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 (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 (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 (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, s
s: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::exception::exception(char const * cons
t &)
.text:0040100D C7 06 08    BB 42 00                         mov     dwo
rd 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 10
h
.text:00401020 C7 01 08    BB 42 00                         mov     dwo
rd ptr [ecx],    offset off_42BB08
.text:00401026 E9 26 1C    00 00                             jmp     su
b_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     dwo
rd ptr [esi],    offset off_42BB08
.text:00401039 E8 13 1C    00 00                               call    su
b_402C51
.text:0040103E F6 44 24    08 01                               test    by
te 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:00401043□j
.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/ (http://blog.kaggle.com/2015/05/26/microsoft-malware-winners-interview-1st-place-no-to-overfitting/)
https://arxiv.org/pdf/1511.04317.pdf (https://arxiv.org/pdf/1511.04317.pdf)
First place solution in Kaggle competition: https://www.youtube.com/watch?v=VLQTRILGz5Y (https://www.youtube.com/watch?v=VLQTRILGz5Y)
https://github.com/dchad/malware-detection (https://github.com/dchad/malware-detection)
http://vizsec.org/files/2011/Nataraj.pdf (http://vizsec.org/files/2011/Nataraj.pdf)
https://www.dropbox.com/sh/gfqzv0ckgs4l1bf/AAB6EelnEjvvuQg2nu_pIB6ua?dl=0 (https://www.dropbox.com/sh/gfqzv0ckgs4l1bf/AAB6EelnEjvvuQg2nu_pIB6ua?dl=0)
" Cross validation is more trustworthy than domain knowledge."

3. Exploratory Data Analysis

In [5]:

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

from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

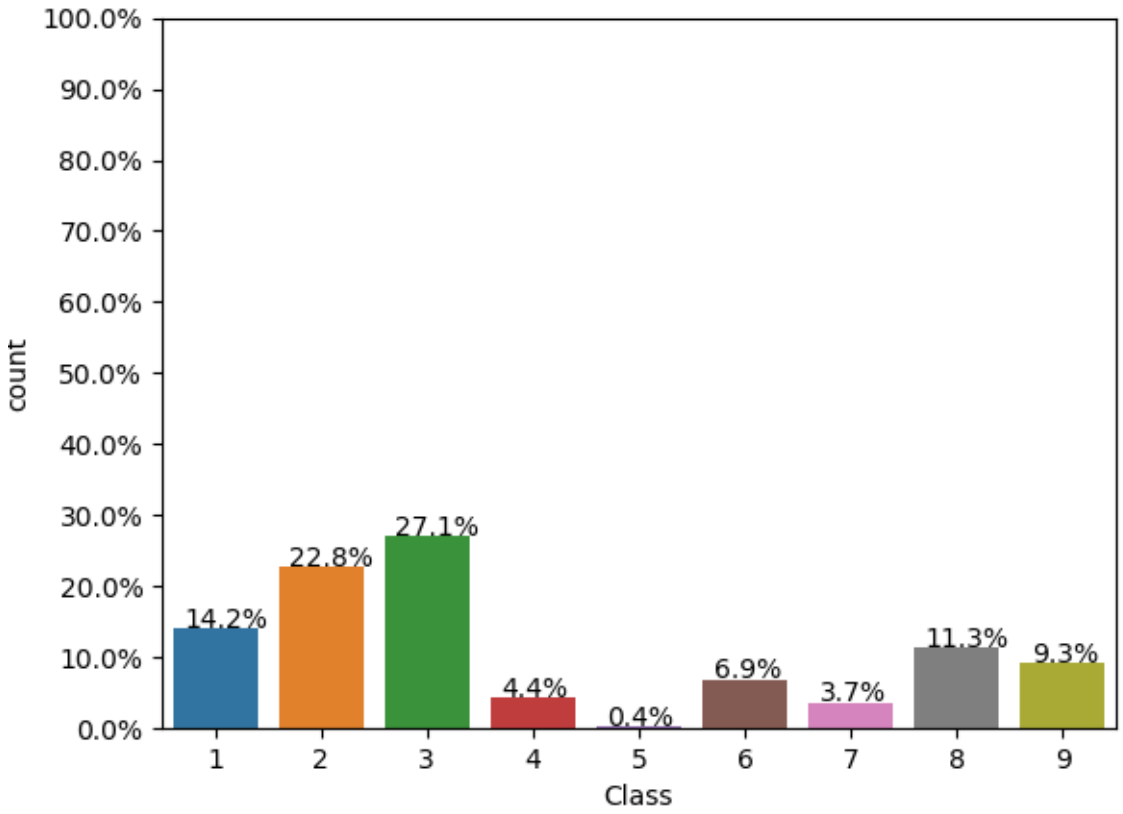
In [2]:
```
source = 'train'
destination = 'byteFiles'

#We will check if the folder 'byteFiles' exists if it not there we will creat
if not os.path.isdir(destination):
    os.makedirs(destination)

# if we have folder called 'train' (train folder contains both .asm files and
# for every file that we have in our 'asmFiles' directory we check if it is e
# 'byteFiles' folder

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

print("All byte files moved to 'byteFiles' folder and all asm files moved to
```

```
All byte files moved to 'byteFiles' folder and all asm files moved to 'asmFile
s' folder..
```

3.1. Distribution of malware classes in whole data set

In [43]:
```
Y=pd.read_csv("trainLabels.csv")
total = len(Y)*1.
ax=sns.countplot(x="Class", data=Y)
for p in ax.patches:
        ax.annotate('{:.1f}%'.format(100*p.get_height()/total), (p.get_x()+0.

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

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

<IPython.core.display.Javascript object>



Here we should keep in mind that the dataset is highly imbalanced. We can see that class 1,2,3 are

the ones which has maximum number of datapoints. These 3 classes are closely followed by classes 6,8,9. Class 5 has the lowest number of files. Class 4,6 and 7 also has considerably less number of data points. So this is basically a multi-class problem with an imbalanced dataset.

3.2. Feature extraction

3.2.1 File size of byte files as a feature

In [23]:
```
#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=356157170
    # st_size=3680109, st_atime=1519638522, st_mtime=1519638522, st_ctime=151
    # read more about os.stat: here https://www.tutorialspoint.com/python/os_
    statinfo=os.stat('byteFiles/'+file)
    # split the file name at '.' and take the first part of it i.e the file n
    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
data_size_byte.head()
```

Out[23]:

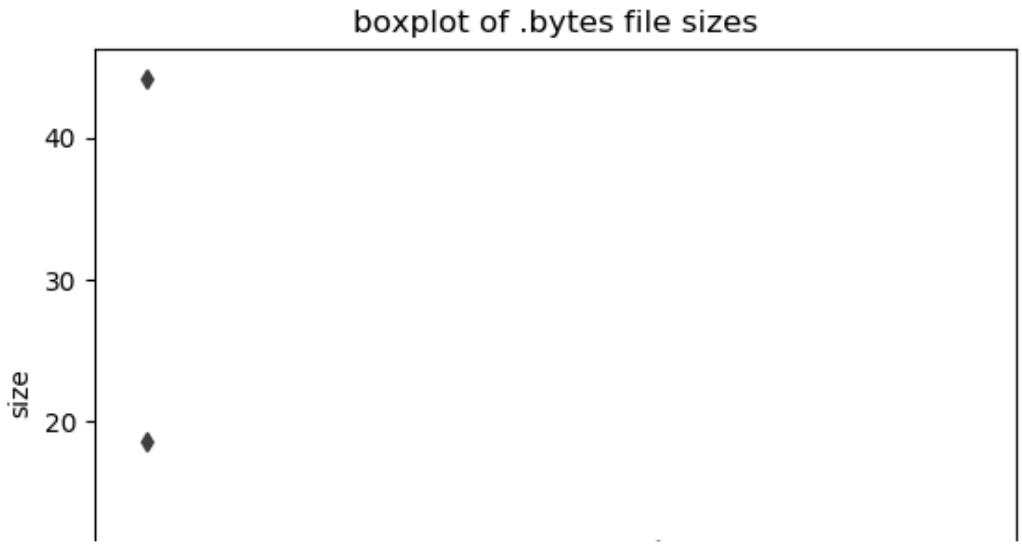
	ID	size	Class
0	01azqd4InC7m9JpocGv5	4.148438	9
1	01IsoiSMh5gxyDYTl4CB	5.425781	2
2	01jsnpXSAlgw6aPeDxrU	3.808594	9
3	01kcPWA9K2BOxQeS5Rju	0.562500	1
4	01SuzwMJEIXsK7A8dQbl	0.363281	8

In [24]:
```
#Save byte file size dataframe
if not os.path.isdir("features"):
    os.makedirs("features")

data_size_byte.to_csv("features/data_size_byte.csv")
```

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

In [25]:
```
#boxplot of byte files
ax = sns.boxplot(x="Class", y="size", data=data_size_byte)
plt.title("boxplot of .bytes file sizes")
plt.show()
```

```
<IPython.core.display.Javascript object>
```



Looking at the box plot carefully, we can see that the size feature is somewhat useful in determining some of the class labels if not all. In the above box plot, class 2 can be clearly separated from other classes (1,3,4,6,7,8) by just using the size feature. Class 3 has one of the lowest file sizes and they can be easily separated by classes. IF not fully, file sizes partially helps us to differentiate between few classes. So file sizes are indeed useful features. We will keep them and make use of them while doing our analysis and also while building our models.

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
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 [26]:
```
byte_features=pd.read_csv("result.csv").drop(columns=["Unnamed: 0"])
byte_features['ID']  = byte_features['ID'].str.split('.').str[0]
byte_features["size"]=data_size_byte["size"]
byte_features.head()
```

Out[26]:

	ID	0	1	2	3	4	5	6	7	8	...	f9	
0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	2965	...	3101	32
1	01IsoiSMh5gxyDYTI4CB	39755	8337	7249	7186	8663	6844	8420	7589	9291	...	439	2
2	01jsnpXSAlgw6aPeDxrU	93506	9542	2568	2438	8925	9330	9007	2342	9107	...	2242	28
3	01kcPWA9K2BOxQeS5Rju	21091	1213	726	817	1257	625	550	523	1078	...	485	4
4	01SuzwMJEIXsK7A8dQbl	19764	710	302	433	559	410	262	249	422	...	350	2

5 rows × 260 columns

In [27]:
```
byte_features_with_size = byte_features
byte_features_with_size.to_csv("features/byte_features_with_size.csv",index=N
```

In [71]:
```
byte_features_with_size=pd.read_csv("features/byte_features_with_size.csv")
byte_features_with_size.head()
```

Out[71]:

	ID	0	1	2	3	4	5	6	7	8	...	f9	
0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	2965	...	3101	32
1	01IsoiSMh5gxyDYTI4CB	39755	8337	7249	7186	8663	6844	8420	7589	9291	...	439	2
2	01jsnpXSAlgw6aPeDxrU	93506	9542	2568	2438	8925	9330	9007	2342	9107	...	2242	28
3	01kcPWA9K2BOxQeS5Rju	21091	1213	726	817	1257	625	550	523	1078	...	485	4
4	01SuzwMJEIXsK7A8dQbl	19764	710	302	433	559	410	262	249	422	...	350	2

5 rows × 260 columns

In [2]:
```
# 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_val
    return result1
```

In [59]:
```
result = normalize(byte_features_with_size)
result.head(5)
```

Out[59]:

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

5 rows × 260 columns

In [101]:
```
data_y = result['Class']
result.head()
```

Out[101]:

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

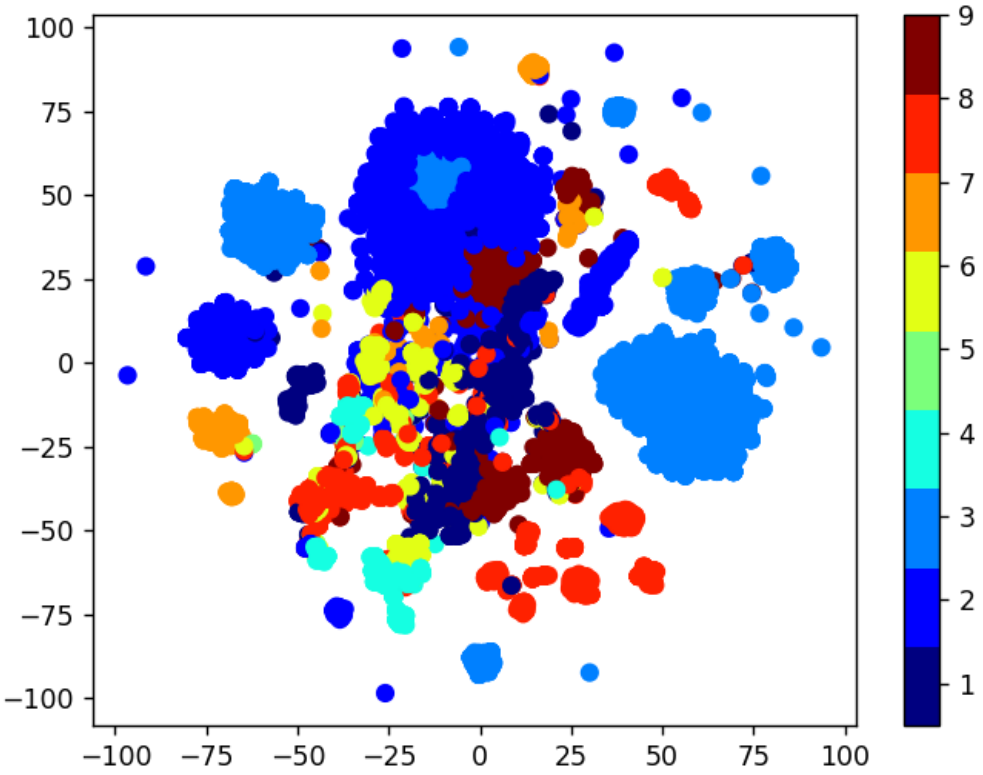
5 rows × 260 columns

3.2.4 Multivariate Analysis Plot TSNE

In [0]:

```
#Multivariate analysis on byte files features extracted using unigrams.
def draw_tsne_byte(p):
    xtsne=TSNE(perplexity=p)
    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()

draw_tsne_byte(30)
```

```
<IPython.core.display.Javascript object>
```



At various values of perplexity we can see that the clusters are partially separable. There is some overlapping but in general classes 1,2,3 are well separated from the rest. The red points belonging to cluster 8 are scattered over a larger area, but inspite of this, there is no significant overlapping of class 8 with other clusters. This tells us that the unigrams features extracted from using a custom bag of words approach is pretty useful in separating the data.

Train Test split

In [102]:
```
data_y = result['Class']
# split the data into test and train by maintaining same distribution of outp
X_train, X_test, y_train, y_test = train_test_split(result.drop(['ID','Class'
# split the train data into train and cross validation by maintaining same di
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,stratify=y_t
```

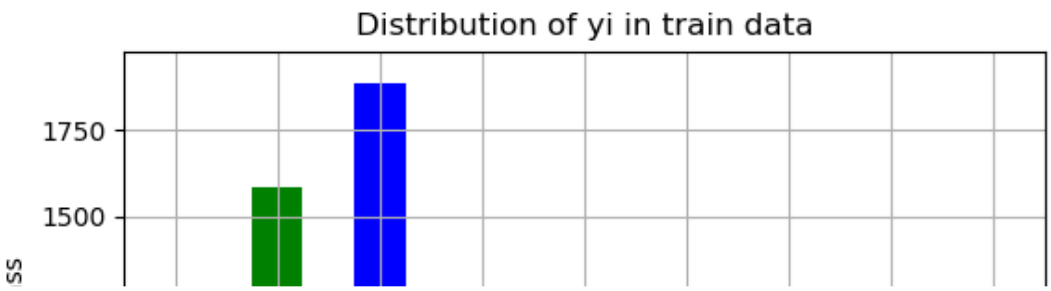
In [103]:
```
print('Number of data points in train data:', X_train.shape[0])
print('Number of data points in test data:', X_test.shape[0])
print('Number of data points in cross validation data:', X_cv.shape[0])
```

```
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 [107]:

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

my_colors = ["r","g","b","orange","y","m","c","g","black"]
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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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

print('-'*80)
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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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.

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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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.va

```

```
<IPython.core.display.Javascript object>
```


Distribution of yi in train data
1750
1500
ss

In [3]:

```
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    print("Percentage of misclassified points ",(len(test_y)-np.trace(C))/len
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i

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

    # 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
    # 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 t
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to
    # 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, ytic
    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, ytic
    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, ytic
    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

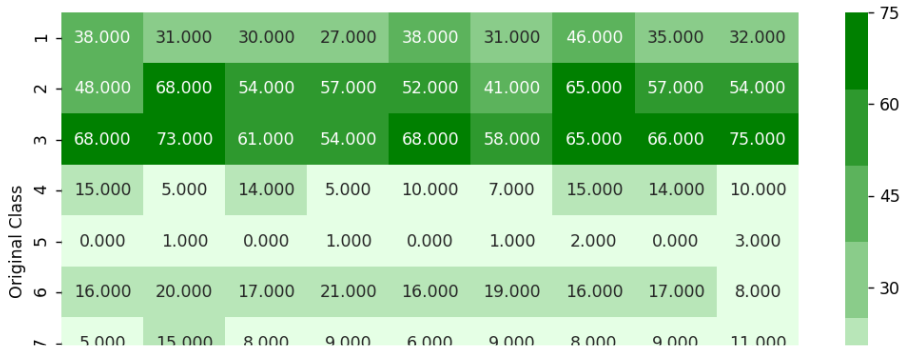
4.1. Machine Leaning Models on bytes files

4.1.1. Random Model

In [0]:

```
# 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 the
# 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

# 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_predict

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 2.45615644965
Log loss on Test Data using Random Model 2.48503905509
Number of misclassified points  88.5004599816
---------------------------------------------------- Confusion matrix ---------
----------------------------------------

<IPython.core.display.Javascript object>
```



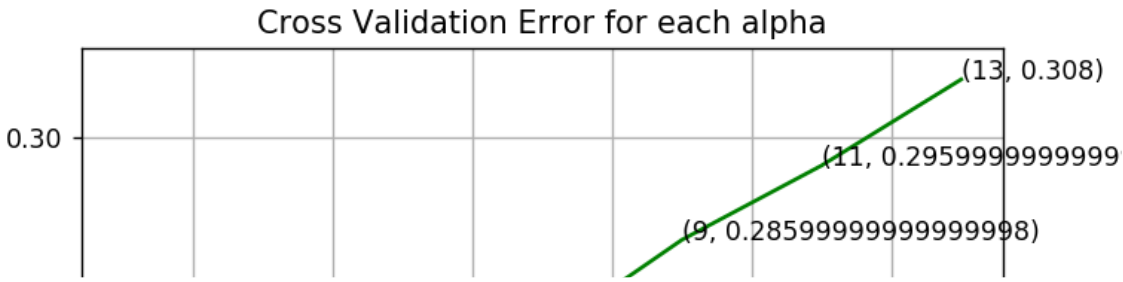
4.1.2. K Nearest Neighbour Classification

In [0]:

```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/
# ------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', le
# 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
#-------------------------------------


# find more about CalibratedClassifierCV here at http://scikit-learn.org/stab
# ----------------------------
# default paramters
# sklearn.calibration.CalibratedClassifierCV(base_estimator=None, method='sig
#
# 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_

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
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is
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

<IPython.core.display.Javascript object>
```



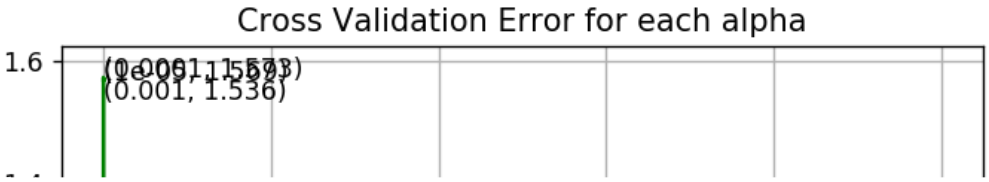
4.1.3. Logistic Regression

In [0]:

```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/g
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning
# 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
# predict(X)    Predict class labels for samples in X.

#-------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online
#-------------------------------

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.clas

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()colc

logisticR=LogisticRegression(penalty='l2',C=alpha[best_alpha],class_weight='b
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=logistic
predict_y = sig_clf.predict_proba(X_cv)
print ('log loss for cv data',log_loss(y_cv, predict_y, labels=logisticR.clas
predict_y = sig_clf.predict_proba(X_test)
print ('log loss for test data',log_loss(y_test, predict_y, labels=logisticR.
plot_confusion_matrix(y_test, sig_clf.predict(X_test))
```

```
log_loss for c =  1e-05 is 1.56916911178
log_loss for c =  0.0001 is 1.57336384417
```

```
log_loss for c =  0.001 is 1.53598598273
log_loss for c =  0.01 is 1.01720972418
log_loss for c =  0.1 is 0.857766083873
log_loss for c =  1 is 0.711154393309
log_loss for c =  10 is 0.583929522635
log_loss for c =  100 is 0.549929846589
log_loss for c =  1000 is 0.624746769121

<IPython.core.display.Javascript object>
```



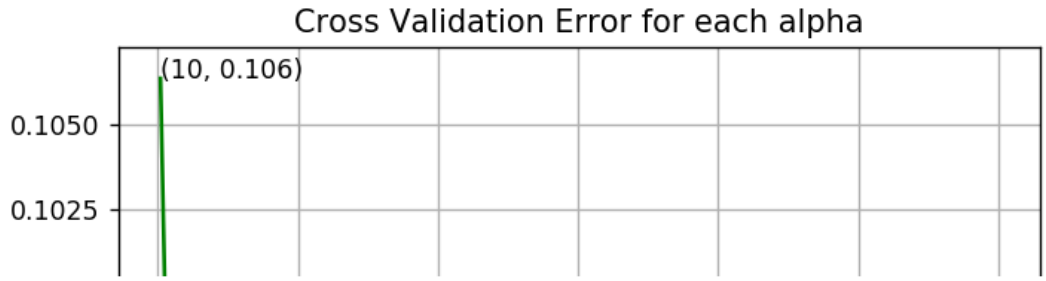
4.1.4. Random Forest Classifier

In [0]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini',
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given trai
# 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
# --------------------------------

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_

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
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 i
```

```
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is
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

<IPython.core.display.Javascript object>
```



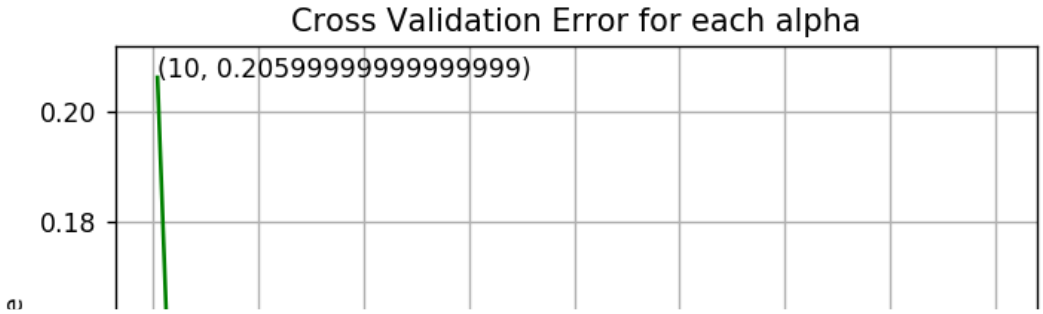
4.1.5. XgBoost Classification

In [0]:

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

# find more about XGBClassifier function here http://xgboost.readthedocs.io/e
# ------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# -----------------------

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_

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
predict_y = sig_clf.predict_proba(X_cv)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
predict_y = sig_clf.predict_proba(X_test)
```

```
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is
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

<IPython.core.display.Javascript object>
```



4.1.5. XgBoost Classification with best hyper parameters using RandomSearch

In [0]:
```
# https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tunin
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_j
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:  5.4mi
n
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed: 10.1min remaining:  3.1mi
n
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed: 14.0min remaining:  1.6mi
n
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 14.2min finished
```

Out[75]:
```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=1, colsampl
e_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], 'co
lsample_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=10)
```

In [0]:
```
print (random_cfl1.best_params_)
```

```
{'subsample': 1, 'n_estimators': 500, 'max_depth': 5, 'learning_rate': 0.05, 'c
olsample_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/e
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# -----------------------

x_cfl=XGBClassifier(n_estimators=2000, learning_rate=0.05, colsample_bytree=1
x_cfl.fit(X_train,y_train)
c_cfl=CalibratedClassifierCV(x_cfl,method='sigmoid')
c_cfl.fit(X_train,y_train)

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

```
train loss 0.022540976086
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 par
allel we can use all the cores that are present in our computer.

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

We read the top solutions and handpicked the features from those papers/v
ideos/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
#https://en.wikipedia.org/wiki/X86_instruction_listings
#https://en.wikipedia.org/wiki/Data_segment

"""The x86 instruction set refers to the set of instructions that x86-compati
executed on the processor. The x86 instruction set has been extended several

"""In computing, a data segment (often denoted .data) is a portion of an obje
global variables and static local variables. The size of this segment is dete


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
    #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', 'su
    #best keywords that are taken from different blogs
    keywords = ['.dll','std::',':dword']
    #Below taken registers are general purpose registers and special register
    #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] #Contains the file names
        file1.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 f
            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' seg
                        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
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'su
    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+",")

        with codecs.open('second/'+f,encoding='cp1252',errors ='replace') as
            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
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'su
    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+",")

        with codecs.open('thrid/'+f,encoding='cp1252',errors ='replace') as
            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
                            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
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'su
    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+",")

        with codecs.open('fourth/'+f,encoding='cp1252',errors ='replace') as
            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
```

```
    opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'su
    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+",")

        with codecs.open('fifth/'+f,encoding='cp1252',errors ='replace') as f
            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 [66]:

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

Out[66]:

	ID	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdata:	.edata:	.rsrc:	...
0	01kcPWA9K2BOxQeS5Rju	19	744	0	127	57	0	323	0	3	...
1	1E93CpP60RHFNiT5Qfvn	17	838	0	103	49	0	0	0	3	...
2	3ekVow2ajZHbTnBcsDfX	17	427	0	50	43	0	145	0	3	...
3	3X2nY7iQaPBIWDrAZqJe	17	227	0	43	19	0	0	0	3	...
4	46OZzdsSKDCFV8h7XWxf	17	402	0	59	170	0	0	0	3	...

5 rows × 53 columns

4.2.1.1 Files sizes of each .asm file

In [23]:
```
#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 tqdm(files):
    # print(os.stat('byteFiles/0A32eTdBKayjCWhZqDOQ.txt'))
    # os.stat_result(st_mode=33206, st_ino=1125899906874507, st_dev=356157170
    # st_size=3680109, st_atime=1519638522, st_mtime=1519638522, st_ctime=151
    # read more about os.stat: here https://www.tutorialspoint.com/python/os_
    statinfo=os.stat('asmFiles/'+file)
    # split the file name at '.' and take the first part of it i.e the file n
    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}
asm_size_byte.head()
```

```
100%|██████████| 10868/10868 [00:48<00:00, 223.06it/s]
```

Out[23]:

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

In [27]:
```
#Save ASM file size dataframe
if not os.path.isdir("features"):
    os.makedirs("features")

asm_size_byte.to_csv("features/asm_size_df.csv", index=False)
```

In [34]:
```
#Adding the file size feature to previous extracted features
asm_features_with_size=pd.merge(asm_size_byte,result_asm.drop(columns=["Class
asm_features_with_size.head()
```

Out[34]:

	ID	size	Class	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rd
0	01azqd4InC7m9JpocGv5	56.229886	9	18	22430	0	1158	1366754	0	1
1	01IsoiSMh5gxyDYTl4CB	13.999378	2	0	109939	0	616	24568	0	26
2	01jsnpXSAlgw6aPeDxrU	8.507785	9	18	68883	0	304	662	0	1
3	01kcPWA9K2BOxQeS5Rju	0.078190	1	19	744	0	127	57	0	
4	01SuzwMJEIXsK7A8dQbl	0.996723	8	18	10368	0	206	4595	92	

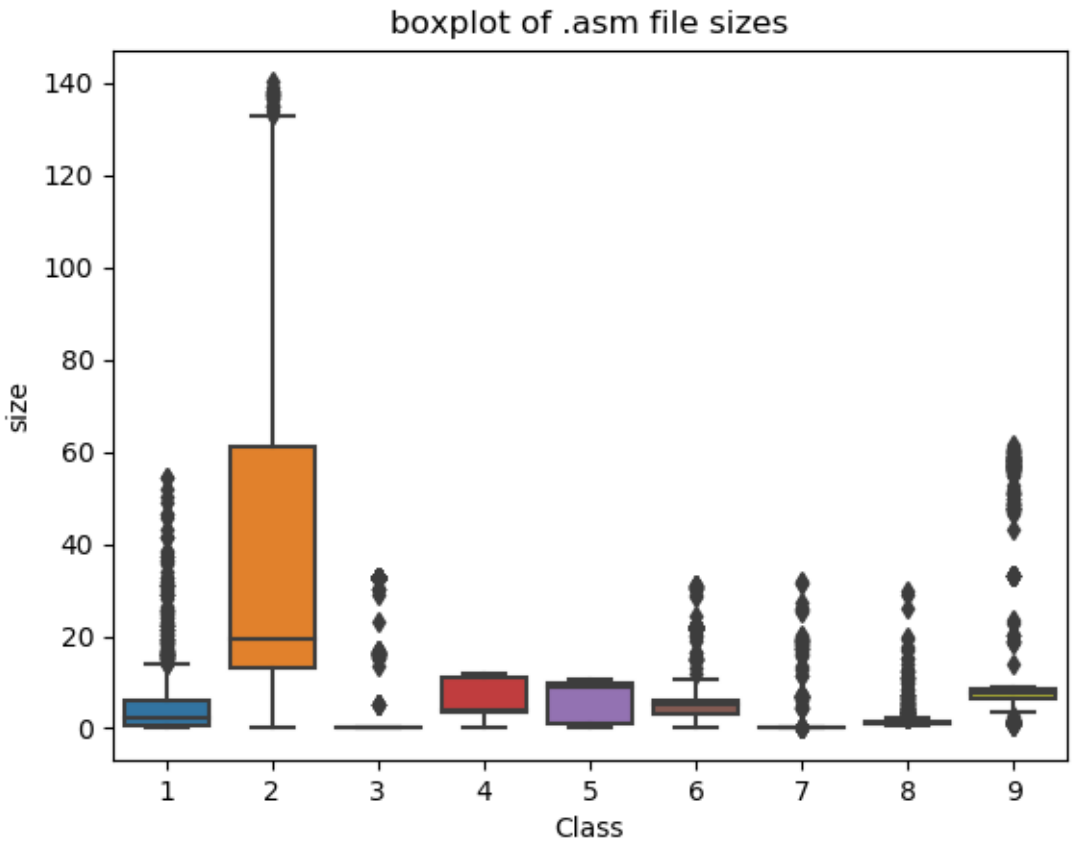
5 rows × 54 columns

In [35]:
```
#Save the ASM Dataframe
asm_features_with_size.to_csv("features/asm_features_with_size.csv",index=Non
```

4.2.1.2 Distribution of .asm file sizes

In [36]:
```
#boxplot of asm files
ax = sns.boxplot(x="Class", y="size", data=asm_size_byte)
plt.title("boxplot of .asm file sizes")
plt.show()
```

```
<IPython.core.display.Javascript object>
```



By looking at the distribution of the ASM file sizes, we can see that class 2 type of malwares can be easily separated from the rest the classes. Class 2 type malwares has the highest spread of file sizes. Among the rest of the classes 7,8 have the least file sizes. But they cannot be strictly separated from the file sizes alone.

In [69]:
```
# add the file size feature to previous extracted features
result_asm=asm_features_with_size
print(result_asm.shape)
print(asm_size_byte.shape)
result_asm.head()
```

```
(10868, 54)
(10868, 3)
```

Out[69]:

	ID	size	Class	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rd
0	01azqd4InC7m9JpocGv5	56.229886	9	18	22430	0	1158	1366754	0	1
1	01IsoiSMh5gxyDYTl4CB	13.999378	2	0	109939	0	616	24568	0	26
2	01jsnpXSAlgw6aPeDxrU	8.507785	9	18	68883	0	304	662	0	1
3	01kcPWA9K2BOxQeS5Rju	0.078190	1	19	744	0	127	57	0	
4	01SuzwMJEIXsK7A8dQbl	0.996723	8	18	10368	0	206	4595	92	

5 rows × 54 columns

In [78]:
```
byte_features_with_size.head()
```

Out[78]:

	ID	0	1	2	3	4	5	6	7	8	...	f9	
0	01azqd4InC7m9JpocGv5	601905	3905	2816	3832	3345	3242	3650	3201	2965	...	3101	32
1	01IsoiSMh5gxyDYTl4CB	39755	8337	7249	7186	8663	6844	8420	7589	9291	...	439	2
2	01jsnpXSAlgw6aPeDxrU	93506	9542	2568	2438	8925	9330	9007	2342	9107	...	2242	28
3	01kcPWA9K2BOxQeS5Rju	21091	1213	726	817	1257	625	550	523	1078	...	485	4
4	01SuzwMJEIXsK7A8dQbl	19764	710	302	433	559	410	262	249	422	...	350	2

5 rows × 260 columns

In [70]:
```
asm_features_with_size.head(3)
```

Out[70]:

	ID	size	Class	HEADER:	.text:	.Pav:	.idata:	.data:	.bss:	.rdat
0	01azqd4InC7m9JpocGv5	56.229886	9	18	22430	0	1158	1366754	0	17
1	01IsoiSMh5gxyDYTl4CB	13.999378	2	0	109939	0	616	24568	0	264
2	01jsnpXSAlgw6aPeDxrU	8.507785	9	18	68883	0	304	662	0	10

3 rows × 54 columns

In [85]:
```
#Combined the byte and unigrams features along with their sizes and save it i
labels=byte_features_with_size["Class"] #Get class labels and ID from byte un
with open('features/class_labels.pkl', 'wb') as file:
    pkl.dump(labels, file)

combined_unigrams = pd.merge(byte_features_with_size.drop(columns=["Class"]),
combined_unigrams=combined_unigrams.drop(columns=["ID"])
combined_unigrams.to_csv("features/combined_asm_byte_unigram.csv",index=None)
combined_unigrams.head()
```

Out[85]:

	0	1	2	3	4	5	6	7	8	9	...	:dword	edx	esi	eax	
0	601905	3905	2816	3832	3345	3242	3650	3201	2965	3205	...	4371	808	2290	1281	
1	39755	8337	7249	7186	8663	6844	8420	7589	9291	358	...	1446	260	1090	391	
2	93506	9542	2568	2438	8925	9330	9007	2342	9107	2457	...	903	5	547	5	
3	21091	1213	726	817	1257	625	550	523	1078	473	...	137	18	66	15	
4	19764	710	302	433	559	410	262	249	422	223	...	1220	18	1228	24	1

5 rows × 307 columns

In [91]:
```
#We normalize the data each column
result_asm = normalize(result_asm)
result_asm.head()
```

Out[91]:

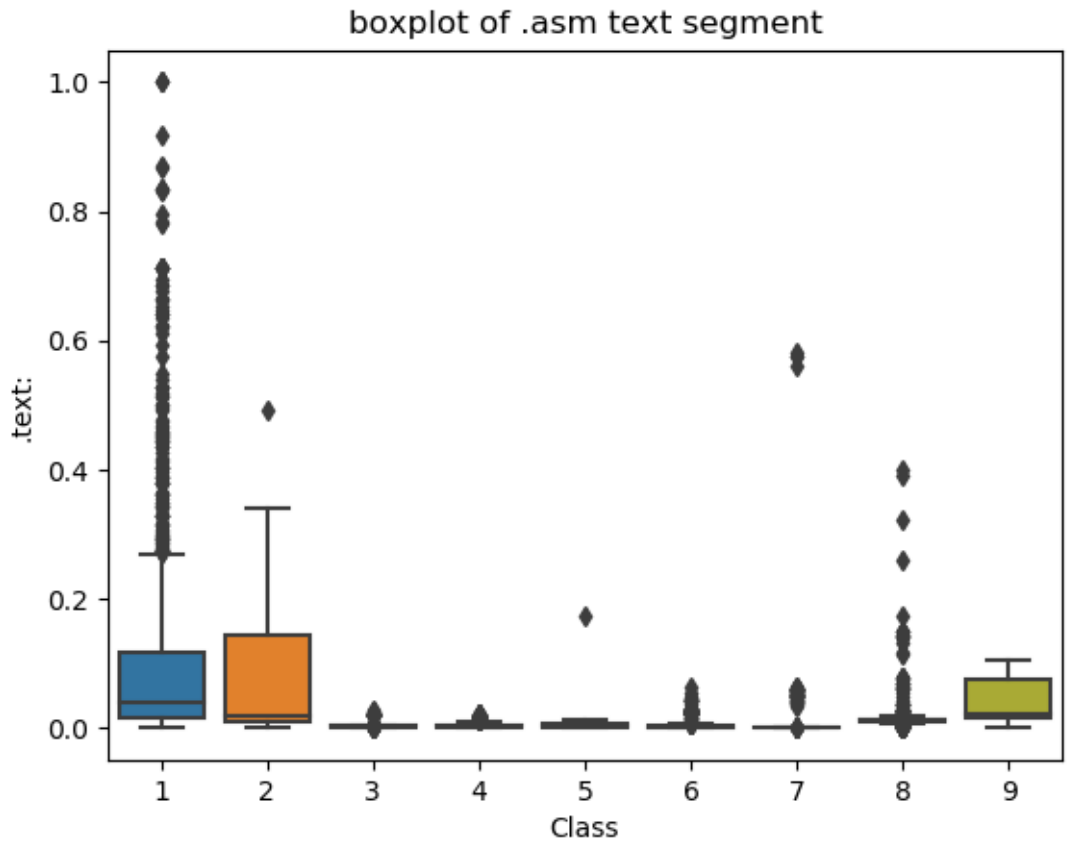
	ID	size	Class	HEADER:	.text:	.Pav:	.idata:	.data:	.b
0	01azqd4InC7m9JpocGv5	0.400910	9	0.101695	0.032927	0.0	0.006937	0.542847	0.000(
1	01IsoiSMh5gxyDYTl4CB	0.099719	2	0.000000	0.161391	0.0	0.003690	0.009758	0.000(
2	01jsnpXSAlgw6aPeDxrU	0.060553	9	0.101695	0.101121	0.0	0.001821	0.000263	0.000(
3	01kcPWA9K2BOxQeS5Rju	0.000432	1	0.107345	0.001092	0.0	0.000761	0.000023	0.000(
4	01SuzwMJEIXsK7A8dQbl	0.006983	8	0.101695	0.015220	0.0	0.001234	0.001825	0.012(

5 rows × 54 columns

4.2.2 Univariate analysis on asm file features

In [92]:
```
#Distribution of text keyword segment
ax = sns.boxplot(x="Class", y=".text:", data=result_asm)
plt.title("boxplot of .asm text segment")
plt.show()
```

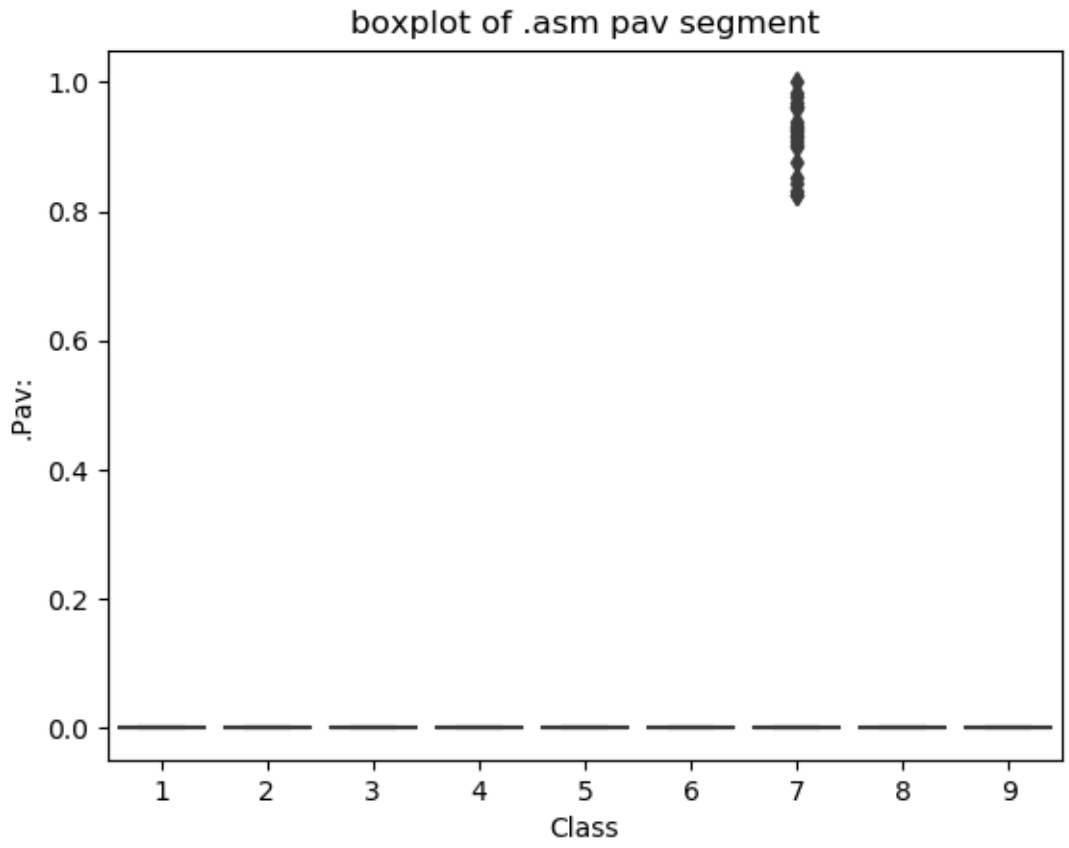
```
<IPython.core.display.Javascript object>
```



This plot is between the text segment features vs the class labels. Here we can see that classes 1,2 and 9 can be easily separated using this feature. The rest of the classes aren't easily separated.

In [93]:
```
#Distribution of .Pav segments
ax = sns.boxplot(x="Class", y=".Pav:", data=result_asm)
plt.title("boxplot of .asm pav segment")
plt.show()
```

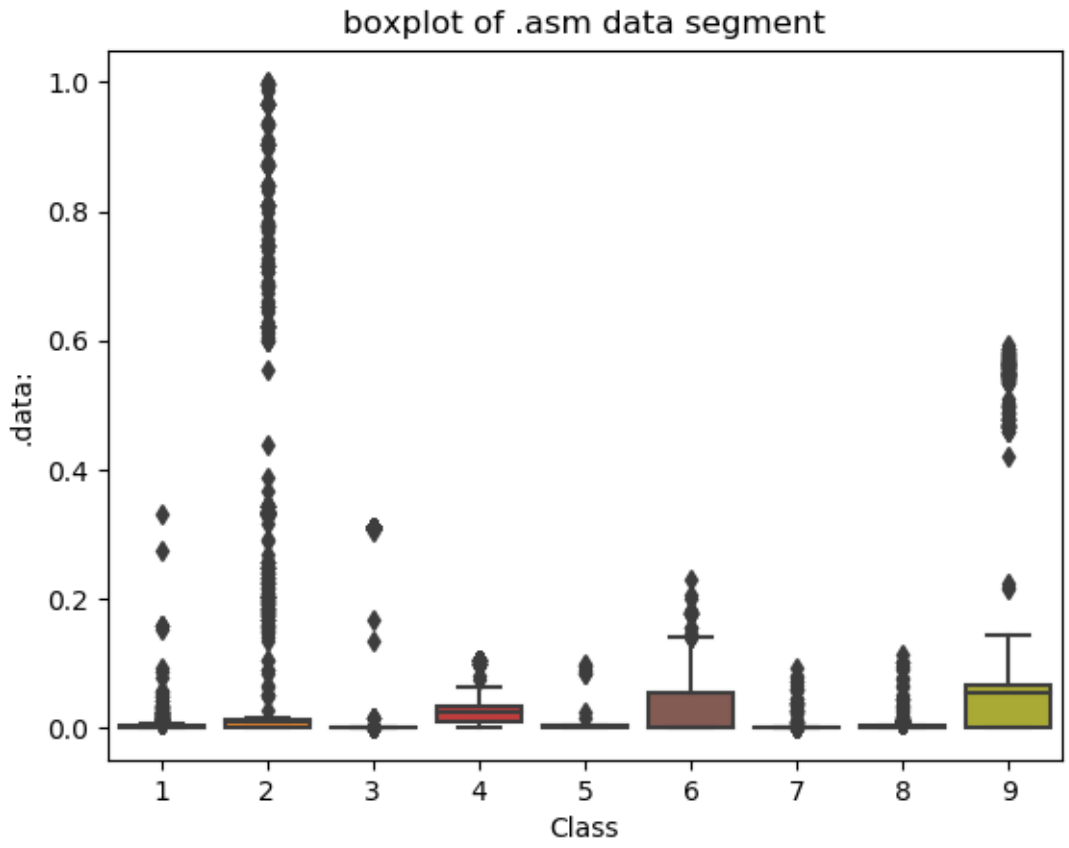
```
<IPython.core.display.Javascript object>
```



Here none of the classes can be well separated. Hoewever, an important point to note is class 7 type of malware are having the highest spread of the .pav segments.

In [94]:
```
#Distribution of .data segments
ax = sns.boxplot(x="Class", y=".data:", data=result_asm)
plt.title("boxplot of .asm data segment")
plt.show()
```

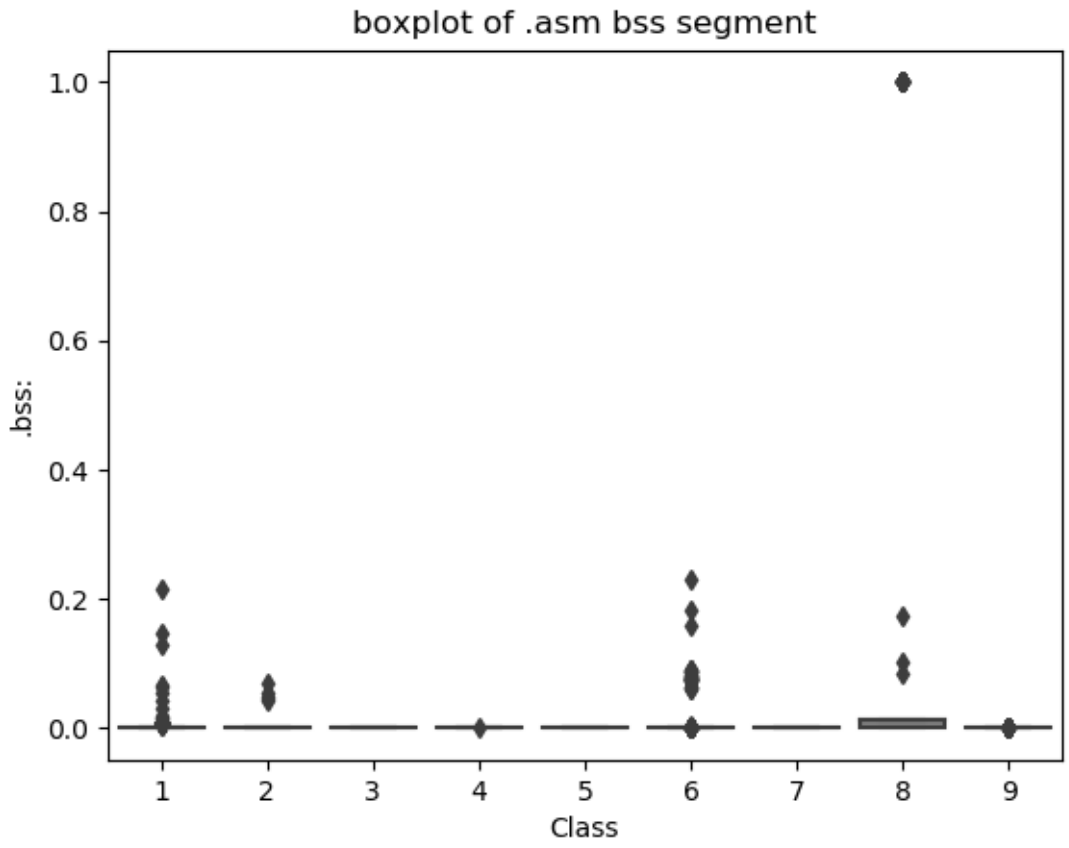
```
<IPython.core.display.Javascript object>
```



In this plot, class 6 and 9 can be well separated from the rest of the classes. For the rest of the classes the spread is extremely small to come to a conclusion solely based on this feature alone.

In [95]:
```
#Distribution of .bss segments
ax = sns.boxplot(x="Class", y=".bss:", data=result_asm)
plt.title("boxplot of .asm bss segment")
plt.show()
```

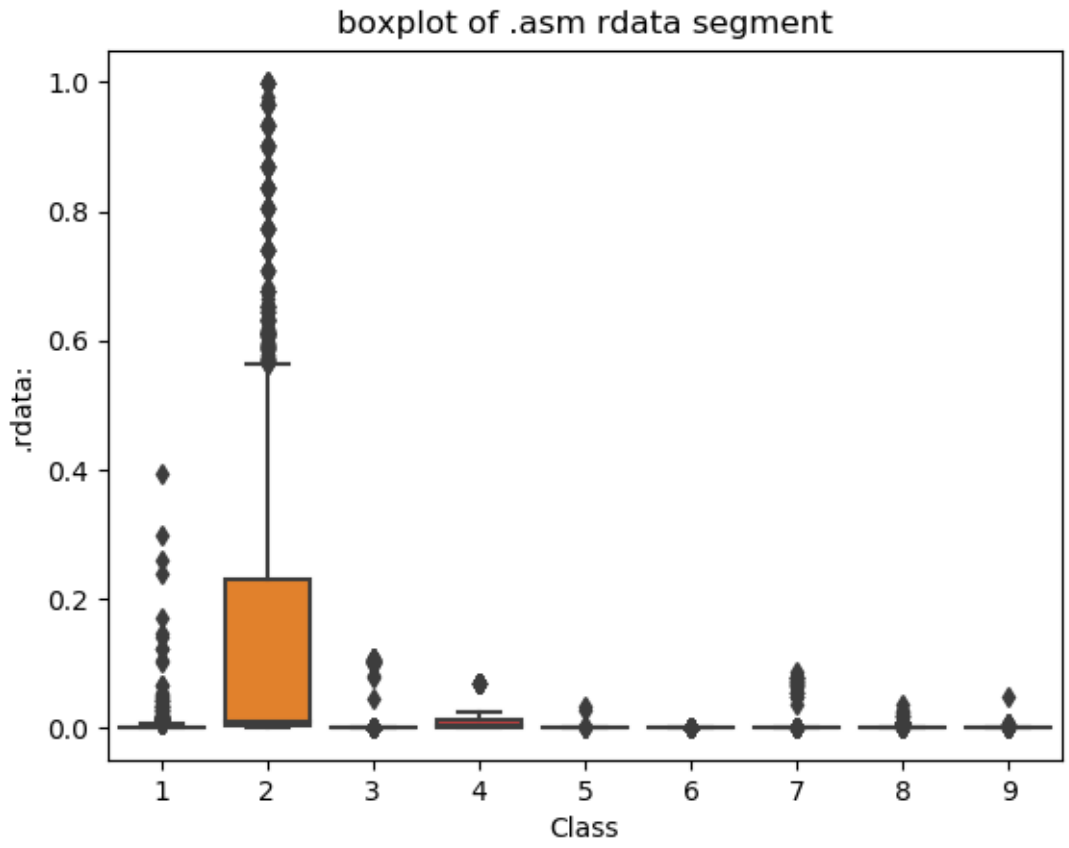
```
<IPython.core.display.Javascript object>
```



Here we can see that very less number of files has .bss segments. The classes cannot be separated well from this.

In [96]:
```
#Distribution of .rdata segments
ax = sns.boxplot(x="Class", y=".rdata:", data=result_asm)
plt.title("boxplot of .asm rdata segment")
plt.show()
```

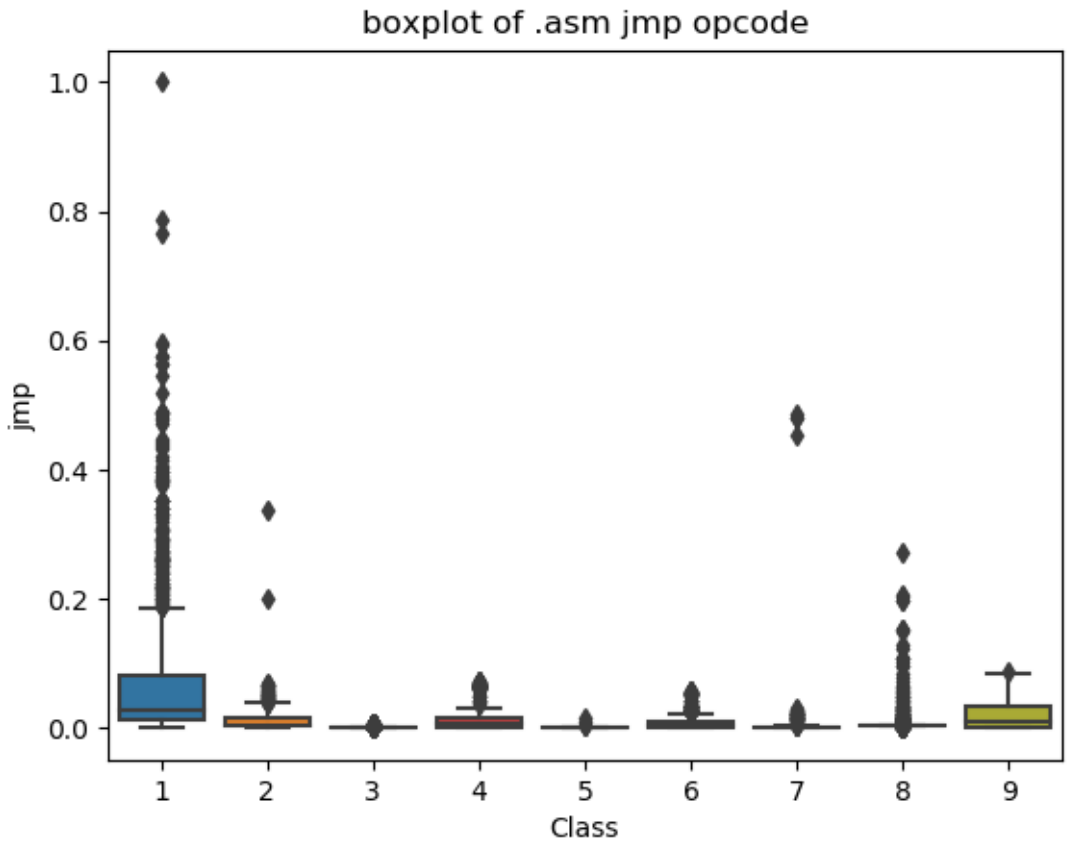
```
<IPython.core.display.Javascript object>
```



Here we can see that using .rdata segments, class 2 can be very well separated from the rest of the malware classes. However for rest of the malware classes the .rdata segment distribution looks pretty off.

In [97]:
```
#Distribution of .jmp segments
ax = sns.boxplot(x="Class", y="jmp", data=result_asm)
plt.title("boxplot of .asm jmp opcode")
plt.show()
```

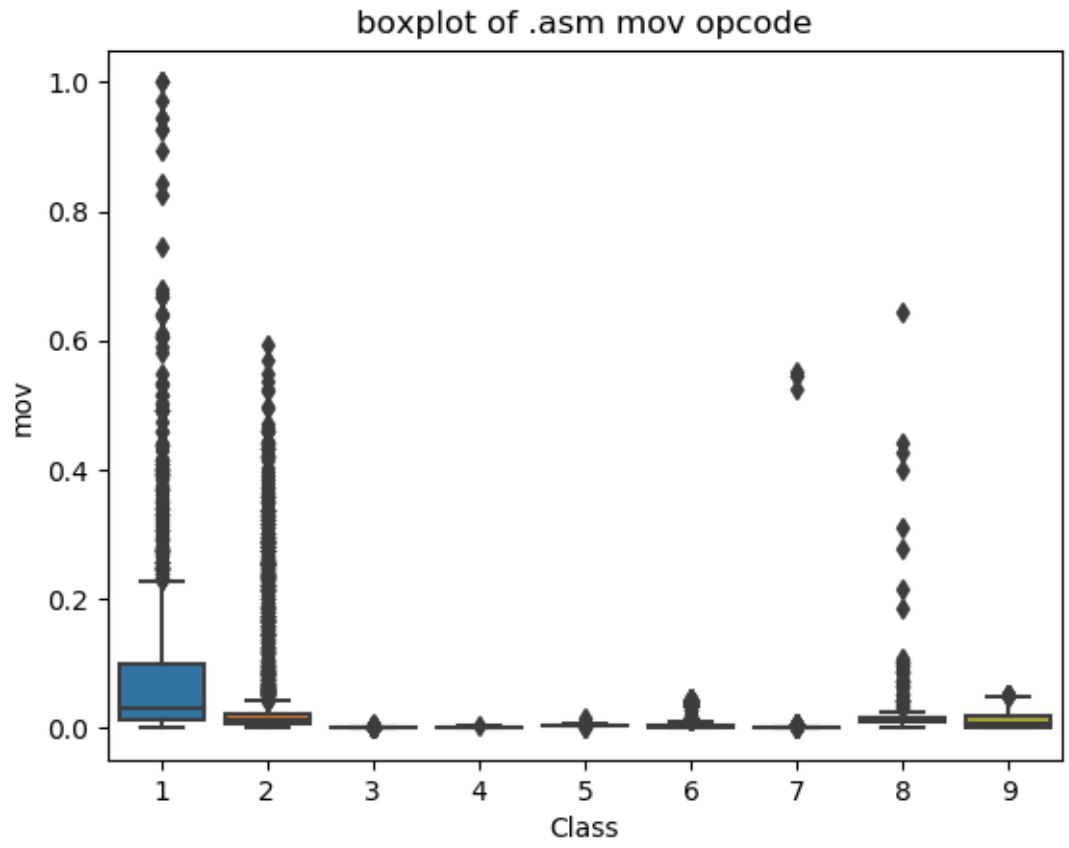
```
<IPython.core.display.Javascript object>
```



Here class 1 can be well separated from the rest of the files. However, this feature cannot separate other classes too well. We see almost 75% of points in class 2 have approximately 2000 jmp segments.

In [98]:
```
#Distribution of mov segments
ax = sns.boxplot(x="Class", y="mov", data=result_asm)
plt.title("boxplot of .asm mov opcode")
plt.show()
```

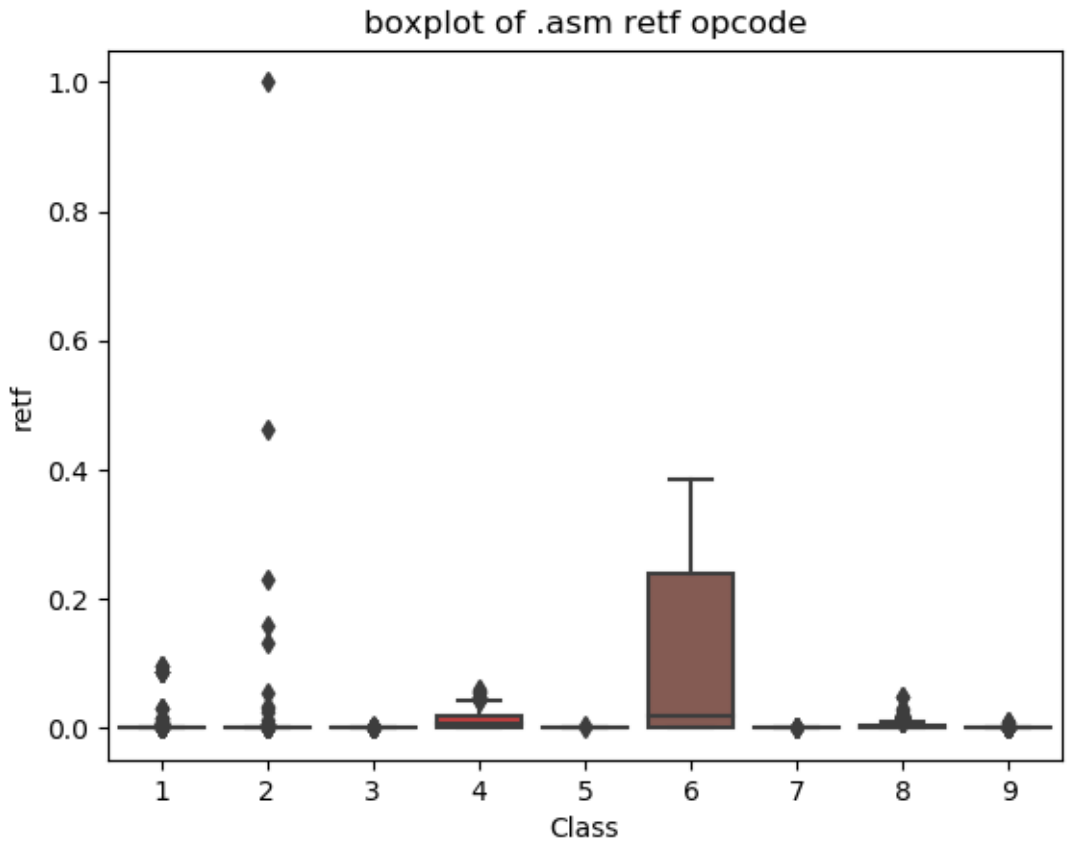
```
<IPython.core.display.Javascript object>
```



Here class 1 can be well separated from the rest of the files. However, this feature cannot separate other classes too well. We see almost 75% of points in class 2 have approximately 2000 jmp segments.

In [99]:
```
#Distribution of retf vs class labels
ax = sns.boxplot(x="Class", y="retf", data=result_asm)
plt.title("boxplot of .asm retf opcode")
plt.show()
```

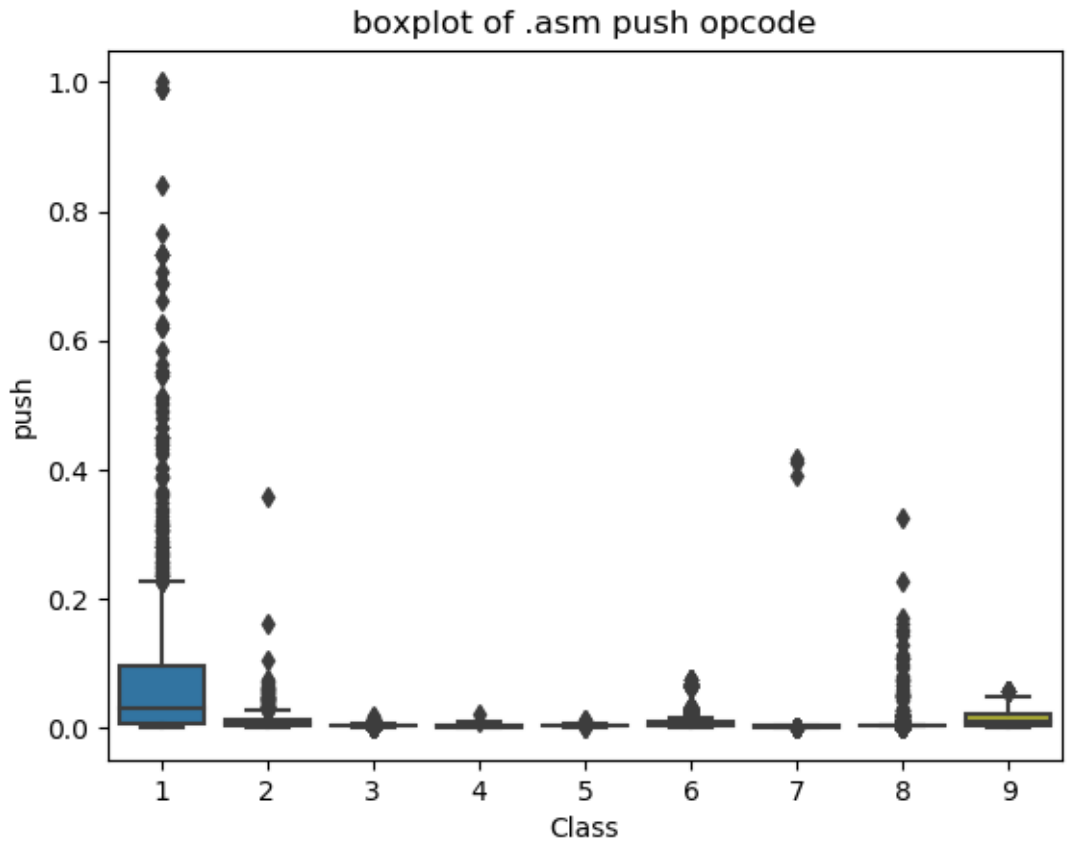
```
<IPython.core.display.Javascript object>
```



Here we see that using retf features, class 6 type of malware can be very easily separated from the rest of the malware classes.

In [100]:
```
#Distribution of push vs class labels
ax = sns.boxplot(x="Class", y="push", data=result_asm)
plt.title("boxplot of .asm push opcode")
plt.show()
```

```
<IPython.core.display.Javascript object>
```



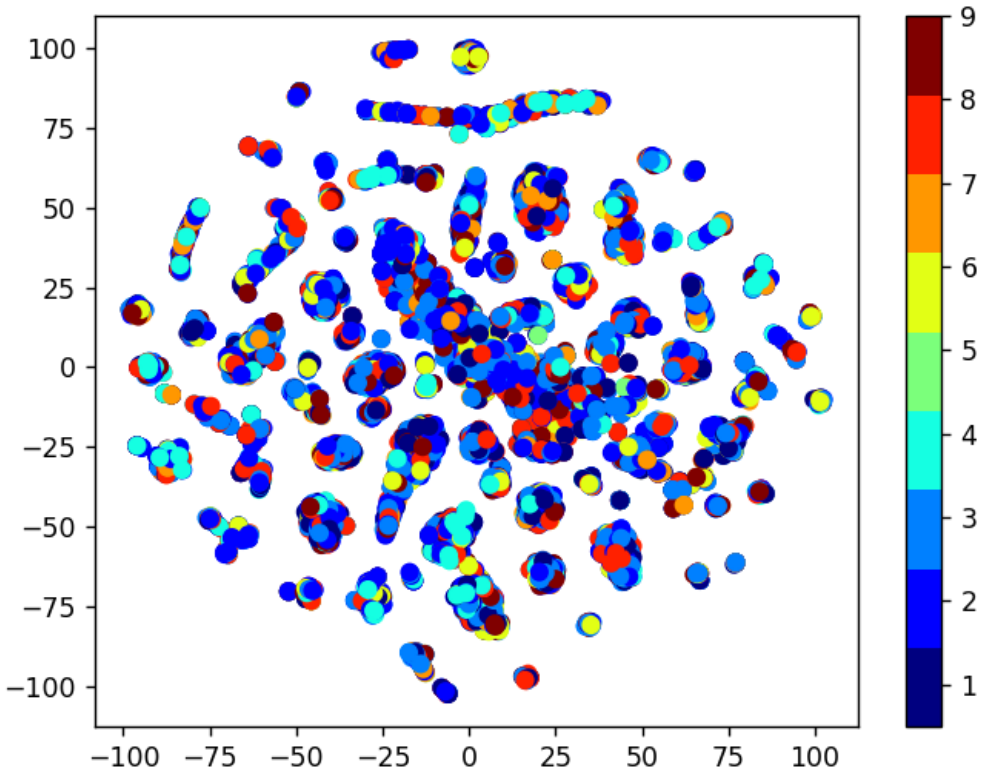
Here class 1 can be very well separated from the rest of classes using push features. The variance is very low for all other classes for this feature.

4.2.2 Multivariate Analysis on .asm file features

In [0]:

```
# by univariate analysis on the .asm file features we are getting very neglig
# 'rtn', '.BSS:' '.CODE' features, so here we are trying multivariate analysi
# the plot looks very messy

#Multivariate analysis on asm files features extracted using unigrams. We use

#Multivariate analysis on byte files features extracted using unigrams.
def draw_tsne_asm(p):
    xtsne=TSNE(perplexity=p)
    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()

draw_tsne_asm(30)
```

```
<IPython.core.display.Javascript object>
```



From the above TSNE plot, it's clear that the features we have extracted are certainly useful in determining the classes. There is a partial separability amongst all the features.

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.

Key Take-aways from the EDA section.

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 [51]:
```
#We will drop .BSS, .rtn, .CODE features from the dataset because we have see
asm_y = result_asm['Class']
asm_x = result_asm.drop(['ID','Class','.BSS:','rtn','.CODE'], axis=1)
```

In [52]:
```
#Train: 64%, Cross Validation 16%, Test 20%.
X_train_asm, X_test_asm, y_train_asm, y_test_asm = train_test_split(asm_x,asm
X_train_asm, X_cv_asm, y_train_asm, y_cv_asm = train_test_split(X_train_asm,
```

In [53]:
```
print( X_cv_asm.isnull().all())
```

```
size       False
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
```

4.4. Machine Learning models on features of .asm files

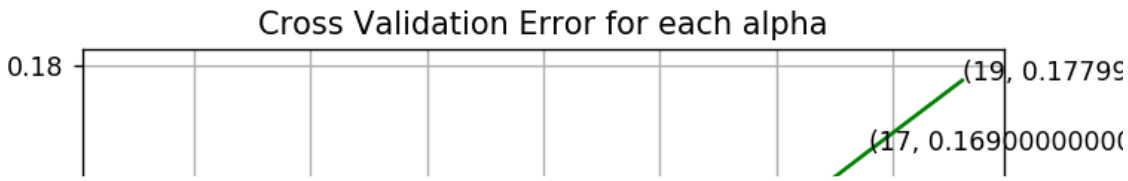
4.4.1 K-Nearest Neigbors

In [0]:

```
# find more about KNeighborsClassifier() here http://scikit-learn.org/stable/
# ------------------------
# default parameter
# KNeighborsClassifier(n_neighbors=5, weights='uniform', algorithm='auto', le
# 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
#-------------------------------------


# find more about CalibratedClassifierCV here at http://scikit-learn.org/stab
# ----------------------------
# default paramters
# sklearn.calibration.CalibratedClassifierCV(base_estimator=None, method='sig
#
# 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.clas

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 0.104531321344
log_loss for k =  3 is 0.0958800580948
log_loss for k =  5 is 0.0995466557335
log_loss for k =  7 is 0.107227274345
log_loss for k =  9 is 0.119239543547
log_loss for k =  11 is 0.133926642781
log_loss for k =  13 is 0.147643793967
log_loss for k =  15 is 0.159439699615
log_loss for k =  17 is 0.16878376444
log_loss for k =  19 is 0.178020728839

<IPython.core.display.Javascript object>
```



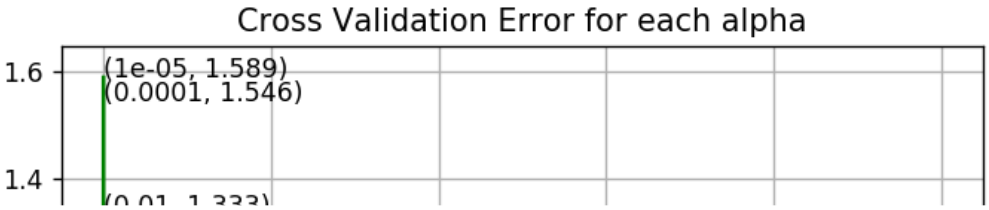
4.4.2 Logistic Regression

In [0]:

```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/g
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning
# 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
# predict(X)    Predict class labels for samples in X.

#------------------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online
#------------------------------


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.

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='b
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=log
predict_y = sig_clf.predict_proba(X_cv_asm)
print ('log loss for cv data',(log_loss(y_cv_asm, predict_y, labels=logisticR
predict_y = sig_clf.predict_proba(X_test_asm)
print ('log loss for test data',(log_loss(y_test_asm, predict_y, labels=logis
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

<IPython.core.display.Javascript object>
```



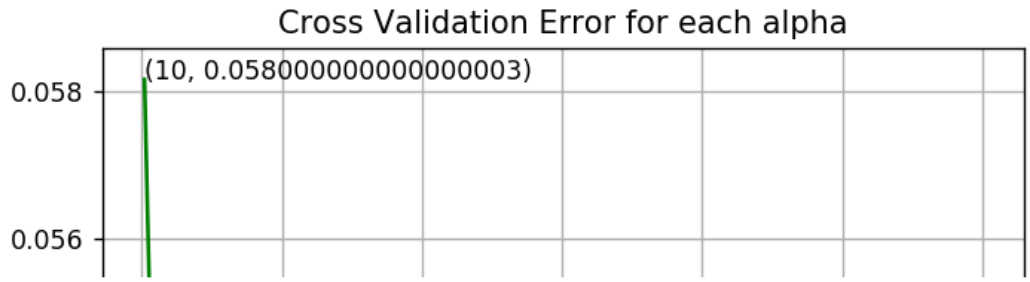
4.4.3 Random Forest Classifier

In [0]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini',
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given trai
# 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
# --------------------------------

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.clas

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
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
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.c
predict_y = sig_clf.predict_proba(X_test_asm)
print ('log loss for test data',(log_loss(y_test_asm, predict_y, labels=sig_c
```

```
57 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

<IPython.core.display.Javascript object>
```



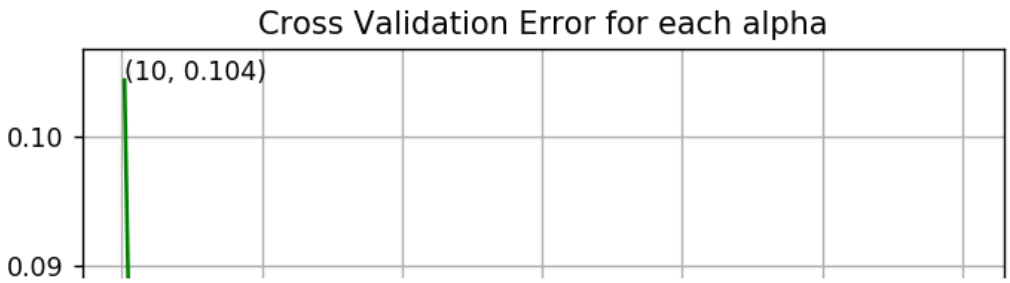
4.4.4 XgBoost Classifier

In [0]:

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

# find more about XGBClassifier function here http://xgboost.readthedocs.io/e
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# -----------------------

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.clas

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
predict_y = sig_clf.predict_proba(X_cv_asm)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
predict_y = sig_clf.predict_proba(X_test_asm)
```

```
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is
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

<IPython.core.display.Javascript object>
```



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_jo
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:   39.3
s
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  1.3min remaining:   23.0
s
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  1.4min remaining:    9.2
s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  2.3min finished
```

Out[163]:
```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=1, colsampl
e_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], 'co
lsample_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=10)
```

In [0]:
```
print (random_cfl.best_params_)
```

```
{'subsample': 1, 'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.15, 'c
olsample_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/e
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# -----------------------

x_cfl=XGBClassifier(n_estimators=200,subsample=0.5,learning_rate=0.15,colsamp
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 [60]:
```
1 result.head()
```

Out[60]:

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

5 rows × 260 columns

In [61]:
```
1 result_asm.head()
```

Out[61]:

	ID	size	Class	HEADER:	.text:	.Pav:	.idata:	.data:	.b
0	01azqd4InC7m9JpocGv5	0.400910	9	0.101695	0.032927	0.0	0.006937	0.542847	0.000
1	01IsoiSMh5gxyDYTl4CB	0.099719	2	0.000000	0.161391	0.0	0.003690	0.009758	0.000
2	01jsnpXSAlgw6aPeDxrU	0.060553	9	0.101695	0.101121	0.0	0.001821	0.000263	0.000
3	01kcPWA9K2BOxQeS5Rju	0.000432	1	0.107345	0.001092	0.0	0.000761	0.000023	0.000
4	01SuzwMJEIXsK7A8dQbl	0.006983	8	0.101695	0.015220	0.0	0.001234	0.001825	0.012

5 rows × 54 columns

In [62]:
```
1 print(result.shape)
2 print(result_asm.shape)
```

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

In [63]:
```
1 result_x = pd.merge(result,result_asm.drop(['Class'], axis=1),on='ID', how='l
2 result_y = result_x['Class']
3 result_x = result_x.drop(['ID','rtn','.BSS:','.CODE','Class'], axis=1)
4 result_x.head()
```

Out[63]:

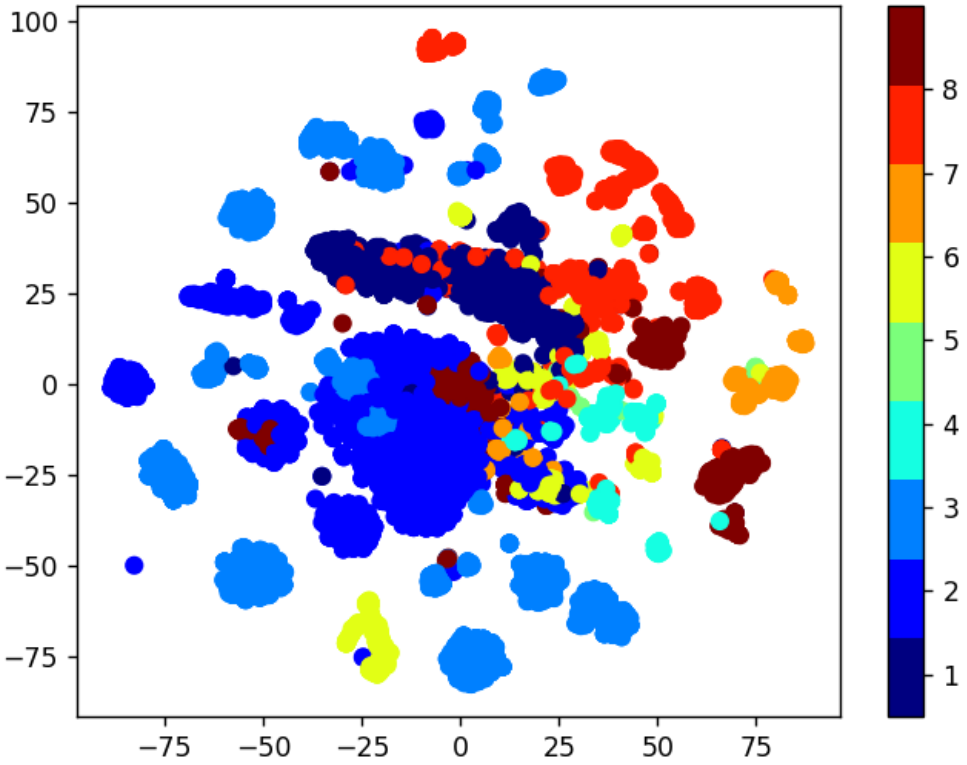
	0	1	2	3	4	5	6	7	8	
0	0.262806	0.005498	0.001567	0.002067	0.002048	0.001835	0.002058	0.002946	0.002638	0.003
1	0.017358	0.011737	0.004033	0.003876	0.005303	0.003873	0.004747	0.006984	0.008267	0.000
2	0.040827	0.013434	0.001429	0.001315	0.005464	0.005280	0.005078	0.002155	0.008104	0.002
3	0.009209	0.001708	0.000404	0.000441	0.000770	0.000354	0.000310	0.000481	0.000959	0.000
4	0.008629	0.001000	0.000168	0.000234	0.000342	0.000232	0.000148	0.000229	0.000376	0.000

5 rows × 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()
```

```
<IPython.core.display.Javascript object>
```



4.5.3. Train and Test split

In [0]:
```
X_train, X_test_merge, y_train, y_test_merge = train_test_split(result_x, res
X_train_merge, X_cv_merge, y_train_merge, y_cv_merge = train_test_split(X_tra
```

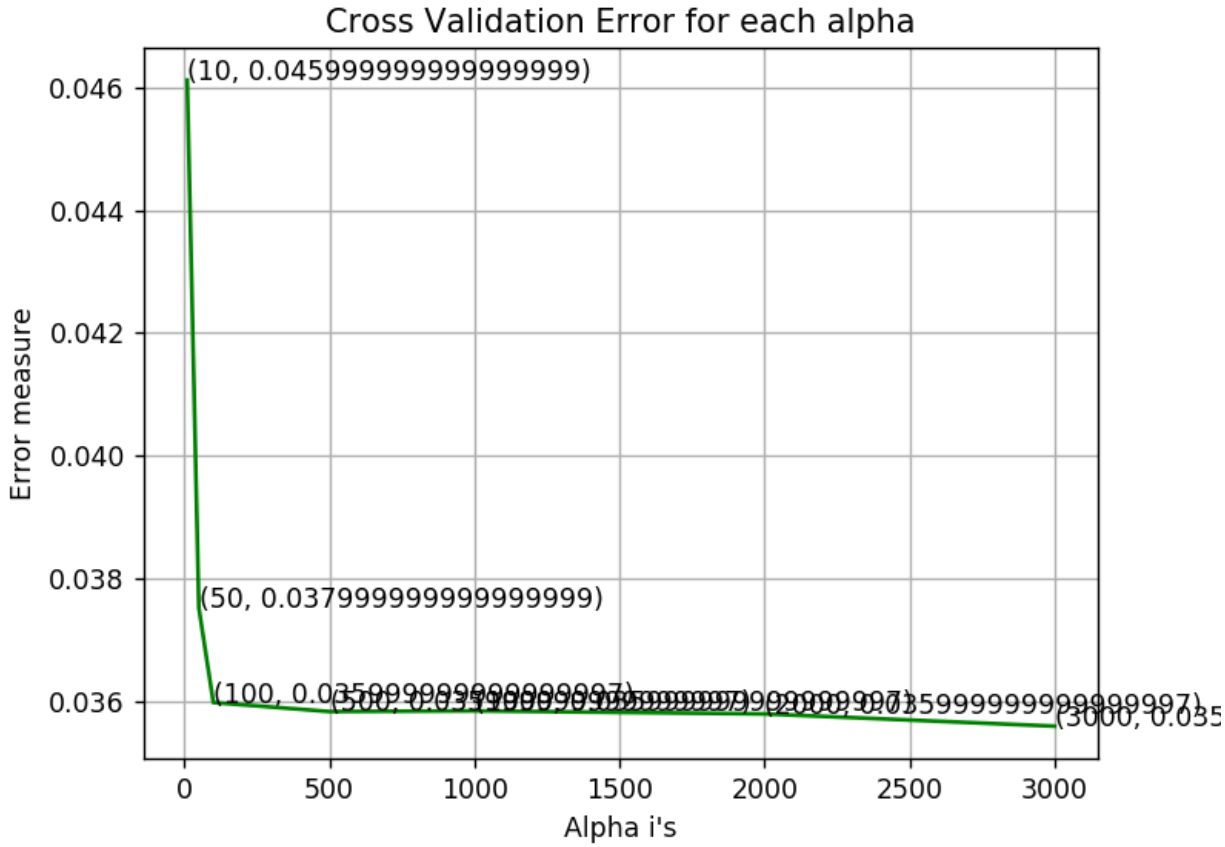
4.5.4. Random Forest Classifier on final features

In [0]:

```
# --------------------------------
# default parameters
# sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini',
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_
# class_weight=None)

# Some of methods of RandomForestClassifier()
# fit(X, y, [sample_weight])    Fit the SVM model according to the given trai
# 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
# --------------------------------

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.cl

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
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
predict_y = sig_clf.predict_proba(X_cv_merge)
```

```
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
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 for c =  10 is 0.0461221662017
log_loss for c =  50 is 0.0375229563452
log_loss for c =  100 is 0.0359765822455
log_loss for c =  500 is 0.0358291883873
log_loss for c =  1000 is 0.0358403093496
log_loss for c =  2000 is 0.0357908022178
log_loss for c =  3000 is 0.0355909487962

<IPython.core.display.Javascript object>
```



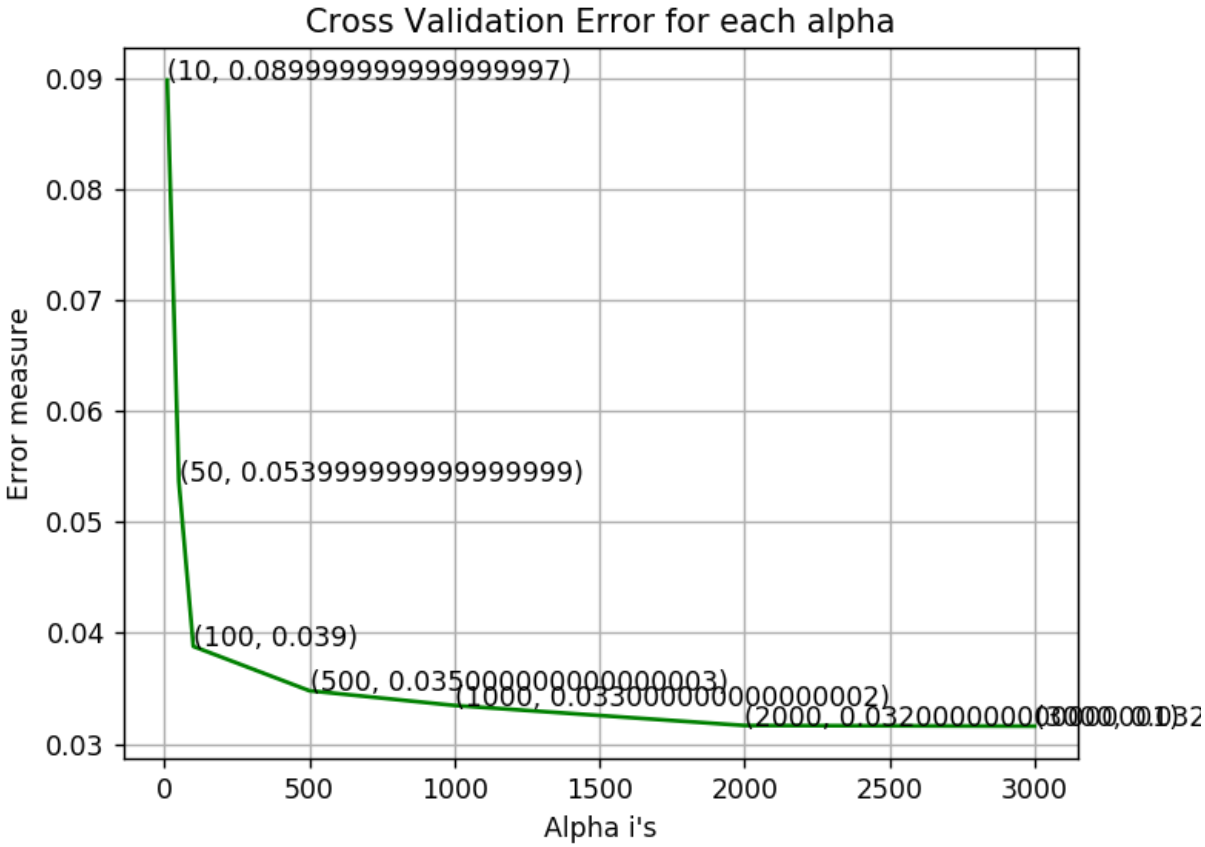

```
For values of best alpha =  3000 The train log loss is: 0.0166267614753
For values of best alpha =  3000 The cross validation log loss is: 0.0355909487
962
For values of best alpha =  3000 The test log loss is: 0.0401141303589
```

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/e
# -------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# -----------------------

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.cl

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


best_alpha = np.argmin(cv_log_error_array)

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

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

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

<IPython.core.display.Javascript object>
```




```
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: 0.0315972694
477
For values of best alpha =  3000 The test log loss is: 0.0323978515915
```

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_jo
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:  2.6mi
n
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  5.8min remaining:  1.8mi
n
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  6.7min remaining:   44.5
s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  7.4min finished
```

Out[187]:
```
RandomizedSearchCV(cv=None, error_score='raise',
          estimator=XGBClassifier(base_score=0.5, colsample_bylevel=1, colsampl
e_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], 'co
lsample_bytree': [0.1, 0.3, 0.5, 1], 'subsample': [0.1, 0.3, 0.5, 1]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=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/e
# ------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=10
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamm
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stoppi
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-onlin
# ----------------------

x_cfl=XGBClassifier(n_estimators=1000,max_depth=10,learning_rate=0.15,colsamp
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
predict_y = sig_clf.predict_proba(X_cv_merge)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
predict_y = sig_clf.predict_proba(X_test_merge)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is
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: 0.0344955487
471
For values of best alpha =  3000 The test log loss is: 0.0317041132442
```

5. Assignments

1. Add bi-grams and n-gram features on byte files and improve the log-loss
2. Using the 'dchad' github account (https://github.com/dchad/malware-detection) (https://github.com/dchad/malware-detection)), decrease the logloss to <=0.01
3. Watch the video (https://www.youtube.com/watch?v=VLQTRlLGz5Y (https://www.youtube.com/watch?v=VLQTRlLGz5Y)) that was in reference section and implement the image features to improve the logloss

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
import shutil
import os
import pandas as pd
import matplotlib
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
# matplotlib.use(u'nbAgg')
# %matplotib inline
```

5.1 Bigrams Feature extraction from byte files

Get the bigrams corpus

In [ ]:
```
byte_vocab = "00,01,02,03,04,05,06,07,08,09,0a,0b,0c,0d,0e,0f,10,11,12,13,14,
```

In [2]:
```
#This function will return all the possible 257*257 combinations of bigrams t
def get_bigram_tokens(tokens):
    sent=""
    byte_bigram_vocab=[]
    for i in range(len(tokens)):
        for j in range(len(tokens)):
            bigram=tokens[i]+" "+tokens[j]
            sent=sent+bigram+","
            byte_bigram_vocab.append(bigram)
    return byte_bigram_vocab

byte_bigram_vocab=get_bigram_tokens(tokens) #This will contain all the possib
```

Extract the byte bigram features and save the dataframe containing bi-

gram features

In [5]:
```
#Extract the byte bigram features and save the dataframe containing bi-gram f
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('byteFiles')
features=["ID"]+vectorizer.get_feature_names()
byte_bigram_df=pd.DataFrame(columns=features)

with open("features/byte_bigram_df.csv", mode='w') as byte_bigram_df:
    byte_bigram_df.write(','.join(map(str, features)))
    byte_bigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        file_id=file.split(".")[0] #ID of each file
        file = open('byteFiles/' + file)
        corpus=[file.read().replace('\n', ' ').lower()] #This will contain al
        bigrams=vectorizer.transform(corpus) #This will return a sparse vecto
        row=scipy.sparse.csr_matrix(bigrams).toarray() #Update each row of th
        byte_bigram_df.write(','.join(map(str, [file_id]+list(row[0])))) #Wri
        byte_bigram_df.write('\n')
        file.close()
```

```
10868it [3:29:50,  3.07it/s]
```

Read the byte bigrams count dataset

In [ ]:
```
#Use dask dataframe to avoid memory problems
byte_bigram_df=dd.read_csv("features/byte_bigram_df.csv",sample=256000000)
```

5.2 Registers Bigrams Feature extraction from ASM files

Get the registers sequence from the ASM files

In [6]:
```
registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']
registers_dict = dict(zip(registers, [1 for i in range(len(registers))]))
```

In [7]:
```
if not os.path.isdir("asmFilesRegisters"):
    os.mkdir('asmFilesRegisters')

#Get registers sequences for each of the files and save it as a text file. Ea
#at regular intervals with some words between them. So we have to extract the
#a bigram matrix of vectors can be calculated which will give us the 2 grams
def get_registers_seq():
    filenames=os.listdir('asmFiles')
    for asmfile in tqdm(filenames):
        registers_file = open("asmFilesRegisters/{}_registers_bigrams.txt".fo
        registers_sequence = ""
        with codecs.open('asmFiles/' + asmfile, encoding='cp1252', errors ='r
            for lines in file:
                line = lines.rstrip().split()
                for word in line:
                    if registers_dict.get(word)==1:
                        registers_sequence += word + ' '
        registers_file.write(registers_sequence + "\n")
        registers_file.close()

get_registers_seq()

registers_bigram_vocab=get_bigram_tokens(registers) #This will contain all th
```

```
100%|██████████| 10868/10868 [9:05:09<00:00,  1.03s/it]
```

Extract the registers bigram features and save the dataframe containing bi-gram features

In [8]:
```
#Extract the bigram features and save the dataframe containing bi-gram featur
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('asmFilesRegisters')
features=["ID"]+vectorizer.get_feature_names()
registers_bigram_df=pd.DataFrame(columns=features)

with open("features/registers_bigram_df.csv", mode='w') as registers_bigram_d
    registers_bigram_df.write(','.join(map(str, features)))
    registers_bigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        file_id=file.split("_")[0] #ID of each file
        file = open('asmFilesRegisters/' + file)
        corpus=[file.read().replace('\n', ' ').lower()] #This will contain al
        bigrams=vectorizer.transform(corpus) #This will return a sparse vecto
        row=scipy.sparse.csr_matrix(bigrams).toarray() #Update each row of th
        registers_bigram_df.write(','.join(map(str, [file_id]+list(row[0]))))
        registers_bigram_df.write('\n')
        file.close()
```

```
10868it [03:18, 54.69it/s]
```

Display the registers bigrams count dataset

In [129]:
```
registers_bigram_df=pd.read_csv("features/registers_bigram_df.csv")
registers_bigram_df.head()
```

Out[129]:

	ID	edx edx	edx esi	edx eax	edx ebx	edx ecx	edx edi	edx ebp	edx esp	edx eip	...	esp eip	eip edx	eip esi	eip eax
0	01azqd4InC7m9JpocGv5	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1	01IsoiSMh5gxyDYTl4CB	31	12	72	15	68	23	5	8	0	...	0	0	0	0
2	01jsnpXSAlgw6aPeDxrU	66	0	72	1	50	0	5	0	0	...	0	0	0	0
3	01kcPWA9K2BOxQeS5Rju	1	1	4	4	0	0	0	0	0	...	0	0	0	0
4	01SuzwMJEIXsK7A8dQbl	8	1	374	0	12	1	8	3	0	...	0	0	0	0

5 rows × 82 columns

In [ ]:
```
del(registers_bigram_df)
```

5.3 Registers Trigrams Feature extraction from ASM files

Get the trigram corpus

In [9]:
```
#TRIGRAMS
registers=['edx','esi','eax','ebx','ecx','edi','ebp','esp','eip']

#This function will return all the possible n*n combinations of trigrams that
def get_trigram_tokens(tokens):
    sent=""
    registers_trigram_vocab=[]
    for i in range(len(tokens)):
        for j in range(len(tokens)):
            for k in range(len(tokens)):
                trigram=tokens[i]+" "+tokens[j]+" "+tokens[k]
                registers_trigram_vocab.append(trigram)
    return registers_trigram_vocab

registers_trigram_vocab=get_trigram_tokens(registers) #This will contain all
```

Extract the registers trigram features and save the dataframe containing tri-gram features

In [10]:
```
#Extract the trigram features and save the dataframe containing tri-gram feat
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('asmFilesRegisters')
features=["ID"]+vectorizer.get_feature_names()
registers_trigram_df=pd.DataFrame(columns=features)

with open("features/registers_trigram_df.csv", mode='w') as registers_trigram
    registers_trigram_df.write(','.join(map(str, features)))
    registers_trigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        file_id=file.split("_")[0] #ID of each file
        file = open('asmFilesRegisters/' + file)
        corpus=[file.read().replace('\n', ' ').lower()] #This will contain al
        trigrams=vectorizer.transform(corpus) #This will return a sparse vect
        row=scipy.sparse.csr_matrix(trigrams).toarray() #Update each row of t
        registers_trigram_df.write(','.join(map(str, [file_id]+list(row[0]))))
        registers_trigram_df.write('\n')
        file.close()
```

```
10868it [01:12, 148.92it/s]
```

Display the registers trigrams count dataset

In [138]:
```
registers_trigram_df=pd.read_csv("features/registers_trigram_df.csv")
registers_trigram_df.head()
```

Out[138]:

	ID	edx edx edx	edx edx esi	edx edx eax	edx edx ebx	edx edx ecx	edx edx edi	edx edx ebp	edx edx esp	edx edx eip	...	eip esp eip	eip eip edx	eip eip esi	eip eip eax
0	01azqd4InC7m9JpocGv5	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1	01IsoiSMh5gxyDYTl4CB	6	1	10	0	12	2	0	0	0	...	0	0	0	0
2	01jsnpXSAlgw6aPeDxrU	23	0	18	0	23	0	2	0	0	...	0	0	0	0
3	01kcPWA9K2BOxQeS5Rju	0	0	0	1	0	0	0	0	0	...	0	0	0	0
4	01SuzwMJEIXsK7A8dQbl	3	0	1	0	2	0	2	0	0	...	0	0	0	0

5 rows × 730 columns

In [ ]:
```
del(registers_trigram_df)
```

5.4 Opcodes Bigrams Feature extraction from ASM files

In [11]:
```
#Putting the list in a dictionary to decrease time complexity
opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub',
opcode_dict = dict(zip(opcodes, [1 for i in range(len(opcodes))]))
```

Get the opcodes sequence from the ASM files

In [3]:
```
opcode_dict = dict(zip(opcodes, [1 for i in range(len(opcodes))]))
if not os.path.isdir("asmFilesOpcodes"):
    os.mkdir('asmFilesOpcodes')

#Get opcode sequences for each of the files and save it as a text file. Each
#at regular intervals with some words between them. So we have to extract the
#a bigram matrix of vectors can be calculated which will give us the 2 grams
def get_opcode_seq():
    filenames=os.listdir('asmFiles')
    for asmfile in tqdm(filenames):
        opcode_file = open("asmFilesOpcodes/{}_opcode_bigrams.txt".format(asm
        opcode_sequence = ""
        with codecs.open('asmFiles/' + asmfile, encoding='cp1252', errors ='r
            for lines in file:
                line = lines.rstrip().split()
                for word in line:
                    if opcode_dict.get(word)==1:
                        opcode_sequence += word + ' '
        opcode_file.write(opcode_sequence + "\n")
        opcode_file.close()

get_opcode_seq()

opcodes_bigram_vocab=get_bigram_tokens(opcodes)
```

```
100%|██████████| 10868/10868 [10:12:45<00:00,  1.09s/it]
```

Extract the opcodes bigram features and save the dataframe containing bi-gram features

In [14]:
```
#Extract the bigram features and save the dataframe containing bi-gram featur
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('asmFilesOpcodes')
features=["ID"]+vectorizer.get_feature_names()
opcodes_bigram_df=pd.DataFrame(columns=features)

with open("features/opcodes_bigram_df.csv", mode='w') as opcodes_bigram_df:
    opcodes_bigram_df.write(','.join(map(str, features)))
    opcodes_bigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        file_id=file.split("_")[0] #ID of each file
        file = open('asmFilesOpcodes/' + file)
        corpus=[file.read().replace('\n', ' ').lower()] #This will contain al
        bigrams=vectorizer.transform(corpus) #This will return a sparse vecto
        row=scipy.sparse.csr_matrix(bigrams).toarray() #Update each row of th
        opcodes_bigram_df.write(','.join(map(str, [file_id]+list(row[0])))) #
        opcodes_bigram_df.write('\n')
        file.close()
```

```
10868it [03:47, 47.81it/s]
```

Display the opcodes bigrams count dataset

In [2]:
```
opcodes_bigram_df=dd.read_csv("features/opcodes_bigram_df.csv")
opcodes_bigram_df.head()
```

Out[2]:

	ID	jmp jmp	jmp mov	jmp retf	jmp push	jmp pop	jmp xor	jmp retn	jmp nop	jmp sub	...	movzx cmp	movzx call
0	01azqd4InC7m9JpocGv5	440	192	0	6	0	17	0	0	24	...	0	0
1	01IsoiSMh5gxyDYTl4CB	0	32	0	3	1	3	1	0	0	...	1	0
2	01jsnpXSAlgw6aPeDxrU	0	0	0	0	0	0	0	0	0	...	12	0
3	01kcPWA9K2BOxQeS5Rju	0	5	0	1	0	2	1	0	0	...	0	0
4	01SuzwMJEIXsK7A8dQbl	5	57	1	4	1	1	0	0	0	...	11	0

5 rows × 677 columns

In [ ]:
```
del(opcodes_bigram_df)
```

5.5 Opcodes Trigrams Feature extraction from ASM files

Get the trigram corpus

In [16]:
```
#Putting the list in a dictionary to decrease time complexity
opcodes = ['jmp', 'mov', 'retf', 'push', 'pop', 'xor', 'retn', 'nop', 'sub',
opcodes_trigram_vocab=get_trigram_tokens(opcodes) #This will contain all the
```

Extract the opcodes trigrams features and save the dataframe containing tri-gram features

In [17]:
```
#Extract the trigram features and save the dataframe containing tri-gram feat
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('asmFilesOpcodes')
features=["ID"]+vectorizer.get_feature_names()
opcodes_trigram_df=pd.DataFrame(columns=features)

with open("features/opcodes_trigram_df.csv", mode='w') as opcodes_trigram_df:
    opcodes_trigram_df.write(','.join(map(str, features)))
    opcodes_trigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        file_id=file.split("_")[0] #ID of each file
        file = open('asmFilesOpcodes/' + file)
        corpus=[file.read().replace('\n', ' ').lower()] #This will contain al
        trigrams=vectorizer.transform(corpus) #This will return a sparse vect
        row=scipy.sparse.csr_matrix(trigrams).toarray() #Update each row of t
        opcodes_trigram_df.write(','.join(map(str, [file_id]+list(row[0]))))
        opcodes_trigram_df.write('\n')
        file.close()
```

```
10868it [06:25, 32.60it/s]
```

Load the opcodes trigrams count dataset

In [151]:
```
opcodes_trigram_df=pd.read_csv("features/opcodes_trigram_df.csv")
opcodes_trigram_df.head()
```

Out[151]:

	ID	jmp jmp jmp	jmp jmp mov	jmp jmp retf	jmp jmp push	jmp jmp pop	jmp jmp xor	jmp jmp retn	jmp jmp nop	jmp jmp sub	...	movzx movzx cmp	movzx movzx call
0	01azqd4InC7m9JpocGv5	437	0	0	0	0	1	0	0	0	...	0	0
1	01IsoiSMh5gxyDYTl4CB	0	0	0	0	0	0	0	0	0	...	0	0
2	01jsnpXSAlgw6aPeDxrU	0	0	0	0	0	0	0	0	0	...	1	0
3	01kcPWA9K2BOxQeS5Rju	0	0	0	0	0	0	0	0	0	...	0	0
4	01SuzwMJEIXsK7A8dQbl	2	1	1	1	0	0	0	0	0	...	1	0

5 rows × 17577 columns

In [ ]:
```
1 del(opcodes_trigram_df)
```

5.6 Extract Image features from the ASM files

Refer: https://www.kaggle.com/c/malware-classification/discussion/13897#latest-105551 (https://www.kaggle.com/c/malware-classification/discussion/13897#latest-105551)

I have used the code snippets by:

1. Xiaozhou Wang, xiaozhou@ualberta.ca (mailto:xiaozhou@ualberta.ca)
2. Jiwei Liu, University of Pittsburgh, aixueer4ever@gmail.com (mailto:aixueer4ever@gmail.com)
3. Xueer Chen, University of Pittsburgh, xuer.chen.human@gmail.com (mailto:xuer.chen.human@gmail.com)

I have used the code from the pdf provided at: https://www.kaggle.com/c/malware-classification/discussion/13897#latest-105551 (https://www.kaggle.com/c/malware-classification/discussion/13897#latest-105551)

I have also used this as a reference: https://github.com/dchad/malware-detection (https://github.com/dchad/malware-detection)

Convert the ASM files and BYTE files to images. (Original Image Dimensions are retained here)

In [19]:
```
import numpy as np
import os
import codecs
import imageio
import array
from datetime import datetime as dt

if not os.path.isdir("asmFileImages"):
    os.mkdir("asmFileImages")
if not os.path.isdir("byteFileImages"):
    os.mkdir("byteFileImages")

asmfile_list=os.listdir("asmFiles/")
bytefile_list=os.listdir("byteFiles/")

#This function will generate images from ASM files and Byte files.
def get_images_from_text(filename_list, save_folder):
    for filename in tqdm(filename_list):

        if(filename.endswith("asm")):
            file = codecs.open("asmFiles/"+filename, 'rb')
            file_size = os.path.getsize("asmFiles/"+filename)
        else:
            file = open("byteFiles/"+filename, 'rb')
            file_size = os.path.getsize("byteFiles/"+filename)

        file_width = int(file_size**0.5)
        rem = file_size%file_width
        img_array = array.array('B')
        img_array.fromfile(file,file_size-rem)
        file.close()
        img_arr_final = np.reshape(img_array[:file_width * file_width], (file
        img_arr_final = np.uint8(img_arr_final)
        imageio.imsave(save_folder+'/' + filename.split(".")[0] + '.png',resi
```

In [ ]:
```
#Convert ASM files to Images
get_images_from_text(asmfile_list,'asmFileImages')
```

In [ ]:
```
#Convert Byte files to Images
get_images_from_text(bytefile_list,'byteFileImages')
```

Resize the ASM and Byte image files to 256x256 dimensions. Keep the original images untouched.

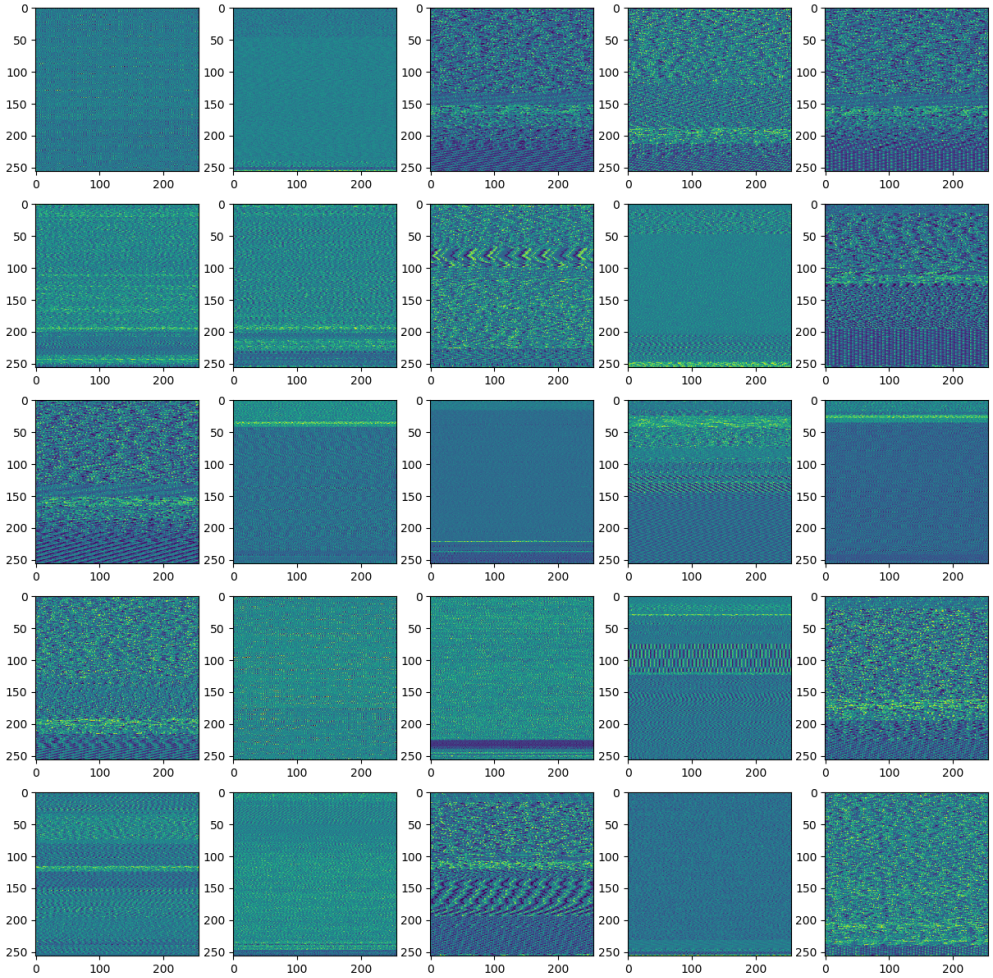
Own Reference: https://stackoverflow.com/questions/44650888/resize-an-image-without-distortion-opencv/49208362#49208362 (https://stackoverflow.com/questions/44650888/resize-an-image-without-distortion-opencv/49208362#49208362)

In [4]:
```
import cv2
import os
import imageio
from tqdm import tqdm
import random

#Take any image as input, resize it to 256x256, return the resized image
def resize_image(image):
    resized_image = cv2.resize(image, (256,256), interpolation = cv2.INTER_AR
    return resized_image
```

Display some sample images that we have obtained from ASM files.

In [6]:
```
image_dir = "asmFileImages/"
filenames=random.sample(os.listdir(image_dir),26)

#Display 25 images from ASM files
plt.figure(figsize=(15,15))
for i in range(1,len(filenames)):
    row = i
    image = imageio.imread(image_dir+filenames[i]) #Image(filename=image_dir+
    image = resize_image(image)
    plt.subplot(5,5,row)
    plt.imshow(image)
plt.show()
```

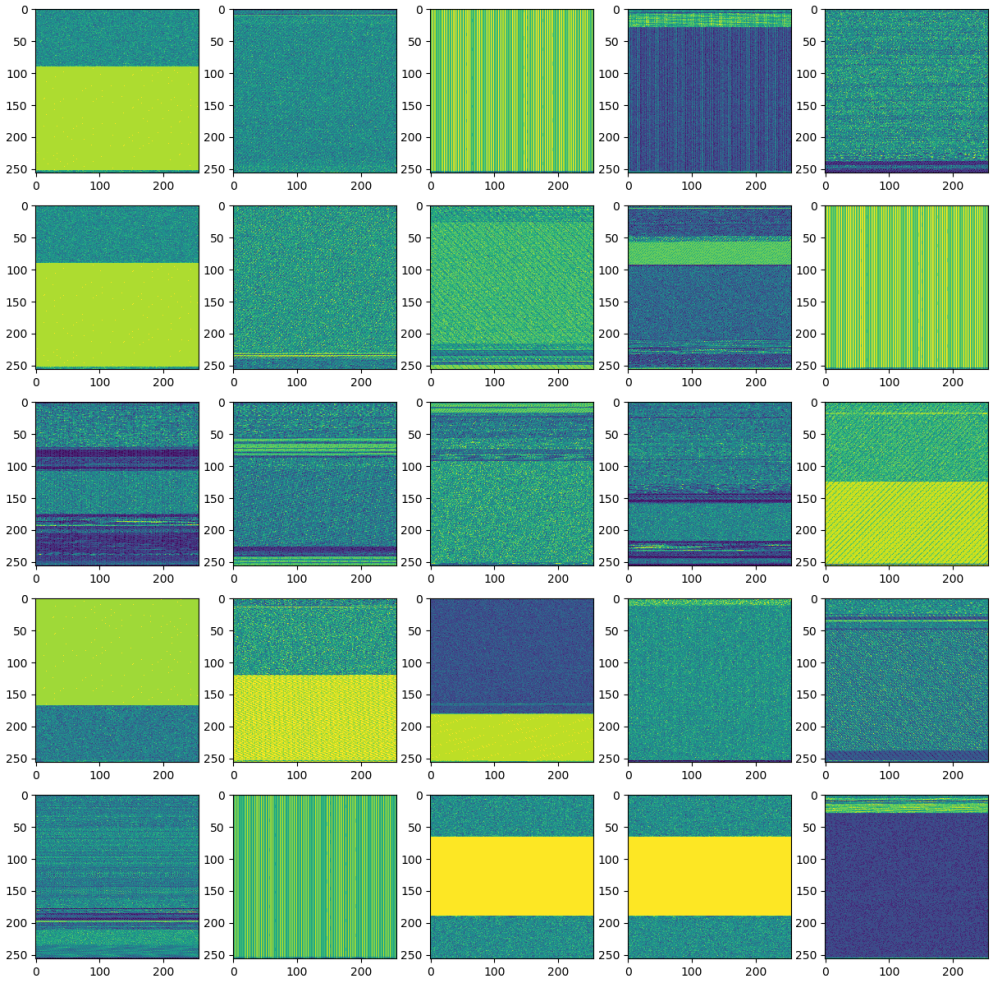
```
<IPython.core.display.Javascript object>
```



Display some sample images that we have obtained from Byte files.

In [5]:
```
image_dir = "byteFileImages/"
filenames=random.sample(os.listdir(image_dir),26)

#Display 25 images from BYTE files
plt.figure(figsize=(15,15))
for i in range(1,len(filenames)):
    row = i
    image = imageio.imread(image_dir+filenames[i]) #Image(filename=image_dir+
    image = resize_image(image)
    plt.subplot(5,5,row)
    plt.imshow(image)
plt.show()
```

```
<IPython.core.display.Javascript object>
```



Load the image, convert it into a numpy array and take the first 800 pixels from each image.

In [10]:
```
import os
from scipy.misc import imread
import imageio
from tqdm import tqdm

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

Get first 800 pixel information from ASM File Images

In [50]:
```
file_lists=os.listdir('asmFileImages/')

with open("features/asm_image_df.csv", mode='w') as asm_image_df: #file_lists
    asm_image_df.write(','.join(map(str, ["ID"]+["Pixel{}".format(i) for i in
    asm_image_df.write('\n')

    for image in tqdm(file_lists):
        file_id=image.split(".")[0]
        image_array=imageio.imread("asmFileImages/"+image) #This will contain
        image_array=image_array.flatten()[:800] #Taking the first 1000 pixels
        asm_image_df.write(','.join(map(str, [file_id]+list(image_array))))
        asm_image_df.write('\n') #Write to the dataframe
```

100%|██████████| 10868/10868 [20:59<00:00, 20.28it/s]

Display the ASM Image dataframe

In [51]:
```
asm_image_df=pd.read_csv("features/asm_image_df.csv")
asm_image_df.head()
```

Out[51]:

	ID	Pixel0	Pixel1	Pixel2	Pixel3	Pixel4	Pixel5	Pixel6	Pixel7	Pixel8	...
0	01azqd4InC7m9JpocGv5	72	69	65	68	69	82	58	48	48	...
1	01IsoiSMh5gxyDYTl4CB	46	116	101	120	116	58	48	48	52	...
2	01jsnpXSAlgw6aPeDxrU	72	69	65	68	69	82	58	48	48	...
3	01kcPWA9K2BOxQeS5Rju	72	69	65	68	69	82	58	49	48	...
4	01SuzwMJEIXsK7A8dQbl	72	69	65	68	69	82	58	48	48	...

5 rows × 801 columns

In [54]:
```
del(asm_image_df)
```

Get first 800 pixel information from Byte File Images

In [52]:
```
file_lists=os.listdir('byteFileImages/')

with open("features/byte_image_df.csv", mode='w') as byte_image_df: #file_lis
    byte_image_df.write(','.join(map(str, ["ID"]+["Pixel{}".format(i) for i i
    byte_image_df.write('\n')

    for image in tqdm(file_lists):
        file_id=image.split(".")[0]
        image_array=imageio.imread("byteFileImages/"+image) #This will contai
        image_array=image_array.flatten()[:800] #Taking the first 1000 pixels
        byte_image_df.write(','.join(map(str, [file_id]+list(image_array))))
        byte_image_df.write('\n') #Write to the dataframe
```

```
100%|██████████| 10868/10868 [10:51<00:00, 16.67it/s]
```

Display the BYTE image dataframe

In [53]:
```
byte_image_df=pd.read_csv("features/byte_image_df.csv")
byte_image_df.head()
```

Out[53]:

	ID	Pixel0	Pixel1	Pixel2	Pixel3	Pixel4	Pixel5	Pixel6	Pixel7	Pixel8	...
0	01azqd4InC7m9JpocGv5	69	56	32	48	66	32	48	48	32	...
1	01IsoiSMh5gxyDYTI4CB	67	55	32	48	49	32	50	52	32	...
2	01jsnpXSAlgw6aPeDxrU	67	66	32	67	66	32	67	66	32	...
3	01kcPWA9K2BOxQeS5Rju	54	65	32	70	70	32	54	56	32	...
4	01SuzwMJEIXsK7A8dQbl	65	52	32	65	67	32	52	65	32	...

5 rows × 801 columns

In [55]:
```
del(byte_image_df)
```

5.7 Extract CNN Codes from the image files using Pretrained VGG-16 on ImageNet data

In [4]:
```
from datetime import datetime as dt
from keras.preprocessing.image import ImageDataGenerator
from keras import applications
import numpy as np
```

```
Using TensorFlow backend.
```

Get CNN codes for ASM Files

In [4]:

```
global_start=dt.now()

#We will take 256 x 256 image dimensions, because the least dimension that wa
img_width, img_height = 256, 256
batch_size=44

#Declaration of parameters needed for training and validation
data_dir = 'finalASMimages'
global bottleneck_features

#Get the bottleneck features by  Weights.T * Xi
def save_bottleneck_features_asm():
    datagen = ImageDataGenerator(rescale=1./255)

    #Load the pre trained VGG16 model from Keras, we will initialize only the
    model = applications.VGG16(include_top=False, weights='imagenet')

    generator_tr = datagen.flow_from_directory(data_dir,
                                               target_size=(img_width, img_heigh
                                               batch_size=batch_size,
                                               class_mode=None, #class_mode=None
                                               shuffle=False) #We won't shuffle
    nb_train_samples = len(generator_tr.filenames)
    bottleneck_features = model.predict_generator(generator_tr, nb_train_samp

    np.save('features/final_features/asm_files_bottleneck_features.npy',bottl
    print("Got the bottleneck features in time: ",dt.now()-global_start)

save_bottleneck_features_asm()
```

```
Found 10868 images belonging to 1 classes.
Got the bottleneck features in time:  1:41:29.963485
```

Get CNN codes for Byte Files

In [6]:
```
global_start=dt.now()

#We will take 256 x 256 image dimensions, because the least dimension that wa
img_width, img_height = 256, 256
batch_size=44

#Declaration of parameters needed for training and validation
data_dir = "finalBYTEimages"

#Get the bottleneck features by  Weights.T * Xi
def save_bottleneck_features_byte():
    datagen = ImageDataGenerator(rescale=1./255)

    #Load the pre trained VGG16 model from Keras, we will initialize only the
    model = applications.VGG16(include_top=False, weights='imagenet')

    generator_tr = datagen.flow_from_directory(data_dir,
                                               target_size=(img_width, img_heigh
                                               batch_size=batch_size,
                                               class_mode=None, #class_mode=None
                                               shuffle=False) #We won't shuffle
    nb_train_samples = len(generator_tr.filenames)
    bottleneck_features = model.predict_generator(generator_tr, nb_train_samp

    np.save('features/final_features/byte_files_bottleneck_features.npy',bott
    print("Got the bottleneck features in time: ",dt.now()-global_start)

save_bottleneck_features_byte()
```

```
Found 10868 images belonging to 1 classes.
Got the bottleneck features in time:  1:52:11.927833
```

Prediction using only CNN Codes

In [2]:
```
import numpy as np
asm_bottleneck = np.load("features/final_features/asm_files_bottleneck_featur
asm_bottleneck.shape
```

Out[2]:
```
(10868, 8, 8, 512)
```

In [1]:
```
import numpy as np
asm_bottleneck = np.load("features/final_features/asm_files_bottleneck_featur
byte_bottleneck = np.load("features/final_features/byte_files_bottleneck_feat
bot_feats = np.hstack((asm_bottleneck,byte_bottleneck))
np.save('features/final_features/bot_feats.npy',bot_feats)

import gc
gc.collect()
```

Out[1]:
```
16
```

TODO: Trigrams + Fourgrams + Fivegrams + 6Grams Feature extraction

from byte + ASM files

TODO: Get count of malicious words

In [114]:
```
#TRIGRAMS
"""tokens="00,01,02,03,04,05,06,07,08,09,0a,0b,0c,0d,0e,0f,10,11,12,13,14,15,
tokens=tokens.split(",")

#This function will return all the possible 257*257*257 combinations of trigr
def get_trigram_tokens(tokens):
    sent=""
    byte_trigram_vocab=[]
    for i in tqdm(range(len(tokens))):
        for j in range(len(tokens)):
            for k in range(len(tokens)):
                trigram=tokens[i]+" "+tokens[j]+" "+tokens[k]
                sent=sent+trigram+","
                byte_trigram_vocab.append(trigram)
    return byte_trigram_vocab

byte_trigram_vocab=get_trigram_tokens(tokens) #This will contain all the poss

#Extract the trigram features and save the dataframe containing bi-gram featu
"""vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False
file_lists=os.listdir('byteFiles')
bytetrigram_vector = scipy.sparse.csr_matrix((1, len(byte_trigram_vocab))) #f

byte_trigram_df=pd.DataFrame(columns=vectorizer.get_feature_names())

with open("features/byte_trigram_df.csv", mode='w') as byte_trigram_df:
    byte_trigram_df.write(','.join(map(str, vectorizer.get_feature_names())))
    byte_trigram_df.write('\n')
    for _, file in tqdm(enumerate(file_lists)):
        f = open('byteFiles/' + file)
        corpus=[f.read().replace('\n', ' ').lower()] #This will contain all t
        trigrams=vectorizer.fit_transform(corpus) #This will return a sparse
        row=scipy.sparse.csr_matrix(trigrams).toarray() #Update each row of t
        byte_trigram_df.write(','.join(map(str, row[0])))
        byte_trigram_df.write('\n')
        f.close() """

print("TODO: Trigrams Feature extraction from byte files ")
```

```
TODO: Trigrams Feature extraction from byte files
```

6.0 Getting the most important features using using SelectKBest with Chi-Square Test

In [ ]:
```
from sklearn.feature_selection import SelectKBest, chi2

if not os.path.isdir("features/final_features"):
    os.mkdir("features/final_features")

if not os.path.isdir("features/feature_score"):
    os.mkdir("features/feature_score")

if not os.path.isdir("features/final_features"):
    os.mkdir("features/final_features")

#Load the class labels for training with random forest feature selector
with open('features/class_labels.pkl', 'rb') as file:
    labels=pkl.load(file)
```

6.1 Getting the 50 most important features for Registers bigrams

In [7]:
```
#Load the non normalized bigrams dataset
X=pd.read_csv('features/registers_bigram_df.csv')
y=labels
X.head()
```

Out[7]:

	ID	edx edx	edx esi	edx eax	edx ebx	edx ecx	edx edi	edx ebp	edx esp	edx eip	...	esp eip	eip edx	eip esi	eip eax
0	01azqd4InC7m9JpocGv5	55	97	211	33	130	40	15	0	0	...	0	0	0	0
1	01IsoiSMh5gxyDYTl4CB	31	12	72	15	68	23	5	8	0	...	0	0	0	0
2	01jsnpXSAlgw6aPeDxrU	66	0	72	1	50	0	5	0	0	...	0	0	0	0
3	01kcPWA9K2BOxQeS5Rju	1	1	4	4	0	0	0	0	0	...	0	0	0	0
4	01SuzwMJEIXsK7A8dQbl	8	1	374	0	12	1	8	3	0	...	0	0	0	0

5 rows × 82 columns

In [9]:
```
#Get the best 50 features using SelectKBest. Save the feature scores along wi
kbest_object=SelectKBest(score_func=chi2, k=50)
best_features=kbest_object.fit(X.drop("ID", axis=1),y)
df_scores=pd.DataFrame(best_features.scores_)
df_columns=pd.DataFrame(X.columns)
feature_score_df=pd.concat([df_columns,df_scores],axis=1)
feature_score_df.columns=["Feature_Name","Feature_Score"]

#Let's look at the top 50 features along with their scores + Save the feature
feature_score_df=feature_score_df.nlargest(50,"Feature_Score")
feature_score_df.to_csv("features/feature_score/registers_bigram_df.csv", ind
feature_score_df.head(5)
```

Out[9]:

	Feature_Name	Feature_Score
47	edi esi	27901.216442
20	eax esi	25442.443807
23	eax ecx	24936.321815
21	eax eax	20482.605329
11	esi esi	19799.204224

In [10]:
```
#Get the first 50 feature names in a list
top_50_feats=list(feature_score_df["Feature_Name"])

#Get the dataframe containing the top 50 features
reduced_features=pd.concat([X["ID"],X[top_50_feats]], axis=1)

#Save the dataframe containing the top 50 features
reduced_features.to_csv("features/final_features/top50_registers_bigram_df.cs
```

In [ ]:
```
del(X, feature_score_df, reduced_features)
```

6.2 Getting the 300 most important features from Registers trigrams

In [14]:
```
#Load the non normalized bigrams dataset
X=pd.read_csv('features/registers_trigram_df.csv')
y=labels
X.head()
```

Out[14]:

	ID	edx edx edx	edx edx esi	edx edx eax	edx edx ebx	edx edx ecx	edx edx edi	edx edx ebp	edx edx esp	edx edx eip	...	eip esp eip	eip eip edx	eip eip esi	eip eip eax
0	01azqd4InC7m9JpocGv5	7	2	27	6	9	3	1	0	0	...	0	0	0	0
1	01IsoiSMh5gxyDYTl4CB	6	1	10	0	12	2	0	0	0	...	0	0	0	0
2	01jsnpXSAlgw6aPeDxrU	23	0	18	0	23	0	2	0	0	...	0	0	0	0
3	01kcPWA9K2BOxQeS5Rju	0	0	0	1	0	0	0	0	0	...	0	0	0	0
4	01SuzwMJEIXsK7A8dQbl	3	0	1	0	2	0	2	0	0	...	0	0	0	0

5 rows × 730 columns

In [15]:
```
#Get the best 300 features using SelectKBest. Save the feature scores along w
kbest_object=SelectKBest(score_func=chi2, k=300)
best_features=kbest_object.fit(X.drop("ID", axis=1),y)
df_scores=pd.DataFrame(best_features.scores_)
df_columns=pd.DataFrame(X.columns)
feature_score_df=pd.concat([df_columns,df_scores],axis=1)
feature_score_df.columns=["Feature_Name","Feature_Score"]

#Let's look at the top 300 features along with their scores + Save the featur
feature_score_df=feature_score_df.nlargest(300,"Feature_Score")
feature_score_df.to_csv("features/feature_score/registers_trigram_df.csv", in
feature_score_df.head(5)
```

Out[15]:

	Feature_Name	Feature_Score
637	esp esp ebp	19633.605891
50	edx edi ecx	11379.497387
189	eax eax eip	11371.244132
182	eax eax esi	11124.759127
410	edi edx ecx	11075.744257

In [16]:
```
#Get the first 300 feature names in a list
top_300_feats=list(feature_score_df["Feature_Name"])

#Get the dataframe containing the top 300 features
reduced_features=pd.concat([X["ID"],X[top_300_feats]], axis=1)

#Save the dataframe containing the top 300 features
reduced_features.to_csv("features/final_features/top300_registers_trigram_df.
```

In [ ]:
```
del(X, feature_score_df, reduced_features)
```

6.3 Getting the 500 most important features from Opcodes bigrams

In [17]:
```
#Load the non normalized bigrams dataset
X=pd.read_csv('features/opcodes_bigram_df.csv')
y=labels
X.head()
```

Out[17]:

	ID	jmp jmp	jmp mov	jmp retf	jmp push	jmp pop	jmp xor	jmp retn	jmp nop	jmp sub	...	movzx cmp	movzx call
0	01azqd4InC7m9JpocGv5	440	192	0	6	0	17	0	0	24	...	0	0
1	01IsoiSMh5gxyDYTl4CB	0	32	0	3	1	3	1	0	0	...	1	0
2	01jsnpXSAlgw6aPeDxrU	0	0	0	0	0	0	0	0	0	...	12	0
3	01kcPWA9K2BOxQeS5Rju	0	5	0	1	0	2	1	0	0	...	0	0
4	01SuzwMJEIXsK7A8dQbl	5	57	1	4	1	1	0	0	0	...	11	0

5 rows × 677 columns

In [18]:
```
#Get the best 500 features using SelectKBest. Save the feature scores along w
kbest_object=SelectKBest(score_func=chi2, k=500)
best_features=kbest_object.fit(X.drop("ID", axis=1),y)
df_scores=pd.DataFrame(best_features.scores_)
df_columns=pd.DataFrame(X.columns)
feature_score_df=pd.concat([df_columns,df_scores],axis=1)
feature_score_df.columns=["Feature_Name","Feature_Score"]

#Let's look at the top 500 features along with their scores + Save the featur
feature_score_df=feature_score_df.nlargest(500,"Feature_Score")
feature_score_df.to_csv("features/feature_score/opcodes_bigram_df.csv", index
feature_score_df.head(5)
```

Out[18]:

	Feature_Name	Feature_Score
200	nop call	284660.375541
27	mov jmp	276173.423650
475	shl retn	225563.920296
38	mov add	111179.349251
313	imul jmp	106299.863432

In [19]:
```
#Get the first 500 feature names in a list
top_500_feats=list(feature_score_df["Feature_Name"])

#Get the dataframe containing the top 500 features
reduced_features=pd.concat([X["ID"],X[top_500_feats]], axis=1)

#Save the dataframe containing the top 500 features
reduced_features.to_csv("features/final_features/top500_opcodes_bigram_df.csv
```

In [ ]:
```
del(X, feature_score_df, reduced_features)
```

6.4 Getting the 500 most important features from Opcodes trigrams

In [20]:
```
#Load the non normalized bigrams dataset
X=pd.read_csv('features/opcodes_trigram_df.csv')
y=labels
X.head()
```

Out[20]:

	ID	jmp jmp jmp	jmp jmp mov	jmp jmp retf	jmp jmp push	jmp jmp pop	jmp jmp xor	jmp jmp retn	jmp jmp nop	jmp jmp sub	...	movzx movzx cmp	movzx movzx call
0	01azqd4InC7m9JpocGv5	437	0	0	0	0	1	0	0	0	...	0	0
1	01IsoiSMh5gxyDYTl4CB	0	0	0	0	0	0	0	0	0	...	0	0
2	01jsnpXSAlgw6aPeDxrU	0	0	0	0	0	0	0	0	0	...	1	0
3	01kcPWA9K2BOxQeS5Rju	0	0	0	0	0	0	0	0	0	...	0	0
4	01SuzwMJEIXsK7A8dQbl	2	1	1	1	0	0	0	0	0	...	1	0

5 rows × 17577 columns

In [21]:
```
#Get the best 500 features using SelectKBest. Save the feature scores along w
kbest_object=SelectKBest(score_func=chi2, k=500)
best_features=kbest_object.fit(X.drop("ID", axis=1),y)
df_scores=pd.DataFrame(best_features.scores_)
df_columns=pd.DataFrame(X.columns)
feature_score_df=pd.concat([df_columns,df_scores],axis=1)
feature_score_df.columns=["Feature_Name","Feature_Score"]

#Let's look at the top 500 features along with their scores + Save the featur
feature_score_df=feature_score_df.nlargest(500,"Feature_Score")
feature_score_df.to_csv("features/feature_score/opcodes_trigram_df.csv", inde
feature_score_df.head(5)
```

Out[21]:

	Feature_Name	Feature_Score
12368	shl nop call	361070.460585
703	mov mov jmp	239711.417051
8312	imul nop call	201312.047619
5207	nop shl retn	201052.627929
10496	shr xchg call	200793.864581

In [22]:
```
#Get the first 500 feature names in a list
top_500_feats=list(feature_score_df["Feature_Name"])

#Get the dataframe containing the top 500 features
reduced_features=pd.concat([X["ID"],X[top_500_feats]], axis=1)

#Save the dataframe containing the top 500 features
reduced_features.to_csv("features/final_features/top500_opcodes_trigram_df.cs
```

In [ ]:
```
del(X, feature_score_df, reduced_features)
```

6.5 Getting the 1000 most important features from Byte bigrams

In [5]:
```
#Load the non normalized bigrams dataset
X=dd.read_csv('features/byte_bigram_df.csv', sample=25600000)
y=labels
X.head()
```

Out[5]:

	ID	00 00	00 01	00 02	00 03	00 04	00 05	00 06	00 07	00 08	...	?? f7	?? f8
0	01azqd4InC7m9JpocGv5	274425	1269	1029	1469	1227	1144	1437	1263	1174	...	0	0
1	01IsoiSMh5gxyDYTl4CB	21075	752	73	48	175	12	10	11	42	...	0	0
2	01jsnpXSAlgw6aPeDxrU	16798	596	159	144	513	595	557	146	528	...	0	0
3	01kcPWA9K2BOxQeS5Rju	10417	225	61	69	114	40	25	22	63	...	0	0
4	01SuzwMJEIXsK7A8dQbl	16271	62	22	126	9	11	3	5	11	...	0	0

5 rows × 66050 columns

In [6]:
```
#Get the best 1000 features using SelectKBest. Save the feature scores along
kbest_object=SelectKBest(score_func=chi2, k=1000)
best_features=kbest_object.fit(X.drop("ID", axis=1),y)
df_scores=pd.DataFrame(best_features.scores_)
df_columns=pd.DataFrame(X.columns)
feature_score_df=pd.concat([df_columns,df_scores],axis=1)
feature_score_df.columns=["Feature_Name","Feature_Score"]

#Let's look at the top 1000 features along with their scores + Save the featu
feature_score_df=feature_score_df.nlargest(1000,"Feature_Score")
feature_score_df.to_csv("features/feature_score/byte_bigram_df.csv", index=No
feature_score_df.head(5)
```

Out[6]:

	Feature_Name	Feature_Score
66048	?? ff	1.269512e+07
22258	56 9b	1.150512e+07
22251	56 94	1.143470e+07
22319	56 d8	1.136046e+07
38379	95 55	1.133120e+07

In [ ]:
```
#Get the first 1000 feature names in a list
top_1000_feats=list(feature_score_df["Feature_Name"])

#Get the dataframe containing the top 1000 features
reduced_features=dd.concat([X["ID"],X[top_1000_feats]], axis=1)

#Save the dataframes containing the top 1000 features
reduced_features.to_csv("features/final_features/temp/top1000_byte_bigram_df*
```

In [ ]:
```
del(X, feature_score_df, reduced_features)
```

In [ ]:
```
#Concatenate all the dataframes and save it as "top1000_byte_bigram_df.csv"
file_lists=os.listdir('features/final_features/temp/')
final_byte_bigram_df=pd.read_csv('features/final_features/temp/'+file_lists[0

for i in range(1,len(file_lists)):
    df = pd.read_csv('features/final_features/temp/'+file_lists[i])
    final_byte_bigram_df=pd.concat([final_byte_bigram_df,df], axis=0)

final_byte_bigram_df.to_csv("features/final_features/top1000_byte_bigram_df.c
```

In [ ]:
```
del(final_byte_bigram_df, file_lists)
```

Code for bigram creation using sparse matrix.

In [ ]:

```
"""

#Extract the byte bigram features and save the dataframe containing bi-gram f
vectorizer = CountVectorizer(tokenizer=lambda x: x.split(),lowercase=False,ng
file_lists=os.listdir('byteFiles/')
byte_bigram_data=sp.csr_matrix((1, 66049))

file = open('byteFiles/' + file_lists[0])
corpus = [file.read().replace('\n', ' ').lower()] #Read the file content. Rep
bigrams=vectorizer.fit_transform(corpus)
byte_bigram_data = sp.csr_matrix(bigrams)

for i in tqdm(range(1,10868)): ##The open() function returns a file object, w
    file = open('byteFiles/' + file_lists[i])
    corpus = [file.read().replace('\n', ' ').lower()] #Read the file content.
    bigrams=vectorizer.fit_transform(corpus)
    byte_bigram_data = sp.vstack((byte_bigram_data,bigrams))
    file.close()
"""
```

Use this code section in future for extremly large datasets

In [91]:

```
#This code snippet iteratively builds a dataframe containing the most feature
"""

final_score_df=pd.DataFrame()

start=0
end=100
count=1
while(end<66051):
    #Get the col names we want for this iteration.
    col=columns[start:end]
    X=df[col]

    best_features=SelectKBest(score_func=chi2, k=X.shape[1])
    fit=best_features.fit(X,y)

    df_scores=pd.DataFrame(fit.scores_)
    df_columns=pd.DataFrame(X.columns)

    feature_score=pd.concat([df_columns,df_scores],axis=1)
    feature_score.columns=["Feature Name","Feature Score"]


    start=start+100
    end=end+100

    if(end>66049):
        end=66050

    final_score_df=pd.concat([final_score_df,feature_score],ignore_index=True


    del(X)

    if(start>end):
        break


    print("Iteration {} completed".format(count))
    count+=1
    gc.collect()
final_score_df.nlargest(50,"Score")

#Load the class labels for training with random forest feature selector
with open('features/class_labels.pkl', 'rb') as file:
    labels=pkl.load(file)

#Load the sparse data as a sparse matrix
byte_bigram_stage1=normalize(scipy.sparse.load_npz('features/sparse/byte_bigr


#TODO: Correct the issues and parallalize the dask dataframes

"""import pandas as pd

from dask.distributed import Client
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import dask.dataframe as dd
from sklearn.externals.joblib import parallel_backend

client = Client()  # start a local Dask client
byte_bigram_df=dd.read_csv("features/byte_bigram_df.csv", sample=2560000)
labels=pd.read_csv('features/byte_unigrams_df.csv')['Class']

with parallel_backend('dask'):
    #Scikit learn code here
    rf_clf=DecisionTreeClassifier(random_state=0)
    rf_clf.fit(byte_bigram_df,labels)
    feature_index=np.argsort(rf_clf.feature_importances_)[::-1]
    most_imp_feat_idx=feature_index[:5000]

most_imp_feat_idx"""

print("Execute this code for iteratively getting feature scores..")
```

```
Execute this code for iteratively getting feature scores..
```

6.6 Use the CNN Codes features

Ignore the bottleneck features for now. The final dimensions of the the bottleneck features is 20 less than the actual number of images. TODO: Debug this.

In [2]:
```
X_cnn = np.load('final_features_cnn')
Y_cnn = pd.read_csv('final_features_cnn')['Class']
X_cnn.shape
```

Out[2]:
```
(10868, 65536)
```

In [3]:
```
#Split the data into test and train by maintaining same distribution of outpu
X_train, X_test, y_train, y_test = train_test_split(X_cnn,Y_cnn, stratify=y,
#Split the train data into train and cross validation by maintaining same dis
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, stratify=y_
```

In [5]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.calibration import CalibratedClassifierCV
from xgboost import XGBClassifier
```

In [ ]:

```
estimators=[10,50,100,500,1000,2000,3000,4000]
cv_log_error_array=[]
for i in estimators:
    x_cfl=XGBClassifier(n_estimators=i, n_jobs=-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

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=estimators[best_estimators],nthread=-1,n_job
x_cfl.fit(X_train ,y_train ,verbose=True)
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 estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t
```

7.0 Stack all the features together and save it as one single large feature dataframe

In [3]:

```
#Load the byte unigrams dataframe
byte_features_with_size = pd.read_csv("features/byte_features_with_size.csv")

#Load the ASM unigrams dataframe
asm_features_with_size = pd.read_csv("features/asm_features_with_size.csv").d

#Load the byte bigram dataframe with reduced features
top1000_byte_bigram_df = pd.read_csv("features/final_features/top1000_byte_bi

#Load the ASM Opcodes bigram dataframe with reduced features
top500_opcodes_bigram_df = pd.read_csv("features/final_features/top500_opcode

#Load the ASM Registers bigram dataframe with reduced features
top50_registers_bigram_df = pd.read_csv("features/final_features/top50_regist

#Load the ASM Opcodes trigram dataframe with reduced features
top500_opcodes_trigram_df = pd.read_csv("features/final_features/top500_opcod

#Load the ASM Registers trigram dataframe with reduced features
top300_registers_trigram_df = pd.read_csv("features/final_features/top300_reg

#Load the ASM Image dataframe
asm_image_df = pd.read_csv("features/asm_image_df.csv")

#Load the Byte Image dataframe
byte_image_df = pd.read_csv("features/byte_image_df.csv")

#Join all the dataframes togther on "ID" and save it as one single dataframe
final_features_df=byte_features_with_size
dfs = [asm_features_with_size,
       top1000_byte_bigram_df,
       top500_opcodes_bigram_df,
       top50_registers_bigram_df,
       top500_opcodes_trigram_df,
       top300_registers_trigram_df,
       asm_image_df,
       byte_image_df]

for df in dfs:
    final_features_df=pd.merge(final_features_df,df,on="ID",how="left")

final_features_df.to_csv("features/final_features/final_features_df.csv", ind
```

In [7]:
```
#Load the byte unigrams dataframe
byte_features_with_size = pd.read_csv("features/byte_features_with_size.csv")

#Load the ASM unigrams dataframe
asm_features_with_size = pd.read_csv("features/asm_features_with_size.csv").d

#Load the byte bigram dataframe with reduced features
top1000_byte_bigram_df = pd.read_csv("features/final_features/top1000_byte_bi

#Load the ASM Opcodes bigram dataframe with reduced features
top500_opcodes_bigram_df = pd.read_csv("features/final_features/top500_opcode

#Load the ASM Registers bigram dataframe with reduced features
top50_registers_bigram_df = pd.read_csv("features/final_features/top50_regist

#Load the ASM Opcodes trigram dataframe with reduced features
top500_opcodes_trigram_df = pd.read_csv("features/final_features/top500_opcod

#Load the ASM Registers trigram dataframe with reduced features
top300_registers_trigram_df = pd.read_csv("features/final_features/top300_reg

#Join all the dataframes togther on "ID" and save it as one single dataframe
final_features_df=byte_features_with_size
dfs = [asm_features_with_size,
       top1000_byte_bigram_df,
       top500_opcodes_bigram_df,
       top50_registers_bigram_df,
       top500_opcodes_trigram_df,
       top300_registers_trigram_df]

for df in dfs:
    final_features_df=pd.merge(final_features_df,df,on="ID",how="left")

final_features_df.to_csv("features/final_features/final_features_df.csv", ind
```

In [8]:
```
import gc
del(final_features_df,byte_features_with_size,asm_features_with_size,top1000_
gc.collect()
```

Out[8]: 219

8.1 Train Test Split. 64% Train, 16% Cross Validation, 20% Test

In [ ]:
```
X = pd.read_csv('final_features_df.csv')
#normalizing it

X = normalize(X)
```

Load the normalized DF along with the class labels

In [4]:
```
X=pd.read_csv("features/final_features/final_features_df_normalized.csv").fil
y=pd.read_csv("features/final_features/final_features_df.csv")["Class"]
```

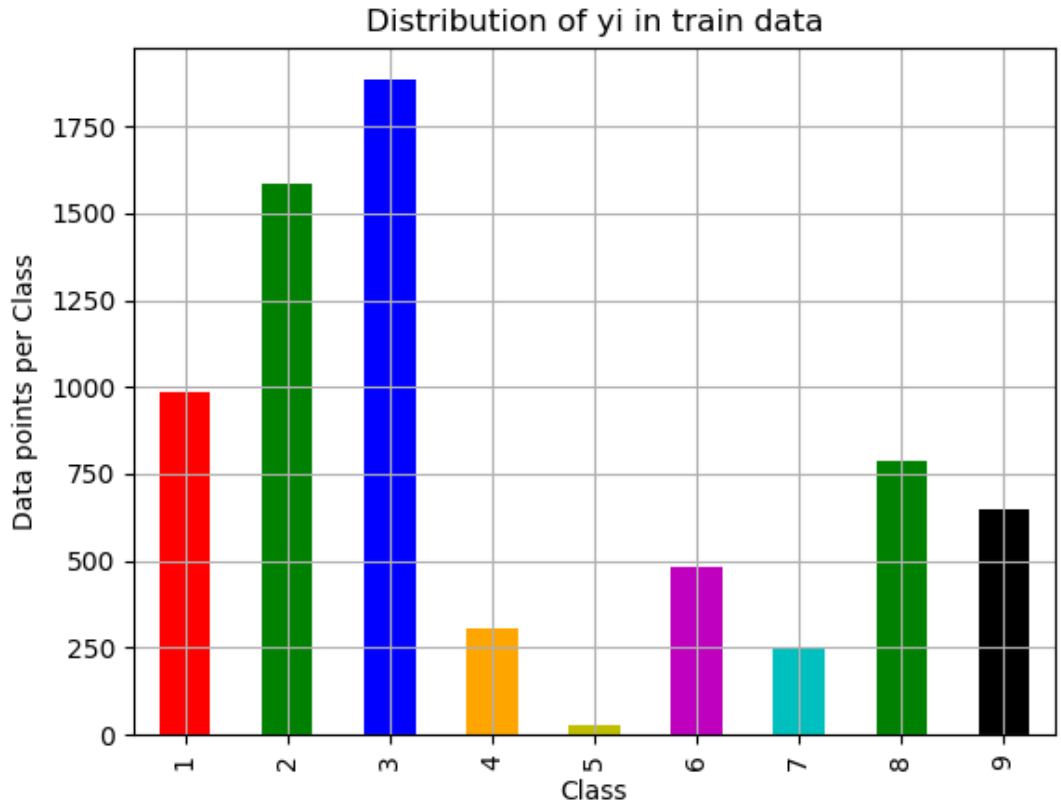
In [5]:
```
#Split the data into test and train by maintaining same distribution of outpu
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_si

#Split the train data into train and cross validation by maintaining same dis
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, stratify=y_
```

8.2 Check the distribution of Labels in Train, Test and Cross Validation Dataset

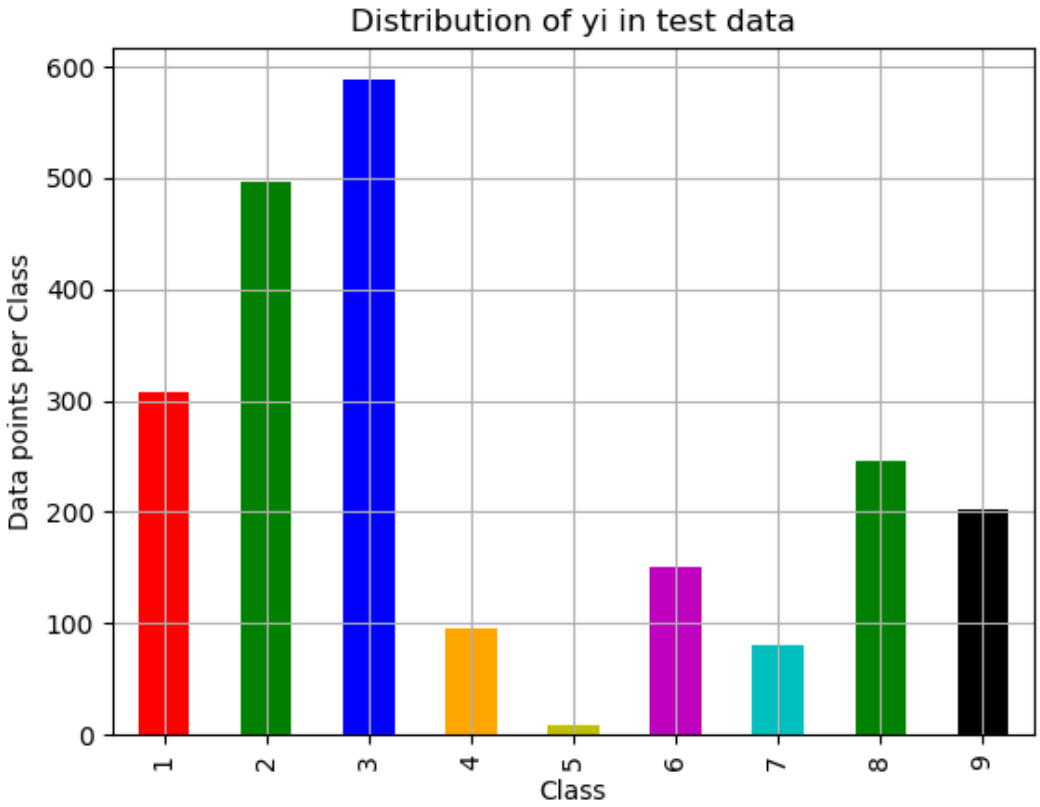
In [7]:

```
#It returns a dict, keys as class labels and values as the number of data poi
train_class_distribution = y_train.value_counts().sortlevel()
test_class_distribution = y_test.value_counts().sortlevel()
cv_class_distribution = y_cv.value_counts().sortlevel()

my_colors = ["r","g","b","orange","y","m","c","g","black"]
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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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


print('-'*80)
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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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.

print('-'*80)
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.arg
# -(train_class_distribution.values): the minus sign will give us in decreasi
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.va
```

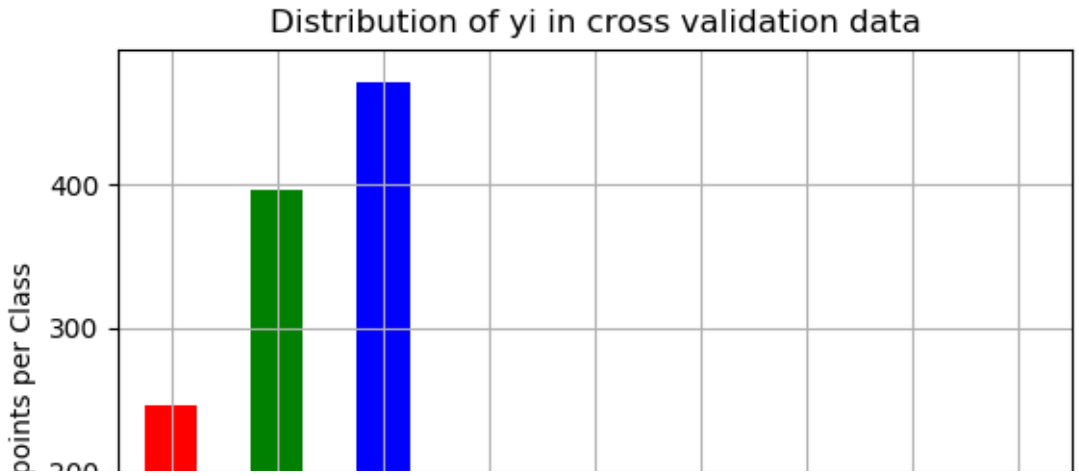
<IPython.core.display.Javascript object>




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

<IPython.core.display.Javascript object>
```




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

<IPython.core.display.Javascript object>
```




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

8.3 Code for Confusion, Precision and Recall matrix

In [8]:

```
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    print("Percentage of misclassified points ",(len(test_y)-np.trace(C))/len
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i

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

    # 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
    # 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 t
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to
    # 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, ytic
    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, ytic
    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, ytic
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in precision matrix",A.sum(axis=1))
```

Machine learninng models

10.1 Training a Random Forest Classifier on the final sets of features

In [3]:
```
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

In [4]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.calibration import CalibratedClassifierCV
from xgboost import XGBClassifier
import pandas as pd
```

Tune the hyperparameter n_estimators.

In [6]:
```
estimator=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
from sklearn.ensemble import RandomForestClassifier
for i in estimator:
    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

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


best_estimator = np.argmin(cv_log_error_array)

r_cfl=RandomForestClassifier(n_estimators=estimator[best_estimator],random_st
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 estimator = ', estimator[best_estimator], "The tra
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimator = ', estimator[best_estimator], "The cros
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimator = ', estimator[best_estimator], "The test

```

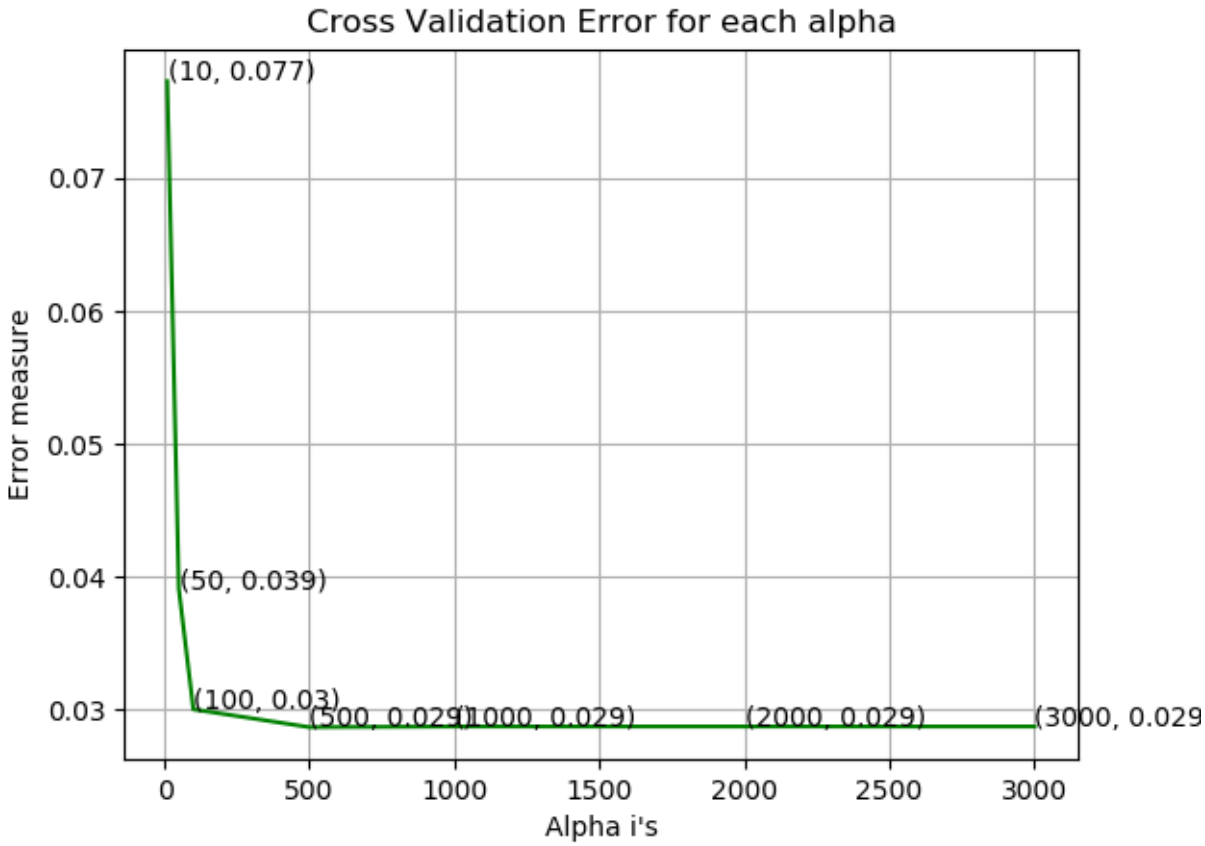
```
log_loss for c =  10 is 0.05860248748022682
log_loss for c =  50 is 0.046068787750972805
log_loss for c =  100 is 0.04794121453575634
log_loss for c =  500 is 0.04627045596291302
log_loss for c =  1000 is 0.046136037788736546
log_loss for c =  2000 is 0.046206151064847226
log_loss for c =  3000 is 0.04622147586641312

For values of best alpha =  50 The train log loss is: 0.017737131711228 62
For values of best alpha =  50 The cross validation log loss is: 0.046068787750
972805
For values of best alpha =  50 The test log loss is: 0.051558208326363784
```

10.2 Training an XGBoost Classifier on the final sets of features

In [12]:

```
estimators=[10,50,100,500,1000,2000,3000]
cv_log_error_array=[]
for i in estimators:
    x_cfl=XGBClassifier(n_estimators=i, n_jobs=-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

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


best_estimators = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=estimators[best_estimators],nthread=-1,n_job
x_cfl.fit(X_train ,y_train ,verbose=True)
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 estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t
```

```
log_loss for c =  10 is 0.07733012736364236
log_loss for c =  50 is 0.03905875498959229
log_loss for c =  100 is 0.02999076721501786
log_loss for c =  500 is 0.02864663745787661
log_loss for c =  1000 is 0.028697083167181243
log_loss for c =  2000 is 0.02869700239044487
log_loss for c =  3000 is 0.02869688851297395

<IPython.core.display.Javascript object>
```




```
For values of best alpha =  500 The train log loss is: 0.013021228130231977
For values of best alpha =  500 The cross validation log loss is: 0.02864663745
787661
For values of best alpha =  500 The test log loss is: 0.030512075737233454
```

10.3 Selecting top features using Random Forest + Apply XBGoost on top of the 1500 selected fetaures

In [9]:
```
1 from xgboost import XGBClassifier
```

10.3.1 Code for Selecting best features with random forest.

In [10]:
```
from sklearn.ensemble import RandomForestClassifier
import numpy as np

def get_feature_importance(X, y, nb_imp_feats): #For selecting top 1500 featu
    n_estimators=[10,50,80,100,125,250,500,1000,2000,3000]
    cv_log_error_array=[]
    for i in tqdm(n_estimators):
        rf_clf=RandomForestClassifier(n_estimators=i,n_jobs=-1, random_state=
        rf_clf.fit(X,y)
        sig_clf = CalibratedClassifierCV(rf_clf, 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=rf_clf.cl


    best_estimator = np.argmin(cv_log_error_array)
    rf_clf=RandomForestClassifier(n_estimators=n_estimators[best_estimator],r
    rf_clf.fit(X_train ,y_train)

    feature_index=np.argsort(rf_clf.feature_importances_)[::-1]
    most_imp_feat_idx=feature_index[:nb_imp_feats]
    return most_imp_feat_idx
```

10.3.2. Using the best features to construct train, test and cross-validation dataset

In [11]:
```
#Get all the feature names in a list
features = list(X_train.columns)

#Get the top 1500 features indexes
top_1500_features_index = get_feature_importance(X_train, y_train, 1500)

#Get the top 1500 features
top_1500_features = np.take(features,top_1500_features_index)

#Create a train, test and cv dataset with top 1500 features obtained using ra
X_train=X_train[list(top_1500_features)]
X_test=X_test[list(top_1500_features)]
X_cv=X_cv[list(top_1500_features)]
```

```
100%|██████████| 10/10 [05:17<00:00, 66.72s/it]
```

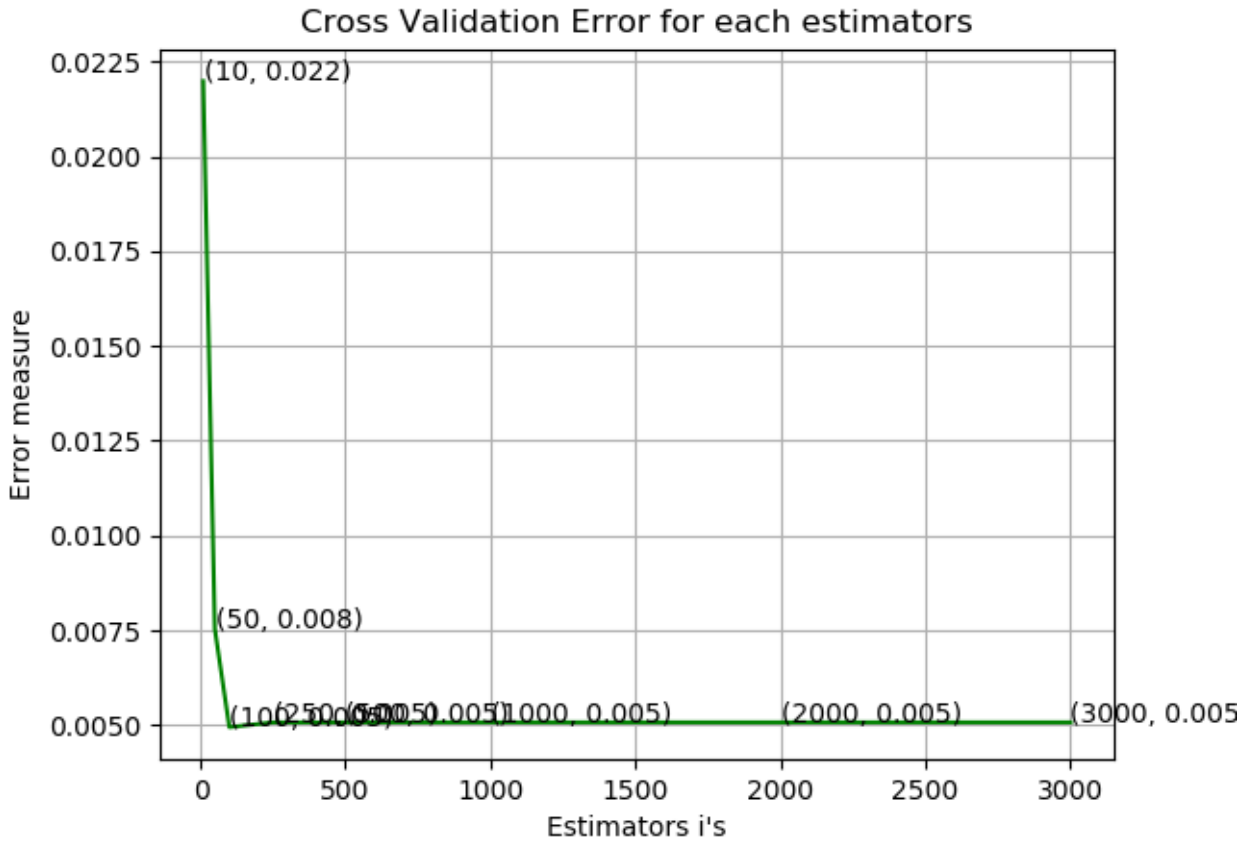
10.3.3. Training an XGBoost classifier on the final set of 1500 features. (Tuning the number of estimators)

In [13]:

```
estimators=[10,50,100,250,500,1000,2000,3000]
cv_log_error_array=[]
for i in tqdm(estimators):
    x_cfl=XGBClassifier(n_estimators=i, n_jobs=-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

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


best_estimators = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=estimators[best_estimators],nthread=-1,n_job
x_cfl.fit(X_train ,y_train ,verbose=True)
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 estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t
```

```
100%|██████████| 8/8 [1:33:17<00:00, 1238.39s/it]

log_loss for c =  10 is 0.021982833032912527
log_loss for c =  50 is 0.0075346142355446205
log_loss for c =  100 is 0.004945830182961919
log_loss for c =  250 is 0.005071604155408008
log_loss for c =  500 is 0.00507270568428335
log_loss for c =  1000 is 0.005072926974678231
log_loss for c =  2000 is 0.005072718941999207
log_loss for c =  3000 is 0.005072960627925119
```

```
<IPython.core.display.Javascript object>
```




```
For values of best estimators =  100 The train log loss is: 0.00458187138362535
2
For values of best estimators =  100 The cross validation log loss is: 0.004945
830182961919
For values of best estimators =  100 The test log loss is: 0.004481605018364259
```

11. Experimenting with best 500 selected features

11.1 Using the best features to construct train, test and cross-validation dataset

In [11]:
```
#Get all the feature names in a list
features = list(X_train.columns)

#Get the top 500 features indexes
top_500_features_index = get_feature_importance(X_train, y_train, 500)

#Get the top 500 features
top_500_features = np.take(features,top_500_features_index)

#Create a train, test and cv dataset with top 500 features obtained using ran
X_train=X_train[list(top_500_features)]
X_test=X_test[list(top_500_features)]
X_cv=X_cv[list(top_500_features)]

#Save the list of features
with open('features/top_500_features.pkl', 'wb') as file:
    pkl.dump(top_500_features, file)
```

```
100%|██████████| 10/10 [05:13<00:00, 66.20s/it]
```

11.2.1 XGBoost: Hyper-parameter tuning + Predicting on Test Data (Tuning the number of estimators)

In [13]:

```
from tqdm import tqdm
from xgboost import XGBClassifier

estimators=[70,80,90,105,110,115,130,150,180,200,250,300]
cv_log_error_array=[]
for i in tqdm(estimators):
    x_cfl=XGBClassifier(n_estimators=i, n_jobs=-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

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=estimators[best_estimators],nthread=-1,n_job
x_cfl.fit(X_train ,y_train ,verbose=True)
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 estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

plot_confusion_matrix(y_test, x_cfl.predict(X_test))
```

```
100%|██████████| 12/12 [15:08<00:00, 97.20s/it]
```

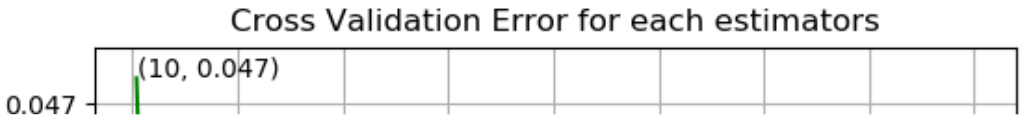
```
log_loss for n_estimators =  70 is 0.005502279196150079
log_loss for n_estimators =  80 is 0.005085534323274856
log_loss for n_estimators =  90 is 0.004872238584347242
log_loss for n_estimators =  105 is 0.004776526887835807
log_loss for n_estimators =  110 is 0.004787429118714052
log_loss for n_estimators =  115 is 0.004806338024363514
```

11.5 RandomForestClassifier: Hyper-parameter tuning + Predicting on Test Data

In [19]:

```
from sklearn.ensemble import RandomForestClassifier

estimators=[10,50,100,200,350,500,1000,2000]
cv_log_error_array=[]
for i in tqdm(estimators):
    rf_clf=RandomForestClassifier(n_estimators=i, n_jobs=-1, class_weight='ba
    rf_clf.fit(X_train ,y_train )
    sig_clf = CalibratedClassifierCV(rf_clf, 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=rf_clf.classe

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

rf_clf=RandomForestClassifier(n_estimators=estimators[best_estimators],n_jobs
rf_clf.fit(X_train ,y_train)
sig_clf = CalibratedClassifierCV(rf_clf, method="sigmoid")
sig_clf.fit(X_train , y_train )

predict_y = sig_clf.predict_proba(X_train )
print ('For values of best estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

#Plot confusion matrices
plot_confusion_matrix(y_test, rf_clf.predict(X_test))
```

```
100%|██████████| 8/8 [02:26<00:00, 31.69s/it]

log_loss for n_estimators =  10 is 0.04731188287459294
log_loss for n_estimators =  50 is 0.04132885135890258
log_loss for n_estimators =  100 is 0.04423992031938117
log_loss for n_estimators =  200 is 0.03984525650634593
log_loss for n_estimators =  350 is 0.04156142917464634
log_loss for n_estimators =  500 is 0.04162118116948644
log_loss for n_estimators =  1000 is 0.041954036786431295
log_loss for n_estimators =  2000 is 0.04113752448585498



<IPython.core.display.Javascript object>
```



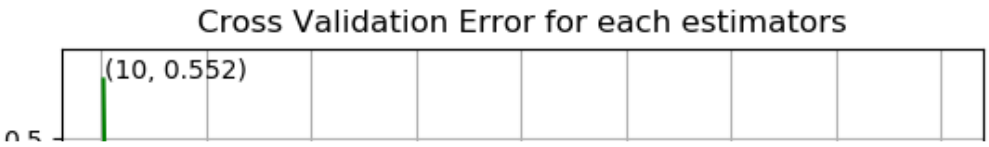
11.6 Stacking Classifiers : XGBClassifier meta classifier

In [29]:

```
from mlxtend.classifier import StackingClassifier

xgb_1 = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bytree=1, gamma=0, learning_rate=0.1, max_del
                      max_depth=3, min_child_weight=1, missing=None, n_estima
                      n_jobs=-1, nthread=-1, objective='multi:softprob', rand
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=Non
                      silent=True, subsample=1)

xgb_2 = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bytree=1, gamma=0, learning_rate=0.1, max_del
                      max_depth=3, min_child_weight=1, missing=None, n_estima
                      n_jobs=-1, nthread=-1, objective='multi:softprob', rand
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=Non
                      silent=True, subsample=1)


lgb_1=LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytre
                     importance_type='split', learning_rate=0.1, max_depth=-1
                     min_child_samples=20, min_child_weight=0.001, min_split_
                     n_estimators=190, n_jobs=-1, nthread=-1, num_leaves=31,
                     objective=None, random_state=None, reg_alpha=0.0, reg_la
                     silent=True, subsample=1.0, subsample_for_bin=200000,
                     subsample_freq=0)

lgb_2=LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytre
                     importance_type='split', learning_rate=0.1, max_depth=-1
                     min_child_samples=20, min_child_weight=0.001, min_split_
                     n_estimators=190, n_jobs=-1, nthread=-1, num_leaves=31,
                     objective=None, random_state=None, reg_alpha=0.0, reg_la
                     silent=True, subsample=1.0, subsample_for_bin=200000,
                     subsample_freq=0)

cv_log_error_array=[]
estimators = [10,50,100,150,250,500,750,1000,2000,3000,4000]
for i in estimators:
    meta_clf = XGBClassifier(n_estimators=i, n_jobs=-1)
    sig_clf = StackingClassifier(classifiers=[xgb_1,xgb_2,lgb_1,lgb_2], meta_
    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, eps=1e-15))


for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

```
plt.ylabel("Error measure")
plt.show()

meta_clf = XGBClassifier(n_estimators=estimators[best_estimators], n_jobs=-1)
sig_clf=StackingClassifier(classifiers=[xgb_1,xgb_2,lgb_1,lgb_2], meta_classi
sig_clf.fit(X_train,y_train)

predict_y = sig_clf.predict_proba(X_train )
print ('For values of best estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

plot_confusion_matrix(y_test,sig_clf.predict(X_test))
```

```
log_loss for n_estimators =  10 is 0.5518787449430363
log_loss for n_estimators =  50 is 0.010307589801839195
log_loss for n_estimators =  100 is 0.0008983027434716662
log_loss for n_estimators =  150 is 0.0007903983087084497
log_loss for n_estimators =  250 is 0.0007623319212748128
log_loss for n_estimators =  500 is 0.0007594183390671436
log_loss for n_estimators =  750 is 0.000759415734148798
log_loss for n_estimators =  1000 is 0.000759415734148798
log_loss for n_estimators =  2000 is 0.0007594162214998865
log_loss for n_estimators =  3000 is 0.0007594162214998865
log_loss for n_estimators =  4000 is 0.000759418826418232

<IPython.core.display.Javascript object>
```



12. Experimenting with Image features + Best 500 features.

12.1 Using the best features to construct train, test and cross-validation dataset

In [48]:

```
#Load and merge the dataframes
asm_image_df=pd.read_csv("features/asm_image_df.csv")
asm_image_df_norm = normalize(asm_image_df).fillna(0)

combined_df = pd.concat([X[list(top_500_features)],asm_image_df_norm.drop(["I
```

In [54]:
```
X = combined_df.drop(["Class"],axis=1)
y = combined_df["Class"]

#Split the data into test and train by maintaining same distribution of outpu
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_si

#Split the train data into train and cross validation by maintaining same dis
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, stratify=y_

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
```

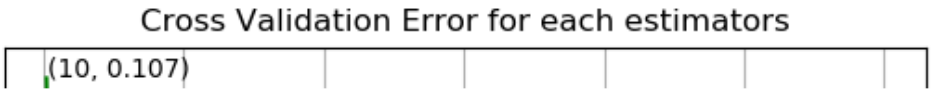
In [5]:
```
del(best_features_df,asm_image_df,combined_df, X, y)
```

12.2 XGBoost: Hyper-parameter tuning + Predicting on Test Data

In [55]:

```
from tqdm import tqdm
estimators=[10,50,100,250,500,1000,2000,3000]
cv_log_error_array=[]
for i in tqdm(estimators):
    x_cfl=XGBClassifier(n_estimators=i, n_jobs=-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

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

x_cfl=XGBClassifier(n_estimators=estimators[best_estimators],nthread=-1,n_job
x_cfl.fit(X_train ,y_train ,verbose=True)
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 estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

#Plot confusion matrices
plot_confusion_matrix(y_test, x_cfl.predict(X_test))
```

```
100%|██████████| 8/8 [1:18:49<00:00, 978.67s/it]

log_loss for n_estimators =  10 is 0.1065423079653175
log_loss for n_estimators =  50 is 0.061644552270603836
log_loss for n_estimators =  100 is 0.05031276599984848
log_loss for n_estimators =  250 is 0.048096991796449724
log_loss for n_estimators =  500 is 0.04772363821774151
log_loss for n_estimators =  1000 is 0.04759632347924493
log_loss for n_estimators =  2000 is 0.047776135523249774
log_loss for n_estimators =  3000 is 0.04777639490629287



<IPython.core.display.Javascript object>
```



12.4 ExtraTreesClassifier: Hyper-parameter tuning + Predicting on Test Data

In [57]:

```
from sklearn.ensemble import ExtraTreesClassifier

estimators=[200,210,220,230,240,250,260,270,280,290,300]
cv_log_error_array=[]
for i in tqdm(estimators):
    extra_clf=ExtraTreesClassifier(n_estimators=i, n_jobs=-1, class_weight='b
    extra_clf.fit(X_train ,y_train )
    sig_clf = CalibratedClassifierCV(extra_clf, 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=extra_clf.cla

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

extra_clf=ExtraTreesClassifier(n_estimators=estimators[best_estimators],n_job
extra_clf.fit(X_train ,y_train)
sig_clf = CalibratedClassifierCV(extra_clf, method="sigmoid")
sig_clf.fit(X_train , y_train )

predict_y = sig_clf.predict_proba(X_train )
print ('For values of best estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

#Plot confusion matrices
plot_confusion_matrix(y_test, extra_clf.predict(X_test))
```

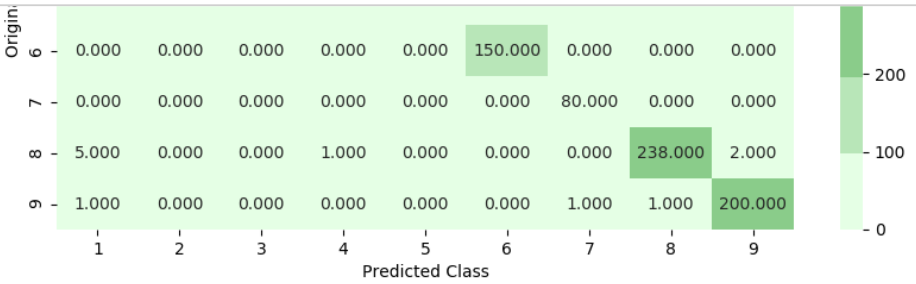
```
100%|██████████| 11/11 [01:33<00:00,  9.36s/it]

log_loss for n_estimators =  200 is 0.05821910745413007
log_loss for n_estimators =  210 is 0.05664206175410856
log_loss for n_estimators =  220 is 0.056079021386598156
log_loss for n_estimators =  230 is 0.05564309916566966
log_loss for n_estimators =  240 is 0.05747641782647607
log_loss for n_estimators =  250 is 0.05539290671043567
log_loss for n_estimators =  260 is 0.057051025361702375
log_loss for n_estimators =  270 is 0.0567654098411044
log_loss for n_estimators =  280 is 0.056530599130382136
log_loss for n_estimators =  290 is 0.05629446841052641
log_loss for n_estimators =  300 is 0.056685125738838577
```

```
<IPython.core.display.Javascript object>
```

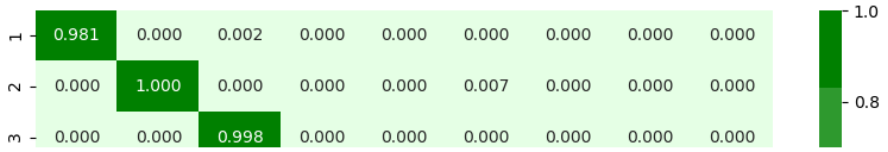
12.5 RandomForestClassifier: Hyper-parameter tuning + Predicting on Test Data

In [58]:

```
from sklearn.ensemble import RandomForestClassifier

estimators=[150,160,170,180,190,200,210,220,230,240]
cv_log_error_array=[]
for i in tqdm(estimators):
    rf_clf=RandomForestClassifier(n_estimators=i, n_jobs=-1, class_weight='ba
    rf_clf.fit(X_train ,y_train )
    sig_clf = CalibratedClassifierCV(rf_clf, 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=rf_clf.classe

for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

rf_clf=RandomForestClassifier(n_estimators=estimators[best_estimators],n_jobs
rf_clf.fit(X_train ,y_train)
sig_clf = CalibratedClassifierCV(rf_clf, method="sigmoid")
sig_clf.fit(X_train , y_train )

predict_y = sig_clf.predict_proba(X_train )
print ('For values of best estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

#Plot confusion matrices
plot_confusion_matrix(y_test, rf_clf.predict(X_test))
```




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

<IPython.core.display.Javascript object>
```



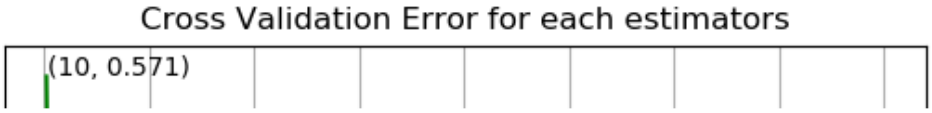
12.6 Stacking Classifiers : XGBClassifier meta classifier

In [59]:

```
from mlxtend.classifier import StackingClassifier

xgb_1 = x_cfl
xgb_2 = x_cfl


lgb_1 = lgbm_clf
lgb_2 = lgbm_clf

cv_log_error_array=[]
estimators = [10,50,100,150,250,500,750,1000,2000,3000,4000]
for i in estimators:
    meta_clf = XGBClassifier(n_estimators=i, n_jobs=-1)
    sig_clf = StackingClassifier(classifiers=[xgb_1,xgb_2,lgb_1,lgb_2], meta_
    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, eps=1e-15))


for i in range(len(cv_log_error_array)):
    print ('log_loss for n_estimators = ',estimators[i],'is',cv_log_error_arr


best_estimators = np.argmin(cv_log_error_array)

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

meta_clf = XGBClassifier(n_estimators=estimators[best_estimators], n_jobs=-1)
sig_clf=StackingClassifier(classifiers=[xgb_1,xgb_2,lgb_1,lgb_2], meta_classi
sig_clf.fit(X_train,y_train)

predict_y = sig_clf.predict_proba(X_train )
print ('For values of best estimators = ', estimators[best_estimators], "The
predict_y = sig_clf.predict_proba(X_cv )
print('For values of best estimators = ', estimators[best_estimators], "The c
predict_y = sig_clf.predict_proba(X_test )
print('For values of best estimators = ', estimators[best_estimators], "The t

plot_confusion_matrix(y_test,sig_clf.predict(X_test))
```

```
log_loss for n_estimators =  10 is 0.5710341889601867
log_loss for n_estimators =  50 is 0.06353912034991523
log_loss for n_estimators =  100 is 0.07225381782059646
log_loss for n_estimators =  150 is 0.07304243437228607
log_loss for n_estimators =  250 is 0.07339369495270898
log_loss for n_estimators =  500 is 0.07343474542690308
log_loss for n_estimators =  750 is 0.07343476643762605
log_loss for n_estimators =  1000 is 0.07343476753443377
```

```
log_loss for n_estimators =  2000 is 0.073434769048971
log_loss for n_estimators =  3000 is 0.07343476795216328
log_loss for n_estimators =  4000 is 0.07343476997440251

<IPython.core.display.Javascript object>
```



Display the results in a table.

In [7]:

```
from prettytable import PrettyTable

#Table 1
print("Initial Models using simple BYTE features:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["Random Model", 2.4561 , 2.4851, 88.5004])
table.add_row(["KNN", 0.0782 , 0.2415, 4.5078])
table.add_row(["Logistic Regression", 0.4989 , 0.5283, 12.3275])
table.add_row(["Random Forest", 0.0266 , 0.0858, 2.0239])
table.add_row(["XGBoost", 0.0225 , 0.0792, 1.2419])
table.add_row(["XGBoost (Parameter Tuned)", 0.0225 , 0.0782, "----"])
print(table)

#Table 2
print("\n\nInitial Models using simple ASM features:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["KNN", 0.0476 , 0.0894, 2.0239])
table.add_row(["Logistic Regression", 0.3962 , 0.4156, 9.6136])
table.add_row(["Random Forest", 0.0166 , 0.0571, 1.1499])
table.add_row(["XGBoost", 0.0117 , 0.0491, 0.8739])
table.add_row(["XGBoost (Parameter Tuned)", 0.0102 , 0.0483, "----"])
print(table)

#Table 3
print("\n\nMerging both ASM and BYTE features:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["Random Forest", 0.0166 , 0.0401, "----"])
table.add_row(["XGBoost", 0.0111 , 0.0323, "----"])
table.add_row(["XGBoost (Parameter Tuned)", 0.0121 , 0.0317, "----"])
print(table)

print("\n\nAdvanced features - top 1500 features:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["Random Forest on advanced features", 0.0177 , 0.0515, "----"]
table.add_row(["XGBoost on advanced features", 0.0131 , 0.0305, 0.5059])
table.add_row(["XGBoost on top 1500 advanced features", 0.0045 , 0.0044, 0.00

print(table)

print("\n\nTop 500 features + ASM top 800 pixels:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["XGBoost", 0.0117 , 0.0212, 0.2759])
table.add_row(["RandomForest", 0.0159 , 0.0393, 0.6899])
table.add_row(["EnsembleModel1", 0.0103 , 0.0285, 0.2759])
print(table)

print("\n\nAdvanced features - top 500 features:")
table =PrettyTable()
table.field_names = ["Model", "Train Log Loss", "Test Log loss", "%tage Misca
table.add_row(["XGBoost", 0.0045 , 0.0044, 0.0000])
table.add_row(["RandomForest", 0.0125 , 0.0284, 0.5519])
```

```
table.add_row(["EnsembleModel1", 0.0007 , 0.0007, 0.0000])

print(table)
```

```
Initial Models using simple BYTE features:
+---------------------------+----------------+--------------+----------------
-----------+
|           Model           | Train Log Loss | Test Log loss | %tage Miscalssif
ied points |
+---------------------------+----------------+--------------+----------------
-----------+
|        Random Model       |     2.4561     |     2.4851    |          88.5004
|
|            KNN            |     0.0782     |     0.2415    |           4.5078
|
|    Logistic Regression    |     0.4989     |     0.5283    |          12.3275
|
|       Random Forest       |     0.0266     |     0.0858    |           2.0239
|
|          XGBoost          |     0.0225     |     0.0792    |           1.2419
|
| XGBoost (Parameter Tuned) |     0.0225     |     0.0782    |            ----
|
+---------------------------+----------------+--------------+----------------
-----------+


Initial Models using simple ASM features:
+---------------------------+----------------+--------------+----------------
-----------+
|           Model           | Train Log Loss | Test Log loss | %tage Miscalssif
ied points |
+---------------------------+----------------+--------------+----------------
-----------+
|            KNN            |     0.0476     |     0.0894    |           2.0239
|
|    Logistic Regression    |     0.3962     |     0.4156    |           9.6136
|
|       Random Forest       |     0.0166     |     0.0571    |           1.1499
|
|          XGBoost          |     0.0117     |     0.0491    |           0.8739
|
| XGBoost (Parameter Tuned) |     0.0102     |     0.0483    |            ----
|
+---------------------------+----------------+--------------+----------------
-----------+


Merging both ASM and BYTE features:
+---------------------------+----------------+--------------+----------------
-----------+
|           Model           | Train Log Loss | Test Log loss | %tage Miscalssif
ied points |
+---------------------------+----------------+--------------+----------------
-----------+
|       Random Forest       |     0.0166     |     0.0401    |            ----
|
|          XGBoost          |     0.0111     |     0.0323    |            ----
```

```
|
| XGBoost (Parameter Tuned) |     0.0121     |     0.0317    |            ----
|
+---------------------------+----------------+---------------+-----------------
-----------+
```

Advanced features - top 1500 features:

```
+--------------------------------------+----------------+--------------+-----
----------------------+
|                 Model                | Train Log Loss | Test Log loss | %tag
e Miscalssified points |
+--------------------------------------+----------------+--------------+-----
----------------------+
|   Random Forest on advanced features  |     0.0177     |     0.0515    |
----            |
|      XGBoost on advanced features     |     0.0131     |     0.0305    |
0.5059          |
| XGBoost on top 1500 advanced features |     0.0045     |     0.0044    |
0.0             |
+--------------------------------------+----------------+--------------+-----
----------------------+
```

Top 500 features + ASM top 800 pixels:

```
+----------------+----------------+--------------+---------------------------
+
|     Model      | Train Log Loss | Test Log loss | %tage Miscalssified points
|
+----------------+----------------+--------------+---------------------------
+
|    XGBoost     |     0.0117     |     0.0212    |           0.2759
|
|  RandomForest  |     0.0159     |     0.0393    |           0.6899
|
| EnsembleModel1 |     0.0103     |     0.0285    |           0.2759
|
+----------------+----------------+--------------+---------------------------
+
```

Advanced features - top 500 features:

```
+----------------+----------------+--------------+---------------------------
+
|     Model      | Train Log Loss | Test Log loss | %tage Miscalssified points
|
+----------------+----------------+--------------+---------------------------
+
|    XGBoost     |     0.0045     |     0.0044    |            0.0
|
|  RandomForest  |     0.0125     |     0.0284    |           0.5519
|
| EnsembleModel1 |     0.0007     |     0.0007    |            0.0
|
+----------------+----------------+--------------+---------------------------
+
```

What is the objective?

The main purpose of this case study was to classify a given .byte or a .asm file in one of the 9 categories of malware. The 9 categories are Ramnit, Lollipop, Kelihos_ver3, Vundo, Simda, Tracur, Kelihos_ver1, Obfuscator, ACY and Gatak.

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 software 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 malware.

Since it's a multiclass classification problem, we have to choose our KPI (Key Performance Indicator) in such a way so that it minimizes the overall error on all the 9 classes. We want to know not only which file belongs to which class but also what is the probability of that belonging to a particular class. Without probability scores that model would just say that a file belongs to class 9(say). So the ideal KPI for this problem would be multi-class log loss.

Conclusions:

1. First i tried with Byte bigrams and got the best score of 0.0782 for XGBoost
2. Then ASM image 500 features and got 0.483 for XGboost
3. Next for ASM image features(500)+byte bigrams(1000)+byte trigrams(1000) i got 0.037 for boosted trees
4. Next, finally for advanced top 5000 features i got a log loss of 0.0007