## In [1]:

```
import numpy as np
import pandas as pd
import sklearn
import scipy
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report,accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn.svm import OneClassSVM
from pylab import rcParams
rcParams['figure.figsize'] = 14, 8
RANDOM_SEED = 42
LABELS = ["Normal", "Fraud"]
```

## In [3]:

```
data = pd.read_csv('creditcard_data.csv',sep=',')
data.head()
```

### Out[3]:

	Time	V1	V2	V3	V4	V5	V6	<b>V</b> 7	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 rows × 31 columns

## In [4]:

```
data.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 284806 entries, 0 to 284805 Data columns (total 31 columns): Column Non-Null Count Dtype -----Time 0 284806 non-null float64 1 V1 284806 non-null float64 2 V2 284806 non-null float64 3 V3 284806 non-null float64 4 ٧4 284806 non-null float64 5 ۷5 284806 non-null float64 6 ۷6 284806 non-null float64 7 ٧7 float64 284806 non-null 8 ٧8 284806 non-null float64 9 ۷9 284806 non-null float64 10 V10 284806 non-null float64 284806 non-null float64 11 V11 284806 non-null 12 V12 float64 13 V13 284806 non-null float64 14 V14 284806 non-null float64 284806 non-null float64 15 V15 V16 284806 non-null float64 16 17 V17 284806 non-null float64 18 V18 284806 non-null float64 19 V19 284806 non-null float64 20 V20 284806 non-null float64 21 V21 284806 non-null float64 V22 284806 non-null float64 22 23 V23 284806 non-null float64 float64 24 V24 284806 non-null float64 25 V25 284806 non-null 284806 non-null float64 26 V26 27 V27 284806 non-null float64 28 V28 284806 non-null float64 Amount float64 29 284806 non-null Class 284806 non-null int64 dtypes: float64(30), int64(1)

memory usage: 67.4 MB

#### In [5]:

```
data.isnull().values.any()
```

## Out[5]:

False

### In [6]:

```
count_classes = pd.value_counts(data['Class'], sort = True)

count_classes.plot(kind = 'bar', rot=0)

plt.title("Transaction Class Distribution")

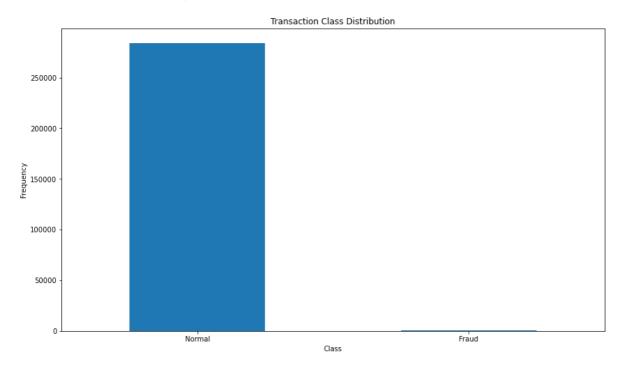
plt.xticks(range(2), LABELS)

plt.xlabel("Class")

plt.ylabel("Frequency")
```

# Out[6]:

Text(0, 0.5, 'Frequency')



## In [7]:

```
fraud = data[data['Class']==1]
normal = data[data['Class']==0]
```

## In [8]:

```
print(fraud.shape,normal.shape)
```

```
(492, 31) (284314, 31)
```

## In [9]:

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

## Out[9]:

```
count
          492.000000
          122.211321
mean
std
          256.683288
min
            0.000000
25%
            1.000000
50%
            9.250000
75%
          105.890000
         2125.870000
max
```

Name: Amount, dtype: float64

## In [10]:

```
normal.Amount.describe()
```

## Out[10]:

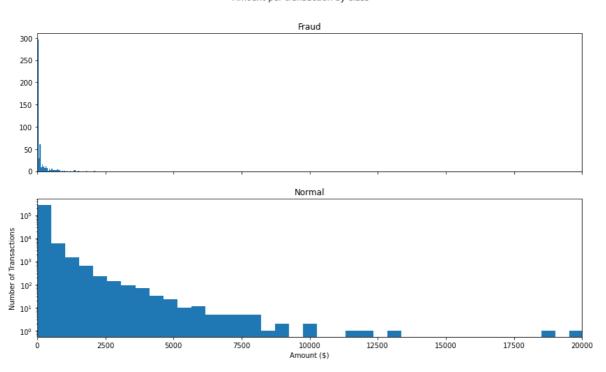
284314.000000 count mean 88.290570 std 250.105416 min 0.000000 5.650000 25% 50% 22.000000 75% 77.050000  ${\sf max}$ 25691.160000

Name: Amount, dtype: float64

## In [11]:

```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')
bins = 50
ax1.hist(fraud.Amount, bins = bins)
ax1.set_title('Fraud')
ax2.hist(normal.Amount, bins = bins)
ax2.set_title('Normal')
plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show();
```

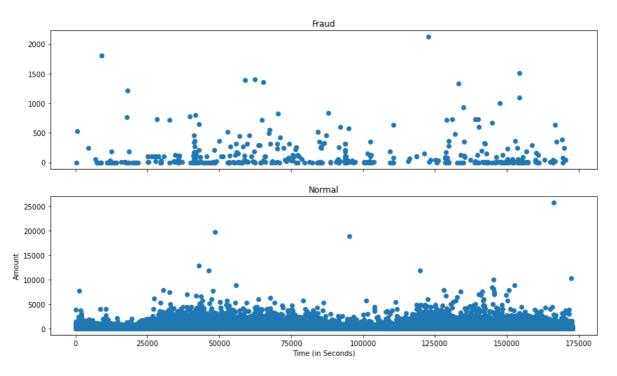
#### Amount per transaction by class



### In [14]:

```
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()
```

Time of transaction vs Amount by class



### In [15]:

```
data1= data.sample(frac = 0.1,random_state=1)
data1.shape
```

### Out[15]:

(28481, 31)

## In [16]:

```
data.shape
```

## Out[16]:

(284806, 31)

### In [17]:

```
Fraud = data1[data1['Class']==1]

Valid = data1[data1['Class']==0]

outlier_fraction = len(Fraud)/float(len(Valid))
```

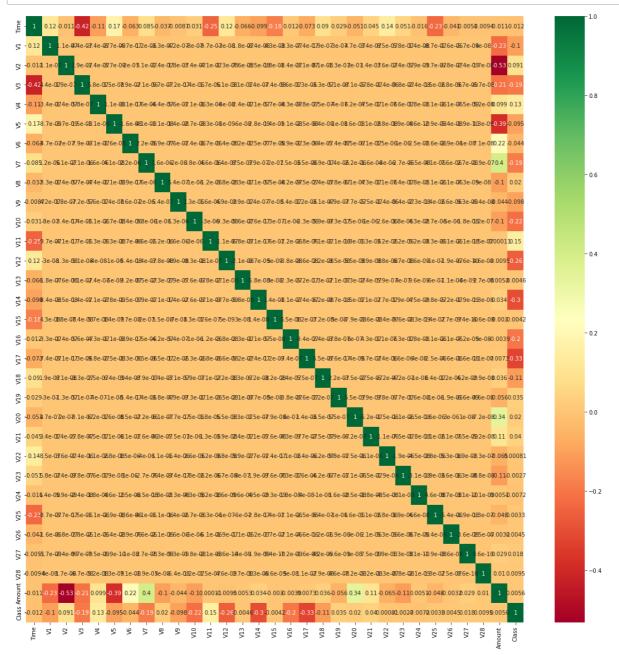
#### In [18]:

```
print(outlier_fraction)
print("Fraud Cases : {}".format(len(Fraud)))
print("Valid Cases : {}".format(len(Valid)))
```

0.0016529506928325245
Fraud Cases : 47
Valid Cases : 28434

### In [19]:

```
import seaborn as sns
corrmat = data1.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
#plot heat map
g=sns.heatmap(data[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



```
In [20]:
```

```
columns = data1.columns.tolist()
columns = [c for c in columns if c not in ["Class"]]
target = "Class"
state = np.random.RandomState(42)
X = data1[columns]
Y = data1[target]
X_outliers = state.uniform(low=0, high=1, size=(X.shape[0], X.shape[1]))
print(X.shape)
print(Y.shape)
(28481, 30)
(28481,)
In [22]:
classifiers = {
    "Isolation Forest": IsolationForest(n_estimators=100, max_samples=len(X),
                                        contamination=outlier_fraction,random_state=state, v
    "Local Outlier Factor":LocalOutlierFactor(n_neighbors=20, algorithm='auto',
                                               leaf_size=30, metric='minkowski',
                                               p=2, metric_params=None, contamination=outlie
    "Support Vector Machine":OneClassSVM(kernel='rbf', degree=3, gamma=0.1,nu=0.05,
                                          max_iter=-1)
```

### In [23]:

}

```
type(classifiers)
```

## Out[23]:

dict

## In [24]:

```
n outliers = len(Fraud)
for i, (clf_name,clf) in enumerate(classifiers.items()):
   if clf_name == "Local Outlier Factor":
        y_pred = clf.fit_predict(X)
        scores_prediction = clf.negative_outlier_factor_
   elif clf_name == "Support Vector Machine":
        clf.fit(X)
        y_pred = clf.predict(X)
   else:
        clf.fit(X)
        scores_prediction = clf.decision_function(X)
        y_pred = clf.predict(X)
   y_pred[y_pred == 1] = 0
   y_pred[y_pred == -1] = 1
   n_errors = (y_pred != Y).sum()
   print("{}: {}".format(clf_name,n_errors))
   print("Accuracy Score :")
   print(accuracy_score(Y,y_pred))
   print("Classification Report :")
   print(classification_report(Y,y_pred))
Isolation Forest: 67
```

```
Accuracy Score :
0.9976475545100242
Classification Report :
              precision
                            recall f1-score
                                                support
           0
                              1.00
                                         1.00
                                                   28434
                    1.00
           1
                    0.29
                              0.30
                                         0.29
                                                      47
                                         1.00
                                                   28481
    accuracy
                                         0.65
                                                   28481
   macro avg
                    0.65
                              0.65
weighted avg
                    1.00
                              1.00
                                         1.00
                                                   28481
Local Outlier Factor: 93
Accuracy Score :
0.9967346652154068
Classification Report :
              precision
                            recall f1-score
                                                support
           0
                    1.00
                              1.00
                                         1.00
                                                   28434
           1
                    0.02
                              0.02
                                         0.02
                                                      47
                                         1.00
                                                   28481
    accuracy
   macro avg
                    0.51
                              0.51
                                         0.51
                                                   28481
weighted avg
                    1.00
                              1.00
                                         1.00
                                                   28481
Support Vector Machine: 8412
Accuracy Score :
0.7046452020645343
Classification Report :
              precision
                            recall f1-score
                                                 support
                    1.00
                              0.71
                                         0.83
                                                   28434
           0
           1
                    0.00
                              0.34
                                         0.00
                                                      47
                                         0.70
                                                   28481
    accuracy
   macro avg
                    0.50
                              0.52
                                         0.42
                                                   28481
```

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weighted avg 1.00 0.70

0.83 28481

In [ ]: