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Project : Credit Card Fraud Detection

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In this notebook I will try to predict fraud transactions from a given data set. Given that the data is imbalanced, standard metrics for evaluating classification algorithm (such as accuracy) are invalid. I will focus on the following metrics: Sensitivity (true positive rate) and Specificity (true negative rate). Of course, they are dependent on each other, so we want to find optimal trade-off between them. Such trade-off usually depends on the application of the algorithm, and in case of fraud detection I would prefer to see high sensitivity (e.g. given that a transaction is fraud, I want to be able to detect it with high probability).

IMPORTING LIBRARIES:

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pylab import rcParams
import warnings
warnings.filterwarnings('ignore')
```

READING DATASET :

In [2]:

```
data=pd.read_csv('/kaggle/input/creditcardfraud/creditcard.csv')
```

In [3]:

```
data.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458

5 rows × 31 columns

NULL VALUES:

In [4]:

```
data.isnull().sum()
```

Out[4]:

```
Time      0
V1        0
V2        0
V3        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
```

Thus there are no null values in the dataset.

INFORMATION

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
Time      284807 non-null float64
V1        284807 non-null float64
V2        284807 non-null float64
V3        284807 non-null float64
V4        284807 non-null float64
V5        284807 non-null float64
V6        284807 non-null float64
V7        284807 non-null float64
V8        284807 non-null float64
V9        284807 non-null float64
V10       284807 non-null float64
V11       284807 non-null float64
V12       284807 non-null float64
V13       284807 non-null float64
V14       284807 non-null float64
V15       284807 non-null float64
V16       284807 non-null float64
V17       284807 non-null float64
V18       284807 non-null float64
V19       284807 non-null float64
V20       284807 non-null float64
V21       284807 non-null float64
V22       284807 non-null float64
V23       284807 non-null float64
V24       284807 non-null float64
V25       284807 non-null float64
V26       284807 non-null float64
V27       284807 non-null float64
V28       284807 non-null float64
Amount    284807 non-null float64
Class     284807 non-null int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

DESCRIPTIVE STATISTICS

In [6]:

```
data.describe().T.head()
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
Time	284807.0	9.481386e+04	47488.145955	0.000000	54201.500000	84692.000000	139320.500000	172792.000000
V1	284807.0	3.919560e-15	1.958696	-56.407510	-0.920373	0.018109	1.315642	2.454930
V2	284807.0	5.688174e-16	1.651309	-72.715728	-0.598550	0.065486	0.803724	22.057729
V3	284807.0	-8.769071e-15	1.516255	-48.325589	-0.890365	0.179846	1.027196	9.382558
V4	284807.0	2.782312e-15	1.415869	-5.683171	-0.848640	-0.019847	0.743341	16.875344

In [7]:

```
data.shape
```

Out[7]:

```
(284807, 31)
```

Thus there are 284807 rows and 31 columns.

In [8]:

```
data.columns
```

Out[8]:

```
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')
```

FRAUD CASES AND GENUINE CASES

In [9]:

```
fraud_cases=len(data[data['Class']==1])
```

In [10]:

```
print(' Number of Fraud Cases:',fraud_cases)
```

```
 Number of Fraud Cases: 492
```

In [11]:

```
non_fraud_cases=len(data[data['Class']==0])
```

In [12]:

```
print('Number of Non Fraud Cases:',non_fraud_cases)
```

```
Number of Non Fraud Cases: 284315
```

In [13]:

```
fraud=data[data['Class']==1]
```

In [14]:

```
genuine=data[data['Class']==0]
```

In [15]:

```
fraud.Amount.describe()
```

Out[15]:

```
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
```

In [16]:

```
genuine.Amount.describe()
```

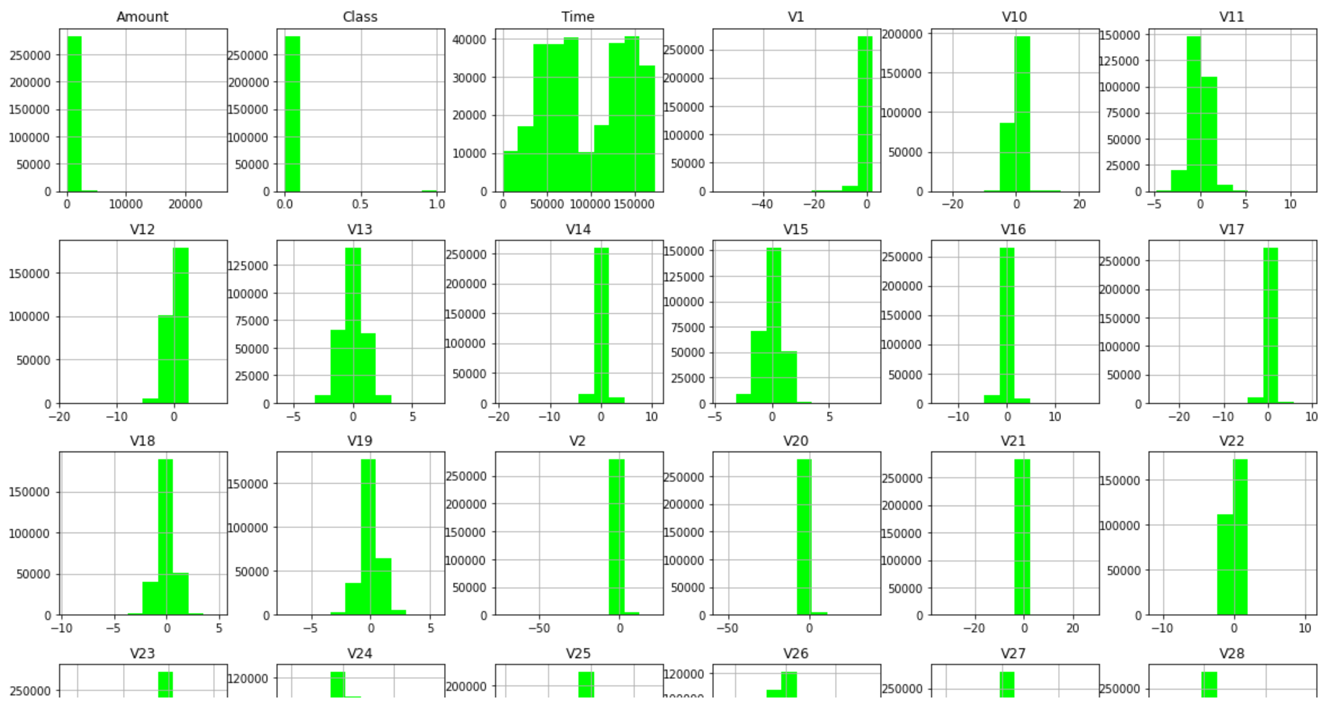
Out[16]:

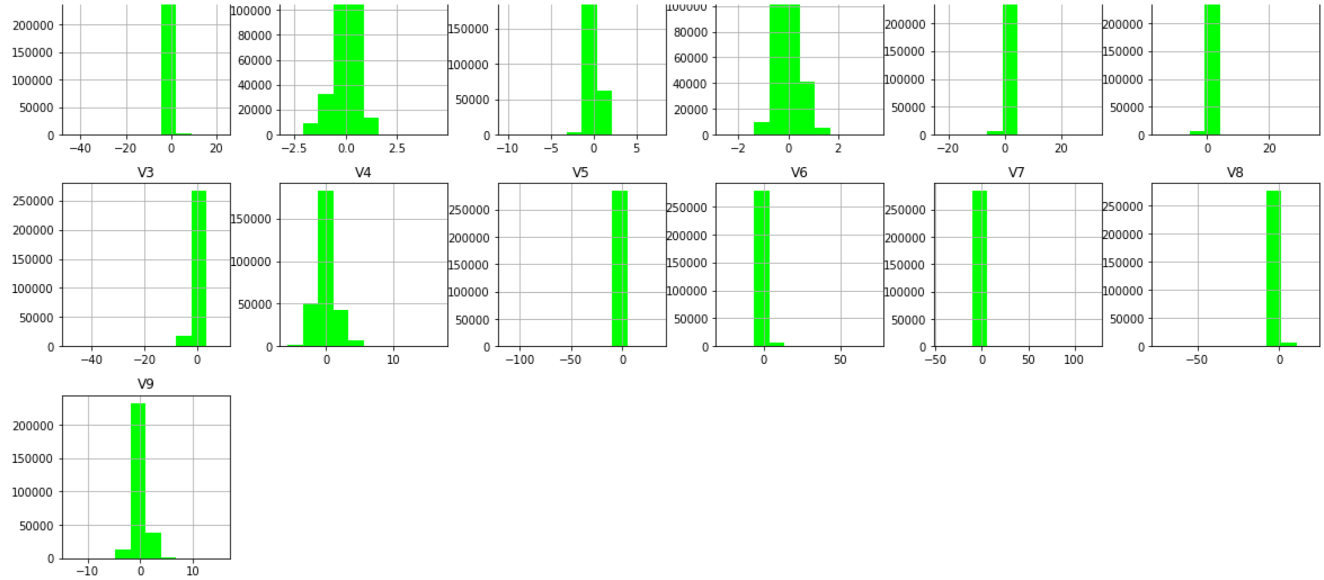
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

EDA

In [17]:

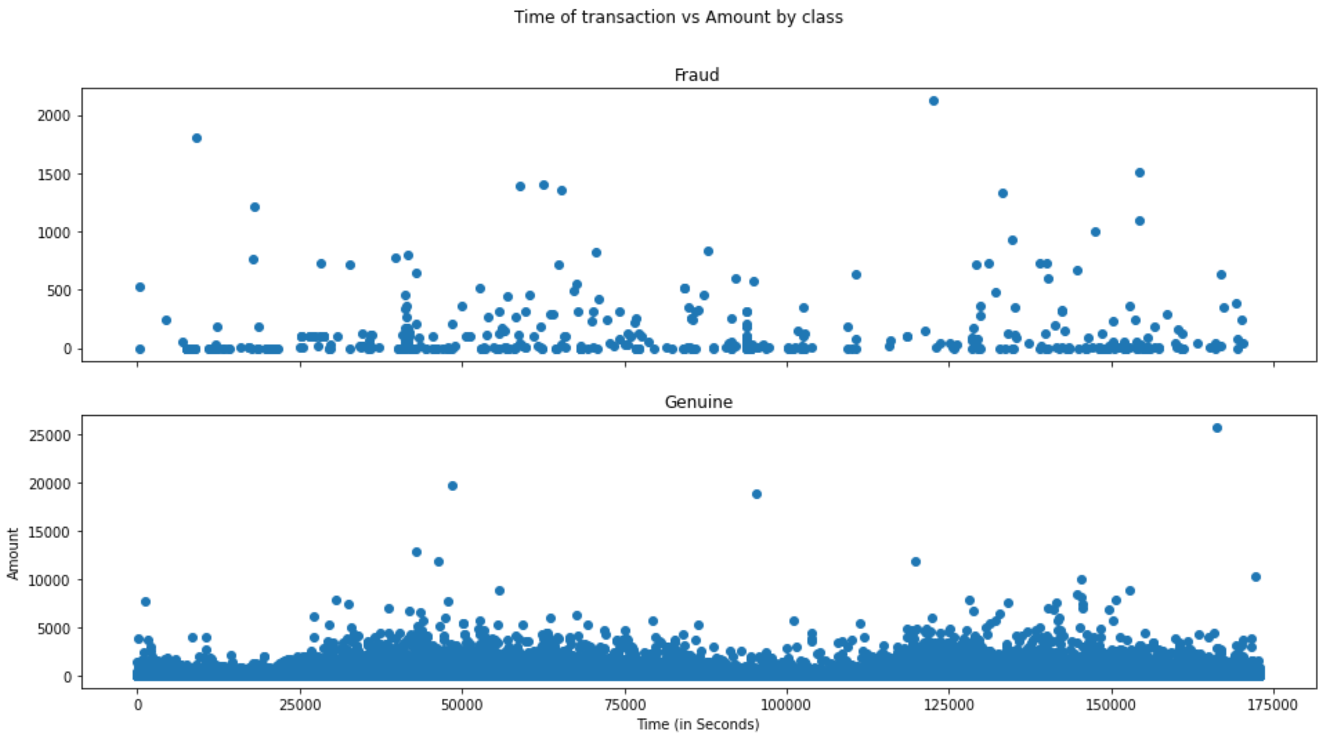
```
data.hist(figsize=(20,20),color='lime')
plt.show()
```





In [18]:

```
rcParams['figure.figsize'] = 16, 8
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(genuine.Time, genuine.Amount)
ax2.set_title('Genuine')
plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```



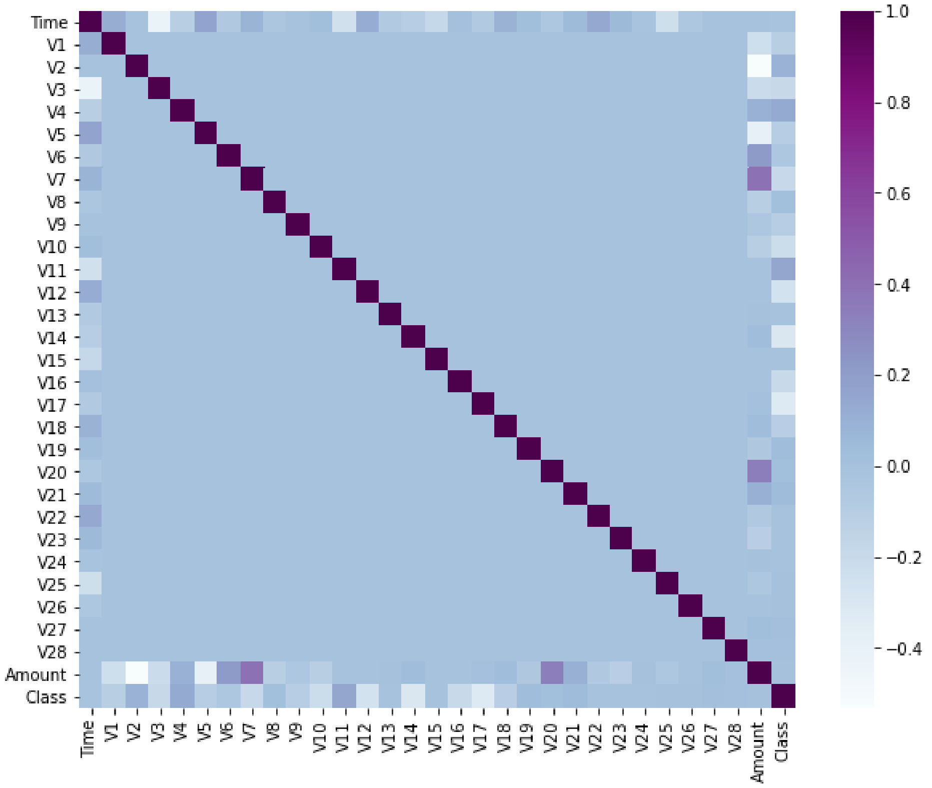
CORRELATION

In [19]:

```
plt.figure(figsize=(10,8))
corr=data.corr()
sns.heatmap(corr,cmap='BuPu')
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4c890f89b0>
```



Let us build our models:

In [20]:

```
from sklearn.model_selection import train_test_split
```

Model 1:

In [21]:

```
X=data.drop(['Class'],axis=1)
```

In [22]:

```
y=data['Class']
```

In [23]:

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.30,random_state=123)
```

In [24]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [25]:

```
rfc=RandomForestClassifier()
```

In [26]:

```
model=rfc.fit(X_train,y_train)
```

In [27]:

```
prediction=model.predict(X_test)
```

```
prediction=model.predict(X_test)
```

In [28]:

```
from sklearn.metrics import accuracy_score
```

In [29]:

```
accuracy_score(y_test,prediction)
```

Out[29]:

```
0.9995786664794073
```

Model 2:

In [30]:

```
from sklearn.linear_model import LogisticRegression
```

In [31]:

```
X1=data.drop(['Class'],axis=1)
```

In [32]:

```
y1=data['Class']
```

In [33]:

```
X1_train,X1_test,y1_train,y1_test=train_test_split(X1,y1,test_size=0.3,random_state=123)
```

In [34]:

```
lr=LogisticRegression()
```

In [35]:

```
model2=lr.fit(X1_train,y1_train)
```

In [36]:

```
prediction2=model2.predict(X1_test)
```

In [37]:

```
accuracy_score(y1_test,prediction2)
```

Out[37]:

```
0.9988764439450862
```

Model 3:

In [38]:

```
from sklearn.tree import DecisionTreeRegressor
```

In [39]:

```
X2=data.drop(['Class'],axis=1)
```

In [40]:

In [40]:

```
y2=data['Class']
```

In [41]:

```
dt=DecisionTreeRegressor()
```

In [42]:

```
X2_train,X2_test,y2_train,y2_test=train_test_split(X2,y2,test_size=0.3,random_state=123)
```

In [43]:

```
model3=dt.fit(X2_train,y2_train)
```

In [44]:

```
prediction3=model3.predict(X2_test)
```

In [45]:

```
accuracy_score(y2_test,prediction3)
```

Out[45]:

```
0.999133925541004
```

Overall models performed with a very high accuracy.

In [ ]:

```

```