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)

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@@QAE@ABQBD@Z ; std::exc
eption::exception(char const * const &)
.text:0040100D C7 06 08 BB 42 00                      mov     dword ptr [esi], offset 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], offset 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], offset 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    ; operator delete(void *
)
.text:0040104B 83 C4 04                               add     esp, 4
.text:0040104E
.text:0040104E                            loc_40104E:                 ; CODE XREF: .text: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
00401080 00 00 01 00 00 04 00 10 02 C1 80 80 00 20 20 00
00401090 08 A0 01 01 44 28 00 00 08 10 20 00 02 08 00 00
004010A0 00 40 00 00 00 34 40 40 00 04 00 08 80 08 00 08
004010B0 10 00 40 00 68 02 40 04 E1 00 28 14 00 08 20 0A
004010C0 06 01 02 00 40 00 00 00 00 00 00 20 00 02 00 04
004010D0 80 18 90 00 00 10 A0 00 45 09 00 10 04 40 44 82
004010E0 90 00 26 10 00 00 04 00 82 00 00 00 20 40 00 00
004010F0 B4 00 00 40 00 02 20 25 08 00 00 00 00 00 00 00
00401100 08 00 00 50 00 08 40 50 00 02 06 22 08 85 30 00
00401110 00 80 00 80 60 00 09 00 04 20 00 00 00 00 00 00
00401120 00 82 40 02 00 11 46 01 4A 01 8C 01 E6 00 86 10
00401130 4C 01 22 00 64 00 AE 01 EA 01 2A 11 E8 10 26 11
00401140 4E 11 8E 11 C2 00 6C 00 0C 11 60 01 CA 00 62 10
00401150 6C 01 A0 11 CE 10 2C 11 4E 10 8C 00 CE 01 AE 01
00401160 6C 10 6C 11 A2 01 AE 00 46 11 EE 10 22 00 A8 00
00401170 EC 01 08 11 A2 01 AE 10 6C 00 6E 00 AC 11 8C 00
00401180 EC 01 2A 10 2A 01 AE 00 40 00 C8 10 48 01 4E 11
00401190 0E 00 EC 11 24 10 4A 10 04 01 C8 11 E6 01 C2 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)

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=VLQTRILGz5Y
https://github.com/dchad/malware-detection
http://vizsec.org/files/2011/Nataraj.pdf
https://www.dropbox.com/sh/gfqzv0ckgs4l1bf/AAB6EeInEjvvuQg2nu_pIB6ua?dl=0
" Cross validation is more trustworthy than domain knowledge."

3. Exploratory Data Analysis

In [1]:

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

%matplotlib inline

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
```

```
/usr/local/lib/python3.5/site-packages/sklearn/ensemble/weight_boosting.py:29: DeprecationWarning: n
umpy.core.umath_tests is an internal NumPy module and should not be imported. It will be removed in
a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [2]:

```
!wget --header="Host: storage.googleapis.com" --header="User-Agent: Mozilla/5.0 (Windows NT 6.1; Win64; x64) Appl
eWebKit/537.36 (KHTML, like Gecko) Chrome/77.0.3865.120 Safari/537.36" --header="Accept: text/html,application/xh
tml+xml,application/xml;q=0.9,image/webp,image/apng,*/*;q=0.8,application/signed-exchange;v=b3" --header="Accept-
Language: en-US,en;q=0.9" --header="Referer: https://www.kaggle.com/" "https://storage.googleapis.com/kagglesdsda
ta/competitions/4117/46665/train.7z?GoogleAccessId=web-data@kaggle-161607.iam.gserviceaccount.com&Expires=1587850
083&Signature=ssPxjpTIyyuanOXCifjuMN0XI1J%2BEco%2FUbRqGXOj3bUE7tyVAGGyfHQOpYPBMLKjeVtScXgijYi204vN4VvZ%2FE%2BJLBS
GnL4Sim9SbzV48Ddk6rZ%2BRWMtPVD8PBmyjZtFVIvsIZy0iHN6kzZK9DBWdcW0OeZ1DZmyUUyxufpQwMZk%2FxMYKvn7UsXNbB%2BnV2FWSzCjn%
2FDcNtUXvu1IZspR0CbGjk2q2dNzwD8ry2g%2BJGYLNEE6Hz7BSyawEpurgL%2BkO8cawvgcuuXNM3X948KNjTtgIrqbxo08A0R6dqMi3GtB0O3Pi
C4o%2BqNcvjIyGMa6MyD8mwM52ZXT%2B2Cg%2FBhfdg%3D%3D&response-content-disposition=attachment%3B+filename%3Dtrain.7z"
-c -O 'train.7z'
```

```
--2020-04-24 20:38:27--  https://storage.googleapis.com/kagglesdsdata/competitions/4117/46665/train.
7z?GoogleAccessId=web-data@kaggle-161607.iam.gserviceaccount.com&Expires=1587850083&Signature=ssPxjp
TIyyuanOXCifjuMN0XI1J%2BEco%2FUbRqGXOj3bUE7tyVAGGyfHQOpYPBMLKjeVtScXgijYi204vN4VvZ%2FE%2BJLBSGnL4Sim
9SbzV48Ddk6rZ%2BRWMtPVD8PBmyjZtFVIvsIZy0iHN6kzZK9DBWdcW0OeZ1DZmyUUyxufpQwMZk%2FxMYKvn7UsXNbB%2BnV2FW
SzCjn%2FDcNtUXvu1IZspR0CbGjk2q2dNzwD8ry2g%2BJGYLNEE6Hz7BSyawEpurgL%2BkO8cawvgcuuXNM3X948KNjTtgIrqbxo
08A0R6dqMi3GtB0O3PiC4o%2BqNcvjIyGMa6MyD8mwM52ZXT%2B2Cg%2FBhfdg%3D%3D&response-content-disposition=at
tachment%3B+filename%3Dtrain.7z
Resolving storage.googleapis.com (storage.googleapis.com)... 74.125.20.128, 2607:f8b0:400e:c08::80
Connecting to storage.googleapis.com (storage.googleapis.com)|74.125.20.128|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 18810691091 (18G) [application/x-7z-compressed]
Saving to: ‘train.7z’

train.7z            100%[===================>]  17.52G  70.3MB/s    in 4m 24s

2020-04-24 20:42:51 (68.1 MB/s) - ‘train.7z’ saved [18810691091/18810691091]
```

In [3]:

```
count=0
source = 'train'
destination_1 = 'byteFiles'
destination_2 = 'asmFiles'

# 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_1):
    os.makedirs(destination_1)
if not os.path.isdir(destination_2):
    os.makedirs(destination_2)
```

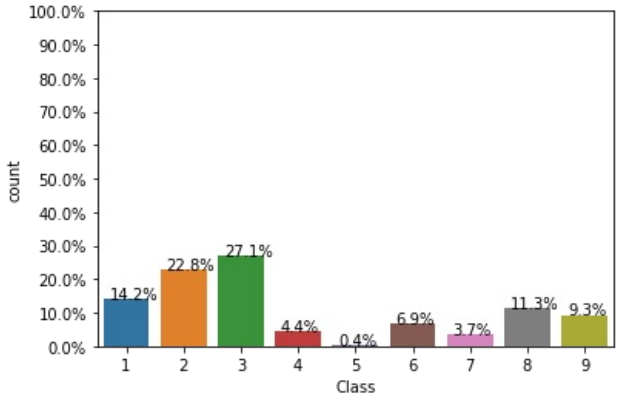
In [ ]:

```
#separating byte files and asm files
source = 'train'
destination_1 = 'byteFiles'
destination_2 = 'asmFiles'

# 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_1):
    os.makedirs(destination_1)
if not os.path.isdir(destination_2):
    os.makedirs(destination_2)

# if we have folder called 'train' (train folder contains both .asm files and .bytes files) we will rename it 'as
mFiles'
# for every file that we have in our 'asmFiles' directory we check if it is ending with .bytes, if yes we will mo
ve 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):
    data_files = os.listdir(source)
    for file in data_files:
        print(file)
        if (file.endswith("bytes")):
            shutil.move(source+'/'+file,destination_1)
        if (file.endswith("asm")):
            shutil.move(source+'/'+file,destination_2)
```

3.1. Distribution of malware classes in whole data set

In [27]:

```
Y=pd.read_csv("preprocessed/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 dataframe
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 [8]:

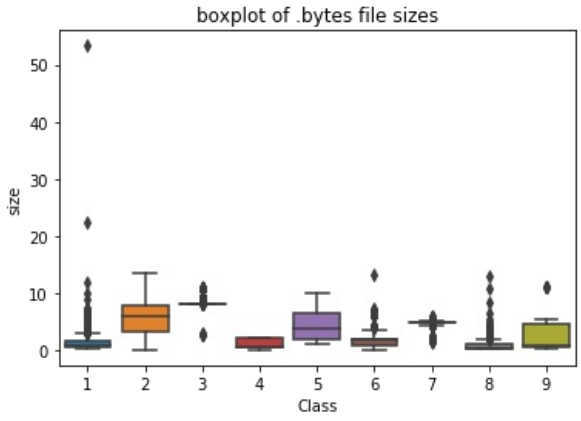
```
#file sizes of byte files

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=1519638522)
    # 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())
```

```
   Class                    ID      size
0      1  5PIwjdM6ROvnbiN9Dx0a  0.792969
1      6  5LM8dkt1OsGXwp3JSP2T  0.495605
2      2  FPX8CW9NolmqKYbh3nVt  7.122559
3      3  an85Um7qeAbI0uSrwF2C  8.099609
4      2  EatOQHsRMXTLP8jYxu04  1.925781
```

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

In [5]:

```
plt.close()
#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 [0]:

```
#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+')
        with open('byteFiles/'+file+".bytes","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+".bytes")
        text_file.close()

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


#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,0,1,2,3,4,5,6,7,8,9,0a,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,30,31,32,33,34,35,36,37,38,39,3a,3b,3c,3d,3e,3f,40,41,42,43,44,4
5,46,47,48,49,4a,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,80,81,82,83,84,85,86,87,88,89,8a,8b,8c,8d,8e,8f,90
,91,92,93,94,95,96,97,98,99,9a,9b,9c,9d,9e,9f,a0,a1,a2,a3,a4,a5,a6,a7,a8,a9,aa,ab,ac,ad,ae,af,b0,b1,b2,b3,b4,b5,b
6,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,f1,f2,f3,f4,f5,f6,f7,f8,f9,fa,fb,fc,fd,fe,ff,??")
byte_feature_file.write("\n")
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, row in enumerate(feature_matrix[k]):
        if i!=len(feature_matrix[k])-1:
            byte_feature_file.write(str(row)+",")
        else:
            byte_feature_file.write(str(row))
    byte_feature_file.write("\n")

    k += 1

byte_feature_file.close()
```

In [4]:

```
byte_features=pd.read_csv("preprocessed/result.csv")
byte_features['ID']  = byte_features['ID'].str.split('.').str[0]
byte_features.head(2)
```

Out[4]:

	ID	0	1	2	3	4	5	6	7	8	...	f7	f8	f9	fa	fb	fc	fd
0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	2965	...	2804	3687	3101	3211	3097	2758	3099
1	01IsoiSMh5gxyDYTl4CB	39755	8337	7249	7186	8663	6844	8420	7589	9291	...	451	6536	439	281	302	7639	518

2 rows × 258 columns

In [8]:

```
data_size_byte.head(2)
```

Out[8]:

	Class	ID	size
0	1	5PlwjdM6ROvnbiN9Dx0a	0.792969
1	6	5LM8dkt1OsGXwp3JSP2T	0.495605

In [ ]:

```
byte_features_with_size = byte_features.merge(data_size_byte, on='ID')
byte_features_with_size.to_csv("result_with_size.csv")
```

In [2]:

```
byte_features_with_size=pd.read_csv("preprocessed/result_with_size.csv")
byte_features_with_size=byte_features_with_size.drop(columns='Unnamed: 0',axis=1)
byte_features_with_size.head(2)
```

Out[2]:

	ID	0	1	2	3	4	5	6	7	8	...	f9	fa	fb	fc	fd	fe	
0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	2965	...	3101	3211	3097	2758	3099	2759	5
1	01IsoiSMh5gxyDYTl4CB	39755	8337	7249	7186	8663	6844	8420	7589	9291	...	439	281	302	7639	518	17001	54

2 rows × 260 columns

In [3]:

```
# 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(byte_features_with_size)
```

In [29]:

```
data_y = result['Class']
result.head()
```

Out[29]:

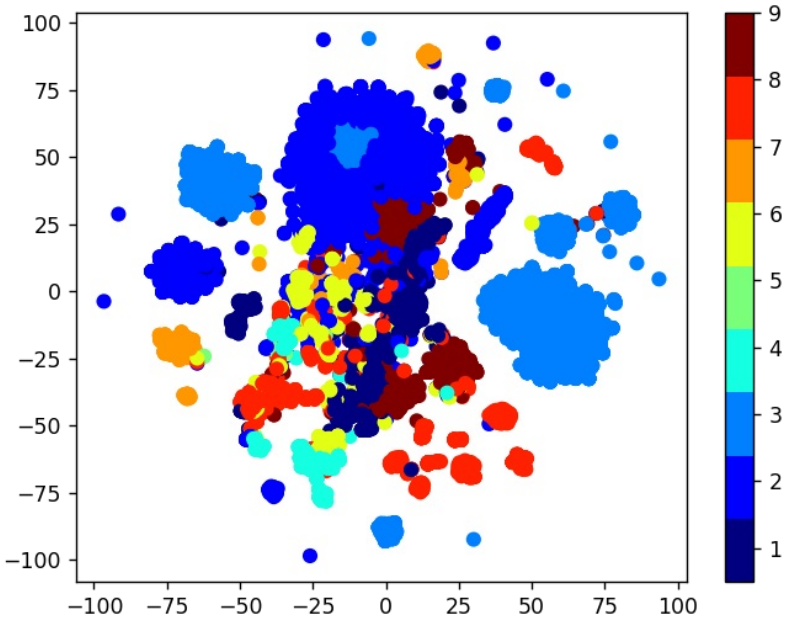
	ID	0	1	2	3	4	5	6	7	8	...	f9
0	01azqd4InC7m9JpocGv5	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	...	0.013560
1	01IsoiSMh5gxyDYTl4CB	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	...	0.001920
2	01jsnpXSAlgw6aPeDxrU	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	...	0.009804
3	01kcPWA9K2BOxQeS5Rju	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	...	0.002121
4	01SuzwMJEIXsK7A8dQbl	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	...	0.001530

5 rows × 260 columns

3.2.4 Multivariate Analysis

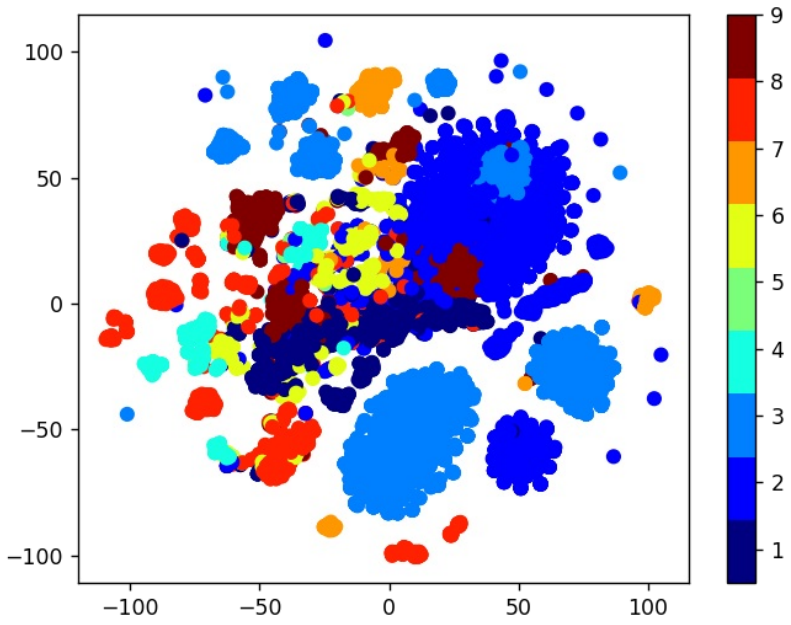
In [0]:

```
#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 [0]:

```
#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 varaible 'y_true' [stratify=y_true]
X_train, X_test, y_train, y_test = train_test_split(result.drop(['ID','Class'], axis=1), data_y,stratify=data_y,test_size=0.20)
# split the train data into train and cross validation by maintaining same distribution 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)
```

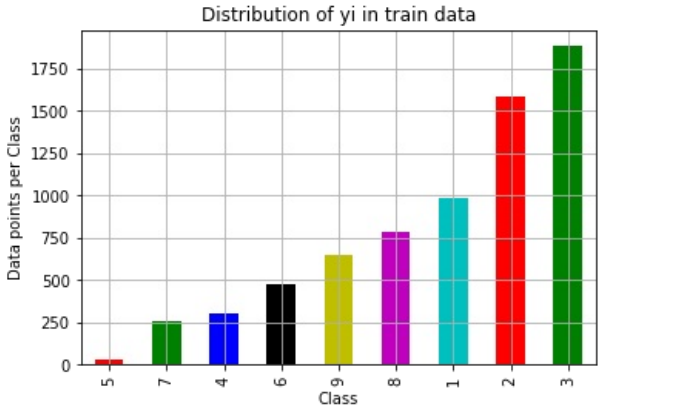
In [10]:

```
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])
```

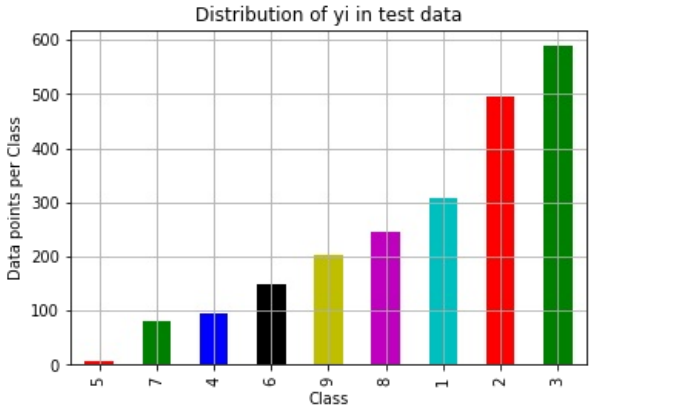
```
Number of data points in train data: 6955
Number of data points in test data: 2174
Number of data points in cross validation data: 1739
```

In [16]:

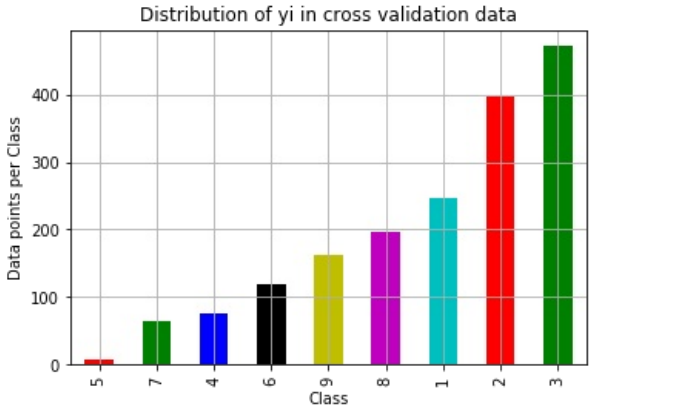
```
# it returns a dict, keys as class labels and values as the number of data points in that class
train_class_distribution = y_train.value_counts().sort_values()
test_class_distribution = y_test.value_counts().sort_values()
cv_class_distribution = y_cv.value_counts().sort_values()

my_colors = ['r','g','b','k','y','m','c']
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 order
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.values[i], '(', np.round((train_cla
ss_distribution.values[i]/y_train.shape[0]*100), 3), '%)')


print('-'*80)
#my_colors = 'rgbkymc'
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 order
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.values[i], '(', np.round((test_class
_distribution.values[i]/y_test.shape[0]*100), 3), '%)')

print('-'*80)
#my_colors = 'rgbkymc'
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 order
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_dis
tribution.values[i]/y_cv.shape[0]*100), 3), '%)')
```




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




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




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

In [30]:

```
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 predicted class j

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

    # 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 row
    # 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, yticklabels=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, yticklabels=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, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in precision matrix",A.sum(axis=1))
```

4. Machine Learning Models

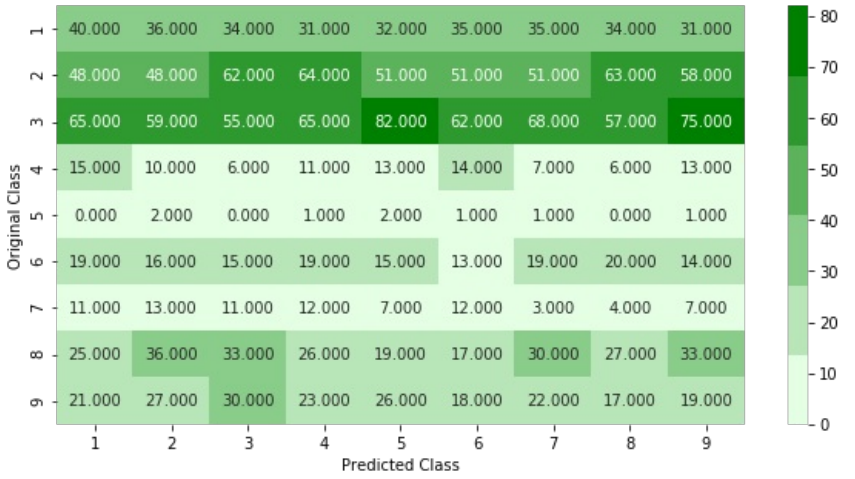
4.1. Machine Leaning Models on bytes files

4.1.1. Random Model

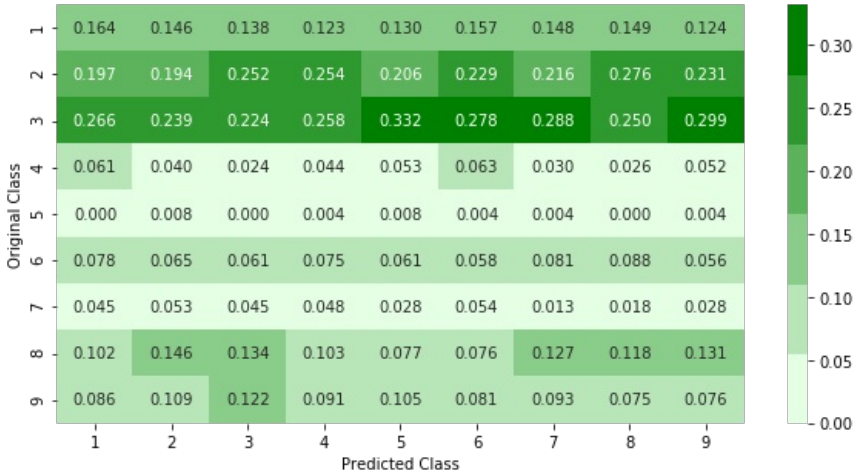
In [44]:

```
# 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 sum
# 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_predicted_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 2.4746046186165627
Log loss on Test Data using Random Model 2.502804808620262
Number of misclassified points  89.97240110395585
-------------------------------------------------- Confusion matrix ------------------------------
------------------
```




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




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

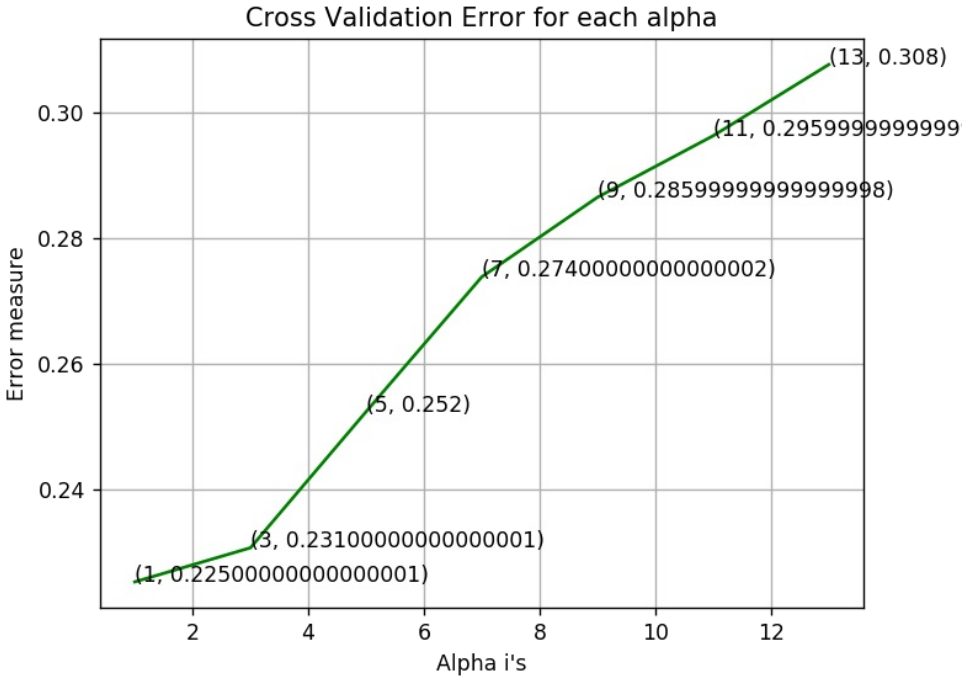

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.2. K Nearest Neighbour Classification

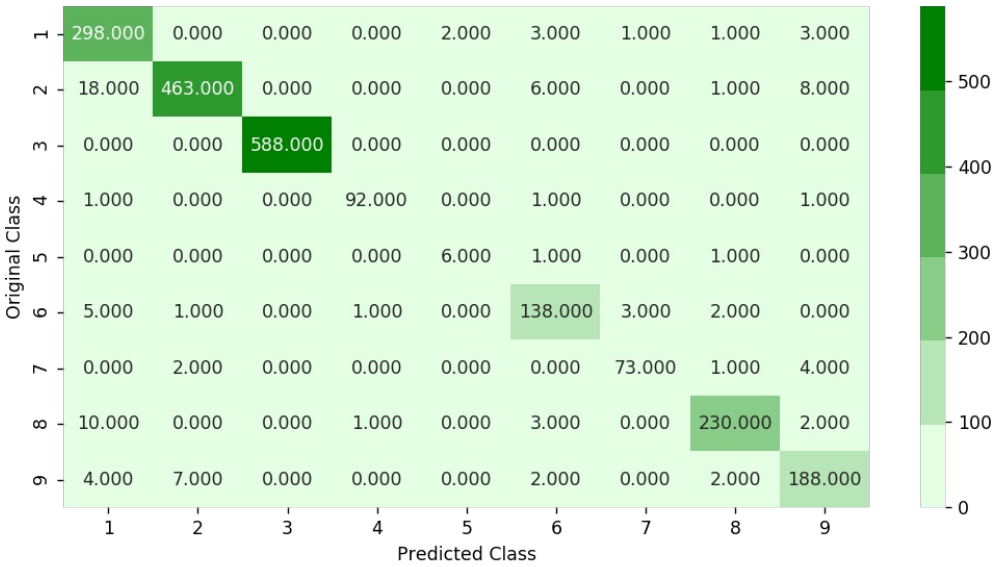
In [0]:

```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.
KNeighborsClassifier.html
# -------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', leaf_size=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/lessons/k-nearest-neighbors-geometr
ic-intuition-with-a-toy-example-1/
#--------------------------------------


# find more about CalibratedClassifierCV here at http://scikit-learn.org/stable/modules/generated/sklearn.calibra
tion.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)

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))
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predic
t_y))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y))
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

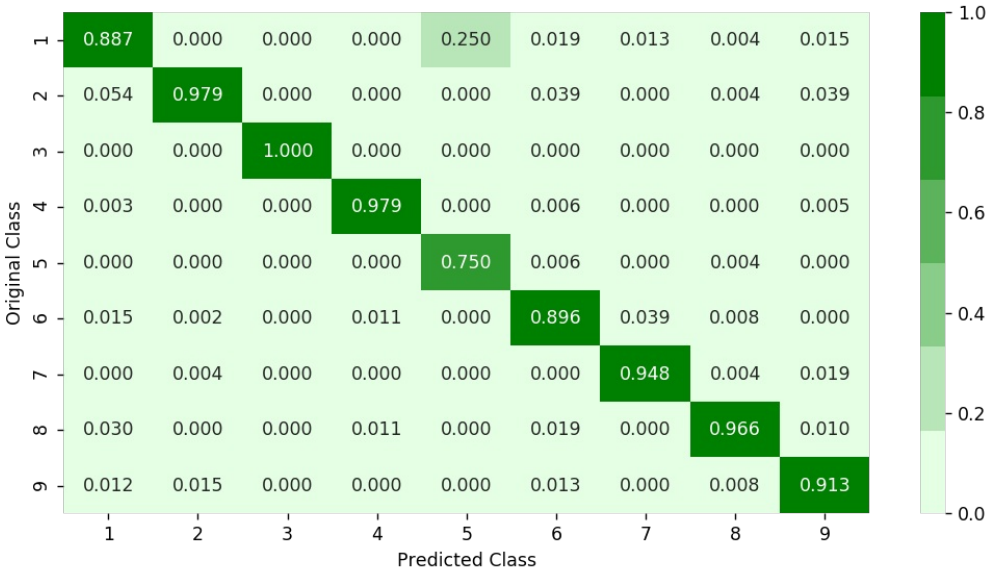
```
log_loss for k =  1 is 0.225386237304
log_loss for k =  3 is 0.230795229168
log_loss for k =  5 is 0.252421408646
log_loss for k =  7 is 0.273827486888
log_loss for k =  9 is 0.286469181555
log_loss for k =  11 is 0.29623391147
log_loss for k =  13 is 0.307551203154
```



For values of best alpha = 1 The train log loss is: 0.0782947669247
For values of best alpha = 1 The cross validation log loss is: 0.225386237304
For values of best alpha = 1 The test log loss is: 0.241508604195
Number of misclassified points 4.50781968721
---------- Confusion matrix ----------

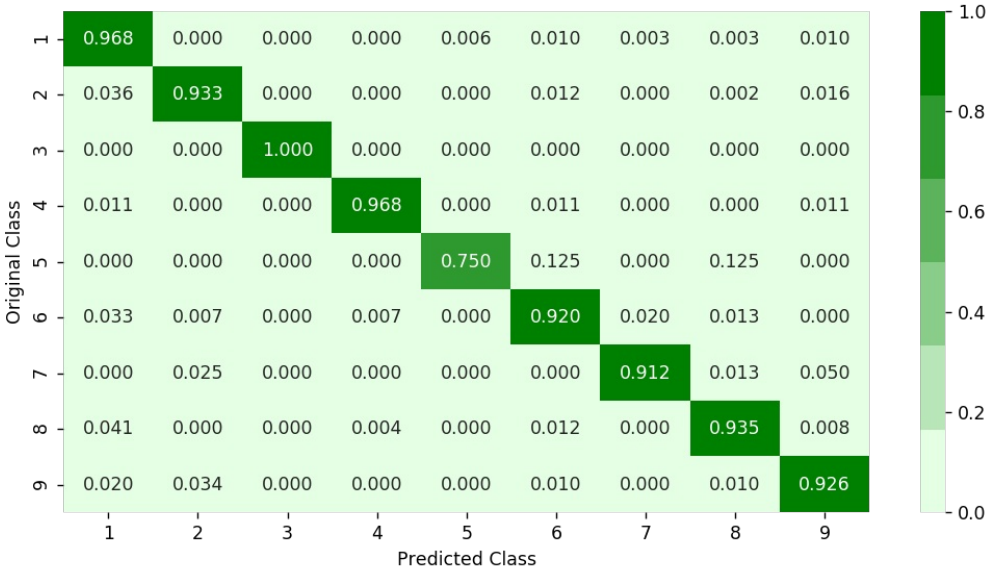


---------- Precision matrix ----------



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

---------- Recall matrix ----------



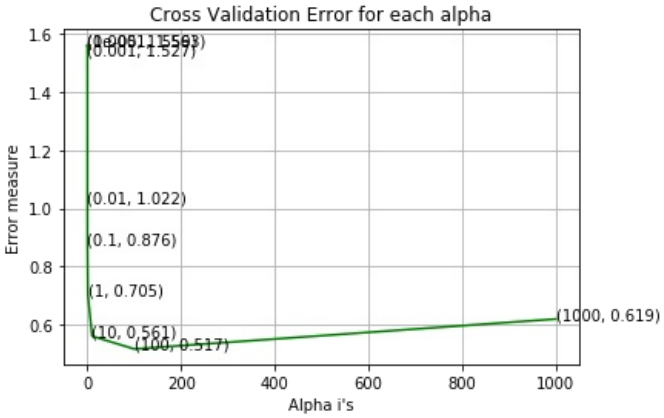
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

4.1.3. Logistic Regression

In [18]:

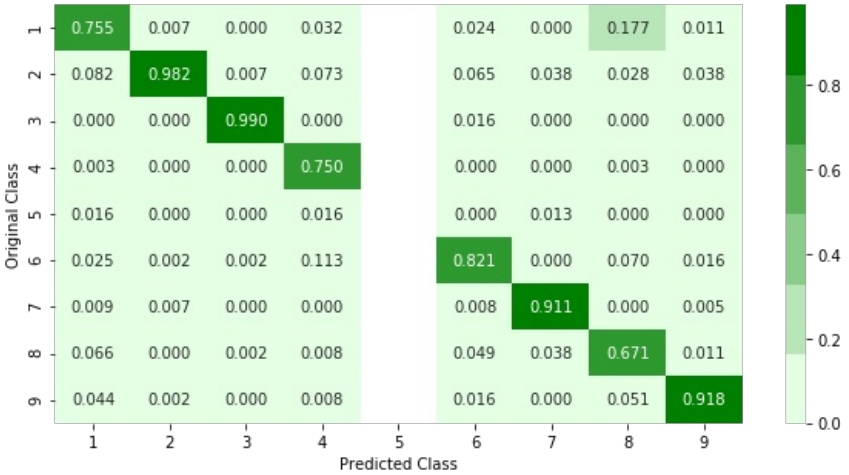
```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# 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,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='balanced')
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.classes_, 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.classes_, eps=1e-15))
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

```
log_loss for c =  1e-05 is 1.5585818274938525
log_loss for c =  0.0001 is 1.5628326333537284
log_loss for c =  0.001 is 1.5272620748599233
log_loss for c =  0.01 is 1.0219168689478242
log_loss for c =  0.1 is 0.8761005596321169
log_loss for c =  1 is 0.7045148619932136
log_loss for c =  10 is 0.5605514861149757
log_loss for c =  100 is 0.5165511906561815
log_loss for c =  1000 is 0.6194372723900103
```

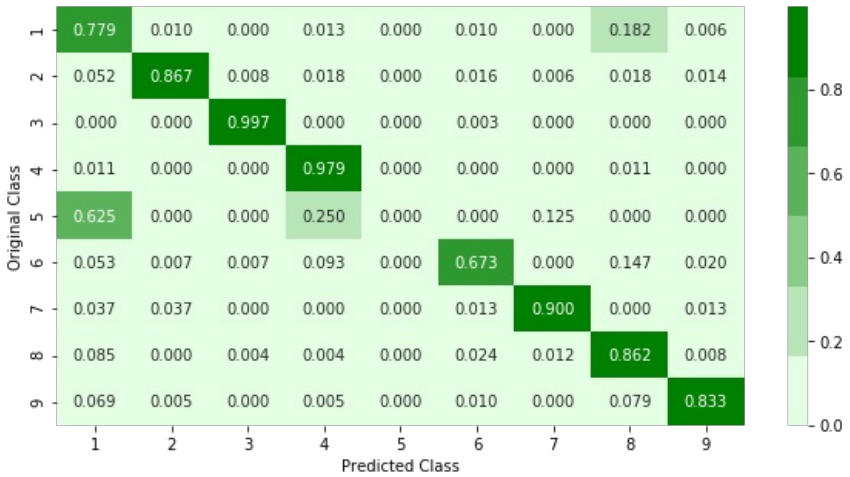


log loss for train data 0.5055736745298081
log loss for cv data 0.5165511906561815
log loss for test data 0.5458465519967389
Number of misclassified points 12.465501379944802
---------- Confusion matrix ----------

---------- Precision matrix ----------



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



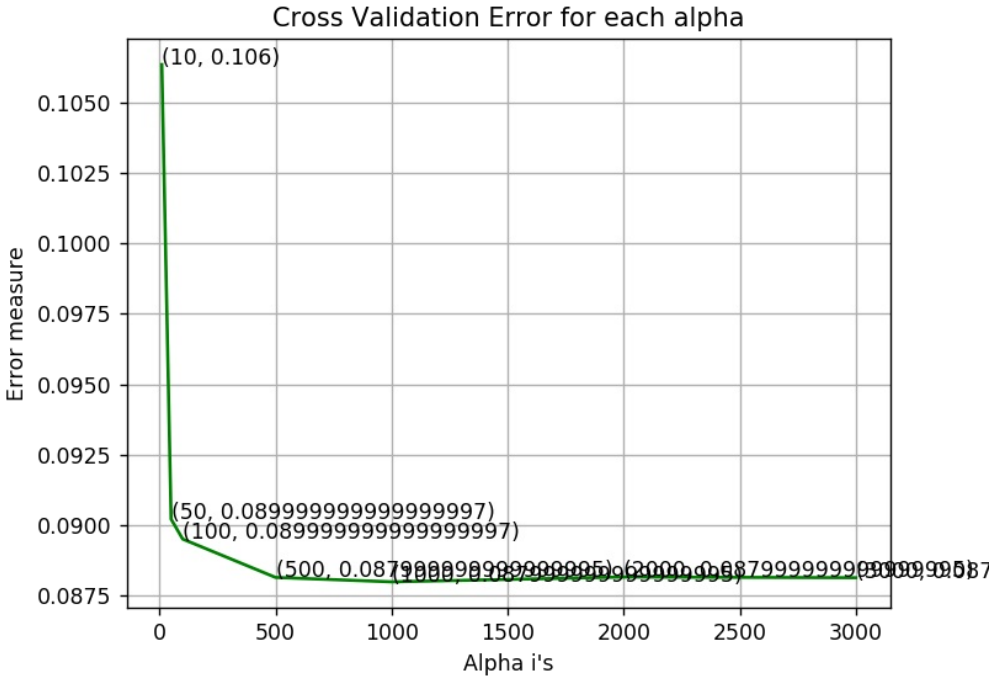

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.1.4. Random Forest Classifier

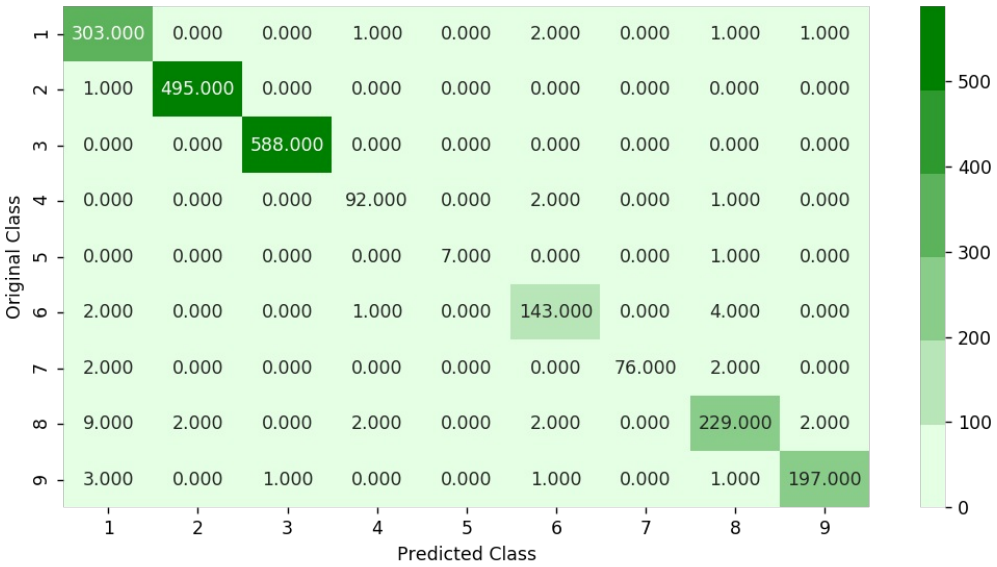
In [0]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrea
se=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=Fa
lse,
# 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/lessons/random-forest-and-their-con
struction-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:",log_loss(y_train, predict_y))
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predic
t_y))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y))
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

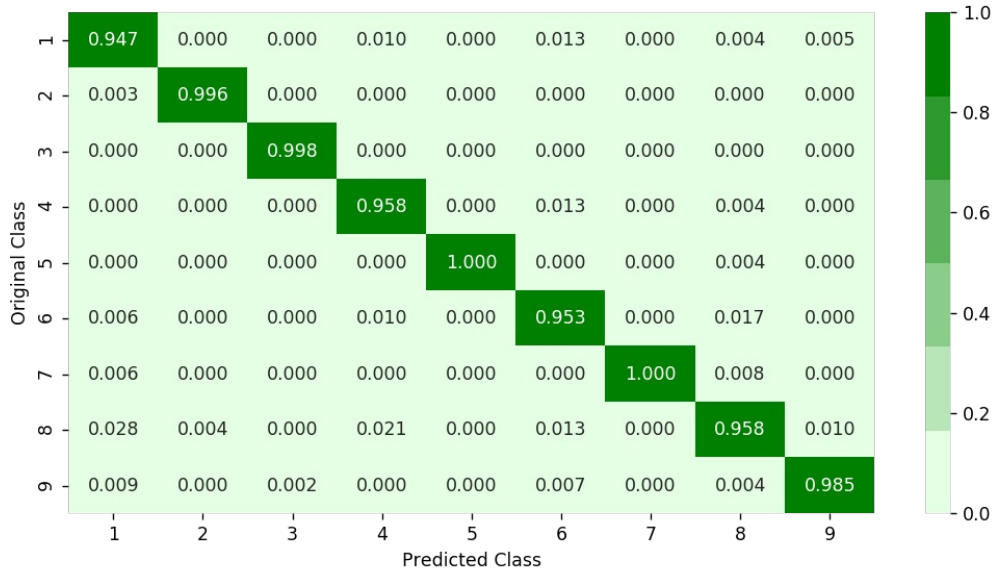
```
log_loss for c =  10 is 0.106357709164
log_loss for c =  50 is 0.0902124124145
log_loss for c =  100 is 0.0895043339776
log_loss for c =  500 is 0.0881420869288
log_loss for c =  1000 is 0.0879849524621
log_loss for c =  2000 is 0.0881566647295
log_loss for c =  3000 is 0.0881318948443
```



For values of best alpha = 1000 The train log loss is: 0.0266476291801
For values of best alpha = 1000 The cross validation log loss is: 0.0879849524621
For values of best alpha = 1000 The test log loss is: 0.0858346961407
Number of misclassified points 2.02391904324
---------- Confusion matrix ----------

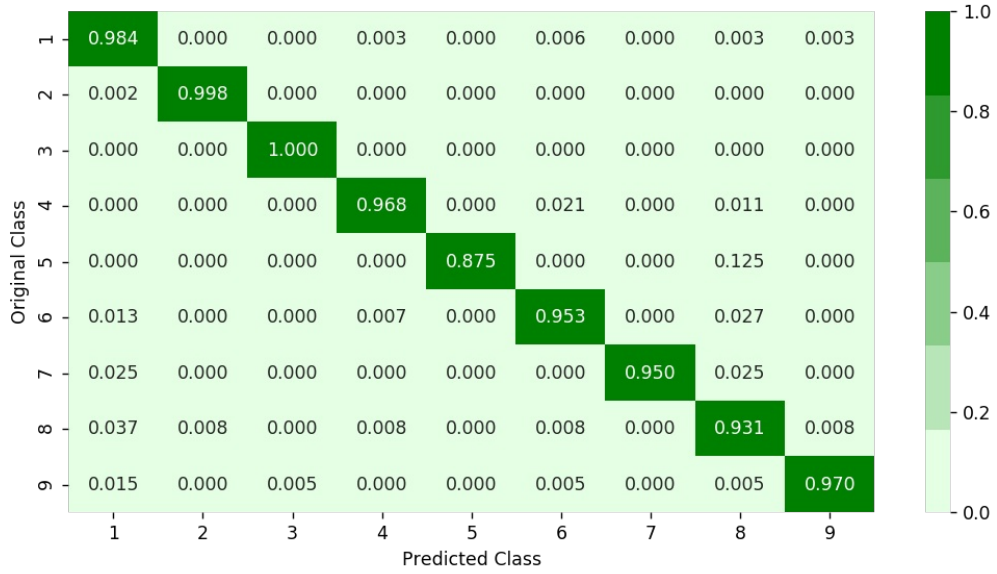


---------- Precision matrix ----------



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

---------- Recall matrix ----------



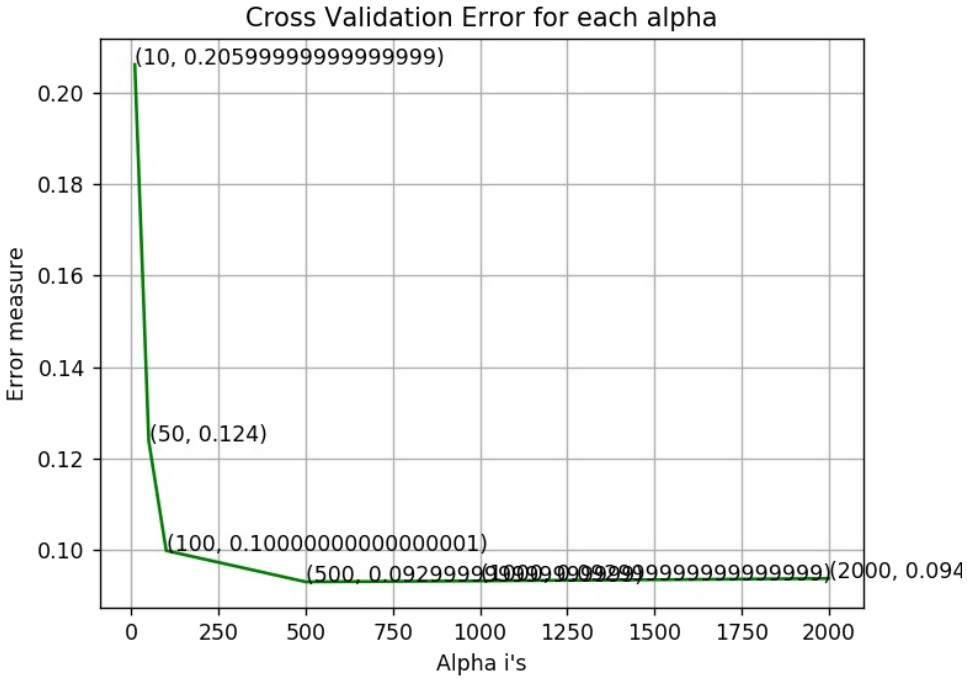
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

4.1.5. XgBoost Classification

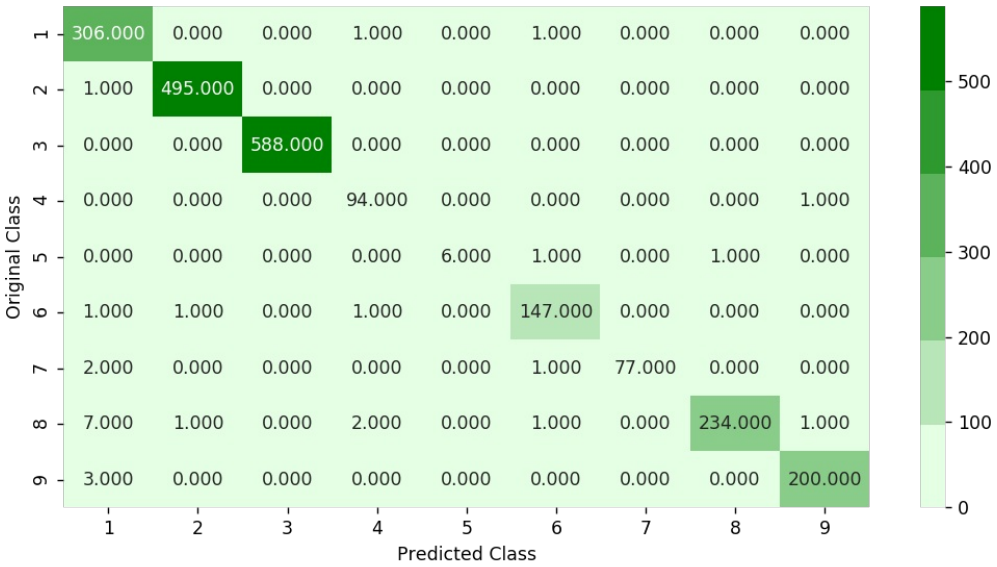
In [0]:

```
# 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?#xgb
oost.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_mo
del=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))
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predic
t_y))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y))
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

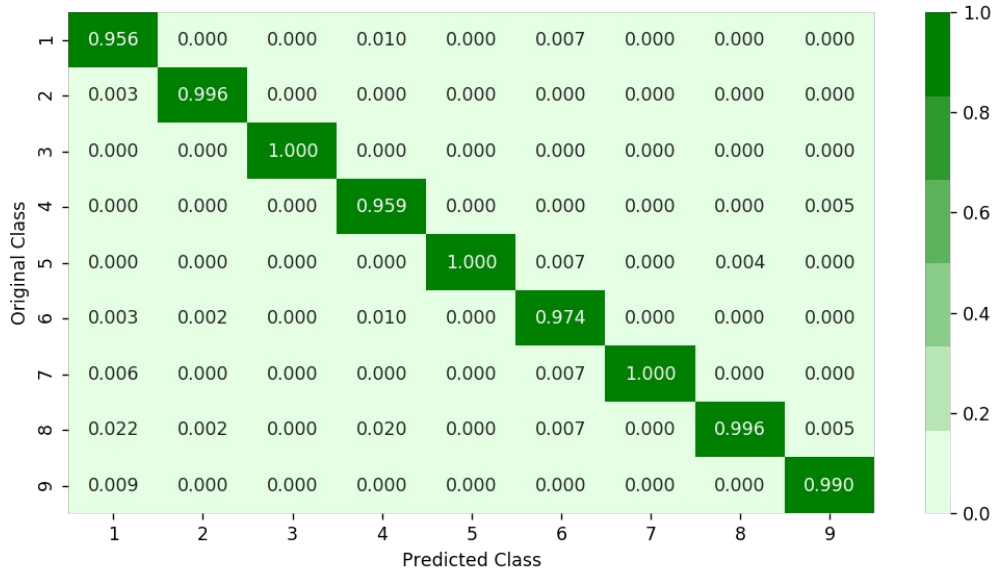
```
log_loss for c =  10 is 0.20615980494
log_loss for c =  50 is 0.123888382365
log_loss for c =  100 is 0.099919437112
log_loss for c =  500 is 0.0931035681289
log_loss for c =  1000 is 0.0933084876012
log_loss for c =  2000 is 0.0938395690309
```



For values of best alpha = 500 The train log loss is: 0.0225231805824
For values of best alpha = 500 The cross validation log loss is: 0.0931035681289
For values of best alpha = 500 The test log loss is: 0.0792067651731
Number of misclassified points 1.24195032199
---------- Confusion matrix ----------

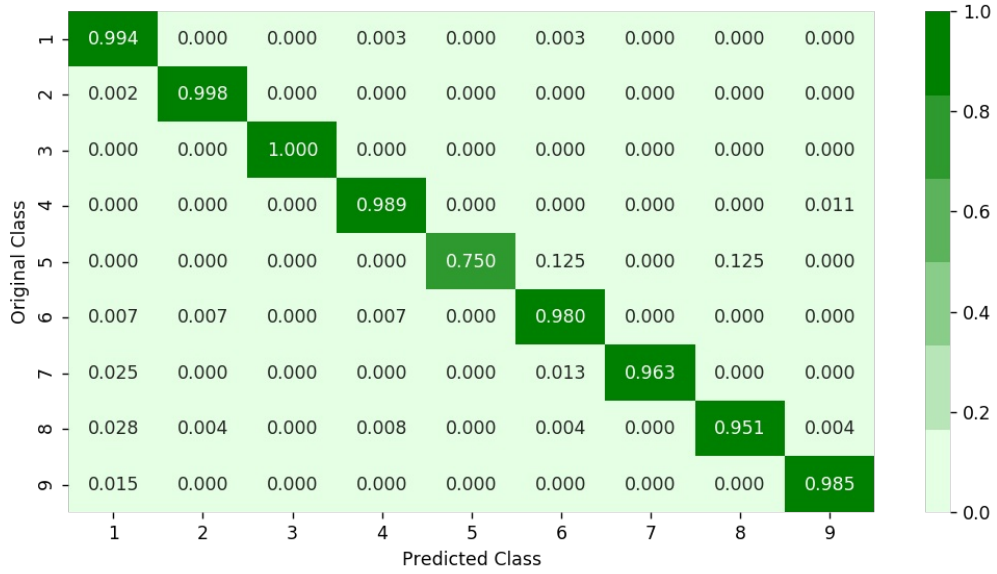


---------- Precision matrix ----------



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 [0]:

```
# https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tuning-xgboost-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)]: Done   2 tasks      | elapsed:   26.5s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  5.8min
[Parallel(n_jobs=-1)]: Done  19 out of  30 | elapsed:  9.3min remaining:  5.4min
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed: 10.1min remaining:  3.1min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed: 14.0min remaining:  1.6min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 14.2min finished
```

Out[0]:

```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=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, nthread=-1,
       objective='binary:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1),
          fit_params=None, iid=True, 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], 'colsample_bytree': [0.1, 0.3, 0.5, 1], 'subsa
mple': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=10)
```

In [0]:

```
print (random_cfl1.best_params_)
```

```
{'subsample': 1, 'n_estimators': 500, 'max_depth': 5, 'learning_rate': 0.05, 'colsample_bytree': 0.5
}
```

In [0]:

```
# 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?#xgb
oost.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_mo
del=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/
# ------------------------

x_cfl=XGBClassifier(n_estimators=2000, learning_rate=0.05, colsample_bytree=1, max_depth=3)
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 0.022540976086
cv loss 0.0928710624158
test loss 0.0782688587098
```

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 tha
t 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 [0]:

```
#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 [0]:

```
#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)+",")
        for opcode in opcodescount:
            file1.write(str(opcode)+",")
        for register in registerscount:
            file1.write(str(register)+",")
        for key in keywordcount:
            file1.write(str(key)+",")
        file1.write("\n")
    file1.close()


#same as above
def secondprocess():
    prefixes = ['HEADER:','.text:','.Pav:','.idata:','.data:','.bss:','.rdata:','.edata:','.rsrc:','.tls:','.reloc:','.BSS:','.CODE']
    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']
    keywords = ['.dll','std::',':dword']
    registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
    file1=open("output\mediumasmfile.txt","w+")
    files = os.listdir('second')
    for f in files:
        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+" ")
        with codecs.open('second/'+f,encoding='cp1252',errors ='replace') as fli:
            for lines in fli:
                line=lines.rstrip().split()
                l=line[0]
                for i in range(len(prefixes)):
                    if prefixes[i] in line[0]:
                        prefixescount[i]+=1
                line=line[1:]
                for i in range(len(opcodes)):
                    if any(opcodes[i]==li for li in line):
                        features.append(opcodes[i])
                        opcodescount[i]+=1
                for i in range(len(registers)):
                    for li in line:
                        if registers[i] in li and ('text' in l or 'CODE' in l):
                            registerscount[i]+=1
                for i in range(len(keywords)):
                    for li in line:
                        if keywords[i] in li:
                            keywordcount[i]+=1
        for prefix in prefixescount:
            file1.write(str(prefix)+",")
        for opcode in opcodescount:
            file1.write(str(opcode)+",")
        for register in registerscount:
            file1.write(str(register)+",")
        for key in keywordcount:
            file1.write(str(key)+",")
        file1.write("\n")
    file1.close()

# same as smallprocess() functions
def thirdprocess():
    prefixes = ['HEADER:','.text:','.Pav:','.idata:','.data:','.bss:','.rdata:','.edata:','.rsrc:','.tls:','.reloc:','.BSS:','.CODE']
```

```
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub', 'inc', 'dec', 'add','imul', 'xch
g', 'or', 'shr', 'cmp', 'call', 'shl', 'ror', 'rol', 'jnb','jz','rtn','lea','movzx']
    keywords = ['.dll','std::',':dword']
    registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
    file1=open("output\largeasmfile.txt","w+")
    files = os.listdir('thrid')
    for f in files:
        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+" ")
        with codecs.open('thrid/'+f,encoding='cp1252',errors ='replace') as fli:
            for lines in fli:
                line=lines.rstrip().split()
                l=line[0]
                for i in range(len(prefixes)):
                    if prefixes[i] in line[0]:
                        prefixescount[i]+=1
                line=line[1:]
                for i in range(len(opcodes)):
                    if any(opcodes[i]==li for li in line):
                        features.append(opcodes[i])
                        opcodescount[i]+=1
                for i in range(len(registers)):
                    for li in line:
                        if registers[i] in li and ('text' in l or 'CODE' in l):
                            registerscount[i]+=1
                for i in range(len(keywords)):
                    for li in line:
                        if keywords[i] in li:
                            keywordcount[i]+=1
        for prefix in prefixescount:
            file1.write(str(prefix)+",")
        for opcode in opcodescount:
            file1.write(str(opcode)+",")
        for register in registerscount:
            file1.write(str(register)+",")
        for key in keywordcount:
            file1.write(str(key)+",")
        file1.write("\n")
    file1.close()


def fourthprocess():
    prefixes = ['HEADER:','.text:','.Pav:','.idata:','.data:','.bss:','.rdata:','.edata:','.rsrc:','.tls:','.relo
c:','.BSS:','.CODE']
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub', 'inc', 'dec', 'add','imul', 'xch
g', 'or', 'shr', 'cmp', 'call', 'shl', 'ror', 'rol', 'jnb','jz','rtn','lea','movzx']
    keywords = ['.dll','std::',':dword']
    registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
    file1=open("output\hugeasmfile.txt","w+")
    files = os.listdir('fourth/')
    for f in files:
        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+" ")
        with codecs.open('fourth/'+f,encoding='cp1252',errors ='replace') as fli:
            for lines in fli:
                line=lines.rstrip().split()
                l=line[0]
                for i in range(len(prefixes)):
                    if prefixes[i] in line[0]:
                        prefixescount[i]+=1
                line=line[1:]
                for i in range(len(opcodes)):
                    if any(opcodes[i]==li for li in line):
                        features.append(opcodes[i])
                        opcodescount[i]+=1
                for i in range(len(registers)):
                    for li in line:
                        if registers[i] in li and ('text' in l or 'CODE' in l):
                            registerscount[i]+=1
                for i in range(len(keywords)):
                    for li in line:
```

```
                        if keywords[i] in li:

                            keywordcount[i]+=1
        for prefix in prefixescount:
            file1.write(str(prefix)+",")
        for opcode in opcodescount:
            file1.write(str(opcode)+",")
        for register in registerscount:
            file1.write(str(register)+",")
        for key in keywordcount:
            file1.write(str(key)+",")
        file1.write("\n")
    file1.close()


def fifthprocess():
    prefixes = ['HEADER:','.text:','.Pav:','.idata:','.data:','.bss:','.rdata:','.edata:','.rsrc:','.tls:','.reloc:','.BSS:','.CODE']
    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']
    keywords = ['.dll','std::',':dword']
    registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
    file1=open("output\trainasmfile.txt","w+")
    files = os.listdir('fifth/')
    for f in files:
        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+" ")
        with codecs.open('fifth/'+f,encoding='cp1252',errors ='replace') as fli:
            for lines in fli:
                line=lines.rstrip().split()
                l=line[0]
                for i in range(len(prefixes)):
                    if prefixes[i] in line[0]:
                        prefixescount[i]+=1
                line=line[1:]
                for i in range(len(opcodes)):
                    if any(opcodes[i]==li for li in line):
                        features.append(opcodes[i])
                        opcodescount[i]+=1
                for i in range(len(registers)):
                    for li in line:
                        if registers[i] in li and ('text' in l or 'CODE' in l):
                            registerscount[i]+=1
                for i in range(len(keywords)):
                    for li in line:
                        if keywords[i] in li:
                            keywordcount[i]+=1
        for prefix in prefixescount:
            file1.write(str(prefix)+",")
        for opcode in opcodescount:
            file1.write(str(opcode)+",")
        for register in registerscount:
            file1.write(str(register)+",")
        for key in keywordcount:
            file1.write(str(key)+",")
        file1.write("\n")
    file1.close()


def main():
    #the below code is used for multiprogramming
    #the number of process depends upon the number of cores present System
    #process is used to call multiprogramming
    manager=multiprocessing.Manager()
    p1=Process(target=firstprocess)
    p2=Process(target=secondprocess)
    p3=Process(target=thirdprocess)
    p4=Process(target=fourthprocess)
    p5=Process(target=fifthprocess)
    #p1.start() is used to start the thread execution
    p1.start()
    p2.start()
    p3.start()
    p4.start()
    p5.start()
    #After completion all the threads are joined
    p1.join()
    p2.join()
```

```
    p3.join()

    p4.join()
    p5.join()

if __name__=="__main__":
    main()
```

In [31]:

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

Out[31]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	edx	esi	eax	ebx	ecx	edi	eb
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	18	66	15	43	83	0	1
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	18	29	48	82	12	0	1
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	13	42	10	67	14	0	1
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	6	8	14	7	2	0	
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	12	9	18	29	5	0	1

5 rows x 53 columns

4.2.1.1 Files sizes of each .asm file

In [32]:

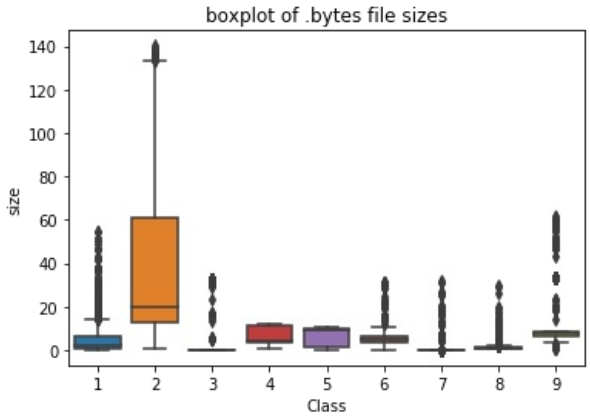
```
#file sizes of byte files

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=1519638522)
    # 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())
```

```
   Class                    ID       size
0      9  C5RGotXVrOxI3Np8g10A   8.415636
1      2  8O7mDBd4HqE3PxFtWnug  87.405348
2      2  fqom9xYgBEHIZ6iRA78s  81.022170
3      1  Evpm2HCFWB0buXNO3kQj   0.674126
4      2  kfgxDSAKF7tJqEwP4T10  33.393025
```

4.2.1.2 Distribution of .asm file sizes

In [16]:

```
#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 [33]:

```
# 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', how='left')
result_asm.head()
```

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

Out[33]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	eax	ebx	ecx	edi	ebp	es
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...	66	15	43	83	0	17	4
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...	29	48	82	12	0	14	
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...	42	10	67	14	0	11	
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...	8	14	7	2	0	8	
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...	9	18	29	5	0	11	

5 rows x 54 columns

In [34]:

```
# we normalize the data each column
result_asm = normalize(result_asm)
result_asm.head()
```

Out[34]:

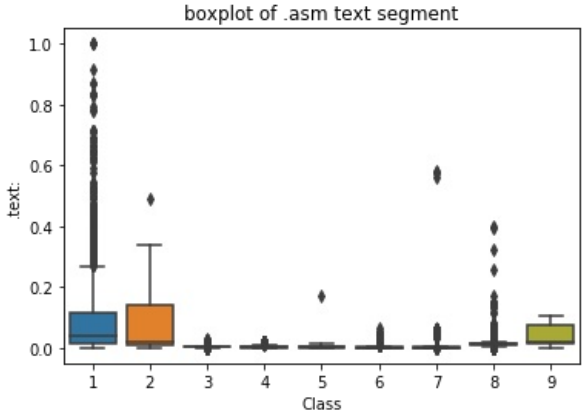
	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	ea
0	01kcPWA9K2BOxQeS5Rju	0.107345	0.001092	0.0	0.000761	0.000023	0.0	0.000084	0.0	0.000072	...	0.000746	0.0003
1	1E93CpP60RHFNiT5Qfvn	0.096045	0.001230	0.0	0.000617	0.000019	0.0	0.000000	0.0	0.000072	...	0.000328	0.0009
2	3ekVow2ajZHbTnBcsDfX	0.096045	0.000627	0.0	0.000300	0.000017	0.0	0.000038	0.0	0.000072	...	0.000475	0.0002
3	3X2nY7iQaPBIWDrAZqJe	0.096045	0.000333	0.0	0.000258	0.000008	0.0	0.000000	0.0	0.000072	...	0.000090	0.0002
4	46OZzdsSKDCFV8h7XWxf	0.096045	0.000590	0.0	0.000353	0.000068	0.0	0.000000	0.0	0.000072	...	0.000102	0.0003

5 rows x 54 columns

4.2.2 Univariate analysis on asm file features

In [24]:

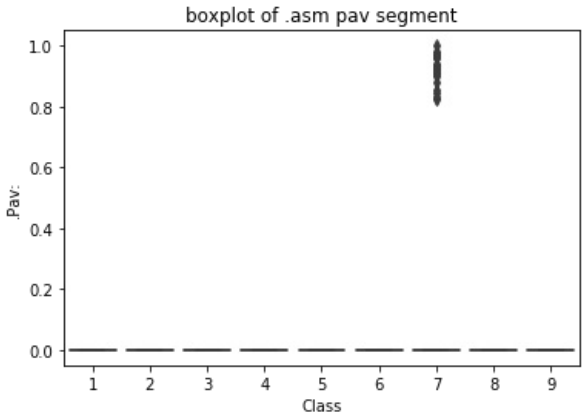
```
ax = sns.boxplot(x="Class", y=".text:", data=result_asm)
plt.title("boxplot of .asm text segment")
plt.show()
```



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

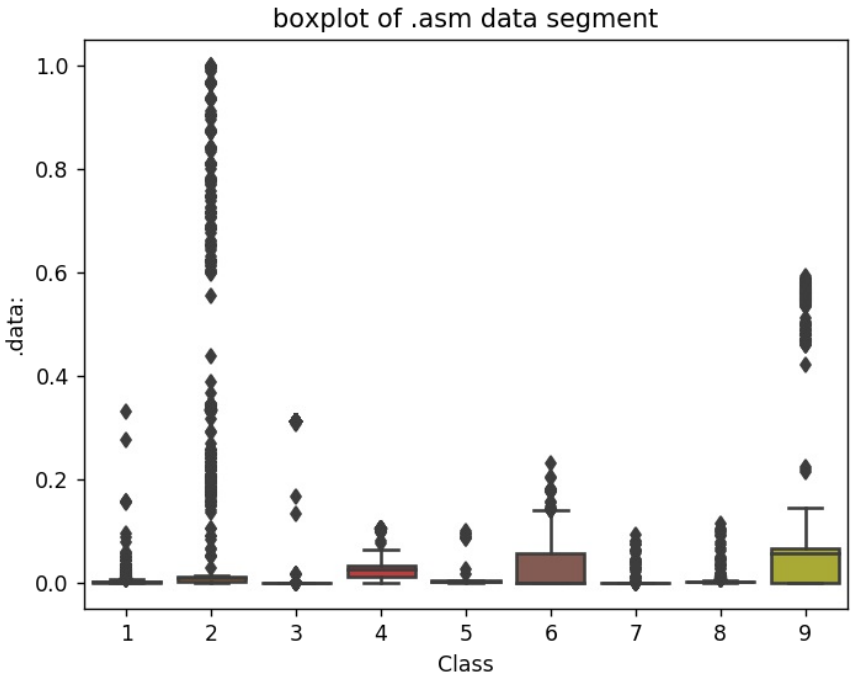
In [25]:

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



In [0]:

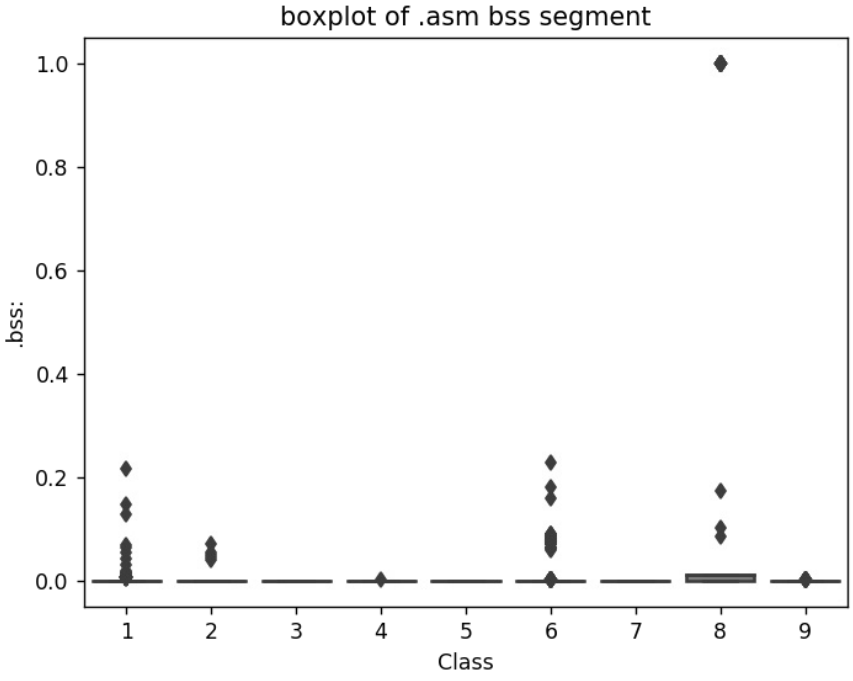
```
ax = sns.boxplot(x="Class", y=".data:", data=result_asm)
plt.title("boxplot of .asm data segment")
plt.show()
```



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

In [0]:

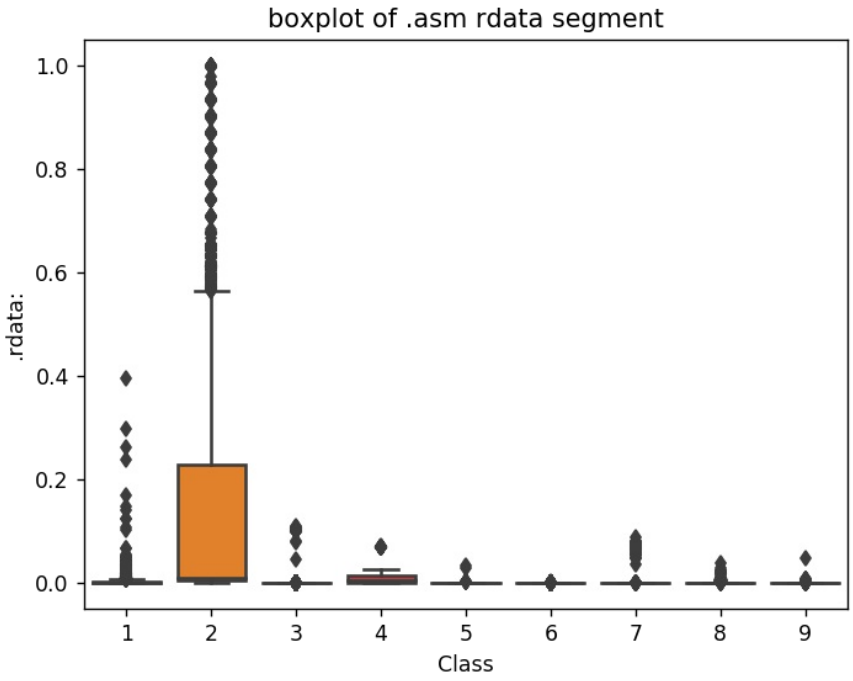
```
ax = sns.boxplot(x="Class", y=".bss:", data=result_asm)
plt.title("boxplot of .asm bss segment")
plt.show()
```



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

In [0]:

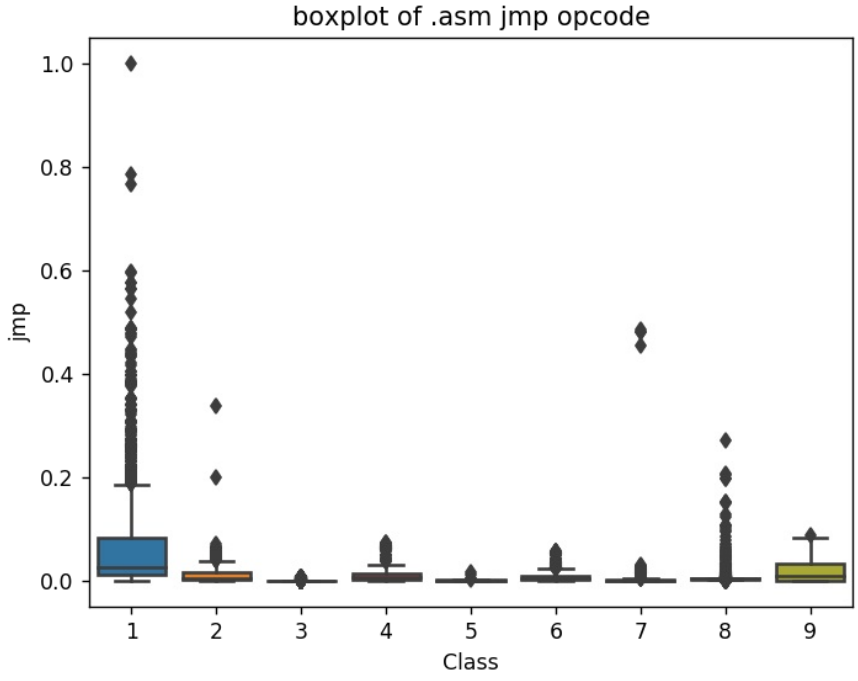
```
ax = sns.boxplot(x="Class", y=".rdata:", data=result_asm)
plt.title("boxplot of .asm rdata segment")
plt.show()
```



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

In [0]:

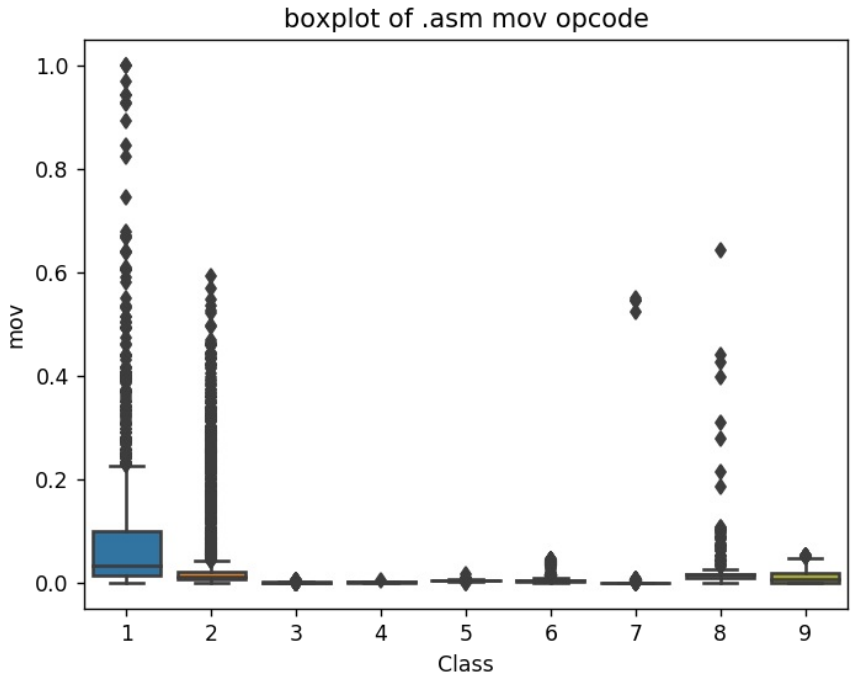
```
ax = sns.boxplot(x="Class", y="jmp", data=result_asm)
plt.title("boxplot of .asm jmp opcode")
plt.show()
```



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

In [0]:

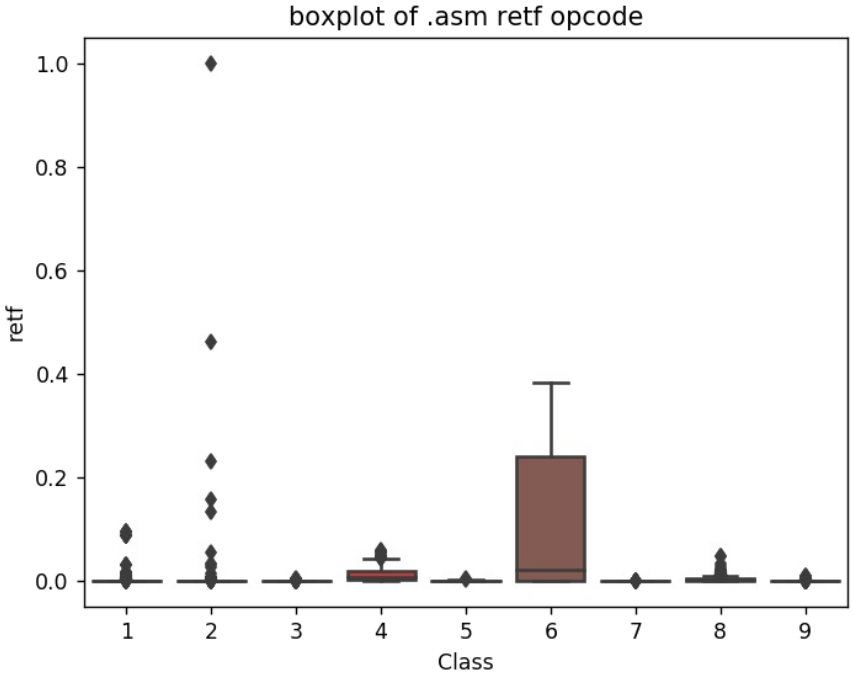
```
ax = sns.boxplot(x="Class", y="mov", data=result_asm)
plt.title("boxplot of .asm mov opcode")
plt.show()
```



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

In [0]:

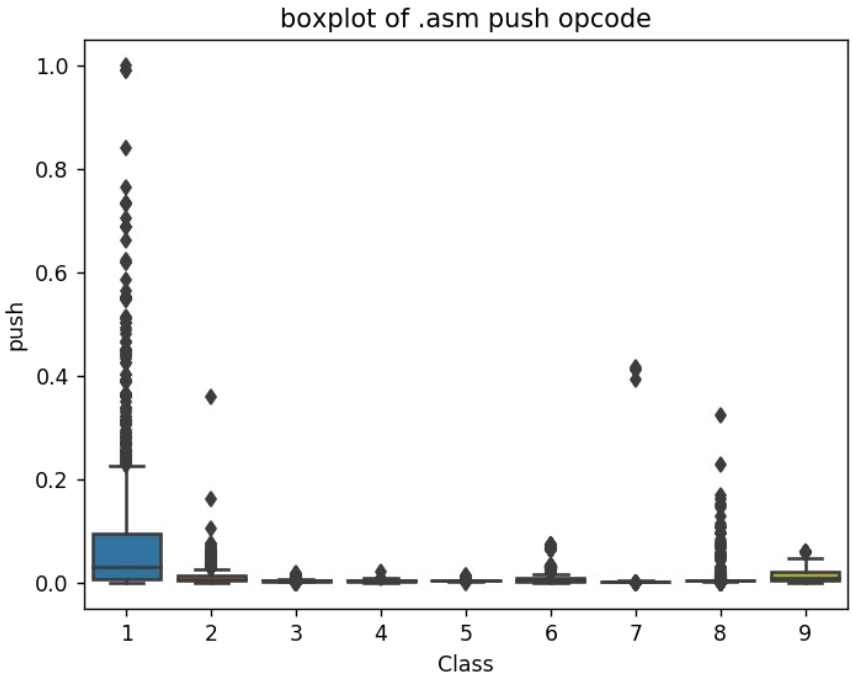
```
ax = sns.boxplot(x="Class", y="retf", data=result_asm)
plt.title("boxplot of .asm retf opcode")
plt.show()
```



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

In [0]:

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

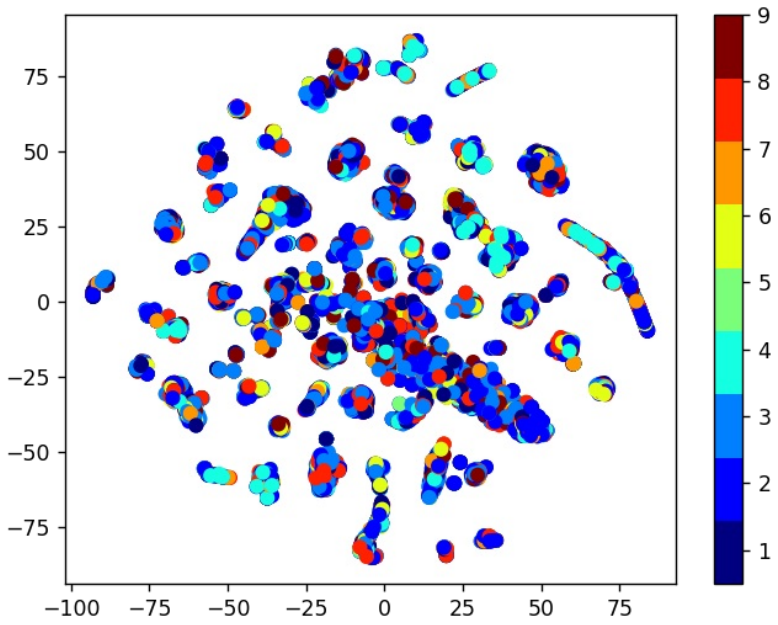


plot between push opcode and Class label
Class 1 is having 75 precentile files with push opcodes of frequency 1000

4.2.2 Multivariate Analysis on .asm file features

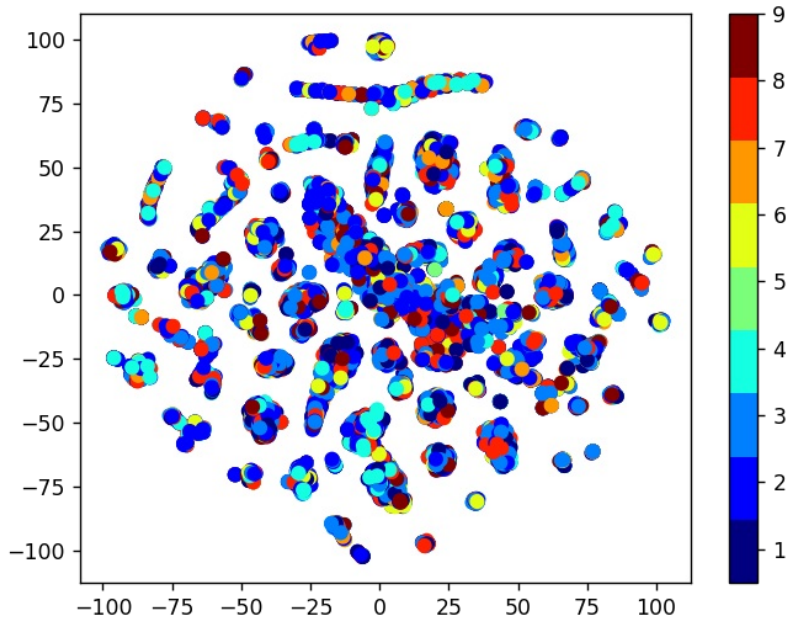
In [0]:

```
# check out the course content for more explantion on tsne algorithm
# https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/t-distributed-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 [0]:

```
# 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 [16]:

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

In [17]:

```
X_train_asm, X_test_asm, y_train_asm, y_test_asm = train_test_split(asm_x,asm_y ,stratify=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_train_asm,stratify=y_train_asm,tes
t_size=0.20)
```

In [18]:

```
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
```

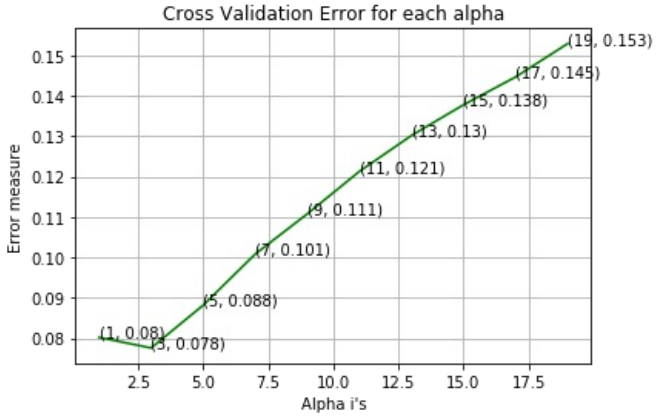
4.4. Machine Learning models on features of .asm files

4.4.1 K-Nearest Neigbors

In [29]:

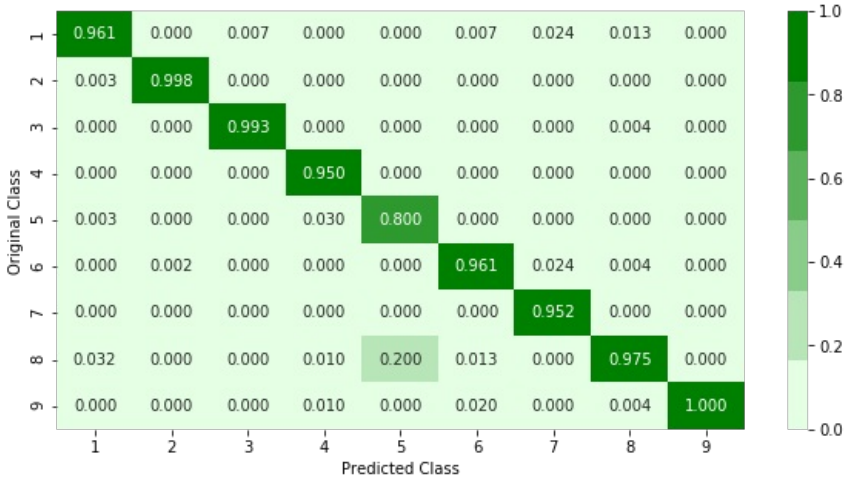
```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.
KNeighborsClassifier.html
# -------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', leaf_size=30, p=2,
# metric='minkowski', 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/lessons/k-nearest-neighbors-geometr
ic-intuition-with-a-toy-example-1/
#--------------------------------------


# find more about CalibratedClassifierCV here at http://scikit-learn.org/stable/modules/generated/sklearn.calibra
tion.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, 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")
sig_clf.fit(X_train_asm, y_train_asm)
pred_y=sig_clf.predict(X_test_asm)


predict_y = sig_clf.predict_proba(X_train_asm)
print ('log loss for train data',log_loss(y_train_asm, predict_y))
predict_y = sig_clf.predict_proba(X_cv_asm)
print ('log loss for cv data',log_loss(y_cv_asm, predict_y))
predict_y = sig_clf.predict_proba(X_test_asm)
print ('log loss for test data',log_loss(y_test_asm, predict_y))
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_asm))
```

```
log_loss for k =  1 is 0.08023336727656329
log_loss for k =  3 is 0.07761596679908572
log_loss for k =  5 is 0.08818997868851604
log_loss for k =  7 is 0.10084741860946644
log_loss for k =  9 is 0.11079205042993832
log_loss for k =  11 is 0.12128314287652475
log_loss for k =  13 is 0.1301608691187635
log_loss for k =  15 is 0.13776375201246166
log_loss for k =  17 is 0.1446460333336359
log_loss for k =  19 is 0.15289937313052757
```

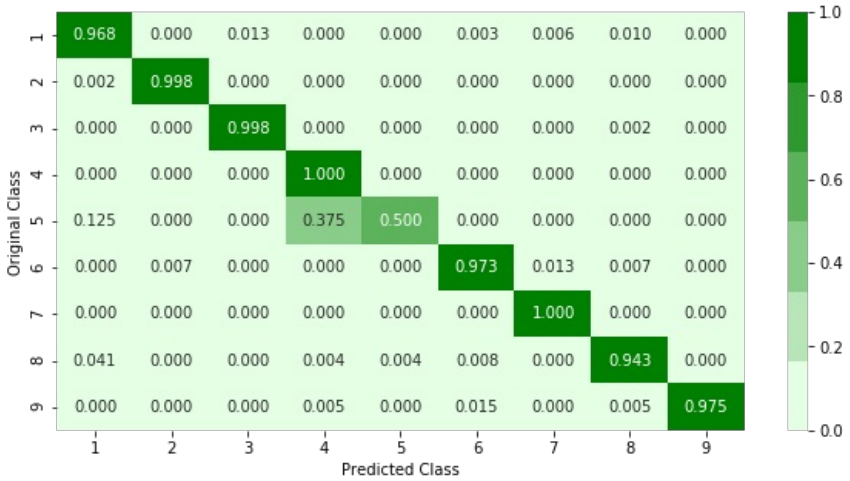



```
log loss for train data 0.0517736246553744
log loss for cv data 0.07761596679908572
log loss for test data 0.08127252052742263
Number of misclassified points  1.7939282428702852
---------------------------------------------------- Confusion matrix -----------------------------------
------------------
```


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




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



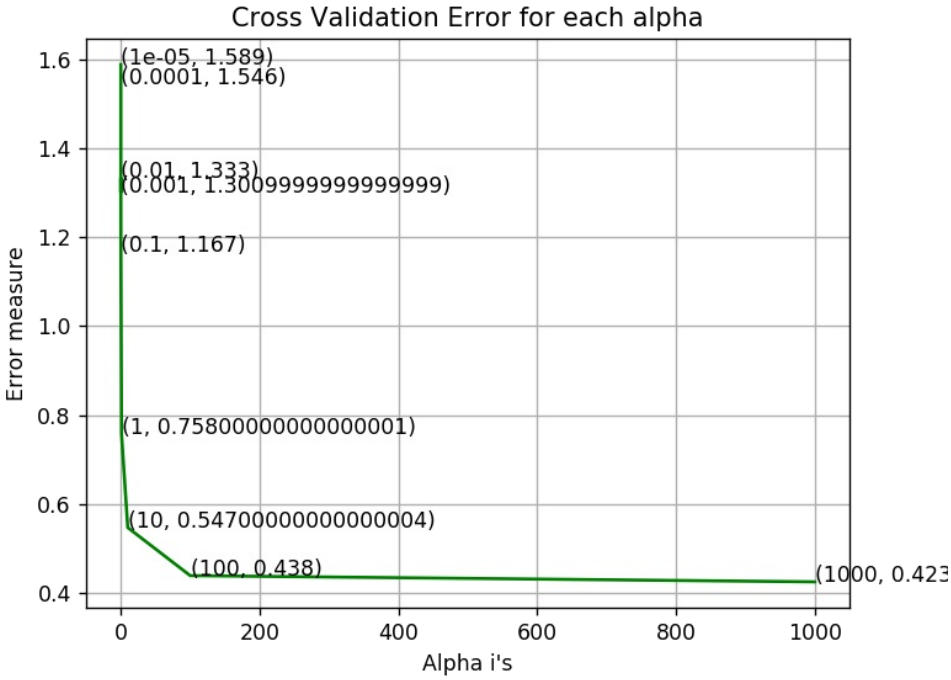

```
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

4.4.2 Logistic Regression

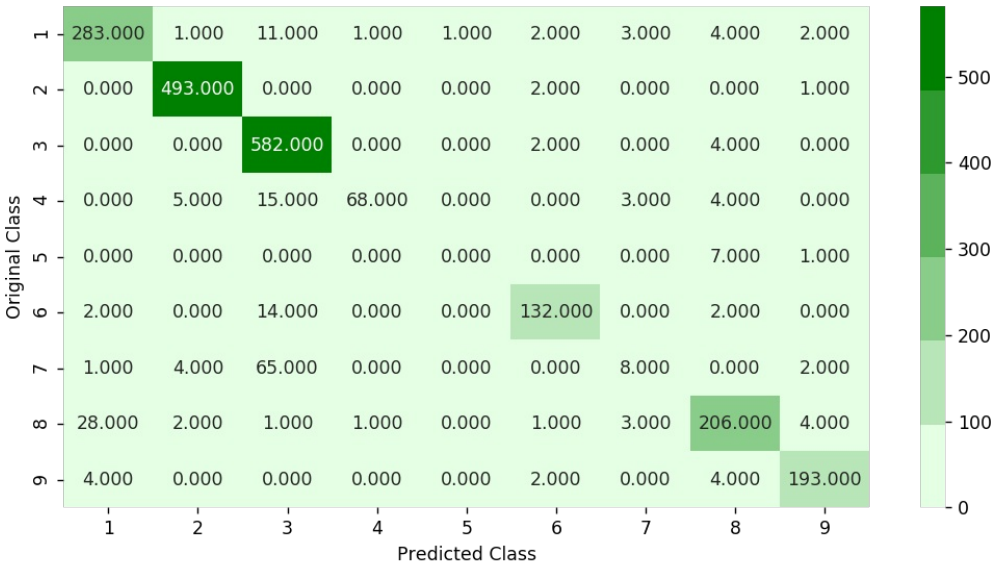
In [0]:

```
# 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))
```

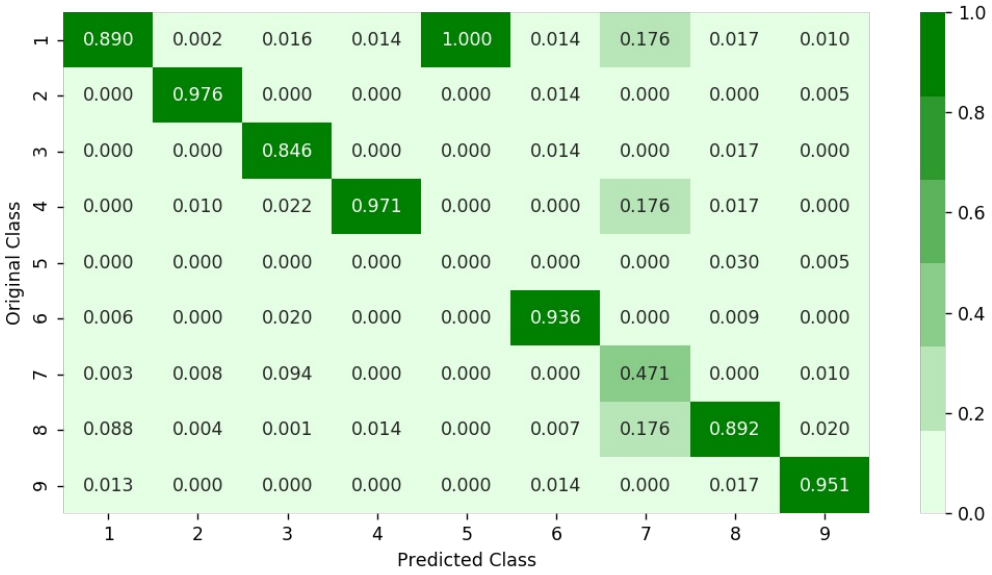
```
log_loss for c =  1e-05 is 1.58867274165
log_loss for c =  0.0001 is 1.54560797884
log_loss for c =  0.001 is 1.30137786807
log_loss for c =  0.01 is 1.33317456931
log_loss for c =  0.1 is 1.16705751378
log_loss for c =  1 is 0.757667807779
log_loss for c =  10 is 0.546533939819
log_loss for c =  100 is 0.438414998062
log_loss for c =  1000 is 0.424423536526
```



log loss for train data 0.396219394701
log loss for cv data 0.424423536526
log loss for test data 0.415685592517
Number of misclassified points 9.61361545538
---------- Confusion matrix ----------

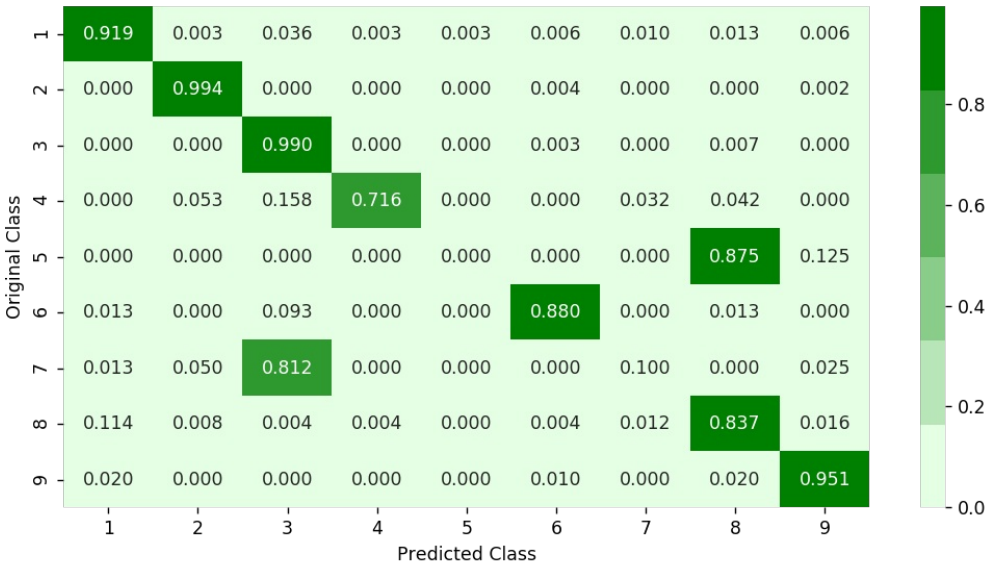


---------- Precision matrix ----------



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

---------- Recall matrix ----------



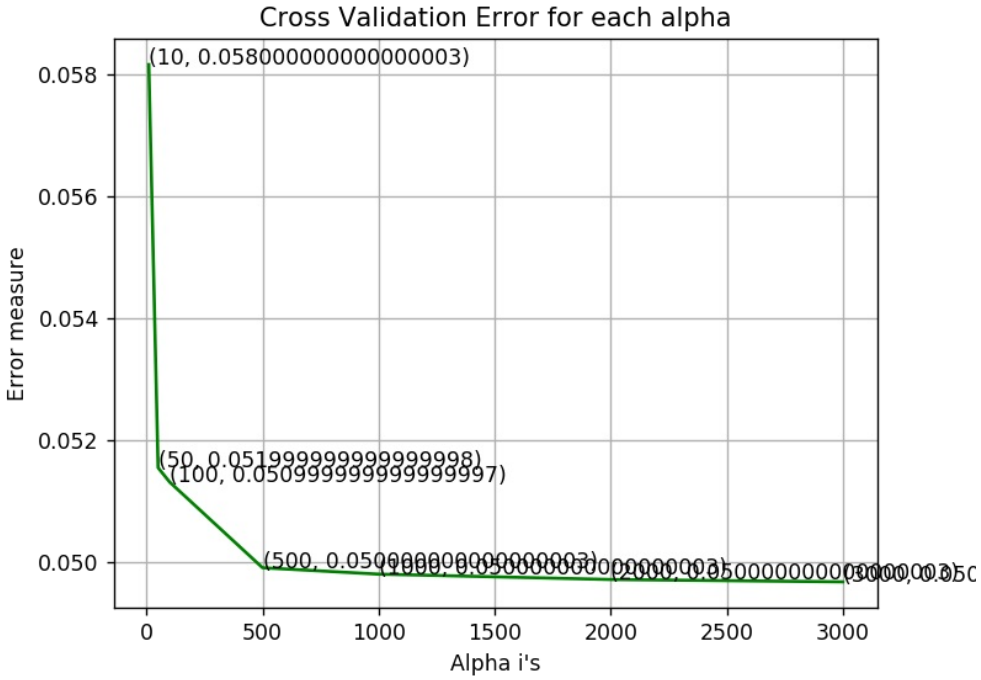
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

4.4.3 Random Forest Classifier

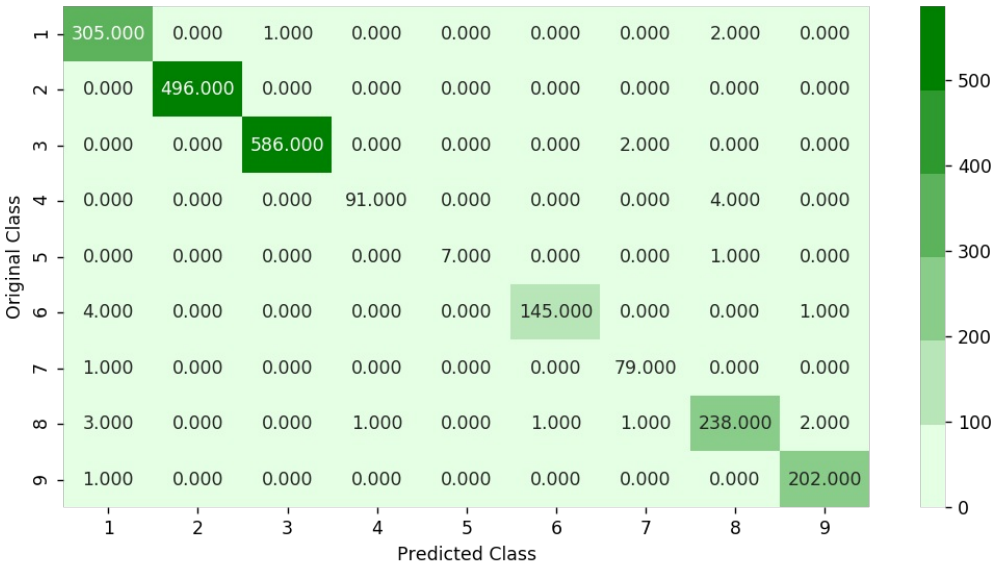
In [0]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrea
se=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=Fa
lse,
# 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/lessons/random-forest-and-their-con
struction-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.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=sig_clf.classes_, eps=1e-15)))
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_asm))
```

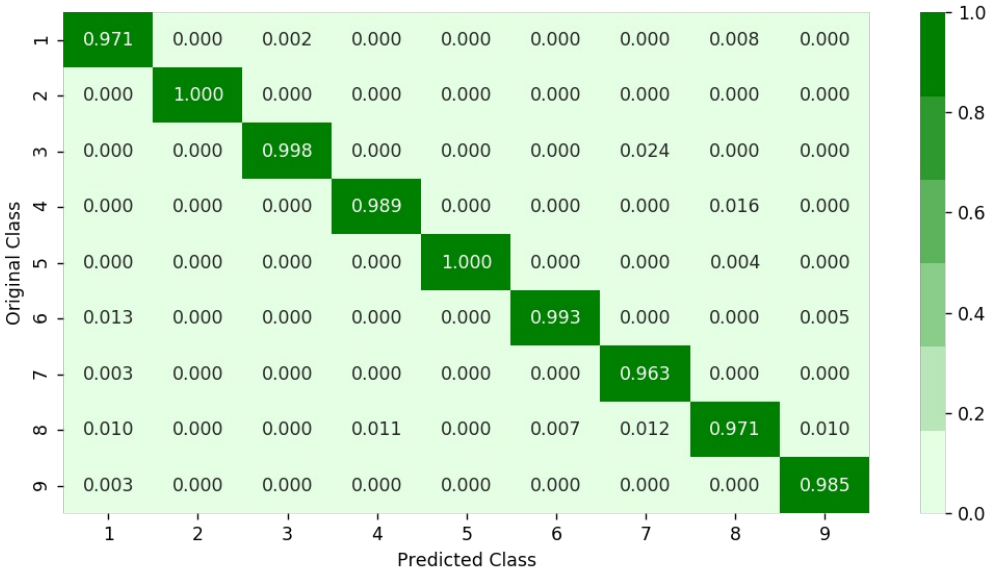
```
log_loss for c =  10 is 0.0581657906023
log_loss for c =  50 is 0.0515443148419
log_loss for c =  100 is 0.0513084973231
log_loss for c =  500 is 0.0499021761479
log_loss for c =  1000 is 0.0497972474298
log_loss for c =  2000 is 0.0497091690815
log_loss for c =  3000 is 0.0496706817633
```



log loss for train data 0.0116517052676
log loss for cv data 0.0496706817633
log loss for test data 0.0571239496453
Number of misclassified points 1.14995400184
---------- Confusion matrix ----------

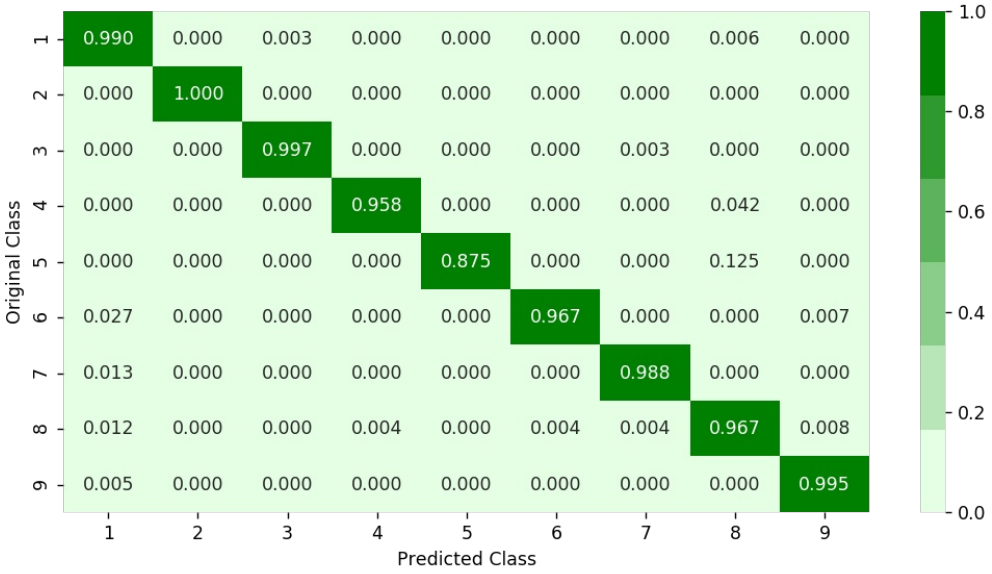


---------- Precision matrix ----------



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

---------- Recall matrix ----------



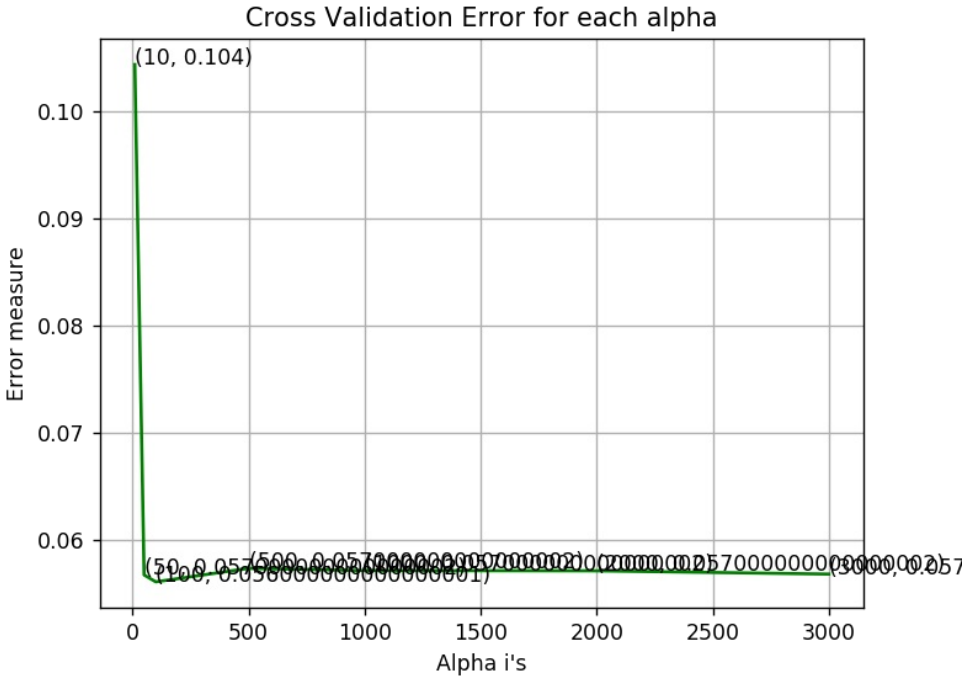
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

4.4.4 XgBoost Classifier

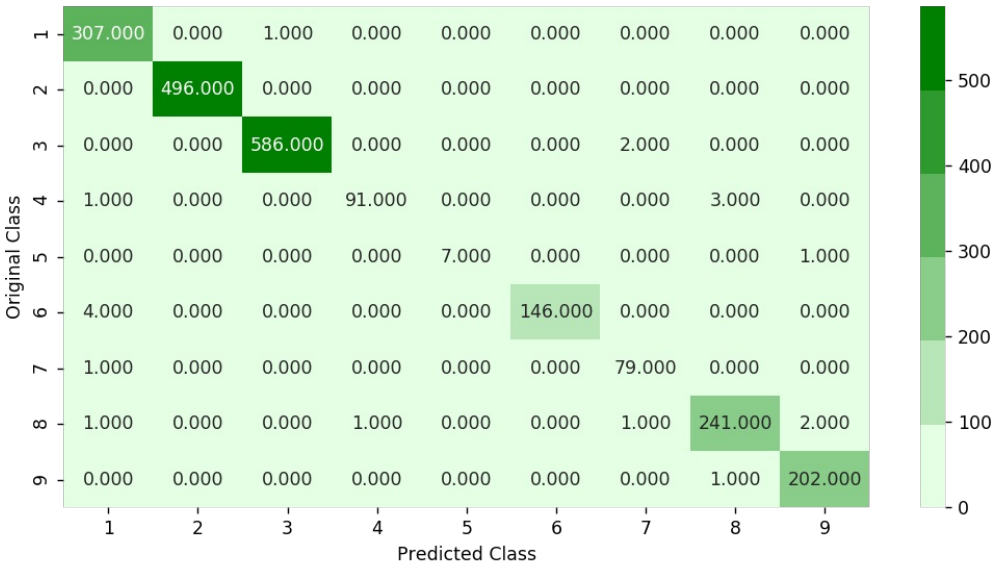
In [0]:

```
# 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?#xgb
oost.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_mo
del=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=[10,50,100,500,1000,2000,3000]
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)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv_asm, pr
edict_y))
predict_y = sig_clf.predict_proba(X_test_asm)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test_asm, predict_y))
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_asm))
```

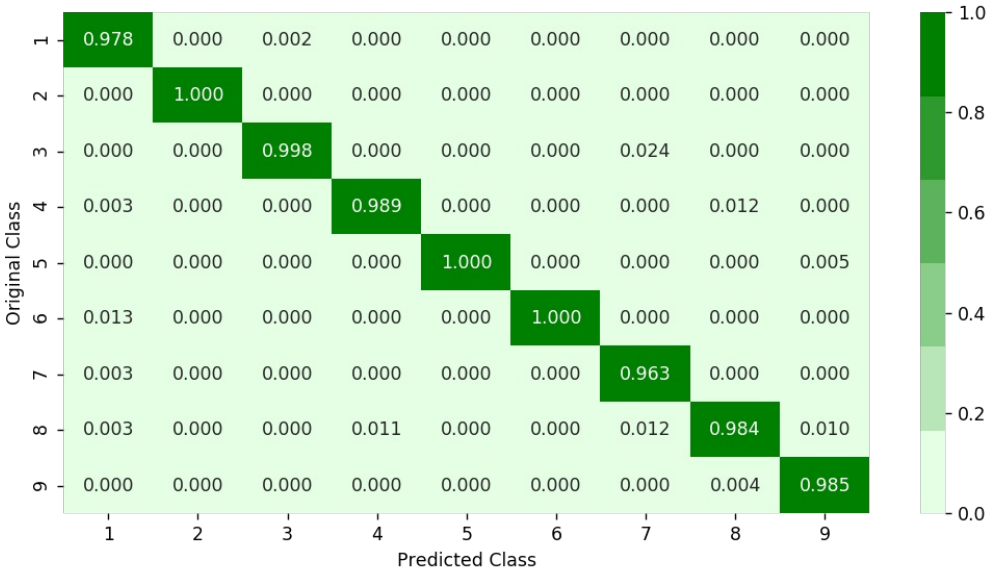
```
log_loss for c =  10 is 0.104344888454
log_loss for c =  50 is 0.0567190635611
log_loss for c =  100 is 0.056075038646
log_loss for c =  500 is 0.057336051683
log_loss for c =  1000 is 0.0571265109903
log_loss for c =  2000 is 0.057103406781
log_loss for c =  3000 is 0.0567993215778
```



For values of best alpha = 100 The train log loss is: 0.0117883742574
For values of best alpha = 100 The cross validation log loss is: 0.056075038646
For values of best alpha = 100 The test log loss is: 0.0491647763845
Number of misclassified points 0.873965041398
---------- Confusion matrix ----------

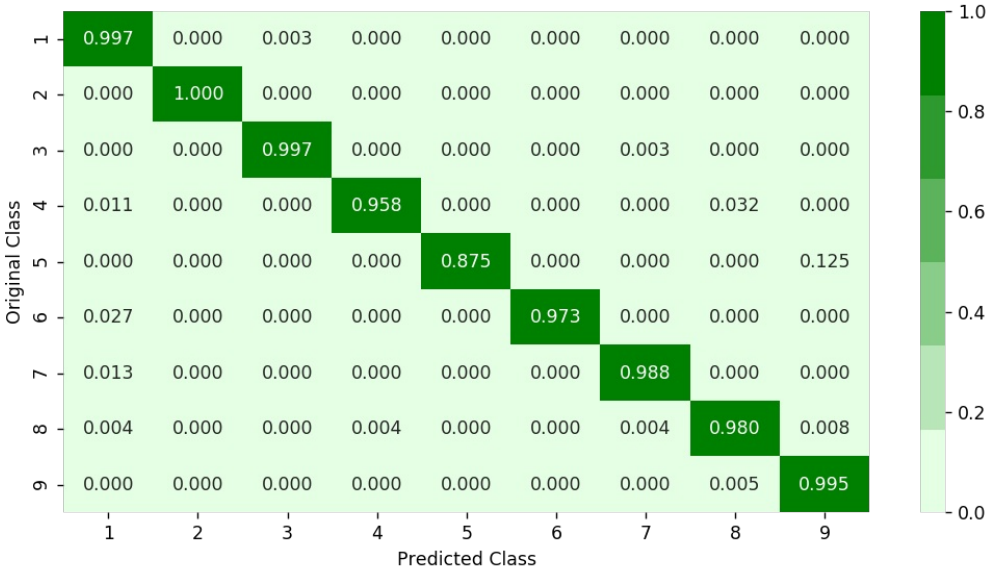


---------- Precision matrix ----------



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 [0]:

```
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)]: Done   2 tasks      | elapsed:    8.1s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:   32.8s
[Parallel(n_jobs=-1)]: Done  19 out of  30 | elapsed:  1.1min remaining:   39.3s
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  1.3min remaining:   23.0s
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  1.4min remaining:    9.2s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  2.3min finished
```

Out[0]:

```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=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, nthread=-1,
       objective='binary:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1),
          fit_params=None, iid=True, 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], 'colsample_bytree': [0.1, 0.3, 0.5, 1], 'subsa
mple': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=10)
```

In [0]:

```
print (random_cfl.best_params_)
```

```
{'subsample': 1, 'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.15, 'colsample_bytree': 0.5
}
```

In [0]:

```
# 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?#xgb
oost.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_mo
del=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/
# ------------------------

x_cfl=XGBClassifier(n_estimators=200,subsample=0.5,learning_rate=0.15,colsample_bytree=0.5,max_depth=3)
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 0.0102661325822
cv loss 0.0501201796687
test loss 0.0483908764397
```

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

4.5.1. Merging both asm and byte file features

In [19]:

```
result.head()
```

Out[19]:

	ID	0	1	2	3	4	5	6	7	8	...	f9
0	01azqd4InC7m9JpocGv5	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	...	0.013560
1	01IsoiSMh5gxyDYTl4CB	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	...	0.001920
2	01jsnpXSAlgw6aPeDxrU	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	...	0.009804
3	01kcPWA9K2BOxQeS5Rju	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	...	0.002121
4	01SuzwMJEIXsK7A8dQbl	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	...	0.001530

5 rows x 260 columns

In [20]:

```
result_asm.head()
```

Out[20]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...	esi	ea
0	01kcPWA9K2BOxQeS5Rju	0.107345	0.001092	0.0	0.000761	0.000023	0.0	0.000084	0.0	0.000072	...	0.000746	0.0003(
1	1E93CpP60RHFNiT5Qfvn	0.096045	0.001230	0.0	0.000617	0.000019	0.0	0.000000	0.0	0.000072	...	0.000328	0.00096
2	3ekVow2ajZHbTnBcsDfX	0.096045	0.000627	0.0	0.000300	0.000017	0.0	0.000038	0.0	0.000072	...	0.000475	0.0002(
3	3X2nY7iQaPBIWDrAZqJe	0.096045	0.000333	0.0	0.000258	0.000008	0.0	0.000000	0.0	0.000072	...	0.000090	0.00028
4	46OZzdsSKDCFV8h7XWxf	0.096045	0.000590	0.0	0.000353	0.000068	0.0	0.000000	0.0	0.000072	...	0.000102	0.00036

5 rows x 54 columns

In [21]:

```
print(result.shape)
print(result_asm.shape)
```

```
(10868, 260)
(10868, 54)
```

In [22]:

```
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[22]:

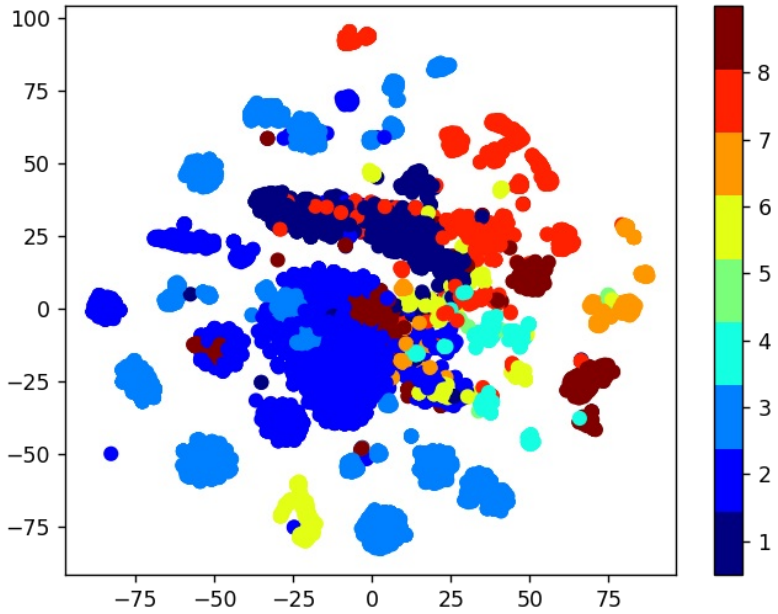
	0	1	2	3	4	5	6	7	8	9	...	edx	esi	
0	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	0.003531	...	0.015418	0.025875	0.02
1	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	0.000394	...	0.004961	0.012316	0.00
2	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	0.002707	...	0.000095	0.006181	0.00
3	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	0.000521	...	0.000343	0.000746	0.00
4	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	0.000246	...	0.000343	0.013875	0.00

5 rows x 307 columns

4.5.2. Multivariate Analysis on final fearures

In [0]:

```
xtsne=TSNE(perplexity=50)
results=xtsne.fit_transform(result_x, axis=1))
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 [25]:

```
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_si
ze=0.20)
```

4.5.4. Random Forest Classifier on final features

In [104]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrea
se=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=Fa
lse,
# 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/lessons/random-forest-and-their-con
struction-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)
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:",log_loss(y_test_merge, predict_y)
)
```

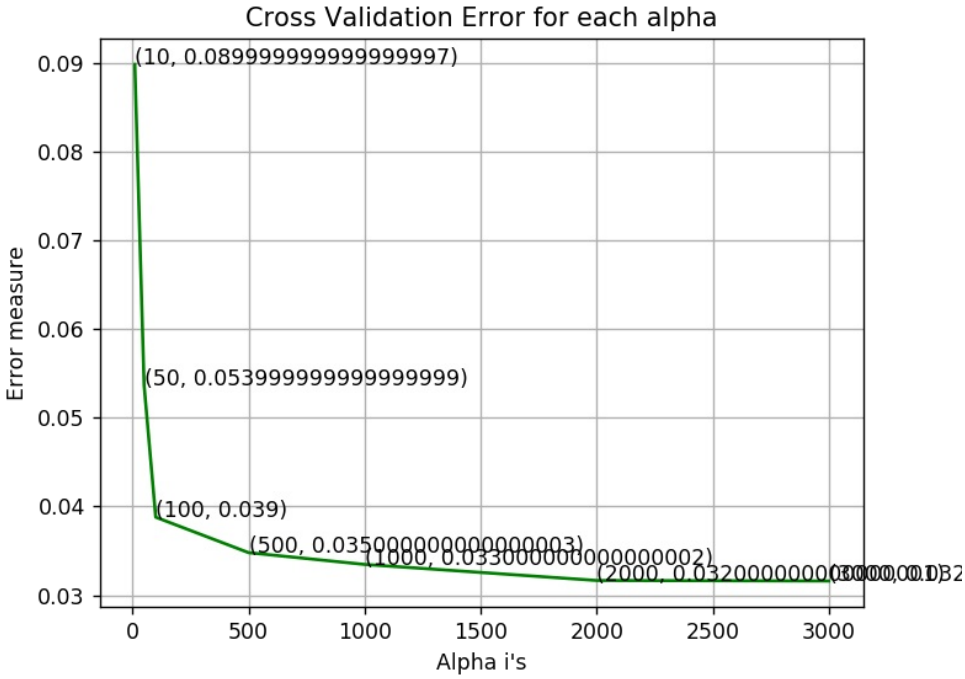
```
For values of best alpha =  3000 The train log loss is: 0.01567007166401768
For values of best alpha =  3000 The cross validation log loss is: 0.04916599617866672
For values of best alpha =  3000 The test log loss is: 0.04072417974343821
```

4.5.5. XgBoost Classifier on final features

In [0]:

```
# 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?#xgb
oost.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_mo
del=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=[10,50,100,500,1000,2000,3000]
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=alpha[best_alpha],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:",log_loss(y_test_merge, predict_y)
)
```

```
log_loss for c =  10 is 0.0898979446265
log_loss for c =  50 is 0.0536946658041
log_loss for c =  100 is 0.0387968186177
log_loss for c =  500 is 0.0347960327293
log_loss for c =  1000 is 0.0334668083237
log_loss for c =  2000 is 0.0316569078846
log_loss for c =  3000 is 0.0315972694477
```




```
For values of best alpha =  3000 The train log loss is: 0.0111918809342
For values of best alpha =  3000 The cross validation log loss is: 0.0315972694477
For values of best alpha =  3000 The test log loss is: 0.0323978515915
```

In [ ]:

```
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)
```

In [28]:

```
predict_y = sig_clf.predict_proba(X_train_merge)
print ('For values of best alpha = ', 3000, "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 = ', 3000, "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 = ', 3000, "The test log loss is:",log_loss(y_test_merge, predict_y))
```

```
For values of best alpha =  3000 The train log loss is: 0.012733767326755002
For values of best alpha =  3000 The cross validation log loss is: 0.031168928148674408
For values of best alpha =  3000 The test log loss is: 0.030639112825356914
```

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

In [0]:

```
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)

print (random_cfl.best_params_)


# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#xgb
oost.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_mo
del=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/
# -------------------------

x_cfl=XGBClassifier(n_estimators=1000,max_depth=10,learning_rate=0.15,colsample_bytree=0.3,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:",log_loss(y_test_merge, predict_y)
)
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_merge))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)]: Done   2 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done  19 out of  30 | elapsed:  4.5min remaining:  2.6min
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  5.8min remaining:  1.8min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  6.7min remaining:   44.5s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  7.4min finished
```

Out[0]:

```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=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, nthread=-1,
       objective='binary:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1),
          fit_params=None, iid=True, 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], 'colsample_bytree': [0.1, 0.3, 0.5, 1], 'subsa
mple': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=10)
```

In [0]:

```
print (random_cfl.best_params_)
```

```
{'subsample': 1, 'n_estimators': 1000, 'max_depth': 10, 'learning_rate': 0.15, 'colsample_bytree': 0
.3}
```

In [0]:

```
# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#xgb
oost.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_mo
del=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/
# -----------------------

x_cfl=XGBClassifier(n_estimators=1000,max_depth=10,learning_rate=0.15,colsample_bytree=0.3,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:",log_loss(y_test_merge, predict_y)
)
plot_confusion_matrix(y_test_asm,sig_clf.predict(X_test_merge))
```

```
For values of best alpha =  3000 The train log loss is: 0.0121922832297
For values of best alpha =  3000 The cross validation log loss is: 0.0344955487471
For values of best alpha =  3000 The test log loss is: 0.0317041132442
```

5. Assignments

1. Add bi-grams on byte files and improve the log-loss
2. Watch the video (video (https://www.youtube.com/watch?v=VLQTRILGz5Y#t=13m11s)) and include pixel intensity features to improve the logloss

1. you need to donwload the train from kaggle, which is of size ~17GB, after extracting it will occupy ~128 GB data your dirve

2. if you are having computation power limitations, you can try using google colab, with GPU option enabled (you can search for how to enable GPU in colab) or you can work with the Google Cloud, check this tutorials by one of our student: https://www.youtube.com/channel/UCRH_z-oM0LROvHPe_KYR4Wg (we suggest you to use GCP over Colab)

3. To Extract the .7z file in google cloud, once after you upload the file into server, in your ipython not ebook create a new cell and write thess commands
   a. !sudo apt-get install p7zip
   b. !7z x file_name.7z -o path/where/you/want/to/extract

https://askubuntu.com/a/341637

Calculating the bigram features from byte files.

In [14]:

```
#Calculating bigram vocabulary.
voc = "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,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,80,81,82,83,84,85,86,87,88,89,8a,8b,8c,8d,8e,8f,90,91,92,93,94,95,96,97,98,99,9a,9b,9c,9d,9e,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,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,f1,f2,f3,f4,f5,f6,f7,f8,f9,fa,fb,fc,fd,fe,ff,??"
bigram_voc=[]
for i in voc.split(','):
    for j in range(0,len(voc.split(','))):
        bigram_voc.append(i+' '+voc.split(',')[j])
print("Length of bigram vocabulary",len(bigram_voc))
```

```
Length of bigram vocabulary 66049
```

In [15]:

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

#Calculating bigram vectors for each byte file.
vec = CountVectorizer(lowercase=False,ngram_range=(2,2), vocabulary=bigram_voc)
bigram_vec = np.zeros((10868,len(bigram_voc)))
print("bigram computation is in progress...")
for i,file in enumerate((result['ID']+'.bytes')):
    bigram_vec[i]=vec.transform([open('byteFiles/'+file).read().replace('\n',' ')]).toarray()
print("completed.")

#Converting to dataframe
result_bigram=pd.DataFrame(data=bigram_vec,columns=bigram_voc)
result_bigram['ID']=result['ID']
result_bigram.head()
result_bigram.to_csv('result_bigram', encoding='utf-8', index=False)
```

```
bigram computation is in progress...
completed.
```

Out[15]:

	00 00	00 01	00 02	00 03	00 04	00 05	00 06	00 07	00 08	00 09	...	?? f8	?? f9	?? fa	?? fb	?? fc	?? fd	?? fe	?? ff	?? ??	
0	273053.0	1002.0	801.0	1170.0	943.0	840.0	1125.0	1003.0	860.0	987.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01azqd
1	19852.0	719.0	64.0	43.0	159.0	10.0	6.0	10.0	35.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01lsoi
2	16032.0	592.0	157.0	144.0	509.0	590.0	551.0	146.0	523.0	154.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01jsnp
3	9903.0	204.0	59.0	69.0	103.0	34.0	19.0	21.0	55.0	14.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01kcPWA
4	15289.0	58.0	20.0	110.0	8.0	11.0	3.0	5.0	8.0	2.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	01Suzw

5 rows × 66050 columns

In [ ]:

```
#Loading the dataset from the CSM file
chunks=pd.read_csv('result_bigram',chunksize=500) # the number of rows per chunk
chunk_list = []
i=1
for chunk in chunks:
    chunk_list.append(chunk)
    #print('rows processed',i*500)
    i=i+1
result_bigram = pd.concat(chunk_list,sort=False)
```

In [74]:

```
#Selecting the top 2000 features and storing it to CSV.
from sklearn.feature_selection import SelectKBest, chi2
select_k_best=SelectKBest(chi2, k=2000).fit(result_bigram.drop(["ID"], axis=1),result["Class"])

scores=pd.DataFrame(select_k_best.scores_)
columns=pd.DataFrame(result_bigram.columns[:-1])
feature_with_scores=pd.concat([columns,scores],axis=1)
feature_with_scores.columns=["Feat_name","Feat_score"]
feature_with_scores=feature_with_scores.nlargest(2000,"Feat_score") #top 2000 among the sorted in descending orde
r by "Feature score"
top_2k_feat=list(feature_with_scores["Feat_name"])
top_2k_feat.append("ID")
result_bigram_with_top_2k_feat=result_bigram[top_2k_feat]
result_bigram_with_top_2k_feat.to_csv('result_bigram_with_top_2k_feat', encoding='utf-8', index=False)

#Displaying the dataset with top 2k features.
result_bigram_with_top_2k_feat.head()
```

Out[74]:

	00 00	02 02	10 10	06 06	04 04	03 03	01 00	14 14	18 18	01 01	...	72 76	10 63	06 73	20 17	05 07	41 30	13 98	97 06	33 17	
0	273053.0	74.0	98.0	92.0	97.0	103.0	1787.0	78.0	102.0	76.0	...	13.0	7.0	11.0	8.0	3.0	9.0	5.0	5.0	4.0	01azqd4l
1	19852.0	22.0	178.0	8.0	2.0	11.0	768.0	2.0	0.0	151.0	...	1.0	1.0	0.0	0.0	13.0	3.0	0.0	0.0	8.0	01IsoiSM
2	16032.0	4.0	5.0	75.0	67.0	1.0	542.0	3.0	7.0	65.0	...	4.0	6.0	23.0	4.0	21.0	3.0	7.0	17.0	3.0	01jsnpXS
3	9903.0	3.0	9.0	5.0	25.0	10.0	222.0	4.0	1.0	31.0	...	6.0	0.0	2.0	0.0	1.0	13.0	2.0	3.0	0.0	01kcPWA9I
4	15289.0	0.0	2.0	1.0	0.0	1.0	229.0	1.0	0.0	1.0	...	2.0	2.0	1.0	2.0	2.0	2.0	1.0	2.0	1.0	01SuzwM

5 rows × 2001 columns

In [36]:

```
#Reading the dataset from CSV file.
result_bigram_with_top_2k_feat=pd.read_csv("result_bigram_with_top_2k_feat")

#Normalizing the data.
result_bigram_normalized=normalize(result_bigram_with_top_2k_feat)

#Replacing the nan values with zero.
for col in result_bigram_normalized.columns:
    result_bigram_normalized[col]=result_bigram_normalized[col].fillna(0)
```

In [37]:

```
#Taking only 1000 bigram features due to runtime issues.
result_bigram_normalized_1k=result_bigram_normalized.iloc[:,range(1000)]
result_bigram_normalized_1k['ID']=result_bigram_normalized['ID']
result_bigram_normalized_1k.head()
```

Out[37]:

	00 00	02 02	10 10	06 06	04 04	03 03	01 00	14 14	18 18	01 01	...	21 20	08 11	
0	0.127389	0.001514	0.004457	0.003005	0.002917	0.004133	0.105428	0.005865	0.003011	0.000342	...	0.000272	0.000939	0.00
1	0.009262	0.000450	0.008096	0.000261	0.000060	0.000441	0.045310	0.000150	0.000000	0.000680	...	0.000000	0.000000	0.00
2	0.007479	0.000082	0.000227	0.002450	0.002015	0.000040	0.031976	0.000226	0.000207	0.000293	...	0.000545	0.004320	0.00
3	0.004620	0.000061	0.000409	0.000163	0.000752	0.000401	0.013097	0.000301	0.000030	0.000140	...	0.000000	0.000188	0.00
4	0.007133	0.000000	0.000091	0.000033	0.000000	0.000040	0.013510	0.000075	0.000000	0.000005	...	0.000136	0.000000	0.00

5 rows × 1001 columns

In [39]:

```
#Merging the byte unigram, asm and byte bigram features.
result_x = pd.merge(result,result_asm.drop(['Class'], axis=1),on='ID', how='left')
result_x = pd.merge(result_x,result_bigram_normalized_1k,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[39]:

	0	1	2	3	4	5	6	7	8	9	...	31 20	21 20	08
0	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	0.003531	...	0.000620	0.000272	0.0009
1	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	0.000394	...	0.000000	0.000000	0.0000
2	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	0.002707	...	0.001241	0.000545	0.0043
3	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	0.000521	...	0.000372	0.000000	0.0001
4	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	0.000246	...	0.000248	0.000136	0.0000

5 rows × 1307 columns

In [40]:

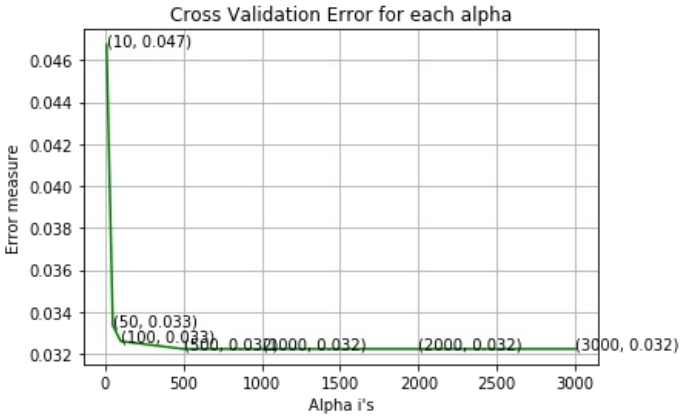
```
#Train-Test splitting.
X_train, X_test_merge, y_train, y_test_merge = train_test_split(result_x, result_y,stratify=result_y,test_size=0.
20)
X_train_merge, X_cv_merge, y_train_merge, y_cv_merge = train_test_split(X_train, y_train,stratify=y_train,test_si
ze=0.20)
```

5.1: XgBoost Classifier on byte unigram, asm unigram and byte bigram features with hyperparameter tuning using simple for loop.

In [ ]:

```
#Using simple for loop to find the best parameter.

from tqdm import tqdm

alpha=[10,50,100,500,1000,2000,3000]

cv_log_error_array=[]
for i in tqdm(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()
```

```
100%|██████████| 7/7 [5:02:51<00:00, 2595.97s/it]

log_loss for c =  10 is 0.04673751784690343
log_loss for c =  50 is 0.03335330385783029
log_loss for c =  100 is 0.03259806451085167
log_loss for c =  500 is 0.03222813252224704
log_loss for c =  1000 is 0.032228154204379966
log_loss for c =  2000 is 0.03222817720849508
log_loss for c =  3000 is 0.032228258356129615
```



In [44]:

```
#Training the model using the best hyperparameter
x_cfl=XGBClassifier(n_estimators=alpha[best_alpha],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:",log_loss(y_test_merge, predict_y)
)
```

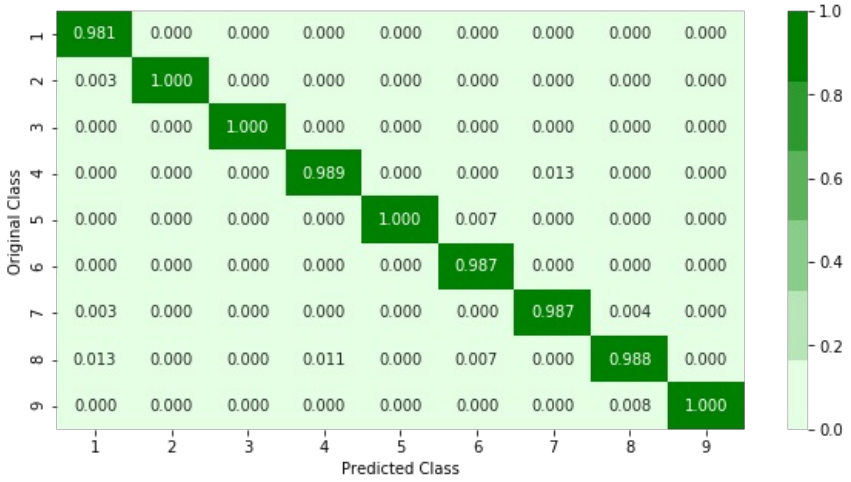
```
For values of best alpha =  500 The train log loss is: 0.01227314185183307
For values of best alpha =  500 The cross validation log loss is: 0.04856629598626968
For values of best alpha =  500 The test log loss is: 0.0268704121204925
```

In [45]:

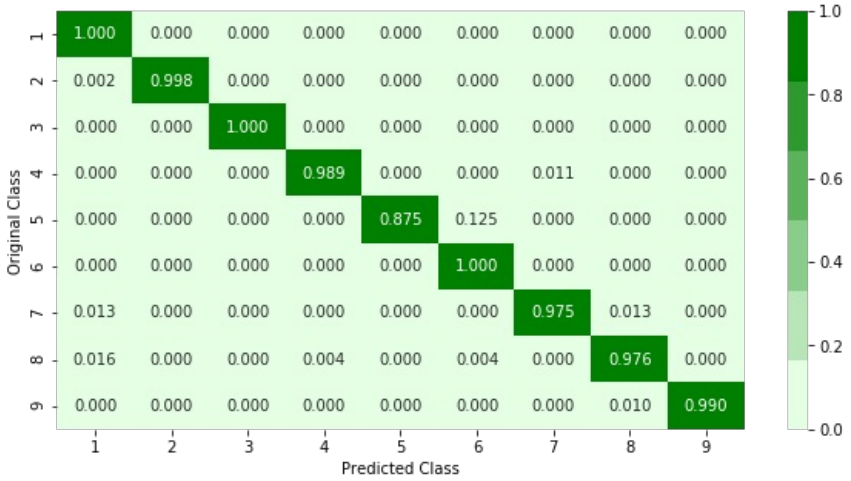
```
#Plotting confusion matrix
plot_confusion_matrix(y_test_merge,sig_clf.predict(X_test_merge))
```

```
Number of misclassified points  0.5979760809567618
-------------------------------------------------- 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.]
```

5.2: XgBoost Classifier on byte unigram, asm unigram and byte bigram features with hyperparameter tuning using RandomizedSearchCV.

In [ ]:

```
#Using RandomizedSearchCV to perform hyperparameter tuning
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=0,n_jobs=-1,)
random_cfl.fit(X_train_merge, y_train_merge)
```

In [47]:

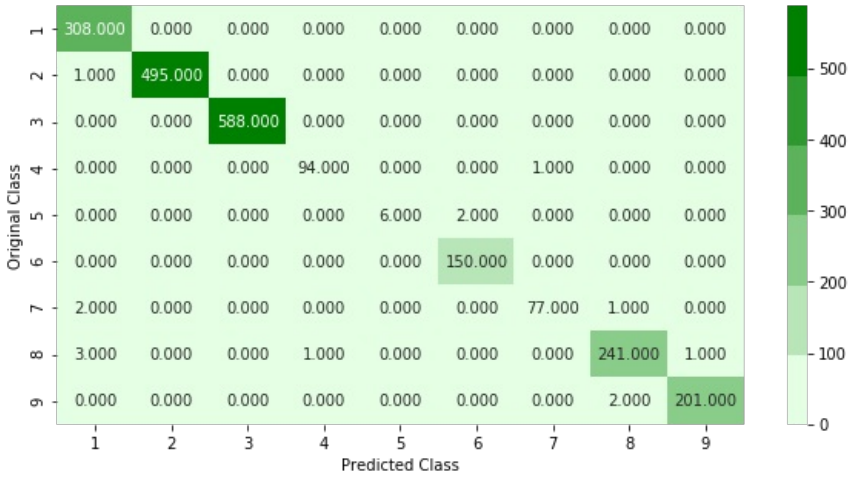
```
#Getting the hyperparameters of the best model.
print (random_cfl.best_params_)
```

```
{'max_depth': 3, 'colsample_bytree': 0.5, 'learning_rate': 0.01, 'subsample': 1, 'n_estimators': 100
0}
```

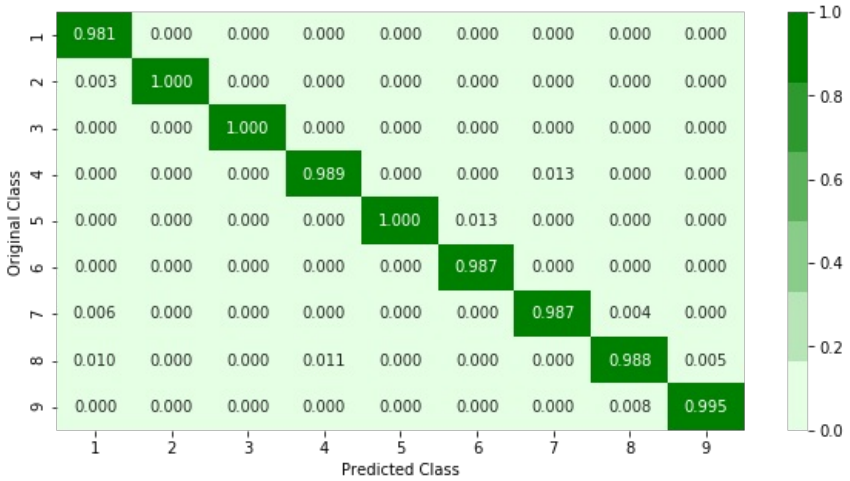
In [50]:

```
#Training the model using the best hyperparameters.
x_cfl=XGBClassifier(n_estimators=1000,max_depth=3,learning_rate=0.01,colsample_bytree=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 parameters, 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 parameters,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 parameters,The test log loss is:',log_loss(y_test_merge, predict_y))

#Plotting the confusion matrix.
plot_confusion_matrix(y_test_merge,sig_clf.predict(X_test_merge))
```

```
For values of best parameters, The train log loss is: 0.011050251794238606
For values of best parameters,The cross validation log loss is: 0.04967976131762874
For values of best parameters,The test log loss is: 0.026738929198488522
Number of misclassified points  0.6439742410303588
---------------------------------------------------- Confusion matrix ----------------------------------
------------------
```

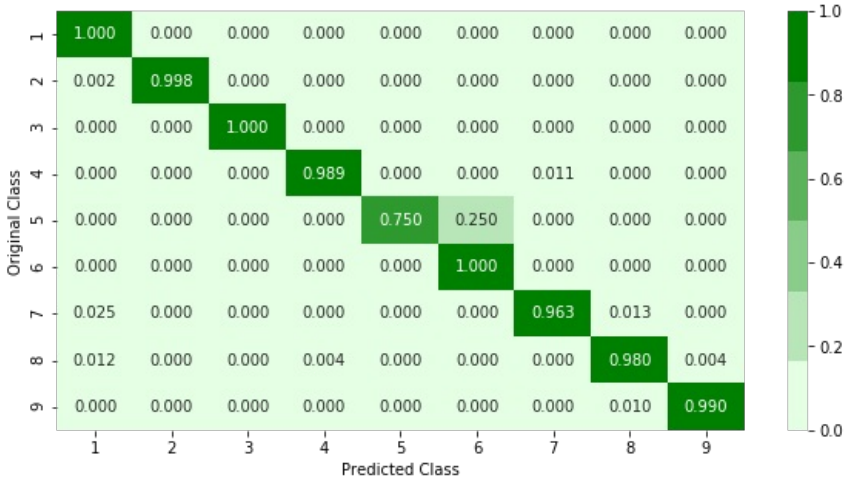



```
---------------------------------------------------- Precision matrix ----------------------------------
------------------
```



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

---------- Recall matrix ----------



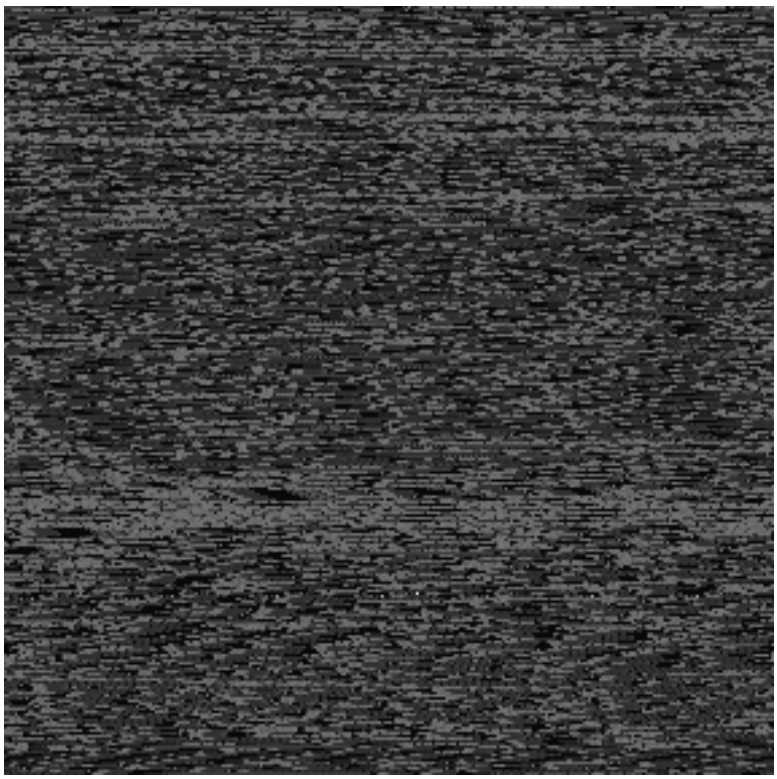
Sum of rows in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1.]

Extracting the image features from asm files.

In [88]:

```
#Getting image features from asm file and saving it to asm_image folder.
from array import array
import imageio

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)
    arr = array('B')
    arr.frombytes(file.read())
    file.close()
    reshaped = np.reshape(arr[:width * width], (width, width))
    imageio.imwrite('asm_image/' + filename + '.png', reshaped)

from IPython.display import Image
Image(filename='asm_image/01kcPWA9K2BOxQeS5Rju.png',width=500,height=500)
```

Out[88]:



In [93]:

```
#Getting top 1000 features from the image data and creating a dataframe
from array import array
import imageio

imagefeatures=np.zeros((10868,1000))
for i, asmid in enumerate(result_asm['ID']):
    img = imageio.imread("asm_image/" + asmid + '.png')
    img_arr = img.flatten()[:1000]
    imagefeatures[i] += img_arr

#Creating dataframe for image features.
feature_names=[]
for i in range(1000):
    feature_names.append('pix'+str(i))
result_asm_img_top_1k=pd.DataFrame(data=imagefeatures,columns=feature_names)
result_asm_img_top_1k['ID']=result_asm['ID']

#Saving the top 1k image features
result_asm_img_top_1k.to_csv('result_asm_img_top_1k', encoding='utf-8', index=False)
```

In [54]:

```
#Loading the top 1k image features
result_asm_img_top_1k=pd.read_csv('result_asm_img_top_1k')

#Normalizing the image features.
result_asm_img_top_1k = normalize(result_asm_img_top_1k)

result_asm_img_top_1k.head()
```

Out[54]:

	pix0	pix1	pix2	pix3	pix4	pix5	pix6	pix7	pix8	pix9	...	pix991	pix992	pix993	pix994
0	0.481928	0.302632	0.0	0.277778	0.291667	0.5	1.0	0.058824	0.000000	0.000000	...	0.660194	0.540541	0.644860	0.675676
1	0.481928	0.302632	0.0	0.277778	0.291667	0.5	1.0	0.352941	0.863636	0.227273	...	0.223301	0.207207	0.214953	0.441441
2	0.481928	0.302632	0.0	0.277778	0.291667	0.5	1.0	0.058824	0.000000	0.000000	...	0.223301	0.549550	0.953271	0.945946
3	0.481928	0.302632	0.0	0.277778	0.291667	0.5	1.0	0.058824	0.045455	0.000000	...	0.223301	0.207207	0.214953	0.441441
4	0.481928	0.302632	0.0	0.277778	0.291667	0.5	1.0	0.411765	0.272727	0.136364	...	0.223301	0.207207	0.214953	0.441441

5 rows × 1001 columns

In [56]:

```
#Merging the byte unigram, asm and asm image features
result_x = pd.merge(result,result_asm.drop(['Class'], axis=1),on='ID', how='left')
result_x = pd.merge(result_x,result_asm_img_top_1k,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[56]:

	0	1	2	3	4	5	6	7	8	9	...	pix990	pix991	pi
0	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	0.003531	...	1.000000	0.893204	1.00
1	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	0.000394	...	0.009346	0.359223	0.96
2	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	0.002707	...	1.000000	0.893204	1.00
3	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	0.000521	...	0.579439	0.660194	0.54
4	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	0.000246	...	1.000000	0.893204	1.00

5 rows × 1307 columns

In [57]:

```
#Train-Test splitting.
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_si
ze=0.20)
```

5.3: XgBoost Classifier on byte unigram, asm unigram and asm image features with hyperparameter tuning using simple for loop.

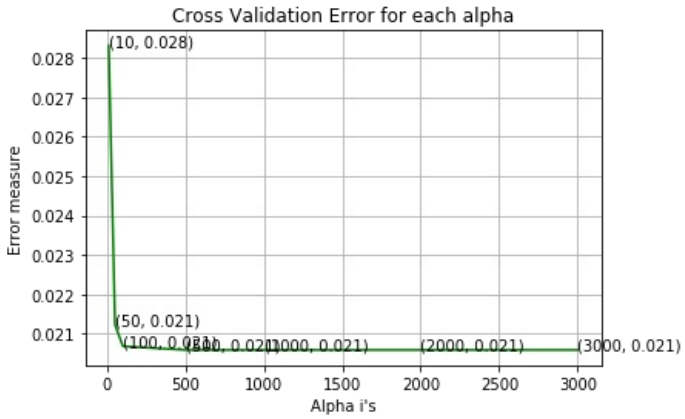
In [ ]:

```
#Hyperparameter tuning using simple for loop
from tqdm import tqdm

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))
```

In [62]:

```
#Plotting the cross validation error for each alpha.
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 0.028317380311720194
log_loss for c =  50 is 0.02122780847413944
log_loss for c =  100 is 0.020680160560193762
log_loss for c =  500 is 0.02058627088118032
log_loss for c =  1000 is 0.020585387615198368
log_loss for c =  2000 is 0.020585589248031062
log_loss for c =  3000 is 0.020585644597960907
```



In [64]:

```
#Training the model using the best hyperprameter.
x_cfl=XGBClassifier(n_estimators=alpha[best_alpha],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:",log_loss(y_test_merge, predict_y)
)
```

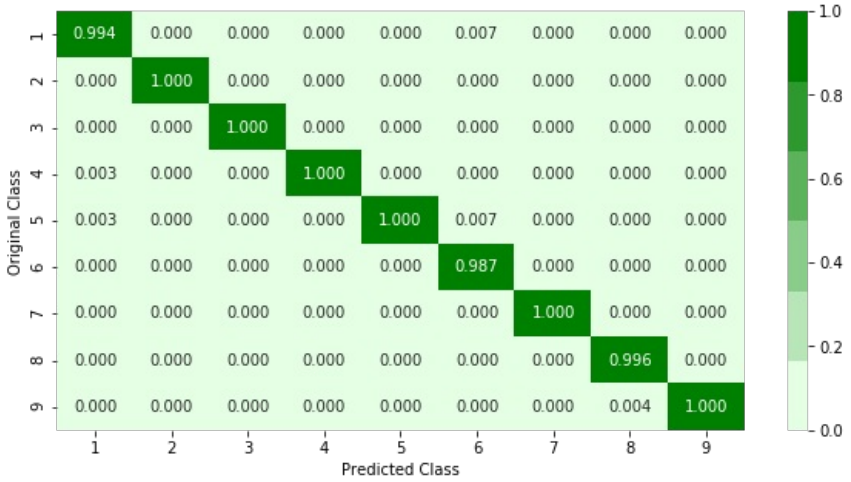
```
For values of best alpha =  1000 The train log loss is: 0.009703317548851498
For values of best alpha =  1000 The cross validation log loss is: 0.020585387615198368
For values of best alpha =  1000 The test log loss is: 0.014890210085913283
```

In [65]:

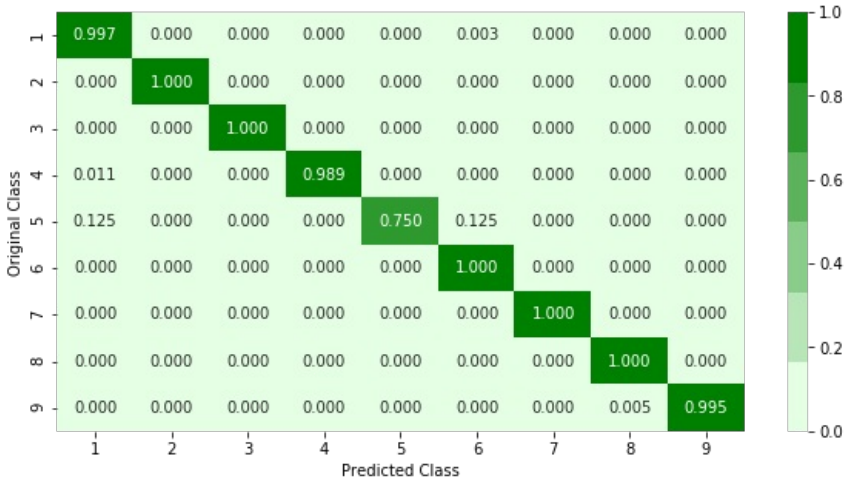
```
#Plotting the confusion matrix.
plot_confusion_matrix(y_test_merge,sig_clf.predict(X_test_merge))
```

```
Number of misclassified points  0.22999080036798528
-------------------------------------------------- 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.]
```

5.4: XgBoost Classifier on byte unigram, asm unigram, byte bigram and asm image features with hyperparameter tuning using simple for loop.

In [68]:

```
#Merging the byte unigram, asm, byte bigram and asm image features.
result_x = pd.merge(result,result_asm.drop(['Class'], axis=1),on='ID', how='left')
result_x = pd.merge(result_x,result_bigram_normalized_1k,on='ID', how='left')
result_x = pd.merge(result_x,result_asm_img_top_1k,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[68]:

	0	1	2	3	4	5	6	7	8	9	...	pix990	pix991	pix9
0	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	0.003531	...	1.000000	0.893204	1.0000
1	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	0.000394	...	0.009346	0.359223	0.9639
2	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	0.002707	...	1.000000	0.893204	1.0000
3	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	0.000521	...	0.579439	0.660194	0.5405
4	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	0.000246	...	1.000000	0.893204	1.0000

5 rows × 2307 columns

In [89]:

```
#Train-Test splitting.
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_si
ze=0.20)
```

In [95]:

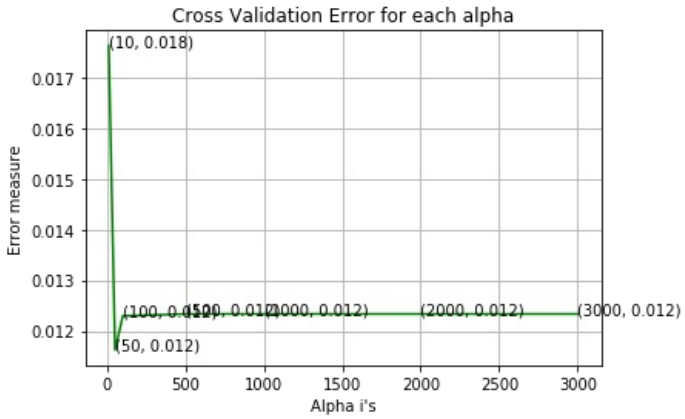
```
#Hyperparameter tuning using simple for loop.
from tqdm import tqdm

alpha=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
for i in tqdm(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))
```

100%|██████████| 7/7 [7:56:16<00:00, 4082.38s/it]

In [96]:

```
#Plotting the cross validation error for each alpha.
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 0.01763156156638052
log_loss for c =  50 is 0.011624610452342374
log_loss for c =  100 is 0.012296443669369602
log_loss for c =  500 is 0.012335168903850884
log_loss for c =  1000 is 0.01233610487851186
log_loss for c =  2000 is 0.012335428292948572
log_loss for c =  3000 is 0.01233582005395194
```



In [97]:

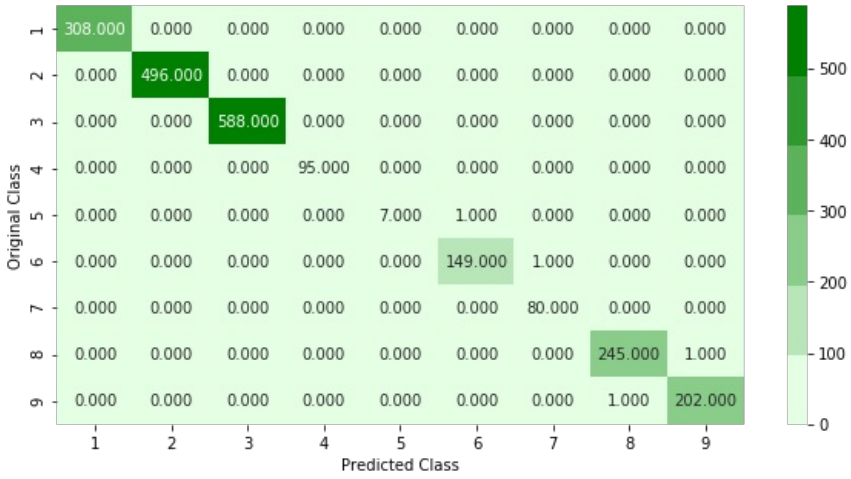
```
#Training the model using the best hyperparameter.
x_cfl=XGBClassifier(n_estimators=alpha[best_alpha],nthread=-1)
x_cfl.fit(X_train_merge,y_train_merge,verbose=True)
sig_clf = CalibratedClassifierCV(x_cfl, method="sigmoid")
sig_clf.fit(X_train_merge, y_train_merge)

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:",log_loss(y_test_merge, predict_y)
)
```

```
For values of best alpha =  50 The train log loss is: 0.010574318858118732
For values of best alpha =  50 The cross validation log loss is: 0.011624610452342374
For values of best alpha =  50 The test log loss is: 0.019715562307024464
```

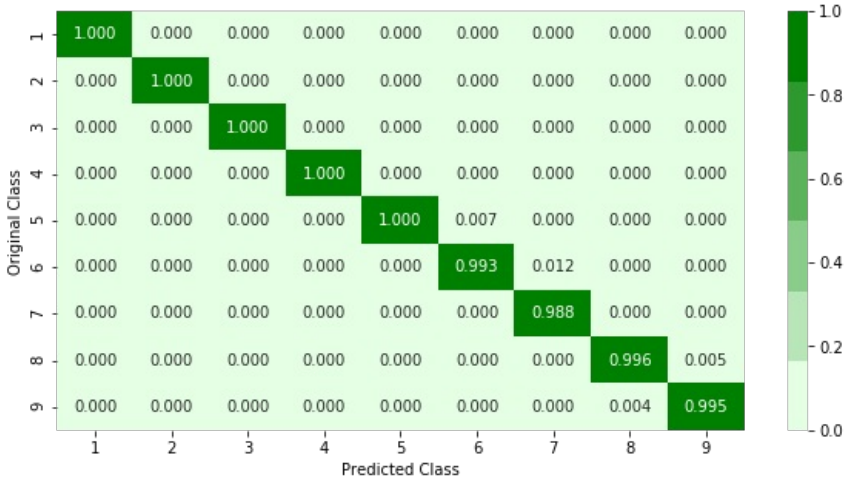
In [98]:

```
#Plotting the confusion matrix.
plot_confusion_matrix(y_test_merge,sig_clf.predict(X_test_merge))
```

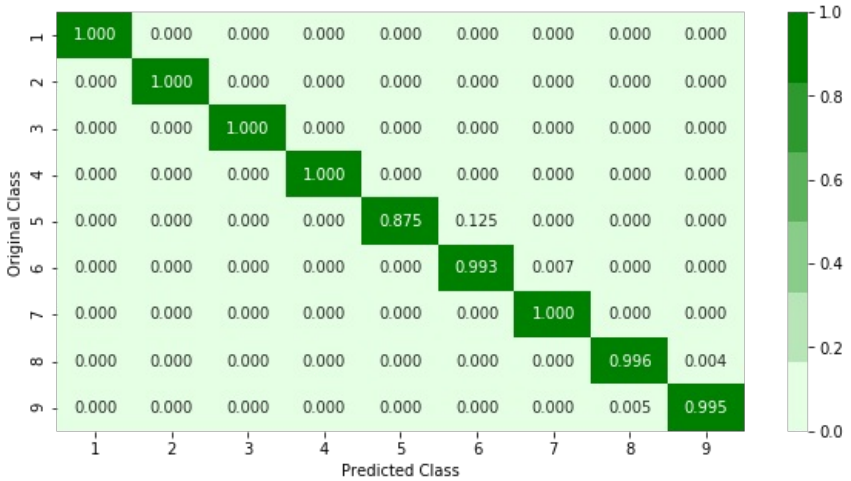
```
Number of misclassified points  0.18399264029438822
-------------------------------------------------- Confusion matrix ------------------------------
------------------
```




```
-------------------------------------------------- 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.]
```

Summary:

In [131]:

```
from prettytable import PrettyTable
prettytable=PrettyTable()
prettytable.field_names = ['Model type','Best param', 'Train loss', 'Test log loss','Missclass.']
prettytable.add_row(['1.XGboost using byte-unigram,\n asm-unigram and byte-bigram features.\n(Tuned using simple
for loop)\n','alpha=500', '0.0122', '0.0268', '0.59'])
prettytable.add_row(['2.XGboost using byte-unigram,\n asm-unigram and byte-bigram features.\n(Tuned using Randomi
zedSearchCV)\n','alpha=1000\n max_depth=3\n learning_rate=0.01', '0.0110', '0.0267', '0.64'])
prettytable.add_row(['3.XGboost using byte-unigram,\n asm-unigram and asm-image features.\n(Tuned using simple fo
r loop)\n','alpha=1000', '0.0097', '0.0149', '0.23'])
prettytable.add_row(['4.XGboost using byte-unigram\n asm-unigram,byte-bigram and asm-image\nfeatures.(Tuned using
simple for loop)\n','alpha=50', '0.0106', '0.0197', '0.18'])
print(prettytable)
```

```
+-------------------------------------+--------------------+------------+--------------+-------
-----+
|               Model type            |      Best param    | Train loss | Test log loss | Misscl
ass. |
+-------------------------------------+--------------------+------------+--------------+-------
-----+
|     1.XGboost using byte-unigram,   |      alpha=500     |   0.0122   |     0.0268    |    0.5
9    |
|  asm-unigram and byte-bigram features. |                    |            |               |
|
|     (Tuned using simple for loop)   |                    |            |               |
|
|                                     |                    |            |               |
|
|     2.XGboost using byte-unigram,   |      alpha=1000    |   0.0110   |     0.0267    |    0.6
4    |
|  asm-unigram and byte-bigram features. |      max_depth=3   |            |               |
|
|    (Tuned using RandomizedSearchCV) |  learning_rate=0.01 |            |               |
|
|                                     |                    |            |               |
|
|     3.XGboost using byte-unigram,   |      alpha=1000    |   0.0097   |     0.0149    |    0.2
3    |
|   asm-unigram and asm-image features.  |                    |            |               |
|
|     (Tuned using simple for loop)   |                    |            |               |
|
|                                     |                    |            |               |
|
|      4.XGboost using byte-unigram   |       alpha=50     |   0.0106   |     0.0197    |    0.1
8    |
|  asm-unigram,byte-bigram and asm-image |                    |            |               |
|
| features.(Tuned using simple for loop) |                    |            |               |
|
|                                     |                    |            |               |
|
+-------------------------------------+--------------------+------------+--------------+-------
-----+
```

1. Adding byte bigram and asm image features results in significant improvement in train/test log loss and missclassification error over the previous models.

2. Due to high time complexity, I could train only few xgboost models and I have used mainly simple for loop to tune hyperparameters as RandomSearchCV was taking too much time.

3. Model3(trained using asm image features) gives the lowest log loss on test data.

4. Model4(trained using all the features) gives the the lowest missclassification error.