INTRUSION DETECTION SYSTEM USING LOGISTIC REGRESSION MODEL

A PROJECT REPORT

for

INFORMATION SECURITY ANALYSIS AND AUDIT (CSE3501)

in

B.Tech – Information Technology and Engineering

by

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VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

School of Information Technology and Engineering

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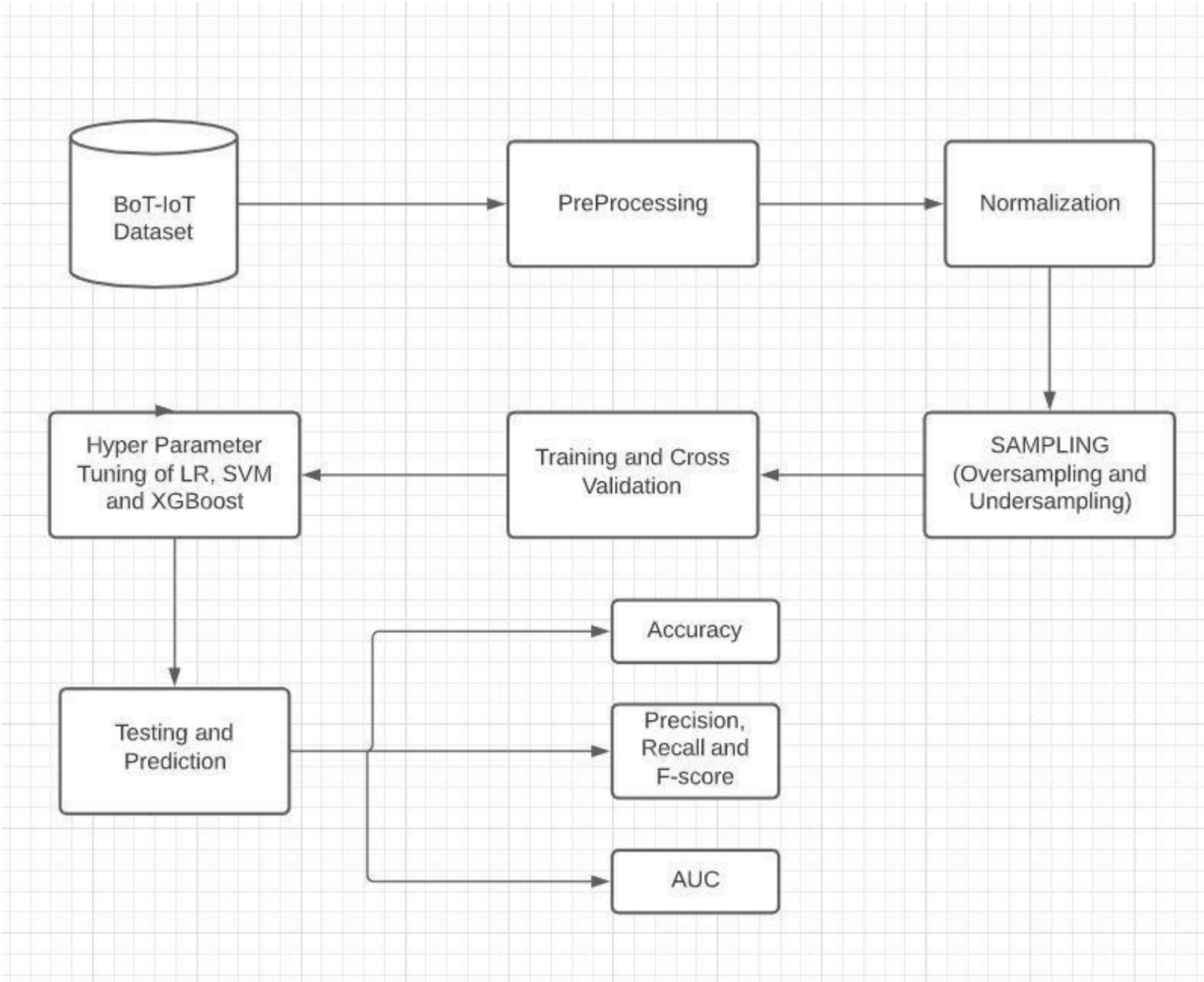
Intrusion Detection System using Logistic Regression model

Design of the system: -



Description: -

We aim to develop an Intrusion Detection System that monitors network traffic for suspicious activity and issues alerts when such activity is discovered

Dataset: The BoT-ioT dataset was created by designing a realistic network environment in the Cyber Range Lab of the center of UNSW Canberra Cyber. The environment incorporates a combination of normal and botnet traffic. The dataset's source files are provided in different formats, including the original pcap files, the generated argues files and csv files. The files used for the model, are split into training and testing datasets of 10 best features.

Preprocessing: Data processing is the method of processing raw data and making it suitable for the machine learning model. An important step in the development of a machine learning model and while we do any data processing, is that the dataset should be cleaned and be setted in a formatted form, to better predict the target. We have implemented preprocessing by dropping the columns who doesn't help in better predicting of the model.

Normalization: Normalization is a method used in the preparation of machine learning model. The goal is to convert numeric column values in the in order to use the same scale, without distorting the differences in the range of values and loss of information. We implement normalization by standard scalar.

Sampling: Data sampling is a method used for selecting observations from the information about the population based on the statistics from a sample. For our dataset we have used under sampling.

Cross-validation: It is a sampling procedure used to evaluate machine learning models on a given data sample. The procedure has a single parameter called k that refers to the number of groups that a given data sample is to be split into. Generally, it is known as k-fold cross-validation, we have implemented cross validation with k=10.

Hyper Parameter Tuning: Choosing a set of optimal hyper parameters for a learning algorithm. A hyperparameter is a parameter whose value is used to control the learning process.

Testing and Prediction: The model which will give best accuracy will be taken for prediction. Precision, Recall and f-score are also calculated for knowing more about the particular algorithm. To determine the value of the parameters which enhance the scores of the model, we have used grid search.

Implementation: -

Importing the required libraries.

- Numpy is a python library used for working with arrays.
- Pandas is a high level data manipulation tool.
- Seaborn is a data visualization library based on matplotlib.
- Sklearn deals with the machine learning models.
- The dataset provided to us was already divided into train and test.
- Reading the two datasets and performed the command data.head().
- head() returns the first 5 rows of the dataset.

18BIT0318_IDS_nasscom.ipynb

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```
import pandas as pd
import numpy as np
import seaborn as sns
import sklearn
import warnings; warnings.simplefilter('ignore')
from sklearn.preprocessing import StandardScaler
```

```
[2] data_train=pd.read_csv("/content/drive/My Drive/DATASETIOT/UNSW_2018_IoT_Botnet_Final_10_best_Training.csv")
```

```
[3] data_test=pd.read_csv("/content/drive/My Drive/DATASETIOT/UNSW_2018_IoT_Botnet_Final_10_best_Testing.csv")
```

```
[4] data_train.head()
```

	pkSeqID	proto	saddr	sport	daddr	dport	seq	stddev	N_IN_Conn_P_SrcIP	min	state_number	mean	N_IN_Conn_P_DstIP	drate	srate	max	attack
0	3142762	udp	192.168.100.150	6551	192.168.100.3	80	251984	1.900363	100	0.000000	4	2.687519	100	0.0	0.494549	4.031619	1
1	2432264	tcp	192.168.100.150	5532	192.168.100.3	80	256724	0.078003	38	3.856930	3	3.934927	100	0.0	0.256493	4.012924	1
2	1976315	tcp	192.168.100.147	27165	192.168.100.3	80	62921	0.268666	100	2.974100	3	3.341429	100	0.0	0.294880	3.609205	1
3	1240757	udp	192.168.100.150	48719	192.168.100.3	80	99168	1.823185	63	0.000000	4	3.222832	63	0.0	0.461435	4.942302	1
4	3257991	udp	192.168.100.147	22461	192.168.100.3	80	105063	0.822418	100	2.979995	4	3.983222	100	0.0	1.002999	4.994452	1

- data.shape tells about the number of rows and columns present in the datasets, append is used to merge the datasets

- data.info() gives the information of the data types present in the dataset.

```
[5] data_train.info()

    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 2934817 entries, 0 to 2934816
    Data columns (total 19 columns):
     #   Column              Dtype
    ---  ------              -----
     0   pkSeqID             int64
     1   proto               object
     2   saddr               object
     3   sport               object
     4   daddr               object
     5   dport               object
     6   seq                 int64
     7   stddev              float64
     8   N_IN_Conn_P_SrcIP   int64
     9   min                 float64
     10  state_number        int64
     11  mean                float64
     12  N_IN_Conn_P_DstIP   int64
     13  drate               float64
     14  srate               float64
     15  max                 float64
     16  attack              int64
     17  category            object
     18  subcategory         object
    dtypes: float64(6), int64(6), object(7)
    memory usage: 425.4+ MB
```

```
[6] data_train.shape

    (2934817, 19)
```

```
[7] data_test.shape

    (733705, 19)
```

- data.drop is used here to drop the unwanted columns that are do not help in prediction of the model

- data.isnull.sum() gives the count of null values present in each column in the dataset. In the dataset no null values are present so no null treatment is required.

- data.dtypes==’objects’ gives the object data types and value_counts() give the occurrence of unique values in a particular column.

```
[8] data_train.isnull().sum()
```

```
pkSeqID             0
proto               0
saddr               0
sport               0
daddr               0
dport               0
seq                 0
stddev              0
N_IN_Conn_P_SrcIP   0
min                 0
state_number        0
mean                0
N_IN_Conn_P_DstIP   0
drate               0
srate               0
max                 0
attack              0
category            0
subcategory         0
dtype: int64
```

```
[9] data_train.drop(["pkSeqID","seq","subcategory"], axis=1, inplace=True)
```



```
[9] data_train.drop(["pkSeqID","seq","subcategory"], axis=1, inplace=True)
```



```
[10] data_test.drop(["pkSeqID","seq","subcategory"], axis=1, inplace=True)
```

```
[11] data_train.dtypes[data_train.dtypes=='object']
```

```
proto       object
saddr       object
sport       object
daddr       object
dport       object
category    object
dtype: object
```

```
[12] data_train['saddr'].value_counts()
```

```
192.168.100.147              761360
192.168.100.148              738642
192.168.100.150              712260
192.168.100.149              711466
192.168.100.3                  6609
192.168.100.5                  4107
192.168.100.6                   272
192.168.100.7                    34
192.168.100.4                    17
192.168.100.1                    14
192.168.100.27                    9
192.168.100.46                    8
fe80::250:56ff:febe:254           5
192.168.100.55                    3
fe80::250:56ff:febe:c038          2
fe80::250:56ff:febe:89ee          2
fe80::250:56ff:febe:26db          2
fe80::2c6a:ff9b:7e14:166a         2
fe80::c0c0:aa20:45b9:bdd9         2
fe80::250:56ff:febe:e9d9          1
Name: saddr, dtype: int64
```

```
[13] data_train['sport'].value_counts()
```

```
0x0303    7156
80        3220
1822       878
60541      869
1216       868
          ...
961         31
18992       30
39305       30
0x000d      10
0x0011       8
Name: sport, Length: 65541, dtype: int64
```

```
[14] data_train['daddr'].value_counts()
```

```
192.168.100.3      1900562
192.168.100.5       361192
192.168.100.7       332161
192.168.100.6       329679
192.168.100.150       3040
                   ...
205.251.194.84           1
198.41.0.4               1
192.54.112.30            1
205.251.194.154          1
205.251.199.148          1
Name: daddr, Length: 81, dtype: int64
```

```
[15] data_train['dport'].value_counts()
```

```
80       2858794
1           5379
3306        3757
53           275
-1           166
          ...
48247          1
8370           1
1161           1
39162          1
25528          1
Name: dport, Length: 6906, dtype: int64
```

Now we will evaluate our target column which is category of the attack.

```
[16] data_train['category'].value_counts()
```

```
DDoS              1541315
DoS               1320148
Reconnaissance      72919
Normal                370
Theft                  65
Name: category, dtype: int64
```

```
[17] data_train.shape
```

```
(2934817, 16)
```

We can see that we are having 5 categories of attacks, DDoS, DoS, Reconnaissance, Normal and Theft.

As the values of Normal and Theft are exponentially less than the other three hence we will be following 2 approaches of sampling to get the best accuracy and at the same time avoiding overfitting.

Approach-1: -

Dropping both Normal and Theft attack.

```
[18] indexNames = data_train[data_train['category']=='Theft'].index
     data_train.drop(indexNames , inplace=True)
```

```
[19] indexNames = data_train[data_train['category']=='Normal'].index
     data_train.drop(indexNames , inplace=True)
```

```
[20] data_train.shape

     (2934382, 16)
```

```
[21] data_train['sport']=data_train['sport'].replace(['0x0303'],'771')
     data_train['sport']=data_train['sport'].replace(['0x0011'],'17')
     data_train['sport']=data_train['sport'].replace(['0x000d'],'13')
     data_train['sport']=data_train['sport'].replace(['0x0008'],'8')
```

Converting object data types are converted into int or float data types

```
[22] data_train["sport"] = data_train["sport"].astype(str).astype(int)
```

```
[23] data_test['sport']=data_test['sport'].replace(['0x0303'],'771')
     data_test['sport']=data_test['sport'].replace(['0x0011'],'17')
     data_test['sport']=data_test['sport'].replace(['0x000d'],'13')
     data_test['sport']=data_test['sport'].replace(['0x0008'],'8')
```

```
[24] data_test["sport"] = data_test["sport"].astype(str).astype(int)
```

```
[25] data_train['dport']=data_train.dport.apply(lambda x: int(x,16) if len(x)>1 and x[1]=="x" else int(x))
```

```
[26] data_test['dport']=data_test.dport.apply(lambda x: int(x,16) if len(x)>1 and x[1]=="x" else int(x))
```

```
[27] data_train['dport'].value_counts()
```

```
80       2858779
1           5379
3306        3755
465          161
993          161
           ...
9031           1
37712          1
9030           1
37715          1
13117          1
Name: dport, Length: 6773, dtype: int64
```

```
[28] data_train['sport'].value_counts()
```

```
771      7203
80       3209
1822      878
60541     869
1216      868
         ...
27738      31
39364      31
7813       31
18992      30
39305      30
Name: sport, Length: 65537, dtype: int64
```

Performing Label Encoding for converting the labels into numeric form so as to convert it into the machine-readable format.

```
[29] from sklearn.preprocessing import LabelEncoder
     le = LabelEncoder()
     data_train["saddr_enc"]= le.fit_transform(data_train.saddr)
     data_train["daddr_enc"]= le.fit_transform(data_train.daddr)
     data_train["proto_enc"]= le.fit_transform(data_train.proto)
     data_train["category_enc"]= le.fit_transform(data_train.category)
     data_train.drop(['saddr','daddr','proto','category'], axis=1, inplace=True)
```

```
[30] from sklearn.preprocessing import LabelEncoder
     le = LabelEncoder()
     data_test["saddr_enc"]= le.fit_transform(data_test.saddr)
     data_test["daddr_enc"]= le.fit_transform(data_test.daddr)
     data_test["proto_enc"]= le.fit_transform(data_test.proto)
     data_test["category_enc"]= le.fit_transform(data_test.category)
     data_test.drop(['saddr','daddr','proto','category'], axis=1, inplace=True)
```

All the object data types are now converted into int or float.

As we can see that the category is now having 3 values, as we dropped the Theft and normal attacks. 0 represents DDoS 1 represents DoS and 2 represents Reconnaissance.

```
[31] data_train.head()
```

	sport	dport	stddev	N_IN_Conn_P_SrcIP	min	state_number	mean	N_IN_Conn_P_DstIP	drate	srate	max	attack	saddr_enc	daddr_enc	proto_enc	category_enc
0	6551	80	1.900363	100	0.000000	4	2.687519	100	0.0	0.494549	4.031619	1	3	4	3	0
1	5532	80	0.078003	38	3.856930	3	3.934927	100	0.0	0.256493	4.012924	1	3	4	2	0
2	27165	80	0.268666	100	2.974100	3	3.341429	100	0.0	0.294880	3.609205	1	0	4	2	0
3	48719	80	1.823185	63	0.000000	4	3.222832	63	0.0	0.461435	4.942302	1	3	4	3	1
4	22461	80	0.822418	100	2.979995	4	3.983222	100	0.0	1.002999	4.994452	1	0	4	3	0

```
[32] data_train['category_enc'].value_counts()

0    1541315
1    1320148
2      72919
Name: category_enc, dtype: int64
```

```
[33] data_train.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2934382 entries, 0 to 2934816
Data columns (total 16 columns):
 #   Column             Dtype
---  ------             -----
 0   sport              int64
 1   dport              int64
 2   stddev             float64
 3   N_IN_Conn_P_SrcIP  int64
 4   min                float64
 5   state_number       int64
 6   mean               float64
 7   N_IN_Conn_P_DstIP  int64
 8   drate              float64
 9   srate              float64
 10  max                float64
 11  attack             int64
 12  saddr_enc          int64
 13  daddr_enc          int64
 14  proto_enc          int64
 15  category_enc       int64
dtypes: float64(6), int64(10)
memory usage: 380.6 MB
```

Storing the target variable in y so that we can drop it from the dataset.

```
[34] y_train=data_train["category_enc"]
```

```
[35] y_test=data_test["category_enc"]
```

Applying Normalization to the data using standard scalar , it standardizes a feature by subtracting the mean and then scaling to unit variance (dividing all the values by standard deviation).

```
[36] from sklearn.preprocessing import StandardScaler
     scaler=StandardScaler()
     features = data_train.iloc[:,:-1]
     cols=features.columns
     scaled_features= scaler.fit_transform(features)
     data_train= pd.DataFrame(scaled_features,columns=cols)
```

```
[37] from sklearn.preprocessing import StandardScaler
     scaler=StandardScaler()
     features = data_test.iloc[:,:-1]
     cols=features.columns
     scaled_features= scaler.fit_transform(features)
     data_test= pd.DataFrame(scaled_features,columns=cols)
```

```
[38] data_train.head()
```

	sport	dport	stddev	N_IN_Conn_P_SrcIP	min	state_number	mean	N_IN_Conn_P_DstIP	drate	srate	max	attack	saddr_enc	daddr_enc	proto_enc
0	-1.380839	-0.093994	1.260872	0.715398	-0.685704	0.729306	0.300989	0.415117	-0.007602	-0.005638	0.543863	0.0	1.339437	-0.629945	0.910667
1	-1.434151	-0.093994	-1.006793	-1.827708	1.914031	-0.113115	1.122922	0.415117	-0.007602	-0.006392	0.533816	0.0	1.339437	-0.629945	-1.075645
2	-0.302362	-0.093994	-0.769541	0.715398	1.318966	-0.113115	0.731858	0.415117	-0.007602	-0.006271	0.316849	0.0	-1.306088	-0.629945	-1.075645
3	0.825293	-0.093994	1.164835	-0.802262	-0.685704	0.729306	0.653713	-1.624605	-0.007602	-0.005743	1.033284	0.0	1.339437	-0.629945	0.910667
4	-0.548465	-0.093994	-0.080476	0.715398	1.322940	0.729306	1.154744	0.415117	-0.007602	-0.004028	1.061310	0.0	-1.306088	-0.629945	0.910667

```
[39] data_train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2934382 entries, 0 to 2934381
Data columns (total 15 columns):
 #   Column             Dtype
---  ------             -----
 0   sport              float64
 1   dport              float64
 2   stddev             float64
 3   N_IN_Conn_P_SrcIP  float64
 4   min                float64
 5   state_number       float64
 6   mean               float64
 7   N_IN_Conn_P_DstIP  float64
 8   drate              float64
 9   srate              float64
 10  max                float64
 11  attack             float64
 12  saddr_enc          float64
 13  daddr_enc          float64
 14  proto_enc          float64
dtypes: float64(15)
memory usage: 335.8 MB
```

Now to balance the dataset we apply Random Under sampling.

We will evaluate our accuracy and the best score using k folds and Hyper parameter tuning, after which we will go for our second approach.

```
[40] y_train.value_counts()

     0    1541315
     1    1320148
     2      72919
     Name: category_enc, dtype: int64
```

```
[41] import imblearn
     from imblearn.under_sampling import RandomUnderSampler
     samp_strat= { 0 : 72919, 1 : 72919, 2 : 72919}
     random_under= RandomUnderSampler(sampling_strategy=samp_strat,random_state=1)
     Xres,yres = random_under.fit_resample(data_train,y_train)
```

```
[42] pd.Series(yres).value_counts()

     2    72919
     1    72919
     0    72919
     dtype: int64
```

```
[43] from sklearn.linear_model import LogisticRegression
     logisticRegr = LogisticRegression()
     logisticRegr.fit(Xres, yres)
     pred= logisticRegr.predict(data_test)
     score = logisticRegr.score(data_test, y_test)
     score

     0.9588281393748168
```

<u>Here we got the accuracy of 95.88%</u>

Precision, Recall, F-score, Accuracy

```
[44] from sklearn.metrics import classification_report,confusion_matrix
     classification_report(y_test,pred)

     '              precision    recall  f1-score   support\n\n           0       0.98      0.99      0.98    385309\n           1       0.99      0.98      0.98    330112\n           2
     0.00      0.13      0.00       107\n           3       0.00      0.00      0.00     18163\n           4       0.00      0.00      0.00        14\n\n    accuracy
     0.96    733705\n   macro avg       0.39      0.42      0.39    733705\nweighted avg       0.96      0.96      0.96    733705\n'
```

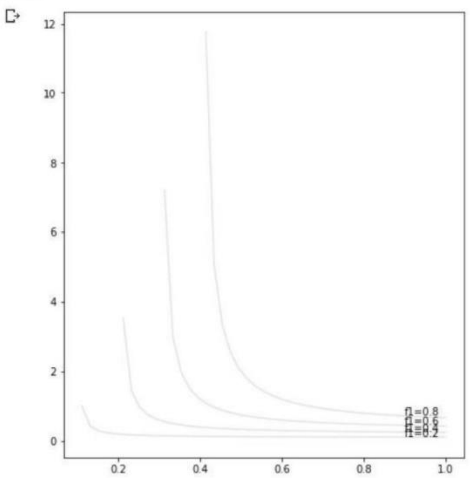
```
[45] confusion_matrix(y_test,pred)

     array([[380962,   2502,   1845,      0,      0],
            [  7423, 322521,    168,      0,      0],
            [    12,     81,     14,      0,      0],
            [   424,    522,  17217,      0,      0],
            [     0,      5,      9,      0,      0]])
```

```
[46] from sklearn.metrics import f1_score
     f1_score(y_test,pred,average='micro')

     0.9588281393748168
```

```
[47] from sklearn.metrics import recall_score
     recall_score(y_test, pred, average='micro')

     0.9588281393748168
```

```
[48] from sklearn.metrics import precision_score
     precision_score(y_test,pred, average='micro')

     0.9588281393748168
```

```python
from sklearn.metrics import f1_score
import matplotlib.pyplot as plt
from itertools import cycle

plt.figure(figsize=(7, 8))
f_scores = np.linspace(0.2, 0.8, num=4)
lines = []
labels = []
for f1_score in f_scores:
    x = np.linspace(0.01, 1)
    y = f1_score * x / (2 * x - f1_score)
    l, = plt.plot(x[y >= 0], y[y >= 0], color='gray', alpha=0.2)
    plt.annotate('f1={0:0.1f}'.format(f1_score), xy=(0.9, y[45] + 0.02))
lines.append(l)
labels.append('iso-f1 curves')
plt.show()
```



Before moving to k-fold and hyper parameter tuning.

Trying to improve accuracy by hit and trial method of parameters.

```python
[53] lr2 = LogisticRegression(penalty='l2',C = 3, solver = 'lbfgs',max_iter=1000,n_jobs=100)
     lr2.fit (Xres,yres)
     prediction= lr2.predict(data_test)
     score = lr2.score(data_test, y_test)
     score

     0.9614708908893902
```

Performing K fold cross validation

Cross-Validation is a resampling procedure used to evaluate ML models on a limited data sample. Stratified K-fold cross validation is applied on the dataset. n_splits means number of folds. In Stratified K-fold it shuffles the data and since number of folds is 10 it splits the data into 9:1 ratio. Accuracy obtained is nearly 100%.

```
[60] from sklearn.model_selection import cross_val_score
     scores = cross_val_score(lr2, Xres, yres, cv=10)
     scores
```

```
array([0.97984092, 0.97878954, 0.98066374, 0.97979521, 0.9786524 ,
       0.97906381, 0.98006948, 0.98006857, 0.97924571, 0.98148571])
```

```
[61] scores.mean()
```

```
0.9797675114280489
```

Doing hyper parameter tuning using GridSearchCV

```
[54] logModel = LogisticRegression()
     param_grid = [
         {'penalty': ['l1', 'l2'],'C':[0.001,.009,0.01,.09,1,5,10,25] }]
```

```
[55] from sklearn.model_selection import GridSearchCV
```

```
[56] clf = GridSearchCV(logModel, param_grid = param_grid, cv = 3, verbose=3)
```

```
[57] best_clf = clf.fit(data_train,y_train)
```

```
[CV] C=0.09, penalty=l1 ..............................................
[CV] .................... C=0.09, penalty=l1, score=nan, total=   0.1s
[CV] C=0.09, penalty=l1 ..............................................
[CV] .................... C=0.09, penalty=l1, score=nan, total=   0.1s
[CV] C=0.09, penalty=l2 ..............................................
[CV] .................. C=0.09, penalty=l2, score=0.985, total= 1.2min
[CV] C=0.09, penalty=l2 ..............................................
[CV] .................. C=0.09, penalty=l2, score=0.985, total= 1.2min
[CV] C=0.09, penalty=l2 ..............................................
[CV] .................. C=0.09, penalty=l2, score=0.985, total= 1.2min
[CV] C=1, penalty=l1 .................................................
[CV] ....................... C=1, penalty=l1, score=nan, total=   0.2s
[CV] C=1, penalty=l1 .................................................
[CV] ....................... C=1, penalty=l1, score=nan, total=   0.1s
[CV] C=1, penalty=l1 .................................................
[CV] ....................... C=1, penalty=l1, score=nan, total=   0.1s
[CV] C=1, penalty=l2 .................................................
[CV] ..................... C=1, penalty=l2, score=0.986, total= 1.2min
[CV] C=1, penalty=l2 .................................................
[CV] ..................... C=1, penalty=l2, score=0.986, total= 1.2min
[CV] C=1, penalty=l2 .................................................
[CV] ..................... C=1, penalty=l2, score=0.986, total= 1.2min
```

```
[CV] C=5, penalty=l2 ...............................................
[CV] ..................... C=5, penalty=l2, score=0.986, total= 1.2min
[CV] C=5, penalty=l2 ...............................................
[CV] ..................... C=5, penalty=l2, score=0.987, total= 1.3min
[CV] C=10, penalty=l1 ..............................................
[CV] ...................... C=10, penalty=l1, score=nan, total=   0.1s
[CV] C=10, penalty=l1 ..............................................
[CV] ...................... C=10, penalty=l1, score=nan, total=   0.1s
[CV] C=10, penalty=l1 ..............................................
[CV] ...................... C=10, penalty=l1, score=nan, total=   0.1s
[CV] C=10, penalty=l2 ..............................................
[CV] .................... C=10, penalty=l2, score=0.986, total= 1.2min
[CV] C=10, penalty=l2 ..............................................
[CV] .................... C=10, penalty=l2, score=0.986, total= 1.2min
[CV] C=10, penalty=l2 ..............................................
[CV] .................... C=10, penalty=l2, score=0.987, total= 1.2min
[CV] C=25, penalty=l1 ..............................................
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l1 ..............................................
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l1 ..............................................
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l2 ..............................................
[CV] .................... C=25, penalty=l2, score=0.986, total= 1.2min
[CV] C=25, penalty=l2 ..............................................
[CV] .................... C=25, penalty=l2, score=0.986, total= 1.2min
[CV] C=25, penalty=l2 ..............................................
[CV] .................... C=25, penalty=l2, score=0.986, total= 1.2min
[Parallel(n_jobs=1)]: Done  48 out of  48 | elapsed: 29.4min finished
```

It took 29.4 mins in performing the Grid SearchCV

Best parameters:- ‘C’ : ‘10’, ‘penalty’ : ‘l2’

```
[58] best_clf.best_score_

0.9862499156898746
```

```
[59] best_clf.best_params_

{'C': 10, 'penalty': 'l2'}
```

After choosing the best parameters we test our model:-

```
[62] lr2 = LogisticRegression(penalty='l2',C = 10, solver = 'lbfgs',max_iter=1000,n_jobs=100)
     lr2.fit (Xres,yres)
     prediction= lr2.predict(data_test)
     score = lr2.score(data_test, y_test)
     score

0.9635671012191548
```

We observe that the best accuracy is <u>96.35%</u>

Second Approach:-

Now we move to our second approach:-

<u>Dropping only Theft attack</u> as it is having only 65 values.

The category variable is encoded as category_enc where

0 – DDoS

1 – DoS

2 – Normal

3 - Reconnaissance

```
[ ]  data_train['category_enc'].value_counts()

0    1541315
1    1320148
3      72919
2        370
Name: category_enc, dtype: int64
```

Now we perform oversampling for Theft and then under sampling for DDoS and DoS

```
[ ]
    import imblearn
    from imblearn.over_sampling import RandomOverSampler
    samp_strat= { 0 : 1541315, 1 : 1320148, 2 : 72919, 3 : 72919}
    random_over= RandomOverSampler(sampling_strategy=samp_strat,random_state=1)
    Xres,yres = random_over.fit_resample(data_train,y_train)
```

```
[ ]  pd.Series(yres).value_counts()

0    1541315
1    1320148
3      72919
2      72919
dtype: int64
```

```
[ ] import imblearn
    from imblearn.under_sampling import RandomUnderSampler
    samp_strat= { 0 : 72919, 1 : 72919, 2 : 72919, 3 : 72919}
    random_under= RandomUnderSampler(sampling_strategy=samp_strat,random_state=1)
    Xres1,yres1 = random_under.fit_resample(Xres,yres)
```

```
[ ] pd.Series(yres1).value_counts()

    3    72919
    2    72919
    1    72919
    0    72919
    dtype: int64
```

After following all the steps as used in the previous approach

We get accuracy of 97.98% which is better than the previous.

Hence as we get better accuracy in our base model, we will consider this approach as a better one.

```
from sklearn.linear_model import LogisticRegression
import time
start = time.time()
logisticRegr = LogisticRegression()
logisticRegr.fit(Xres1, yres1)
pred= logisticRegr.predict(data_test)
score = logisticRegr.score(data_test, y_test)
end = time.time()
print(end - start, "seconds\n")
score

24.95344567298889 seconds

0.9798488493331788
```

Metrics: -

Precision, Recall, F-score, Accuracy

```python
from sklearn.metrics import classification_report,confusion_matrix
classification_report(y_test,pred)
```

```
'              precision    recall  f1-score   support\n\n           0       0.98      0.99      0.98    385309\n           1       0.99      0.97      0.98    330112\n           2
1.00      1.00      1.00       107\n           3       0.83      0.96      0.89     18163\n           4       0.00      0.00      0.00        14\n\n    accuracy
0.98    733705\n   macro avg       0.76      0.78      0.77    733705\nweighted avg       0.98      0.98      0.98    733705\n'
```

```python
from sklearn.metrics import f1_score
f1_score(y_test,pred,average='micro')
```

```
0.9798488493331788
```

```python
from sklearn.metrics import recall_score
recall_score(y_test, pred, average='micro')
```

```
0.9798488493331788
```

```python
from sklearn.metrics import precision_score
precision_score(y_test,pred, average='micro')
```

```
0.9798488493331788
```

```python
from sklearn.metrics import classification_report,confusion_matrix
prediction = logisticRegr.predict(data_test)
print(classification_report(y_test,prediction))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98    385309
           1       0.99      0.97      0.98    330112
           2       1.00      1.00      1.00       107
           3       0.83      0.96      0.89     18163
           4       0.00      0.00      0.00        14

    accuracy                           0.98    733705
   macro avg       0.76      0.78      0.77    733705
weighted avg       0.98      0.98      0.98    733705
```

Now performing Hyper Parameter Tuning on the same

```
[ ] logModel = LogisticRegression()
    param_grid = [
        {'penalty': ['l1', 'l2'],'C':[0.001,.009,0.01,.09,1,5,10,25] }]
```

```
[ ] from sklearn.model_selection import GridSearchCV
```

```
[ ] clf = GridSearchCV(logModel, param_grid = param_grid, cv = 3, verbose=3)
```

```
[ ] best_clf = clf.fit(data_train,y_train)
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV] C=0.001, penalty=l1 ..........................................
[CV] .................. C=0.001, penalty=l1, score=nan, total=   0.3s
[CV] C=0.001, penalty=l1 ..........................................
[CV] .................. C=0.001, penalty=l1, score=nan, total=   0.1s
[CV] C=0.001, penalty=l1 ..........................................
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.4s remaining:    0.0s
[CV] .................. C=0.001, penalty=l1, score=nan, total=   0.1s
[CV] C=0.001, penalty=l2 ..........................................
[CV] ................ C=0.001, penalty=l2, score=0.978, total= 1.4min
```

```
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l1 ...............................................
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l1 ...............................................
[CV] ...................... C=25, penalty=l1, score=nan, total=   0.1s
[CV] C=25, penalty=l2 ...............................................
[CV] .................... C=25, penalty=l2, score=0.989, total= 1.4min
[CV] C=25, penalty=l2 ...............................................
[CV] .................... C=25, penalty=l2, score=0.988, total= 1.4min
[CV] C=25, penalty=l2 ...............................................
[CV] .................... C=25, penalty=l2, score=0.988, total= 1.3min
[Parallel(n_jobs=1)]: Done  48 out of  48 | elapsed: 33.0min finished
```

```
[ ] best_clf.best_score_

0.9883618785006213
```

```
[ ] best_clf.best_params_

{'C': 25, 'penalty': 'l2'}
```

Took 33 minutes of time with the best parameters results as

‘C’ : 25, ‘penalty’ : ‘l2’

K-fold Cross Validation

```
from sklearn.linear_model import LogisticRegression
lr2 = LogisticRegression(penalty='l2',C = 25, solver = 'lbfgs',max_iter=1000,n_jobs=100)
from sklearn.model_selection import cross_val_score
scores = cross_val_score(lr2, Xres1, yres1, cv=10)
scores
```

```
array([0.98608064, 0.98649205, 0.98693774, 0.987452  , 0.98669775,
       0.98676632, 0.98717729, 0.98724586, 0.98587445, 0.987143  ])
```

```
[55] scores.mean()
```

```
0.986786709546766
```

Score= 98.67%

Final accuracy after applying the best parameters: -

```
[56] import time
     start = time.time()
     lr2.fit (Xres1,yres1)
     prediction= lr2.predict(data_test)
     score = lr2.score(data_test, y_test)
     end = time.time()
     print(end - start, "seconds\n")
     score
```

```
166.57019662857056 seconds

0.9861851834184039
```

Final accuracy = <u>98.61%</u>