Network Intrusion Detection System(NIDS)

1. Business Problem

- Intrusion/attacks are a set of events which can compromise the principles of computer network such as integrity, availability, authority and confidentiality. Modern attacks environments cannot be detected by firewalls so that NIDS are designed to achieve high protection from cyber attacks.
- A Network Intrusion Detection System (NIDS) monitors network traffic flow to detect malicious activity.NIDS are classified basically into two types viz Signature based and Anomaly based detection system.Anomaly based detection system are used nowadays due their superiority in detecting unknown attacks.

1.1 Problem statement :

To Detect Malicious Activity and Normal Activity by monitoring network traffic

1.2 Source/Useful Links :

Some articles and reference blogs about the problem statement

1. http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html (http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html)
2. https://en.wikipedia.org/wiki/Intrusion_detection_system (https://en.wikipedia.org/wiki/Intrusion_detection_system)
3. https://www.geeksforgeeks.org/intrusion-detection-system-ids/ (https://www.geeksforgeeks.org/intrusion-detection-system-ids/)

1.3. Real-world/Business objectives and constraints.

- No low-latency requirement.
- Errors can be very costly.

2. Machine Learning Problem Formulation

2.1. Data

2.1.1. Data Overview

- Source:- http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html (http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html)

- We have dataset containing 494021 datapoints and 42 features.Dataset have missing name for columns.Dataset consists of 41 features to work upon and 1 class label
- Label:
  - 0: Normal Activity
  - 1: Malicious Activity

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

2.2.1. Type of Machine Learning Problem

```
We need to predict a given datapoint belongs to label 0 or 1 => Binary classifi
cation problem
```

2.2.2. Performance Metric

- Accuracy
- Confusion matrix

2.3. Train, CV and Test Datasets

The dataset is split randomly into three parts train, cross validation and test with 64%,16%, 20% of total data respectively

2.4 Importing important Libraries

In [570]:

```
import warnings
warnings.filterwarnings("ignore")
import shutil
import os
import pandas as pd
import matplotlib
matplotlib.use(u'nbAgg')
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pickle
from sklearn.manifold import TSNE
from sklearn import preprocessing
import pandas as pd
from multiprocessing import Process# this is used for multithreading
import multiprocessing
import codecs# this is used for file operations
import random as r
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from tqdm import tqdm
%matplotlib inline
```

2.5. Reading Data

In [571]:

```
col = ["duration","protocol_type","service","flag","src_bytes",
    "dst_bytes","land","wrong_fragment","urgent","hot","num_failed_logins",
    "logged_in","num_compromised","root_shell","su_attempted","num_root",
    "num_file_creations","num_shells","num_access_files","num_outbound_cmds",
    "is_host_login","is_guest_login","count","srv_count","serror_rate",
    "srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
    "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
    "dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
    "dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
    "dst_host_rerror_rate","dst_host_srv_rerror_rate","label"]
```

In [572]:

```
total_data=pd.read_csv('kddcup.data_10_percent_corrected',header=None, names = col)
```

In [573]:

```
total_data.head(2)
```

Out[573]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent
0	0	tcp	http	SF	181	5450	0	0	0
1	0	tcp	http	SF	239	486	0	0	0

2 rows × 42 columns

In [574]:

```
total_data.shape
```

Out[574]:

```
(494021, 42)
```

In [575]:

```
total_data.describe()
```

Out[575]:

	duration	src_bytes	dst_bytes	land	wrong_fragment	urge
count	494021.000000	4.940210e+05	4.940210e+05	494021.000000	494021.000000	494021.0000
mean	47.979302	3.025610e+03	8.685324e+02	0.000045	0.006433	0.0000
std	707.746472	9.882181e+05	3.304000e+04	0.006673	0.134805	0.0055
min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.0000
25%	0.000000	4.500000e+01	0.000000e+00	0.000000	0.000000	0.0000
50%	0.000000	5.200000e+02	0.000000e+00	0.000000	0.000000	0.0000
75%	0.000000	1.032000e+03	0.000000e+00	0.000000	0.000000	0.0000
max	58329.000000	6.933756e+08	5.155468e+06	1.000000	3.000000	3.0000

8 rows × 38 columns

In [576]:

```
total_data.columns.values
```

Out[576]:

```
array(['duration', 'protocol_type', 'service', 'flag', 'src_bytes',
       'dst_bytes', 'land', 'wrong_fragment', 'urgent', 'hot',
       'num_failed_logins', 'logged_in', 'num_compromised', 'root_shell',
       'su_attempted', 'num_root', 'num_file_creations', 'num_shells',
       'num_access_files', 'num_outbound_cmds', 'is_host_login',
       'is_guest_login', 'count', 'srv_count', 'serror_rate',
       'srv_serror_rate', 'rerror_rate', 'srv_rerror_rate',
       'same_srv_rate', 'diff_srv_rate', 'srv_diff_host_rate',
       'dst_host_count', 'dst_host_srv_count', 'dst_host_same_srv_rate',
       'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate',
       'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
       'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
       'dst_host_srv_rerror_rate', 'label'], dtype=object)
```

In [577]:

```
total_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 494021 entries, 0 to 494020
Data columns (total 42 columns):
duration                       494021 non-null int64
protocol_type                  494021 non-null object
service                        494021 non-null object
flag                           494021 non-null object
src_bytes                      494021 non-null int64
dst_bytes                      494021 non-null int64
land                           494021 non-null int64
wrong_fragment                 494021 non-null int64
urgent                         494021 non-null int64
hot                            494021 non-null int64
num_failed_logins              494021 non-null int64
logged_in                      494021 non-null int64
num_compromised                494021 non-null int64
root_shell                     494021 non-null int64
su_attempted                   494021 non-null int64
num_root                       494021 non-null int64
num_file_creations             494021 non-null int64
num_shells                     494021 non-null int64
num_access_files               494021 non-null int64
num_outbound_cmds              494021 non-null int64
is_host_login                  494021 non-null int64
is_guest_login                 494021 non-null int64
count                          494021 non-null int64
srv_count                      494021 non-null int64
serror_rate                    494021 non-null float64
srv_serror_rate                494021 non-null float64
rerror_rate                    494021 non-null float64
srv_rerror_rate                494021 non-null float64
same_srv_rate                  494021 non-null float64
diff_srv_rate                  494021 non-null float64
srv_diff_host_rate             494021 non-null float64
dst_host_count                 494021 non-null int64
dst_host_srv_count             494021 non-null int64
dst_host_same_srv_rate         494021 non-null float64
dst_host_diff_srv_rate         494021 non-null float64
dst_host_same_src_port_rate    494021 non-null float64
dst_host_srv_diff_host_rate    494021 non-null float64
dst_host_serror_rate           494021 non-null float64
dst_host_srv_serror_rate       494021 non-null float64
dst_host_rerror_rate           494021 non-null float64
dst_host_srv_rerror_rate       494021 non-null float64
label                          494021 non-null object
dtypes: float64(15), int64(23), object(4)
memory usage: 158.3+ MB
```

3. Exploratory Data Analysis

3.1 Basic preprocessing

In [578]:

```
total_data['label'].value_counts()
```

Out[578]:

```
smurf.              280790
neptune.            107201
normal.              97278
back.                 2203
satan.                1589
ipsweep.              1247
portsweep.            1040
warezclient.          1020
teardrop.              979
pod.                   264
nmap.                  231
guess_passwd.           53
buffer_overflow.        30
land.                   21
warezmaster.            20
imap.                   12
rootkit.                10
loadmodule.              9
ftp_write.               8
multihop.                7
phf.                     4
perl.                    3
spy.                     2
Name: label, dtype: int64
```

In [579]:

```
attack=['smurf.','neptune.',' normal.','back.','satan.','ipsweep.','portsweep.','warezclier
```

In [580]:

```
total_data['label']=total_data['label'].replace(attack,'attacks')
```

In [581]:

```
total_data['label'].value_counts()
```

Out[581]:

```
attacks    396743
normal.     97278
Name: label, dtype: int64
```

In [582]:

```
total_data['label']=total_data['label'].replace('normal.',0)
total_data['label']=total_data['label'].replace('attacks',1)
```

In [583]:

```
total_data['label'].value_counts()
```

Out[583]:

```
1    396743
0     97278
Name: label, dtype: int64
```

In [584]:

```
total_data['service'].value_counts()
```

Out[584]:

```
ecr_i      281400
private    110893
http        64293
smtp         9723
other        7237
            ...  
X11            11
tim_i           7
pm_dump         1
tftp_u          1
red_i           1
Name: service, Length: 66, dtype: int64
```

In [585]:

```
total_data['protocol_type'].value_counts()
```

Out[585]:

```
icmp    283602
tcp     190065
udp      20354
Name: protocol_type, dtype: int64
```

In [586]:

```
total_data['flag'].value_counts()
```

Out[586]:

```
SF        378440
S0         87007
REJ        26875
RSTR         903
RSTO         579
SH           107
S1            57
S2            24
RSTOS0        11
S3            10
OTH            8
Name: flag, dtype: int64
```

In [587]:

```
total_data.columns.isnull().sum()
```

Out[587]:

```
0
```

In [588]:

```
total_data.columns.values
```

Out[588]:

```
array(['duration', 'protocol_type', 'service', 'flag', 'src_bytes',
       'dst_bytes', 'land', 'wrong_fragment', 'urgent', 'hot',
       'num_failed_logins', 'logged_in', 'num_compromised', 'root_shell',
       'su_attempted', 'num_root', 'num_file_creations', 'num_shells',
       'num_access_files', 'num_outbound_cmds', 'is_host_login',
       'is_guest_login', 'count', 'srv_count', 'serror_rate',
       'srv_serror_rate', 'rerror_rate', 'srv_rerror_rate',
       'same_srv_rate', 'diff_srv_rate', 'srv_diff_host_rate',
       'dst_host_count', 'dst_host_srv_count', 'dst_host_same_srv_rate',
       'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate',
       'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
       'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
       'dst_host_srv_rerror_rate', 'label'], dtype=object)
```

In [589]:

```
total_data['flag'].value_counts()
```

Out[589]:

```
SF        378440
S0         87007
REJ        26875
RSTR         903
RSTO         579
SH           107
S1            57
S2            24
RSTOS0        11
S3            10
OTH            8
Name: flag, dtype: int64
```

3.2 Correlation Analysis

In [590]:

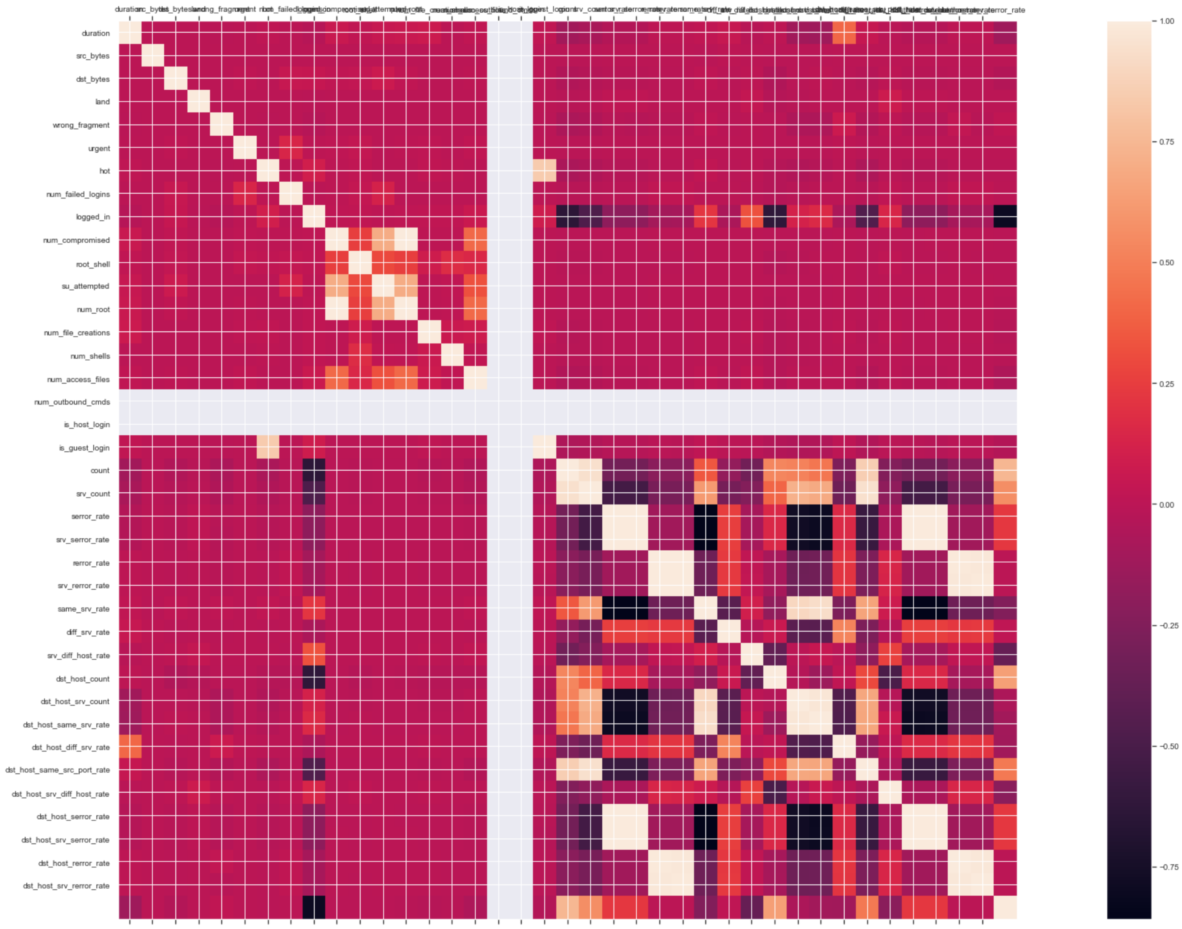
```
corr_mat=total_data.corr()
```

In [591]:

```
numcolumn=['duration','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']
```

In [592]:

```
plt.figure(figsize=(40,20))
plt.matshow(corr_mat,fignum=1)
plt.xticks(range(len(numcolumn)),numcolumn)
plt.yticks(range(len(numcolumn)),numcolumn)
plt.colorbar()
plt.show()
```



In [593]:

```
def corr_columns(corr_matrix):
    numcolumn=list(corr_matrix.columns.values)
    b=[]
    for i in range(len(numcolumn)):
        for j in range(len(numcolumn)):
            a=[]
            if i!=j:
                if corr_matrix.iat[i,j]>0.80:
                    a.append(numcolumn[i])
                    a.append(numcolumn[j])
                    b.append(a)
    return b
```

In [594]:

```
c=corr_columns(corr_mat)
```

In [595]:

```
for i in range(len(c)):
        for j in range(len(c)):
            try:
                if c[i][0]==c[j][1] and c[i][1]==c[j][0]:
                    print(c.pop(j))
            except IndexError:
                pass
```

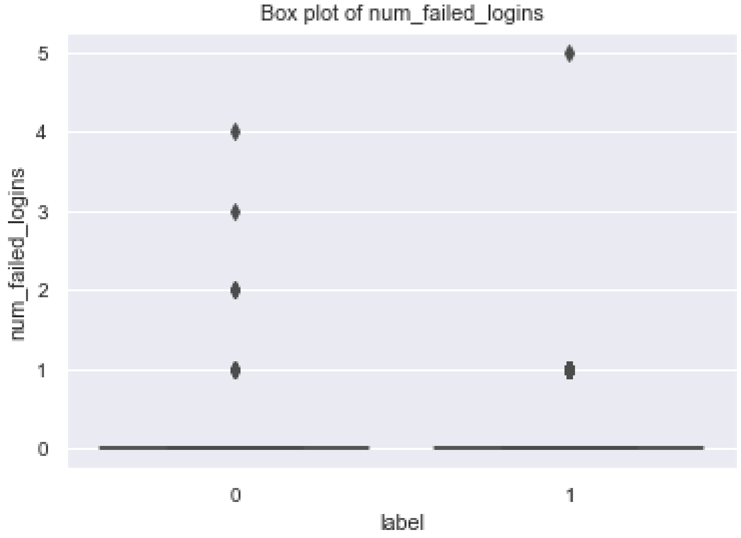
```
['is_guest_login', 'hot']
['num_root', 'num_compromised']
['srv_count', 'count']
['dst_host_same_src_port_rate', 'count']
['dst_host_same_src_port_rate', 'srv_count']
['srv_serror_rate', 'serror_rate']
['dst_host_serror_rate', 'serror_rate']
['dst_host_srv_serror_rate', 'serror_rate']
['dst_host_serror_rate', 'srv_serror_rate']
['dst_host_srv_serror_rate', 'srv_serror_rate']
['srv_rerror_rate', 'rerror_rate']
['dst_host_rerror_rate', 'rerror_rate']
['dst_host_srv_rerror_rate', 'rerror_rate']
['dst_host_rerror_rate', 'srv_rerror_rate']
['dst_host_srv_rerror_rate', 'srv_rerror_rate']
['dst_host_srv_count', 'same_srv_rate']
['dst_host_same_srv_rate', 'same_srv_rate']
['dst_host_same_srv_rate', 'dst_host_srv_count']
['dst_host_srv_serror_rate', 'dst_host_serror_rate']
['dst_host_srv_rerror_rate', 'dst_host_rerror_rate']
```

3.3. Univariate Analysis

3.3.1 Boxplot of features

In [596]:

```
ax = sns.boxplot(y='num_failed_logins',x="label",data=total_data)
plt.title("Box plot of num_failed_logins")
plt.show()
```

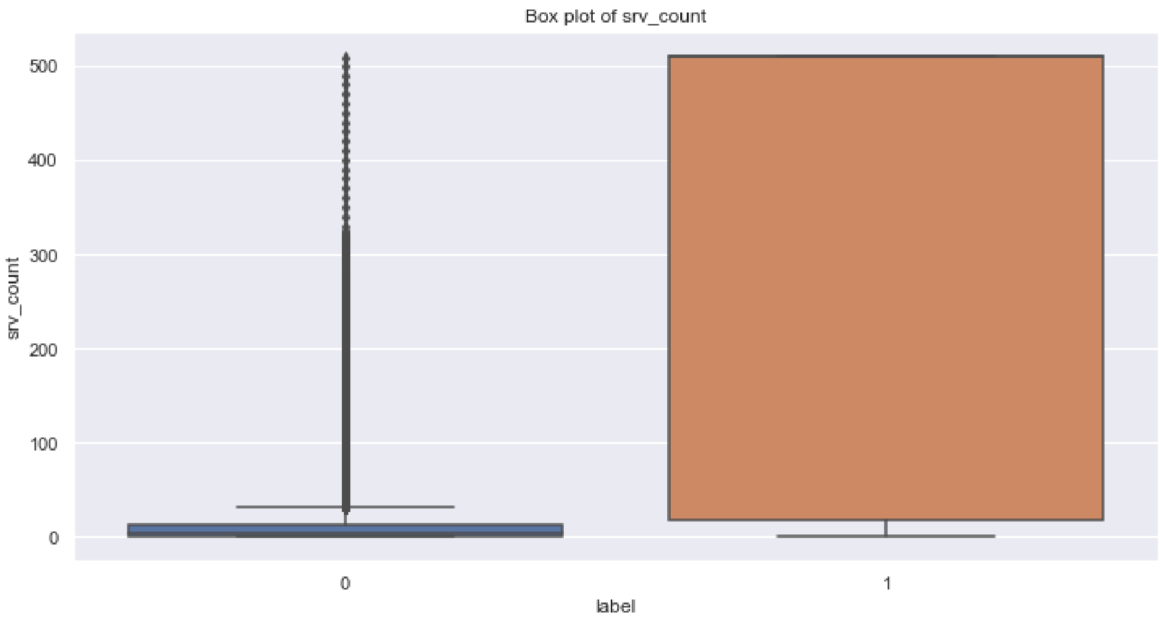


Observations:

1. number of failed logins for class 1 are 5 or 1 maximum times but for class o ,they are evenly distributed.

In [266]:

```
ax = sns.boxplot(y='srv_count',x="label",data=total_data)
plt.title("Box plot of srv_count")
plt.show()
```

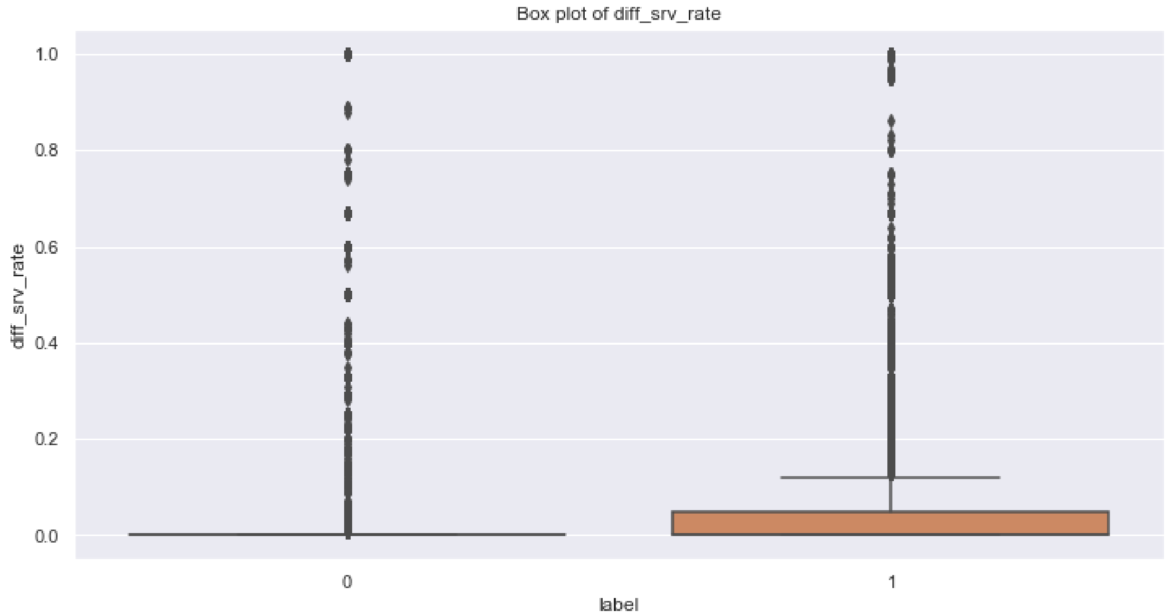


Observations:

1. 75% of srv_count are less than 10 for class 0 but for class 1 srv_count is very high.

In [267]:

```
ax = sns.boxplot(y='diff_srv_rate',x="label",data=total_data)
plt.title("Box plot of diff_srv_rate")
plt.show()
```

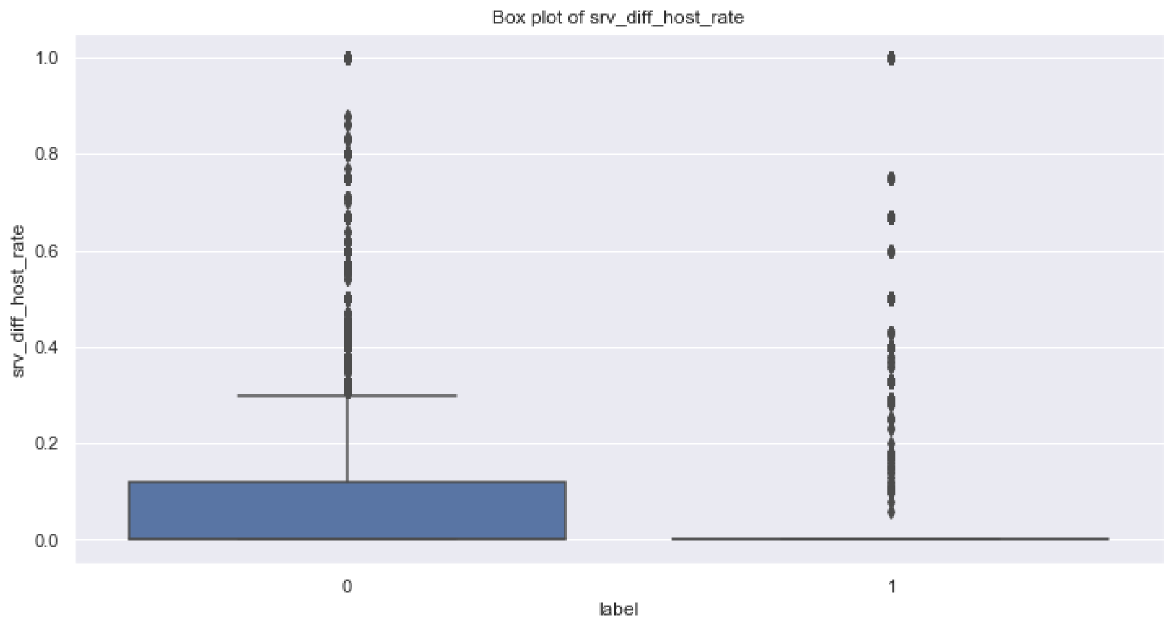


Observations:

1. for label 0 diff_serv_rate has value in range of 0 to 1 but for label 1 it has value less than 0.1 except some outliers.

In [268]:

```
ax = sns.boxplot(y='srv_diff_host_rate',x="label",data=total_data)
plt.title("Box plot of srv_diff_host_rate")
plt.show()
```



Observations:

1. srv_diff_host_rate has 3rd quartile values less than 0.1 for label 0

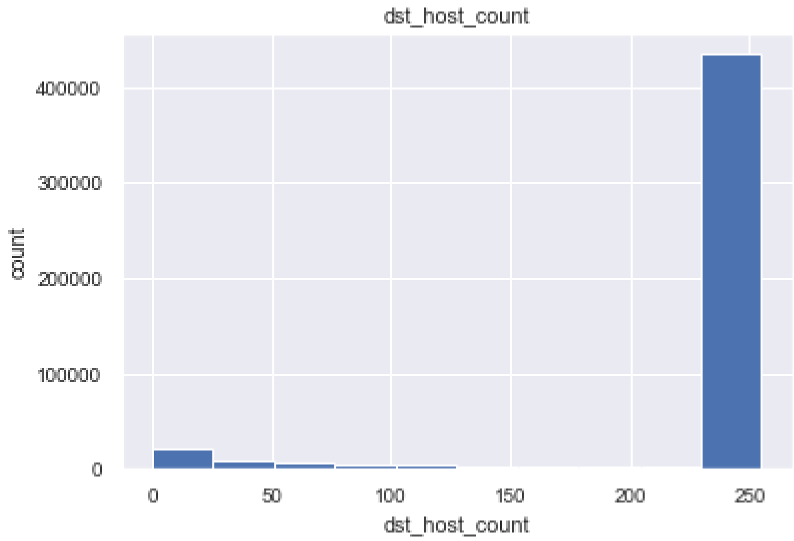
3.3.2 Histogram of features

In [215]:

```
ax=total_data.hist(column='dst_host_count')
pl.xlabel('dst_host_count')
pl.ylabel('count')
```

Out[215]:

```
Text(0, 0.5, 'count')
```



Observations:

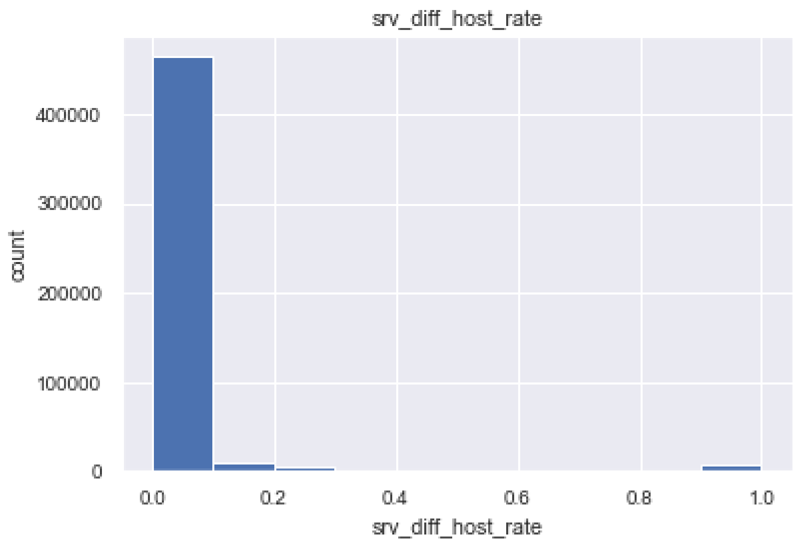
1. dst houst count has most of the values greater than 225.

In [214]:

```
ax=total_data.hist(column='srv_diff_host_rate')
pl.xlabel('srv_diff_host_rate')
pl.ylabel('count')
```

Out[214]:

```
Text(0, 0.5, 'count')
```



Observations:

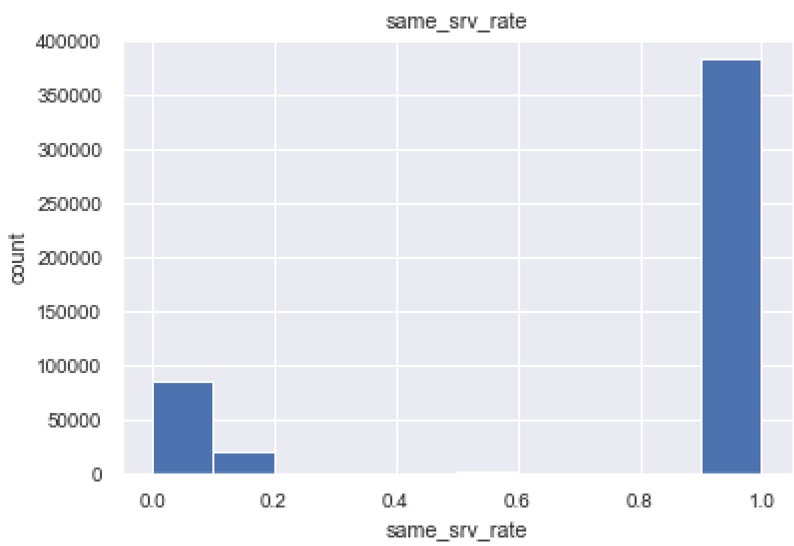
1. srv_diff_host_rate is most of the times less than 0.2.

In [219]:

```
import pylab as pl
ax=total_data.hist(column='same_srv_rate')
pl.xlabel('same_srv_rate')
pl.ylabel('count')
```

Out[219]:

```
Text(0, 0.5, 'count')
```



Observations:

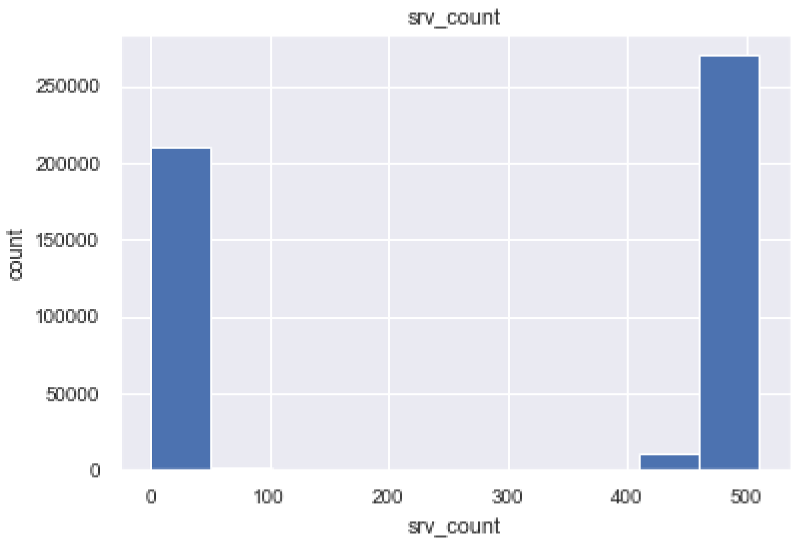
1. same_srv_rate has most of the values greater than 225.

In [208]:

```
ax=total_data.hist(column='srv_count')
pl.xlabel('srv_count')
pl.ylabel('count')
```

Out[208]:

```
Text(0, 0.5, 'count')
```



Observations:

1. srv_count is either less than 50 or greater than 400.

3.3.3 Barplots of categorical data

In [220]:

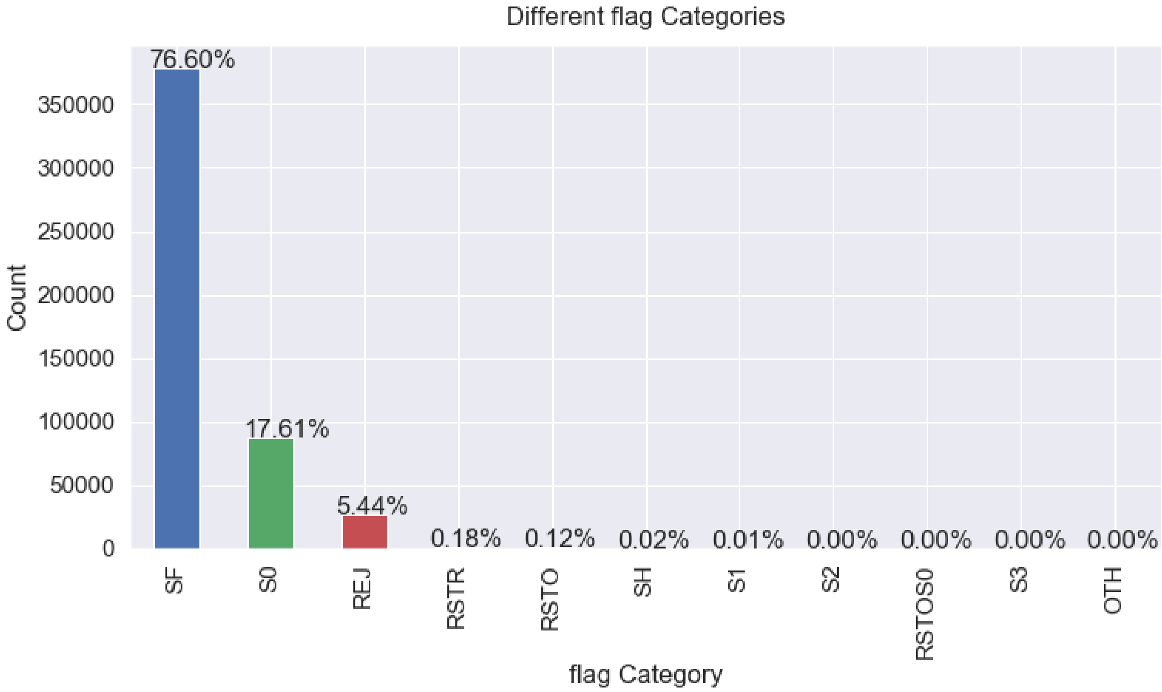
```
total=len(total_data)
```

In [222]:

```
sns.set(font_scale=1.4)
ax=total_data['flag'].value_counts().plot(kind='bar',color=['b','g','r','y','m','c','k'],fi
for p in ax.patches:
        ax.annotate('{:.2f}%'.format(100*p.get_height()/total), (p.get_x()-0.05, p.get_heig
plt.xlabel("flag Category")
plt.ylabel("Count")
plt.title("Different flag Categories",y=1.02)
```

Out[222]:

```
Text(0.5, 1.02, 'Different flag Categories')
```



Observations:

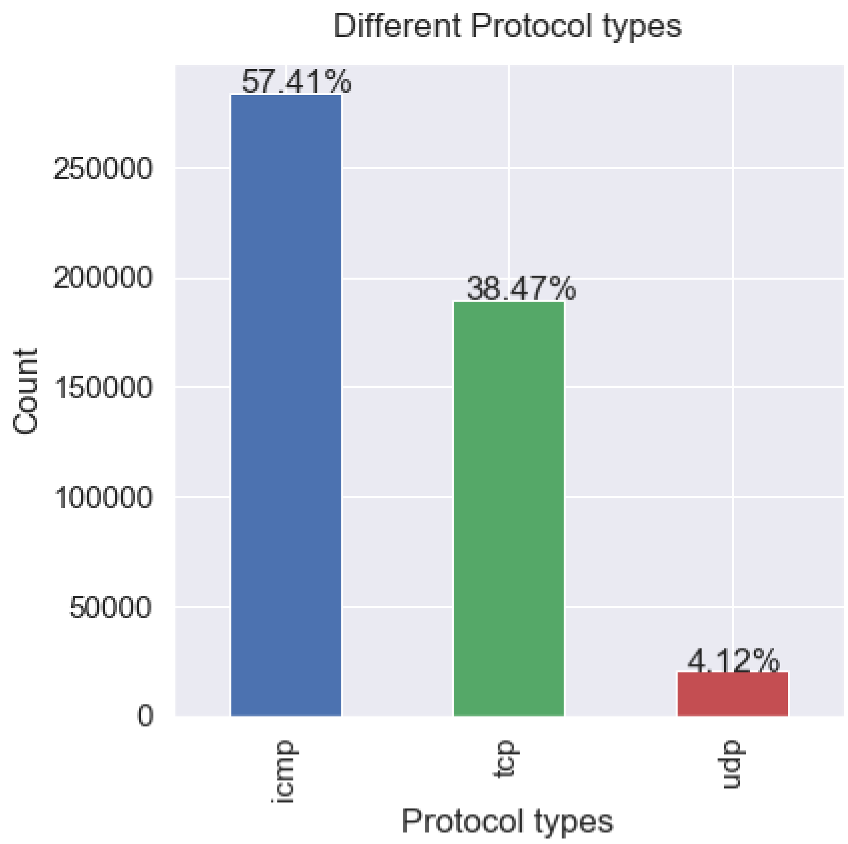
1. SF,S0 and REJ flags present in almost 90% of data.
2. SF flag is most commonly occuring in the data

In [226]:

```
sns.set(font_scale=1.4)
ax=total_data['protocol_type'].value_counts().plot(kind='bar',color=['b','g','r','y','m','c
for p in ax.patches:
        ax.annotate('{:.2f}%'.format(100*p.get_height()/total), (p.get_x()+0.05, p.get_heig
plt.xlabel("Protocol types")
plt.ylabel("Count")
plt.title("Different Protocol types",y=1.02)
```

Out[226]:

```
Text(0.5, 1.02, 'Different Protocol types')
```



Observations:

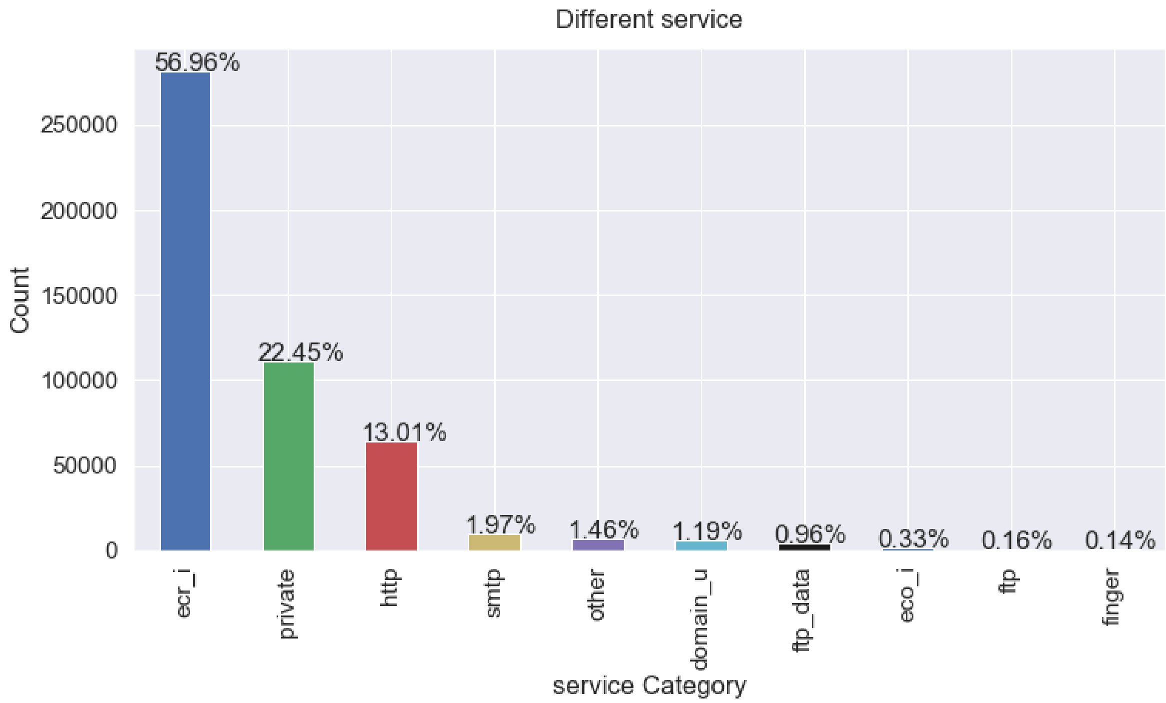
1. icmp and tcp protocols present in almost 95% of data.
2. icmp protocol is most commonly occuring protocol in the data

In [227]:

```
sns.set(font_scale=1.4)
ax=total_data['service'].value_counts()[0:10].plot(kind='bar',color=['b','g','r','y','m','c
for p in ax.patches:
        ax.annotate('{:.2f}%'.format(100*p.get_height()/total), (p.get_x()-0.05, p.get_heig
plt.xlabel("service Category")
plt.ylabel("Count")
plt.title("Different service",y=1.02)
```

Out[227]:

```
Text(0.5, 1.02, 'Different service')
```



Observations:

1. Out of 66 service category present in data only 3 categories occur most frequently.
2. The 3 most commonly occuring service categories are ecr_i, private and http.

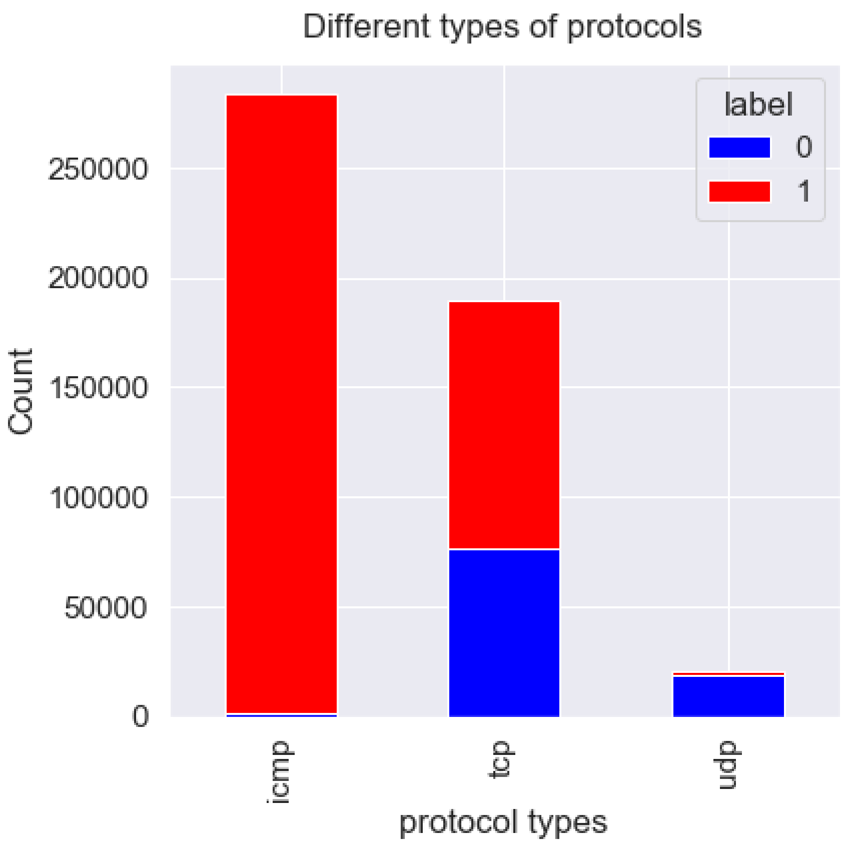
3.3.4 Stacked bar plot of features

In [235]:

```
ax=total_data.groupby(['protocol_type','label']).protocol_type.count()
ax.unstack().sort_values(by=[0 or 1],ascending=False)[0:10].plot(kind='bar',stacked=True,cc
plt.xlabel("protocol types")
plt.ylabel("Count")
plt.title("Different types of protocols",y=1.02)
```

Out[235]:

```
Text(0.5, 1.02, 'Different types of protocols')
```



Observations:

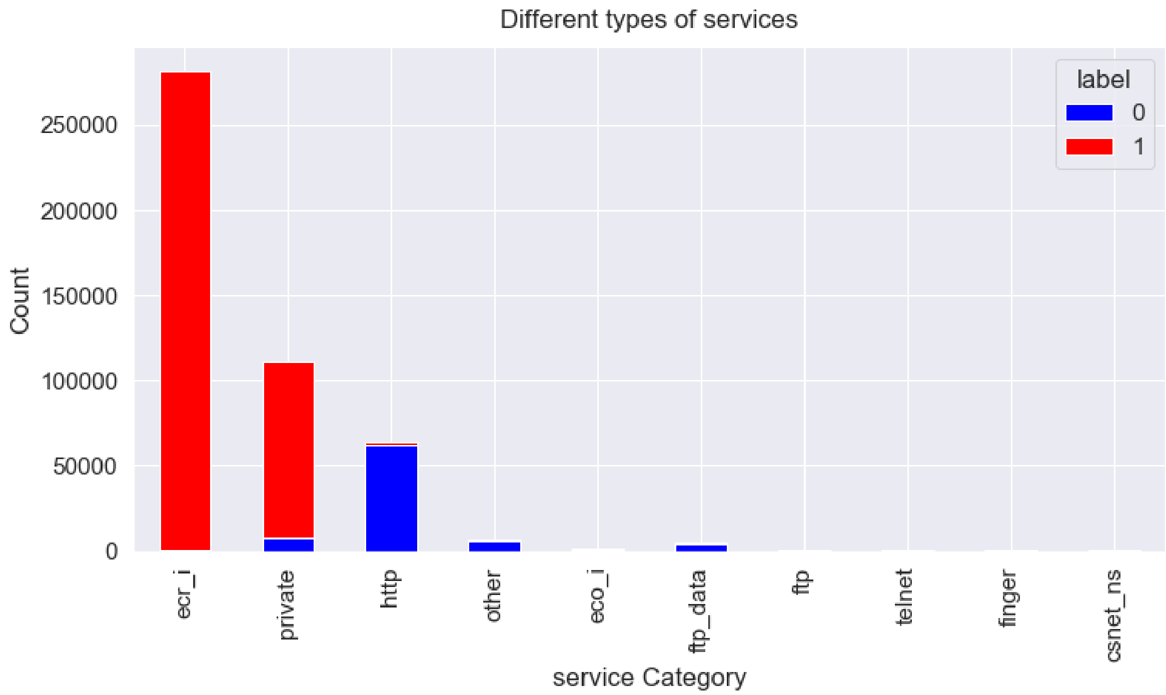
1. icmp protocol contains almost all the data labeled as 1
2. udp protocol has most of the label 0 data

In [240]:

```
ax=total_data.groupby(['service','label']).service.count()
ax=ax.unstack()
ax=ax.sort_values(by=[0 or 1],ascending=False)[0:10]
ax.plot(kind='bar',stacked=True,color=['blue','red'],figsize=(12,6))
plt.xlabel("service Category")
plt.ylabel("Count")
plt.title("Different types of services",y=1.02)
```

Out[240]:

```
Text(0.5, 1.02, 'Different types of services')
```



Observations:

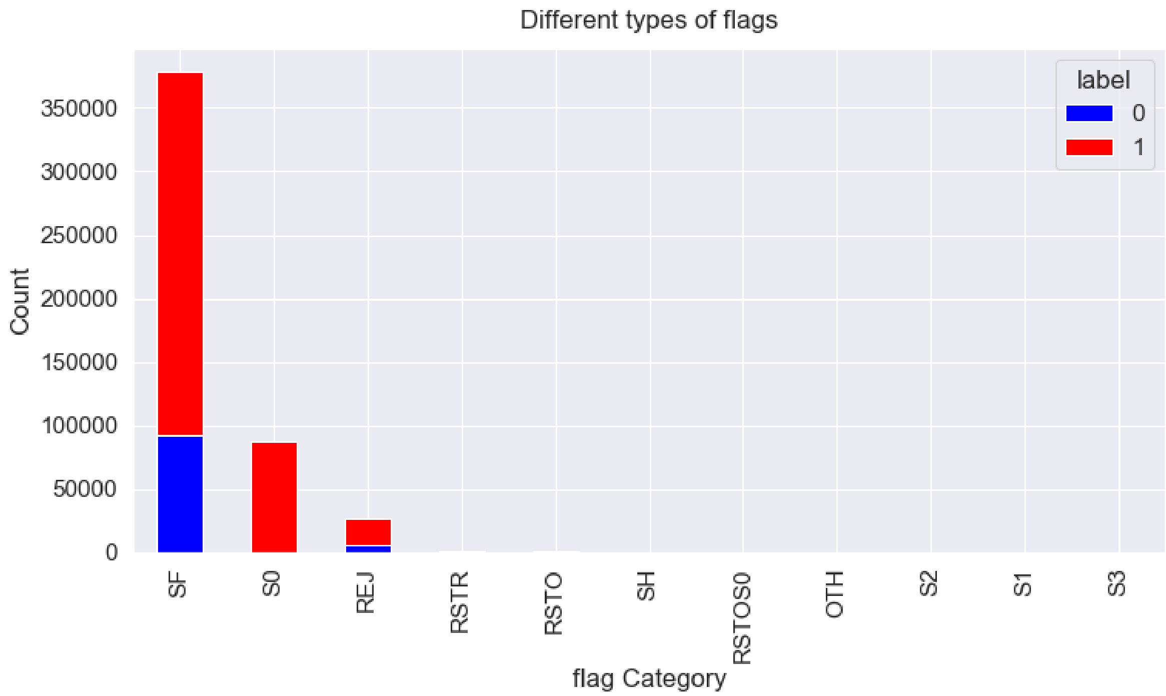
1. Most of the data having service category as ecr_i and private is labeled as class 1.
2. Most of the data having service category as http is labeled as class 0.

In [241]:

```
ax=total_data.groupby(['flag','label']).flag.count()
ax.unstack().sort_values(by=[0 or 1],ascending=False).plot(kind='bar',stacked=True,color=['
plt.xlabel("flag Category")
plt.ylabel("Count")
plt.title("Different types of flags",y=1.02)
```

Out[241]:

```
Text(0.5, 1.02, 'Different types of flags')
```



Observations:

1. S0 and REJ flag are labeled as 1 for most of the times.

3.4 Multivariate Analysis

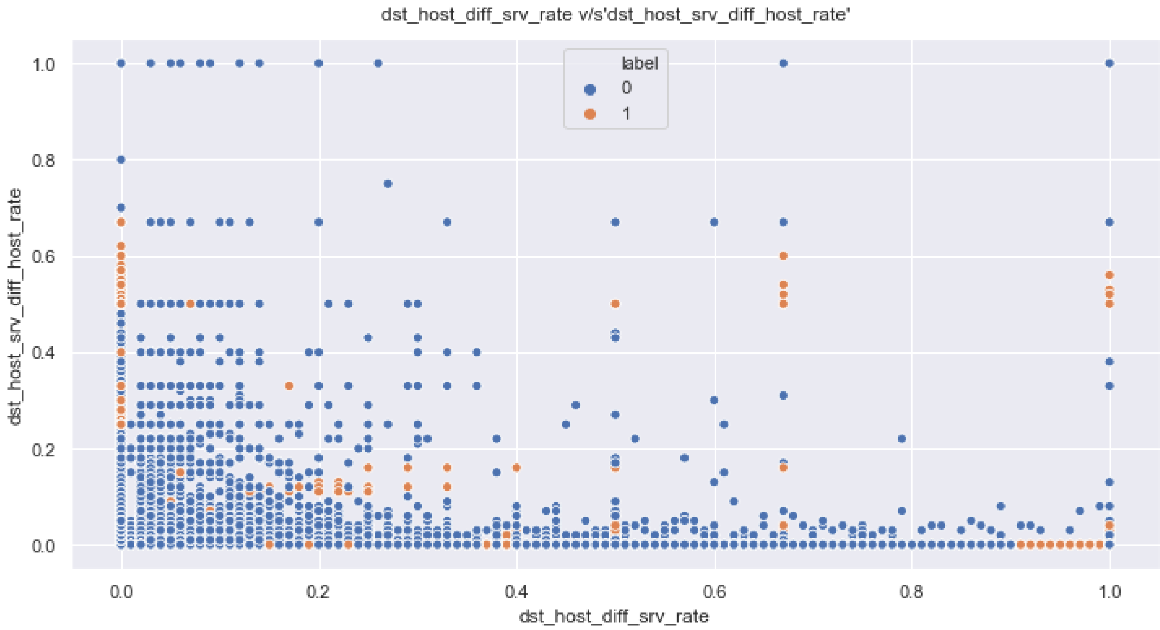
3.4.1 Scatter plot between pair of features

In [270]:

```
sns.scatterplot(x='dst_host_diff_srv_rate',y='dst_host_srv_diff_host_rate',data=total_data,
plt.title("dst_host_diff_srv_rate v/s'dst_host_srv_diff_host_rate'",y=1.02)
```

Out[270]:

```
Text(0.5, 1.02, "dst_host_diff_srv_rate v/s'dst_host_srv_diff_host_rate'")
```



Observations:

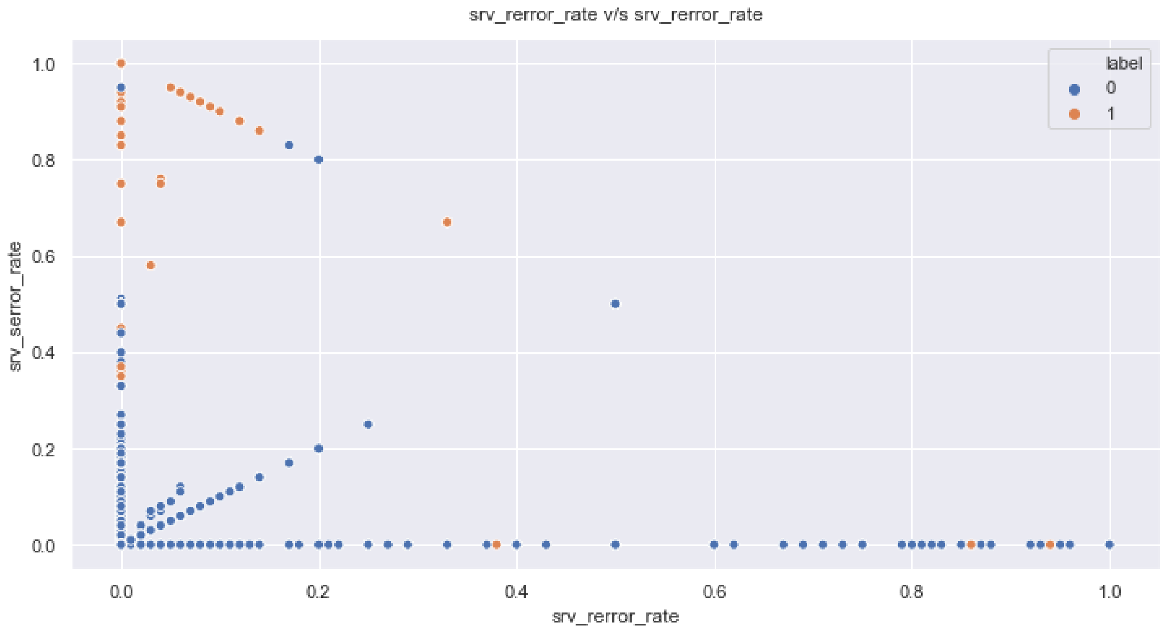
1. dst_host_diff_srv_rate and dst_host_srv_diff_host_rate are always less than1

In [271]:

```
sns.scatterplot(x='srv_rerror_rate',y='srv_serror_rate',data=total_data,hue='label')
plt.title("srv_rerror_rate v/s srv_rerror_rate",y=1.02)
```

Out[271]:

```
Text(0.5, 1.02, 'srv_rerror_rate v/s srv_rerror_rate')
```



Observations:

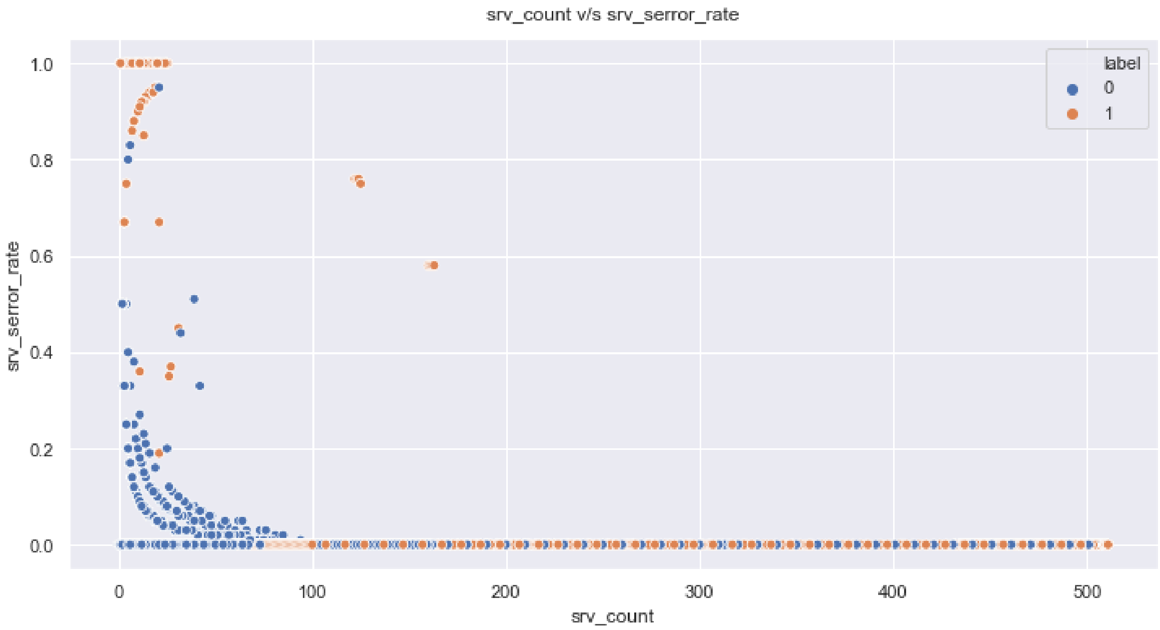
1. srv_serror_rate and srv_rerror_rate have linear relationship for rate less than 0.2

In [272]:

```
sns.scatterplot(x='srv_count',y='srv_serror_rate',data=total_data,hue='label')
plt.title("srv_count v/s srv_serror_rate",y=1.02)
```

Out[272]:

```
Text(0.5, 1.02, 'srv_count v/s srv_serror_rate')
```



Observations: 1.for srv_count less than 100 srv_serror_rate decreases parabolically as srv_count increases

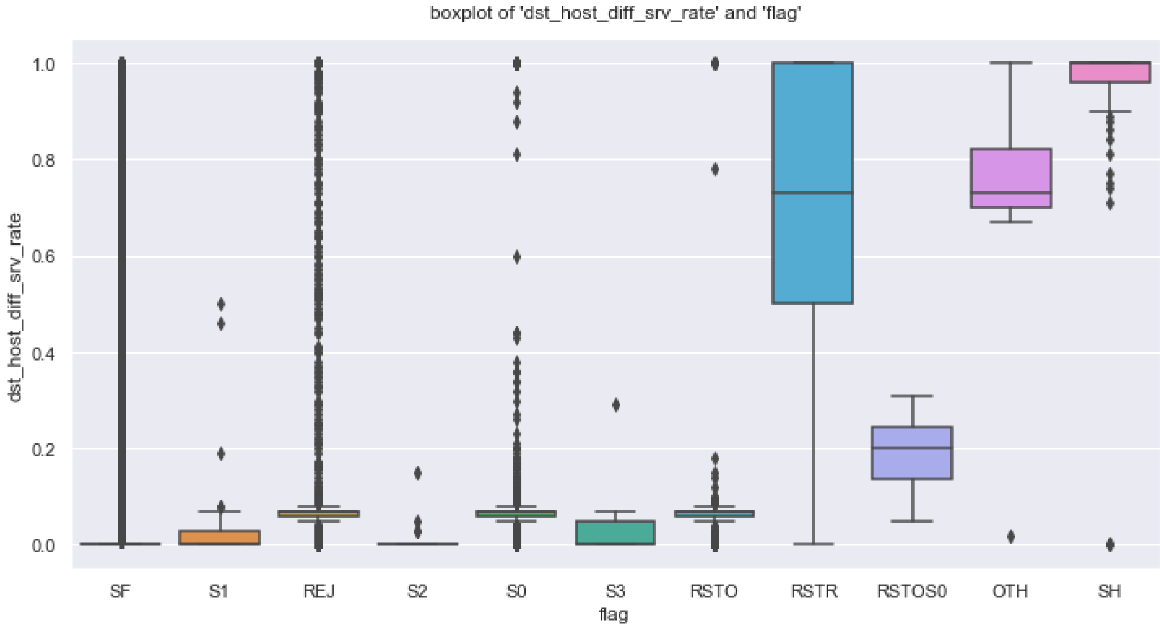
3.4.2 Boxplot between pair of features

In [273]:

```
sns.boxplot(x='flag',y='dst_host_diff_srv_rate',data=total_data)
plt.title("boxplot of dst_host_diff_srv_rate and flag",y=1.02)
```

Out[273]:

```
Text(0.5, 1.02, "boxplot of 'dst_host_diff_srv_rate' and 'flag'")
```



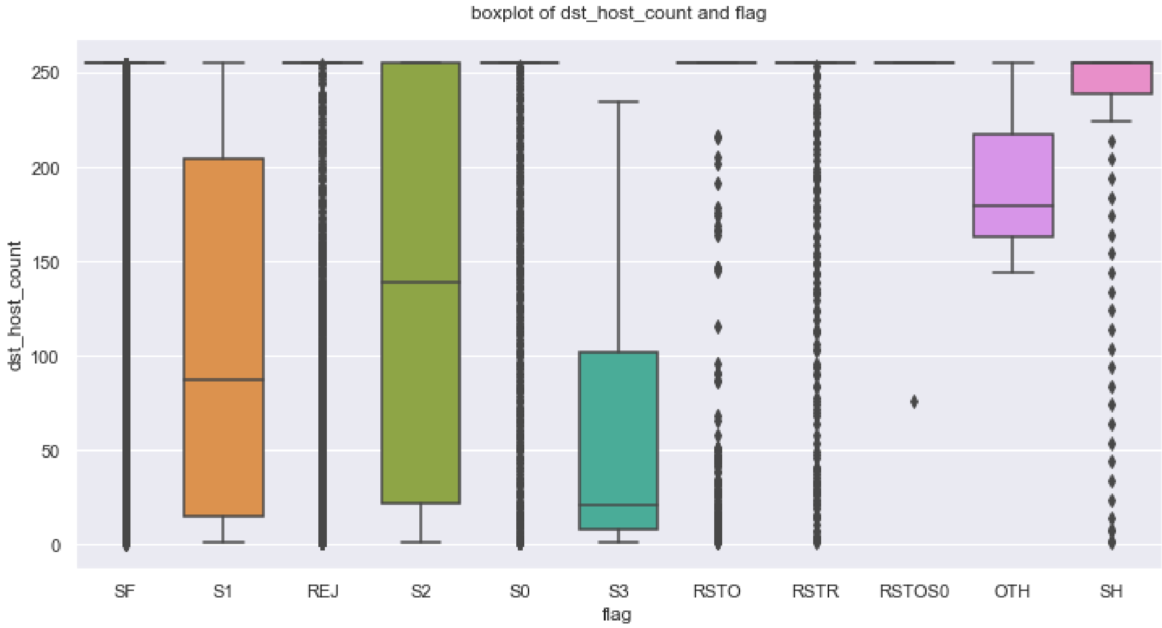
Observations: 1.RSTR ,OTH and SH flags can be separated from others on the basis of dst_host_diff_srv_rate.

In [274]:

```
sns.boxplot(x='flag',y='dst_host_count',data=total_data)
plt.title("boxplot of dst_host_count and flag",y=1.02)
```

Out[274]:

```
Text(0.5, 1.02, 'boxplot of dst_host_count and flag')
```



Observations:

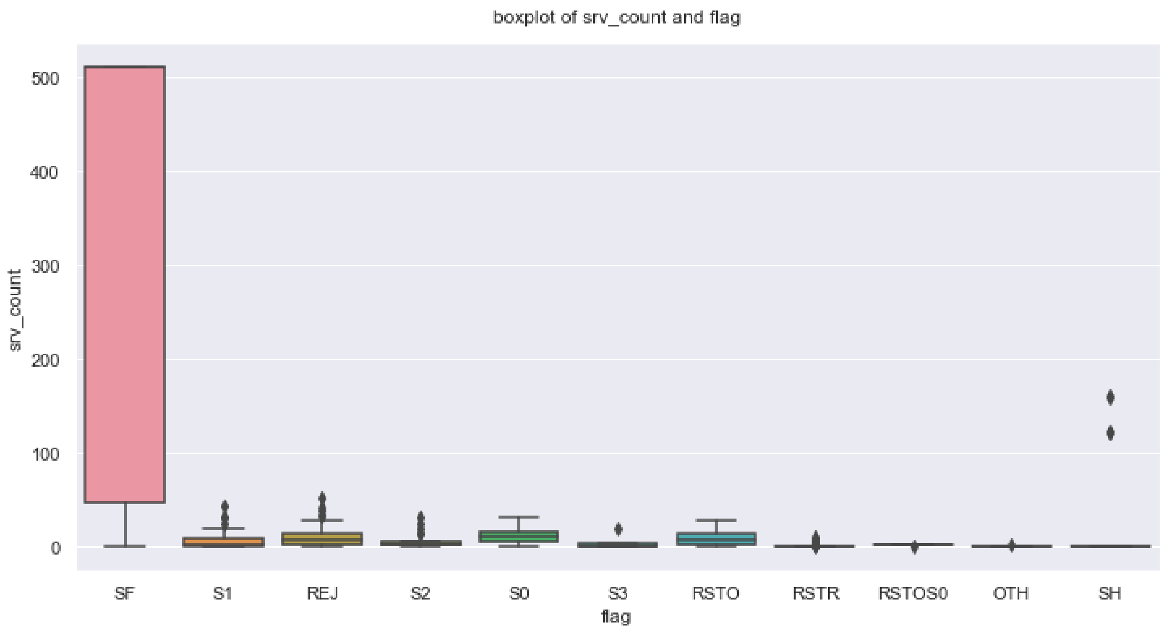
1. S3 flag has 75% dst_host_count values less than 100.

In [275]:

```
sns.boxplot(x='flag',y='srv_count',data=total_data)
plt.title("boxplot of srv_count and flag",y=1.02)
```

Out[275]:

```
Text(0.5, 1.02, 'boxplot of srv_count and flag')
```



Observations:

1. SF flag can be easily separated from rest of the flags on the basis of srv_count values
2. SF flag has most of the srv_count values greater than 50

3.5 PDF and CDF plots dst_bytes

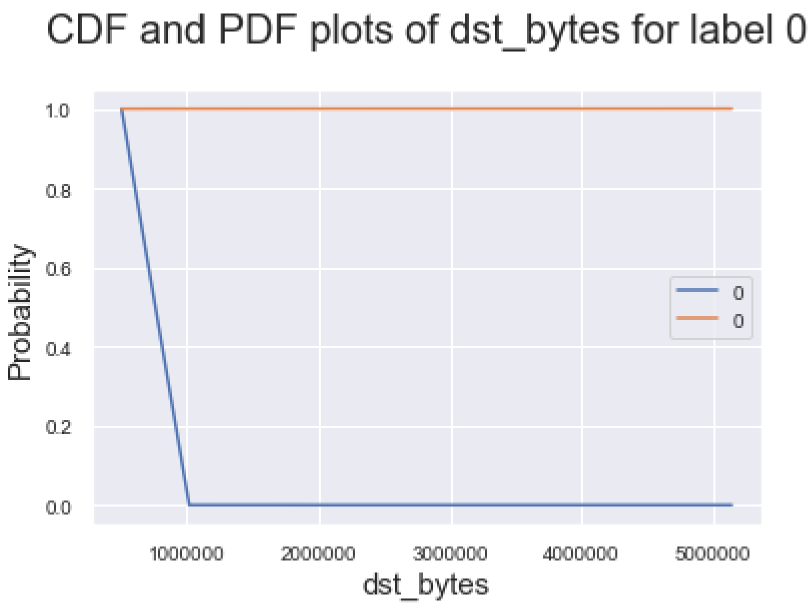
In [597]:

```
td_0 = total_data.loc[total_data["label"] == 0];
td_1 = total_data.loc[total_data["label"] == 1];
```

In [613]:

```
counts, bin_edges = np.histogram(td_0['dst_bytes'], bins=10,
                                 density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)

plt.title("CDF and PDF plots of dst_bytes for label 0",y=1.08,fontsize=20)
plt.xlabel('dst_bytes',fontsize=15)
plt.ylabel('Probability',fontsize=15)
plt.legend("00")

plt.show();
```

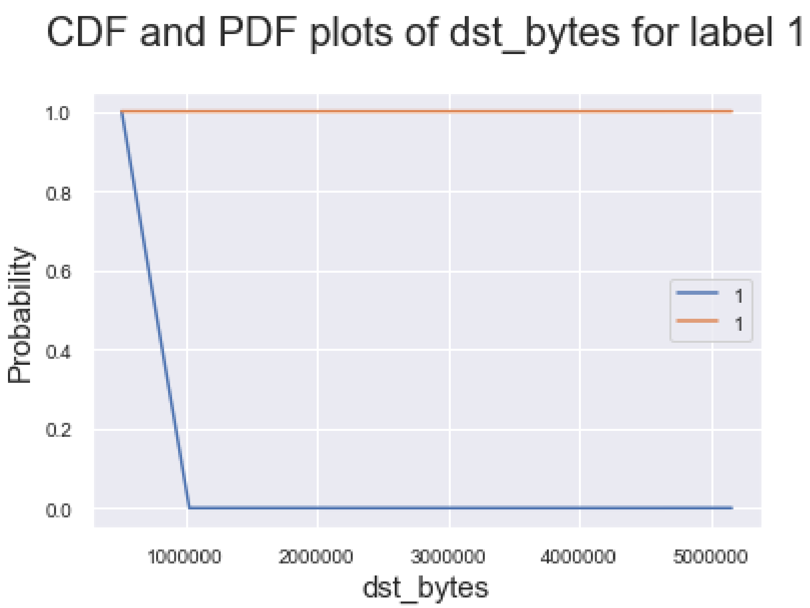
```
[9.99588807e-01 1.74756882e-04 1.13077983e-04 4.11192664e-05
 4.11192664e-05 1.02798166e-05 0.00000000e+00 2.05596332e-05
 0.00000000e+00 1.02798166e-05]
[      0.   513421.8 1026843.6 1540265.4 2053687.2 2567109.  3080530.8
 3593952.6 4107374.4 4620796.2 5134218. ]
```



In [614]:

```
counts, bin_edges = np.histogram(td_1['dst_bytes'], bins=10,
                                 density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)
plt.title("CDF and PDF plots of dst_bytes for label 1",y=1.08,fontsize=20)
plt.xlabel('dst_bytes',fontsize=15)
plt.ylabel('Probability',fontsize=15)
plt.legend("11")
#Y=survived N=Not Survived



plt.show();
```

```
[9.99954631e-01 5.04104672e-06 2.52052336e-06 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 3.78078504e-05]
[      0.    515546.8 1031093.6 1546640.4 2062187.2 2577734.  3093280.8
 3608827.6 4124374.4 4639921.2 5155468. ]
```



Observation:

1. Both cdf and pdf plots for label 0 and label 1 are overlapping.
2. As the number of dst_bytes increases probability decreases for both class labels.

3.5 Conclusions from EDA

1. EDA shows that there are 20 pairs of numerical features which are highly correlated having correlation coefficient greater than 0.8.
2. There are only few sub_categories in every category that are dominant than others.
3. Univariate analysis is carried out using boxplot,barplot and histogram shows the frequency of data with respect to each feature.
4. Bivariate analysis using scatter plot shows the relation between pair of features.
5. It seems from eda that dst_host_count,srv_count,S0,SF,icmp,http could be the best features for modelling.

4.Preparing Data For Models

In [27]:

```
X=total_data
```

In [28]:

```
y=total_data['label'].values
total_data.drop(['label','hot','num_compromised','count','dst_host_same_src_port_rate','ser
total_data.head(1)
```

Out[28]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent
0	0	tcp	http	SF	181	5450	0	0	0

1 rows × 29 columns

4.1 Train-Test split

In [29]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y,random_
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.2,stratify=y_
```

In [30]:

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
print(X_cv.shape)
print(y_cv.shape)
```

```
(316172, 29)
(98805, 29)
(316172,)
(98805,)
(79044, 29)
(79044,)
```

In [31]:

```
total_data.columns.values
```

Out[31]:

```
array(['duration', 'protocol_type', 'service', 'flag', 'src_bytes',
       'dst_bytes', 'land', 'wrong_fragment', 'urgent',
       'num_failed_logins', 'logged_in', 'root_shell', 'su_attempted',
       'num_root', 'num_file_creations', 'num_shells', 'num_access_files',
       'num_outbound_cmds', 'is_host_login', 'is_guest_login',
       'srv_count', 'srv_serror_rate', 'srv_rerror_rate', 'same_srv_rate',
       'diff_srv_rate', 'srv_diff_host_rate', 'dst_host_count',
       'dst_host_diff_srv_rate', 'dst_host_srv_diff_host_rate'],
      dtype=object)
```

In [32]:

```
b=['duration','src_bytes','dst_bytes','land','wrong_fragment','urgent',
       'num_failed_logins', 'logged_in', 'root_shell', 'su_attempted',
       'num_root', 'num_file_creations', 'num_shells', 'num_access_files',
       'num_outbound_cmds', 'is_host_login', 'is_guest_login',
       'srv_count','srv_serror_rate', 'srv_rerror_rate', 'same_srv_rate',
       'diff_srv_rate','srv_diff_host_rate', 'dst_host_count',
       'dst_host_diff_srv_rate', 'dst_host_srv_diff_host_rate']
```

4.2 Encoding Catagorical Features

In [33]:

```
from sklearn.feature_extraction.text import CountVectorizer
```

In [34]:

```
a=[]

vec = CountVectorizer()
X_train_proto_ohe = vec.fit_transform(X_train['protocol_type'].values)
X_cv_proto_ohe = vec.transform(X_cv['protocol_type'].values)
X_test_proto_ohe = vec.transform(X_test['protocol_type'].values)
print("After vectorizations")
print(X_train_proto_ohe.shape, y_train.shape)
print(X_cv_proto_ohe.shape, y_cv.shape)
print(X_test_proto_ohe.shape, y_test.shape)
print(vec.get_feature_names())
print("-"*125)
a.extend(vec.get_feature_names())
```

```
After vectorizations
(316172, 3) (316172,)
(79044, 3) (79044,)
(98805, 3) (98805,)
['icmp', 'tcp', 'udp']
----------------------------------------------------------------------------
-------------------------------------------------
```

In [35]:

```
vec = CountVectorizer()
X_train_service_ohe = vec.fit_transform(X_train['service'].values)
X_cv_service_ohe = vec.transform(X_cv['service'].values)
X_test_service_ohe = vec.transform(X_test['service'].values)
print("After vectorizations")
print(X_train_service_ohe.shape, y_train.shape)
print(X_cv_service_ohe.shape, y_cv.shape)
print(X_test_service_ohe.shape, y_test.shape)
print(vec.get_feature_names())
print("-"*125)
a.extend(vec.get_feature_names())
```

```
After vectorizations
(316172, 64) (316172,)
(79044, 64) (79044,)
(98805, 64) (98805,)
['auth', 'bgp', 'courier', 'csnet_ns', 'ctf', 'daytime', 'discard', 'domai
n', 'domain_u', 'echo', 'eco_i', 'ecr_i', 'efs', 'exec', 'finger', 'ftp', 'f
tp_data', 'gopher', 'hostnames', 'http', 'http_443', 'imap4', 'irc', 'iso_ts
ap', 'klogin', 'kshell', 'ldap', 'link', 'login', 'mtp', 'name', 'netbios_dg
m', 'netbios_ns', 'netbios_ssn', 'netstat', 'nnsp', 'nntp', 'ntp_u', 'othe
r', 'pm_dump', 'pop_2', 'pop_3', 'printer', 'private', 'remote_job', 'rje',
'shell', 'smtp', 'sql_net', 'ssh', 'sunrpc', 'supdup', 'systat', 'telnet',
'tim_i', 'time', 'urh_i', 'urp_i', 'uucp', 'uucp_path', 'vmnet', 'whois', 'x
11', 'z39_50']
----------------------------------------------------------------------------
-------------------------------------------------
```

In [37]:

```
vec = CountVectorizer()
X_train_flag_ohe = vec.fit_transform(X_train['flag'].values)
X_cv_flag_ohe = vec.transform(X_cv['flag'].values)
X_test_flag_ohe = vec.transform(X_test['flag'].values)
print("After vectorizations")
print(X_train_flag_ohe.shape, y_train.shape)
print(X_cv_flag_ohe.shape, y_cv.shape)
print(X_test_flag_ohe.shape, y_test.shape)
print(vec.get_feature_names())
print("-"*125)
a.extend(vec.get_feature_names())
```

```
After vectorizations
(316172, 11) (316172,)
(79044, 11) (79044,)
(98805, 11) (98805,)
['oth', 'rej', 'rsto', 'rstos0', 'rstr', 's0', 's1', 's2', 's3', 'sf', 'sh']
----------------------------------------------------------------------------
-------------------------------------------------
```

4.3 Encoding Numerical Features

In [38]:

```
col_names=b
```

In [39]:

```
from sklearn.preprocessing import Normalizer
scalar = Normalizer()
X_train_num_scalar = scalar.fit_transform(X_train[col_names].values)
X_cv_num_scalar = scalar.transform(X_cv[col_names].values)
X_test_num_scalar = scalar.transform(X_test[col_names].values)
print("After vectorizations")
print(X_train_num_scalar.shape, y_train.shape)
print(X_cv_num_scalar.shape, y_cv.shape)
print(X_test_num_scalar.shape, y_test.shape)
print("-"*125)
a.extend(b)
```

```
After vectorizations
(316172, 26) (316172,)
(79044, 26) (79044,)
(98805, 26) (98805,)
----------------------------------------------------------------------------
-------------------------------------------------
```

In [40]:

```
from scipy.sparse import hstack
X_tr = hstack((X_train_proto_ohe,X_train_service_ohe,X_train_flag_ohe,X_train_num_scalar))
X_te = hstack((X_test_proto_ohe,X_test_service_ohe,X_test_flag_ohe,X_test_num_scalar))
X_cv = hstack((X_cv_proto_ohe,X_cv_service_ohe,X_cv_flag_ohe,X_cv_num_scalar))
print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_te.shape, y_test.shape)
print(X_cv.shape, y_cv.shape)
print("-"*125)
```

```
Final Data matrix
(316172, 104) (316172,)
(98805, 104) (98805,)
(79044, 104) (79044,)
----------------------------------------------------------------------------
-------------------------------------------------
```

In [41]:

```
len(a)
```

Out[41]:

```
104
```

5. Machine Learning Models

In [42]:

```
from sklearn.metrics import accuracy_score as accuracy
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
```

In [43]:

```
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
```

In [294]:

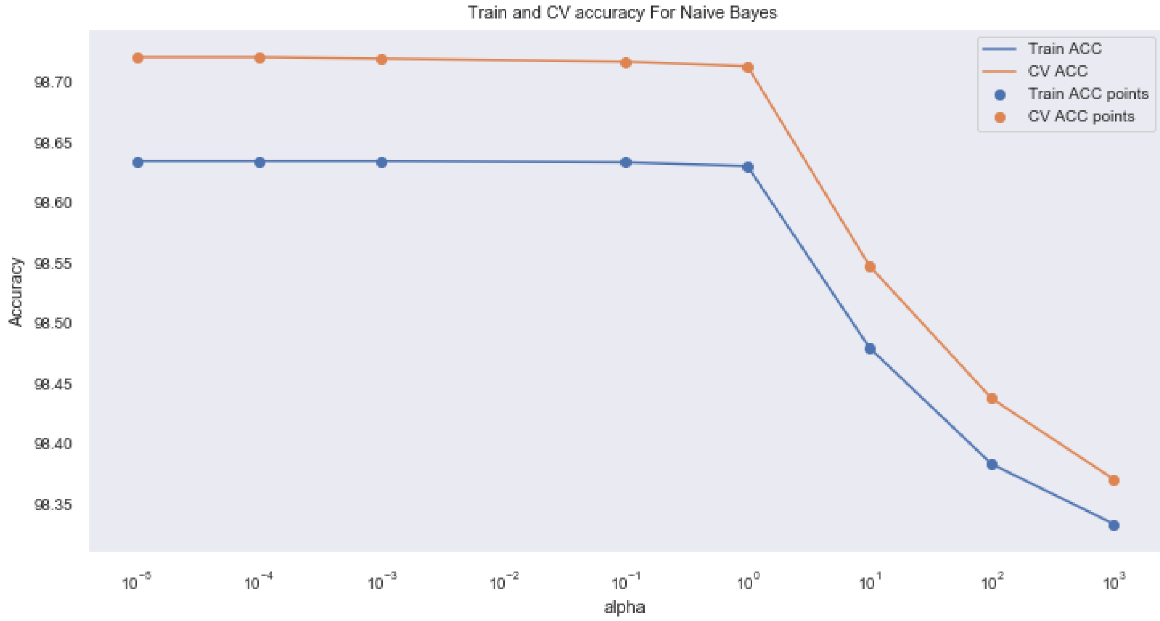
```
sns.set(font_scale=0.9)
```

5.1 Multinomial Naive Bayes

In [401]:

```
train_accuracy=[]
cv_accuracy = []
alpha = [0.00001, 0.0001, 0.001, 0.1, 1, 10, 100,1000]
for i in alpha:
    print("for alpha =", i)
    clf = MultinomialNB(alpha=i)
    clf.fit(X_tr, y_train)
    y_train_pred = clf.predict(X_tr)
    y_cv_pred = clf.predict(X_cv)
    train_accuracy.append(accuracy(y_train,y_train_pred)*100)
    cv_accuracy.append(accuracy(y_cv,y_cv_pred)*100)
    print("Train Accuracy: {}%  CV Accuracy: {}%".format(np.round(accuracy(y_train,y_train_
    print("-"*50)
plt.plot(alpha, train_accuracy, label='Train ACC')
plt.plot(alpha, cv_accuracy, label='CV ACC')
plt.scatter(alpha, train_accuracy, label='Train ACC points')
plt.scatter(alpha, cv_accuracy, label='CV ACC points')
plt.legend()
plt.xlabel("alpha")
plt.xscale("log")
plt.ylabel("Accuracy")
plt.title("Train and CV accuracy For Naive Bayes ")
plt.grid()
plt.show()
```

```
for alpha = 1e-05
Train Accuracy: 98.6346%  CV Accuracy: 98.721%
--------------------------------------------------
for alpha = 0.0001
Train Accuracy: 98.6346%  CV Accuracy: 98.721%
--------------------------------------------------
for alpha = 0.001
Train Accuracy: 98.6346%  CV Accuracy: 98.7197%
--------------------------------------------------
for alpha = 0.1
Train Accuracy: 98.6337%  CV Accuracy: 98.7172%
--------------------------------------------------
for alpha = 1
Train Accuracy: 98.6305%  CV Accuracy: 98.7134%
--------------------------------------------------
for alpha = 10
Train Accuracy: 98.4796%  CV Accuracy: 98.5476%
--------------------------------------------------
for alpha = 100
Train Accuracy: 98.3832%  CV Accuracy: 98.4376%
--------------------------------------------------
for alpha = 1000
Train Accuracy: 98.3335%  CV Accuracy: 98.3705%
--------------------------------------------------
```



In [328]:

```
best_alpha = np.argmax(cv_accuracy)
clf = MultinomialNB(alpha=alpha[best_alpha])
clf.fit(X_tr,y_train)
predict_y_tr = clf.predict(X_tr)
print('For values of best alpha = ', alpha[best_alpha], "The Train Accuracy is:",np.round(a
predict_y_cv = clf.predict(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation Accuracy is:"
predict_y_te = clf.predict(X_te)
print('For values of best alpha = ', alpha[best_alpha], "The test Accuracy is:",np.round(ac
```

```
For values of best alpha =  1e-05 The Train Accuracy is: 98.6346
For values of best alpha =  1e-05 The cross validation Accuracy is: 98.721
For values of best alpha =  1e-05 The test Accuracy is: 98.6731
```

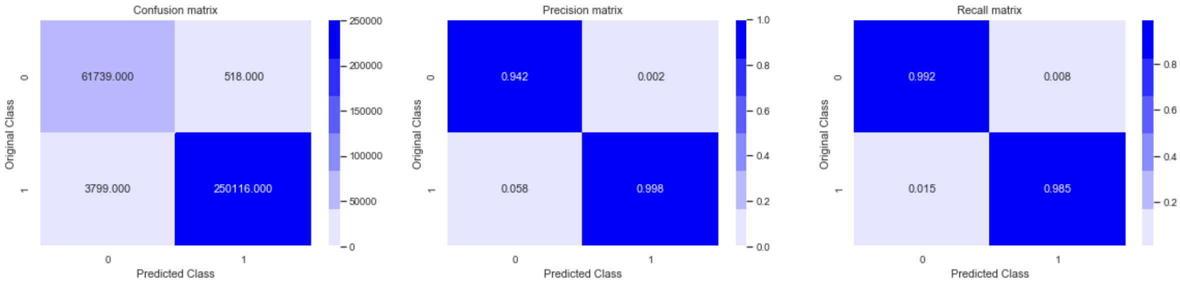
In [329]:

```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels
    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=labels
    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=labels
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

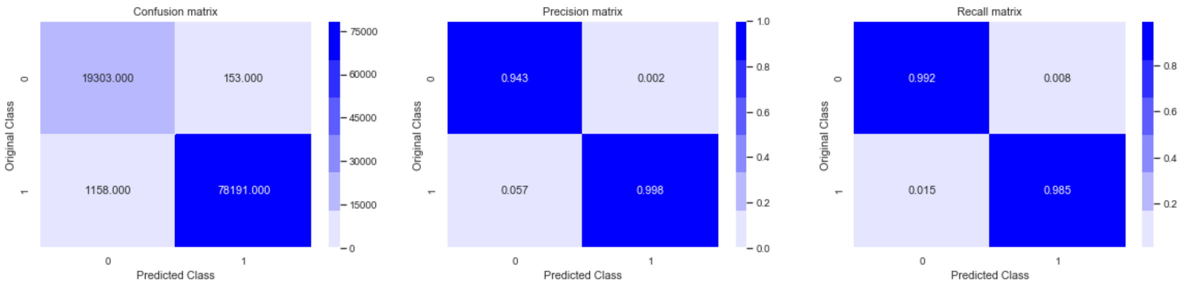
In [330]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict_y_tr)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict_y_te)
```

```
Train confusion_matrix
```




```
Test confusion_matrix
```



5.1.1 Top 10 important class label 1 features

In [389]:

```
sorted_idx1 = np.argsort( clf.feature_log_prob_ )[1][::-1][0:10]
top_pos=np.take(a,sorted_idx1)
print("Top 10 important class label 1 features are:",top_pos)
```

```
Top 10 important class label 1 features are: ['sf' 'icmp' 'ecr_i' 'src_byte
s' 'dst_host_count' 'srv_count' 'tcp'
 'private' 's0' 'rej']
```

5.1.2 Top 10 important class label 0 features

In [391]:

```
sorted_idx2 = np.argsort( clf.feature_log_prob_ )[0][::-1][0:10]
top_neg=np.take(a,sorted_idx2)
print("Top 10 important class label 0 features are:",top_neg)
```

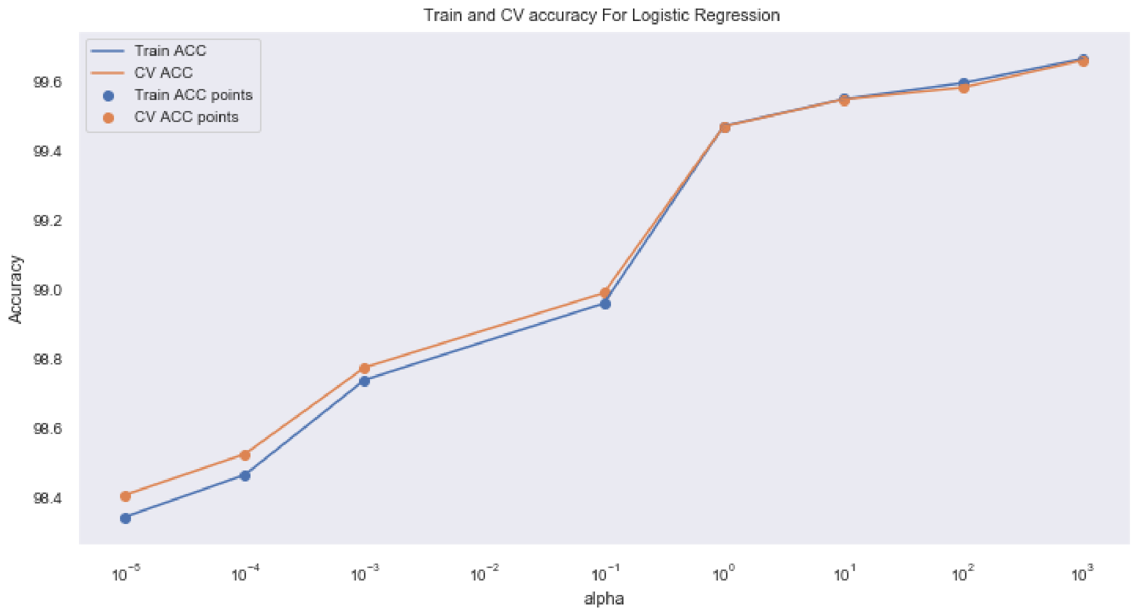
```
Top 10 important class label 0 features are: ['sf' 'tcp' 'http' 'dst_bytes'
'src_bytes' 'dst_host_count' 'udp' 'smtp'
 'private' 'domain_u']
```

5.2 Logistic Regression

In [429]:

```
from sklearn.linear_model import LogisticRegression
train_accuracy=[]
cv_accuracy = []
C = [0.00001, 0.0001, 0.001, 0.1, 1, 10, 100,1000]
for i in C:
    print("for C =", i)
    clf = LogisticRegression(C=i,class_weight='balanced')
    clf.fit(X_tr, y_train)
    y_train_pred = clf.predict(X_tr)
    y_cv_pred = clf.predict(X_cv)
    train_accuracy.append(accuracy(y_train,y_train_pred)*100)
    cv_accuracy.append(accuracy(y_cv,y_cv_pred)*100)
    print("Train Accuracy: {}%  CV Accuracy: {}%".format(np.round(accuracy(y_train,y_train_
    print("-"*50)
plt.plot(C, train_accuracy, label='Train ACC')
plt.plot(C, cv_accuracy, label='CV ACC')
plt.scatter(C, train_accuracy, label='Train ACC points')
plt.scatter(C, cv_accuracy, label='CV ACC points')
plt.legend()
plt.xlabel("alpha")
plt.xscale("log")
plt.ylabel("Accuracy")
plt.title("Train and CV accuracy For Logistic Regression ")
plt.grid()
plt.show()
```

```
for C = 1e-05
Train Accuracy: 98.3436%  CV Accuracy: 98.4072%
--------------------------------------------------
for C = 0.0001
Train Accuracy: 98.4651%  CV Accuracy: 98.5249%
--------------------------------------------------
for C = 0.001
Train Accuracy: 98.7383%  CV Accuracy: 98.7741%
--------------------------------------------------
for C = 0.1
Train Accuracy: 98.9591%  CV Accuracy: 98.9892%
--------------------------------------------------
for C = 1
Train Accuracy: 99.4699%  CV Accuracy: 99.4687%
--------------------------------------------------
for C = 10
Train Accuracy: 99.5477%  CV Accuracy: 99.5471%
--------------------------------------------------
for C = 100
Train Accuracy: 99.5942%  CV Accuracy: 99.5812%
--------------------------------------------------
for C = 1000
Train Accuracy: 99.6638%  CV Accuracy: 99.6597%
--------------------------------------------------
```



In [430]:

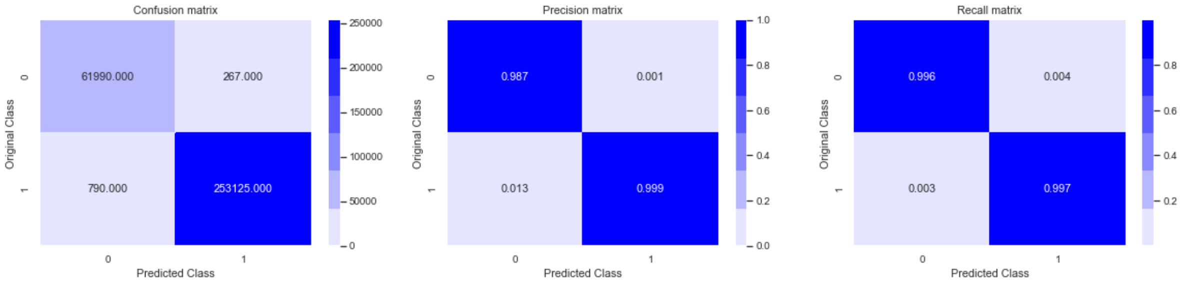
```
best_C = np.argmax(cv_accuracy)
clf = LogisticRegression(C=C[best_C])
clf.fit(X_tr,y_train)
predict_y_tr = clf.predict(X_tr)
print('For values of best alpha = ',C[best_C], "The Train Accuracy is:",np.round(accuracy(y
predict_y_cv = clf.predict(X_cv)
print('For values of best alpha = ', C[best_C], "The cross validation Accuracy is:",np.rour
predict_y_te = clf.predict(X_te)
print('For values of best alpha = ', C[best_C], "The test Accuracy is:",np.round(accuracy(y
```

```
For values of best alpha =  1000 The Train Accuracy is: 99.6657
For values of best alpha =  1000 The cross validation Accuracy is: 99.642
For values of best alpha =  1000 The test Accuracy is: 99.6195
```

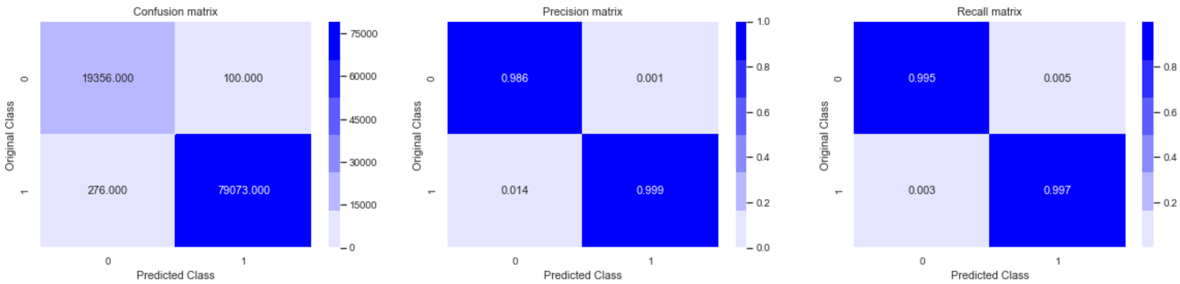
In [431]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict_y_tr)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict_y_te)
```

```
Train confusion_matrix
```



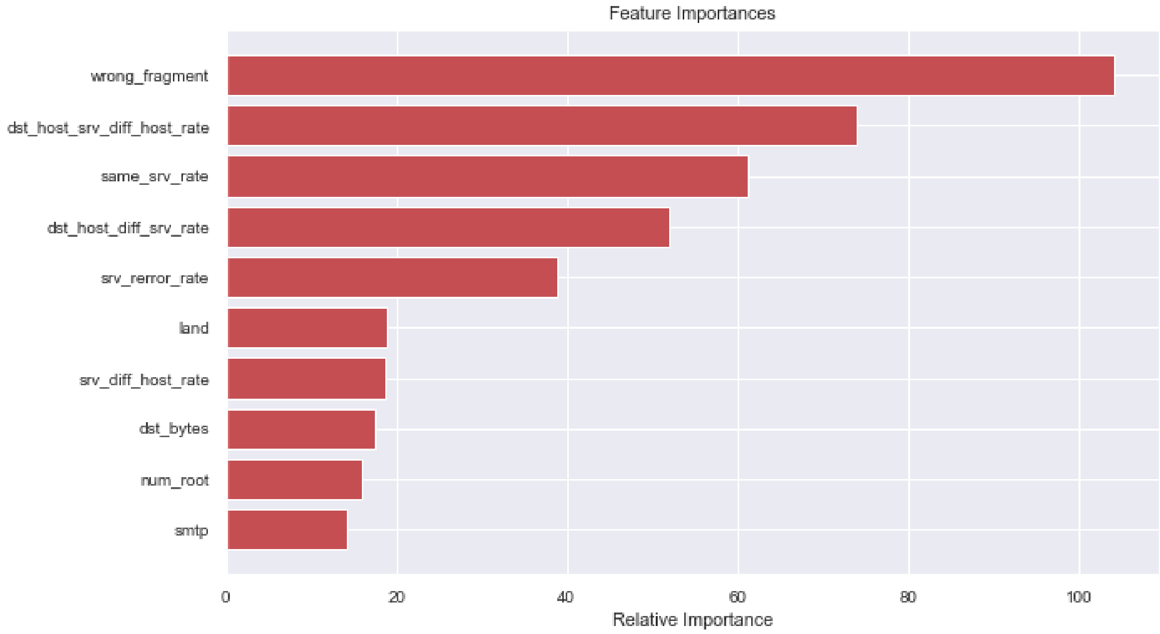

```
Test confusion_matrix
```



5.2.2 Important Features from LR model

In [494]:

```
features=a
importances=abs(clf.coef_[0])
indices = (np.argsort(importances))[-10:]
plt.figure(figsize=(10,6))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

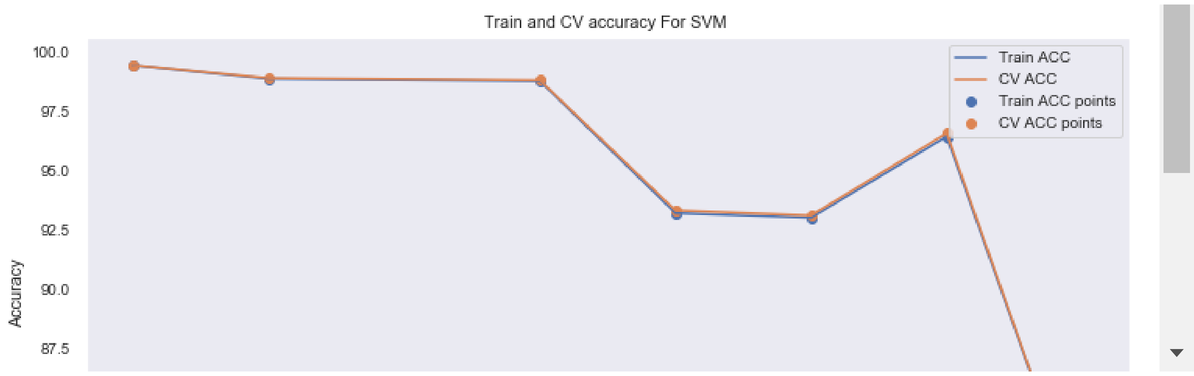


5.3 Support Vector Machines

In [495]:

```
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train_accuracy=[]
cv_accuracy = []
alpha = [0.0001, 0.001, 0.1, 1, 10, 100,1000]
for i in alpha:
    print("for alpha =", i)
    clf =SGDClassifier(alpha=i,loss='hinge',class_weight='balanced')
    #clf = CalibratedClassifierCV(SVM, cv=5, method='sigmoid')
    clf.fit(X_tr, y_train)
    y_train_pred = clf.predict(X_tr)
    y_cv_pred = clf.predict(X_cv)
    train_accuracy.append(accuracy(y_train,y_train_pred)*100)
    cv_accuracy.append(accuracy(y_cv,y_cv_pred)*100)
    print("Train Accuracy: {}%  CV Accuracy: {}%".format(np.round(accuracy(y_train,y_train_
    print("-"*50)
plt.plot(alpha, train_accuracy, label='Train ACC')
plt.plot(alpha, cv_accuracy, label='CV ACC')
plt.scatter(alpha, train_accuracy, label='Train ACC points')
plt.scatter(alpha, cv_accuracy, label='CV ACC points')
plt.legend()
plt.xlabel("alpha")
plt.xscale("log")
plt.ylabel("Accuracy")
plt.title("Train and CV accuracy For SVM ")
plt.grid()
plt.show()
```

```
for alpha = 0.0001
Train Accuracy: 99.4158%  CV Accuracy: 99.4218%
--------------------------------------------------
for alpha = 0.001
Train Accuracy: 98.8557%  CV Accuracy: 98.8842%
--------------------------------------------------
for alpha = 0.1
Train Accuracy: 98.7621%  CV Accuracy: 98.7981%
--------------------------------------------------
for alpha = 1
Train Accuracy: 93.192%  CV Accuracy: 93.3037%
--------------------------------------------------
for alpha = 10
Train Accuracy: 92.9994%  CV Accuracy: 93.0937%
--------------------------------------------------
for alpha = 100
Train Accuracy: 96.4222%  CV Accuracy: 96.5589%
--------------------------------------------------
for alpha = 1000
Train Accuracy: 80.3091%  CV Accuracy: 80.3084%
--------------------------------------------------
```



In [496]:

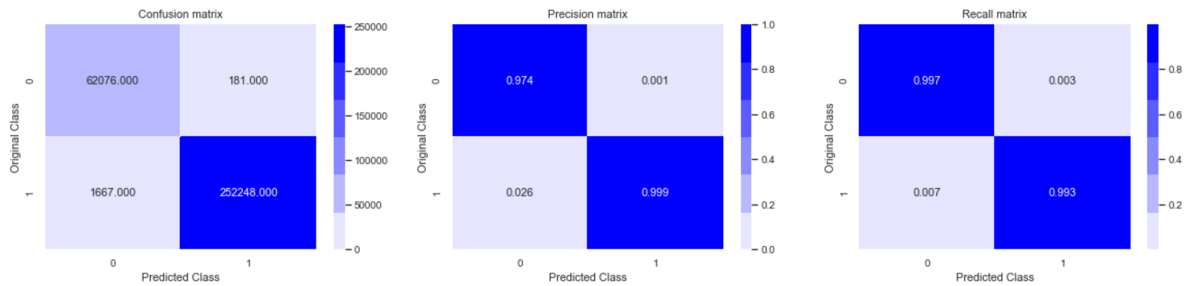
```
best_alpha = np.argmax(cv_accuracy)
clf =SGDClassifier(alpha=alpha[best_alpha],loss='hinge',class_weight='balanced')
#clf = CalibratedClassifierCV(SVM, cv=5, method='sigmoid')
clf.fit(X_tr,y_train)
predict_y_tr = clf.predict(X_tr)
print('For values of best alpha = ',alpha[best_alpha], "The Train Accuracy is:",np.round(ac
predict_y_cv = clf.predict(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation Accuracy is:"
predict_y_te = clf.predict(X_te)
print('For values of best alpha = ', alpha[best_alpha], "The test Accuracy is:",np.round(ac
```

```
For values of best alpha =  0.0001 The Train Accuracy is: 99.4155
For values of best alpha =  0.0001 The cross validation Accuracy is: 99.4168
For values of best alpha =  0.0001 The test Accuracy is: 99.3765
```

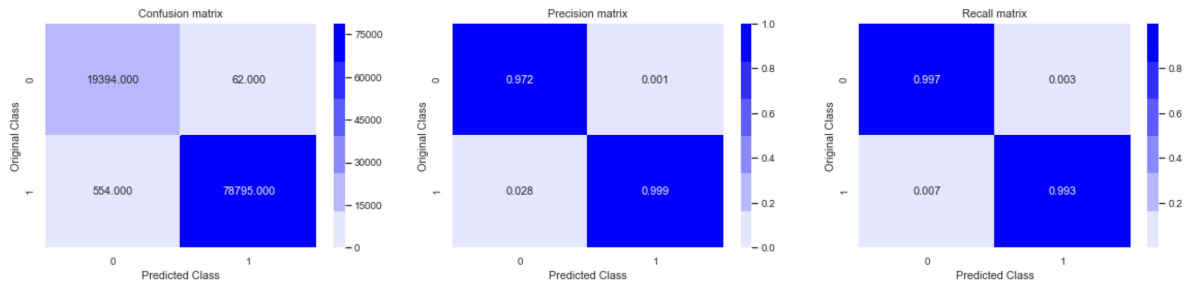
In [497]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict_y_tr)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict_y_te)
```

```
Train confusion_matrix
```



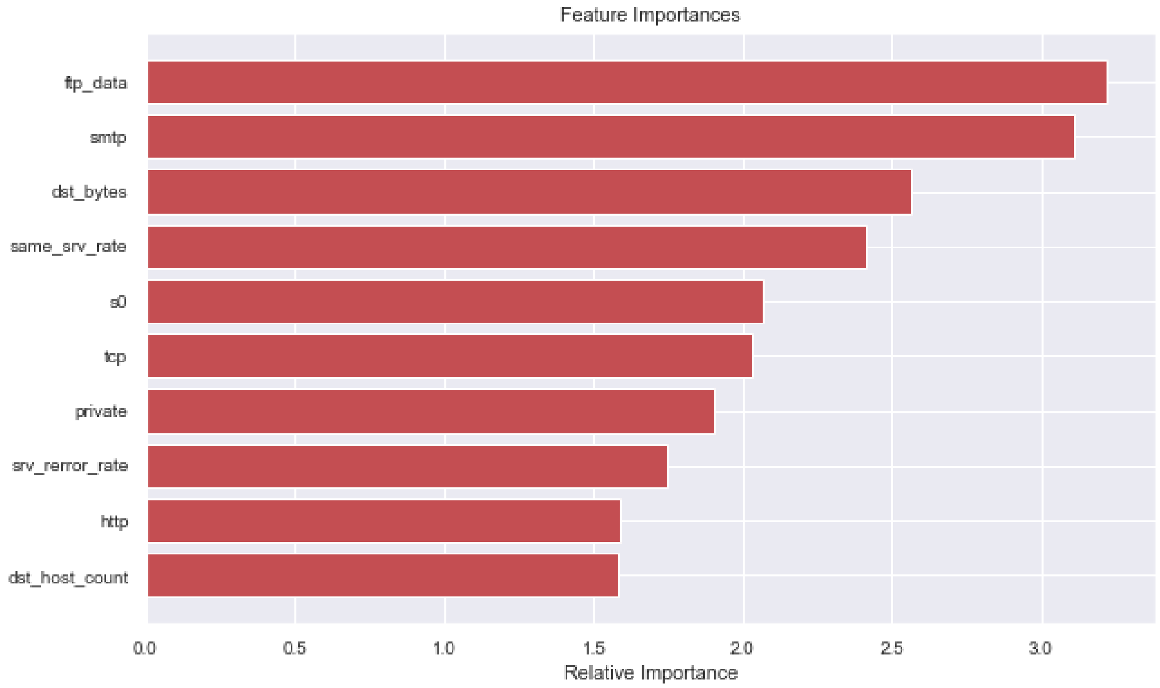

```
Test confusion_matrix
```



5.3.2 Important features from SVM model

In [520]:

```
features=a
importances=abs(clf.coef_[0])
indices = (np.argsort(importances))[-10:]
plt.figure(figsize=(10,6))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



5.4 Random Forest Classifier

In [521]:

```
from datetime import datetime
from sklearn.metrics import f1_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
start=datetime.now()
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,class_weight='balanced')

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

rf_random.fit(X_tr,y_train)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
print('Total time taken is {}'.format(datetime.now()-start))
```

```
mean test scores [0.99724517 0.99741596 0.99701745 0.99713131 0.99803588]
mean train scores [0.99728629 0.99750031 0.99706981 0.99720335 0.9981023 ]
Total time taken is 0:14:28.288663
```

In [522]:

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

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            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 [523]:

```
clf=RandomForestClassifier(bootstrap=True, class_weight='balanced', 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 [524]:

```
clf.fit(X_tr,y_train)
y_train_pred = clf.predict(X_tr)
y_test_pred = clf.predict(X_te)
```

In [525]:

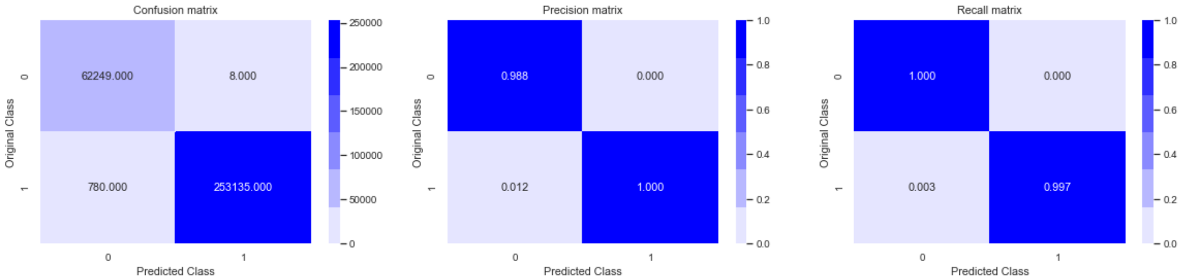
```
print('Train accuracy is {}%'.format(accuracy(y_train,y_train_pred)*100))
print('Test accuracy is {}%'.format(accuracy(y_test,y_test_pred)*100))
```

```
Train accuracy is 99.75076856900674%
Test accuracy is 99.74495217853348%
```

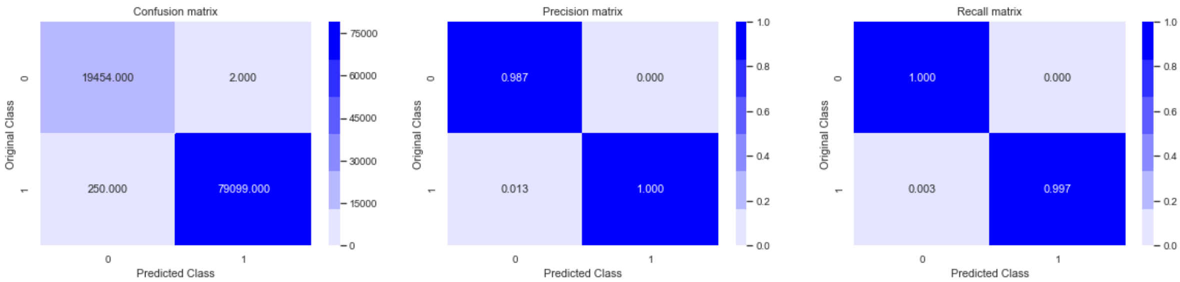
In [526]:

```
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
```



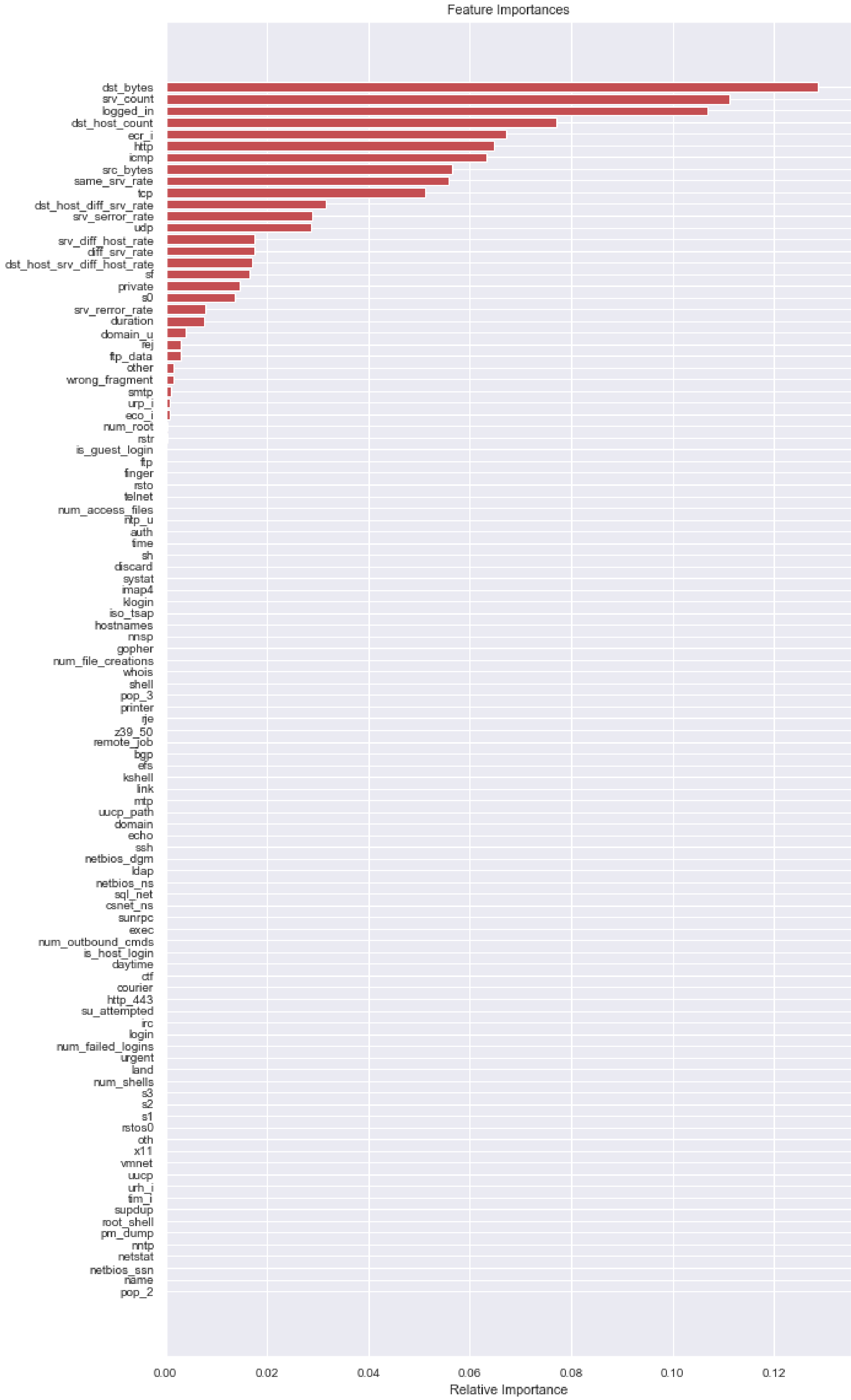

```
Test confusion_matrix
```



5.4.2 Top features using Random Forest

In [532]:

```
features = a
importances = clf.feature_importances_
indices = (np.argsort(importances))
plt.figure(figsize=(10,20))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
print("Total number of features are: ",len(indices))
```




```
Total number of features are:  104
```

5.4.2.1 Visualizing Decision Tree(max_depth=3)

In [59]:

```
from sklearn import tree
GF = tree.DecisionTreeClassifier(max_depth=3)
e=pd.DataFrame(a)
e=e.T
e.columns=a
GF = GF.fit(X_tr, y_train)
e.head(2)
```

Out[59]:

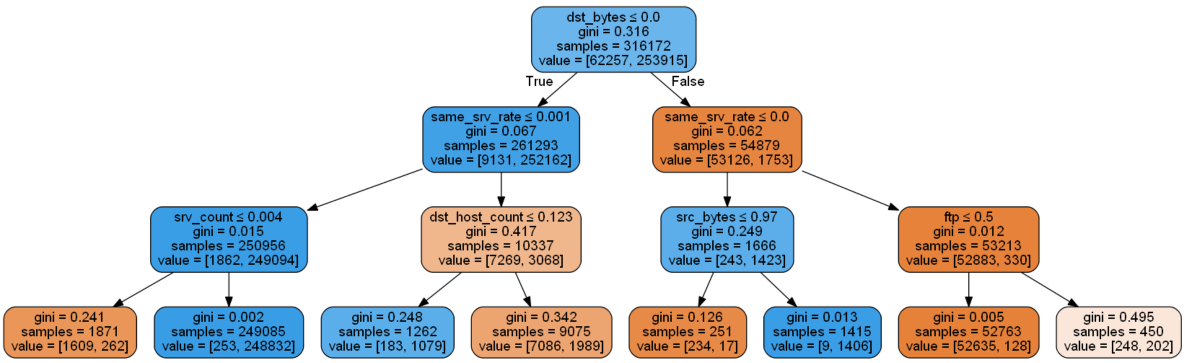
	icmp	tcp	udp	auth	bgp	courier	csnet_ns	ctf	daytime	discard	...	is_guest_login	srv
0	icmp	tcp	udp	auth	bgp	courier	csnet_ns	ctf	daytime	discard	...	is_guest_login	sr

1 rows × 104 columns

In [60]:

```
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
dot_data = StringIO()
tree.export_graphviz(GF,out_file=dot_data,feature_names=e.columns,filled=True, rounded=True
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.set_size(100,100)
Image(graph.create_png())
```

Out[60]:



5.4.2.2 Visualizing Decision Tree(max_depth=4)

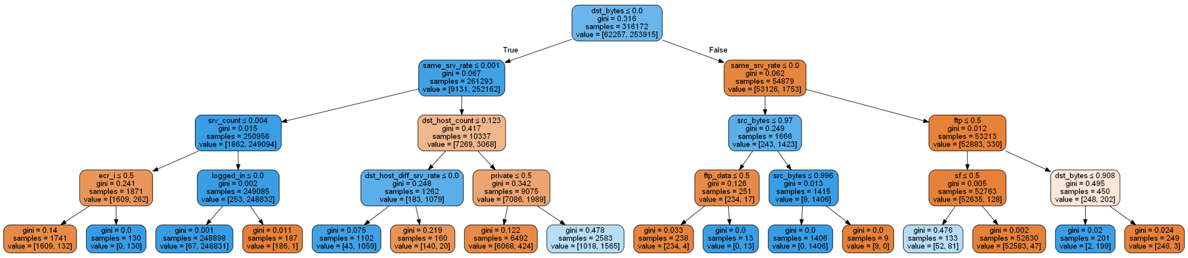
In [64]:

```
from sklearn import tree
GF = tree.DecisionTreeClassifier(max_depth=4)
GF = GF.fit(X_tr, y_train)
```

In [65]:

```
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
dot_data = StringIO()
tree.export_graphviz(GF,out_file=dot_data,feature_names=e.columns,filled=True, rounded=True
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

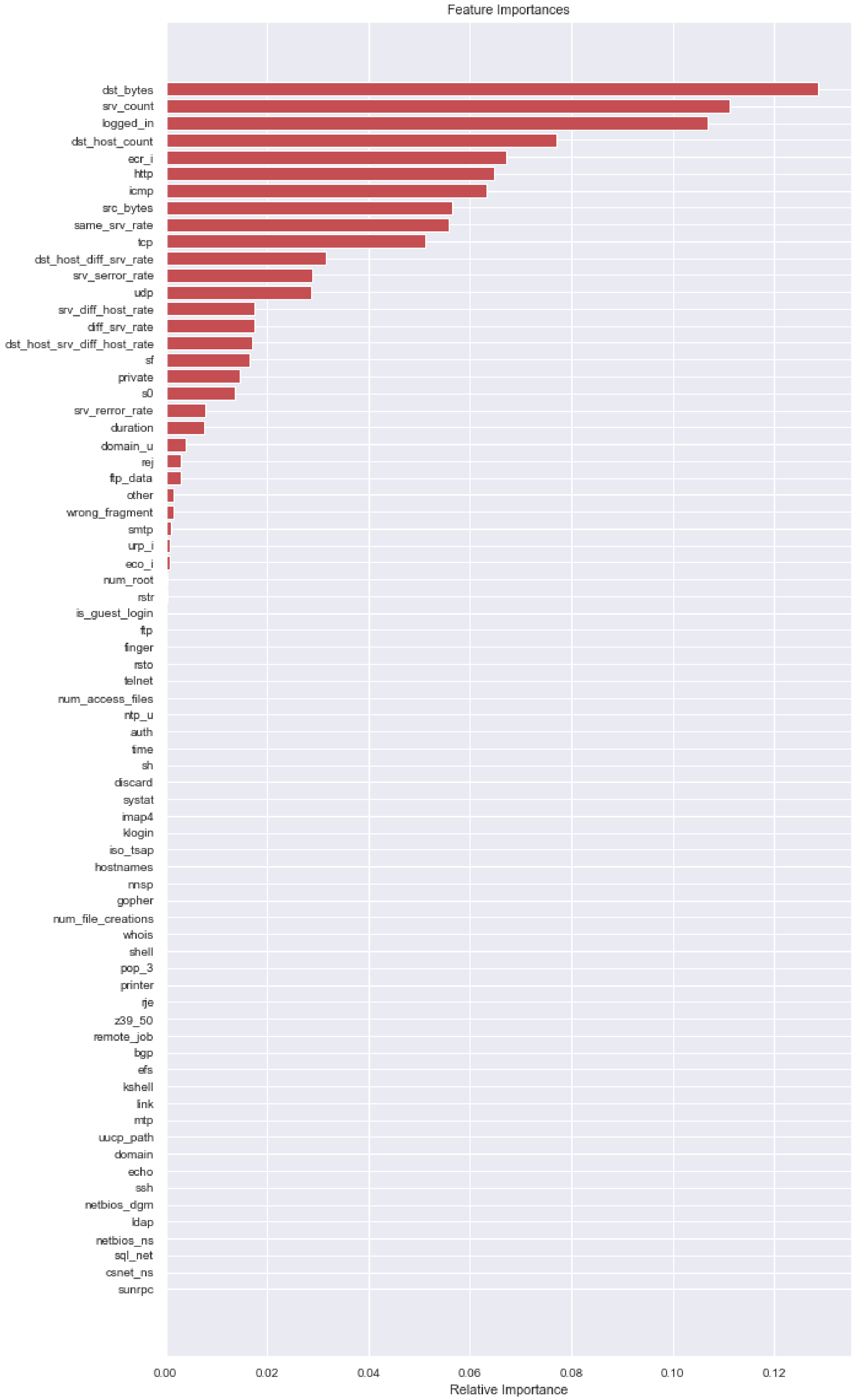
Out[65]:



5.4.3 Top features excluding 0 feature importance features

In [540]:

```
features = a
importances = clf.feature_importances_
indices = (np.argsort(importances))
indices=[i for i in indices if importances[i]!=0]
plt.figure(figsize=(10,20))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
print("Total number of features after removing 0 feature importance features are: ",len(inc
```




```
Total number of features after removing 0 feature importance features are: 
72
```

Note:Some features have feature importance value close to zero but not exactly zero so they are shown in plot

5.5 Random Forest with Important Features

In [541]:

```
X_tr1=X_tr.tocsr()[:,indices].tocoo()
X_cv1=X_cv.tocsr()[:,indices].tocoo()
X_te1=X_te.tocsr()[:,indices].tocoo()
```

In [542]:

```
from sklearn.metrics import f1_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
start=datetime.now()
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,class_weight='balanced')

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

rf_random.fit(X_tr1,y_train)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
print('Total time taken is {}'.format(datetime.now()-start))
```

```
mean test scores [0.99806434 0.99830788 0.99740331 0.99787774 0.99852296]
mean train scores [0.99814377 0.99835251 0.99740401 0.99789355 0.99856618]
Total time taken is 0:14:56.497277
```

In [543]:

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

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            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 [544]:

```
clf=RandomForestClassifier(bootstrap=True, class_weight='balanced', 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 [545]:

```
clf.fit(X_tr1,y_train)
y_train_pred = clf.predict(X_tr1)
y_test_pred = clf.predict(X_te1)
```

In [546]:

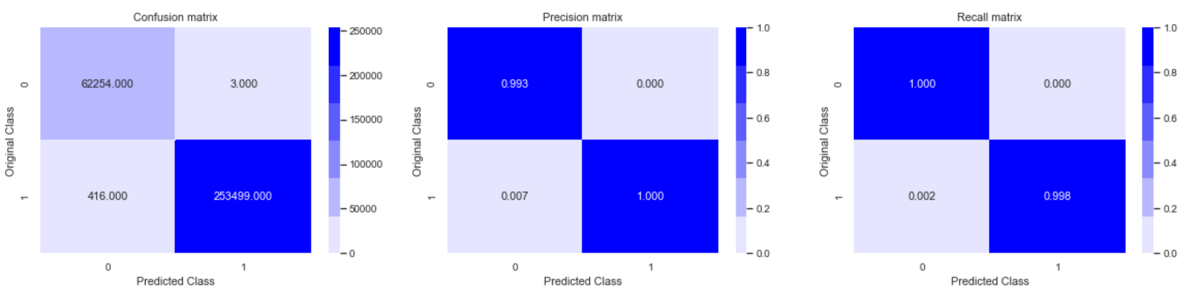
```
print('Train Accuracy',accuracy(y_train,y_train_pred)*100)
print('Test Accuracy',accuracy(y_test,y_test_pred)*100)
```

```
Train Accuracy 99.86747719595664
Test Accuracy 99.86033095491119
```

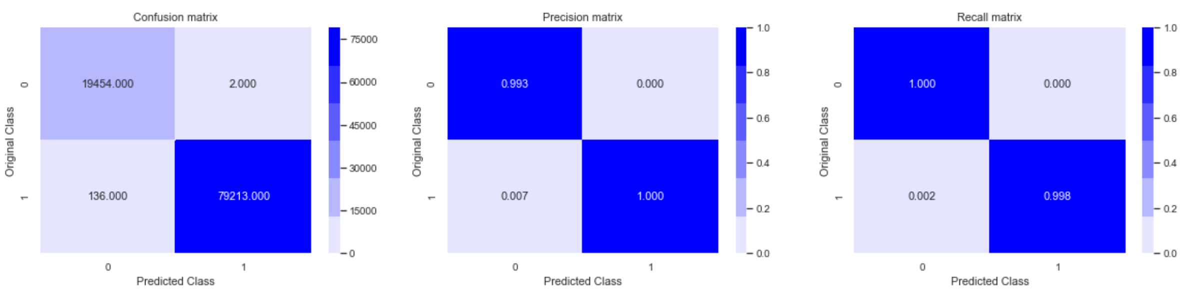
In [547]:

```
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
```



5.6 XGBoost classifier

In [548]:

```
from xgboost import XGBClassifier
n_estimators = [100,200,300,400,500]
max_depth = [2,4,6,8,10]
params = {"n_estimators":n_estimators,"max_depth":max_depth}
xgb = XGBClassifier(class_weight='balanced')
rsm = RandomizedSearchCV(xgb,params,cv=5,scoring='accuracy',n_jobs=-1)
rsm.fit(X_tr,y_train)
print("Best parameter obtained from RandomSearch CV: \n", rsm.best_params_)
print("Best Score : ", rsm.best_score_)
```

```
Best parameter obtained from RandomSearch CV:
 {'n_estimators': 100, 'max_depth': 8}
Best Score :  0.9997659501790165
```

In [549]:

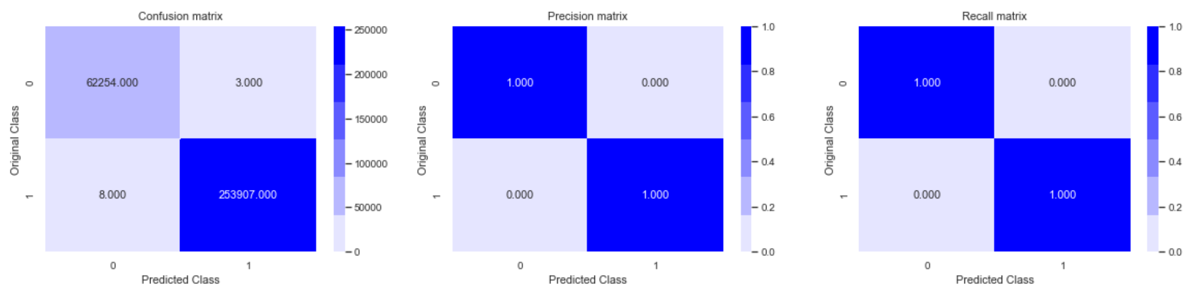
```
clf_xgb = XGBClassifier(n_estimators=100, max_depth= 8,class_weight='balanced')
clf_xgb.fit(X_tr,y_train)
y_train_pred_xgb = clf_xgb.predict(X_tr)
y_test_pred_xgb = clf_xgb.predict(X_te)
print('Train Accuracy',accuracy(y_train,y_train_pred_xgb)*100)
print('Test Accuracy',accuracy(y_test,y_test_pred_xgb)*100)
```

```
Train Accuracy 99.99652088103943
Test Accuracy 99.97672182581853
```

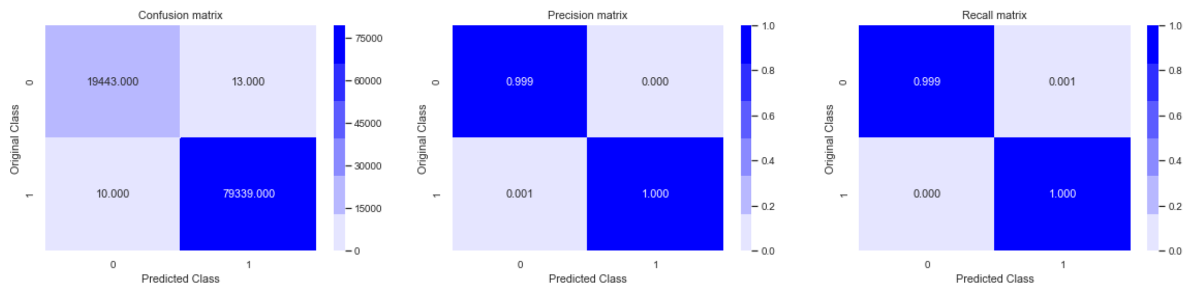
In [550]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred_xgb)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred_xgb)
```

```
Train confusion_matrix
```



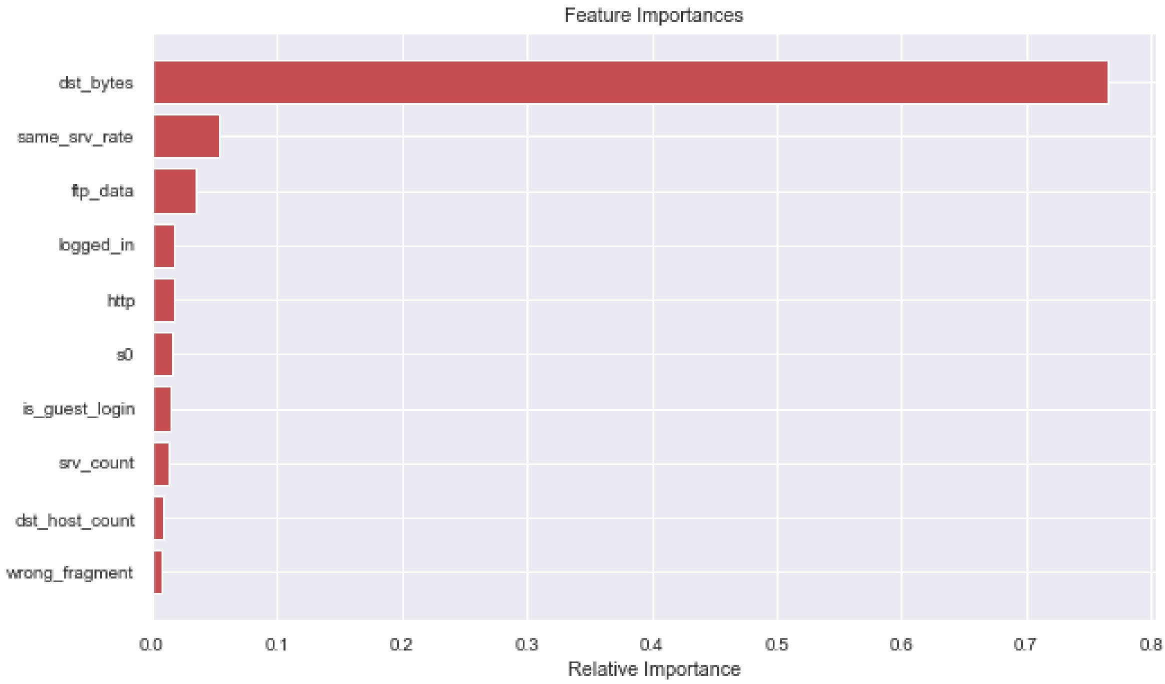

```
Test confusion_matrix
```



5.6.2 Top 10 features using Xgboost

In [551]:

```
features = a
importances = clf_xgb.feature_importances_
indices = (np.argsort(importances))[-10:]
plt.figure(figsize=(10,6))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



6.Summary

In [553]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model","Hyperparameter","Hyperparameter value","Train Accuracy","Test Acc

x.add_row([ "Naive Bayes", 'alpha',0.0001,'98.63%','98.67%'])
x.add_row([ "Logistic Regression", 'C',1000 ,'99.66%','99.61%'])
x.add_row([ "SVM", 'alpha', 0.0001,'99.41%','99.35%'])
x.add_row([ "Random Forest", 'n_estimators',121, '99.75%','99.74%'])
x.add_row([ "RF with feature importance",'n_estimators',121,'99.86%','99.86%'])
x.add_row(["XGboost",'n_estimators',100,'99.99%','99.97%'])
print(x)
```

Model	Hyperparameter	Hyperparameter value	Train Accuracy	Test Accuracy
Naive Bayes	alpha	0.0001	98.63%	98.67%
Logistic Regression	C	1000	99.66%	99.61%
SVM	alpha	0.0001	99.41%	99.35%
Random Forest	n_estimators	121	99.75%	99.74%
RF with feature importance	n_estimators	121	99.86%	99.86%
XGboost	n_estimators	100	99.99%	99.97%

7.Conclusion

1. The problem statement was to detect whether given network traffic is normal or malicious.
2. The dataset consists of 494021 datapoints and 41 features.there are 3 catrgorical features and 38 numerical features.
3. EDA is carried out on the dataset which shows that there are 2-3 sub_categories in each category which are more dominant than others.
4. EDA also shown that most of the numerical features are highly correlated and having both does not add value to the modelling.
5. Then dataset is then split into train,test and cv dataset with 64% ,20%, 16% respectively.
6. Then catagorical features are encoded using one hot encoding whereas numerical features are normalized.
7. Prepared data is then applied to different machine learning models like Naive Bayes,Logistic Regression,SVM,Random Forest,and Xgboost for hyperparameter tuning.
8. All the models are performing really well.Best model is Xgboost which gives 99.99% train accuracy and 99.97% test accuracy.
9. Models are not overfitting as train and test accuracy is almost same.
10. Top features are selected using feature_importances_ of RF.We get improved accuracy.

11. From Confusion Matrix we conclude that we have successfully classified Normal Network Traffic and Malicious Network Traffic with 99.97% accuracy.

In [ ]: