ADFA-LD - Model Evaluation

In [1]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from IPython.display import display
pd.options.display.max_columns = None
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from IPython.display import display
from sklearn import metrics
from sklearn.model_selection import train_test_split
import statistics
import numpy as np
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
from sklearn.feature_selection import SelectKBest
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical
from keras.callbacks import EarlyStopping
from keras.layers import Dropout
import re
```

```
Using TensorFlow backend.
```

In [150]:

```
import glob
import math
from collections import Counter
import csv

import numpy as np

def evaluate(model, test_features, test_labels):
    predictions = model.predict(test_features)
    accuracy = metrics.accuracy_score(test_labels, predictions)
    print('Accuracy: {:.2f}'.format(accuracy))

def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):
    import matplotlib.pyplot as plt
    import numpy as np
    import itertools

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]


    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy,
    plt.show()

# returns a dictionary of n-grams frequency for any list
def ngrams_freq(listname, n):
    counts = dict()
```

```
    # make n-grams as string iteratively
    grams = [' '.join(listname[i:i+n]) for i in range(len(listname)-n)]
    for gram in grams:
        if gram not in counts:
            counts[gram] = 1
        else:
            counts[gram] += 1
    return counts

# returns the values of features for any list
def feature_freq(listname,n,features):
    counts = dict()
    # make n-grams as string iteratively
    grams = [' '.join(listname[i:i+n]) for i in range(len(listname)-n)]
    for gram in grams:
        counts[gram] = 0
    for gram in grams:
        if gram in features:
            counts[gram] += 1
    return counts

# values of n for finding n-grams
n_values = [1]

# Base address for attack data files
add = "ADFA-LD/ADFA-LD/Attack_Data_Master/"
# list of attacks
attack = ['Adduser','Hydra_FTP','Hydra_SSH','Java_Meterpreter','Meterpreter','Web_Shel

# initializing dictionary for n-grams from all files
traindict = {}

Attack_list_new = []
print("Generating Training Data ..................................")
for term in attack:
    print(" Training data from " + term)
    globals()['%s_list' % term] = []
    in_address = add+term
    k = 1
    # finding list of data from all files
    for i in range (1,11):
        read_files = glob.glob(in_address+"_"+str(i)+"/*.txt")
        for f in read_files:
            with open(f, "r") as infile:
                globals()['%s_list_array' % term+str(k)] = ALine =infile.read()
                #ALine = ALine[:820]
                Attack_list_new.append(term +','+ str(ALine))
                globals()['%s_list' % term].extend(globals()['%s_list_array' % term+st
                k += 1
    # number of lists for distinct files
    globals()['%s_size' % term] = k-1
    # combined list of all files
    listname = globals()['%s_list' % term]
    # finding n-grams and extracting top 30%
    for n in n_values:
        #print("        Extracting top 30% "+str(n)+"-grams from "+term+"............
        dictname = ngrams_freq(listname,n)
        top = math.ceil(0.3*len(dictname))
        dictname = Counter(dictname)
        for k, v in dictname.most_common(top):
            traindict.update({k : v})
```

```python

# finding training data for Normal file
print(" Training data from Normal")
Normal_list = []
Normal_list_new = []
in_address = "ADFA-LD/ADFA-LD/Training_Data_Master/"
k = 1
read_files = glob.glob(in_address+"/*.txt")
for f in read_files:
    with open(f, "r") as infile:
        globals()['Normal%s_list_array' % str(k)] = Line = infile.read()
        Normal_list_new.append('Normal,'+ str(Line))
        Normal_list.extend(globals()['Normal%s_list_array' % str(k)])
        k += 1

# number of lists for distinct files
Normal_list_size = k-1
# combined list of all files
listname = Normal_list


print("\nnew_train.csv created..............................................\n")

```

```
Generating Training Data ..................................
        Training data from Adduser
        Training data from Hydra_FTP
        Training data from Hydra_SSH
        Training data from Java_Meterpreter
        Training data from Meterpreter
        Training data from Web_Shell
        Training data from Normal

new_train.csv created..............................................
```

In [4]:

```python
new_train_list = []
new_train_list = Normal_list_new + Attack_list_new
#new_train_list[1]
#Attack_list_new[1]

```

In [5]:

```python
new_train_list = []
new_train_list = Normal_list_new + Attack_list_new


with open('new_train.csv', 'w') as f:
    for item in new_train_list:
        f.write("%s\n" % item)
```

In [6]:

```
train = pd.read_csv("./new_train.csv", sep=',',error_bad_lines=False, header=None, nam
train.head(5)
train.shape
#train.info()

#train.describe(include = 'all')
train_df = train.copy()
train['Label'] = train['Label'].astype('category')
train['CallTrace'] = train['CallTrace'].astype('category')

train['Label'].value_counts()
#train['CallTrace'].value_counts()
```

Out[6]:

```
Normal             833
Hydra_SSH          176
Hydra_FTP          162
Java_Meterpreter   124
Web_Shell          118
Adduser             91
Meterpreter         75
Name: Label, dtype: int64
```

In [7]:

```
train['Label_Codes'] = train['Label'].cat.codes
train['CallTrace_Codes'] = train['CallTrace'].cat.codes
train['Label_Codes'].value_counts()
```

Out[7]:

```
5    833
2    176
1    162
3    124
6    118
0     91
4     75
Name: Label_Codes, dtype: int64
```

In [8]:

```
train.head()
```

Out[8]:

	Label	CallTrace	Label_Codes	CallTrace_Codes
0	Normal	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...	5	1407
1	Normal	54 175 120 175 175 3 175 175 120 175 120 175 1...	5	1239
2	Normal	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...	5	1286
3	Normal	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...	5	1465
4	Normal	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...	5	93

Multinominal Logistic Regression

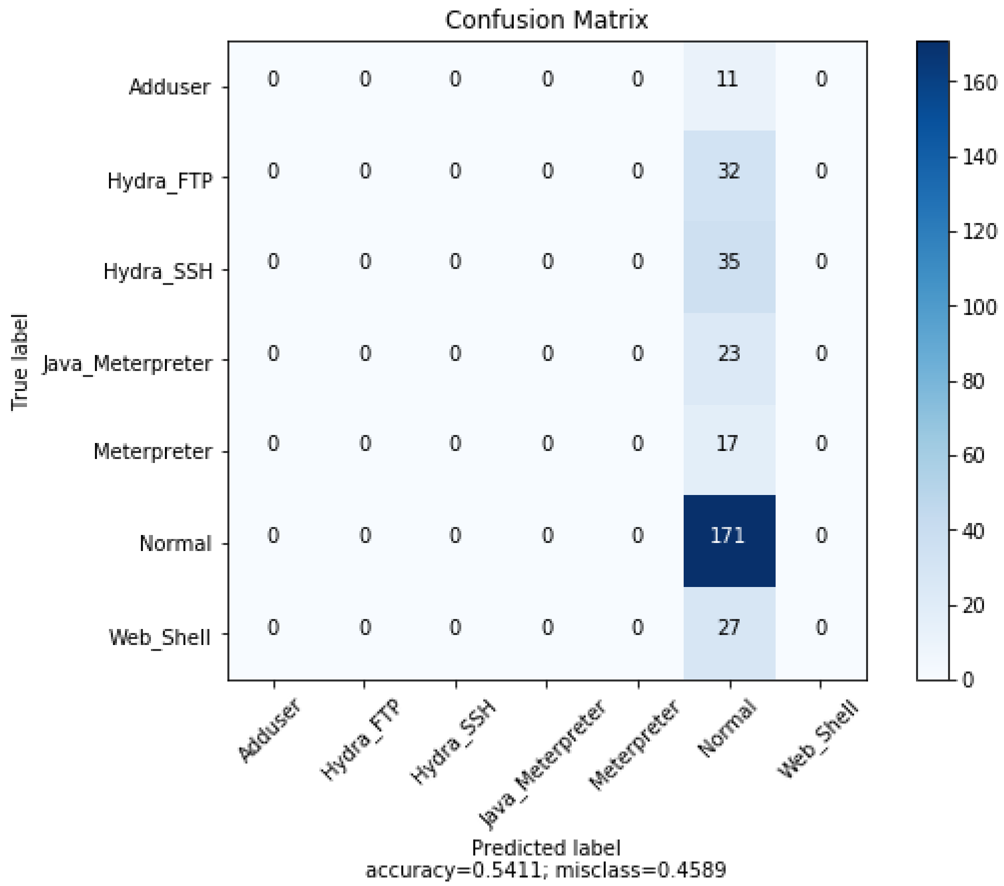
In [152]:

```
import warnings
warnings.filterwarnings("ignore")

# split the dataset in train and test
X = train.iloc[:, [3]].values
y = train.iloc[:, 2].values


# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_stat

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(multi_class='ovr', solver = 'lbfgs')
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# How did our model perform?
from sklearn import metrics
count_misclassified = (y_test != y_pred).sum()
#print('Misclassified samples: {}'.format(count_misclassified))
accuracy = metrics.accuracy_score(y_test, y_pred)
#print('Accuracy: {:.2f}'.format(accuracy))

print("Evaluate MLR on Train features")
grid_accuracy = evaluate(classifier, X_train, y_train)
print("Evaluate MLR on Test features")
grid_accuracy = evaluate(classifier, X_test, y_test)

```

```
Evaluate MLR on Train features
Accuracy: 0.52
Evaluate MLR on Test features
Accuracy: 0.54
```

In [10]:

```python
#classifier.predict_proba(X_test)

# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Adduser', 'Hydra_FTP', 'Hydra_SSH', 'Java_Meter
                      title        = "Confusion Matrix")
```



Logistic Regression Binary Classification

In [11]:

```
train.loc[train.Label != 'Normal','Label_Binary']= 1
train.loc[train.Label == 'Normal','Label_Binary']= 0
train['Label_Binary'].value_counts()
#train.head()
```

Out[11]:

```
0.0    833
1.0    746
Name: Label_Binary, dtype: int64
```

In [12]:

```
train.head()
```

Out[12]:

	Label	CallTrace	Label_Codes	CallTrace_Codes	Label_Binary
0	Normal	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...	5	1407	0.0
1	Normal	54 175 120 175 175 3 175 175 120 175 120 175 1...	5	1239	0.0
2	Normal	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...	5	1286	0.0
3	Normal	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...	5	1465	0.0
4	Normal	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...	5	93	0.0

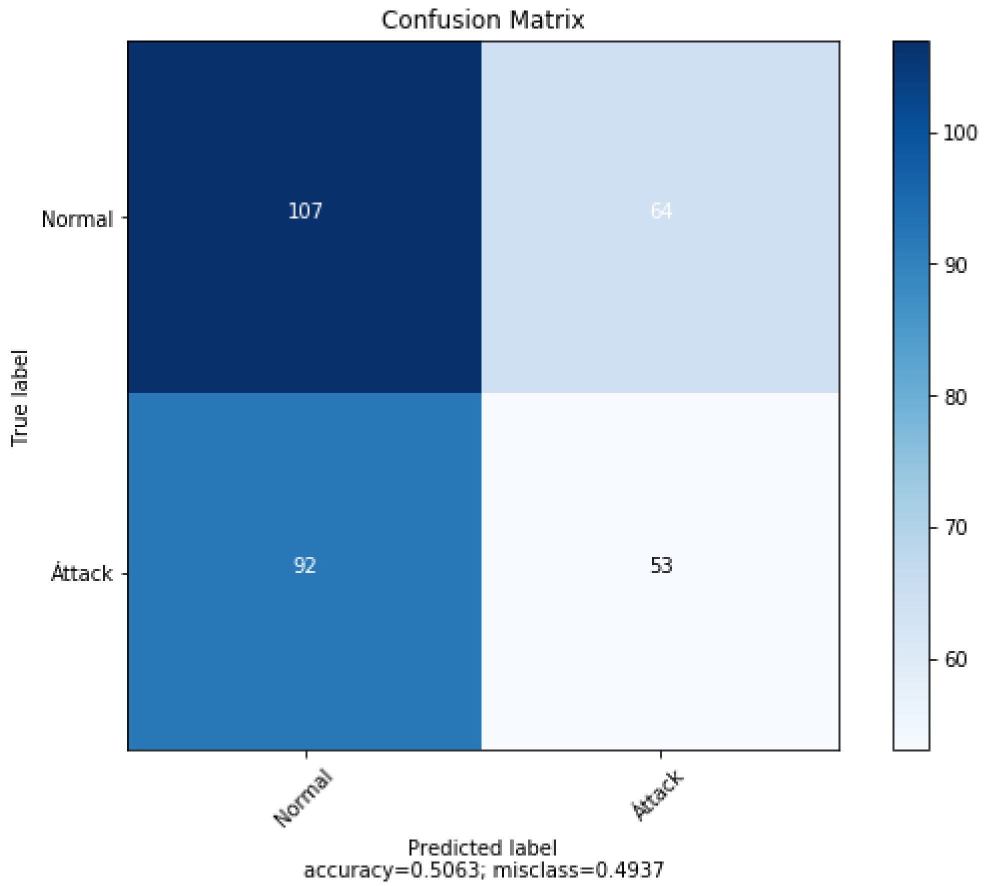
In [154]:

```
import warnings
warnings.filterwarnings("ignore")

# split the dataset in train and test
X = train.iloc[:, [3]].values
y = train.iloc[:, 4].values


# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_stat

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
#classifier = LogisticRegression(multi_class='ovr', solver = 'lbfgs')
classifier = LogisticRegression()
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# How did our model perform?
from sklearn import metrics
count_misclassified = (y_test != y_pred).sum()
#print('Misclassified samples: {}'.format(count_misclassified))
accuracy = metrics.accuracy_score(y_test, y_pred)
#print('Accuracy: {:.2f}'.format(accuracy))

print("Evaluate BLR on Train features")
grid_accuracy = evaluate(classifier, X_train, y_train)
print("Evaluate BLR on Test features")
grid_accuracy = evaluate(classifier, X_test, y_test)
```

```
Evaluate BLR on Train features
Accuracy: 0.54
Evaluate BLR on Test features
Accuracy: 0.51
```

In [14]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Normal', 'Áttack'],
                      title        = "Confusion Matrix")
```



In [15]:

```
print(metrics.classification_report(y_pred, y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.63      0.54      0.58       199
         1.0       0.37      0.45      0.40       117

   micro avg       0.51      0.51      0.51       316
   macro avg       0.50      0.50      0.49       316
weighted avg       0.53      0.51      0.51       316
```

OneHotEncoding for LogisticRegression

In [16]:

```
# Split into predictor and response dataframes.
train_df_enc = train_df.copy()
X_df = train_df_enc.drop('Label', axis=1)
y = train_df_enc['Label']

X_df.shape,y.shape
```

Out[16]:

```
((1579, 1), (1579,))
```

In [17]:

```
X_df.head()
```

Out[17]:

	CallTrace
0	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...
1	54 175 120 175 175 3 175 175 120 175 120 175 1...
2	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...
3	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...
4	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...

In [18]:

```
train_df.head()
```

Out[18]:

	Label	CallTrace
0	Normal	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...
1	Normal	54 175 120 175 175 3 175 175 120 175 120 175 1...
2	Normal	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...
3	Normal	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...
4	Normal	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...

In [19]:

```
# Map response variable to integers 0,1.
y = pd.Series(np.where(y.values != 'Normal',1,0), y.index)
y.value_counts()
```

Out[19]:

```
0    833
1    746
dtype: int64
```

In [20]:

```
# Label Encode instead of dummy variables

mappings = []

from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

label_df = train.drop('Label', axis=1)
label_df = train.drop('Label_Binary', axis=1)
label_df = train.drop('Label_Codes', axis=1)
label_df['CallTrace'] = label_df['CallTrace_Codes']
label_df = X_df.copy()
for i, col in enumerate(label_df):
    if label_df[col].dtype == 'object':
        label_df[col] = label_encoder.fit_transform(np.array(label_df[col].astype(str)
        mappings.append(dict(zip(label_encoder.classes_, range(1, len(label_encoder.cl
```

In [21]:

```
label_df.head()
```

Out[21]:

	CallTrace
0	1407
1	1239
2	1286
3	1465
4	93

In [22]:

```
from sklearn.preprocessing import OneHotEncoder


onehot_encoder = OneHotEncoder()
for i, col in enumerate(label_df):
    if label_df[col].dtype == 'object':
        label_df[col] = onehot_encoder.fit_transform(np.array(label_df[col].astype(str
        mappings.append(dict(zip(onehot_encoder.classes_, range(1, len(onehot_encoder.
```

In [23]:

```
 label_df[col].head()
```

Out[23]:

```
0    1407
1    1239
2    1286
3    1465
4      93
Name: CallTrace, dtype: int32
```

In [24]:

```
X_train, X_test, y_train, y_test = train_test_split(label_df, y, test_size = 0.2, rand
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[24]:

```
((1263, 1), (316, 1), (1263,), (316,))
```

In [25]:

```
clf = LogisticRegression()
model_mix = clf.fit(X_train, y_train)
# y_pred = model_norm.predict(X_test)
print("Model accuracy is", model_mix.score(X_test, y_test))
```

```
Model accuracy is 0.5569620253164557
```

In [26]:

```
model_mix
```

Out[26]:

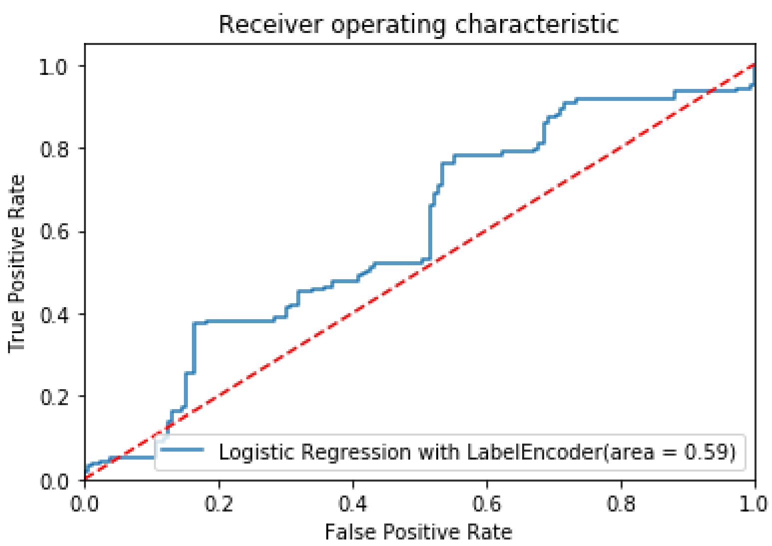
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [27]:

```
# logit_roc_auc = roc_auc_score(y_test, model_norm.predict(X_test))
# fpr, tpr, thresholds = roc_curve(y_test, model_norm.predict_proba(X_test)[:,1])

classes = model_mix.predict(X_test)
probs = model_mix.predict_proba(X_test)
preds = probs[:,1]
#preds
```

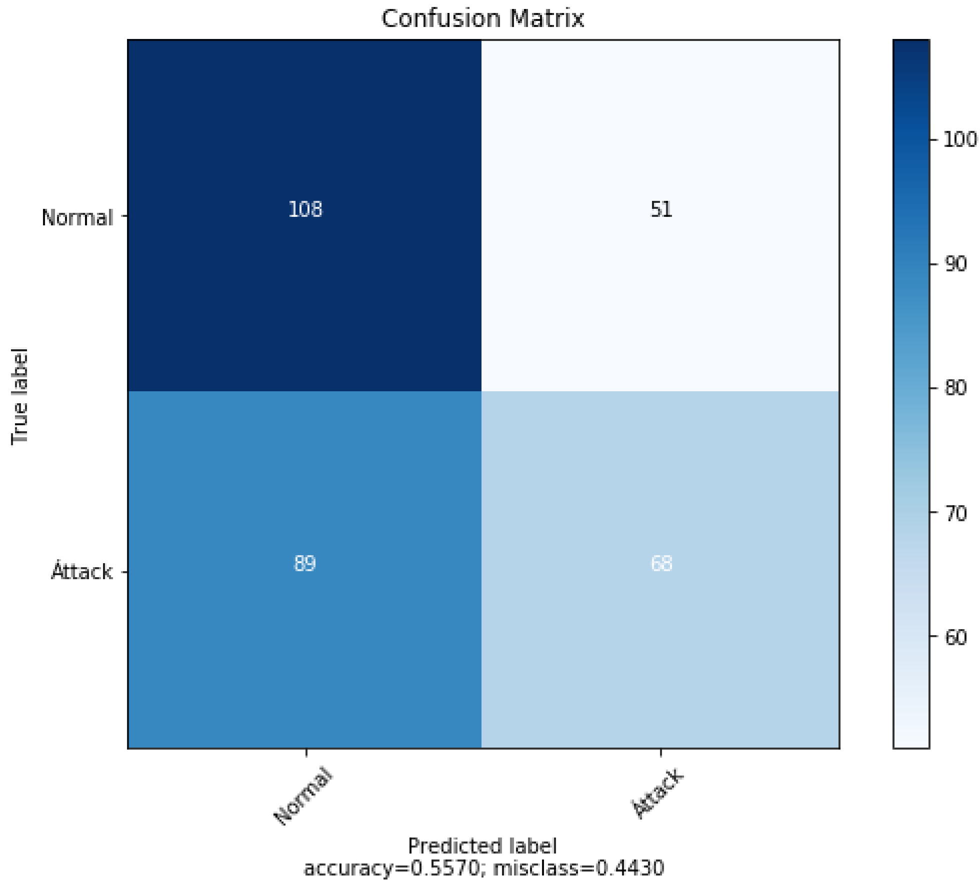
In [28]:

```
labelfpr, labeltpr, labelthreshold = metrics.roc_curve(y_test, preds)
label_roc_auc = metrics.auc(labelfpr, labeltpr)

plt.figure()
plt.plot(labelfpr, labeltpr, label='Logistic Regression with LabelEncoder(area = %0.2f
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



In [29]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, classes)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Normal', 'Áttack'],
                      title        = "Confusion Matrix")
```



In [30]:

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[30]:

```
((1263, 1), (316, 1), (1263,), (316,))
```

In [31]:

```
print(metrics.classification_report(classes, y_test))
```

```
              precision    recall  f1-score   support

           0       0.68      0.55      0.61       197
           1       0.43      0.57      0.49       119

   micro avg       0.56      0.56      0.56       316
   macro avg       0.56      0.56      0.55       316
weighted avg       0.59      0.56      0.56       316
```

RandomForest Classification

In [32]:

```
# Normalize using MinMaxScaler to constrain values to between 0 and 1.
from sklearn.preprocessing import MinMaxScaler, StandardScaler

scaler = MinMaxScaler(feature_range = (0,1))

scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

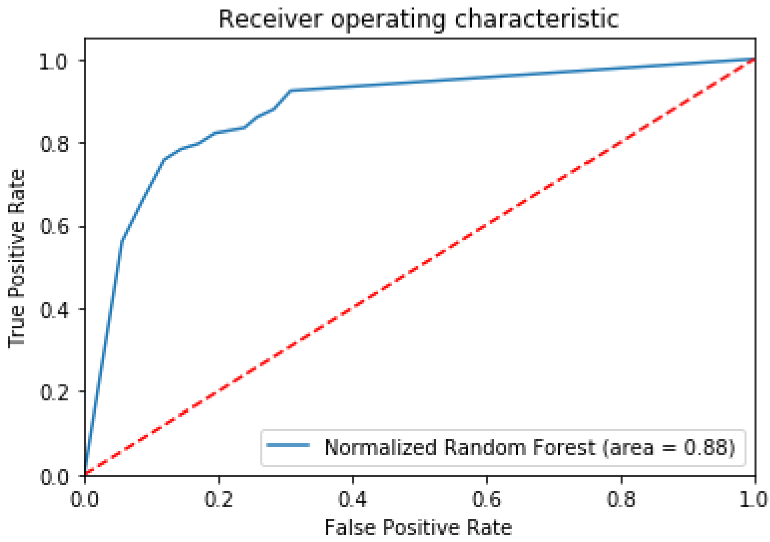
In [33]:

```
clf = RandomForestClassifier(n_jobs=-1)
model_rf = clf.fit(X_train, y_train)
print('Model accuracy is',model_rf.score(X_test, y_test))
```

```
Model accuracy is 0.8132911392405063
```

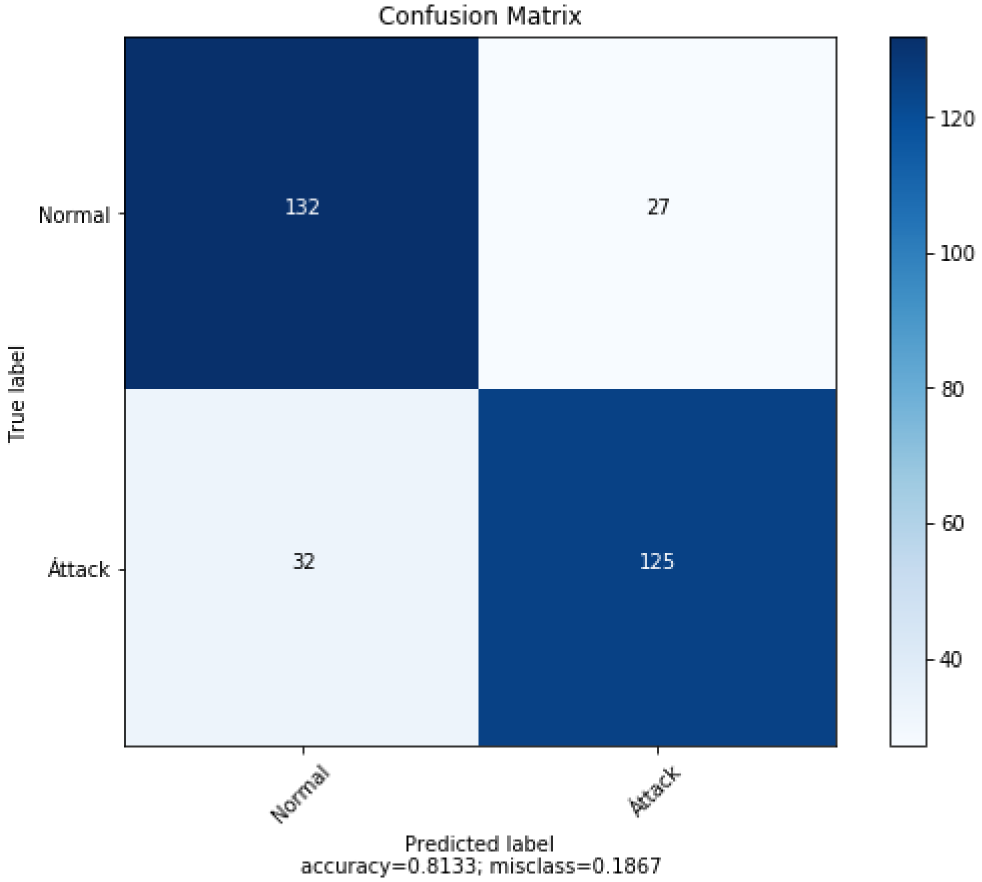
In [34]:

```
probs = model_rf.predict_proba(X_test)
preds = probs[:,1]
rffpr, rftpr, rfthreshold = metrics.roc_curve(y_test, preds)
rf_roc_auc = metrics.auc(rffpr, rftpr)

plt.figure()
plt.plot(rffpr, rftpr, label='Normalized Random Forest (area = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



In [35]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
classes = model_rf.predict(X_test)
cm = confusion_matrix(y_test, classes)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Normal', 'Áttack'],
                      title        = "Confusion Matrix")
```



In [36]:

```
print(metrics.classification_report(classes, y_test))
```

```
              precision    recall  f1-score   support

           0       0.83      0.80      0.82       164
           1       0.80      0.82      0.81       152

   micro avg       0.81      0.81      0.81       316
   macro avg       0.81      0.81      0.81       316
weighted avg       0.81      0.81      0.81       316
```

Train Data with ngrams

In [37]:

```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, recall_score, roc_auc_sc

X, y = make_classification(
    n_classes=2, class_sep=1.5, weights=[0.1, 0.9],
    n_features=20, n_samples=1000, random_state=10
)

#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_stat

clf = LogisticRegression(class_weight="balanced")
clf.fit(X_train, y_train)
THRESHOLD = 0.5
preds = np.where(clf.predict_proba(X_test)[:,1] > THRESHOLD, 1, 0)

pd.DataFrame(data=[accuracy_score(y_test, preds), recall_score(y_test, preds),
                   precision_score(y_test, preds), roc_auc_score(y_test, preds)],
             index=["accuracy", "recall", "precision", "roc_auc_score"])
```

Out[37]:

	0
accuracy	0.531646
recall	0.579618
precision	0.526012
roc_auc_score	0.531947

In [38]:

```
from sklearn import model_selection, preprocessing, linear_model, naive_bayes, metrics
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn import decomposition, ensemble

import pandas, xgboost, numpy, textblob, string
from keras.preprocessing import text, sequence
from keras import layers, models, optimizers

def train_model(classifier, feature_vector_train, label, feature_vector_valid, is_neur
    # fit the training dataset on the classifier
    classifier.fit(feature_vector_train, label)

    # predict the labels on validation dataset
    predictions = classifier.predict(feature_vector_valid)

    if is_neural_net:
        predictions = predictions.argmax(axis=-1)

    return metrics.accuracy_score(predictions, valid_y)

# load the dataset
#data = open('data/corpus').read()
#labels, texts = [], []
#for i, line in enumerate(data.split("\n")):
#    content = line.split()
#    labels.append(content[0])
#    texts.append(" ".join(content[1:]))

# create a dataframe using texts and lables
#trainDF = pandas.DataFrame()
#trainDF['text'] = texts
#trainDF['label'] = labels
```

In [39]:

```
X_df.head()
```

Out[39]:

	CallTrace
0	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...
1	54 175 120 175 175 3 175 175 120 175 120 175 1...
2	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...
3	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...
4	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...

In [40]:

```
# create a dataframe using texts and lables
trainDF = train_df.copy()

trainDF['CallTrace_T'] = trainDF.CallTrace.str.split(' ').str.join(',').astype(str)
#X_df = trainDF.drop('Label', axis=1)
X_df = trainDF.drop(['Label', 'CallTrace'], axis=1)
y = trainDF['Label']

# split the dataset into training and validation datasets
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(X_df, y)

# label encode the target variable
encoder = preprocessing.LabelEncoder()
train_y = encoder.fit_transform(train_y)
valid_y = encoder.fit_transform(valid_y)

X_df.head()
#list(encoder.classes_)
#le_name_mapping = dict(zip(encoder.classes_, encoder.transform(encoder.classes_)))
#print(le_name_mapping)
```

Out[40]:

	CallTrace_T
0	6,6,63,6,42,120,6,195,120,6,6,114,114,1,1,252,...
1	54,175,120,175,175,3,175,175,120,175,120,175,1...
2	6,11,45,33,192,33,5,197,192,6,33,5,3,197,192,1...
3	7,174,174,5,197,197,6,13,195,4,4,118,6,91,38,5...
4	11,45,33,192,33,5,197,192,6,33,5,3,197,192,192...

In [41]:

```
train_x.shape, valid_x.shape, train_y.shape, valid_y.shape
```

Out[41]:

```
((1184, 1), (395, 1), (1184,), (395,))
```

In [42]:

```
1 trainDF.head()
```

Out[42]:

	Label	CallTrace	CallTrace_T
0	Normal	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...	6,6,63,6,42,120,6,195,120,6,6,114,114,1,1,252,...
1	Normal	54 175 120 175 175 3 175 175 120 175 120 175 1...	54,175,120,175,175,3,175,175,120,175,120,175,1...
2	Normal	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...	6,11,45,33,192,33,5,197,192,6,33,5,3,197,192,1...
3	Normal	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...	7,174,174,5,197,197,6,13,195,4,4,118,6,91,38,5...
4	Normal	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...	11,45,33,192,33,5,197,192,6,33,5,3,197,192,192...

Feature Engineering - 1n, 2n, 3n-grams

In [43]:

```
1 trainDF.head()
```

Out[43]:

	Label	CallTrace	CallTrace_T
0	Normal	6 6 63 6 42 120 6 195 120 6 6 114 114 1 1 252 ...	6,6,63,6,42,120,6,195,120,6,6,114,114,1,1,252,...
1	Normal	54 175 120 175 175 3 175 175 120 175 120 175 1...	54,175,120,175,175,3,175,175,120,175,120,175,1...
2	Normal	6 11 45 33 192 33 5 197 192 6 33 5 3 197 192 1...	6,11,45,33,192,33,5,197,192,6,33,5,3,197,192,1...
3	Normal	7 174 174 5 197 197 6 13 195 4 4 118 6 91 38 5...	7,174,174,5,197,197,6,13,195,4,4,118,6,91,38,5...
4	Normal	11 45 33 192 33 5 197 192 6 33 5 3 197 192 192...	11,45,33,192,33,5,197,192,6,33,5,3,197,192,192...

In [44]:

```
train_1n = pd.read_csv("./train_1n.csv")
train_1n.columns
train_1n_bkp = train_1n.copy()
train_1n.head()
```

Out[44]:

	Label	168	265	3	54	162	142	309	146	114	175	43	104	5	78	102	13	6
0	Adduser	193	75	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
1	Adduser	0	110	139	0	0	286	0	55	0	64	0	50	0	0	0	0	0
2	Adduser	249	133	112	0	0	0	0	0	0	0	60	0	0	0	0	0	0
3	Adduser	0	1	51	809	0	0	202	0	0	0	0	0	0	0	0	0	0
4	Adduser	426	234	157	0	0	0	0	0	0	0	0	0	0	2	0	0	0

In [45]:

```
train_1n.columns
```

Out[45]:

```
Index(['Label', '168', '265', '3', '54', '162', '142', '309', '146', '114',
       '175', '43', '104', '5', '78', '102', '13', '6', '240', '4', '192',
       '195', '91', '85', '125', '197', '140', '19', '174', '301', '221', '3
3',
       '180', '45', '196', '120', '7', '220', '42', '63', '11', '1', '252',
       '201', '243', '199', '308', '122', '118', '219'],
      dtype='object')
```

Modelling Logistic Regression - 1n-grams

In [46]:

```
import warnings
warnings.filterwarnings("ignore")

# split the dataset in train and test

#y = train_1n.iloc[:, 0].values
#train_1n_no_y = train_1n.drop('Label', axis=1)
#X = train_1n_no_y.iloc[:, :].values
y = train_1n.iloc[:, 0]
train_1n_no_y = train_1n.drop('Label', axis=1)
X = train_1n_no_y.iloc[:, :]


# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_stat

```

In [47]:

```
X_test_bkp = X_test
```

In [48]:

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape, type(X), type(y)
```

Out[48]:

```
((1070, 49),
 (268, 49),
 (1070,),
 (268,),
 pandas.core.frame.DataFrame,
 pandas.core.series.Series)
```

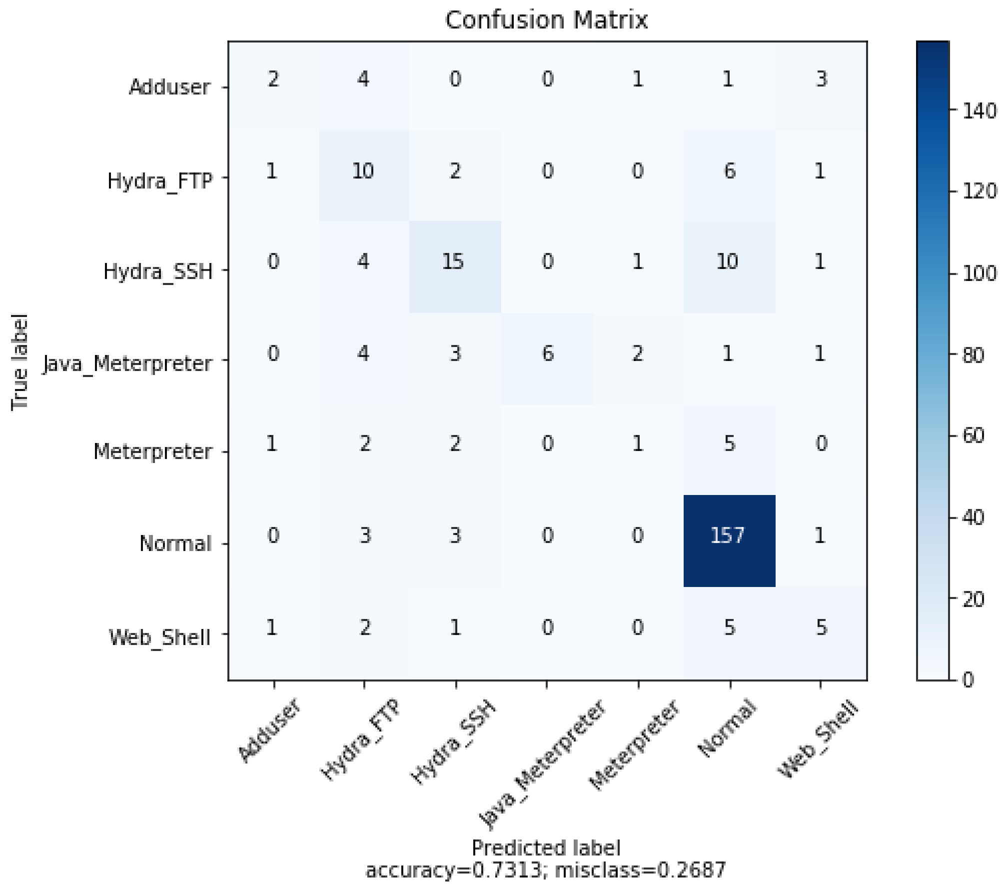
In [49]:

```

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(multi_class='ovr', solver = 'lbfgs')
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# How did our model perform?
from sklearn import metrics
count_misclassified = (y_test != y_pred).sum()
print('Misclassified samples: {}'.format(count_misclassified))
accuracy = metrics.accuracy_score(y_test, y_pred)
print('Accuracy: {:.2f}'.format(accuracy))

```

```
Misclassified samples: 72
Accuracy: 0.73
```

In [50]:

```
#classifier.predict_proba(X_test)

# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Adduser', 'Hydra_FTP', 'Hydra_SSH', 'Java_Meter
                      title        = "Confusion Matrix")
```



In [51]:

```
y_pred.shape, y_test.shape, type(y_test)
```

Out[51]:

```
((268,), (268,), pandas.core.series.Series)
```

In [52]:

```
# Merge predicted results into original dataframe
# y_test['preds'] = y_pred
# df_out = pd.merge(train_1n, y_test[['preds']], how = 'left', right_index = True)
```

In [53]:

```
train_1n.index
```

Out[53]:

```
RangeIndex(start=0, stop=1338, step=1)
```

In [54]:

```
train_2n = pd.read_csv("./train_2n.csv")
train_2n.columns
train_2n_bkp = train_2n.copy()
train_2n.head()
```

Out[54]:

	Label	168 168	54 54	168 265	162 162	265 168	3 168	168 3	265 265	3 3	265 3	3 265	54 309	309 54	114 162	162 114	142 142
0	Adduser	138	0	48	0	47	0	0	24	0	0	0	0	0	0	0	0
1	Adduser	0	0	0	0	0	0	0	24	45	17	20	0	0	0	0	126
2	Adduser	110	0	60	0	55	48	52	28	16	31	32	0	0	0	0	0
3	Adduser	0	594	0	0	0	0	0	0	1	0	0	172	165	0	0	0
4	Adduser	236	0	117	0	119	69	71	69	38	46	48	0	0	0	0	0

In [55]:

```
train_3n = pd.read_csv("./train_3n.csv")
train_3n.columns
train_3n_bkp = train_3n.copy()
train_3n.head()
```

Out[55]:

	Label	168 168 168	54 54 54	162 162 162	168 265 168	265 168 168	168 168 265	168 3 168	168 168 3	3 168 168	54 309 54	54 54 309	265 168 265	309 54 54	168 265 265	265 265 168	162 114 162
0	Adduser	101	0	0	31	34	31	0	0	0	0	0	12	0	14	14	0
1	Adduser	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	Adduser	49	0	0	25	26	25	22	23	21	0	0	12	0	11	14	0
3	Adduser	0	431	0	0	0	0	0	0	0	137	128	0	124	0	0	0
4	Adduser	132	0	0	63	68	60	33	42	36	0	0	32	0	32	31	0

In [56]:

```
train_1n.shape, train_2n.shape, train_3n.shape
```

Out[56]:

```
((1338, 50), (1338, 800), (1338, 4148))
```

In [57]:

```
train_1n_30 = train_1n.iloc[:, 0:30]
train_2n_30 = train_2n.iloc[:, 0:30]
train_3n_30 = train_3n.iloc[:, 0:30]
```

Modelling Logistic Regression/SVM/RandomForrest - 1n-grams + 2n-grams + 3n-grams

In [58]:

```
frames=[train_1n_30, train_2n_30, train_3n_30]
result=pd.concat(frames, axis=1)
result.shape
```

Out[58]:

```
(1338, 90)
```

In [59]:

```
result.head()
```

Out[59]:

	Label	168	265	3	54	162	142	309	146	114	175	43	104	5	78	102	13	6
0	Adduser	193	75	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
1	Adduser	0	110	139	0	0	286	0	55	0	64	0	50	0	0	0	0	0
2	Adduser	249	133	112	0	0	0	0	0	0	0	60	0	0	0	0	0	0
3	Adduser	0	1	51	809	0	0	202	0	0	0	0	0	0	0	0	0	0
4	Adduser	426	234	157	0	0	0	0	0	0	0	0	0	0	2	0	0	0

In [60]:

```
1 result.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 90 columns):
Label          1338 non-null object
168            1338 non-null int64
265            1338 non-null int64
3              1338 non-null int64
54             1338 non-null int64
162            1338 non-null int64
142            1338 non-null int64
309            1338 non-null int64
146            1338 non-null int64
114            1338 non-null int64
175            1338 non-null int64
43             1338 non-null int64
104            1338 non-null int64
5              1338 non-null int64
78             1338 non-null int64
102            1338 non-null int64
13             1338 non-null int64
6              1338 non-null int64
240            1338 non-null int64
4              1338 non-null int64
192            1338 non-null int64
195            1338 non-null int64
91             1338 non-null int64
85             1338 non-null int64
125            1338 non-null int64
197            1338 non-null int64
140            1338 non-null int64
19             1338 non-null int64
174            1338 non-null int64
301            1338 non-null int64
Label          1338 non-null object
168 168        1338 non-null int64
54 54          1338 non-null int64
168 265        1338 non-null int64
162 162        1338 non-null int64
265 168        1338 non-null int64
3 168          1338 non-null int64
168 3          1338 non-null int64
265 265        1338 non-null int64
3 3            1338 non-null int64
265 3          1338 non-null int64
3 265          1338 non-null int64
54 309         1338 non-null int64
309 54         1338 non-null int64
114 162        1338 non-null int64
162 114        1338 non-null int64
142 142        1338 non-null int64
142 3          1338 non-null int64
3 142          1338 non-null int64
142 265        1338 non-null int64
265 142        1338 non-null int64
3 54           1338 non-null int64
174 174        1338 non-null int64
309 309        1338 non-null int64
```

```
43 168          1338 non-null int64
168 146         1338 non-null int64
142 146         1338 non-null int64
146 3           1338 non-null int64
146 142         1338 non-null int64
175 175         1338 non-null int64
Label           1338 non-null object
168 168 168     1338 non-null int64
54 54 54        1338 non-null int64
162 162 162     1338 non-null int64
168 265 168     1338 non-null int64
265 168 168     1338 non-null int64
168 168 265     1338 non-null int64
168 3 168       1338 non-null int64
168 168 3       1338 non-null int64
3 168 168       1338 non-null int64
54 309 54       1338 non-null int64
54 54 309       1338 non-null int64
265 168 265     1338 non-null int64
309 54 54       1338 non-null int64
168 265 265     1338 non-null int64
265 265 168     1338 non-null int64
162 114 162     1338 non-null int64
114 162 162     1338 non-null int64
162 162 114     1338 non-null int64
3 168 265       1338 non-null int64
168 265 3       1338 non-null int64
265 3 168       1338 non-null int64
3 265 168       1338 non-null int64
265 168 3       1338 non-null int64
168 3 265       1338 non-null int64
265 265 265     1338 non-null int64
3 168 3         1338 non-null int64
3 3 168         1338 non-null int64
168 3 3         1338 non-null int64
3 3 3           1338 non-null int64
dtypes: int64(87), object(3)
memory usage: 940.9+ KB
```

In [61]:

```
import warnings
warnings.filterwarnings("ignore")

# split the dataset in train and test
result = result.loc[:,~result.columns.duplicated()]

y = result.iloc[:, 0].values
result_no_y = result.drop('Label', axis=1)
X = result_no_y.iloc[:, :].values
```

In [62]:

```
#result
```

In [63]:

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_stat
X_train.shape, X_test.shape, y_train.shape, y_test.shape, type(X), type(y)
```

Out[63]:

```
((1070, 87), (268, 87), (1070,), (268,), numpy.ndarray, numpy.ndarray)
```

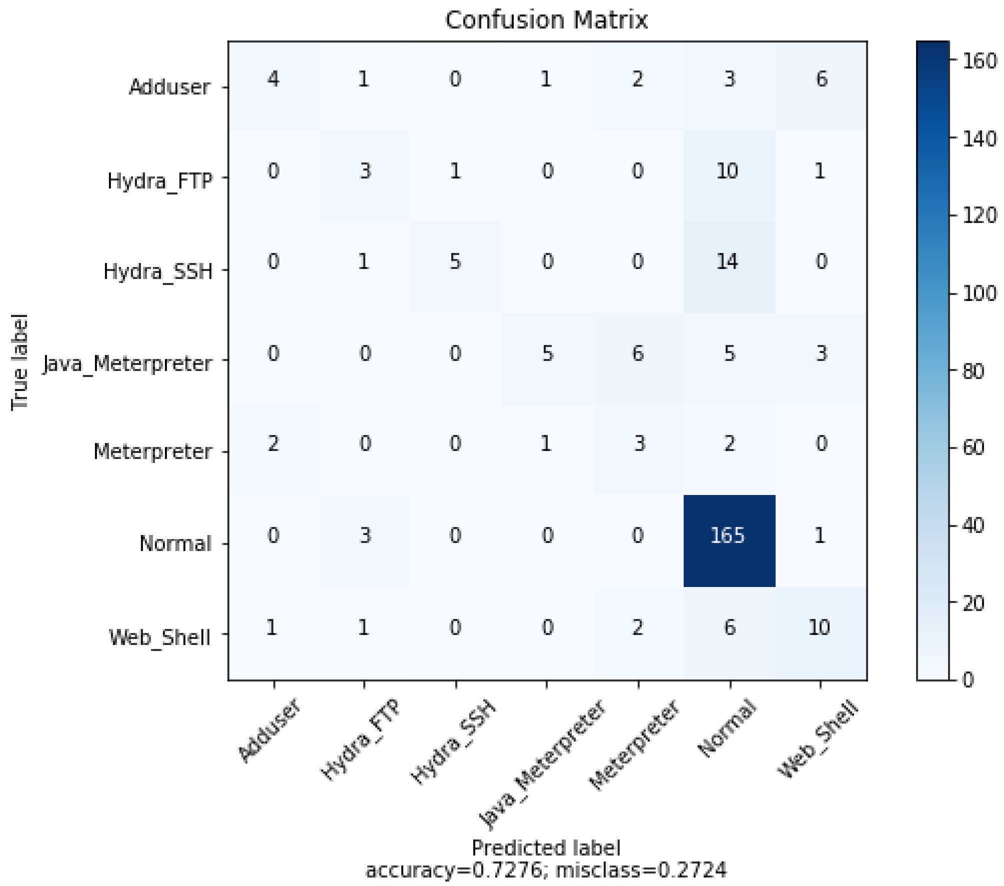
In [64]:

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
#classifier = LogisticRegression(multi_class='ovr', solver = 'lbfgs')
#classifier = SVC(kernel = 'linear', random_state = 0)
#classifier = SVC(kernel = 'rbf', random_state = 0)
clf = RandomForestClassifier(n_jobs=-1)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# How did our model perform?
from sklearn import metrics
count_misclassified = (y_test != y_pred).sum()
print('Misclassified samples: {}'.format(count_misclassified))
accuracy = metrics.accuracy_score(y_test, y_pred)
print('Accuracy: {:.2f}'.format(accuracy))
#y_pred
```

```
Misclassified samples: 73
Accuracy: 0.73
```

In [65]:

```
#classifier.predict_proba(X_test)

# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cm,
                      normalize    = False,
                      target_names = ['Adduser', 'Hydra_FTP', 'Hydra_SSH', 'Java_Meter
                      title        = "Confusion Matrix")
```



Applying 10-Fold cross-validation

In [66]:

```
from sklearn.model_selection import cross_val_score
import numpy as np

print(np.mean(cross_val_score(clf, X_train, y_train, cv=10)))
```

```
0.811048126315949
```

Comparing Different Models BinaryCalssification - 1n-grams + 2n-grams + 3n-grams

In [160]:

```
# Compare Algorithms
# https://machinelearningmastery.com/compare-machine-learning-algorithms-python-scikit

import pandas
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

# load dataset
Y = result.iloc[:, 0].values
result_no_y = result.drop('Label', axis=1)
X = result_no_y.iloc[:, :].values
#X = array[:,0:8]
#Y = array[:,8]

# Prepare configuration for cross validation test harness
seed = 7


```

In [161]:

```
# Prepare models
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
models.append(('RandomForest', RandomForestClassifier()))


```

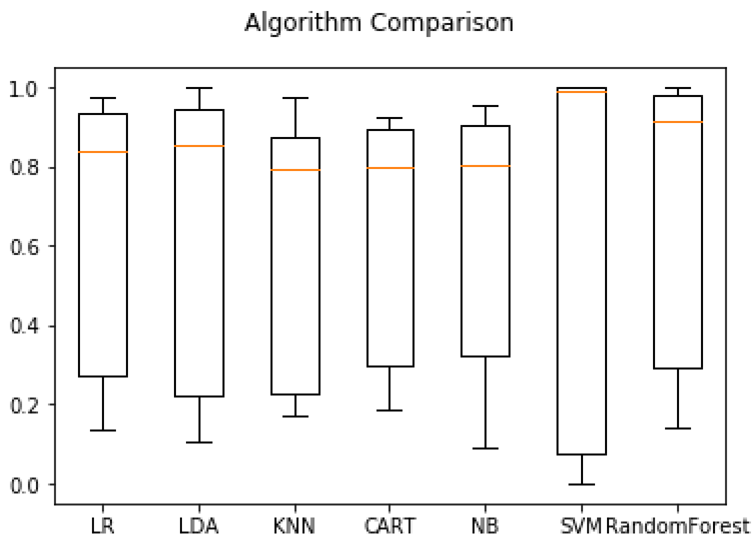
In [162]:

```
# Evaluate each model in turn
results = []
names = []
scoring = 'accuracy'
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X, Y, cv=kfold, scoring=scorin
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.784996 (0.141693)
LDA: 0.775351 (0.216176)
KNN: 0.840865 (0.070821)
CART: 0.865537 (0.058849)
NB: 0.799983 (0.206253)
SVM: 0.664134 (0.388340)
RandomForest: 0.887291 (0.101620)
```

In [70]:

```
# Boxplot algorithm comparison
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



Random Forest & Logistic Regression gave best accuracy so far

Random Forest Model Parameter Tuning

In [71]:

```
train_1n_30 = train_1n.iloc[:, 0:30]
train_2n_30 = train_2n.iloc[:, 0:30]
train_3n_30 = train_3n.iloc[:, 0:30]
```

In [72]:

```
train_1n_30.shape
```

Out[72]:

```
(1338, 30)
```

In [73]:

```
train_2n_30.shape
```

Out[73]:

```
(1338, 30)
```

In [74]:

```
train_3n_30.shape
```

Out[74]:

```
(1338, 30)
```

In [75]:

```
#frames = [train_1n, train_2n, train_3n]
frames = [train_1n_30, train_2n_30, train_3n_30]
result = pd.concat(frames, axis=1)

result = result.loc[:,~result.columns.duplicated()]

result.loc[result.Label != 'Normal','Label']= 1
result.loc[result.Label == 'Normal','Label']= 0
result.head()
#result['Label_Binary'].value_counts()

# Extract features and labels
labels = result['Label']
features = result.drop('Label', axis = 1)
#features.head(5)
#labels.head(5)


# One Hot Encoding
#features = pd.get_dummies(result)
#features.head(5)


#from sklearn import preprocessing

#le = preprocessing.LabelEncoder()
#features['Label_Normal'] = le.fit_transform(features['Label_Normal'])


#cols_drop = [ 'Label_Meterpreter', 'Label_Web_Shell', 'Label_Adduser',
#        'Label_Hydra_FTP', 'Label_Hydra_SSH', 'Label_Java_Meterpreter', 'Label_Normal'_

# Extract features and labels
#labels = features['Label_Normal']
#labels['Label_Normal'].astype(object).astype(int)
#labels = labels.loc[:,~labels.columns.duplicated()]
#features = features.drop(cols_drop, axis = 1)
#features.head(5)
#labels.head(5)

```

In [76]:

```
 to numpy arrays
mpy as np

= np.array(features)
np.array(labels)

g and Testing Sets
arn.model_selection import train_test_split

tures, test_features, train_labels, test_labels = train_test_split(features, labels,
                                                                    test_size = 0.25, random_
```

In [77]:

```
print('Training Features Shape:', train_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Features Shape:', test_features.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (1003, 87)
Training Labels Shape: (1003,)
Testing Features Shape: (335, 87)
Testing Labels Shape: (335,)
```

Examine the Default Random Forest to Determine Parameters

In [78]:

```
# Reference : https://towardsdatascience.com/hyperparameter-tuning-the-random-forest-i

from sklearn.ensemble import RandomForestClassifier
from pprint import pprint

rf = RandomForestClassifier(random_state=42)

#Look at parameters used by  our current forest
pprint(rf.get_params())
```

```
{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 'warn',
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

Random Search with Cross Validation

In [79]:

```
from sklearn.model_selection import RandomizedSearchCV

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

pprint(random_grid)
```

```
{'bootstrap': [True, False],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}
```

In [80]:

```
# Use the random grid to search for best hyperparameters
# First create the base model to tune
rf = RandomForestClassifier(random_state = 42)
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator=rf, param_distributions=random_grid,
                              n_iter = 100, scoring='accuracy',
                              cv = 3, verbose=2, random_state=42, n_jobs=-1,
                              return_train_score=True)

# Fit the random search model
rf_random.fit(train_features, train_labels);
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    9.5s
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:   48.9s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  1.7min finished
```

Best Parameters Identified

In [81]:

```
rf_random.best_params_
```

Out[81]:

```
{'n_estimators': 400,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': None,
 'bootstrap': False}
```

In [82]:

```
#rf_random.cv_results_
```

Evaluate Random Search

To determine if random search yielded a better model, we compare the base model with the best random search model.

In [83]:

```
def evaluate(model, test_features, test_labels):
    predictions = model.predict(test_features)
    accuracy = metrics.accuracy_score(test_labels, predictions)
    print('Accuracy: {:.2f}'.format(accuracy))

```

Evaluate the Default Model

In [ ]:

```
# Prepare models

#models.append(('LR', LogisticRegression()))
#models.append(('LDA', LinearDiscriminantAnalysis()))
#models.append(('KNN', KNeighborsClassifier()))
#models.append(('CART', DecisionTreeClassifier()))
#models.append(('NB', GaussianNB()))
#models.append(('SVM', SVC()))
#models.append(('RandomForest', RandomForestClassifier()))

```

In [168]:

```
base_model_lr = LogisticRegression()
base_model_lr.fit(train_features, train_labels)
print("Evaluate on Train features")
lr_train_accuracy = evaluate(base_model_lr, train_features, train_labels)
print("Evaluate on Test features")
lr_test_accuracy = evaluate(base_model_lr, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 0.91
Evaluate on Test features
Accuracy: 0.84
```

In [170]:

```
base_model_lda = LinearDiscriminantAnalysis()
base_model_lda .fit(train_features, train_labels)
print("Evaluate on Train features")
lda_train_accuracy = evaluate(base_model_lda, train_features, train_labels)
print("Evaluate on Test features")
lda_test_accuracy = evaluate(base_model_lda, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 0.83
Evaluate on Test features
Accuracy: 0.80
```

In [164]:

```
base_model_knn = KNeighborsClassifier()
base_model_knn.fit(train_features, train_labels)
print("Evaluate on Train features")
knn_train_accuracy = evaluate(base_model_knn, train_features, train_labels)
print("Evaluate on Test features")
knn_test_accuracy = evaluate(base_model_knn, test_features, test_labels)

```

```
Evaluate on Train features
Accuracy: 0.96
Evaluate on Test features
Accuracy: 0.89
```

In [165]:

```
base_model_dtc = DecisionTreeClassifier()
base_model_dtc.fit(train_features, train_labels)
print("Evaluate on Train features")
dtc_train_accuracy = evaluate(base_model_dtc, train_features, train_labels)
print("Evaluate on Test features")
dtc_test_accuracy = evaluate(base_model_dtc, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 1.00
Evaluate on Test features
Accuracy: 0.94
```

In [166]:

```
base_model_gb = GaussianNB()
base_model_gb.fit(train_features, train_labels)
print("Evaluate on Train features")
gb_train_accuracy = evaluate(base_model_gb, train_features, train_labels)
print("Evaluate on Test features")
gb_test_accuracy = evaluate(base_model_gb, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 0.82
Evaluate on Test features
Accuracy: 0.81
```

In [167]:

```
base_model_svc = SVC()
base_model_svc.fit(train_features, train_labels)
print("Evaluate on Train features")
svc_train_accuracy = evaluate(base_model_svc, train_features, train_labels)
print("Evaluate on Test features")
svc_test_accuracy = evaluate(base_model_svc, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 1.00
Evaluate on Test features
Accuracy: 0.68
```

In [146]:

```
base_model = RandomForestClassifier(n_estimators = 10, random_state = 42)
base_model.fit(train_features, train_labels)
print("Evaluate on Train features")
base_accuracy = evaluate(base_model, train_features, train_labels)
print("Evaluate on Test features")
base_accuracy = evaluate(base_model, test_features, test_labels)

```

```
Evaluate on Train features
Accuracy: 0.99
Evaluate on Test features
Accuracy: 0.96
```

Evaluate the Best Random Search Model

In [147]:

```
best_random = rf_random.best_estimator_
print("Evaluate on Train features")
random_accuracy = evaluate(best_random, train_features, train_labels)
print("Evaluate on Test features")
random_accuracy = evaluate(best_random, test_features, test_labels)

```

```
Evaluate on Train features
Accuracy: 1.00
Evaluate on Test features
Accuracy: 0.97
```

Grid Search

We can now perform grid search building on the result from the random search. We will test a range of hyperparameters around the best values returned by random search.

In [86]:

```
from sklearn.model_selection import GridSearchCV

# Create the parameter grid based on the results of random search
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}

# Create a base model
rf = RandomForestClassifier(random_state = 42)

# Instantiate the grid search model
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
                           cv = 3, n_jobs = -1, verbose = 2, return_train_score=True)
```

In [87]:

```
# Fit the grid search to the data
grid_search.fit(train_features, train_labels);
```

```
Fitting 3 folds for each of 288 candidates, totalling 864 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    2.4s
[Parallel(n_jobs=-1)]: Done 179 tasks      | elapsed:   15.4s
[Parallel(n_jobs=-1)]: Done 382 tasks      | elapsed:   31.6s
[Parallel(n_jobs=-1)]: Done 665 tasks      | elapsed:   55.1s
[Parallel(n_jobs=-1)]: Done 864 out of 864 | elapsed:  1.2min finished
```

In [88]:

```
grid_search.best_params_
```

Out[88]:

```
{'bootstrap': True,
 'max_depth': 80,
 'max_features': 3,
 'min_samples_leaf': 3,
 'min_samples_split': 8,
 'n_estimators': 300}
```

Evaluate the Best Model from Grid Search

In [149]:

```
best_grid = grid_search.best_estimator_
print("Evaluate on Train features")
grid_accuracy = evaluate(best_grid, train_features, train_labels)
print("Evaluate on Test features")
grid_accuracy = evaluate(best_grid, test_features, test_labels)
```

```
Evaluate on Train features
Accuracy: 0.94
Evaluate on Test features
Accuracy: 0.91
```

Final Model

In [90]:

```
final_model = grid_search.best_estimator_

print('Final Model Parameters:\n')
pprint(final_model.get_params())
print('\n')
grid_final_accuracy = evaluate(final_model, test_features, test_labels)
```

```
Final Model Parameters:

{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 80,
 'max_features': 3,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 3,
 'min_samples_split': 8,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 300,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}


Accuracy: 0.91
```

Deep Autoencoder Model

In [91]:

```
# https://www.kaggle.com/kredy10/simple-lstm-for-text-classification
# https://www.curiousily.com/posts/credit-card-fraud-detection-using-autoencoders-in-ke

```

In [92]:

```
import pandas as pd
import numpy as np
import pickle
import matplotlib.pyplot as plt
from scipy import stats
import tensorflow as tf
import seaborn as sns
from pylab import rcParams
from sklearn.model_selection import train_test_split
from keras.models import Model, load_model
from keras.layers import Input, Dense
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers

%matplotlib inline

sns.set(style='whitegrid', palette='muted', font_scale=1.5)

rcParams['figure.figsize'] = 14, 8

RANDOM_SEED = 42
LABELS = ["Normal", "Attack"]
```

In [93]:

```
#result = result.loc[:,~result.columns.duplicated()]

#result.loc[result.Label != 'Normal','Label']= 1
#result.loc[result.Label == 'Normal','Label']= 0
result.head()


```

Out[93]:

	Label	168	265	3	54	162	142	309	146	114	175	43	104	5	78	102	13	6	24(
0	1	193	75	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	(
1	1	0	110	139	0	0	286	0	55	0	64	0	50	0	0	0	0	0	(
2	1	249	133	112	0	0	0	0	0	0	0	60	0	0	0	0	0	0	(
3	1	0	1	51	809	0	0	202	0	0	0	0	0	0	0	0	0	0	4
4	1	426	234	157	0	0	0	0	0	0	0	0	0	0	2	0	0	0	(

In [94]:

```
attack = result[result.Label == 1]
normal = result[result.Label == 0]
```

In [95]:

```
attack.shape
```

Out[95]:

```
(505, 88)
```

In [96]:

```
normal.shape
```

Out[96]:

```
(833, 88)
```

In [ ]:

```

```

In [97]:

```
X_train, X_test = train_test_split(result, test_size=0.2, random_state=RANDOM_SEED)
X_train = X_train[X_train.Label == 0]
X_train = X_train.drop(['Label'], axis=1)

y_test = X_test['Label']
X_test = X_test.drop(['Label'], axis=1)

X_train = X_train.values
X_test = X_test.values

```

In [98]:

```
X_train.shape
```

Out[98]:

```
(662, 87)
```

Building the model Our Autoencoder uses 4 fully connected layers with 14, 7, 7 and 29 neurons respectively. The first two layers are used for our encoder, the last two go for the decoder. Additionally, L1 regularization will be used during training:

In [99]:

```
input_dim = X_train.shape[1]
encoding_dim = 87
```

In [100]:

```
input_layer = Input(shape=(input_dim, ))

encoder = Dense(encoding_dim, activation="tanh",
                activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(int(encoding_dim / 2), activation="relu")(encoder)

decoder = Dense(int(encoding_dim / 2), activation='tanh')(encoder)
decoder = Dense(input_dim, activation='relu')(decoder)

autoencoder = Model(inputs=input_layer, outputs=decoder)
autoencoder.summary()
```

```
WARNING:tensorflow:From C:\Users\kuna\AppData\Local\Continuum\anaconda3\lib
\site-packages\tensorflow\python\framework\op_def_library.py:263: colocate_w
ith (from tensorflow.python.framework.ops) is deprecated and will be removed
in a future version.
Instructions for updating:
Colocations handled automatically by placer.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 87)                0
_________________________________________________________________
dense_1 (Dense)              (None, 87)                7656
_________________________________________________________________
dense_2 (Dense)              (None, 43)                3784
_________________________________________________________________
dense_3 (Dense)              (None, 43)                1892
_________________________________________________________________
dense_4 (Dense)              (None, 87)                3828
=================================================================
Total params: 17,160
Trainable params: 17,160
Non-trainable params: 0
_________________________________________________________________
```

In [101]:

```
nb_epoch = 100
batch_size = 32

autoencoder.compile(optimizer='adam',
                    loss='mean_squared_error',
                    metrics=['accuracy'])

checkpointer = ModelCheckpoint(filepath="model.h5",
                               verbose=0,
                               save_best_only=True)
tensorboard = TensorBoard(log_dir='./logs',
                          histogram_freq=0,
                          write_graph=True,
                          write_images=True)

history = autoencoder.fit(X_train, X_train,
                    epochs=nb_epoch,
                    batch_size=batch_size,
                    shuffle=True,
                    validation_data=(X_test, X_test),
                    verbose=1,
                    callbacks=[checkpointer, tensorboard]).history
```

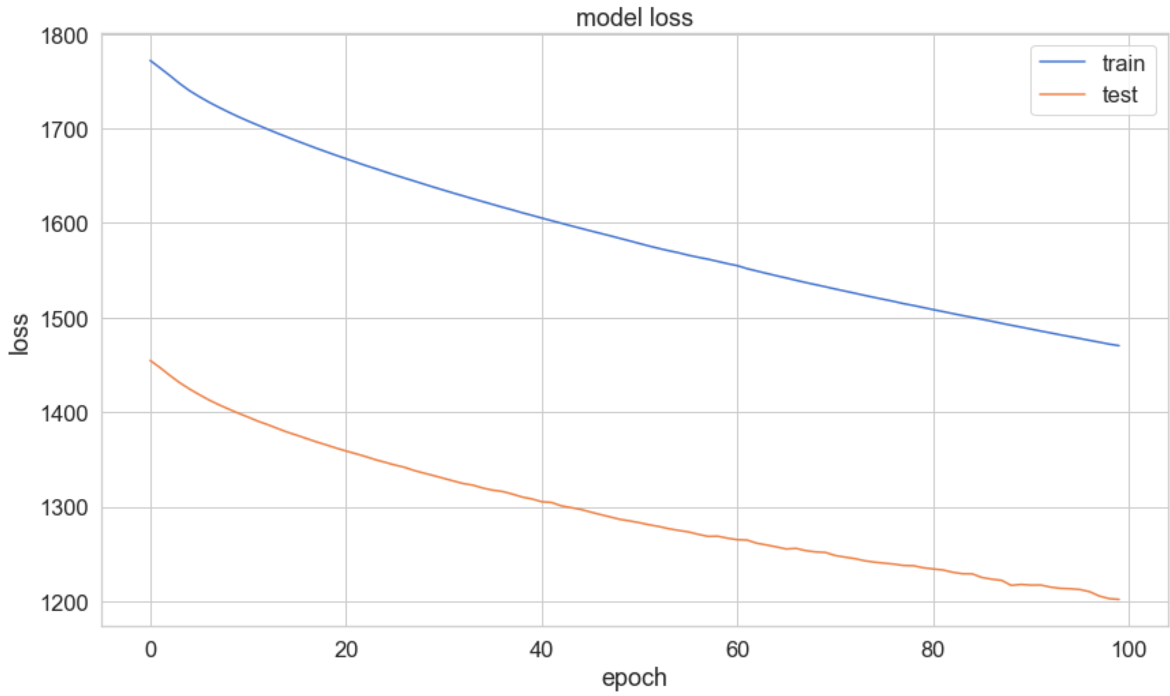
```
Epoch 46/100
662/662 [==============================] - 0s 62us/step - loss: 1591.7632
- acc: 0.6148 - val_loss: 1294.4265 - val_acc: 0.6082
Epoch 47/100
662/662 [==============================] - 0s 62us/step - loss: 1589.1563
- acc: 0.6239 - val_loss: 1291.7608 - val_acc: 0.6157
Epoch 48/100
662/662 [==============================] - 0s 66us/step - loss: 1586.5648
- acc: 0.6269 - val_loss: 1289.2515 - val_acc: 0.6119
Epoch 49/100
662/662 [==============================] - 0s 60us/step - loss: 1583.8405
- acc: 0.6269 - val_loss: 1286.6870 - val_acc: 0.6194
Epoch 50/100
662/662 [==============================] - 0s 69us/step - loss: 1581.1459
- acc: 0.6299 - val_loss: 1285.0217 - val_acc: 0.6343

Epoch 51/100
662/662 [==============================] - 0s 65us/step - loss: 1578.4038
- acc: 0.6344 - val_loss: 1283.1292 - val_acc: 0.6269
Epoch 52/100
```

In [102]:

```
# Evaluation
```

In [103]:

```
plt.plot(history['loss'])
plt.plot(history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right');
```



The reconstruction error on our training and test data seems to converge nicely. Is it low enough? Let's have a closer look at the error distribution:

In [104]:

```
predictions = autoencoder.predict(X_test)
```

In [105]:

```
mse = np.mean(np.power(X_test - predictions, 2), axis=1)
error_df = pd.DataFrame({'reconstruction_error': mse,
                        'true_class': y_test})
```

In [106]:

```
error_df.describe()
```

Out[106]:

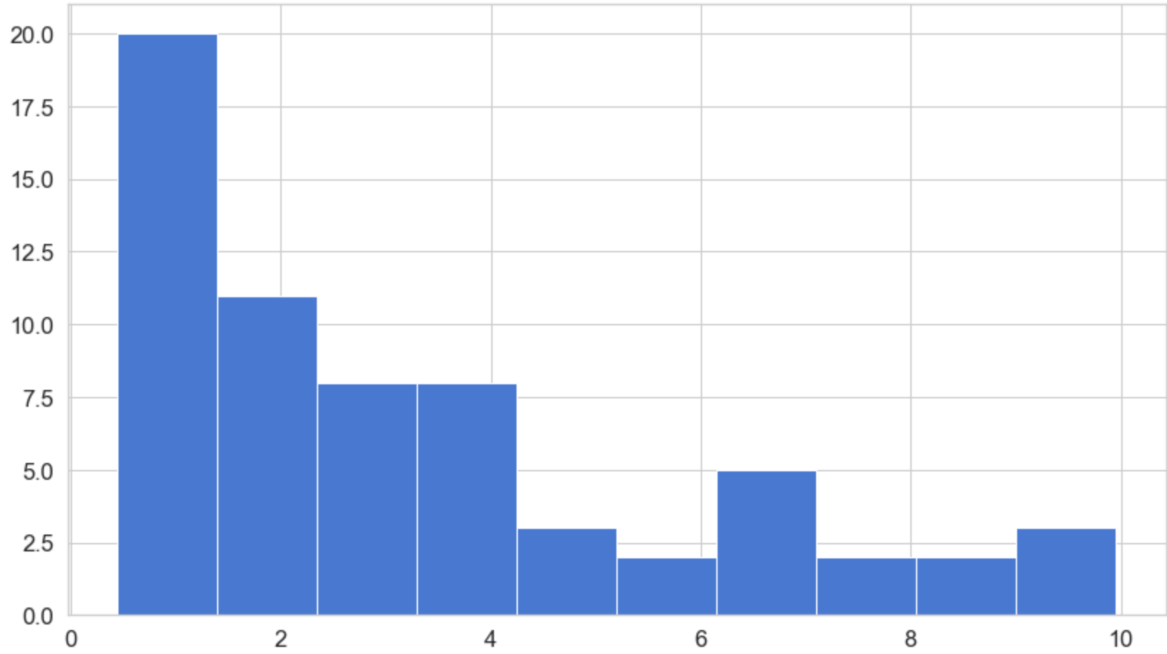
	reconstruction_error	true_class
count	268.000000	268.000000
mean	1201.825967	0.361940
std	4310.467226	0.481461
min	0.446176	0.000000
25%	6.975698	0.000000
50%	50.988017	0.000000
75%	452.632138	1.000000
max	44357.166427	1.000000

In [107]:

```
# Reconstruction error without Attack
```

In [108]:

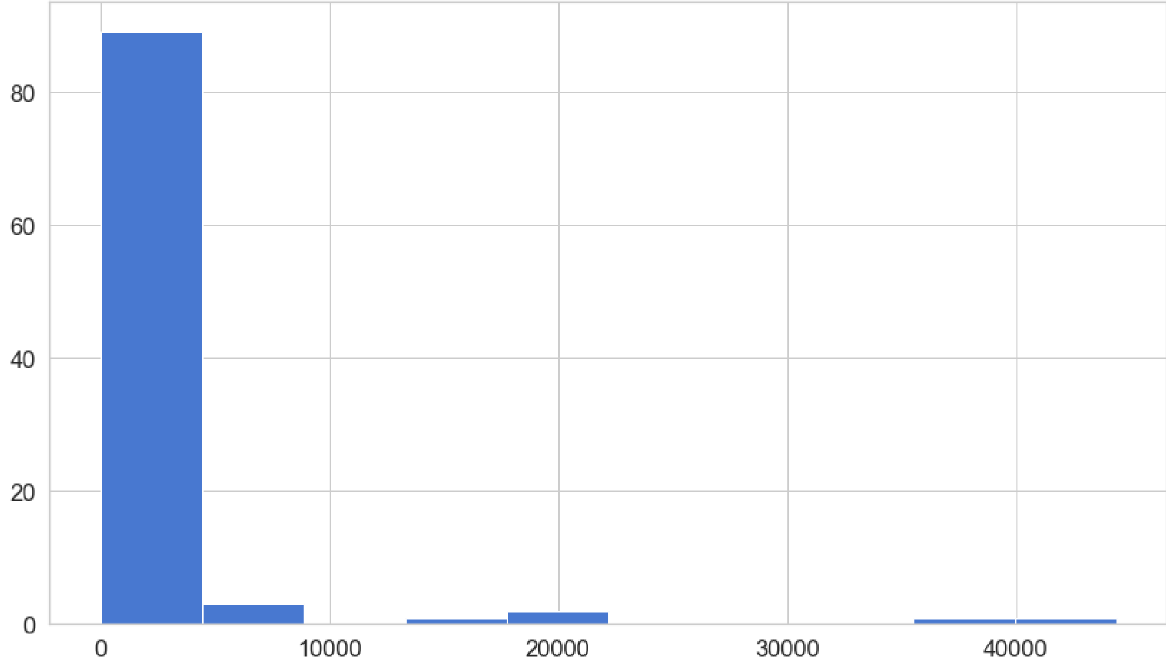
```
fig = plt.figure()
ax = fig.add_subplot(111)
normal_error_df = error_df[(error_df['true_class']== 0) & (error_df['reconstruction_er
_ = ax.hist(normal_error_df.reconstruction_error.values, bins=10)
```



Reconstruction error with Attack

In [109]:

```
fig = plt.figure()
ax = fig.add_subplot(111)
fraud_error_df = error_df[error_df['true_class'] == 1]
_ = ax.hist(fraud_error_df.reconstruction_error.values, bins=10)
```



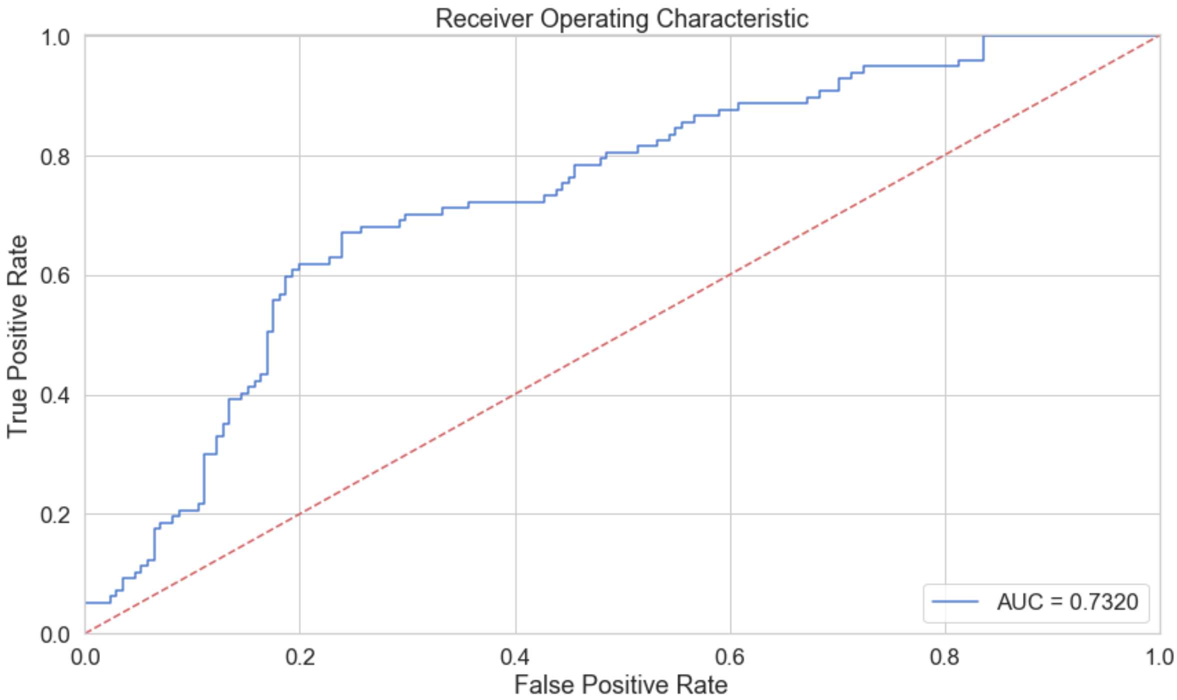
In [110]:

```
from sklearn.metrics import (confusion_matrix, precision_recall_curve, auc,
                             roc_curve, recall_score, classification_report, f1_score,
                             precision_recall_fscore_support)
```

ROC curves are very useful tool for understanding the performance of binary classifiers. However, our case is a bit out of the ordinary. We have a very imbalanced dataset. Nonetheless, let's have a look at our ROC curve:

In [111]:

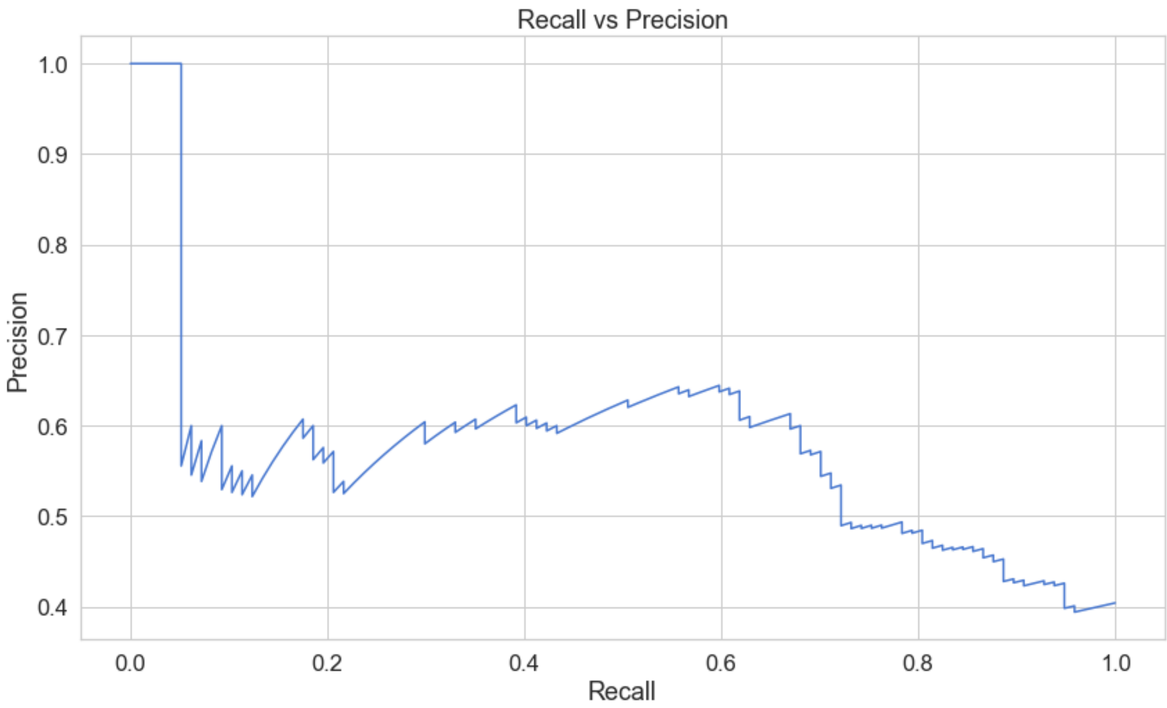
```
fpr, tpr, thresholds = roc_curve(error_df.true_class, error_df.reconstruction_error)
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, label='AUC = %0.4f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.001, 1])
plt.ylim([0, 1.001])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show();
```



The ROC curve plots the true positive rate versus the false positive rate, over different threshold values. Basically, we want the blue line to be as close as possible to the upper left corner. While our results look pretty good, we have to keep in mind of the nature of our dataset. ROC doesn't look very useful for us. Onward...

In [112]:

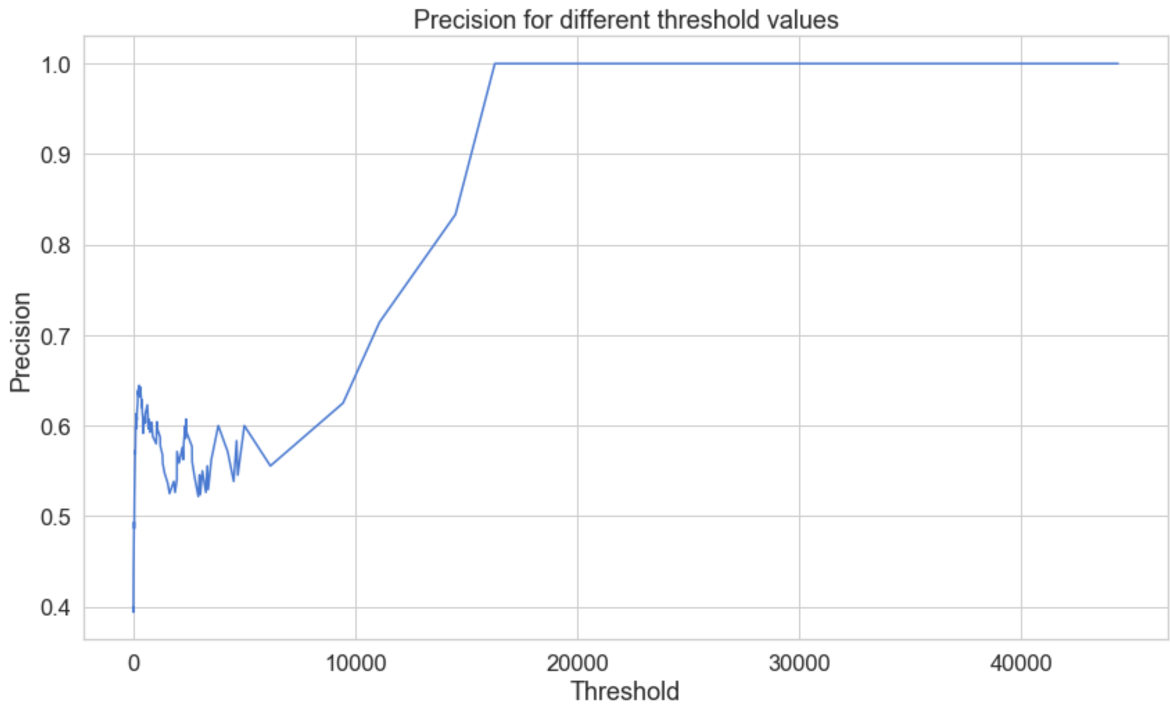
```
precision, recall, th = precision_recall_curve(error_df.true_class, error_df.reconstru
plt.plot(recall, precision, 'b', label='Precision-Recall curve')
plt.title('Recall vs Precision')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()
```



A high area under the curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall).

In [113]:

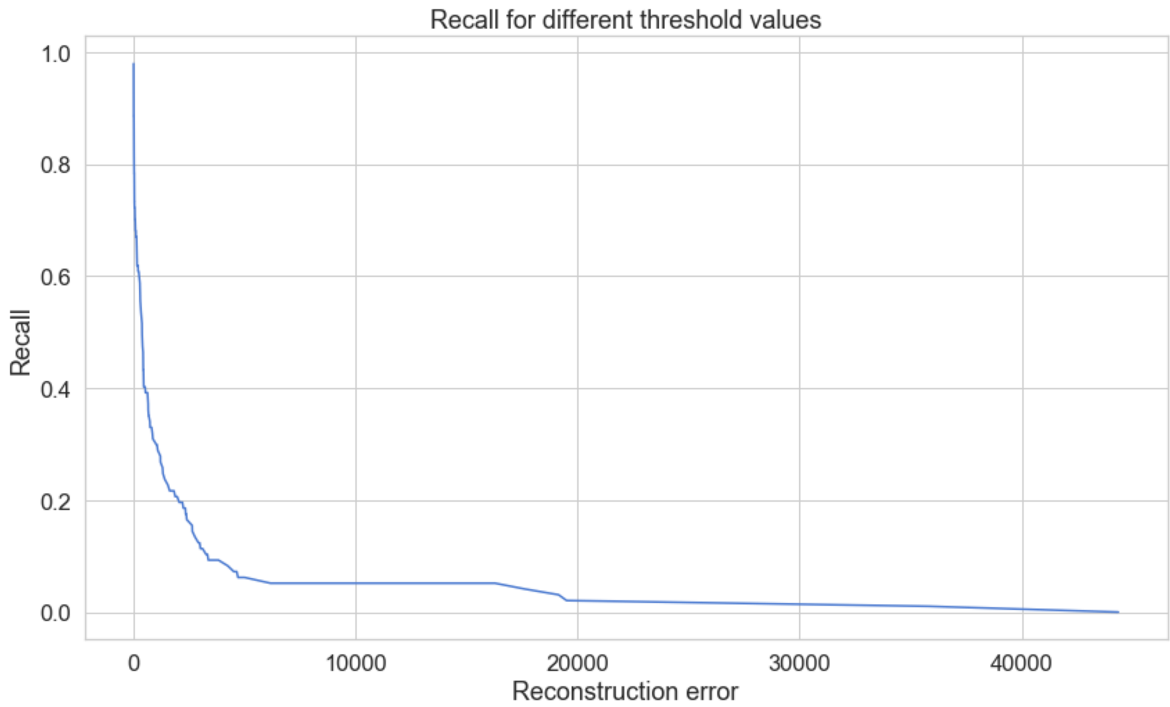
```
plt.plot(th, precision[1:], 'b', label='Threshold-Precision curve')
plt.title('Precision for different threshold values')
plt.xlabel('Threshold')
plt.ylabel('Precision')
plt.show()
```



You can see that as the reconstruction error increases our precision rises as well. Let's have a look at the recall:

In [114]:

```
plt.plot(th, recall[1:], 'b', label='Threshold-Recall curve')
plt.title('Recall for different threshold values')
plt.xlabel('Reconstruction error')
plt.ylabel('Recall')
plt.show()
```



Here, we have the exact opposite situation. As the reconstruction error increases the recall decreases.

Prediction Our model is a bit different this time. It doesn't know how to predict new values. But we don't need that. In order to predict whether or not a new/unseen system call sequence is normal or attack, we'll calculate the reconstruction error from the systemcall data itself. If the error is larger than a predefined threshold, we'll mark it as a attack (since our model should have a low error on normal transactions). Let's pick that value:

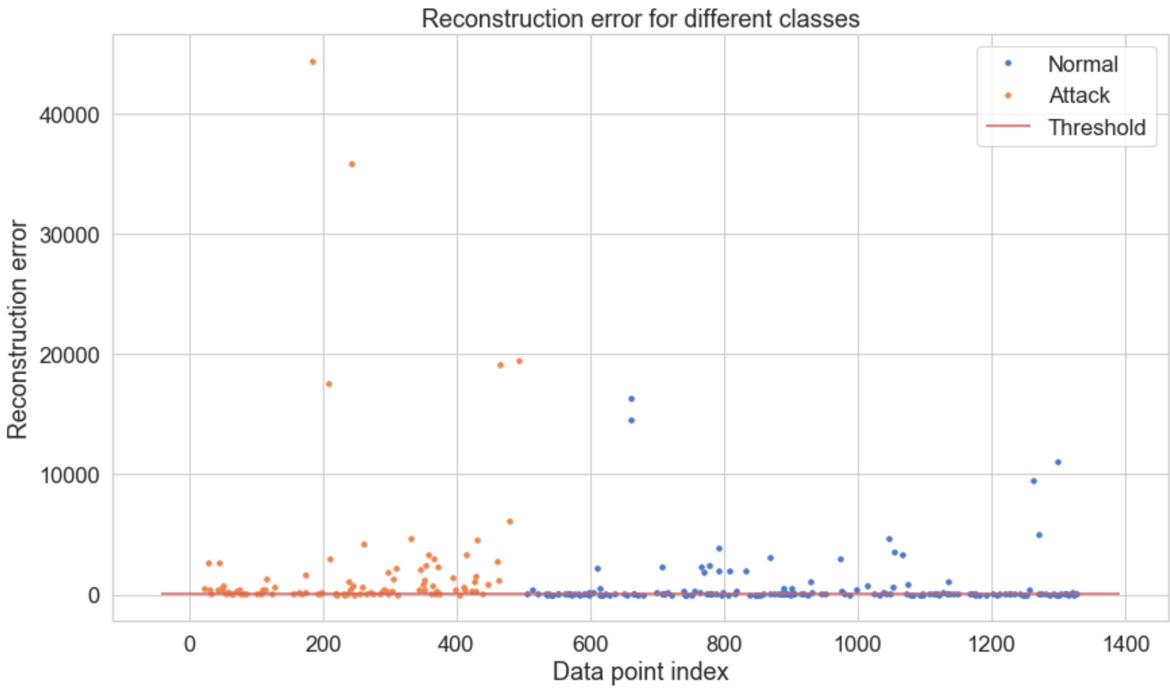
In [115]:

```
threshold = 20
```

And see how well we're dividing the two types of transactions:

In [116]:

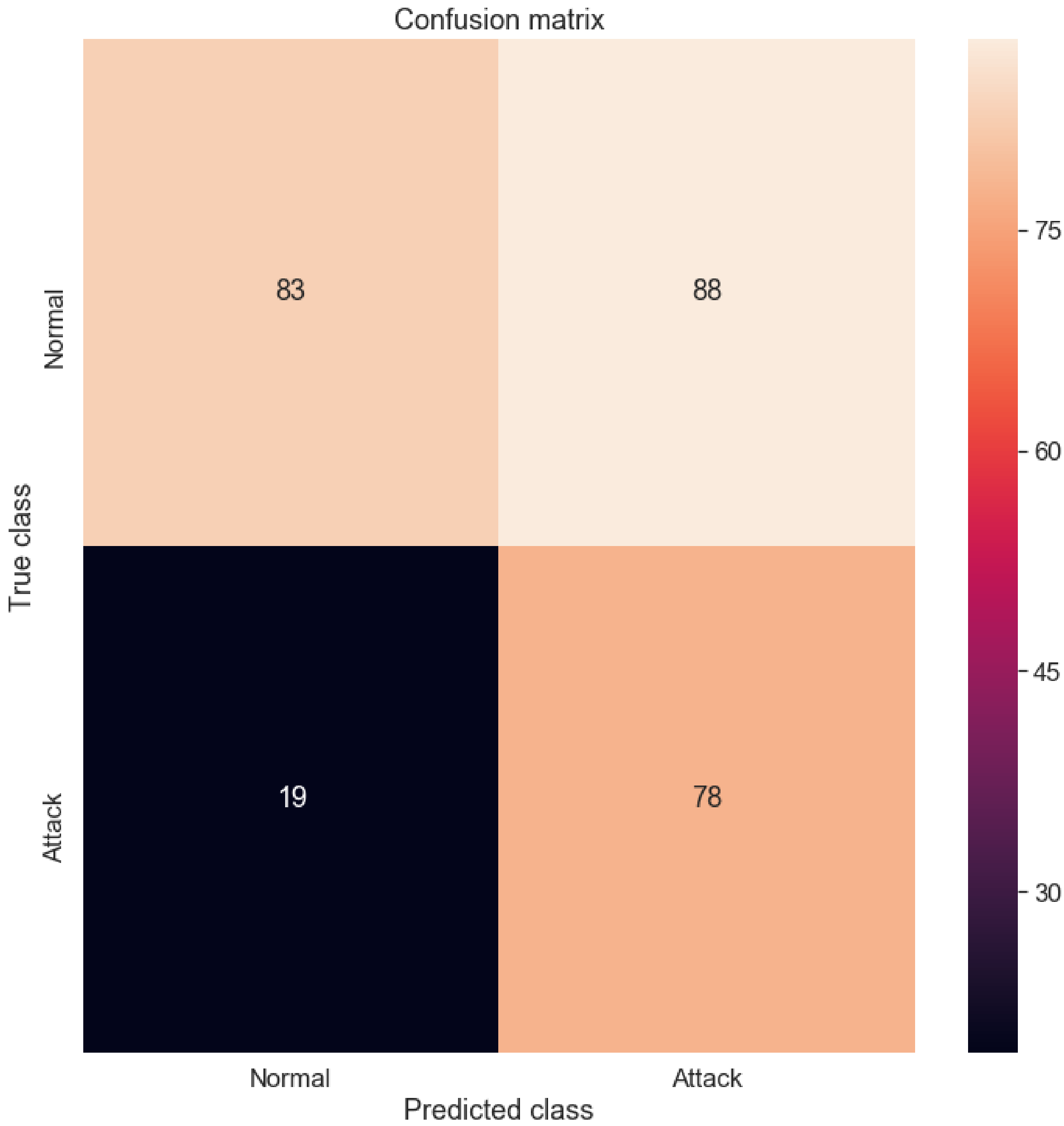
```
groups = error_df.groupby('true_class')
fig, ax = plt.subplots()

for name, group in groups:
    ax.plot(group.index, group.reconstruction_error, marker='o', ms=3.5, linestyle='',
            label= "Attack" if name == 1 else "Normal")
ax.hlines(threshold, ax.get_xlim()[0], ax.get_xlim()[1], colors="r", zorder=100, label
ax.legend()
plt.title("Reconstruction error for different classes")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show();
```



I know, that chart might be a bit deceiving. Let's have a look at the confusion matrix:

In [117]:

```
y_pred = [1 if e > threshold else 0 for e in error_df.reconstruction_error.values]
conf_matrix = confusion_matrix(error_df.true_class, y_pred)

plt.figure(figsize=(12, 12))
sns.heatmap(conf_matrix, xticklabels=LABELS, yticklabels=LABELS, annot=True, fmt="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



Our model seems to catch a lot of the attack cases. Of course, there is a catch (see what I did there?). The number of normal transactions classified as Attack is really high. Is this really a problem? Probably it is. You might want to increase or decrease the value of the threshold, depending on the problem. That one is up to you.

Conclusion

We've created a very simple Deep Autoencoder in Keras that can reconstruct what normal system call looks like. Initially, I was a bit skeptical about whether or not this whole thing is gonna work out, bit it kinda did. Think about it, we gave a lot of one-class examples (normal systemcalls) to a model and it learned (somewhat) how to discriminate whether or not new examples belong to that same class. Isn't that cool? Our dataset was kind of magical, though. We really don't know what the original features look like.

Keras gave us very clean and easy to use API to build a non-trivial Deep Autoencoder. You can search for TensorFlow implementations and see for yourself how much boilerplate you need in order to train one. Can you apply a similar model to a different problem?

References

Building Autoencoders in Keras Stanford tutorial on Autoencoders Stacked Autoencoders in TensorFlow

LSTM Autoencoder Classifier Model

In [118]:

```
# LsTM autoencoder - https://machinelearningmastery.com/lstm-autoencoders/
# LSTM Autoencoder - https://towardsdatascience.com/lstm-autoencoder-for-extreme-rare-e
```

Prepare data for LSTM models

LSTM is a bit more demanding than other models. Significant amount of time and attention goes in preparing the data that fits an LSTM.

First, we will create the 3-dimensional arrays of shape: (samples x timesteps x features). Samples mean the number of data points. Timesteps is the number of time steps we look back at any time t to make a prediction. This is also referred to as lookback period. The features is the number of features the data has, in other words, the number of predictors in a multivariate data.

In [119]:

```
result.head()
```

Out[119]:

	Label	168	265	3	54	162	142	309	146	114	175	43	104	5	78	102	13	6	24(
0	1	193	75	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	(
1	1	0	110	139	0	0	286	0	55	0	64	0	50	0	0	0	0	0	(
2	1	249	133	112	0	0	0	0	0	0	0	60	0	0	0	0	0	0	(
3	1	0	1	51	809	0	0	202	0	0	0	0	0	0	0	0	0	0	4
4	1	426	234	157	0	0	0	0	0	0	0	0	0	0	2	0	0	0	(

In [120]:

```
input_X = result.loc[:, result.columns != 'Label'].values  # converts the df to a numpy
input_y = result['Label'].values

n_features = input_X.shape[1]  # number of features

```

In [121]:

```
def temporalize(X, y, lookback):
    output_X = []
    output_y = []
    for i in range(len(X)-lookback-1):
        t = []
        for j in range(1,lookback+1):
            # Gather past records upto the lookback period
            t.append(X[[(i+j+1)], :])
        output_X.append(t)
        output_y.append(y[i+lookback+1])
    return output_X, output_y
```

In LSTM, to make prediction at any time t, we will look at data from (t-lookback):t. In the following, we have an example to show how the input data are transformed with the temporalize function with lookback=5. For the modeling, we may use a longer lookback.

In [122]:

```python
'''
Test: The 3D tensors (arrays) for LSTM are forming correctly.
'''
print('First instance of y = 1 in the original data')
display(result.iloc[(np.where(np.array(input_y) == 1)[0][0]-5):(np.where(np.array(inpu

lookback = 5  # Equivalent to 10 min of past data.
# Temporalize the data
X, y = temporalize(X = input_X, y = input_y, lookback = lookback)

print('For the same instance of y = 1, we are keeping past 5 samples in the 3D predict
display(pd.DataFrame(np.concatenate(X[np.where(np.array(y) == 1)[0][0]], axis=0 )))
```

```
First instance of y = 1 in the original data
```

Label	168	265	3	54	162	142	309	146	114	175	43	104	5	78	102	13	6	240	4

```
For the same instance of y = 1, we are keeping past 5 samples in the 3D pred
ictor array, X.
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	249	133	112	0	0	0	0	0	0	0	60	0	0	0	0	0	0	0	0	0	4
1	0	1	51	809	0	0	202	0	0	0	0	0	0	0	0	0	0	4	0	0	0
2	426	234	157	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
3	227	115	90	1	3	0	0	40	0	0	0	0	0	10	0	0	0	0	4	0	0
4	0	0	0	0	325	0	0	0	98	0	0	0	0	0	0	0	0	0	0	0	0

Divide the data into train, valid, and test

In [123]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

import pandas as pd
import numpy as np
from pylab import rcParams

import tensorflow as tf
from keras import optimizers, Sequential
from keras.models import Model
from keras.utils import plot_model
from keras.layers import Dense, LSTM, RepeatVector, TimeDistributed
from keras.callbacks import ModelCheckpoint, TensorBoard

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, precision_recall_curve
from sklearn.metrics import recall_score, classification_report, auc, roc_curve
from sklearn.metrics import precision_recall_fscore_support, f1_score

from numpy.random import seed
seed(7)
from tensorflow import set_random_seed
set_random_seed(11)

from sklearn.model_selection import train_test_split

SEED = 123 #used to help randomly select the data points
DATA_SPLIT_PCT = 0.2

rcParams['figure.figsize'] = 8, 6
LABELS = ["Normal","Attack"]

X_train, X_test, y_train, y_test = train_test_split(np.array(X), np.array(y), test_size
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=DATA_

```

In [124]:

```
X_train.shape
```

Out[124]:

```
(852, 5, 1, 87)
```

In [125]:

```
X_train_y0 = X_train[y_train==0]
X_train_y1 = X_train[y_train==1]

X_valid_y0 = X_valid[y_valid==0]
X_valid_y1 = X_valid[y_valid==1]
```

In [126]:

```
X_train_y0.shape
```

Out[126]:

```
(542, 5, 1, 87)
```

Reshaping the data

The tensors we have here are 4-dimensional. We will reshape them into the desired 3-dimensions corresponding to sample x lookback x features.

In [127]:

```
X_train = X_train.reshape(X_train.shape[0], lookback, n_features)
X_train_y0 = X_train_y0.reshape(X_train_y0.shape[0], lookback, n_features)
X_train_y1 = X_train_y1.reshape(X_train_y1.shape[0], lookback, n_features)

X_test = X_test.reshape(X_test.shape[0], lookback, n_features)

X_valid = X_valid.reshape(X_valid.shape[0], lookback, n_features)
X_valid_y0 = X_valid_y0.reshape(X_valid_y0.shape[0], lookback, n_features)
X_valid_y1 = X_valid_y1.reshape(X_valid_y1.shape[0], lookback, n_features)
```

In [128]:

```
n_features
```

Out[128]:

```
87
```

Standardize the data It is usually better to use a standardized data (transformed to Gaussian, mean 0 and sd 1) for autoencoders.

One common mistake is: we normalize the entire data and then split into train-test. This is not correct. Test data should be completely unseen to anything during the modeling. We should normalize the test data using the feature summary statistics computed from the training data. For normalization, these statistics are the mean and variance for each feature.

The same logic should be used for the validation set. This makes the model more stable for a test data.

To do this, we will require two UDFs.

flatten: This function will re-create the original 2D array from which the 3D arrays were created. This function is the inverse of temporalize, meaning X = flatten(temporalize(X)). scale: This function will scale a 3D array that we created as inputs to the LSTM.

In [129]:

```
def flatten(X):
    '''
    Flatten a 3D array.

    Input
    X            A 3D array for lstm, where the array is sample x timesteps x features

    Output
    flattened_X  A 2D array, sample x features.
    '''
    flattened_X = np.empty((X.shape[0], X.shape[2]))  # sample x features array.
    for i in range(X.shape[0]):
        flattened_X[i] = X[i, (X.shape[1]-1), :]
    return(flattened_X)

def scale(X, scaler):
    '''
    Scale 3D array.

    Inputs
    X            A 3D array for lstm, where the array is sample x timesteps x features
    scaler       A scaler object, e.g., sklearn.preprocessing.StandardScaler, sklearn.

    Output
    X            Scaled 3D array.
    '''
    for i in range(X.shape[0]):
        X[i, :, :] = scaler.transform(X[i, :, :])

    return X
```

In [130]:

```
# Initialize a scaler using the training data.
scaler = StandardScaler().fit(flatten(X_train_y0))
```

In [131]:

```
X_train_y0_scaled = scale(X_train_y0, scaler)
X_train_y1_scaled = scale(X_train_y1, scaler)
X_train_scaled = scale(X_train, scaler)
```

In [132]:

```
'''
Test: Check if the scaling is correct.

The test succeeds if all the column means
and variances are 0 and 1, respectively, after
flattening.
'''
a = flatten(X_train_y0_scaled)
print('colwise mean', np.mean(a, axis=0).round(6))
print('colwise variance', np.var(a, axis=0))
```

```
colwise mean [0.169742 0.142066 0.195572 0.156827 0.051661 0.073801 0.055351
0.125461
 0.136531 0.132841 0.        0.        0.175277 0.178967 0.177122 0.178967
 0.114391 0.145756 0.154982 0.180812 0.182657 0.125461 0.051661 0.142066
 0.145756 0.190037 0.04797  0.193727 0.042435 0.156827 0.075646 0.123616
 0.042435 0.119926 0.114391 0.140221 0.105166 0.162362 0.081181 0.079336
 0.        0.        0.        0.        0.073801 0.051661 0.046125 0.
 0.        0.068266 0.208487 0.042435 0.        0.110701 0.        0.077491
 0.        0.154982 0.180812 0.057196 0.042435 0.101476 0.062731 0.094096
 0.107011 0.127306 0.136531 0.        0.        0.114391 0.        0.070111
 0.079336 0.        0.        0.        0.094096 0.090406 0.105166 0.081181
 0.081181 0.092251 0.081181 0.110701 0.086716 0.114391 0.145756]
colwise variance [0.71657521 0.77502008 0.62595825 0.7226379  0.95674079 0.9
4289293
 0.96003595 0.84403807 0.7931673  0.83475171 0.         0.
 0.67592013 0.70413325 0.69925518 0.67461295 0.81717297 0.75919786
 0.72505821 0.60937351 0.64006822 0.8071377  0.9382906  0.70121935
 0.68908716 0.64838782 0.98293869 0.53627061 0.97421399 0.68942757
 0.85590134 0.80944227 0.97421399 0.83617121 0.82086301 0.784766
 0.81366335 0.70795605 0.87532849 0.87746967 0.         0.
 0.         0.         0.90230253 0.98626108 0.97757724 0.
 0.         0.92338408 0.61520472 0.97421399 0.         0.82538364
 0.         0.90543429 0.         0.76564862 0.73114473 0.92846298
 0.97421399 0.84394616 0.95178443 0.85276957 0.78928664 0.83065658
 0.80054738 0.         0.         0.82455304 0.         0.92128375
 0.91068    0.         0.         0.         0.88966994 0.89035076
 0.8690139  0.89746872 0.90115875 0.86602851 0.91222886 0.90656445
 0.89469438 0.87621356 0.77395801]
```

The test succeeded. Now we will *scale* the validation and test sets.

In [133]:

```
X_valid_scaled = scale(X_valid, scaler)
X_valid_y0_scaled = scale(X_valid_y0, scaler)

X_test_scaled = scale(X_test, scaler)
```

LSTM Autoencoder training

First we will initialize the Autoencoder architecture. We are building a simple autoencoder. More complex architectures and other configurations should be explored.

In [134]:

```
timesteps =  X_train_y0_scaled.shape[1] # equal to the lookback
n_features =  X_train_y0_scaled.shape[2] # 87

epochs = 200
batch = 64
lr = 0.0001
```

In [135]:

```
n_features
```

Out[135]:

```
87
```

In [136]:

```
lstm_autoencoder = Sequential()
# Encoder
lstm_autoencoder.add(LSTM(32, activation='relu', input_shape=(timesteps, n_features), 
lstm_autoencoder.add(LSTM(16, activation='relu', return_sequences=False))
lstm_autoencoder.add(RepeatVector(timesteps))
# Decoder
lstm_autoencoder.add(LSTM(16, activation='relu', return_sequences=True))
lstm_autoencoder.add(LSTM(32, activation='relu', return_sequences=True))
lstm_autoencoder.add(TimeDistributed(Dense(n_features)))

lstm_autoencoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_1 (LSTM)                (None, 5, 32)             15360     
_________________________________________________________________
lstm_2 (LSTM)                (None, 16)                3136      
_________________________________________________________________
repeat_vector_1 (RepeatVecto (None, 5, 16)             0         
_________________________________________________________________
lstm_3 (LSTM)                (None, 5, 16)             2112      
_________________________________________________________________
lstm_4 (LSTM)                (None, 5, 32)             6272      
_________________________________________________________________
time_distributed_1 (TimeDist (None, 5, 87)             2871      
=================================================================
Total params: 29,751
Trainable params: 29,751
Non-trainable params: 0
_________________________________________________________________
```

As a rule-of-thumb, look at the number of parameters. If not using any regularization, keep this less than the number of samples. If using regularization, depending on the degree of regularization you can let more parameters in the model that is greater than the sample size. For example, if using dropout with 0.5, you can have up to double the sample size (loosely speaking).

In [137]:

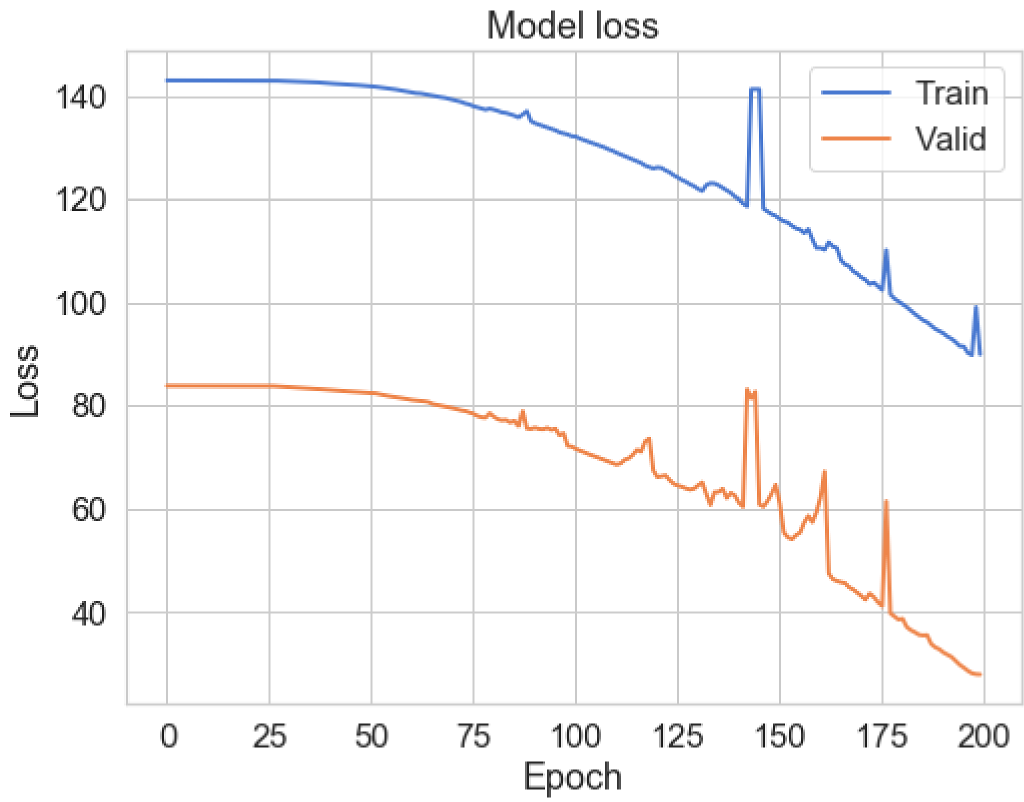
```
adam = optimizers.Adam(lr)
lstm_autoencoder.compile(loss='mse', optimizer=adam)

cp = ModelCheckpoint(filepath="lstm_autoencoder_classifier.h5",
                               save_best_only=True,
                               verbose=0)

tb = TensorBoard(log_dir='./logs',
                 histogram_freq=0,
                 write_graph=True,
                 write_images=True)

lstm_autoencoder_history = lstm_autoencoder.fit(X_train_y0_scaled, X_train_y0_scaled,
                                                epochs=epochs,
                                                batch_size=batch,
                                                validation_data=(X_valid_y0_scaled, X_
                                                verbose=2).history
```

```
Epoch 78/200
 - 0s - loss: 137.6295 - val_loss: 77.7723
Epoch 79/200
 - 0s - loss: 137.3492 - val_loss: 77.6882
Epoch 80/200
 - 0s - loss: 137.5576 - val_loss: 78.5771

Epoch 81/200
 - 0s - loss: 137.3605 - val_loss: 77.8956
Epoch 82/200
 - 0s - loss: 137.1182 - val_loss: 77.3980
Epoch 83/200
 - 0s - loss: 136.8163 - val_loss: 77.1785
Epoch 84/200
 - 0s - loss: 136.7135 - val_loss: 77.2695
Epoch 85/200
 - 0s - loss: 136.4470 - val_loss: 76.7656
Epoch 86/200
 - 0s - loss: 136.2070 - val_loss: 77.0984
Epoch 87/200
```

Plotting the change in the loss over the epochs.

In [138]:

```
plt.plot(lstm_autoencoder_history['loss'], linewidth=2, label='Train')
plt.plot(lstm_autoencoder_history['val_loss'], linewidth=2, label='Valid')
plt.legend(loc='upper right')
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.show()
```



Sanity check

Doing a sanity check by validating the reconstruction error on the train data. Here we will reconstruct the entire train data with both 0 and 1 labels.

Expectation: the reconstruction error of 0 labeled data should be smaller than 1.

Caution: do not use this result for model evaluation. It may result into overfitting issues.

In [139]:

```
train_x_predictions = lstm_autoencoder.predict(X_train_scaled)
mse = np.mean(np.power(flatten(X_train_scaled) - flatten(train_x_predictions), 2), axi

error_df = pd.DataFrame({'Reconstruction_error': mse,
                        'True_class': y_train.tolist()})

groups = error_df.groupby('True_class')
fig, ax = plt.subplots()

for name, group in groups:
    ax.plot(group.index, group.Reconstruction_error, marker='o', ms=3.5, linestyle='',
            label= "Attack" if name == 1 else "Normal")
ax.legend()
plt.title("Reconstruction error for different classes")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show();
```

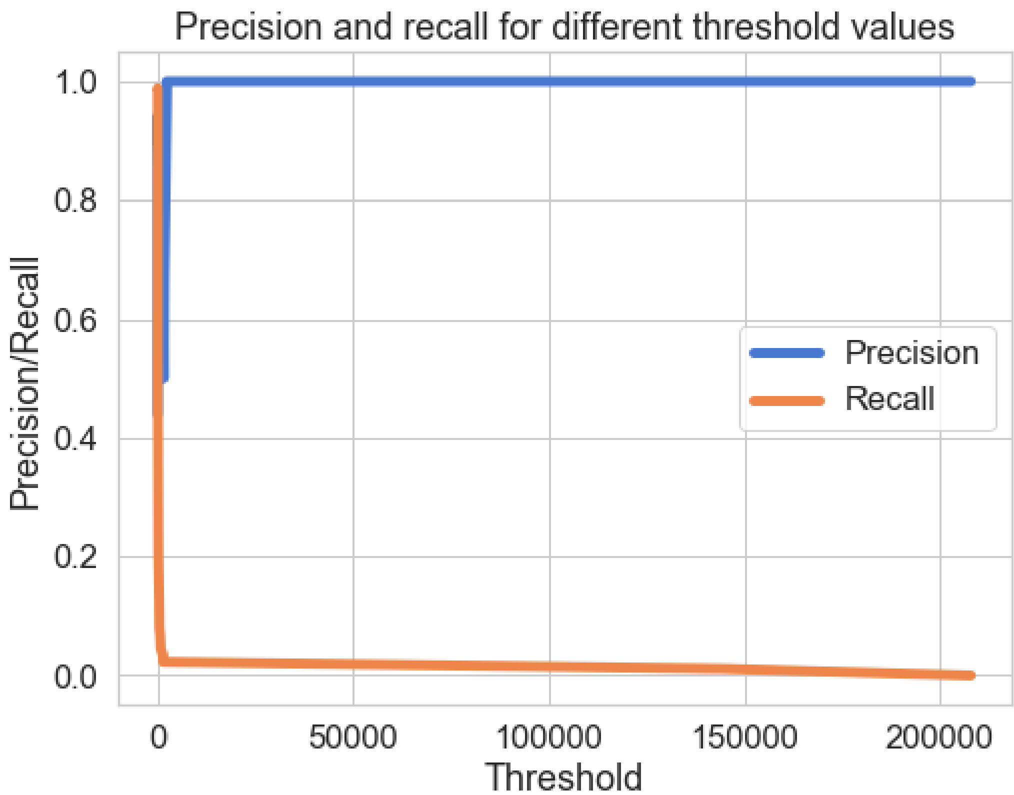
Predictions using the Autoencoder

Here we show how we can use an Autoencoder reconstruction error for the rare-event classification. We follow this concept: the autoencoder is expected to reconstruct a noif the reconstruction error is high, we will classify it as a sheet-break.

We will need to determine the threshold for this. Also, note that here we will be using the entire validation set containing both y = 0 or 1.

In [140]:

```
valid_x_predictions = lstm_autoencoder.predict(X_valid_scaled)
mse = np.mean(np.power(flatten(X_valid_scaled) - flatten(valid_x_predictions), 2), axi

error_df = pd.DataFrame({'Reconstruction_error': mse,
                        'True_class': y_valid.tolist()})

precision_rt, recall_rt, threshold_rt = precision_recall_curve(error_df.True_class, er
plt.plot(threshold_rt, precision_rt[1:], label="Precision",linewidth=5)
plt.plot(threshold_rt, recall_rt[1:], label="Recall",linewidth=5)
plt.title('Precision and recall for different threshold values')
plt.xlabel('Threshold')
plt.ylabel('Precision/Recall')
plt.legend()
plt.show()
```



In [141]:

```
test_x_predictions = lstm_autoencoder.predict(X_test_scaled)
mse = np.mean(np.power(flatten(X_test_scaled) - flatten(test_x_predictions), 2), axis=

error_df = pd.DataFrame({'Reconstruction_error': mse,
                        'True_class': y_test.tolist()})

threshold_fixed = 0.3
groups = error_df.groupby('True_class')
fig, ax = plt.subplots()

for name, group in groups:
    ax.plot(group.index, group.Reconstruction_error, marker='o', ms=3.5, linestyle='',
            label= "Attack" if name == 1 else "Normal")
ax.hlines(threshold_fixed, ax.get_xlim()[0], ax.get_xlim()[1], colors="r", zorder=100,
ax.legend()
plt.title("Reconstruction error for different classes")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show();
```

The orange and blue dot above the threshold line represents the True Positive and False Positive, respectively. As we can see, we have good number of false positives.

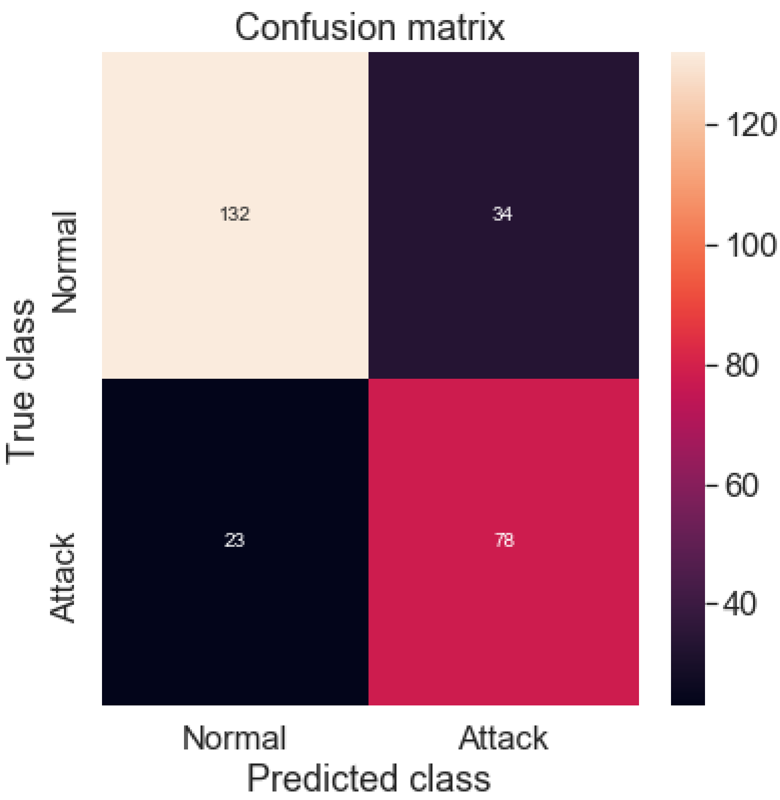
Let’s see the accuracy results.

In [142]:

```
pred_y = [1 if e > threshold_fixed else 0 for e in error_df.Reconstruction_error.value:
```

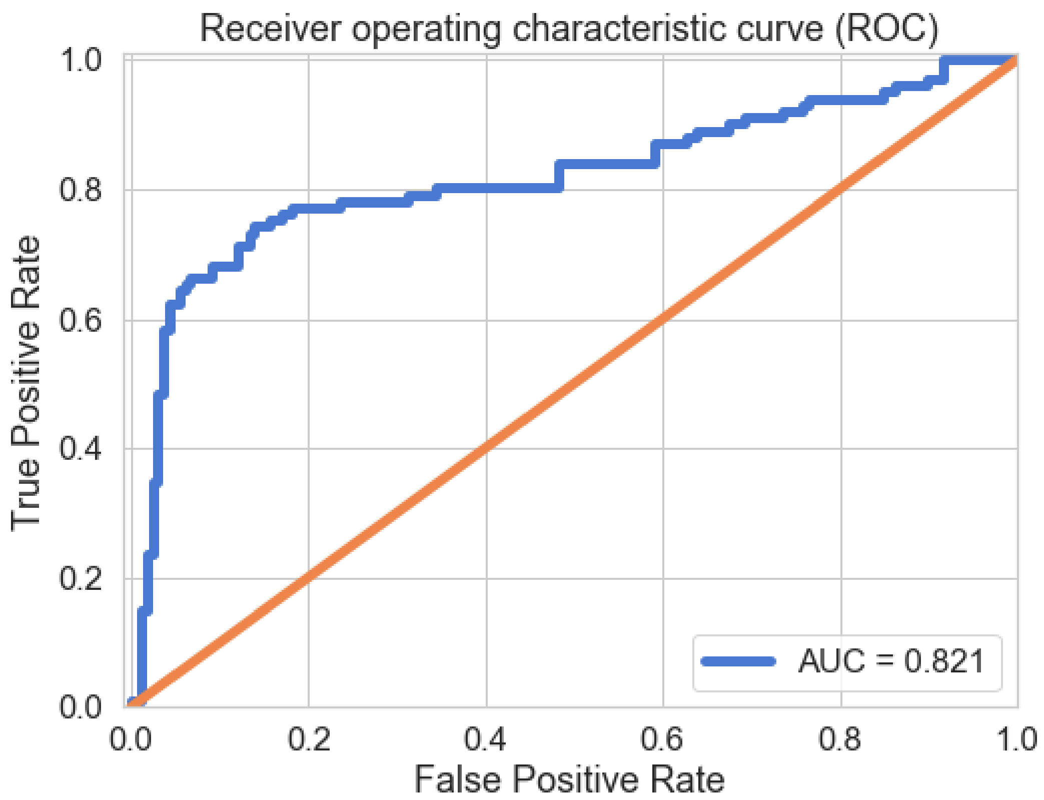
In [143]:

```
conf_matrix = confusion_matrix(error_df.True_class, pred_y)

plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, xticklabels=LABELS, yticklabels=LABELS, annot=True, fmt="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



In [144]:

```
false_pos_rate, true_pos_rate, thresholds = roc_curve(error_df.True_class, error_df.Re
roc_auc = auc(false_pos_rate, true_pos_rate,)

plt.plot(false_pos_rate, true_pos_rate, linewidth=5, label='AUC = %0.3f'% roc_auc)
plt.plot([0,1],[0,1], linewidth=5)

plt.xlim([-0.01, 1])
plt.ylim([0, 1.01])
plt.legend(loc='lower right')
plt.title('Receiver operating characteristic curve (ROC)')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Conclusion

From the Confusion Matrix in Figure above, we could predict 76 out of 101 Attack instances.

The primary reason is LSTM model has more parameters to estimate. It becomes important to use regularization with LSTMs.