KNN on Credit Card Fraud Detection Dataset

Please download the data from https://www.kaggle.com/dalpozz/creditcardfraud/data (https://www.kaggle.com/dalpozz/creditcardfraud/data)

Task 1. Propose a suitable error metrics for this problem.

Task 2. Apply KNN on the dataset, find out the best k using grid search.

Task 3. Report the value of performance

Info about data: it is a CSV file, contains 31 features, the last feature is used to classify the transaction whether it is a fraud or not

Information about data set

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

It contains only numerical input variables which are the result of a PCA transformation. Unfortunately, due to confidentiality issues, we cannot provide the original features and more background information about the data. 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'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-senstive learning. **Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.**

Given the class imbalance ratio, we recommend measuring the accuracy using the Area Under the Precision-Recall Curve (AUPRC). Confusion matrix accuracy is not meaningful for unbalanced classification.

The dataset has been collected and analysed during a research collaboration of Worldline and the Machine Learning Group (http://mlg.ulb.ac.be (http://mlg.ulb.ac.be)) of ULB (Université Libre de Bruxelles) on big data mining and fraud detection.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler

from sklearn import cross_validation
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cross_validation import cross_val_score
```

```
C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module was deprec
ated in version 0.18 in favor of the model_selection module into which all the refactored classes and functions are mov
ed. Also note that the interface of the new CV iterators are different from that of this module. This module will be re
moved in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
data = pd.read_csv("creditcard.csv")
```

In [3]:
```
data.shape
```

Out[3]: (284807, 31)

In [4]:
```
data.head()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V
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	0.066
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	-0.339
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	-0.689
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	-1.175
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	0.141

5 rows × 31 columns

In [5]:
```
data["Class"].value_counts()
```

Out[5]:
```
0    284315
1       492
Name: Class, dtype: int64
```

In [9]:
```
#taking first 20000 samples
data_20000 = data[:20000]
```

In [10]:
```
data_20000.shape
```

Out[10]:
```
(20000, 31)
```

In [11]:
```
data_20000["Class"].value_counts()
```

Out[11]:
```
0    19915
1       85
Name: Class, dtype: int64
```

Our dataset is heavily imbalanced

In [12]:
```
data20000 = data_20000.drop(['Class'], axis=1)
data20000.shape
```

Out[12]:
```
(20000, 30)
```

In [13]:
```
data20000_labels = data_20000["Class"]
data20000_labels.shape
```

Out[13]:
```
(20000,)
```

In [14]:
```
data20000_Std = StandardScaler().fit_transform(data20000)
print(data20000_Std.shape)
print(type(data20000_Std))
```

```
(20000, 30)
<class 'numpy.ndarray'>
```

Task1: Propose a suitable error metrics for this problem.

Since our dataset is heavily imbalanced therefore I am proposing "Recall" as a suitable error metric for our problem

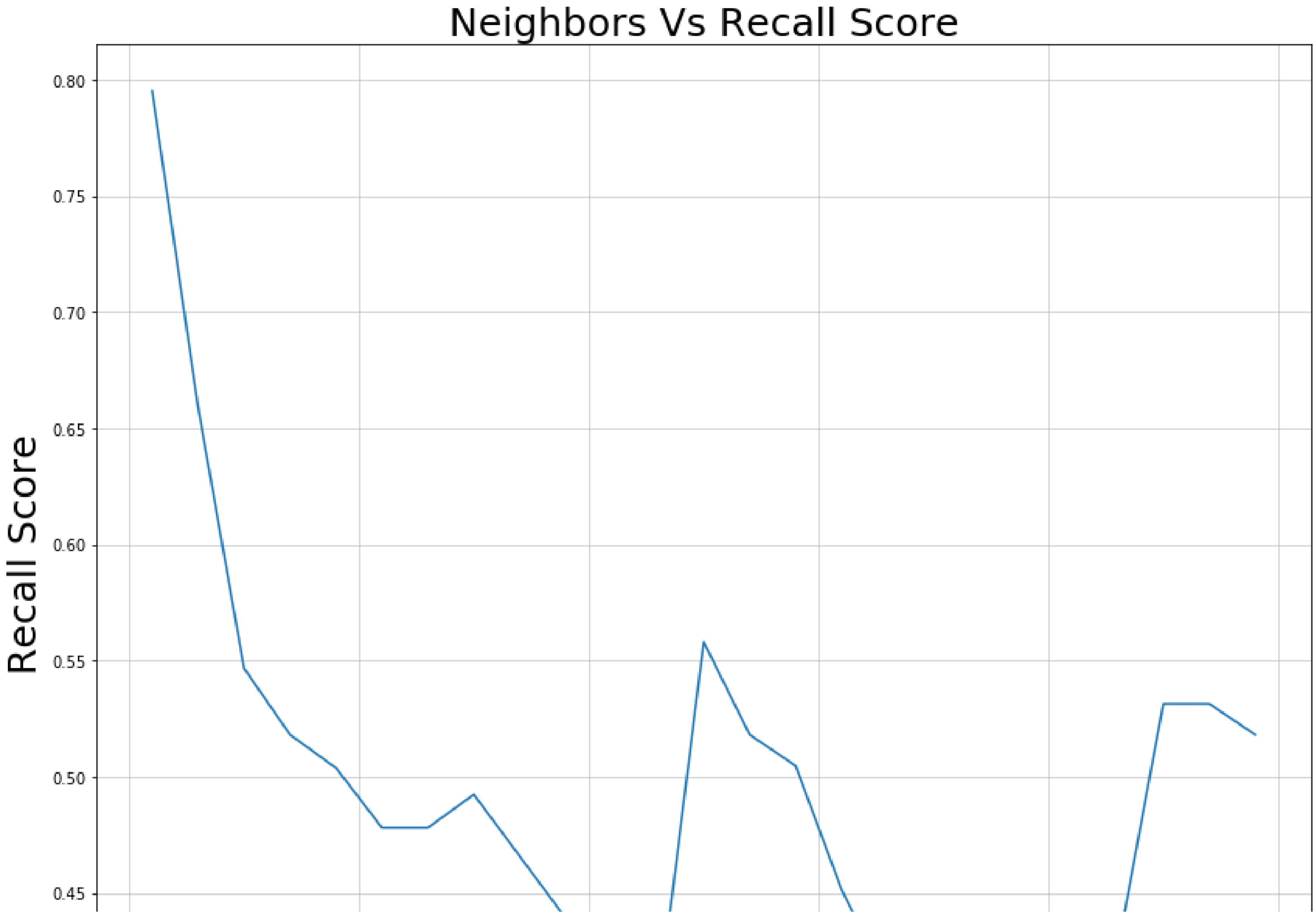
Task 2: Apply KNN on the dataset, find out the best k using 5-Folds CV.

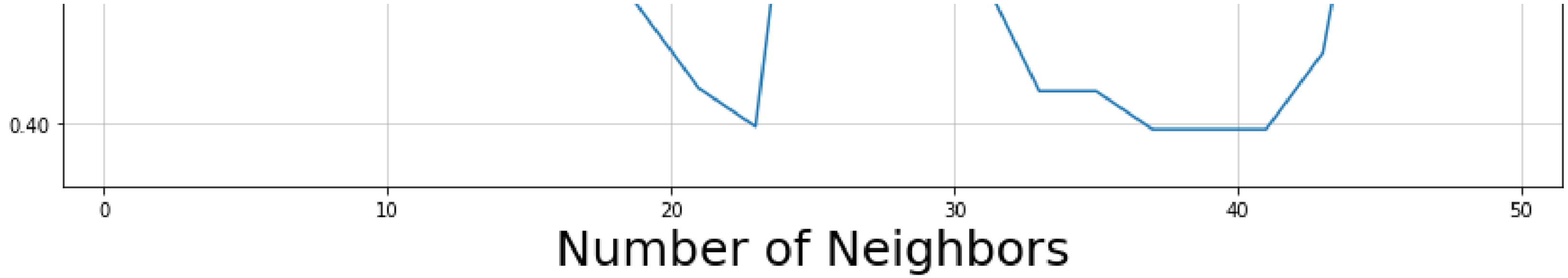
In [16]:
```
X1 = data20000_Std[0:16000]
XTest = data20000_Std[16000:20000]
Y1 = data20000_labels[0:16000]
YTest = data20000_labels[16000:20000]
#taking last 4k points as test data and first 16k points as train data

myList = list(range(0,50))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only ranging from 0 to 50

CV_Scores = []

for k in neighbors:
    KNN = KNeighborsClassifier(n_neighbors = k, algorithm = 'kd_tree')
    scores = cross_val_score(KNN, X1, Y1, cv = 5, scoring='recall')
    CV_Scores.append(scores.mean())
```

In [17]:
```
CV_Scores
```

Out[17]:
```
[0.7952380952380952,
 0.659047619047619,
 0.5466666666666666,
 0.5180952380952382,
 0.5038095238095238,
 0.4780952380952381,
 0.4780952380952381,
 0.4923809523809524,
 0.46571428571428564,
 0.4390476190476191,
 0.41238095238095235,
 0.39904761904761904,
 0.5580952380952381,
 0.518095238095238,
 0.5047619047619047,
 0.4514285714285714,
 0.41142857142857137,
 0.41142857142857137,
 0.3980952380952381,
 0.3980952380952381,
 0.3980952380952381,
 0.4247619047619048,
 0.5314285714285715,
 0.5314285714285715,
 0.5180952380952382]
```

In [18]:
```
plt.figure(figsize = (14, 12))
plt.plot(neighbors, CV_Scores)
plt.title("Neighbors Vs Recall Score", fontsize=25)
plt.xlabel("Number of Neighbors", fontsize=25)
plt.ylabel("Recall Score", fontsize=25)
plt.grid(linestyle='-', linewidth=0.5)
```





In [20]:
```
best_k = neighbors[CV_Scores.index(max(CV_Scores))]
best_k
```

Out[20]: 1

Best 'K' value is chosen as 1

In [21]:
```
from sklearn.metrics import recall_score

KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'kd_tree')

KNN_best.fit(X1, Y1)

prediction = KNN_best.predict(XTest)

recallTest = recall_score(YTest, prediction)

print("Recall Score of the knn classifier for best k values of "+str(best_k)+" is: "+str(recallTest))

cm = confusion_matrix(YTest, prediction)

print(cm)

tn, fp, fn, tp = cm.ravel()

(tn, fp, fn, tp)
```

```
Recall Score of the knn classifier for best k values of 1 is: 0.8333333333333334
[[3978   10]
 [   2   10]]
```

Out[21]:
```
(3978, 10, 2, 10)
```

In [22]:
```
YTest.value_counts()
```

Out[22]:
```
0    3988
1      12
Name: Class, dtype: int64
```

There are total 4000 points in our test dataset, out of which 3988 points belongs to class label '0' and 12 points belong to class label '1'. Now from confusion matrix we can see that the value of "True Negative" is 3978 which means that out of 3988 points which belong to class '0', 3978 points are predicted as '0'. Furthermore, from the same confusion matrix we can see that the value of "True Positive" is 10 which means that out of 12 points which belong to class '1', 10 points are detected as '1'. 10 point from class '0' and 2 points from class '1' are detected falsely

In conclusion, despite being an imbalanced dataset, our model is performing well. Even thought, there are only 12 points out of 4000 belongs to class '1', still our model is able to detect 10 of them correctly.

Task 3: Report the value of performance

In [30]:
```
# Calculating R square value of our model
from sklearn.metrics import r2_score

print("Recall Score of the knn classifier for best k values of "+str(best_k)+" is: "+str(recallTest))
```

```
Recall Score of the knn classifier for best k values of 1 is: 0.8333333333333334
```