Find out and remove outliers from Credit card data

Information about Credit Card Fraud Detection:

- The datasets 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.
- It contains only numerical input variables which are the result of a PCA transformation.
- Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'.

Features Information:

- (i). Amount: is the transaction Amount
- (ii). Time : contains the seconds elapsed between each transaction and the first transaction in the dataset.
- (iii).V1,V2,....V28: are the principal components obtained with PCA.
- (IV). Class: fraud =1,otherwise =0

Link: https://www.kaggle.com/mlg-ulb/creditcardfraud (https://www.kaggle.com/mlg-ulb/creditcardfraud)

In [24]:

```
# import the required library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

```

In [2]:

```
# load the Credit Card Fraud Detection dataset
# recap the the dataset

credit = pd.read_csv('creditcard.csv')
credit.head() # show the 5 datapoints of dataset
```

Out[2]:

	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 rows × 31 columns

In [3]:

```
# change column Class to Fraud
credit = credit.rename(columns= {'Class':'Fraud'})
credit.head()
```

Out[3]:

	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 rows × 31 columns

In [4]:

```
# split the  features and lables
X = credit.iloc[:,:-1]
y = credit.iloc[:,-1]

```

In [5]:

```
# Dataset is very large,so we should standardize the data
# StandardScaler(): Standardize features by removing the mean and scaling to unit varia

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

```

In [6]:

```
# IMPORT the PCA scikit-learn library
from sklearn.decomposition import PCA
pca = PCA() # pca() function
pca.fit(X_scaled)
```

Out[6]:

```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)
```

Find out and remove outliers from Credit card data

In [7]:

```
from sklearn.neighbors import LocalOutlierFactor


```

In [8]:

```
%%time

lof = LocalOutlierFactor(n_jobs=-1) # n_jobs = -1 means that use all cores of cpu
lof.fit(X_scaled)
```

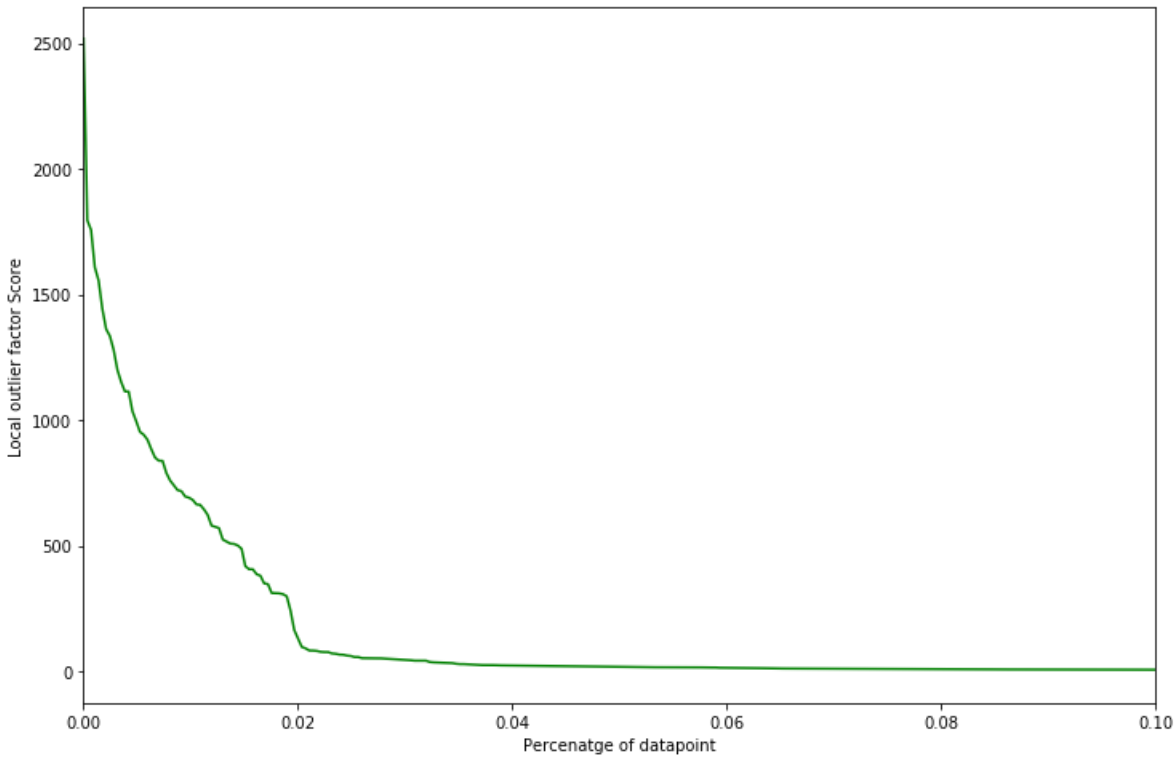
```
Wall time: 40min 26s
```

In [25]:

```
lof_score = -np.sort(lof.negative_outlier_factor_) # """ negative_outlier_factor_:  Tl

plt.figure(figsize=(12, 8))
plt.plot(np.linspace(0, 100, len(lof_score)), lof_score,color  ='green')
plt.ylabel('Local outlier factor Score')
plt.xlabel('Percenatge of datapoint')
plt.xlim((0, 0.1))

# Local Outlier Factor  score of each datapoint sorted in descending order
# negative sign means that convert neagtive to positive

```

Out[25]:

```
(0, 0.1)
```



- LOF start at 0.02 % of datapoits and we are getting elbow shape at 0.02%
- choose contamination = 0.02%

In [13]:

```
%%time

lof.contamination = 0.02 / 100
inliers = lof.fit_predict(X_scaled)
```

```
Wall time: 41min 43s
```

In [14]:

```
# count the total numbers of outliers

(inliers == -1).sum()

```

Out[14]:

```
57
```

In [15]:

```
y[inliers == -1].value_counts()
```

Out[15]:

```
0    57
Name: Fraud, dtype: int64
```

In [18]:

```
# here we have Removed the  outliers
X_cleaned_scaled = X_scaled[inliers == 1]
y_cleaned = y[inliers == 1]
```

In [23]:

```
X_cleaned_scaled #x_ceaned_sclaed outliers

```

Out[23]:

```
array([[-1.99658302, -0.69424232, -0.04407492, ...,  0.33089162,
        -0.06378115,  0.24496426],
       [-1.99658302,  0.60849633,  0.16117592, ..., -0.02225568,
         0.04460752, -0.34247454],
       [-1.99656197, -0.69350046, -0.81157783, ..., -0.13713686,
        -0.18102083,  1.16068593],
       ...,
       [ 1.6419735 ,  0.98002374, -0.18243372, ...,  0.01103672,
        -0.0804672 , -0.0818393 ],
       [ 1.6419735 , -0.12275539,  0.32125034, ...,  0.26960398,
         0.31668678, -0.31324853],
       [ 1.64205773, -0.27233093, -0.11489898, ..., -0.00598394,
         0.04134999,  0.51435531]])
```

In [21]:

```
1 y_cleaned.head() #y_cleaned outliers
```

Out[21]:

```
0    0
1    0
2    0
3    0
4    0
Name: Fraud, dtype: int64
```

In [ ]:

```
1
```