Microsoft Malware detection

1.Business/Real-world Problem

1.1. What is Malware?

The term malware is a contraction of malicious software. Put simply, malware is any piece of software that was written with the intent of doing harm to data, devices or to people.
Source: [https://www.avg.com/en/signal/what-is-malware (https://www.avg.com/en/signal/what-is-malware)](https://www.avg.com/en/signal/what-is-malware)

1.2. Problem Statement

In the past few years, the malware industry has grown very rapidly that, the syndicates invest heavily in technologies to evade traditional protection, forcing the anti-malware groups/communities to build more robust softwares to detect and terminate these attacks. The major part of protecting a computer system from a malware attack is to **identify whether a given piece of file/software is a malware.**

1.3 Source/Useful Links

Microsoft has been very active in building anti-malware products over the years and it runs it's anti-malware utilities over 150 million computers around the world. This generates tens of millions of daily data points to be analyzed as potential malware. In order to be effective in analyzing and classifying such large amounts of data, we need to be able to group them into groups and identify their respective families.

This dataset provided by Microsoft contains about 9 classes of malware. ,

Source: https://www.kaggle.com/c/malware-classification

1.4. Real-world/Business objectives and constraints.

1. **Minimize multi-class error.**
2. **Multi-class probability estimates.**
3. **Malware detection should not take hours and block the user's computer. It should fininsh in a few seconds or a minute.**

2. Machine Learning Problem

2.1. Data

2.1.1. Data Overview

Source : https://www.kaggle.com/c/malware-classification/data
For every malware, we have two files

1. **.asm file (read more: https://www.reviversoft.com/file-extensions/asm)**
2. **.bytes file (the raw data contains the hexadecimal representation of the file's binary content, without the PE header)**

Total train dataset consist of 200GB data out of which 50Gb of data is .bytes files and 150GB of data is .asm files:
Lots of Data for a single-box/computer.
There are total 10,868 .bytes files and 10,868 asm files total 21,736 files
There are 9 types of malwares (9 classes) in our give data
Types of Malware:

1. **Ramnit**
2. **Lollipop**
3. **Kelihos_ver3**
4. **Vundo**
5. **Simda**
6. **Tracur**
7. **Kelihos_ver1**
8. **Obfuscator.ACY**
9. **Gatak**

2.1.2. Example Data Point

.asm file

```
.text:00401000                              assume es:nothing, ss:nothing, ds:_
data, fs:nothing, gs:nothing
.text:00401000 56                           push    esi
.text:00401001 8D 44 24 08                      lea     eax, [esp+8]
.text:00401005 50                           push    eax
.text:00401006 8B F1                            mov     esi, ecx
.text:00401008 E8 1C 1B 00 00                       call    ??0exception@std@@Q
AE@ABQBD@Z ; std::exception::exception(char const * const &)
.text:0040100D C7 06 08 BB 42 00                    mov     dword ptr [esi], of
fset off_42BB08
.text:00401013 8B C6                            mov     eax, esi
.text:00401015 5E                           pop     esi
.text:00401016 C2 04 00                         retn    4
.text:00401016                         ; ----------------------------------------
---------------------------------
.text:00401019 CC CC CC CC CC CC CC                 align 10h
.text:00401020 C7 01 08 BB 42 00                    mov     dword ptr [ecx], of
fset off_42BB08
.text:00401026 E9 26 1C 00 00                       jmp     sub_402C51
.text:00401026                         ; ----------------------------------------
---------------------------------
.text:0040102B CC CC CC CC CC                       align 10h
.text:00401030 56                           push    esi
.text:00401031 8B F1                            mov     esi, ecx
.text:00401033 C7 06 08 BB 42 00                    mov     dword ptr [esi], of
fset off_42BB08
.text:00401039 E8 13 1C 00 00                       call    sub_402C51
.text:0040103E F6 44 24 08 01                       test    byte ptr [esp+8], 1
.text:00401043 74 09                            jz      short loc_40104E
.text:00401045 56                           push    esi
.text:00401046 E8 6C 1E 00 00                       call    ??3@YAXPAX@Z    ; o
perator delete(void *)
.text:0040104B 83 C4 04                         add     esp, 4
.text:0040104E
.text:0040104E                         loc_40104E:                 ; CODE XREF: .t
ext:00401043j
.text:0040104E 8B C6                            mov     eax, esi
.text:00401050 5E                           pop     esi
.text:00401051 C2 04 00                         retn    4
.text:00401051                         ; ----------------------------------------
---------------------------------
```

.bytes file

```
00401000 00 00 80 40 40 28 00 1C 02 42 00 C4 00 20 04 20
00401010 00 00 20 09 2A 02 00 00 00 00 8E 10 41 0A 21 01
00401020 40 00 02 01 00 90 21 00 32 40 00 1C 01 40 C8 18
00401030 40 82 02 63 20 00 00 09 10 01 02 21 00 82 00 04
00401040 82 20 08 83 00 08 00 00 00 00 02 00 60 80 10 80
00401050 18 00 00 20 A9 00 00 00 00 04 04 78 01 02 70 90
00401060 00 02 00 08 20 12 00 00 00 40 10 00 80 00 40 19
00401070 00 00 00 00 11 20 80 04 80 10 00 20 00 00 25 00
```

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

2.2.1. Type of Machine Learning Problem

There are nine different classes of malware that we need to classify a given a data point => Multi class classification problem

2.2.2. Performance Metric

Source: [https://www.kaggle.com/c/malware-classification#evaluation (https://www.kaggle.com/c/malware-classification#evaluation)](https://www.kaggle.com/c/malware-classification#evaluation)

Metric(s):

- **Multi class log-loss**
- **Confusion matrix**

2.2.3. Machine Learing Objectives and Constraints

Objective: Predict the probability of each data-point belonging to each of the nine classes.

Constraints:

- **Class probabilities are needed.**
- **Penalize the errors in class probabilites => Metric is Log-loss.**
- **Some Latency constraints.**

2.3. Train and Test Dataset

Split the dataset randomly into three parts train, cross validation and test with 64%,16%, 20% of data respectively

2.4. Useful blogs, videos and reference papers

http://blog.kaggle.com/2015/05/26/microsoft-malware-winners-interview-1st-place-no-to-overfitting/
https://arxiv.org/pdf/1511.04317.pdf
First place solution in Kaggle competition: https://www.youtube.com/watch?v=VLQTRlLGz5Y
https://github.com/dchad/malware-detection
http://vizsec.org/files/2011/Nataraj.pdf
https://www.dropbox.com/sh/gfqzv0ckgs4l1bf/AAB6EelnEjvvuQg2nu_plB6ua?dl=0
" Cross validation is more trustworthy than domain knowledge."

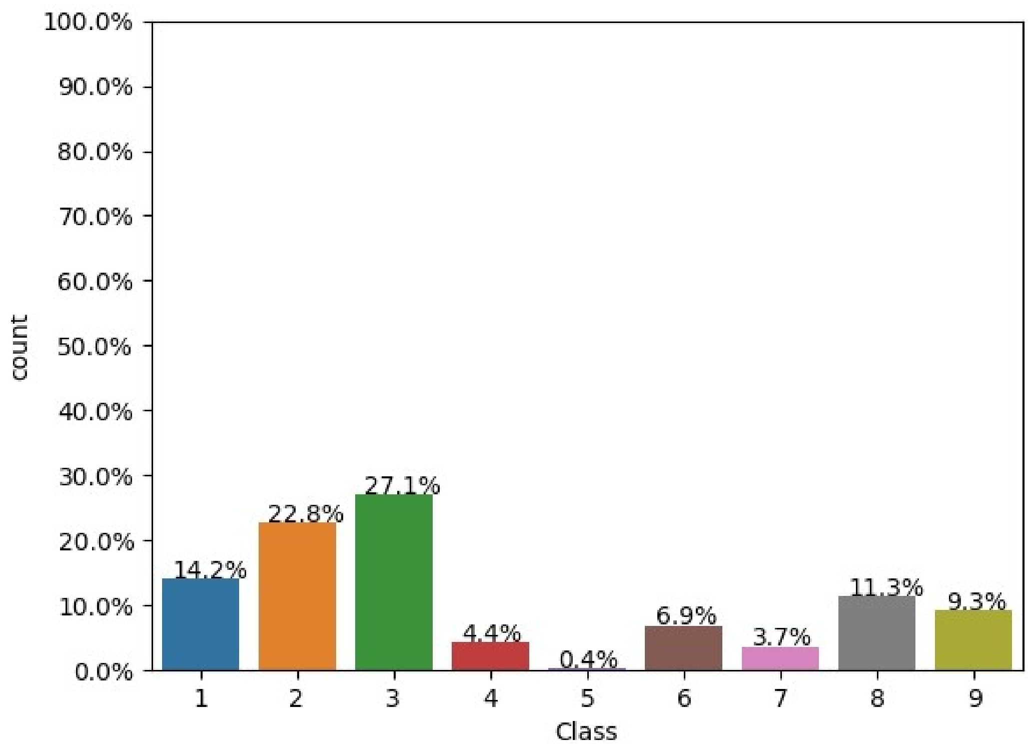
3. Exploratory Data Analysis

In [1]:
```
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
```

In [3]:
```
source = 'train'
destination = 'byteFiles'

# we will check if the folder 'byteFiles' exists if it not there we will create a folder with the same name
if not os.path.isdir(destination):
    os.makedirs(destination)

# if we have folder called 'train' (train folder contains both .asm files and .bytes files) we will rename it 'asmFiles'
# for every file that we have in our 'asmFiles' directory we check if it is ending with .bytes, if yes we will move it to
# 'byteFiles' folder

# so by the end of this snippet we will separate all the .byte files and .asm files
if os.path.isdir(source):
    os.rename(source,'asmFiles')
    source='asmFiles'
    data_files = os.listdir(source)
    for file in data_files:
        if (file.endswith("bytes")):
            shutil.move(source+file,destination)
```

3.1. Distribution of malware classes in whole data set

In [2]:
```
Y=pd.read_csv("trainLabels.csv")
total = len(Y)*1.
ax=sns.countplot(x="Class", data=Y)
for p in ax.patches:
        ax.annotate('{:.1f}%'.format(100*p.get_height()/total), (p.get_x()+0.1, p.
get_height()+5))

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

#adjust the ticklabel to the desired format, without changing the position of the
ticks.
ax.set_yticklabels(map('{:.1f}%'.format, 100*ax.yaxis.get_majorticklocs()/total))
plt.show()
```



3.2. Feature extraction

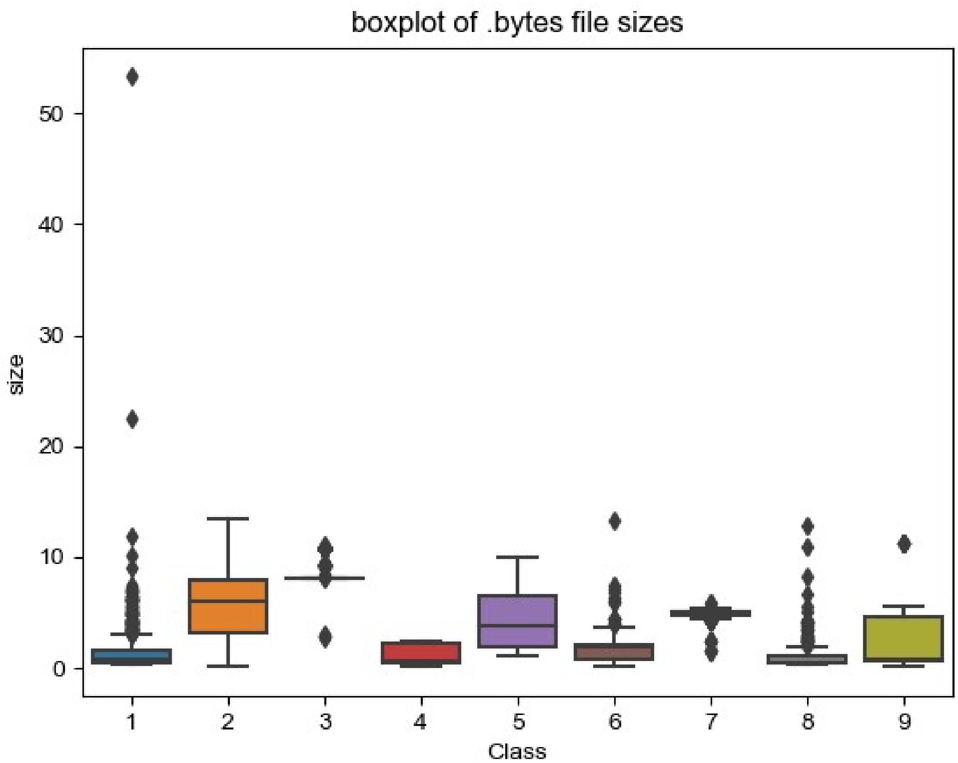
3.2.1 File size of byte files as a feature

In [3]:
```
files=os.listdir('byteFiles')
filenames=Y['Id'].tolist()
class_y=Y['Class'].tolist()
class_bytes=[]
sizebytes=[]
fnames=[]
for file in files:
    # print(os.stat('byteFiles/0A32eTdBKayjCWhZqDOQ.txt'))
    # os.stat_result(st_mode=33206, st_ino=1125899906874507, st_dev=3561571700, st
_nlink=1, st_uid=0, st_gid=0,
    # st_size=3680109, st_atime=1519638522, st_mtime=1519638522, st_ctime=15196385
22)
    # read more about os.stat: here https://www.tutorialspoint.com/python/os_stat.
htm
    statinfo=os.stat('byteFiles/'+file)
    # split the file name at '.' and take the first part of it i.e the file name
    file=file.split('.')[0]
    if any(file == filename for filename in filenames):
        i=filenames.index(file)
        class_bytes.append(class_y[i])
        # converting into Mb's
        sizebytes.append(statinfo.st_size/(1024.0*1024.0))
        fnames.append(file)
data_size_byte=pd.DataFrame({'ID':fnames,'size':sizebytes,'Class':class_bytes})
print (data_size_byte.head())
```

```
                     ID      size  Class
0  01azqd4InC7m9JpocGv5  5.012695      9
1  01IsoiSMh5gxyDYTl4CB  6.556152      2
2  01jsnpXSAlgw6aPeDxrU  4.602051      9
3  01kcPWA9K2BOxQeS5Rju  0.679688      1
4  01SuzwMJEIXsK7A8dQbl  0.438965      8
```

3.2.2 box plots of file size (.byte files) feature

In [4]:
```
#boxplot of byte files
ax = sns.boxplot(x="Class", y="size", data=data_size_byte)
plt.title("boxplot of .bytes file sizes")
plt.show()
```



3.2.3 feature extraction from byte files

In [5]:

```
#removal of addres from byte files
# contents of .byte files
# ----------------
#00401000 56 8D 44 24 08 50 8B F1 E8 1C 1B 00 00 C7 06 08
#-------------------
#we remove the starting address 00401000

files = os.listdir('byteFiles')
filenames=[]
array=[]
for file in files:
    if(file.endswith("bytes")):
        file=file.split('.')[0]
        text_file = open('byteFiles/'+file+".txt", 'w+')
        file = file+'.bytes'
        with open('byteFiles/'+file,"r") as fp:
            lines=""
            for line in fp:
                a=line.rstrip().split(" ")[1:]
                b=' '.join(a)
                b=b+"\n"
                text_file.write(b)
            fp.close()
            os.remove('byteFiles/'+file)
        text_file.close()

files = os.listdir('byteFiles')
filenames2=[]
feature_matrix = np.zeros((len(files),257),dtype=int)
k=0
```

In [ ]:

In [ ]:

In [7]:

```
#program to convert into bag of words of bytefiles
#this is custom-built bag of words this is unigram bag of words
byte_feature_file=open('result.csv','w+')
byte_feature_file.write("ID,1,2,3,4,5,6,7,8,9,0a,0b,0c,0d,0e,0f,10,11,12,13,14,15,
16,17,18,19,1a,1b,1c,1d,1e,1f,20,21,22,23,24,25,26,27,28,29,2a,2b,2c,2d,2e,2f,30,3
1,32,33,34,35,36,37,38,39,3a,3b,3c,3d,3e,3f,40,41,42,43,44,45,46,47,48,49,4a,4b,4c
,4d,4e,4f,50,51,52,53,54,55,56,57,58,59,5a,5b,5c,5d,5e,5f,60,61,62,63,64,65,66,67,
68,69,6a,6b,6c,6d,6e,6f,70,71,72,73,74,75,76,77,78,79,7a,7b,7c,7d,7e,7f,80,81,82,8
3,84,85,86,87,88,89,8a,8b,8c,8d,8e,8f,90,91,92,93,94,95,96,97,98,99,9a,9b,9c,9d,9e
,9f,a0,a1,a2,a3,a4,a5,a6,a7,a8,a9,aa,ab,ac,ad,ae,af,b0,b1,b2,b3,b4,b5,b6,b7,b8,b9,
ba,bb,bc,bd,be,bf,c0,c1,c2,c3,c4,c5,c6,c7,c8,c9,ca,cb,cc,cd,ce,cf,d0,d1,d2,d3,d4,d
5,d6,d7,d8,d9,da,db,dc,dd,de,df,e0,e1,e2,e3,e4,e5,e6,e7,e8,e9,ea,eb,ec,ed,ee,ef,f0
,f1,f2,f3,f4,f5,f6,f7,f8,f9,fa,fb,fc,fd,fe,ff,??")
for file in files:
    filenames2.append(file)
    byte_feature_file.write(file+",")
    if(file.endswith("txt")):
        with open('byteFiles/'+file,"r") as byte_flie:
            for lines in byte_flie:
                line=lines.rstrip().split(" ")
                for hex_code in line:
                    if hex_code=='??':
                        feature_matrix[k][256]+=1
                    else:
                        feature_matrix[k][int(hex_code,16)]+=1
        byte_flie.close()
    for i in feature_matrix[k]:
        byte_feature_file.write(str(i)+",")
    byte_feature_file.write("\n")

    k += 1

byte_feature_file.close()
```

mk

In [19]:

```
result = pd.merge(byte_features, data_size_byte,on='ID', how='left')
result.head()
```

Out[19]:

	Unnamed: 0	ID	0	1	2	3	4	5	6	7	...	fb	fc	
0	0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	...	3097	2758	3
1	1	01IsoiSMh5gxyDYTl4CB	39755	8337	7249	7186	8663	6844	8420	7589	...	302	7639	
2	2	01jsnpXSAlgw6aPeDxrU	93506	9542	2568	2438	8925	9330	9007	2342	...	2863	2471	2
3	3	01kcPWA9K2BOxQeS5Rju	21091	1213	726	817	1257	625	550	523	...	516	1133	
4	4	01SuzwMJEIXsK7A8dQbl	19764	710	302	433	559	410	262	249	...	239	653	

5 rows × 263 columns

In [4]:
```
byte_features=pd.read_csv("result.csv")
print (byte_features.head())
```

```
   Unnamed: 0                    ID       0     1     2     3     4     5  \
0           0  01azqd4InC7m9JpocGv5  601905  3905  2816  3832  3345  3242
1           1  01IsoiSMh5gxyDYTl4CB   39755  8337  7249  7186  8663  6844
2           2  01jsnpXSAlgw6aPeDxrU   93506  9542  2568  2438  8925  9330
3           3  01kcPWA9K2BOxQeS5Rju   21091  1213   726   817  1257   625
4           4  01SuzwMJEIXsK7A8dQbl   19764   710   302   433   559   410

      6     7  ...    f9    fa    fb    fc    fd     fe     ff     ??  \
0  3650  3201  ...  3101  3211  3097  2758  3099   2759   5753   1824
1  8420  7589  ...   439   281   302  7639   518  17001  54902   8588
2  9007  2342  ...  2242  2885  2863  2471  2786   2680  49144    468
3   550   523  ...   485   462   516  1133   471    761   7998  13940
4   262   249  ...   350   209   239   653   221    242   2199   9008

       size  Class
0  5.012695      9
1  6.556152      2
2  4.602051      9
3  0.679688      1
4  0.438965      8

[5 rows x 261 columns]
```

In [5]:
```
result=byte_features
```

In [6]:
```
# https://stackoverflow.com/a/29651514
def normalize(df):
    result1 = df.copy()
    for feature_name in df.columns:
        if (str(feature_name) != str('ID') and str(feature_name)!=str('Class')):
            max_value = df[feature_name].max()
            min_value = df[feature_name].min()
            result1[feature_name] = (df[feature_name] - min_value) / (max_value -
min_value)
    return result1
result = normalize(result)
```

In [ ]:
```
```

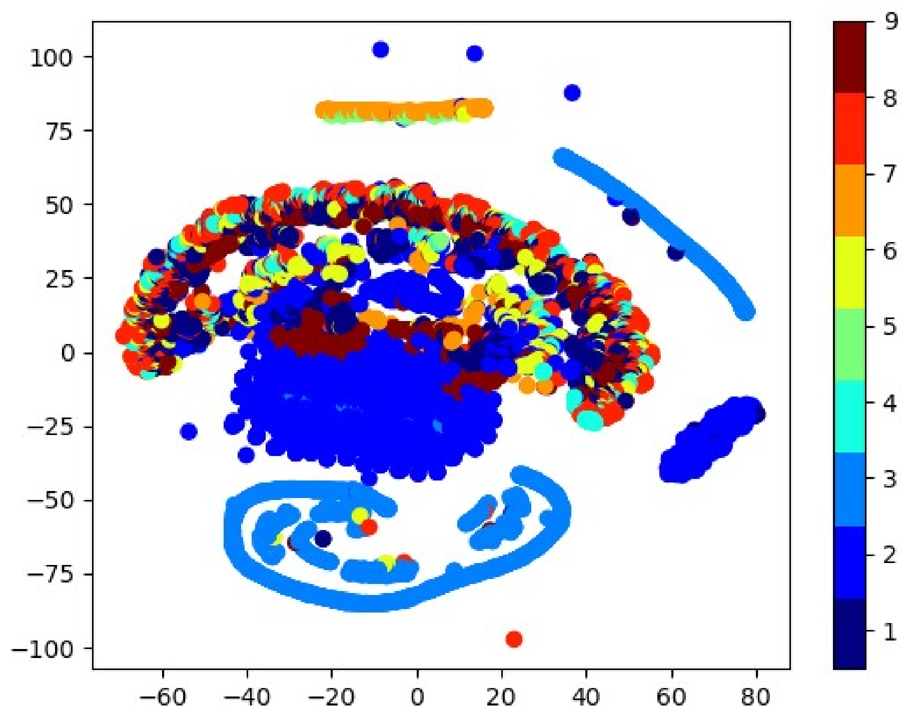
In [7]:
```
from sklearn.externals import joblib
```

In [8]:
```
joblib.dump(result, 'result.pkl')
```

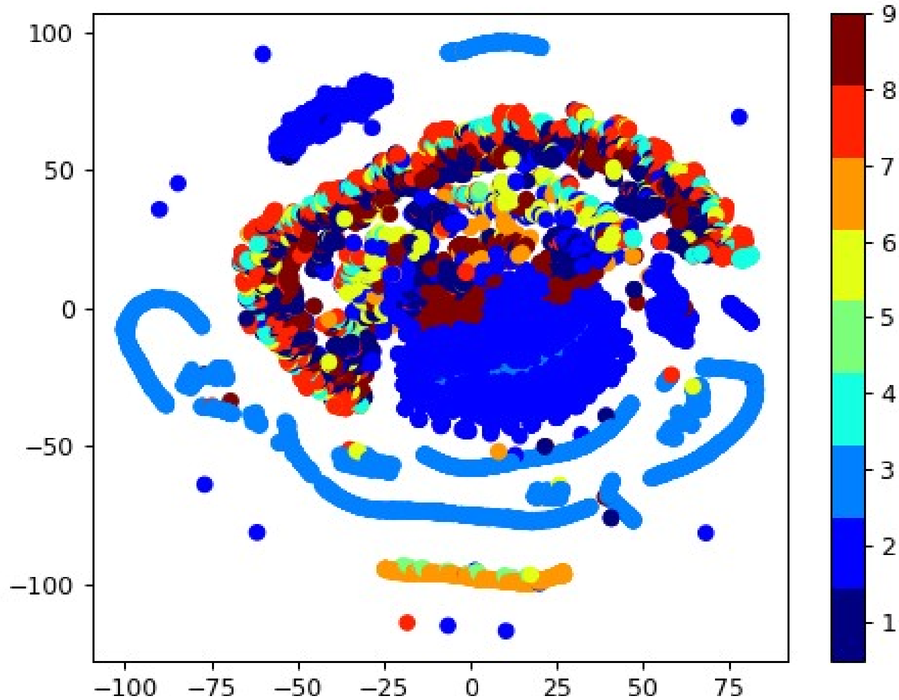
Out[8]:
```
['result.pkl']
```

3.2.4 Multivariate Analysis

In [11]:
```
#multivariate analysis on byte files
#this is with perplexity 50
xtsne=TSNE(perplexity=50)
results=xtsne.fit_transform(result.drop(['ID','Class'], axis=1))
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=data_y, cmap=plt.cm.get_cmap("jet", 9))
plt.colorbar(ticks=range(10))
plt.clim(0.5, 9)
plt.show()
```



In [15]:
```
#this is with perplexity 30
xtsne=TSNE(perplexity=30)
results=xtsne.fit_transform(result.drop(['ID','Class'], axis=1))
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=data_y, cmap=plt.cm.get_cmap("jet", 9))
plt.colorbar(ticks=range(10))
plt.clim(0.5, 9)
plt.show()
```



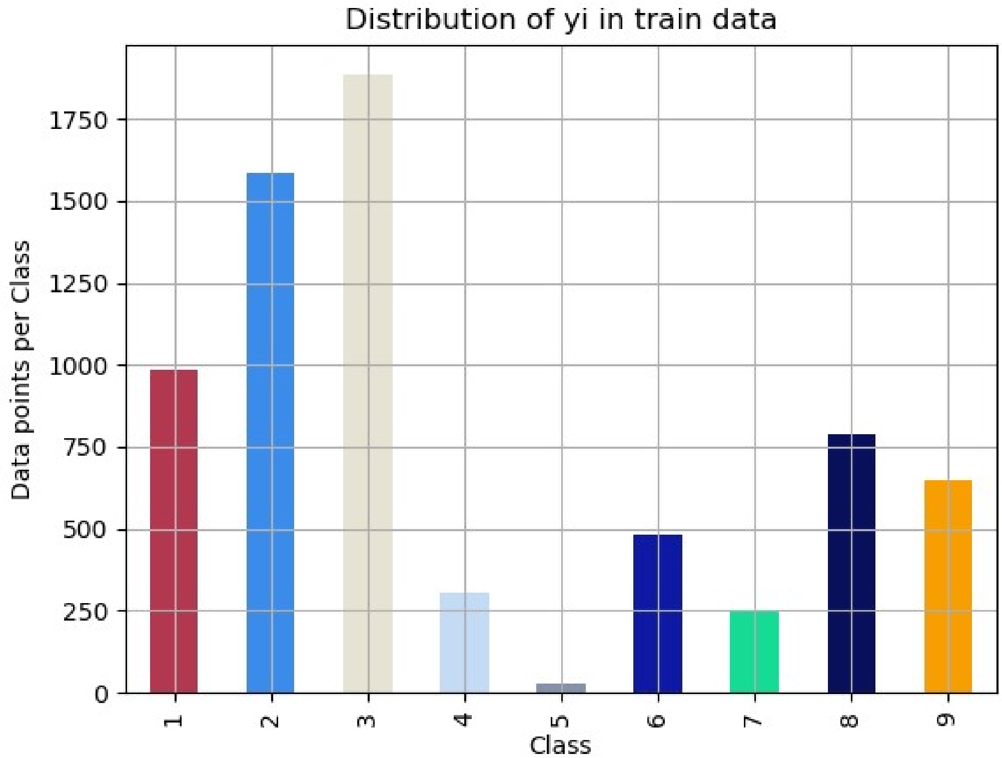
Train Test split

In [9]:
```
data_y = result['Class']
# split the data into test and train by maintaining same distribution of output va
raible 'y_true' [stratify=y_true]
X_train, X_test, y_train, y_test = train_test_split(result.drop(['ID','Class'], ax
is=1), data_y,stratify=data_y,test_size=0.20)
# split the train data into train and cross validation by maintaining same distrib
ution of output varaible 'y_train' [stratify=y_train]
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,stratify=y_train,
test_size=0.20)
```

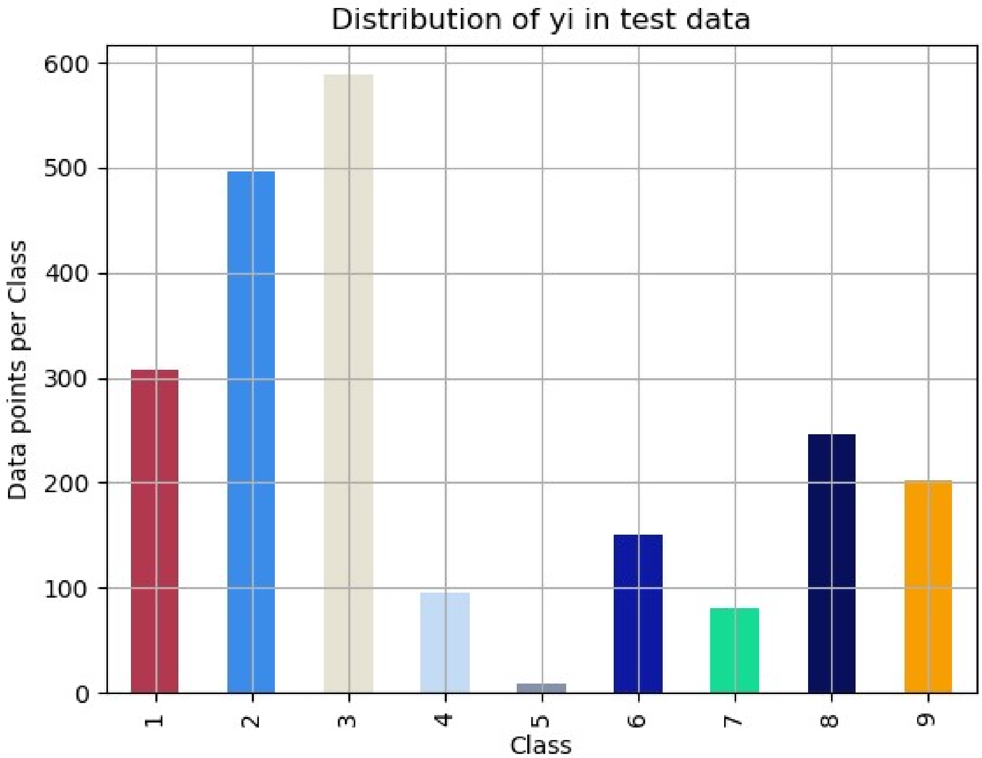
In [10]:
```
print('Number of data points in train data:', X_train.shape[0])
print('Number of data points in test data:', X_test.shape[0])
print('Number of data points in cross validation data:', X_cv.shape[0])
```

```
Number of data points in train data: 6955
Number of data points in test data: 2174
Number of data points in cross validation data: 1739
```

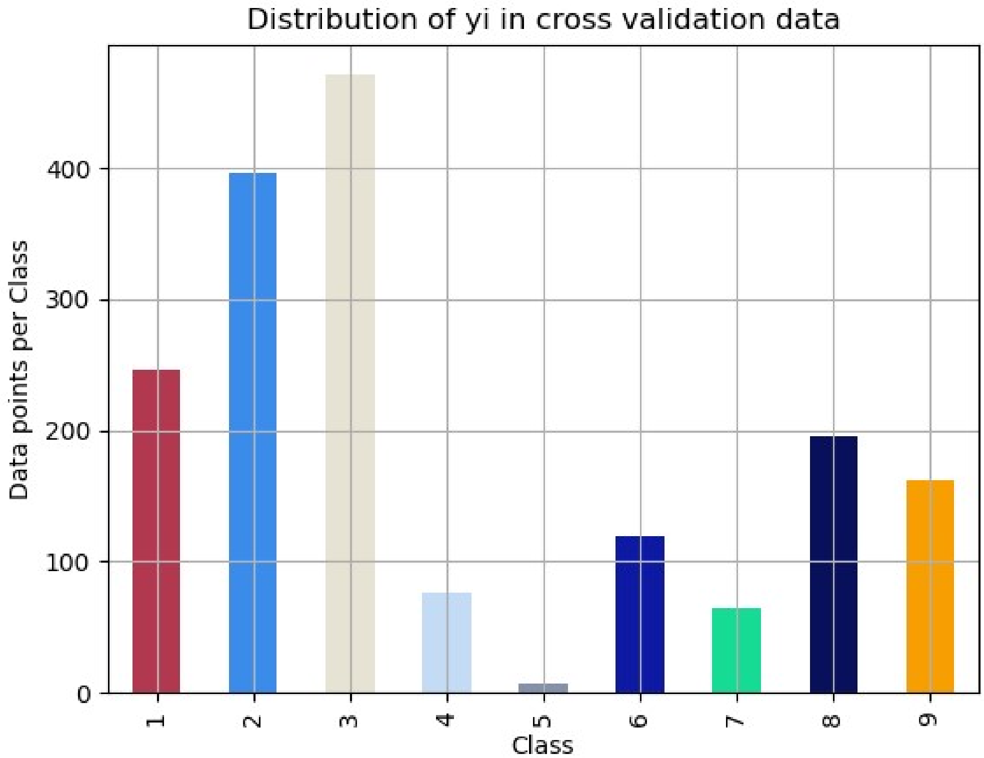
In [11]:
```
# it returns a dict, keys as class labels and values as the number of data points
in that class
train_class_distribution = y_train.value_counts().sortlevel()
test_class_distribution = y_test.value_counts().sortlevel()
cv_class_distribution = y_cv.value_counts().sortlevel()

my_colors = ['#b23850', '#3b8beb', '#e7e3d4', '#c4dbf6', '#8590aa', '#0d19a3', '#1
5db95', '#080f5b', '#f79e02']
train_class_distribution.plot(kind='bar', color=my_colors)
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in train data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/numpy.argsort.
html
# -(train_class_distribution.values): the minus sign will give us in decreasing or
der
sorted_yi = np.argsort(-train_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',train_class_distribution.valu
es[i], '(', np.round((train_class_distribution.values[i]/y_train.shape[0]*100), 3)
, '%)')


print('-'*80)
my_colors = ['#b23850', '#3b8beb', '#e7e3d4', '#c4dbf6', '#8590aa', '#0d19a3', '#1
5db95', '#080f5b', '#f79e02']
test_class_distribution.plot(kind='bar', color=my_colors)
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in test data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/numpy.argsort.
html
# -(train_class_distribution.values): the minus sign will give us in decreasing or
der
sorted_yi = np.argsort(-test_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',test_class_distribution.value
s[i], '(', np.round((test_class_distribution.values[i]/y_test.shape[0]*100), 3), '
%)')

print('-'*80)
my_colors = ['#b23850', '#3b8beb', '#e7e3d4', '#c4dbf6', '#8590aa', '#0d19a3', '#1
5db95', '#080f5b', '#f79e02']
cv_class_distribution.plot(kind='bar', color=my_colors)
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in cross validation data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/numpy.argsort.
html
# -(train_class_distribution.values): the minus sign will give us in decreasing or
der
sorted_yi = np.argsort(-train_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',cv_class_distribution.values[
i], '(', np.round((cv_class_distribution.values[i]/y_cv.shape[0]*100), 3), '%)')
```




```
Number of data points in class 3 : 1883 ( 27.074 %)
Number of data points in class 2 : 1586 ( 22.804 %)
Number of data points in class 1 : 986 ( 14.177 %)
Number of data points in class 8 : 786 ( 11.301 %)
Number of data points in class 9 : 648 ( 9.317 %)
Number of data points in class 6 : 481 ( 6.916 %)
Number of data points in class 4 : 304 ( 4.371 %)
Number of data points in class 7 : 254 ( 3.652 %)
Number of data points in class 5 : 27 ( 0.388 %)
--------------------------------------------------------------------------------
```




```
Number of data points in class 3 : 588 ( 27.047 %)
Number of data points in class 2 : 496 ( 22.815 %)
Number of data points in class 1 : 308 ( 14.167 %)
Number of data points in class 8 : 246 ( 11.316 %)
Number of data points in class 9 : 203 ( 9.338 %)
Number of data points in class 6 : 150 ( 6.9 %)
Number of data points in class 4 : 95 ( 4.37 %)
Number of data points in class 7 : 80 ( 3.68 %)
Number of data points in class 5 : 8 ( 0.368 %)
--------------------------------------------------------------------------------
```




```
Number of data points in class 3 : 471 ( 27.085 %)
Number of data points in class 2 : 396 ( 22.772 %)
Number of data points in class 1 : 247 ( 14.204 %)
Number of data points in class 8 : 196 ( 11.271 %)
Number of data points in class 9 : 162 ( 9.316 %)
Number of data points in class 6 : 120 ( 6.901 %)
Number of data points in class 4 : 76 ( 4.37 %)
Number of data points in class 7 : 64 ( 3.68 %)
Number of data points in class 5 : 7 ( 0.403 %)
```

In [13]:
```
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    print("Number of misclassified points ",(len(test_y)-np.trace(C))/len(test_y)*
100)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are p
redicted class j

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

    # 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 two diamensional array
    # 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 r
ow
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows
in two diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                      [3/4, 4/6]]

    labels = [1,2,3,4,5,6,7,8,9]
    cmap=sns.light_palette("green")
    # representing A in heatmap format
    print("-"*50, "Confusion matrix", "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabe
ls=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*50, "Precision matrix", "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabe
ls=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of columns in precision matrix",B.sum(axis=0))

    # representing B in heatmap format
    print("-"*50, "Recall matrix"    , "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabe
ls=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

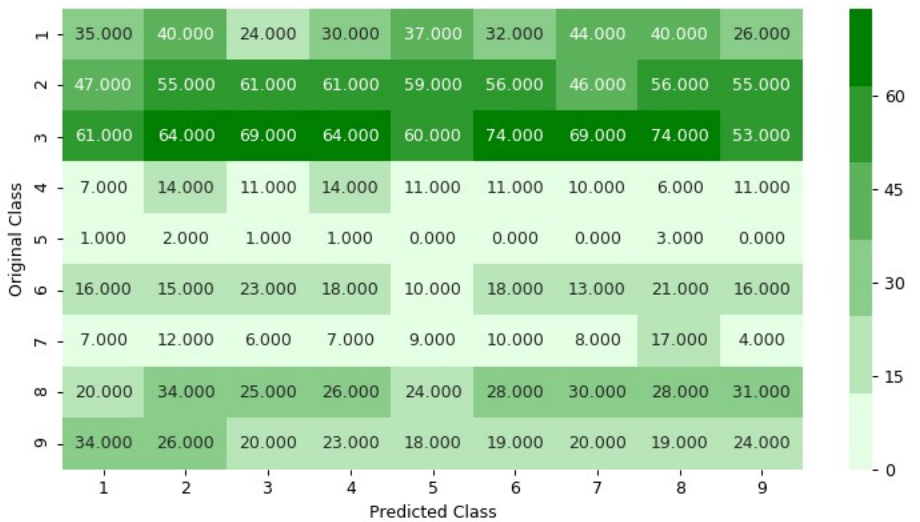
4. Machine Learning Models

4.1. Machine Leaning Models on bytes files

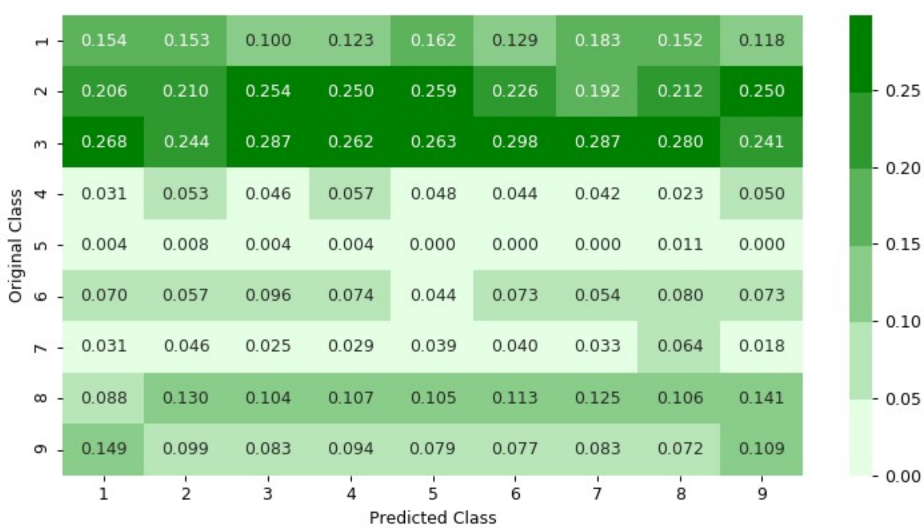
4.1.1. Random Model

In [20]:
```
# we need to generate 9 numbers and the sum of numbers should be 1
# one solution is to genarate 9 numbers and divide each of the numbers by their su
m
# ref: https://stackoverflow.com/a/18662466/4084039

test_data_len = X_test.shape[0]
cv_data_len = X_cv.shape[0]

# we create a output array that has exactly same size as the CV data
cv_predicted_y = np.zeros((cv_data_len,9))
for i in range(cv_data_len):
    rand_probs = np.random.rand(1,9)
    cv_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Cross Validation Data using Random Model",log_loss(y_cv,cv_pred
icted_y, eps=1e-15))


# Test-Set error.
#we create a output array that has exactly same as the test data
test_predicted_y = np.zeros((test_data_len,9))
for i in range(test_data_len):
    rand_probs = np.random.rand(1,9)
    test_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_test,test_predicted_y,
eps=1e-15))

predicted_y =np.argmax(test_predicted_y, axis=1)
plot_confusion_matrix(y_test, predicted_y+1)
```

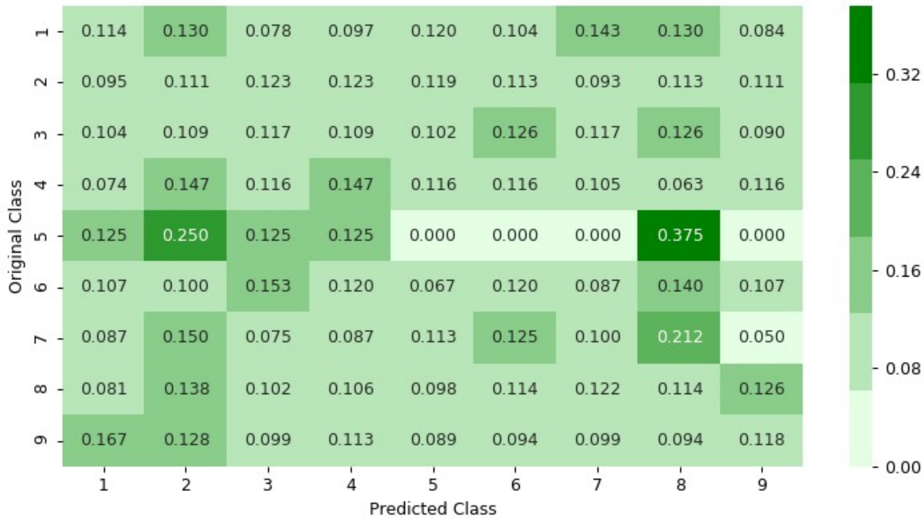
```
Log loss on Cross Validation Data using Random Model 2.4987116946656167
Log loss on Test Data using Random Model 2.4553327958473936
Number of misclassified points  88.45446182152715
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```




```
-------------------------------------------------- Precision matrix ------------
--------------------------------------
```




```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-------------------------------------------------- Recall matrix ---------------
-----------------------------------
```

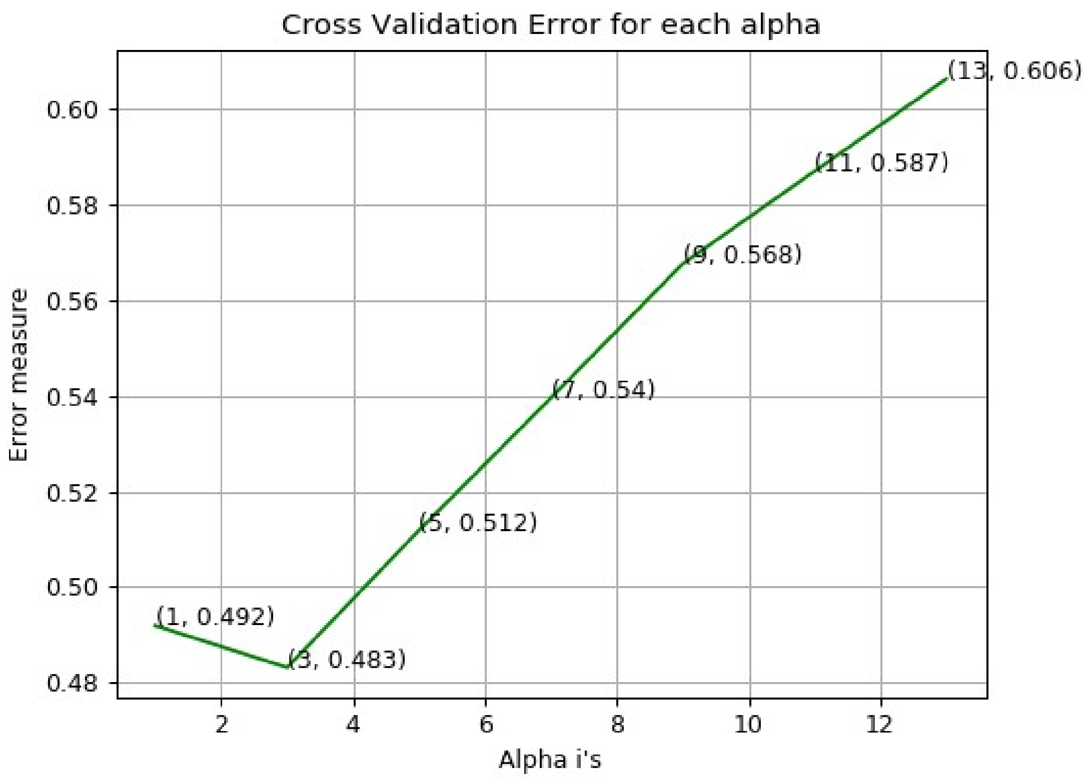



```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.2. K Nearest Neighbour Classification

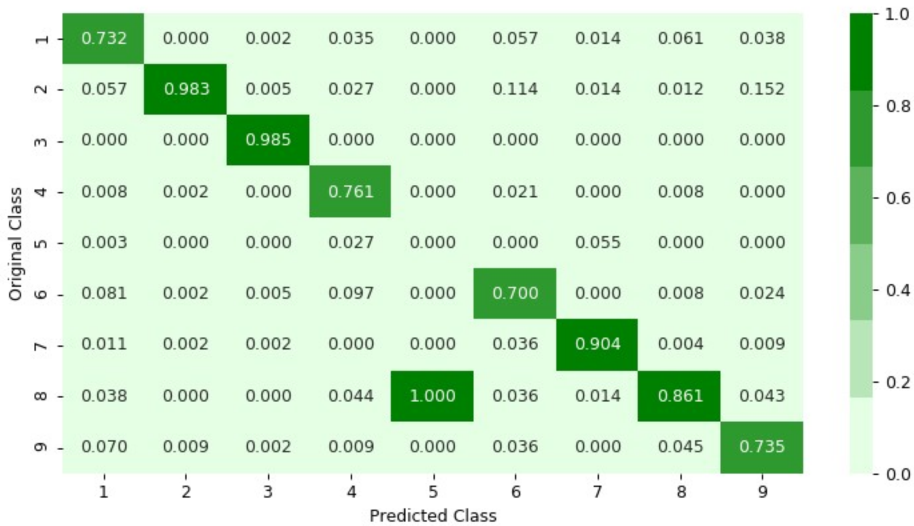
In [21]:
```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/modul
es/generated/sklearn.neighbors.KNeighborsClassifier.html
# -------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', leaf_si
ze=30, p=2,
# metric='minkowski', metric_params=None, n_jobs=1, **kwargs)

# methods of
# fit(X, y) : Fit the model using X as training data and y as target values
# predict(X):Predict the class labels for the provided data
# predict_proba(X):Return probability estimates for the test data X.
#-------------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/k-nearest-neighbors-geometric-intuition-with-a-toy-example-1/
#-------------------------------------


# find more about CalibratedClassifierCV here at http://scikit-learn.org/stable/mo
dules/generated/sklearn.calibration.CalibratedClassifierCV.html
# ----------------------------
# default paramters
# sklearn.calibration.CalibratedClassifierCV(base_estimator=None, method='sigmoid'
, cv=3)
#
# some of the methods of CalibratedClassifierCV()
# fit(X, y[, sample_weight])    Fit the calibrated model
# get_params([deep])    Get parameters for this estimator.
# predict(X)    Predict the target of new samples.
# predict_proba(X)      Posterior probabilities of classification
#-------------------------------------
# video link:
#-------------------------------------

alpha = [x for x in range(1, 15, 2)]
cv_log_error_array=[]
for i in alpha:
    k_cfl=KNeighborsClassifier(n_neighbors=i)
    k_cfl.fit(X_train,y_train)
    sig_clf = CalibratedClassifierCV(k_cfl, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_cv)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=k_cfl.classes_, eps
=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for k = ',alpha[i],'is',cv_log_error_array[i])

best_alpha = np.argmin(cv_log_error_array)

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

k_cfl=KNeighborsClassifier(n_neighbors=alpha[best_alpha])
k_cfl.fit(X_train,y_train)
sig_clf = CalibratedClassifierCV(k_cfl, method="sigmoid")
sig_clf.fit(X_train, y_train)
```

```
log_loss for k =  1 is 0.49188045368463196
log_loss for k =  3 is 0.483116902642161
log_loss for k =  5 is 0.5118350087441232
log_loss for k =  7 is 0.5395490778512431
log_loss for k =  9 is 0.5676371813660702
log_loss for k =  11 is 0.5870170308367498
log_loss for k =  13 is 0.606375118318671
```

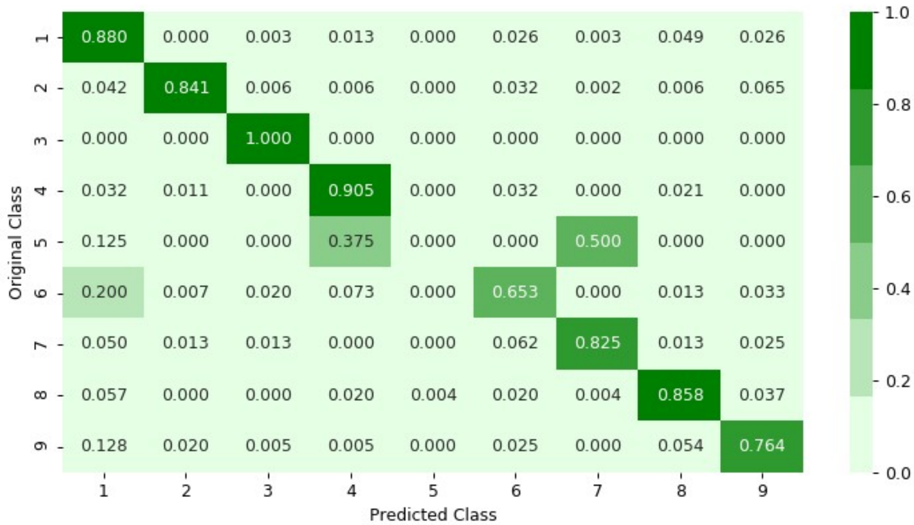



```
For values of best alpha =  3 The train log loss is: 0.29320594139515405
For values of best alpha =  3 The cross validation log loss is: 0.48311690264216
1
For values of best alpha =  3 The test log loss is: 0.4851954874286108
Number of misclassified points  12.97148114075437
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```

-- Precision matrix ---



Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-- Recall matrix ---

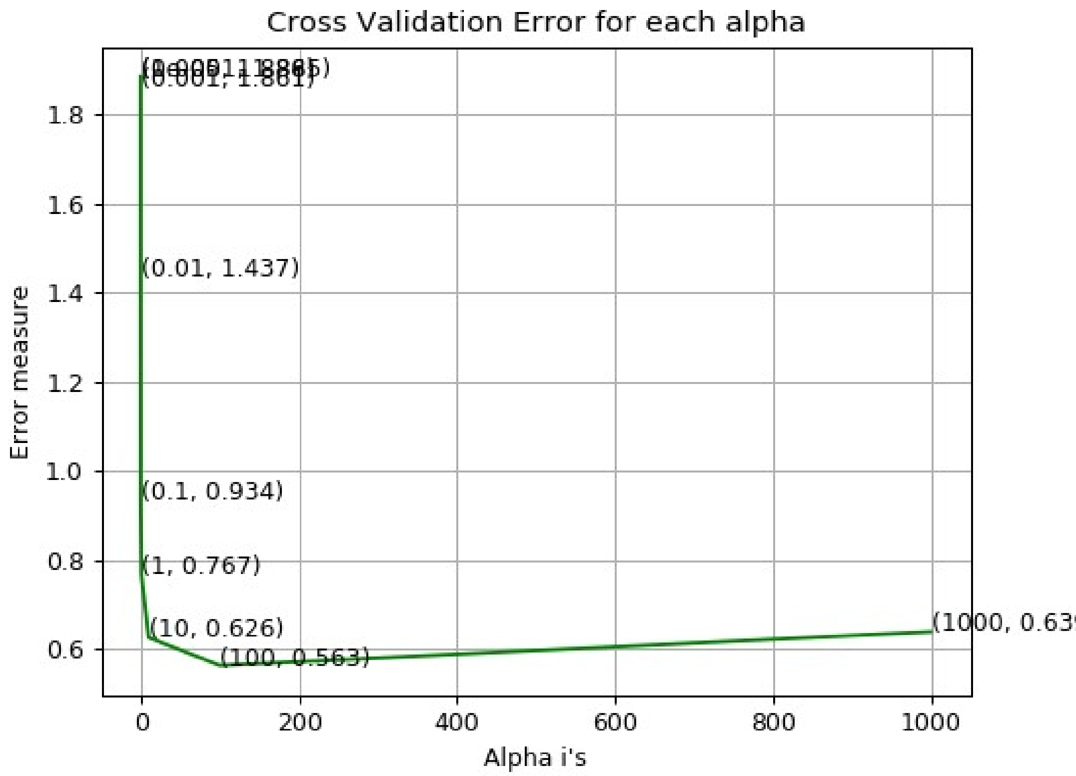



```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.3. Logistic Regression

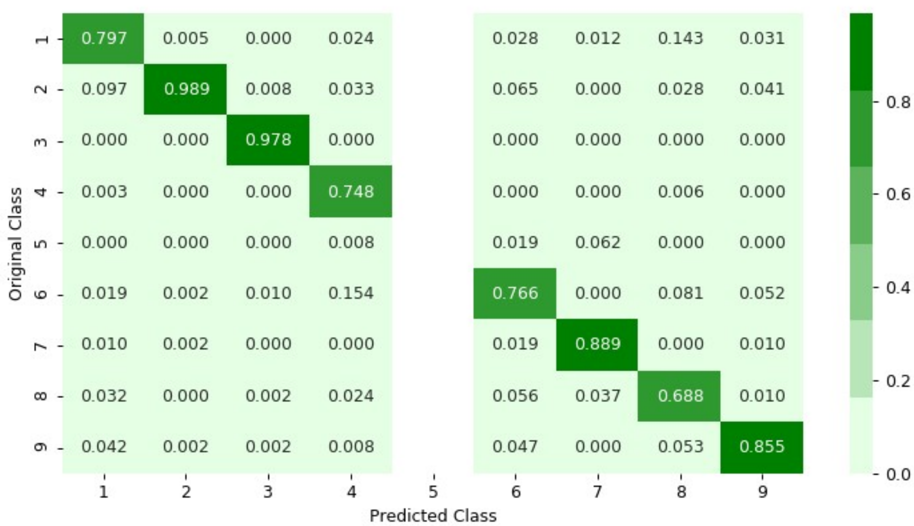
In [22]:
```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/genera
ted/sklearn.linear_model.SGDClassifier.html
# -------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_inter
cept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate
='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …])     Fit linear model with Stochastic G
radient Descent.
# predict(X)    Predict class labels for samples in X.

#-------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/geometric-intuition-1/
#------------------------------

alpha = [10 ** x for x in range(-5, 4)]
cv_log_error_array=[]
for i in alpha:
    logisticR=LogisticRegression(penalty='l2',C=i,class_weight='balanced')
    logisticR.fit(X_train,y_train)
    sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_cv)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=logisticR.classes_,
eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])

best_alpha = np.argmin(cv_log_error_array)

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

logisticR=LogisticRegression(penalty='l2',C=alpha[best_alpha],class_weight='balanc
ed')
logisticR.fit(X_train,y_train)
sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
sig_clf.fit(X_train, y_train)
pred_y=sig_clf.predict(X_test)

predict_y = sig_clf.predict_proba(X_train)
print ('log loss for train data',log_loss(y_train, predict_y, labels=logisticR.cla
sses_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_cv)
print ('log loss for cv data',log_loss(y_cv, predict_y, labels=logisticR.classes_,
eps=1e-15))
predict_y = sig_clf.predict_proba(X_test)
print ('log loss for test data',log_loss(y_test, predict_y, labels=logisticR.class
es_, eps=1e-15))
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

```
log_loss for c =  1e-05 is 1.8861109311791922
log_loss for c =  0.0001 is 1.8845880471197165
log_loss for c =  0.001 is 1.8614285515198798
log_loss for c =  0.01 is 1.437434379095915
log_loss for c =  0.1 is 0.9337959204695321
log_loss for c =  1 is 0.7667190017910965
log_loss for c =  10 is 0.6257185173536978
log_loss for c =  100 is 0.56294262675526
log_loss for c =  1000 is 0.6385231825855628
```

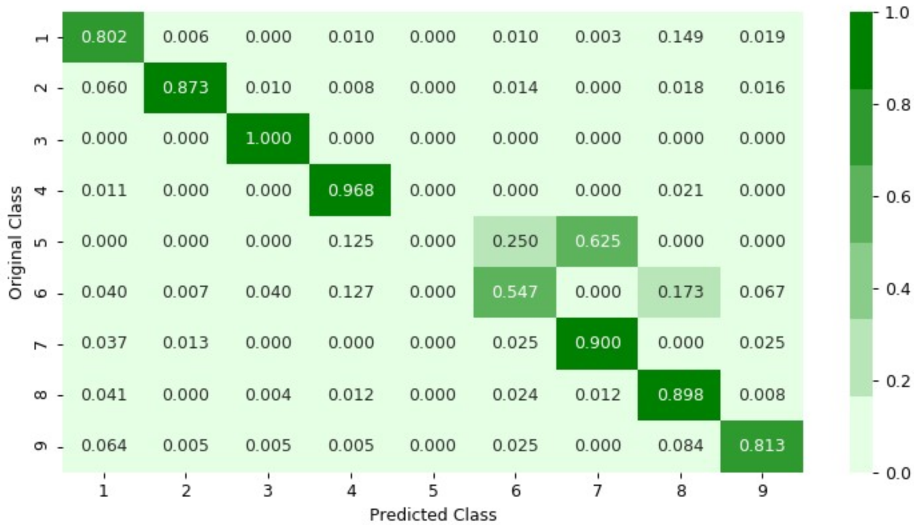



```
log loss for train data 0.4871437301878761
log loss for cv data 0.56294262675526
log loss for test data 0.5294168099375685
Number of misclassified points  12.603495860165593
-------------------------------------------------- Confusion matrix ------------
-------------------------------------
```

-- Precision matrix --



Sum of columns in precision matrix [1.   1.   1.   1. nan 1.   1.   1.   1.]
-- Recall matrix --

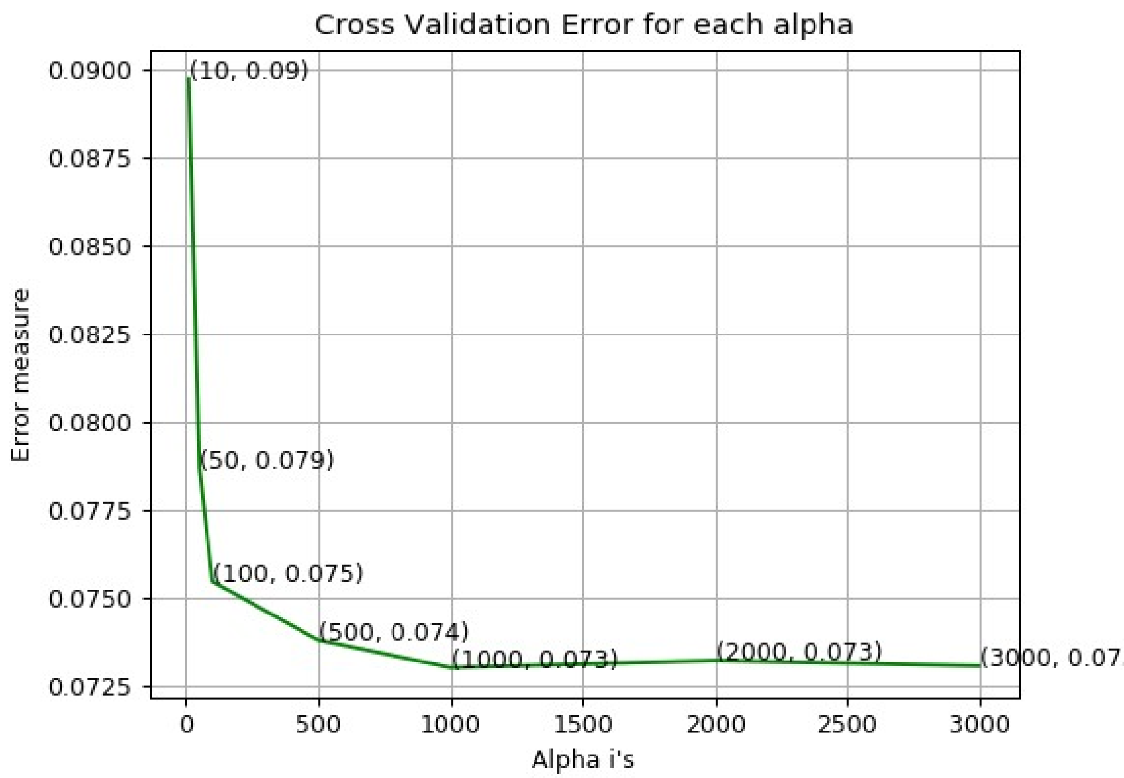



```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.4. Random Forest Classifier

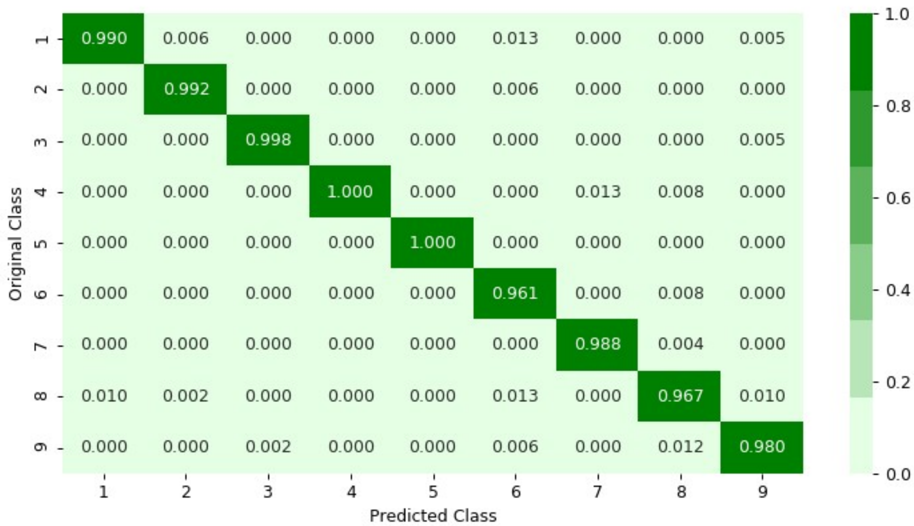
In [23]:
```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_d
epth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_
nodes=None, min_impurity_decrease=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state
=None, verbose=0, warm_start=False,
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given training
data.
# predict(X)    Perform classification on samples in X.
# predict_proba (X)     Perform classification on samples in X.

# some of attributes of  RandomForestClassifier()
# feature_importances_ : array of shape = [n_features]
# The feature importances (the higher, the more important the feature).

# --------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/random-forest-and-their-construction-2/
# --------------------------------

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
train_log_error_array=[]
from sklearn.ensemble import RandomForestClassifier
for i in alpha:
    r_cfl=RandomForestClassifier(n_estimators=i,random_state=42,n_jobs=-1)
    r_cfl.fit(X_train,y_train)
    sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_cv)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=r_cfl.classes_, eps
=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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


r_cfl=RandomForestClassifier(n_estimators=alpha[best_alpha],random_state=42,n_jobs
=-1)
r_cfl.fit(X_train,y_train)
sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",l
og_loss(y_train, predict_y))
```

```
log_loss for c =  10 is 0.08975272796356877
log_loss for c =  50 is 0.07869374681057625
log_loss for c =  100 is 0.07546292664044586
log_loss for c =  500 is 0.07379883728342362
log_loss for c =  1000 is 0.07302077078516724
log_loss for c =  2000 is 0.07321813574020479
log_loss for c =  3000 is 0.073068132864414
```




```
For values of best alpha =  1000 The train log loss is: 0.02941015229514485
For values of best alpha =  1000 The cross validation log loss is: 0.07302077078
516724
For values of best alpha =  1000 The test log loss is: 0.06623869322452512
Number of misclassified points  1.2419503219871204
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```


```
-------------------------------------------------- Precision matrix ------------
--------------------------------------
```

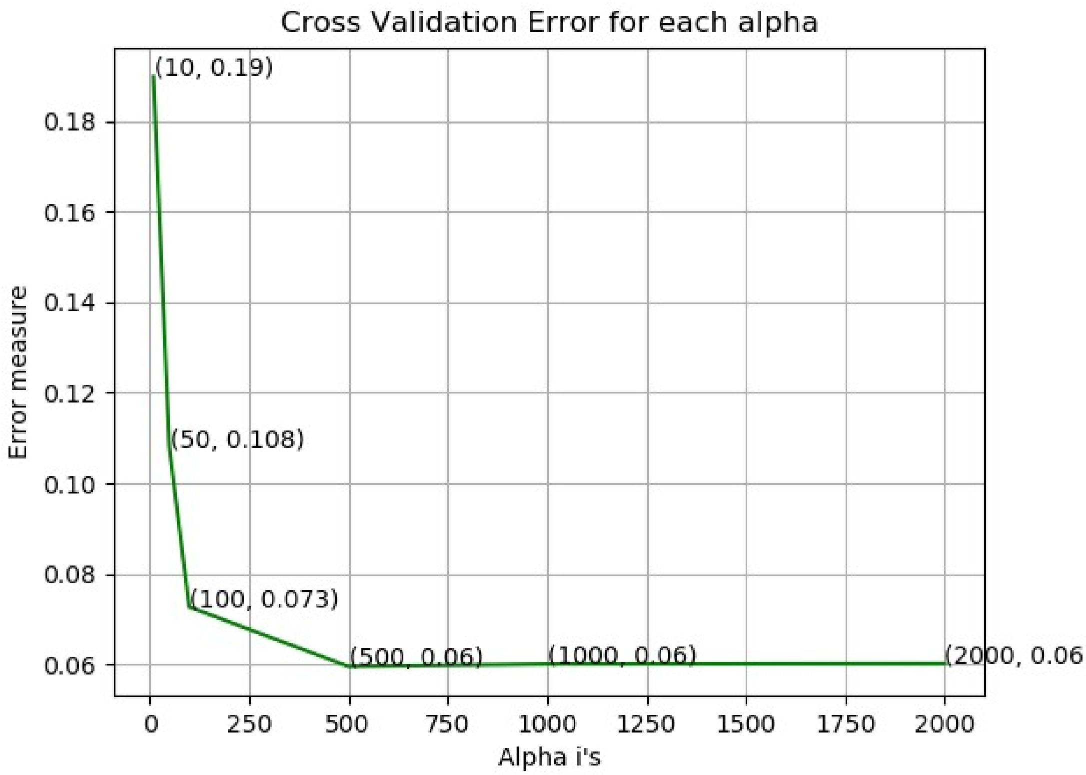



```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-------------------------------------------------- Recall matrix ---------------
-----------------------------------


Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.5. XgBoost Classification

In [14]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alpha=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **kwargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep])     Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# -----------------------

alpha=[10,50,100,500,1000,2000]
cv_log_error_array=[]
for i in alpha:
    x_cfl=XGBClassifier(n_estimators=i,nthread=-1)
    x_cfl.fit(X_train,y_train)
    sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_cv)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=x_cfl.classes_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=alpha[best_alpha],nthread=-1)
x_cfl.fit(X_train,y_train)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:", log_loss(y_train, predict_y))
```

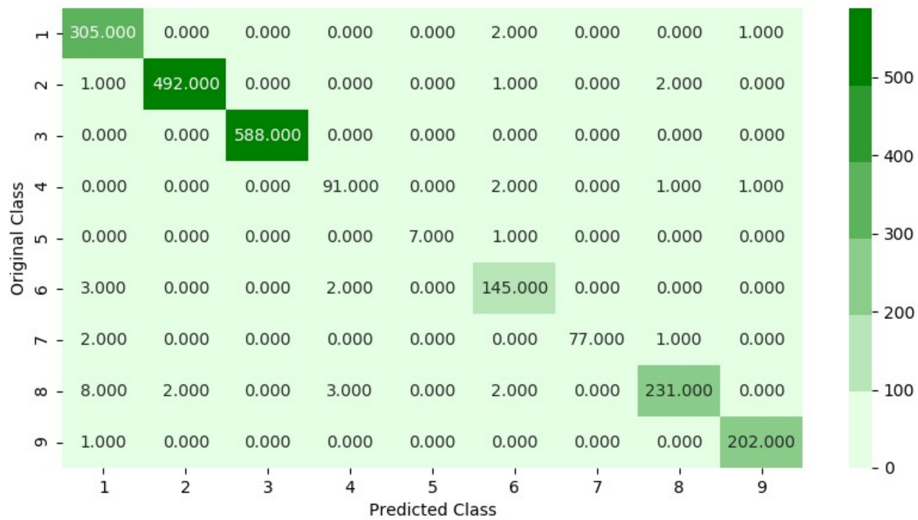
```
log_loss for c =  10 is 0.18972194520294353
log_loss for c =  50 is 0.10788109266220497
log_loss for c =  100 is 0.0727450829972164
log_loss for c =  500 is 0.059635927131908094
log_loss for c =  1000 is 0.06014538270053144
log_loss for c =  2000 is 0.060249389062255305
```



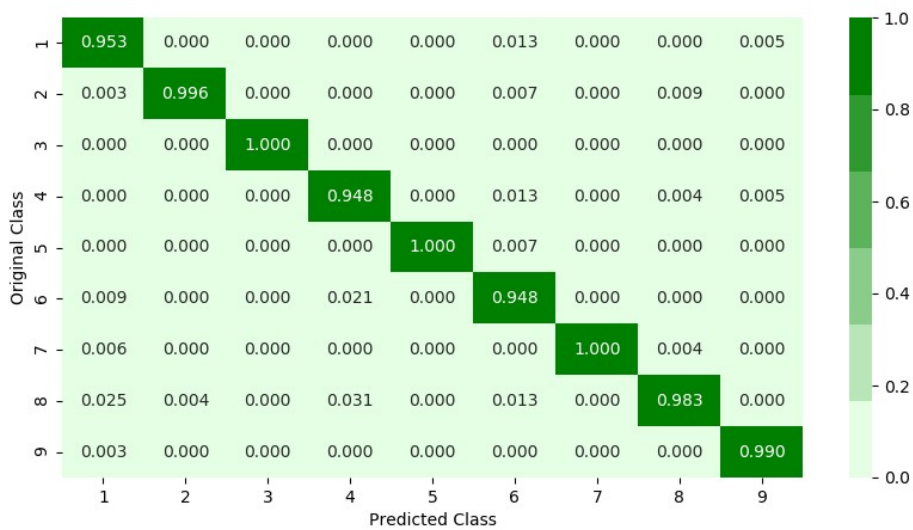

```
For values of best alpha =  500 The train log loss is: 0.02468009568654092
For values of best alpha =  500 The cross validation log loss is: 0.059635927131
908094
For values of best alpha =  500 The test log loss is: 0.07847700799402009
```

In [15]:
```
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

```
Number of misclassified points  1.6559337626494939
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```




```
-------------------------------------------------- Precision matrix ------------
--------------------------------------
```




```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-------------------------------------------------- Recall matrix ---------------
-----------------------------------
```


```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.5. XgBoost Classification with best hyper parameters using RandomSearch

In [22]:
```
# https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tuning-xgb
oost-with-codes-python/
x_cfl=XGBClassifier()

prams={
    'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],
     'n_estimators':[100,200,500,1000,2000],
     'max_depth':[3,5,10],
    'colsample_bytree':[0.1,0.3,0.5,1],
    'subsample':[0.1,0.3,0.5,1]
}
random_cfl1=RandomizedSearchCV(x_cfl,param_distributions=prams,verbose=10,n_jobs=-
1,)
random_cfl1.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  4.1min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  9.8min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed: 31.8min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed: 48.9min remaining:  5.4min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 54.2min finished
```

Out[22]:
```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
          estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_by
level=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1),
          fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
          param_distributions={'learning_rate': [0.01, 0.03, 0.05, 0.1, 0.15, 0.
2], 'n_estimators': [100, 200, 500, 1000, 2000], 'max_depth': [3, 5, 10], 'colsa
mple_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=10)
```

In [ ]:
```
print (random_cfl1.best_params_)
```

```
{'subsample': 1, 'n_estimators': 2000, 'max_depth': 5, 'learning_rate': 0.01, 'c
olsample_bytree': 0.5}
```

In [16]:
```
x_cfl=XGBClassifier(n_estimators=2000, learning_rate=0.01, colsample_bytree=0.5, m
ax_depth=5,subsample=1)
x_cfl.fit(X_train,y_train)
c_cfl=CalibratedClassifierCV(x_cfl,method='sigmoid')
c_cfl.fit(X_train,y_train)

predict_y = c_cfl.predict_proba(X_train)
print ('train loss',log_loss(y_train, predict_y))
predict_y = c_cfl.predict_proba(X_cv)
print ('cv loss',log_loss(y_cv, predict_y))
predict_y = c_cfl.predict_proba(X_test)
print ('test loss',log_loss(y_test, predict_y))
```

```
train loss 0.024348854759529453
cv loss 0.06210692336009718
test loss 0.07717065282799755
```

In [ ]:

4.2 Modeling with .asm files

There are 10868 files of asm
All the files make up about 150 GB
The asm files contains :
1. Address
2. Segments
3. Opcodes
4. Registers
5. function calls
6. APIs
With the help of parallel processing we extracted all the features.In parallel we can use all the cores that are present in our computer.

Here we extracted 52 features from all the asm files which are important.

We read the top solutions and handpicked the features from those papers/videos/blogs.
Refer:https://www.kaggle.com/c/malware-classification/discussion

4.2.1 Feature extraction from asm files

To extract the unigram features from the .asm files we need to process ~150GB of data

Note: Below two cells will take lot of time (over 48 hours to complete)

We will provide you the output file of these two cells, which you can directly use it

In [ ]:
```
#intially create five folders
#first
#second
#thrid
#fourth
#fifth
#this code tells us about random split of files into five folders
folder_1 ='first'
folder_2 ='second'
folder_3 ='third'
folder_4 ='fourth'
folder_5 ='fifth'
folder_6 = 'output'
for i in [folder_1,folder_2,folder_3,folder_4,folder_5,folder_6]:
    if not os.path.isdir(i):
        os.makedirs(i)

source='train/'
files = os.listdir('train')
ID=df['Id'].tolist()
data=range(0,10868)
r.shuffle(data)
count=0
for i in range(0,10868):
    if i % 5==0:
        shutil.move(source+files[data[i]],'first')
    elif i%5==1:
        shutil.move(source+files[data[i]],'second')
    elif i%5 ==2:
        shutil.move(source+files[data[i]],'thrid')
    elif i%5 ==3:
        shutil.move(source+files[data[i]],'fourth')
    elif i%5==4:
        shutil.move(source+files[data[i]],'fifth')
```

In [ ]:
```
#http://flint.cs.yale.edu/cs421/papers/x86-asm/asm.html

def firstprocess():
    #The prefixes tells about the segments that are present in the asm files
    #There are 450 segments(approx) present in all asm files.
    #this prefixes are best segments that gives us best values.
    #https://en.wikipedia.org/wiki/Data_segment

    prefixes = ['HEADER:','.text:','.Pav:','.idata:','.data:','.bss:','.rdata:','.
edata:','.rsrc:','.tls:','.reloc:','.BSS:','.CODE']
    #this are opcodes that are used to get best results
    #https://en.wikipedia.org/wiki/X86_instruction_listings

    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub', '
inc', 'dec', 'add','imul', 'xchg', 'or', 'shr', 'cmp', 'call', 'shl', 'ror', 'rol'
, 'jnb','jz','rtn','lea','movzx']
    #best keywords that are taken from different blogs
    keywords = ['.dll','std::',':dword']
    #Below taken registers are general purpose registers and special registers
    #All the registers which are taken are best
    registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
    file1=open("output\asmsmallfile.txt","w+")
    files = os.listdir('first')
    for f in files:
        #filling the values with zeros into the arrays
        prefixescount=np.zeros(len(prefixes),dtype=int)
        opcodescount=np.zeros(len(opcodes),dtype=int)
        keywordcount=np.zeros(len(keywords),dtype=int)
        registerscount=np.zeros(len(registers),dtype=int)
        features=[]
        f2=f.split('.')[0]
        file1.write(f2+",")
        opcodefile.write(f2+" ")
        # https://docs.python.org/3/library/codecs.html#codecs.ignore_errors
        # https://docs.python.org/3/library/codecs.html#codecs.Codec.encode
        with codecs.open('first/'+f,encoding='cp1252',errors ='replace') as fli:
            for lines in fli:
                # https://www.tutorialspoint.com/python3/string_rstrip.htm
                line=lines.rstrip().split()
                l=line[0]
                #counting the prefixs in each and every line
                for i in range(len(prefixes)):
                    if prefixes[i] in line[0]:
                        prefixescount[i]+=1
                line=line[1:]
                #counting the opcodes in each and every line
                for i in range(len(opcodes)):
                    if any(opcodes[i]==li for li in line):
                        features.append(opcodes[i])
                        opcodescount[i]+=1
                #counting registers in the line
                for i in range(len(registers)):
                    for li in line:
                        # we will use registers only in 'text' and 'CODE' segments
                        if registers[i] in li and ('text' in l or 'CODE' in l):
                            registerscount[i]+=1
                #counting keywords in the line
                for i in range(len(keywords)):
                    for li in line:
                        if keywords[i] in li:
                            keywordcount[i]+=1
        #pushing the values into the file after reading whole file
        for prefix in prefixescount:
            file1.write(str(prefix)+",")
```

In [14]:
```
# asmoutputfile.csv(output genarated from the above two cells) will contain all th
e extracted features from .asm files
# this file will be uploaded in the drive, you can directly use this
dfasm=pd.read_csv("asmoutputfile.csv")
Y.columns = ['ID', 'Class']
result_asm = pd.merge(dfasm, Y,on='ID', how='left')
result_asm.head()
```

Out[14]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	edx	esi
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	18	66
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	18	29
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	13	42
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	6	8
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	12	9

5 rows × 53 columns

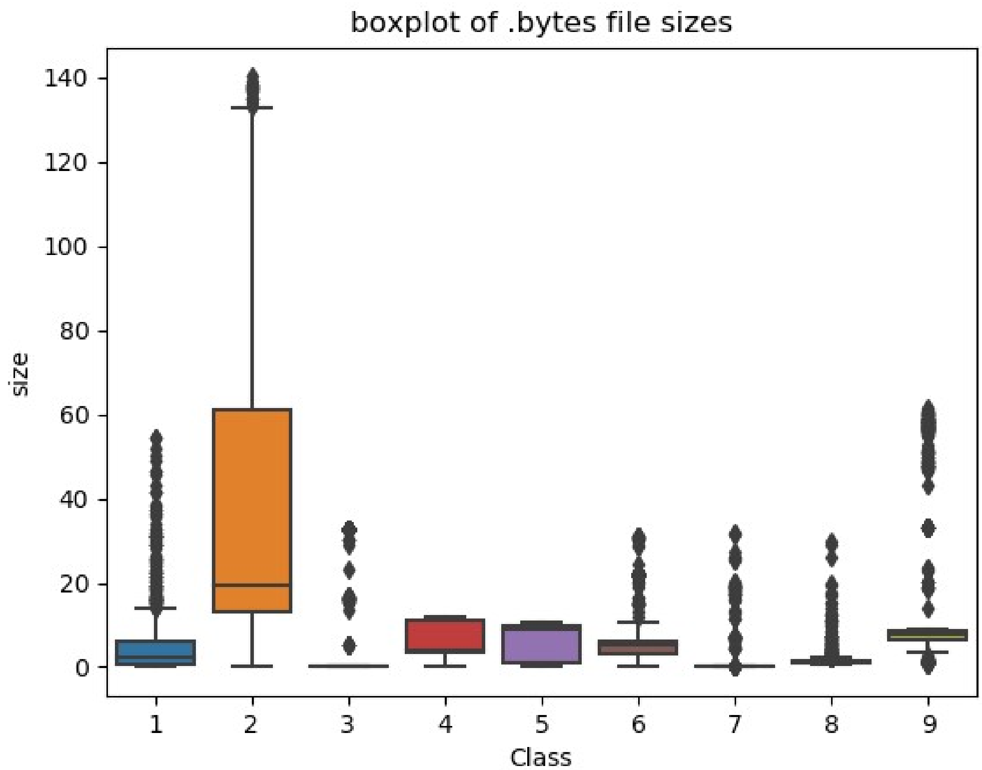
4.2.1.1 Files sizes of each .asm file

In [15]:
```
#file sizes of byte files

files=os.listdir('asmFiles')
filenames=Y['ID'].tolist()
class_y=Y['Class'].tolist()
class_bytes=[]
sizebytes=[]
fnames=[]
for file in files:
    # print(os.stat('byteFiles/0A32eTdBKayjCWhZqDOQ.txt'))
    # os.stat_result(st_mode=33206, st_ino=1125899906874507, st_dev=3561571700, st
_nlink=1, st_uid=0, st_gid=0,
    # st_size=3680109, st_atime=1519638522, st_mtime=1519638522, st_ctime=15196385
22)
    # read more about os.stat: here https://www.tutorialspoint.com/python/os_stat.
htm
    statinfo=os.stat('asmFiles/'+file)
    # split the file name at '.' and take the first part of it i.e the file name
    file=file.split('.')[0]
    if any(file == filename for filename in filenames):
        i=filenames.index(file)
        class_bytes.append(class_y[i])
        # converting into Mb's
        sizebytes.append(statinfo.st_size/(1024.0*1024.0))
        fnames.append(file)
asm_size_byte=pd.DataFrame({'ID':fnames,'size':sizebytes,'Class':class_bytes})
print (asm_size_byte.head())
```

```
                     ID       size  Class
0  01azqd4InC7m9JpocGv5  56.229886      9
1  01IsoiSMh5gxyDYTl4CB  13.999378      2
2  01jsnpXSAlgw6aPeDxrU   8.507785      9
3  01kcPWA9K2BOxQeS5Rju   0.078190      1
4  01SuzwMJEIXsK7A8dQbl   0.996723      8
```

4.2.1.2 Distribution of .asm file sizes

In [15]:
```
#boxplot of asm files
ax = sns.boxplot(x="Class", y="size", data=asm_size_byte)
plt.title("boxplot of .bytes file sizes")
plt.show()
```



In [16]:
```
# add the file size feature to previous extracted features
print(result_asm.shape)
print(asm_size_byte.shape)
result_asm = pd.merge(result_asm, asm_size_byte.drop(['Class'], axis=1),on='ID', h
ow='left')
result_asm.head()
```

```
(10868, 53)
(10868, 3)
```

Out[16]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	eax
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	66	15
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	29	48
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	42	10
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	8	14
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	9	18

5 rows × 54 columns

In [17]:
```
# we normalize the data each column
result_asm.head()
```

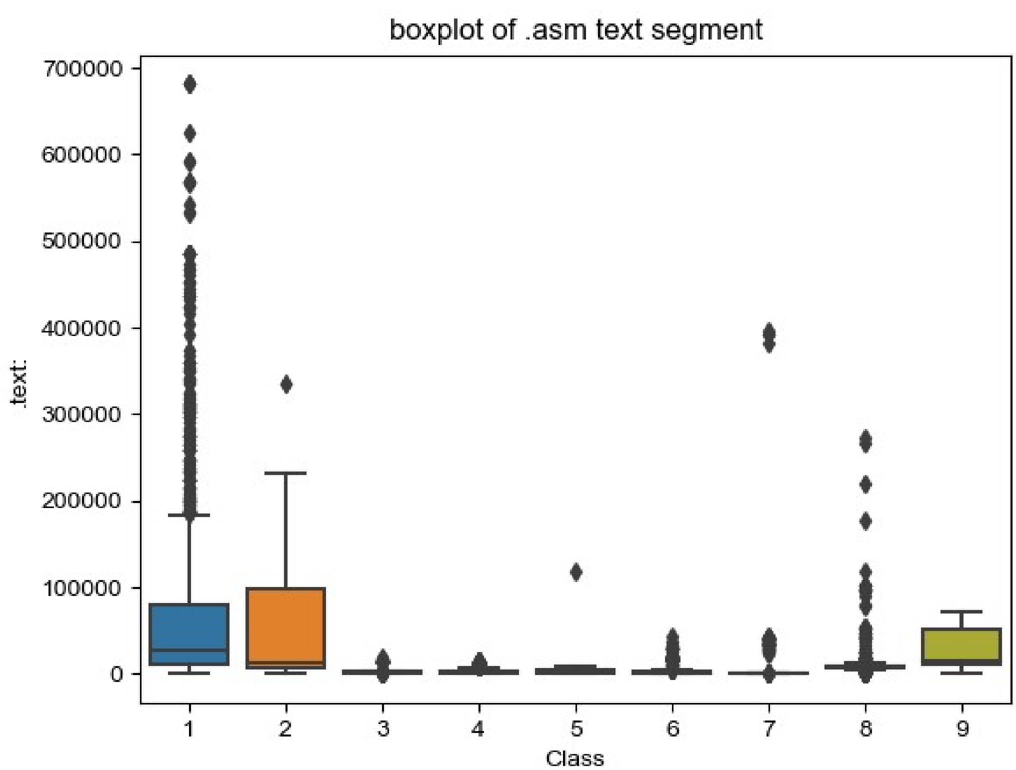
Out[17]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	eax
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	66	15
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	29	48
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	42	10
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	8	14
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	9	18

5 rows × 54 columns

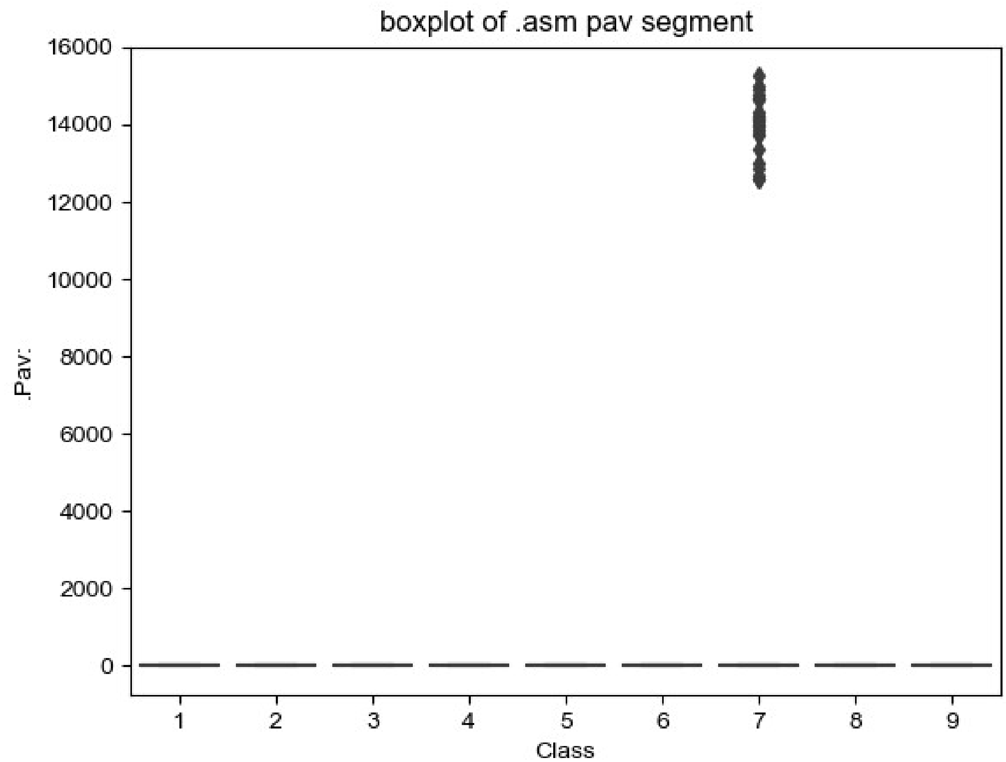
4.2.2 Univariate analysis on asm file features

In [18]:
```
ax = sns.boxplot(x="Class", y=".text:", data=result_asm)
plt.title("boxplot of .asm text segment")
plt.show()
```

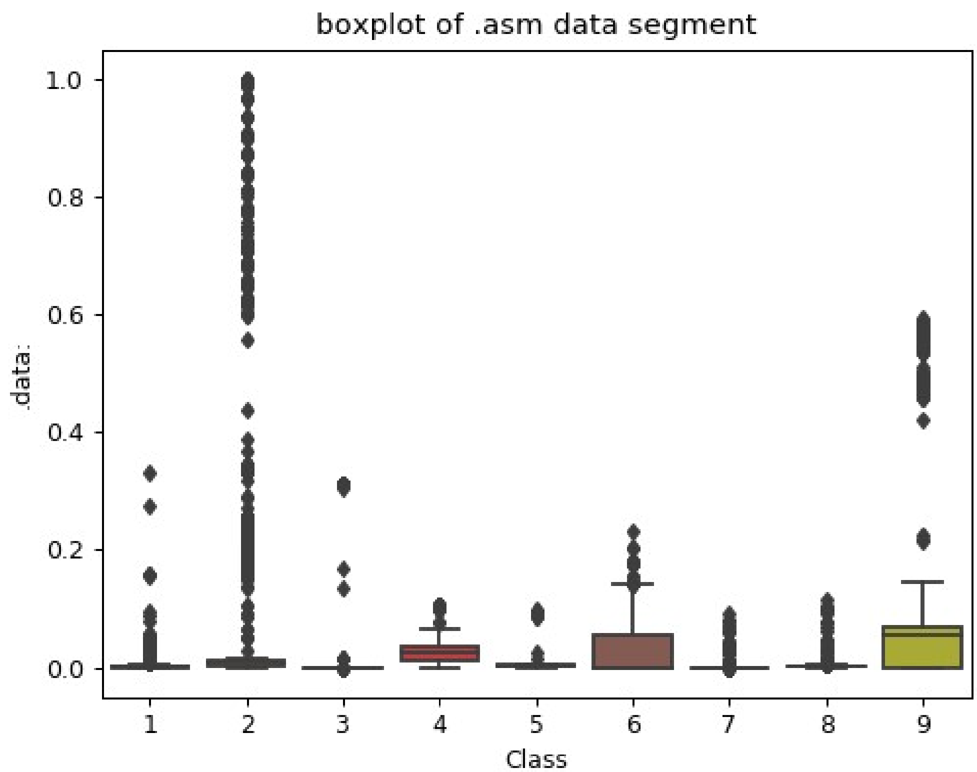



```
The plot is between Text and class
Class 1,2 and 9 can be easly separated
```

In [19]:
```
ax = sns.boxplot(x="Class", y=".Pav:", data=result_asm)
plt.title("boxplot of .asm pav segment")
plt.show()
```

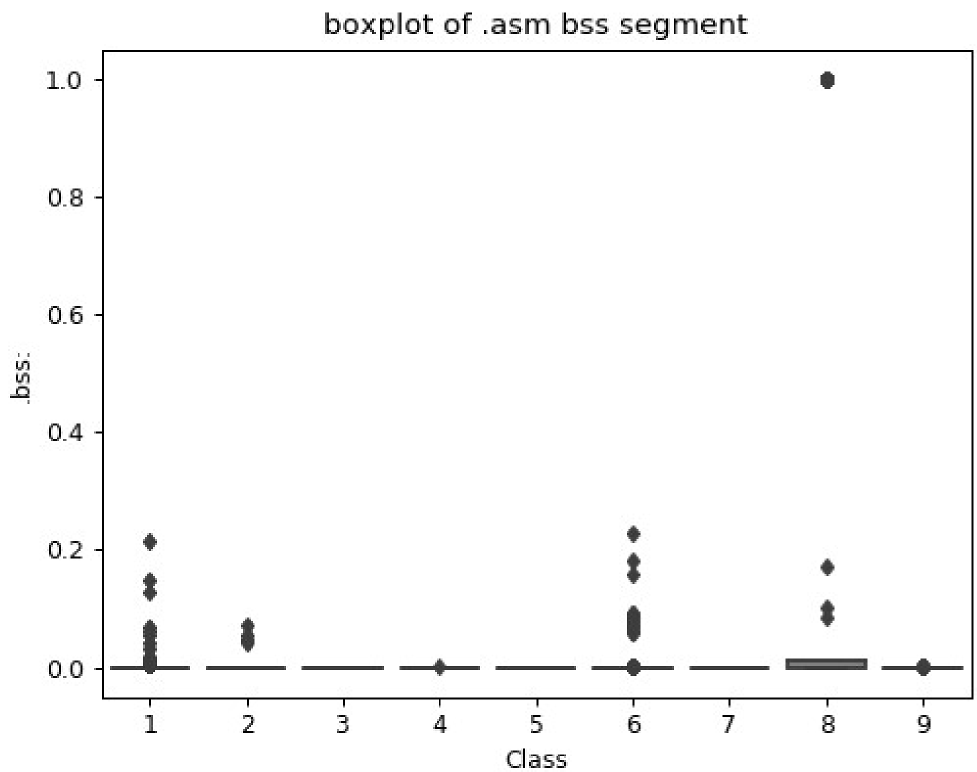


In [19]:
```
ax = sns.boxplot(x="Class", y=".data:", data=result_asm)
plt.title("boxplot of .asm data segment")
plt.show()
```



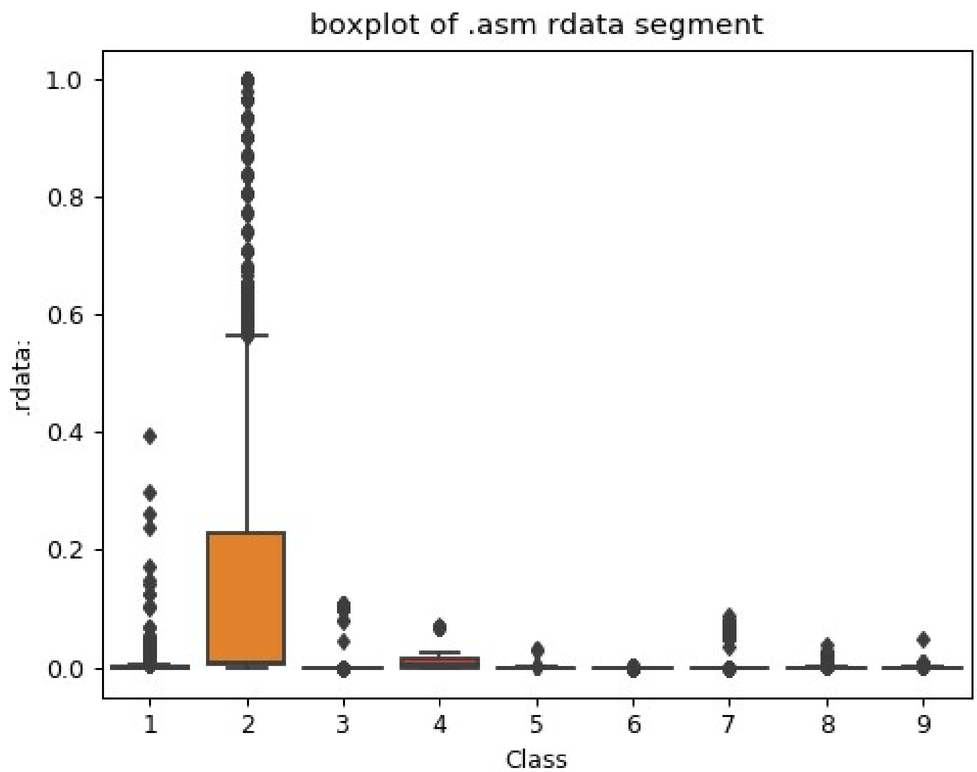
The plot is between data segment and class label
class 6 and class 9 can be easily separated from given points

In [20]:
```
ax = sns.boxplot(x="Class", y=".bss:", data=result_asm)
plt.title("boxplot of .asm bss segment")
plt.show()
```



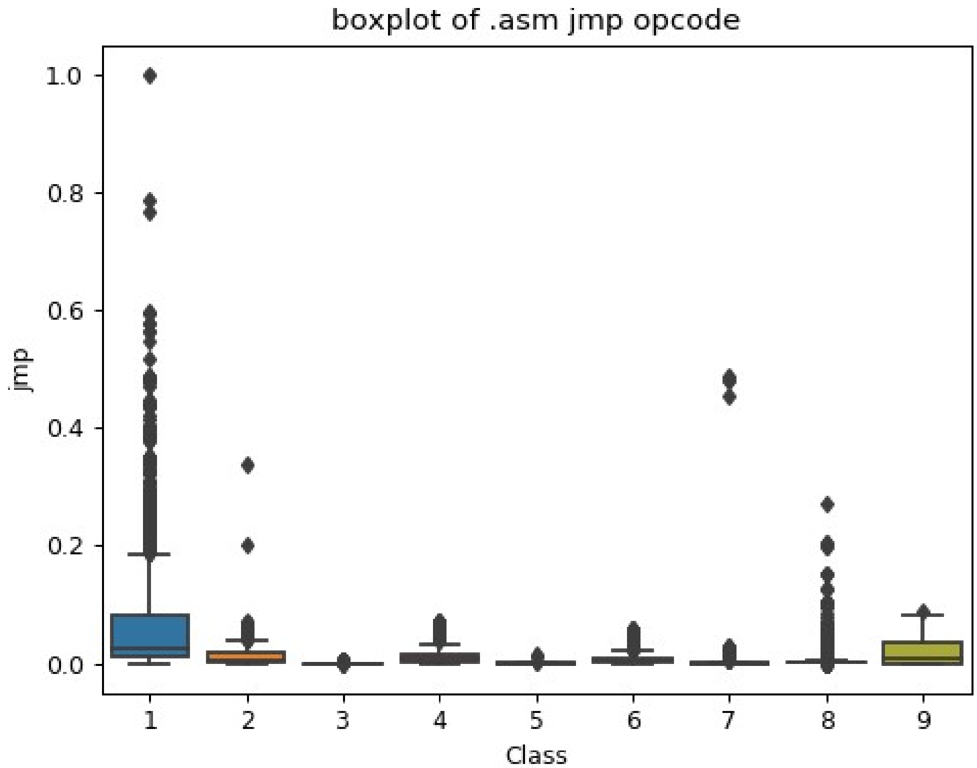
plot between bss segment and class label
very less number of files are having bss segment

In [21]:
```
ax = sns.boxplot(x="Class", y=".rdata:", data=result_asm)
plt.title("boxplot of .asm rdata segment")
plt.show()
```



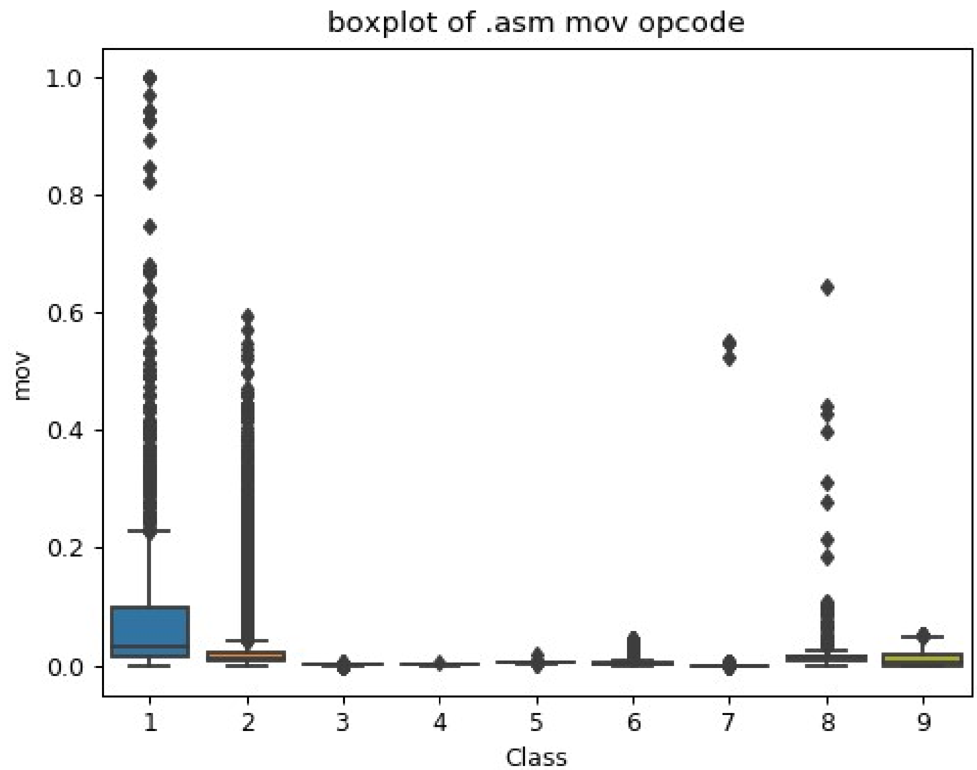
Plot between rdata segment and Class segment
Class 2 can be easily separated 75 pecentile files are having 1M rdata lines

In [22]:
```
ax = sns.boxplot(x="Class", y="jmp", data=result_asm)
plt.title("boxplot of .asm jmp opcode")
plt.show()
```



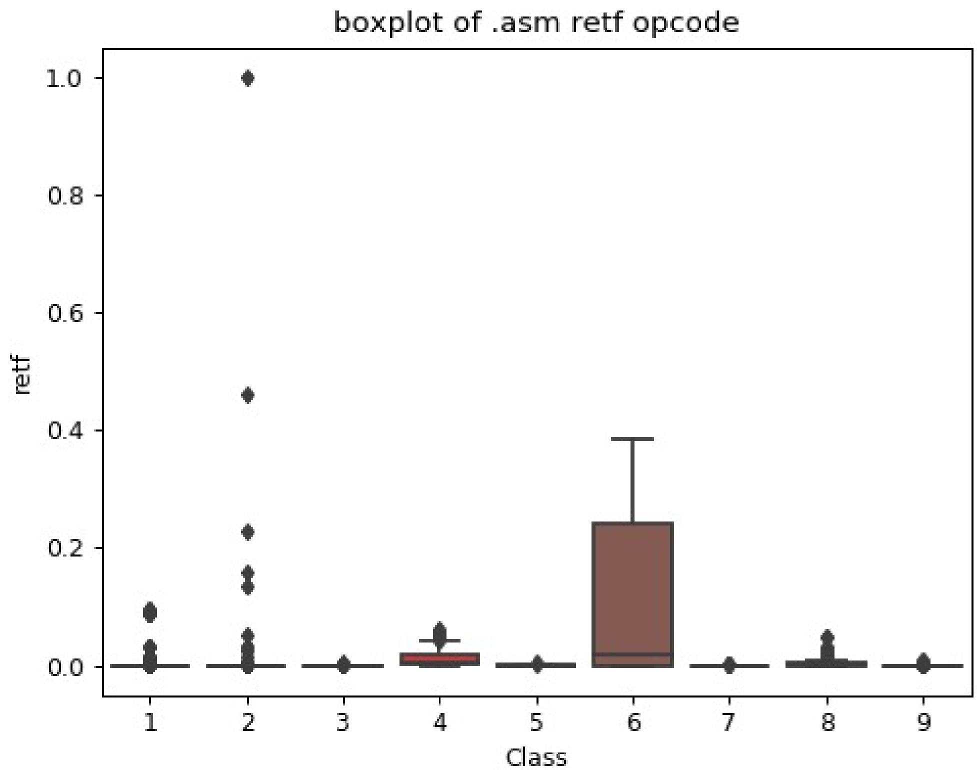
plot between jmp and Class label
Class 1 is having frequency of 2000 approx in 75 perentile of files

In [23]:
```
ax = sns.boxplot(x="Class", y="mov", data=result_asm)
plt.title("boxplot of .asm mov opcode")
plt.show()
```



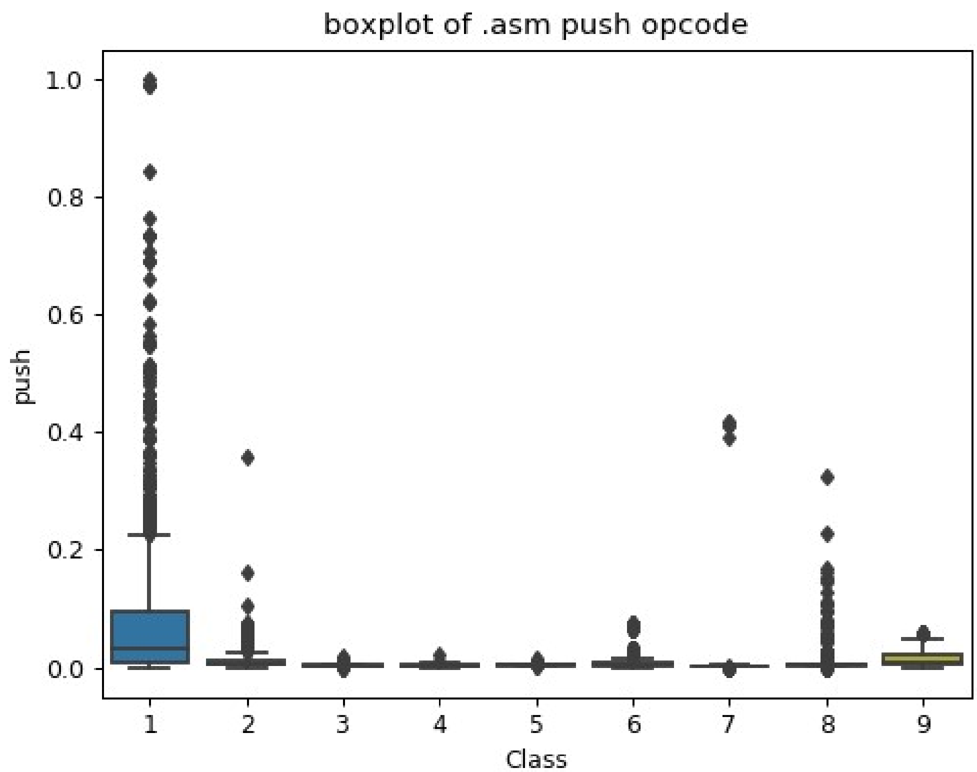
plot between Class label and mov opcode
Class 1 is having frequency of 2000 approx in 75 perentile of files

In [24]:
```
ax = sns.boxplot(x="Class", y="retf", data=result_asm)
plt.title("boxplot of .asm retf opcode")
plt.show()
```



plot between Class label and retf
Class 6 can be easily separated with opcode retf
The frequency of retf is approx of 250.

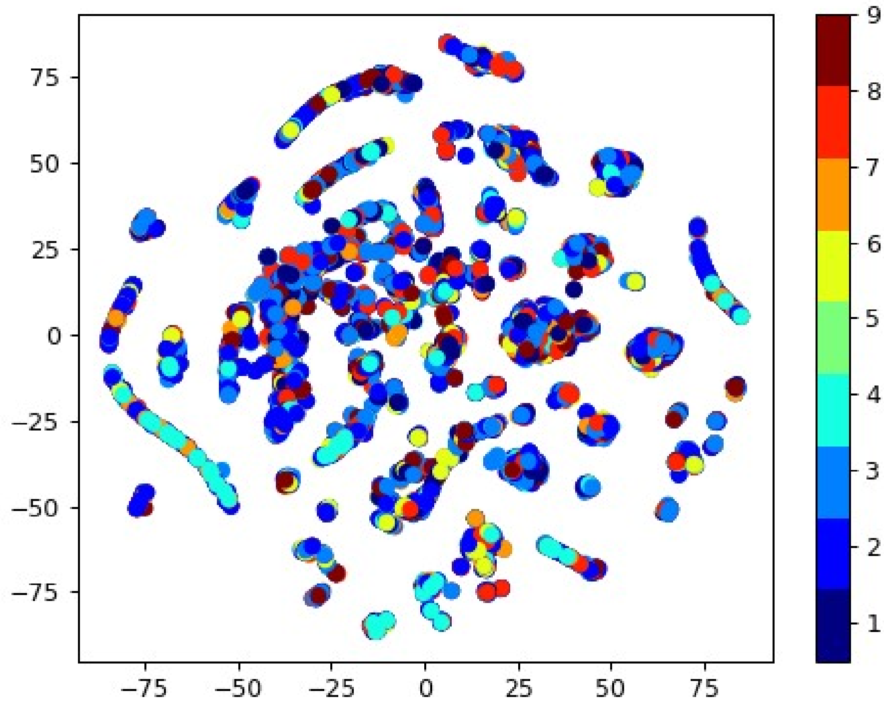
In [25]:
```
ax = sns.boxplot(x="Class", y="push", data=result_asm)
plt.title("boxplot of .asm push opcode")
plt.show()
```



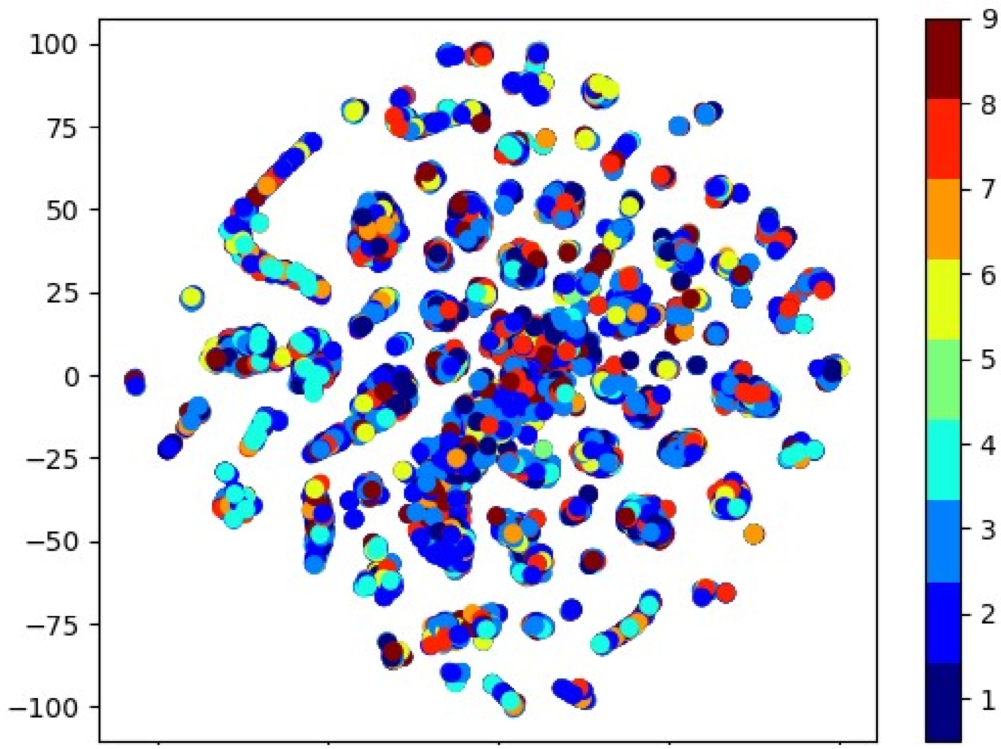

```
plot between push opcode and Class label
Class 1 is having 75 precentile files with push opcodes of frequency 1000
```

4.2.2 Multivariate Analysis on .asm file features

In [16]:
```
# check out the course content for more explantion on tsne algorithm
# https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/t-distri
buted-stochastic-neighbourhood-embeddingt-sne-part-1/

#multivariate analysis on byte files
#this is with perplexity 50
xtsne=TSNE(perplexity=50)
results=xtsne.fit_transform(result_asm.drop(['ID','Class'], axis=1).fillna(0))
vis_x = results[:, 0]
vis_y = results[:, 1   ]
plt.scatter(vis_x, vis_y, c=data_y, cmap=plt.cm.get_cmap("jet", 9))
plt.colorbar(ticks=range(10))
plt.clim(0.5, 9)
plt.show()
```



In [30]:
```
# by univariate analysis on the .asm file features we are getting very negligible information from
# 'rtn', '.BSS:' '.CODE' features, so heare we are trying multivariate analysis after removing those features
# the plot looks very messy

xtsne=TSNE(perplexity=30)
results=xtsne.fit_transform(result_asm.drop(['ID','Class', 'rtn', '.BSS:', '.CODE','size'], axis=1))
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=data_y, cmap=plt.cm.get_cmap("jet", 9))
plt.colorbar(ticks=range(10))
plt.clim(0.5, 9)
plt.show()
```




```
TSNE for asm data with perplexity 50
```

4.2.3 Conclusion on EDA

We have taken only 52 features from asm files (after reading through many blogs and research papers)
The univariate analysis was done only on few important features.
Take-aways

- **1. Class 3 can be easily separated because of the frequency of segments,opcodes and keywords being less**
- **2. Each feature has its unique importance in separating the Class labels.**

4.3 Train and test split

In [18]:
```
asm_y = result_asm['Class']
asm_x = result_asm.drop(['ID','Class','.BSS:','rtn','.CODE'], axis=1)
```

In [19]:
```
X_train_asm, X_test_asm, y_train_asm, y_test_asm = train_test_split(asm_x,asm_y ,s
tratify=asm_y,test_size=0.20)
X_train_asm, X_cv_asm, y_train_asm, y_cv_asm = train_test_split(X_train_asm, y_tra
in_asm,stratify=y_train_asm,test_size=0.20)
```

In [20]:
```
print( X_cv_asm.isnull().all())
```

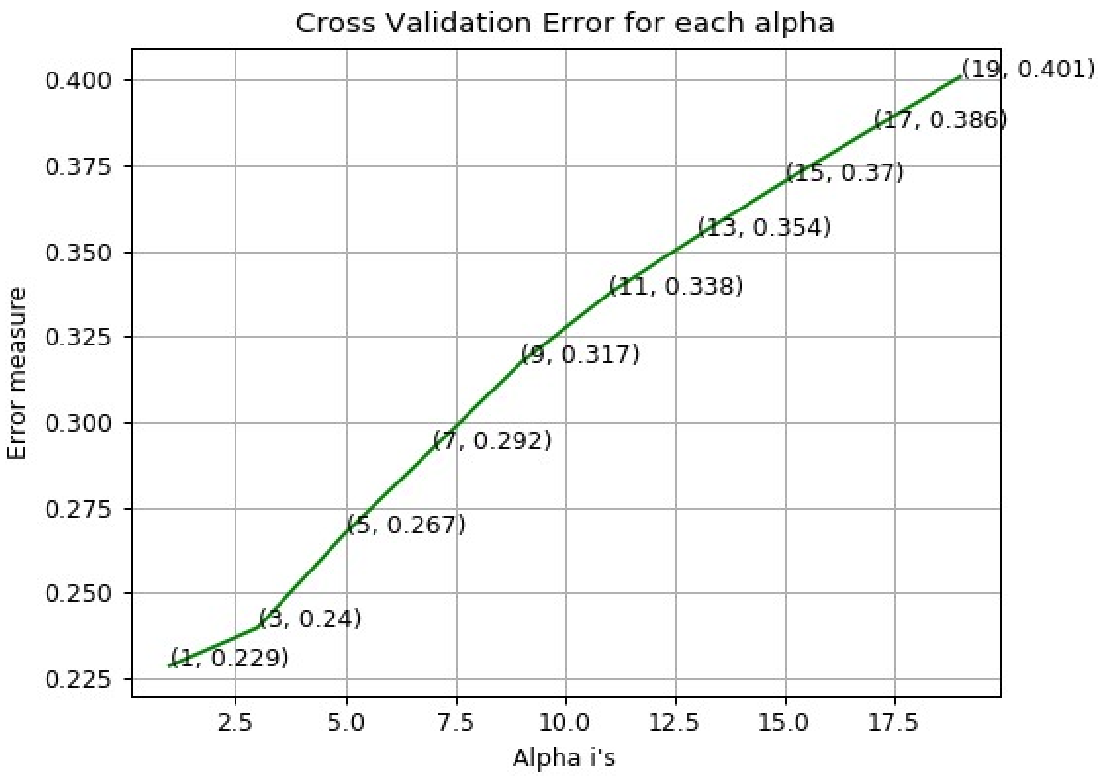
```
HEADER:     False
.text:      False
.Pav:       False
.idata:     False
.data:      False
.bss:       False
.rdata:     False
.edata:     False
.rsrc:      False
.tls:       False
.reloc:     False
jmp         False
mov         False
retf        False
push        False
pop         False
xor         False
retn        False
nop         False
sub         False
inc         False
dec         False
add         False
imul        False
xchg        False
or          False
shr         False
cmp         False
call        False
shl         False
ror         False
rol         False
jnb         False
jz          False
lea         False
movzx       False
.dll        False
std::       False
:dword      False
edx         False
esi         False
eax         False
ebx         False
ecx         False
edi         False
ebp         False
esp         False
eip         False
size        False
dtype: bool
```

4.4. Machine Learning models on features of .asm files

4.4.1 K-Nearest Neigbors

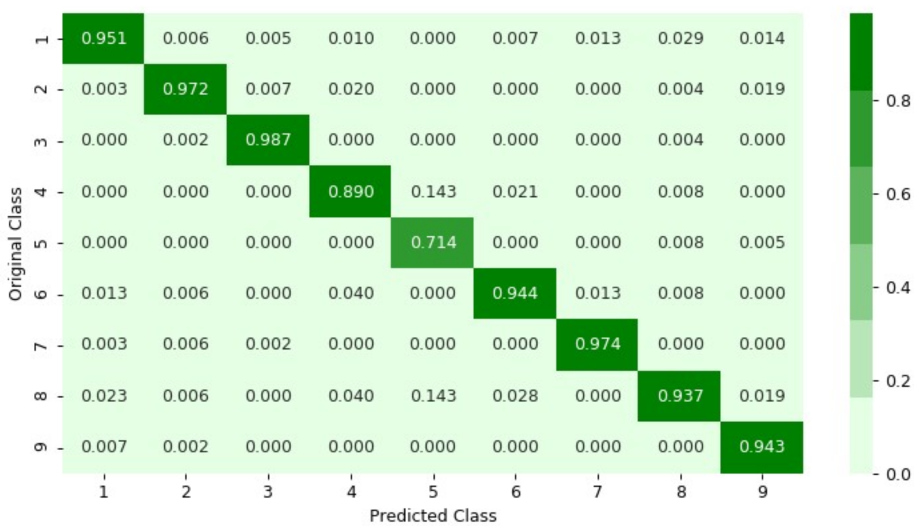
In [35]:
```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/modul
es/generated/sklearn.neighbors.KNeighborsClassifier.html
# -------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', leaf_si
ze=30, p=2,
# metric='minkowski', metric_params=None, n_jobs=1, **kwargs)

# methods of
# fit(X, y) : Fit the model using X as training data and y as target values
# predict(X):Predict the class labels for the provided data
# predict_proba(X):Return probability estimates for the test data X.
#-------------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/k-nearest-neighbors-geometric-intuition-with-a-toy-example-1/
#-------------------------------------


# find more about CalibratedClassifier
#CV here at http://scikit-learn.org/stable/modules/generated/sklearn.calibration.C
alibratedClassifierCV.html
# ----------------------------
# default paramters
# sklearn.calibration.CalibratedClassifierCV(base_estimator=None, method='sigmoid'
, cv=3)
#
# some of the methods of CalibratedClassifierCV()
# fit(X, y[, sample_weight])    Fit the calibrated model
# get_params([deep])    Get parameters for this estimator.
# predict(X)    Predict the target of new samples.
# predict_proba(X)      Posterior probabilities of classification
#-------------------------------------
# video link:
#-------------------------------------

alpha = [x for x in range(1, 21,2)]
cv_log_error_array=[]
for i in alpha:
    k_cfl=KNeighborsClassifier(n_neighbors=i)
    k_cfl.fit(X_train_asm,y_train_asm)
    sig_clf = CalibratedClassifierCV(k_cfl, method="sigmoid")
    sig_clf.fit(X_train_asm, y_train_asm)
    predict_y = sig_clf.predict_proba(X_cv_asm)
    cv_log_error_array.append(log_loss(y_cv_asm, predict_y, labels=k_cfl.classes_,
eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for k = ',alpha[i],'is',cv_log_error_array[i])

best_alpha = np.argmin(cv_log_error_array)

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

k_cfl=KNeighborsClassifier(n_neighbors=alpha[best_alpha])
k_cfl.fit(X_train_asm,y_train_asm)
sig_clf = CalibratedClassifierCV(k_cfl, method="sigmoid")
```

```
log_loss for k =  1 is 0.2286951008264786
log_loss for k =  3 is 0.23974604909767921
log_loss for k =  5 is 0.26743767182569295
log_loss for k =  7 is 0.2922812711849662
log_loss for k =  9 is 0.3173517943176062
log_loss for k =  11 is 0.3375272301343973
log_loss for k =  13 is 0.3542581717184334
log_loss for k =  15 is 0.3703567252351854
log_loss for k =  17 is 0.3857570471590401
log_loss for k =  19 is 0.40090334916939535
```



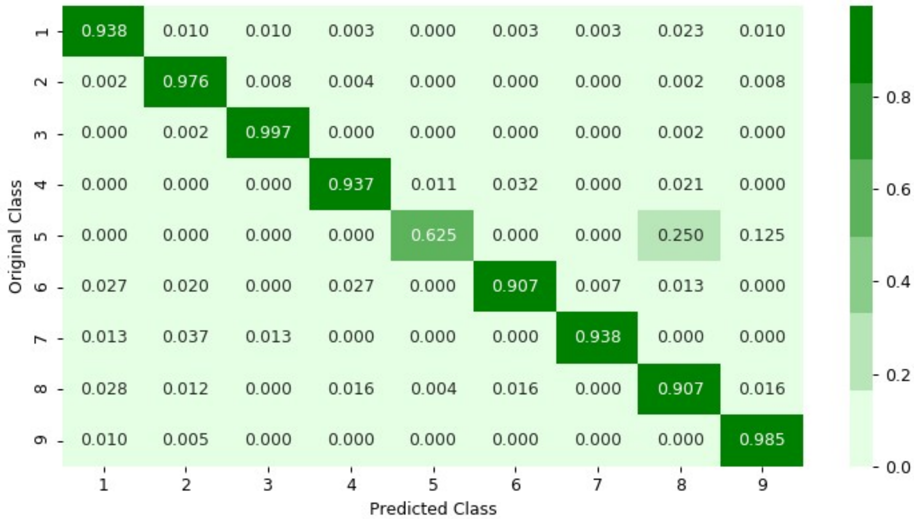

```
log loss for train data 0.07371820550676085
log loss for cv data 0.2286951008264786
log loss for test data 0.2135354369723588
Number of misclassified points  4.001839926402944
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```

-- Precision matrix --



Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

-- Recall matrix --

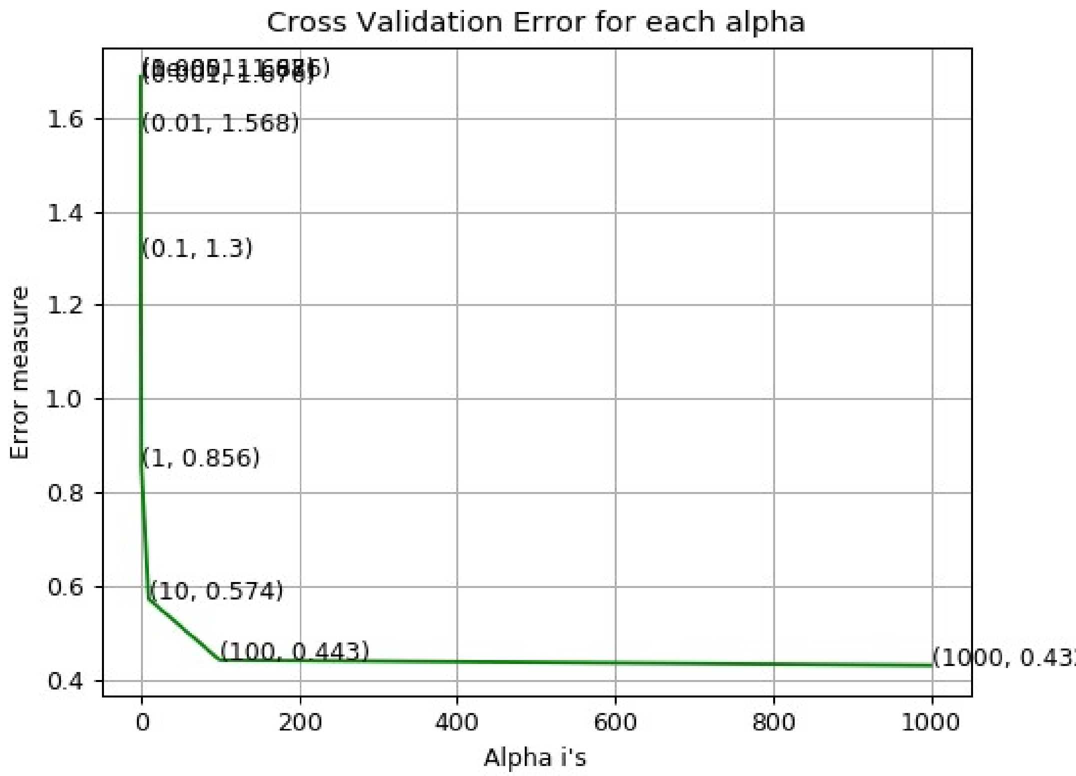



```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.4.2 Logistic Regression

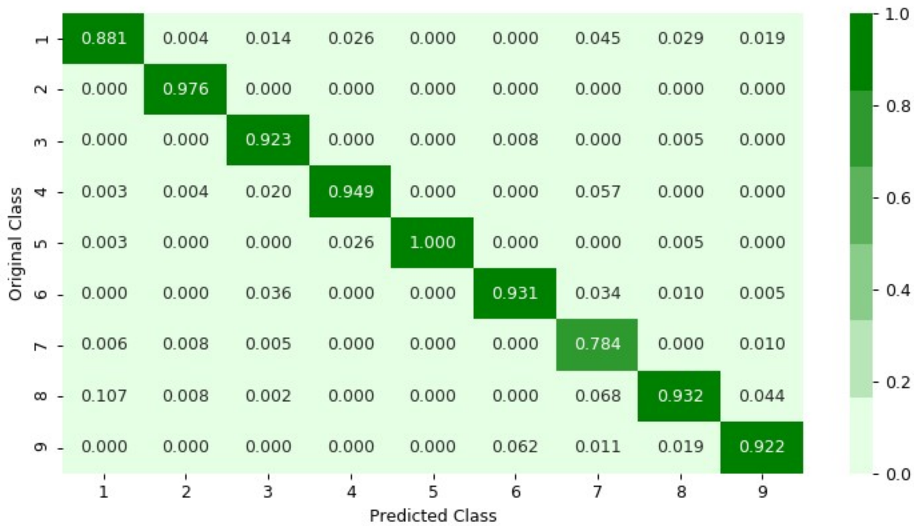
In [36]:
```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …])     Fit linear model with Stochastic Gradient Descent.
# predict(X)    Predict class labels for samples in X.

#-------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/geometric-intuition-1/
#------------------------------


alpha = [10 ** x for x in range(-5, 4)]
cv_log_error_array=[]
for i in alpha:
    logisticR=LogisticRegression(penalty='l2',C=i,class_weight='balanced')
    logisticR.fit(X_train_asm,y_train_asm)
    sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
    sig_clf.fit(X_train_asm, y_train_asm)
    predict_y = sig_clf.predict_proba(X_cv_asm)
    cv_log_error_array.append(log_loss(y_cv_asm, predict_y, labels=logisticR.classes_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])

best_alpha = np.argmin(cv_log_error_array)

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

logisticR=LogisticRegression(penalty='l2',C=alpha[best_alpha],class_weight='balanced')
logisticR.fit(X_train_asm,y_train_asm)
sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
sig_clf.fit(X_train_asm, y_train_asm)

predict_y = sig_clf.predict_proba(X_train_asm)
print ('log loss for train data',(log_loss(y_train_asm, predict_y, labels=logisticR.classes_, eps=1e-15)))
predict_y = sig_clf.predict_proba(X_cv_asm)
print ('log loss for cv data',(log_loss(y_cv_asm, predict_y, labels=logisticR.classes_, eps=1e-15)))
predict_y = sig_clf.predict_proba(X_test_asm)
print ('log loss for test data',(log_loss(y_test_asm, predict_y, labels=logisticR.classes_, eps=1e-15)))
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_asm))
```

```
log_loss for c =  1e-05 is 1.6869859868957804
log_loss for c =  0.0001 is 1.6855010192472757
log_loss for c =  0.001 is 1.6755781562152487
log_loss for c =  0.01 is 1.5677273322121714
log_loss for c =  0.1 is 1.3002573116338927
log_loss for c =  1 is 0.856048258533692
log_loss for c =  10 is 0.5735687649879864
log_loss for c =  100 is 0.4431214718098947
log_loss for c =  1000 is 0.43157353232283385
```

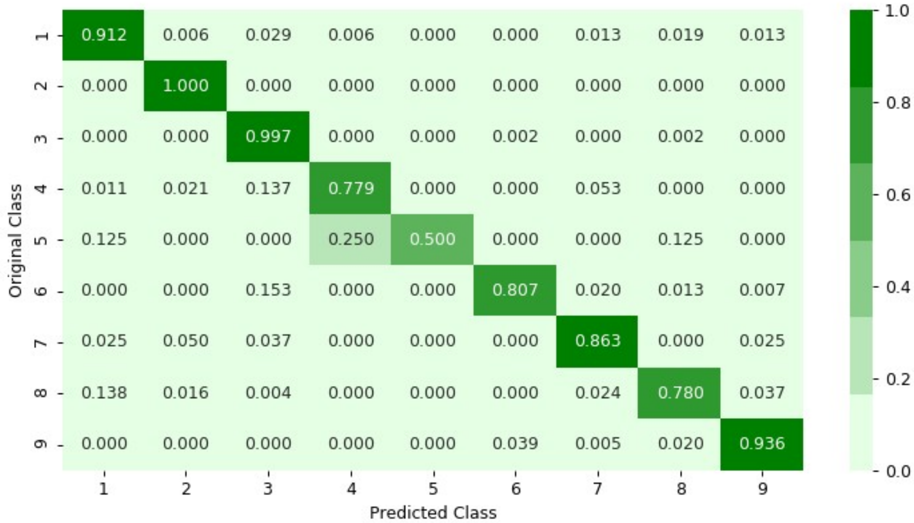



```
log loss for train data 0.38150548196180933
log loss for cv data 0.43157353232283385
log loss for test data 0.38308926013384326
Number of misclassified points  7.405703771849126
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```

-- Precision matrix ---



Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-- Recall matrix ---



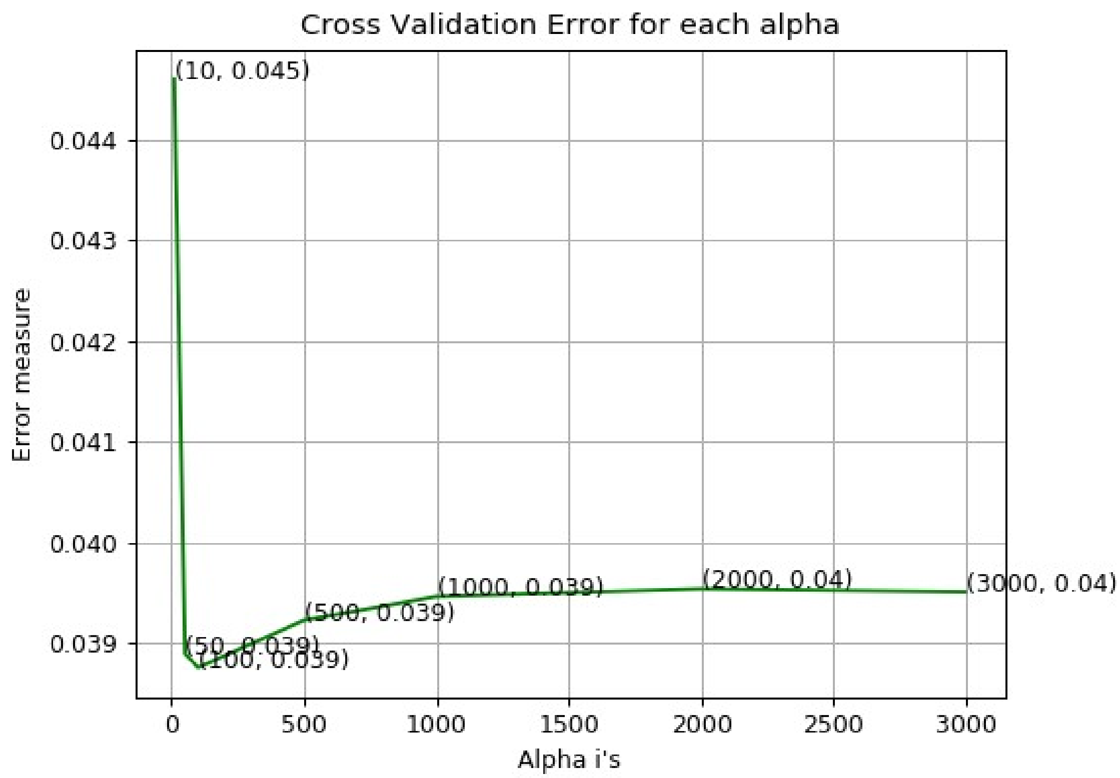

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.4.3 Random Forest Classifier

In [37]:

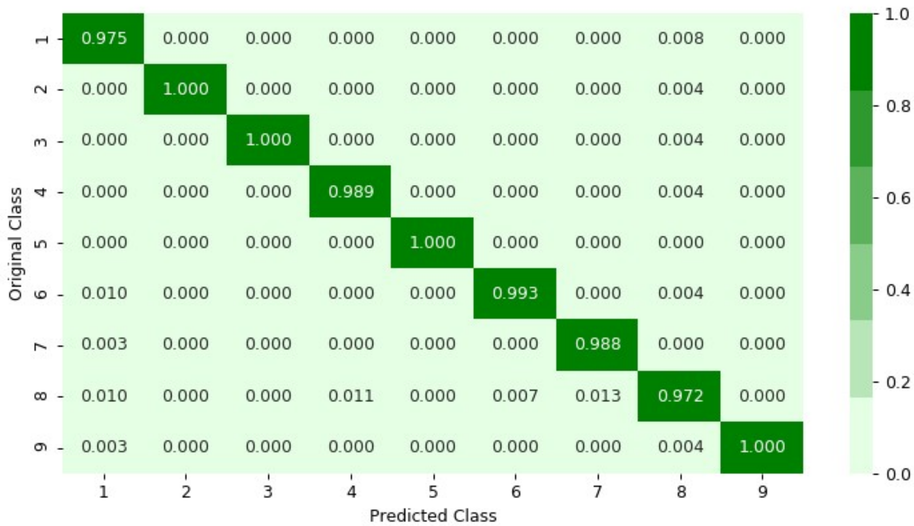
```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_d
epth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_
nodes=None, min_impurity_decrease=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state
=None, verbose=0, warm_start=False,
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given training
data.
# predict(X)    Perform classification on samples in X.
# predict_proba (X)     Perform classification on samples in X.

# some of attributes of  RandomForestClassifier()
# feature_importances_ : array of shape = [n_features]
# The feature importances (the higher, the more important the feature).

# --------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/random-forest-and-their-construction-2/
# --------------------------------

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
for i in alpha:
    r_cfl=RandomForestClassifier(n_estimators=i,random_state=42,n_jobs=-1)
    r_cfl.fit(X_train_asm,y_train_asm)
    sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
    sig_clf.fit(X_train_asm, y_train_asm)
    predict_y = sig_clf.predict_proba(X_cv_asm)
    cv_log_error_array.append(log_loss(y_cv_asm, predict_y, labels=r_cfl.classes_,
eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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

r_cfl=RandomForestClassifier(n_estimators=alpha[best_alpha],random_state=42,n_jobs
=-1)
r_cfl.fit(X_train_asm,y_train_asm)
sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
sig_clf.fit(X_train_asm, y_train_asm)
predict_y = sig_clf.predict_proba(X_train_asm)
print ('log loss for train data',(log_loss(y_train_asm, predict_y, labels=sig_clf.
classes_, eps=1e-15)))
predict_y = sig_clf.predict_proba(X_cv_asm)
print ('log loss for cv data',(log_loss(y_cv_asm, predict_y, labels=sig_clf.classe
s_, eps=1e-15)))
predict_y = sig_clf.predict_proba(X_test_asm)
```

```
log_loss for c =  10 is 0.044604000720488056
log_loss for c =  50 is 0.038892329851189296
log_loss for c =  100 is 0.03875524544813011
log_loss for c =  500 is 0.039224440805809314
log_loss for c =  1000 is 0.03945941790783839
log_loss for c =  2000 is 0.03953659123286974
log_loss for c =  3000 is 0.03950608587732239
```




```
log loss for train data 0.012379247850927044
log loss for cv data 0.03875524544813011
log loss for test data 0.039428378936875376
Number of misclassified points  0.8279668813247469
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```

-- Precision matrix --



Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-- Recall matrix --

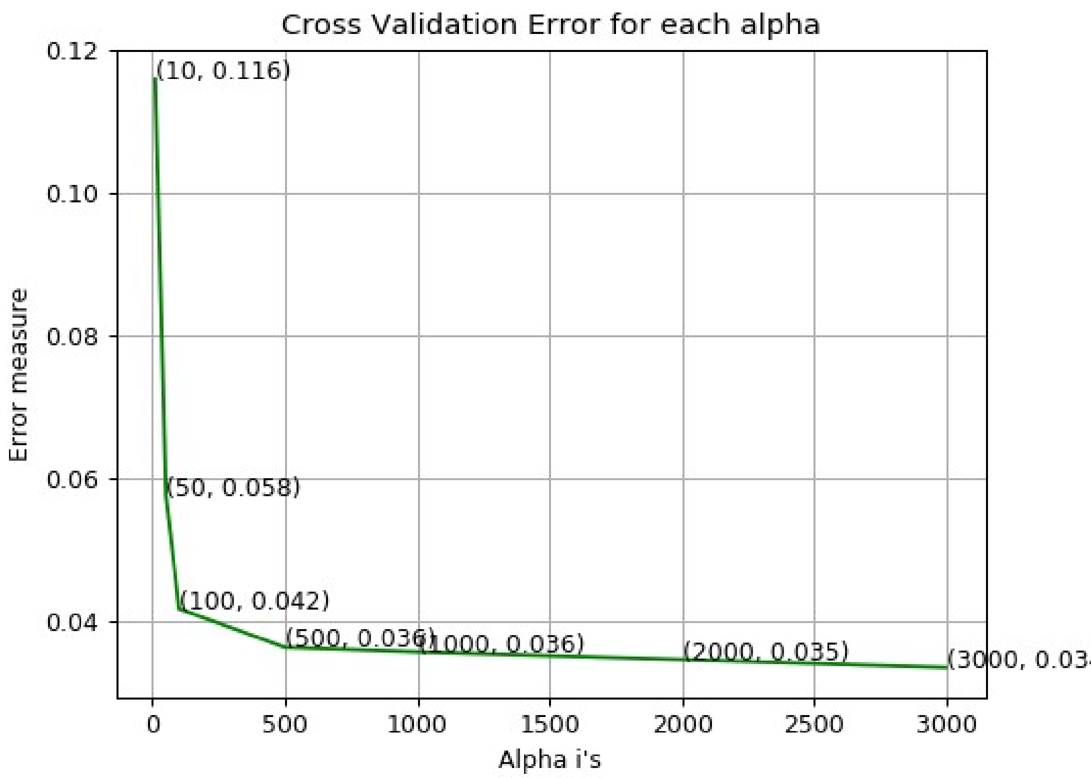

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.4.4 XgBoost Classifier

In [38]:

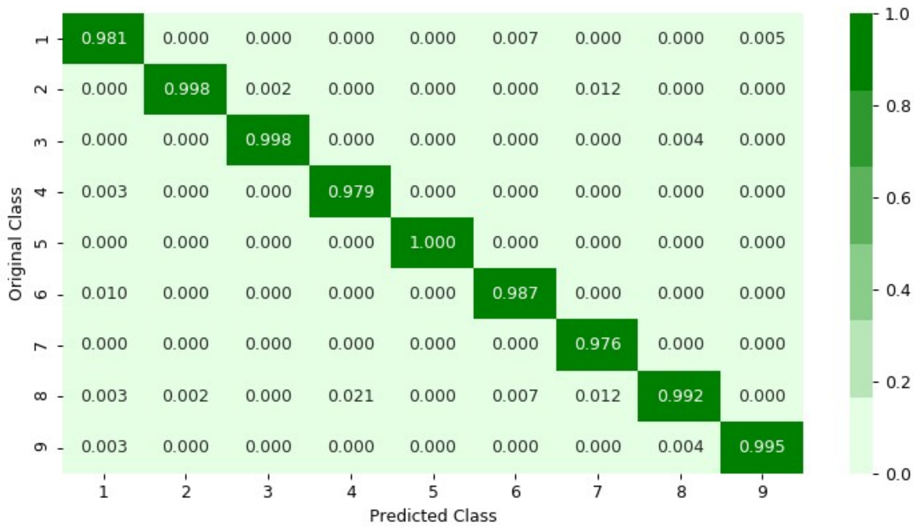
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/lat
est/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, si
lent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0,
min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alph
a=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **k
wargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_ro
unds=None, verbose=True, xgb_model=None)
# get_params([deep])     Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: Thi
s function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/les
sons/what-are-ensembles/
# -----------------------

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
for i in alpha:
    x_cfl=XGBClassifier(n_estimators=i,nthread=-1)
    x_cfl.fit(X_train_asm,y_train_asm)
    sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
    sig_clf.fit(X_train_asm, y_train_asm)
    predict_y = sig_clf.predict_proba(X_cv_asm)
    cv_log_error_array.append(log_loss(y_cv_asm, predict_y, labels=x_cfl.classes_,
eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=alpha[best_alpha],nthread=-1)
x_cfl.fit(X_train_asm,y_train_asm)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(X_train_asm, y_train_asm)

predict_y = sig_clf.predict_proba(X_train_asm)

print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",
log_loss(y_train_asm, predict_y))
predict_y = sig_clf.predict_proba(X_cv_asm)
```

```
log_loss for c =  10 is 0.11588105338340265
log_loss for c =  50 is 0.057658250882591494
log_loss for c =  100 is 0.04186141305711363
log_loss for c =  500 is 0.03649854125696994
log_loss for c =  1000 is 0.035859619519393905
log_loss for c =  2000 is 0.03478236752207586
log_loss for c =  3000 is 0.033667303437409195
```




```
For values of best alpha =  3000 The train log loss is: 0.00982726018742022
For values of best alpha =  3000 The cross validation log loss is: 0.03366730343
7409195
For values of best alpha =  3000 The test log loss is: 0.042877055973511075
Number of misclassified points  0.78196872125115
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```

-- Precision matrix --



Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-- Recall matrix --

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.4.5 Xgboost Classifier with best hyperparameters

In [39]:
```
x_cfl=XGBClassifier()

prams={
    'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],
     'n_estimators':[100,200,500,1000,2000],
     'max_depth':[3,5,10],
    'colsample_bytree':[0.1,0.3,0.5,1],
    'subsample':[0.1,0.3,0.5,1]
}
random_cfl=RandomizedSearchCV(x_cfl,param_distributions=prams,verbose=10,n_jobs=-1
,)
random_cfl.fit(X_train_asm,y_train_asm)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  5.6min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  6.4min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  9.3min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed: 15.6min remaining:  1.7min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 16.7min finished
```

Out[39]:
```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
          estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_by
level=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1),
          fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
          param_distributions={'learning_rate': [0.01, 0.03, 0.05, 0.1, 0.15, 0.
2], 'n_estimators': [100, 200, 500, 1000, 2000], 'max_depth': [3, 5, 10], 'colsa
mple_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=10)
```

In [40]:
```
print (random_cfl.best_params_)
```

```
{'subsample': 0.5, 'n_estimators': 2000, 'max_depth': 10, 'learning_rate': 0.01,
'colsample_bytree': 0.5}
```

In [42]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/lat
est/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, si
lent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0,
min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alph
a=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **k
wargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_ro
unds=None, verbose=True, xgb_model=None)
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: Thi
s function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/les
sons/what-are-ensembles/
# -----------------------

x_cfl=XGBClassifier(n_estimators=2000,subsample=0.5,learning_rate=0.01,colsample_b
ytree=0.5,max_depth=10)
x_cfl.fit(X_train_asm,y_train_asm)
c_cfl=CalibratedClassifierCV(x_cfl,method='sigmoid')
c_cfl.fit(X_train_asm,y_train_asm)

predict_y = c_cfl.predict_proba(X_train_asm)
print ('train loss',log_loss(y_train_asm, predict_y))
predict_y = c_cfl.predict_proba(X_cv_asm)
print ('cv loss',log_loss(y_cv_asm, predict_y))
predict_y = c_cfl.predict_proba(X_test_asm)
print ('test loss',log_loss(y_test_asm, predict_y))
```

```
train loss 0.010626478719576738
cv loss 0.033016089856804966
test loss 0.04082419520278345
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

4.5. Machine Learning models on features of both .asm and .bytes files

4.5.1. Merging both asm and byte file features

In [21]:
```
result.head()
```

Out[21]:

	Unnamed: 0	ID	0	1	2	3	4	5	6
0	0.000000	01azqd4InC7m9JpocGv5	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058
1	0.000092	01IsoiSMh5gxyDYTl4CB	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747
2	0.000184	01jsnpXSAlgw6aPeDxrU	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078
3	0.000276	01kcPWA9K2BOxQeS5Rju	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310
4	0.000368	01SuzwMJEIXsK7A8dQbl	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148

5 rows × 261 columns

In [22]:
```
result_asm.head()
```

Out[22]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	eax
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	66	15
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	29	48
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	42	10
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	8	14
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	9	18

5 rows × 54 columns

In [23]:
```
print(result.shape)
print(result_asm.shape)
```

```
(10868, 261)
(10868, 54)
```

In [24]:
```
result_x = pd.merge(result,result_asm.drop(['Class'], axis=1),on='ID', how='left')
result_y = result_x['Class']
result_x = result_x.drop(['ID','rtn','.BSS:','.CODE','Class'], axis=1)
result_x.head()
```

Out[24]:

	Unnamed: 0	0	1	2	3	4	5	6	7	8	...	ec
0	0.000000	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	...	8(
1	0.000092	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	...	2(
2	0.000184	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	...	
3	0.000276	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	...	1
4	0.000368	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	...	1

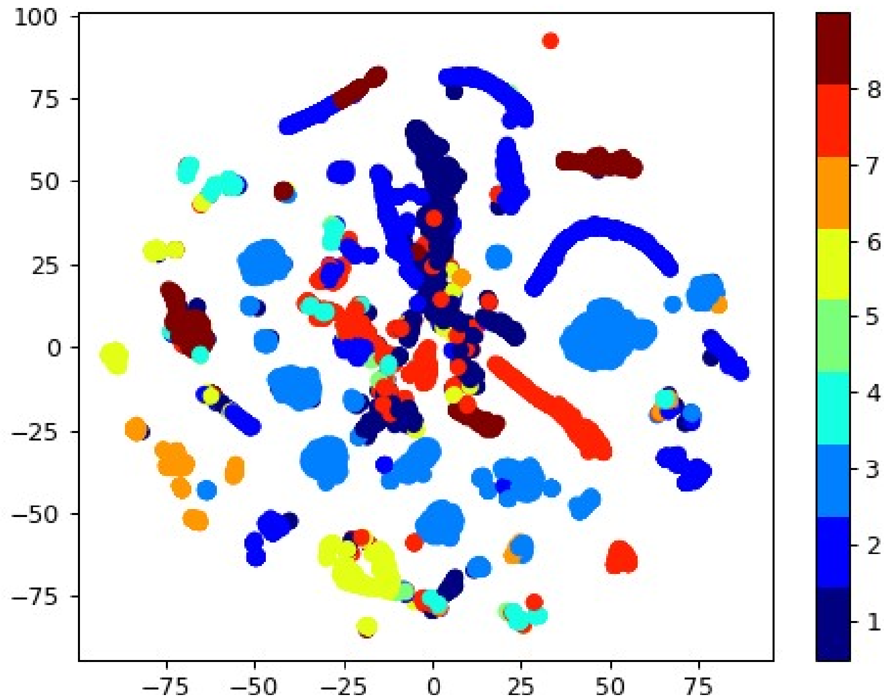
5 rows × 308 columns

In [25]:
```
result_y.head()
```

Out[25]:
```
0    9
1    2
2    9
3    1
4    8
Name: Class, dtype: int64
```

4.5.2. Multivariate Analysis on final fearures

In [25]:
```
xtsne=TSNE(perplexity=50)
results=xtsne.fit_transform(result_x)
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=result_y, cmap=plt.cm.get_cmap("jet", 9))
plt.colorbar(ticks=range(9))
plt.clim(0.5, 9)
plt.show()
```



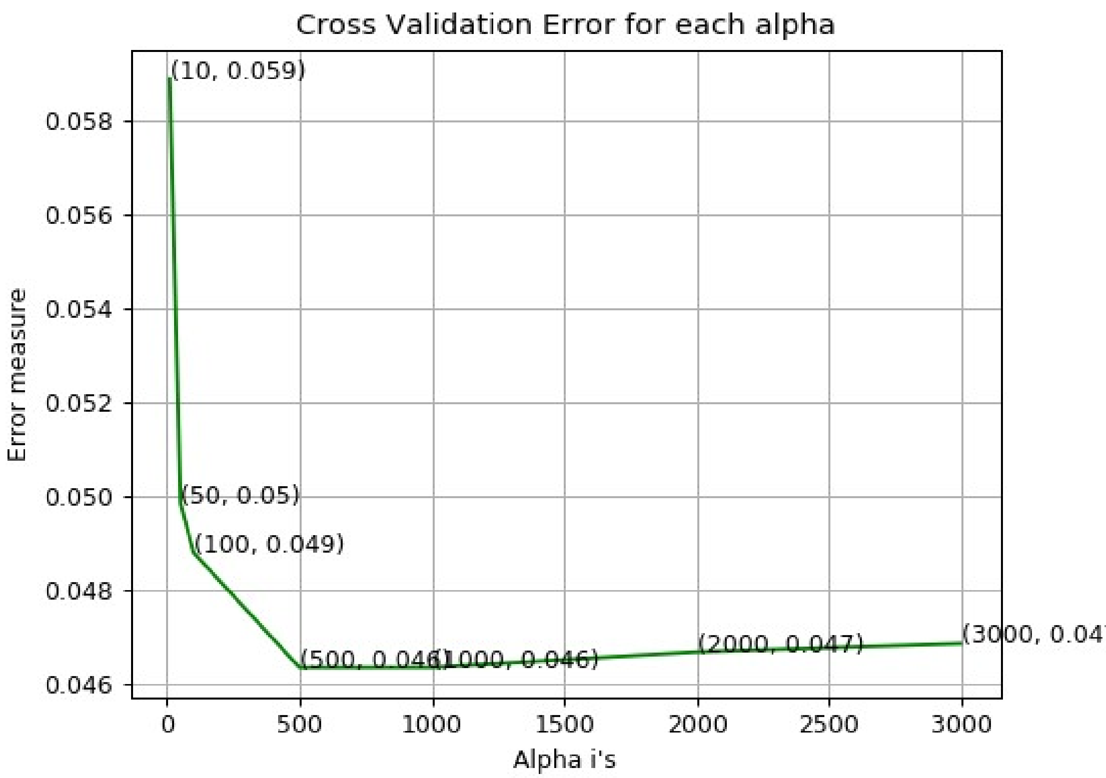
4.5.3. Train and Test split

In [26]:
```
X_train, X_test_merge, y_train, y_test_merge = train_test_split(result_x, result_y
,stratify=result_y,test_size=0.20)
X_train_merge, X_cv_merge, y_train_merge, y_cv_merge = train_test_split(X_train, y
_train,stratify=y_train,test_size=0.20)
```

4.5.4. Random Forest Classifier on final features

In [34]:
```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_d
epth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_
nodes=None, min_impurity_decrease=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state
=None, verbose=0, warm_start=False,
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given training
data.
# predict(X)    Perform classification on samples in X.
# predict_proba (X)     Perform classification on samples in X.

# some of attributes of  RandomForestClassifier()
# feature_importances_ : array of shape = [n_features]
# The feature importances (the higher, the more important the feature).

# --------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/less
ons/random-forest-and-their-construction-2/
# --------------------------------

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
from sklearn.ensemble import RandomForestClassifier
for i in alpha:
    r_cfl=RandomForestClassifier(n_estimators=i,random_state=42,n_jobs=-1)
    r_cfl.fit(X_train_merge,y_train_merge)
    sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
    sig_clf.fit(X_train_merge, y_train_merge)
    predict_y = sig_clf.predict_proba(X_cv_merge)
    cv_log_error_array.append(log_loss(y_cv_merge, predict_y, labels=r_cfl.classes
_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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


r_cfl=RandomForestClassifier(n_estimators=alpha[best_alpha],random_state=42,n_jobs
=-1)
r_cfl.fit(X_train_merge,y_train_merge)
sig_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
sig_clf.fit(X_train_merge, y_train_merge)

predict_y = sig_clf.predict_proba(X_train_merge)
print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",
log_loss(y_train_merge, predict_y))
predict_y = sig_clf.predict_proba(X_cv_merge)
```

```
log_loss for c =  10 is 0.058864988008900165
log_loss for c =  50 is 0.04982171352389583
log_loss for c =  100 is 0.04877439563993806
log_loss for c =  500 is 0.04633136949419593
log_loss for c =  1000 is 0.04633282669842955
log_loss for c =  2000 is 0.04666148931304081
log_loss for c =  3000 is 0.04684161733430787
```

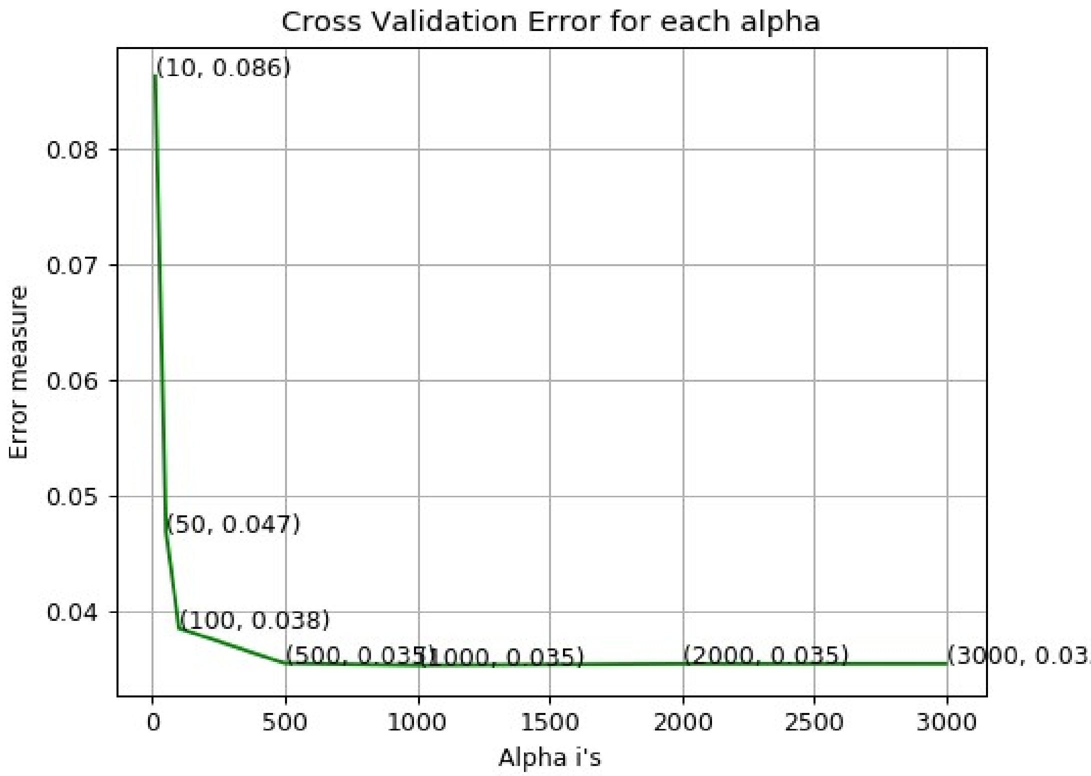



```
For values of best alpha =  500 The train log loss is: 0.015045746557915482
For values of best alpha =  500 The cross validation log loss is: 0.046331369494
19593
For values of best alpha =  500 The test log loss is: 0.0419437056294099
```

4.5.5. XgBoost Classifier on final features

In [35]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/lat
est/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, si
lent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0,
min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alph
a=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **k
wargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_ro
unds=None, verbose=True, xgb_model=None)
# get_params([deep])     Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: Thi
s function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/les
sons/what-are-ensembles/
# -----------------------

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
for i in alpha:
    x_cfl=XGBClassifier(n_estimators=i)
    x_cfl.fit(X_train_merge,y_train_merge)
    sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
    sig_clf.fit(X_train_merge, y_train_merge)
    predict_y = sig_clf.predict_proba(X_cv_merge)
    cv_log_error_array.append(log_loss(y_cv_merge, predict_y, labels=x_cfl.classes
_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=3000,nthread=-1)
x_cfl.fit(X_train_merge,y_train_merge,verbose=True)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(X_train_merge, y_train_merge)

predict_y = sig_clf.predict_proba(X_train_merge)
print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",
log_loss(y_train_merge, predict_y))
predict_y = sig_clf.predict_proba(X_cv_merge)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log
```

```
log_loss for c =  10 is 0.08634410259197668
log_loss for c =  50 is 0.0467962200270487
log_loss for c =  100 is 0.03846464669244138
log_loss for c =  500 is 0.03542509345482663
log_loss for c =  1000 is 0.03524790113745623
log_loss for c =  2000 is 0.03537820448736872
log_loss for c =  3000 is 0.035384159245550155
```




```
For values of best alpha =  1000 The train log loss is: 0.010771162453744454
For values of best alpha =  1000 The cross validation log loss is: 0.03538415924
5550155
For values of best alpha =  1000 The test log loss is: 0.024834218493213808
```

4.5.5. XgBoost Classifier on final features with best hyper parameters using Random search

In [36]:
```
x_cfl=XGBClassifier()

prams={
    'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],
     'n_estimators':[100,200,500,1000,2000],
     'max_depth':[3,5,10],
    'colsample_bytree':[0.1,0.3,0.5,1],
    'subsample':[0.1,0.3,0.5,1]
}
random_cfl=RandomizedSearchCV(x_cfl,param_distributions=prams,verbose=10,n_jobs=-1
,)
random_cfl.fit(X_train_merge, y_train_merge)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed: 11.0min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed: 17.5min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed: 28.6min remaining:  3.2min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 37.0min finished
```

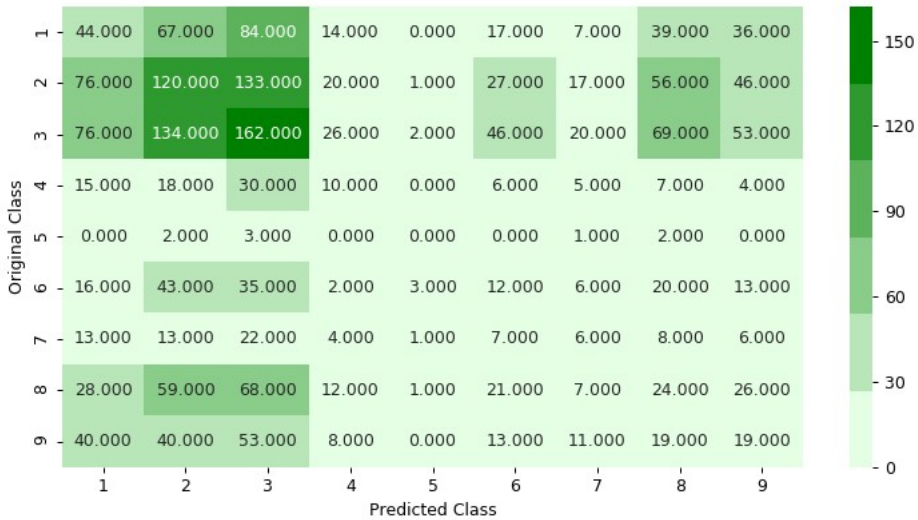
Out[36]:
```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
          estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_by
level=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1),
          fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
          param_distributions={'learning_rate': [0.01, 0.03, 0.05, 0.1, 0.15, 0.
2], 'n_estimators': [100, 200, 500, 1000, 2000], 'max_depth': [3, 5, 10], 'colsa
mple_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=10)
```

In [37]:
```
print (random_cfl.best_params_)
```

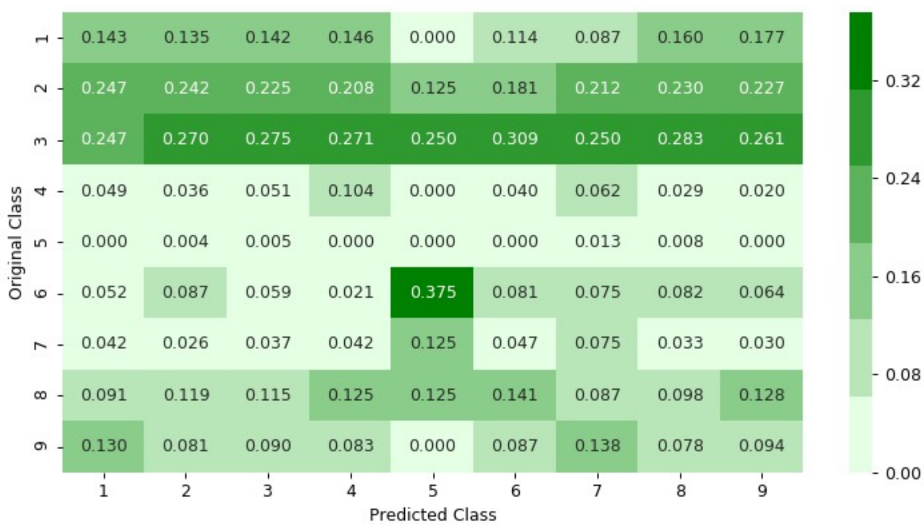
```
{'subsample': 1, 'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.1, 'col
sample_bytree': 0.5}
```

In [39]:
```
# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/lat
est/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, si
lent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0,
min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alph
a=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **k
wargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_ro
unds=None, verbose=True, xgb_model=None)
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: Thi
s function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/les
sons/what-are-ensembles/
# -----------------------

x_cfl=XGBClassifier(n_estimators=1000,max_depth=5,learning_rate=0.1,colsample_bytr
ee=0.5,subsample=1,nthread=-1)
x_cfl.fit(X_train_merge,y_train_merge,verbose=True)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(X_train_merge, y_train_merge)

predict_y = sig_clf.predict_proba(X_train_merge)
print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",
log_loss(y_train_merge, predict_y))
predict_y = sig_clf.predict_proba(X_cv_merge)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log
loss is:",log_loss(y_cv_merge, predict_y))
predict_y = sig_clf.predict_proba(X_test_merge)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",lo
g_loss(y_test_merge, predict_y))
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_merge))
```

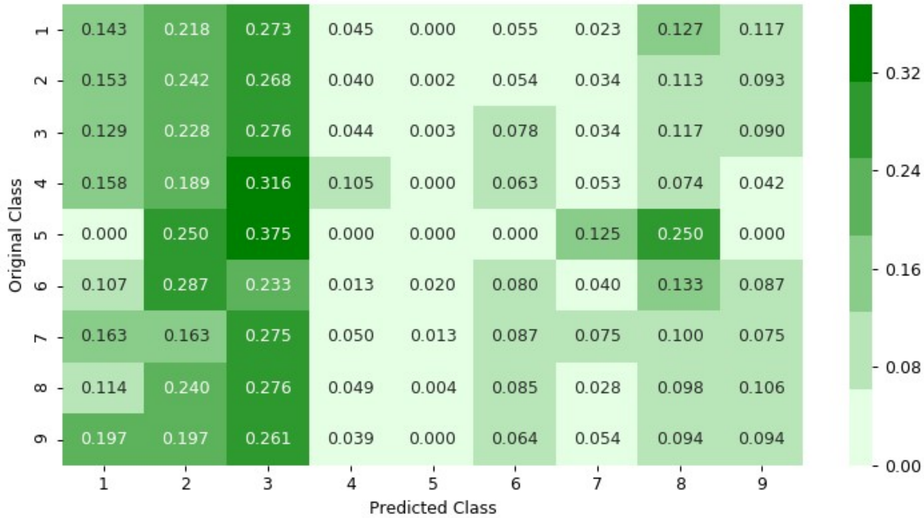
```
For values of best alpha =  1000 The train log loss is: 0.010849938040281054
For values of best alpha =  1000 The cross validation log loss is: 0.03269108838
914283
For values of best alpha =  1000 The test log loss is: 0.02814277993749233
Number of misclassified points  81.73873045078197
-------------------------------------------------- Confusion matrix ------------
-------------------------------------
```




```
-------------------------------------------------- Precision matrix ------------
-------------------------------------
```




```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
-------------------------------------------------- Recall matrix ---------------
-----------------------------------
```




```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

byte features

In [25]:
```
result_x['ID'] = result.ID
```

In [23]:
```
byte_vocab = "00,01,02,03,04,05,06,07,08,09,0a,0b,0c,0d,0e,0f,10,11,12,13,14,15,16
,17,18,19,1a,1b,1c,1d,1e,1f,20,21,22,23,24,25,26,27,28,29,2a,2b,2c,2d,2e,2f,30,31,
32,33,34,35,36,37,38,39,3a,3b,3c,3d,3e,3f,40,41,42,43,44,45,46,47,48,49,4a,4b,4c,4
d,4e,4f,50,51,52,53,54,55,56,57,58,59,5a,5b,5c,5d,5e,5f,60,61,62,63,64,65,66,67,68
,69,6a,6b,6c,6d,6e,6f,70,71,72,73,74,75,76,77,78,79,7a,7b,7c,7d,7e,7f,80,81,82,83,
84,85,86,87,88,89,8a,8b,8c,8d,8e,8f,90,91,92,93,94,95,96,97,98,99,9a,9b,9c,9d,9e,9
f,a0,a1,a2,a3,a4,a5,a6,a7,a8,a9,aa,ab,ac,ad,ae,af,b0,b1,b2,b3,b4,b5,b6,b7,b8,b9,ba
,bb,bc,bd,be,bf,c0,c1,c2,c3,c4,c5,c6,c7,c8,c9,ca,cb,cc,cd,ce,cf,d0,d1,d2,d3,d4,d5,
d6,d7,d8,d9,da,db,dc,dd,de,df,e0,e1,e2,e3,e4,e5,e6,e7,e8,e9,ea,eb,ec,ed,ee,ef,f0,f
1,f2,f3,f4,f5,f6,f7,f8,f9,fa,fb,fc,fd,fe,ff,??"
```

In [29]:
```
def byte_bigram():
    byte_bigram_vocab = []
    for i, v in enumerate(byte_vocab.split(',')):
        for j in range(0, len(byte_vocab.split(','))):
            byte_bigram_vocab.append(v + ' ' +byte_vocab.split(',')[j])
    len(byte_bigram_vocab)
```

In [26]:
```
byte_bigram()
```

Out[26]:
```
66049
```

In [27]:
```
byte_bigram_vocab[:5]
```

Out[27]:
```
['00 00', '00 01', '00 02', '00 03', '00 04']
```

In [30]:
```
def byte_trigram():
    byte_trigram_vocab = []
    for i, v in enumerate(byte_vocab.split(',')):
        for j in range(0, len(byte_vocab.split(','))):
            for k in range(0, len(byte_vocab.split(','))):
                byte_trigram_vocab.append(v + ' ' +byte_vocab.split(',')[j]+' '+by
te_vocab.split(',')[k])
    len(byte_trigram_vocab)
```

In [6]:
```
byte_trigram()
```

Out[6]:
```
16974593
```

In [7]:
```
byte_trigram_vocab[:5]
```

Out[7]:
```
['00 00 00', '00 00 01', '00 00 02', '00 00 03', '00 00 04']
```

In [28]:
```
from tqdm import tqdm
from sklearn.feature_extraction.text import CountVectorizer
```

In [38]:
```
vector = CountVectorizer(lowercase=False,ngram_range=(2,2), vocabulary=byte_bigram
_vocab)
bytebigram_vect = scipy.sparse.csr_matrix((10868, 66049))
for i, file in tqdm(enumerate(os.listdir('byteFiles'))):
    f = open('byteFiles/' + file)
    a[i:]+= scipy.sparse.csr_matrix(vect.fit_transform([f.read().replace('\n', ' '
).lower()]))
    f.close()
```

```
10868it [3:49:23,  2.10it/s]
```

In [39]:
```
bytebigram_vect
```

Out[39]:
```
<10868x66049 sparse matrix of type '<class 'numpy.float64'>'
        with 0 stored elements in Compressed Sparse Row format>
```

In [40]:
```
scipy.sparse.save_npz('bytebigram.npz', bytebigram_vect)
```

In [30]:
```
from sklearn.preprocessing import normalize
byte_bigram_vect = normalize(scipy.sparse.load_npz('bytebigram.npz'), axis = 0)
```

N-Gram(2-Gram, 3-Gram, 4-Gram) Opcode Vectorization

In [31]:
```
opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub', 'inc'
, 'dec', 'add','imul', 'xchg', 'or', 'shr', 'cmp', 'call', 'shl', 'ror', 'rol', 'j
nb','jz','rtn','lea','movzx']
```

In [31]:
```
def asmopcodebigram():
    asmopcodebigram = []
    for i, v in enumerate(opcodes):
        for j in range(0, len(opcodes)):
            asmopcodebigram.append(v + ' ' + opcodes[j])
    len(asmopcodebigram)
```

In [32]:
```
asmopcodebigram
```

Out[32]:
```
676
```

In [33]:
```
def asmopcodetrigram():
    asmopcodetrigram = []
    for i, v in enumerate(opcodes):
        for j in range(0, len(opcodes)):
            for k in range(0, len(opcodes)):
                asmopcodetrigram.append(v + ' ' + opcodes[j] + ' ' + opcodes[k])
    len(asmopcodetrigram)
```

In [33]:
```
asmopcodetrigram
```

Out[33]:
```
17576
```

In [34]:
```
def asmopcodetetragram():
    asmopcodetetragram = []
    for i, v in enumerate(opcodes):
        for j in range(0, len(opcodes)):
            for k in range(0, len(opcodes)):
                for l in range(0, len(opcodes)):
                    asmopcodetetragram.append(v + ' ' + opcodes[j] + ' ' + opcodes
[k] + ' ' + opcodes[l])
    len(asmopcodetetragram)
```

In [34]:
```
asmopcodetetragram
```

Out[34]:
```
456976
```

In [ ]:
```
def opcode_collect():
    op_file = open("opcode_file.txt", "w+")
    for asmfile in os.listdir('asmFiles'):
        opcode_str = ""
        with codecs.open('asmFiles/' + asmfile, encoding='cp1252', errors ='replac
e') as fli:
            for lines in fli:
                line = lines.rstrip().split()
                for li in line:
                    if li in opcodes:
                        opcode_str += li + ' '
        op_file.write(opcode_str + "\n")
    op_file.close()
opcode_collect()
```

In [47]:
```
vect = CountVectorizer(ngram_range=(2, 2), vocabulary = asmopcodebigram)
opcodebivect = scipy.sparse.csr_matrix((10868, len(asmopcodebigram)))
raw_opcode = open('opcode_file.txt').read().split('\n')

for indx in range(10868):
    opcodebivect[indx, :] += scipy.sparse.csr_matrix(vect.transform([raw_opcode[in
dx]]))
```

In [48]:
```
opcodebivect
```

Out[48]:
```
<10868x676 sparse matrix of type '<class 'numpy.float64'>'
	with 1877309 stored elements in Compressed Sparse Row format>
```

In [49]:
```
scipy.sparse.save_npz('opcodebigram.npz', opcodebivect)
```

In [51]:
```
vect = CountVectorizer(ngram_range=(3, 3), vocabulary = asmopcodetrigram)
opcodetrivect = scipy.sparse.csr_matrix((10868, len(asmopcodetrigram)))

for indx in range(10868):
    opcodetrivect[indx, :] += scipy.sparse.csr_matrix(vect.transform([raw_opcode[i
ndx]]))
```

In [52]:
```
opcodetrivect
```

Out[52]:
```
<10868x17576 sparse matrix of type '<class 'numpy.float64'>'
	with 7332672 stored elements in Compressed Sparse Row format>
```

In [53]:
```
scipy.sparse.save_npz('opcodetrigram.npz', opcodetrivect)
```

In [54]:
```
vect = CountVectorizer(ngram_range=(4, 4), vocabulary = asmopcodetetragram)
opcodetetravect = scipy.sparse.csr_matrix((10868, len(asmopcodetetragram)))

for indx in range(10868):
    opcodetetravect[indx, :] += scipy.sparse.csr_matrix(vect.transform([raw_opcode
[indx]]))
```

In [55]:
```
opcodetetravect
```

Out[55]:
```
<10868x456976 sparse matrix of type '<class 'numpy.float64'>'
	with 16605229 stored elements in Compressed Sparse Row format>
```

In [56]:
```
scipy.sparse.save_npz('opcodetetragram.npz', opcodetetravect)
```

In [35]:
```
opcodetetravect = scipy.sparse.load_npz('opcodetetragram.npz')
```

In [36]:
```
opcodetrivect=scipy.sparse.load_npz('opcodetrigram.npz')
```

In [37]:
```
opcodebivect=scipy.sparse.load_npz('opcodebigram.npz')
```

Image Feature Extraction From ASM Files

In [35]:
```
import array
```

In [64]:
```
def collect_img_asm():
    for asmfile in os.listdir("asmFiles"):
        filename = asmfile.split('.')[0]
        file = codecs.open("asmFiles/" + asmfile, 'rb')
        filelen = os.path.getsize("asmFiles/" + asmfile)
        width = int(filelen ** 0.5)
        rem = int(filelen / width)
        arr = array.array('B')
        arr.frombytes(file.read())
        file.close()
        reshaped = np.reshape(arr[:width * width], (width, width))
        reshaped = np.uint8(reshaped)
        scipy.misc.imsave('asm_image/' + filename + '.png',reshaped)
```

In [65]:
```
collect_img_asm()
```

In [ ]:
```
from IPython.display import Image
Image(filename='asm_image/deTXH9Zau7qmM0yfYsRS.png')
```

First 200 Image Pixels

In [38]:
```
import cv2
imagefeatures = np.zeros((10868, 200))
```

In [67]:
```
for i, asmfile in enumerate(os.listdir("asmFiles")):
    img = cv2.imread("asm_image/" + asmfile.split('.')[0] + '.png')
    img_arr = img.flatten()[:200]
    imagefeatures[i, :] += img_arr
```

In [68]:
```
imgfeatures_name = []
for i in range(200):
    img_features_name.append('pix' + str(i))
imgdf = pd.DataFrame(normalize(imagefeatures, axis = 0), columns = imgfeatures_nam
e)
```

In [69]:
```
imgdf['ID'] = result.ID
```

In [70]:
```
imgdf.head()
```

Out[70]:

	pix0	pix1	pix2	pix3	pix4	pix5	pix6	pix7	pix8	pix9	...	p
0	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
1	0.006560	0.006560	0.006560	0.013504	0.013504	0.013504	0.012927	0.012927	0.012927	0.013963	...	0.0(
2	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
3	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
4	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(

5 rows × 201 columns

In [71]:
```
joblib.dump(imgdf, 'img_df')
```

Out[71]: ['img_df']

In [72]:
```
img_df=joblib.load('img_df')
```

In [73]:
```
img_df.head()
```

Out[73]:

	pix0	pix1	pix2	pix3	pix4	pix5	pix6	pix7	pix8	pix9	...	p
0	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
1	0.006560	0.006560	0.006560	0.013504	0.013504	0.013504	0.012927	0.012927	0.012927	0.013963	...	0.0(
2	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
3	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(
4	0.010268	0.010268	0.010268	0.008033	0.008033	0.008033	0.008320	0.008320	0.008320	0.007913	...	0.0(

5 rows × 201 columns

Important Feature Selection Using Random Forest

In [38]:
```
def imp_features(data, features, keep):
    rf = RandomForestClassifier(n_estimators = 100, n_jobs = -1)
    rf.fit(data, result_y)
    imp_feature_indx = np.argsort(rf.feature_importances_)[::-1]
    imp_value = np.take(rf.feature_importances_, imp_feature_indx[:20])
    imp_feature_name = np.take(features, imp_feature_indx[:20])
    sns.set()
    plt.figure(figsize = (10, 5))
    ax = sns.barplot(x = imp_feature_name, y = imp_value)
    ax.set_xticklabels(labels = imp_feature_name, rotation = 45)
    sns.set_palette(reversed(sns.color_palette("husl", 10)), 10)
    plt.title('Important Features')
    plt.xlabel('Feature Names')
    plt.ylabel('Importance')
    return imp_feature_indx[:keep]
```

Important Feature Among Opcode Bi-Gram

In [44]:
```
op_bi_indxes = imp_features(normalize(opcodebivect, axis = 0), asmopcodebigram, 20
0)
```

In [45]:
```
op_bi_df = pd.SparseDataFrame(normalize(opcodebivect, axis = 0), columns = asmopco
debigram)
for col in op_bi_df.columns:
    if col not in np.take(asmopcodebigram, op_bi_indxes):
        op_bi_df.drop(col, axis = 1, inplace = True)
```

In [46]:
```
op_bi_df.to_dense().to_csv('op_bi.csv')
```

In [47]:
```
op_bi_df = pd.read_csv('op_bi.csv').drop('Unnamed: 0', axis = 1).fillna(0)
```

In [48]:
```
op_bi_df['ID'] = result.ID
op_bi_df.head()
```

Out[48]:

	jmp jmp	jmp mov	jmp retf	jmp push	jmp pop	jmp xor	jmp sub	jmp dec	jmp add	jmp cmp	...	movz: jmן
0	0.031815	0.003894	0.000000	0.00042	0.000000	0.002374	0.00895	0.001268	0.016752	0.000112	...	0.(
1	0.000000	0.000649	0.000000	0.00021	0.000374	0.000419	0.00000	0.000000	0.001971	0.000000	...	0.(
2	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	...	0.(
3	0.000000	0.000101	0.000000	0.00007	0.000000	0.000279	0.00000	0.000000	0.000000	0.000000	...	0.(
4	0.000362	0.001156	0.001467	0.00028	0.000374	0.000140	0.00000	0.000000	0.000000	0.000112	...	0.(

5 rows × 201 columns

Important Feature Among Opcode 3-Gram

In [39]:
```
op_tri_indxes = imp_features(normalize(opcodetrivect, axis = 0), asmopcodetrigram,
200)
```

In [40]:
```
op_tri_df = pd.SparseDataFrame(normalize(opcodetrivect, axis = 0), columns = asmop
codetrigram)
op_tri_df = op_tri_df.loc[:, np.intersect1d(op_tri_df.columns, np.take(asmopcodetr
igram, op_tri_indxes))]
```

In [41]:
```
op_tri_df.to_dense().to_csv('op_tri.csv')
```

In [42]:
```
op_tri_df = pd.read_csv('op_tri.csv').drop('Unnamed: 0', axis = 1).fillna(0)
```

In [43]:
```
op_tri_df['ID'] = result.ID
op_tri_df.head()
```

Out[43]:

	add cmp jmp	add mov add	add mov cmp	add mov jmp	add mov mov	add pop call	add pop mov	add pop pop	add pop push	add pop retn	...	sub push push
0	0.000000	0.002183	0.001340	0.001563	0.003593	0.0	0.005354	0.000342	0.000000	0.00084	...	0.006742
1	0.000000	0.001364	0.000670	0.000625	0.002705	0.0	0.001785	0.000000	0.000000	0.00028	...	0.001556
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.000000	0.00000	...	0.001383
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.000000	0.00000	...	0.000000
4	0.001292	0.001091	0.004914	0.002814	0.014009	0.0	0.000000	0.000000	0.000441	0.00000	...	0.000000

5 rows × 201 columns

Important Feature Among Opcode 4-Gram

In [49]:
```
op_tetra_indxes = imp_features(normalize(opcodetetravect, axis = 0), asmopcodetetr
agram, 200)
```

In [50]:
```
op_tetra_df = pd.SparseDataFrame(normalize(opcodetetravect, axis = 0), columns = a
smopcodetetragram)
op_tetra_df = op_tetra_df.loc[:, np.intersect1d(op_tetra_df.columns, np.take(asmop
codetetragram, op_tetra_indxes))]
```

In [51]:
```
op_tetra_df.to_dense().to_csv('op_tetra.csv')
```

In [52]:
```
op_tetra_df = pd.read_csv('op_tetra.csv').drop('Unnamed: 0', axis = 1).fillna(0)
```

In [53]:
```
op_tetra_df['ID'] = result.ID
op_tetra_df.head()
```

Out[53]:

	add mov add mov	add mov add pop	add mov cmp jnb	add mov mov add	add mov mov mov	add pop mov push	add pop pop pop	add pop push call	add retn push push	call add mov sub	...	xor cmp cmp jnb	xor cmp inc cmp	xor lea or mov
0	0.001593	0.007668	0.000000	0.002031	0.002517	0.0	0.0	0.0	0.00116	0.000000	...	0.0	0.0	0.0
1	0.000000	0.007668	0.000000	0.001625	0.002760	0.0	0.0	0.0	0.00000	0.000000	...	0.0	0.0	0.0
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	0.00000	0.000000	...	0.0	0.0	0.0
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	0.00000	0.000000	...	0.0	0.0	0.0
4	0.002125	0.000000	0.023352	0.023558	0.006657	0.0	0.0	0.0	0.00000	0.009682	...	0.0	0.0	0.0

5 rows × 201 columns

Important Feature Among Byte Bi-Gram

In [54]:
```
byte_bi_indxes = imp_features(normalize(bytebigram_vect, axis = 0), byte_bigram_vo
cab, 300)
```

In [55]:
```
np.save('byte_bi_indx', byte_bi_indxes)
```

In [56]:
```
byte_bi_indxes = np.load('byte_bi_indx.npy')
```

In [57]:
```
top_byte_bi = np.zeros((10868, 0))
for i in byte_bi_indxes:
    sliced = bytebigram_vect[:, i].todense()
    top_byte_bi = np.hstack([top_byte_bi, sliced])
```

In [58]:
```
byte_bi_df = pd.SparseDataFrame(top_byte_bi, columns = np.take(byte_bigram_vocab,
byte_bi_indxes))
```

In [59]:
```
byte_bi_df.to_dense().to_csv('byte_bi.csv')
```

In [60]:
```
byte_bi_df = pd.read_csv('byte_bi.csv').drop('Unnamed: 0', axis = 1).fillna(0)
```

In [61]:
```
byte_bi_df['ID'] = result.ID
```

In [62]:
```
byte_bi_df.head()
```

Out[62]:

	?? ??	55 95	55 b3	55 b2	55 b1	55 b0	55 af	55 ae	55 ad	55 ac	...	54 b3	54 b4	54 c4	54 d1	54 d0	54 cf	54 ce	54 cd	54 cc	
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01azqd4InC7m!
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01IsoiSMh5gx)
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01jsnpXSAlgw
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01kcPWA9K2BO
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01SuzwMJEIXsI

5 rows × 301 columns

Advanced features

Adding 300 bytebigram,200 opcode bigram,200 opcode trigram,200 opcode tetragram ,first 200 image pixels

In [74]:
```
final_data = pd.concat([result_x, op_bi_df, op_tri_df, op_tetra_df, byte_bi_df,img_df], axis = 1, join = 'inner')
```

In [75]:
```
final_data = final_data.drop('ID', axis = 1)
```

In [76]:
```
final_data.head()
```

Out[76]:

	Unnamed: 0	0	1	2	3	4	5	6	7	8	...	
0	0.000000	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	...	0.
1	0.000092	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	...	0.
2	0.000184	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	...	0.
3	0.000276	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	...	0.
4	0.000368	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	...	0.

5 rows × 1408 columns

In [77]:
```
final_data.to_csv('final_data.csv')
```

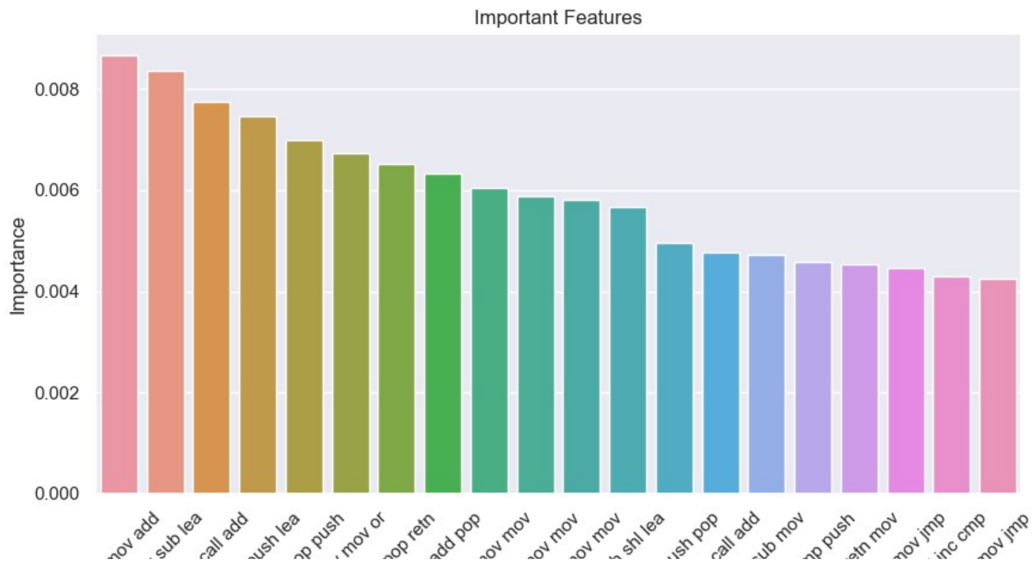
In [27]:
```
final_data = pd.read_csv('final_data.csv')
```

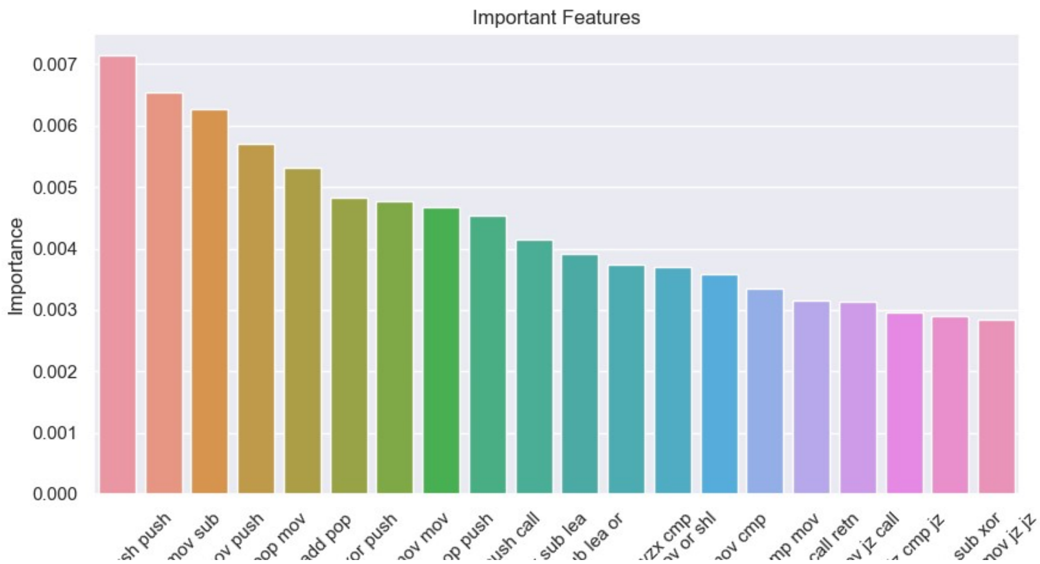
In [37]:
```
x_train_final, x_test_final, y_train_final, y_test_final = train_test_split(final_data, result_y, stratify = result_y, test_size = 0.20)
x_trn_final, x_cv_final, y_trn_final, y_cv_final = train_test_split(x_train_final, y_train_final, stratify = y_train_final, test_size = 0.20)
```

Machine Learning Models on ASM Features + Byte Features + Advanced Features

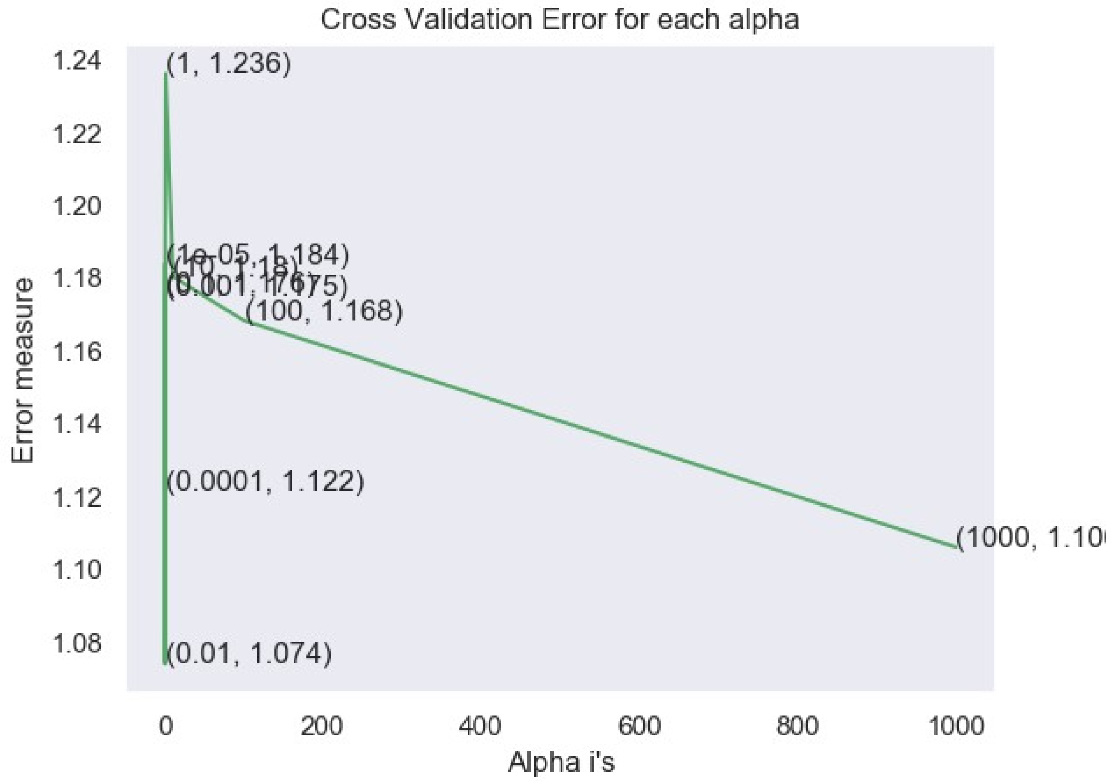
In [80]:
```
alpha = [10 ** x for x in range(-5, 4)]
cv_log_error_array=[]
for i in alpha:
    logisticR=LogisticRegression(penalty='l2',C=i,class_weight='balanced')
    logisticR.fit(x_trn_final,y_trn_final)
    sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
    sig_clf.fit(x_trn_final,y_trn_final)
    predict_y = sig_clf.predict_proba(x_cv_final)
    cv_log_error_array.append(log_loss(y_cv_final, predict_y, labels=logisticR.cla
sses_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])

best_alpha = np.argmin(cv_log_error_array)

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

```
log_loss for c =  1e-05 is 1.1840039867727614
log_loss for c =  0.0001 is 1.1217881098745714
log_loss for c =  0.001 is 1.174936322460997
log_loss for c =  0.01 is 1.0741224260174453
log_loss for c =  0.1 is 1.1761396828975654
log_loss for c =  1 is 1.2362570810343723
log_loss for c =  10 is 1.1804717850739066
log_loss for c =  100 is 1.1684083137157295
log_loss for c =  1000 is 1.1061521197568476
```




Important Features
Importance
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000


Important Features
Importance
0.04
0.02
0.00
−0.02
−0.04
?? ??
55 95
55 b3
55 b2
55 b1
55 b0
55 af
55 ae
55 ad
55 ac
55 ab
55 aa
55 a9
55 a8
55 a7
55 a6
55 a5
55 a4
55 a3
55 a2



In [35]:

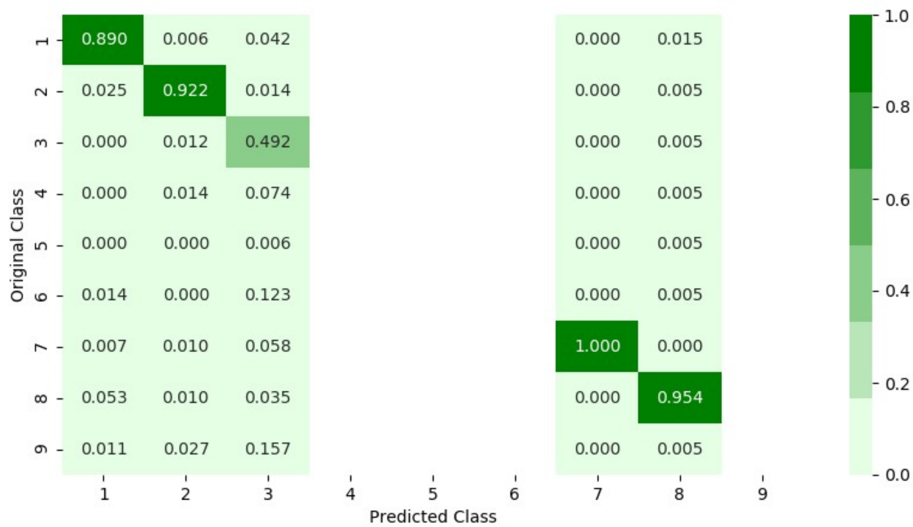
```
logisticR=LogisticRegression(penalty='l2',C=alpha[best_alpha],class_weight='balanc
ed')
logisticR.fit(x_trn_final,y_trn_final)
sig_clf = CalibratedClassifierCV(logisticR, method="sigmoid")
sig_clf.fit(x_trn_final,y_trn_final)

predict_y = sig_clf.predict_proba(x_trn_final)
print ('log loss for train data',(log_loss(y_trn_final, predict_y, labels=logistic
R.classes_, eps=1e-15)))
predict_y = sig_clf.predict_proba(x_cv_final)
print ('log loss for cv data',(log_loss(y_cv_final, predict_y, labels=logisticR.cl
asses_, eps=1e-15)))
predict_y = sig_clf.predict_proba(x_test_final)
print ('log loss for test data',(log_loss(y_test_final, predict_y, labels=logistic
R.classes_, eps=1e-15)))
```

```
C:\Users\Sai charan\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converg
enceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Sai charan\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converg
enceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Sai charan\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converg
enceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Sai charan\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converg
enceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)

log loss for train data 1.193174530266704
log loss for cv data 1.1785070578048291
log loss for test data 1.2060464393477006
```

In [39]:
```
plot_confusion_matrix(y_test_final,sig_clf.predict(x_test_final))
```

```
Number of misclassified points  31.324747010119598
-------------------------------------------------- Confusion matrix ------------
--------------------------------------
```


```
-------------------------------------------------- Precision matrix ------------
--------------------------------------
```



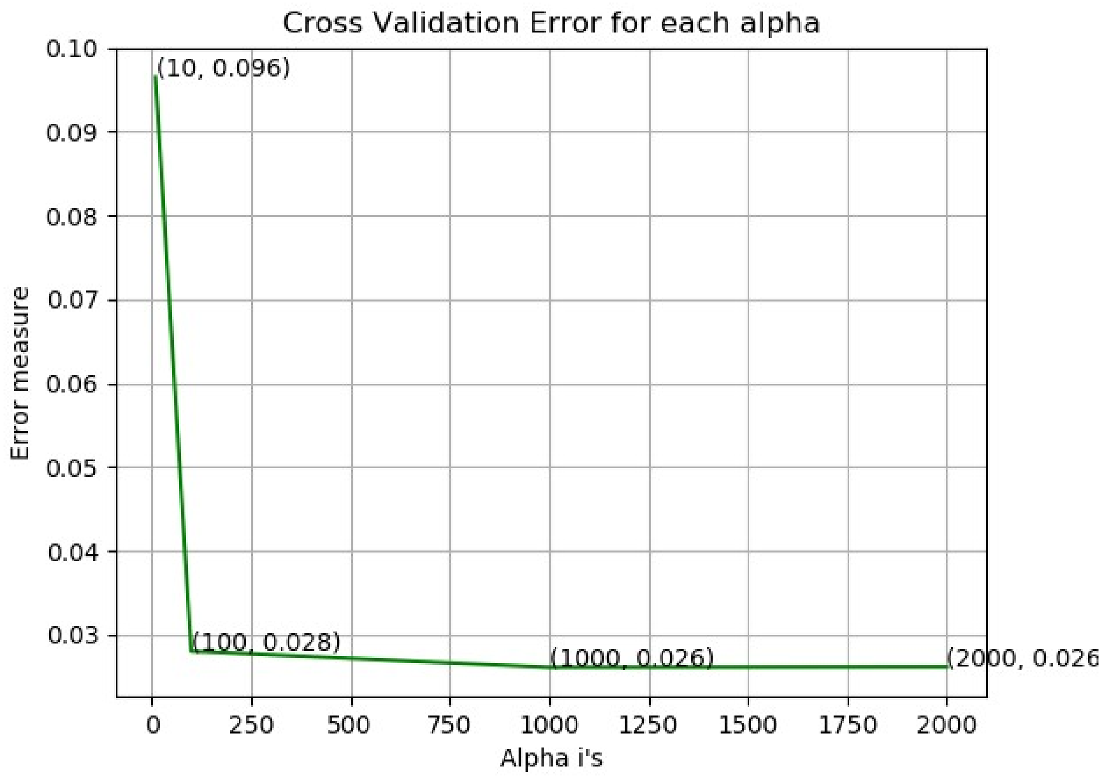

```
Sum of columns in precision matrix [ 1.   1.   1. nan nan nan  1.   1. nan]
-------------------------------------------------- Recall matrix ---------------
-----------------------------------
```


```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

In [ ]:

In [29]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#xgboost.XGBClassifier
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alpha=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **kwargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# -----------------------

alpha=[10,100,1000,2000]
cv_log_error_array=[]
for i in alpha:
    x_cfl=XGBClassifier(n_estimators=i)
    x_cfl.fit(x_trn_final,y_trn_final)
    sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
    sig_clf.fit(x_trn_final, y_trn_final)
    predict_y = sig_clf.predict_proba(x_cv_final)
    cv_log_error_array.append(log_loss(y_cv_final, predict_y, labels=x_cfl.classes_, eps=1e-15))

for i in range(len(cv_log_error_array)):
    print ('log_loss for c = ',alpha[i],'is',cv_log_error_array[i])


best_alpha = np.argmin(cv_log_error_array)

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

```
log_loss for c =  10 is 0.09649648467635132
log_loss for c =  100 is 0.028026994875892948
log_loss for c =  1000 is 0.02610102301724636
log_loss for c =  2000 is 0.026155764643162237
```



In [84]:
```
x_cfl=XGBClassifier(n_estimators=2000,nthread=-1)
x_cfl.fit(x_trn_final,y_trn_final,verbose=True)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(x_trn_final, y_trn_final)

predict_y = sig_clf.predict_proba(x_trn_final)
print ('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",
log_loss(y_trn_final, predict_y))
predict_y = sig_clf.predict_proba(x_cv_final)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log
loss is:",log_loss(y_cv_final, predict_y))
predict_y = sig_clf.predict_proba(x_test_final)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",lo
g_loss(y_test_final, predict_y))
```

```
For values of best alpha =  0.01 The train log loss is: 0.010187974436441512
For values of best alpha =  0.01 The cross validation log loss is: 0.02395762856
614576
For values of best alpha =  0.01 The test log loss is: 0.018309505637434106
```

Procedure:

1.First I took the byte file and made Exploratory Data Analysis.

2.used uni-gram count features and applied machine learning models.

3.preprocessed the asm file and extracted various segment count as features.

4.applied machine learning models on asm segment count.

5.combined byte features and asm segment features.

6.applied machine learning models on combined features.

7.extracted features like byte bigram,opcode bi gram,opcode trigram , opcode tetra gram and 200 pixels of asm image.

8.appplied machine learning models on combined features.

Results

In [18]:

```
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model Comparision "
ptable.field_names = ["Model",'Features','log loss']
ptable.add_row(["random","Byte files","2.45"])
ptable.add_row(["knn","Byte files","0.48"])
ptable.add_row(["Logistic Regression","Byte files","0.52"])
ptable.add_row(["Random Forest Classifier ","Byte files","0.06"])
ptable.add_row(["XgBoost Classification","Byte files","0.07"])
ptable.add_row(["\n","\n","\n"])
ptable.add_row(["knn","asmfiles","0.21"])
ptable.add_row(["Logistic Regression","asmfiles","0.38"])
ptable.add_row(["Random Forest Classifier ","asmfiles","0.03"])
ptable.add_row(["XgBoost Classification","asmfiles","0.04"])
ptable.add_row(["\n","\n","\n"])
ptable.add_row(["Random Forest Classifier ","Byte files+asmfiles","0.04"])
ptable.add_row(["XgBoost Classification","Byte files+asmfiles","0.02"])
ptable.add_row(["\n","\n","\n"])
ptable.add_row(["Logistic Regression","Byte files+asmfiles+advanced features","1.1
2"])
ptable.add_row(["XgBoost Classification","Byte files+asmfiles+advanced features","
0.01"])
print(ptable)
```

```
+---------------------------+----------------------------------------+----------+
|           Model           |                Features                | log loss |
+---------------------------+----------------------------------------+----------+
|           random          |               Byte files               |   2.45   |
|            knn            |               Byte files               |   0.48   |
|    Logistic Regression    |               Byte files               |   0.52   |
| Random Forest Classifier  |               Byte files               |   0.06   |
|   XgBoost Classification  |               Byte files               |   0.07   |
|                           |                                        |          |
|                           |                                        |          |
|            knn            |                asmfiles                |   0.21   |
|    Logistic Regression    |                asmfiles                |   0.38   |
| Random Forest Classifier  |                asmfiles                |   0.03   |
|   XgBoost Classification  |                asmfiles                |   0.04   |
|                           |                                        |          |
|                           |                                        |          |
| Random Forest Classifier  |          Byte files+asmfiles           |   0.04   |
|   XgBoost Classification  |          Byte files+asmfiles           |   0.02   |
|                           |                                        |          |
|                           |                                        |          |
|    Logistic Regression    | Byte files+asmfiles+advanced features  |   1.12   |
|   XgBoost Classification  | Byte files+asmfiles+advanced features  |   0.01   |
+---------------------------+----------------------------------------+----------+
```

In [ ]: