Analysis of Network Intrusion Detection System

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STAGE 1: DATA PRE-PROCESSING

All features are made numerical using one-Hot-encoding. The features are scaled to avoid features with large values that may weigh too much in the results.

Importing neccessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import sys
import sklearn

from sklearn.preprocessing import LabelEncoder,OneHotEncoder
from sklearn import preprocessing
from sklearn.feature_selection import SelectPercentile, f_classif

from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier

from sklearn.model_selection import cross_val_score
from sklearn import metrics

import matplotlib.pyplot as plt
from sklearn.feature_selection import RFECV
from sklearn.model_selection import StratifiedKFold
%matplotlib inline

from sklearn.model_selection import StratifiedKFold
```

Define Column Names for the Dataset

In [2]:
```
col_names = ["duration","protocol_type","service","flag","src_bytes",
    "dst_bytes","land","wrong_fragment","urgent","hot","num_failed_logins",
    "logged_in","num_compromised","root_shell","su_attempted","num_root",
    "num_file_creations","num_shells","num_access_files","num_outbound_cmds",
    "is_host_login","is_guest_login","count","srv_count","serror_rate",
    "srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
    "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
    "dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
    "dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
    "dst_host_rerror_rate","dst_host_srv_rerror_rate","label"]
```

Import Dataset and Check Dimensions

In [3]:
```
df_train = pd.read_csv("../Data/KDDTrain+_2.csv", header=None, names = col_names)
df_test = pd.read_csv("../Data/KDDTest+_2.csv", header=None, names = col_names)
```

```
print('Dimensions of the Training set:',df_train.shape)
print('Dimensions of the Test set:',df_test.shape)
```

```
Dimensions of the Training set: (125973, 42)
Dimensions of the Test set: (22544, 42)
```

Check Dataframe and description

In [4]:

```
df_train.head(5)
```

Out[4]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot
0	0	tcp	ftp_data	SF	491	0	0	0	0	0
1	0	udp	other	SF	146	0	0	0	0	0
2	0	tcp	private	S0	0	0	0	0	0	0
3	0	tcp	http	SF	232	8153	0	0	0	0
4	0	tcp	http	SF	199	420	0	0	0	0

5 rows × 42 columns

In [5]:

```
df_train.describe()
```

Out[5]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	
count	125973.00000	1.259730e+05	1.259730e+05	125973.000000	125973.000000	125973.000000	1
mean	287.14465	4.556674e+04	1.977911e+04	0.000198	0.022687	0.000111	
std	2604.51531	5.870331e+06	4.021269e+06	0.014086	0.253530	0.014366	
min	0.00000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
25%	0.00000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
50%	0.00000	4.400000e+01	0.000000e+00	0.000000	0.000000	0.000000	
75%	0.00000	2.760000e+02	5.160000e+02	0.000000	0.000000	0.000000	
max	42908.00000	1.379964e+09	1.309937e+09	1.000000	3.000000	3.000000	

8 rows × 38 columns

In [6]:

```
df_test.head(5)
```

Out[6]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	ho
0	0	tcp	private	REJ	0	0	0	0	0	
1	0	tcp	private	REJ	0	0	0	0	0	
2	2	tcp	ftp_data	SF	12983	0	0	0	0	
3	0	icmp	eco_i	SF	20	0	0	0	0	
4	1	tcp	telnet	RSTO	0	15	0	0	0	

5 rows × 42 columns

In [7]:
```
df_test.describe()
```

Out[7]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	
count	22544.000000	2.254400e+04	2.254400e+04	22544.000000	22544.000000	22544.000000	225
mean	218.859076	1.039545e+04	2.056019e+03	0.000311	0.008428	0.000710	
std	1407.176612	4.727864e+05	2.121930e+04	0.017619	0.142599	0.036473	
min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
25%	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
50%	0.000000	5.400000e+01	4.600000e+01	0.000000	0.000000	0.000000	
75%	0.000000	2.870000e+02	6.010000e+02	0.000000	0.000000	0.000000	
max	57715.000000	6.282565e+07	1.345927e+06	1.000000	3.000000	3.000000	1

8 rows × 38 columns

Analysing Label Distribution of Training and Testing Dataset

In [8]:
```
print('Label distribution of Training set:')
print(df_train['label'].value_counts())
```

```
Label distribution of Training set:
normal             67343
neptune            41214
satan               3633
ipsweep             3599
portsweep           2931
smurf               2646
nmap                1493
back                 956
teardrop             892
warezclient          890
pod                  201
guess_passwd          53
buffer_overflow       30
warezmaster           20
land                  18
imap                  11
rootkit               10
loadmodule             9
ftp_write              8
multihop               7
phf                    4
perl                   3
spy                    2
Name: label, dtype: int64
```

In [9]:
```
print('Label distribution of Testing set:')
print(df_test['label'].value_counts())
```

```
Label distribution of Testing set:
normal             9711
neptune            4657
guess_passwd       1231
mscan               996
warezmaster         944
apache2             737
satan               735
processtable        685
smurf               665
```

```
back               359
snmpguess          331
saint              319
mailbomb           293
snmpgetattack      178
portsweep          157
ipsweep            141
httptunnel         133
nmap                73
pod                 41
buffer_overflow     20
multihop            18
named               17
ps                  15
sendmail            14
xterm               13
rootkit             13
teardrop            12
xlock                9
land                 7
xsnoop               4
ftp_write            3
sqlattack            2
perl                 2
phf                  2
udpstorm             2
worm                 2
loadmodule           2
imap                 1
Name: label, dtype: int64
```

Features Description

For Training Dataset

In [10]:
```
print('Training Dataset:')
for col_name in df_train.columns:
    if df_train[col_name].dtypes == 'object' :
        unique_cat = len(df_train[col_name].unique())
        print("Feature '{col_name}' has {unique_cat} categories".format(col_name=col
```

```
Training Dataset:
Feature 'protocol_type' has 3 categories
Feature 'service' has 70 categories
Feature 'flag' has 11 categories
Feature 'label' has 23 categories
```

In [11]:
```
print('Distribution of categories in service:')
print(df_train['service'].value_counts().sort_values(ascending=False).head())
```

```
Distribution of categories in service:
http        40338
private     21853
domain_u     9043
smtp         7313
ftp_data     6860
Name: service, dtype: int64
```

For Testing Dataset

In [12]:
```
print('Testing Dataset:')
for col_name in df_test.columns:
    if df_test[col_name].dtypes == 'object' :
        unique_cat = len(df_test[col_name].unique())
        print("Feature '{col_name}' has {unique_cat} categories".format(col_name=col
```

```
Testing Dataset:
Feature 'protocol_type' has 3 categories
Feature 'service' has 64 categories
```

```
Feature 'flag' has 11 categories
Feature 'label' has 38 categories
```

Dataset Column Manipulation

In [13]:
```
categorical_columns=['protocol_type', 'service', 'flag']

df_categorical_values = df_train[categorical_columns]
testdf_categorical_values = df_test[categorical_columns]
df_categorical_values.head()
```

Out[13]:

	protocol_type	service	flag
0	tcp	ftp_data	SF
1	udp	other	SF
2	tcp	private	S0
3	tcp	http	SF
4	tcp	http	SF

Assign column names to dummy

In [14]:
```
# protocol type
unique_protocol=sorted(df_train.protocol_type.unique())
string1 = 'Protocol_type_'
unique_protocol2=[string1 + x for x in unique_protocol]

# service
unique_service=sorted(df_train.service.unique())
string2 = 'service_'
unique_service2=[string2 + x for x in unique_service]

# flag
unique_flag=sorted(df_train.flag.unique())
string3 = 'flag_'
unique_flag2=[string3 + x for x in unique_flag]
```

Merge Dummy Categories

In [15]:
```
dumcols=unique_protocol2 + unique_service2 + unique_flag2
print(len(dumcols), end="\n\n")
print(dumcols)
```

```
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['Protocol_type_icmp', 'Protocol_type_tcp', 'Protocol_type_udp', 'service_IRC', 'ser
vice_X11', 'service_Z39_50', 'service_aol', 'service_auth', 'service_bgp', 'service_
courier', 'service_csnet_ns', 'service_ctf', 'service_daytime', 'service_discard',
'service_domain', 'service_domain_u', 'service_echo', 'service_eco_i', 'service_ecr_
i', 'service_efs', 'service_exec', 'service_finger', 'service_ftp', 'service_ftp_dat
a', 'service_gopher', 'service_harvest', 'service_hostnames', 'service_http', 'servi
ce_http_2784', 'service_http_443', 'service_http_8001', 'service_imap4', 'service_is
o_tsap', 'service_klogin', 'service_kshell', 'service_ldap', 'service_link', 'servic
e_login', 'service_mtp', 'service_name', 'service_netbios_dgm', 'service_netbios_n
s', 'service_netbios_ssn', 'service_netstat', 'service_nnsp', 'service_nntp', 'servi
ce_ntp_u', 'service_other', 'service_pm_dump', 'service_pop_2', 'service_pop_3', 'se
rvice_printer', 'service_private', 'service_red_i', 'service_remote_job', 'service_r
je', 'service_shell', 'service_smtp', 'service_sql_net', 'service_ssh', 'service_sun
rpc', 'service_supdup', 'service_systat', 'service_telnet', 'service_tftp_u', 'servi
ce_tim_i', 'service_time', 'service_urh_i', 'service_urp_i', 'service_uucp', 'servic
e_uucp_path', 'service_vmnet', 'service_whois', 'flag_OTH', 'flag_REJ', 'flag_RSTO',
'flag_RSTOS0', 'flag_RSTR', 'flag_S0', 'flag_S1', 'flag_S2', 'flag_S3', 'flag_SF',
'flag_SH']
```

Repeat for Test Dataset

In [16]:
```
unique_service_test=sorted(df_test.service.unique())
unique_service2_test=[string2 + x for x in unique_service_test]
testdumcols=unique_protocol2 + unique_service2_test + unique_flag2

print(len(testdumcols))
```

```
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```

Transform Categorical Features into numbers

In [17]:
```
df_categorical_values_enc=df_categorical_values.apply(LabelEncoder().fit_transform)
print(df_categorical_values_enc.head())

testdf_categorical_values_enc=testdf_categorical_values.apply(LabelEncoder().fit_tra
```

```
   protocol_type  service  flag
0              1       20     9
1              2       44     9
2              1       49     5
3              1       24     9
4              1       24     9
```

Encode categorical features

In [18]:
```
enc = OneHotEncoder()
df_categorical_values_encenc = enc.fit_transform(df_categorical_values_enc)
df_cat_data = pd.DataFrame(df_categorical_values_encenc.toarray(),columns=dumcols)

testdf_categorical_values_encenc = enc.fit_transform(testdf_categorical_values_enc)
testdf_cat_data = pd.DataFrame(testdf_categorical_values_encenc.toarray(),columns=te
```

In [19]:
```
df_cat_data.head()
```

Out[19]:

	Protocol_type_icmp	Protocol_type_tcp	Protocol_type_udp	service_IRC	service_X11	service_Z39_5
0	0.0	1.0	0.0	0.0	0.0	0.
1	0.0	0.0	1.0	0.0	0.0	0.
2	0.0	1.0	0.0	0.0	0.0	0.
3	0.0	1.0	0.0	0.0	0.0	0.
4	0.0	1.0	0.0	0.0	0.0	0.

5 rows × 84 columns

Add Missing Categories to Testing Dataset

In [20]:
```
trainservice=df_train['service'].tolist()
testservice= df_test['service'].tolist()
difference=list(set(trainservice) - set(testservice))
string = 'service_'
difference=[string + x for x in difference]
difference
```

Out[20]:
```
['service_http_8001',
 'service_aol',
 'service_urh_i',
 'service_harvest',
 'service_red_i',
 'service_http_2784']
```

In [21]:
```
for col in difference:
    testdf_cat_data[col] = 0

testdf_cat_data.shape
```

Out[21]: (22544, 84)

Join Encoded Categorical Dataframe

In [22]:
```
newdf=df_train.join(df_cat_data)
newdf.drop('flag', axis=1, inplace=True)
newdf.drop('protocol_type', axis=1, inplace=True)
newdf.drop('service', axis=1, inplace=True)
# test data
newdf_test=df_test.join(testdf_cat_data)
newdf_test.drop('flag', axis=1, inplace=True)
newdf_test.drop('protocol_type', axis=1, inplace=True)
newdf_test.drop('service', axis=1, inplace=True)
print(newdf.shape)
print(newdf_test.shape)
```

```
(125973, 123)
(22544, 123)
```

In [23]:
```
newdf.head(5)
```

Out[23]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logged_in
0	0	491	0	0	0	0	0	0	0
1	0	146	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	232	8153	0	0	0	0	0	1
4	0	199	420	0	0	0	0	0	1

5 rows × 123 columns

In [24]:
```
print(list(newdf.columns))
```

```
['duration', 'src_bytes', 'dst_bytes', 'land', 'wrong_fragment', 'urgent', 'hot', 'n
um_failed_logins', 'logged_in', 'num_compromised', 'root_shell', 'su_attempted', 'nu
m_root', 'num_file_creations', 'num_shells', 'num_access_files', 'num_outbound_cmd
s', 'is_host_login', 'is_guest_login', 'count', 'srv_count', 'serror_rate', 'srv_ser
ror_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_rat
e', 'dst_host_serror_rate', 'dst_host_srv_serror_rate', 'dst_host_rerror_rate', 'dst
_host_srv_rerror_rate', 'label', 'Protocol_type_icmp', 'Protocol_type_tcp', 'Protoco
l_type_udp', 'service_IRC', 'service_X11', 'service_Z39_50', 'service_aol', 'service
_auth', 'service_bgp', 'service_courier', 'service_csnet_ns', 'service_ctf', 'servic
e_daytime', 'service_discard', 'service_domain', 'service_domain_u', 'service_echo',
'service_eco_i', 'service_ecr_i', 'service_efs', 'service_exec', 'service_finger',
'service_ftp', 'service_ftp_data', 'service_gopher', 'service_harvest', 'service_hos
tnames', 'service_http', 'service_http_2784', 'service_http_443', 'service_http_800
1', 'service_imap4', 'service_iso_tsap', 'service_klogin', 'service_kshell', 'servic
e_ldap', 'service_link', 'service_login', 'service_mtp', 'service_name', 'service_ne
tbios_dgm', 'service_netbios_ns', 'service_netbios_ssn', 'service_netstat', 'service
_nnsp', 'service_nntp', 'service_ntp_u', 'service_other', 'service_pm_dump', 'servic
e_pop_2', 'service_pop_3', 'service_printer', 'service_private', 'service_red_i', 's
ervice_remote_job', 'service_rje', 'service_shell', 'service_smtp', 'service_sql_ne
t', 'service_ssh', 'service_sunrpc', 'service_supdup', 'service_systat', 'service_te
```

```
lnet', 'service_tftp_u', 'service_tim_i', 'service_time', 'service_urh_i', 'service_
urp_i', 'service_uucp', 'service_uucp_path', 'service_vmnet', 'service_whois', 'flag
_OTH', 'flag_REJ', 'flag_RSTO', 'flag_RSTOS0', 'flag_RSTR', 'flag_S0', 'flag_S1', 'f
lag_S2', 'flag_S3', 'flag_SF', 'flag_SH']
```

Split Dataset for different Attacks

Label:

- Normal : 0
- DoS : 1
- Probe : 2
- R2L : 3
- U2R : 4

In [25]:

```
# take label column
labeldf=newdf['label']
labeldf_test=newdf_test['label']

# change the label column
newlabeldf=labeldf.replace({'normal' : 0, 'neptune' : 1 ,'back': 1, 'land': 1, 'pod'
                            'mailbomb': 1, 'apache2': 1, 'processtable': 1, 'udpstor
                            'ipsweep' : 2,'nmap' : 2,'portsweep' : 2,'satan' : 2,'ms
                            'ftp_write': 3,'guess_passwd': 3,'imap': 3,'multihop': 3
                            'warezmaster': 3,'sendmail': 3,'named': 3,'snmpgetattack
                            'xsnoop': 3,'httptunnel': 3,
                            'buffer_overflow': 4,'loadmodule': 4,'perl': 4,'rootkit'

newlabeldf_test=labeldf_test.replace({'normal' : 0, 'neptune' : 1 ,'back': 1, 'land'
                            'mailbomb': 1, 'apache2': 1, 'processtable': 1, 'udpstor
                            'ipsweep' : 2,'nmap' : 2,'portsweep' : 2,'satan' : 2,'ms
                            'ftp_write': 3,'guess_passwd': 3,'imap': 3,'multihop': 3
                            'warezmaster': 3,'sendmail': 3,'named': 3,'snmpgetattack
                            'xsnoop': 3,'httptunnel': 3,
                            'buffer_overflow': 4,'loadmodule': 4,'perl': 4,'rootkit'

# put the new label column back
newdf['label'] = newlabeldf
newdf_test['label'] = newlabeldf_test
print(newdf['label'].head())
```

```
0    0
1    0
2    1
3    0
4    0
Name: label, dtype: int64
```

In [26]:

```
to_drop_DoS = [2,3,4]
to_drop_Probe = [1,3,4]
to_drop_R2L = [1,2,4]
to_drop_U2R = [1,2,3]
DoS_df=newdf[~newdf['label'].isin(to_drop_DoS)];
Probe_df=newdf[~newdf['label'].isin(to_drop_Probe)];
R2L_df=newdf[~newdf['label'].isin(to_drop_R2L)];
U2R_df=newdf[~newdf['label'].isin(to_drop_U2R)];

#test
DoS_df_test=newdf_test[~newdf_test['label'].isin(to_drop_DoS)];
Probe_df_test=newdf_test[~newdf_test['label'].isin(to_drop_Probe)];
R2L_df_test=newdf_test[~newdf_test['label'].isin(to_drop_R2L)];
U2R_df_test=newdf_test[~newdf_test['label'].isin(to_drop_U2R)];
```

In [27]:

```
print('Train:')
```

```
print('Dimensions of DoS:' ,DoS_df.shape)
print('Dimensions of Probe:' ,Probe_df.shape)
print('Dimensions of R2L:' ,R2L_df.shape)
print('Dimensions of U2R:' ,U2R_df.shape)
```

```
Train:
Dimensions of DoS: (113270, 123)
Dimensions of Probe: (78999, 123)
Dimensions of R2L: (68338, 123)
Dimensions of U2R: (67395, 123)
```

In [28]:

```
print('Test:')
print('Dimensions of DoS:' ,DoS_df_test.shape)
print('Dimensions of Probe:' ,Probe_df_test.shape)
print('Dimensions of R2L:' ,R2L_df_test.shape)
print('Dimensions of U2R:' ,U2R_df_test.shape)
```

```
Test:
Dimensions of DoS: (17171, 123)
Dimensions of Probe: (12132, 123)
Dimensions of R2L: (12596, 123)
Dimensions of U2R: (9778, 123)
```

STAGE 2: FEATURE SCALING

Split Dataset into X & Y

X: Dataframe of Feautures

Y: Series of Outcome Variables

In [29]:

```
X_DoS = DoS_df.drop('label',1)
Y_DoS = DoS_df.label
X_Probe = Probe_df.drop('label',1)
Y_Probe = Probe_df.label
X_R2L = R2L_df.drop('label',1)
Y_R2L = R2L_df.label
X_U2R = U2R_df.drop('label',1)
Y_U2R = U2R_df.label
```

For Test Dataset

In [30]:

```
X_DoS_test = DoS_df_test.drop('label',1)
Y_DoS_test = DoS_df_test.label
X_Probe_test = Probe_df_test.drop('label',1)
Y_Probe_test = Probe_df_test.label
X_R2L_test = R2L_df_test.drop('label',1)
Y_R2L_test = R2L_df_test.label
X_U2R_test = U2R_df_test.drop('label',1)
Y_U2R_test = U2R_df_test.label
```

In [31]:

```
colNames=list(X_DoS)
colNames_test=list(X_DoS_test)
```

Scaling the Dataframes

In [32]:

```
scaler1 = preprocessing.StandardScaler().fit(X_DoS)
X_DoS=scaler1.transform(X_DoS)
scaler2 = preprocessing.StandardScaler().fit(X_Probe)
X_Probe=scaler2.transform(X_Probe)
scaler3 = preprocessing.StandardScaler().fit(X_R2L)
X_R2L=scaler3.transform(X_R2L)
scaler4 = preprocessing.StandardScaler().fit(X_U2R)
```

```
X_U2R=scaler4.transform(X_U2R)

scaler5 = preprocessing.StandardScaler().fit(X_DoS_test)
X_DoS_test=scaler5.transform(X_DoS_test)
scaler6 = preprocessing.StandardScaler().fit(X_Probe_test)
X_Probe_test=scaler6.transform(X_Probe_test)
scaler7 = preprocessing.StandardScaler().fit(X_R2L_test)
X_R2L_test=scaler7.transform(X_R2L_test)
scaler8 = preprocessing.StandardScaler().fit(X_U2R_test)
X_U2R_test=scaler8.transform(X_U2R_test)
```

Checking Standard Deviation

In [33]:
```
print(X_DoS.std(axis=0))
```

```
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1.
 1. 1.]
```

In [34]:
```
X_Probe.std(axis=0);
X_R2L.std(axis=0);
X_U2R.std(axis=0);
```

STAGE 3: FEATURE SELECTION

Eliminate redundant and irrelevant data by selecting a subset of relevant features that fully represents the given problem.

Univariate feature selection with ANOVA F-test. This analyzes each feature individually to detemine the strength of the relationship between the feature and labels. Using SecondPercentile method (sklearn.feature_selection) to select features based on percentile of the highest scores. When this subset is found: Recursive Feature Elimination (RFE) is applied.

1. Univariate Feature Selection using ANOVA F-test

In [35]:
```
np.seterr(divide='ignore', invalid='ignore');
selector=SelectPercentile(f_classif, percentile=10)
X_newDoS = selector.fit_transform(X_DoS,Y_DoS)
X_newDoS.shape
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\_univariate_sel
ection.py:114: UserWarning: Features [ 16  44  63  66  68  86 114] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
```

Out[35]:
```
(113270, 13)
```

Get the features that were selected: DoS

In [36]:
```
true=selector.get_support()
newcolindex_DoS=[i for i, x in enumerate(true) if x]
newcolname_DoS=list( colNames[i] for i in newcolindex_DoS )
newcolname_DoS
```

Out[36]:
```
['logged_in',
 'count',
 'serror_rate',
 'srv_serror_rate',
 'same_srv_rate',
 'dst_host_count',
```

```
 'dst_host_srv_count',
 'dst_host_same_srv_rate',
 'dst_host_serror_rate',
 'dst_host_srv_serror_rate',
 'service_http',
 'flag_S0',
 'flag_SF']
```

In [37]:
```
X_newProbe = selector.fit_transform(X_Probe,Y_Probe)
X_newProbe.shape
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\_univariate_sel
ection.py:114: UserWarning: Features [ 4 16] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
```

Out[37]:
```
(78999, 13)
```

Get the features that were selected: Probe

In [38]:
```
true=selector.get_support()
newcolindex_Probe=[i for i, x in enumerate(true) if x]
newcolname_Probe=list( colNames[i] for i in newcolindex_Probe )
newcolname_Probe
```

Out[38]:
```
['logged_in',
 'rerror_rate',
 'srv_rerror_rate',
 'dst_host_srv_count',
 'dst_host_diff_srv_rate',
 'dst_host_same_src_port_rate',
 'dst_host_srv_diff_host_rate',
 'dst_host_rerror_rate',
 'dst_host_srv_rerror_rate',
 'Protocol_type_icmp',
 'service_eco_i',
 'service_private',
 'flag_SF']
```

In [39]:
```
X_newR2L = selector.fit_transform(X_R2L,Y_R2L)
X_newR2L.shape
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\_univariate_sel
ection.py:114: UserWarning: Features [  4  16  43  44  46  47  48  49  50  51  54  5
7  58  62  63  64  66  67
  68  70  71  72  73  74  76  77  78  79  80  81  82  83  86  87  89  92
  93  96  98  99 100 107 108 109 110 114] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
```

Out[39]:
```
(68338, 13)
```

Get the features that were selected: R2L

In [40]:
```
true=selector.get_support()
newcolindex_R2L=[i for i, x in enumerate(true) if x]
newcolname_R2L=list( colNames[i] for i in newcolindex_R2L)
newcolname_R2L
```

Out[40]:
```
['src_bytes',
 'dst_bytes',
 'hot',
 'num_failed_logins',
 'is_guest_login',
 'dst_host_srv_count',
 'dst_host_same_src_port_rate',
 'dst_host_srv_diff_host_rate',
 'service_ftp',
 'service_ftp_data',
 'service_http',
```

```
 'service_imap4',
 'flag_RSTO']
```

In [41]:
```
X_newU2R = selector.fit_transform(X_U2R,Y_U2R)
X_newU2R.shape
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\feature_selection\_univariate_sel
ection.py:114: UserWarning: Features [  4  16  43  44  46  47  48  49  50  51  54  5
7  58  62  63  64  66  67
  68  70  71  72  73  74  75  76  77  78  79  80  81  82  83  86  87  89
  92  93  96  98  99 100 107 108 109 110 114] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
```

Out[41]:
```
(67395, 13)
```

Get the features that were selected: U2R

In [42]:
```
true=selector.get_support()
newcolindex_U2R=[i for i, x in enumerate(true) if x]
newcolname_U2R=list( colNames[i] for i in newcolindex_U2R)
newcolname_U2R
```

Out[42]:
```
['urgent',
 'hot',
 'root_shell',
 'num_file_creations',
 'num_shells',
 'srv_diff_host_rate',
 'dst_host_count',
 'dst_host_srv_count',
 'dst_host_same_src_port_rate',
 'dst_host_srv_diff_host_rate',
 'service_ftp_data',
 'service_http',
 'service_telnet']
```

Summary of features selected by Univariate Feature Selection

In [43]:
```
print('Features selected for DoS:',newcolname_DoS)
print()
print('Features selected for Probe:',newcolname_Probe)
print()
print('Features selected for R2L:',newcolname_R2L)
print()
print('Features selected for U2R:',newcolname_U2R)
```

```
Features selected for DoS: ['logged_in', 'count', 'serror_rate', 'srv_serror_rate',
'same_srv_rate', 'dst_host_count', 'dst_host_srv_count', 'dst_host_same_srv_rate',
'dst_host_serror_rate', 'dst_host_srv_serror_rate', 'service_http', 'flag_S0', 'flag
_SF']

Features selected for Probe: ['logged_in', 'rerror_rate', 'srv_rerror_rate', 'dst_ho
st_srv_count', 'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate', 'dst_host_sr
v_diff_host_rate', 'dst_host_rerror_rate', 'dst_host_srv_rerror_rate', 'Protocol_typ
e_icmp', 'service_eco_i', 'service_private', 'flag_SF']

Features selected for R2L: ['src_bytes', 'dst_bytes', 'hot', 'num_failed_logins', 'i
s_guest_login', 'dst_host_srv_count', 'dst_host_same_src_port_rate', 'dst_host_srv_d
iff_host_rate', 'service_ftp', 'service_ftp_data', 'service_http', 'service_imap4',
'flag_RSTO']

Features selected for U2R: ['urgent', 'hot', 'root_shell', 'num_file_creations', 'nu
m_shells', 'srv_diff_host_rate', 'dst_host_count', 'dst_host_srv_count', 'dst_host_s
ame_src_port_rate', 'dst_host_srv_diff_host_rate', 'service_ftp_data', 'service_htt
p', 'service_telnet']
```

The authors state that "After obtaining the adequate number of features during the univariate selection process, a recursive feature elimination (RFE) was operated with the number of features passed as parameter to identify the features selected". This either implies that RFE is only used for obtaining the features previously selected but also obtaining the rank. This use of RFE is however very redundant as the features selected can be obtained in another way (Done in this project). One can also not say that the features were selected by RFE, as it was not used for this. The quote could however also imply that only the number 13 from univariate feature selection was used. RFE is then used for feature selection trying to find the best 13 features. With this use of RFE one can actually say that it was used for feature selection. However the authors obtained different numbers of features for every attack category, 12 for DoS, 15 for Probe, 13 for R2L and 11 for U2R. This concludes that it is not clear what mechanism is used for feature selection.

To procede with the data mining, the second option is considered as this uses RFE. From now on the number of features for every attack category is 13.

2.1. Recursive Feature Elimination for feature ranking (Get importance from previous selected)

In [44]:
```
# Create a decision tree classifier. By convention, clf means 'classifier'
clf = DecisionTreeClassifier(random_state=0)

#rank all features, i.e continue the elimination until the last one
rfe = RFE(clf, n_features_to_select=1)
rfe.fit(X_newDoS, Y_DoS)
print ("DoS Features sorted by their rank:")
print (sorted(zip(map(lambda x: round(x, 4), rfe.ranking_), newcolname_DoS)))
```

```
DoS Features sorted by their rank:
[(1, 'same_srv_rate'), (2, 'count'), (3, 'flag_SF'), (4, 'dst_host_serror_rate'),
(5, 'dst_host_same_srv_rate'), (6, 'dst_host_srv_count'), (7, 'dst_host_count'), (8,
'logged_in'), (9, 'serror_rate'), (10, 'dst_host_srv_serror_rate'), (11, 'srv_serror
_rate'), (12, 'service_http'), (13, 'flag_S0')]
```

In [45]:
```
rfe.fit(X_newProbe, Y_Probe)
print ("Probe Features sorted by their rank:")
print (sorted(zip(map(lambda x: round(x, 4), rfe.ranking_), newcolname_Probe)))
```

```
Probe Features sorted by their rank:
[(1, 'dst_host_same_src_port_rate'), (2, 'dst_host_srv_count'), (3, 'dst_host_rerror
_rate'), (4, 'service_private'), (5, 'logged_in'), (6, 'dst_host_diff_srv_rate'),
(7, 'dst_host_srv_diff_host_rate'), (8, 'flag_SF'), (9, 'service_eco_i'), (10, 'rerr
or_rate'), (11, 'Protocol_type_icmp'), (12, 'dst_host_srv_rerror_rate'), (13, 'srv_r
error_rate')]
```

In [46]:
```
rfe.fit(X_newR2L, Y_R2L)

print ("R2L Features sorted by their rank:")
print (sorted(zip(map(lambda x: round(x, 4), rfe.ranking_), newcolname_R2L)))
```

```
R2L Features sorted by their rank:
[(1, 'src_bytes'), (2, 'dst_bytes'), (3, 'hot'), (4, 'dst_host_srv_diff_host_rate'),
(5, 'service_ftp_data'), (6, 'dst_host_same_src_port_rate'), (7, 'dst_host_srv_coun
t'), (8, 'num_failed_logins'), (9, 'service_imap4'), (10, 'is_guest_login'), (11, 's
ervice_ftp'), (12, 'flag_RSTO'), (13, 'service_http')]
```

In [47]:
```
rfe.fit(X_newU2R, Y_U2R)

print ("U2R Features sorted by their rank:")
print (sorted(zip(map(lambda x: round(x, 4), rfe.ranking_), newcolname_U2R)))
```

```
U2R Features sorted by their rank:
[(1, 'hot'), (2, 'dst_host_srv_count'), (3, 'dst_host_count'), (4, 'root_shell'),
(5, 'num_shells'), (6, 'service_ftp_data'), (7, 'dst_host_srv_diff_host_rate'), (8,
```

```
'num_file_creations'), (9, 'dst_host_same_src_port_rate'), (10, 'service_telnet'),
(11, 'srv_diff_host_rate'), (12, 'service_http'), (13, 'urgent')]
```

2.2. Recursive Feature Elimination, select 13 features each of 122 (Get 13 best features from 122 from RFE)

In [48]:
```
clf = DecisionTreeClassifier(random_state=0)
rfe = RFE(estimator=clf, n_features_to_select=13, step=1)
rfe.fit(X_DoS, Y_DoS)
X_rfeDoS=rfe.transform(X_DoS)
true=rfe.support_
rfecolindex_DoS=[i for i, x in enumerate(true) if x]
rfecolname_DoS=list(colNames[i] for i in rfecolindex_DoS)
```

In [49]:
```
rfe.fit(X_Probe, Y_Probe)
X_rfeProbe=rfe.transform(X_Probe)
true=rfe.support_
rfecolindex_Probe=[i for i, x in enumerate(true) if x]
rfecolname_Probe=list(colNames[i] for i in rfecolindex_Probe)
```

In [50]:
```
rfe.fit(X_R2L, Y_R2L)
X_rfeR2L=rfe.transform(X_R2L)
true=rfe.support_
rfecolindex_R2L=[i for i, x in enumerate(true) if x]
rfecolname_R2L=list(colNames[i] for i in rfecolindex_R2L)
```

In [51]:
```
rfe.fit(X_U2R, Y_U2R)
X_rfeU2R=rfe.transform(X_U2R)
true=rfe.support_
rfecolindex_U2R=[i for i, x in enumerate(true) if x]
rfecolname_U2R=list(colNames[i] for i in rfecolindex_U2R)
```

Summary of features selected by RFE

In [52]:
```
print('Features selected for DoS:',rfecolname_DoS)
print()
print('Features selected for Probe:',rfecolname_Probe)
print()
print('Features selected for R2L:',rfecolname_R2L)
print()
print('Features selected for U2R:',rfecolname_U2R)
```

```
Features selected for DoS: ['src_bytes', 'dst_bytes', 'wrong_fragment', 'num_comprom
ised', 'same_srv_rate', 'diff_srv_rate', 'dst_host_count', 'dst_host_same_srv_rate',
'dst_host_serror_rate', 'dst_host_srv_serror_rate', 'service_ecr_i', 'flag_RSTR', 'f
lag_S0']

Features selected for Probe: ['src_bytes', 'dst_bytes', 'rerror_rate', 'dst_host_sam
e_srv_rate', 'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate', 'dst_host_rerr
or_rate', 'service_finger', 'service_ftp_data', 'service_http', 'service_private',
'service_smtp', 'service_telnet']

Features selected for R2L: ['duration', 'src_bytes', 'dst_bytes', 'hot', 'num_failed
_logins', 'num_access_files', 'dst_host_count', 'dst_host_srv_count', 'dst_host_same
_srv_rate', 'dst_host_same_src_port_rate', 'dst_host_srv_diff_host_rate', 'service_f
tp_data', 'service_imap4']

Features selected for U2R: ['duration', 'src_bytes', 'dst_bytes', 'hot', 'root_shel
l', 'num_file_creations', 'num_shells', 'srv_count', 'dst_host_count', 'dst_host_sam
e_srv_rate', 'dst_host_srv_diff_host_rate', 'service_ftp_data', 'service_other']
```

In [53]:
```
print(X_rfeDoS.shape)
print(X_rfeProbe.shape)
```

```
print(X_rfeR2L.shape)
print(X_rfeU2R.shape)
```

```
(113270, 13)
(78999, 13)
(68338, 13)
(67395, 13)
```

STAGE 4: Build the Model

Classifier is trained for all features and for reduced features, for later comparison.
(The classifier model itself is stored in the clf variable)

In [54]:
```
# all features
clf_DoS=DecisionTreeClassifier(random_state=0)
clf_Probe=DecisionTreeClassifier(random_state=0)
clf_R2L=DecisionTreeClassifier(random_state=0)
clf_U2R=DecisionTreeClassifier(random_state=0)
clf_DoS.fit(X_DoS, Y_DoS)
clf_Probe.fit(X_Probe, Y_Probe)
clf_R2L.fit(X_R2L, Y_R2L)
clf_U2R.fit(X_U2R, Y_U2R)
```

Out[54]:
```
DecisionTreeClassifier(random_state=0)
```

In [55]:
```
# selected features
clf_rfeDoS=DecisionTreeClassifier(random_state=0)
clf_rfeProbe=DecisionTreeClassifier(random_state=0)
clf_rfeR2L=DecisionTreeClassifier(random_state=0)
clf_rfeU2R=DecisionTreeClassifier(random_state=0)
clf_rfeDoS.fit(X_rfeDoS, Y_DoS)
clf_rfeProbe.fit(X_rfeProbe, Y_Probe)
clf_rfeR2L.fit(X_rfeR2L, Y_R2L)
clf_rfeU2R.fit(X_rfeU2R, Y_U2R)
```

Out[55]:
```
DecisionTreeClassifier(random_state=0)
```

STAGE 5: Prediction & Evaluation (Validation)

5.1. Using all Features for each category.

Confusion Matrices

DoS

In [56]:
```
# Apply the classifier we trained to the test data (which it has never seen before)
clf_DoS.predict(X_DoS_test)
```

Out[56]:
```
array([1, 1, 0, ..., 0, 0, 0], dtype=int64)
```

In [57]:
```
# View the predicted probabilities of the first 10 observations
clf_DoS.predict_proba(X_DoS_test)[0:10]
```

Out[57]:
```
array([[0., 1.],
       [0., 1.],
```

```
        [1., 0.],
        [1., 0.],
        [1., 0.],
        [1., 0.],
        [1., 0.],
        [0., 1.],
        [1., 0.],
        [1., 0.]])
```

In [58]:
```
Y_DoS_pred=clf_DoS.predict(X_DoS_test)
# Create confusion matrix
pd.crosstab(Y_DoS_test, Y_DoS_pred, rownames=['Actual attacks'], colnames=['Predicte
```

Out[58]:

Predicted attacks	0	1
Actual attacks		
0	9499	212
1	2830	4630

Probe

In [59]:
```
Y_Probe_pred=clf_Probe.predict(X_Probe_test)
# Create confusion matrix
pd.crosstab(Y_Probe_test, Y_Probe_pred, rownames=['Actual attacks'], colnames=['Pred
```

Out[59]:

Predicted attacks	0	2
Actual attacks		
0	2337	7374
2	212	2209

R2L

In [60]:
```
Y_R2L_pred=clf_R2L.predict(X_R2L_test)
# Create confusion matrix
pd.crosstab(Y_R2L_test, Y_R2L_pred, rownames=['Actual attacks'], colnames=['Predicte
```

Out[60]:

Predicted attacks	0	3
Actual attacks		
0	9707	4
3	2573	312

U2R

In [61]:
```
Y_U2R_pred=clf_U2R.predict(X_U2R_test)
# Create confusion matrix
pd.crosstab(Y_U2R_test, Y_U2R_pred, rownames=['Actual attacks'], colnames=['Predicte
```

Out[61]:

Predicted attacks	0	4
Actual attacks		
0	9703	8
4	60	7

Cross Validation: Accuracy, Precision, Recall, F-measure

DoS

In [62]:
```
accuracy = cross_val_score(clf_DoS, X_DoS_test, Y_DoS_test, cv=10, scoring='accuracy
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_DoS, X_DoS_test, Y_DoS_test, cv=10, scoring='precisi
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_DoS, X_DoS_test, Y_DoS_test, cv=10, scoring='recall')
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_DoS, X_DoS_test, Y_DoS_test, cv=10, scoring='f1')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.99639 (+/- 0.00341)
Precision: 0.99505 (+/- 0.00477)
Recall: 0.99665 (+/- 0.00483)
F-measure: 0.99585 (+/- 0.00392)
```

Probe

In [63]:
```
accuracy = cross_val_score(clf_Probe, X_Probe_test, Y_Probe_test, cv=10, scoring='ac
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_Probe, X_Probe_test, Y_Probe_test, cv=10, scoring='p
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_Probe, X_Probe_test, Y_Probe_test, cv=10, scoring='reca
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_Probe, X_Probe_test, Y_Probe_test, cv=10, scoring='f1_macro'
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.99571 (+/- 0.00328)
Precision: 0.99392 (+/- 0.00684)
Recall: 0.99267 (+/- 0.00405)
F-measure: 0.99329 (+/- 0.00512)
```

R2L

In [64]:
```
accuracy = cross_val_score(clf_R2L, X_R2L_test, Y_R2L_test, cv=10, scoring='accuracy
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_R2L, X_R2L_test, Y_R2L_test, cv=10, scoring='precisi
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_R2L, X_R2L_test, Y_R2L_test, cv=10, scoring='recall_mac
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_R2L, X_R2L_test, Y_R2L_test, cv=10, scoring='f1_macro')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.97920 (+/- 0.01053)
Precision: 0.97151 (+/- 0.01736)
Recall: 0.96958 (+/- 0.01379)
F-measure: 0.97051 (+/- 0.01478)
```

U2R

In [65]:
```
accuracy = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='accuracy
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='precisi
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='recall_mac
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='f1_macro')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

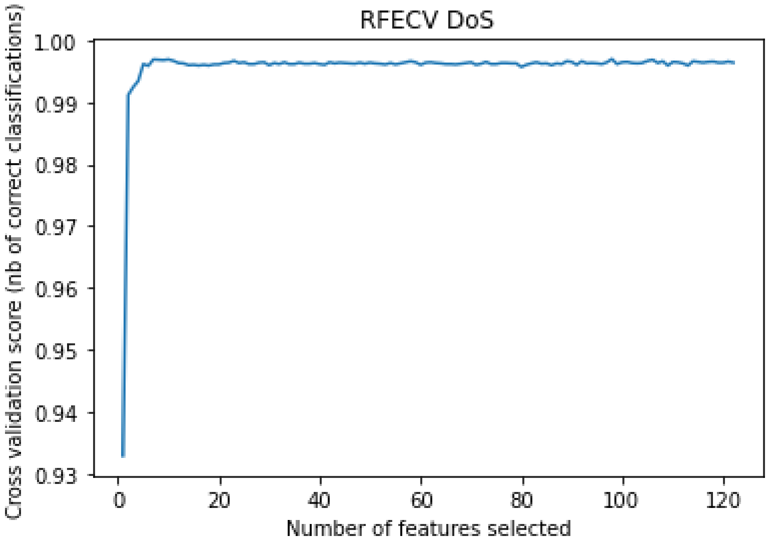
```
Accuracy: 0.99652 (+/- 0.00228)
Precision: 0.86295 (+/- 0.08961)
Recall: 0.90958 (+/- 0.09211)
F-measure: 0.88210 (+/- 0.06559)
```

RFECV for illustration

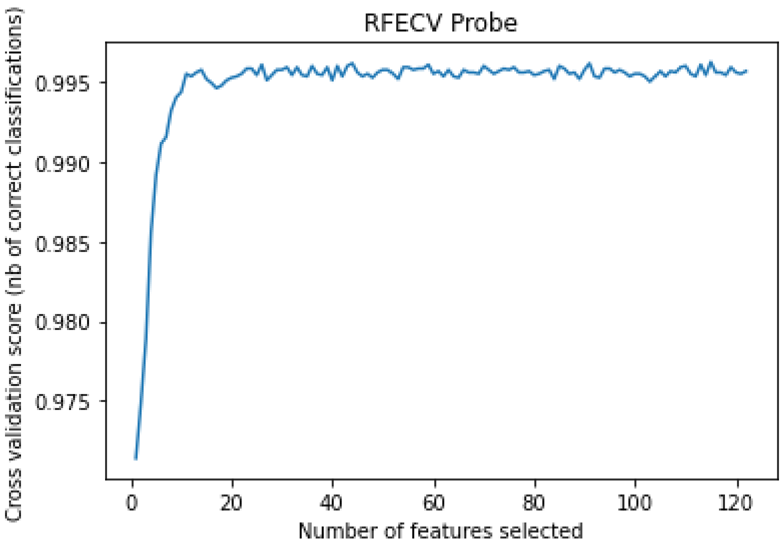
In [66]:
```
print(__doc__)
```

```
Automatically created module for IPython interactive environment
```

In [67]:
```python
# Create the RFE object and compute a cross-validated score.
# The "accuracy" scoring is proportional to the number of correct
# classifications
rfecv_DoS = RFECV(estimator=clf_DoS, step=1, cv=10, scoring='accuracy')
rfecv_DoS.fit(X_DoS_test, Y_DoS_test)
# Plot number of features VS. cross-validation scores
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.title('RFECV DoS')
plt.plot(range(1, len(rfecv_DoS.grid_scores_) + 1), rfecv_DoS.grid_scores_)
plt.show()
```

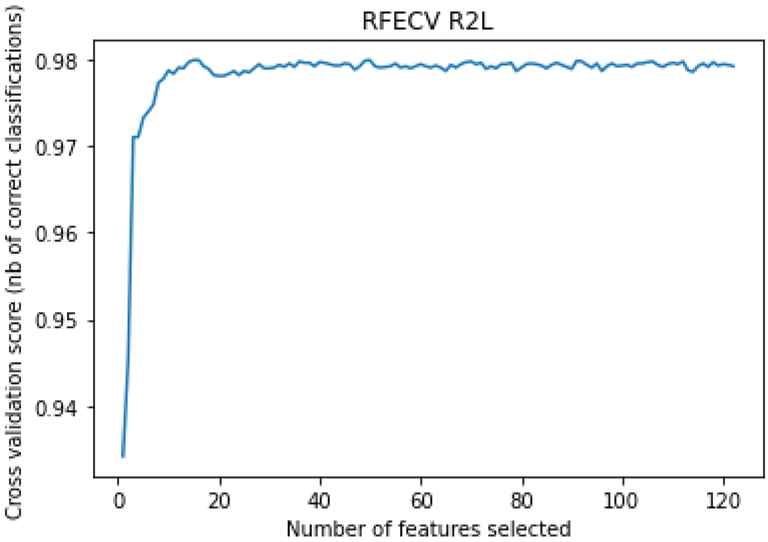


In [68]:
```python
rfecv_Probe = RFECV(estimator=clf_Probe, step=1, cv=10, scoring='accuracy')
rfecv_Probe.fit(X_Probe_test, Y_Probe_test)
# Plot number of features VS. cross-validation scores
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.title('RFECV Probe')
plt.plot(range(1, len(rfecv_Probe.grid_scores_) + 1), rfecv_Probe.grid_scores_)
plt.show()
```

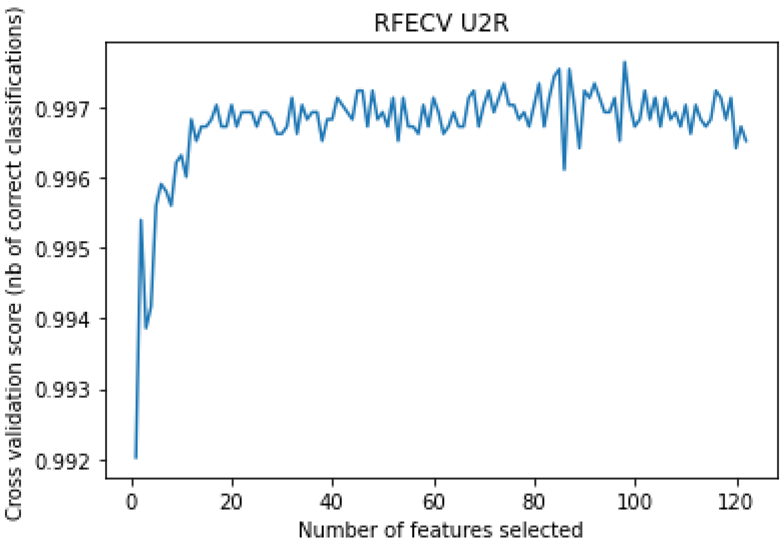


In [69]:
```python
rfecv_R2L = RFECV(estimator=clf_R2L, step=1, cv=10, scoring='accuracy')
rfecv_R2L.fit(X_R2L_test, Y_R2L_test)
```

```
# Plot number of features VS. cross-validation scores
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.title('RFECV R2L')
plt.plot(range(1, len(rfecv_R2L.grid_scores_) + 1), rfecv_R2L.grid_scores_)
plt.show()
```



In [70]:
```
rfecv_U2R = RFECV(estimator=clf_U2R, step=1, cv=10, scoring='accuracy')
rfecv_U2R.fit(X_U2R_test, Y_U2R_test)
# Plot number of features VS. cross-validation scores
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.title('RFECV U2R')
plt.plot(range(1, len(rfecv_U2R.grid_scores_) + 1), rfecv_U2R.grid_scores_)
plt.show()
```



5.2. Using 13 Features for each category

Confusion Matrices

DoS

In [71]:
```
# reduce test dataset to 13 features, use only features described in rfecolname_DoS
```

```
X_DoS_test2=X_DoS_test[:,rfecolindex_DoS]
X_Probe_test2=X_Probe_test[:,rfecolindex_Probe]
X_R2L_test2=X_R2L_test[:,rfecolindex_R2L]
X_U2R_test2=X_U2R_test[:,rfecolindex_U2R]
X_U2R_test2.shape
```

Out[71]: (9778, 13)

In [72]:
```
Y_DoS_pred2=clf_rfeDoS.predict(X_DoS_test2)
# Create confusion matrix
pd.crosstab(Y_DoS_test, Y_DoS_pred2, rownames=['Actual attacks'], colnames=['Predict
```

Out[72]:

Predicted attacks	0	1
Actual attacks		
0	9602	109
1	2625	4835

Probe

In [73]:
```
Y_Probe_pred2=clf_rfeProbe.predict(X_Probe_test2)
# Create confusion matrix
pd.crosstab(Y_Probe_test, Y_Probe_pred2, rownames=['Actual attacks'], colnames=['Pre
```

Out[73]:

Predicted attacks	0	2
Actual attacks		
0	8709	1002
2	944	1477

R2L

In [74]:
```
Y_R2L_pred2=clf_rfeR2L.predict(X_R2L_test2)
# Create confusion matrix
pd.crosstab(Y_R2L_test, Y_R2L_pred2, rownames=['Actual attacks'], colnames=['Predict
```

Out[74]:

Predicted attacks	0	3
Actual attacks		
0	9649	62
3	2560	325

U2R

In [75]:
```
Y_U2R_pred2=clf_rfeU2R.predict(X_U2R_test2)
# Create confusion matrix
pd.crosstab(Y_U2R_test, Y_U2R_pred2, rownames=['Actual attacks'], colnames=['Predict
```

Out[75]:

Predicted attacks	0	4
Actual attacks		
0	9706	5
4	52	15

Cross Validation: Accuracy, Precision, Recall, F-measure

DoS

In [76]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='pre
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='recall
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='f1')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.99738 (+/- 0.00267)
Precision: 0.99692 (+/- 0.00492)
Recall: 0.99705 (+/- 0.00356)
F-measure: 0.99698 (+/- 0.00307)
```

Probe

In [77]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scoring
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scorin
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scoring='
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scoring='f1_ma
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.99085 (+/- 0.00559)
Precision: 0.98674 (+/- 0.01179)
Recall: 0.98467 (+/- 0.01026)
F-measure: 0.98566 (+/- 0.00871)
```

R2L

In [78]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='pre
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='recall
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='f1_macro')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.97459 (+/- 0.00910)
Precision: 0.96689 (+/- 0.01311)
Recall: 0.96086 (+/- 0.01571)
F-measure: 0.96379 (+/- 0.01305)
```

U2R

In [79]:
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='pre
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='recall
print("Recall: %0.5f (+/- %0.5f)" % (recall.mean(), recall.std() * 2))
f = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='f1_macro')
print("F-measure: %0.5f (+/- %0.5f)" % (f.mean(), f.std() * 2))
```

```
Accuracy: 0.99652 (+/- 0.00278)
Precision: 0.87538 (+/- 0.15433)
Recall: 0.89540 (+/- 0.14777)
F-measure: 0.87731 (+/- 0.09647)
```

Stratified CV => Stays the same

In [80]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=StratifiedKFold(1
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99738 (+/- 0.00267)
```

In [81]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=StratifiedK
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99085 (+/- 0.00559)
```

In [82]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=StratifiedKFold(1
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.97459 (+/- 0.00910)
```

In [83]:
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=StratifiedKFold(1
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99652 (+/- 0.00278)
```

CV: 2, 5, 10, 30, 50 Fold

DoS

In [84]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=2, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99662 (+/- 0.00116)
```

In [85]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=5, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99709 (+/- 0.00064)
```

In [86]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99738 (+/- 0.00267)
```

In [87]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=30, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99726 (+/- 0.00430)
```

In [88]:
```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=50, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99703 (+/- 0.00622)
```

Probe

In [89]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=2, scoring=
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99060 (+/- 0.00165)
```

In [90]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=5, scoring=
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99093 (+/- 0.00233)
```

In [91]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scoring
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

```
Accuracy: 0.99085 (+/- 0.00559)
```

In [92]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=30, scoring
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99118 (+/- 0.00742)

In [93]:
```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=50, scoring
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99085 (+/- 0.01122)

R2L

In [94]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=2, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.97118 (+/- 0.00143)

In [95]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=5, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.97388 (+/- 0.00624)

In [96]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.97459 (+/- 0.00910)

In [97]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=30, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.97467 (+/- 0.01644)

In [98]:
```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=50, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.97523 (+/- 0.01795)

U2R

In [99]:
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=2, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99519 (+/- 0.00184)

In [100…
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=5, scoring='accur
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99714 (+/- 0.00153)

In [101…
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99652 (+/- 0.00278)

In [102…
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=30, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99693 (+/- 0.00571)

In [104…
```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=50, scoring='accu
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

Accuracy: 0.99662 (+/- 0.00755)
