Intrusion Detection Analysis

October 7, 2018

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

0.1 1. Introduce the Data

0.1.1 Import the dataset

dataset.txt is a tab delimited file that has around 5 lac rows and 24 features. We read the data into an object called df and then assign the labels of the features to their respective columns in the dataframe df.

```
In [2]: df = pd.read_csv('dataset.txt', sep = "\t", header = None) #use nrows attribute for limi
        column_list = [
            'duration',
            'service',
            'source_bytes',
            'destination_bytes',
            'count',
            'same_srv_rate',
            'serror_rate',
            'srv_serror_rate',
            'dst_host_count',
            'dst_host_srv_count',
            'dst_host_same_src_port_rate',
            'dst_host_serror_rate',
            'dst_host_srv_serror_rate',
            'flag',
            'ids_detection',
            'malware_detection',
            'ashula_detection',
            'label',
            'source_ip_address',
            'source_port_number',
            'destination_ip_address',
            'destination_port_number',
            'start_time',
```

```
    'protocol'
]
df.columns = column_list
```

```
/home/chrx/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785: DtypeWar
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:
```
#reading the first 5 rows of the data

df.head()
```

Out[3]:
```
   duration service  source_bytes  destination_bytes  count  same_srv_rate  \
0  0.000393     dns            43                100      9            1.0
1  0.000400     dns            43                100     11            1.0
2  0.000432     dns            61                 77     14            1.0
3  0.000442     dns            61                 77     15            1.0
4  0.000452     dns            61                112     16            1.0

   serror_rate  srv_serror_rate  dst_host_count  dst_host_srv_count    ...     \
0          0.0              0.0              60                  99    ...
1          0.0              0.0              61                  99    ...
2          0.0              0.0              60                  99    ...
3          0.0              0.0              39                  99    ...
4          0.0              0.0              39                  99    ...

   ids_detection  malware_detection  ashula_detection label  \
0              0                  0                 0    -1
1              0                  0                 0    -1
2              0                  0                 0    -1
3              0                  0                 0     1
4              0                  0                 0     1

                        source_ip_address source_port_number  \
0  fd95:ec1e:6a61:df6b:7de2:27ad:6105:3709              46071
1  fd95:ec1e:6a61:df6b:7de2:27ad:6105:3709              51986
2  fd95:ec1e:6a61:df6b:7de2:27ad:6105:3709              48133
3  fd95:ec1e:6a61:b804:7dcb:276f:0751:0ff5              58986
4  fd95:ec1e:6a61:b804:7dcb:276f:0751:0ff5              35589

                   destination_ip_address  destination_port_number  \
0  fd95:ec1e:6a61:435f:7de5:27b0:7d84:3c0d                       53
1  fd95:ec1e:6a61:435f:7de5:27b0:7d84:3c0d                       53
2  fd95:ec1e:6a61:435f:7de5:27b0:7d84:3c0d                       53
3  fd95:ec1e:6a61:435f:7de5:27b0:7d84:3c0d                       53
4  fd95:ec1e:6a61:435f:7de5:27b0:7d84:3c0d                       53

  start_time  protocol
```

```
0   00:00:00       udp
1   00:00:00       udp
2   00:00:00       udp
3   00:00:00       udp
4   00:00:00       udp

[5 rows x 24 columns]
```

```
In [4]: #shape of the data is the number of rows by the number of features
        df.shape
```

```
Out[4]: (499999, 24)
```

0.1.2 Remove the target variable from the dataset

the target variable will be `label`

Important -- `label = 0 if no Intrusion 1 Otherwise`

although `malware detection`, `ids_detection`, and `ashula_detection` could also be taken as labels, we decided against it since they were only indicative of the detection of intrusion by a software and therefore may not be correctly labelled.

```
In [5]: df['label'] = [0 if x == 1 else 1 for x in df['label']]
```

```
In [6]: label_target = df.pop('label').values

        #dropping these labels because they aren't really needed in training
        df.pop('ids_detection').values
        df.pop('malware_detection').values
        df.pop('ashula_detection').values

        df.shape
```

```
Out[6]: (499999, 20)
```

```
In [7]: #creating a variable y that contains the target column `label` for the training set
        y = label_target
```

0.1.3 Checking String Based Features

Here we check the unique values of string based features and determine if they are necessary. If there are a lot of unique values then the feature is ignored since it might lead to overfitting of the model

```
In [8]: #count the unique values in service feature(string based)
        service_value_counts = df['service'].value_counts()
        print("Number of unique values = ", service_value_counts.shape[0], "\n")
        print(service_value_counts)
```

```
Number of unique values =  12

dns          313014
other        114253
ssh           71349
sip             617
snmp            199
smtp            182
radius          157
rdp              94
http             89
smtp,ssl         33
dhcp             11
ssl               1
Name: service, dtype: int64
```

In [9]:
```python
#count the unique values in protocol feature(string based)
protocol_value_counts = df['protocol'].value_counts()
print("Number of unique values = ", protocol_value_counts.shape[0], "\n")
print(protocol_value_counts)
```

```
Number of unique values =  3

udp     320156
tcp     177207
icmp      2636
Name: protocol, dtype: int64
```

In [10]:
```python
#count the unique values in flag feature(string based)
protocol_value_counts = df['flag'].value_counts()
print("Number of unique values = ", protocol_value_counts.shape[0], "\n")
print(protocol_value_counts)
```

```
Number of unique values =  12

SF        378699
S0        101335
OTH         9414
REJ         5520
RSTO        2250
SHR         1522
RSTRH        659
RSTOS0       320
S1           152
RSTR         104
S2            13
SH            11
```

```
Name: flag, dtype: int64
```

0.1.4 Unique values for each feature in the dataset

```
In [11]: df.T.apply(lambda x: x.nunique(), axis=1)
```

```
Out[11]: duration                       94392
         service                           12
         source_bytes                     490
         destination_bytes                371
         count                            101
         same_srv_rate                     54
         serror_rate                       80
         srv_serror_rate                  101
         dst_host_count                   101
         dst_host_srv_count               101
         dst_host_same_src_port_rate       40
         dst_host_serror_rate              98
         dst_host_srv_serror_rate         101
         flag                              12
         source_ip_address              12815
         source_port_number             60971
         destination_ip_address           974
         destination_port_number         3148
         start_time                     74672
         protocol                           3
         dtype: int64
```

0.1.5 Removing unnecessary features

Everything from source_ip_address to start_time is of no use because these things are really random...

```
In [12]: df.pop('source_ip_address').values
         df.pop('source_port_number').values
         df.pop('destination_ip_address').values
         df.pop('destination_port_number').values
         df.pop('start_time').values
         df.head()
```

```
Out[12]:    duration service  source_bytes  destination_bytes  count  same_srv_rate  \
         0  0.000393     dns            43                100      9            1.0
         1  0.000400     dns            43                100     11            1.0
         2  0.000432     dns            61                 77     14            1.0
         3  0.000442     dns            61                 77     15            1.0
         4  0.000452     dns            61                112     16            1.0

            serror_rate  srv_serror_rate  dst_host_count  dst_host_srv_count  \
```

```
0           0.0              0.0              60                   99
1           0.0              0.0              61                   99
2           0.0              0.0              60                   99
3           0.0              0.0              39                   99
4           0.0              0.0              39                   99

   dst_host_same_src_port_rate  dst_host_serror_rate  \
0                          0.0                   0.0
1                          0.0                   0.0
2                          0.0                   0.0
3                          0.0                   0.0
4                          0.0                   0.0

   dst_host_srv_serror_rate flag protocol
0                       0.0   SF      udp
1                       0.0   SF      udp
2                       0.0   SF      udp
3                       0.0   SF      udp
4                       0.0   SF      udp
```

0.1.6 Features to use

```
In [13]: list(df)
```

```
Out[13]: ['duration',
          'service',
          'source_bytes',
          'destination_bytes',
          'count',
          'same_srv_rate',
          'serror_rate',
          'srv_serror_rate',
          'dst_host_count',
          'dst_host_srv_count',
          'dst_host_same_src_port_rate',
          'dst_host_serror_rate',
          'dst_host_srv_serror_rate',
          'flag',
          'protocol']
```

0.1.7 What the data looks like now in terms of data type

```
In [14]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 499999 entries, 0 to 499998
Data columns (total 15 columns):
duration                       499999 non-null float64
service                        499999 non-null object
```

```
source_bytes                  499999 non-null int64
destination_bytes             499999 non-null int64
count                         499999 non-null int64
same_srv_rate                 499999 non-null float64
serror_rate                   499999 non-null float64
srv_serror_rate               499999 non-null float64
dst_host_count                499999 non-null int64
dst_host_srv_count            499999 non-null int64
dst_host_same_src_port_rate   499999 non-null float64
dst_host_serror_rate          499999 non-null float64
dst_host_srv_serror_rate      499999 non-null float64
flag                          499999 non-null object
protocol                      499999 non-null object
dtypes: float64(7), int64(5), object(3)
memory usage: 57.2+ MB
```

0.1.8 Transfrom Catergorical Data to Numerical Data

From the above result it can be seen that `service`, `flag`, and `protocol` are not numeric data. Since we have to supply the machine learing models with numeric data we have to somehow transform the categorical data to numeric data.

For this purpose we use a Label Encoder that encodes the unique values of a feature to a unique numeric constant(number). We do this encoding for all the rows in the data.

```
In [15]: from sklearn import preprocessing
```

```
In [16]: #get the unique values for the following categorical data
         categorical_data = ['service', 'flag', 'protocol']
         unique_flag_data = df['flag'].unique()
         unique_service_data = df['service'].unique()
         unique_protocol_data = df['protocol'].unique()
```

Encoder for feature : Flag This shows an example of how categorical data like flag may be encoded and then decoded from categorical to numeric and then from numeric to categorical respectively.

```
In [17]: le_flag = preprocessing.LabelEncoder()
         #Fit the label encoder to unique values
         le_flag.fit(unique_flag_data)

         #Fit the label data to some example data
         example_flag_data = list(df.head()['flag'])
         #Fit the label encoder and return encoded labels
         encoded_flag_data = le_flag.transform(example_flag_data)

         #Transform labels back to original encoding
         decoded_flag_data = list(le_flag.inverse_transform(encoded_flag_data))
```

```
print(example_flag_data)
print(encoded_flag_data)
print(decoded_flag_data)
#Ignore any warnings
```

```
['SF', 'SF', 'SF', 'SF', 'SF']
[9 9 9 9 9]
['SF', 'SF', 'SF', 'SF', 'SF']


/home/chrx/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: Deprecation
  if diff:
```

Encoder for feature : service and protocol

In [18]:
```
le_service = preprocessing.LabelEncoder()
le_service.fit(unique_service_data)

le_protocol = preprocessing.LabelEncoder()
le_protocol.fit(unique_protocol_data)
```

Out[18]:
```
LabelEncoder()
```

Encode the categorical features for all rows in the data

In [19]:
```
df['flag'] = le_flag.transform(df['flag'])
df['service'] = le_service.transform(df['service'])
df['protocol'] = le_protocol.transform(df['protocol'])
df.head()
```

Out[19]:
```
   duration  service  source_bytes  destination_bytes  count  same_srv_rate  \
0  0.000393        1            43                100      9            1.0
1  0.000400        1            43                100     11            1.0
2  0.000432        1            61                 77     14            1.0
3  0.000442        1            61                 77     15            1.0
4  0.000452        1            61                112     16            1.0

   serror_rate  srv_serror_rate  dst_host_count  dst_host_srv_count  \
0          0.0              0.0              60                  99
1          0.0              0.0              61                  99
2          0.0              0.0              60                  99
3          0.0              0.0              39                  99
4          0.0              0.0              39                  99

   dst_host_same_src_port_rate  dst_host_serror_rate  \
0                          0.0                   0.0
1                          0.0                   0.0
```

```
2                         0.0                    0.0
3                         0.0                    0.0
4                         0.0                    0.0

   dst_host_srv_serror_rate  flag  protocol
0                       0.0     9         2
1                       0.0     9         2
2                       0.0     9         2
3                       0.0     9         2
4                       0.0     9         2
```

0.1.9 PCA

PCA stands for Principal Component Analysis. This algorithm is used for dimensionality reduction. The algorithm is supplied with the number of dimension to output and then the PCA algorithm automatically calculates the new dimensions from the old dimensions. New dimensions are really a linear combination of the old dimensions.

```
In [20]: from sklearn.decomposition import PCA

         pca = PCA(n_components = 2)
         X_pca = pd.DataFrame(pca.fit_transform(df))

In [21]: X_pca.head()

Out[21]:             0          1
         0 -241.430381 -83.353206
         1 -241.431096 -83.369025
         2 -264.278958 -65.191378
         3 -264.274311 -65.113415
         4 -229.275807 -65.414867
```

0.2 Model Building

We have used 3 different types of machine learning models which are:

```
-KMeans
-Logistic Regression
-Random Forests
```

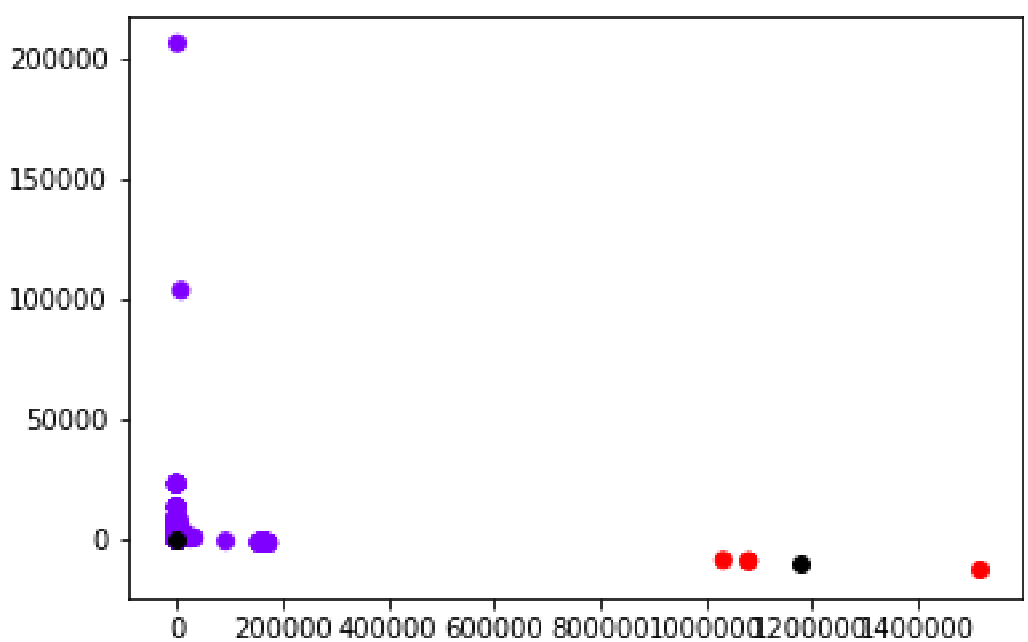
Here KMeans is a Unsupervised Learning model and the other 2 are Supervised Learning Models.

0.2.1 Kmeans

Here we use 2 clusters because we want the data to cluster into 2 clusters: Intrusion or Not Intrusion

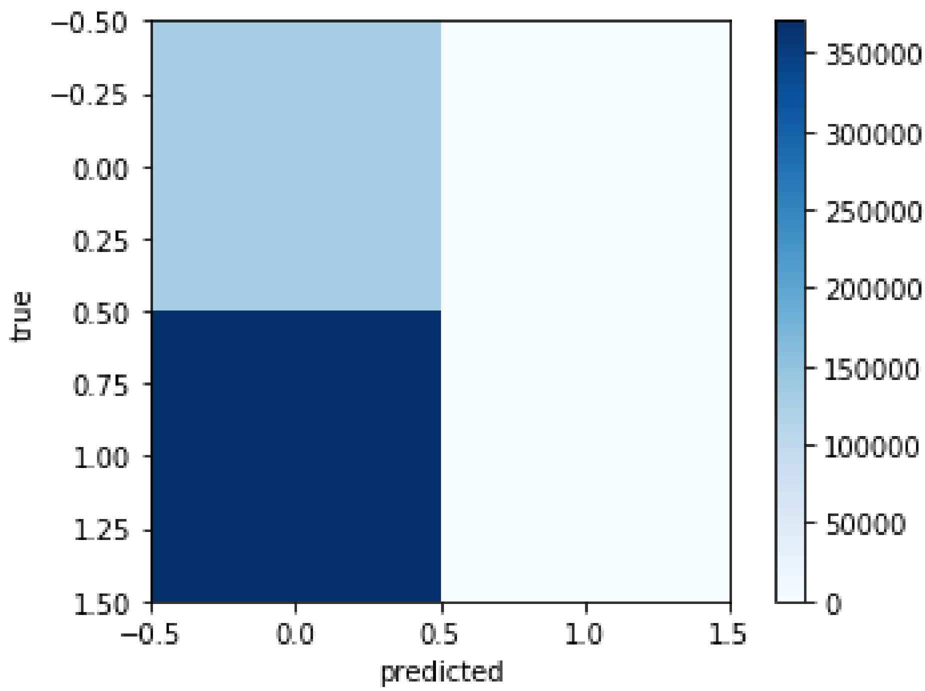
In [22]:
```python
from sklearn.cluster import KMeans

#converting to numpy array : format needed by sklearn
X_pca_np = np.array(X_pca).astype(float)

#creating a model
kmeans = KMeans(n_clusters = 2, random_state = 0)

#fitting the data to the model
kmeans.fit(X_pca_np)

#plotting the points and the cluster centroids
plt.scatter(X_pca_np[:,0],X_pca_np[:,1], c = kmeans.labels_, cmap = 'rainbow')
plt.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1], color='black')

#frequency of labels
predicted = kmeans.predict(X_pca_np)
unique, counts = np.unique(predicted, return_counts=True)
print(np.asarray((unique, counts)).T)
unique, counts = np.unique(y, return_counts=True)
print(np.asarray((unique, counts)).T)
```

```
[[     0 499995]
 [     1      4]]
[[     0 129616]
 [     1 370383]]
```



```
In [23]: #calculating the percentage of correct clusterings
         from sklearn.metrics import accuracy_score
         print("accuracy Score : ",accuracy_score(y, kmeans.predict(X_pca_np)))

         #printing confusion matrix
         from sklearn.metrics import confusion_matrix
         print("Confusion Matrix\n",confusion_matrix(y, kmeans.predict(X_pca_np)))

         #plotting confusion matrix
         plt.imshow(confusion_matrix(y, kmeans.predict(X_pca_np)),
                    cmap='Blues', interpolation='nearest')
         plt.colorbar()
         plt.grid(False)
         plt.ylabel('true')
         plt.xlabel('predicted');
```

```
accuracy Score :  0.25924051848103696
Confusion Matrix
 [[129616      0]
 [370379      4]]
```

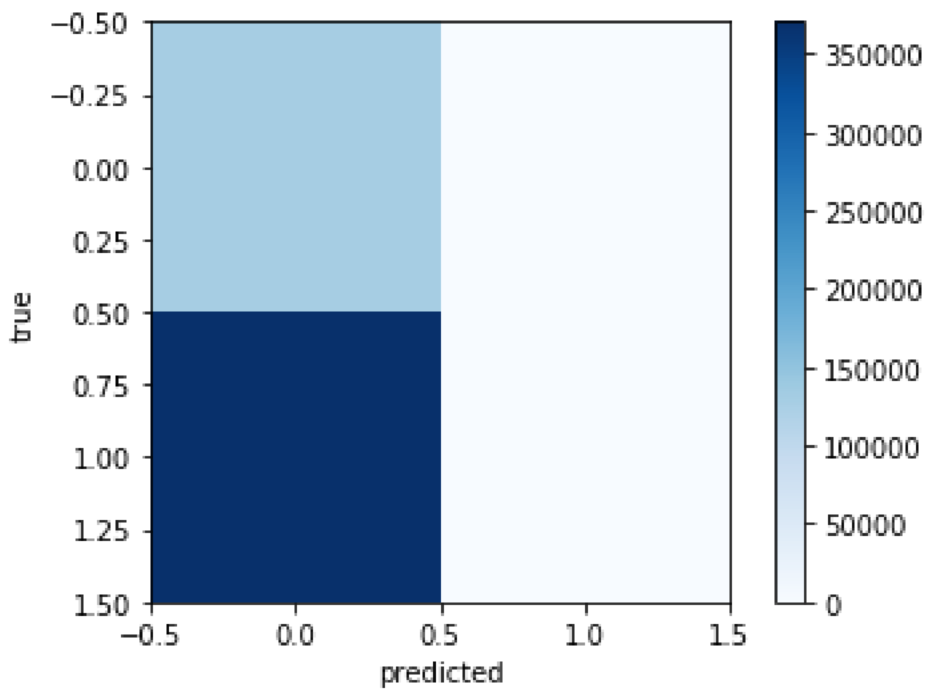


Lets try with a change in hyperparameters to kmeans

```
In [24]: #fitting data to modded kmeans model
         kmeans_modded = KMeans(n_clusters = 2, random_state = 0, max_iter = 100, algorithm = 'a
```

```
kmeans_modded.fit(X_pca_np)

#calculating the percentage of correct labels
print("accuracy Score : ",accuracy_score(y, kmeans_modded.predict(X_pca_np)))
#printing confusion matrix
print("Confusion Matrix\n",confusion_matrix(y, kmeans_modded.predict(X_pca_np)))

#plotting confusion matrix
plt.imshow(confusion_matrix(y, kmeans_modded.predict(X_pca_np)),
           cmap='Blues', interpolation='nearest')
plt.colorbar()
plt.grid(False)
plt.ylabel('true')
plt.xlabel('predicted');
```

```
accuracy Score :  0.25924051848103696
Confusion Matrix
 [[129616      0]
 [370379      4]]
```



Lets try to scale the data and then run kmeans

```
In [25]: scaler = preprocessing.MinMaxScaler()
```

```
#scaling the data
X_pca_np_scaled = scaler.fit_transform(X_pca_np)

#fitting the data to modded kmeans
kmeans_modded.fit(X_pca_np_scaled)

#caclulating the percentage of correct labels
print("accuracy Score : ",accuracy_score(y, kmeans_modded.predict(X_pca_np_scaled)))
#printing confusion matrix
print("Confusion Matrix\n",confusion_matrix(y, kmeans_modded.predict(X_pca_np_scaled)))
```

```
accuracy Score :  0.25924051848103696
Confusion Matrix
 [[129616      0]
 [370379      4]]
```

0.2.2 Regression

Splitting the dataset We split the data into Training and Test set based on the parameter train_size.

Example : if train_size = 0.70 then Training Set contains 80% of the data and Testing Set other 20%

```
In [26]: # Use train_test_split in sklearn.cross_validation to split data into train and test se
         from sklearn.cross_validation import train_test_split

         X_train, X_test, y_train, y_test = train_test_split(df, y, train_size=0.70, random_stat
```

```
/home/chrx/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarn
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [27]: # Function to build model and find model performance
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import roc_auc_score

         def find_model_perf(X_train, y_train, X_test, y_test, func):
             model = func()
             model.fit(X_train, y_train)
             y_hat = [x[1] for x in model.predict_proba(X_test)]
             auc = roc_auc_score(y_test, y_hat)

             return auc
```

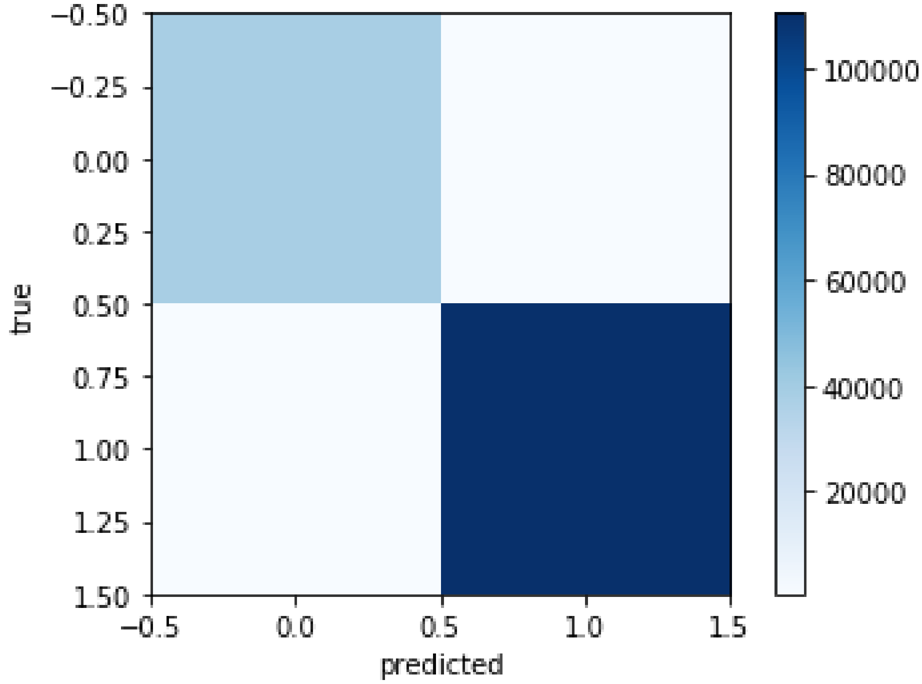
```
In [28]: # Find performance of model using preprocessed data
         auc_processed = find_model_perf(X_train, y_train, X_test, y_test, LogisticRegression)
         print(auc_processed)
```

```
0.9274834718737871
```

This shows that Regression can correctly predict 98.5% of data

0.2.3 Random Forests

```
In [29]: from sklearn.ensemble import RandomForestClassifier
         randomForest = RandomForestClassifier(n_estimators=100, random_state=0)

In [30]: randomForest.fit(X_train, y_train)

Out[30]: RandomForestClassifier(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=100, n_jobs=1,
                     oob_score=False, random_state=0, verbose=0, warm_start=False)

In [31]: #caclulating the percentage of correct labels
         print("accuracy Score : ",accuracy_score(y_test, randomForest.predict(X_test)))
         #printing confusion matrix
         print("Confusion Matrix\n",confusion_matrix(y_test, randomForest.predict(X_test)))

         #plotting confusion matrix
         plt.imshow(confusion_matrix(y_test, randomForest.predict(X_test)),
                    cmap='Blues', interpolation='nearest')
         plt.colorbar()
         plt.grid(False)
         plt.ylabel('true')
         plt.xlabel('predicted');

accuracy Score :  0.9901333333333333
Confusion Matrix
 [[ 38059    874]
 [   606 110461]]
```



0.2.4 Conclusion

Random Forests is the best available predictor for intrusion detection with Accuracy Score of 99.01%