Report and code for IAF-604 project - 02

Importing libraries to handle, process and analyse the data.

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn import preprocessing
```

Reading both the datasets to understand which dataset is better for further classification.

In [3]:

```
data1 = pd.read_csv('nslkdd-version1.csv')
data2 = pd.read_csv('nslkdd-version2.csv')
```

What is the total number of observations in each dataset?

In [4]:

```
print(' shape of dataset1',data1.shape,'\n','shape of dataset2',data2.shape)
```

```
 shape of dataset1 (25192, 42)
 shape of dataset2 (25192, 36)
```

In [4]:

```
data1.head(5)
```

Out[4]:

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	...	a33	a34	a35	a36	a37	a38	a39	a40	a41	a42
0	0	tcp	ftp_data	SF	491	0	0	0	0	0	...	25	0.17	0.03	0.17	0.00	0.00	0.00	0.05	0.00	normal
1	0	udp	other	SF	146	0	0	0	0	0	...	1	0.00	0.60	0.88	0.00	0.00	0.00	0.00	0.00	normal
2	0	tcp	private	S0	0	0	0	0	0	0	...	26	0.10	0.05	0.00	0.00	1.00	1.00	0.00	0.00	neptune
3	0	tcp	http	SF	232	8153	0	0	0	0	...	255	1.00	0.00	0.03	0.04	0.03	0.01	0.00	0.01	normal
4	0	tcp	http	SF	199	420	0	0	0	0	...	255	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	normal

5 rows × 42 columns

In [5]:

```
data2.head(5)
```

Out[5]:

	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	...	a33	a34	a35	a36	a37	a38	a39	a40	a41	a42
0	0	0	0	0	0	0	0	0	0	0	...	25	0.17	0.03	0.17	0.00	0.00	0.00	0.05	0.00	0
1	0	0	0	0	0	0	0	0	0	0	...	1	0.00	0.60	0.88	0.00	0.00	0.00	0.00	0.00	0
2	0	0	0	0	0	0	0	0	0	0	...	26	0.10	0.05	0.00	0.00	1.00	1.00	0.00	0.00	1
3	0	0	0	0	0	0	0	1	0	0	...	255	1.00	0.00	0.03	0.04	0.03	0.01	0.00	0.01	0
4	0	0	0	0	0	0	0	1	0	0	...	255	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0

5 rows × 36 columns

List all the relevant statistical information about the dataset! In other words, compare these two datasets and document the similarities and the dissimilarities in these two datasets.

In [6]:

```
data1.describe() #stats of dataset 1
```

Out[6]:

	a1	a5	a6	a7	a8	a9	a10	a11	a12	
count	25192.000000	2.519200e+04	2.519200e+04	25192.000000	25192.000000	25192.00000	25192.000000	25192.000000	25192.000000	25192.00
mean	305.054104	2.433063e+04	3.491847e+03	0.000079	0.023738	0.00004	0.198039	0.001191	0.394768	0.22
std	2686.555640	2.410805e+06	8.883072e+04	0.008910	0.260221	0.00630	2.154202	0.045418	0.488811	10.41

min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.00
25%	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.00
50%	0.000000	4.400000e+01	0.000000e+00	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.00
75%	0.000000	2.790000e+02	5.302500e+02	0.000000	0.000000	0.00000	0.000000	0.000000	1.000000	0.00
max	42862.000000	3.817091e+08	5.151385e+06	1.000000	3.000000	1.00000	77.000000	4.000000	1.000000	884.00

8 rows × 38 columns

In [7]:

```
data2.describe()  #stats of dataset 2
```

Out[7]:

	a7	a8	a9	a10	a11	a12	a13	a14	a15	
count	25192.000000	25192.000000	25192.000000	25192.000000	25192.00000	25192.000000	25192.000000	25192.000000	25192.000000	25192.00
mean	0.000079	0.023738	0.000079	0.023738	0.00004	0.198039	0.001191	0.394768	0.227850	0.00
std	0.008910	0.260221	0.008910	0.260221	0.00630	2.154202	0.045418	0.488811	10.417352	0.03
min	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.00
50%	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.00
75%	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	1.000000	0.000000	0.00
max	1.000000	3.000000	1.000000	3.000000	1.00000	77.000000	4.000000	1.000000	884.000000	1.00

8 rows × 36 columns

In [8]:

```
data1.isnull() #check null values of dataset 1
```

Out[8]:

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	...	a33	a34	a35	a36	a37	a38	a39	a40	a41	a42
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
25187	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25188	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25189	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25190	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25191	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

25192 rows × 42 columns

In [9]:

```
data1.isnull().sum()
```

Out[9]:

```
a1      0
a2      0
a3      0
a4      0
a5      0
a6      0
a7      0
a8      0
a9      0
a10     0
a11     0
a12     0
a13     0
a14     0
a15     0
a16     0
a17     0
a18     0
a19     0
a20     0
a21     0
```

```
a22    0
a23    0
a24    0
a25    0
a26    0
a27    0
a28    0
a29    0
a30    0
a31    0
a32    0
a33    0
a34    0
a35    0
a36    0
a37    0
a38    0
a39    0
a40    0
a41    0
a42    0
dtype: int64
```

In [10]:

```
data2.isnull() #check null values of dataset 2
```

Out[10]:

	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	...	a33	a34	a35	a36	a37	a38	a39	a40	a41	a42
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
25187	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25188	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25189	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25190	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
25191	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

25192 rows × 36 columns

In [11]:

```
data2.isnull().sum()
```

Out[11]:

```
a7     0
a8     0
a9     0
a10    0
a11    0
a12    0
a13    0
a14    0
a15    0
a16    0
a17    0
a18    0
a19    0
a20    0
a21    0
a22    0
a23    0
a24    0
a25    0
a26    0
a27    0
a28    0
a29    0
a30    0
a31    0
a32    0
a33    0
a34    0
a35    0
a36    0
a37    0
a38    0
```

```
a39    0
a40    0
a41    0
a42    0
dtype: int64
```

Also, document the useful and not useful data characteristics in both datasets. Which one of these two datasets is useful to perform network traffic classification using random forest technique? Do you think this dataset needs further processing for cleaning, training, efficiency,…?

Similarities:

- Both datasets have common columns from a7 to a42.
- Columns in both datasets have the same statistical properties
- two data sets have the same number of observations or cases

Dissimilarities:

- The two data sets have different dimensions. i.e they have different number of variables
- The two data sets are of different size.
- The column name a42 are of different, version 1 has string datatype and version 2 dataset has been encoded numerically.

Data characteristics:

In terms of volumne and variety both datasets are limited but, dataset 1 has more features which means benefits while training a model. value and variety of the data remains same in both datasets, we can understand by observing statistical data of both datasets(common columns). Both datasets have no null values/Nan's. But, most of the columns has '0' values which might be useful or not until we perform classification and understanding feature importance.

In order to perform network traffic classification on the data set, it is optimal to use complete dataset i.e. dataset1. Therefore, version 1 having a more complete observation will be found more useful in the accurate classification of network traffic.

We have to pre-process this data for further analysis. It is important for us to transform all string variables to numeric data types that our random classifier can training. Therefore in order to train the model, there may be need for further processing. For efficiency we can remove or adjust features accordingly.

Then apply random forest technique to classify the traffic types and extract variables of importance.

Performing random forest model from sklearn library for dataset 1.

In [12]:

```
data1.dtypes
```

Out[12]:

```
a1       int64
a2      object
a3      object
a4      object
a5       int64
a6       int64
a7       int64
a8       int64
a9       int64
a10      int64
a11      int64
a12      int64
a13      int64
a14      int64
a15      int64
a16      int64
a17      int64
a18      int64
a19      int64
a20      int64
a21      int64
a22      int64
a23      int64
a24      int64
a25    float64
a26    float64
a27    float64
a28    float64
a29    float64
a30    float64
```

```
a31     float64
a32       int64
a33       int64
a34     float64
a35     float64
a36     float64
a37     float64
a38     float64
a39     float64
a40     float64
a41     float64
a42      object
dtype: object
```

Encoded numerical values to string typed columns

In [13]:

```
label = preprocessing.LabelEncoder()
data1["a2"] = label.fit_transform(data1["a2"])
data1["a3"] = label.fit_transform(data1["a3"])
data1["a4"] = label.fit_transform(data1["a4"])
data1["a42"] = label.fit_transform(data1["a42"])
```

label column

In [14]:

```
y = data1.iloc[:,41]
y
```

Out[14]:

```
0        11
1        11
2         9
3        11
4        11
         ..
25187     9
25188    20
25189     9
25190     9
25191     9
Name: a42, Length: 25192, dtype: int32
```

train/test columns

In [15]:

```
X = data1.iloc[:,:40]
X
```

Out[15]:

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	...	a31	a32	a33	a34	a35	a36	a37	a38	a39	a40
0	0	1	19	9	491	0	0	0	0	0	...	0.00	150	25	0.17	0.03	0.17	0.00	0.00	0.00	0.05
1	0	2	41	9	146	0	0	0	0	0	...	0.00	255	1	0.00	0.60	0.88	0.00	0.00	0.00	0.00
2	0	1	46	5	0	0	0	0	0	0	...	0.00	255	26	0.10	0.05	0.00	0.00	1.00	1.00	0.00
3	0	1	22	9	232	8153	0	0	0	0	...	0.00	30	255	1.00	0.00	0.03	0.04	0.03	0.01	0.00
4	0	1	22	9	199	420	0	0	0	0	...	0.09	255	255	1.00	0.00	0.00	0.00	0.00	0.00	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
25187	0	1	16	2	0	0	0	0	0	0	...	0.00	255	7	0.03	0.06	0.00	0.00	0.00	0.00	1.00
25188	0	1	19	9	334	0	0	0	0	0	...	0.00	1	39	1.00	0.00	1.00	0.18	0.00	0.00	0.00
25189	0	1	46	1	0	0	0	0	0	0	...	0.00	255	13	0.05	0.07	0.00	0.00	0.00	0.00	1.00
25190	0	1	38	5	0	0	0	0	0	0	...	0.00	255	20	0.08	0.06	0.00	0.00	1.00	1.00	0.00
25191	0	1	17	5	0	0	0	0	0	0	...	0.00	255	49	0.19	0.03	0.01	0.00	1.00	1.00	0.00

25192 rows × 40 columns

In [16]:

```
tmp = np.array(X)
X1 = tmp[:,0:41]
Y1 = np.array(y)
# Machine learning with 80:20
# Split the data into 80:20
row, col = X.shape
TR = round(row*0.8)
TT = row-TR
```

```
# Training with 80% data
X1_train = X1[0:TR-1,:]
Y1_train = Y1[0:TR-1]
```

We are taking randomclassifier from skleran.metrics library. which has n-estimator, This is the number of trees you wish to construct before using maximum voting or prediction averages. While having a larger number of trees improves efficiency, it also slows down your code.

In [17]:

```
rF = RandomForestClassifier(random_state=0, n_estimators=1000, oob_score=True, n_jobs=-1)
model = rF.fit(X1_train,Y1_train)
```

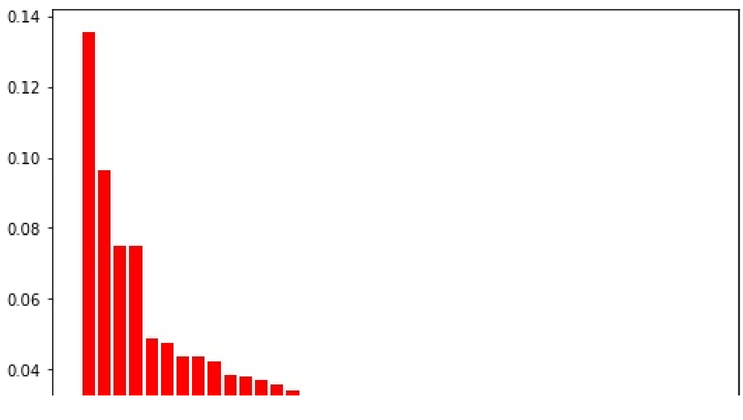
(For variable importance, in python there is a way to select the important features—plot it as a histogram). It means the random forest algorithm provides the variable list with an order of importance for the classification accuracy that was achieved.

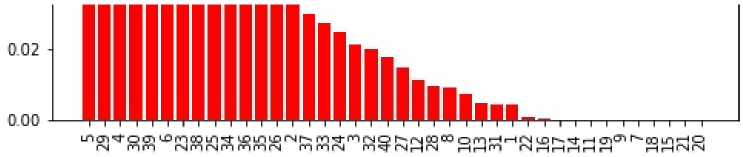
Listing features according to theri importance. Also ploting the histogram of these features.

In [18]:

```
importance = model.feature_importances_
indices = importance.argsort()[::-1]
for f in range(X.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f]+1, importance[indices[f]]))
plt.figure(figsize=(8, 6))
plt.bar(range(X.shape[1]), importance[indices], color="r", align="center")
plt.xticks(range(X.shape[1]), indices+1, rotation=90)
plt.show()
```

```
1. feature 5 (0.135336)
2. feature 29 (0.096357)
3. feature 4 (0.075013)
4. feature 30 (0.074948)
5. feature 39 (0.048864)
6. feature 6 (0.047298)
7. feature 23 (0.043720)
8. feature 38 (0.043473)
9. feature 25 (0.042263)
10. feature 34 (0.038218)
11. feature 36 (0.037724)
12. feature 35 (0.036891)
13. feature 26 (0.035682)
14. feature 2 (0.033995)
15. feature 37 (0.030115)
16. feature 33 (0.027591)
17. feature 24 (0.025071)
18. feature 3 (0.021467)
19. feature 32 (0.020234)
20. feature 40 (0.018038)
21. feature 27 (0.014955)
22. feature 12 (0.011247)
23. feature 28 (0.009480)
24. feature 8 (0.009097)
25. feature 10 (0.007359)
26. feature 13 (0.004853)
27. feature 31 (0.004479)
28. feature 1 (0.004310)
29. feature 22 (0.000867)
30. feature 16 (0.000247)
31. feature 17 (0.000208)
32. feature 14 (0.000193)
33. feature 11 (0.000159)
34. feature 19 (0.000110)
35. feature 9 (0.000053)
36. feature 7 (0.000032)
37. feature 18 (0.000031)
38. feature 15 (0.000023)
39. feature 21 (0.000000)
40. feature 20 (0.000000)
```





Performance evaluation by:

- *sklearn.metrics*
- *confusion matric*
- *out of bag estimate*

In [19]:

```
# Testing with 20% data
X1_test = X1[TR:row,:]
y_test = Y1[TR:row]
yhat_test = rF.predict(X1_test)
in_accuracy = metrics.accuracy_score(y_test, yhat_test)
print("sklearn.metrics_Accuracy:",in_accuracy,'\n')
print(classification_report(y_test, yhat_test, labels=np.unique(data1['a42'])))
#confusion matrix
cm = confusion_matrix(y_test, yhat_test)
print("Confusion matrix:\n%s" % cm)
model.oob_score_
```

```
sklearn.metrics_Accuracy: 0.9974196109567288

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        39
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         0
           3       1.00      1.00      1.00         3
           4       1.00      1.00      1.00         1
           5       1.00      0.99      0.99       152
           6       0.00      0.00      0.00         0
           7       0.00      0.00      0.00         0
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00      1648
          10       0.98      1.00      0.99        61
          11       1.00      1.00      1.00      2675
          12       0.00      0.00      0.00         0
          13       1.00      1.00      1.00         8
          14       1.00      0.99      1.00       127
          15       0.00      0.00      0.00         0
          16       0.99      0.97      0.98       144
          17       1.00      1.00      1.00        96
          18       0.00      0.00      0.00         1
          19       1.00      1.00      1.00        38
          20       0.98      0.95      0.96        43
          21       1.00      1.00      1.00         1

   micro avg       1.00      1.00      1.00      5038
   macro avg       0.63      0.63      0.63      5038
weighted avg       1.00      1.00      1.00      5038

Confusion matrix:
[[  39    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    3    0    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    1    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    0  150    0    0    1    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0 1648    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0   61    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0 2673    0    0    1    0    0    0
     1    0]
 [   0    0    0    0    0    0    0    0    8    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    1    0  126    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    4    0    0  140    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0   96    0    0
     0    0]
 [   0    0    0    0    0    0    0    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0    0   38
```

```
    0    0]
 [   0    0    0    0    0    0    0    2    0    0    0    0    0    0
    41    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    1]]
```

Out[19]:

```
0.9966754329380241
```

In [20]:

```
indices = indices+1
indices
```

Out[20]:

```
array([ 5, 29,  4, 30, 39,  6, 23, 38, 25, 34, 36, 35, 26,  2, 37, 33, 24,
        3, 32, 40, 27, 12, 28,  8, 10, 13, 31,  1, 22, 16, 17, 14, 11, 19,
        9,  7, 18, 15, 21, 20], dtype=int64)
```

As the next step, by eliminating one feature at a time, from the least important to the most important, get accuracies for the random forest and use them to decide how much dimensionality reduction can be achieved. In other words, find the subset of features (subspace) that gives similar accuracy as the entire feature space.

Stopping condition: As we have overall accuracy of 0.99, if we perform feature reduction cannot be less than 0.98.

Removing least important feature one at time and applying classification using random classifier and printing accuracy.

In [21]:

```
temp = data1.copy()
temp.drop(columns = 'a42',inplace = True)
elim = []
for i in indices[::-1]:
    elim.append(i)
    temp.drop(columns = 'a%s'%str(i),inplace = True)
    tmp = np.array(temp)
    #print(tmp.shape)
    y=data1['a42']
    X1 = tmp
    Y1 = np.array(y)
    row, col = X.shape
    TR = round(row*0.8)
    TT = row-TR
    X1_train = X1[0:TR-1,:]
    Y1_train = Y1[0:TR-1]
    rF = RandomForestClassifier(random_state=0, n_estimators=1000, oob_score=True, n_jobs=-1)
    model = rF.fit(X1_train,Y1_train)
    X1_test = X1[TR:row,:]
    y_test = Y1[TR:row]
    yhat_test = rF.predict(X1_test)
    accuracy = metrics.accuracy_score(y_test, yhat_test)
    print(len(elim),'.',"Accuracy:", accuracy, 'after removing:', elim)
    if(accuracy < 0.98):
        print('Accuracy:', accuracy)
        break
```

```
1 . Accuracy: 0.9972211194918619 after removing: [20]
2 . Accuracy: 0.9972211194918619 after removing: [20, 21]
3 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15]
4 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18]
5 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7]
6 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9]
7 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19]
8 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11]
9 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14]
10 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17]
11 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16]
12 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22]
13 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1]
14 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31]
15 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13]
16 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10]
17 . Accuracy: 0.9968241365621279 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
]
18 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28]
19 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12]
20 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27]
21 . Accuracy: 0.9972211194918619 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40]
22 . Accuracy: 0.9970226280269948 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32]
```

```
23 . Accuracy: 0.9964271536323938 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3]
24 . Accuracy: 0.9968241365621279 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24]
25 . Accuracy: 0.9966256450972608 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33]
26 . Accuracy: 0.9872965462485113 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37]
27 . Accuracy: 0.9855101230647082 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2]
28 . Accuracy: 0.9855101230647082 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26]
29 . Accuracy: 0.9853116315998413 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26, 35]
30 . Accuracy: 0.9849146486701071 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26, 35, 36]
31 . Accuracy: 0.9805478364430329 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26, 35, 36, 34]
32 . Accuracy: 0.980349344978166 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8,
28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26, 35, 36, 34, 25]
33 . Accuracy: 0.9793568876538309 after removing: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8
, 28, 12, 27, 40, 32, 3, 24, 33, 37, 2, 26, 35, 36, 34, 25, 38]
Accuracy: 0.9793568876538309
```

- *case1: After removing features: [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8] there is there is significant loss in accuracy = 0.9970226280269948.*
- *case 2: Again after removing features [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10, 8, 28, 12, 27, 40] accuracy (0.9972211194918619) remained same but, this might lead to missclassification.*

so, we will continue with features after removing [20, 21, 15, 18, 7, 9, 19, 11, 14, 17, 16, 22, 1, 31, 13, 10], this is just before case-1.

Dimenstionality resuced till 16 features removal, but accuracy remains almost same.

In [22]:

```
fet = data1[['a2', 'a3', 'a4', 'a5', 'a6', 'a8', 'a12', 'a23', 'a24', 'a25', 'a26', 'a27', 'a28', 'a29', 'a30', '
tmp = np.array(fet)
y=data1['a42']
X1 = tmp
Y1 = np.array(y)
row, col = X.shape
TR = round(row*0.8)
TT = row-TR
X1_train = X1[0:TR-1,:]
Y1_train = Y1[0:TR-1]
rF = RandomForestClassifier(random_state=0, n_estimators=1000, oob_score=True, n_jobs=-1)
model = rF.fit(X1_train,Y1_train)
X1_test = X1[TR:row,:]
y_test = Y1[TR:row]
yhat_test = rF.predict(X1_test)
accuracy = metrics.accuracy_score(y_test, yhat_test)
```

Use quantitative measures (accuracy, sensitivity, specificity, etc.). Also, use misclassification and out-of-bag errors as measures to interpret and discuss the results.

As label column is of multiclass, we cannot generate sklearn sensitivity, specificity. But, can be interpreted by confusion matric and also generated a classification report to understand the performance of the model.

In [23]:

```
print('sklearn.metrics_Accuracy',accuracy,'\n') #sklearn.metrics accuracy
cm = confusion_matrix(y_test, yhat_test) #confusion matrix
print(classification_report(y_test, yhat_test, labels=np.unique(data1['a42'])))
print("Confusion matrix:\n%s" % cm)
model.oob_score_ #out of bag errors
```

```
sklearn.metrics_Accuracy 0.9970226280269948

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        39
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         0
           3       1.00      1.00      1.00         3
           4       1.00      1.00      1.00         1
           5       1.00      0.99      0.99       152
           6       0.00      0.00      0.00         0
           7       0.00      0.00      0.00         0
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00      1648
          10       0.98      1.00      0.99        61
```

```
          11       1.00      1.00      1.00      2675
          12       0.00      0.00      0.00         0
          13       1.00      1.00      1.00         8
          14       1.00      0.98      0.99       127
          15       0.00      0.00      0.00         0
          16       0.99      0.97      0.98       144
          17       1.00      1.00      1.00        96
          18       0.00      0.00      0.00         1
          19       1.00      1.00      1.00        38
          20       0.98      0.93      0.95        43
          21       1.00      1.00      1.00         1

   micro avg       1.00      1.00      1.00      5038
   macro avg       0.63      0.63      0.63      5038
weighted avg       1.00      1.00      1.00      5038

Confusion matrix:
[[  39    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    3    0    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    1    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    0  150    0    0    1    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0 1648    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0   61    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0 2673    0    0    1    0    0    0
     1    0]
 [   0    0    0    0    0    0    0    0    8    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    2    0  125    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    4    0    0  140    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0   96    0    0
     0    0]
 [   0    0    0    0    0    0    0    1    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0    0   38
     0    0]
 [   0    0    0    0    0    0    0    3    0    0    0    0    0    0
    40    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    1]]
```

Out[23]:

```
0.9967250533419342
```

Conclusion

After removing certain features and traing the random classifier on remaining subset of features, the following assertion could me made:

- *From the above confusion matrix above, we were able to maximize the TP(true positives) and TN(true negative) values and minimize both the FP(false positives) and FN(false negative). The result shows a model with a good classification results.*
- *The accuracy of the random forest model is given as 99.7% which is almost same when calculated with the out of bag samples. Hence, we have truely gotten an optimal model for the data set.*
- *The final model contains variables with high importance.*
- *The 17 x 17 confusion matrix shows an extremely small amount of misclassification.*

References:

- *Big Data Scalability, Machine Learning Models and Algorithms for Big Data Classification – Shan Suthahara*

In [ ]: