Content Page

Abstract

In this report, the NSL-KDD dataset is analyzed and several machine learning models are used. The problem being addressed here is to create a binary classification model that classifies either malicious or benign network data.

The dataset has 41 features in total however, the analysis is only kept to the most highly ranked features.

The machine learning models used are:

1. Regression (Multiple Linear Regression and Logistic Regression)
2. Decision Tree
3. Multi Layer Perceptron (aka Feedforward Neural Network)
4. Naive Bayes
5. Long Short Term Memory Networks (LSTMs), a variant of Recurrent Neural Networks

The machine learning models are created using R, Python and Weka.

Data Management

The dataset is obtained from [1]. The dataset is called the Network Security Lab - Knowledge Discovery and Data Mining (NSL-KDD) dataset. The aim of this dataset is to act as an effective benchmark data set to help researchers compare various intrusion detection methods [2].

The dataset can either be downloaded from the Github repository or hosted directly at the Canadian Institute for Cybersecurity, University of Brunswick's website.

From the repository, the NSL-KDD dataset has 2 parts, the training and test sets. They are available in either .csv or .arff file formats.

The training set has 125,973 rows whereas the test set has 22,543 rows. There are 41 feature columns along with an associated class label (*xAttack*).

To keep our analysis unbiased, we will only be analysing the training set file. The test set file will only be used to obtain the test set results for each classification model.

The features of this dataset comes from network data captured and categorized into 5 labels: normal, probes, remote-to-local attack, user-to-root attack, denial-of-service attack. The features represent network data such as protocol type, number of failed logins and source bytes.

All of the features have already been converted to integer or floats.

Data Visualization

Distribution of xAttack Labels

For the *xAttack* labels, the counts and pie chart (detailing the distribution for each label) are as follows:

xAttack Category	Counts
1 (*dos*): Denial of service attacks. The attacker aims to make the host too busy to process other requests from legitimate users.	45,927
2 (*u2r*): User to Root attacks. The attacker would exploit vulnerabilities to gain root privileges.	52
3 (*r2l*): Remote to Local attacks. The attacker would exploit vulnerabilities in the system to gain local access.	995
4 (*probe*). The attacker would attempt to gather important reconnaissance information about a network.	11,656
5 (*normal*): Benign, legitimate communications.	67,343

Table 1. Counts for each *xAttack* label

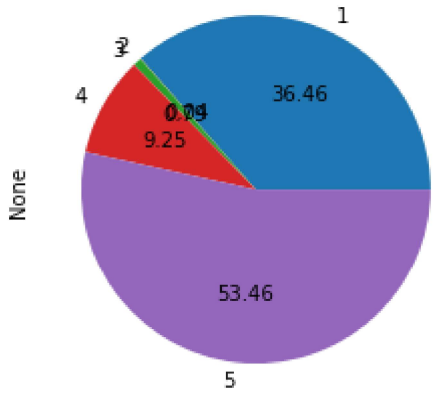


Figure 1. Pie chart showing distribution of *xAttack* labels

We can observe that there is a significant class imbalance of *xAttack* classes 2 (*u2r*) and 3 (*r2l*).

Other Features

The other 41 features are as follows:

No.	Feature name	No.	Feature name
1	duration	21	is_hot_login
2	protocol_type	22	is_guest_login
3	service	23	count
4	src_bytes	24	serror_rate
5	dst_bytes	25	rerror_rate
6	flag	26	same_srv_rate
7	land	27	diff_srv_rate
8	wrong_fragment	28	srv_count
9	urgent	29	srv_serror_rate
10	hot	30	srv_rerror_rate
11	num_failed_logins	31	srv_diff_host_rate
12	logged_in	32	dst_host_count
13	num_compromised	33	dst_host_srv_count
14	root_shell	34	dst_host_same_srv_rate
15	su_attempted	35	dst_host_diff_srv_rate
16	num_root	36	dst_host_same_src_port_rate
17	num_file_creations	37	dst_host_srv_diff_host_rate
18	num_shells	38	dst_host_serror_rate
19	num_access_files	39	dst_host_srv_serror_rate
20	num_outbond_cmd	40	dst_host_rerror_rate

Table 2. Features in NSL-KDD dataset

Most of the features are quantitative values. Filtering for categorical values (ie features with small number of values yields the following):

```
for col in train_set:
    unique_vals = (train_set[col].unique())
    if len(unique_vals) < 50:
        print(col, 'has ', len(unique_vals), 'unique vals. They are:', np.sort(unique_vals))

protocol_type has  3 unique vals. They are: [1 2 3]
flag has  10 unique vals. They are: [ 1  2  3  4  5  6  7  8  9 11]
land has  2 unique vals. They are: [0 1]
wrong_fragment has  3 unique vals. They are: [0 1 3]
urgent has  4 unique vals. They are: [0 1 2 3]
hot has  28 unique vals. They are: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 14 15 17 18 19 20 21 22 24 25
28 30 33 44 77]
num_failed_logins has  6 unique vals. They are: [0 1 2 3 4 5]
logged_in has  2 unique vals. They are: [0 1]
root_shell has  2 unique vals. They are: [0 1]
su_attempted has  3 unique vals. They are: [0 1 2]
num_file_creations has  35 unique vals. They are: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17
18 19 20 21 22 23 25 26 27 28 29 33 34 36 38 40 43]
num_shells has  3 unique vals. They are: [0 1 2]
num_access_files has  10 unique vals. They are: [0 1 2 3 4 5 6 7 8 9]
num_outbound_cmds has  1 unique vals. They are: [0]
is_host_login has  2 unique vals. They are: [0 1]
is_guest_login has  2 unique vals. They are: [0 1]
xAttack has  5 unique vals. They are: [1 2 3 4 5]
```

Python output of features with few categorical values

We can observe that the categorical features have already been encoded into integer variables.

Note that the feature *num_outbound_cmds* has only one possible value, 0. This could be a possible redundant column.

Correlation Analysis

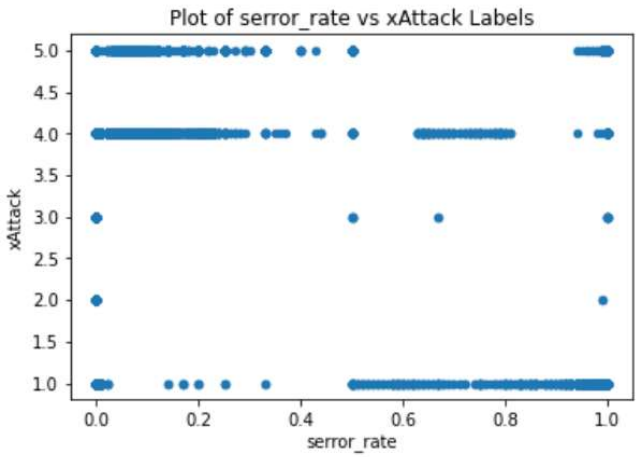
As there are a whopping 41 features, we will be focusing our visualizations only on the more relevant features. We have decided to limit our scope to features that are strongly correlated with the *xAttack* labels. In this case, only features with correlation magnitudes larger than 0.7 will be analyzed via visualizations.

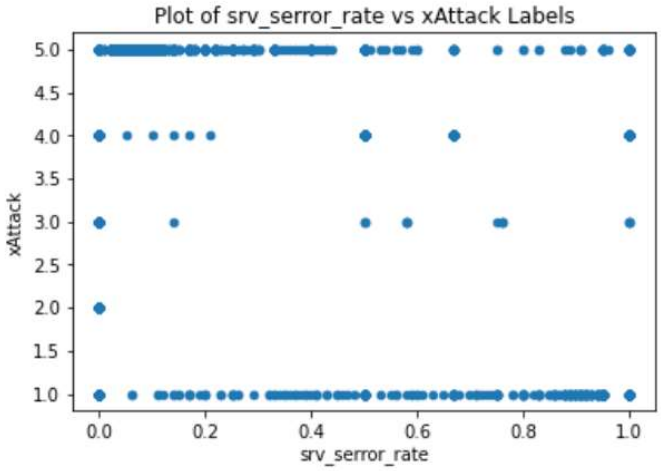
```
# Get features which are correlated with xAttack labels ie correlation magnitude of above 0.7
correlations = train_set.corr()
for index, row in (correlations[['xAttack']]).iterrows():
    correlation_with_xattack = row['xAttack']
    if abs(correlation_with_xattack) > 0.7:
        print(index, correlation_with_xattack)

serror_rate -0.7779543353136086
srv_serror_rate -0.7767725719685258
same_srv_rate 0.8203949901293894
dst_host_same_srv_rate 0.700547657783034
dst_host_serror_rate -0.7799095886878171
dst_host_srv_serror_rate -0.7827871811434195
```

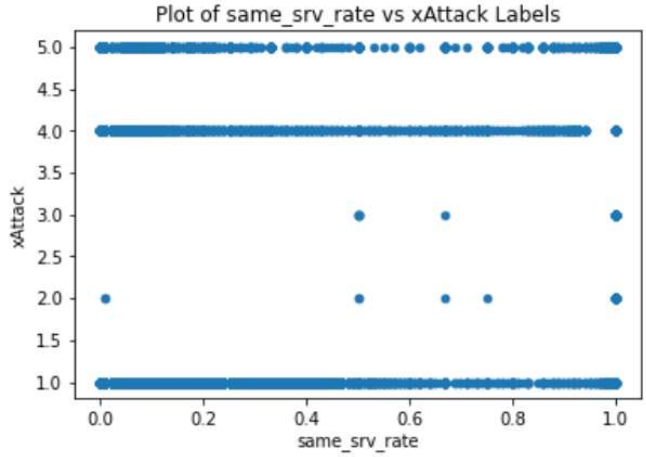
Python output of features strongly correlated with *xAttack*

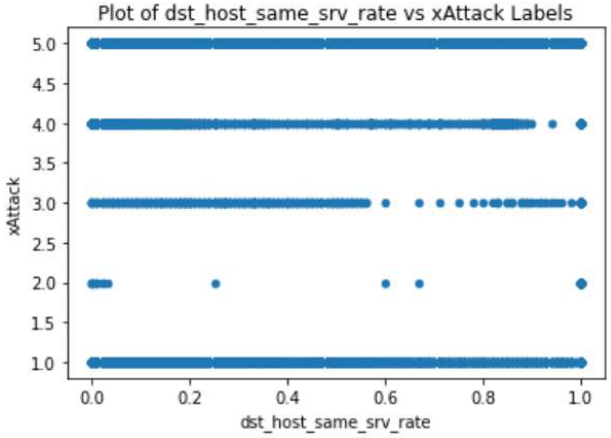
The features which have correlations magnitudes larger than 0.7 are *serror_rate, srv_serror_rate, same_srv_rate, dst_host_same_srv_rate, dst_host_serror_rate* and *dst_host_srv_serror_rate*.

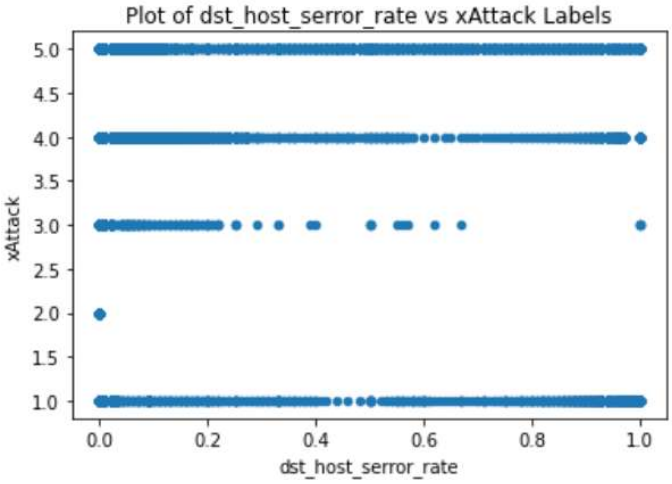
Scatterplots vs xAttack Labels











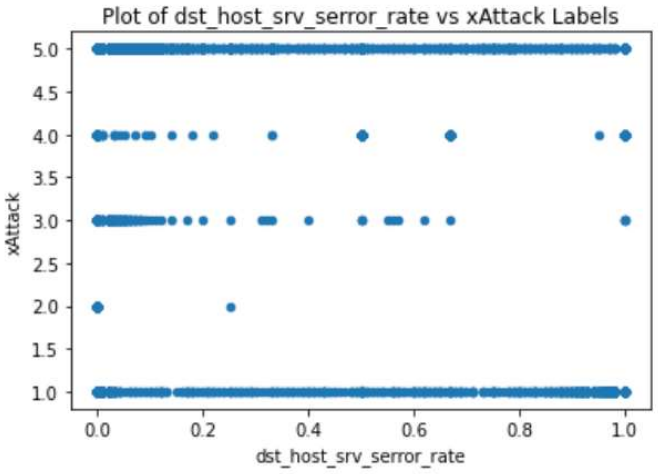


Figure 2. Scatterplots of top 6 strongly correlated features vs xAttack labels

No clear distinction can be seen to distinguish each label. Hence, a linear classifier may not be adequate.

Combining xAttack Labels

As there is a significant class imbalance for some of the classes (u2r and r2l), the labels will be combined into benign (5) and malicious (1-4).

```
train_set['xAttack'] = np.where(train_set['xAttack'] == 5, 0, 1)
test_set['xAttack'] = np.where(test_set['xAttack'] == 5, 0, 1)
```

Python code re-assigning labels to Benign vs Malicious

New xAttack Label	Counts
0 ie benign	67343
1 ie malicious	58630

Table 3. Counts for Benign vs Malicious labels

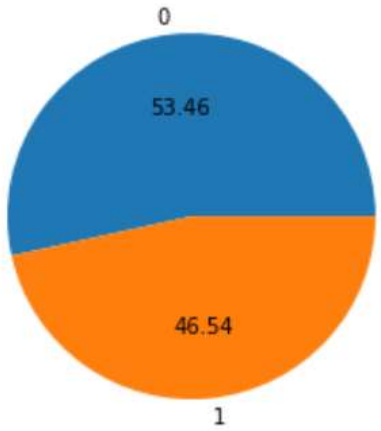


Figure 3. Pie chart showing new distribution of xAttack labels

After adjusting the labels, the number of samples for each class is much more balanced. This will address the class imbalance problem we faced earlier. Hence, our subsequent analysis will be used on this dataset of binary (malicious vs benign) labels.

Correlation Analysis

When we redid the correlation analysis, there are only 2 features which are strongly correlated with the new labels.

```
# Get features which are correlated with xAttack labels ie correlation magnitude of above 0.7
correlations = train_set.corr()
for index, row in (correlations[['xAttack']]).iterrows():
    correlation_with_xattack = row['xAttack']
    if abs(correlation_with_xattack) > 0.7:
        print(index, correlation_with_xattack)

same_srv_rate -0.7519134368764228
dst_host_srv_count -0.7225353705394968
```

Python output of features strongly correlated with binary *xAttack* labels

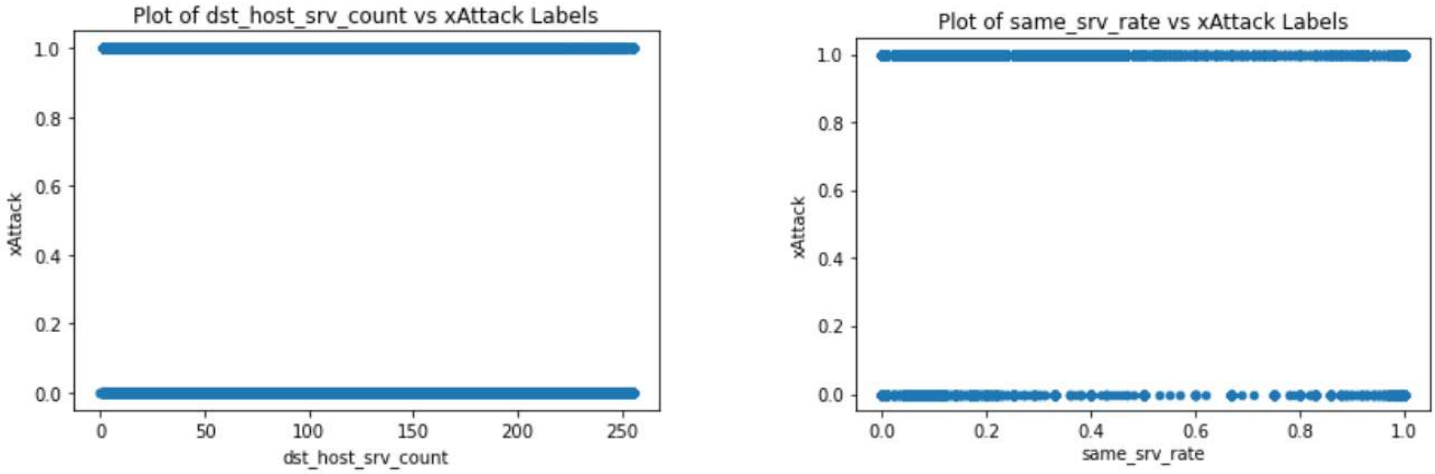


Figure 4. Scatterplots of top 2 strongly correlated features vs xAttack labels

Similar as before, we cannot see any differences between the classes for each single feature.

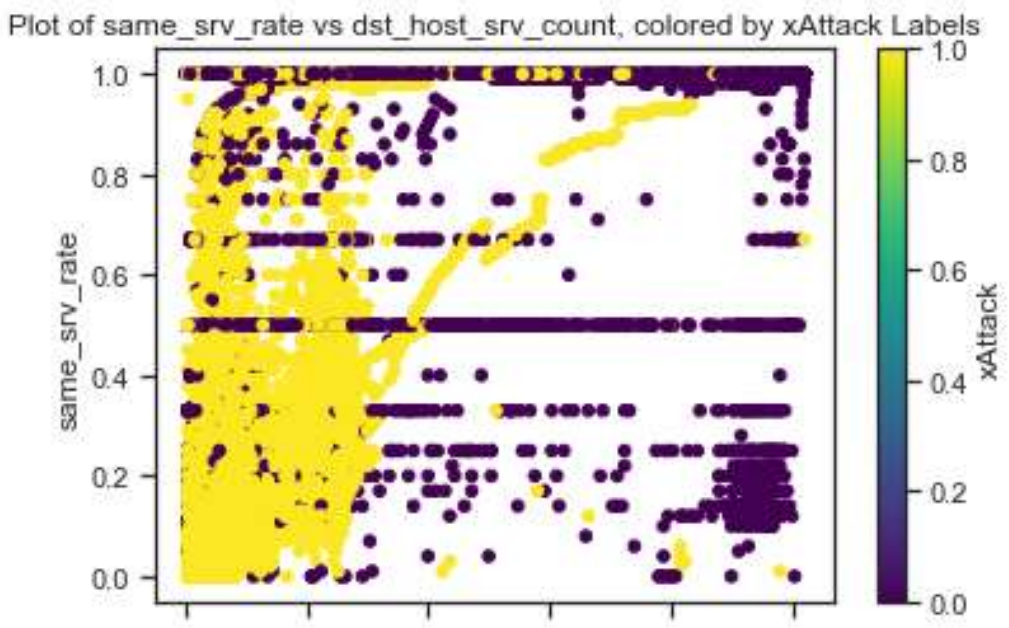


Figure 5. Scatterplot of *same_srv_rate* vs *dst_host_srv_count* colored by *xAttack* labels

However, if we plot *same_srv_rate* vs *dst_host_srv_count*, we can see that most of the malicious points (*xAttack* == 1) are at the left side of the graph, with what appears to be a curved boundary.

Hence, it would be easier to train a model classifying benign vs malicious rather than for all 5 separate classes. This supports our earlier decision to combine the labels, rather than use the 5 separate labels with imbalanced data.

Data Analytics

Correlation Analysis

The full table (of correlations with the xAttack labels) is as follows:

Feature name	Correlation
same_srv_rate	-0.7519134369
dst_host_srv_count	-0.7225353705
dst_host_same_srv_rate	-0.6938028328
logged_in	-0.6901707396
protocol_type	-0.1356434215
srv_diff_host_rate	-0.1193771824
is_guest_login	-0.03927902588
num_access_files	-0.03670050589
su_attempted	-0.02244849665
num_file_creations	-0.02127072945
root_shell	-0.02028540195
hot	-0.01308341431
num_root	-0.01145249134
num_compromised	-0.01019832758
num_shells	-0.009471997357
num_failed_logins	-0.003755073924
urgent	-0.002787032403
is_host_login	-0.002628915973
srv_count	0.0007707123314
dst_bytes	0.004117535029
src_bytes	0.005921322756
land	0.007190758995
duration	0.04878532742
dst_host_srv_diff_host_rate	0.06233233827
dst_host_same_src_port_rate	0.09244443089
wrong_fragment	0.0959054807
diff_srv_rate	0.2036599647

dst_host_diff_srv_rate	0.2428979585
dst_host_rerror_rate	0.2525627248
rerror_rate	0.253397111
srv_rerror_rate	0.2535039621
service	0.2790234199
dst_host_count	0.3750520924
flag	0.5087038065
count	0.5764442653
srv_serror_rate	0.6482888316
serror_rate	0.6506522402
dst_host_serror_rate	0.6518416167
dst_host_srv_serror_rate	0.6549854452
num_outbond_cmd	NA

Table 4. Table of features with their correlations with respect to *xAttack* labels

Highlighted in yellow are features with correlation magnitudes larger than 0.7. Highlighted in green are features with correlation magnitudes larger than 0.65.

Note that *num_outbond_cmd* is NA as it only has 1 value throughout the dataset.

Hence, there are 7 important features when we consider correlation magnitudes: *same_srv_rate, dst_host_srv_count, dst_host_same_srv_rate, logged_in, serror_rate, dst_host_serror_rate, dst_host_srv_serror_rate*

Feature Ranking using Weka

```
=== Attribute Selection on all input data ===

Search Method:
        Greedy Stepwise (forwards).
        Start set: no attributes
        Merit of best subset found:    0.816

Attribute Subset Evaluator (supervised, Class (numeric): 42 xAttack):
        CFS Subset Evaluator
        Including locally predictive attributes

Selected attributes: 8,12,29,33,35,39 : 6
                     wrong_fragment
                     logged_in
                     same_srv_rate
                     dst_host_srv_count
                     dst_host_diff_srv_rate
                     dst_host_srv_serror_rate
```

Output for attribute selection using CFS Subset Evaluator

Using the CFS Subset Evaluator, the feature ranking (top 6) is: *wrong_fragment, logged_in, same_srv_rate, dst_host_srv_count, dst_host_diff_srv_rate, dst_host_srv_serror_rate.*

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 42 class):
        Gain Ratio feature evaluator

Ranked attributes:
 0.2681   28 srv_rerror_rate
 0.2323   12 logged_in
 0.2288   41 dst_host_srv_rerror_rate
 0.2181   27 rerror_rate
 0.2158    4 flag
 0.2127    6 dst_bytes
 0.1975    5 src_bytes
 0.1935   30 diff_srv_rate
 0.163    29 same_srv_rate
 0.1617   40 dst_host_rerror_rate
 0.1431    3 service
 0.1417   25 serror_rate
 0.137    26 srv_serror_rate
 0.1367   39 dst_host_srv_serror_rate
 0.133    34 dst_host_same_srv_rate
 0.1203   31 srv_diff_host_rate
 0.1198   35 dst_host_diff_srv_rate
 0.1182   33 dst_host_srv_count
 0.1178   37 dst_host_srv_diff_host_rate
 0.1117   11 num_failed_logins
```

Output for attribute selection using GainRatioAttributeEval with Ranker

Using the GainRatioAttributeEval with Ranker, the top 6 features are: *srv_rerror_rate, logged_in, dst_host_srv_rerror_rate, rerror_rate, flag, dst_bytes.*

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 42 class):
        Information Gain Ranking Filter

Ranked attributes:
 0.77273     5 src_bytes
 0.692733    6 dst_bytes
 0.484801    3 service
 0.340669    4 flag
 0.337167   33 dst_host_srv_count
 0.334063   35 dst_host_diff_srv_rate
 0.326465   34 dst_host_same_srv_rate
 0.307324   40 dst_host_rerror_rate
 0.26572    41 dst_host_srv_rerror_rate
 0.259631   23 count
 0.25786    30 diff_srv_rate
 0.243368   29 same_srv_rate
 0.230089   12 logged_in
 0.226113   27 rerror_rate
 0.217487   28 srv_rerror_rate
 0.190418   37 dst_host_srv_diff_host_rate
 0.165708   36 dst_host_same_src_port_rate
 0.147335   31 srv_diff_host_rate
 0.122839   38 dst_host_serror_rate
 0.122387   32 dst_host_count
 0.113507   25 serror_rate
 0.108604   39 dst_host_srv_serror_rate
 0.09408     1 duration
 0.092326   26 srv_serror_rate
 0.085731   24 srv_count
 0.040533    2 protocol_type
 0.031069   10 hot
 0.016736   11 num_failed_logins
 0.013958   22 is_guest_login
 0.011118   13 num_compromised
 0.000993   16 num_root
 0.000937    8 wrong_fragment
```

Output for attribute selection using InfoRatioAttributeEval with Ranker

Using the InfoGainAttributeEval with Ranker, the top 6 features are: src_bytes, dst_bytes, service, flag, dst_host_srv_count, dst_host_diff_srv_rate.

Analysis of Variance (Single Factor)

Single-factor ANOVA is done on features that have both higher correlation magnitudes and are ranked highly from Weka.

These features are: *same_srv_rate, dst_host_srv_count, logged_in, dst_host_srv_serror_rate, dst_bytes*

SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
dst_bytes_benign	58630	2.5E+08	4248.16	3.7E+09		
dst_bytes_malicious	58630	2.2E+09	37524.5	3.5E+13		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.2E+13	1	3.2E+13	1.86864	0.17163	3.84154
Within Groups	2E+18	117258	1.7E+13			
Total	2E+18	117259				

Anova results for the feature *dst_bytes*

SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
same_srv_rate_benign	58630	56833.6	0.96936	0.02079		
same_srv_rate_malicious	58630	17979.4	0.30666	0.15654		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	12874.4	1	12874.4	145202	0	3.84154
Within Groups	10396.7	117258	0.08867			
Total	23271.1	117259				

Anova results for the feature *same_srv_rate*

SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
dst_host_srv_count_benign	58630	1.1E+07	190.325	8570.87		
dst_host_srv_count_malicious	58630	1754742	29.9291	2734.17		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	7.5E+08	1	7.5E+08	133424	0	3.84154
Within Groups	6.6E+08	117258	5652.52			
Total	1.4E+09	117259				

Anova results for the feature *dst_host_srv_count*

SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
dst_host_srv_serror_rate_benign	58630	354.1	0.00604	0.00313		
dst_host_srv_serror_rate_malicious	58630	34669.6	0.59133	0.23998		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	10042.2616	1	10042.3	82613	0	3.84154
Within Groups	14253.6289	117258	0.12156			
Total	24295.8905	117259				

Anova results for the feature *dst_host_srv_serror_rate*

SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
logged_in_benign	58630	41624	0.70994	0.20593		
logged_in_malicious	58630	1995	0.03403	0.03287		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	13392.9528	1	13393	112170	0	3.84154
Within Groups	14000.4191	117258	0.1194			
Total	27393.3718	117259				

Anova results for the feature *logged_in*

From all the above ANOVA outputs, all the p-values (except for *dst_bytes*) are less than the significance value, 0.05. This means that the null hypothesis (H0: Both groups are not different) is rejected. Hence, we can conclude that based on each separate feature, both benign and malicious groups are different.

Hence, these features (except for *dst_bytes*) are significant.

Choice of Features

Ranking (1 - Most Important)	Correlation	CFS Subset Evaluator	Gain Ratio Ranking	Info Gain Ranking
1	same_srv_rate	wrong_fragment	srv_rerror_rate	src_bytes
2	dst_host_srv_count	logged_in	logged_in	dst_bytes
3	dst_host_same_srv_rate	same_srv_rate	dst_host_srv_rerror_rate	service
4	logged_in	dst_host_srv_count	rerror_rate	flag
5	dst_host_srv_serror_rate	dst_host_diff_srv_rate	flag	dst_host_srv_count
6	dst_host_serror_rate	dst_host_srv_serror_rate	dst_bytes	dst_host_diff_srv_rate

Table 5. Overall ranking of top features

The top 4 features shared by all 4 measures are: *dst_bytes, dst_host_srv_count, logged_in, dst_host_srv_serror_rate*

However, *dst_bytes* is dropped as it is not significant in the single factor ANOVA.

Hence, the 3 chosen features are: d*st_host_srv_count, logged_in, dst_host_srv_serror_rate*

They are chosen as:

1. They have a high magnitude of correlation with respect to the class labels.
2. Weka has ranked them highly when using the CFS Subset Evaluator, Gain Ratio Ranking and Info Gain Ranking.
3. These features are significant in single-factor ANOVA.

Parallel Coordinates Visualizations

With the top 4 features, we can have an easier time in visualizing the parallel coordinate plots.

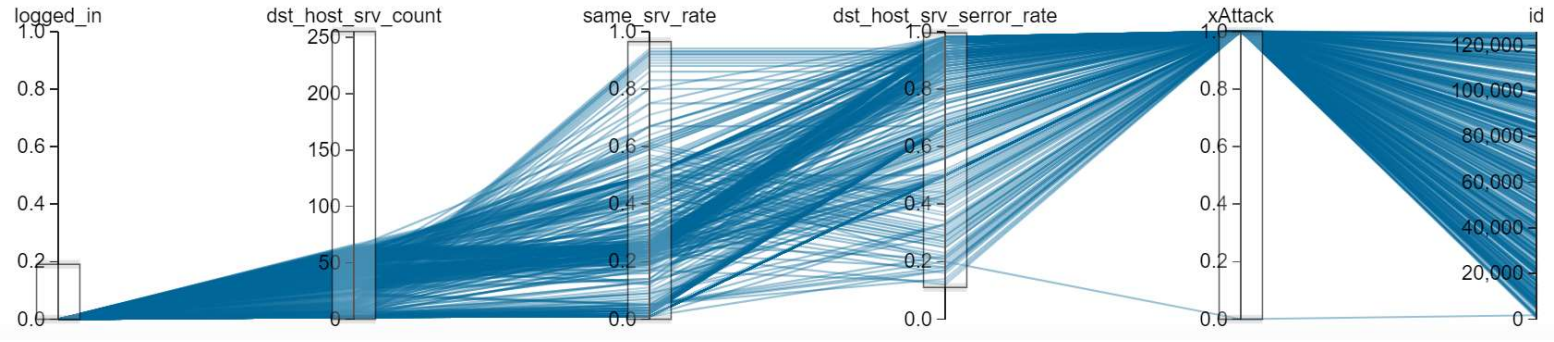


Figure 6. Parallel Coordinate Visualization I

Observe that when *logged_in* (a binary variable) is 0, *same_srv_rate* is slightly below 1 and *dst_host_srv_serror_rate* is more than 0.1, the majority of the points are classified as malicious (*xAttack* = 1).

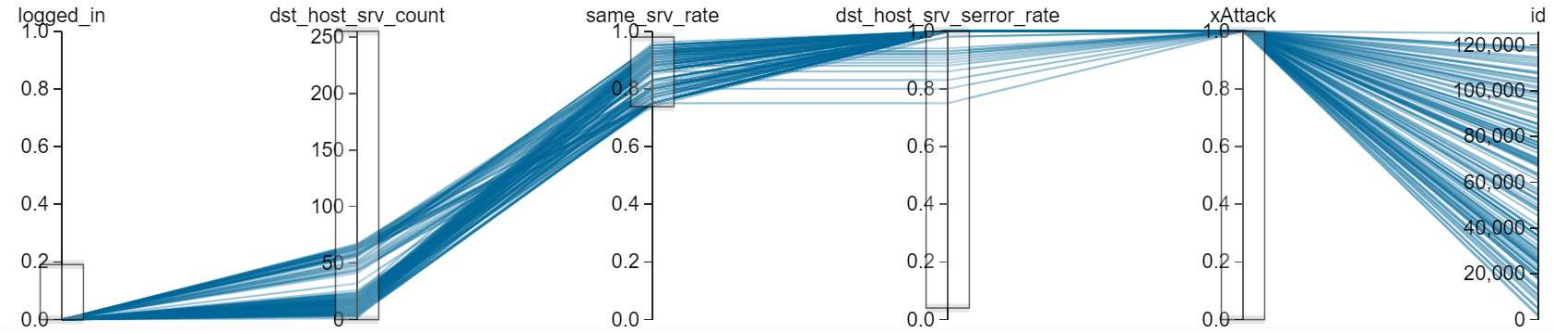


Figure 7. Parallel Coordinate Visualization II

The effect is even more clear, when we further restrict same_srv_rate to between 0.75 to below 1.0.

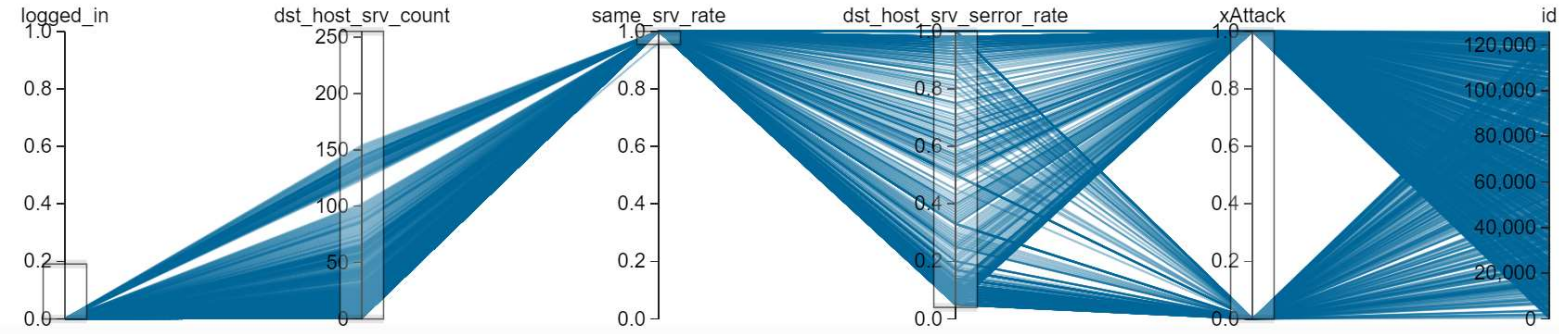


Figure 8. Parallel Coordinate Visualization III

However, when we consider same_srv_rate to be 1.0, there are both lots of malicious (xAttack = 1) and benign (xAttack = 0) samples.

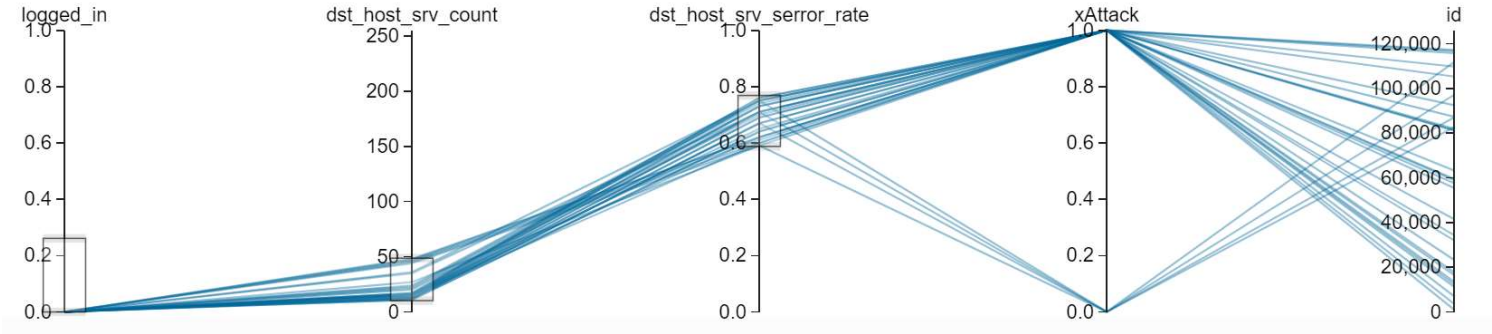


Figure 9. Parallel Coordinate Visualization IV

With the chosen 3 features, we can also see a trend where when logged_in = 0, dst_host_srv_count is between 25 and 50 and dst_host_srv_error_rate is between 0.6 and 0.8, the majority of the data points are classified as malicious (xAttack = 1).

Hence, this shows that visually, the 3 chosen features are significant in deciding the class labels.

K-Means Clustering

Using the following R code, the total within cluster sum of squares is obtained with each cluster number.

```r
# Load libraries
library(cluster)    # clustering algorithms
library(factoextra) # clustering algorithms & visualization
library(tidyverse)

# Do K-means
# function to compute total within-cluster sum of square
wss <- function(k) {
  kmeans(train_set, k, nstart = 10 )$tot.withinss
}

# Compute and plot wss for k = 1 to k = 15
k.values <- 1:15

# extract wss for 2-15 clusters
wss_values <- map_dbl(k.values, wss)

plot(k.values, wss_values,
     type="b", pch = 19, frame = FALSE,
     xlab="Number of clusters K",
     ylab="Total within-clusters sum of squares")
```

R code for plotting WSS cluster graph

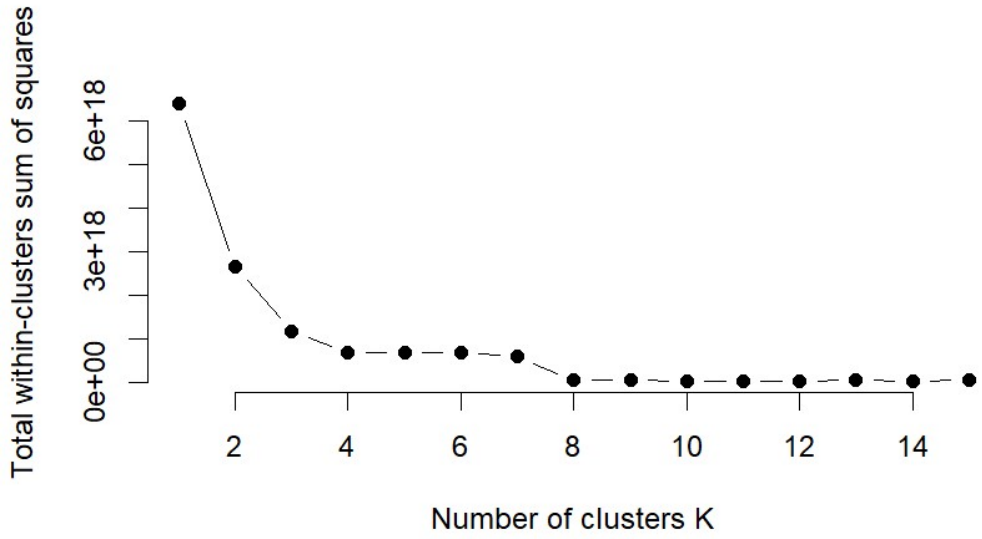


Figure 10. Total within cluster sum of squares for each cluster size

From the above plot, we can see that there is an ‘elbow’ at k=2 and k=8. The ‘elbow’ can be described as the point where there is a change from a steep negative gradient to a less steep negative gradient.

Hence, this supports our decision to use 2 classes instead of the 5 given labels.

Data Modelling

Regression using R

For regression, we will limit our scope to the top 5 features. This will give us $2^5 - 1 = 31$ possible models. If we had only used our chosen 3 features, we would only have $2^3 - 1 = 8$ possible models. This would not allow us to run at least 10 experiments.

We use the 'olsrr' package in R to create all the possible values.

The top 5 features we will use (from *Choice of Features* section) are: *dst_bytes, dst_host_srv_count, logged_in, dst_host_srv_serror_rate, same_srv_rate.*

```
library('olsrr')

model <- lm(xAttack ~ dst_bytes + dst_host_srv_count +
              logged_in + dst_host_srv_serror_rate + same_srv_rate,
            data = train_set)
k <- ols_step_all_possible(model)
(k)
```

R code for generating all possible regression models

```
   Index N                                                                    Predictors     R-Square Adj. R-Square  Mallow's Cp
5      1 1                                                                 same_srv_rate 5.653738e-01  5.653704e-01 5.363051e+04
2      2 1                                                           dst_host_srv_count 5.220574e-01  5.220536e-01 7.153006e+04
3      3 1                                                                    logged_in 4.763356e-01  4.763315e-01 9.042354e+04
4      4 1                                                       dst_host_srv_serror_rate 4.290059e-01  4.290014e-01 1.099815e+05
1      5 1                                                                   dst_bytes 1.695409e-05  9.015894e-06 2.872515e+05
14     6 2                                                        logged_in same_srv_rate 6.544312e-01  6.544257e-01 1.683155e+04
12     7 2                                                 dst_host_srv_count same_srv_rate 6.388481e-01  6.388424e-01 2.327091e+04
10     8 2                                                    dst_host_srv_count logged_in 6.157079e-01  6.157018e-01 3.283310e+04
11     9 2                                       dst_host_srv_count dst_host_srv_serror_rate 6.105236e-01  6.105174e-01 3.497539e+04
13    10 2                                               logged_in dst_host_srv_serror_rate 6.070907e-01  6.070845e-01 3.639395e+04
15    11 2                                    dst_host_srv_serror_rate same_srv_rate 5.806410e-01  5.806344e-01 4.732367e+04
9     12 2                                                 dst_bytes same_srv_rate 5.654223e-01  5.654154e-01 5.361246e+04
6     13 2                                              dst_bytes dst_host_srv_count 5.220585e-01  5.220509e-01 7.153160e+04
7     14 2                                                    dst_bytes logged_in 4.763401e-01  4.763318e-01 9.042368e+04
8     15 2                                           dst_bytes dst_host_srv_serror_rate 4.290425e-01  4.290334e-01 1.099684e+05
23    16 3                                 dst_host_srv_count logged_in same_srv_rate 6.856981e-01  6.856906e-01 3.913212e+03
22    17 3                       dst_host_srv_count logged_in dst_host_srv_serror_rate 6.718476e-01  6.718398e-01 9.636602e+03
25    18 3                            logged_in dst_host_srv_serror_rate same_srv_rate 6.653025e-01  6.652946e-01 1.234122e+04
20    19 3                                dst_bytes logged_in same_srv_rate 6.544566e-01  6.544483e-01 1.682307e+04
24    20 3                    dst_host_srv_count dst_host_srv_serror_rate same_srv_rate 6.503581e-01  6.503497e-01 1.851668e+04
18    21 3                                 dst_bytes dst_host_srv_count same_srv_rate 6.388669e-01  6.388583e-01 2.326516e+04
16    22 3                                    dst_bytes dst_host_srv_count logged_in 6.157088e-01  6.156996e-01 3.283471e+04
17    23 3                       dst_bytes dst_host_srv_count dst_host_srv_serror_rate 6.105326e-01  6.105233e-01 3.497368e+04
19    24 3                              dst_bytes logged_in dst_host_srv_serror_rate 6.071062e-01  6.070968e-01 3.638954e+04
21    25 3                          dst_bytes dst_host_srv_serror_rate same_srv_rate 5.806897e-01  5.806797e-01 4.730557e+04
30    26 4           dst_host_srv_count logged_in dst_host_srv_serror_rate same_srv_rate 6.951494e-01  6.951397e-01 9.685807e+00
27    27 4                        dst_bytes dst_host_srv_count logged_in same_srv_rate 6.857113e-01  6.857013e-01 3.909767e+03
26    28 4                dst_bytes dst_host_srv_count logged_in dst_host_srv_serror_rate 6.718542e-01  6.718437e-01 9.635901e+03
29    29 4                     dst_bytes logged_in dst_host_srv_serror_rate same_srv_rate 6.653284e-01  6.653178e-01 1.233252e+04
28    30 4           dst_bytes dst_host_srv_count dst_host_srv_serror_rate same_srv_rate 6.503774e-01  6.503663e-01 1.851068e+04
31    31 5 dst_bytes dst_host_srv_count logged_in dst_host_srv_serror_rate same_srv_rate 6.951631e-01  6.951510e-01 6.000000e+00
```

R output for all possible regression models

From the above printout, the model with the highest adjusted R^2 value is 0.6951510. It is the model with all 5 predictors: *dst_bytes, dst_host_srv_count, logged_in, dst_host_srv_serror_rate, same_srv_rate.*

```
> summary(model)

Call:
lm(formula = xAttack ~ dst_bytes + dst_host_srv_count + logged_in +
    dst_host_srv_serror_rate + same_srv_rate, data = train_set)

Residuals:
     Min       1Q   Median       3Q      Max
-0.88831 -0.07765  0.01758  0.02863  1.02863

Coefficients:
                          Estimate Std. Error  t value Pr(>|t|)
(Intercept)              8.798e-01  2.561e-03  343.592   <2e-16 ***
dst_bytes                4.601e-10  1.930e-10    2.384   0.0171 *
dst_host_srv_count      -1.175e-03  1.058e-05 -111.034   <2e-16 ***
logged_in               -2.890e-01  2.124e-03 -136.039   <2e-16 ***
dst_host_srv_serror_rate 1.696e-01  2.713e-03   62.496   <2e-16 ***
same_srv_rate           -3.198e-01  3.259e-03  -98.142   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2754 on 125967 degrees of freedom
Multiple R-squared:  0.6952,    Adjusted R-squared:  0.6952
F-statistic: 5.745e+04 on 5 and 125967 DF,  p-value: < 2.2e-16
```

```
> AIC(model)
[1] 32616.93
```

R output for model with highest adjusted R-squared value

Fitting this model, we can see that all variables are significant for each t-test. The t-test is a hypothesis test where H_0: $\beta_j = 0$ vs H_1: $\beta_j \neq 0$ for variable j. If H_0 is not rejected, it implies that variable j can be deleted from the model. If H_0 is rejected (p-value < 0.05), it implies that variable j is significant and cannot be deleted from the model.

From the above model summary, all the p-values are lower than 0.05. Hence, we can conclude that all the variables are significant in predicting *xAttack* in a regression model.

Stepwise Regression

It is impossible to enumerate all possible models, as we did above, as we would be dealing with 2^{41} - 1 possible models. Hence, to investigate all 41 features, we will be using stepwise regression.

```
# Do stepwise regression on all features
require('MASS')
full.model <- lm(xAttack ~., data = train_set)
step.model <- stepAIC(full.model, direction = "both",
                      trace = FALSE)
summary(step.model)

Call:
lm(formula = xAttack ~ duration + protocol_type + service + flag +
    src_bytes + land + wrong_fragment + hot + num_failed_logins +
    logged_in + num_compromised + root_shell + su_attempted +
    num_root + num_file_creations + num_access_files + 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, data = train_set)

Residuals:
     Min       1Q   Median       3Q      Max
-1.97632 -0.04576 -0.00898  0.07275  1.27946

Coefficients:
                             Estimate Std. Error  t value Pr(>|t|)
(Intercept)                 6.394e-01  7.329e-03   87.243  < 2e-16 ***
duration                   -2.075e-06  2.676e-07   -7.756 8.84e-15 ***
protocol_type              -1.420e-01  2.092e-03  -67.874  < 2e-16 ***
service                    -7.938e-05  4.336e-05   -1.831  0.06715 .
flag                        4.209e-02  1.114e-03   37.780  < 2e-16 ***
src_bytes                   6.278e-10  1.015e-10    6.188 6.12e-10 ***
land                       -5.446e-01  4.243e-02  -12.834  < 2e-16 ***
wrong_fragment              3.090e-01  2.520e-03  122.619  < 2e-16 ***
hot                         2.595e-02  5.433e-04   47.761  < 2e-16 ***
num_failed_logins           3.175e-02  1.327e-02    2.392  0.01676 *
logged_in                  -1.545e-01  3.788e-03  -40.804  < 2e-16 ***
num_compromised             8.435e-03  7.389e-04   11.415  < 2e-16 ***
root_shell                  1.560e-01  2.053e-02    7.598 3.03e-14 ***
su_attempted               -6.092e-02  2.114e-02   -2.883  0.00395 **
num_root                   -8.396e-03  7.359e-04  -11.409  < 2e-16 ***
num_file_creations         -1.102e-02  1.253e-03   -8.799  < 2e-16 ***
num_access_files            3.785e-02  8.206e-03    4.613 3.98e-06 ***
is_guest_login             -2.778e-01  1.224e-02  -22.699  < 2e-16 ***
count                       3.184e-05  1.152e-05    2.763  0.00572 **
srv_count                   1.197e-03  1.597e-05   74.982  < 2e-16 ***
serror_rate                -3.368e-01  1.391e-02  -24.206  < 2e-16 ***
srv_serror_rate             2.621e-01  1.500e-02   17.471  < 2e-16 ***
rerror_rate                -2.570e-01  1.471e-02  -17.468  < 2e-16 ***
srv_rerror_rate             3.484e-01  1.498e-02   23.257  < 2e-16 ***
same_srv_rate              -5.311e-01  4.689e-03 -113.261  < 2e-16 ***
diff_srv_rate              -1.841e-01  4.779e-03  -38.525  < 2e-16 ***
```

```
srv_diff_host_rate           1.152e-01  2.632e-03   43.771  < 2e-16 ***
dst_host_count               5.686e-04  9.088e-06   62.569  < 2e-16 ***
dst_host_srv_count          -1.035e-03  1.544e-05  -67.045  < 2e-16 ***
dst_host_same_srv_rate       2.151e-01  4.597e-03   46.786  < 2e-16 ***
dst_host_diff_srv_rate       1.497e-01  5.249e-03   28.519  < 2e-16 ***
dst_host_same_src_port_rate  3.432e-01  2.785e-03  123.224  < 2e-16 ***
dst_host_srv_diff_host_rate  5.757e-01  6.889e-03   83.563  < 2e-16 ***
dst_host_serror_rate         1.454e-01  8.889e-03   16.356  < 2e-16 ***
dst_host_srv_serror_rate     1.638e-01  1.057e-02   15.498  < 2e-16 ***
dst_host_rerror_rate         3.362e-02  6.092e-03    5.519 3.42e-08 ***
dst_host_srv_rerror_rate     1.188e-01  8.360e-03   14.207  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2105 on 125936 degrees of freedom
Multiple R-squared:  0.8219,     Adjusted R-squared:  0.8218
F-statistic: 1.614e+04 on 36 and 125936 DF,  p-value: < 2.2e-16

> AIC(step.model)
[1] -35012.53
```

R output for stepwise regression

Using stepwise regression, we end up with only 35 variables in the model. All the variables above are significant (at 5% significance level) with the exception of *service*.

This model has an adjusted R^2 value of 0.8218 and AIC of -35,012.

Hence, this model is much better than the previous model (which only has 5 variables).

Logistic Regression

As we are doing binary classification, it would be more appropriate to fit a logistic regression model to our features.

Firstly, we fit a logistic model to our top 5 features.

```
logit_model_1 <- glm(formula = xAttack ~ dst_bytes + dst_host_srv_count +
                       logged_in + dst_host_srv_serror_rate + same_srv_rate,
    family = binomial(link = "logit"), data = train_set)
summary(logit_model_1)

Call:
glm(formula = xAttack ~ dst_bytes + dst_host_srv_count + logged_in +
    dst_host_srv_serror_rate + same_srv_rate, family = binomial(link = "logit"),
    data = train_set)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-3.11675  -0.26265  -0.17592   0.09908   2.89011

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)               2.279e+00  2.931e-02   77.74   <2e-16 ***
dst_bytes                 1.013e-08  1.777e-08    0.57    0.569
dst_host_srv_count       -8.914e-03  1.163e-04  -76.63   <2e-16 ***
logged_in                -2.511e+00  2.712e-02  -92.59   <2e-16 ***
dst_host_srv_serror_rate  3.407e+00  7.116e-02   47.88   <2e-16 ***
same_srv_rate            -1.656e+00  3.445e-02  -48.07   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 174033  on 125972  degrees of freedom
Residual deviance:  59177  on 125967  degrees of freedom
AIC: 59189

Number of Fisher Scoring iterations: 7
```

R output for logistic regression model with top 5 variables

From the output, only the variable *dst_bytes* is not significant in the final logistic model.

J48 Decision Tree

As Weka will split the data within the program itself, we will combine the train and test sets into a single csv file. As the original split was 15% test set, 85% train set, we will use these settings for Weka's train-test split.

Recall that our top 3 chosen features are: d*st_host_srv_count, logged_in, dst_host_srv_serror_rate.* Using Weka's J48 decision tree, the following tree was obtained.

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     chosen_features_weka
Instances:    148516
Attributes:   4
              logged_in
              dst_host_srv_count
              dst_host_srv_serror_rate
              xAttack
Test mode:    split 85.0% train, remainder test

=== Classifier model (full training set) ===

J48 pruned tree
------------------

logged_in <= 0
|   dst_host_srv_serror_rate <= 0.33
|   |   dst_host_srv_count <= 165
|   |   |   dst_host_srv_count <= 20
|   |   |   |   dst_host_srv_serror_rate <= 0.02: malicious (23098.0/4571.0)
|   |   |   |   dst_host_srv_serror_rate > 0.02
|   |   |   |   |   dst_host_srv_serror_rate <= 0.06: malicious (32.0/14.0)
|   |   |   |   |   dst_host_srv_serror_rate > 0.06: benign (221.0/74.0)
|   |   |   dst_host_srv_count > 20
|   |   |   |   dst_host_srv_serror_rate <= 0.14
|   |   |   |   |   dst_host_srv_serror_rate <= 0
|   |   |   |   |   |   dst_host_srv_count <= 88: malicious (7226.0/2732.0)
|   |   |   |   |   |   dst_host_srv_count > 88
|   |   |   |   |   |   |   dst_host_srv_count <= 91
|   |   |   |   |   |   |   |   dst_host_srv_count <= 89: malicious (72.0/27.0)
|   |   |   |   |   |   |   |   dst_host_srv_count > 89: benign (209.0/89.0)
|   |   |   |   |   |   |   dst_host_srv_count > 91
|   |   |   |   |   |   |   |   dst_host_srv_count <= 130: malicious (2196.0/861.0)
|   |   |   |   |   |   |   |   dst_host_srv_count > 130
|   |   |   |   |   |   |   |   |   dst_host_srv_count <= 131: benign (101.0/25.0)
|   |   |   |   |   |   |   |   |   dst_host_srv_count > 131: malicious (1457.0/509.0)
|   |   |   |   |   dst_host_srv_serror_rate > 0
|   |   |   |   |   |   dst_host_srv_count <= 96
|   |   |   |   |   |   |   dst_host_srv_count <= 27: benign (69.0/16.0)
|   |   |   |   |   |   |   dst_host_srv_count > 27
|   |   |   |   |   |   |   |   dst_host_srv_serror_rate <= 0.01: benign (76.0/34.0)
|   |   |   |   |   |   |   |   dst_host_srv_serror_rate > 0.01: malicious (230.0/70.0)
|   |   |   |   |   |   dst_host_srv_count > 96
|   |   |   |   |   |   |   dst_host_srv_serror_rate <= 0.02: benign (134.0/4.0)
```

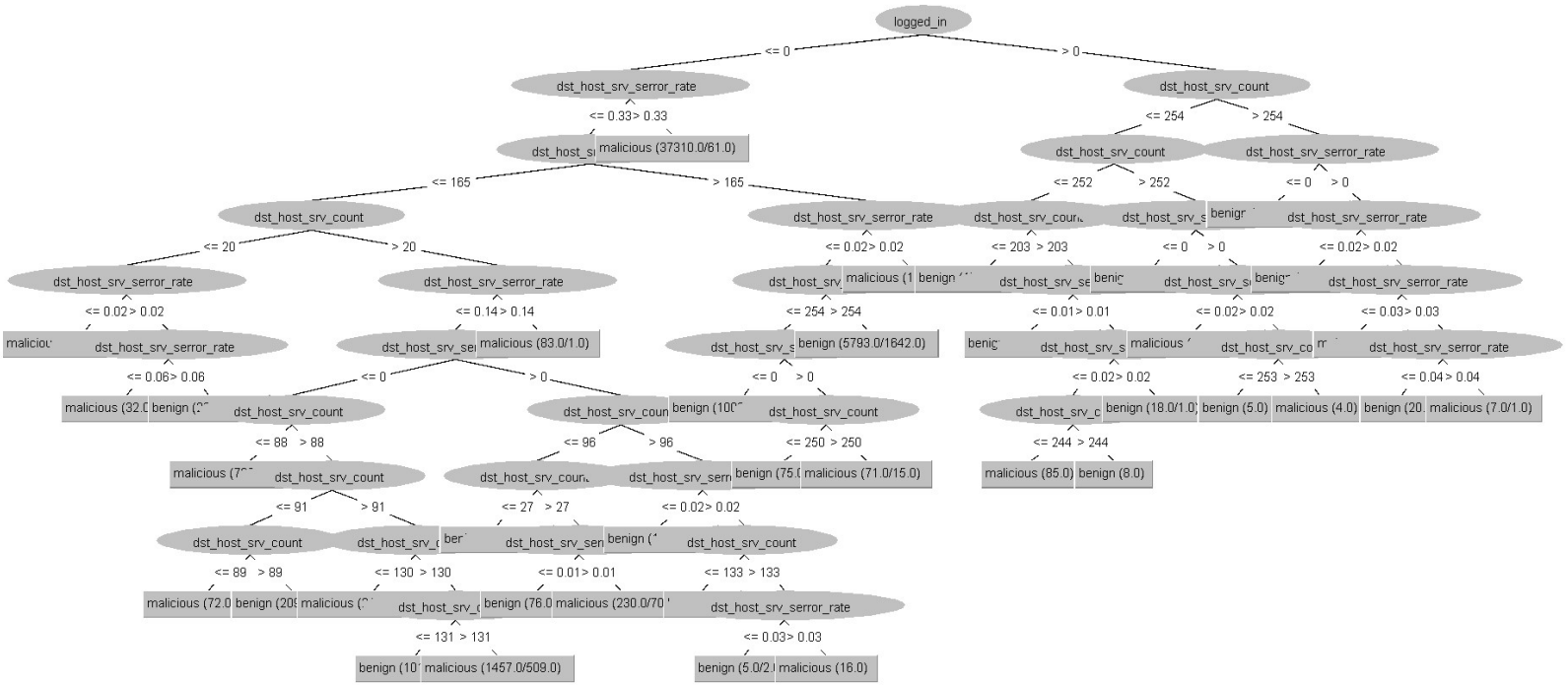
```
|   |   |   |   |   |   |   dst_host_srv_serror_rate > 0.02
|   |   |   |   |   |   |   |   dst_host_srv_count <= 133: benign (7.0)
|   |   |   |   |   |   |   |   dst_host_srv_count > 133
|   |   |   |   |   |   |   |   |   dst_host_srv_serror_rate <= 0.03: benign (5.0/2.0)
|   |   |   |   |   |   |   |   |   dst_host_srv_serror_rate > 0.03: malicious (16.0)
|   |   |   |   dst_host_srv_serror_rate > 0.14: malicious (83.0/1.0)
|   |   dst_host_srv_count > 165
|   |   |   dst_host_srv_serror_rate <= 0.02
|   |   |   |   dst_host_srv_count <= 254
|   |   |   |   |   dst_host_srv_serror_rate <= 0: benign (10034.0/1853.0)
|   |   |   |   |   dst_host_srv_serror_rate > 0
|   |   |   |   |   |   dst_host_srv_count <= 250: benign (75.0/5.0)
|   |   |   |   |   |   dst_host_srv_count > 250: malicious (71.0/15.0)
|   |   |   |   dst_host_srv_count > 254: benign (5793.0/1642.0)
|   |   |   dst_host_srv_serror_rate > 0.02: malicious (180.0/5.0)
|   dst_host_srv_serror_rate > 0.33: malicious (37310.0/61.0)
logged_in > 0
|   dst_host_srv_count <= 254
|   |   dst_host_srv_count <= 252
|   |   |   dst_host_srv_count <= 203: benign (17747.0/2875.0)
|   |   |   dst_host_srv_count > 203
|   |   |   |   dst_host_srv_serror_rate <= 0.01: benign (3781.0/803.0)
|   |   |   |   dst_host_srv_serror_rate > 0.01
|   |   |   |   |   dst_host_srv_serror_rate <= 0.02
|   |   |   |   |   |   dst_host_srv_count <= 244: malicious (85.0)
|   |   |   |   |   |   dst_host_srv_count > 244: benign (8.0)
|   |   |   |   |   dst_host_srv_serror_rate > 0.02: benign (18.0/1.0)
|   |   dst_host_srv_count > 252
|   |   |   dst_host_srv_serror_rate <= 0: benign (529.0/172.0)
|   |   |   dst_host_srv_serror_rate > 0
|   |   |   |   dst_host_srv_serror_rate <= 0.02: malicious (133.0/18.0)
|   |   |   |   dst_host_srv_serror_rate > 0.02
|   |   |   |   |   dst_host_srv_count <= 253: benign (5.0)
|   |   |   |   |   dst_host_srv_count > 253: malicious (4.0)
|   dst_host_srv_count > 254
|   |   dst_host_srv_serror_rate <= 0: benign (35028.0/405.0)
|   |   dst_host_srv_serror_rate > 0
|   |   |   dst_host_srv_serror_rate <= 0.02: benign (2449.0/141.0)
|   |   |   dst_host_srv_serror_rate > 0.02
|   |   |   |   dst_host_srv_serror_rate <= 0.03: malicious (7.0)
|   |   |   |   dst_host_srv_serror_rate > 0.03
|   |   |   |   |   dst_host_srv_serror_rate <= 0.04: benign (20.0)
|   |   |   |   |   dst_host_srv_serror_rate > 0.04: malicious (7.0/1.0)

Number of Leaves  :     37

Size of the tree :      73


Time taken to build model: 0.67 seconds
```

```
=== Evaluation on test split ===

Time taken to test model on test split: 0.01 seconds

=== Summary ===

Correctly Classified Instances       19754               88.6744 %
Incorrectly Classified Instances      2523               11.3256 %
Kappa statistic                          0.7733
Mean absolute error                      0.1716
Root mean squared error                  0.2926
Relative absolute error                 34.3719 %
Root relative squared error             58.561  %
Total Number of Instances               22277

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
               0.878     0.104     0.902      0.878    0.890      0.774    0.949     0.940     benign
               0.896     0.122     0.871      0.896    0.883      0.774    0.949     0.938     malicious
Weighted Avg.  0.887     0.113     0.887      0.887    0.887      0.774    0.949     0.939

=== Confusion Matrix ===

     a     b   <-- classified as
 10194  1410 |     a = benign
  1113  9560 |     b = malicious
```

Weka output for decision tree

Above is Weka's print out for the J48 decision tree.

Weka's decision tree has accuracy 88.67%, recall 89.6% and precision 87.1%.
Weka's decision tree can be visualized below.



Manual Implementation of Decision Tree

Using Python, the decision tree is implemented in a series of if-else statements. The code can be found in Appendix A.

Using our tree, we split the dataset to obtain a 15% test set. Subsequently, we obtained our classification metrics on this test set (Appendix B).

```
Accuracy: 0.9012883242806482
Precision: 0.8722222222222222
Recall: 0.9232623156271088
```

Decision tree metrics

	Predicted Benign	Predicted Malicious
Actual Benign	10501	796
Actual Malicious	1403	9577

Confusion matrix for decision tree

The manually implemented decision tree has similar metrics to Weka's decision tree. The differences could be due to how the test sets were obtained for each implementation. Both Weka and our implementation obtained the test set randomly.

Naive Bayes

Using Weka's Naive Bayes classifier, the following model was obtained.

```
=== Run information ===

Scheme:       weka.classifiers.bayes.NaiveBayes
Relation:     chosen_features_weka
Instances:    148516
Attributes:   4
              logged_in
              dst_host_srv_count
              dst_host_srv_serror_rate
              xAttack
Test mode:    split 85.0% train, remainder test

=== Classifier model (full training set) ===

Naive Bayes Classifier

                             Class
Attribute                  benign malicious
                           (0.52)    (0.48)
================================================
logged_in
  mean                      0.7165    0.0646
  std. dev.                 0.4507    0.2458
  weight sum                 77053     71463
  precision                      1         1

dst_host_srv_count
  mean                    193.6543   39.4691
  std. dev.                91.1676   66.4627
  weight sum                 77053     71463
  precision                      1         1

dst_host_srv_serror_rate
  mean                      0.0056    0.5162
  std. dev.                 0.0545    0.4953
  weight sum                 77053     71463
  precision                   0.01      0.01



Time taken to build model: 0.12 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.04 seconds
```

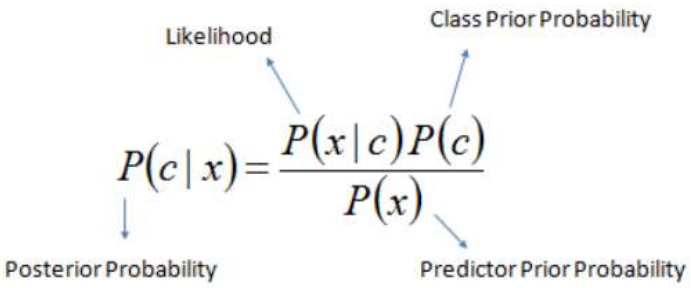
```
=== Summary ===

Correctly Classified Instances       19283               86.5601 %
Incorrectly Classified Instances      2994               13.4399 %
Kappa statistic                          0.7297
Mean absolute error                      0.1662
Root mean squared error                  0.3353
Relative absolute error                 33.2913 %
Root relative squared error             67.1249 %
Total Number of Instances            22277

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.913    0.186    0.842      0.913    0.876      0.733    0.941     0.940     benign
                 0.814    0.087    0.896      0.814    0.853      0.733    0.940     0.936     malicious
Weighted Avg.    0.866    0.139    0.868      0.866    0.865      0.733    0.940     0.938

=== Confusion Matrix ===

     a     b   <-- classified as
 10596  1008 |     a = benign
  1986  8687 |     b = malicious
```

Weka output for Naive Bayes model

Weka's Naive Bayes has accuracy 86.56%, recall 81.4% and precision 89.6%.

Manual Implementation of Naive Bayes

Using the summary statistics obtained from Weka, a manual implementation of Naive Bayes was possible (Appendix C).



Our posterior probability [P(classification | data)] is what we are interested in.
Our likelihood [P(data | classification)] and prior [P(classification)] can be obtained from Weka's summary statistics. We can calculate the likelihood by assuming a Gaussian distribution.

Define X1: *logged_in*, X2: *dst_host_srv_count*, X3: *dst_host_srv_serror_rate*

The pseudo code is as follows:

1. Obtain prior class probabilities, mean and standard deviation from Weka.
2. For each row,
    a. Obtain P(class=0 | X1, X2, X3) ≈ P(X1|class=0) * P(X2|class=0) * P(X3|class=0) * P(class=0).
    b. Obtain P(class=1 | X1, X2, X3) ≈ P(X1|class=1) * P(X2|class=1) * P(X3|class=1) * P(class=1).
    c. Return predicted class as class with higher probability. Note that we are ignoring the denominator as they are the same for both posterior probabilities.

Subsequently, we obtained our classification metrics on this test set (Appendix D).

```
Accuracy: 0.885217937783364
Precision: 0.8756969813497404
Recall: 0.8781451846139015
```

Naive Bayes metrics

	Predicted Benign	Predicted Malicious
Actual Benign	10611	1264
Actual Malicious	1293	9109

Confusion matrix for Naive Bayes

The manually implemented Naive Bayes algorithm has similar metrics to Weka's implementation. The differences could be due to how the test sets were obtained for each implementation. Both Weka and our implementation obtained the test set randomly.

Multi Layer Perceptron

Using Weka's Multi Layer Perceptron, the following model was obtained.

```
=== Run information ===

Scheme:       weka.classifiers.functions.MultilayerPerceptron -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a
Relation:     chosen_features_weka
Instances:    148516
Attributes:   4
              logged_in
              dst_host_srv_count
              dst_host_srv_serror_rate
              xAttack
Test mode:    split 85.0% train, remainder test

=== Classifier model (full training set) ===

Sigmoid Node 0
    Inputs    Weights
    Threshold    2.9386866537532312
    Node 2    -3.5497231078100104
    Node 3    -8.42281183346259
Sigmoid Node 1
    Inputs    Weights
    Threshold    -2.9386866537532312
    Node 2    3.5497231078100104
    Node 3    8.422811833462587
Sigmoid Node 2
    Inputs    Weights
    Threshold    -6.178574965522042
    Attrib logged_in    -2.1528845325622834
    Attrib dst_host_srv_count    -2.78772303592114
    Attrib dst_host_srv_serror_rate    -5.280187278884462
Sigmoid Node 3
    Inputs    Weights
    Threshold    -8.399289908252548
    Attrib logged_in    -42.89292787638223
    Attrib dst_host_srv_count    17.919887555684497
    Attrib dst_host_srv_serror_rate    56.427914833209606
Class benign
    Input
    Node 0
Class malicious
    Input
    Node 1


Time taken to build model: 17.41 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.03 seconds
```

```
=== Summary ===

Correctly Classified Instances       19631               88.1223 %
Incorrectly Classified Instances      2646               11.8777 %
Kappa statistic                          0.7621
Mean absolute error                      0.1818
Root mean squared error                  0.3018
Relative absolute error                 36.4195 %
Root relative squared error             60.4104 %
Total Number of Instances            22277

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.881    0.118    0.890      0.881    0.885      0.762    0.945     0.941     benign
                 0.882    0.119    0.872      0.882    0.877      0.762    0.945     0.944     malicious
Weighted Avg.    0.881    0.119    0.881      0.881    0.881      0.762    0.945     0.942

=== Confusion Matrix ===

     a     b   <-- classified as
 10222  1382 |     a = benign
  1264  9409 |     b = malicious
```

Weka output for Multi Layer Perceptron

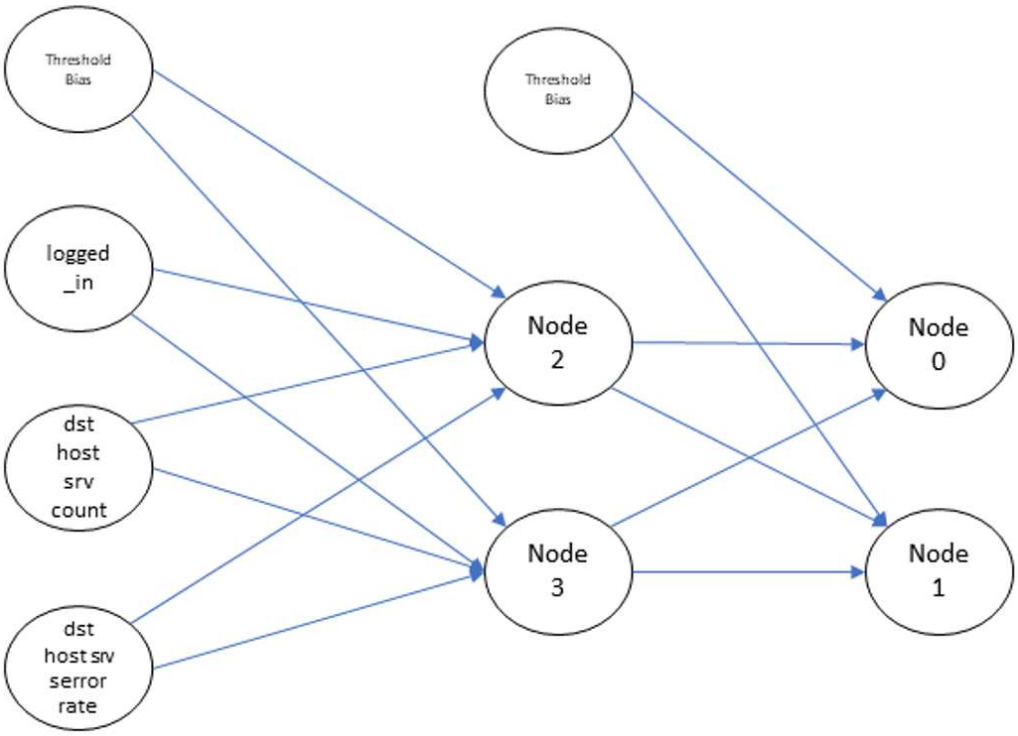


Figure 11. Neural network architecture

The neural network can be visualized as above.

Manual Implementation of Multi Layer Perceptron

To manually implement the MLP, we extract the obtained weights from Weka and create our own feed-forward network. Our activation function uses the logistic function (Appendix E).

Note that we had to normalize our features before putting them into the feed-forward network.

Subsequently, we obtained our classification metrics on this test set (Appendix F).

```
Accuracy: 0.7097005880504557
Precision: 0.749537251272559
Recall: 0.6009646600500881
```

MLP metrics

	Predicted Benign	Predicted Malicious
Actual Benign	9331	4302
Actual Malicious	2165	6479

Confusion matrix for MLP

The manually implemented MLP algorithm has similar metrics to Weka's implementation. The differences could be due to how the test sets were obtained for each implementation. Both Weka and our implementation obtained the test set randomly.

Recurrent Neural Network

Using Keras and TensorFlow, a simple RNN network was created for this binary classification problem.

2 model architectures were tested; a simple model and a complex model. The architectures are as follows:

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_17 (LSTM)               (None, 1, 100)            41600
_________________________________________________________________
dropout_6 (Dropout)          (None, 1, 100)            0
_________________________________________________________________
lstm_18 (LSTM)               (None, 100)               80400
_________________________________________________________________
dropout_7 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_4 (Dense)              (None, 32)                3232
_________________________________________________________________
dropout_8 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 33
=================================================================
Total params: 125,265
Trainable params: 125,265
Non-trainable params: 0
_________________________________________________________________
```

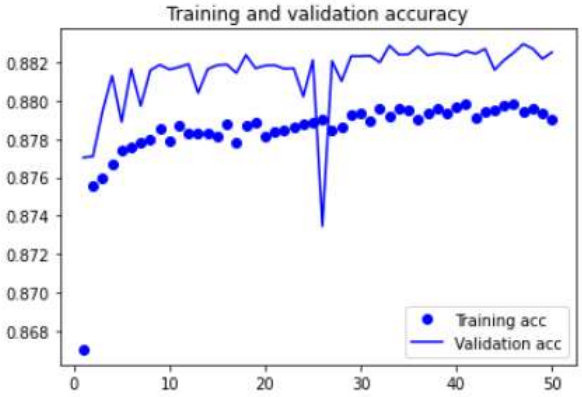
Figure 12. Architecture of complex RNN model

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_19 (LSTM)               (None, 1, 100)            41600
_________________________________________________________________
dense_6 (Dense)              (None, 1, 1)              101
=================================================================
Total params: 41,701
Trainable params: 41,701
Non-trainable params: 0
_________________________________________________________________
```

Figure 13. Architecture of simple RNN model

To see the notebook with the implementation code, please see Appendix G or the file '`STL - Data Analytics - LSTM model.ipynb`'. To see the raw Python code, see Appendix H.

The models are trained using 50 epochs and batch size of 64.



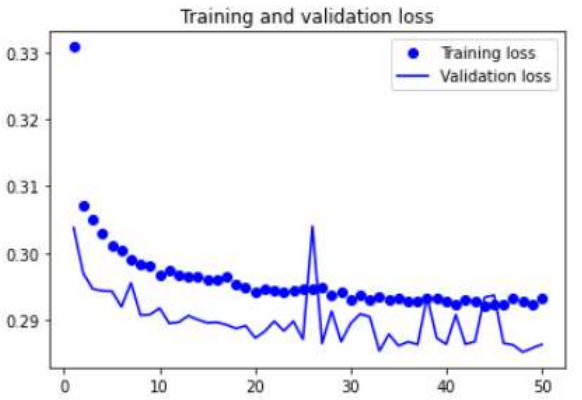
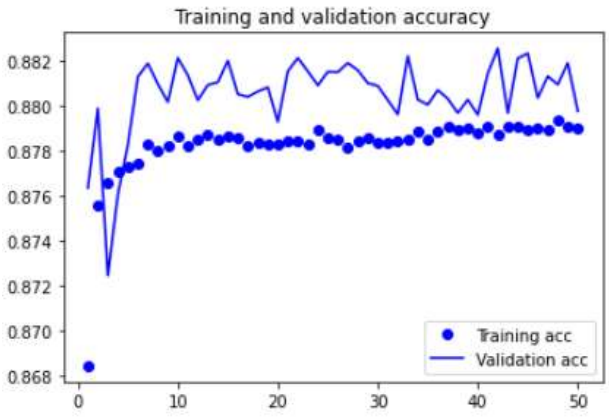


Figure 14. Loss and accuracy graphs for complex RNN model



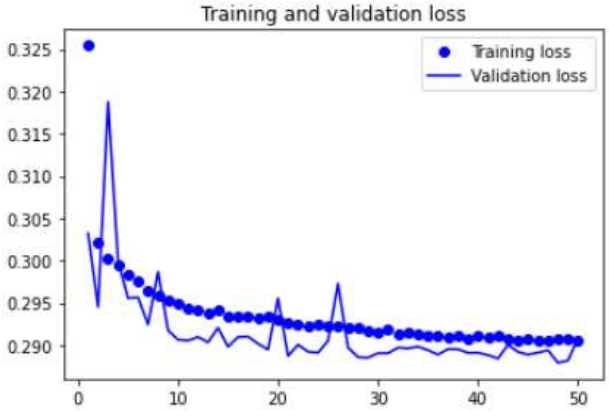


Figure 15. Loss and accuracy graphs for simple RNN model

	Predicted Benign	Predicted Malicious
Actual Benign	22360	2749
Actual Malicious	2995	20907

Table 6. Confusion matrix for simple RNN model

	Predicted Benign	Predicted Malicious
Actual Benign	22174	2572
Actual Malicious	3181	21084

Table 7. Confusion matrix for complex RNN model

	Simple RNN Model	Complex RNN Model
Accuracy	0.882801819999592	0.8826181877537695
Precision	0.8746966781022508	0.8689058314444673
Recall	0.8837926952992898	0.891274940818397

Table 8. Classification metrics for RNN models

From the loss and accuracy graphs (figures 14 and 15), we can see that both accuracy and loss graphs have converged quickly and stabilized.

The error rates have decreased exponentially to a very low value over various epochs.

The classification metrics (obtained on the test set) are also quite good. The RNN classification metrics are comparable to the various models implemented on Weka.

Conclusion

In this report, multiple machine learning models were created for the purpose of malicious network classification.

The model with the highest accuracy is the **decision tree**. However, other models (such as the gradient boosting classifier) were not tested and could possibly yield better accuracy metrics.

Furthermore, more experiments could have been done to further tweak the Neural Network architectures, to achieve much better performance.

With these models and possibly more data, a more comprehensive, data-driven approach to Network Intrusion Detection could be implemented.

References

[1] Botes, F., Leenen, L. and De La Harpe, R. (2017). Ant Colony Induced Decision Trees for Intrusion Detection. In: 16th European Conference on Cyber Warfare and Security. ACPI (June 12, 2017), pp.74-83. Retrieved from https://github.com/InitRoot/NSLKDD-Dataset

[2] NSL-KDD dataset. Canadian Institute for Cybersecuirty, University of New Brunswick. Retrieved from https://www.unb.ca/cic/datasets/nsl.html

Appendix

A. Decision Tree Function

```
def classification_tree(logged_in, dst_host_srv_count, dst_host_srv_serror_rate):
    # Rename variables for easier splitting
    log = logged_in
    count = dst_host_srv_count
    error = dst_host_srv_serror_rate
    rate = dst_host_srv_serror_rate

    # Do splitting logic
    if log > 0:
        if count <= 254:
            if count <= 252:
                if count <= 203:
                    return('benign')
                else: #count > 203
                    if error <= 0.01:
                        return('benign')
                    elif error > 0.01:
                        if error <= 0.02:
                            if count <= 244:
                                return('malicious')
                            elif count > 244:
                                return('benign')
                        elif error > 0.02:
                            return('benign')
            elif count > 252:
                if error <= 0:
                    return('benign')
                elif error > 0:
                    if error <= 0.02:
                        return('malicious')
                    elif error > 0.02:
                        if count <= 253:
                            return('benign')
                        elif count > 253:
                            return('malicious')
        elif count > 254:
            if error <= 0:
                return('benign')
            elif error > 0:
                if error <= 0.02:
                    return('benign')
                elif error > 0.02:
                    if error <= 0.03:
                        return('malicious')
                    elif error > 0.03:
                        if error <= 0.04:
                            return('benign')
                        elif error > 0.04:
                            return('malicious')

    if log <= 0:
        if error <= 0.33:
```

```
            if count <= 165:
                if count <= 20:
                    if error <= 0.02:
                        return('malicious')
                    elif error > 0.02:
                        if error <= 0.02:
                            return('malicious')
                        elif error > 0.02:
                            if error <= 0.06:
                                return('malicious')
                            elif error > 0.06:
                                return('benign')
                elif count > 20:
                    if error <= 0.14:
                        if error <= 0:
                            if count <= 88:
                                return('malicious')
                            elif count > 88:
                                if count <= 91:
                                    if count <= 89:
                                        return('malicious')
                                    elif count > 89:
                                        return('benign')
                                if count > 91:
                                    if count <= 130:
                                        return('malicious')
                                    if count > 130:
                                        if count <= 131:
                                            return('benign')
                                        elif count > 131:
                                            return('malicious')
                        if error > 0:
                            if count <= 96:
                                if count <= 27:
                                    return('benign')
                                elif count > 27:
                                    if error <= 0.01:
                                        return('benign')
                                    elif error > 0.01:
                                        return('benign')
                            if count > 96:
                                if error <= 0.02:
                                    return('benign')
                                elif error > 0.02:
                                    if count <= 133 :
                                        return('benign')
                                    elif count > 133:
                                        if error <= 0.03:
                                            return('benign')
                                        elif error > 0.03:
                                            return('malicious')
                    elif error > 0.14:
                        return('malicious')
            elif count > 165:
                if error <= 0.02:
                    if count <= 254:
                        if rate <= 0:
                            return('benign')
                        elif rate > 0:
```

```
                        if count <= 250:
                            return('benign')
                        elif count > 250:
                            return('malicious')
                elif count > 254:
                    return('benign')
            elif error > 0.02:
                return('malicious')
    elif error > 0.33:
        return('malicious')

return('No match found')
```

B. Classification Metrics of Decision Tree

```
# Training set is 85% of dataset, test set is 15% of dataset
tree_test_set = dataset.head(int(0.15 * len(dataset)))
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index, row in tree_test_set.iterrows():
    logged_in = row['logged_in']
    srv_count = row['dst_host_srv_count']
    error_rate = row['dst_host_srv_serror_rate']
    actual_label = row['xAttack']

    predicted_label = classification_tree(logged_in = logged_in, dst_host_srv_count = srv_count,
                                          dst_host_srv_serror_rate = error_rate)

    # Error checking
    if predicted_label not in ['malicious', 'benign']:
        print(predicted_label)

    # Calculate confusion matrix values
    if actual_label == 'malicious' and predicted_label == 'malicious':
        true_positive += 1
    elif actual_label == 'benign' and predicted_label == 'benign':
        true_negative += 1
    elif actual_label == 'malicious' and predicted_label == 'benign':
        false_negative += 1
    elif actual_label == 'benign' and predicted_label == 'malicious':
        false_positive += 1
    else:
        print('error')

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
```

	Predicted Benign	Predicted Malicious
Actual Benign	10501	796
Actual Malicious	1403	9577

```
# Print other classification metrics
print('Accuracy:', (true_positive + true_negative) / len(tree_test_set))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))

Accuracy: 0.9012883242806482
Precision: 0.8722222222222222
Recall: 0.9232623156271088
```

C. Naive Bayes Function

```
from math import sqrt
from math import pi
from math import exp

# Read in test set data
dataset = pd.read_csv('chosen_features_weka.csv')
nb_test_set = dataset.head(int(0.15 * len(dataset)))

# Calculate the Gaussian probability distribution function for x
def calculate_probability(x, mean, stdev):
    exponent = exp(-((x-mean)**2 / (2 * stdev**2 )))
    return (1 / (sqrt(2 * pi) * stdev)) * exponent

# Define statistics from Weka
weka_stats = {
    'class_0_prior': 0.52, 'class_1_prior': 0.48,

    'class_0_logged_in_mean': 0.7165, 'class_0_logged_in_sd': 0.4507,
    'class_1_logged_in_mean': 0.0646, 'class_1_logged_in_sd': 0.2458,

    'class_0_count_mean': 193.6543, 'class_0_count_sd': 91.1676,
    'class_1_count_mean': 39.4691, 'class_1_count_sd': 66.4627,

    'class_0_error_mean': 0.0056, 'class_0_error_sd': 0.0545,
    'class_1_error_mean': 0.5162, 'class_1_error_sd': 0.4953
}

def nb_pred(test_row, weka_stats):

    # Calculate class 0 probability
    class_0_prob = weka_stats['class_0_prior']
    class_0_prob *= calculate_probability(test_row['logged_in'], weka_stats['class_0_logged_in_mean'],
                                                                 weka_stats['class_0_logged_in_sd'])
    class_0_prob *= calculate_probability(test_row['dst_host_srv_count'],
weka_stats['class_0_count_mean'],
                                                                 weka_stats['class_0_count_sd'])
    class_0_prob *= calculate_probability(test_row['dst_host_srv_serror_rate'],
weka_stats['class_0_error_mean'],
                                                                 weka_stats['class_0_error_sd'])
    # Calculate class 1 probability
    class_1_prob = weka_stats['class_1_prior']
    class_1_prob *= calculate_probability(test_row['logged_in'], weka_stats['class_1_logged_in_mean'],
                                                                 weka_stats['class_1_logged_in_sd'])
    class_1_prob *= calculate_probability(test_row['dst_host_srv_count'],
weka_stats['class_1_count_mean'],
                                                                 weka_stats['class_1_count_sd'])
    class_1_prob *= calculate_probability(test_row['dst_host_srv_serror_rate'],
weka_stats['class_1_error_mean'],
                                                                 weka_stats['class_1_error_sd'])
    # Return classification
    if class_0_prob > class_1_prob:
        return('benign')
    else:
        return('malicious')
```

D. Classification Metrics of Naive Bayes

```
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index, row in nb_test_set.iterrows():
    actual_label = row['xAttack']
    predicted_label = nb_pred(test_row = row, weka_stats = weka_stats)

    # Error checking
    if predicted_label not in ['malicious', 'benign']:
        print(predicted_label)

    # Calculate confusion matrix values
    if actual_label == 'malicious' and predicted_label == 'malicious':
        true_positive += 1
    elif actual_label == 'benign' and predicted_label == 'benign':
        true_negative += 1
    elif actual_label == 'malicious' and predicted_label == 'benign':
        false_negative += 1
    elif actual_label == 'benign' and predicted_label == 'malicious':
        false_positive += 1
    else:
        print('error')

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
df
```

	Predicted Benign	Predicted Malicious
Actual Benign	10611	1264
Actual Malicious	1293	9109

```
# Print other classification metrics
print('Accuracy:', (true_positive + true_negative) / len(nb_test_set))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))
Accuracy: 0.885217937783364
Precision: 0.8756969813497404
Recall: 0.8781451846139015
```

E. Multi Layer Perceptron Function

```
from scipy.stats import logistic

def logistic_function(x):
    return (logistic.cdf(x))

def mlp_classifier(row):
    log_in, count, error = row['logged_in'], row['dst_host_srv_count'], row['dst_host_srv_serror_rate']

    node_2 = -6.178574965522042 + (-2.1528845325622834 * log_in) + (-2.78772303592114 * count) +
(-5.280187278884462 * error)
    node_3 = -8.399289908252548 + (-42.89292787638223 * log_in) + (17.919887555684497 * count) +
(56.427914833209606 * error)

    node_2 = logistic_function(node_2)
    node_3 = logistic_function(node_3)

    node_0 = 2.9386866537532312 + (-3.5497231078100104 * node_2) + (-8.42281183346259 * node_3)
    node_1 = -2.9386866537532312 + (3.5497231078100104 * node_2) + (8.422811833462587 * node_3)

    node_0 = logistic_function(node_0)
    node_1 = logistic_function(node_1)

    if node_0 > node_1:
        return('benign')
    else:
        return('malicious')
```

F. Classification Metrics of Multi Layer Perceptron

```
# Read in test set data
dataset = pd.read_csv('chosen_features_weka.csv')

# Normalize dataset
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
dataset[['logged_in', 'dst_host_srv_count', 'dst_host_srv_serror_rate']] =
scaler.fit_transform(dataset[['logged_in', 'dst_host_srv_count', 'dst_host_srv_serror_rate']])

# Extract test set
mlp_test_set = dataset.sample(int(0.15 * len(dataset)))

true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index, row in mlp_test_set.iterrows():
    actual_label = row['xAttack']
    predicted_label = mlp_classifier(row)

    # Error checking
    if predicted_label not in ['malicious', 'benign']:
        print(predicted_label)

    # Calculate confusion matrix values
    if actual_label == 'malicious' and predicted_label == 'malicious':
        true_positive += 1
    elif actual_label == 'benign' and predicted_label == 'benign':
        true_negative += 1
    elif actual_label == 'malicious' and predicted_label == 'benign':
        false_negative += 1
    elif actual_label == 'benign' and predicted_label == 'malicious':
        false_positive += 1
    else:
        print('error')

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
df
```

	Predicted Benign	Predicted Malicious
Actual Benign	9331	4302
Actual Malicious	2165	6479

```
# Print other classification metrics
print('Accuracy:', (true_positive + true_negative) / len(mlp_test_set))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))

Accuracy: 0.7097005880504557
Precision: 0.749537251272559
Recall: 0.6009646600500881
```

G. Recurrent Neural Network Notebook


```
# Upload chosen_features_weka.csv
from google.colab import files
files.upload()
```

Choose Files chosen_feat…s_weka.csv

- **chosen_features_weka.csv**(application/vnd.ms-excel) - 2782898 bytes, last modified: 10/12/2021 - 1

done

```
Saving chosen_features_weka.csv to chosen_features_weka.csv
{'chosen_features_weka.csv': b'logged_in,dst_host_srv_count,dst_host_srv_serror_rate,
```

```
# Define a function to print accuracy graphs
def print_graphs(history):
  acc = history.history['accuracy']
  val_acc = history.history['val_accuracy']
  loss = history.history['loss']
  val_loss = history.history['val_loss']
  epochs = range(1, len(acc) + 1)

  plt.plot(epochs, acc, 'bo', label='Training acc')
  plt.plot(epochs, val_acc, 'b', label='Validation acc')
  plt.title('Training and validation accuracy')
  plt.legend()

  plt.figure()

  plt.plot(epochs, loss, 'bo', label='Training loss')
  plt.plot(epochs, val_loss, 'b', label='Validation loss')
  plt.title('Training and validation loss')
  plt.legend()

  plt.show()
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Load dataset
dataset = pd.read_csv('chosen_features_weka.csv')

# Change labels to binary
dataset['xAttack'] = np.where(dataset['xAttack'] == 'benign', 0, 1)
dataset.head()
```

```
      logged_in  dst_host_srv_count  dst_host_srv_serror_rate  xAttack
```

```
# Split into test and train set
from sklearn.model_selection import train_test_split
X, y = dataset[['logged_in', 'dst_host_srv_count', 'dst_host_srv_serror_rate']], datase
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=

# Reshape dataset
X_train = X_train.values.reshape(-1,·1,·3)
X_test  = X_test.values.reshape(-1, 1, 3)
y_train = y_train.values.reshape(-1, 1, 1)
y_test = y_test.values.reshape(-1, 1, 1)
```

```
import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM

model_complex = tensorflow.keras.models.Sequential()
model_complex.add(tensorflow.keras.layers.LSTM(100, input_shape=(1, 3), activation='rel
model_complex.add(Dropout(0.2))

model_complex.add(LSTM(100))
model_complex.add(Dropout(0.2))
model_complex.add(Dense(32, activation='relu'))
model_complex.add(Dropout(0.2))


model_complex.add(tensorflow.keras.layers.Dense(1, activation='sigmoid'))
model_complex.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'
```

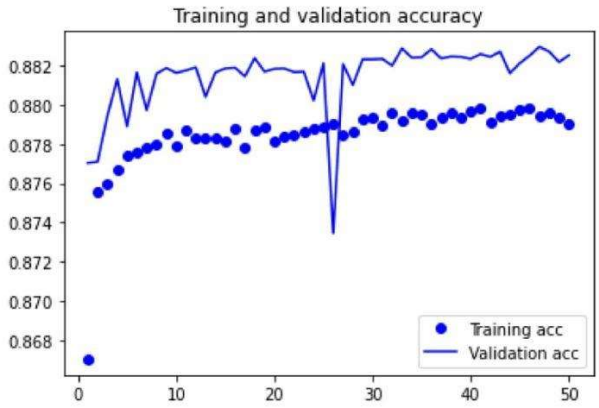
```
model_complex.summary()
```

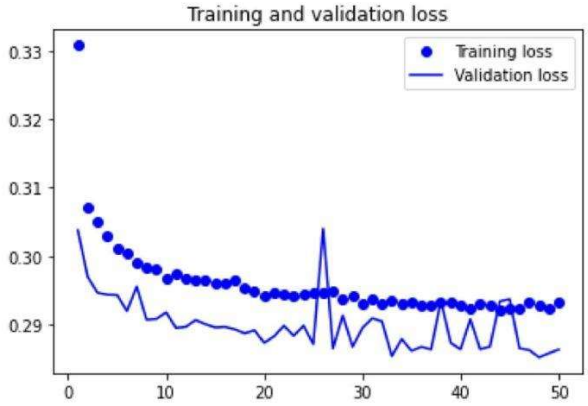
```
Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_20 (LSTM)               (None, 1, 100)            41600
_________________________________________________________________
dropout_9 (Dropout)          (None, 1, 100)            0
_________________________________________________________________
lstm_21 (LSTM)               (None, 100)               80400
_________________________________________________________________
dropout_10 (Dropout)         (None, 100)               0
_________________________________________________________________
dense_7 (Dense)              (None, 32)                3232
_________________________________________________________________
dropout_11 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 33
=================================================================
Total params: 125,265
Trainable params: 125,265
Non-trainable params: 0
_________________________________________________________________
```

```
history = model_complex.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=
```

```
Epoch 22/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2947 - accuracy
Epoch 23/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2945 - accuracy
Epoch 24/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2946 - accuracy
Epoch 25/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2938 - accuracy
Epoch 26/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2945 - accuracy
Epoch 27/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2941 - accuracy
Epoch 28/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2951 - accuracy
Epoch 29/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2940 - accuracy
Epoch 30/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2944 - accuracy
Epoch 31/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2936 - accuracy
Epoch 32/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2941 - accuracy
Epoch 33/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2932 - accuracy
Epoch 34/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2937 - accuracy
Epoch 35/50
1555/1555 [==============================] - 13s 8ms/step - loss: 0.2934 - accuracy
Epoch 36/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2938 - accuracy
Epoch 37/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2935 - accuracy
Epoch 38/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2926 - accuracy
Epoch 39/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2936 - accuracy
Epoch 40/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2931 - accuracy
Epoch 41/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2931 - accuracy
Epoch 42/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2928 - accuracy
Epoch 43/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2922 - accuracy
Epoch 44/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2927 - accuracy
Epoch 45/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2927 - accuracy
Epoch 46/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2923 - accuracy
Epoch 47/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2926 - accuracy
Epoch 48/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2926 - accuracy
Epoch 49/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2923 - accuracy
Epoch 50/50
1555/1555 [==============================] - 12s 8ms/step - loss: 0.2929 - accuracy
```

```
1 print_graphs(history)
```






```
1 model_simple = tensorflow.keras.models.Sequential()
2 model_simple.add(tensorflow.keras.layers.LSTM(100, input_shape=(1, 3), activation='relu
3 model_simple.add(tensorflow.keras.layers.Dense(1, activation='sigmoid'))
4 model_simple.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy']
5 model_simple.summary()
```

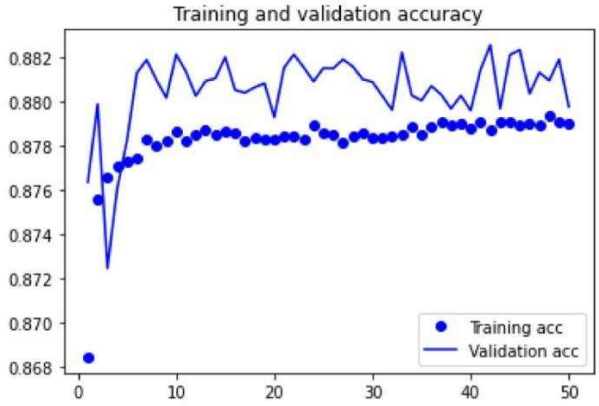
```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_22 (LSTM)               (None, 1, 100)            41600
_________________________________________________________________
dense_9 (Dense)              (None, 1, 1)              101
=================================================================
Total params: 41,701
Trainable params: 41,701
Non-trainable params: 0
_________________________________________________________________
```

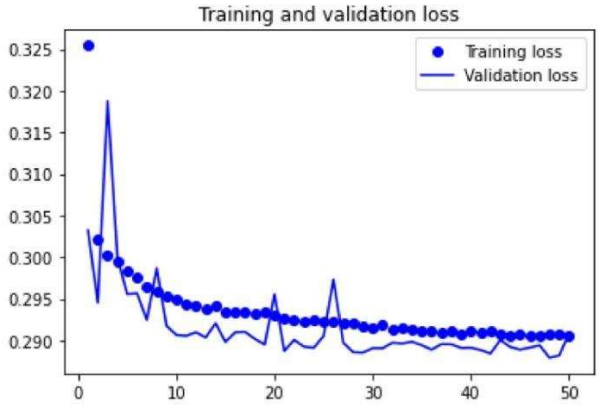
```
1 history = model_simple.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=5
```

```
Epoch 1/50
1555/1555 [==============================] - 8s 4ms/step - loss: 0.3354 - accuracy
```

```
Epoch 2/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.3037 - accuracy
Epoch 3/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.3007 - accuracy
Epoch 4/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.3005 - accuracy
Epoch 5/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2996 - accuracy
Epoch 6/50
1555/1555 [==============================] - 7s 4ms/step - loss: 0.2987 - accuracy
Epoch 7/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2972 - accuracy
Epoch 8/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2971 - accuracy
Epoch 9/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2967 - accuracy
Epoch 10/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2956 - accuracy
Epoch 11/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2956 - accuracy
Epoch 12/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2950 - accuracy
Epoch 13/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2948 - accuracy
Epoch 14/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2944 - accuracy
Epoch 15/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2945 - accuracy
Epoch 16/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2942 - accuracy
Epoch 17/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2936 - accuracy
Epoch 18/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2933 - accuracy
Epoch 19/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2931 - accuracy
Epoch 20/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2930 - accuracy
Epoch 21/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2927 - accuracy
Epoch 22/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2922 - accuracy
Epoch 23/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2921 - accuracy
Epoch 24/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2921 - accuracy
Epoch 25/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2921 - accuracy
Epoch 26/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2919 - accuracy
Epoch 27/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2915 - accuracy
Epoch 28/50
1555/1555 [==============================] - 7s 4ms/step - loss: 0.2916 - accuracy
Epoch 29/50
1555/1555 [==============================] - 6s 4ms/step - loss: 0.2914 - accuracy
```

```
1 print_graphs(history)
```





Get classification metrics on test set

```
# Get metrics for model_simple
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index in range(len(X_test)):
  test_row = X_test[index,]
  test_row = test_row.reshape(-1, 1, 3)
  predicted_prob = model_simple.predict(test_row)[0][0][0]

  predicted_label = None
  if predicted_prob >= 0.50:
    predicted_label = 1
  else:
    predicted_label = 0

  actual_label = y_test[index][0][0]

  if actual_label == 1 and predicted_label == 1:
      true_positive += 1
  elif actual_label == 0 and predicted_label == 0:
      true_negative += 1
  elif actual_label == 1 and predicted_label == 0:
      false_negative += 1
  elif actual_label == 0 and predicted_label == 1:
```

```
      false_positive += 1
  else:
      print('error')

  if index % 1000 == 0:
    print(index)

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
df
```

```
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
11000
12000
13000
14000
```

```
# Print other classification metrics for model_simple
print('Accuracy:', (true_positive + true_negative) / len(X_test))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))
```

```
Accuracy: 0.882801819999592
Precision: 0.8746966781022508
Recall: 0.8837926952992898
```

```
25000
```

```

```

```
0.06705746
```

```
30000
```

```
# Get metrics for model_complex
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index in range(len(X_test)):
  test_row = X_test[index,]
  test_row = test_row.reshape(-1, 1, 3)
  predicted_prob = model_complex.predict(test_row)[0][0]

  predicted_label = None
  if predicted_prob >= 0.50:
    predicted_label = 1
  else:
    predicted_label = 0

  actual_label = y_test[index][0][0]

  if actual_label == 1 and predicted_label == 1:
      true_positive += 1
  elif actual_label == 0 and predicted_label == 0:
      true_negative += 1
  elif actual_label == 1 and predicted_label == 0:
      false_negative += 1
  elif actual_label == 0 and predicted_label == 1:
      false_positive += 1
  else:
      print('error')
```

```
  if index % 1000 == 0:
    print(index)

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
df
```

```
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
```

```
# Print other classification metrics for model_complex
print('Accuracy:', (true_positive + true_negative) / len(X_test))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))
```

```
Accuracy: 0.8826181877537695
Precision: 0.8689058314444673
Recall: 0.891274940818397

21000
22000
23000
24000
25000
26000
27000
28000
29000
30000
31000
32000
33000
34000
35000
36000
37000
38000
39000
40000
41000
42000
43000
44000
```

✓ 0s completed at 5:49 PM

H. Recurrent Neural Network Code

```
# -*- coding: utf-8 -*-
"""STL1 - P1 - LSTM.ipynb

Automatically generated by Colaboratory.

"""

# Upload chosen_features_weka.csv
from google.colab import files
files.upload()

# Define a function to print accuracy graphs
def print_graphs(history):
  acc = history.history['accuracy']
  val_acc = history.history['val_accuracy']
  loss = history.history['loss']
  val_loss = history.history['val_loss']
  epochs = range(1, len(acc) + 1)

  plt.plot(epochs, acc, 'bo', label='Training acc')
  plt.plot(epochs, val_acc, 'b', label='Validation acc')
  plt.title('Training and validation accuracy')
  plt.legend()

  plt.figure()

  plt.plot(epochs, loss, 'bo', label='Training loss')
  plt.plot(epochs, val_loss, 'b', label='Validation loss')
  plt.title('Training and validation loss')
  plt.legend()

  plt.show()

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Load dataset
dataset = pd.read_csv('chosen_features_weka.csv')

# Change labels to binary
dataset['xAttack'] = np.where(dataset['xAttack'] == 'benign', 0, 1)
dataset.head()

# Split into test and train set
from sklearn.model_selection import train_test_split
X, y = dataset[['logged_in', 'dst_host_srv_count', 'dst_host_srv_serror_rate']], dataset[['xAttack']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)

# Reshape dataset
X_train = X_train.values.reshape(-1, 1, 3)
X_test  = X_test.values.reshape(-1, 1, 3)
y_train = y_train.values.reshape(-1, 1, 1)
y_test = y_test.values.reshape(-1, 1, 1)

import tensorflow
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM

model_complex = tensorflow.keras.models.Sequential()
model_complex.add(tensorflow.keras.layers.LSTM(100, input_shape=(1, 3), activation='relu',
return_sequences=True))
model_complex.add(Dropout(0.2))

model_complex.add(LSTM(100))
model_complex.add(Dropout(0.2))
model_complex.add(Dense(32, activation='relu'))
model_complex.add(Dropout(0.2))


model_complex.add(tensorflow.keras.layers.Dense(1, activation='sigmoid'))
model_complex.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

model_complex.summary()

history = model_complex.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50,
batch_size=64)

print_graphs(history)

model_simple = tensorflow.keras.models.Sequential()
model_simple.add(tensorflow.keras.layers.LSTM(100, input_shape=(1, 3), activation='relu',
return_sequences=True))
model_simple.add(tensorflow.keras.layers.Dense(1, activation='sigmoid'))
model_simple.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model_simple.summary()

history = model_simple.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50, batch_size=64)

print_graphs(history)

"""## Get classification metrics on test set"""

# Get metrics for model_simple
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index in range(len(X_test)):
  test_row = X_test[index,]
  test_row = test_row.reshape(-1, 1, 3)
  predicted_prob = model_simple.predict(test_row)[0][0][0]

  predicted_label = None
  if predicted_prob >= 0.50:
    predicted_label = 1
  else:
    predicted_label = 0

  actual_label = y_test[index][0][0]

  if actual_label == 1 and predicted_label == 1:
      true_positive += 1
  elif actual_label == 0 and predicted_label == 0:
      true_negative += 1
  elif actual_label == 1 and predicted_label == 0:
      false_negative += 1
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  elif actual_label == 0 and predicted_label == 1:
      false_positive += 1
  else:
      print('error')

  if index % 1000 == 0:
    print(index)

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
df

# Print other classification metrics for model_simple
print('Accuracy:', (true_positive + true_negative) / len(X_test))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))



# Get metrics for model_complex
true_positive, true_negative, false_positive, false_negative = 0, 0, 0, 0

for index in range(len(X_test)):
  test_row = X_test[index,]
  test_row = test_row.reshape(-1, 1, 3)
  predicted_prob = model_complex.predict(test_row)[0][0]

  predicted_label = None
  if predicted_prob >= 0.50:
    predicted_label = 1
  else:
    predicted_label = 0

  actual_label = y_test[index][0][0]

  if actual_label == 1 and predicted_label == 1:
      true_positive += 1
  elif actual_label == 0 and predicted_label == 0:
      true_negative += 1
  elif actual_label == 1 and predicted_label == 0:
      false_negative += 1
  elif actual_label == 0 and predicted_label == 1:
      false_positive += 1
  else:
      print('error')

  if index % 1000 == 0:
    print(index)

# Print confusion matrix
data = {'Predicted Benign':[true_negative, false_positive],
        'Predicted Malicious':[false_negative, true_positive]}
df = pd.DataFrame(data, index =['Actual Benign',
                                'Actual Malicious',
                               ])
```

```
df

# Print other classification metrics for model_complex
print('Accuracy:', (true_positive + true_negative) / len(X_test))
print('Precision:', (true_positive) / (true_positive + false_positive))
print('Recall:', (true_positive) / (true_positive + false_negative))
```