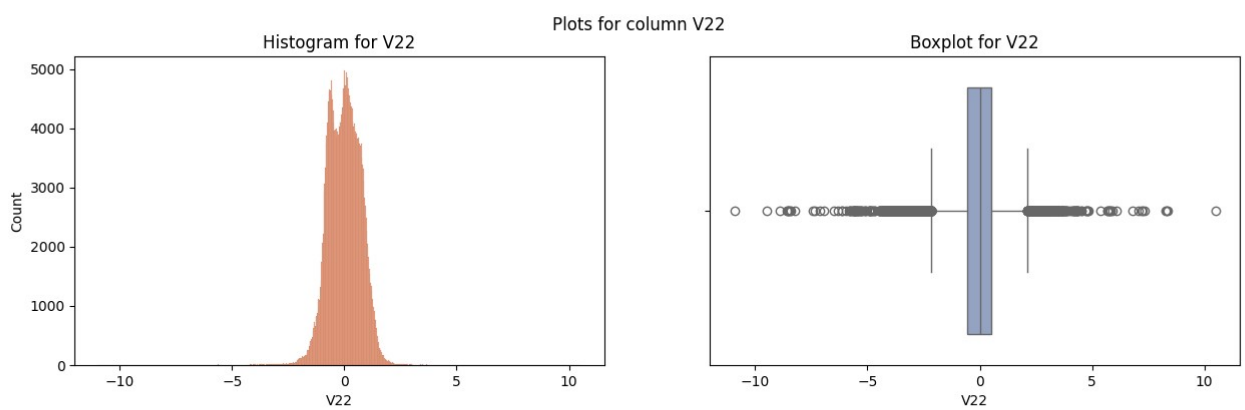

Plots for column V17
Histogram for V17
Boxplot for V17
Count
V17

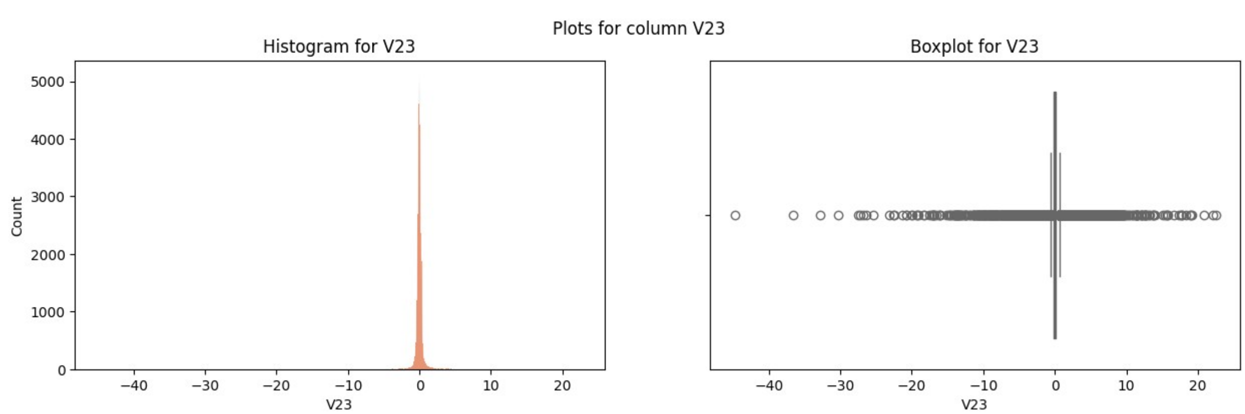

Plots for column V18
Histogram for V18
Boxplot for V18
Count
V18


Plots for column V19
Histogram for V19
Boxplot for V19
Count
V19

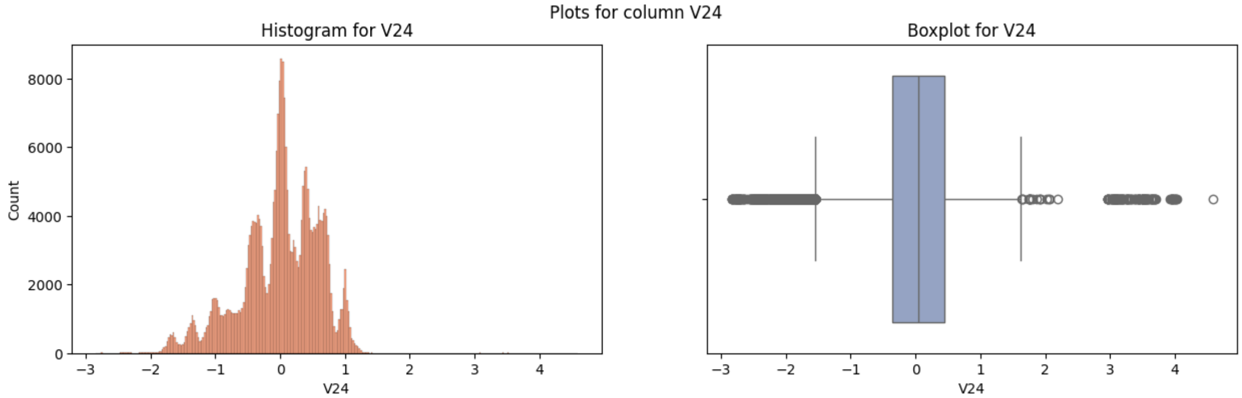

Plots for column V20
Histogram for V20
Boxplot for V20
Count
V20


Plots for column V21
Histogram for V21
Boxplot for V21
Count
V21

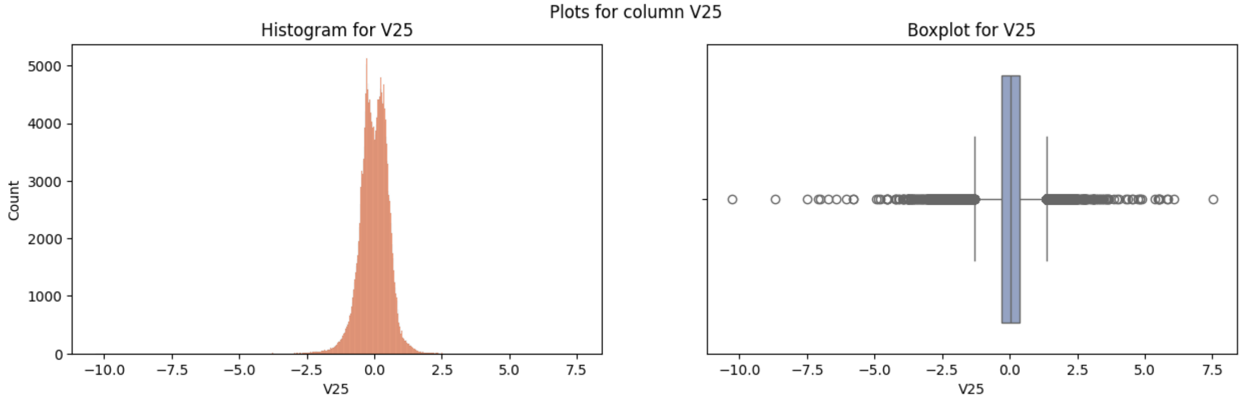

Plots for column V22
Histogram for V22
Boxplot for V22
Count
V22


Plots for column V23
Histogram for V23
Boxplot for V23
Count
V23

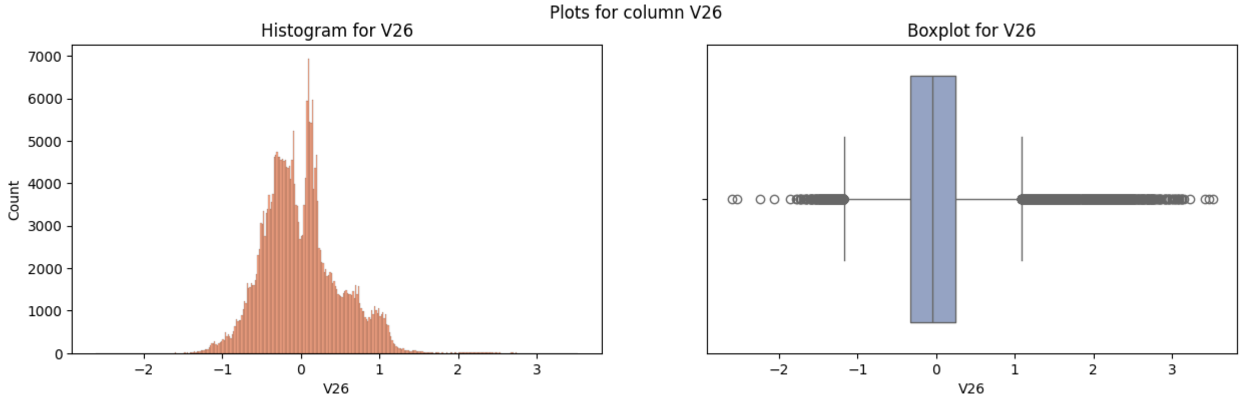
Plots for column V24



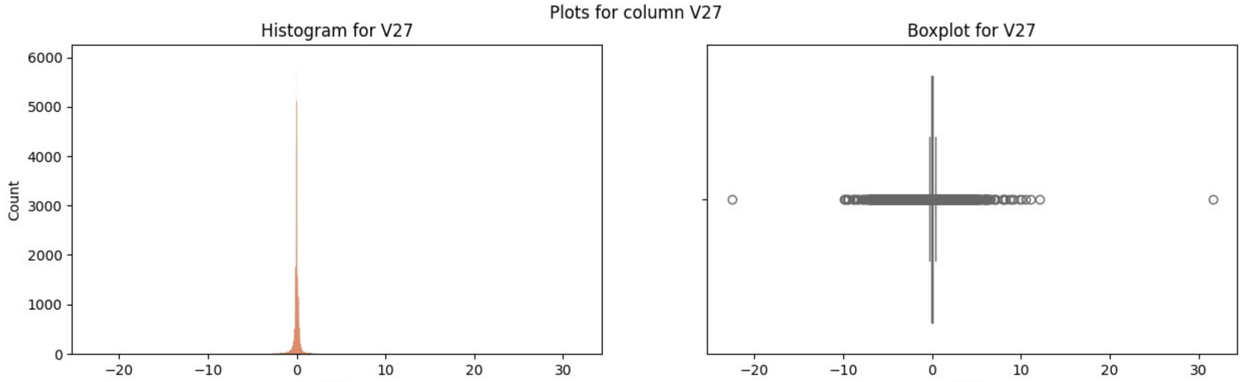
Plots for column V25

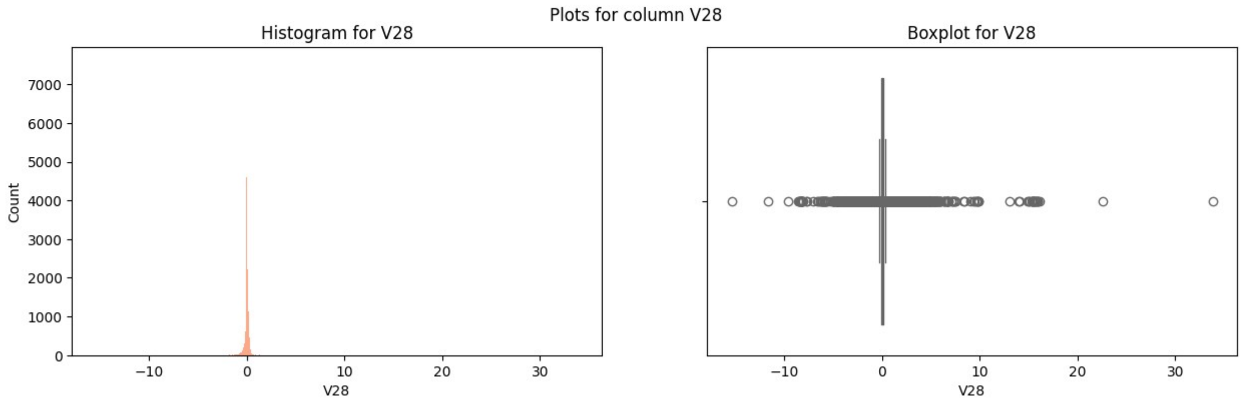


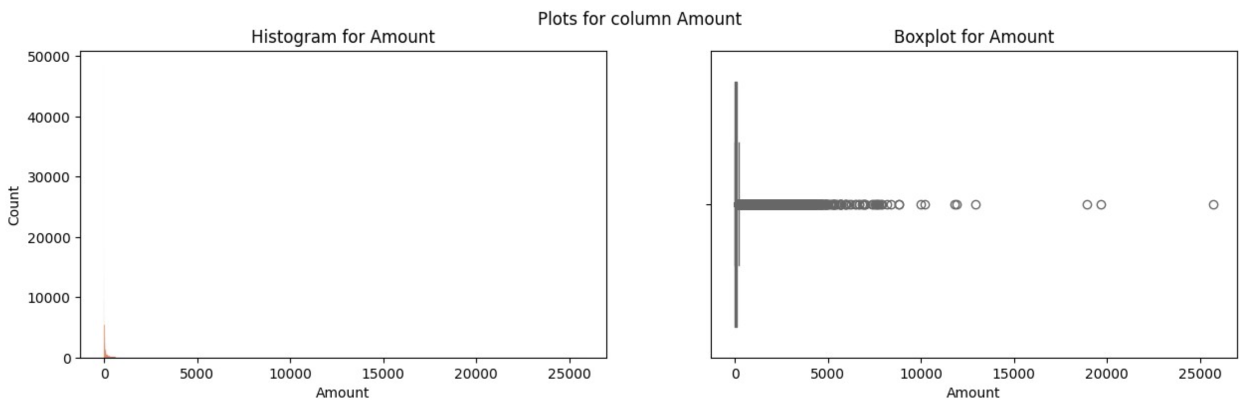
Plots for column V26

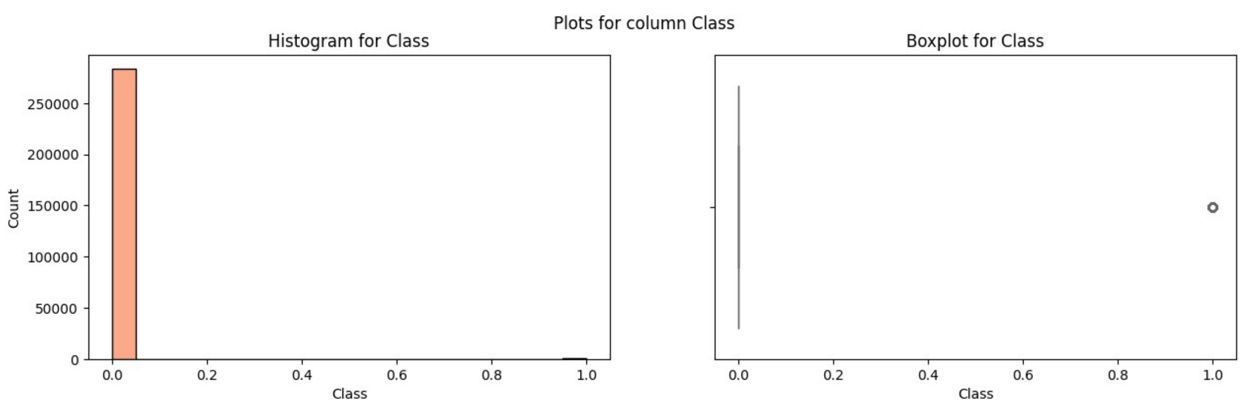


Plots for column V27

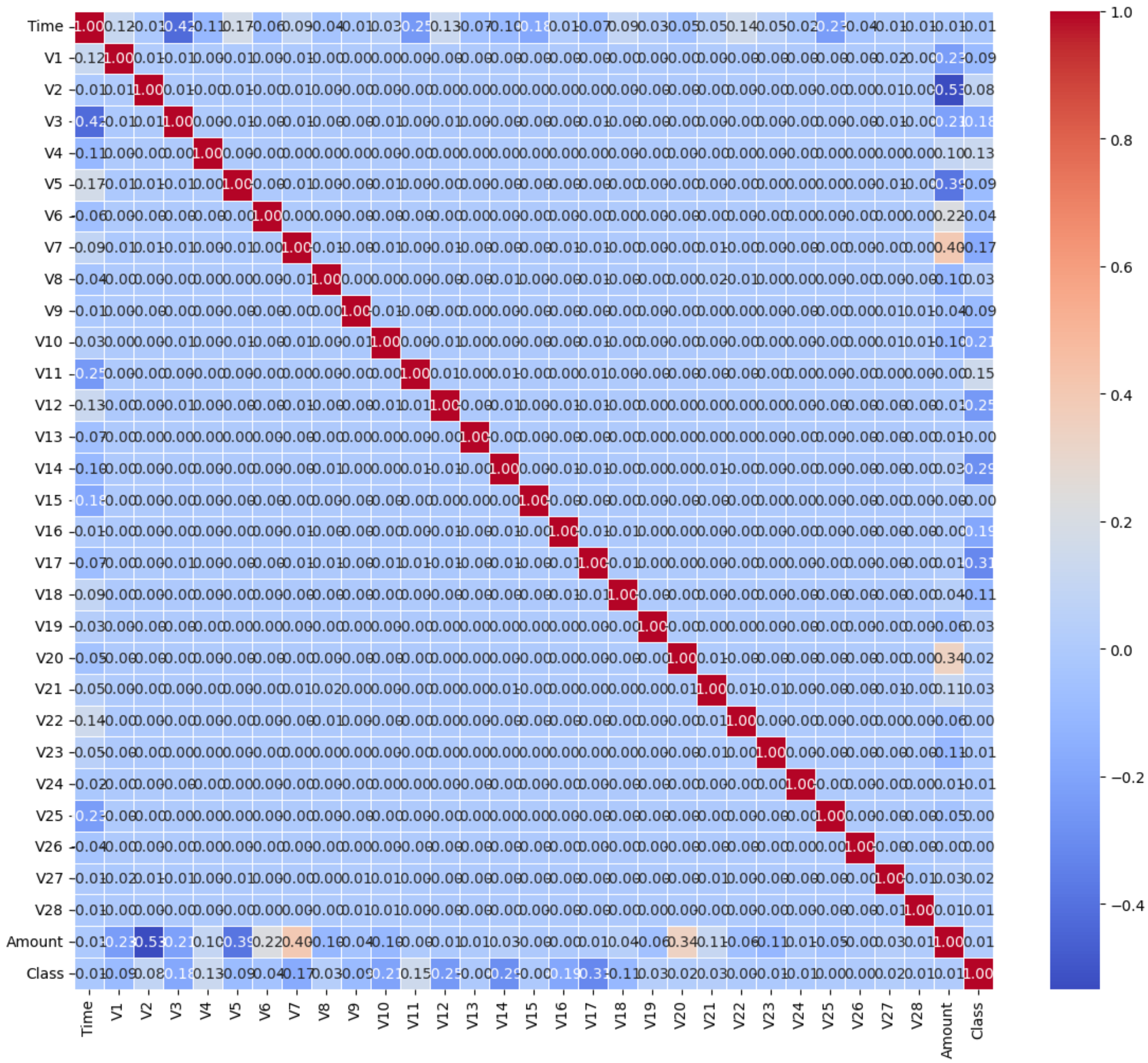









```
# Checking the correlation between all numerical columns
correlation_matrix = df.corr()
plt.figure(figsize=(14, 12))
sns.heatmap(correlation_matrix, cmap='coolwarm', annot=True,
fmt=".2f", linewidths=0.5)
plt.show()
```




```
# We are scaling data using standard scalar
# splitting data
x_dummy = df.drop(columns=['Class'],axis=1)
Y = df['Class']

#Standard scalar
sc = StandardScaler()
X = sc.fit_transform(x_dummy)

#Splitting data into train and test
x_train,x_test,y_train,y_test =
train_test_split(X,Y,test_size=0.2,random_state=0)
print(f'x_train : {x_train.shape},y_train : {y_train.shape},x_test :
{x_test.shape},y_test : {y_test.shape}')
```

```
x_train : (226980, 30),y_train : (226980,),x_test : (56746, 30),y_test
: (56746,)
```

```
# Defining a function for training model and calculating
classification report
def find_logistic_regression(x_train,y_train,x_test):
    # calling logistic regression model and fitting data
    lgr = LogisticRegression()
    lgr.fit(x_train,y_train)
    # prediction for train data
    y_pred_train = lgr.predict(x_train)
    # prediction for test data
    y_pred_test = lgr.predict(x_test)
    # classification report for train model
    y_train_cl_report =
classification_report(y_train,y_pred_train,target_names = ['Non
Fraud','Fraud'])
    # classification report for test model
    y_test_cl_report =
classification_report(y_test,y_pred_test,target_names = ['Non
Fraud','Fraud'])
    # printing the classification report and returning y_test_pred and
logistic regression model
    print('_' * 100)
    print('CLASSIFICATION REPORT FOR TRAIN MODEL')
    print('_' * 100)
    print(y_train_cl_report)
    print('_' * 100)
    print('CLASSIFICATION REPORT FOR TEST MODEL')
    print('_' * 100)
    print(y_test_cl_report)
    return y_pred_test,lgr

# calling function for given train and test data
y_pred,lgr = find_logistic_regression(x_train,y_train,x_test)
```

```
____________________________________________________________________________________________________
CLASSIFICATION REPORT FOR TRAIN MODEL
____________________________________________________________________________________________________
              precision    recall  f1-score   support

   Non Fraud       1.00      1.00      1.00    226594
       Fraud       0.89      0.63      0.74       386

    accuracy                           1.00    226980
   macro avg       0.94      0.81      0.87    226980
weighted avg       1.00      1.00      1.00    226980
```

```
______________________________________________________________________
______________________________
CLASSIFICATION REPORT FOR TEST MODEL
______________________________________________________________________
______________________________
              precision    recall  f1-score   support

   Non Fraud       1.00      1.00      1.00     56659
       Fraud       0.83      0.55      0.66        87

    accuracy                           1.00     56746
   macro avg       0.91      0.78      0.83     56746
weighted avg       1.00      1.00      1.00     56746


# Defining a custom function for confusion matrix
def plot_confusion_matrix(y_test,y_pred):
    cnfn_matrx = confusion_matrix(y_test,y_pred)
    labels = ['Non Fraud','Fraud']

sns.heatmap(cnfn_matrx,annot=True,fmt='d',xticklabels=labels,yticklabe
ls=labels)
    plt.xlabel('Actual')
    plt.ylabel('Predicted')
    plt.show()

# ploting confusion matrix for above logistic regression model
plot_confusion_matrix(y_test,y_pred)
```


```
df['Class'].value_counts()

Class
0    283253
1       473
Name: count, dtype: int64

# Different df for both groups
df1 = df[df['Class'] == 0].sample(n = 473,random_state = 42)
df2 = df[df['Class'] == 1].sample(n = 473,random_state = 42)
print(f'Non fraud df with shape {df1.shape} and Fraud df with shape
{df2.shape}')

Non fraud df with shape (473, 31) and Fraud df with shape (473, 31)

#combining them
df_final = pd.concat([df1,df2],ignore_index=True)
df_final['Class'].value_counts()

Class
0    473
1    473
Name: count, dtype: int64
```

```python
# splitting for x and y
X_balanced_dummy = df_final.drop(columns=['Class'],axis=1)
Y_balanced = df_final['Class']

# Scaling independent variables using Standard Scalar
sc_bal = StandardScaler()
X_balanced = sc_bal.fit_transform(X_balanced_dummy)

# Splitting for train and test
x_train_bal,x_test_bal,y_train_bal,y_test_bal =
train_test_split(X_balanced,Y_balanced,test_size=0.2,random_state=0)
print(f'x_train : {x_train_bal.shape},y_train :
{y_train_bal.shape},x_test : {x_test_bal.shape},y_test :
{y_test_bal.shape}')
```

```
x_train : (756, 30),y_train : (756,),x_test : (190, 30),y_test :
(190,)
```

```python
# training model and printing classification report
lgr = LogisticRegression()
lgr.fit(x_train_bal,y_train_bal)
# prediction for train data
y_pred_train_bal = lgr.predict(x_train_bal)
# prediction for test data
y_pred_test_bal = lgr.predict(x_test_bal)
# classification report for train model
y_train_cl_report =
classification_report(y_train_bal,y_pred_train_bal)
# classification report for test model
y_test_cl_report = classification_report(y_test_bal,y_pred_test_bal)
# printing the classification report and returning y_test_pred and
logistic regression model
print('_' * 100)
print('CLASSIFICATION REPORT FOR TRAIN MODEL')
print('_' * 100)
print(y_train_cl_report)
print('_' * 100)
print('CLASSIFICATION REPORT FOR TEST MODEL')
print('_' * 100)
print(y_test_cl_report)
```

```
____________________________________________________________________________________________________
CLASSIFICATION REPORT FOR TRAIN MODEL
____________________________________________________________________________________________________
              precision    recall  f1-score   support

           0       0.92      0.98      0.95       378
           1       0.98      0.92      0.95       378
```

```
    accuracy                           0.95       756
   macro avg       0.95      0.95      0.95       756
weighted avg       0.95      0.95      0.95       756

------------------------------------------------------------------------
CLASSIFICATION REPORT FOR TEST MODEL
------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.93      0.97      0.95        95
           1       0.97      0.93      0.95        95

    accuracy                           0.95       190
   macro avg       0.95      0.95      0.95       190
weighted avg       0.95      0.95      0.95       190


# plotting confusion matrix
plot_confusion_matrix(y_test_bal,y_pred_test_bal)
```

Thank you