Exploring NSL-KDD dataset

The purpose of this notebook is a basic exploration of the NSL-KDD dataset. Here are the goals of this exploration:

- Gain a basic understanding of the data set
- Look at how the data set might be used to predict network anomalies or attacks
- Walk through some fundemental concepts of building machine learning models

Throughout we'll do some work by hand that could be done in more effective ways using delivered functionality within sci-kit. The intent here is to be more deliberate about the process of understanding what we're doing and why. We will look at how to approach some of these problems using the built-in toools in a later notebook.

```
# module imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import itertools
import random

# model imports
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

# processing imports
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix

print('Welcome!')
```

```
Welcome!
```

Data extraction

We'll start by fetching our data set. There's a few options for data sets here, so we'll build a couple paths and use comments to pick and choose the ones we want.

```python
# fetch the training file
file_path_20_percent = '../input/nslkdd/KDDTrain+_20Percent.txt'
file_path_full_training_set = '../input/nslkdd/KDDTrain+.txt'
file_path_test = '../input/nslkdd/KDDTest+.txt'

#df = pd.read_csv(file_path_20_percent)
df = pd.read_csv(file_path_full_training_set)
test_df = pd.read_csv(file_path_test)
```

The data set doesn't include column names, so let's add them.

```python
# add the column labels
columns = (['duration'
,'protocol_type'
,'service'
,'flag'
,'src_bytes'
,'dst_bytes'
,'land'
,'wrong_fragment'
,'urgent'
,'hot'
,'num_failed_logins'
,'logged_in'
,'num_compromised'
,'root_shell'
,'su_attempted'
,'num_root'
,'num_file_creations'
,'num_shells'
,'num_access_files'
,'num_outbound_cmds'
,'is_host_login'
,'is_guest_login'
,'count'
,'srv_count'
,'serror_rate'
,'srv_serror_rate'
,'rerror_rate'
,'srv_rerror_rate'
,'same_srv_rate'
,'diff_srv_rate'
,'srv_diff_host_rate'
,'dst_host_count'
,'dst_host_srv_count'
,'dst_host_same_srv_rate'
,'dst_host_diff_srv_rate'
,'dst_host_same_src_port_rate'
,'dst_host_srv_diff_host_rate'
```

```
,'dst_host_serror_rate'
,'dst_host_srv_serror_rate'
,'dst_host_rerror_rate'
,'dst_host_srv_rerror_rate'
,'attack'
,'level'])

df.columns = columns
test_df.columns = columns

# sanity check
df.head()
```

```
   duration protocol_type  service flag  src_bytes  dst_bytes  land  \
0         0           udp    other   SF        146          0     0
1         0           tcp  private   S0          0          0     0
2         0           tcp     http   SF        232       8153     0
3         0           tcp     http   SF        199        420     0
4         0           tcp  private  REJ          0          0     0

   wrong_fragment  urgent  hot  ...  dst_host_same_srv_rate  \
0               0       0    0  ...                    0.00
1               0       0    0  ...                    0.10
2               0       0    0  ...                    1.00
3               0       0    0  ...                    1.00
4               0       0    0  ...                    0.07

   dst_host_diff_srv_rate  dst_host_same_src_port_rate  \
0                    0.60                         0.88
1                    0.05                         0.00
2                    0.00                         0.03
3                    0.00                         0.00
4                    0.07                         0.00

   dst_host_srv_diff_host_rate  dst_host_serror_rate  \
0                         0.00                  0.00
1                         0.00                  1.00
2                         0.04                  0.03
3                         0.00                  0.00
4                         0.00                  0.00

   dst_host_srv_serror_rate  dst_host_rerror_rate
dst_host_srv_rerror_rate  \
0                      0.00                   0.0
0.00
1                      1.00                   0.0
0.00
2                      0.01                   0.0
0.01
3                      0.00                   0.0
```

```
0.00
4                      0.00                    1.0
1.00

    attack  level
0   normal     15
1  neptune     19
2   normal     21
3   normal     21
4  neptune     21

[5 rows x 43 columns]
```

Data transformations

The first transformations that we'll want to do are around the attack field. We'll start by adding a column that encodes 'normal' values as 0 and any other value as 1. We will use this as our classifier for a simple binary model that idenfities any attack.

```
# map normal to 0, all attacks to 1
is_attack = df.attack.map(lambda a: 0 if a == 'normal' else 1)
test_attack = test_df.attack.map(lambda a: 0 if a == 'normal' else 1)

#data_with_attack = df.join(is_attack, rsuffix='_flag')
df['attack_flag'] = is_attack
test_df['attack_flag'] = test_attack

# view the result
df.head()

   duration protocol_type  service flag  src_bytes  dst_bytes  land  \
0         0           udp    other   SF        146          0     0
1         0           tcp  private   S0          0          0     0
2         0           tcp     http   SF        232       8153     0
3         0           tcp     http   SF        199        420     0
4         0           tcp  private  REJ          0          0     0

   wrong_fragment  urgent  hot  ...  dst_host_diff_srv_rate  \
0               0       0    0  ...                    0.60
1               0       0    0  ...                    0.05
2               0       0    0  ...                    0.00
3               0       0    0  ...                    0.00
4               0       0    0  ...                    0.07

   dst_host_same_src_port_rate  dst_host_srv_diff_host_rate  \
0                         0.88                         0.00
1                         0.00                         0.00
2                         0.03                         0.04
```

```
3                          0.00                           0.00
4                          0.00                           0.00

   dst_host_serror_rate  dst_host_srv_serror_rate
dst_host_rerror_rate  \
0                  0.00                      0.00
0.0
1                  1.00                      1.00
0.0
2                  0.03                      0.01
0.0
3                  0.00                      0.00
0.0
4                  0.00                      0.00
1.0

   dst_host_srv_rerror_rate   attack  level  attack_flag
0                      0.00   normal     15            0
1                      0.00  neptune     19            1
2                      0.01   normal     21            0
3                      0.00   normal     21            0
4                      1.00  neptune     21            1

[5 rows x 44 columns]
```

Next, we'll classify each of the attacks according to attack type for a more granular prediction model.

- Denial of Service attacks:
  - apache2
  - back
  - land
  - neptune
  - mailbomb
  - pod
  - processtable
  - smurf
  - teardrop
  - udpstorm
  - worm
- Probe attacks:
  - ipsweep
  - mscan
  - nmap
  - portsweep
  - saint
  - satan

- Privilege escalation attacks
  - buffer_overflow
  - loadmdoule
  - perl
  - ps
  - rootkit
  - sqlattack
  - xterm
- Remote access attacks
  - ftp_write
  - guess_passwd
  - http_tunnel
  - imap
  - multihop
  - named
  - phf
  - sendmail
  - snmpgetattack
  - snmpguess
  - spy
  - warezclient
  - warezmaster
  - xclock
  - xsnoop

```
# lists to hold our attack classifications
dos_attacks =
['apache2','back','land','neptune','mailbomb','pod','processtable','sm
urf','teardrop','udpstorm','worm']
probe_attacks = ['ipsweep','mscan','nmap','portsweep','saint','satan']
privilege_attacks =
['buffer_overflow','loadmdoule','perl','ps','rootkit','sqlattack','xte
rm']
access_attacks =
['ftp_write','guess_passwd','http_tunnel','imap','multihop','named','p
hf','sendmail','snmpgetattack','snmpguess','spy','warezclient','warezm
aster','xclock','xsnoop']

# we will use these for plotting below
attack_labels = ['Normal','DoS','Probe','Privilege','Access']

# helper function to pass to data frame mapping
def map_attack(attack):
    if attack in dos_attacks:
        # dos_attacks map to 1
        attack_type = 1
```

```
    elif attack in probe_attacks:
        # probe_attacks mapt to 2
        attack_type = 2
    elif attack in privilege_attacks:
        # privilege escalation attacks map to 3
        attack_type = 3
    elif attack in access_attacks:
        # remote access attacks map to 4
        attack_type = 4
    else:
        # normal maps to 0
        attack_type = 0

    return attack_type

# map the data and join to the data set
attack_map = df.attack.apply(map_attack)
df['attack_map'] = attack_map

test_attack_map = test_df.attack.apply(map_attack)
test_df['attack_map'] = test_attack_map

# view the result
df.head()
```

```
   duration protocol_type  service flag  src_bytes  dst_bytes  land  \
0         0           udp    other   SF        146          0     0
1         0           tcp  private   S0          0          0     0
2         0           tcp     http   SF        232       8153     0
3         0           tcp     http   SF        199        420     0
4         0           tcp  private  REJ          0          0     0

   wrong_fragment  urgent  hot  ...  dst_host_same_src_port_rate  \
0               0       0    0  ...                         0.88
1               0       0    0  ...                         0.00
2               0       0    0  ...                         0.03
3               0       0    0  ...                         0.00
4               0       0    0  ...                         0.00

   dst_host_srv_diff_host_rate  dst_host_serror_rate  \
0                         0.00                  0.00
1                         0.00                  1.00
2                         0.04                  0.03
3                         0.00                  0.00
4                         0.00                  0.00

   dst_host_srv_serror_rate  dst_host_rerror_rate
dst_host_srv_rerror_rate  \
0                      0.00                   0.0
0.00
```

```
1                        1.00                     0.0
0.00
2                        0.01                     0.0
0.01
3                        0.00                     0.0
0.00
4                        0.00                     1.0
1.00

    attack  level  attack_flag  attack_map
0   normal     15            0           0
1  neptune     19            1           1
2   normal     21            0           0
3   normal     21            0           0
4  neptune     21            1           1

[5 rows x 45 columns]
```

Data profiling

Some intital investigations of what we have in the set. First is a simple table of attack by protocol. In network traffic analysis protocol is a simple tool to create some initial buckets to categorize our data. 'normal' is left in the set at this point as a benchmark.

```
# use a crosstab to get attack vs protocol
attack_vs_protocol = pd.crosstab(df.attack, df.protocol_type)
attack_vs_protocol
```

```
protocol_type    icmp    tcp    udp
attack
back                0    956      0
buffer_overflow     0     30      0
ftp_write           0      8      0
guess_passwd        0     53      0
imap                0     11      0
ipsweep          3117    482      0
land                0     18      0
loadmodule          0      9      0
multihop            0      7      0
neptune             0  41214      0
nmap              981    265    247
normal           1309  53599  12434
perl                0      3      0
phf                 0      4      0
pod               201      0      0
portsweep           5   2926      0
rootkit             0      7      3
```

```
satan                  32    2184    1417
smurf                2646       0       0
spy                     0       2       0
teardrop                0       0     892
warezclient             0     890       0
warezmaster             0      20       0
```

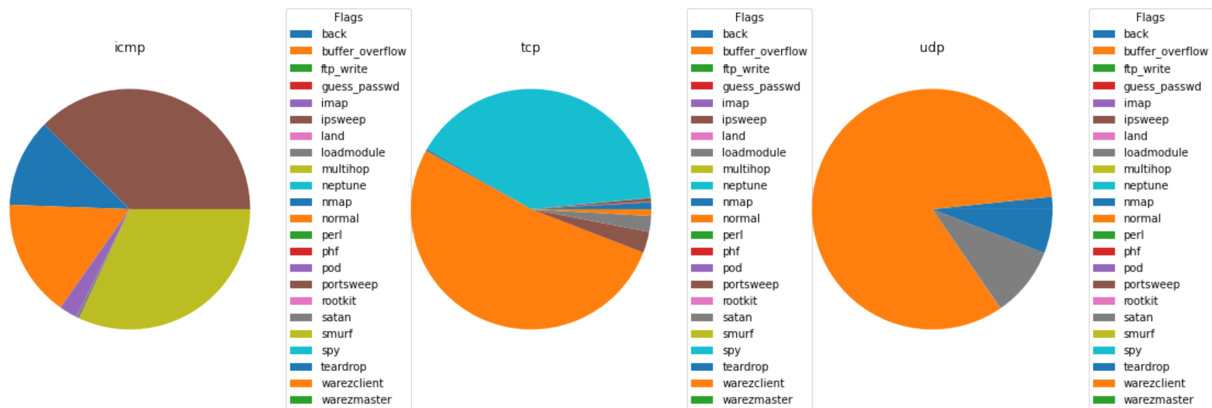
That helps us see that most attacks are going to target a specific protocol. There are several (satan, nmap, ipsweep) that are cross-prototcol attacks. Think about why that may be--what is the purpose of those attacks and why would they be cross-protocol?

Also notice how icmp data is less frequently found in normal traffic.

Let's take a look at some charts to see how things are distributed.

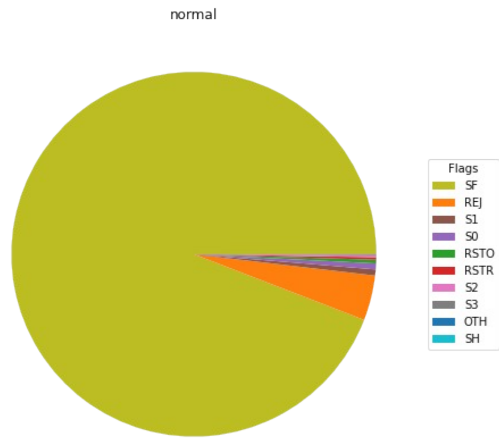
```
# helper function for drawing mulitple charts.
def bake_pies(data_list,labels):
    list_length = len(data_list)

    # setup for mapping colors
    color_list = sns.color_palette()
    color_cycle = itertools.cycle(color_list)
    cdict = {}

    # build the subplots
    fig, axs = plt.subplots(1, list_length,figsize=(18,10),
tight_layout=False)
    plt.subplots_adjust(wspace=1/list_length)

    # loop through the data sets and build the charts
    for count, data_set in enumerate(data_list):

        # update our color mapt with new values
        for num, value in enumerate(np.unique(data_set.index)):
            if value not in cdict:
                cdict[value] = next(color_cycle)

        # build the wedges
        wedges,texts = axs[count].pie(data_set,
                           colors=[cdict[v] for v in data_set.index])

        # build the legend
        axs[count].legend(wedges, data_set.index,
                           title="Flags",
                           loc="center left",
                           bbox_to_anchor=(1, 0, 0.5, 1))
        # set the title
        axs[count].set_title(labels[count])
```

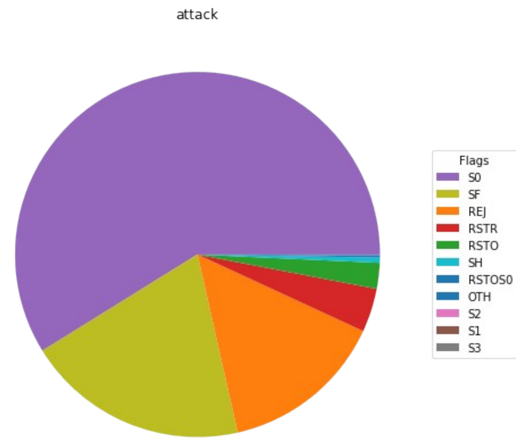
```
    return axs


# get the series for each protocol
icmp_attacks = attack_vs_protocol.icmp
tcp_attacks = attack_vs_protocol.tcp
udp_attacks = attack_vs_protocol.udp

# create the charts
bake_pies([icmp_attacks, tcp_attacks, udp_attacks],
['icmp','tcp','udp'])
plt.show()
```



The thing to notice here is the difference in each protocol type. Our initial impression is that protocol may be useful in being able to identify the type of traffic we are observing. Let's see if flag behaves the same way.

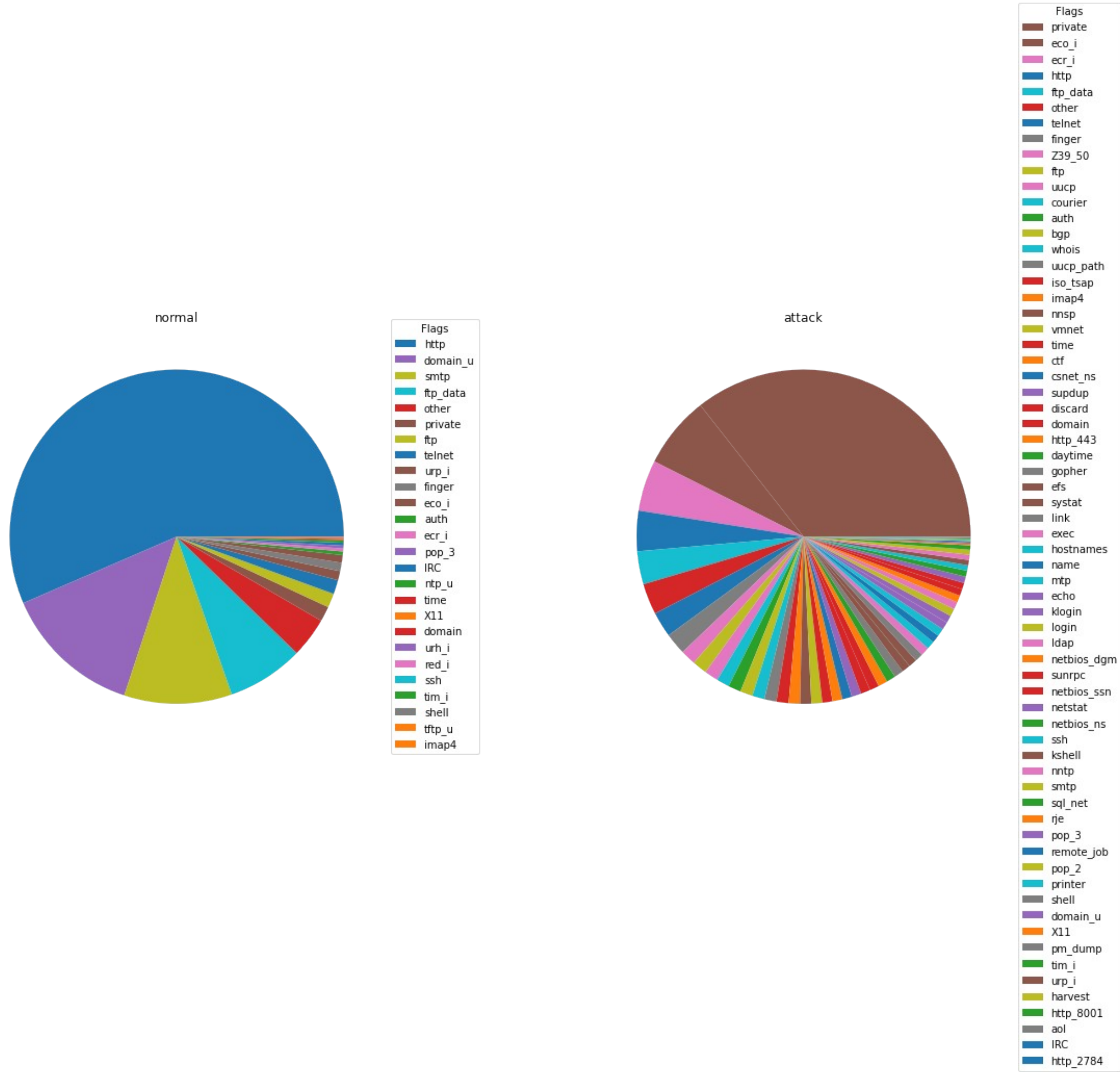
```
# get a series with the count of each flag for attack and normal
traffic
normal_flags = df.loc[df.attack_flag == 0].flag.value_counts()
attack_flags = df.loc[df.attack_flag == 1].flag.value_counts()

# create the charts
flag_axs = bake_pies([normal_flags, attack_flags],
['normal','attack'])
plt.show()
```





And service?

```
# get a series with the count of each service for attack and normal
traffic
normal_services = df.loc[df.attack_flag == 0].service.value_counts()
attack_services = df.loc[df.attack_flag == 1].service.value_counts()

# create the charts
service_axs = bake_pies([normal_services, attack_services],
['normal','attack'])
plt.show()
```



Wow! Look at how many services are in the attack set! Whereas a huge amount of normal traffic is http, our attack traffic is all over the place. That is interesting as it means that attacks are searching for many different paths into systems--some well traveled and some not.

If we think about this from the eyes of a network adminstrator, the combination of protocol, flag and service seem like they should tell us a lot about the nature of our traffic. Coupling them with the duration of a connection and the amount of data in that connection seems like a good starting point for us.

Feature engineering

So let's dive into some feature building. It seems like that items above would make a good place to start: protocol_type, service and flag. There's enough variation between these that we should be able to get some base level of identification. We're also going to throw in some basic numeric data: duration, src_bytes, dst_bytes. All of these are going to be readily available from modern network equipment and should tell us a lot about what is happening on our network.

```
# get the intial set of encoded features and encode them
features_to_encode = ['protocol_type', 'service', 'flag']
encoded = pd.get_dummies(df[features_to_encode])
test_encoded_base = pd.get_dummies(test_df[features_to_encode])

# not all of the features are in the test set, so we need to account
for diffs
test_index = np.arange(len(test_df.index))
column_diffs = list(set(encoded.columns.values)-
set(test_encoded_base.columns.values))

diff_df = pd.DataFrame(0, index=test_index, columns=column_diffs)

# we'll also need to reorder the columns to match, so let's get those
column_order = encoded.columns.to_list()

# append the new columns
test_encoded_temp = test_encoded_base.join(diff_df)

# reorder the columns
test_final = test_encoded_temp[column_order].fillna(0)

# get numeric features, we won't worry about encoding these at this
point
numeric_features = ['duration', 'src_bytes', 'dst_bytes']

# model to fit/test
to_fit = encoded.join(df[numeric_features])
test_set = test_final.join(test_df[numeric_features])
```

It's worth drawing attention to a few things here. First, `pd.get_dummies` is a method that allows us to do a quick one hot encoding on our columns. This takes every value it finds in a single column and makes an individual column for each value, with a `0` or `1` indicating whether that column is 'hot'.

One thing we find is that note every value is in the test data. So that creates different shapes of our data frame. That's why we added some columns, filled them in and reorded them. We know they are all zeros because they aren't in the data.

Now let's go ahead and set our classification targets. We'l do both training sets to start: binrary and multi classifications.

```
# create our target classifications
binary_y = df['attack_flag']
multi_y = df['attack_map']

test_binary_y = test_df['attack_flag']
```

```
test_multi_y = test_df['attack_map']

# build the training sets
binary_train_X, binary_val_X, binary_train_y, binary_val_y =
train_test_split(to_fit, binary_y, test_size=0.6)
multi_train_X, multi_val_X, multi_train_y, multi_val_y =
train_test_split(to_fit, multi_y, test_size = 0.6)
```

Model fitting

Based on the nature of the data we saw above, decision trees are a good starting point for building out predictive models. In this case we'll use a random forest to build and combine multiple trees. We'll start by simply taking the defaults.

```
# model for the binary classification
binary_model = RandomForestClassifier()
binary_model.fit(binary_train_X, binary_train_y)
binary_predictions = binary_model.predict(binary_val_X)

# calculate and display our base accuracty
base_rf_score = accuracy_score(binary_predictions,binary_val_y)
base_rf_score

0.9936097586790855
```

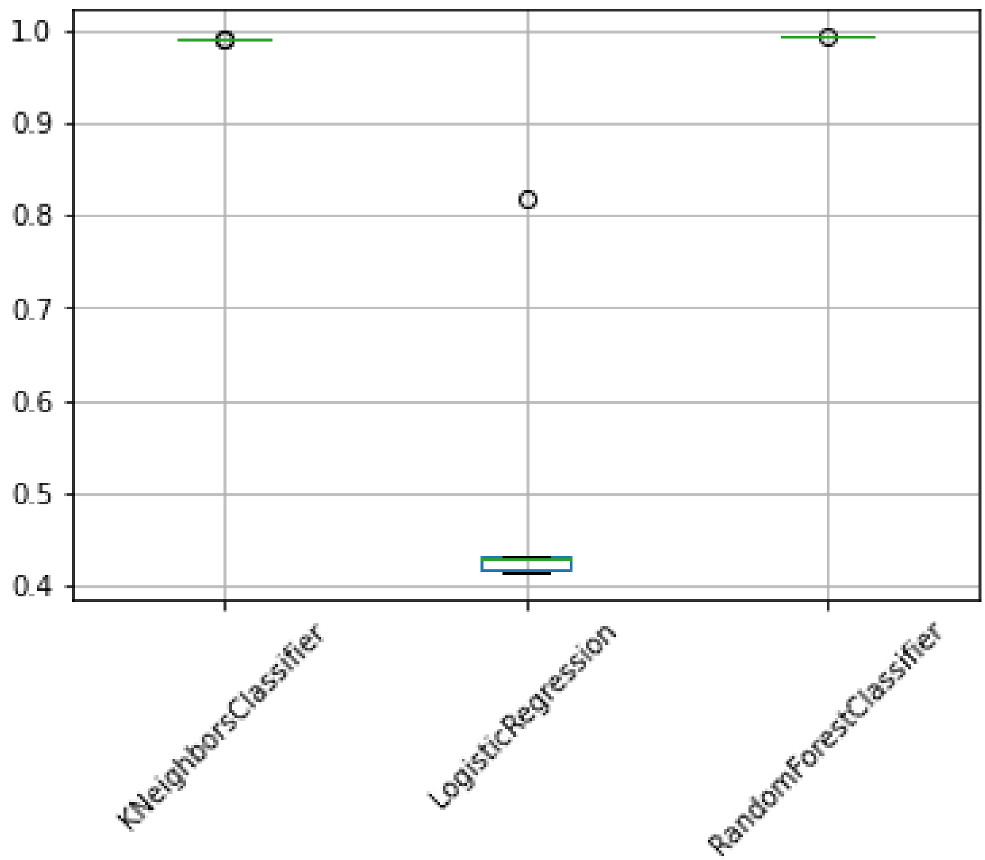
99% accuracy on our first try! Not bad, right? Let's see how it plays out.

It might be interesting to see how diffrent models compare against a data set like this. That is easy enought to do with `cross_val_score`.

```
# define the list of models that we want to test
models = [
    RandomForestClassifier(),
    LogisticRegression(max_iter=250),
    KNeighborsClassifier(),
]

# an empty list to capture the performance of each model
model_comps = []

# walk through the models and populate our list
for model in models:
    model_name = model.__class__.__name__
    accuracies = cross_val_score(model, binary_train_X,
binary_train_y, scoring='accuracy')
    for count, accuracy in enumerate(accuracies):
        model_comps.append((model_name, count, accuracy))
```

```python
# a box plot will do well to show us overall performance and the variation in the models.
result_df = pd.DataFrame(model_comps, columns=['model_name', 'count', 'accuracy'])
result_df.pivot(index='count',columns='model_name',values='accuracy').boxplot(rot=45)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73068501d0>
```



What we find is some inconsistency across the models. The random forest and K-nearest neighbors are tight groupings with solid performance. Our logistic regression didn't perform as well. That may be in part because we didn't do sufficient preprocessing on our data to shape it into a form optimized for that model. That too is an exercise for another day.

Analyzing our predictions

Let's take a look at how our predictions fared. We are going to create a helper function to pull some relevant metrics from our results.

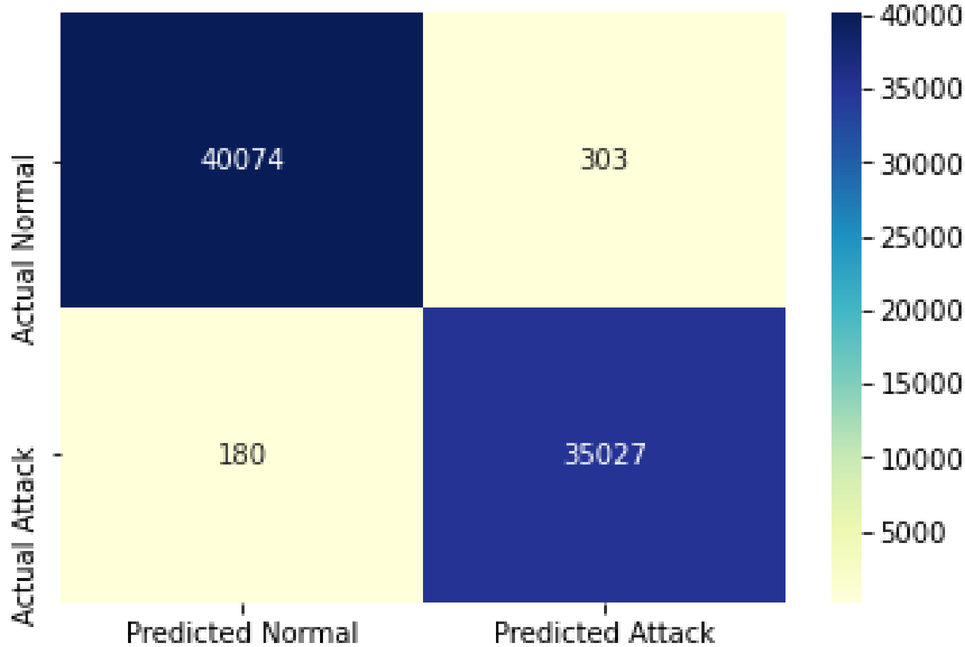
```python
# a helper function for getting some analytical data about our predictions
```

```python
def add_predictions(data_set,predictions,y):
    prediction_series = pd.Series(predictions, index=y.index)

    # we need to add the predicted and actual outcomes to the data
    predicted_vs_actual = data_set.assign(predicted=prediction_series)
    original_data = predicted_vs_actual.assign(actual=y).dropna()
    conf_matrix = confusion_matrix(original_data['actual'],
                                   original_data['predicted'])

    # capture rows with failed predictions
    base_errors = original_data[original_data['actual'] !=
original_data['predicted']]

    # drop columns with no value
    non_zeros = base_errors.loc[:,(base_errors != 0).any(axis=0)]

    # idetify the type of error
    false_positives = non_zeros.loc[non_zeros.actual==0]
    false_negatives = non_zeros.loc[non_zeros.actual==1]

    # put everything into an object
    prediction_data = {'data': original_data,
                       'confusion_matrix': conf_matrix,
                       'errors': base_errors,
                       'non_zeros': non_zeros,
                       'false_positives': false_positives,
                       'false_negatives': false_negatives}

    return prediction_data
```

Now we can take a closer look at our results. The first thing that we can do is look at a confusion matrix, which in this case will map the predicted classification to the actual classification.

```python
# capture our prediction data
binary_prediction_data = add_predictions(df,
                                         binary_predictions,
                                         binary_val_y)

# create a heatmap of the confusion matrix
sns.heatmap(data=binary_prediction_data['confusion_matrix'],
            xticklabels = ['Predicted Normal','Predicted Attack'],
            yticklabels = ['Actual Normal','Actual Attack'],
            cmap="YlGnBu",
            fmt='d',
            annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7306701110>
```



We see a lot of false positives (normal traffic that got flagged as an attack) and false negatives (attack traffic that got flagged as normal) there.

So let's explore the prediction errors a bit and see if there is more information to extract.

```
# dataframe to store incorrect classification
binary_prediction_data['errors'].describe()
```

```
           duration     src_bytes     dst_bytes        land  
wrong_fragment  \
count    483.000000  4.830000e+02  4.830000e+02  483.000000  
483.0
mean      57.188406  1.492597e+06  7.310814e+03    0.006211  
0.0
std      673.241958  3.155596e+07  7.814234e+04    0.078647  
0.0
min        0.000000  0.000000e+00  0.000000e+00    0.000000  
0.0
25%        0.000000  0.000000e+00  0.000000e+00    0.000000  
0.0
50%        0.000000  0.000000e+00  0.000000e+00    0.000000  
0.0
75%        0.000000  0.000000e+00  0.000000e+00    0.000000  
0.0
max    12743.000000  6.933756e+08  1.159100e+06    1.000000  
0.0

       urgent         hot  num_failed_logins   logged_in  
num_compromised  \
```

```
count   483.0  483.000000         483.000000  483.000000
483.000000
mean      0.0    0.115942           0.010352    0.084886
0.047619
std       0.0    0.912690           0.227508    0.279001
0.427054
min       0.0    0.000000           0.000000    0.000000
0.000000
25%       0.0    0.000000           0.000000    0.000000
0.000000
50%       0.0    0.000000           0.000000    0.000000
0.000000
75%       0.0    0.000000           0.000000    0.000000
0.000000
max       0.0   18.000000           5.000000    1.000000
6.000000

       ...  dst_host_srv_diff_host_rate  dst_host_serror_rate  \
count  ...                   483.000000            483.000000
mean   ...                     0.046004              0.093354
std    ...                     0.165300              0.227875
min    ...                     0.000000              0.000000
25%    ...                     0.000000              0.000000
50%    ...                     0.000000              0.000000
75%    ...                     0.020000              0.040000
max    ...                     1.000000              1.000000

       dst_host_srv_serror_rate  dst_host_rerror_rate  \
count                483.000000            483.000000
mean                   0.035259              0.338778
std                    0.143536              0.456293
min                    0.000000              0.000000
25%                    0.000000              0.000000
50%                    0.000000              0.010000
75%                    0.010000              1.000000
max                    1.000000              1.000000

       dst_host_srv_rerror_rate       level  attack_flag
attack_map  \
count                483.000000  483.000000   483.000000  483.000000

mean                   0.372319   15.476190     0.372671    0.604555

std                    0.468769    5.395648     0.484017    0.993203

min                    0.000000    0.000000     0.000000    0.000000

25%                    0.000000   14.000000     0.000000    0.000000

50%                    0.010000   18.000000     0.000000    0.000000
```

```
75%                     1.000000   19.000000     1.000000    1.000000

max                     1.000000   21.000000     1.000000    4.000000


        predicted      actual
count  483.000000  483.000000
mean     0.627329    0.372671
std      0.484017    0.484017
min      0.000000    0.000000
25%      0.000000    0.000000
50%      1.000000    0.000000
75%      1.000000    1.000000
max      1.000000    1.000000

[8 rows x 43 columns]
```

Notice there are several columns with a standard deviation of 0. That tells us that there is no additional information to glean from those columns. So we can start by dropping those.

```
# data minus the rows with no variance
binary_prediction_data['non_zeros'].describe()

           duration     src_bytes     dst_bytes        land
hot  \
count    483.000000  4.830000e+02  4.830000e+02  483.000000
483.000000
mean      57.188406  1.492597e+06  7.310814e+03    0.006211
0.115942
std      673.241958  3.155596e+07  7.814234e+04    0.078647
0.912690
min        0.000000  0.000000e+00  0.000000e+00    0.000000
0.000000
25%        0.000000  0.000000e+00  0.000000e+00    0.000000
0.000000
50%        0.000000  0.000000e+00  0.000000e+00    0.000000
0.000000
75%        0.000000  0.000000e+00  0.000000e+00    0.000000
0.000000
max    12743.000000  6.933756e+08  1.159100e+06    1.000000
18.000000

       num_failed_logins   logged_in  num_compromised  root_shell  \
count         483.000000  483.000000       483.000000  483.000000
mean            0.010352    0.084886         0.047619    0.018634
std             0.227508    0.279001         0.427054    0.135367
min             0.000000    0.000000         0.000000    0.000000
25%             0.000000    0.000000         0.000000    0.000000
50%             0.000000    0.000000         0.000000    0.000000
```

```
75%            0.000000   0.000000        0.000000   0.000000
max            5.000000   1.000000        6.000000   1.000000

       su_attempted  ...  dst_host_srv_diff_host_rate
dst_host_serror_rate  \
count    483.000000  ...                   483.000000
483.000000
mean       0.002070  ...                     0.046004
0.093354
std        0.045502  ...                     0.165300
0.227875
min        0.000000  ...                     0.000000
0.000000
25%        0.000000  ...                     0.000000
0.000000
50%        0.000000  ...                     0.000000
0.000000
75%        0.000000  ...                     0.020000
0.040000
max        1.000000  ...                     1.000000
1.000000

       dst_host_srv_serror_rate  dst_host_rerror_rate  \
count                483.000000            483.000000
mean                   0.035259              0.338778
std                    0.143536              0.456293
min                    0.000000              0.000000
25%                    0.000000              0.000000
50%                    0.000000              0.010000
75%                    0.010000              1.000000
max                    1.000000              1.000000

       dst_host_srv_rerror_rate       level  attack_flag
attack_map  \
count                483.000000  483.000000   483.000000  483.000000

mean                   0.372319   15.476190     0.372671    0.604555

std                    0.468769    5.395648     0.484017    0.993203

min                    0.000000    0.000000     0.000000    0.000000

25%                    0.000000   14.000000     0.000000    0.000000

50%                    0.010000   18.000000     0.000000    0.000000

75%                    1.000000   19.000000     1.000000    1.000000

max                    1.000000   21.000000     1.000000    4.000000
```

```
       predicted      actual
count  483.000000  483.000000
mean     0.627329    0.372671
std      0.484017    0.484017
min      0.000000    0.000000
25%      0.000000    0.000000
50%      1.000000    0.000000
75%      1.000000    1.000000
max      1.000000    1.000000

[8 rows x 39 columns]
```

```
# see the standard deviation of the false positives
binary_prediction_data['false_positives'].std()
```

```
duration                                 4.734560
src_bytes                           837828.727795
dst_bytes                             1046.144245
land                                     0.099174
hot                                      0.206182
num_failed_logins                        0.000000
logged_in                                0.139550
num_compromised                          0.081110
root_shell                               0.057448
su_attempted                             0.000000
num_root                                 0.000000
num_file_creations                       0.229794
num_shells                               0.114897
num_access_files                         0.000000
is_guest_login                           0.000000
count                                    1.480167
srv_count                                3.566875
serror_rate                              0.313117
srv_serror_rate                          0.298007
rerror_rate                              0.443229
srv_rerror_rate                          0.437000
same_srv_rate                            0.075992
diff_srv_rate                            0.099117
srv_diff_host_rate                       0.269540
dst_host_count                          90.051633
dst_host_srv_count                     106.003876
dst_host_same_srv_rate                   0.361702
dst_host_diff_srv_rate                   0.103036
dst_host_same_src_port_rate              0.287326
dst_host_srv_diff_host_rate              0.088943
dst_host_serror_rate                     0.272787
dst_host_srv_serror_rate                 0.161004
dst_host_rerror_rate                     0.296618
dst_host_srv_rerror_rate                 0.376715
```

```
level                                   3.838610
attack_flag                             0.000000
attack_map                              0.000000
predicted                               0.000000
actual                                  0.000000
dtype: float64
```

Now we should see some variance across our features. Here, though, we're going to look into our false positives and false negatives separately and see what we notice.

```
# see the standard deviation of the false negatives
binary_prediction_data['false_negatives'].std()
```

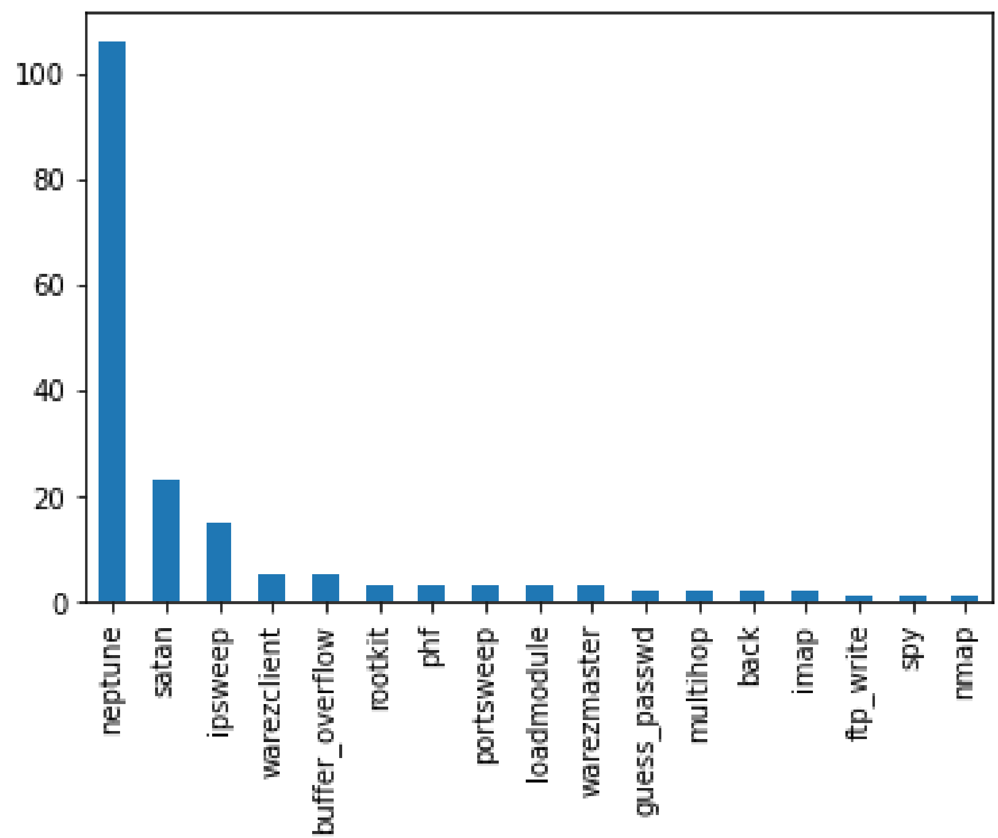
```
duration                        1.098122e+03
src_bytes                       5.167893e+07
dst_bytes                       1.273155e+05
land                            0.000000e+00
hot                             1.460200e+00
num_failed_logins               3.726780e-01
logged_in                       3.968764e-01
num_compromised                 6.872746e-01
root_shell                      2.066553e-01
su_attempted                    7.453560e-02
num_root                        7.678155e-01
num_file_creations              2.114323e+00
num_shells                      1.662938e-01
num_access_files                1.647939e-01
is_guest_login                  1.051144e-01
count                           1.255470e+02
srv_count                       6.263895e+00
serror_rate                     1.301809e-01
srv_serror_rate                 1.462328e-01
rerror_rate                     4.452671e-01
srv_rerror_rate                 4.649678e-01
same_srv_rate                   4.271710e-01
diff_srv_rate                   2.832991e-01
srv_diff_host_rate              1.304760e-01
dst_host_count                  9.914482e+01
dst_host_srv_count              4.846741e+01
dst_host_same_srv_rate          3.281122e-01
dst_host_diff_srv_rate          2.993165e-01
dst_host_same_src_port_rate     2.900602e-01
dst_host_srv_diff_host_rate     2.432097e-01
dst_host_serror_rate            5.710739e-02
dst_host_srv_serror_rate        1.062784e-01
dst_host_rerror_rate            4.338758e-01
dst_host_srv_rerror_rate        4.586329e-01
level                           7.092149e+00
attack_flag                     0.000000e+00
```

```
attack_map                       9.980739e-01
predicted                        0.000000e+00
actual                           0.000000e+00
dtype: float64
```

Notice in the false positives all of columns with no variance? In the false negatives, though, all the columns have some degree of variance. That suggests to us that there may be some good information in those columns because there is a difference bewteen the observations in one classification vs the other.

Let's also take a look at the false-negatives and see what types of attacks we missed.

```
# distribution of false negatives--what attacks did we miss?
binary_prediction_data['false_negatives'].attack.value_counts().plot.b
ar()

<matplotlib.axes._subplots.AxesSubplot at 0x7f7306638690>
```



Neptune and Satan are the biggest misses. Let's see if we can correct that.

The last data set we were working with was to_fit. So we'll work with that. Since the rest of the values are numeric features, we can add them easily.

```
# we'll need to pull these from the data set
outcomes = ['attack_flag','attack_map', 'actual']

# get the new features we're interested in and drop the outcomes
new_features =
(binary_prediction_data['false_positives']==0).all(axis=0)
feature_cols =
binary_prediction_data['false_positives'].loc[:,new_features]
feature_cols = feature_cols.drop(outcomes,axis=1)

# Let's get these in a list and take a look
new_feature_columns = list(feature_cols.columns)
new_feature_columns
```

```
['num_failed_logins',
 'su_attempted',
 'num_root',
 'num_access_files',
 'is_guest_login']
```

```
# add the new features
to_fit_new_features = to_fit.join(df[new_feature_columns])

# build the training sets
new_feature_train_X, new_feature_val_X, new_feature_train_y,
new_feature_val_y = train_test_split(to_fit_new_features, binary_y)
```

Now, let's see how we performed.

```
# model for the binary classification
new_feature_model = RandomForestClassifier()
new_feature_model.fit(new_feature_train_X, new_feature_train_y)
new_feature_predictions = new_feature_model.predict(new_feature_val_X)

# get the score for the model
new_feature_score =
accuracy_score(new_feature_predictions,new_feature_val_y)

new_feature_score
```

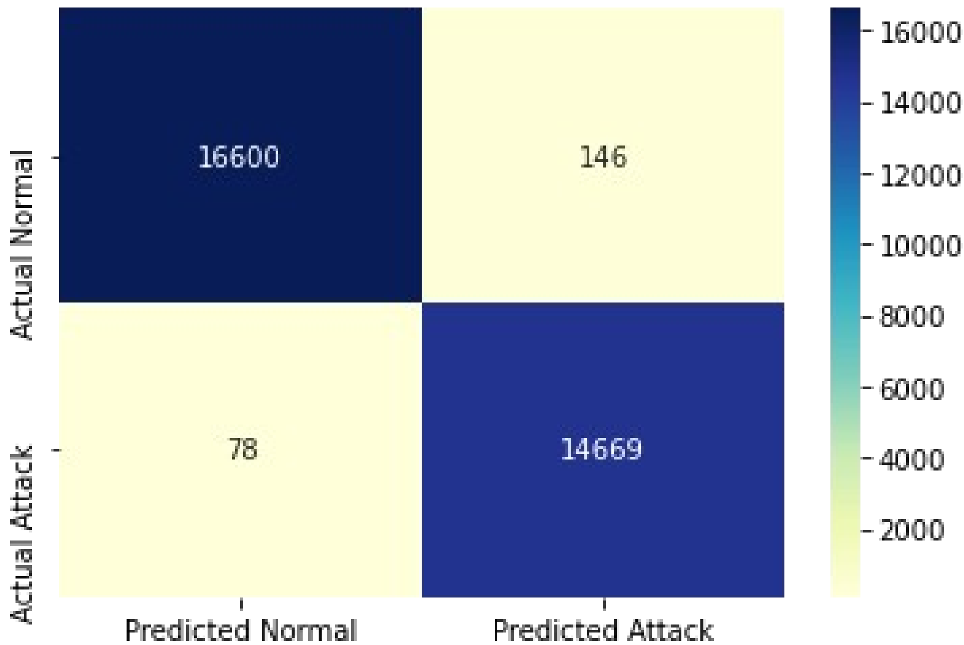
```
0.9928873082907312
```

We'll run another confustion matrix to see our missed predictions...

```
# capture the prediction data
new_prediction_data = add_predictions(df,
                                      new_feature_predictions,
                                      new_feature_val_y)

# create a heatmap of the confusion matrix
```

```python
sns.heatmap(data=new_prediction_data['confusion_matrix'],
            xticklabels = ['Predicted Normal','Predicted Attack'],
            yticklabels = ['Actual Normal','Actual Attack'],
            cmap="YlGnBu",
            fmt='d',
            annot=True)
```

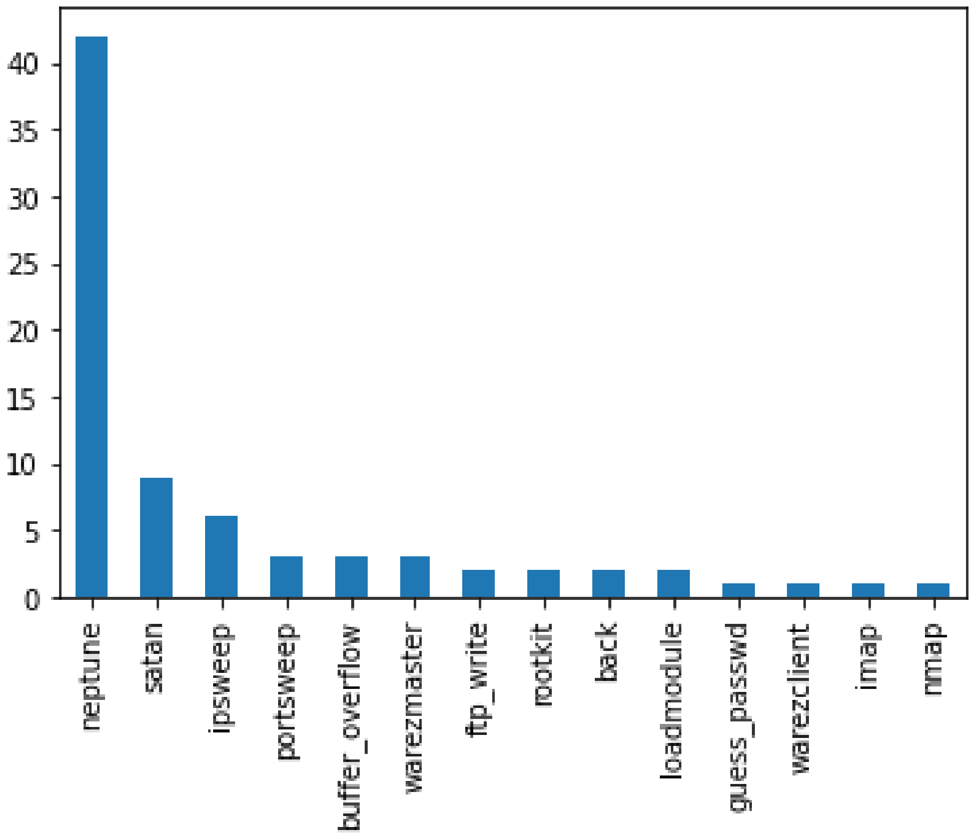
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7306521790>
```



That's looking better! Still a few that we missed. How about specific attacks?

```python
# distribuition of the false negatives--what attacks did we miss?
new_prediction_data['false_negatives'].attack.value_counts().plot.bar(
)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7306764950>
```



Overall, things are looking better. We're just missing a few isolated instances of most specific attacks. Neptune is still the hardest to find.

Now it's time to for the real thing. Let's run our model against some unseen data. We can think of this as new network traffic.

We will fit our model on full dataset and then run it against the test set to see how we did.

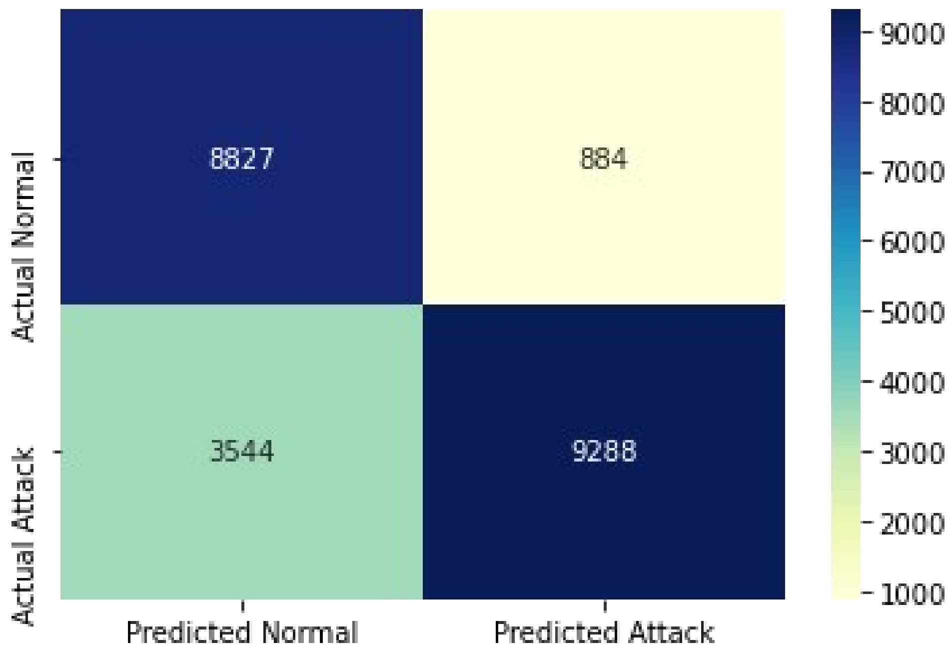
```
# model for the binary classification
full_model = RandomForestClassifier(random_state=1)
full_model.fit(to_fit, binary_y)
full_predictions = full_model.predict(test_set)

# get the score
full_score = accuracy_score(full_predictions,test_binary_y)
full_score

0.8035753892560884
```

Wait, what!? Weren't we running 99%+ with our model? What happened? Let's look at our confusion matrix.

```
# capture the prediction data
full_prediction_data = add_predictions(test_df, full_predictions,
```

```
test_binary_y)

# create a heatmap of the confusion matrix
sns.heatmap(data=full_prediction_data['confusion_matrix'],
            xticklabels = ['Predicted Normal','Predicted Attack'],
            yticklabels = ['Actual Normal','Actual Attack'],
            cmap="YlGnBu",
            fmt='d',
            annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f730621a050>
```



Yikes! That's a lot of bad predictions! Because we are not setting the random_state, the specifics will vary for each run. Generally, though, we are seeing a lot of false negatives--missed attacks.

This sure looks a lot like over fitting our data. Since the RandomForestClassifier tends to have good default settings, one likely scenario is that we have too many features. Remember how we had all those services and one-hot encoded them? That creates a lot of columns (features). Let's start by walking back a bit and shifting how we encode that. We'll use label encoding instead to generate a single feature with a unique numeric value for each string value in the original data set.

```
# create our label encoder
label_encoder = LabelEncoder()

# get the intial set of encoded features and encode them
features_to_encode = ['protocol_type', 'flag']
dummy_encoded = pd.get_dummies(df[features_to_encode])
test_dummy_encoded = pd.get_dummies(test_df[features_to_encode])
```

```
# now we'll label encode the service column
label_encoder.fit(df.service)
dummy_encoded['service'] = label_encoder.transform(df.service)
test_dummy_encoded['service'] =
label_encoder.transform(test_df.service)

# get numeric features, we won't worry about encoding these at this
point
numeric_features = ['duration', 'src_bytes', 'dst_bytes']

# model to fit/test
to_fit = dummy_encoded.join(df[numeric_features])
test_set = test_dummy_encoded.join(test_df[numeric_features])

# make sure our columns match
print(to_fit.columns)
print(test_set.columns)
```

```
Index(['protocol_type_icmp', 'protocol_type_tcp', 'protocol_type_udp',
       'flag_OTH', 'flag_REJ', 'flag_RSTO', 'flag_RSTOS0',
'flag_RSTR',
       'flag_S0', 'flag_S1', 'flag_S2', 'flag_S3', 'flag_SF',
'flag_SH',
       'service', 'duration', 'src_bytes', 'dst_bytes'],
      dtype='object')
Index(['protocol_type_icmp', 'protocol_type_tcp', 'protocol_type_udp',
       'flag_OTH', 'flag_REJ', 'flag_RSTO', 'flag_RSTOS0',
'flag_RSTR',
       'flag_S0', 'flag_S1', 'flag_S2', 'flag_S3', 'flag_SF',
'flag_SH',
       'service', 'duration', 'src_bytes', 'dst_bytes'],
      dtype='object')
```

```
# model for the binary classification
full_model = RandomForestClassifier(random_state=1)
full_model.fit(to_fit, binary_y)
full_predictions = full_model.predict(test_set)

# get the score
full_score = accuracy_score(full_predictions,test_binary_y)
full_score
```

```
0.7955462893137559
```

Let's try it with the additional features.

```
# add new features
to_fit_new_features = to_fit.join(df[new_feature_columns])
test_set_new_features = test_set.join(test_df[new_feature_columns])
```

```
# run the model
full_model.fit(to_fit_new_features,binary_y)
full_predictions = full_model.predict(test_set_new_features)

# get the score
full_score = accuracy_score(full_predictions,test_binary_y)
full_score
```

```
0.7963447633411702
```

It doesn't seem like there's going to be a quick way to get past that. We're going to have to spend some time drilling into the data a little deeper to build a more robust model. There's obviously some overfitting going on and we're going to need to do some work to build a model that does a better job of generalizing the fit. At this point, we're going to let that be an exercise for a future notebook and turn our attention to our multi-classification scenario. Here we are going to see if we can identify the type of attack from the data. Remember, we have four attack types:

- DOS
- Probe
- Privilege escalation
- Remote access

Let's go ahead and check our base model to start with.

```
# model for the mulit classification
multi_model = RandomForestClassifier()
multi_model.fit(multi_train_X, multi_train_y)
multi_predictions = multi_model.predict(multi_val_X)

# get the score
accuracy_score(multi_predictions,multi_val_y)
```

```
0.9760134419983065
```

Now let's add the new features.

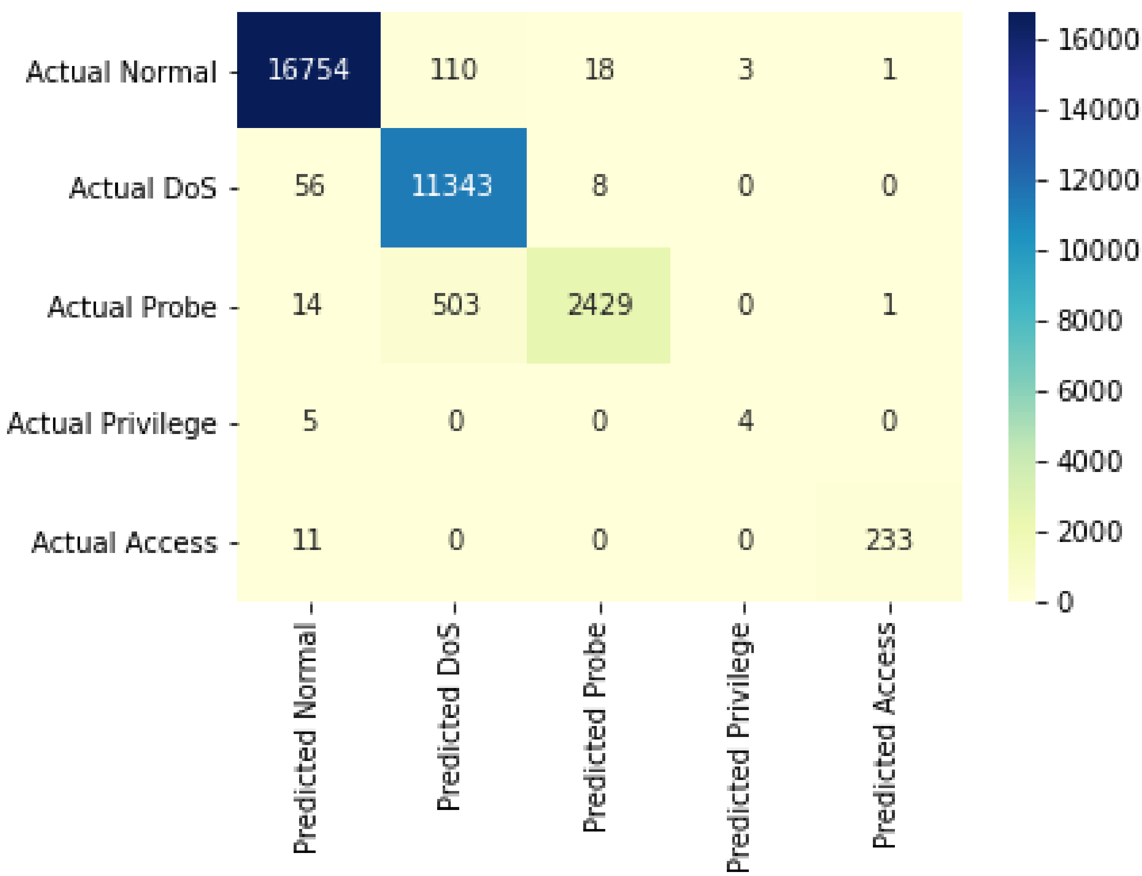
```
# build the training sets
multi_feature_train_X, multi_feature_val_X, multi_feature_train_y,
multi_feature_val_y = train_test_split(to_fit_new_features, multi_y)

# model for the mulit classification
multi_model = RandomForestClassifier()
multi_model.fit(multi_feature_train_X, multi_feature_train_y)
multi_predictions = multi_model.predict(multi_feature_val_X)

# get the score
accuracy_score(multi_predictions,multi_feature_val_y)
```

```
0.976820245768901
```

Again--strong ability to identify the attack types based on the data coming through. A quick dive into some specifics of the performance.

```
# capture the prediction data
multi_prediction_data = add_predictions(df, multi_predictions,
multi_feature_val_y)

# create a heatmap of the confusion matrix
sns.heatmap(data=multi_prediction_data['confusion_matrix'],
            xticklabels = ['Predicted ' + x for x in attack_labels],
            yticklabels = ['Actual ' + x for x in attack_labels],
            cmap="YlGnBu",
            fmt='d',
            annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73045270d0>
```



What about the full data set are we going to see the same overfitting?

```
# fit on the full data set
multi_model.fit(to_fit_new_features, multi_y)
full_multi_predictions = multi_model.predict(test_set_new_features)
```

```
# get the score
accuracy_score(full_multi_predictions,test_multi_y)
```

```
0.7683094530452912
```

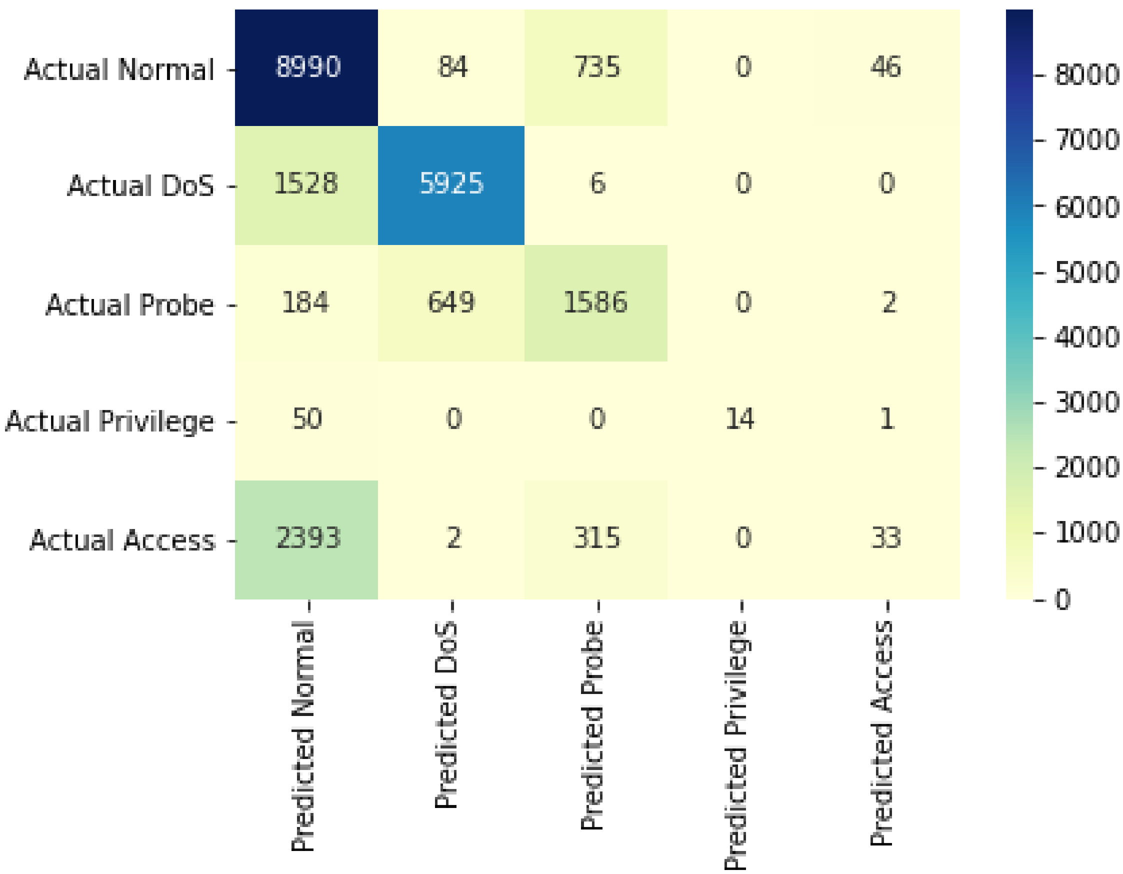
Ugh! Again, looks like some significant over fitting. What if we use our smaller `to_fit` object with less features?

```
# run the model on the smaller column set
multi_model.fit(to_fit, multi_y)
full_multi_predictions = multi_model.predict(test_set)

# get the score
accuracy_score(full_multi_predictions,test_multi_y)
```

```
0.7340637892028568
```

```
# build our prediction data
multi_prediction_data = add_predictions(df, full_multi_predictions,
test_multi_y)

# create a heatmap of the confusion matrix
sns.heatmap(data=multi_prediction_data['confusion_matrix'],
            xticklabels = ['Predicted ' + x for x in attack_labels],
            yticklabels = ['Actual ' + x for x in attack_labels],
            cmap="YlGnBu",
            fmt='d',
            annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7304552d10>
```



Looks like we have a lot of room for some future exploration! We'll use a future notebook to drill into things a bit more and see if we can improve the scores as well as incorporate some more of the delivered sci-kit features to make our work more efficient.