Network Intrusion Detection System (NIDS - KDD CUP 99)

.

1 : Business/Real-world Problem

1.1 : what is Nerwork intrusion ?

A **network intrusion** is any unauthorized activity on a computer network.
The unauthorized activities or abnormal network activities threaten users' privacy and potentially damage the function and infrastructure of the whole network

Intrusion detector :

The Intrusion detection system will detect network intrusions protects a computer network from unauthorized users, including perhaps insiders

1.2 : Problem Statement

The intrusion detector learning task is to build a predictive model (i.e. a classifier) capable of distinguishing between bad connections, called intrusions or attacks, and good normal connections.

1.3 : Source/Useful Links

The data set used here is NSL KDD (new version of kdd-cup99)

The 1998 DARPA Intrusion Detection Evaluation Program was prepared and managed by MIT Lincoln Labs. The objective was to survey and evaluate research in intrusion detection. A standard set of data to be audited, which includes a wide variety of intrusions simulated in a military network environment, was provided. The 1999 KDD intrusion detection contest uses a version of this dataset.

NSL_KDD which is the new version of kdd-cup99 has the following advantages:

- No redundant records in the train set, so the classifier will not produce any biased result
- No duplicate record in the test set which have better reduction rates.
- The number of selected records from each difficult level group is inversely proportional to the percentage of records in the original KDD data set

In this dataset Attacks fall into four main categories:

- DOS: denial-of-service, e.g. syn flood.
- R2L: unauthorized access from a remote machine, e.g. guessing password.
- U2R: unauthorized access to local superuser (root) privileges, e.g., various buffer overflow attacks.
- probing: surveillance and other probing, e.g., port scanning.

Source of the dataset : https://www.unb.ca/cic/datasets/nsl.html (https://www.unb.ca/cic/datasets/nsl.html)

usefull links:

- https://medium.com/analytics-vidhya/building-an-intrusion-detection-model-using-kdd-cup99-dataset-fb4cba4189ed (https://medium.com/analytics-vidhya/building-an-intrusion-detection-model-using-kdd-cup99-dataset-fb4cba4189ed)
- https://github.com/dimtics/Network-Intrusion-Detection-Using-Machine-Learning-Techniqu (https://github.com/dimtics/Network-Intrusion-Detection-Using-Machine-Learning-Techniqu)
- https://github.com/imRP26/Network-based-Intrusion-Detection-Systems (https://github.com/imRP26/Network-based-Intrusion-Detection-Systems)
- https://nycdatascience.com/blog/student-works/network-intrusion-detection/ (https://nycdatascience.com/blog/student-works/network-intrusion-detection/)
- https://www.youtube.com/watch?v=M50pQfj9ZOI&feature=youtu.be (https://www.youtube.com/watch?v=M50pQfj9ZOI&feature=youtu.be)

1.4. Real-world/Business objectives and constraints.

- No low-latency requirement.
- Interpretability partially is important.
- Intrusion Detection should not take hours.It should fininsh in a few seconds or a minute.
- It should detect the network intrusion as well as possible.

2 : Machine learning problem formulation

2.1 : Data

2.1.1 : Data Overview

Source of the data : https://www.unb.ca/cic/datasets/nsl.html (https://www.unb.ca/cic/datasets/nsl.html)

we have 2 dataset

- Train data : It has 125973 datapoints with 42 features
- Test data : it has 22544 datapoints with 42 features

here is a detailed description about the dataset http://kdd.ics.uci.edu/databases/kddcup99/task.html (http://kdd.ics.uci.edu/databases/kddcup99/task.html)

example data point

```
duration                        -       0
protocol_type                   -       tcp
service                         -       ftp_data
flag                            -       SF
src_bytes                       -       491
```

```
dst_bytes                      -      0
land                           -      0
wrong_fragment                 -      0
urgent                         -      0
hot                            -      0
num_failed_logins              -      0
logged_in                      -      0
num_compromised                -      0
root_shell                     -      0
su_attempted                   -      0
num_root                       -      0
num_file_creations             -      0
num_shells                     -      0
num_access_files               -      0
num_outbound_cmds              -      0
is_host_login                  -      0
is_guest_login                 -      0
count                          -      2
srv_count                      -      0.0
serror_rate                    -      0.0
srv_serror_rate                -      0.0
rerror_rate                    -      0.0
srv_rerror_rate                -      1.0
same_srv_rate                  -      0.0
diff_srv_rate                  -      0.0
srv_diff_host_rate             -      150
dst_host_count                 -      25
dst_host_srv_count             -      0.17
dst_host_same_srv_rate         -      0.03
dst_host_diff_srv_rate         -      0.17
dst_host_same_src_port_rate    -      0.0
dst_host_srv_diff_host_rate    -      0.0
dst_host_serror_rate           -      0.0
dst_host_srv_serror_rate       -      0.0
dst_host_rerror_rate           -      0.05
dst_host_srv_rerror_rate       -      0.0
attack                         -      normal
```

2.2. Mapping the real-world problem to an ML problem

2.2.1. Type of Machine Learning Problem

```
There are 2 type of class we need to classify attack or normal -> This is a binary
classification task
```

2.2.2. Performance Metric

```
some of the research papers and solution have been used this metric
* AUC
* f1 score
lets use this metric also to get some interpretability
* Binary Confusion matrix
* Detection rate - It it nothing but the recall
```

2.2.3. Machine Learing Objectives and Constraints

```
Objective : Given a datapoint classfy is it an attack or not -> Binary Classificat
ion

Constraints:
    1. reasonable latency
    2. Interpritability
```

2.2.4 Train Test Datasets

we already have train and test data set from the source.

3. Exploratory Data Analysis

3.1 Reading the data

In [1]:

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score
from sklearn.tree import DecisionTreeClassifier as DTC
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix
from scipy.sparse import hstack
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import RFECV
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import f1_score
from sklearn.model_selection import TimeSeriesSplit
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import recall_score
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
import xgboost as xgb
from sklearn.utils import shuffle
from sklearn.utils import resample
from mlxtend.classifier import StackingClassifier

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
# to display all column of datapoints
pd.set_option('display.max_columns', None)
```

3.1.1 Reading train data

In [3]:

```
# reading the train data
# giving feature name explitícly as in the train data these are missing
fetaures_name =  ["duration","protocol_type","service","flag","src_bytes",
    "dst_bytes","land","wrong_fragment","urgent","hot","num_failed_logins",
    "logged_in","num_compromised","root_shell","su_attempted","num_root",
    "num_file_creations","num_shells","num_access_files","num_outbound_cmds",
    "is_host_login","is_guest_login","count","srv_count","serror_rate",
    "srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
    "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
    "dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
    "dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
    "dst_host_rerror_rate","dst_host_srv_rerror_rate","attack", "last_flag"]


# please specify the sep = ',' parameter ,else all the datapoints will placed in the f
train_data =  pd.read_table("KDDTrain+.txt",sep = ',', names=fetaures_name)
train_data.head()
```

Out[3]:

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

In [4]:

```
# there is an extra feature present at 43 number column which is not useful remove it.
# for this lets use iloc : integer location , where we will do indexing for selection l
train_data = train_data.iloc[:,:-1]
train_data.head()
```

Out[4]:

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

In [5]:

```
print("Shape of the training data",train_data.shape)
print("number of data points ",train_data.shape[0])
print("Number of feature ",train_data.shape[1])
```

```
Shape of the training data (125973, 42)
number of data points  125973
Number of feature  42
```

In [6]:

```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125973 entries, 0 to 125972
Data columns (total 42 columns):
duration                       125973 non-null int64
protocol_type                  125973 non-null object
service                        125973 non-null object
flag                           125973 non-null object
src_bytes                      125973 non-null int64
dst_bytes                      125973 non-null int64
land                           125973 non-null int64
wrong_fragment                 125973 non-null int64
urgent                         125973 non-null int64
hot                            125973 non-null int64
num_failed_logins              125973 non-null int64
logged_in                      125973 non-null int64
num_compromised                125973 non-null int64
root_shell                     125973 non-null int64
su_attempted                   125973 non-null int64
num_root                       125973 non-null int64
num_file_creations             125973 non-null int64
num_shells                     125973 non-null int64
num_access_files               125973 non-null int64
num_outbound_cmds              125973 non-null int64
is_host_login                  125973 non-null int64
is_guest_login                 125973 non-null int64
count                          125973 non-null int64
srv_count                      125973 non-null int64
serror_rate                    125973 non-null float64
srv_serror_rate                125973 non-null float64
rerror_rate                    125973 non-null float64
srv_rerror_rate                125973 non-null float64
same_srv_rate                  125973 non-null float64
diff_srv_rate                  125973 non-null float64
srv_diff_host_rate             125973 non-null float64
dst_host_count                 125973 non-null int64
dst_host_srv_count             125973 non-null int64
dst_host_same_srv_rate         125973 non-null float64
dst_host_diff_srv_rate         125973 non-null float64
dst_host_same_src_port_rate    125973 non-null float64
dst_host_srv_diff_host_rate    125973 non-null float64
dst_host_serror_rate           125973 non-null float64
dst_host_srv_serror_rate       125973 non-null float64
dst_host_rerror_rate           125973 non-null float64
dst_host_srv_rerror_rate       125973 non-null float64
attack                         125973 non-null object
dtypes: float64(15), int64(23), object(4)
memory usage: 40.4+ MB
```

3.1.2 : gving class label to the attacks

Normal : 0

all other attack : 1

In [7]:

```
# creating a function to give label
def labeling(x):
    if x == 'normal':
        return 0
    else:
        return 1

#stroing all the attack in the variable label
label = train_data['attack']

# mapping all the attack to the desired output which is 0 and 1
class_label = label.map(labeling)

#creating a new column called label in the training data
train_data['label'] = class_label
```

In [8]:

```
print("shape of the train data",train_data.shape)
train_data.head(3)
```

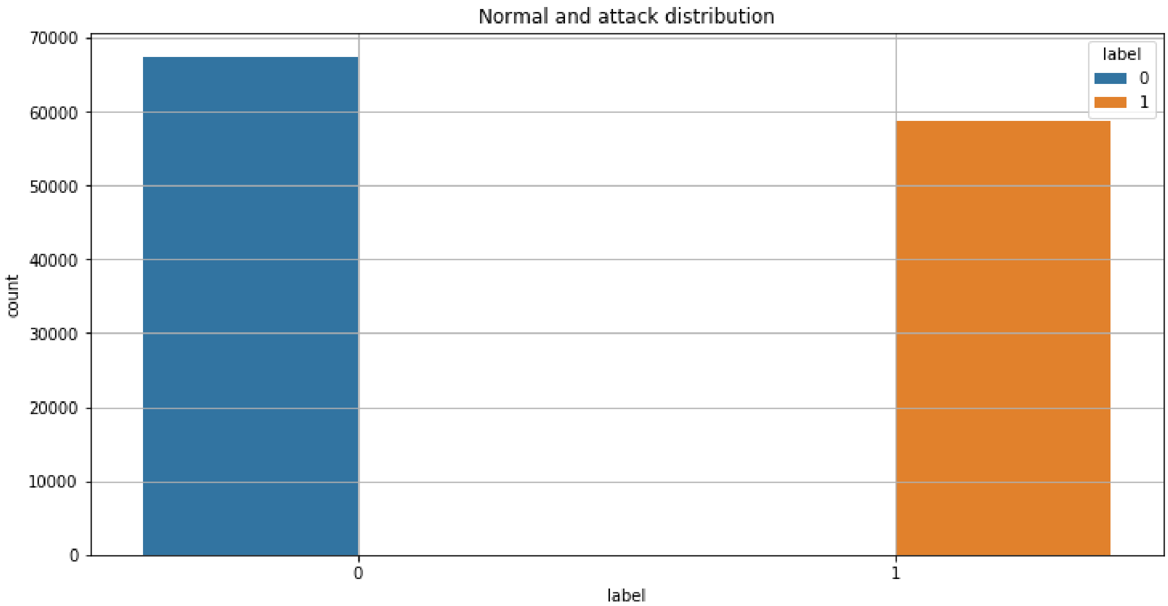
```
shape of the train data (125973, 43)
```

Out[8]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent
0	0	tcp	ftp_data	SF	491	0	0	0	0
1	0	udp	other	SF	146	0	0	0	0
2	0	tcp	private	S0	0	0	0	0	0

In [9]:

```
# distribution plot of class 1 and class 0
f, ax = plt.subplots(figsize=(12,6))
ax = sns.countplot(x = 'label' , data = train_data , hue = 'label')
plt.title("Normal and attack distribution")
plt.grid()
plt.show()
```



3.1.3 Reading Test data

In [10]:

```
# reading test data
test_data =  pd.read_table("KDDTest+.txt",sep = ',', names=fetaures_name)
test_data.head()
```

Out[10]:

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

In [11]:

```
#removing extra useless feature
test_data = test_data.iloc[:,:-1]
test_data.head()
```

Out[11]:

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

In [12]:

```
print("Shape of the test data",test_data.shape)
print("number of data points ",test_data.shape[0])
print("Number of feature ",train_data.shape[1])
```

```
Shape of the test data (22544, 42)
number of data points  22544
Number of feature  43
```

In [13]:

```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22544 entries, 0 to 22543
Data columns (total 42 columns):
duration                       22544 non-null int64
protocol_type                  22544 non-null object
service                        22544 non-null object
flag                           22544 non-null object
src_bytes                      22544 non-null int64
dst_bytes                      22544 non-null int64
land                           22544 non-null int64
wrong_fragment                 22544 non-null int64
urgent                         22544 non-null int64
hot                            22544 non-null int64
num_failed_logins              22544 non-null int64
logged_in                      22544 non-null int64
num_compromised                22544 non-null int64
root_shell                     22544 non-null int64
su_attempted                   22544 non-null int64
num_root                       22544 non-null int64
num_file_creations             22544 non-null int64
num_shells                     22544 non-null int64
num_access_files               22544 non-null int64
num_outbound_cmds              22544 non-null int64
is_host_login                  22544 non-null int64
is_guest_login                 22544 non-null int64
count                          22544 non-null int64
srv_count                      22544 non-null int64
serror_rate                    22544 non-null float64
srv_serror_rate                22544 non-null float64
rerror_rate                    22544 non-null float64
srv_rerror_rate                22544 non-null float64
same_srv_rate                  22544 non-null float64
diff_srv_rate                  22544 non-null float64
srv_diff_host_rate             22544 non-null float64
dst_host_count                 22544 non-null int64
dst_host_srv_count             22544 non-null int64
dst_host_same_srv_rate         22544 non-null float64
dst_host_diff_srv_rate         22544 non-null float64
dst_host_same_src_port_rate    22544 non-null float64
dst_host_srv_diff_host_rate    22544 non-null float64
dst_host_serror_rate           22544 non-null float64
dst_host_srv_serror_rate       22544 non-null float64
dst_host_rerror_rate           22544 non-null float64
dst_host_srv_rerror_rate       22544 non-null float64
attack                         22544 non-null object
dtypes: float64(15), int64(23), object(4)
memory usage: 7.2+ MB
```

3.1.4 : gving class label to the attacks

Normal : 0

all other attack : 1

In [14]:

```
#stroing all the attack in the variable label
label = test_data['attack']

# mapping all the attack to the desired output which is 0 and 1
class_label = label.map(labeling)

#creating a new column called label in the training data
test_data['label'] = class_label
```

In [15]:

```
print("shape of the test data",test_data.shape)
test_data.head(3)
```

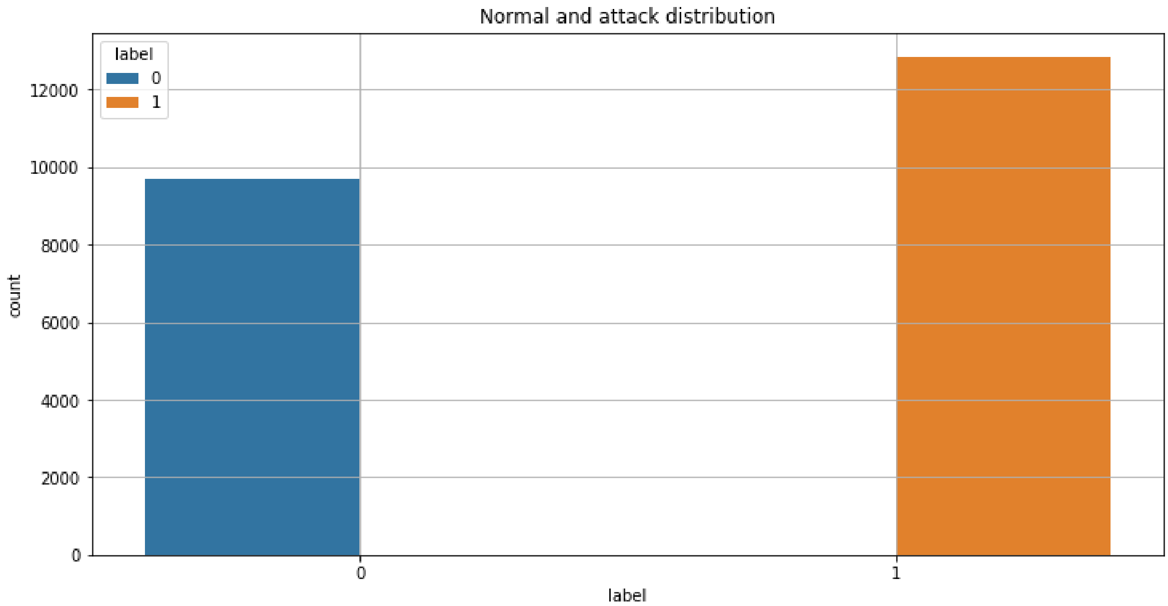
```
shape of the test data (22544, 43)
```

Out[15]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent
0	0	tcp	private	REJ	0	0	0	0	0
1	0	tcp	private	REJ	0	0	0	0	0
2	2	tcp	ftp_data	SF	12983	0	0	0	0

In [16]:

```
#distribution plot of class 0 and class 1
f, ax = plt.subplots(figsize=(12,6))
ax = sns.countplot(x = 'label' , data = test_data , hue = 'label')
plt.title("Normal and attack distribution")
plt.grid()
plt.show()
```



Observation

- There are 42 features both in train and test dataset
- 15 float value , 23 integer value and 4 object value
- its look like we dont have null value , however we will recheck again.
- In the distribution plot of class 0 and 1 : In train dataset class 0 has more datapoints than class 1 and in test dataset class1 has more datapoints than class 0

3.2 Data Cleaning

Checking for duplicates values

In [17]:

```
# drop_duplicates () : this function return DataFrame with duplicate rows removed.
train_data = train_data.drop_duplicates(subset = fetaures_name[:-1] , keep ='first' ,
train_data.shape
```

Out[17]:

```
(125973, 43)
```

In [38]:

```
##### Checking for Null values
```

In [19]:

```
null_rows = train_data[train_data.isnull().any(1)]
print(null_rows)
```

```
Empty DataFrame
Columns: [duration, protocol_type, service, flag, src_bytes, dst_bytes, lan
d, wrong_fragment, urgent, hot, num_failed_logins, logged_in, num_compromise
d, root_shell, su_attempted, num_root, num_file_creations, num_shells, num_a
ccess_files, num_outbound_cmds, is_host_login, is_guest_login, count, srv_co
unt, serror_rate, srv_serror_rate, rerror_rate, srv_rerror_rate, same_srv_ra
te, diff_srv_rate, srv_diff_host_rate, dst_host_count, dst_host_srv_count, d
st_host_same_srv_rate, dst_host_diff_srv_rate, dst_host_same_src_port_rate,
dst_host_srv_diff_host_rate, dst_host_serror_rate, dst_host_srv_serror_rate,
dst_host_rerror_rate, dst_host_srv_rerror_rate, attack, label]
Index: []
```

Observation

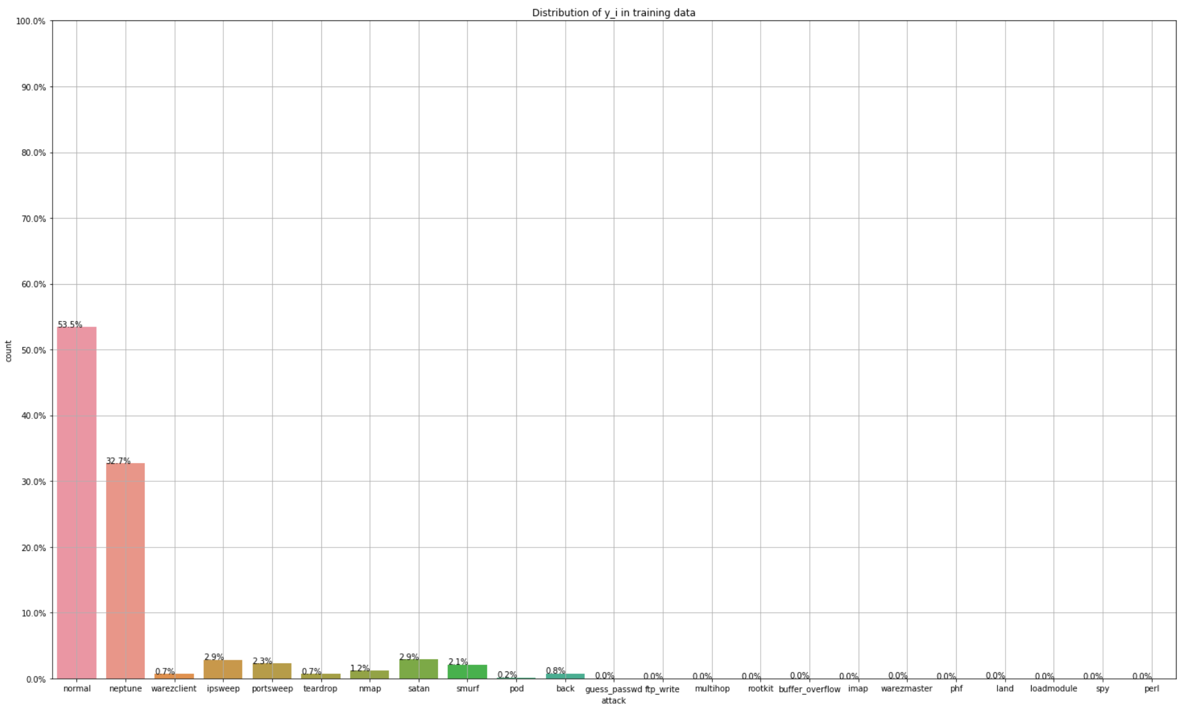
- no duplicate values present
- we dont have null values

3.3 Distribution of attacks in the dataset

3.3.1 : Train data

In [20]:

```
# Initialize the matplotlib figure
f, ax = plt.subplots(figsize=(25,15))

# we need the total number of data to find the percentage later.
total = len(train_data) * 1

# below code will simply plot bar plot where X axis is attack(23 classes) and y will s
ax = sns.countplot(x="attack", data=train_data)


# each p of patches(which is from the countplot) has height(number of data point for a
# then pass p to annotate(it is used to show text) and computing % of data in each cla
for p in ax.patches:
        ax.annotate('{:.1f}%'.format(100*p.get_height()/total), (p.get_x(), p.get_heig


# In th yaxis we are giving interval(11 interval) of datapoints
ax.yaxis.set_ticks(np.linspace(0, total, 11))


# adjust the ticklabel to the desired format, without changing the position of the tic
# map() need the function(what to do) and iterative
# below code : ax.yaxis.get_majorticklocs() - it will give 11 value from 0 to 125973 a
ax.set_yticklabels(map('{:.1f}%'.format, 100*ax.yaxis.get_majorticklocs()/total))

plt.title("Distribution of y_i in training data")
plt.grid()
plt.show()
```



datapoint belonging to each class

In [21]:

```
# take the all the class with datapoints belonging to each classes and sort them by lal
train_class_distribution = train_data['attack'].value_counts()

# it is sorting them in decreasing order (by number of datapoints)
sorted_yi = np.argsort(-train_class_distribution.values)
# now for each i of the sorted datapoints we are printing the number of datapoints and
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',train_class_distribution.values[i
```

```
Number of data points in class 1 : 67343 ( 53.458 %)
Number of data points in class 2 : 41214 ( 32.717 %)
Number of data points in class 3 : 3633 ( 2.884 %)
Number of data points in class 4 : 3599 ( 2.857 %)
Number of data points in class 5 : 2931 ( 2.327 %)
Number of data points in class 6 : 2646 ( 2.1 %)
Number of data points in class 7 : 1493 ( 1.185 %)
Number of data points in class 8 : 956 ( 0.759 %)
Number of data points in class 9 : 892 ( 0.708 %)
Number of data points in class 10 : 890 ( 0.707 %)
Number of data points in class 11 : 201 ( 0.16 %)
Number of data points in class 12 : 53 ( 0.042 %)
Number of data points in class 13 : 30 ( 0.024 %)
Number of data points in class 14 : 20 ( 0.016 %)
Number of data points in class 15 : 18 ( 0.014 %)
Number of data points in class 16 : 11 ( 0.009 %)
Number of data points in class 17 : 10 ( 0.008 %)
Number of data points in class 18 : 9 ( 0.007 %)
Number of data points in class 19 : 8 ( 0.006 %)
Number of data points in class 20 : 7 ( 0.006 %)
Number of data points in class 21 : 4 ( 0.003 %)
Number of data points in class 22 : 3 ( 0.002 %)
Number of data points in class 23 : 2 ( 0.002 %)
```

Observation :

In the above plot we have 23 different kind of attacks and their distributions :

- data set is not uniform distributed as we can see in the above
- there are lots of attacks where data points are very few and some of the attacks like normal and neptune these both have 85% datapoints out of 100% datapoints
- There are 16 attacks out of 23 attacks where the data points are less then 1%

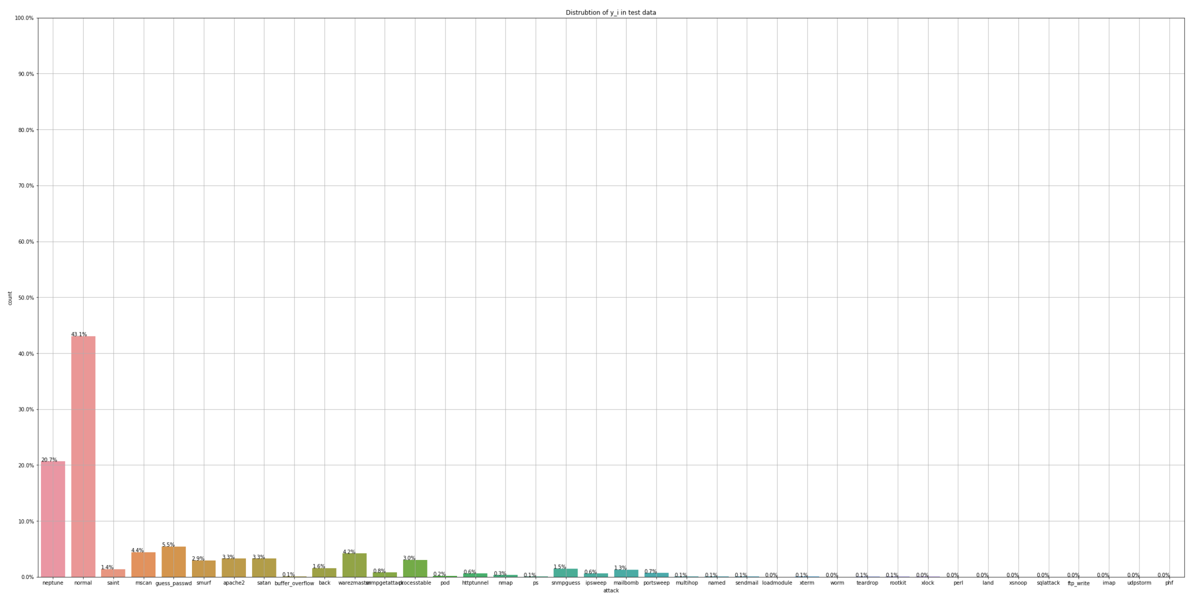
From this we see that : Normal has 53.5% datapoints and all other 22 class has 46.5% datapoints

we got an imbalanced dataset

3.3.2 Test data

In [22]:

```
 #Initialize the matplotlib figure
f, ax = plt.subplots(figsize=(40,20))

# we need the total number of data to find the percentage later.
total = len(test_data) * 1

# below code will simply plot bar plot where X axis is attack(23 classes) and y will s
ax = sns.countplot(x="attack", data= test_data )

# each p has height(number of data point for a given class ),width.
# then pass p to annotate(it is used to show text) and computing % of data in each clas
for p in ax.patches:
        ax.annotate('{:.1f}%'.format(100*p.get_height()/total), (p.get_x(), p.get_heig

# put 11 ticks (therefore 10 steps), from 0 to the total number of rows in the datafra
ax.yaxis.set_ticks(np.linspace(0, total, 11))

# adjust the ticklabel to the desired format, without changing the position of the tic
# map() need the function(what to do) and iterative
ax.set_yticklabels(map('{:.1f}%'.format, 100*ax.yaxis.get_majorticklocs()/total))
plt.grid()
plt.title("Distrubtion of y_i in test data")
plt.show()
```



In [23]:

```
# take the all the class with datapoints belonging to each classes and sort them by lal
test_class_distribution = test_data['attack'].value_counts()

# it is sorting them in decreasing order (by number of datapoints)
sorted_yi = np.argsort(-test_class_distribution.values)
# now for each i of the sorted datapoints we are printing the number of datapoints and
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',test_class_distribution[i], '(', 
```

```
Number of data points in class 1 : 9711 ( 43.076 %)
Number of data points in class 2 : 4657 ( 20.657 %)
Number of data points in class 3 : 1231 ( 5.46 %)
Number of data points in class 4 : 996 ( 4.418 %)
Number of data points in class 5 : 944 ( 4.187 %)
Number of data points in class 6 : 737 ( 3.269 %)
Number of data points in class 7 : 735 ( 3.26 %)
Number of data points in class 8 : 685 ( 3.039 %)
Number of data points in class 9 : 665 ( 2.95 %)
Number of data points in class 10 : 359 ( 1.592 %)
Number of data points in class 11 : 331 ( 1.468 %)
Number of data points in class 12 : 319 ( 1.415 %)
Number of data points in class 13 : 293 ( 1.3 %)
Number of data points in class 14 : 178 ( 0.79 %)
Number of data points in class 15 : 157 ( 0.696 %)
Number of data points in class 16 : 141 ( 0.625 %)
Number of data points in class 17 : 133 ( 0.59 %)
Number of data points in class 18 : 73 ( 0.324 %)
Number of data points in class 19 : 41 ( 0.182 %)
Number of data points in class 20 : 20 ( 0.089 %)
Number of data points in class 21 : 18 ( 0.08 %)
Number of data points in class 22 : 17 ( 0.075 %)
Number of data points in class 23 : 15 ( 0.067 %)
Number of data points in class 24 : 14 ( 0.062 %)
Number of data points in class 25 : 13 ( 0.058 %)
Number of data points in class 26 : 13 ( 0.058 %)
Number of data points in class 27 : 12 ( 0.053 %)
Number of data points in class 28 : 9 ( 0.04 %)
Number of data points in class 29 : 7 ( 0.031 %)
Number of data points in class 30 : 4 ( 0.018 %)
Number of data points in class 31 : 3 ( 0.013 %)
Number of data points in class 32 : 2 ( 0.009 %)
Number of data points in class 33 : 2 ( 0.009 %)
Number of data points in class 34 : 2 ( 0.009 %)
Number of data points in class 35 : 2 ( 0.009 %)
Number of data points in class 36 : 2 ( 0.009 %)
Number of data points in class 37 : 2 ( 0.009 %)
Number of data points in class 38 : 1 ( 0.004 %)
```

- there is an intresting thing that is in the test data we have 38 classes.Which did not come to notice earlier.
- here also Normal and naptune classes has larger number of datapoints
- the same story data is not uniform
- dataset is imbalanced

3.2.3 attacks which are not in train data

In [24]:

```
# put train and test attack ina set and just find the difference we will get the classe
trn = set(train_data['attack'].unique())
tst = set(test_data['attack'].unique())

extra = tst - trn

print(extra)
print("*"*100)
print("number of extra Attacks : ",len(extra))
```

```
{'mailbomb', 'sqlattack', 'apache2', 'udpstorm', 'snmpgetattack', 'ps', 'xte
rm', 'snmpguess', 'worm', 'mscan', 'processtable', 'saint', 'named', 'xsnoo
p', 'httptunnel', 'sendmail', 'xlock'}
****************************************************************************
************************
number of extra Attacks :  17
```

In [25]:

```
e_extra = tst - extra
print(e_extra)
print("*"*100)
print("Attacks which are present in both train and test data ", len(e_extra))
```

```
{'neptune', 'ftp_write', 'teardrop', 'imap', 'nmap', 'multihop', 'portswee
p', 'land', 'perl', 'guess_passwd', 'pod', 'normal', 'back', 'smurf', 'buffe
r_overflow', 'satan', 'rootkit', 'ipsweep', 'loadmodule', 'phf', 'warezmaste
r'}
****************************************************************************
************************
Attacks which are present in both train and test data  21
```

In [26]:

```
ee_extra = trn - e_extra
print("Attacks which are present in train and not in  test data",ee_extra)
```

```
Attacks which are present in train and not in  test data {'spy', 'warezclien
t'}
```

Observation

- we have 17 extra classes in the test data
- 21 attacks present both in testa nd train dataset
- there are 2 classes which are not present in the test data but present in the train data , namely : 'spy', 'warezclient

3.4 Univariate analysis on catagorical features

3.4.1 Univariate analysis on protocol_type

[i] How many category present in this feature

In [27]:

```
unique_proto = train_data['protocol_type'].value_counts()
print("Number of unique proto type : ", unique_proto.shape[0])
print(unique_proto)
```

```
Number of unique proto type :  3
tcp     102689
udp      14993
icmp      8291
Name: protocol_type, dtype: int64
```

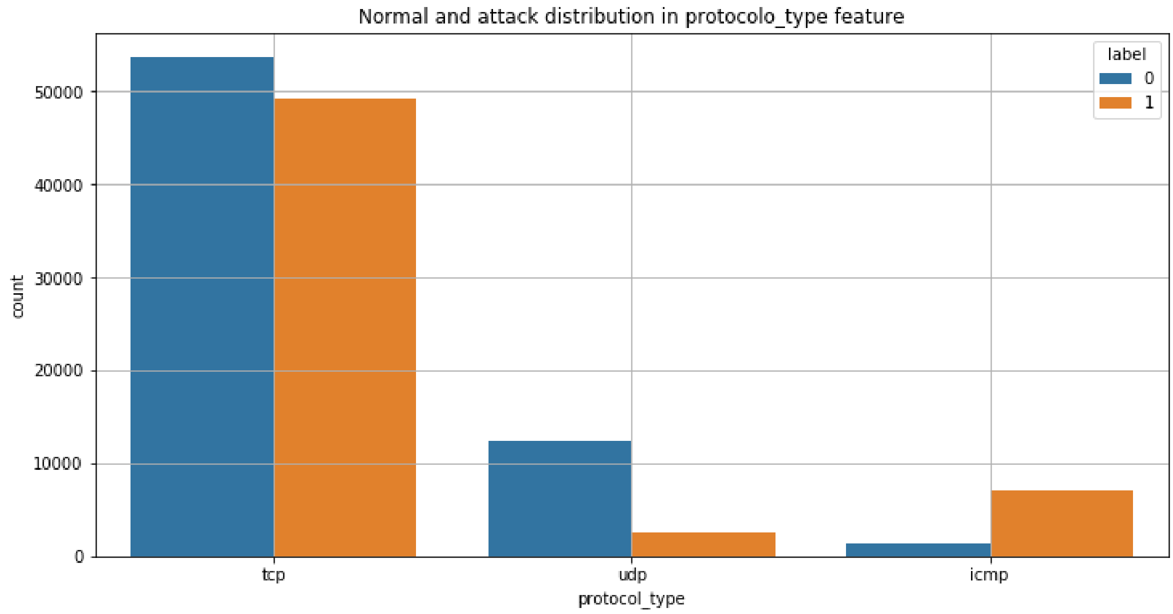
Observation

- we have 3 different category of proto type in the training data namely : TCP , UDP and ICMP
- lots of points belongs to tcp where as udp and icmp has fewer points

[ii] Distribution of the this feature

In [28]:

```
f, ax = plt.subplots(figsize=(12,6))
ax = sns.countplot(x = 'protocol_type' , data = train_data , hue = 'label')
plt.title("Normal and attack distribution in protocolo_type feature")
plt.grid()
plt.show()
```



Observation

- There are lots of point from the training data belongs to tcp prtocol_type (102689) . Normal and attack classes both are uniform only in term of tcp.
- majority of the udp protoype belongs to normal class while there are few points belongs to attack class also.
- In icmp protocol_type majority of points belongs to attack class .

[iii] Featurizing using one hot encoding

In [20]:

```
prototype_vectorizer = CountVectorizer()
train_protocol_type_encoding = prototype_vectorizer.fit_transform(train_data['protocol_
test_protocol_type_encoding = prototype_vectorizer.transform(test_data['protocol_type'
```

In [25]:

```
print("train_protocol_type_encoding is converted feature using one-hot encoding method
```

```
train_protocol_type_encoding is converted feature using one-hot encoding met
hod. The shape of gene feature: (125973, 3)
```

[iv] How good is this protocol_type feature in predicting y_i ?

To answer this question will build a Decision tree model model using only protocol_type feature (one hot encoded) to predict y_i.

In [18]:

```
# defining y_ture , y_test
y_true = train_data['label']
y_test = test_data['label']
```

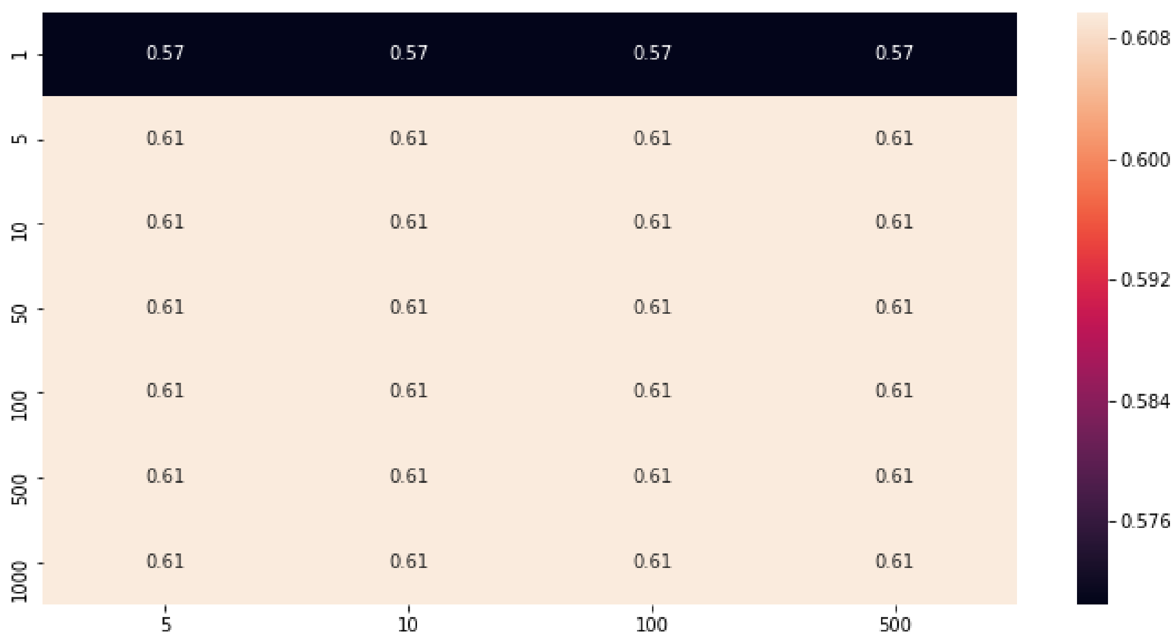
In [19]:

```
# Initializatioin of hyperparam and lets take only two hyperparam to tune
parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000],
              'min_samples_split':[5, 10, 100, 500]}

# using grid search lets find out the best hyperparam value
# Decision tree using gini impurity
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchC
DT_bow = GridSearchCV(DTC(criterion= 'gini'), parameters, cv=3 ,scoring='roc_auc')
DT_bow.fit(train_protocol_type_encoding,y_true)

# cv_results_dict of numpy (masked) ndarrays
# it will give mean train score as an array
cv_auc = DT_bow.cv_results_['mean_train_score']

max_depth = [1,5,10,50,100,500,1000]
min_samples_split = [5,10,100,500]


# reshaping the array (cv_auc) into a shape of (7,4)
# reference:https://qiita.com/bmj0114/items/8009f282c99b77780563
scores = cv_auc.reshape(len(max_depth),len(min_samples_split))
plt.figure(figsize = (12,6))
df = pd.DataFrame(scores, index=max_depth, columns=  min_samples_split)
sns.heatmap(df, annot=True)
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('mean_train_score'), whic
h will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
```

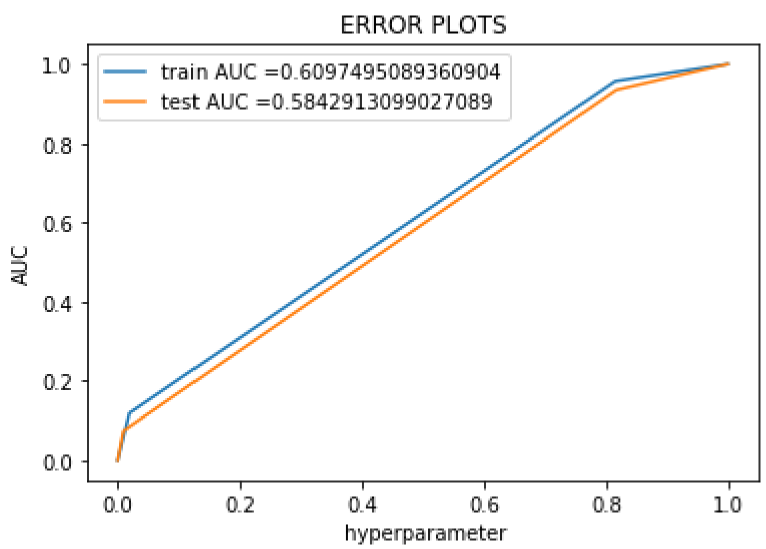
Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xb6125f8>
```



In [20]:

```
DT_bow = DTC(criterion= 'gini', max_depth = 10 , min_samples_split =10 )
DT_bow.fit(train_protocol_type_encoding , y_true)

# roc_curve function will return 3 thing fpr,trp, threshold
# calling predict_proba with the best estimator that we have
# train fpr and tpr give the an arry with flauctuate value
train_fpr, train_tpr, thresholds = roc_curve(y_true, DT_bow.predict_proba(train_protoc
test_fpr, test_tpr, thresholds = roc_curve(y_test, DT_bow.predict_proba(test_protocol_

# auc() : this function will give area under the curve value : using somtehing called
# to know more about this link :https://en.wikipedia.org/wiki/Trapezoidal_rule
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [21]:

```
# to find important feature create a dataframe
# pass data where we have the DTC attribute feature importance will give all the featu
# next pass the index where it will have the feature name coresponding to the feature 
# sort all the value desceding order

importance_feature = pd.DataFrame(data = DT_bow.feature_importances_.T, index = protot
print("Top 20 important features :",importance_feature)
```

```
Top 20 important features :              0
udp   0.59247
tcp   0.40753
icmp  0.00000
```

Observation

- by using only this feature i am getting 58 auc score from this we get to know that this feature may helpful in predicting the yi when we build the actual model using all features.
- the modeling thinking that most important category is udp where as icmp is not at all important

3.4.2 Univariate analysis on service

[i] How many category present in this feature

In [31]:

```
unique_service = train_data['service'].value_counts()
print("Number of unique service : ",unique_service.shape[0])
print(unique_service.head())
```

```
Number of unique service :  70
http        40338
private     21853
domain_u     9043
smtp         7313
ftp_data     6860
Name: service, dtype: int64
```

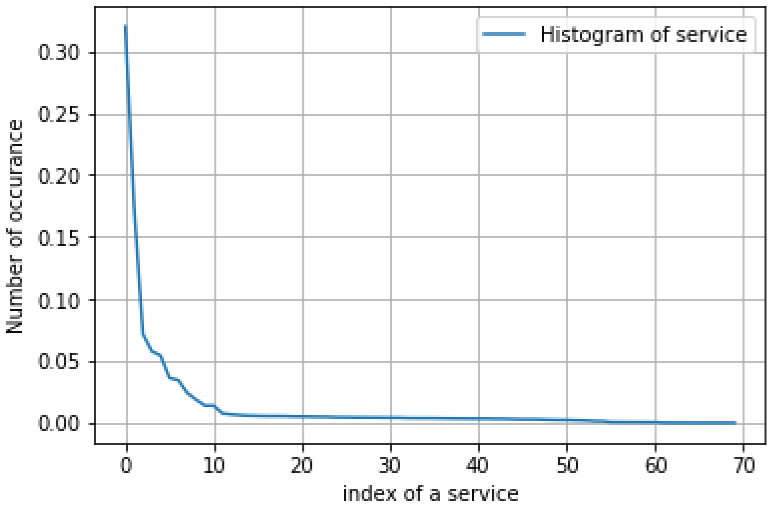
Observation

- there are two services http and private has quite more datapoints than other.

[ii] Distribution of the this feature

In [33]:

```
s = sum(unique_service.values)
h = unique_service.values/s
plt.plot( h , label = 'Histogram of service')
plt.xlabel('index of a service')
plt.ylabel('Number of occurance')
plt.legend()
plt.grid()
plt.show()
```

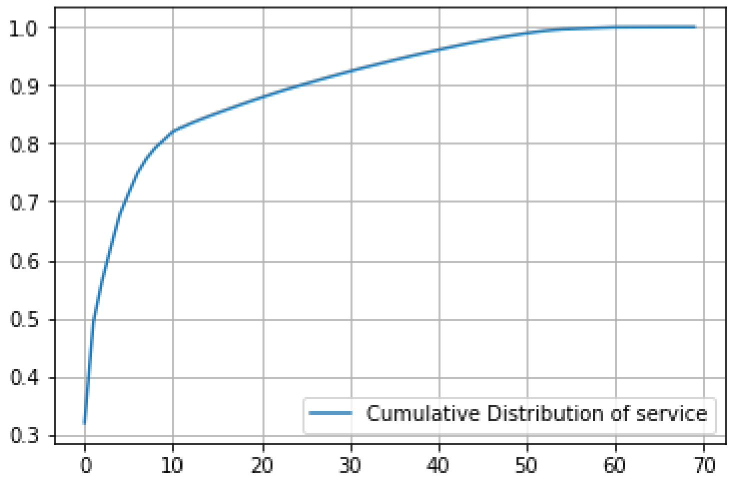


Observation

- this is a skewed distribution
- there are few services occur more and major of service occur less time .
- In this distribution from left to right services in a decreasing order (frequency).
- 0th index contain the http, 1st index contain private etc.

In [34]:

```
c = np.cumsum(h)
plt.plot(c , label = "Cumulative Distribution of service")
plt.grid()
plt.legend()
plt.show()
```



Observation

- Top 20 to 25 services contributed to 90 percent of data.that means these services occur very frequently than other services.

[iii] Featurizing using one hot encoding

In [21]:

```
service_encode = CountVectorizer()
train_service_encoding = service_encode.fit_transform(train_data['service'])
test_service_encoding = service_encode.transform(test_data['service'])
```

In [29]:

```
print("train_service_encoding is converted feature using one-hot encoding method. The s
```

```
train_service_encoding is converted feature using one-hot encoding method. T
he shape of gene feature: (125973, 70)
```

[iv] How good is this protocol_type feature in predicting y_i ?

To answer this question will build a Decision tree model model using only protocol_type feature (one hot encoded) to predict y_i.

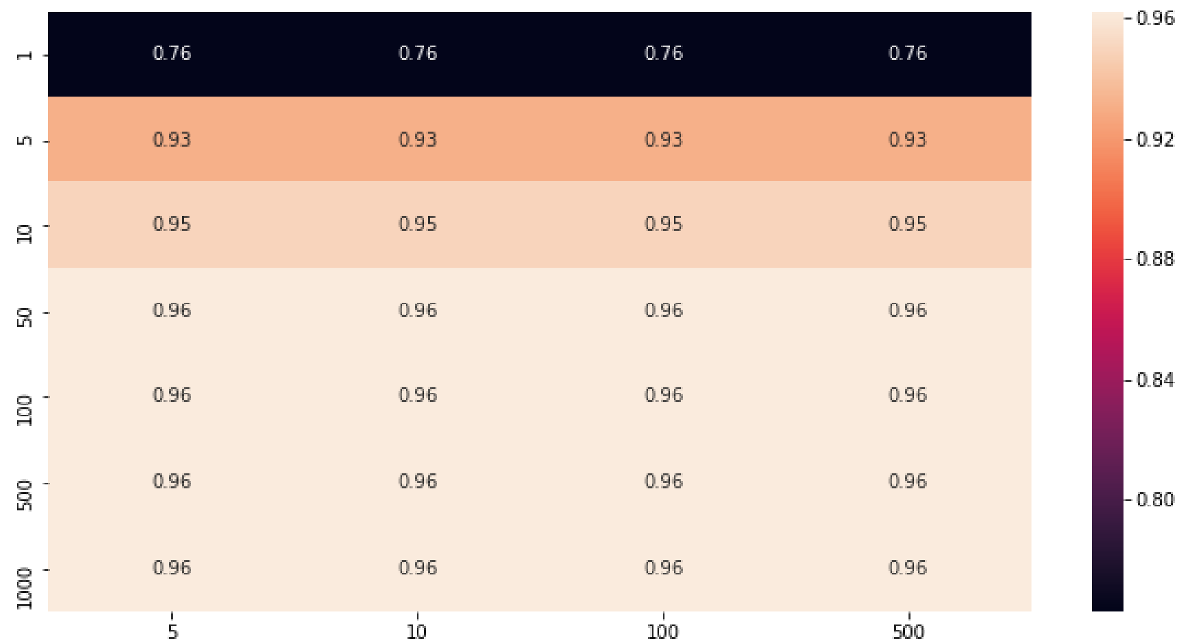
In [31]:

```python
# Initializatioin of hyperparam and lets take only two hyperparam to tune
parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000],
              'min_samples_split':[5, 10, 100, 500]}

# using grid search lets find out the best hyperparam value
# Decision tree using gini impurity
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchC
DT_bow = GridSearchCV(DTC(criterion= 'gini'), parameters, cv=3 ,scoring='roc_auc')
DT_bow.fit(train_service_encoding,y_true)

# cv_results_dict of numpy (masked) ndarrays
# it will give mean train score as an array
cv_auc = DT_bow.cv_results_['mean_train_score']
max_depth = [1,5,10,50,100,500,1000]
min_samples_split = [5,10,100,500]


# reshaping the array (cv_auc) into a shape of (7,4)
# reference:https://qiita.com/bmj0114/items/8009f282c99b77780563
scores = cv_auc.reshape(len(max_depth),len(min_samples_split))

plt.figure(figsize = (12,6))
df = pd.DataFrame(scores, index=max_depth, columns=  min_samples_split)
sns.heatmap(df, annot=True)
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('mean_train_score'), whic
h will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
```

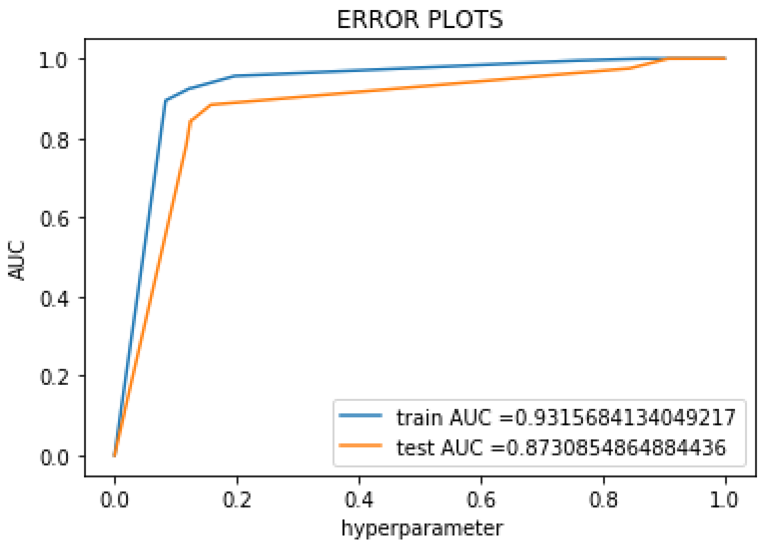
Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x14a5fcf8>
```



In [35]:

```
from sklearn.metrics import roc_curve, auc

DT_bow = DTC(criterion= 'gini', max_depth = 5 , min_samples_split = 5 )
DT_bow.fit(train_service_encoding , y_true)

# roc_curve function will return 3 thing fpr,trp, threshold
# calling predict_proba with the best estimater that we have
# train fpr and tpr give the an arry with flauctuate value
train_fpr, train_tpr, thresholds = roc_curve(y_true, DT_bow.predict_proba(train_servic
test_fpr, test_tpr, thresholds = roc_curve(y_test, DT_bow.predict_proba(test_service_en


# auc() : this function will give area under the curve value : using somtehing called
# to know more about this link :https://en.wikipedia.org/wiki/Trapezoidal_rule
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [37]:

```
# to find important feature create a dataframe
# pass data where we have the DTC attribute feature importance will give all the featu
# next pass the index where it will have the feature name coresponding to the feature 
# sort all the value desceding order

importance_feature = pd.DataFrame(data = DT_bow.feature_importances_.T, index=service_
print("Top 20 important features :",importance_feature)
```

```
Top 20 important features :                     0
http       0.463210
domain_u   0.203939
smtp       0.183398
ftp_data   0.102040
other      0.047413
nntp       0.000000
ntp_u      0.000000
pm_dump    0.000000
pop_2      0.000000
pop_3      0.000000
```

Observation

- by using only this single feature my model giving 87 test auc value which is quite intersting
- Out of 70 feature only 5 of them is important .
- This information might be useful in feature engineering (we can remove feature with 0.0 values)

3.4.3 Univariate analysis on Flag

[i] How many category present in this feature

In [34]:

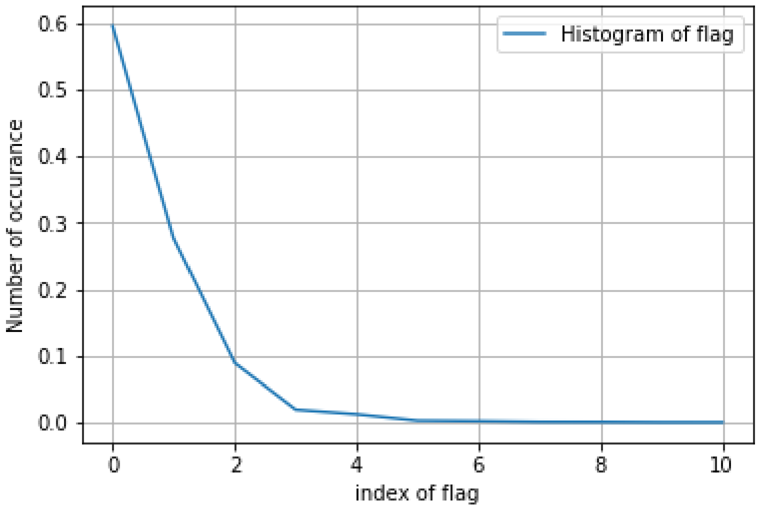
```
flag_unique = train_data['flag'].value_counts()
print("Number of unique flag : ", flag_unique.shape[0])
print(flag_unique.head())
```

```
Number of unique flag :  11
SF      74945
S0      34851
REJ     11233
RSTR     2421
RSTO     1562
Name: flag, dtype: int64
```

[ii] Distribution of the this feature

In [38]:

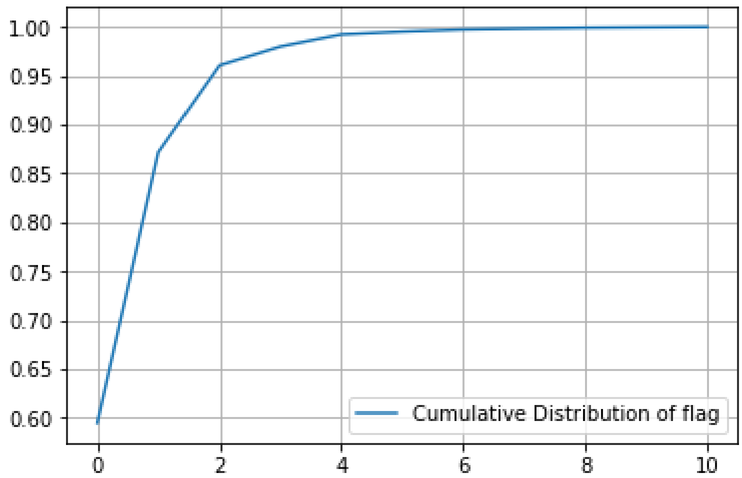
```
# taking sum
s = sum(flag_unique.values)
# diving each falg vaue to sum
h = flag_unique.values/s
plt.plot(h , label = 'Histogram of flag')
plt.xlabel("index of flag")
plt.ylabel('Number of occurance')
plt.grid()
plt.legend()
plt.show()
```



- there are 3 - 4 falg has mpre number of occurance
- skewed distribution

In [39]:

```
c = np.cumsum(h)
plt.plot(c , label = 'Cumulative Distribution of flag')
plt.legend()
plt.grid()
plt.show()
```



- out of 10 falg 4 flag contibuted 98 -99% of data , these 4 flags are occuring more freuntly.

[iii] Featurizing using one hot encoding

In [22]:

```
flag_encoding = CountVectorizer()
train_flag_encoding = flag_encoding.fit_transform(train_data['flag'])
test_flag_encoding = flag_encoding.transform(test_data['flag'])
```

In [27]:

```
print("train_flag_encoding is converted feature using one-hot encoding method. The sha
```

```
train_flag_encoding is converted feature using one-hot encoding method. The
shape of gene feature: (125973, 11)
```

[iv] How good is this protocol_type feature in predicting y_i ?

To answer this question will build a Decision tree model model using only protocol_type feature (one hot encoded) to predict y_i.

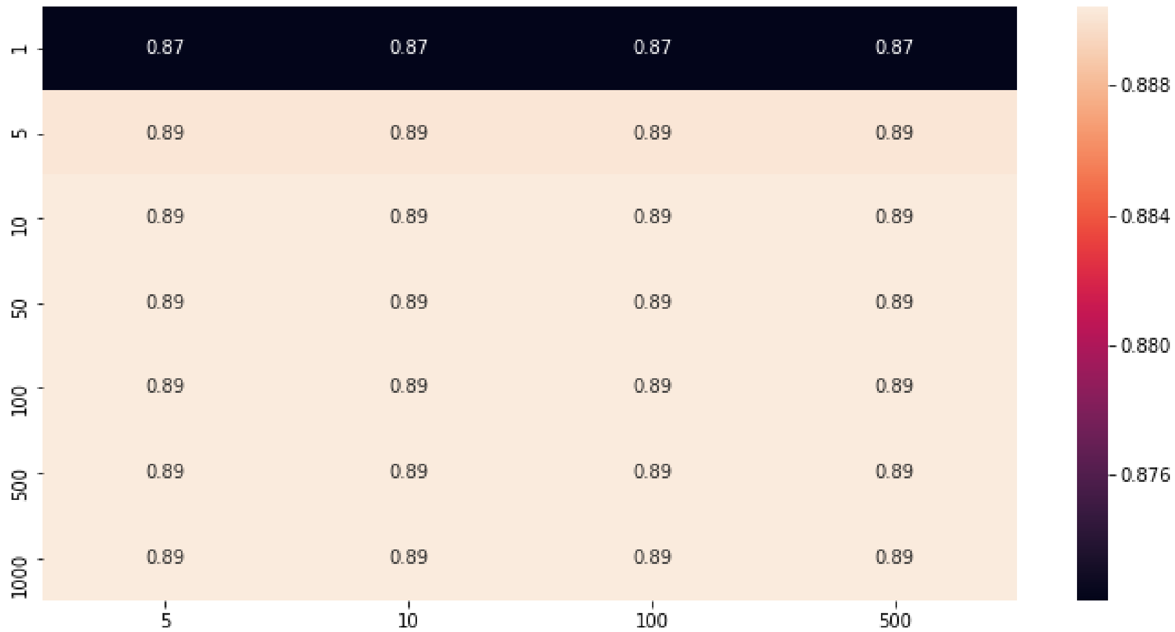
In [40]:

```
# Initializatioin of hyperparam and lets take only two hyperparam to tune

parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000],
              'min_samples_split':[5, 10, 100, 500]}

# using grid search lets find out the best hyperparam value
# Decision tree using gini impurity
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearch(
DT_bow = GridSearchCV(DTC(criterion= 'gini'), parameters, cv=3 ,scoring='roc_auc')
DT_bow.fit(train_flag_encoding,y_true)

# cv_results_dict of numpy (masked) ndarrays
# it will give mean train score as an array
cv_auc = DT_bow.cv_results_['mean_train_score']
max_depth = [1,5,10,50,100,500,1000]
min_samples_split = [5,10,100,500]


# reshaping the array (cv_auc) into a shape of (7,4)
# reference:https://qiita.com/bmj0114/items/8009f282c99b77780563
scores = cv_auc.reshape(len(max_depth),len(min_samples_split))

plt.figure(figsize = (12,6))
df = pd.DataFrame(scores, index=max_depth, columns=  min_samples_split)
sns.heatmap(df, annot=True)
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('mean_train_score'), whic
h will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
```

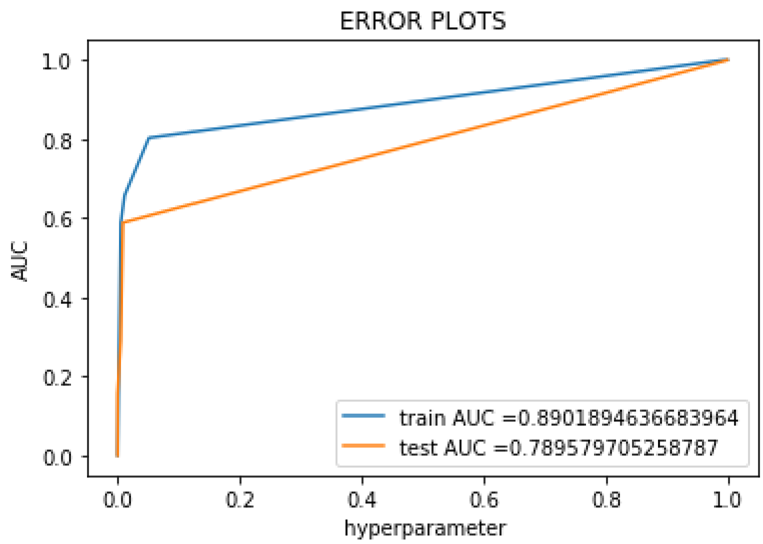
Out[40]:

<matplotlib.axes._subplots.AxesSubplot at 0x558fe10>



In [44]:

```
from sklearn.metrics import roc_curve, auc

DT_bow = DTC(criterion= 'gini', max_depth = 5 , min_samples_split = 10 )
DT_bow.fit(train_flag_encoding , y_true)

# roc_curve function will return 3 thing fpr,trp, threshold
# calling predict_proba with the best estimater that we have
# train fpr and tpr give the an arry with flauctuate value
train_fpr, train_tpr, thresholds = roc_curve(y_true, DT_bow.predict_proba(train_flag_e
test_fpr, test_tpr, thresholds = roc_curve(y_test, DT_bow.predict_proba(test_flag_enco


# auc() : this function will give area under the curve value : using somtehing called
# to know more about this link :https://en.wikipedia.org/wiki/Trapezoidal_rule
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [45]:

```
# to find important feature create a dataframe
# pass data where we have the DTC attribute feature importance will give all the featu
# next pass the index where it will have the feature name coresponding to the feature
# sort all the value desceding order

importance_feature = pd.DataFrame(data = DT_bow.feature_importances_.T, index=flag_enc
print("Top 20 important features :",importance_feature)
```

```
Top 20 important features :                 0
sf       0.954620
s0       0.026476
s1       0.011691
s2       0.003657
rej      0.003556
oth      0.000000
rsto     0.000000
rstos0   0.000000
rstr     0.000000
s3       0.000000
sh       0.000000
```

Observation

- By look at the train and test auc value the model might be overffiting , but we have 78 test auc value, which showing us that this model will helful
- there is one category which is most important : 'sf' this category itself has value of 95 .

3.5 Univariate analysis on some continuous features

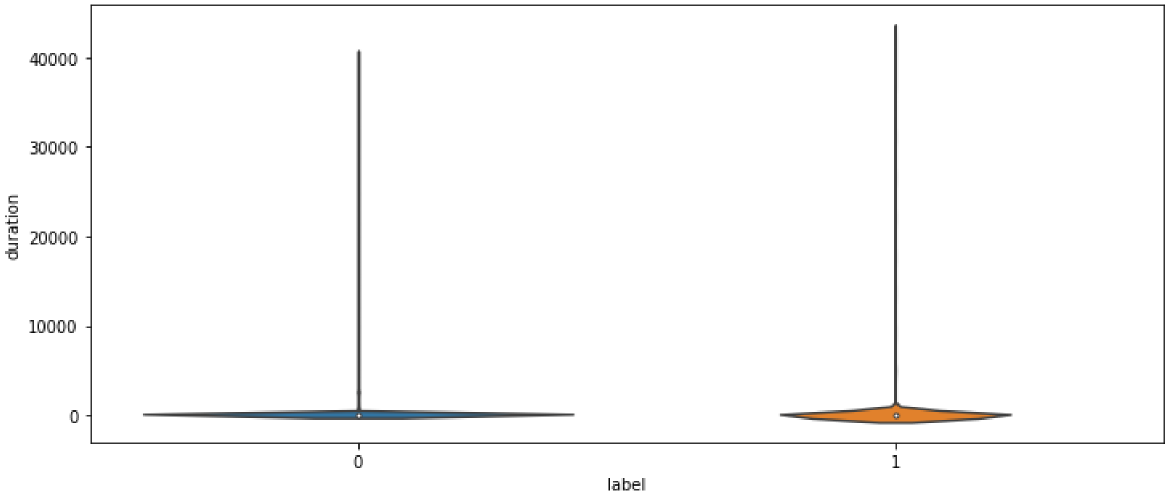
1.Duration

length (number of seconds) of the connection

In [42]:

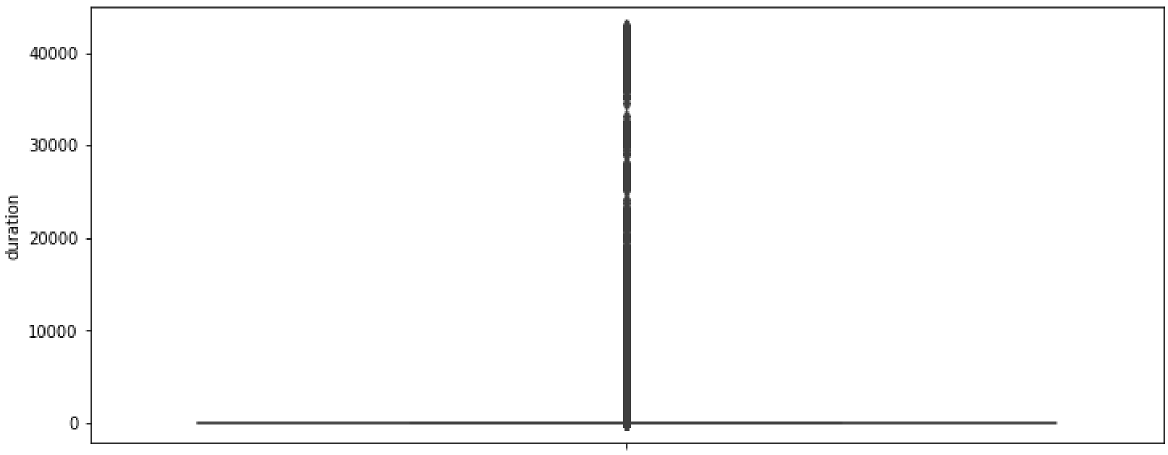
```
plt.figure(figsize =(12,5))
# violin plot
sns.violinplot(x ='label' , y = 'duration' , data = train_data )
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [43]:

```
plt.figure(figsize =(12,5))
# violin plot
sns.boxplot(y ='duration' ,  data = train_data )
plt.show()
```



Observation

- mean, median, 25th ,50th,75th percentile is so small to analyse beacuse most of the duration is 0
- lets look into 0 to 100% percentile value

In [44]:

```
for i in range(0,100,10):
    # take all the value of duration column
    var = train_data['duration'].values
    # falttend them and sort in ascending order
    var = np.sort(var , axis= None)
    # formula to calculate percentile "int(len(var)*float(i)/100"
    print("{} percentile value {}".format(i,var[int(len(var)*float(i)/100)]))
print("100 percentile value is ",var[-1])
```

```
0 percentile value 0
10 percentile value 0
20 percentile value 0
30 percentile value 0
40 percentile value 0
50 percentile value 0
60 percentile value 0
70 percentile value 0
80 percentile value 0
90 percentile value 0
100 percentile value is  42908
```

Observation

- about 90 percentile value of duration is 0
- there are lots of value we can see in 100 percentile
- so lets look at from 90 to 100 percentile

In [45]:

```
#calculating speed values at each percntile 90,91,92,93,94,95,96,97,98,99,100
for i in range(90,100):
    var = train_data['duration'].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print("100 percentile value is ",var[-1])
```

```
90 percentile value is 0
91 percentile value is 0
92 percentile value is 0
93 percentile value is 1
94 percentile value is 2
95 percentile value is 4
96 percentile value is 15
97 percentile value is 31
98 percentile value is 2052
99 percentile value is 9592
100 percentile value is  42908
```

In [101]:

```
#calculating speed values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99
for i in np.arange(0.0, 1.0, 0.1):
    var = train_data['duration'].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 9592
99.1 percentile value is 10910
99.2 percentile value is 12666
99.3 percentile value is 13858
99.4 percentile value is 16693
99.5 percentile value is 19981
99.6 percentile value is 25761
99.7 percentile value is 30679
99.8 percentile value is 37141
99.9 percentile value is 39984
100 percentile value is  42908
```

Observation

- value of duration has increased from 90 percentile onward.
- if we look at the violine plot of class label 1 there is some value which might be upto 2k to 3k
- from 99.0 to 100 percentile the value is increased dramatically..these value might be outlier.

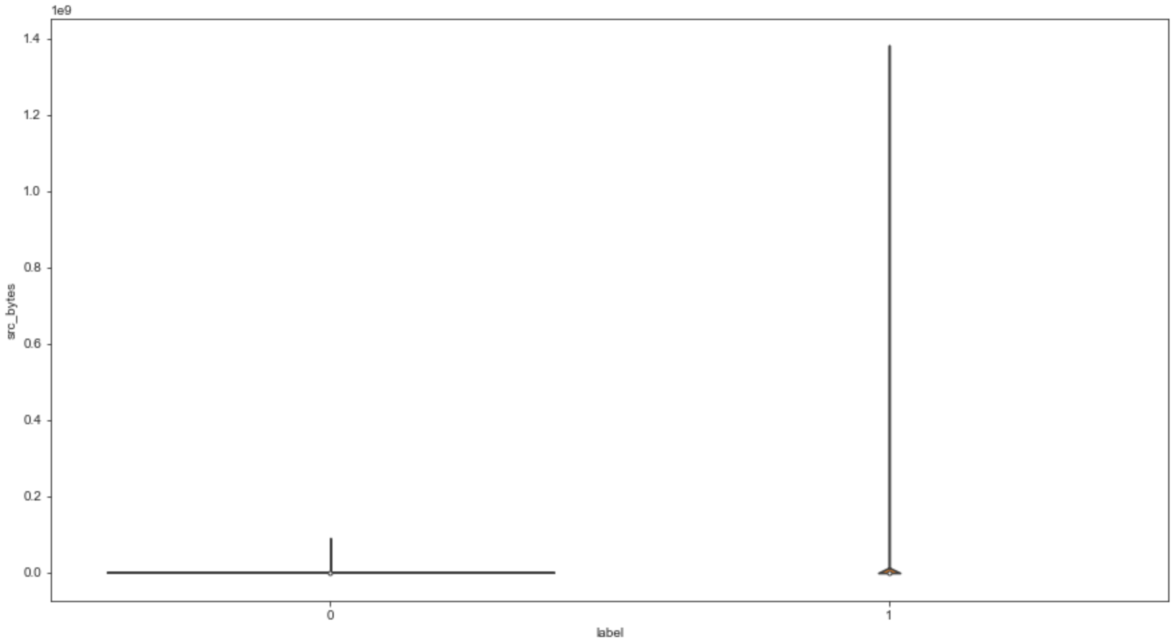
2 . src_bytes

number of data bytes from source to destination

In [71]:

```
plt.figure(figsize=(15,8))
sns.violinplot(x = 'label' , y = 'src_bytes' , data = train_data)
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

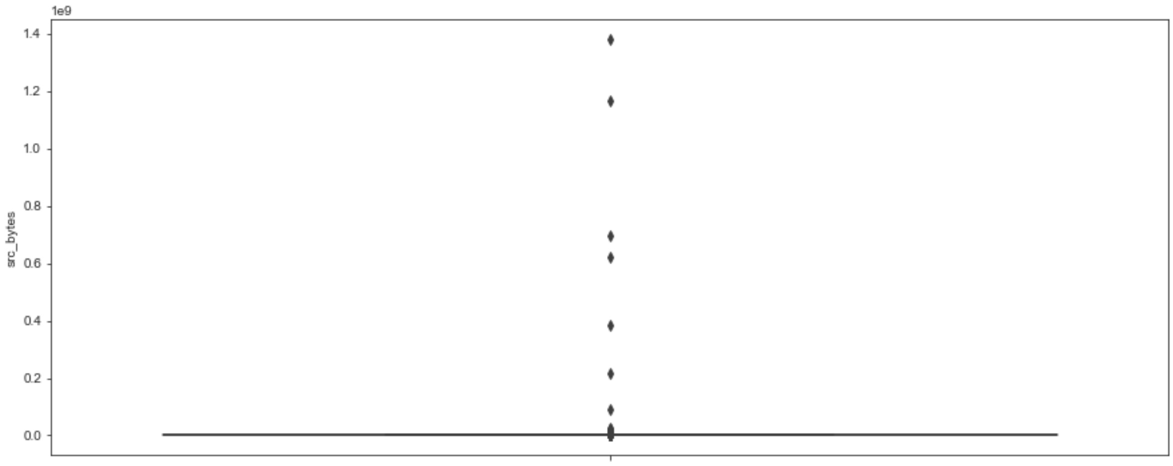


Observation

- for both label 0 and 1 it is hard to analys .but one thing to notice is class 1 which attack has quite larger value than class 0 which is normal

In [75]:

```
plt.figure(figsize = (15,6))
sns.boxplot(y = 'src_bytes' ,data = train_data)
plt.show()
```



Observation

- from this box plot we can see all the value from 25th to 75th percentile has zero. it is hard to interprit.
- lets agaim zoom into the percentile value of src_bytes.

In [76]:

```
# CALCULATING PERCENTILE FROM 0,10,20,30,...,100
for i in range(0,100,10):
    var = train_data['src_bytes'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
0 percentile value is 0
10 percentile value is 0
20 percentile value is 0
30 percentile value is 0
40 percentile value is 1
50 percentile value is 44
60 percentile value is 192
70 percentile value is 235
80 percentile value is 307
90 percentile value is 848
100 percentile is  1379963888
```

Observation

- As we can see there is a big jump from 90% to 100 %

In [77]:

```
# calculating percentile from 90,91,92,...,100
for i in range(90,100):
    var = train_data['src_bytes'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
90 percentile value is 848
91 percentile value is 1006
92 percentile value is 1032
93 percentile value is 1087
94 percentile value is 1264
95 percentile value is 1480
96 percentile value is 1830
97 percentile value is 2974
98 percentile value is 8737
99 percentile value is 54540
100 percentile is  1379963888
```

In [79]:

```
#calculating speed values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99
for i in np.arange(0.0, 1.0, 0.1):
    var = train_data['src_bytes'].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 54540
99.1 percentile value is 54540
99.2 percentile value is 54540
99.3 percentile value is 54540
99.4 percentile value is 54540
99.5 percentile value is 54540
99.6 percentile value is 175337
99.7 percentile value is 501760
99.8 percentile value is 2194619
99.9 percentile value is 2194619
100 percentile value is  1379963888
```

Observation

- there is a huge value in the 100 % which 1379963888byte equivalent to 1.28GB goes from source to destination.

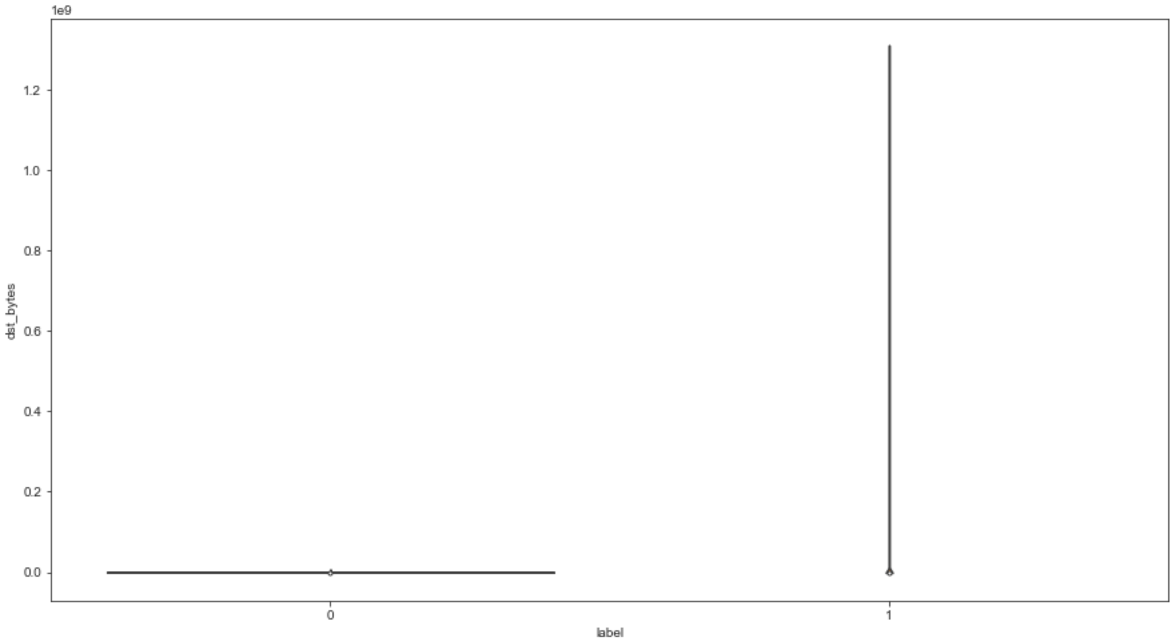
3.dst_bytes

number of data bytes from destination to source

In [80]:

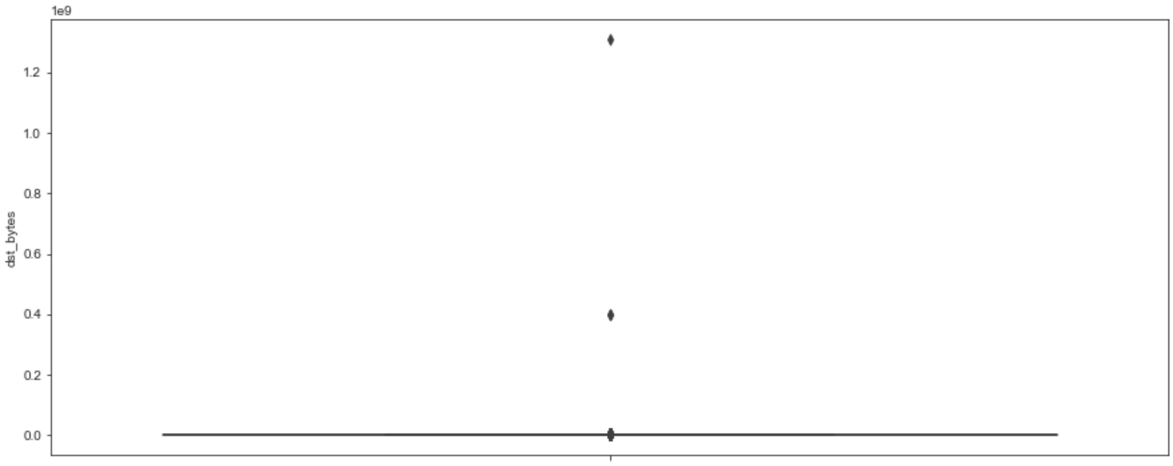
```
plt.figure(figsize=(15,8))
sns.violinplot(x = 'label' , y = 'dst_bytes' , data = train_data)
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [81]:

```
plt.figure(figsize = (15,6))
sns.boxplot(y = 'dst_bytes' ,data = train_data)
plt.show()
```



In [82]:

```
# CALCULATING PERCENTILE FROM 0,10,20,30,...,100
for i in range(0,100,10):
    var = train_data['dst_bytes'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
0 percentile value is 0
10 percentile value is 0
20 percentile value is 0
30 percentile value is 0
40 percentile value is 0
50 percentile value is 0
60 percentile value is 110
70 percentile value is 334
80 percentile value is 1085
90 percentile value is 3376
100 percentile is  1309937401
```

In [84]:

```
# calculating percentile from 90,91,92,...,100
for i in range(90,100):
    var = train_data['dst_bytes'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
90 percentile value is 3376
91 percentile value is 4058
92 percentile value is 4777
93 percentile value is 5876
94 percentile value is 7273
95 percentile value is 8314
96 percentile value is 9432
97 percentile value is 11715
98 percentile value is 15342
99 percentile value is 25519
100 percentile is  1309937401
```

In [90]:

```
#calculating speed values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99
for i in np.arange(0.0, 1.0, 0.1):
    var = train_data['dst_bytes'].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 25519
99.1 percentile value is 27264
99.2 percentile value is 29122
99.3 percentile value is 31377
99.4 percentile value is 34030
99.5 percentile value is 37236
99.6 percentile value is 42766
99.7 percentile value is 52225
99.8 percentile value is 81172
99.9 percentile value is 235008
100 percentile value is  1309937401
```

Observation

- here is also a huge value in the 100 % which 1309937401byte equivalent to 1.21GB goes from destination to source.

4. wrong_fragment

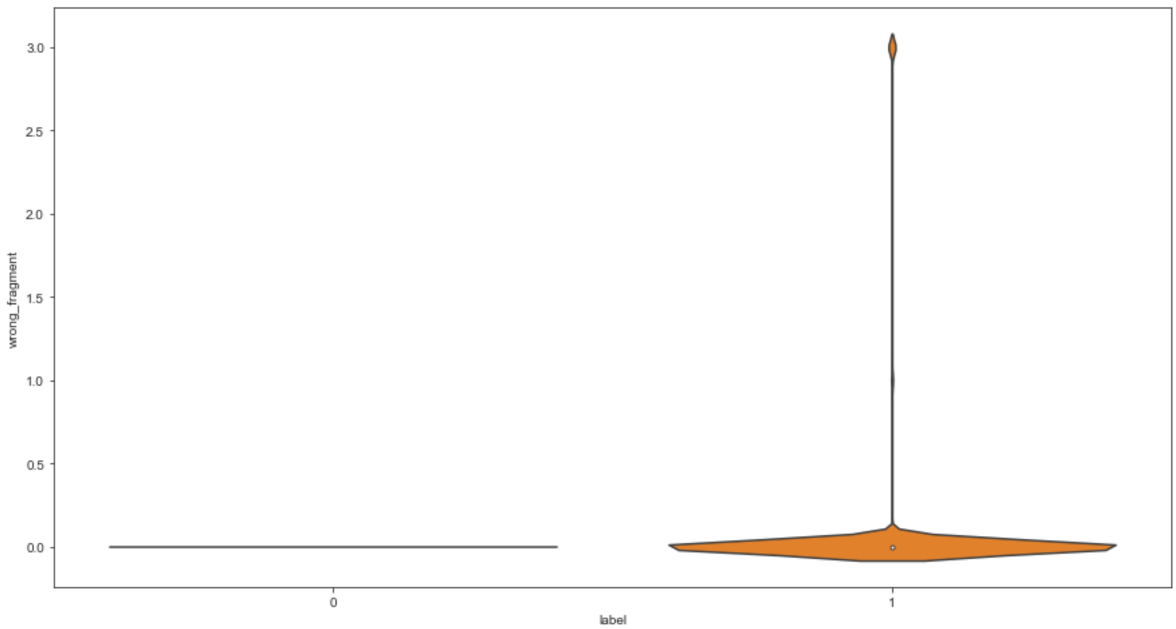
number of wrong fragments

IP fragmentation is an Internet Protocol (IP) process that breaks packets into smaller pieces (fragments)

In [85]:

```
plt.figure(figsize=(15,8))
sns.violinplot(x = 'label' , y = 'wrong_fragment' , data = train_data)
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

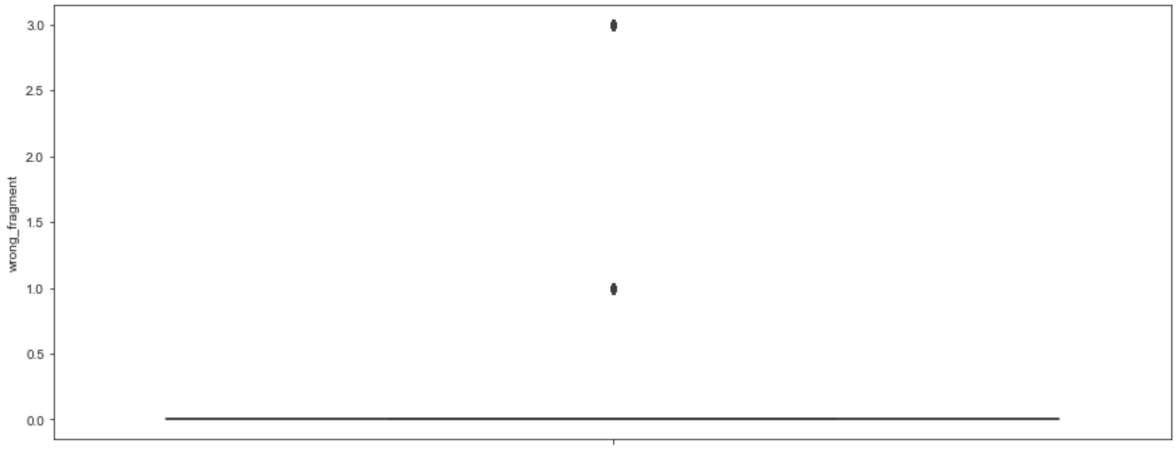


Observation

- there is so much variance in the class 1 while there no variance in class 0
- there is some diffrence in class 0 and 1 .this might help to distinguish from class 1 to 0

In [86]:

```
plt.figure(figsize = (15,6))
sns.boxplot(y = 'wrong_fragment' ,data = train_data)
plt.show()
```



In [87]:

```
# CALCULATING PERCENTILE FROM 0,10,20,30,...,100
for i in range(0,100,10):
    var = train_data['wrong_fragment'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
0 percentile value is 0
10 percentile value is 0
20 percentile value is 0
30 percentile value is 0
40 percentile value is 0
50 percentile value is 0
60 percentile value is 0
70 percentile value is 0
80 percentile value is 0
90 percentile value is 0
100 percentile is  3
```

In [88]:

```
# calculating percentile from 90,91,92,...,100
for i in range(90,100):
    var = train_data['wrong_fragment'].values
    var = np.sort(var , axis = None)
    print("{} percentile value is {}".format(i , var[int(len(var)*float(i)/100)]))
print("100 percentile is ",var[-1])
```

```
90 percentile value is 0
91 percentile value is 0
92 percentile value is 0
93 percentile value is 0
94 percentile value is 0
95 percentile value is 0
96 percentile value is 0
97 percentile value is 0
98 percentile value is 0
99 percentile value is 0
100 percentile is  3
```

In [91]:

```
#calculating speed values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99
for i in np.arange(0.0, 1.0, 0.1):
    var = train_data['wrong_fragment'].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 0
99.1 percentile value is 0
99.2 percentile value is 1
99.3 percentile value is 3
99.4 percentile value is 3
99.5 percentile value is 3
99.6 percentile value is 3
99.7 percentile value is 3
99.8 percentile value is 3
99.9 percentile value is 3
100 percentile value is  3
```

Observation

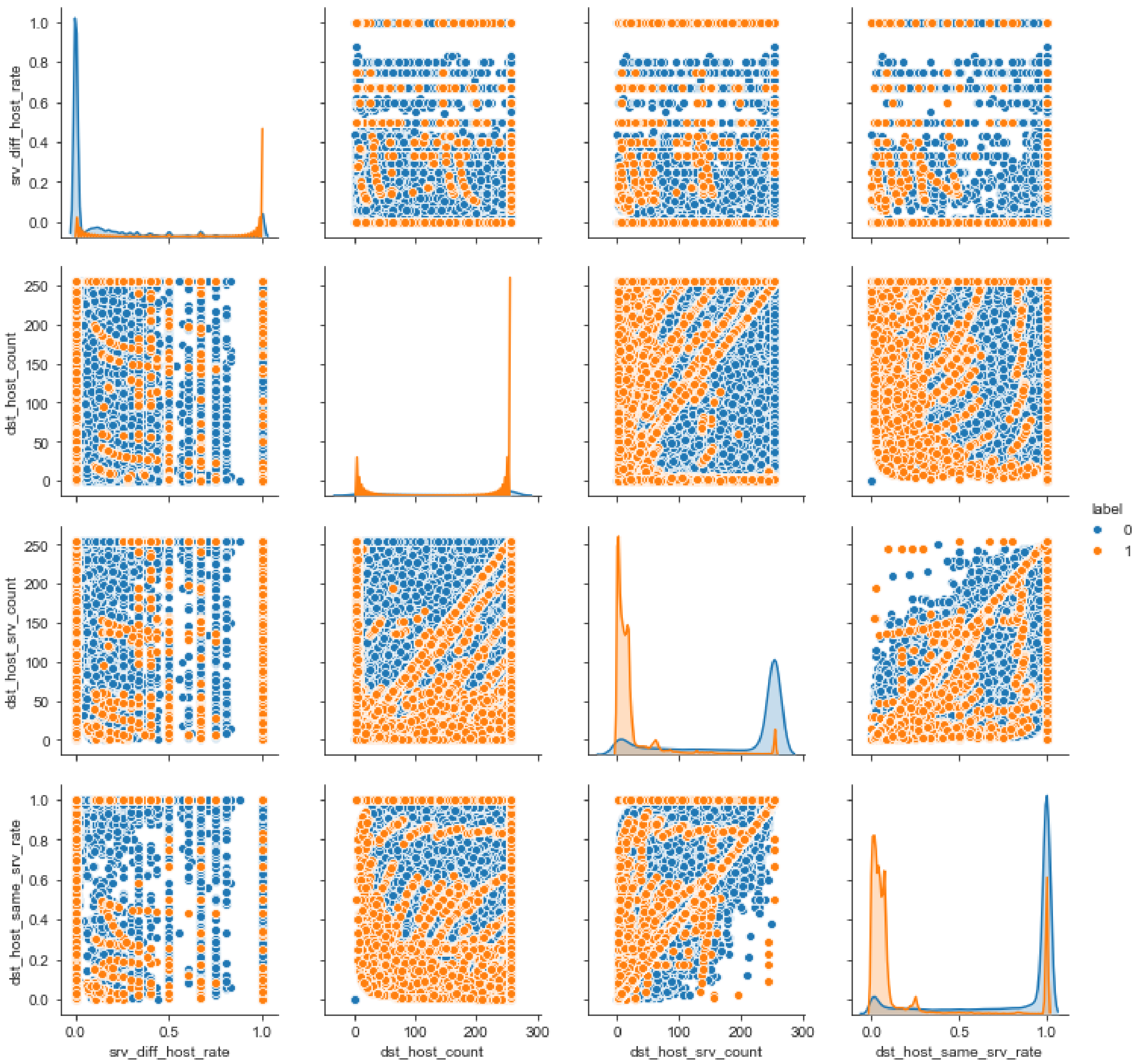
- this feature seems to be ok as there is not so much inflection

3.6 Bivariate Analysis (pair plots)

In [94]:

```
n = train_data.shape[0]
sns.pairplot(train_data[['srv_diff_host_rate','dst_host_count','dst_host_srv_count','d
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Observation

- if we look the dst_host_count and dst_host_same_srv_rate feature there are some point (not fully) but partially separeble ,but there are some overlap point also.
- dst_hst_srv_count and dst_host_count here also in the middle there are some overlap and some of the datapoints are partially separable
- If we look at the pdf of these 4 feature

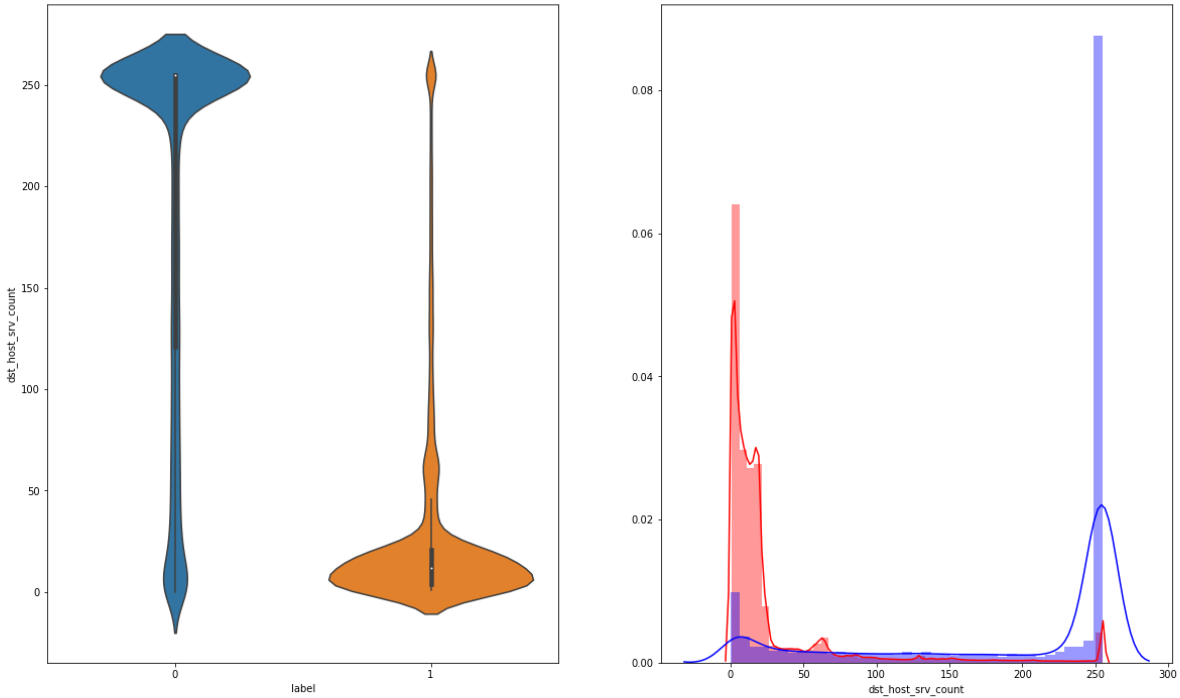
```
  - srv_diff_host_rate : the class 0 have higer value than class 1
  - dst_host_count : all over the class 1 is placed and have much higher value
 than class 0
  - dst_host_srv_count : there is some over lap region between class 1 and 0, c
lass 1 have higher value than class 0.
  - dst_host_same_srv_rate : it look both class 1 and class 0 separated ,but th
ere are quite overlap datapoints.
```

lets try to analyse dst_host_srv_count and dst_host_same_srv_rate

In [45]:

```
plt.subplots(figsize = (20,12))
plt.subplot(1,2,1)
sns.violinplot(x = 'label',y = 'dst_host_srv_count',data = train_data )

plt.subplot(1,2,2)
sns.distplot(train_data[train_data['label'] == 1]['dst_host_srv_count'][0:] , label =
sns.distplot(train_data[train_data['label'] == 0]['dst_host_srv_count'][0:] , label =
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



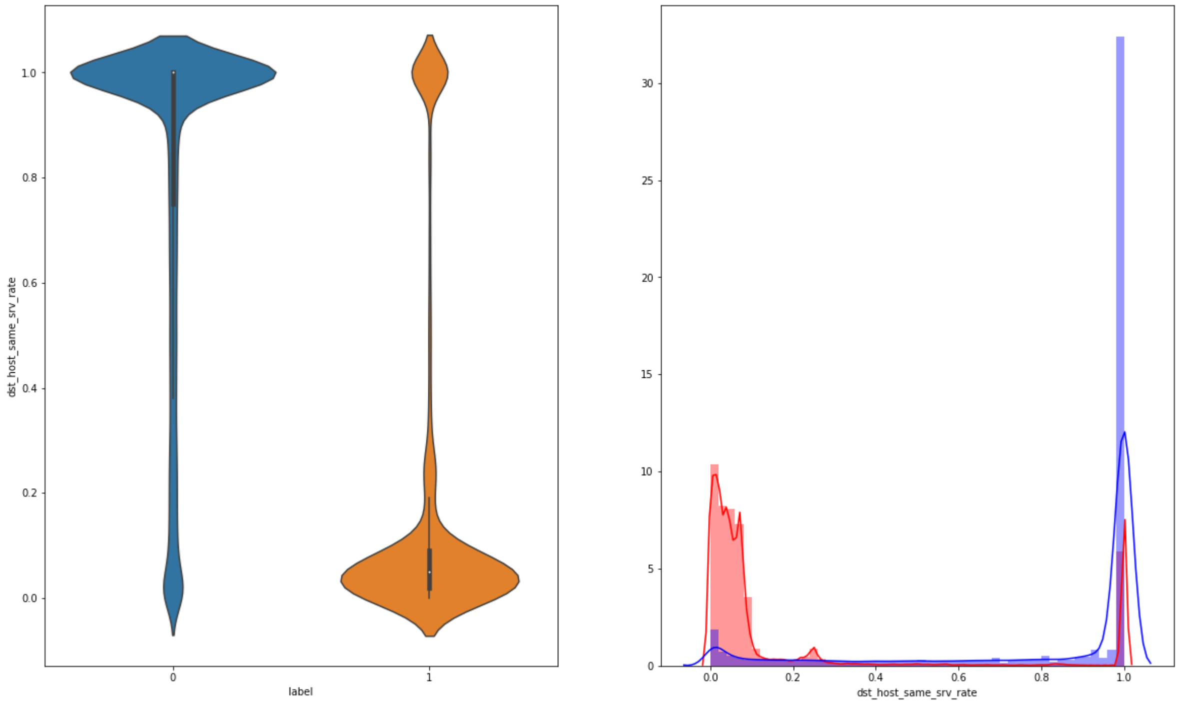
Observation

- These 2 violins are not fully overlap , this "dst_host_srv_count" feature may be usful in classification

In [47]:

```
plt.subplots(figsize = (20,12))
plt.subplot(1,2,1)
sns.violinplot(x = 'label',y = 'dst_host_same_srv_rate',data = train_data )

plt.subplot(1,2,2)
sns.distplot(train_data[train_data['label'] == 1]['dst_host_same_srv_rate'][0:] , labe
sns.distplot(train_data[train_data['label'] == 0]['dst_host_same_srv_rate'][0:] , labe
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is deprecat
ed; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result eithe
r in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Observation

- here also both class is not overlapping fully(in term of 25th 50th and 75th percentile) so there is some separebility in this dst_host_same_srv_rate.

3.7 Multivariate analysis using TSNE

In [46]:

```
# Using TSNE lets visualize the data from 32dim(continuous variable) to 2 dim
train_data_sample = train_data[0:7000]
# why minmax ? : actually there is no specific reason beacuse i have tried both and bo
X = MinMaxScaler()
# we have 32 continuous feature.
X  = X.fit_transform(train_data_sample[["duration","src_bytes",
    "dst_bytes","wrong_fragment","urgent","hot","num_failed_logins","num_compromised",
    "num_file_creations","num_shells","num_access_files","num_outbound_cmds","count","
    "srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
    "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
    "dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
    "dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
    "dst_host_rerror_rate","dst_host_srv_rerror_rate"]])
y = train_data_sample['label'].values
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:323:
DataConversionWarning: Data with input dtype int64, float64 were all convert
ed to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

In [47]:

```
tsne1 = TSNE(n_components=2, perplexity=30.0, early_exaggeration=12.0, learning_rate=2(
```

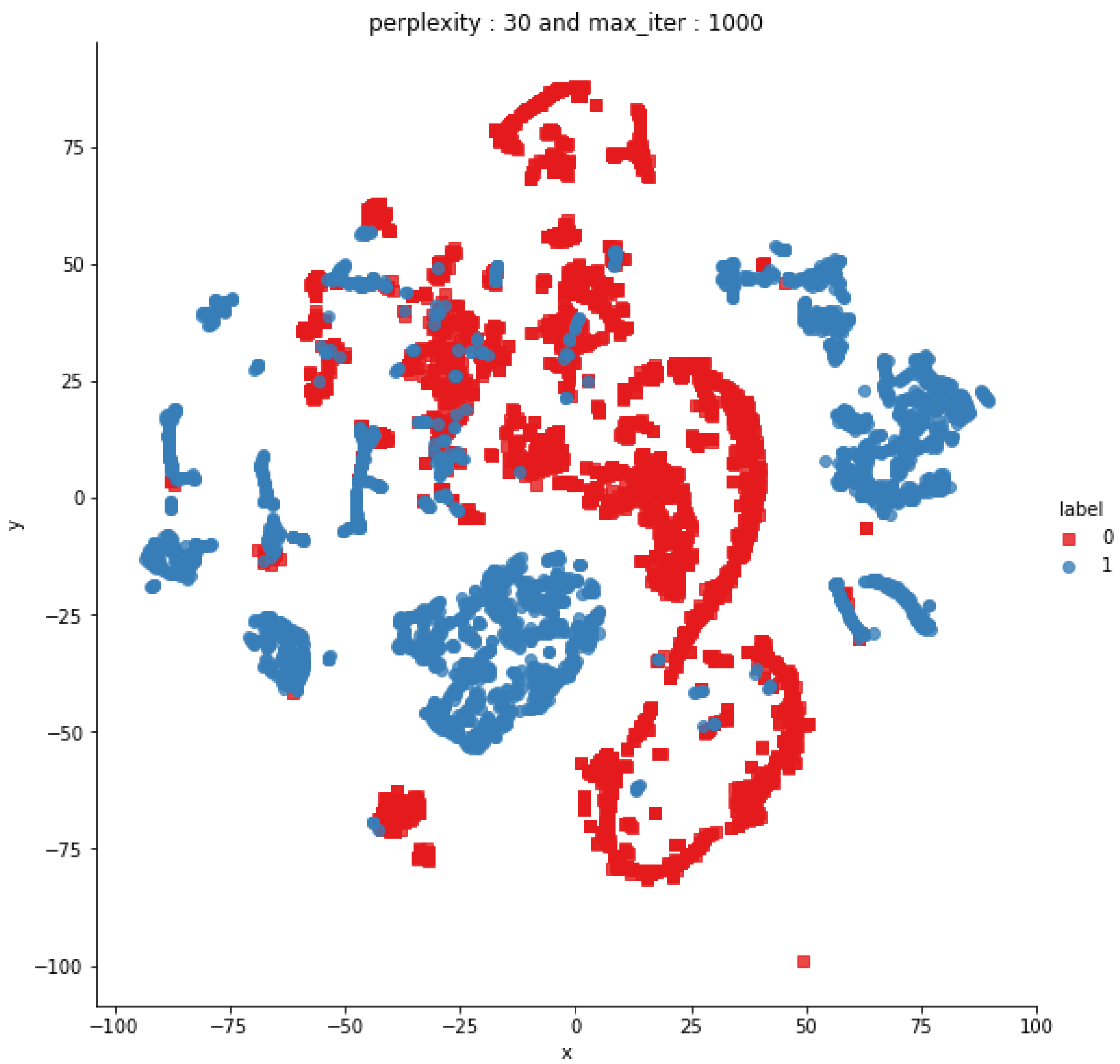
```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 7000 samples in 0.396s...
[t-SNE] Computed neighbors for 7000 samples in 5.179s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7000
[t-SNE] Computed conditional probabilities for sample 2000 / 7000
[t-SNE] Computed conditional probabilities for sample 3000 / 7000
[t-SNE] Computed conditional probabilities for sample 4000 / 7000
[t-SNE] Computed conditional probabilities for sample 5000 / 7000
[t-SNE] Computed conditional probabilities for sample 6000 / 7000
[t-SNE] Computed conditional probabilities for sample 7000 / 7000
[t-SNE] Mean sigma: 0.014220
[t-SNE] Computed conditional probabilities in 0.948s
[t-SNE] Iteration 50: error = 86.3479691, gradient norm = 0.0317327 (50 it
erations in 6.376s)
[t-SNE] Iteration 100: error = 71.6022186, gradient norm = 0.0066577 (50 i
terations in 4.492s)
[t-SNE] Iteration 150: error = 67.9360352, gradient norm = 0.0039589 (50 i
terations in 4.125s)
[t-SNE] Iteration 200: error = 66.0553436, gradient norm = 0.0031575 (50 i
terations in 4.103s)
[t-SNE] Iteration 250: error = 64.9446716, gradient norm = 0.0021098 (50 i
terations in 3.968s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 64.944
672
[t-SNE] Iteration 300: error = 1.8357151, gradient norm = 0.0013166 (50 it
erations in 3.948s)
[t-SNE] Iteration 350: error = 1.2725071, gradient norm = 0.0005831 (50 it
erations in 3.805s)
[t-SNE] Iteration 400: error = 1.0230929, gradient norm = 0.0003397 (50 it
erations in 3.775s)
[t-SNE] Iteration 450: error = 0.8880714, gradient norm = 0.0002247 (50 it
erations in 3.764s)
[t-SNE] Iteration 500: error = 0.8047483, gradient norm = 0.0001652 (50 it
erations in 3.740s)
[t-SNE] Iteration 550: error = 0.7489491, gradient norm = 0.0001293 (50 it
erations in 3.742s)
[t-SNE] Iteration 600: error = 0.7110015, gradient norm = 0.0001106 (50 it
erations in 3.707s)
[t-SNE] Iteration 650: error = 0.6842952, gradient norm = 0.0000967 (50 it
erations in 3.699s)
[t-SNE] Iteration 700: error = 0.6659294, gradient norm = 0.0000916 (50 it
erations in 3.702s)
[t-SNE] Iteration 750: error = 0.6534836, gradient norm = 0.0000848 (50 it
erations in 3.715s)
[t-SNE] Iteration 800: error = 0.6451175, gradient norm = 0.0000811 (50 it
erations in 3.728s)
[t-SNE] Iteration 850: error = 0.6389741, gradient norm = 0.0000780 (50 it
erations in 3.741s)
[t-SNE] Iteration 900: error = 0.6341598, gradient norm = 0.0000768 (50 it
erations in 3.732s)
[t-SNE] Iteration 950: error = 0.6300740, gradient norm = 0.0000758 (50 it
erations in 3.737s)
[t-SNE] Iteration 1000: error = 0.6268264, gradient norm = 0.0000731 (50 i
```

```
terations in 3.733s)
[t-SNE] KL divergence after 1000 iterations: 0.626826
```

In [51]:

```
# creating a dataframe by puting a dict : where x will have all the value from 1st col
# tsne have emmbeding vector of size (7000,2)
df = pd.DataFrame({'x':tsne1[:,0], 'y':tsne1[:,1] ,'label':y})

# drawing the plot in appropriate place in the grid
# implot is basically a combination of facetgrid and regplot.
sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False,palette="Set1",size=8,mar
plt.title("perplexity : {} and max_iter : {}".format(30, 1000))
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\seaborn\regression.py:546: UserWar
ning: The `size` paramter has been renamed to `height`; please update your c
ode.
  warnings.warn(msg, UserWarning)
```



In [62]:

```
tsne1 = TSNE(n_components=2, perplexity=50.0, early_exaggeration=12.0, learning_rate=2(
```

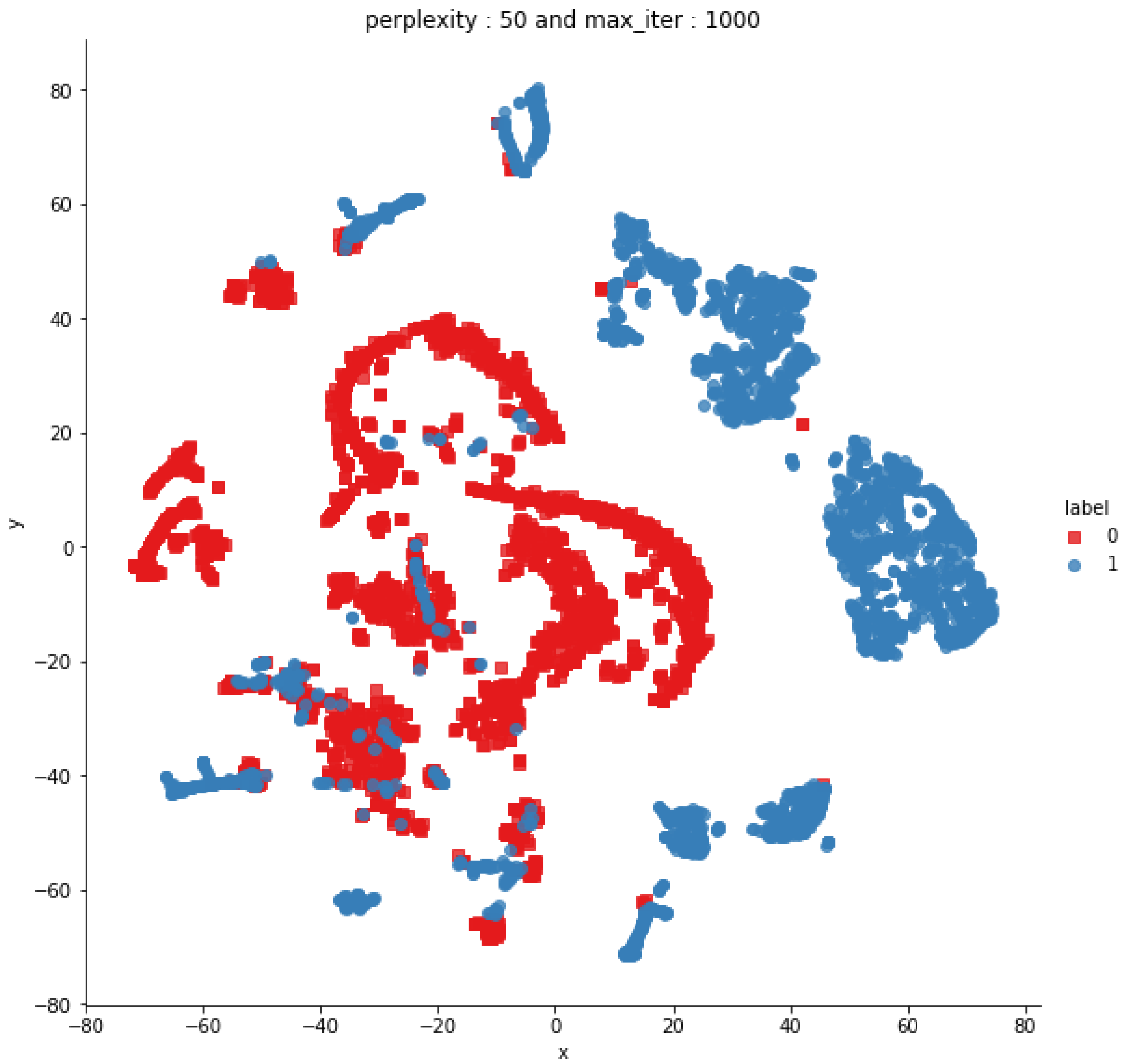
```
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 7000 samples in 0.183s...
[t-SNE] Computed neighbors for 7000 samples in 6.278s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7000
[t-SNE] Computed conditional probabilities for sample 2000 / 7000
[t-SNE] Computed conditional probabilities for sample 3000 / 7000
[t-SNE] Computed conditional probabilities for sample 4000 / 7000
[t-SNE] Computed conditional probabilities for sample 5000 / 7000
[t-SNE] Computed conditional probabilities for sample 6000 / 7000
[t-SNE] Computed conditional probabilities for sample 7000 / 7000
[t-SNE] Mean sigma: 0.020443
[t-SNE] Computed conditional probabilities in 1.965s
[t-SNE] Iteration 50: error = 79.7280273, gradient norm = 0.0344032 (50 it
erations in 17.791s)
[t-SNE] Iteration 100: error = 66.1230011, gradient norm = 0.0054634 (50 i
terations in 13.306s)
[t-SNE] Iteration 150: error = 63.5626068, gradient norm = 0.0031843 (50 i
terations in 11.356s)
[t-SNE] Iteration 200: error = 62.3428917, gradient norm = 0.0021420 (50 i
terations in 12.162s)
[t-SNE] Iteration 250: error = 61.6497078, gradient norm = 0.0016678 (50 i
terations in 14.193s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 61.649
708
[t-SNE] Iteration 300: error = 1.5096163, gradient norm = 0.0012575 (50 it
erations in 14.386s)
[t-SNE] Iteration 350: error = 1.0331581, gradient norm = 0.0005261 (50 it
erations in 14.812s)
[t-SNE] Iteration 400: error = 0.8374314, gradient norm = 0.0002955 (50 it
erations in 13.619s)
[t-SNE] Iteration 450: error = 0.7358792, gradient norm = 0.0001946 (50 it
erations in 13.170s)
[t-SNE] Iteration 500: error = 0.6747422, gradient norm = 0.0001403 (50 it
erations in 14.117s)
[t-SNE] Iteration 550: error = 0.6349469, gradient norm = 0.0001088 (50 it
erations in 11.468s)
[t-SNE] Iteration 600: error = 0.6076544, gradient norm = 0.0000920 (50 it
erations in 12.542s)
[t-SNE] Iteration 650: error = 0.5888336, gradient norm = 0.0000827 (50 it
erations in 12.243s)
[t-SNE] Iteration 700: error = 0.5755293, gradient norm = 0.0000771 (50 it
erations in 15.141s)
[t-SNE] Iteration 750: error = 0.5667673, gradient norm = 0.0000732 (50 it
erations in 14.634s)
[t-SNE] Iteration 800: error = 0.5606773, gradient norm = 0.0000677 (50 it
erations in 14.671s)
[t-SNE] Iteration 850: error = 0.5565989, gradient norm = 0.0000691 (50 it
erations in 14.460s)
[t-SNE] Iteration 900: error = 0.5538476, gradient norm = 0.0000661 (50 it
erations in 11.593s)
[t-SNE] Iteration 950: error = 0.5514524, gradient norm = 0.0000648 (50 it
erations in 14.054s)
[t-SNE] Iteration 1000: error = 0.5494123, gradient norm = 0.0000606 (50 i
```

```
terations in 14.418s)
[t-SNE] KL divergence after 1000 iterations: 0.549412
```

In [63]:

```python
df = pd.DataFrame({'x':tsne1[:,0], 'y':tsne1[:,1] ,'label':y})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,palette="Set1",mar
plt.title("perplexity : {} and max_iter : {}".format(50, 1000))
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\seaborn\regression.py:546: UserWar
ning: The `size` paramter has been renamed to `height`; please update your c
ode.
  warnings.warn(msg, UserWarning)
```



In [53]:

```
1 tsne1 = TSNE(n_components=2, perplexity=15.0, early_exaggeration=12.0, learning_rate=2(
```

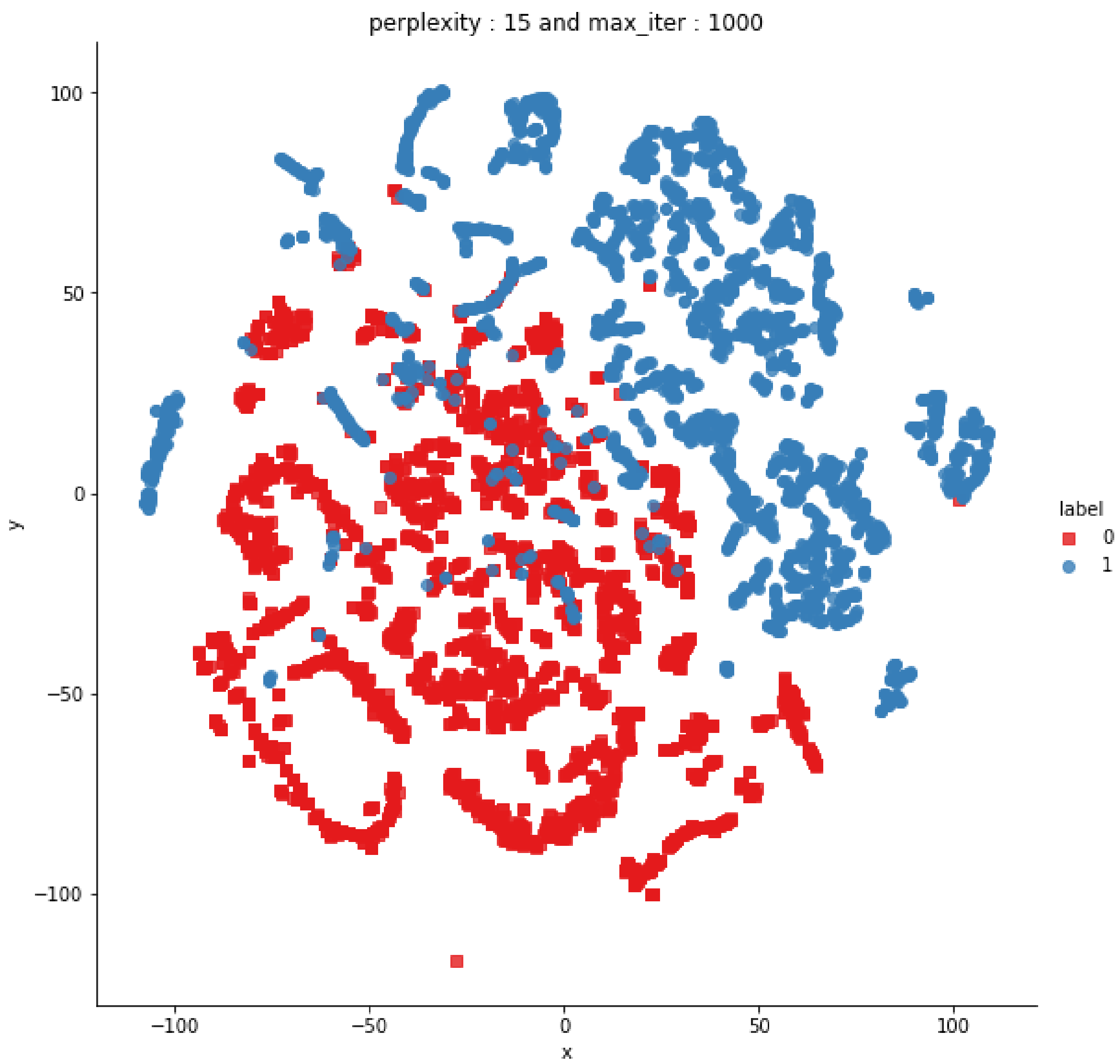
```
[t-SNE] Computing 46 nearest neighbors...
[t-SNE] Indexed 7000 samples in 0.222s...
[t-SNE] Computed neighbors for 7000 samples in 3.771s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7000
[t-SNE] Computed conditional probabilities for sample 2000 / 7000
[t-SNE] Computed conditional probabilities for sample 3000 / 7000
[t-SNE] Computed conditional probabilities for sample 4000 / 7000
[t-SNE] Computed conditional probabilities for sample 5000 / 7000
[t-SNE] Computed conditional probabilities for sample 6000 / 7000
[t-SNE] Computed conditional probabilities for sample 7000 / 7000
[t-SNE] Mean sigma: 0.009311
[t-SNE] Computed conditional probabilities in 0.562s
[t-SNE] Iteration 50: error = 96.1598206, gradient norm = 0.0342754 (50 it
erations in 11.636s)
[t-SNE] Iteration 100: error = 79.1367569, gradient norm = 0.0091972 (50 i
terations in 7.807s)
[t-SNE] Iteration 150: error = 74.5336456, gradient norm = 0.0063158 (50 i
terations in 3.722s)
[t-SNE] Iteration 200: error = 72.0162582, gradient norm = 0.0048745 (50 i
terations in 3.647s)
[t-SNE] Iteration 250: error = 70.3913574, gradient norm = 0.0035437 (50 i
terations in 3.604s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 70.391
357
[t-SNE] Iteration 300: error = 2.3066294, gradient norm = 0.0013838 (50 it
erations in 3.657s)
[t-SNE] Iteration 350: error = 1.6334512, gradient norm = 0.0006587 (50 it
erations in 3.438s)
[t-SNE] Iteration 400: error = 1.3046505, gradient norm = 0.0003949 (50 it
erations in 3.392s)
[t-SNE] Iteration 450: error = 1.1155045, gradient norm = 0.0002701 (50 it
erations in 3.394s)
[t-SNE] Iteration 500: error = 0.9953058, gradient norm = 0.0002047 (50 it
erations in 3.373s)
[t-SNE] Iteration 550: error = 0.9149035, gradient norm = 0.0001659 (50 it
erations in 3.368s)
[t-SNE] Iteration 600: error = 0.8586429, gradient norm = 0.0001389 (50 it
erations in 3.369s)
[t-SNE] Iteration 650: error = 0.8179511, gradient norm = 0.0001232 (50 it
erations in 3.361s)
[t-SNE] Iteration 700: error = 0.7872599, gradient norm = 0.0001122 (50 it
erations in 3.345s)
[t-SNE] Iteration 750: error = 0.7652739, gradient norm = 0.0001026 (50 it
erations in 3.336s)
[t-SNE] Iteration 800: error = 0.7493688, gradient norm = 0.0000984 (50 it
erations in 3.346s)
[t-SNE] Iteration 850: error = 0.7373501, gradient norm = 0.0000903 (50 it
erations in 9.327s)
[t-SNE] Iteration 900: error = 0.7278499, gradient norm = 0.0000894 (50 it
erations in 9.204s)
[t-SNE] Iteration 950: error = 0.7201241, gradient norm = 0.0000850 (50 it
erations in 10.229s)
[t-SNE] Iteration 1000: error = 0.7130318, gradient norm = 0.0000825 (50 i
```

```
terations in 6.454s)
[t-SNE] KL divergence after 1000 iterations: 0.713032
```

In [54]:

```
df = pd.DataFrame({'x':tsne1[:,0], 'y':tsne1[:,1] ,'label':y})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,palette="Set1",mar
plt.title("perplexity : {} and max_iter : {}".format(15, 1000))
plt.show()
```

```
C:\Users\jitu\Anaconda3\lib\site-packages\seaborn\regression.py:546: UserWar
ning: The `size` paramter has been renamed to `height`; please update your c
ode.
  warnings.warn(msg, UserWarning)
```



Observation

- Here 32dim continious variable is taken and reducing them to 2 dim
- from the 3 plot we can observe that thsese 32 continuous variable will gonna be helpful in determining the class label.

- in the First plot where perplexity is 30 : the class 1 and class 0 are separated , yes there are some region of overlapping but most of them are separeted.The same story is we can see on plot number 2 and in the 3.

Summary of EDA

- After reading the dataset got to know that these dataset have not the feature name in their appropriate column so columns name were given
  - Shape of the training data (datapoints : 125973, features : 42)
  - Shape of the test data (datapoints : 22544, features : 42)

- The task is to identify wether a given connection is normal or attack , for that created a column "label" and gave all the attacks which is name normal as class 0 and all other attack as class 1.

- By checking the distribution of the dataset with respect to the class label ,found that dataset is little bit imbalanced(53.5% normal and 46.5% attack).

- Checked for duplicate and null value : there were not null and duplicate value.

- Checked for distribution with respect to different attacks in train and test dataset :

```
 Train data
 * data set is not uniform distributed (by looking at different attacks)
 * there are lots of attacks where data points are very few and some of the att
acks like normal and neptune these
   both have 85% datapoints out of 100% datapoints
 * There are 16 attacks out of 23 attacks where the data points are less then
 1%
 Test data
 * look at the test dataset we got bunch of new attacks which are not in the te
st data
 * here also the normal and neptune attacks has more datapoints than other
```

- To analysis the feature i thought to analyse the categorical feature and numerical feature separetly.

- **Univariate analysis on categorical feature**
  - we have 3 categorical feature : protocol_type , service and flag
  - to analysis these categorical feature i gone have through 4 things

    1. **Number of category present in the dataset** :
       ans :
       - In protocol_feature : 3 category present tcp,upd and icmp where majority of the points are from tcp and udp .
       - In service feature : 70 unique category present
       - In flag feature : 11 unique category present
    2. **Distribution of the categorical feature** :
       ans :
       - In protocol_feature : tcp has both normal and attack class datapoints reasonable, where udp has more class0 (normal) points than class1(attack) and icmp has more class 1
       - In service feature : The distribution is skewed where few services occur more and major of service occur less time.
       - In flag feature : It is also a skewed distribution

3. **featurization of the categorical feature** :
   ans: All of them have been featurize using one hot encoding
4. **How good is this protocol_type feature in predicting y_i** ?
   ans : building a simple model (Decison tree classifer) for each categorical feature and know the important feature.
   - In protocol_feature : we get some feature impotance where udp is the most important feature in predicting yi where icmp is less
   - In service feature : model got test auc value of 87 by only using this feature this means this categorical feature will be useful when we build actual model.There are few feature which is important not all.
   - In flag feature : this fearure also useful as it has 78 test auc score, the model might overfit a little bit as train and test auc has gap.

```
 - There are some category where the model thought that those are not at all impor
tant , we can do some feature engineering by removing those unimportant features.
```

- **Univariate analysis on continuous feature**
  - Duration : majority of points have value of zero of this feature , from 98 percentile onward values are changing.
  - src_bytes : values of this feature are increasing in a slow rate upto 98 - 99.9 , but there is sudden change in the 100 percintile with a quite large value(1.25 gb) which mean 1.25 gb of data goes from source to destination, this might be an outlier.
  - dst_bytes : this is same as the src_byte , in the 100 percentile there is quite big number(1.21 gb of data from destination to source) this could be an outlier or may be these values are sign of attack.
  - wrong_fragment : in the the violin plot class 1 has more variance than class 1 while class 0 has value around 0
- **Bivariate Analysis using pair plot**
  - By looking at the pair plot we can say that there are some overlap between class1 and class0, but not fully.
  - the PDF's of each feature has some information like one pdf(class 0) has more value than another(class1) and vice versa. With this information i looked at the the violin plot and the pdf separetly of some feature , where some of them are not fully overlap so we can say these fearure may helpful in distinguish class0 and class 1
- **Multivariate analysis using tSNE**
  - Here i have taken 32 feature and ploted using tsne with 7k datapoints , there result i get is quite brilliant
  - classes are separable
  - less overlapping points.

4. Machine Learning Models

Machine Learning model as follows :

- we have fewer features so lets build model which are tend to work well on fewer features.

1. Naive Bayes (Base line model)

- Base line model should be simple so that we can compare it with other models .

2. KNN

3. Logistic regression

- Logistic regression beacause , its an experiment may be the line separate well both classes , let see.

4. Decision Tree

5. Random Forest

6. Xgboost

Merging all numerical and categorical feature

In [22]:

```
# read about hstack : https://docs.scipy.org/doc/scipy/reference/generated/scipy.sparse
"""
A = coo_matrix([[1, 2], [3, 4]])
B = coo_matrix([[5], [6]])
hstack([A,B]).toarray()
array([[1, 2, 5],
       [3, 4, 6]])
"""
# take protocol_type one_hot_encoding vector and service one_hot_encoding vector and me
train_protocol_service_encoding = hstack((train_protocol_type_encoding, train_service_
test_protocol_service_encoding = hstack((test_protocol_type_encoding,  test_service_en

# take train_proto_services_encoding vector and flag one_hot_encoding vector and merge
train_protocol_service_flag_encoding = hstack((train_protocol_service_encoding, train_
test_protocol_service_flag_encoding  = hstack((test_protocol_service_encoding ,test_fl

# defining y_train and y_test
y_train = train_data['label']
y_test  = test_data['label']

# removing label, attck,protocol_type,service,flag column from train and test data
train_data.drop(['protocol_type','service','flag','attack','label'], axis=1, inplace=T
test_data.drop(['protocol_type','service','flag','attack','label'], axis=1, inplace=Tr

X_train = hstack((train_protocol_service_flag_encoding , train_data))
X_test = hstack((test_protocol_service_flag_encoding , test_data))
```

Standardization

In [23]:

```
from sklearn.preprocessing import StandardScaler
scalar = StandardScaler(with_mean = False)
X_train = scalar.fit_transform(X_train)
X_test = scalar.transform(X_test)
```

In [24]:

```
print("Shape of the training data after mergeing - datapoints : ",X_train.shape[0],"fe
print("Shape of the test data after mergeing - datapoints : ",X_test.shape[0],"feature
```

```
Shape of the training data after mergeing - datapoints :  125973 features :
122  and y_train : 125973
Shape of the test data after mergeing - datapoints :  22544 features :  122
and y_test :  22544
```

Plot : Confusion matrix , Precision , Recall

In [40]:

```
# This function plots the confusion matrices given y_i, y_i_hat.'
# refer - AAIC
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predi

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that colum

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in 
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in 
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                      [3/4, 4/6]]
    plt.figure(figsize=(20,4))

    labels = [1,2]
    # representing A in heatmap format
    cmap=sns.light_palette("Orange")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

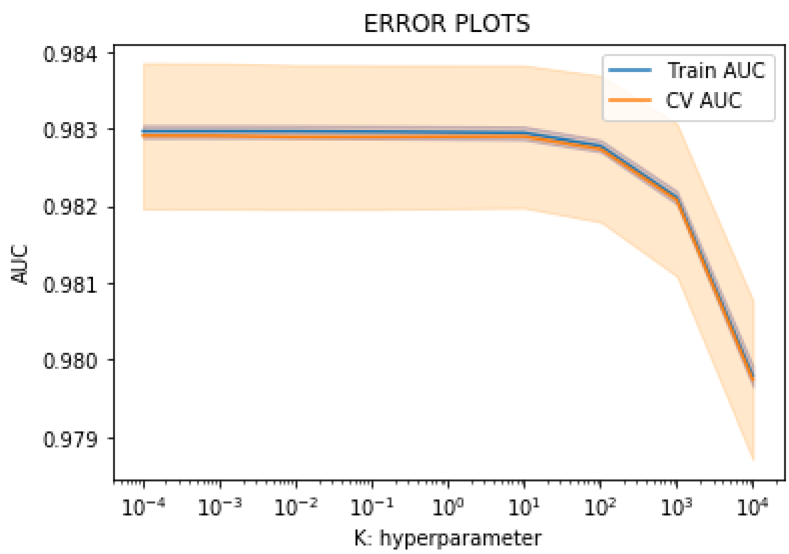
4.1 Base line Model

Naive Bayes

Hyper parameter tuning

In [48]:

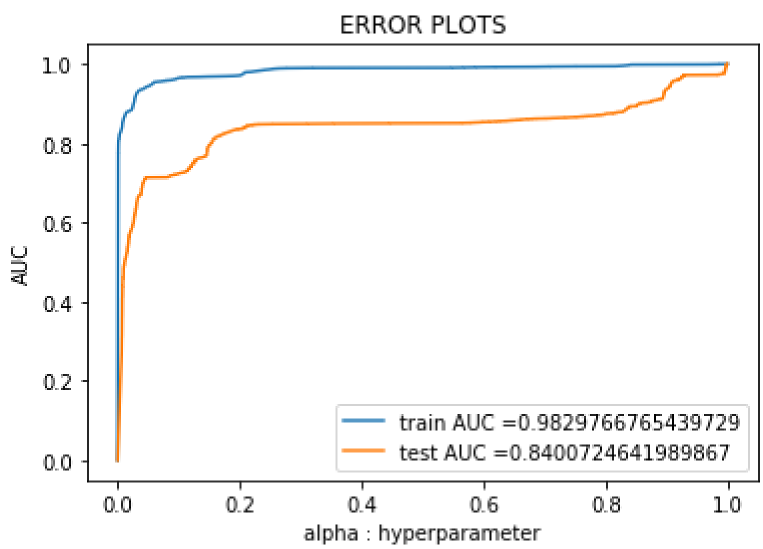
```
# creating object of multinomial naive bayes
multi_NB = MultinomialNB()

# giving bunch of laplace parameter
parameters = {'alpha': [10**-4, 10**-3, 10**-2, 10**-1, 10**1, 10**2, 10**3,10**4]}
alpha_range = [10**-4, 10**-3, 10**-2, 10**-1, 10**1, 10**2, 10**3,10**4]

# putting the model in grid search cv to find the best hyper param
clf = GridSearchCV(multi_NB ,parameters,cv = 10 , scoring='roc_auc' , return_train_sco

#fitting X_train and y_train with the multinomial naive bayes
clf.fit(X_train, y_train)

train_auc = clf.cv_results_['mean_train_score']
train_auc_std = clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

plt.plot(alpha_range, train_auc, label='Train AUC')
# refer : https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(alpha_range,train_auc - train_auc_std,train_auc + train_auc_std

plt.plot(alpha_range, cv_auc, label='CV AUC')
# refer : https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(alpha_range,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,c

plt.legend()
plt.xlabel("K: hyperparameter")
plt.xscale('log')
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



fiiting with best param

In [55]:

```
from sklearn.metrics import roc_curve, auc

multi_NB =MultinomialNB(alpha = 0.01)
multi_NB.fit(X_train,y_train)


train_fpr, train_tpr, thresholds = roc_curve(y_train, multi_NB.predict_proba(X_train)[
test_fpr, test_tpr, thresholds = roc_curve(y_test, multi_NB.predict_proba(X_test)[:,1]

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))


plt.legend()
plt.xlabel("alpha : hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [28]:

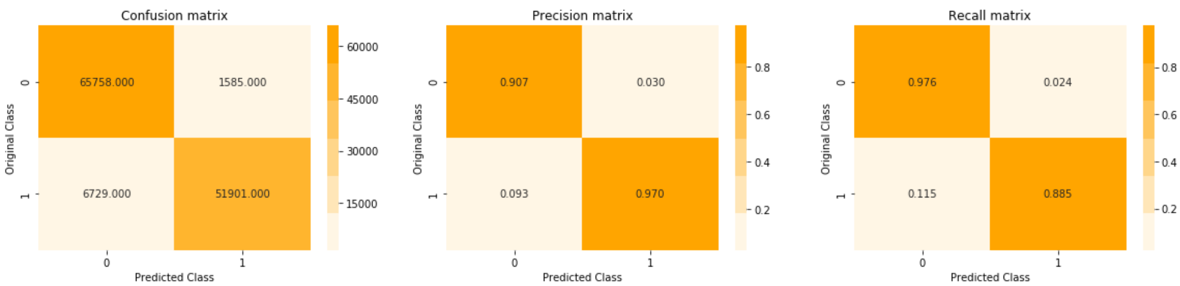
```
y_train_pred = multi_NB.predict(X_train)
y_test_pred = multi_NB.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
print("*"*100)
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))

```

```
Train f1 score 0.9258446608869385
Test f1 score 0.7687546886721681
****************************************************************************
************************
train recall score / detection rate 0.8852294047415998
test recall score / detection rate 0.6388217875788982
```

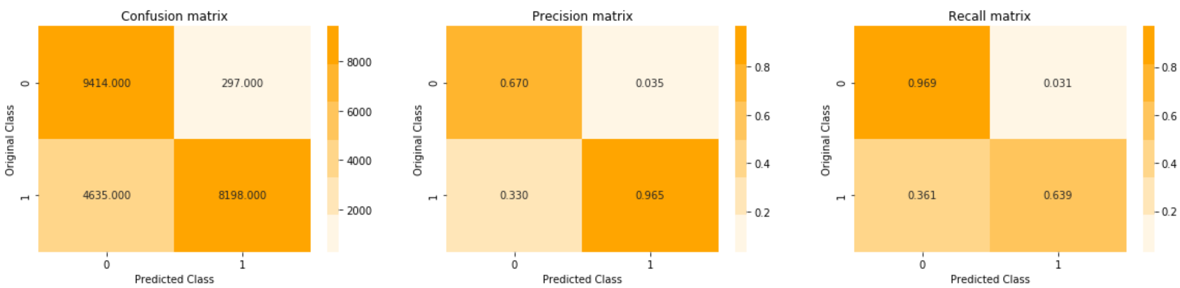
In [57]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Before getting to observation lets know how to read these metric

- what test auc score 64 means :- chance of classfying points correctly is 64%
- F1 score - it is the inverse of avg of precision and recall . it will give high value when both precision and recall is high

- reading precsion and reacll matrix :-
  - precision (columns sums to 1) : of all the point which are predicted to belong to class0 67% are actually belong to class 0 and 33% are belong to class1
  - recall(row sums to 1) : of all the point which are actually belong to class1 63% are predicted to class 1 and 36% class0

Observation :

- there is a gap in trian and test AUC value which mean the model is overfitting
- lets do some feature selection to reduce the overfitting
- feature selection by Recursive feature elemination

4.2 Feature selection by recursive feature elemination

Given an external estimator that assigns weights to features (e.g., the coefficients of a linear model), the goal of recursive feature elimination (RFE) is to select features by recursively considering smaller and smaller sets of features. First, the estimator is trained on the initial set of features and the importance of each feature is obtained either through a coef_ attribute or through a feature_importances_ attribute. Then, the least important features are pruned from current set of features. That procedure is recursively repeated on the pruned set until the desired number of features to select is eventually reached.
refer : [https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html)](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html)

In [26]:

```
## for the whole feature selection section please refer these two link which i have me
### refer : https://github.com/dimtics/Network-Intrusion-Detection-Using-Machine-Learn
### refer : https://towardsdatascience.com/feature-selection-in-python-recursive-featu

#Encoding the categorical data using label enocder
encoder = LabelEncoder()

# get the categorical features
cat_train = train_data.select_dtypes(include = 'object').copy()
cat_test = test_data.select_dtypes(include = 'object').copy()

cat_train_encode = cat_train.apply(encoder.fit_transform)
cat_test_encode = cat_test.apply(encoder.fit_transform)

# dropping attack feature
cat_train_encode = cat_train_encode.drop(['attack'],axis = 1)
cat_test_encode = cat_test_encode.drop(['attack'],axis = 1)
```

In [27]:

```
# shape of the encoded feature
print(cat_train_encode.shape)
print(cat_train_encode.shape)
```

```
(125973, 3)
(125973, 3)
```

In [28]:

```
# get all the numerical feature
num_train = train_data.select_dtypes(include = ['float64','int64'])
num_test = test_data.select_dtypes(include = ['float64','int64'])

# join numerical and categorical feature
features = pd.concat([num_train ,cat_train_encode],axis =1).columns
x_train_encode = np.concatenate((num_train , cat_train_encode),axis=1)
x_test_encode = np.concatenate((num_test , cat_test_encode),axis=1)
```

In [29]:

```
# shape after joining categorical and numerical features
print(x_train_encode.shape)
print(x_train_encode.shape)
```

```
(125973, 42)
(125973, 42)
```

In [30]:

```
# converting the joined feature into a dataframe
x_train_encoder = pd.DataFrame(x_train_encode ,columns = features)
x_test_encoder = pd.DataFrame(x_test_encode , columns = features)

# dropping the label class
x_train_encoder = x_train_encoder.drop(['label'],axis = 1)
x_test_encoder = x_test_encoder.drop(['label'],axis = 1)
```

In [31]:

```
# shape after removing label
print(x_train_encoder.shape)
print(x_test_encoder.shape)
```

```
(125973, 41)
(22544, 41)
```

In [32]:

```
# this feature is useless as it has only contain zeros ,remove from dataframe
x_train_encoder = x_train_encoder.drop(['num_outbound_cmds'],axis = 1)
x_test_encoder = x_test_encoder.drop(['num_outbound_cmds'],axis = 1)
```

In [33]:

```
# print shape
print(x_train_encoder.shape)
print(x_test_encoder.shape)
```

```
(125973, 40)
(22544, 40)
```

In [36]:

```
# put correlated features into set , beacuse it will store only single feature not redu
correlated_features = set()

# create a correlated feature of the train data
# it Compute pairwise correlation of columns, excluding NA/null values.
# by default "pearson correlation "
# refer : https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.c
correlation = x_train_encoder.corr()

#iterate through each column
for i in range(correlation.shape[0]):
    #iterate through ecah value of the given column
    for j in range(i):
        # give the i : column and j : vlaue in that column
        # if the value is > .8 remove them
        if abs(correlation.iloc[i,j]) > 0.8:
            # take that column which is >.8
            column = correlation.columns[i]
            # add it to the above set
            correlated_features.add(column)

```

In [37]:

```
# print which are irrelavant features and how many them
print(correlated_features)
print(len(correlated_features))
```

```
{'is_guest_login', 'srv_serror_rate', 'dst_host_rerror_rate', 'dst_host_srv_
rerror_rate', 'srv_rerror_rate', 'dst_host_same_srv_rate', 'dst_host_srv_ser
ror_rate', 'num_root', 'dst_host_serror_rate'}
9
```

In [38]:

```
# droppin the irrelevant feature
x_train_encoder = x_train_encoder.drop(['is_guest_login', 'dst_host_srv_rerror_rate',
```

In [41]:

```
# shape after dropping the irrelevant fetaures
x_train_encoder.shape
```

Out[41]:

```
(125973, 31)
```

In [43]:

```
# create a randomforest classifer (why :  beacuse random forest tend to work well on fe
rfc = RandomForestClassifier(random_state=101)

# put the object of randomforest into the recursive feature elemination using cross va
# refer : https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.R
rfecv = RFECV(estimator=rfc, step=1, cv=StratifiedKFold(10), scoring='roc_auc')
rfecv.fit(x_train_encoder, y_train)
```

Out[43]:

```
RFECV(cv=StratifiedKFold(n_splits=10, random_state=None, shuffle=False),
   estimator=RandomForestClassifier(bootstrap=True, class_weight=None, crite
rion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
            oob_score=False, random_state=101, verbose=0, warm_start=False),
   min_features_to_select=1, n_jobs=None, scoring='roc_auc', step=1,
   verbose=0)
```

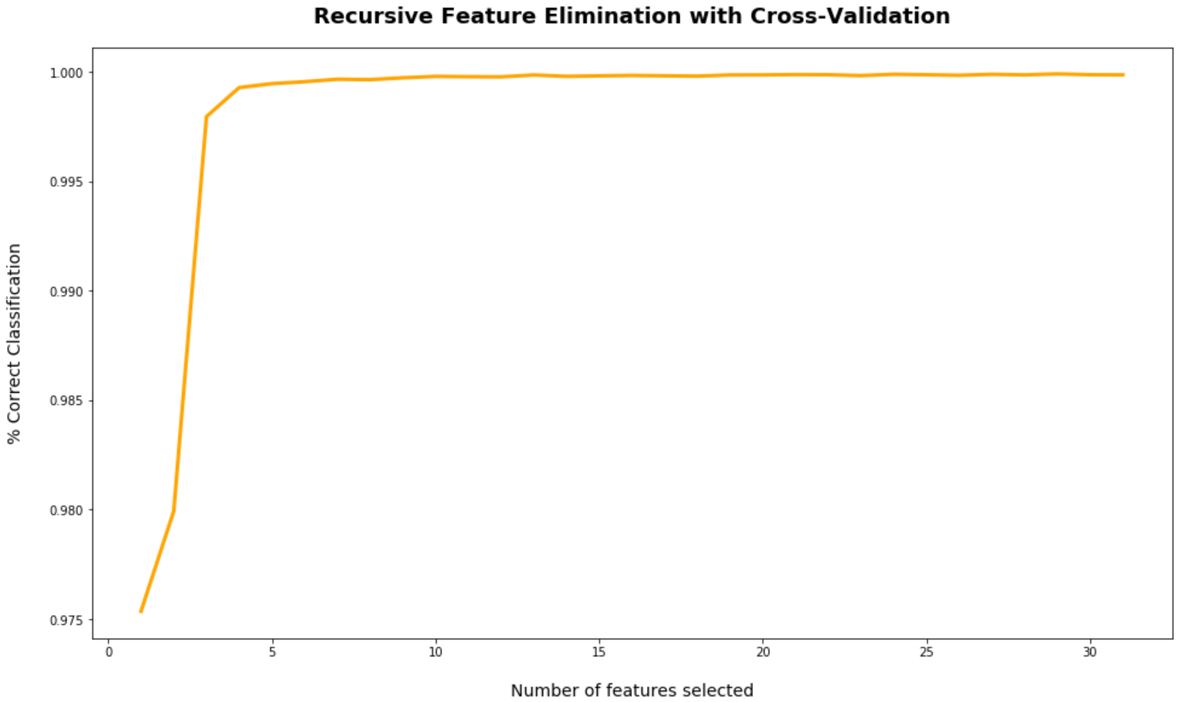
In [44]:

```
print('Optimal number of features: {}'.format(rfecv.n_features_))
```

```
Optimal number of features: 29
```

In [45]:

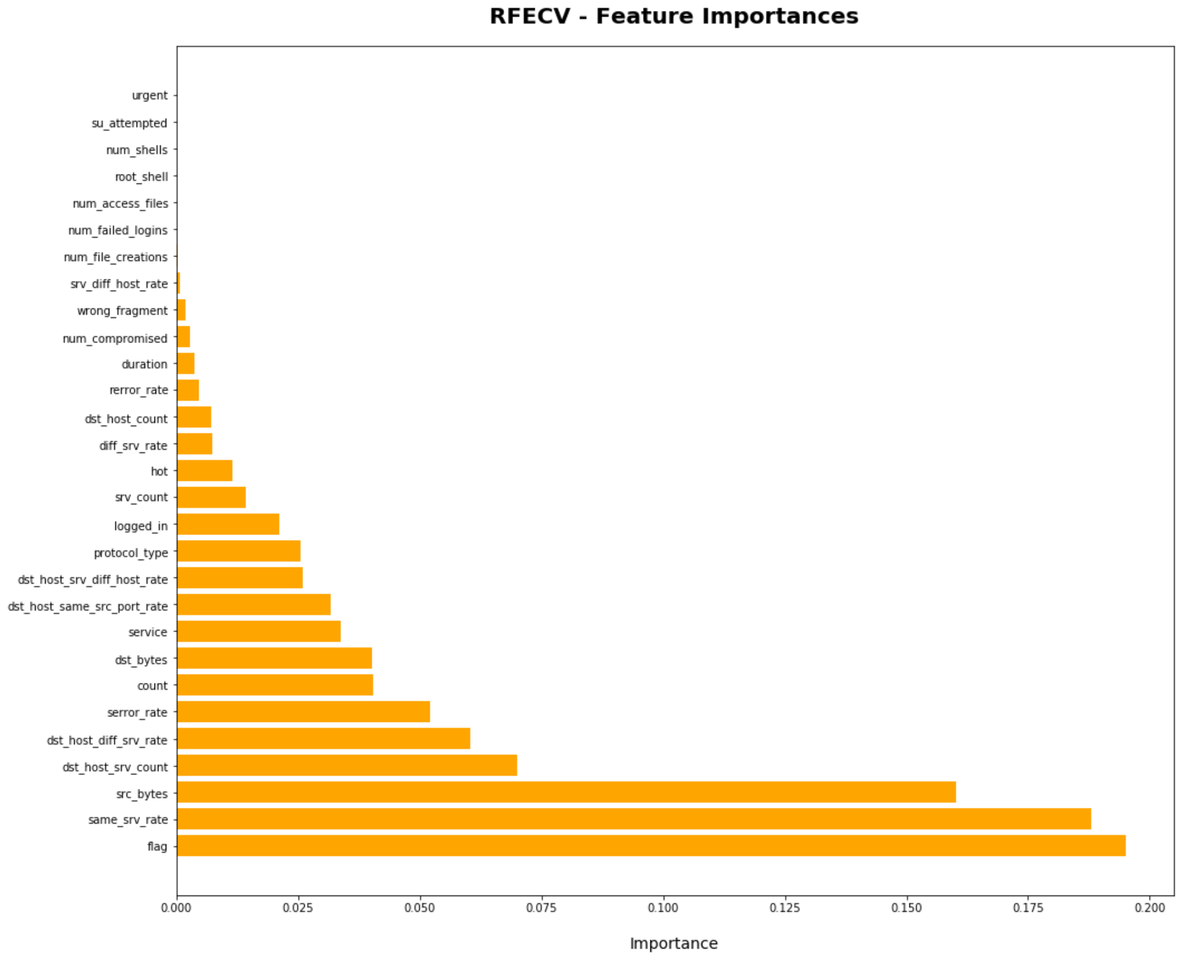
```
plt.figure(figsize=(16, 9))
plt.title('Recursive Feature Elimination with Cross-Validation', fontsize=18, fontweigl
plt.xlabel('Number of features selected', fontsize=14, labelpad=20)
plt.ylabel('% Correct Classification', fontsize=14, labelpad=20)
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_, color='orange', li
plt.show()
```



In [49]:

```
dset = pd.DataFrame()
dset['attr'] = x_train_encoder.columns

dset['importance'] = rfecv.estimator_.feature_importances_

dset = dset.sort_values(by='importance', ascending=False)
print(dset.attr)

plt.figure(figsize=(16, 14))
plt.barh(y=dset['attr'], width=dset['importance'], color='orange')
plt.title('RFECV - Feature Importances', fontsize=20, fontweight='bold', pad=20)
plt.xlabel('Importance', fontsize=14, labelpad=20)
plt.show()
```

```
28                          flag
18                 same_srv_rate
1                      src_bytes
22            dst_host_srv_count
23        dst_host_diff_srv_rate
16                   serror_rate
14                         count
2                      dst_bytes
27                       service
24   dst_host_same_src_port_rate
25   dst_host_srv_diff_host_rate
26                 protocol_type
7                      logged_in
15                     srv_count
5                            hot
19                 diff_srv_rate
21                dst_host_count
17                   rerror_rate
0                       duration
8                num_compromised
3                 wrong_fragment
20            srv_diff_host_rate
11            num_file_creations
6              num_failed_logins
13              num_access_files
9                     root_shell
12                    num_shells
10                  su_attempted
4                         urgent
Name: attr, dtype: object
```



Understanding the above 4.2 section :

- take the object type feature (means categorical) encode using label encoder
- merge both encoder categorical features and numerical features
- compute the correlation matrix using a dataframe method corr() which by default use pearson correlation coefficient
- iterate thorugh two for loop and take out those feature whose value greater than .8 int he correlation matrix
- now by using recursive feature elemination (using random forest model , we can use any model of our choice but RF give good feature importance) it gave 29 feature which are useful in predicting the model(called optimal features)
- Then plot the most important features by looking we can again remove some feature which are vey small value

lets use those selected features

In [23]:

```
# pleae re run the first few cell
# removing correlated features/irrelevant features from train data
X_train_after_FS = train_data.drop(['srv_serror_rate', 'dst_host_rerror_rate', 'dst_ho
X_test_after_FS = test_data.drop(['srv_serror_rate', 'dst_host_rerror_rate', 'dst_host_
```

In [24]:

```
# shape after removing correlated features/irrelevant features from traing data
print(X_train_after_FS.shape )
print(X_test_after_FS.shape )
```

```
(125973, 36)
(22544, 36)
```

In [25]:

```
# removing featues which are adding less value , by looking at the RFECV
X_train_after_FS = X_train_after_FS.drop(['srv_diff_host_rate', 'num_file_creations' ,
X_test_after_FS = X_test_after_FS.drop(['srv_diff_host_rate', 'num_file_creations' , '
```

In [26]:

```
# shape after removing above features
print(X_train_after_FS.shape )
print(X_test_after_FS.shape )
```

```
(125973, 25)
(22544, 25)
```

In [27]:

```
# defining y_train and y_test
y_train = train_data['label']
y_test  = test_data['label']

# removing label, attck,protocol_type,service,flag column from train and test data
X_train_after_FS.drop(['protocol_type','service','flag','label'], axis=1, inplace=True
X_test_after_FS.drop(['protocol_type','service','flag','label'], axis=1, inplace=True)

print(X_train_after_FS.shape)
print(X_train_after_FS.shape)
```

```
(125973, 21)
(125973, 21)
```

In [28]:

```
# take protocol_type one_hot_encoding vector and service one_hot_encoding vector and me
train_protocol_service_encoding = hstack((train_protocol_type_encoding, train_service_
test_protocol_service_encoding = hstack((test_protocol_type_encoding,  test_service_en

# take train_proto_services_encoding vector and flag one_hot_encoding vector and merge
train_protocol_service_flag_encoding = hstack((train_protocol_service_encoding, train_
test_protocol_service_flag_encoding  = hstack((test_protocol_service_encoding ,test_fl
```

In [29]:

```
# merging the categorical onehot encoded feature and numerical feature
X_train = hstack((train_protocol_service_flag_encoding , X_train_after_FS))
X_test = hstack((test_protocol_service_flag_encoding , X_test_after_FS))
```

In [30]:

```
print("Shape of the training data after mergeing - datapoints : ",X_train.shape[0],"fe
print("Shape of the test data after mergeing - datapoints : ",X_test.shape[0],"feature
```

```
Shape of the training data after mergeing - datapoints :  125973 features :
105  and y_train : 125973
Shape of the test data after mergeing - datapoints :  22544 features :  105
and y_test :  22544
```

In [31]:

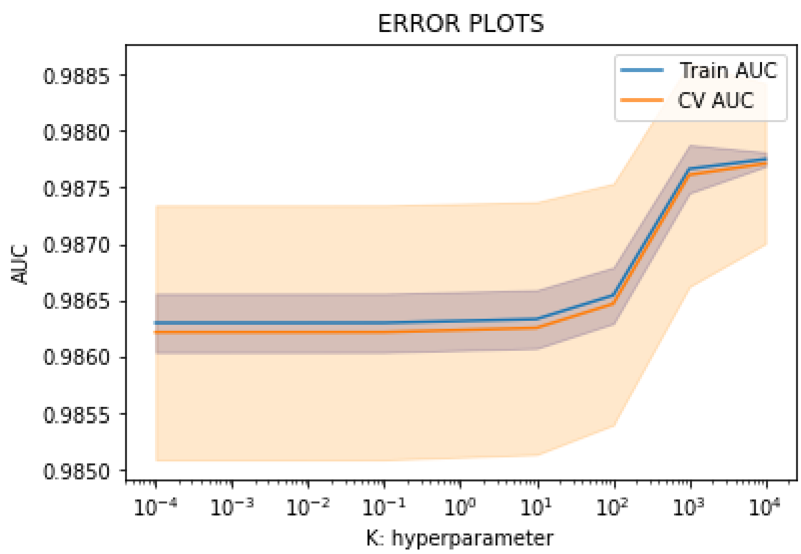
```
# standardization
scalar = StandardScaler(with_mean = False)
X_train = scalar.fit_transform(X_train)
X_test = scalar.transform(X_test)

```

Modeling with selected features

4.3 Naive Bayes with Hyperparameter tuning

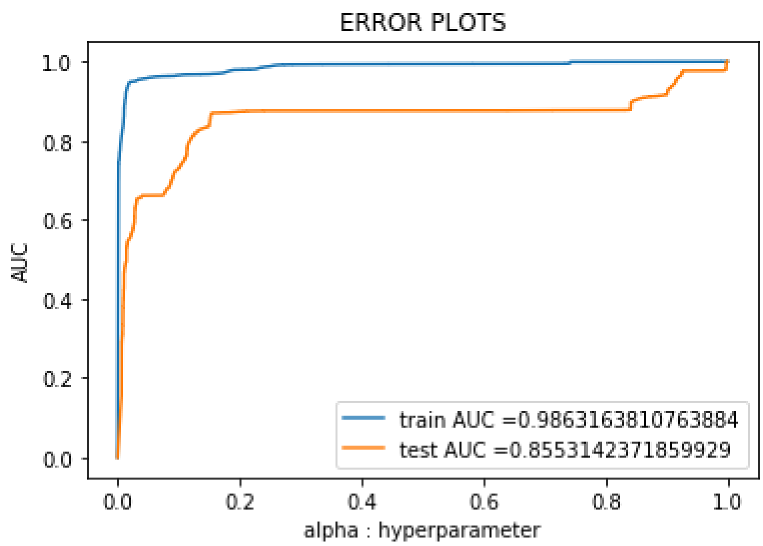
In [66]:

```
# creating object of multinomial naive bayes
multi_NB = MultinomialNB()

# giving bunch of laplace parameter
parameters = {'alpha': [10**-4, 10**-3, 10**-2, 10**-1, 10**1, 10**2, 10**3,10**4]}
alpha_range = [10**-4, 10**-3, 10**-2, 10**-1, 10**1, 10**2, 10**3,10**4]

# putting the model in grid search cv to find the best hyper param
clf = GridSearchCV(multi_NB ,parameters,cv = 10 , scoring='roc_auc' , return_train_scor

#fitting X_train and y_train with the multinomial naive bayes
clf.fit(X_train, y_train)

train_auc = clf.cv_results_['mean_train_score']
train_auc_std = clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

plt.plot(alpha_range, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(alpha_range,train_auc - train_auc_std,train_auc + train_auc_std

plt.plot(alpha_range, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(alpha_range,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,c

plt.legend()
plt.xlabel("K: hyperparameter")
plt.xscale('log')
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [67]:

```
multi_NB =MultinomialNB(alpha = 10)
multi_NB.fit(X_train,y_train)


train_fpr, train_tpr, thresholds = roc_curve(y_train, multi_NB.predict_proba(X_train)[
test_fpr, test_tpr, thresholds = roc_curve(y_test, multi_NB.predict_proba(X_test)[:,1]

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))


plt.legend()
plt.xlabel("alpha : hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [67]:

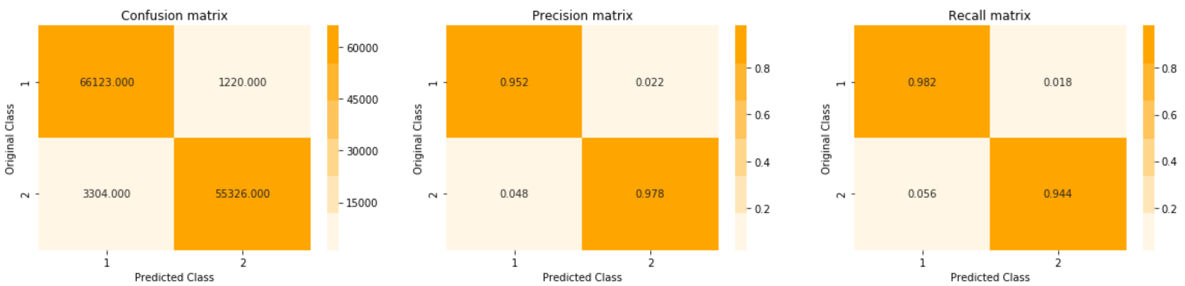
```
y_train_pred = multi_NB.predict(X_train)
y_test_pred = multi_NB.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
print("*"*100)
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Train f1 score 0.9607209835382371
Test f1 score 0.773419258429065
****************************************************************************
************************
train recall score / detection rate 0.9436465973051339
test recall score / detection rate 0.6452894880386504
```

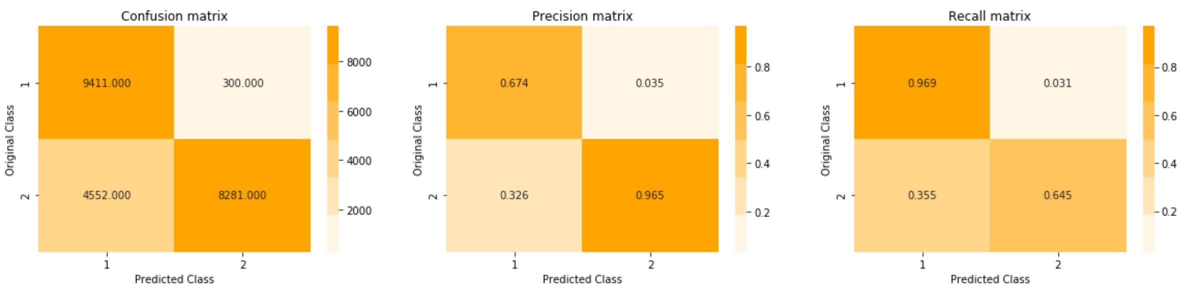
In [71]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

1 -> class 0 and 2 -> class 1

- there is a slight improvement on the f1 score and the recall aswell after removing some irrelavent features

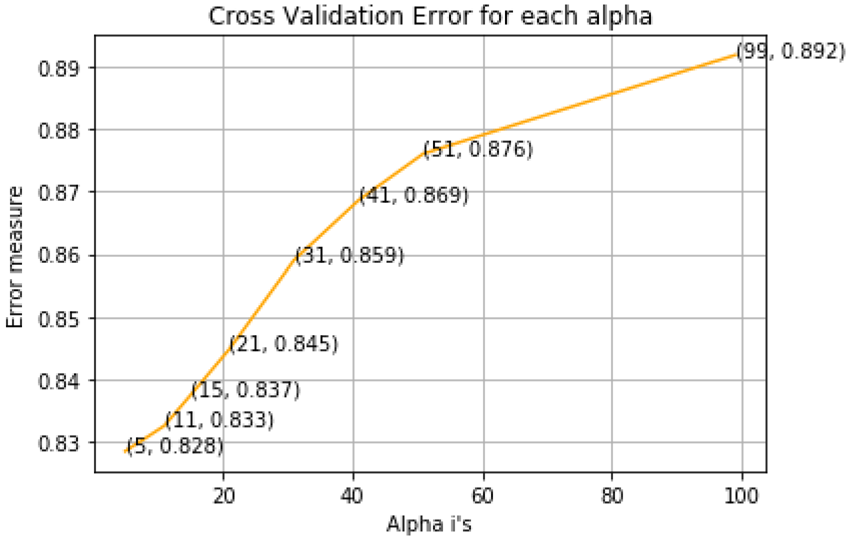
- there seems to be some confusion on recall : of all the actual point 64% are predicted to be class 2 and around 36% predicted to be class 0

4.4 KNN Hyperparameter tuning

In [52]:

```
from sklearn.metrics import roc_auc_score
from sklearn.neighbors import KNeighborsClassifier

alpha = [5, 11, 15, 21, 31, 41, 51, 99]

auc = []
for i in alpha:
    clf = KNeighborsClassifier(n_neighbors = i)
    clf.fit(X_train, y_train)
    predict_y = clf.predict_proba(X_test)[:,1]
    auc.append(roc_auc_score(y_test, predict_y))
    print('For values of alpha = ', i, "The auc score is:",roc_auc_score(y_test, predi

fig, ax = plt.subplots()
ax.plot(alpha, auc,c='orange')
for i, txt in enumerate(np.round(auc,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],auc[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
```

```
For values of alpha =  5 The auc score is: 0.8284514978796195
For values of alpha =  11 The auc score is: 0.832554284897594
For values of alpha =  15 The auc score is: 0.8374096641918964
For values of alpha =  21 The auc score is: 0.8447889306016743
For values of alpha =  31 The auc score is: 0.8590116479560955
For values of alpha =  41 The auc score is: 0.8686272301701836
For values of alpha =  51 The auc score is: 0.8760993378794436
For values of alpha =  99 The auc score is: 0.8918894763568558
```



In [54]:

```
clf = KNeighborsClassifier(n_neighbors =99)
clf.fit(X_train, y_train)
predict_y_train = clf.predict_proba(X_train)[:,1]
print('For values of best alpha = ', 99, "The train auc score is:",roc_auc_score(y_tra
predict_y_test = clf.predict_proba(X_test)[:,1]
print('For values of best alpha = ', 99, "The test auc score is:",roc_auc_score(y_test
```

```
For values of best alpha =  99 The train auc score is: 0.9997159094312437
For values of best alpha =  99 The test auc score is: 0.8918894763568558
```

In [55]:

```
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)
```

...

In [56]:

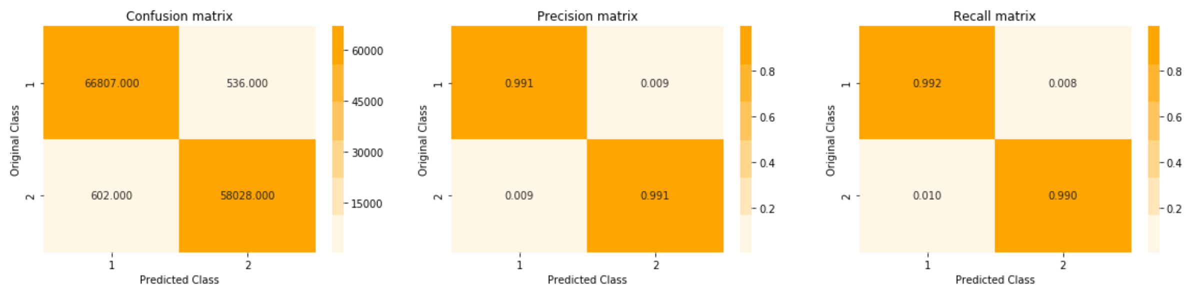
```
print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
print("*"*100)
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Train f1 score 0.9902896052698944
Test f1 score 0.7806070670726082
****************************************************************************************************
train recall score / detection rate 0.9897322190005117
test recall score / detection rate 0.6593158263851009
```

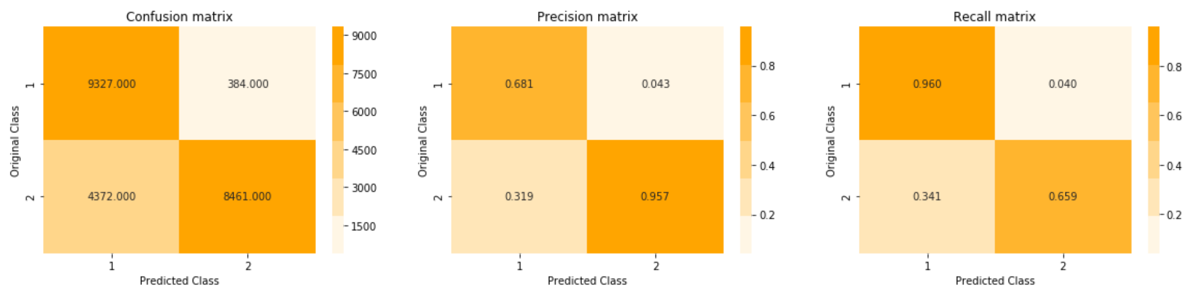
In [59]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

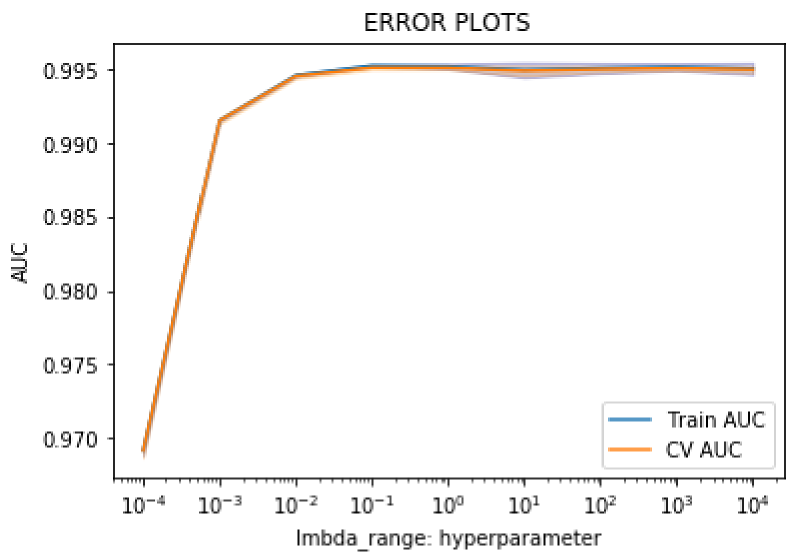
1 -> class 0 and 2 -> class 1

- The simple knn model giving us more auc as well as f1 and recall value which is good sign
- but still there is some confusion on test data between class 2 and class 1 in the recall
- This may be because of the class imbalance

4.5 Logistic regression Hyperparameter tuning

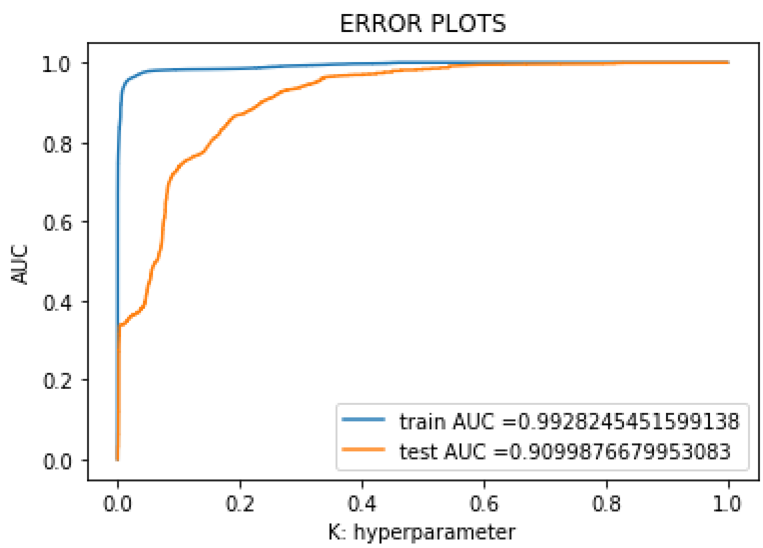
In [161]:

```
# giving range of hyperparam value which we wanted to try to find the best param
parameters = [{'C': [10**-4 , 10**-3 , 10**-2 , 10**-1 , 10**0, 10**1 , 10**2, 10**3, 1

# to find best param use grid search or random search this upto you
clf = GridSearchCV(LogisticRegression(penalty = 'l1'), parameters , cv=3 ,scoring='roc_
# fitting it to the train data
clf.fit(X_train,y_train)

# these below 3 line code will give train,test mean and standard deviation value
train_auc = clf.cv_results_['mean_train_score']
train_auc_std = clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

plt.plot(lambda_range, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(lambda_range,train_auc - train_auc_std,train_auc + train_auc_st

plt.plot(lambda_range, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(lambda_range,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,
plt.legend()
plt.xlabel("lmbda_range: hyperparameter")
plt.xscale("log")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [173]:

```
best_lambda = 0.01
LG = LogisticRegression(C = best_lambda , penalty = 'l1',class_weight={0:.1,1:.15})
LG.fit(X_train , y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, LG.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, LG.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [174]:

```
from sklearn.metrics import f1_score

y_train_pred = LG.predict(X_train)
y_test_pred = LG.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.9671355060034306
Test f1 score 0.7264708642207001
```

In [177]:

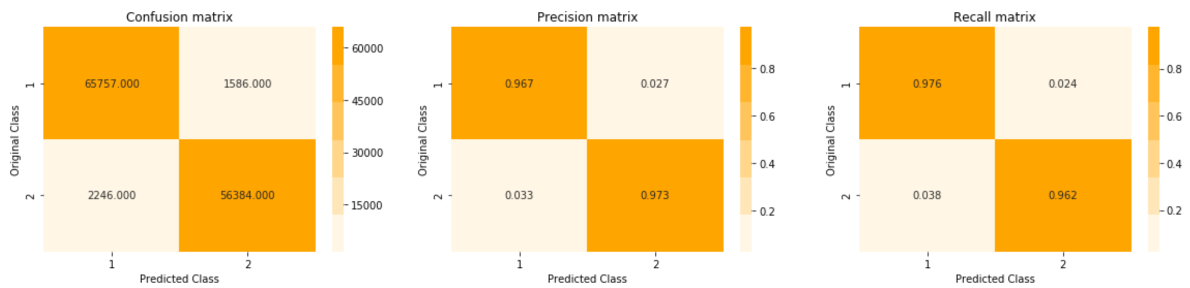
```
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
train recall score / detection rate 0.9616919665700153
test recall score / detection rate 0.6032883971012234
```

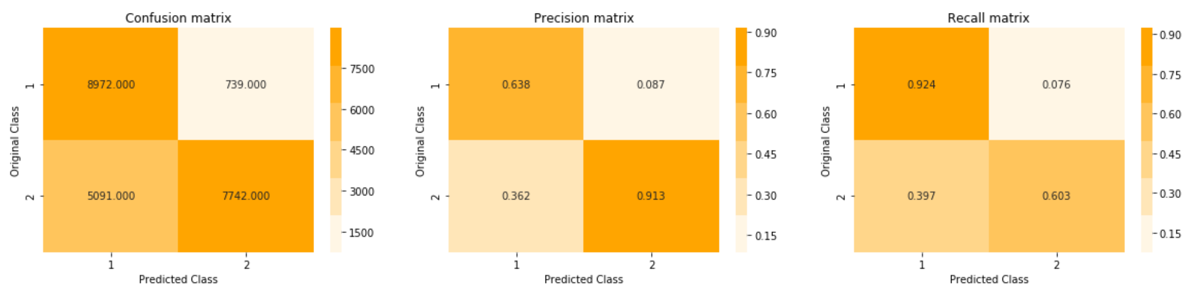
In [175]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

1 -> class 0 and 2 -> class 1

- The model has high auc value but the f1 and recall is lower than the base line model
- here also at recall model has some confusion

4.6 Decision tree with hyperparameter tuning

In [78]:

```
# Initializatioin of hyperparam and lets take only two hyperparam to tune
from scipy.stats import randint as sp_randint
parameters =  parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000],
              'min_samples_split':[5, 10,50,100, 500]}
# using grid search lets find out the best hyperparam value
# Decision tree using gini impurity
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchC
DT = GridSearchCV(DTC(criterion= 'gini'), parameters, cv=3 ,scoring='roc_auc')
DT.fit(X_train,y_train)

print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

...

In [79]:

```
print('mean test scores',DT.cv_results_['mean_test_score'])
print('mean train scores',DT.cv_results_['mean_train_score'])
```

```
mean test scores [0.92156999 0.92156999 0.92156999 0.92156999 0.92156999 0.9
9511075
 0.99511075 0.99511015 0.99514581 0.99510648 0.99737902 0.99749718
 0.99779678 0.99792748 0.99799855 0.9986813  0.99897157 0.99927804
 0.99942874 0.99951991 0.99871326 0.99894064 0.99931134 0.99943723
 0.99952023 0.99867799 0.99895565 0.99930187 0.99941272 0.99949448
 0.99876851 0.99898544 0.99929542 0.99942099 0.99949417]
mean train scores [0.92156999 0.92156999 0.92156999 0.92156999 0.92156999 0.
9951623
 0.9951623  0.9951623  0.9951395  0.99510212 0.99854283 0.99853955
 0.99852493 0.99850043 0.99834232 0.99999981 0.99999894 0.99999132
 0.99996708 0.99982699 0.99999981 0.99999894 0.99999132 0.99996686
 0.99982699 0.9999998  0.99999894 0.99999143 0.99996708 0.99982699
 0.9999998  0.99999896 0.99999143 0.99996686 0.99982699]
```

In [80]:

```
print(DT.best_estimator_)
```

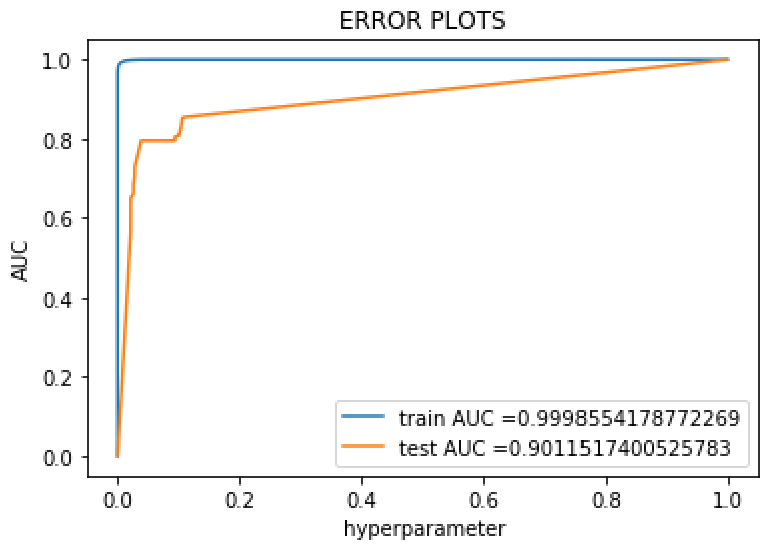
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=100,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [89]:

```
DT =DTC(class_weight={0:.1,1:15}, criterion='gini', max_depth=100,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [90]:

```
from sklearn.metrics import roc_curve, auc

DT.fit(X_train , y_train)

# roc_curve function will return 3 thing fpr,trp, threshold
# calling predict_proba with the best estimater that we have
# train fpr and tpr give the an arry with flauctuate value
train_fpr, train_tpr, thresholds = roc_curve(y_train, DT.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, DT.predict_proba(X_test)[:,1])


# auc() : this function will give area under the curve value : using somtehing called
# to know more about this link :https://en.wikipedia.org/wiki/Trapezoidal_rule
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [95]:

```
y_train_pred = DT.predict(X_train)
y_test_pred = DT.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.9694895073671678
Test f1 score 0.8820999316637859
```

In [97]:

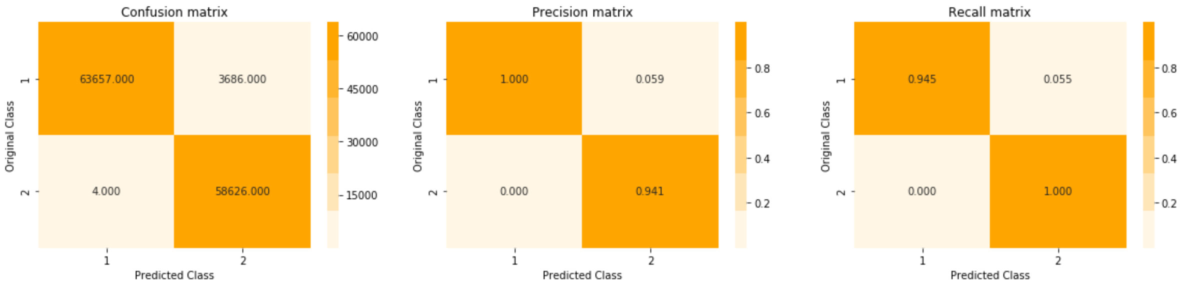
```
print('Train recall score or detection rate',recall_score(y_train,y_train_pred))
print('Train recall score or detection rate',recall_score(y_test,y_test_pred))
```

```
Train recall score or detection rate 0.9999317755415317
Train recall score or detection rate 0.8549832463180862
```

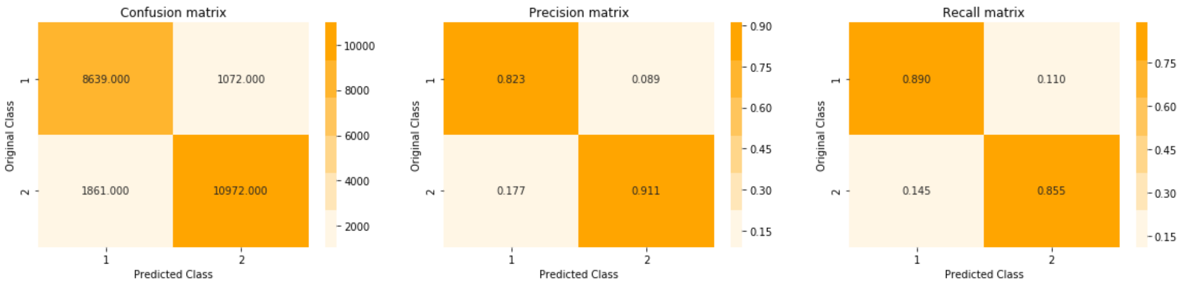
In [92]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

1 -> class 0 and 2 -> class 1

- This is so far the best model we have
- after doing some class balance we have got pretty good auc , f1 score and recall also
- now model not confused as previous on class 1 and class 0

4.7 Random Forest Hyperparameter tuning

In [71]:

```
param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15),
              "min_samples_split": sp_randint(110,190),
              "min_samples_leaf": sp_randint(25,65)}

clf = RandomForestClassifier(random_state=25,n_jobs=-1)

rf_random = RandomizedSearchCV(clf, param_distributions=param_dist,
                                   n_iter=5,cv=10,scoring='roc_auc',random_state=25)

rf_random.fit(X_train,y_train)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

```
mean test scores [0.99973248 0.99975393 0.99967673 0.99971485 0.99977576]
mean train scores [0.99975202 0.99977712 0.99969827 0.99973685 0.99980598]
```

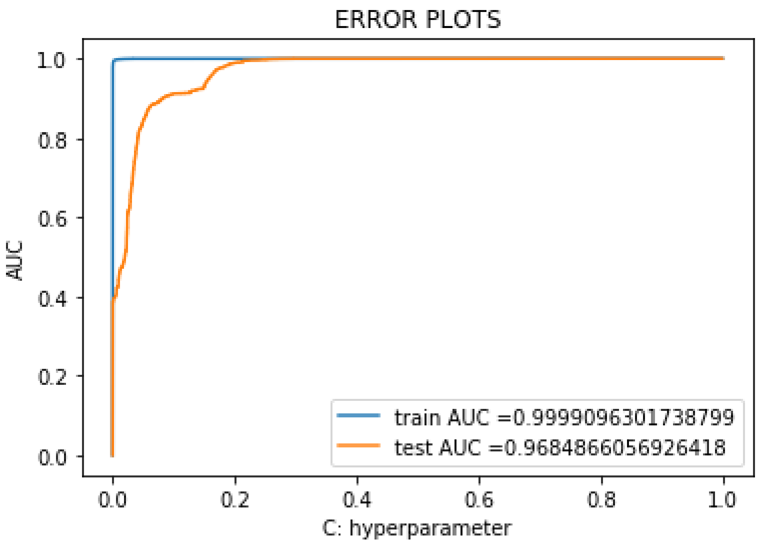
In [128]:

```
print(rf_random.best_estimator_)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=14, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=28, min_samples_split=111,
            min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
```

In [78]:

```
clf = RandomForestClassifier(bootstrap=True, class_weight={0:1,1:20}, criterion='gini'
            max_depth=14, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=28, min_samples_split=111,
            min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
clf.fit(X_train , y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [80]:

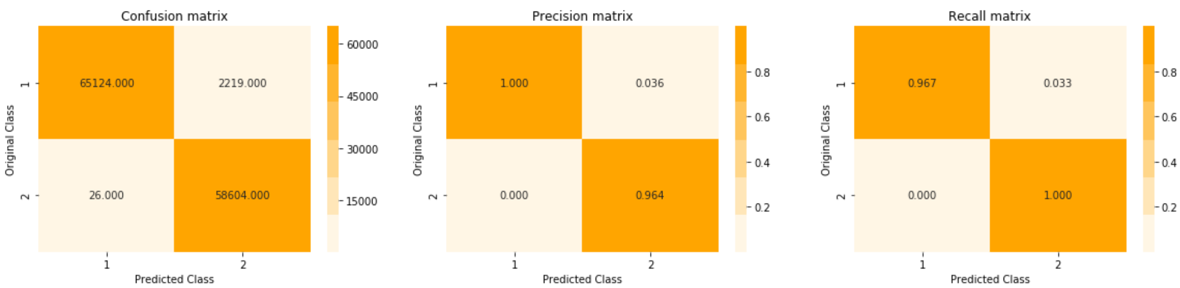
```
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
print("*"*100)
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))

```

```
Train f1 score 0.9812059973378651
Test f1 score 0.8754566307025742
****************************************************************************
************************
train recall score / detection rate 0.9995565410199556
test recall score / detection rate 0.8030078703342944
```

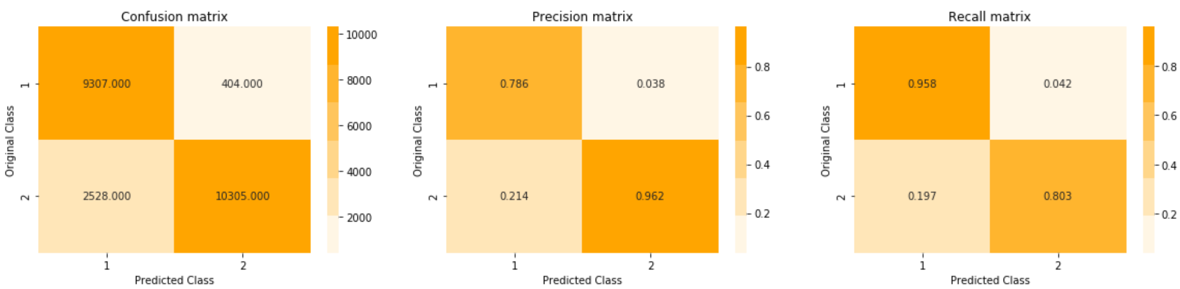
In [81]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

1 -> class 0 and 2 -> class 1

- this model is better from other model in term of AUC , it has also good f1 and recall value but less than Decision tree.

4.8 XGBOOST Hyperparameter tuning

In [119]:

```
param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15),
              "min_samples_split": sp_randint(110,190),
              "min_samples_leaf": sp_randint(25,65)}

clf = xgb.XGBClassifier(random_state=25,n_jobs=-1)

xgboost = RandomizedSearchCV(clf, param_distributions=param_dist,
                                   n_iter=5,cv=10,scoring='roc_auc',random_state=25)

xgboost.fit(X_train,y_train)
print('mean test scores',xgboost.cv_results_['mean_test_score'])
print('mean train scores',xgboost.cv_results_['mean_train_score'])
```

```
mean test scores [0.99999053 0.99999079 0.9999901  0.9999907  0.99999069]
mean train scores [0.99999998 0.99999997 0.99999996 0.99999997 0.99999998]
```

In [120]:

```
print(xgboost.best_estimator_)
```

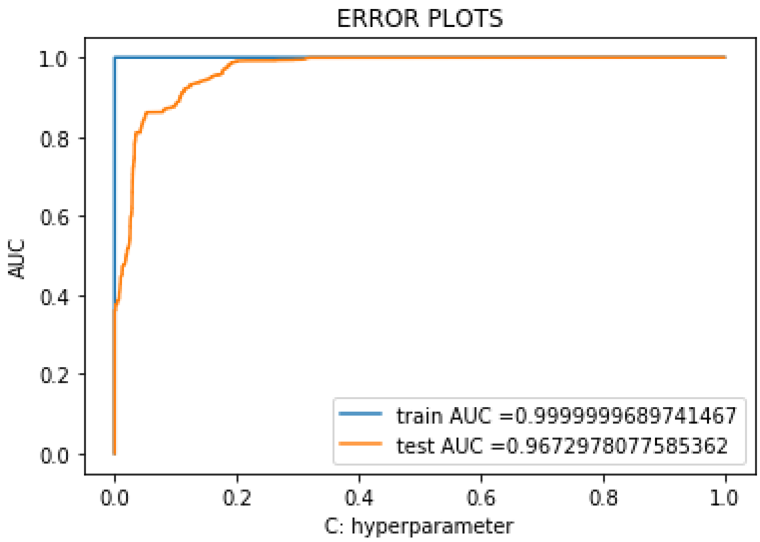
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=12, min_child_weight=1, min_samples_leaf=33,
       min_samples_split=138, missing=None, n_estimators=109, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=25,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [141]:

```
clf = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=12, min_child_weight=1, min_samples_leaf=33,
       min_samples_split=138, missing=None, n_estimators=109, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=25,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [142]:

```
from sklearn.metrics import roc_curve, auc

clf.fit(X_train , y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [144]:

```
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)
print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.999880615342634
Test f1 score 0.7592960544990066
```

In [147]:

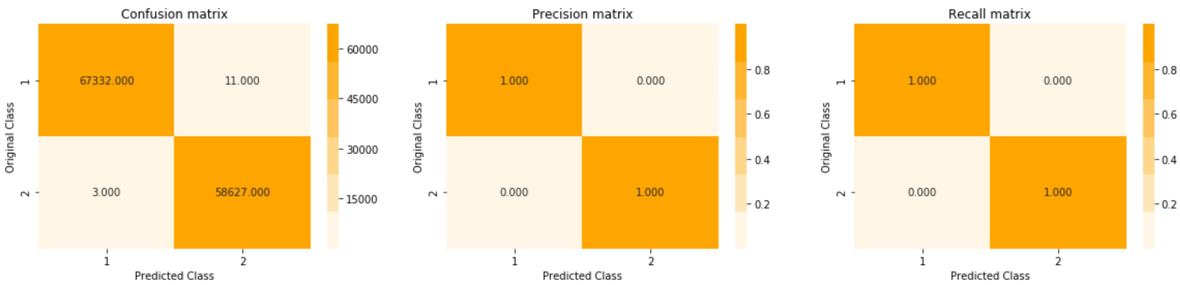
```
print('Train Detecction rate/recall',recall_score(y_train,y_train_pred))
print('Test Detecction rate/recall',recall_score(y_test,y_test_pred))
```

```
Train Detecction rate/recall 0.9999488316561488
Test Detecction rate/recall 0.6253409179459207
```

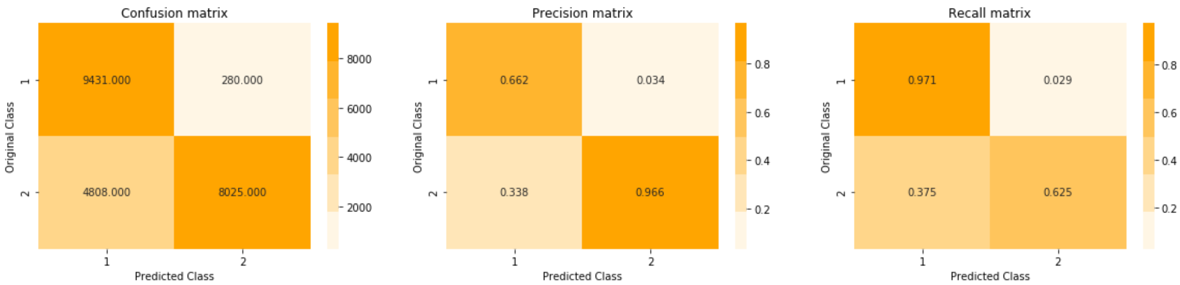
In [148]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation :

1 -> class 0 and 2 -> class 1

- the xgboost model is not performed as expected
- It cant recall well on the test data

4.9 Basic stacking

In [39]:

```
# create base models
# borrowed idea of stacking from AAIC code snippet (from one of the case study)

from sklearn.neighbors import KNeighborsClassifier
# model 1 (KNN)
model_1 = KNeighborsClassifier(n_neighbors =99)
model_1.fit(X_train, y_train)

# model 2 (Decision tree)
model_2 = DTC(class_weight={0:.1,1:15}, criterion='gini', max_depth=100,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
model_2.fit(X_train, y_train)

# model 3 (Randomforest)
model_3 = RandomForestClassifier(bootstrap=True, class_weight={0:1,1:20}, criterion='g
            max_depth=14, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=28, min_samples_split=111,
            min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
model_3.fit(X_train , y_train)

#model 4 (Xgboost)
model_4 = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=12, min_child_weight=1, min_samples_leaf=33,
       min_samples_split=138, missing=None, n_estimators=109, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=25,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
model_4.fit(X_train , y_train)


#model 5 (naive bayes)
model_5 =MultinomialNB(alpha = 10)
model_5.fit(X_train,y_train)
```

Out[39]:

```
MultinomialNB(alpha=10, class_prior=None, fit_prior=True)
```

In [43]:

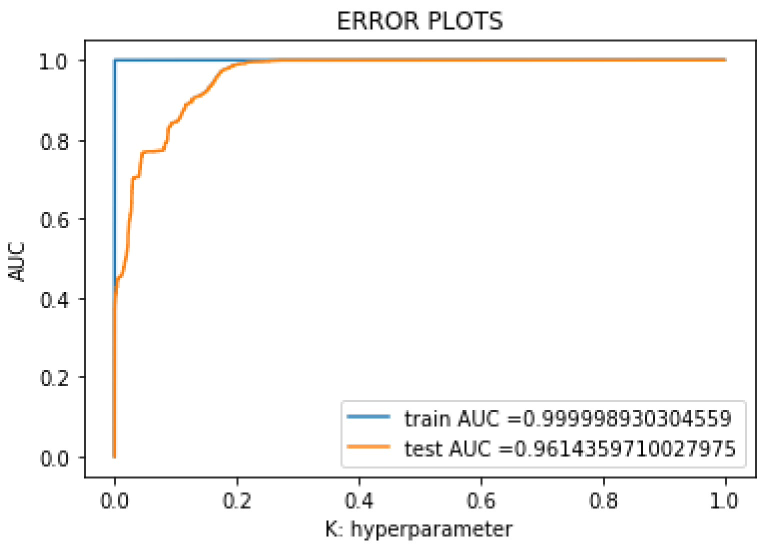
```
# create a meta classfier (we have logstic regression)
# have not done hyperparam tuning because this code snippet only taking around 3 hour
# so just taking the best param from the previous LR model

meta_clsf = LogisticRegression(C=0.01)
# stack all the 5 model and pass the out put of those model to the meta classfier
stack_clf = StackingClassifier(classifiers = [model_1,model_2,model_3,model_4,model_5]
stack_clf.fit(X_train, y_train)
```

Out[43]:

```
StackingClassifier(average_probas=False,
          classifiers=[KNeighborsClassifier(algorithm='auto', leaf_size=30,
metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=99, p=2,
           weights='uniform'), DecisionTreeClassifier(class_weight={0: 0.1,
1: 15}, criterion='gini',
            max_depth=100, max_features=None, m...d=None,
       silent=True, subsample=1), MultinomialNB(alpha=10, class_prior=None,
fit_prior=True)],
          meta_classifier=LogisticRegression(C=0.01, class_weight=None, dual
=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
          store_train_meta_features=False, use_clones=True,
          use_features_in_secondary=False, use_probas=True, verbose=0)
```

In [44]:

```
# get the auc score and plotting
train_fpr, train_tpr, thresholds = roc_curve(y_train, stack_clf.predict_proba(X_train)
test_fpr, test_tpr, thresholds = roc_curve(y_test, stack_clf.predict_proba(X_test)[:,1

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [45]:

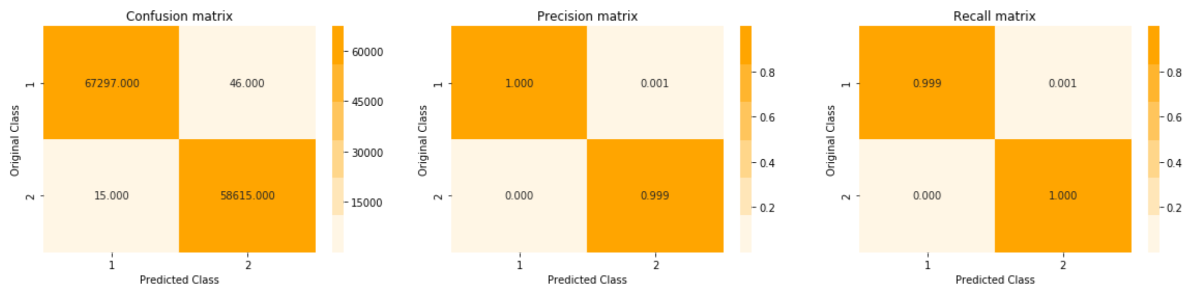
```
y_train_pred = stack_clf.predict(X_train)
y_test_pred = stack_clf.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))

print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Train f1 score 0.9994799259960271
Test f1 score 0.7843464552325313
train recall score / detection rate 0.9997441582807437
test recall score / detection rate 0.6590820540793267
```

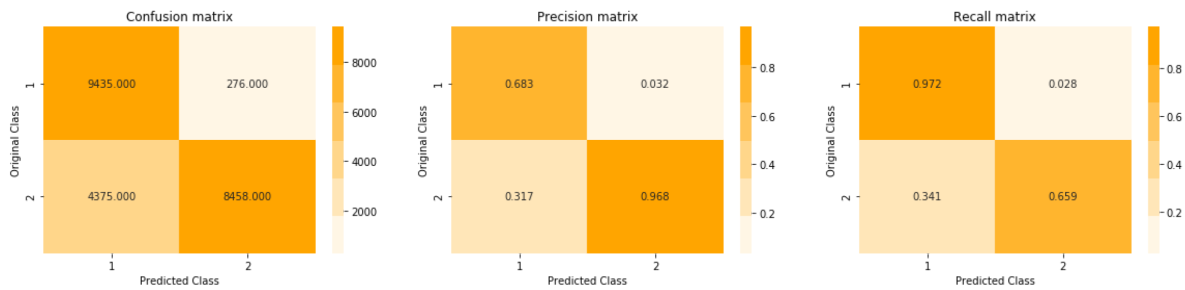
In [47]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation:

- the above code snippet will take time
- the above model is normal staking model where i have taken all the model and stacked them
- pass the output of all model to the meta classfier
- here also we got a nice auc score but f1 score and recall not at that good

4.10 Customized Stacking

Method:

- take the wole data set
- define train and test data
- divide the train data into two part: data 1 and data 2 (here we take 50-50 %)
- create m sample from the train data and fitted with the base learner (xgboost)
- now predict by passing the data2 to each sample that we are fitted
- now train the meta classifier with the given predicted value and target value of data 2 (meta clf : logistic regression)
- now use the fitted meta classifier and predict the test data

In [17]:

```
# create 2 dataset from train data
data1 = train_data[:65000]
data2 = train_data[65000:]
```

In [18]:

```
# This function is for the preprocessing :- it will craete sample datapoints from the 
# here is a good source to learn bootstrap sampling : https://machinelearningmastery.co

def preprocessing(train_x ,cv_data, test_data):
    y_train = train_x['label']
    y_cv = cv_data['label']
    y_test = test_data['label']

    # one hot encoding of protocol, service and flag feature
    prototype_vectorizer = CountVectorizer()
    train_protocol_type_encoding = prototype_vectorizer.fit_transform(train_x['protoco
    cv_protocol_type_encoding = prototype_vectorizer.transform(cv_data['protocol_type'
    test_protocol_type_encoding = prototype_vectorizer.transform(test_data['protocol_t

    service_encode = CountVectorizer()
    train_service_encoding = service_encode.fit_transform(train_x['service'])
    cv_service_encoding = service_encode.transform((cv_data['service']))
    test_service_encoding = service_encode.transform((test_data['service']))

    flag_encoding = CountVectorizer()
    train_flag_encoding = flag_encoding.fit_transform(train_x['flag'])
    cv_flag_encoding = flag_encoding.transform(cv_data['flag'])
    test_flag_encoding = flag_encoding.transform(test_data['flag'])

    # removing correlated features/irrelevant features from train and test data
    X_train_after_FS = train_x.drop(['srv_serror_rate', 'dst_host_rerror_rate', 'dst_h
    X_cv_after_FS = cv_data.drop(['srv_serror_rate', 'dst_host_rerror_rate', 'dst_host_
    X_test_after_FS = test_data.drop(['srv_serror_rate', 'dst_host_rerror_rate', 'dst_


    # removing featues which are adding less value , by looking at the RFECV
    X_train_after_FS = X_train_after_FS.drop(['srv_diff_host_rate', 'num_file_creation
    X_cv_after_FS = X_cv_after_FS.drop(['srv_diff_host_rate', 'num_file_creations' , '
    X_test_after_FS = X_test_after_FS.drop(['srv_diff_host_rate', 'num_file_creations'

    # removing label, attck,protocol_type,service,flag column from train and test data
    X_train_after_FS.drop(['protocol_type','service','flag','label'], axis=1, inplace=
    X_cv_after_FS.drop(['protocol_type','service','flag','label'], axis=1, inplace=Tru
    X_test_after_FS.drop(['protocol_type','service','flag','label'], axis=1, inplace=T


    # take protocol_type one_hot_encoding vector and service one_hot_encoding vector an
    train_protocol_service_encoding = hstack((train_protocol_type_encoding, train_serv
    cv_protocol_service_encoding = hstack((cv_protocol_type_encoding,  cv_service_enco
    test_protocol_service_encoding = hstack((test_protocol_type_encoding,  test_servic

    # take train_proto_services_encoding vector and flag one_hot_encoding vector and me
    train_protocol_service_flag_encoding = hstack((train_protocol_service_encoding, tr
    cv_protocol_service_flag_encoding  = hstack((cv_protocol_service_encoding ,cv_flag
    test_protocol_service_flag_encoding  = hstack((test_protocol_service_encoding ,tes


    # merging the categorical onehot encoded feature and numerical feature
    X_train = hstack((train_protocol_service_flag_encoding , X_train_after_FS))
    cv_test = hstack((cv_protocol_service_flag_encoding , X_cv_after_FS))
    X_test = hstack((test_protocol_service_flag_encoding , X_test_after_FS))

```

```
    #returning X_train ,y_train, X_test , y_test
    return X_train ,y_train,cv_test,y_cv, X_test , y_test
```

In [19]:

```
X_train ,y_train,cv_test,y_cv, X_test , y_test = preprocessing(data1 ,data2,test_data)
```

In [20]:

```
# print data1 and data2 and test data
print(X_train.shape ,y_train.shape)
print(cv_test.shape ,y_cv.shape)
print(X_test.shape , y_test.shape)
```

```
(65000, 102) (65000,)
(60973, 102) (60973,)
(22544, 102) (22544,)
```

In [21]:

```
# this function will shuffle the data and will resample
def shuf_sample(d , y ,num_data_points):
    d , y = shuffle(d, y)
    t_x ,y_x = resample(d ,y, replace=True ,n_samples = num_data_points ,random_state=
    return t_x , y_x
```

In [22]:

```
# refer :  https://www.youtube.com/watch?v=enEerl0feRo
# http://rasbt.github.io/mlxtend/user_guide/classifier/StackingClassifier/

# this function will take each sample and will going to fit with Xgboost classifier
# also predict the the
def compute_base_learner(train_x,train_y,cv_test,X_test , num_samples ,num_data_points
    predict_cv = []
    predict_test = []
    for i in range(1,num_samples):
        print("iteration",i)
        train_x , train_y = shuf_sample(X_train ,y_train ,num_data_points)
        clf = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
            colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
           max_depth=12, min_child_weight=1, min_samples_leaf=33,
           min_samples_split=138, missing=None, n_estimators=109, n_jobs=-1,
           nthread=None, objective='binary:logistic', random_state=25,
           reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
           silent=True, subsample=1)
        clf = clf.fit(train_x , train_y)

        pred_cv = clf.predict_proba(cv_test)
        pred_test = clf.predict_proba(X_test)

        predict_cv.append(pred_cv)
        predict_test.append(pred_test)
    return predict_cv , predict_test
```

In [23]:

```
def meta_classifier(predict_cv , predict_test , y_cv):
    prediction_cv = np.column_stack(predict_cv)
    prediction_test = np.column_stack(predict_test)
    meta_clf = LogisticRegression(C = 0.01)
    meta_clf = meta_clf.fit(prediction_cv , y_cv)
    return meta_clf, prediction_test
```

with 1000 sample

In [23]:

```
from datetime import datetime
start = datetime.now()
predict_cv , predict_test = compute_base_learner(X_train ,y_train,cv_test,X_test , 100
print("Time taken to run this cell :", datetime.now() - start)
```

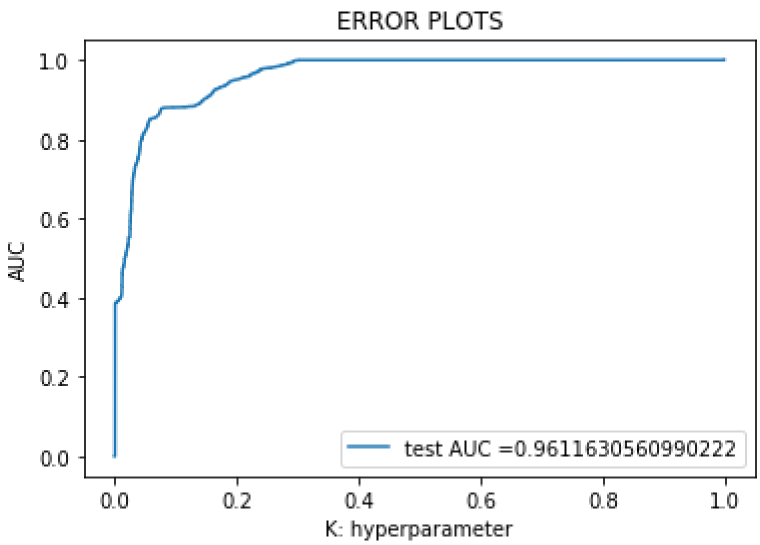
```
iteration 1
iteration 2
iteration 3
iteration 4
iteration 5
iteration 6
iteration 7
iteration 8
iteration 9
iteration 10
iteration 11
iteration 12
iteration 13
iteration 14
iteration 15
iteration 16
iteration 17
iteration 18
iteration 19
```

In [25]:

```
meta_clf ,prediction_test = meta_classifier(predict_cv , predict_test , y_cv)
```

In [26]:

```
# get the auc score and plotting

test_fpr, test_tpr, thresholds = roc_curve(y_test, meta_clf.predict_proba(prediction_t

plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")

plt.title("ERROR PLOTS")
plt.show()
```



In [27]:

```
y_test_pred = meta_clf.predict(prediction_test)

print('Test f1 score',f1_score(y_test,y_test_pred))

print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Test f1 score 0.7845882789317508
test recall score / detection rate 0.6593158263851009
```

with 1500 sample

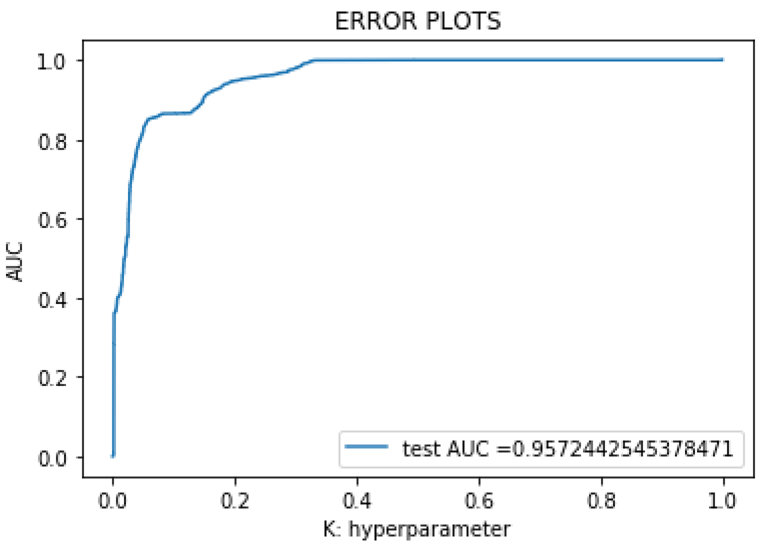
In [28]:

```
from datetime import datetime
start = datetime.now()
predict_cv , predict_test = compute_base_learner(X_train,y_train,cv_test,X_test , 1501
print("Time taken to run this cell :", datetime.now() - start)
```

```
iteration 1
iteration 2
iteration 3
iteration 4
iteration 5
iteration 6
iteration 7
iteration 8
iteration 9
iteration 10
iteration 11
iteration 12
iteration 13
iteration 14
iteration 15
iteration 16
iteration 17
iteration 18
iteration 19
```

In [31]:

```
# get the auc score and plotting
meta_clf ,prediction_test = meta_classifier(predict_cv , predict_test , y_cv)
test_fpr, test_tpr, thresholds = roc_curve(y_test, meta_clf.predict_proba(prediction_t

plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")

plt.title("ERROR PLOTS")
plt.show()
```



In [32]:

```
y_test_pred = meta_clf.predict(prediction_test)

print('Test f1 score',f1_score(y_test,y_test_pred))

print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Test f1 score 0.7895077122009792
test recall score / detection rate 0.666095223252552
```

with 2000 sample

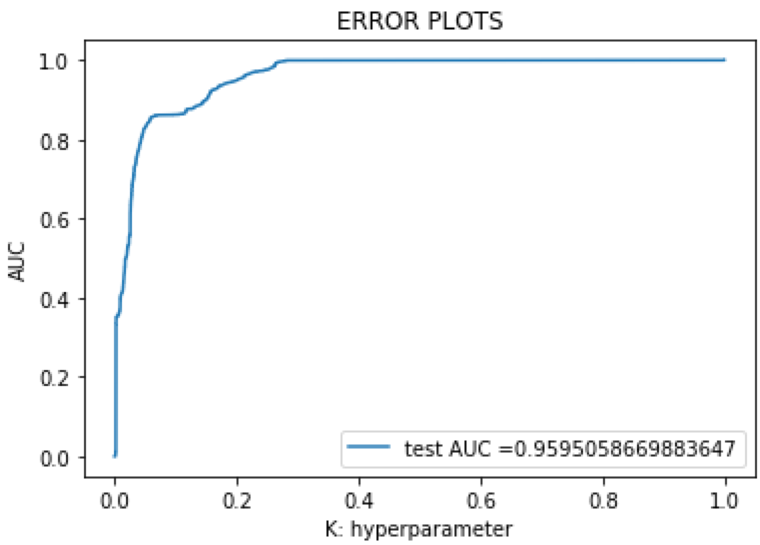
In [34]:

```
from datetime import datetime
start = datetime.now()
predict_cv , predict_test = compute_base_learner(X_train,y_train,cv_test,X_test , 2001
print("Time taken to run this cell :", datetime.now() - start)
```

```
iteration 1
iteration 2
iteration 3
iteration 4
iteration 5
iteration 6
iteration 7
iteration 8
iteration 9
iteration 10
iteration 11
iteration 12
iteration 13
iteration 14
iteration 15
iteration 16
iteration 17
iteration 18
iteration 19
```

In [37]:

```
# get the auc score and plotting
meta_clf ,prediction_test = meta_classifier(predict_cv , predict_test , y_cv)
test_fpr, test_tpr, thresholds = roc_curve(y_test, meta_clf.predict_proba(prediction_t

plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")

plt.title("ERROR PLOTS")
plt.show()
```



In [38]:

```
y_test_pred = meta_clf.predict(prediction_test)

print('Test f1 score',f1_score(y_test,y_test_pred))

print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Test f1 score 0.7801108059034406
test recall score / detection rate 0.6528481259253487
```

10000 data point and 100 samples

In [61]:

```
from datetime import datetime
start = datetime.now()
predict_cv , predict_test = compute_base_learner(X_train,y_train,cv_test,X_test , 1001
print("Time taken to run this cell :", datetime.now() - start)
```

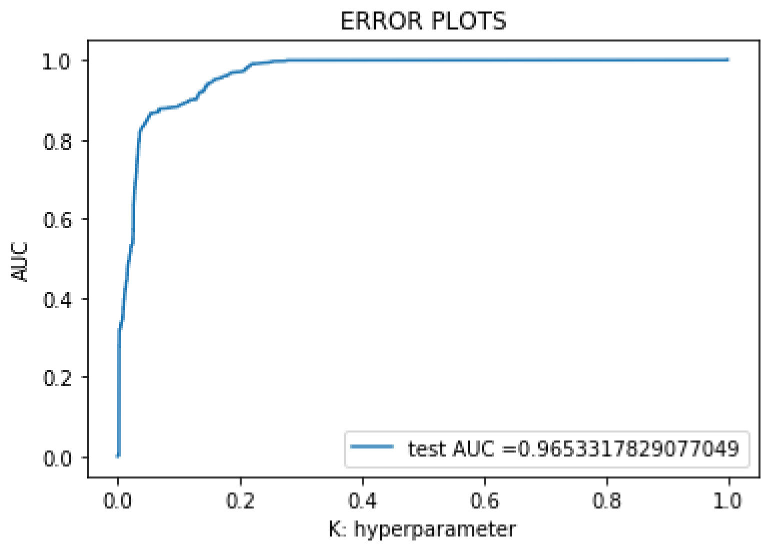
```
iteration 1
iteration 2
iteration 3
iteration 4
iteration 5
iteration 6
iteration 7
iteration 8
iteration 9
iteration 10
iteration 11
iteration 12
iteration 13
iteration 14
iteration 15
iteration 16
iteration 17
iteration 18
iteration 19
```

In [69]:

```
# get the auc score and plotting
meta_clf , prediction_test = meta_classifier(predict_cv , predict_test , y_cv)

```

In [71]:

```
test_fpr, test_tpr, thresholds = roc_curve(y_test, meta_clf.predict_proba(prediction_t

plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")

plt.title("ERROR PLOTS")
plt.show()
```



In [72]:

```
y_test_pred = meta_clf.predict(prediction_test)

print('Test f1 score',f1_score(y_test,y_test_pred))

print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Test f1 score 0.7667231957791597
test recall score / detection rate 0.6341463414634146
```

4.11 Feature Engineering

lets add two new feature

- add 2 most important feature as per feature selection
- use square of an important feature

In [17]:

```
train_data['same_srv_rate_src_bytes'] = train_data['same_srv_rate']+ train_data['src_b
test_data['same_srv_rate_src_bytes'] =test_data['same_srv_rate']+ test_data['src_bytes
```

In [18]:

```
train_data['same_srv_rate_sqr'] = train_data['same_srv_rate'] ** 2
test_data['same_srv_rate_sqr'] =test_data['same_srv_rate'] ** 2
```

- Please run the cell after feature selection section upto standardization

In [50]:

```
train_data.head()
```

Out[50]:

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

In [32]:

```
param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15),
              "min_samples_split": sp_randint(110,190),
              "min_samples_leaf": sp_randint(25,65)}

clf = RandomForestClassifier(random_state=25,n_jobs=-1)

rf_random = RandomizedSearchCV(clf, param_distributions=param_dist,
                                   n_iter=5,cv=10,scoring='roc_auc',random_state=25)

rf_random.fit(X_train,y_train)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

```
mean test scores [0.99978088 0.99980386 0.99974889 0.99977604 0.99983323]
mean train scores [0.99980049 0.9998284  0.99976008 0.9997991  0.99986029]
```

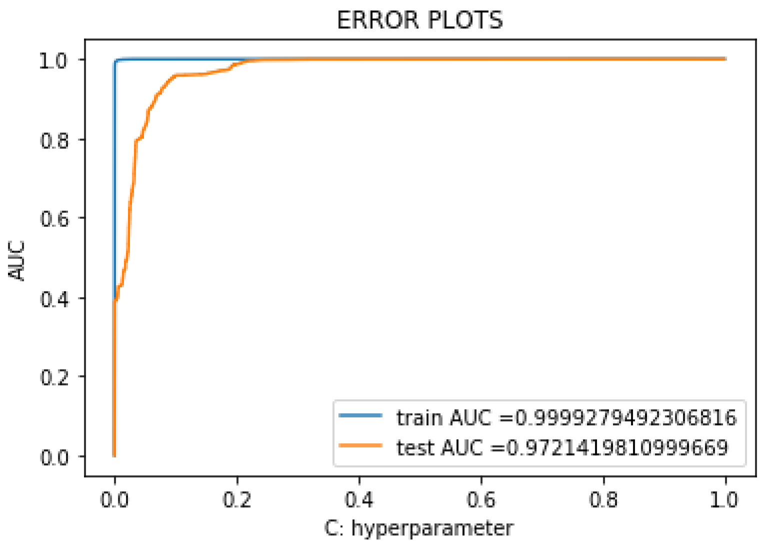
In [33]:

```
print(rf_random.best_estimator_)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=14, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=28, min_samples_split=111,
                       min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
                       oob_score=False, random_state=25, verbose=0, warm_start=False)
```

In [36]:

```
clf = RandomForestClassifier(bootstrap=True, class_weight={0:1,1:20}, criterion='gini'
            max_depth=14, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=28, min_samples_split=111,
            min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
clf.fit(X_train , y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [38]:

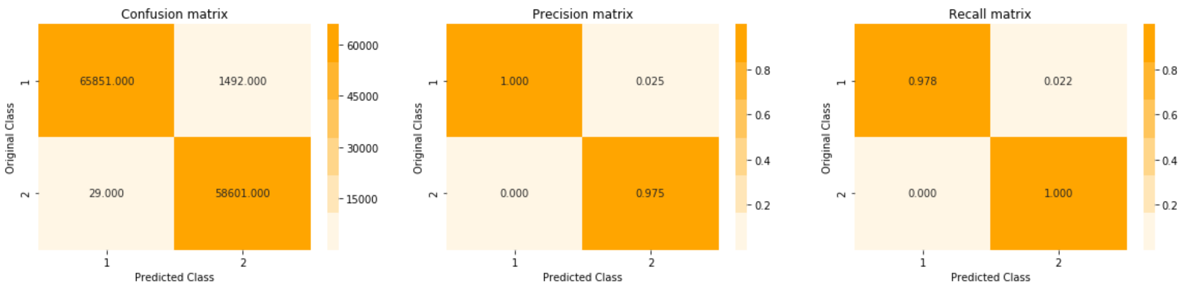
```
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)

print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
print("*"*100)
print("train recall score / detection rate",recall_score(y_train,y_train_pred))
print("test recall score / detection rate",recall_score(y_test,y_test_pred))
```

```
Train f1 score 0.9871886660545977
Test f1 score 0.8739645724480694
****************************************************************************
************************
train recall score / detection rate 0.9995053726761044
test recall score / detection rate 0.8016052364996493
```

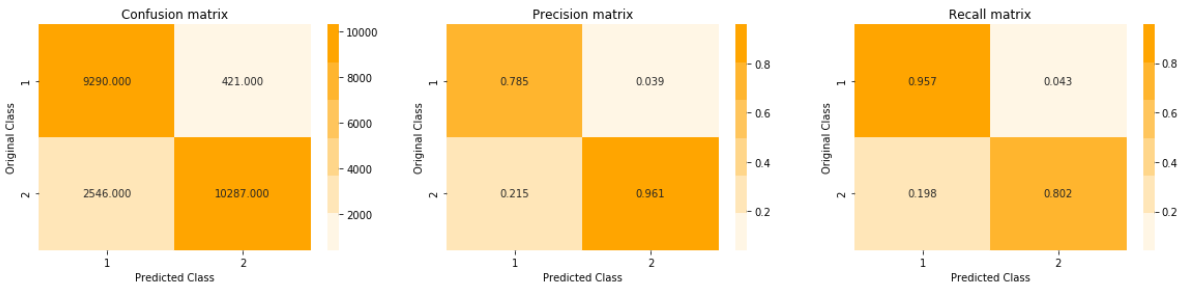
In [41]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



Observation:

```
- this model is giving highest auc value better than our previous random forest mo
del
```

Understanding the whole model building section breifly

- Merge all the encoded categorical and numerical features
- build a base line model in this case we have taken Naive bayes (we can take knn also)
- By looking at the naive bayes model after hyperparameter tuning the model seems to overfit(gap in train and test score)
- to overcome from this problem we select features by recusive feature elemination (please read the "understanding feature selection" after 4.2 section)
- after done that remove all the feature manually from the train data and those features which are not adding value by seeing the important feature plot
- Build the model again starting with the naive bayes model
- after feature selection we got good AUC but there were some problem like f1 score was low and confusion on the test recall , this was beacause the data set is imbalanced , so give some class weight to tackle this , and after that we got pretty good result.
- So far there are two good model Decision tree and Randomforest
- I thought Xgboost will gonna give best result but thats ok .
- tried two kind of stacking but the result were not at all good in term of f1 score and recall score.
- In the feature engineering section i have tried 2 new feature which is take the those feature which are important by our feature selection method , then add those feature and other is square a feature
- The result of feature engineered model(trioed random forest) is great this is highest auc value i have got , but the f1 and recall score is lower than Decision tree and random forest

In [49]:

```
from prettytable import PrettyTable
k = PrettyTable()
p = PrettyTable()
print('*************Before feature selection*************')
k.field_names = ["Model","Train AUC" ,"Test AUC" ,"f1 score on test data" , "recall on
k.add_row(["Naive Bayes" , .9829 , 0.8400,0.7687,.6388])
print(k)
print('*********After feature selection*************')
p.field_names = ["Model","Train AUC" ,"Test AUC" ,"f1 score on test data" , "recall on
p.add_row(["Naive Bayes" , .9863 , 0.8553,0.7734,.6452])
p.add_row(["KNN" , .999 , 0.891,0.7806,.6593])
p.add_row(["Logistic Regression" , .9928 , 0.9049,0.7264,.6032])
p.add_row(["Decision Tree" , .9998 , 0.9011,0.8820,.8549])
p.add_row(["Random Forest" , .9999 , 0.9684,0.8754,.8030])
p.add_row(["Xgboost" , .9999 , 0.9672,0.7592,.6253])
p.add_row(["Basic stacking model" , .9999 , 0.9614,0.7843,.6590])
p.add_row(["Customized stacking model" , "not computed" , 0.957,0.79,.666])
p.add_row([" RF with feature engineering" , .999 , .972 , .873, .801])
print(p)
```

```
*************Before feature selection*************
+-------------+-----------+----------+-----------------------+--------------
-------+
|    Model    | Train AUC | Test AUC | f1 score on test data | recall on tes
t data |
+-------------+-----------+----------+-----------------------+--------------
-------+
| Naive Bayes |   0.9829  |   0.84   |         0.7687        |         0.6388
|
+-------------+-----------+----------+-----------------------+--------------
-------+
*********After feature selection*************
+-------------------------------+--------------+----------+-----------------
-----+---------------------+
|             Model             |  Train AUC   | Test AUC | f1 score on test
data | recall on test data |
+-------------------------------+--------------+----------+-----------------
-----+---------------------+
|          Naive Bayes          |    0.9863    |  0.8553  |         0.7734
|        0.6452       |
|              KNN              |    0.999     |  0.891   |         0.7806
|        0.6593       |
|      Logistic Regression      |    0.9928    |  0.9049  |         0.7264
|        0.6032       |
|         Decision Tree         |    0.9998    |  0.9011  |         0.882
|        0.8549       |
|         Random Forest         |    0.9999    |  0.9684  |         0.8754
|        0.803        |
|            Xgboost            |    0.9999    |  0.9672  |         0.7592
|        0.6253       |
|      Basic stacking model     |    0.9999    |  0.9614  |         0.7843
|        0.659        |
|   Customized stacking model   | not computed |  0.957   |          0.79
|        0.666        |
|  RF with feature engineering  |    0.999     |  0.972   |         0.873
|        0.801        |
```

```
+-----------------------------+--------------+----------+------------------
-----+--------------------+
```