Credit Card Fraud Detection

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Abstract

- **Dataset** - Credit Card dataset is used in this project.
- **Question** - How can we detect fraudulent credit card transactions.
- **Methods used** - Pandas, Matplotlib, Machine Learning Models, Classification Report and Confusion Matrix.
- **Findings** - Number of fraud and valid transactions in the dataset, Amount involved in fraud transactions, Correlations of features in the dataset, Comparing different Machine Learning models.

Motivation

- Credit card fraud costs consumers and the financial company billions of dollars annually, and fraudsters continuously try to find new rules and tactics to commit illegal actions. Thus, fraud detection systems have become essential for banks and financial institution to minimize their losses.
- Through this project we aim to recognize fraudulent credit card transactions so that the customers of credit card companies are not charged for items that they did not purchase.

Dataset(s)

- Credit Card dataset is used in this project which contains transactions made via credit cards in September 2013 by European cardholders.
- This dataset presents 492 frauds out of 284,807 transactions.
- The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.
- I found this dataset from kaggle.

Data Preparation and Cleaning

To prepare the data for analysis, I did the following –

- Checked if there is any null or NA records. If yes, then dropped those records.
- Bifurcated Training and Testing Data to train the model and then evaluate the performance of machine learning models.

Research Question(s)

How to detect fraudulent credit card transactions so that the customers of credit card companies are not charged for items that they did not purchase?

- Identify number of fraud and valid transactions.
- Identify the details of amount involved in fraud transactions.
- Identify which features in the dataset correlate with each which can be helpful in choosing those features that are most relevant for the prediction.

Research Question(s)

- Compare different Machine Learning models and evaluate them.
- Is this a problem of high recall or high precision.

Methods

- Pandas is used to retrieve and manipulate data from the dataset.
- After data preparation and cleaning, Matplotlib is used for data visualization.
- Machine learning models – Logistic Regression, Decision Tree and Random Forest is used for detecting fraud credit card transactions.
- For training the Machine Learning model, data is split into two parts- Training data and Testing data.
- For evaluating classifier, Classification Report and Confusion Matrix is used.

Findings

We can see most of the features of the dataset are clustered around 0 with some or no outliers.

Findings

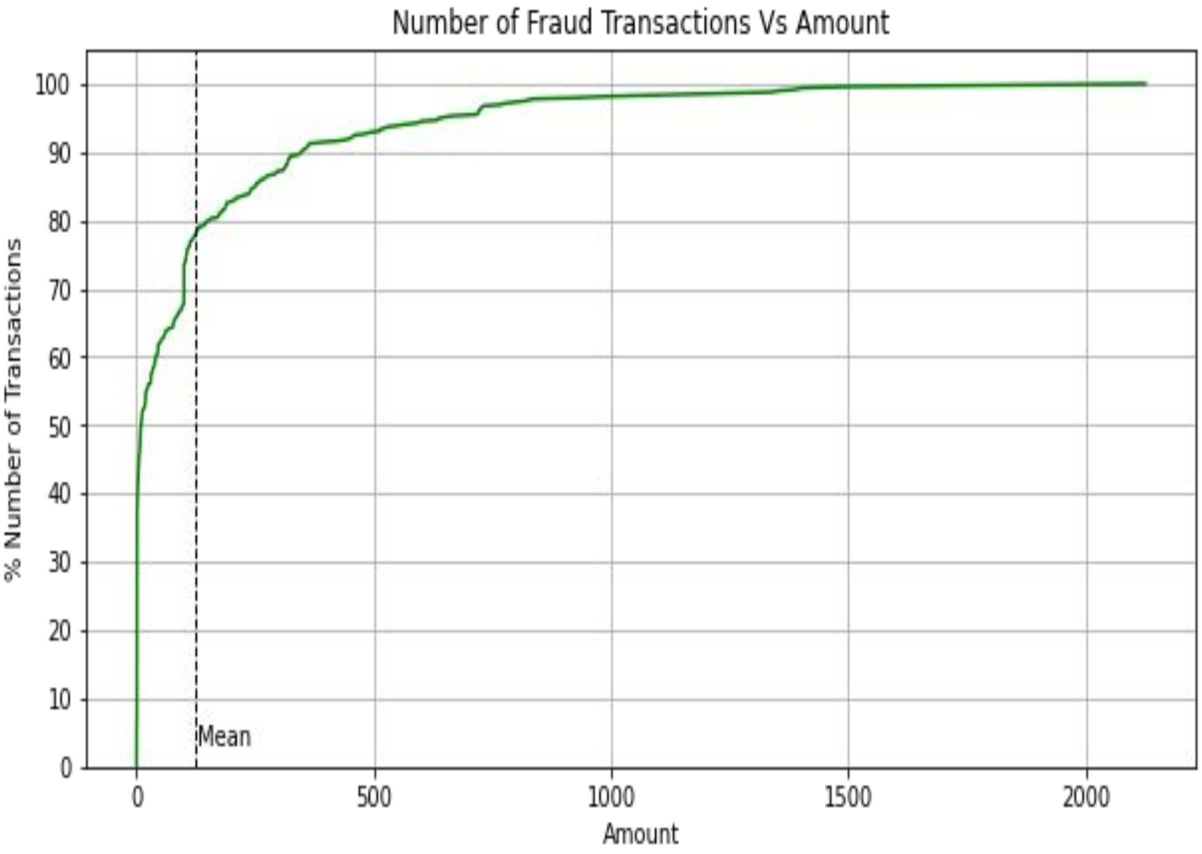
Only 0.17% fraudulent transaction out of all the transactions. The data is highly unbalanced.

```
Fraudulent Transactions: 492
Valid Transactions: 284315
Percentage of Fraudulent Transactions: 0.17%
```

Findings

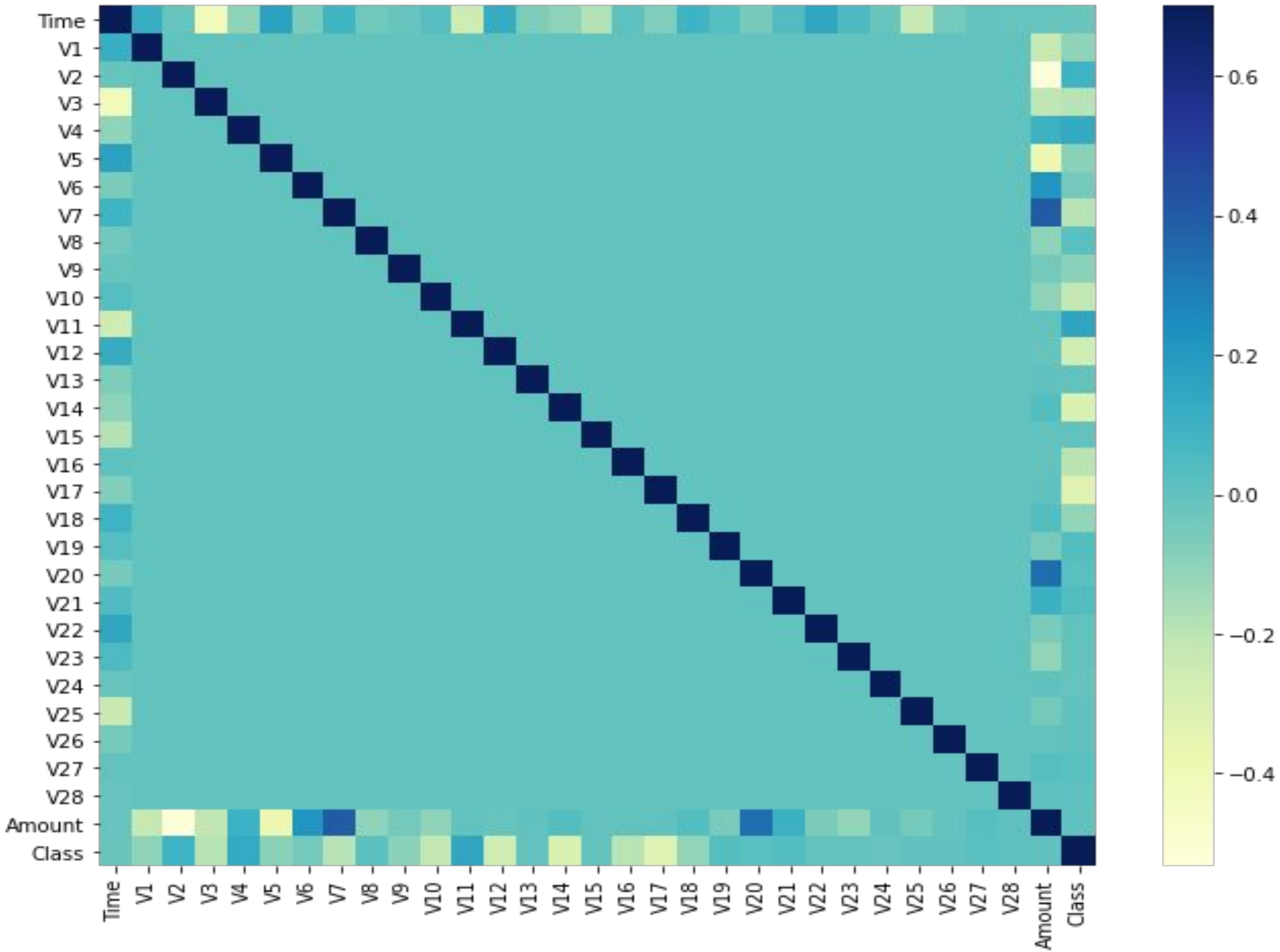
50% of fraud transactions are of less than $9.

Only 5% of fraud transactions are more than $648.



Findings

From the HeatMap, we can clearly see that there are no strongly correlated features in the dataset. There are some features that either has a positive or a negative correlation with each other. Other than that, all the correlation values lie somewhere in the neutral or zero-range.



Findings

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56856
1	0.94	0.75	0.84	106
accuracy			1.00	56962
macro avg	0.97	0.88	0.92	56962
weighted avg	1.00	1.00	1.00	56962

Random Tree

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56856
1	0.83	0.58	0.69	106
accuracy			1.00	56962
macro avg	0.91	0.79	0.84	56962
weighted avg	1.00	1.00	1.00	56962

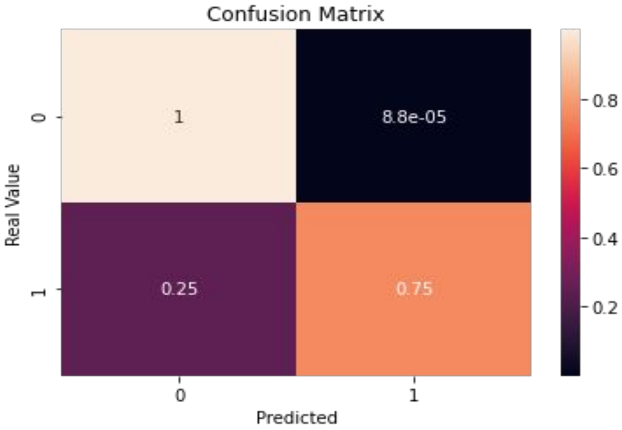
Logistic Regression

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56856
1	0.87	0.73	0.79	106
accuracy			1.00	56962
macro avg	0.93	0.86	0.89	56962
weighted avg	1.00	1.00	1.00	56962

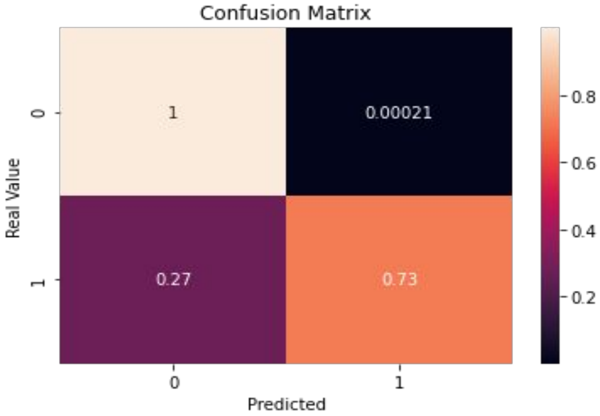
Classification Report

Decision Tree

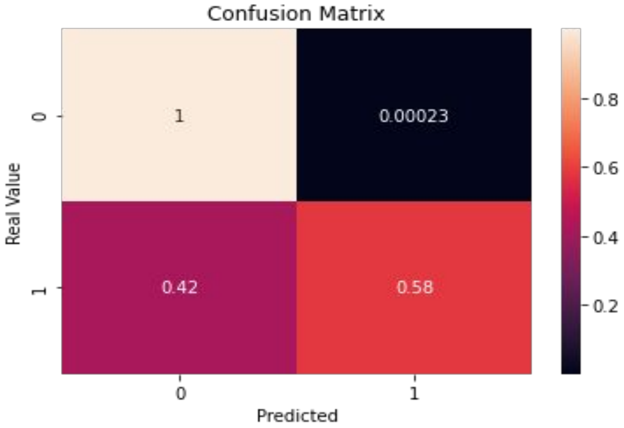
Findings



Random Forest



Decision Tree



Logistic Regression

Confusion Matrix

Limitations

The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions. The data is biased.

Conclusions

- Only 0.17% fraudulent transaction out of all the transactions. The data is biased.
- The features of the dataset are largely uncorrelated.
- 50% of fraud transactions are of less than $9.
- Only 5% of fraud transactions are more than $648.
- Random Forest Model is providing a better result even for the recall.
- This is a problem of high recall as there is a higher cost associated with false negative than false positive. If a fraudulent transaction is labelled as legitimate transaction, it will cause a huge loss to the company and their customers.

Acknowledgements

As the dataset is hosted on Kaggle, I would like to thank entire kaggle community for the knowledge sharing and resource.

References

- UC San DiegoX: DSE200x - Python for Data Science. Thanks to professors - Ilkay Altintas and Leo Porter.
- Kaggle https://www.kaggle.com/mlg-ulb/creditcardfraud

Importing all the necessary libraries

In [29]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import gridspec
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, matthews_corrcoef
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
```

Loading the data

In [57]:
```
data = pd.read_csv('./creditcard.csv', sep=',')
```

Exploring Data

In [58]:
```
data.head(10)
```

Out[58]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314	-
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213	
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864	
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084	-
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539	-

10 rows × 31 columns

In [59]:
```
data.info()
```

```
<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
```

From the above results we can observe that there are total 284807 rows/records and 31 columns

In [60]:
```
data.describe()
```

Out[60]:

	Time	V1	V2	V3	V4	V5
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563e-15
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01

8 rows × 31 columns

Data Cleaning

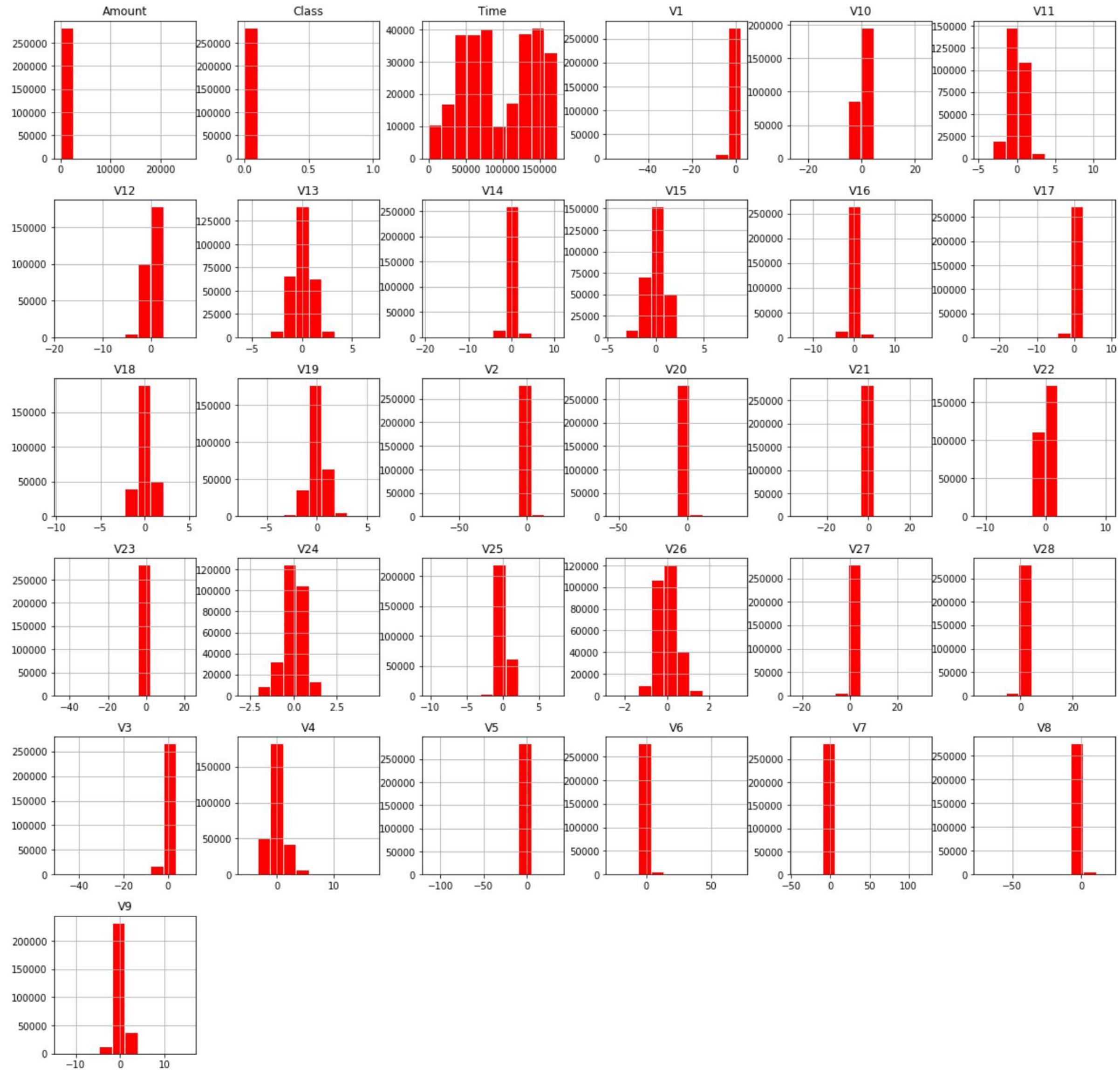
In [79]:
```
data.isnull().sum()
```

Out[79]:
```
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
```

No Null records

Plotting histogram of each feature

In [80]:
```
data.hist(figsize = (20, 20),color = 'red' , edgecolor = 'white' )
plt.show()
```



We can see most of the feature V's are clustered around 0 with some or no outliers.

Indentifying number of fraud and valid cases transactions

In [81]:
```
fraud_cases = data[data['Class'] == 1]
valid_cases = data[data['Class'] == 0]
print('Fraudulent Transactions: {}'.format(len(fraud_cases)))
print('Valid Transactions: {}'.format(len(valid_cases)))
print('Percentage of Fraudulent Transactions: {:.2%}'.format((fraud_cases.shap
e[0] / data.shape[0])))
```

```
Fraudulent Transactions: 492
Valid Transactions: 284315
Percentage of Fraudulent Transactions: 0.17%
```

Inspecting more on Fraudulent Transactions and Valid Transactions

Amount Details of the Fraudulent Transaction

In [82]:
```
fraud_cases.Amount.describe()
```

Out[82]:
```
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
```

Amount Details of the Valid Transaction

In [83]:
```
valid_cases.Amount.describe()
```

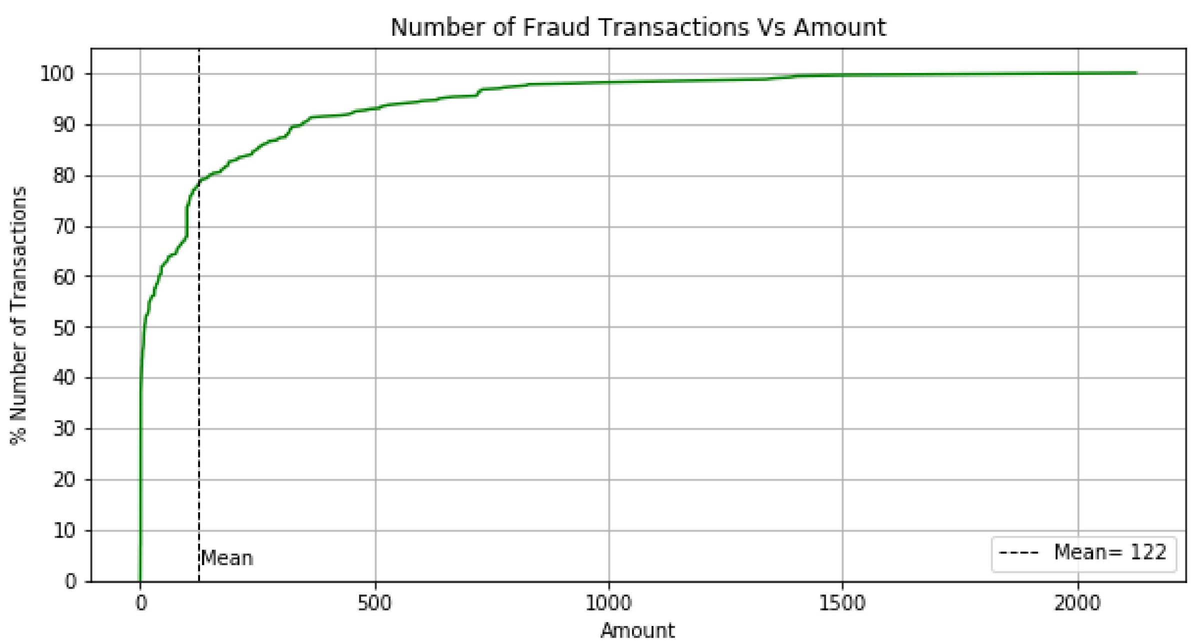
Out[83]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

In [84]:
```
fraud_cases.Amount.tail(25)
```

Out[84]:
```
254395      7.59
255403      4.97
255556      0.77
258403    296.00
261056     45.51
261473      4.90
261925    156.00
262560      4.69
262826      0.77
263080      1.00
263274      0.77
263324    127.14
263877      0.38
268375     39.98
272521     12.31
274382      0.00
274475     39.90
275992    634.30
276071     19.95
276864    349.08
279863    390.00
280143      0.76
280149     77.89
281144    245.00
281674     42.53
Name: Amount, dtype: float64
```

In [85]:
```
fraud_cases.sort_values("Amount", axis = 0, ascending = True, inplace = True,
na_position ='last')
percentage = [(x/491)*100  for x in range(492)]
fraud_amount = fraud_cases.Amount
plt.figure(figsize=(10,5))

plt.plot(fraud_amount, percentage,color='green')
plt.axvline(122, color='black',linestyle='--',linewidth=1,label='Mean= 122')
plt.legend()
plt.text(130,3,'Mean')
plt.title('Number of Fraud Transactions Vs Amount')
plt.xlabel('Amount')
plt.ylabel('% Number of Transactions')
plt.grid()
plt.yticks(np.arange(0,110,10))
plt.ylim(0,105)
plt.show()
```

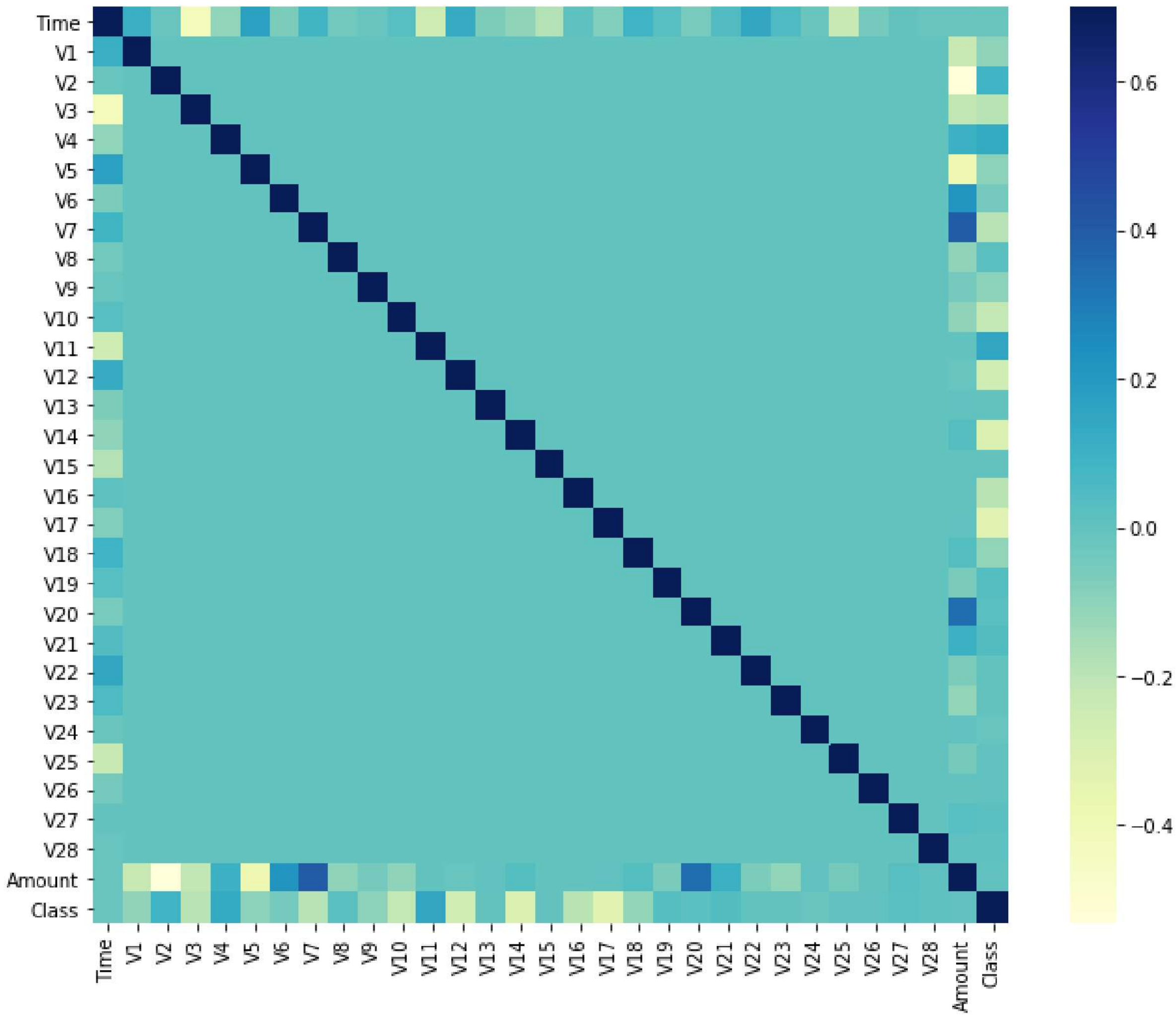
```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```



Plotting the Correlation Matrix

The correlation matrix graphically gives us an idea of how features correlate with each other and can help us predict what are the features that are most relevant for the prediction.

In [86]:
```
correlation_matrix = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(correlation_matrix, vmax = .7, square = True, cmap="YlGnBu")
plt.show()
```



From the HeatMap, we can clearly see that there are no strongly correlated features in the dataset. There are some features that either has a positive or a negative correlation with each other. Other than that, all the correlation values lie somewhere in the neutral or zero-range.

Applying Machine Learning Methods

Bifurcation of Training and Testing Data

We will be dividing the dataset into two main groups. One for training the model and the other for Testing our trained model's performance.

In [87]:
```
X = data.drop(['Class'], axis = 1)
Y = data["Class"]
x_data = X.values
y_data = Y.values
xTrain, xTest, yTrain, yTest = train_test_split(x_data, y_data, test_size = 0.
2, random_state = 43)
```

Random Forest Model

In [88]:
```
random_forest = RandomForestClassifier()
random_forest.fit(xTrain, yTrain)
y_prediction = random_forest.predict(xTest)
```

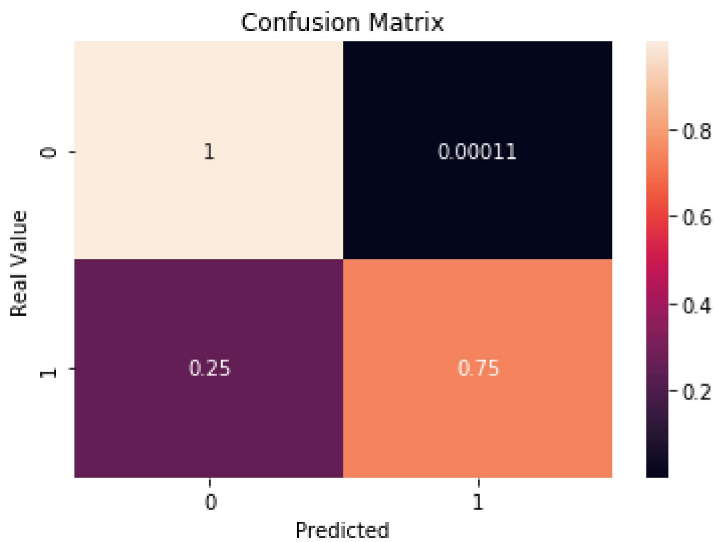
Evaluating the classifier

In [89]:
```
print(classification_report(yTest, y_prediction))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56856
           1       0.93      0.75      0.83       106

    accuracy                           1.00     56962
   macro avg       0.96      0.87      0.91     56962
weighted avg       1.00      1.00      1.00     56962
```

Visulalizing the Confusion Matrix

In [90]:
```
fig, ax = plt.subplots()
sns.heatmap(confusion_matrix(yTest, y_prediction, normalize='true'), annot=Tru
e, ax=ax)
ax.set_title("Confusion Matrix")
ax.set_ylabel("Real Value")
ax.set_xlabel("Predicted")

plt.show()
```



Logistic Regression

In [91]:
```
regress = LogisticRegression(solver="lbfgs",max_iter=1000).fit(xTrain, yTrain)
y_prediction = regress.predict(xTest)
```

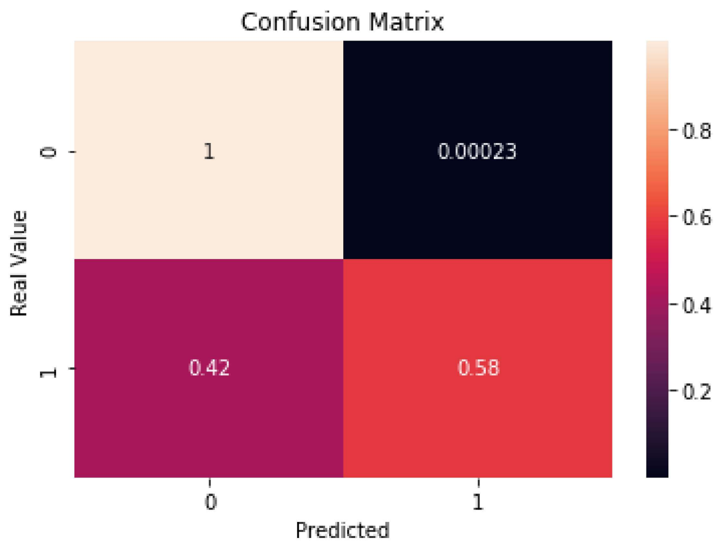
Evaluating the classifier

In [92]:
```
print(classification_report(yTest, y_prediction))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56856
           1       0.83      0.58      0.69       106

    accuracy                           1.00     56962
   macro avg       0.91      0.79      0.84     56962
weighted avg       1.00      1.00      1.00     56962
```

Visulalizing the Confusion Matrix

In [93]:
```
fig, ax = plt.subplots()
sns.heatmap(confusion_matrix(yTest, y_prediction, normalize='true'), annot=Tru
e, ax=ax)
ax.set_title("Confusion Matrix")
ax.set_ylabel("Real Value")
ax.set_xlabel("Predicted")

plt.show()
```



Decision Tree

In [94]:
```
decision_tree = DecisionTreeClassifier(max_depth=4, criterion="entropy")
decision_tree.fit(xTrain, yTrain)
y_prediction = decision_tree.predict(xTest)
```

Evaluating the classifier

In [95]:
```
print(classification_report(yTest, y_prediction))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56856
           1       0.87      0.73      0.79       106

    accuracy                           1.00     56962
   macro avg       0.93      0.86      0.89     56962
weighted avg       1.00      1.00      1.00     56962
```

Visulalizing the Confusion Matrix

In [96]:
```
fig, ax = plt.subplots()
sns.heatmap(confusion_matrix(yTest, y_prediction, normalize='true'), annot=Tru
e, ax=ax)
ax.set_title("Confusion Matrix")
ax.set_ylabel("Real Value")
ax.set_xlabel("Predicted")

plt.show()
```