Modelling Intrusion Detection: Analysis of a Feature Selection Mechanism

Method Description

Step 1: Data preprocessing:

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.

Step 2: 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.

Step 4: Build the model:

Decision tree model is built.

Step 5: Prediction & Evaluation (validation):

Using the test data to make predictions of the model. Multiple scores are considered such as:accuracy score, recall, f-measure, confusion matrix. perform a 10-fold cross-validation.

Version Check

```
import pandas as pd
import numpy as np
import sys
import sklearn
print(pd.__version__)
print(np.__version__)
print(sys.version)
print(sklearn.__version__)
```

```
2.0.3
1.24.3
3.11.5 | packaged by Anaconda, Inc. | (main, Sep 11 2023, 13:26:23) [MSC v.1916 64 bit (
```

```
1.3.0
```

Load the Dataset

```
# attach the column names to the dataset
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"]

# KDDTrain+_2.csv & KDDTest+_2.csv are the datafiles without the last column about the diffi
# these have already been removed.
df = pd.read_csv("KDDTrain+_2.csv", header=None, names = col_names)
df_test = pd.read_csv("KDDTest+_2.csv", header=None, names = col_names)

# shape, this gives the dimensions of the dataset
print('Dimensions of the Training set:',df.shape)
print('Dimensions of the Test set:',df_test.shape)
```

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

Sample view of the training dataset

```
# first five rows
df.head(5)
```

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

5 rows × 42 columns

Statistical Summary

```
df.describe()
```

	duration	src_bytes	dst_bytes	land	wrong_fragment	urg
count	125973.00000	1.259730e+05	1.259730e+05	125973.000000	125973.000000	125973.00
mean	287.14465	4.556674e+04	1.977911e+04	0.000198	0.022687	0.00
std	2604.51531	5.870331e+06	4.021269e+06	0.014086	0.253530	[illegible]
min	0.00000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00
25%	0.00000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00
50%	0.00000	4.400000e+01	0.000000e+00	0.000000	0.000000	0.00
75%	0.00000	2.760000e+02	5.160000e+02	0.000000	0.000000	0.00
max	42908.00000	1.379964e+09	1.309937e+09	1.000000	3.000000	3.00

8 rows × 38 columns

Label Distribution of Training and Test set

```
print('Label distribution Training set:')
print(df['label'].value_counts())
print()
print('Label distribution Test set:')
print(df_test['label'].value_counts())
```

```
Label distribution Training set:
label
```

```
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: count, dtype: int64

Label distribution Test set:
label
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
rootkit              13
xterm                13
teardrop             12
xlock                 9
land                  7
```

Step 1: Data preprocessing:

One-Hot-Encoding (one-of-K) is used to to transform all categorical features into binary features. Requirement for One-Hot-encoding: "The input to this transformer should be a matrix of integers, denoting the values taken on by categorical (discrete) features. The output will be a sparse matrix where each column corresponds to one possible value of one feature. It is assumed that input features take on values in the range [0, n_values)."

Therefore the features first need to be transformed with LabelEncoder, to transform every category to a number.

Identify categorical features

```
# colums that are categorical and not binary yet: protocol_type (column 2), service (column
# explore categorical features
print('Training set:')
for col_name in df.columns:
    if df[col_name].dtypes == 'object' :
        unique_cat = len(df[col_name].unique())
        print("Feature '{col_name}' has {unique_cat} categories".format(col_name=col_name

#see how distributed the feature service is, it is evenly distributed and therefore we need
print()
print('Distribution of categories in service:')
print(df['service'].value_counts().sort_values(ascending=False).head())
```

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

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

```
# Test set
print('Test set:')
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_name, u
```

```
Test set:
Feature 'protocol_type' has 3 categories
Feature 'service' has 64 categories
Feature 'flag' has 11 categories
Feature 'label' has 38 categories
```

Conclusion: Need to make dummies for all categories as the distribution is fairly even. In total: 3+70+11=84 dummies.

Comparing the results shows that the Test set has fewer categories (6), these need to be added as empty columns.

LabelEncoder

Insert categorical features into a 2D numpy array

```
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
categorical_columns=['protocol_type', 'service', 'flag']
# insert code to get a list of categorical columns into a variable, categorical_columns
categorical_columns=['protocol_type', 'service', 'flag']
 # Get the categorical values into a 2D numpy array
df_categorical_values = df[categorical_columns]
testdf_categorical_values = df_test[categorical_columns]
df_categorical_values.head()
```

	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

Make column names for dummies

```
# protocol type
unique_protocol=sorted(df.protocol_type.unique())
string1 = 'Protocol_type_'
unique_protocol2=[string1 + x for x in unique_protocol]
# service
unique_service=sorted(df.service.unique())
string2 = 'service_'
unique_service2=[string2 + x for x in unique_service]
# flag
unique_flag=sorted(df.flag.unique())
string3 = 'flag_'
unique_flag2=[string3 + x for x in unique_flag]
# put together
dumcols=unique_protocol2 + unique_service2 + unique_flag2
print(dumcols)

#do same for test set
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
```

```
['Protocol_type_icmp', 'Protocol_type_tcp', 'Protocol_type_udp', 'service_IRC', 'service
```

Transform categorical features into numbers using LabelEncode

```
df_categorical_values_enc=df_categorical_values.apply(LabelEncoder().fit_transform)
print(df_categorical_values_enc.head())
# test set
testdf_categorical_values_enc=testdf_categorical_values.apply(LabelEncoder().fit_transform)
```

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

One-Hot-Encoding

```
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)
# test set
testdf_categorical_values_encenc = enc.fit_transform(testdf_categorical_values_enc)
testdf_cat_data = pd.DataFrame(testdf_categorical_values_encenc.toarray(),columns=testdumcol
```

```
df_cat_data.head()
```

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

5 rows × 84 columns

Add 6 missing categories from train set to test set

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

```
['service_urh_i',
 'service_http_2784',
 'service_harvest',
 'service_red_i',
 'service_http_8001',
 'service_aol']
```

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

testdf_cat_data.shape
```

```
(22544, 84)
```

Join encoded categorical dataframe with the non-categorical dataframe

```
newdf=df.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)
```

Split Dataset into 4 datasets for every attack category

Rename every attack label: 0=normal, 1=DoS, 2=Probe, 3=R2L and 4=U2R.

Replace labels column with new labels column

Make new datasets

```
# 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': 1, 's
                           'ipsweep' : 2,'nmap' : 2,'portsweep' : 2,'satan' : 2,'mscan' : 2,
                           ,'ftp_write': 3,'guess_passwd': 3,'imap': 3,'multihop': 3,'phf':
                           'buffer_overflow': 4,'loadmodule': 4,'perl': 4,'rootkit': 4,'ps':
newlabeldf_test=labeldf_test.replace({ 'normal' : 0, 'neptune' : 1 ,'back': 1, 'land': 1, 'p
                           'ipsweep' : 2,'nmap' : 2,'portsweep' : 2,'satan' : 2,'mscan' : 2,
                           ,'ftp_write': 3,'guess_passwd': 3,'imap': 3,'multihop': 3,'phf':
                           'buffer_overflow': 4,'loadmodule': 4,'perl': 4,'rootkit': 4,'ps':
# 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
```

```
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)];
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)
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)
```

```
Train:
Dimensions of DoS: (113270, 123)
Dimensions of Probe: (78999, 123)
Dimensions of R2L: (68338, 123)
Dimensions of U2R: (67395, 123)
Test:
Dimensions of DoS: (17171, 123)
Dimensions of Probe: (12132, 123)
Dimensions of R2L: (12596, 123)
Dimensions of U2R: (9778, 123)
```

Step 2: Feature Scaling:

```
# Split dataframes into X & Y
# assign X as a dataframe of feautures and Y as a series of outcome variables
X_DoS = DoS_df.drop('label',axis=1)
Y_DoS = DoS_df.label
X_Probe = Probe_df.drop('label',axis=1)
Y_Probe = Probe_df.label
X_R2L = R2L_df.drop('label',axis=1)
Y_R2L = R2L_df.label
X_U2R = U2R_df.drop('label',axis=1)
Y_U2R = U2R_df.label
# test set
```

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

Save a list of feature names for later use (it is the same for every attack category). Column names are dropped at this stage.

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

Use StandardScaler() to scale the dataframes

```
from sklearn import preprocessing
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)
# test data
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)
```

Check that the Standard Deviation is 1

```
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.]
```

```
X_Probe.std(axis=0);
X_R2L.std(axis=0);
X_U2R.std(axis=0);
```

Step 3: Feature Selection:

1. Univariate Feature Selection using ANOVA F-test

```
#univariate feature selection with ANOVA F-test. using secondPercentile method, then RFE
#Scikit-learn exposes feature selection routines as objects that implement the transform met
#SelectPercentile: removes all but a user-specified highest scoring percentage of features
#f_classif: ANOVA F-value between label/feature for classification tasks.
from sklearn.feature_selection import SelectPercentile, f_classif
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:\Users\ZIAD\anaconda3\Lib\site-packages\sklearn\feature_selection\_univariate_selectic
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
(113270, 13)
```

Get the features that were selected: DoS

```
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
```

```
['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']
```

```
X_newProbe = selector.fit_transform(X_Probe,Y_Probe)
X_newProbe.shape
```

```
c:\Users\ZIAD\anaconda3\Lib\site-packages\sklearn\feature_selection\_univariate_selectic
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
(78999, 13)
```

Get the features that were selected: Probe

```
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
```

```
['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']
```

```
X_newR2L = selector.fit_transform(X_R2L,Y_R2L)
X_newR2L.shape
```

```
c:\Users\ZIAD\anaconda3\Lib\site-packages\sklearn\feature_selection\_univariate_selectic
  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, UserWarning)
(68338, 13)
```

Get the features that were selected: R2L

```
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
```

```
['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']
```

```
X_newU2R = selector.fit_transform(X_U2R,Y_U2R)
X_newU2R.shape
```

```
c:\Users\ZIAD\anaconda3\Lib\site-packages\sklearn\feature_selection\_univariate_selectic
  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, UserWarning)
(67395, 13)
```

Get the features that were selected: U2R

```
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
```

```
['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

```
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', 'sam

Features selected for Probe: ['logged_in', 'rerror_rate', 'srv_rerror_rate', 'dst_host_s

Features selected for R2L: ['src_bytes', 'dst_bytes', 'hot', 'num_failed_logins', 'is_gu

Features selected for U2R: ['urgent', 'hot', 'root_shell', 'num_file_creations', 'num_sh
```

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. Recursive Feature Elimination for feature ranking (Option 1: get importance from previous selected)

```
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
# 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, 'c
```

```
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_rat
```

```
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,
```

```
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, 'r
```

2. Recursive Feature Elimination, select 13 features each of 122 (Option 2: get 13 best features from 122 from RFE)

```
from sklearn.feature_selection import RFE
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)
```

```
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)
```

```
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)
```

```
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

```
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_compromisec

Features selected for Probe: ['src_bytes', 'dst_bytes', 'rerror_rate', 'dst_host_same_sr

Features selected for R2L: ['duration', 'src_bytes', 'dst_bytes', 'hot', 'num_failed_log

Features selected for U2R: ['duration', 'src_bytes', 'dst_bytes', 'hot', 'root_shell', '
```

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

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

Step 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.

```
# 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)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=0)
```

```
# 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)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=0)
```

Step 5: Prediction & Evaluation (validation):

Using all Features for each category

Confusion Matrices

DoS

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

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

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

```
array([[0., 1.],
       [0., 1.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
```

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

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

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

Probe

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

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

R2L

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

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

U2R

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

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

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

DoS

```
from sklearn.model_selection import cross_val_score
from sklearn import metrics
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='precision')
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

```
accuracy = cross_val_score(clf_Probe, X_Probe_test, Y_Probe_test, cv=10, scoring='accuracy')
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='precisior
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='recall_macrc
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

```
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='precision_macro
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_macro')
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

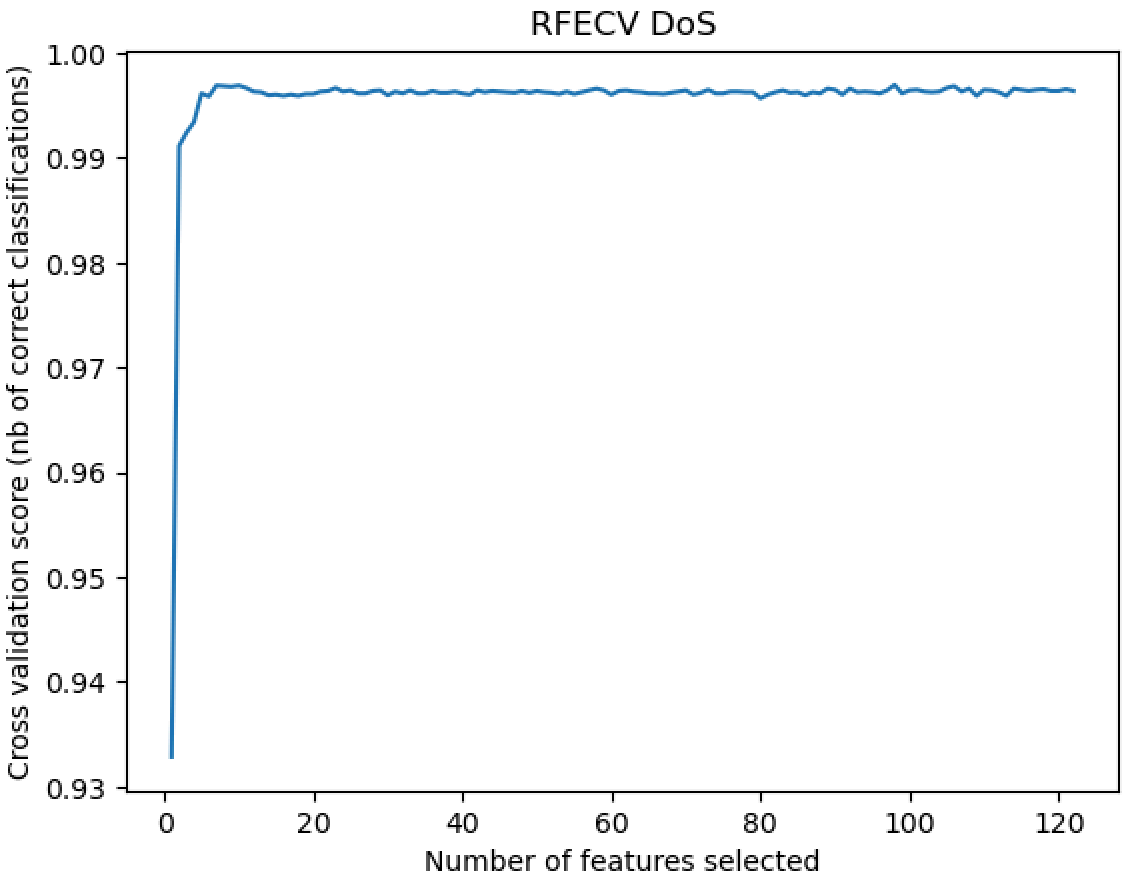
```
accuracy = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='accuracy')
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
precision = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='precision_macro
print("Precision: %0.5f (+/- %0.5f)" % (precision.mean(), precision.std() * 2))
recall = cross_val_score(clf_U2R, X_U2R_test, Y_U2R_test, cv=10, scoring='recall_macro')
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

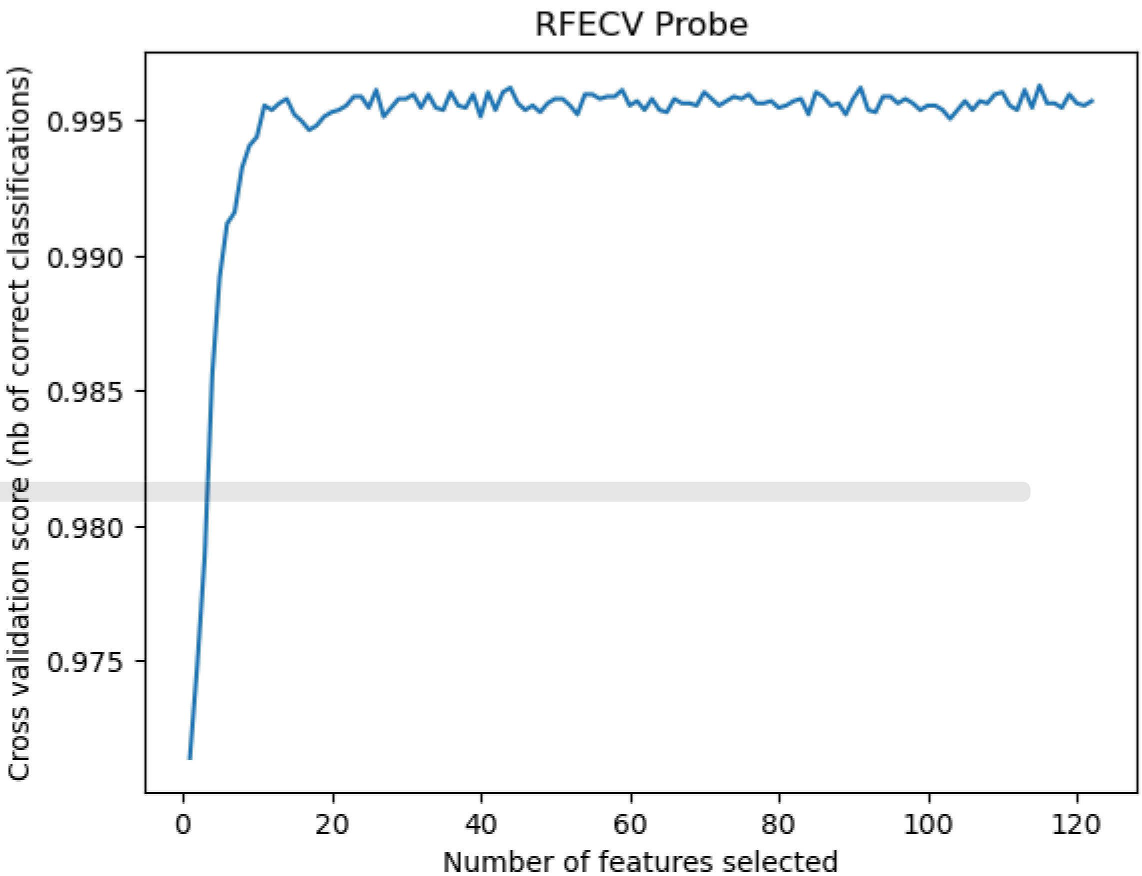
```
%matplotlib inline
```

```
import matplotlib.pyplot as plt

# Assuming rfecv_DoS is your RFECV object
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.title('RFECV DoS')

# Access the mean test scores from the cv_results_ attribute
plt.plot(range(1, len(rfecv_DoS.cv_results_['mean_test_score']) + 1), rfecv_DoS.cv_results_[
plt.show()
```

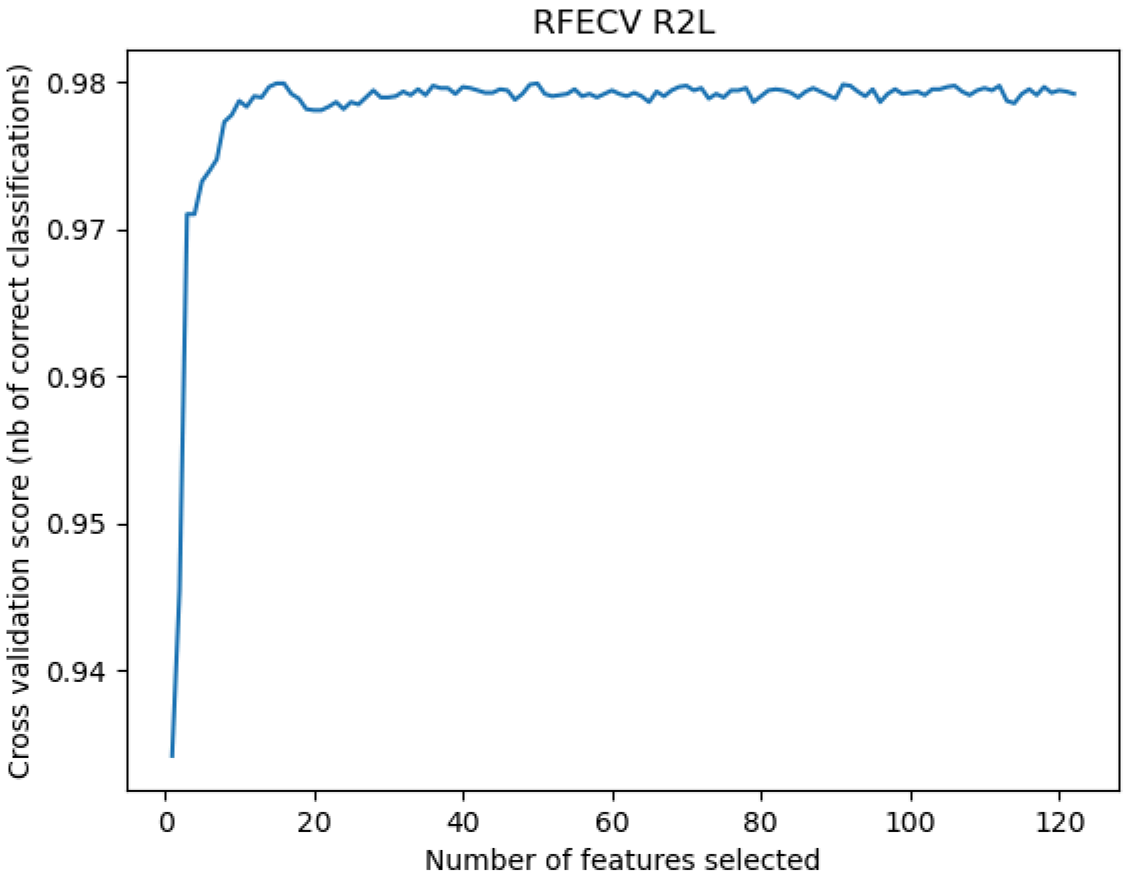



```
import matplotlib.pyplot as plt
from sklearn.feature_selection import RFECV

# Assuming clf_Probe is your classifier and X_Probe_test, Y_Probe_test are your data
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')
```

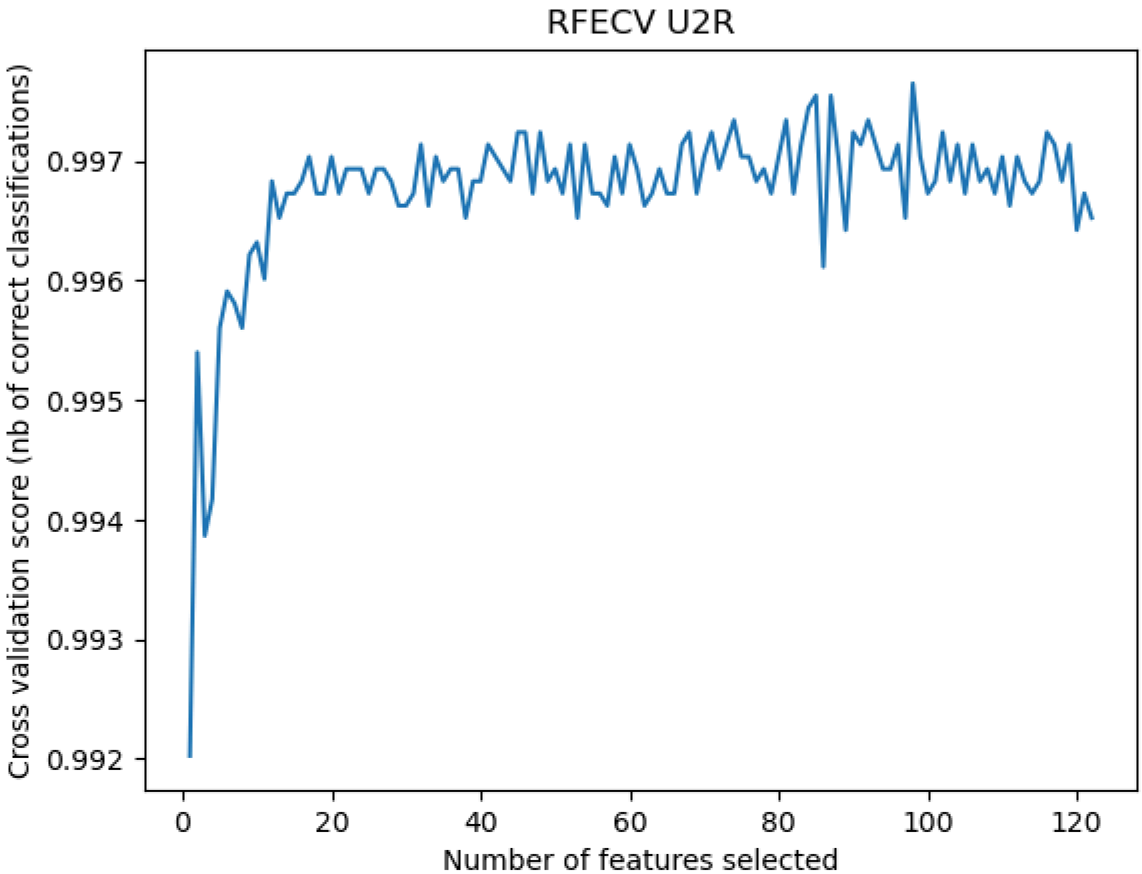
```
# Use cv_results_ to get the mean test scores for each feature set
plt.plot(range(1, len(rfecv_Probe.cv_results_['mean_test_score']) + 1), rfecv_Probe.cv_resul
plt.show()
```




```
# Assuming clf_R2L is your classifier and X_R2L_test, Y_R2L_test are your data
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')

# Use cv_results_ to get the mean test scores for each feature set
plt.plot(range(1, len(rfecv_R2L.cv_results_['mean_test_score']) + 1), rfecv_R2L.cv_results_[
plt.show()
```




```
# Assuming clf_U2R is your classifier and X_U2R_test, Y_U2R_test are your data
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')

# Use cv_results_ to get the mean test scores for each feature set
plt.plot(range(1, len(rfecv_U2R.cv_results_['mean_test_score']) + 1), rfecv_U2R.cv_results_[
plt.show()
```



Using 13 Features for each category

Confusion Matrices

DoS

```
# reduce test dataset to 13 features, use only features described in rfecolname_DoS etc.
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
```

```
(9778, 13)
```

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

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

Probe

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

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

R2L

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

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

U2R

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

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

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

DoS

```
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=10, scoring='accuracy')
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='precision')
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

```
accuracy = cross_val_score(clf_rfeProbe, X_Probe_test2, Y_Probe_test, cv=10, scoring='accura
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, scoring='preci
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='recall_m
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_macro')
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

```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=10, scoring='accuracy')
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='precision_m
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_macro')
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

```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=10, scoring='accuracy')
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='precision_m
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_macro')
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

```
from sklearn.model_selection import StratifiedKFold
accuracy = cross_val_score(clf_rfeDoS, X_DoS_test2, Y_DoS_test, cv=StratifiedKFold(10), scor
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

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

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

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

```
accuracy = cross_val_score(clf_rfeR2L, X_R2L_test2, Y_R2L_test, cv=StratifiedKFold(10), scor
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

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

```
accuracy = cross_val_score(clf_rfeU2R, X_U2R_test2, Y_U2R_test, cv=StratifiedKFold(10), scor
print("Accuracy: %0.5f (+/- %0.5f)" % (accuracy.mean(), accuracy.std() * 2))
```

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

CV 2, 5, 10, 30, 50 fold

DoS

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

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

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

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

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

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

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

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

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

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

Probe

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

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

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

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

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

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

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

```
Accuracy: 0.99118 (+/- 0.00742)
```

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

```
Accuracy: 0.99085 (+/- 0.01122)
```

R2L

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

```
Accuracy: 0.97118 (+/- 0.00143)
```

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

```
Accuracy: 0.97388 (+/- 0.00624)
```

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

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

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

```
Accuracy: 0.97467 (+/- 0.01644)
```