Objective:

Perform an efficient classification of malicious activities using ML techniques.

CRISP-DM Process:

1) Business understanding:

Business need to analyze the incoming traffic and classify each request as a valid request or an attack / malicious activity on the network. There are different types of attacks like 'DoS','Probe','Privilege' and 'Access' types.

Exploratory Data Analysis will be done by using Pandas profiling module, on the training and test data to understand the data involved.

Apply Feature Engineering techniques: like 1) One-hot encoding and 2) Min-Max normalization techniques on features to convert the numerical values.

Selected ML models to use “Logistic Regression” and “Decision Tree” algorithms from “sklearn” library’.

Evaluation will be done by calculating the F1-score, recall, precision and accuracy scores on both the Logistic Regression and Decision Tree models.

Accuracy score should be more than 65% to accept the model.

2) Data Understanding:

Loading the required libraries

In [71]:
```
import pandas as pd
import numpy as np
from pandas_profiling import ProfileReport
import pandas_profiling
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, f1_score, precision_score,recall_score
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import label_binarize

import seaborn as sns
import matplotlib.pyplot as plt
```

Loading the data set

In [72]:
```
# Using KDDTrain+.txt as the train data.
train_data = pd.read_csv('KDDTrain+.txt')
```

In [73]:
```
#Assigning column names for training set
train_data.columns = ['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_s
'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
'dst_host_srv_rerror_rate', 'attack', 'level']
train_data.head()
```

Out[73]:

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

5 rows × 43 columns

In [74]:
```
# Using KDDTest+.txt as the train data.
test_data = pd.read_csv('KDDTest+.txt')
```

In [75]:
```
#Assigning column names for training set
test_data.columns = ['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_s
'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
'dst_host_srv_rerror_rate', 'attack', 'level']
test_data.head()
```

Out[75]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	ho
0	0	tcp	private	REJ	0	0	0	0	0	
1	2	tcp	ftp_data	SF	12983	0	0	0	0	
2	0	icmp	eco_i	SF	20	0	0	0	0	
3	1	tcp	telnet	RSTO	0	15	0	0	0	
4	0	tcp	http	SF	267	14515	0	0	0	

5 rows × 43 columns

Exploratory Data Analysis

Using Pandas Profiling

In [76]:
```
train_data_profile = ProfileReport(train_data, minimal=True)
train_data_profile.to_file(output_file='train_data_eda_profile_output.html')
```

In [77]:
```
test_data_profile = ProfileReport(test_data, minimal=True)
test_data_profile.to_file(output_file='test_data_eda_profile_output.html')
```

In [78]:
```
train_data.describe()
```

Out[78]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent
count	125972.000000	1.259720e+05	1.259720e+05	125972.000000	125972.000000	125972.000000
mean	287.146929	4.556710e+04	1.977927e+04	0.000198	0.022688	0.000111
std	2604.525522	5.870354e+06	4.021285e+06	0.014086	0.253531	0.014366
min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000
25%	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000
50%	0.000000	4.400000e+01	0.000000e+00	0.000000	0.000000	0.000000
75%	0.000000	2.760000e+02	5.160000e+02	0.000000	0.000000	0.000000
max	42908.000000	1.379964e+09	1.309937e+09	1.000000	3.000000	3.000000

8 rows × 39 columns

In [79]:
```
train_data.shape
```

Out[79]:
```
(125972, 43)
```

In [80]:
```
test_data.describe()
```

Out[80]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	
count	22543.000000	2.254300e+04	2.254300e+04	22543.000000	22543.000000	22543.000000	225
mean	218.868784	1.039591e+04	2.056110e+03	0.000311	0.008428	0.000710	
std	1407.207069	4.727969e+05	2.121976e+04	0.017619	0.142602	0.036474	
min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
25%	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
50%	0.000000	5.400000e+01	4.600000e+01	0.000000	0.000000	0.000000	

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	
75%	0.000000	2.870000e+02	6.010000e+02	0.000000	0.000000	0.000000	
max	57715.000000	6.282565e+07	1.345927e+06	1.000000	3.000000	3.000000	1

8 rows × 39 columns

In [81]:
```
test_data.shape
```

Out[81]: (22543, 43)

3) Data Preparation:

Data Wrangling / Pre-processing

In [82]:
```
# Dropping 'level' columns from the train and test data set.
train_data = train_data.drop('level', 1)
test_data = test_data.drop('level', 1)
```

In [83]:
```
# Mapping normal to 0, all attacks to 1 on the 'attack' column of both Train and Tes
train_data_attack = train_data.attack.map(lambda a: 0 if a == 'normal' else 1)
test_data_attack = test_data.attack.map(lambda a: 0 if a == 'normal' else 1)

train_data['attack_flag'] = train_data_attack
test_data['attack_flag'] = test_data_attack

train_data.head()
```

Out[83]:

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

5 rows × 43 columns

In [84]:
```
np.shape(train_data)
```

Out[84]: (125972, 43)

In [85]:
```
train_data
```

Out[85]:

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

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent
4	0	tcp	private	REJ	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
125967	0	tcp	private	S0	0	0	0	0	0
125968	8	udp	private	SF	105	145	0	0	0
125969	0	tcp	smtp	SF	2231	384	0	0	0
125970	0	tcp	klogin	S0	0	0	0	0	0
125971	0	tcp	ftp_data	SF	151	0	0	0	0

125972 rows × 43 columns

In [86]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125972 entries, 0 to 125971
Data columns (total 43 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   duration                     125972 non-null  int64  
 1   protocol_type                125972 non-null  object 
 2   service                      125972 non-null  object 
 3   flag                         125972 non-null  object 
 4   src_bytes                    125972 non-null  int64  
 5   dst_bytes                    125972 non-null  int64  
 6   land                         125972 non-null  int64  
 7   wrong_fragment               125972 non-null  int64  
 8   urgent                       125972 non-null  int64  
 9   hot                          125972 non-null  int64  
 10  num_failed_logins            125972 non-null  int64  
 11  logged_in                    125972 non-null  int64  
 12  num_compromised              125972 non-null  int64  
 13  root_shell                   125972 non-null  int64  
 14  su_attempted                 125972 non-null  int64  
 15  num_root                     125972 non-null  int64  
 16  num_file_creations           125972 non-null  int64  
 17  num_shells                   125972 non-null  int64  
 18  num_access_files             125972 non-null  int64  
 19  num_outbound_cmds            125972 non-null  int64  
 20  is_host_login                125972 non-null  int64  
 21  is_guest_login               125972 non-null  int64  
 22  count                        125972 non-null  int64  
 23  srv_count                    125972 non-null  int64  
 24  serror_rate                  125972 non-null  float64
 25  srv_serror_rate              125972 non-null  float64
 26  rerror_rate                  125972 non-null  float64
 27  srv_rerror_rate              125972 non-null  float64
 28  same_srv_rate                125972 non-null  float64
 29  diff_srv_rate                125972 non-null  float64
 30  srv_diff_host_rate           125972 non-null  float64
 31  dst_host_count               125972 non-null  int64  
 32  dst_host_srv_count           125972 non-null  int64  
 33  dst_host_same_srv_rate       125972 non-null  float64
 34  dst_host_diff_srv_rate       125972 non-null  float64
 35  dst_host_same_src_port_rate  125972 non-null  float64
 36  dst_host_srv_diff_host_rate  125972 non-null  float64
 37  dst_host_serror_rate         125972 non-null  float64
 38  dst_host_srv_serror_rate     125972 non-null  float64
 39  dst_host_rerror_rate         125972 non-null  float64
 40  dst_host_srv_rerror_rate     125972 non-null  float64
 41  attack                       125972 non-null  object 
```

```
 42  attack_flag                 125972 non-null  int64
dtypes: float64(15), int64(24), object(4)
memory usage: 41.3+ MB
```

In [87]:
```
test_data
```

Out[87]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urge
0	0	tcp	private	REJ	0	0	0	0	
1	2	tcp	ftp_data	SF	12983	0	0	0	
2	0	icmp	eco_i	SF	20	0	0	0	
3	1	tcp	telnet	RSTO	0	15	0	0	
4	0	tcp	http	SF	267	14515	0	0	
...	...	...	...	...	...	...	...	...	...
22538	0	tcp	smtp	SF	794	333	0	0	
22539	0	tcp	http	SF	317	938	0	0	
22540	0	tcp	http	SF	54540	8314	0	0	
22541	0	udp	domain_u	SF	42	42	0	0	
22542	0	tcp	sunrpc	REJ	0	0	0	0	

22543 rows × 43 columns

Classification and mapping of attacks feature

In [88]:
```
dos_attacks = ['apache2','back','land','neptune','mailbomb','pod','processtable','sm
probe_attacks = ['ipsweep','mscan','nmap','portsweep','saint','satan']
privilege_attacks = ['buffer_overflow','loadmdoule','perl','ps','rootkit','sqlattack
access_attacks = ['ftp_write','guess_passwd','http_tunnel','imap','multihop','named'

attack_labels = ['Normal','DoS','Probe','Privilege','Access']

def map_attack(attack):
    if attack in dos_attacks:
        # dos_attacks map to 1
        attack_type = 1
    elif attack in probe_attacks:
        # probe_attacks mapt to 2
        attack_type = 2
    elif attack in privilege_attacks:
        # privilege escalation attacks map to 3
        attack_type = 3
    elif attack in access_attacks:
        # remote access attacks map to 4
        attack_type = 4
    else:
        # normal maps to 0
        attack_type = 0

    return attack_type


# map the data and join to the data set
attack_map = train_data.attack.apply(map_attack)
train_data['attack_map'] = attack_map
```

```
test_attack_map = test_data.attack.apply(map_attack)
test_data['attack_map'] = test_attack_map

# view the result
train_data.head()
```

Out[88]:

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

5 rows × 44 columns

In [89]:

```
# use a crosstab to get attack vs protocol. Most of the attacks are related to the t
attack_vs_protocol = pd.crosstab(train_data.attack, train_data.protocol_type)
attack_vs_protocol
```

Out[89]:

protocol_type	icmp	tcp	udp
attack			
back	0	956	0
buffer_overflow	0	30	0
ftp_write	0	8	0
guess_passwd	0	53	0
imap	0	11	0
ipsweep	3117	482	0
land	0	18	0
loadmodule	0	9	0
multihop	0	7	0
neptune	0	41214	0
nmap	981	265	247
normal	1309	53599	12434
perl	0	3	0
phf	0	4	0
pod	201	0	0
portsweep	5	2926	0
rootkit	0	7	3
satan	32	2184	1417
smurf	2646	0	0
spy	0	2	0

protocol_type	icmp	tcp	udp
attack			
teardrop	0	0	892
warezclient	0	890	0
warezmaster	0	20	0

In [90]:
```
set(train_data['protocol_type'])
```

Out[90]:
```
{'icmp', 'tcp', 'udp'}
```

In [91]:
```
set(train_data['attack'])
```

Out[91]:
```
{'back',
 'buffer_overflow',
 'ftp_write',
 'guess_passwd',
 'imap',
 'ipsweep',
 'land',
 'loadmodule',
 'multihop',
 'neptune',
 'nmap',
 'normal',
 'perl',
 'phf',
 'pod',
 'portsweep',
 'rootkit',
 'satan',
 'smurf',
 'spy',
 'teardrop',
 'warezclient',
 'warezmaster'}
```

In [92]:
```
set(train_data['service'])
```

Out[92]:
```
{'IRC',
 'X11',
 'Z39_50',
 'aol',
 'auth',
 'bgp',
 'courier',
 'csnet_ns',
 'ctf',
 'daytime',
 'discard',
 'domain',
 'domain_u',
 'echo',
 'eco_i',
 'ecr_i',
 'efs',
 'exec',
 'finger',
 'ftp',
 'ftp_data',
 'gopher',
 'harvest',
 'hostnames',
 'http',
```

```
 'http_2784',
 'http_443',
 'http_8001',
 'imap4',
 'iso_tsap',
 'klogin',
 'kshell',
 'ldap',
 'link',
 'login',
 'mtp',
 'name',
 'netbios_dgm',
 'netbios_ns',
 'netbios_ssn',
 'netstat',
 'nnsp',
 'nntp',
 'ntp_u',
 'other',
 'pm_dump',
 'pop_2',
 'pop_3',
 'printer',
 'private',
 'red_i',
 'remote_job',
 'rje',
 'shell',
 'smtp',
 'sql_net',
 'ssh',
 'sunrpc',
 'supdup',
 'systat',
 'telnet',
 'tftp_u',
 'tim_i',
 'time',
 'urh_i',
 'urp_i',
 'uucp',
 'uucp_path',
 'vmnet',
 'whois'}
```

In [93]:
```
set(train_data['attack_map'])
```

Out[93]:
```
{0, 1, 2, 3, 4}
```

Checking for NULL values in Train and test data

In [94]:
```
check_for_null = train_data[train_data.isna().any(axis=1)]
print(check_for_null)
```

```
Empty DataFrame
Columns: [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_rat
e, rerror_rate, srv_rerror_rate, same_srv_rate, diff_srv_rate, srv_diff_host_rate, d
st_host_count, dst_host_srv_count, dst_host_same_srv_rate, dst_host_diff_srv_rate, d
st_host_same_src_port_rate, dst_host_srv_diff_host_rate, dst_host_serror_rate, dst_h
ost_srv_serror_rate, dst_host_rerror_rate, dst_host_srv_rerror_rate, attack, attack_
flag, attack_map]
Index: []

[0 rows x 44 columns]
```

In [95]:
```
train_data.isnull().values.any()
```

Out[95]: False

In [96]:
```
test_data.isnull().values.any()
```

Out[96]: False

In [97]:
```
train_data[['protocol_type', 'service', 'flag']].describe()
```

Out[97]:

	protocol_type	service	flag
count	125972	125972	125972
unique	3	70	11
top	tcp	http	SF
freq	102688	40338	74944

Feature Engineering techniques

One-hot encoding

In [98]:
```
column_list = ['protocol_type','service','flag']
```

In [99]:
```
## One-hot encoding
def one_hot(df, cols):
    """
    @param df pandas DataFrame
    @param cols a list of columns to encode
    @return a DataFrame with one-hot encoding
    """
    for each in cols:
        dummies = pd.get_dummies(df[each], prefix=each, drop_first=False)
        df = pd.concat([df, dummies], axis=1)
        df = df.drop(each, 1)
    return df
```

In [100…
```
# Merging train data and test data
combined_data = pd.concat([train_data,test_data])
```

In [101…
```
# Applying one-hot encoding on the combined data set
combined_data = one_hot(combined_data,column_list)
```

In [102…
```
combined_data.shape
```

Out[102… (148515, 125)

In [103…
```
train_data_new = combined_data.iloc[:125973]
test_data_new = combined_data.iloc[125973:]
```

In [104…
```
train_data_new.shape
```

Out[104… (125973, 125)

In [105…
```
test_data_new.shape
```

Out[105… (22542, 125)

In [106…
```
train_data_new
```

Out[106…

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logg
0	0	146	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	
2	0	232	8153	0	0	0	0	0	
3	0	199	420	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	
…	…	…	…	…	…	…	…	…	
125968	8	105	145	0	0	0	0	0	
125969	0	2231	384	0	0	0	0	0	
125970	0	0	0	0	0	0	0	0	
125971	0	151	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	

125973 rows × 125 columns

In [107…
```
test_data_new
```

Out[107…

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logge
1	2	12983	0	0	0	0	0	0	
2	0	20	0	0	0	0	0	0	
3	1	0	15	0	0	0	0	0	
4	0	267	14515	0	0	0	0	0	
5	0	1022	387	0	0	0	0	0	
…	…	…	…	…	…	…	…	…	
22538	0	794	333	0	0	0	0	0	
22539	0	317	938	0	0	0	0	0	
22540	0	54540	8314	0	0	0	2	0	
22541	0	42	42	0	0	0	0	0	
22542	0	0	0	0	0	0	0	0	

22542 rows × 125 columns

Applying Min-Max Normalization

In [108…
```
def normalize(df, cols):
    """
    @param df pandas DataFrame
    @param cols a list of columns to encode
```

```
    @return a DataFrame with normalized specified features
    """
    result = df.copy() # do not touch the original df
    for feature_name in cols:
        max_value = df[feature_name].max()
        min_value = df[feature_name].min()
        if max_value > min_value:
            result[feature_name] = (df[feature_name] - min_value) / (max_value - min
    return result
```

In [109…
```
# Droping "attack" columns to create the Tarin data set
train_tmp = train_data_new.pop('attack')
```

In [110…
```
train_data_new.shape
```

Out[110… (125973, 124)

In [111…
```
# Droping "attack" columns to create the test data set
test_tmp = test_data_new.pop('attack')
```

In [112…
```
test_data_new.shape
```

Out[112… (22542, 124)

In [113…
```
# Invoking Normalization on the "training" Data Set
train_data_new = normalize(train_data_new,train_data_new.columns)
```

In [114…
```
# Invoking Normalization on the "test" Data Set
test_data_new = normalize(test_data_new,test_data_new.columns)
```

In [115…
```
#Fixing Labels for "training" data set
classlist = []
check1 = ("apache2","back","land","neptune","mailbomb","pod","processtable","smurf",
check2 = ("ipsweep","mscan","nmap","portsweep","saint","satan")
check3 = ("buffer_overflow","loadmodule","perl","ps","rootkit","sqlattack","xterm")
check4 = ("ftp_write","guess_passwd","httptunnel","imap","multihop","named","phf","s

for item in train_tmp:
    if item in check1:
        classlist.append("DoS")
    elif item in check2:
        classlist.append("Probe")
    elif item in check3:
        classlist.append("U2R")
    elif item in check4:
        classlist.append("R2L")
    else:
        classlist.append("Normal")
```

In [116…
```
#Appending Class column to "Training" set
train_data_new["Class"] = classlist
```

In [117…
```
train_data_new
```

Out[117…

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logi
0	0.000000	1.057999e-07	0.000000e+00	0.0	0.0	0.0	0.0	(
1	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	(
2	0.000000	1.681203e-07	6.223962e-06	0.0	0.0	0.0	0.0	(

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logi
3	0.000000	1.442067e-07	3.206260e-07	0.0	0.0	0.0	0.0	(
4	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	(
...	...	...	...	...	...	...	...	
125968	0.000186	7.608895e-08	1.106923e-07	0.0	0.0	0.0	0.0	(
125969	0.000000	1.616709e-06	2.931438e-07	0.0	0.0	0.0	0.0	(
125970	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	(
125971	0.000000	1.094232e-07	0.000000e+00	0.0	0.0	0.0	0.0	(
0	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	(

125973 rows × 125 columns

In [118…
```
#Fixing Labels for "testing" data set
testclasslist = []
testcheck1 = ("apache2","back","land","neptune","mailbomb","pod","processtable","smu
testcheck2 = ("ipsweep","mscan","nmap","portsweep","saint","satan")
testcheck3 = ("buffer_overflow","loadmodule","perl","ps","rootkit","sqlattack","xter
testcheck4 = ("ftp_write","guess_passwd","httptunnel","imap","multihop","named","phf

for testitem in test_tmp:
    if testitem in testcheck1:
        testclasslist.append("DoS")
    elif testitem in testcheck2:
        testclasslist.append("Probe")
    elif testitem in testcheck3:
        testclasslist.append("U2R")
    elif testitem in testcheck4:
        testclasslist.append("R2L")
    else:
        testclasslist.append("Normal")
```

In [119…
```
#Appending Class column to testing set
test_data_new["Class"] = testclasslist
```

In [120…
```
train_data_new["Class"] = train_data_new["Class"].astype('category')
train_data_new.dtypes
```

Out[120…
```
duration           float64
src_bytes          float64
dst_bytes          float64
land               float64
wrong_fragment     float64
                    ...
flag_S2            float64
flag_S3            float64
flag_SF            float64
flag_SH            float64
Class             category
Length: 125, dtype: object
```

Plotting top 10 features

Applying encoding to the "Class" feature on Train data

In [121…
```
train_data_new_plot = train_data_new.copy()
```

```
train_data_new_plot["Class_cat"] = train_data_new_plot["Class"].cat.codes
train_data_new_plot.drop(columns = "Class", inplace=True)
train_data_new_plot.head()
# train_data_new["Class_cat"] = train_data_new["Class"].cat.codes
# train_data_new.head()
```

Out[121...

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	lo
0	0.0	1.057999e-07	0.000000e+00	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	0.0	
2	0.0	1.681203e-07	6.223962e-06	0.0	0.0	0.0	0.0	0.0	
3	0.0	1.442067e-07	3.206260e-07	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	0.0	

5 rows × 125 columns

Finding top 10 Features using Pearson Correlation with target value greater than 0.44

In [122...

```
#Using Pearson Correlation
plt.figure(figsize=(60,50))
cor = train_data_new_plot.corr()
```

```
<Figure size 4320x3600 with 0 Axes>
```

In [123...

```
train_data_new_plot
```

Out[123...

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logi
0	0.000000	1.057999e-07	0.000000e+00	0.0	0.0	0.0	0.0	
1	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	
2	0.000000	1.681203e-07	6.223962e-06	0.0	0.0	0.0	0.0	
3	0.000000	1.442067e-07	3.206260e-07	0.0	0.0	0.0	0.0	
4	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	
125968	0.000186	7.608895e-08	1.106923e-07	0.0	0.0	0.0	0.0	
125969	0.000000	1.616709e-06	2.931438e-07	0.0	0.0	0.0	0.0	
125970	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	
125971	0.000000	1.094232e-07	0.000000e+00	0.0	0.0	0.0	0.0	
0	0.000000	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	

125973 rows × 125 columns

In [124...

```
cor
```

Out[124...

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	
duration	1.000000	0.070737	0.034878	-0.001553	-0.009866	0.003830	0.000705	

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot
src_bytes	0.070737	1.000000	0.000204	-0.000109	-0.000693	-0.000059	0.000295
dst_bytes	0.034878	0.000204	1.000000	-0.000069	-0.000440	0.000248	-0.000344
land	-0.001553	-0.000109	-0.000069	1.000000	-0.001261	-0.000109	-0.001340
wrong_fragment	-0.009866	-0.000693	-0.000440	-0.001261	1.000000	-0.000692	-0.008508
...	...	...	...	...	...	...	...
flag_S2	-0.003411	-0.000229	0.000215	-0.000448	-0.002843	-0.000246	0.008963
flag_S3	0.001148	0.000682	-0.000077	-0.000278	-0.001765	-0.000153	-0.000190
flag_SF	-0.068253	-0.006079	-0.004509	-0.017074	0.073841	0.006383	0.074926
flag_SH	-0.005119	-0.000360	-0.000228	-0.000654	-0.004155	-0.000359	-0.004255
Class_cat	0.161694	0.013482	0.008763	-0.010021	-0.101974	0.010625	0.121761

125 rows × 125 columns

In [125...
```
#Correlation with output variable
cor_target = abs(cor["Class_cat"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.44]
relevant_features
```

Out[125...
```
count                          0.485203
serror_rate                    0.670832
srv_serror_rate                0.671683
same_srv_rate                  0.626296
dst_host_same_srv_rate         0.465251
dst_host_same_src_port_rate    0.446733
dst_host_serror_rate           0.672739
dst_host_srv_serror_rate       0.674244
flag_S0                        0.686825
flag_SF                        0.556624
Class_cat                      1.000000
Name: Class_cat, dtype: float64
```

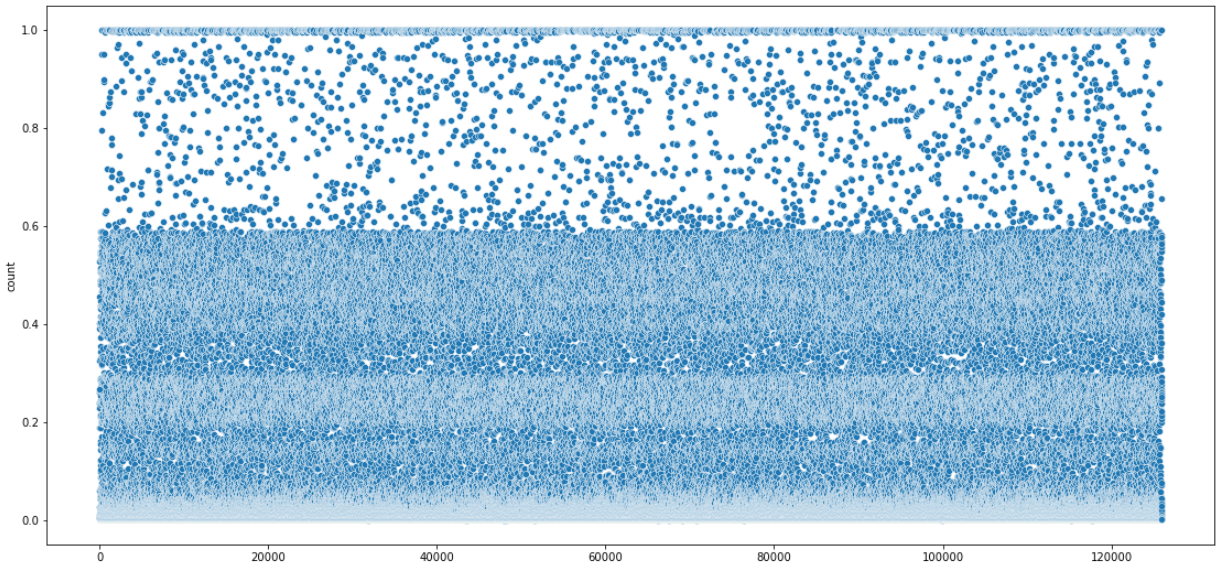
In [126...
```
#Correlation with output variable
cor_target = abs(cor["Class_cat"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.44]
relevant_features
```

Out[126...
```
count                          0.485203
serror_rate                    0.670832
srv_serror_rate                0.671683
same_srv_rate                  0.626296
dst_host_same_srv_rate         0.465251
dst_host_same_src_port_rate    0.446733
dst_host_serror_rate           0.672739
dst_host_srv_serror_rate       0.674244
flag_S0                        0.686825
flag_SF                        0.556624
Class_cat                      1.000000
Name: Class_cat, dtype: float64
```

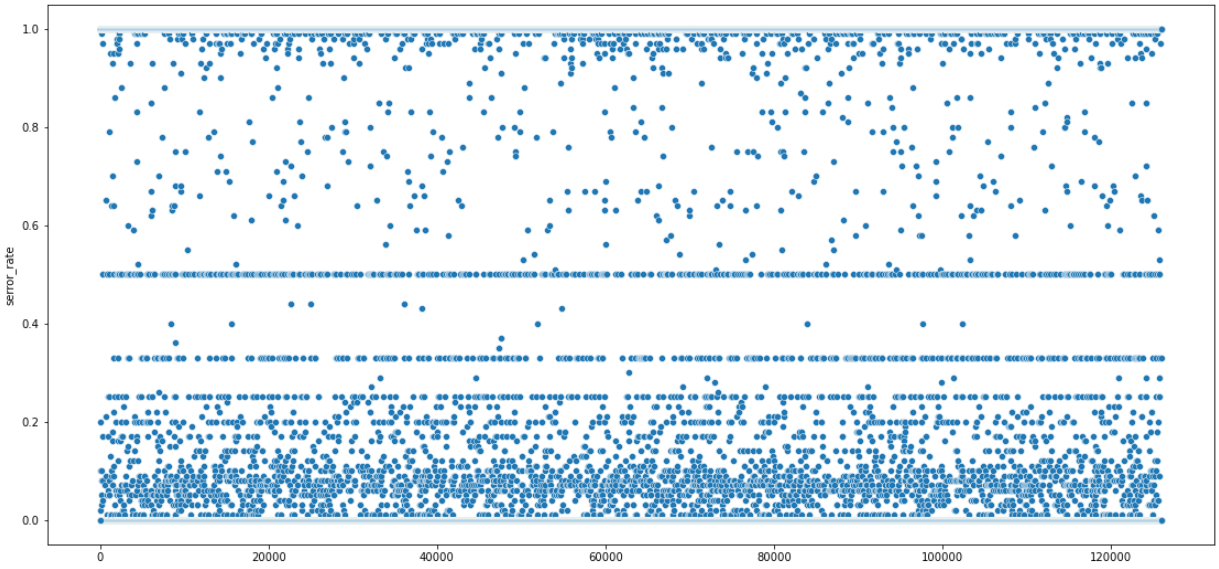
In [127...
```
for key, val in relevant_features.iteritems():
    print (key)
    plt.figure(figsize=(19,9))
```

```
    sns.scatterplot(data=train_data_new_plot[key])
    plt.show()
```

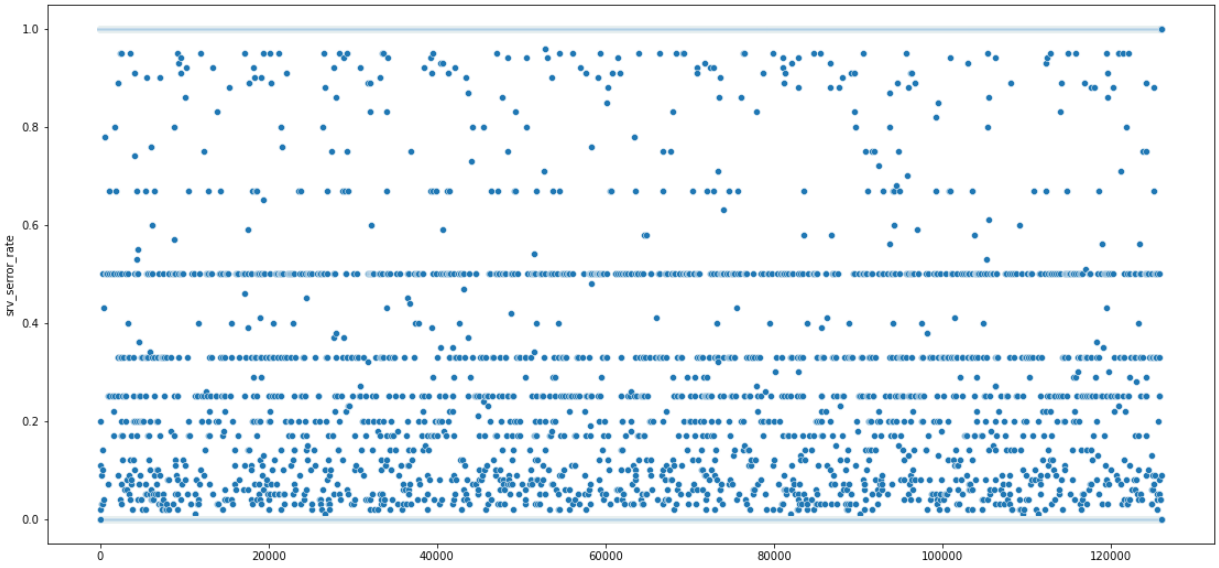
count



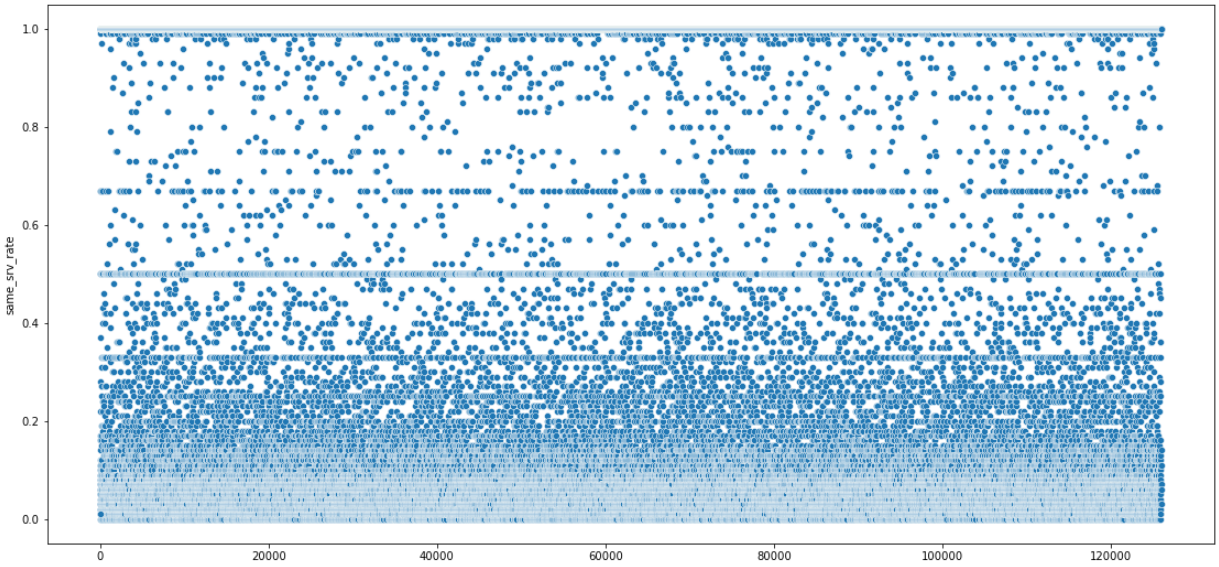
serror_rate



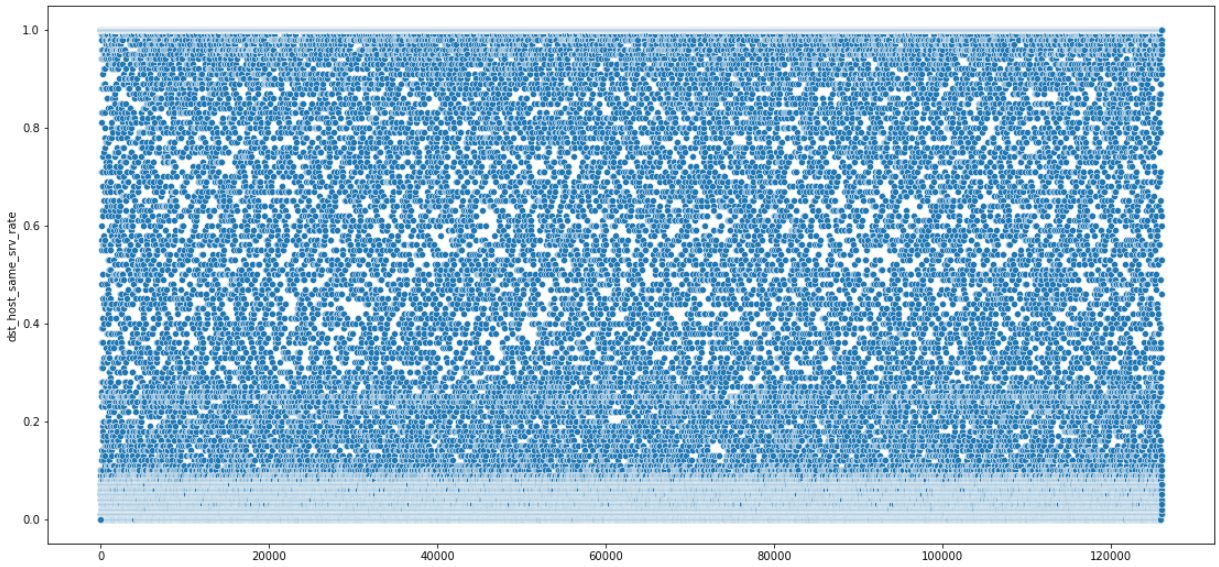
srv_serror_rate



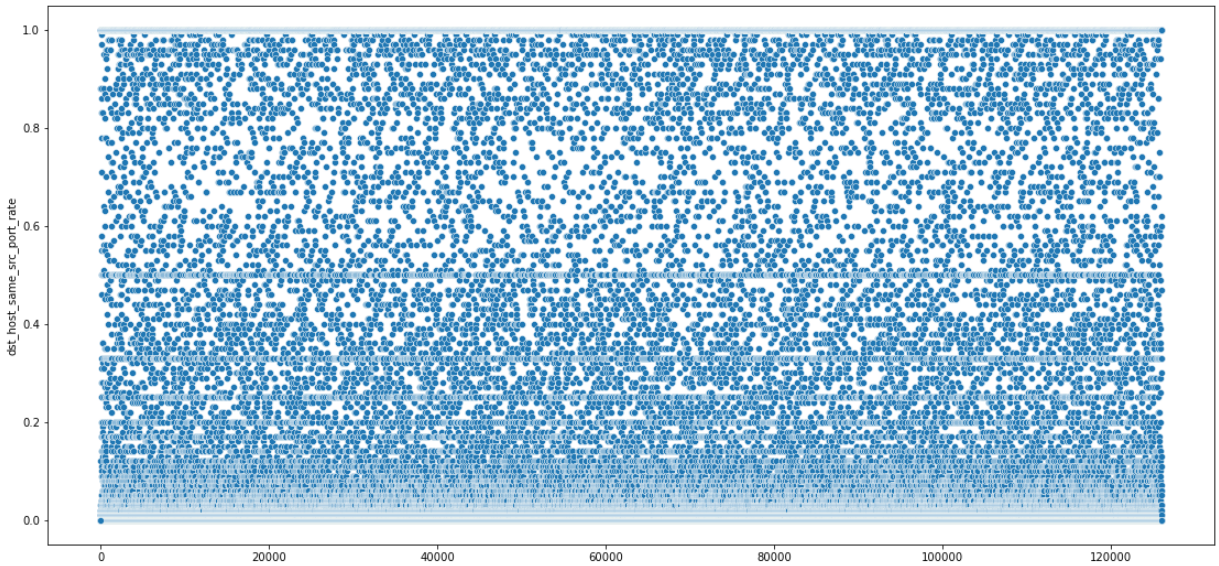
same_srv_rate



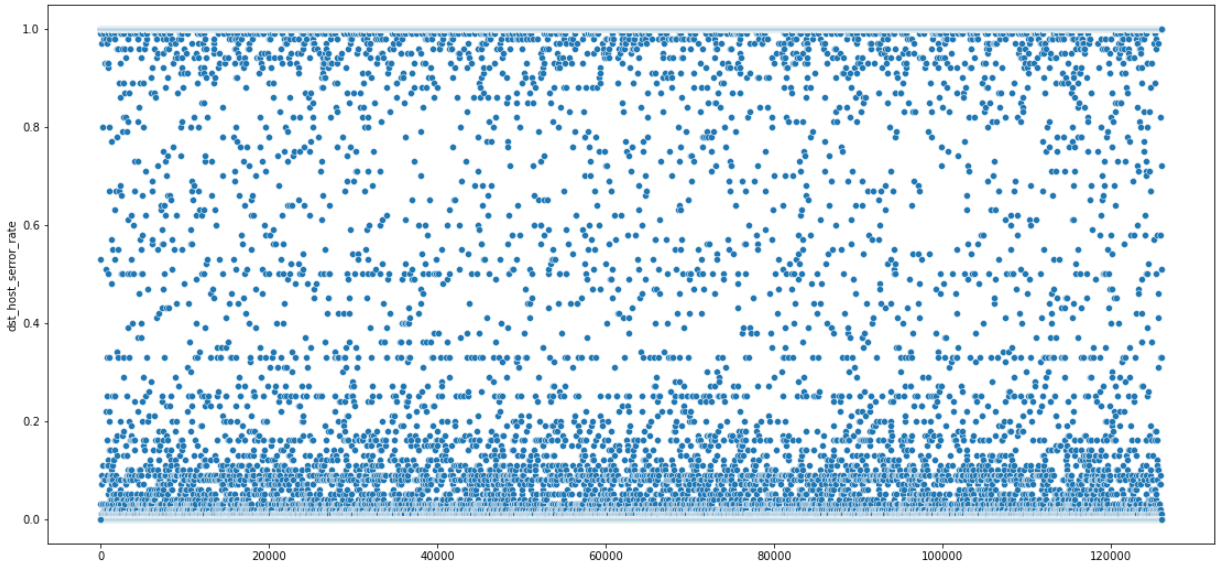
dst_host_same_srv_rate



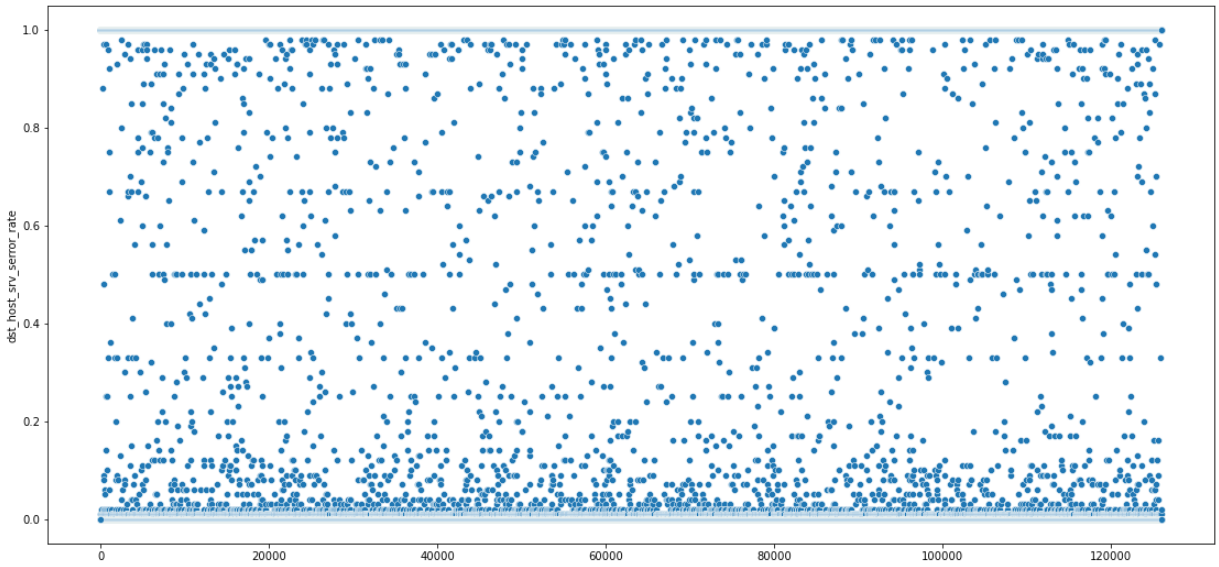
dst_host_same_src_port_rate



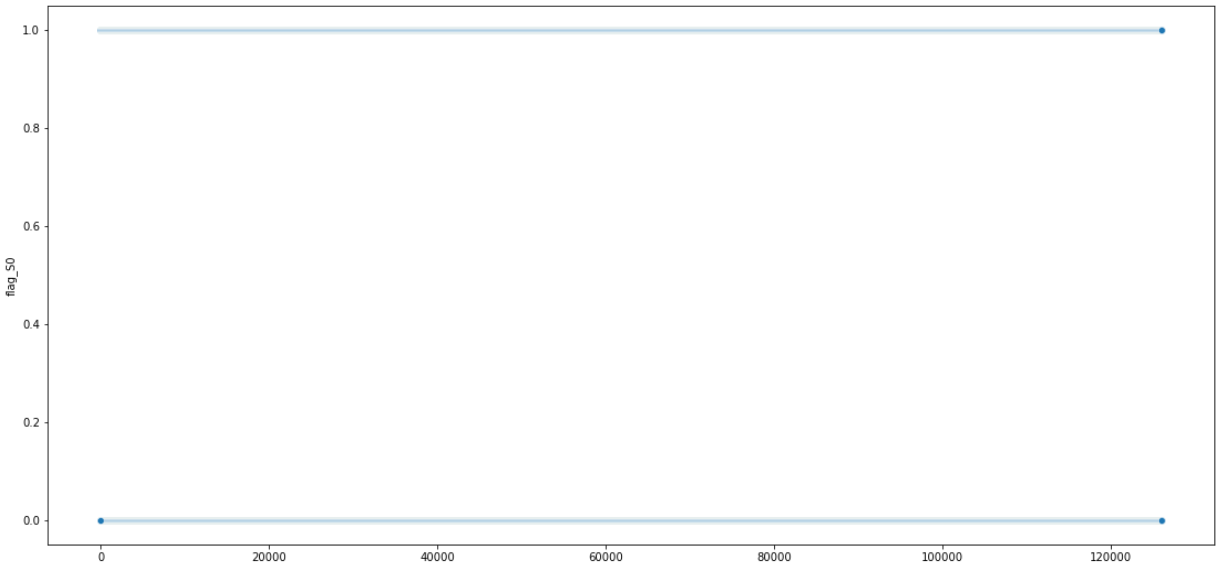
dst_host_serror_rate



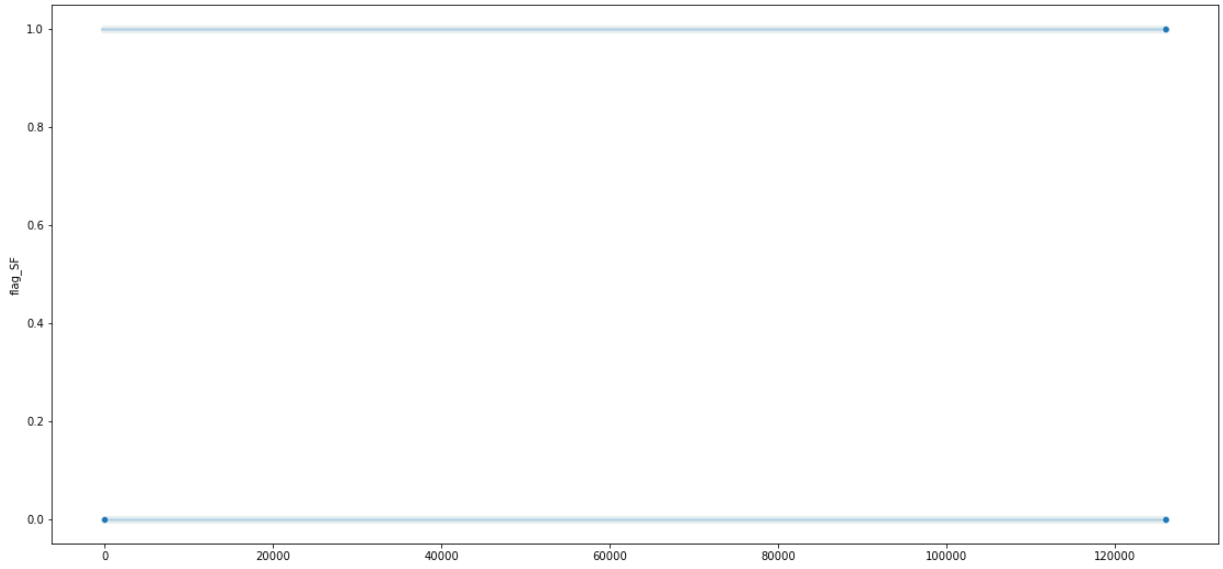
dst_host_srv_serror_rate



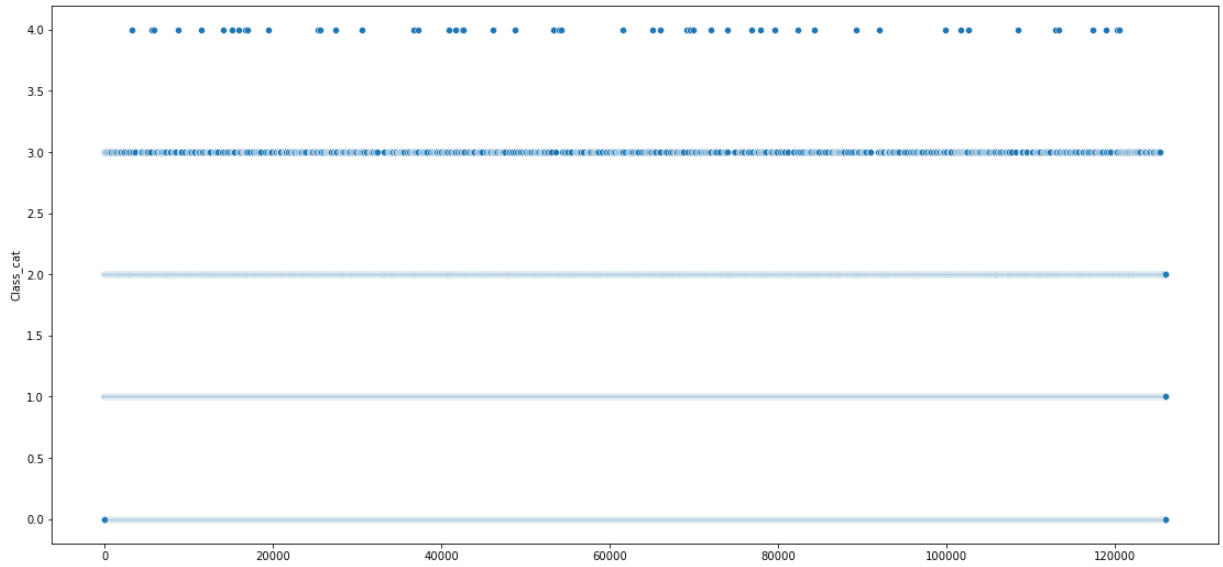
flag_S0



flag_SF



Class_cat



Preparing the Train and test data

In [128…
```
#Preparing X_train, Y_train
training_data = train_data_new.values
X_train = training_data[:,:-1]
Y_train = training_data[:,-1]
```

In [129…
```
#Preparing X_test and Y_test
testing_data = test_data_new.values
X_test = testing_data[:,:-1]
Y_test = testing_data[:,-1]
```

In [130…
```
train_data_new.head()
```

Out[130…

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	lo
0	0.0	1.057999e-07	0.000000e+00	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	0.0	
2	0.0	1.681203e-07	6.223962e-06	0.0	0.0	0.0	0.0	0.0	
3	0.0	1.442067e-07	3.206260e-07	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.000000e+00	0.000000e+00	0.0	0.0	0.0	0.0	0.0	

5 rows × 125 columns

4) Modelling:

Classification Techniques

i) Logistic Regression

In [131…
```
classifier_logit = LogisticRegression(solver='liblinear', multi_class='auto')

## Fitting the Training data
classifier_logit.fit(X_train, Y_train)

train_acc = classifier_logit.score(X_train, Y_train)
test_acc = classifier_logit.score(X_test, Y_test)

#Predicting for test data
y_pred = classifier_logit.predict(X_test)
print("Training accuracy is:", train_acc )
print("Testing accuracy is:", test_acc)
```

```
Training accuracy is: 0.9995713367150103
Testing accuracy is: 0.9425516813060065
```

In [132…
```
#Capturing Performance metrics - "Logistic Regression"
Logistic_f1 = f1_score(Y_test, y_pred, average="macro")
Logistic_precision = precision_score(Y_test, y_pred, average="macro")
Logistic_recall = recall_score(Y_test, y_pred, average="macro")
Logistic_accuracy = accuracy_score(Y_test, y_pred)
```

ii) Decision Tree classifier

In [133…
```
classifier_DT = DecisionTreeClassifier()

## Fitting the Training data
classifier_DT = classifier_DT.fit(X_train, Y_train)
train_acc = classifier_DT.score(X_train, Y_train) # mean acc on train data
test_acc = classifier_DT.score(X_test, Y_test) # mean acc on test data
y_pred = classifier_DT.predict(X_test) # make prediction
print("Training accuracy is:", train_acc )
print("Testing accuracy is:", test_acc)
```

```
Training accuracy is: 1.0
Testing accuracy is: 0.9858042764617159
```

In [134…
```
#Capturing Performance Metrics - Decision Tree
Tree_f1 = f1_score(Y_test, y_pred, average="macro")
Tree_precision = precision_score(Y_test, y_pred, average="macro")
Tree_recall = recall_score(Y_test, y_pred, average="macro")
Tree_accuracy = accuracy_score(Y_test, y_pred)
```

5) Evaluation:

Performance comparison of both the classifiers

In [135…
```
perf_data = [["Logistic Regression",Logistic_accuracy,Logistic_precision,Logistic_re
```

```
metric = pd.DataFrame(perf_data,columns = ['','Mean Accuracy','Mean Precision','Mean
metric
```

Out[135...

		Mean Accuracy	Mean Precision	Mean Recall	Mean F1
0	Logistic Regression	0.942552	0.910542	0.789286	0.825915
1	Decision Tree	0.985804	0.851136	0.985909	0.883542

Confusion Matrix

In [136...

```
class_names = ["Normal","DoS","Probe","U2R","R2L"]
```

In [137...

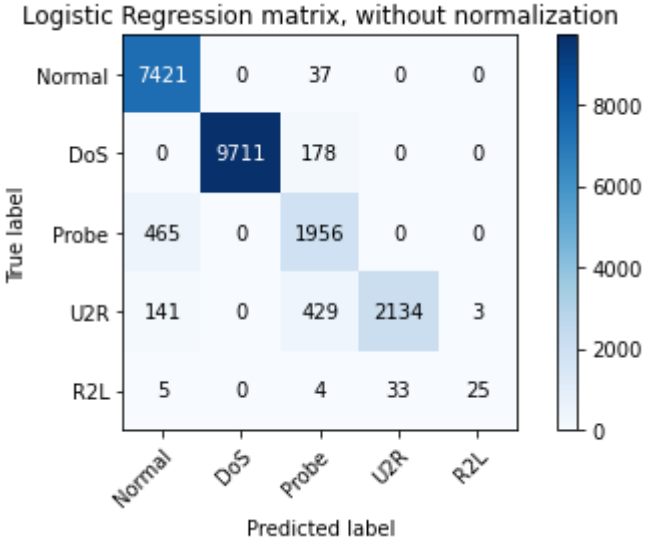
```
def plot_confusion_matrix(y_true, y_pred, classes, normalize=False, title=None,cmap=

    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'


    cm = confusion_matrix(y_true, y_pred)


    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax


np.set_printoptions(precision=2)
```

Logistic Regression Matrix

In [138…

```
#Logistic Regression Matrix
classifier_LRM = LogisticRegression(solver='liblinear', multi_class='auto')
y_pred = classifier_LRM.fit(X_train, Y_train).predict(X_test)
plot_confusion_matrix(Y_test, y_pred, classes=class_names,title='Logistic Regression
plt.show()
```

```
Confusion matrix, without normalization
[[7421    0   37    0    0]
 [   0 9711  178    0    0]
 [ 465    0 1956    0    0]
 [ 141    0  429 2134    3]
 [   5    0    4   33   25]]
```

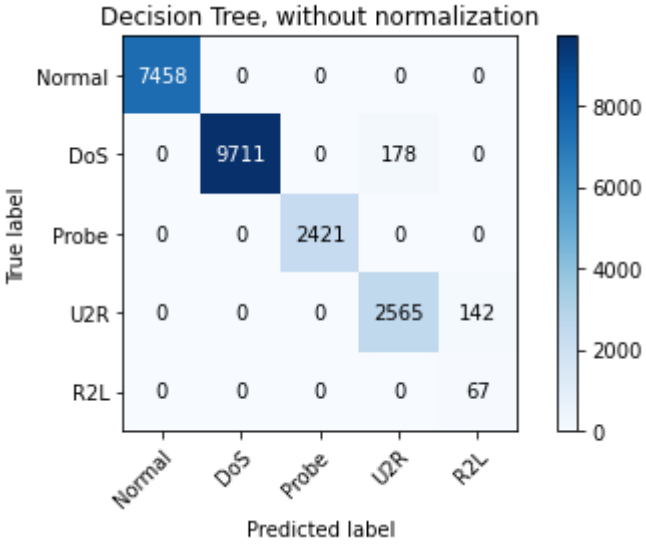


Decision Tree Matrix

In [139…

```
classifier_DTM = DecisionTreeClassifier()
y_pred = classifier_DTM.fit(X_train, Y_train).predict(X_test)
plot_confusion_matrix(Y_test, y_pred, classes=class_names,title='Decision Tree, with
plt.show()
```

```
Confusion matrix, without normalization
[[7458    0    0    0    0]
 [   0 9711    0  178    0]
 [   0    0 2421    0    0]
 [   0    0    0 2565  142]
 [   0    0    0    0   67]]
```



In [ ]: