

ML | Credit Card Fraud Detection

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Overview

1.

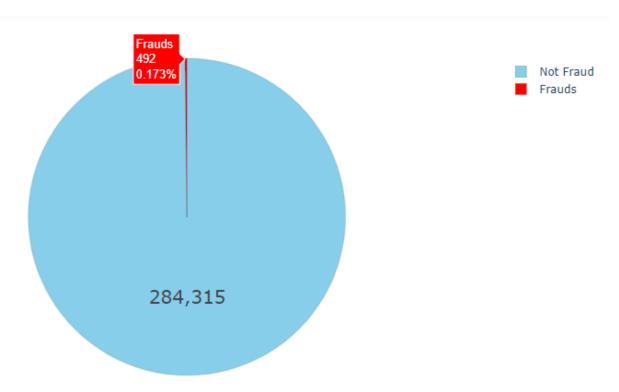
The challenge is to recognize fraudulent credit card transactions so that the customers of credit card companies are not charged for items that they did not purchase.

Data Wrangling Report

As the data was obtained from kaggle therefore it was pretty clean data.



 The dataset is highly imbalanced as only 492 transactions are fraud transaction out of 284807 transactions.



3. Out of **492 fraud transactions** the mean amount turned out to be 122.21 and the maximum fraud transaction amount turned out to be 2125.87.

<pre>fraud.Amount.describe()</pre>	
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

4. Out of **284315 valid transactions** the mean amount turned out to be 88.29 and the maximum valid transaction amount turned out to be 25691.16.

```
normal.Amount.describe()
count
         284315.000000
mean
             88.291022
std
            250.105092
              0.000000
min
25%
              5.650000
50%
             22.000000
75%
             77.050000
max
          25691.160000
Name: Amount, dtype: float64
```

5. It did **not contain** neither null value nor missing value.

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
    Column Non-Null Count Dtype
            -----
            284807 non-null float64
 0
    Time
 1
    ٧1
            284807 non-null float64
            284807 non-null float64
            284807 non-null float64
 3
    V3
 4
    ٧4
            284807 non-null float64
    ۷5
            284807 non-null float64
 5
            284807 non-null float64
 6
    ٧6
 7
    ٧7
            284807 non-null float64
            284807 non-null float64
 8
   V8
 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
            284807 non-null float64
 16 V16
 17 V17
            284807 non-null float64
 18 V18
            284807 non-null float64
 19 V19
            284807 non-null float64
 20 V20
            284807 non-null float64
            284807 non-null float64
 21 V21
 22 V22
            284807 non-null float64
 23 V23
            284807 non-null float64
 24 V24
            284807 non-null float64
 25 V25
            284807 non-null float64
            284807 non-null float64
 26 V26
 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
```

- 6. The dataset does **contain** some extreme outlier, this was **verified by plotting** various graphs such as box plot graphs.
- 7. I also checked on whether the fraud transaction is more during specific period of time frame by plotting a scatter plot between "Time of transaction vs Amount by class" but that did not yield any clear result.

Class and Amount vs Time

```
# We Will check Do fraudulent transactions occur more often during certain time frame ? Let us find out

f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Time of transaction vs Amount by class')
ax1.scatter(fraud.Time, fraud.Amount)
ax1.set_title('Fraud')
ax2.scatter(normal.Time, normal.Amount)
ax2.set_title('Normal')
plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```

