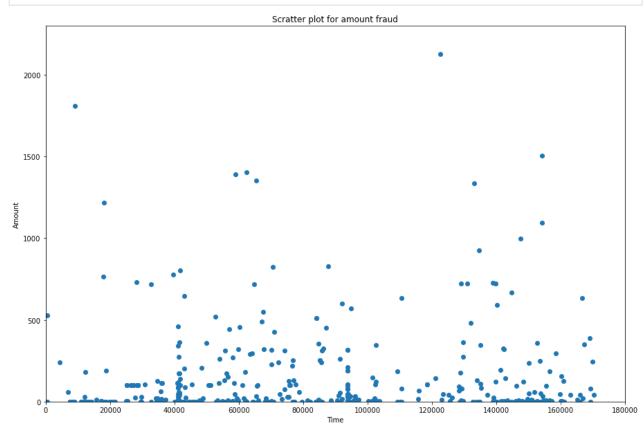
```
In [1]:
          #Importing required librairies
          import pandas as pd
          import numpy as np
          #importing svm from scikit learn
          from sklearn import preprocessing
          from sklearn.metrics import confusion matrix
          from sklearn import svm
          import itertools
          #import matplotlib library to plot the charts
          import matplotlib.pyplot as plt
          import matplotlib.mlab as mlab
          #this is the library for statistic data visualization
          import seaborn
          %matplotlib inline
In [2]:
          data = pd.read csv("C:\\Users\\asims\\Documents\\Machine Learning and Deep Learning\\cr
In [3]:
          dFrame = pd.DataFrame(data) #Dataframe to PandaDataFrame
          dFrame.describe()
                                                      V2
                                                                                                 V5
                                        V1
                                                                    V3
                                                                                   V4
Out[3]:
                        Time
         count 284807.000000
                               2.848070e+05
                                             2.848070e+05
                                                           2.848070e+05
                                                                         2.848070e+05
                                                                                        2.848070e+05
                                                                                                      2.84
         mean
                 94813.859575
                               3.918649e-15
                                              5.682686e-16
                                                           -8.761736e-15
                                                                          2.811118e-15
                                                                                       -1.552103e-15
                                                                                                      2.0
           std
                 47488.145955
                               1.958696e+00
                                             1.651309e+00
                                                           1.516255e+00
                                                                         1.415869e+00
                                                                                        1.380247e+00
                                                                                                      1.33
                                                                                      -1.137433e+02
           min
                     0.000000
                              -5.640751e+01
                                            -7.271573e+01
                                                          -4.832559e+01
                                                                         -5.683171e+00
                                                                                                     -2.61
          25%
                 54201.500000
                                             -5.985499e-01
                                                           -8.903648e-01
                                                                                       -6.915971e-01
                               -9.203734e-01
                                                                         -8.486401e-01
                                                                                                      -7.6
          50%
                 84692.000000
                               1.810880e-02
                                              6.548556e-02
                                                            1.798463e-01
                                                                         -1.984653e-02
                                                                                       -5.433583e-02
                                                                                                      -2.7
          75%
                139320.500000
                               1.315642e+00
                                              8.037239e-01
                                                           1.027196e+00
                                                                          7.433413e-01
                                                                                        6.119264e-01
                                                                                                      3.9
          max 172792.000000
                                             2.205773e+01
                                                           9.382558e+00
                                                                                        3.480167e+01
                               2.454930e+00
                                                                         1.687534e+01
                                                                                                      7.33
        8 rows × 31 columns
In [4]:
          dFrame fraud = dFrame[dFrame['Class'] == 1] #recovering fraud data
          plt.figure(figsize=(15,10)) #assigning figuresize
          plt.scatter(dFrame_fraud['Time'], dFrame_fraud['Amount']) #showing fraud amount with re
          plt.title('Scratter plot for amount fraud')
          plt.xlabel('Time')
```

plt.ylabel('Amount')
plt.xlim([0,180000])

```
plt.ylim([0,2300])
plt.show()
```



```
biggerFraud = dFrame_fraud[dFrame_fraud['Amount'] > 1000].shape[0] #Lets do the recover
print('There are only '+ str(biggerFraud) + ' frauds in total that were bigger than 100
```

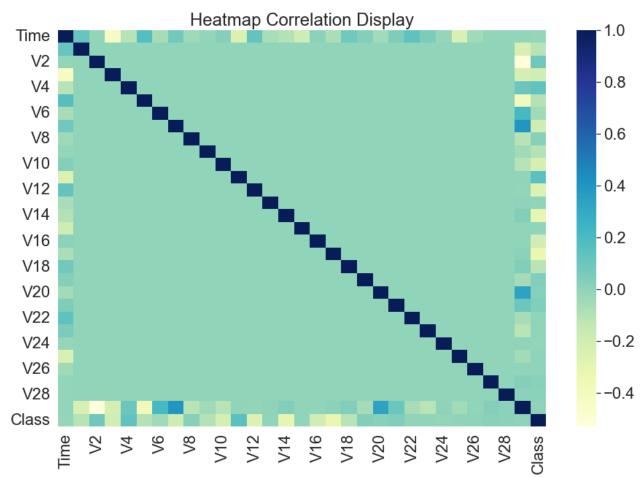
There are only 9 frauds in total that were bigger than 1000 among 492 frauds

```
numOfFrauds = len(data[data.Class == 1])
numOfNoFrauds= len(data[data.Class == 0])
print('There are ' + str(numOfFrauds) + ' frauds in the original dataset, even though t
print("\nNow the Accuracy of classifier: "+ str((284315-492)/284315))
```

There are 492 frauds in the original dataset, even though there are 284315 frauds.

Now the Accuracy of classifier: 0.998269524998681

```
In [10]: dFrame_corr = dFrame.corr() #Correlation coefficients calculation in pairs with the def
In [14]: plt.figure(figsize=(15,10)) #setting the figure size
    seaborn.heatmap(dFrame_corr, cmap="YlGnBu") #heatmap correlation display
    seaborn.set(font_scale=2,style='white')
    plt.title('Heatmap Correlation Display')
    plt.show()
```



```
rank = dFrame_corr['Class'] #Retrieving correlation coefficients as w.r.t feature class dFrame_rank = pd.DataFrame(rank) dFrame_rank = np.abs(dFrame_rank).sort_values(by='Class',ascending=False) #ranking abso dFrame_rank.dropna(inplace=True) #removing the missing data but not number
```

```
#we have to divide data in two groups- train dataset & test dataset

#Now build train dataset

dFrame_train_all = dFrame[0:150000] # start to separate original dataset into frauds &

dFrameTrainds_1 = dFrame_train_all[dFrame_train_all['Class'] == 1]

dFrameTrainds_0 = dFrame_train_all[dFrame_train_all['Class'] == 0]

print('In this dataset, we have ' + str(len(dFrameTrainds_1)) +" frauds so we need to t

dFrame_sample=dFrameTrainds_0.sample(300)

dFrame_train = dFrameTrainds_1.append(dFrame_sample) #collecting frauds along with no f

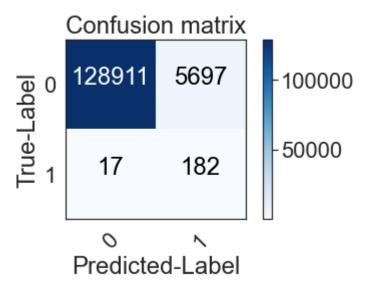
dFrame_train = dFrame_train.sample(frac=1) #Mixing the dataset
```

In this dataset, we have 293 frauds so we need to take a similar number of non-fraud

```
In [19]:

XTrainD = dFrame_train.drop(['Time', 'Class'],axis=1) # We drop the features Time
YTrainD = dFrame_train['Class'] #class as label
XTrainD = np.asarray(XTrainD)
YTrainD = np.asarray(YTrainD)
```

```
TestAll X = TestAll dFrame.drop(['Time', 'Class'],axis=1)
          TestAll Y = TestAll dFrame['Class']
          TestAll X = np.asarray(TestAll X)
          TestAll_Y = np.asarray(TestAll_Y)
In [21]:
          XTrainD rank = dFrame train[dFrame rank.index[1:11]] # 1 to 11 takes only 10 features
          XTrainD rank = np.asarray(XTrainD rank)
In [22]:
          #To check if whether the model learn correctly with respect to dataset
          TestAll X rank = TestAll dFrame[dFrame rank.index[1:11]]
          TestAll X rank = np.asarray(TestAll X rank)
          TestAll Y = np.asarray(TestAll Y)
In [23]:
          class_names=np.array(['0','1']) #FYI Class = 1 is fraud and Class = 0 is no fraud, usin
In [25]:
          # Create Plot Confusion Matirx Method
          def plot Cmrix(cm, classes,
                                     title='Confusion matrix',
                                     cmap=plt.cm.Blues):
              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              plt.colorbar()
              tick marks = np.arange(len(classes))
              plt.xticks(tick marks, classes, rotation=45)
              plt.yticks(tick marks, classes)
              fmt = 'd'
              threshold = cm.max() / 2.0
              for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  plt.text(j, i, format(cm[i, j], fmt),
                           horizontalalignment="center",
                            color="white" if cm[i, j] > threshold else "black")
              plt.tight layout()
              plt.ylabel('True-Label')
              plt.xlabel('Predicted-Label')
In [26]:
          classifier SVM = svm.SVC(kernel='linear') # We set a SVM classifier, the default SVM CL
          classifier SVM.fit(XTrainD, YTrainD) # Then we train our model, with our balanced data
         SVC(kernel='linear')
Out[26]:
In [27]:
          prediction SVM all = classifier SVM.predict(TestAll X) #And finally, we predict our dat
In [28]:
          cm = confusion_matrix(TestAll_Y, prediction_SVM_all)
          plot Cmrix(cm,class names)
```



Criterion Result that we got is 0.9231809868662785

```
In [30]:
    print('So We have detected ' + str(cm[1][1]) + ' frauds / ' + str(cm[1][1]+cm[1][0]) +
    print('\nThe probability to detect a fraud is ' + str(cm[1][1]/(cm[1][1]+cm[1][0])))
    print("\nAccuracy -> "+str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1]))))
```

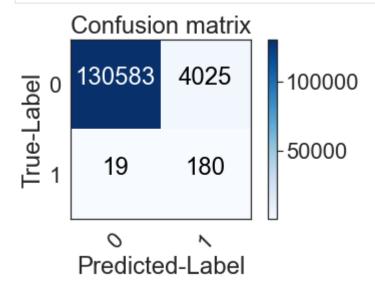
So We have detected 182 frauds / 199 total frauds.

The probability to detect a fraud is 0.914572864321608

Accuracy -> 0.9576134770449606

```
classifier_SVM.fit(XTrainD_rank, YTrainD) #here we train the model with balanced data t
prediction_SVM = classifier_SVM.predict(TestAll_X_rank) # Now predict data test.
```

In [32]: cm = confusion_matrix(TestAll_Y, prediction_SVM)
 plot_Cmrix(cm,class_names)



```
In [33]:
                        print('Criterion Result that we got is '
                                      + str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1])) + 4 * cm[1][1]/(cm[1][0])
                      Criterion Result that we got is 0.917618402008783
In [34]:
                        print('So We have detected' + str(cm[1][1]) + 'frauds / ' + str(cm[1][1]+cm[1][0]) + 'frauds / 'frauds /
                        print('\nThe probability to detect a fraud is ' + str(cm[1][1]/(cm[1][1]+cm[1][0])))
                        print("\nAccuracy -> "+str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1]))))
                      So We have detected 180 frauds / 199 total frauds.
                      The probability to detect a fraud is 0.9045226130653267
                      Accuracy -> 0.9700015577826078
In [35]:
                        classifier_SVM_b = svm.SVC(kernel='linear',class_weight={0:0.6, 1:0.4})
In [36]:
                        classifier SVM b.fit(XTrainD, YTrainD) # Then we train our model, with our balanced dat
                      SVC(class_weight={0: 0.6, 1: 0.4}, kernel='linear')
Out[36]:
In [37]:
                        prediction SVM b all = classifier SVM b.predict(TestAll X) #We predict all the data set
In [38]:
                        cm = confusion_matrix(TestAll_Y, prediction_SVM_b_all)
                        plot Cmrix(cm,class names)
                                       Confusion matrix
                                          131328
                                                                           3280
                                                                                                               100000
                                                                                                              50000
                                                                             179
                                                  20
                                         Predicted-Label
In [39]:
                        print('Criterion Result that we got is '
                                      + str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1])) + 4 * cm[1][1]/(cm[1][0])
                      Criterion Result that we got is 0.9147021017540318
In [40]:
                        print('So We have detected ' + str(cm[1][1]) + ' frauds / ' + str(cm[1][1]+cm[1][0]) +
                        print('\nThe probability to detect a fraud is ' + str(cm[1][1]/(cm[1][1]+cm[1][0])))
```

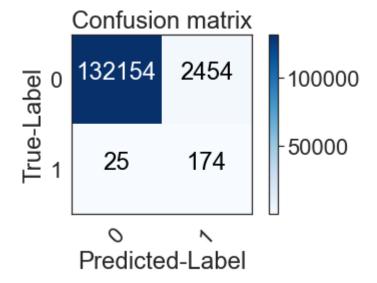
print("\nAccuracy -> "+str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1]))))

So We have detected 179 frauds / 199 total frauds.

The probability to detect a fraud is 0.8994974874371859

Accuracy -> 0.9755205590214158

classifier_SVM_b.fit(XTrainD_rank, YTrainD) # Now train the model with balanced train d
prediction_SVM = classifier_SVM_b.predict(TestAll_X_rank) #Now predict data test.



Criterion Result that we got is 0.8958196368804641

```
In [44]:
    print('So We have detected ' + str(cm[1][1]) + ' frauds / ' + str(cm[1][1]+cm[1][0]) +
    print('\n The probability to detect a fraud is ' + str(cm[1][1]/(cm[1][1]+cm[1][0])))
    print("\nAccuracy -> "+str((cm[0][0]+cm[1][1]) / (sum(cm[0]) + sum(cm[1]))))
```

So We have detected 174 frauds / 199 total frauds.

The probability to detect a fraud is 0.8743718592964824

Accuracy -> 0.9816107472163909

In []: