Personalized Medicine: Redefining Cancer Treatment

1. Problem Statement

Classification of given genetic variations/mutations based on text-evidence into 9 types of mutations (multi-class classification problem)

1.1 Performance Metric

Metircs:

- Multi Class log-loss
- Confusion Matrix

1.2 Machine learning Objectives/Constraints

Objective: Predict the probability of each data-point belonging to each of the nine classes for better interpretation

Constraints:

- Interpretability
- Class probabilities are needed.
- Penalize the errors in class probabilites => Metric is Log-loss.
- No Latency constraints.

2. Exploratory Data Analysis

In [1]:

```
#importing required libraries
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
warnings.filterwarnings("ignore")
import re
import math
import time
import nltk
import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.ensemble import VotingClassifier
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_loss
from sklearn.feature_extraction.text import TfidfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.svm import SVC
from mlxtend.classifier import StackingClassifier
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import normalized_mutual_info_score
```

```
from sklearn.ensemble import RandomForestClassifier


#importing required data
data = pd.read_csv("training_variants")
data_text = pd.read_csv('training_text',sep="\|\|",engine="python",names=["ID","TEXT"],skiprows=1)
```

In [2]:

```
#getting the column names and number of rows in gene variation data
print("Number of Data-points" , data.shape[0])
print("Number of columns in given data", data.shape[1])

#getting the column names
print("Features :" , data.columns.values)
```

```
Number of Data-points 3321
Number of columns in given data 4
Features : ['ID' 'Gene' 'Variation' 'Class']
```

In [3]:

```
#getting the coulmn names and number of rows in text_data
print("Number of data-points" , data_text.shape[0])
print("Number of column in text-data",data_text.shape[1])

#getting the coluimn names
print("Features :" ,data_text.columns.values)
```

```
Number of data-points 3321
Number of column in text-data 2
Features : ['ID' 'TEXT']
```

training/training_variants is a comma separated file containing the description of the genetic mutations used for training.

Description of Features

- ID : the id of the row used to link the mutation to the clinical evidence
- Gene : the gene where this genetic mutation is located
- Variation : the aminoacid change for this mutations
- Class : 1-9 the class this genetic mutation has been classified on
- Text : Text-based clinical evidence

In [4]:

```
#getting the head of the data
print(data.head(5))

print(data_text.head(5))
```

```
   ID    Gene             Variation  Class
0   0  FAM58A  Truncating Mutations      1
1   1     CBL                 W802*      2
2   2     CBL                 Q249E      2
3   3     CBL                 N454D      3
4   4     CBL                 L399V      4
   ID                                               TEXT
0   0  Cyclin-dependent kinases (CDKs) regulate a var...
1   1   Abstract Background  Non-small cell lung canc...
2   2   Abstract Background  Non-small cell lung canc...
3   3  Recent evidence has demonstrated that acquired...
4   4  Oncogenic mutations in the monomeric Casitas B...
```

In [5]:

```
#getting the information about columns
print(data.info())
print(data_text.info())
```

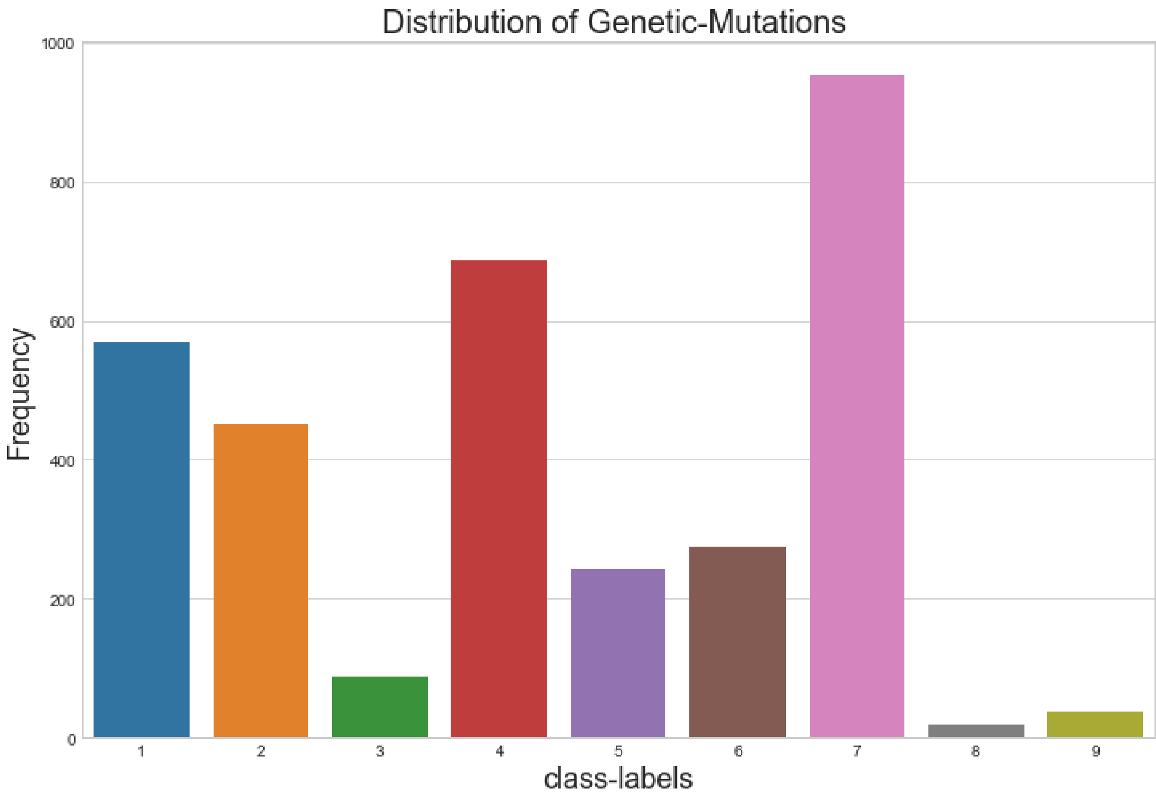
```
<class 'pandas.core.frame.DataFrame'>
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3321 entries, 0 to 3320
Data columns (total 4 columns):
ID           3321 non-null int64
Gene         3321 non-null object
Variation    3321 non-null object
Class        3321 non-null int64
dtypes: int64(2), object(2)
memory usage: 103.9+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3321 entries, 0 to 3320
Data columns (total 2 columns):
ID      3321 non-null int64
TEXT    3316 non-null object
dtypes: int64(1), object(1)
memory usage: 52.0+ KB
None
```

In [6]:

```
#getting the value counts of each-class
class_count = data["Class"].value_counts()
print(class_count)

#ploting the number of data-points for each genetic-mutation
plt.figure(figsize=(12,8))
sns.set_style('whitegrid')
sns.barplot(class_count.index , class_count.values)
plt.title("Distribution of Genetic-Mutations " ,fontsize =20)
plt.ylabel('Frequency', fontsize=18)
plt.xlabel('class-labels', fontsize=18)
plt.show()
```

```
7    953
4    686
1    568
2    452
6    275
5    242
3     89
9     37
8     19
Name: Class, dtype: int64
```



Observations

- Clearly we can see dataset is imbalanced with some classes having majority
- Class labels 3, 8, 9 has significantly low-frequency
- Class labels 5, 6 has medium frequency
- Class labels 1, 2, 4 has comparble high frequency
- Class label 7 has the highest frequecy

In [7]:

```
#merging data
data_no_preprocess = pd.merge(data, data_text,on='ID', how='left')
data_no_preprocess.head()
```

Out[7]:

	ID	Gene	Variation	Class	TEXT
0	0	FAM58A	Truncating Mutations	1	Cyclin-dependent kinases (CDKs) regulate a var...
1	1	CBL	W802*	2	Abstract Background Non-small cell lung canc...
2	2	CBL	Q249E	2	Abstract Background Non-small cell lung canc...
3	3	CBL	N454D	3	Recent evidence has demonstrated that acquired...
4	4	CBL	L399V	4	Oncogenic mutations in the monomeric Casitas B...

3.Text-Preprocessing

In [8]:

```
# loading stop words from nltk library
stop_words = set(stopwords.words('english'))

def nlp_preprocessing(total_text,index,column):
    if type(total_text) is not int:
        string = ""
        # replace every special char with space
        cleanhtml = re.compile('<.*?>')
        total_text = re.sub(cleanhtml,' ',total_text)
        total_text = re.sub('[^a-zA-Z0-9\n]', ' ', total_text)
        # replace multiple spaces with single space
        total_text = re.sub('\s+',' ', total_text)
        # converting all the chars into lower-case.
        total_text = total_text.lower()

        for word in total_text.split():
        # if the word is a not a stop word then retain that word from the data
            if not word in stop_words:
                string += word + " "

        data_text[column][index] = string
```

In [9]:

```
#text processing stage.
start_time = time.clock()
for index, row in data_text.iterrows():
    if type(row['TEXT']) is str:
        nlp_preprocessing(row['TEXT'], index, 'TEXT')
    else:
        print("there is no text description for id:",index)
print('Time took for preprocessing the text :',time.clock() - start_time, "seconds")
```

```
there is no text description for id: 1109
there is no text description for id: 1277
there is no text description for id: 1407
there is no text description for id: 1639
```

```
there is no text description for id: 2755
Time took for preprocessing the text : 118.4915008 seconds
```

In [10]:

```
#merging both gene_variations and text data based on ID
merge_data = pd.merge(data, data_text,on='ID', how='left')
merge_data.head()
```

Out[10]:

	ID	Gene	Variation	Class	TEXT
0	0	FAM58A	Truncating Mutations	1	cyclin dependent kinases cdks regulate variety...
1	1	CBL	W802*	2	abstract background non small cell lung cancer...
2	2	CBL	Q249E	2	abstract background non small cell lung cancer...
3	3	CBL	N454D	3	recent evidence demonstrated acquired uniparen...
4	4	CBL	L399V	4	oncogenic mutations monomeric casitas b lineag...

In [11]:

```
#checking for null-values
merge_data[merge_data.isnull().any(axis=1)]
```

Out[11]:

	ID	Gene	Variation	Class	TEXT
1109	1109	FANCA	S1088F	1	NaN
1277	1277	ARID5B	Truncating Mutations	1	NaN
1407	1407	FGFR3	K508M	6	NaN
1639	1639	FLT1	Amplification	6	NaN
2755	2755	BRAF	G596C	7	NaN

In [12]:

```
#replcaing null values
merge_data.loc[merge_data['TEXT'].isnull(),'TEXT'] = merge_data['Gene'] +' '+ merge_data['Variation
']
merge_data[merge_data['ID']==1109]
```

Out[12]:

	ID	Gene	Variation	Class	TEXT
1109	1109	FANCA	S1088F	1	FANCA S1088F

In [13]:

```
#pre-processing gene and variation data
merge_data.Gene      = merge_data.Gene.str.replace('\s+', '_')
merge_data.Variation = merge_data.Variation.str.replace('\s+', '_')
```

4.Test, Train and Cross Validation Split

In [14]:

```
#splitting data into 64% train-20% test-16% CV data
y = merge_data["Class"].values
```

```
X = merge_data.drop(["Class"],axis=1)

X_train_cv,X_test ,y_train_cv ,y_test = train_test_split(X,y,test_size = 0.2 ,random_state = 123,st
ratify = y )
X_train ,X_cv ,y_train ,y_cv = train_test_split (X_train_cv,y_train_cv,test_size = 0.2 , random_sta
te = 123 )
```

In [15]:

```
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])
```

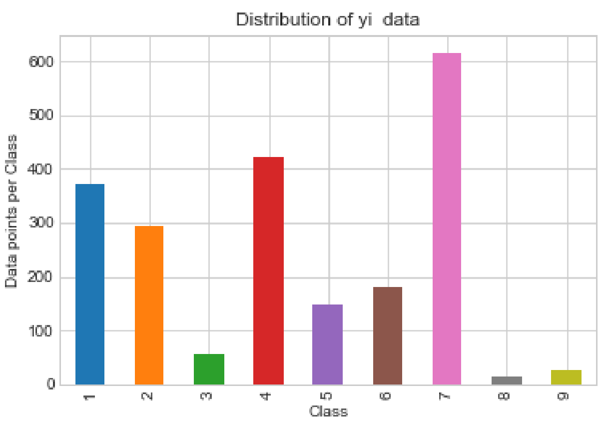
```
Number of data points in train data: 2124
Number of data points in test data: 665
Number of data points in cross validation data: 532
```

4.1 Distribution of classes in Train,Test and cross-validation data

In [16]:

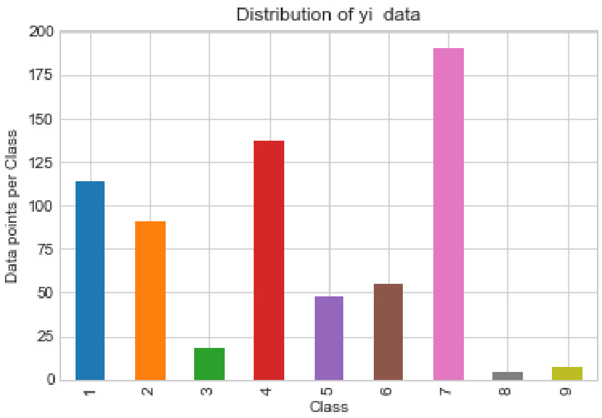
```
#checking for distribution of each class
train_classes =pd.Series( y_train).value_counts().sortlevel()
test_classes =pd.Series( y_test).value_counts().sortlevel()
cv_classes =pd.Series( y_cv).value_counts().sortlevel()


order_list = [0,1,2]
data_type = ["Train-Data","Test-Data" ,"Cross-Validation Data"]
data_list = [train_classes,test_classes,cv_classes]
y_list = [y_train,y_test,y_cv]

#ploting the ditribution
for i in order_list:
    my_colors = 'rgbkymc'
    data_list[i].plot(kind='bar')
    plt.xlabel('Class')
    plt.ylabel('Data points per Class')
    plt.title('Distribution of yi  data')
    print("For :" , data_type[i])
    plt.grid(True)
    plt.show()
    sorted_yi = np.argsort(-data_list[i].values)
    for m in sorted_yi:
        print('Number of data points in class', m+1, ':',data_list[i].values[m],
          '(', np.round((data_list[i].values[m]/y_list[i].shape[0]*100), 3), '%)')


print("*********************************************************************************************
)
```

```
For : Train-Data
```

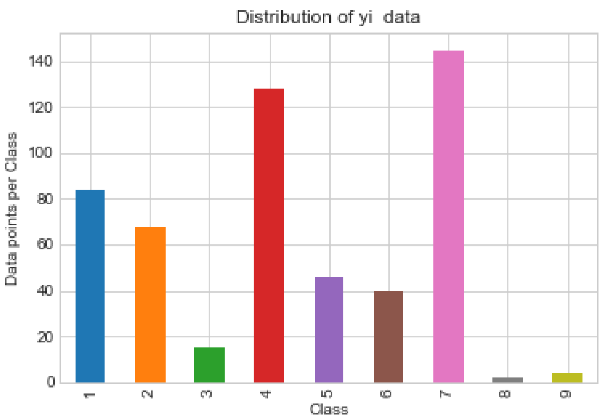



```
Number of data points in class 7 : 617 ( 29.049 %)
Number of data points in class 4 : 421 ( 19.821 %)
```

```
Number of data points in class 1 : 370 ( 17.42 %)
Number of data points in class 2 : 293 ( 13.795 %)
Number of data points in class 6 : 180 ( 8.475 %)
Number of data points in class 5 : 148 ( 6.968 %)
Number of data points in class 3 : 56 ( 2.637 %)
Number of data points in class 9 : 26 ( 1.224 %)
Number of data points in class 8 : 13 ( 0.612 %)
*********************************************************************************************
For : Test-Data
```




```
Number of data points in class 7 : 191 ( 28.722 %)
Number of data points in class 4 : 137 ( 20.602 %)
Number of data points in class 1 : 114 ( 17.143 %)
Number of data points in class 2 : 91 ( 13.684 %)
Number of data points in class 6 : 55 ( 8.271 %)
Number of data points in class 5 : 48 ( 7.218 %)
Number of data points in class 3 : 18 ( 2.707 %)
Number of data points in class 9 : 7 ( 1.053 %)
Number of data points in class 8 : 4 ( 0.602 %)
*********************************************************************************************
For : Cross-Validation Data
```




```
Number of data points in class 7 : 145 ( 27.256 %)
Number of data points in class 4 : 128 ( 24.06 %)
Number of data points in class 1 : 84 ( 15.789 %)
Number of data points in class 2 : 68 ( 12.782 %)
Number of data points in class 5 : 46 ( 8.647 %)
Number of data points in class 6 : 40 ( 7.519 %)
Number of data points in class 3 : 15 ( 2.82 %)
Number of data points in class 9 : 4 ( 0.752 %)
Number of data points in class 8 : 2 ( 0.376 %)
*********************************************************************************************
```

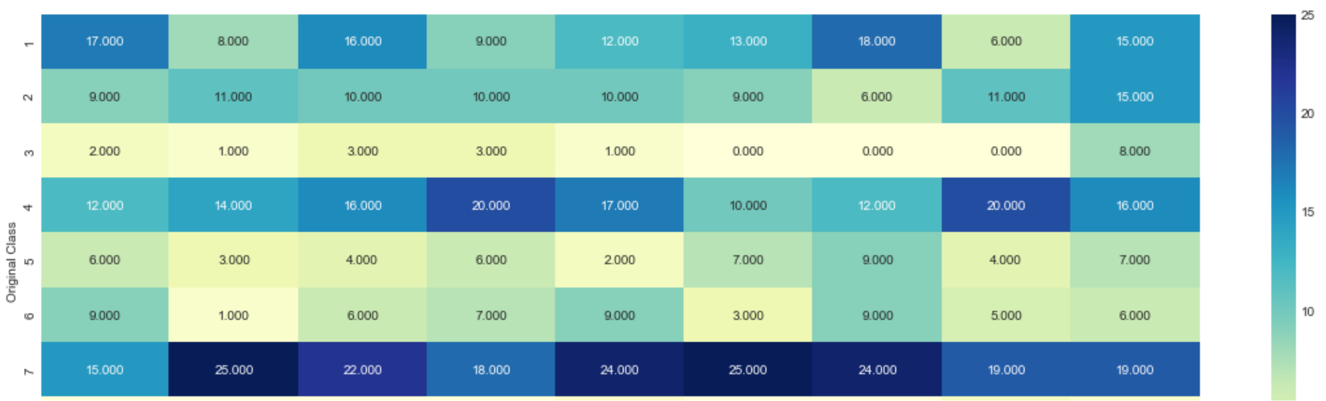
5.Predicting Using a Random Model

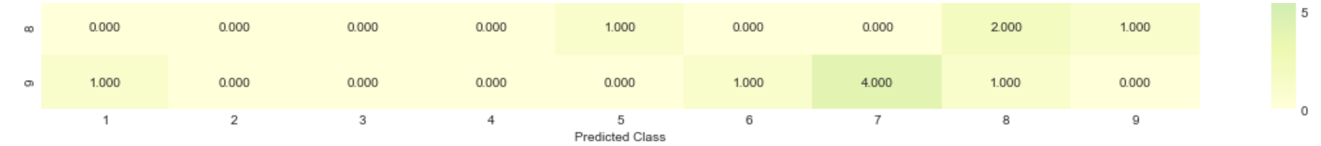
In [17]:

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

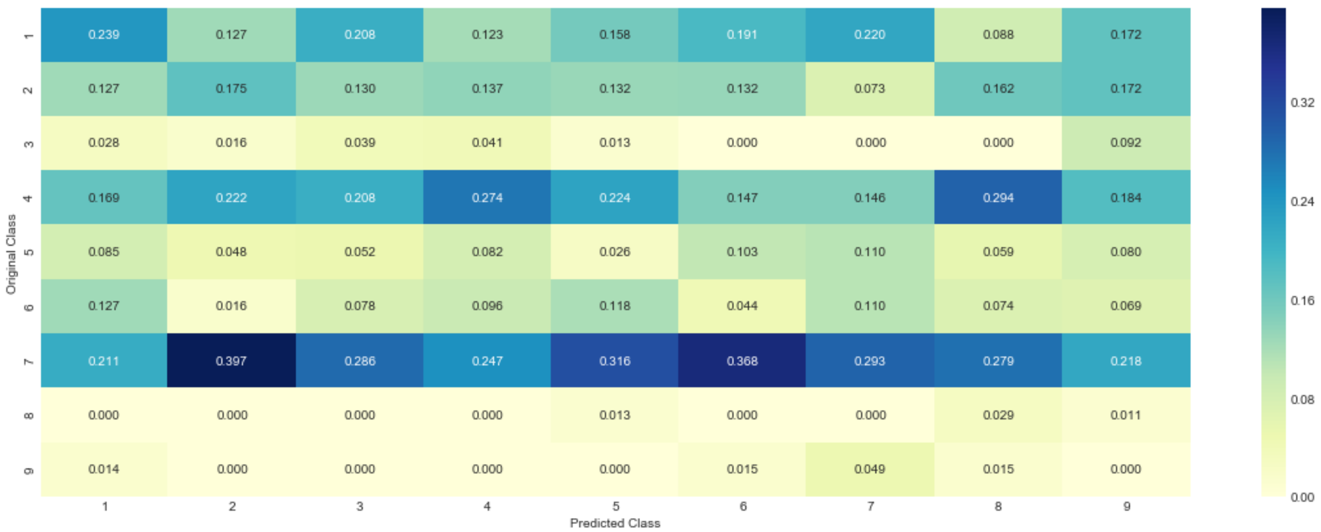
```python
# we create a output array that has exactly same size as the CV data
#computing cross-validation error
cv_predicted_y = np.zeros((cv_data_len,9))
for i in range(cv_data_len):
    rand_probs = np.random.rand(1,9)
    cv_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Cross Validation Data using Random Model",log_loss(y_cv,cv_predicted_y, eps=1e-
10))
log_loss_cv_rm =log_loss(y_cv,cv_predicted_y, eps=1e-10)


#computing test-error
test_predicted_y = np.zeros((test_data_len,9))
for i in range(test_data_len):
    rand_probs = np.random.rand(1,9)
    test_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_test,test_predicted_y, eps=1e-10))
log_loss_test_rm = log_loss(y_test,test_predicted_y, eps=1e-10)


#ploting confusion,precision,recall matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    A =(((C.T)/(C.sum(axis=1))).T)
    B =(C/C.sum(axis=0))


    labels = [1,2,3,4,5,6,7,8,9]
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*20, "Precision matrix (Columm Sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # representing B in heatmap format
    print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()


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 2.494908449118008
Log loss on Test Data using Random Model 2.473914578203381
-------------------- Confusion matrix --------------------
```

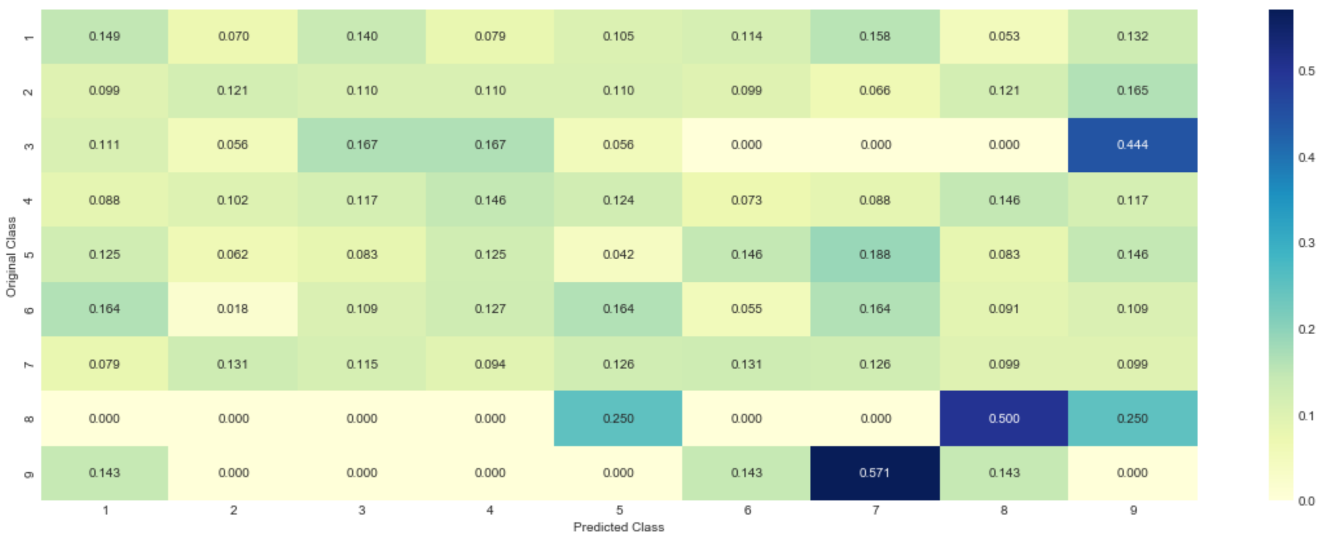





```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



Observations:

```
* A random model got log-loss around 2.5,so we need to build a model which gives log-loss l
ess than 2.5 and that must be the case
```

6. Univariate Analysis

6.1 Univariate Analysis of Gene Feature which is categorical

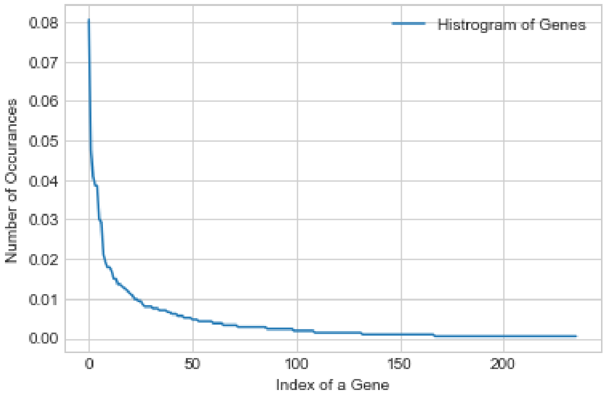
In [18]:

```
#couting the frequency of each gene
unique_genes = X_train['Gene'].value_counts()
print('Number of Unique Genes :', unique_genes.shape[0])
# the top 10 genes that occured most
print(unique_genes.head(10))
```

```
Number of Unique Genes : 236
BRCA1     171
TP53      101
EGFR       87
BRCA2      82
PTEN       82
KIT        64
BRAF       62
ALK        45
ERBB2      41
FLT3       38
Name: Gene, dtype: int64
```

In [19]:

```python
#ploting the distribution of Gene variable
s = sum(unique_genes.values);
h = unique_genes.values/s;
plt.plot(h, label="Histrogram of Genes")
plt.xlabel('Index of a Gene')
plt.ylabel('Number of Occurances')
plt.legend()
plt.grid(True)
plt.show()
```

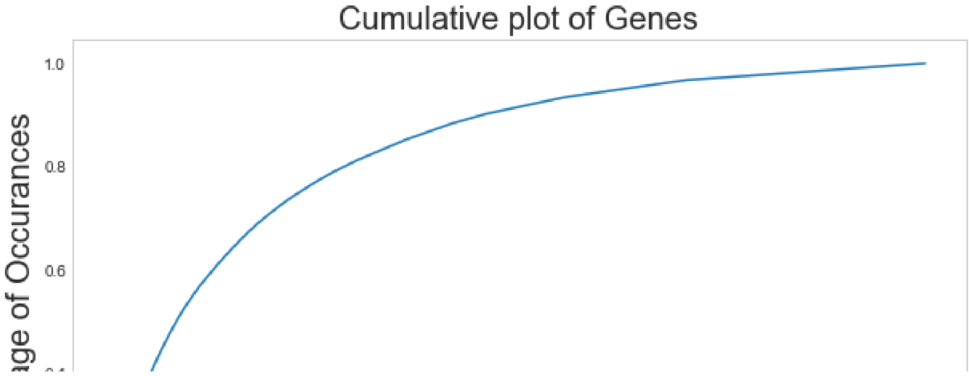


Observations

- Very few genes have high occurences (about 50 out of 236 unique genes)
- Distribution of genes is a right skewed one

In [20]:

```python
s = sum(unique_genes.values)
h = unique_genes.values/s
plt.figure(figsize = (10, 6))
plt.plot(np.cumsum(h))
plt.title("Cumulative plot of Genes", fontsize = 20)
plt.xlabel('Index of a Gene', fontsize = 20)
plt.ylabel('Percentage of Occurances', fontsize = 20)
plt.grid()
plt.show()
```



Featurizing Gene Variable

- one-hot encoding (useful for logisitic-regression or SVM as they can handle high-dimensional data)
- Response-coding(useful for Random-forest and Decsion-tree as they can handle low-dimensional data well)

In [21]:

```
# one-hot encoding of Gene feature.
gene_vectorizer = CountVectorizer()
train_gene_feature_onehotCoding = gene_vectorizer.fit_transform(X_train['Gene'])
test_gene_feature_onehotCoding = gene_vectorizer.transform(X_test['Gene'])
cv_gene_feature_onehotCoding = gene_vectorizer.transform(X_cv['Gene'])
```

In [22]:

```
print("train_gene_feature_onehotCoding is converted feature using one-hot encoding method. The sha
pe of gene feature:" , train_gene_feature_onehotCoding.shape)
```

```
train_gene_feature_onehotCoding is converted feature using one-hot encoding method. The shape of g
ene feature: (2124, 235)
```

In [23]:

```
X_train['Gene'].head()
```

Out[23]:

```
3186      NRAS
2814     BRCA2
1840     SETD2
2079      TET2
3049       KIT
Name: Gene, dtype: object
```

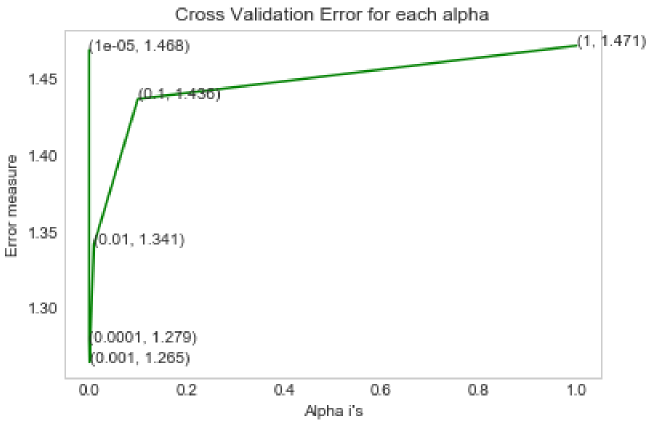
6.2 Checking whethter Gene Feature is important or not

In [24]:

```
alpha = [10 ** x for x in range(-5, 1)] # hyperparam for SGD classifier.

cv_log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(train_gene_feature_onehotCoding, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_gene_feature_onehotCoding, y_train)
    predict_y = sig_clf.predict_proba(cv_gene_feature_onehotCoding)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_cv, predict_y, labels=clf.clas
ses_, eps=1e-15))

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()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
clf.fit(train_gene_feature_onehotCoding, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_gene_feature_onehotCoding, y_train)

predict_y = sig_clf.predict_proba(train_gene_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_gene_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_gene_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

```
For values of alpha =  1e-05 The log loss is: 1.4682808439246737
For values of alpha =  0.0001 The log loss is: 1.2785465186549798
For values of alpha =  0.001 The log loss is: 1.2647319207763883
For values of alpha =  0.01 The log loss is: 1.3413040622000858
For values of alpha =  0.1 The log loss is: 1.4362593194469782
For values of alpha =  1 The log loss is: 1.4709093733823442
```




```
For values of best alpha =  0.001 The train log loss is: 1.0829654179364487
For values of best alpha =  0.001 The cross validation log loss is: 1.2647319207763883
For values of best alpha =  0.001 The test log loss is: 1.2622618733906243
```

Observations:

```
* Since the test and cross-validation log-loss is significantly close to train log-loss,
Gene should be considered as important feature for prediction model
```

In [25]:

```
print("Q6. How many data points in Test and CV datasets are covered by the ", unique_genes.shape[0], " genes in train dataset?")

test_coverage=X_test[X_test['Gene'].isin(list(set(X_train['Gene'])))].shape[0]
cv_coverage=X_cv[X_cv['Gene'].isin(list(set(X_train['Gene'])))].shape[0]

print('Ans\n1. In test data',test_coverage, 'out of',X_test.shape[0], ":",(test_coverage/X_test.shape[0])*100)
print('2. In cross validation data',cv_coverage, 'out of ',X_cv.shape[0],":" ,(cv_coverage/X_cv.shape[0])*100)
```

```
Q6. How many data points in Test and CV datasets are covered by the  236  genes in train dataset?
Ans
1. In test data 647 out of 665 : 97.29323308270676
2. In cross validation data 516 out of  532 : 96.99248120300751
```

Observations:

```
* Gene feature is stable across the train,test and cross-validation datasets
```

6.3 Univariate Analysis on Variation Feature

In [26]:

```
unique_variations = X_train['Variation'].value_counts()
print('Number of Unique Variations :', unique_variations.shape[0])
# the top 10 variations that occured most
print(unique_variations.head(10))
```

```
Number of Unique Variations : 1925
Truncating_Mutations    52
Deletion                51
Amplification           46
Fusions                 23
G12V                     3
Overexpression           3
G13D                     2
G12C                     2
S308A                    2
Q209L                    2
Name: Variation, dtype: int64
```

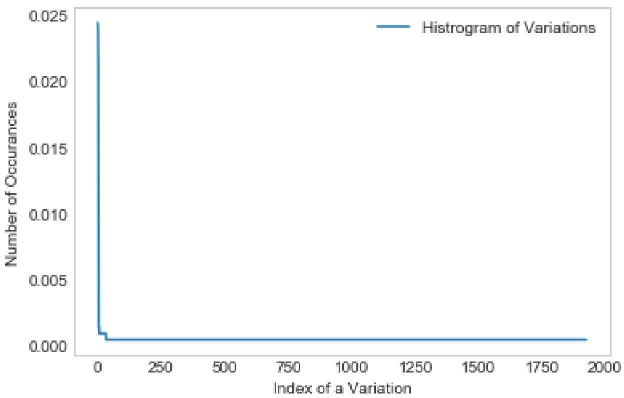
In [27]:

```
print("Ans: There are", unique_variations.shape[0] ,"different categories of variations in the
train data, and they are distibuted as follows",)
```

```
Ans: There are 1925 different categories of variations in the train data, and they are distibuted
as follows
```

In [28]:

```
s = sum(unique_variations.values);
h = unique_variations.values/s;
plt.plot(h, label="Histrogram of Variations")
plt.xlabel('Index of a Variation')
plt.ylabel('Number of Occurances')
plt.legend()
plt.grid()
plt.show()
```

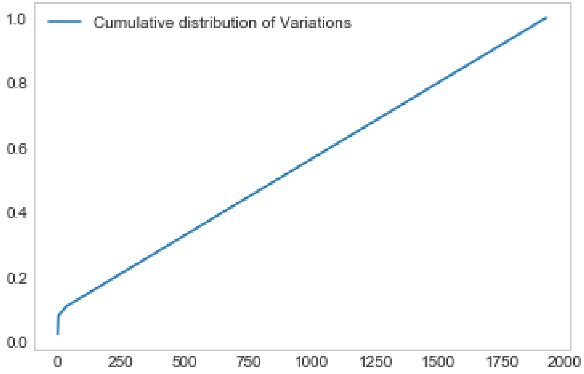


In [29]:

```
c = np.cumsum(h)
print(c)
plt.plot(c,label='Cumulative distribution of Variations')
plt.grid()
plt.legend()
```

```
plt.show()
```

```
[0.02448211 0.04849341 0.07015066 ... 0.99905838 0.99952919 1.        ]
```



In [30]:

```
# one-hot encoding of variation feature.
variation_vectorizer = CountVectorizer()
train_variation_feature_onehotCoding = variation_vectorizer.fit_transform(X_train['Variation'])
test_variation_feature_onehotCoding = variation_vectorizer.transform(X_test['Variation'])
cv_variation_feature_onehotCoding = variation_vectorizer.transform(X_cv['Variation'])
```

In [31]:

```
print("train_variation_feature_onehotEncoded is converted feature using the onne-hot encoding meth
od. The shape of Variation feature:", train_variation_feature_onehotCoding.shape)
```

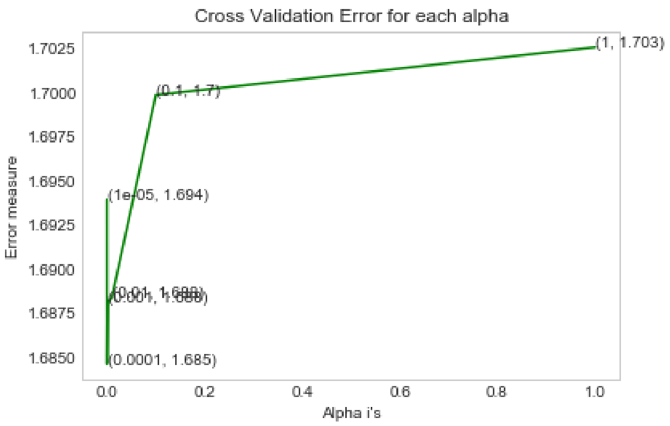
```
train_variation_feature_onehotEncoded is converted feature using the onne-hot encoding method. The
shape of Variation feature: (2124, 1960)
```

In [32]:

```
alpha = [10 ** x for x in range(-5, 1)]

cv_log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(train_variation_feature_onehotCoding, y_train)

    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_variation_feature_onehotCoding, y_train)
    predict_y = sig_clf.predict_proba(cv_variation_feature_onehotCoding)

    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_cv, predict_y, labels=clf.clas
ses_, eps=1e-15))

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()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
clf.fit(train_variation_feature_onehotCoding, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_variation_feature_onehotCoding, y_train)

predict_y = sig_clf.predict_proba(train_variation_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict_y, labels=clf.classes_, eps=1e-15))
```

```
predict_y = sig_clf.predict_proba(cv_variation_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_lo
ss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_variation_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_y, labels=clf.classes_, eps=1e-15))
```

```
For values of alpha =  1e-05 The log loss is: 1.693948500426924
For values of alpha =  0.0001 The log loss is: 1.684601821655645
For values of alpha =  0.001 The log loss is: 1.6880976102680285
For values of alpha =  0.01 The log loss is: 1.688392452073816
For values of alpha =  0.1 The log loss is: 1.699871240007007
For values of alpha =  1 The log loss is: 1.7025733917658608
```




```
For values of best alpha =  0.0001 The train log loss is: 0.7542316587398102
For values of best alpha =  0.0001 The cross validation log loss is: 1.684601821655645
For values of best alpha =  0.0001 The test log loss is: 1.720721078218819
```

Observations:

- Since the log loss of test and cross-validation sets is not significantly differ from that of train log-loss, we would consider the vaiation feature to be important in training a predicting model

In [33]:

```
print("Q12. How many data points are covered by total ", unique_variations.shape[0], " genes in te
st and cross validation data sets?")
test_coverage=X_test[X_test['Variation'].isin(list(set(X_train['Variation'])))].shape[0]
cv_coverage=X_cv[X_cv['Variation'].isin(list(set(X_train['Variation'])))].shape[0]
print('Ans\n1. In test data',test_coverage, 'out of',X_test.shape[0], ":",(test_coverage/X_test.sha
pe[0])*100)
print('2. In cross validation data',cv_coverage, 'out of ',X_cv.shape[0],":" ,(cv_coverage/X_cv.sha
pe[0])*100)
```

```
Q12. How many data points are covered by total  1925  genes in test and cross validation data
sets?
Ans
1. In test data 64 out of 665 : 9.624060150375941
2. In cross validation data 57 out of  532 : 10.714285714285714
```

Observations:

```
* Variation feature is not stable acorss the train,test and cross-validation datasets
```

6.4 Univariate Analysis on Text Feature

In [34]:

```
# building a CountVectorizer with all the words that occured minimum 3 times in train data
text_vectorizer = CountVectorizer(min_df=3,ngram_range = (1,2))
train_text_feature_onehotCoding = text_vectorizer.fit_transform(X_train['TEXT'])
```

```
# getting all the feature names (words)
train_text_features= text_vectorizer.get_feature_names()

# train_text_feature_onehotCoding.sum(axis=0).A1 will sum every row and returns (1*number of featu
res) vector
train_text_fea_counts = train_text_feature_onehotCoding.sum(axis=0).A1

# zip(list(text_features),text_fea_counts) will zip a word with its number of times it occured
text_fea_dict = dict(zip(list(train_text_features),train_text_fea_counts))


print("Total number of unique words in train data :", len(train_text_features))
```

```
Total number of unique words in train data : 669014
```

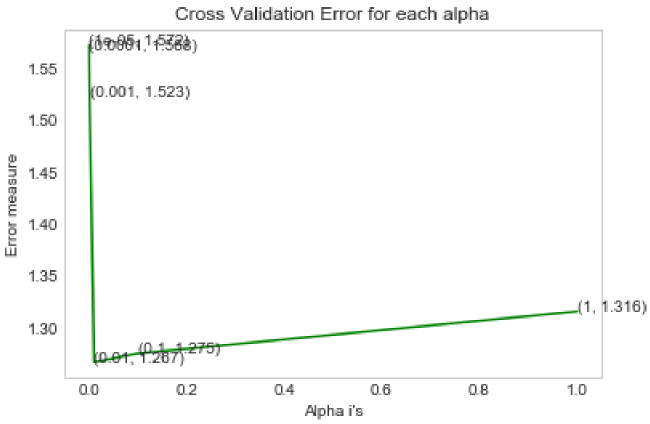
In [35]:

```
#normalizing
train_text_feature_onehotCoding = normalize(train_text_feature_onehotCoding, axis=0)

# we use the same vectorizer that was trained on train data
test_text_feature_onehotCoding = text_vectorizer.transform(X_test['TEXT'])
# don't forget to normalize every feature
test_text_feature_onehotCoding = normalize(test_text_feature_onehotCoding, axis=0)

# we use the same vectorizer that was trained on train data
cv_text_feature_onehotCoding = text_vectorizer.transform(X_cv['TEXT'])
# don't forget to normalize every feature
cv_text_feature_onehotCoding = normalize(cv_text_feature_onehotCoding, axis=0)
```

In [36]:

```
# Train a Logistic regression+Calibration model using text features whicha re on-hot encoded
alpha = [10 ** x for x in range(-5, 1)]

cv_log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(train_text_feature_onehotCoding, y_train)

    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_text_feature_onehotCoding, y_train)
    predict_y = sig_clf.predict_proba(cv_text_feature_onehotCoding)
    cv_log_error_array.append(log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_cv, predict_y, labels=clf.clas
ses_, eps=1e-15))

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()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
clf.fit(train_text_feature_onehotCoding, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_text_feature_onehotCoding, y_train)

predict_y = sig_clf.predict_proba(train_text_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_text_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_lo
ss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_text_feature_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_y, labels=clf.classes_, eps=1e-15))
```

```
For values of alpha =  1e-05 The log loss is: 1.5720816599089507
For values of alpha =  0.0001 The log loss is: 1.5682992377830354
For values of alpha =  0.001 The log loss is: 1.5226694437891164
For values of alpha =  0.01 The log loss is: 1.2668860771693868
For values of alpha =  0.1 The log loss is: 1.2752981288738405
For values of alpha =  1 The log loss is: 1.315814472943989
```




```
For values of best alpha =  0.01 The train log loss is: 0.8103588325809711
For values of best alpha =  0.01 The cross validation log loss is: 1.2668860771693868
For values of best alpha =  0.01 The test log loss is: 1.2388259434746751
```

Observations:

- Since the log loss of test and cross-validation sets is not significantly differ from that of train log-loss, we would consider the text feature to be important in training a predicting model

In [37]:

```
def get_intersec_text(df):
    df_text_vec = CountVectorizer(min_df=3,ngram_range= (1,2))
    df_text_fea = df_text_vec.fit_transform(df['TEXT'])
    df_text_features = df_text_vec.get_feature_names()

    df_text_fea_counts = df_text_fea.sum(axis=0).A1
    df_text_fea_dict = dict(zip(list(df_text_features),df_text_fea_counts))
    len1 = len(set(df_text_features))
    len2 = len(set(train_text_features) & set(df_text_features))
    return len1,len2
```

In [38]:

```
len1,len2 = get_intersec_text(X_test)
print(np.round((len2/len1)*100, 3), "% of word of test data appeared in train data")
len1,len2 = get_intersec_text(X_cv)
print(np.round((len2/len1)*100, 3), "% of word of Cross Validation appeared in train data")
```

```
92.357 % of word of test data appeared in train data
94.393 % of word of Cross Validation appeared in train data
```

7. Machine Learning Models

7.1 Apply Logistic regression with CountVectorizer Features, including both unigrams and bigrams

In [39]:

```
def predict_and_plot_confusion_matrix(train_x, train_y,test_x, test_y, clf):
    clf.fit(train_x, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x, train_y)
```

```
    pred_y = sig_clf.predict(test_x)

    # for calculating log_loss we willl provide the array of probabilities belongs to each class
    print("Log loss :",log_loss(test_y, sig_clf.predict_proba(test_x)))
    # calculating the number of data points that are misclassified
    print("Number of mis-classified points :", np.count_nonzero((pred_y- test_y))/test_y.shape[0])
    plot_confusion_matrix(test_y, pred_y)
```

In [40]:

```
train_gene_var_onehotCoding = 
hstack((train_gene_feature_onehotCoding,train_variation_feature_onehotCoding))
test_gene_var_onehotCoding = 
hstack((test_gene_feature_onehotCoding,test_variation_feature_onehotCoding))
cv_gene_var_onehotCoding = hstack((cv_gene_feature_onehotCoding,cv_variation_feature_onehotCoding)
)

train_x_onehotCoding = hstack((train_gene_var_onehotCoding, train_text_feature_onehotCoding)).tocs
r()
train_y = np.array(list(y_train))

test_x_onehotCoding = hstack((test_gene_var_onehotCoding, test_text_feature_onehotCoding)).tocsr()
test_y = np.array(list(y_test))

cv_x_onehotCoding = hstack((cv_gene_var_onehotCoding, cv_text_feature_onehotCoding)).tocsr()
cv_y = np.array(list(y_cv))
```

In [41]:

```
print("One hot encoding features :")
print("(number of data points * number of features) in train data = ", train_x_onehotCoding.shape)
print("(number of data points * number of features) in test data = ", test_x_onehotCoding.shape)
print("(number of data points * number of features) in cross validation data =", cv_x_onehotCoding
.shape)
```

```
One hot encoding features :
(number of data points * number of features) in train data =  (2124, 671209)
(number of data points * number of features) in test data =  (665, 671209)
(number of data points * number of features) in cross validation data = (532, 671209)
```

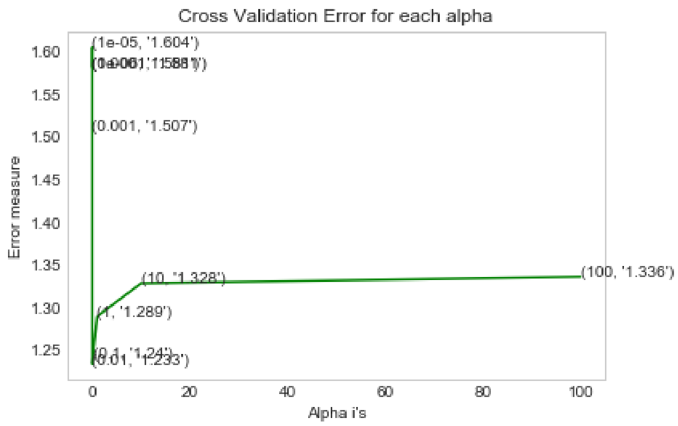
7.1.2 Logistic-Regression

In [42]:

```
#applying logistic-regression
alpha = [10 ** x for x in range(-6, 3)]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = SGDClassifier(class_weight='balanced', alpha=i, penalty='l2', loss='log', random_state=42
)
    clf.fit(train_x_onehotCoding, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x_onehotCoding, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_x_onehotCoding)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probability estimates
    print("Log Loss :",log_loss(cv_y, sig_clf_probs))

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],str(txt)), (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()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', loss='log', ran
```

```
dom_state=42)
clf.fit(train_x_onehotCoding, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_onehotCoding, train_y)

predict_y = sig_clf.predict_proba(train_x_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_onehotCoding)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

```
for alpha = 1e-06
Log Loss : 1.5811038658327974
for alpha = 1e-05
Log Loss : 1.6044832114278227
for alpha = 0.0001
Log Loss : 1.58121456695481
for alpha = 0.001
Log Loss : 1.5074751869654892
for alpha = 0.01
Log Loss : 1.2334697152505552
for alpha = 0.1
Log Loss : 1.2404619493500157
for alpha = 1
Log Loss : 1.2894156547828315
for alpha = 10
Log Loss : 1.3281129970036287
for alpha = 100
Log Loss : 1.3358985244014667
```

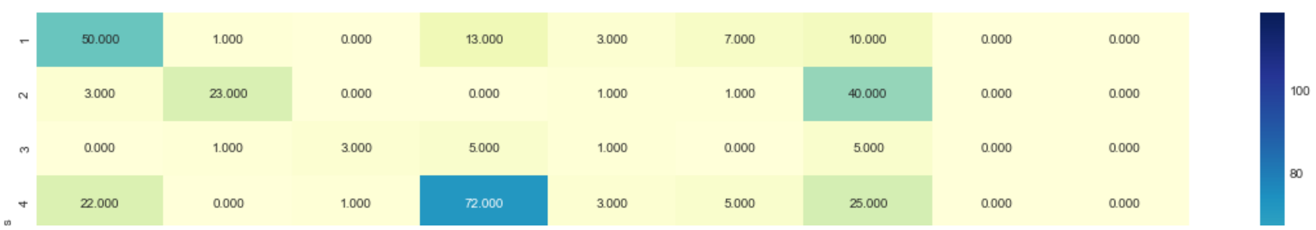


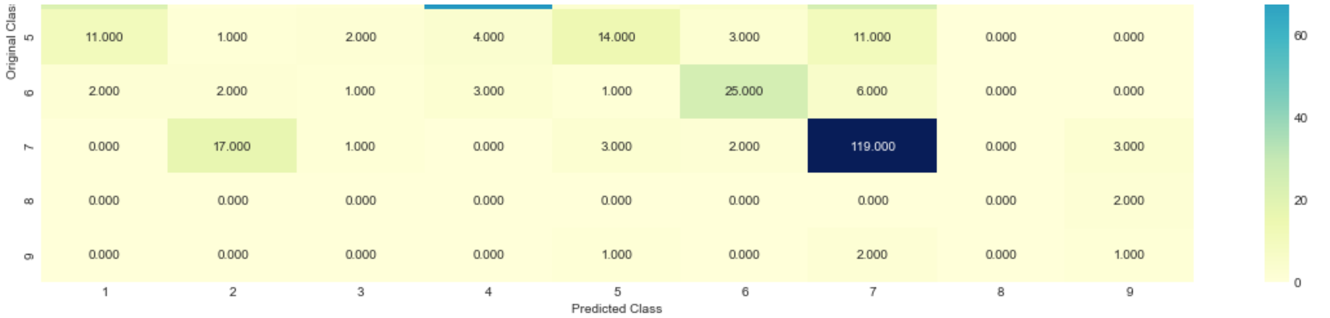

```
For values of best alpha =  0.01 The train log loss is: 0.7830378181780798
For values of best alpha =  0.01 The cross validation log loss is: 1.2334697152505552
For values of best alpha =  0.01 The test log loss is: 1.198656181435184
```

In [43]:

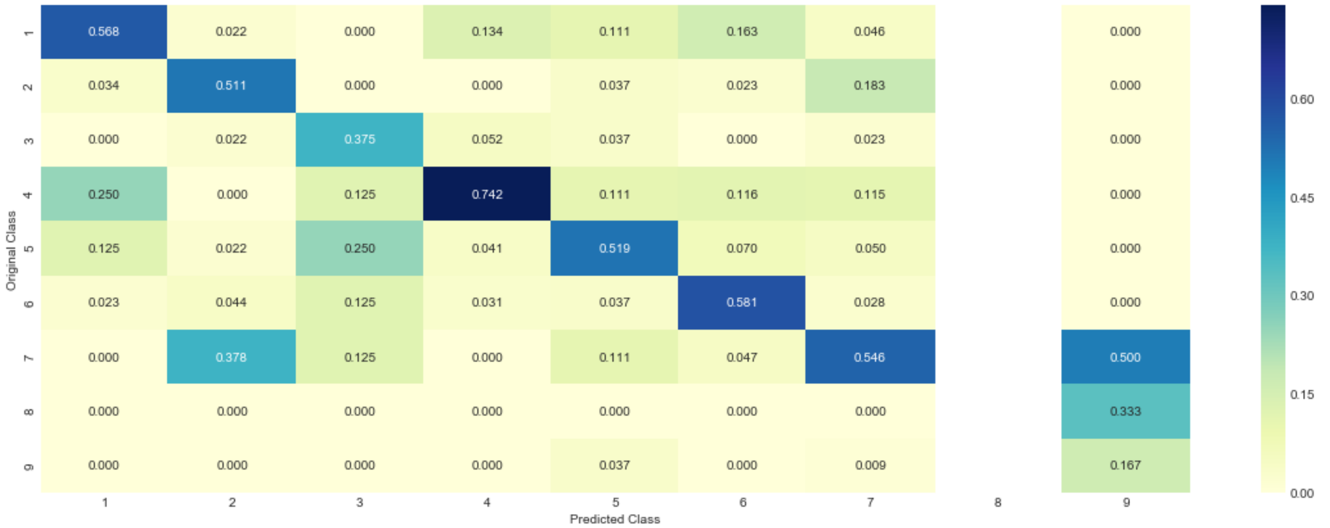
```
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
predict_and_plot_confusion_matrix(train_x_onehotCoding, train_y, cv_x_onehotCoding, cv_y, clf)
```

```
Log loss : 1.2334697152505552
Number of mis-classified points : 0.42293233082706766
-------------------- Confusion matrix --------------------
```






```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```

In [44]:

```
result = pd.DataFrame(columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-loss", "Mis-Cl
assified CV", "Remarks"])
```

In [45]:

```
result = result.append(pd.DataFrame([["Logistic-Regression", 0.7830, 1.2334, 1.1986, "42.29%",  "Go
odFit"]],
                                     columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

Conclusions:

In [46]:

```
result
```

Out[46]:

	Model	Train Log-loss	CV Log-loss	Test Log-loss	Mis-Classified CV	Remarks
0	Logistic-Regression	0.783	1.2334	1.1986	42.29%	GoodFit

8. All the models with top-1000 tfidf features

In [47]:

```
result1 = pd.DataFrame(columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-loss", "Mis-C
lassified CV", "Remarks"])
```

In [48]:

```
#initializing tfidfvectorizer
gene_vectorizer = TfidfVectorizer(strip_accents='unicode', analyzer='word', norm='l2'
,max_features = 1000)
train_gene_feature_tfidf = gene_vectorizer.fit_transform(X_train['Gene'])
test_gene_feature_tfidf = gene_vectorizer.transform(X_test['Gene'])
cv_gene_feature_tfidf = gene_vectorizer.transform(X_cv['Gene'])


# tfidf of variation feature.
variation_vectorizer = TfidfVectorizer(strip_accents='unicode', analyzer='word', norm='l2'
,max_features = 1000)
train_variation_feature_tfidf= variation_vectorizer.fit_transform(X_train['Variation'])
test_variation_feature_tfidf = variation_vectorizer.transform(X_test['Variation'])
cv_variation_feature_tfidf = variation_vectorizer.transform(X_cv['Variation'])

# building a tfidf with all the words that occured minimum 3 times in train data
text_vectorizer = TfidfVectorizer(strip_accents='unicode', analyzer='word', norm='l2'
,max_features = 1000,min_df =5)
train_text_feature_tfidf = text_vectorizer.fit_transform(X_train['TEXT'])
# getting all the feature names (words)
train_text_features= text_vectorizer.get_feature_names()

print("Total number of unique words in train data :", len(train_text_features))


#normalizing
train_text_feature_tfidf1 = normalize(train_text_feature_tfidf, axis=0)

# we use the same vectorizer that was trained on train data
test_text_feature_tfidf = text_vectorizer.transform(X_test['TEXT'])
# don't forget to normalize every feature
test_text_feature_tfidf1 = normalize(test_text_feature_tfidf, axis=0)

# we use the same vectorizer that was trained on train data
cv_text_feature_tfidf = text_vectorizer.transform(X_cv['TEXT'])
# don't forget to normalize every feature
cv_text_feature_tfidf1= normalize(cv_text_feature_tfidf, axis=0)
```

```
Total number of unique words in train data : 1000
```

In [49]:

```
train_gene_var_tfidf = hstack((train_gene_feature_tfidf,train_variation_feature_tfidf))
test_gene_var_tfidf = hstack((test_gene_feature_tfidf,test_variation_feature_tfidf))
cv_gene_var_tfidf = hstack((cv_gene_feature_tfidf,cv_variation_feature_tfidf))

train_x_tfidf= hstack((train_gene_var_tfidf, train_text_feature_tfidf)).tocsr()
train_y = np.array(list(y_train))
```

```
test_x_tfidf= hstack((test_gene_var_tfidf, test_text_feature_tfidf)).tocsr()
test_y = np.array(list(y_test))

cv_x_tfidf = hstack((cv_gene_var_tfidf, cv_text_feature_tfidf)).tocsr()
cv_y = np.array(list(y_cv))
```

In [50]:

```
print("TFIDF features :")
print("(number of data points * number of features) in train data = ", train_x_tfidf.shape)
print("(number of data points * number of features) in test data = ", test_x_tfidf.shape)
print("(number of data points * number of features) in cross validation data =", cv_x_tfidf.shape)
```

```
TFIDF features :
(number of data points * number of features) in train data =  (2124, 2235)
(number of data points * number of features) in test data =  (665, 2235)
(number of data points * number of features) in cross validation data = (532, 2235)
```

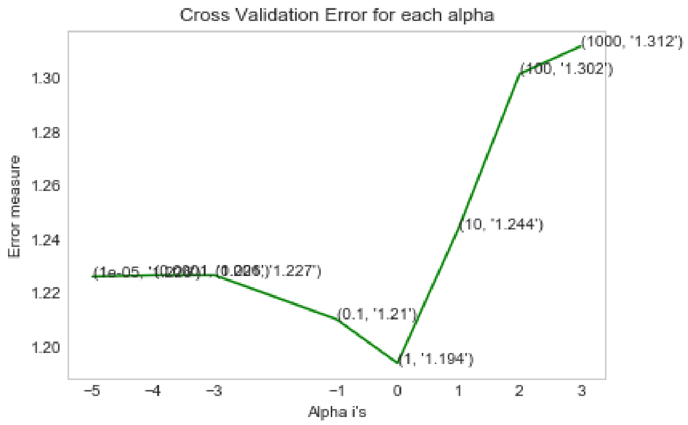
8.1 Naive-Bayes

In [51]:

```
alpha = [0.00001, 0.0001, 0.001, 0.1, 1, 10, 100,1000]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = MultinomialNB(alpha=i)
    clf.fit(train_x_tfidf, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x_tfidf, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_x_tfidf)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probability estimates
    print("Log Loss :",log_loss(cv_y, sig_clf_probs))

fig, ax = plt.subplots()
ax.plot(np.log10(alpha), cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[i],str(txt)), (np.log10(alpha[i]),cv_log_error_array[i]))
plt.grid()
plt.xticks(np.log10(alpha))
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(cv_log_error_array)
clf = MultinomialNB(alpha=alpha[best_alpha])
clf.fit(train_x_tfidf, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_tfidf, train_y)


predict_y = sig_clf.predict_proba(train_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, 
predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_lo
ss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_y, labels=clf.classes_, eps=1e-15))
```

```
for alpha = 1e-05
Log Loss : 1.2259562051248456
for alpha = 0.0001
Log Loss : 1.226492949623155
for alpha = 0.001
Log Loss : 1.226514211352827
for alpha = 0.1
Log Loss : 1.2100441935748834
```

```
for alpha = 1
Log Loss : 1.193621043532439
for alpha = 10
Log Loss : 1.243901686579564
for alpha = 100
Log Loss : 1.3015489413532364
for alpha = 1000
Log Loss : 1.3118654556444598
```

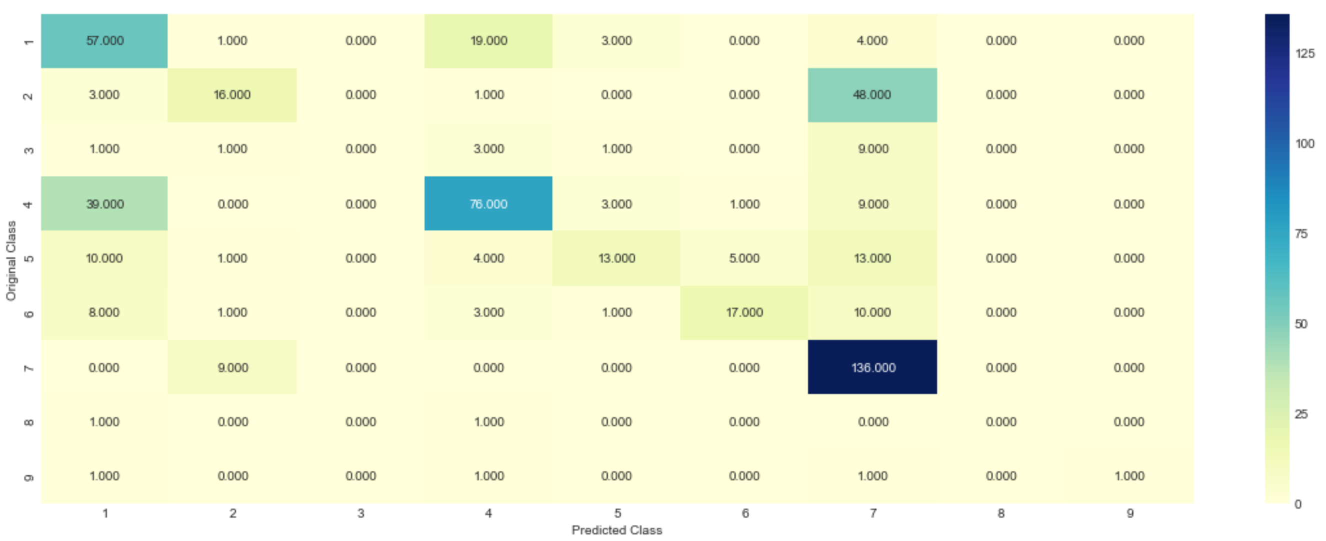



```
For values of best alpha =  1 The train log loss is: 0.9870291992844077
For values of best alpha =  1 The cross validation log loss is: 1.193621043532439
For values of best alpha =  1 The test log loss is: 1.240300891021964
```

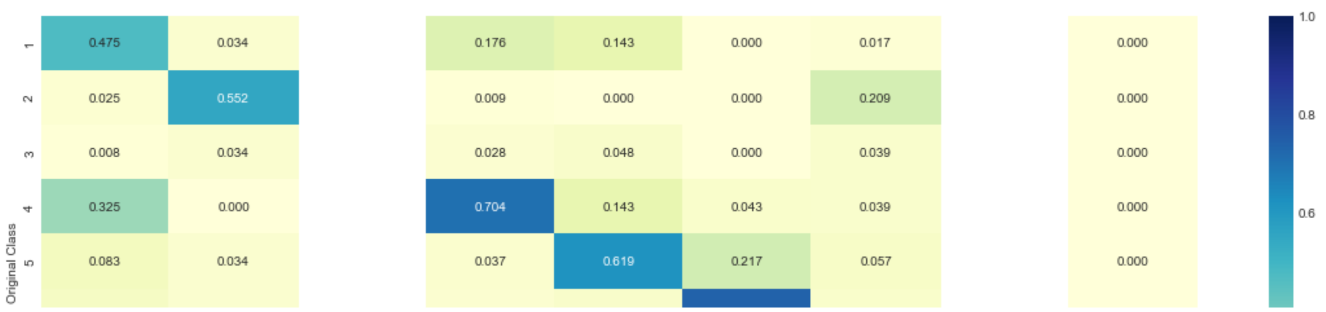
In [52]:

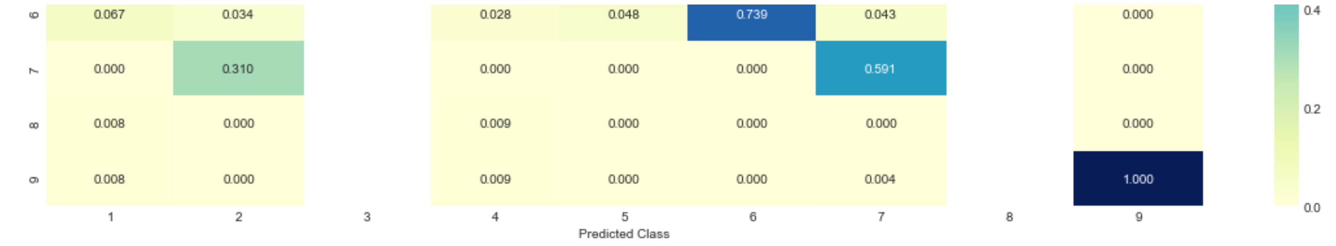
```
#ploting confusion matrix
predict_and_plot_confusion_matrix(train_x_tfidf, train_y, cv_x_tfidf, cv_y, clf)
```

```
Log loss : 1.193621043532439
Number of mis-classified points : 0.40601503759398494
-------------------- Confusion matrix --------------------
```

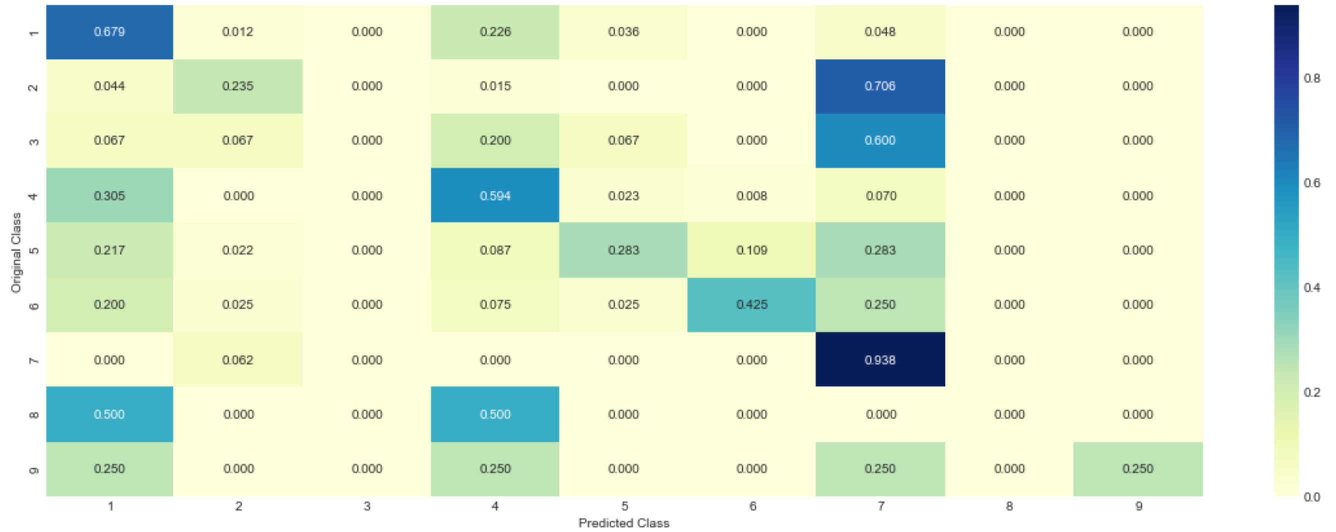



```
-------------------- Precision matrix (Columm Sum=1) --------------------
```






```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [53]:

```
result1 = result1.append(pd.DataFrame([["Naive-Bayes", 0.9870, 1.1936, 1.2304, "40.60%",  "GoodFit"
]],
                                   columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

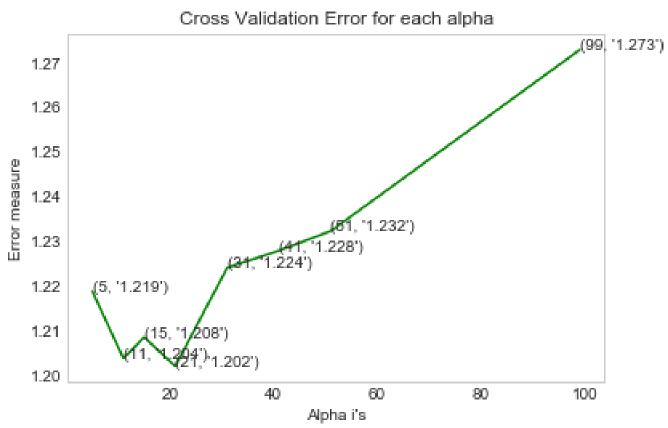
8.2 K-NN

In [54]:

```
alpha = [5, 11, 15, 21, 31, 41, 51, 99]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = KNeighborsClassifier(n_neighbors=i)
    clf.fit(train_x_tfidf, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x_tfidf, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_x_tfidf)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probability estimates
    print("Log Loss :",log_loss(cv_y, sig_clf_probs))

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],str(txt)), (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()


best_alpha = np.argmin(cv_log_error_array)
clf = KNeighborsClassifier(n_neighbors=alpha[best_alpha])
clf.fit(train_x_tfidf, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_tfidf, train_y)
```

```
sig_clf.fit(train_x_tfidf, train_y)

predict_y = sig_clf.predict_proba(train_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

```
for alpha = 5
Log Loss : 1.218793620786283
for alpha = 11
Log Loss : 1.2037074985017382
for alpha = 15
Log Loss : 1.2084481253899635
for alpha = 21
Log Loss : 1.2019297766335362
for alpha = 31
Log Loss : 1.2239934355413786
for alpha = 41
Log Loss : 1.227838103057969
for alpha = 51
Log Loss : 1.2322283993592864
for alpha = 99
Log Loss : 1.2728343366145283
```

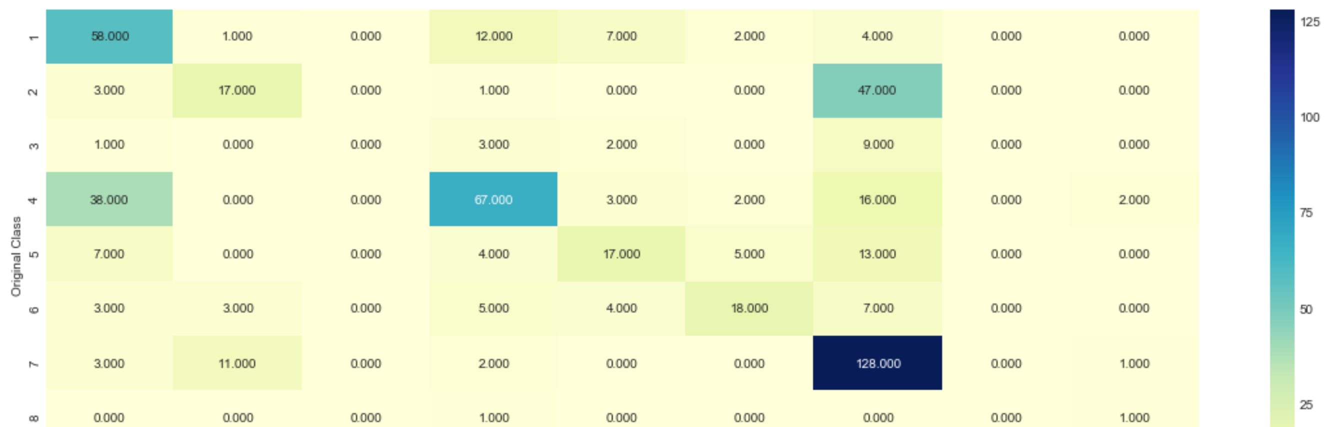


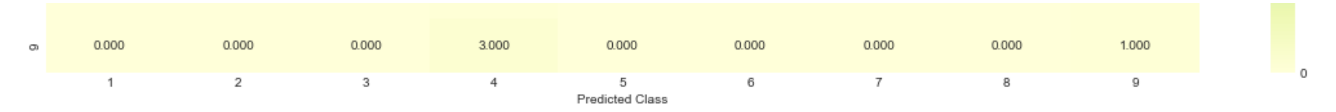

```
For values of best alpha =  21 The train log loss is: 1.1171396324732938
For values of best alpha =  21 The cross validation log loss is: 1.2019297766335362
For values of best alpha =  21 The test log loss is: 1.2438097768275247
```

In [55]:

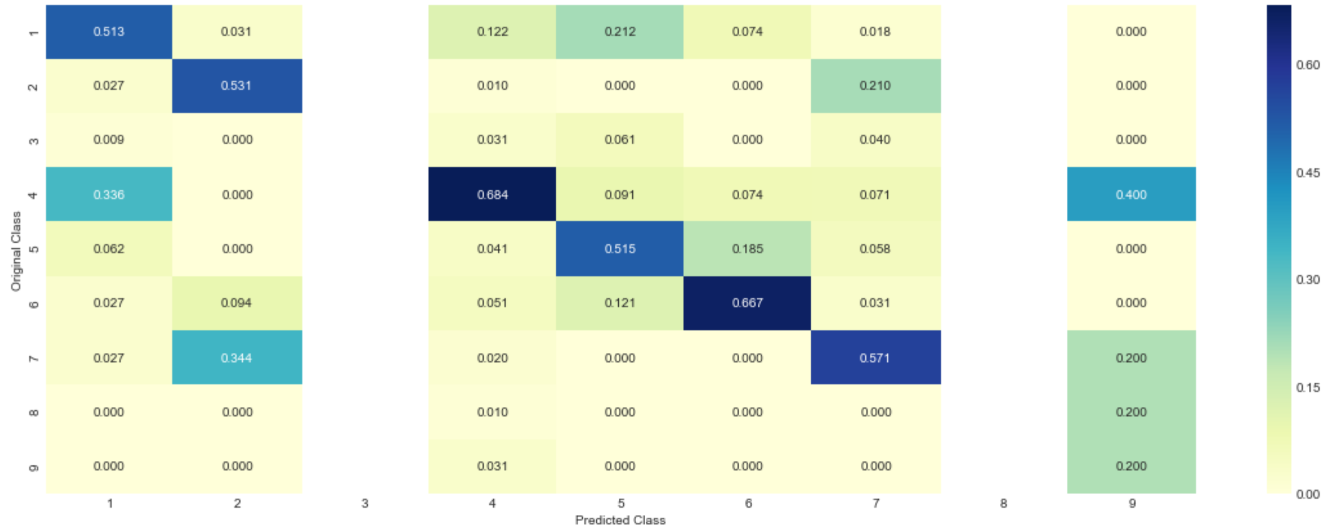
```
predict_and_plot_confusion_matrix(train_x_tfidf, train_y, cv_x_tfidf, cv_y, clf)
```

```
Log loss : 1.2019297766335362
Number of mis-classified points : 0.424812030075188
-------------------- Confusion matrix --------------------
```

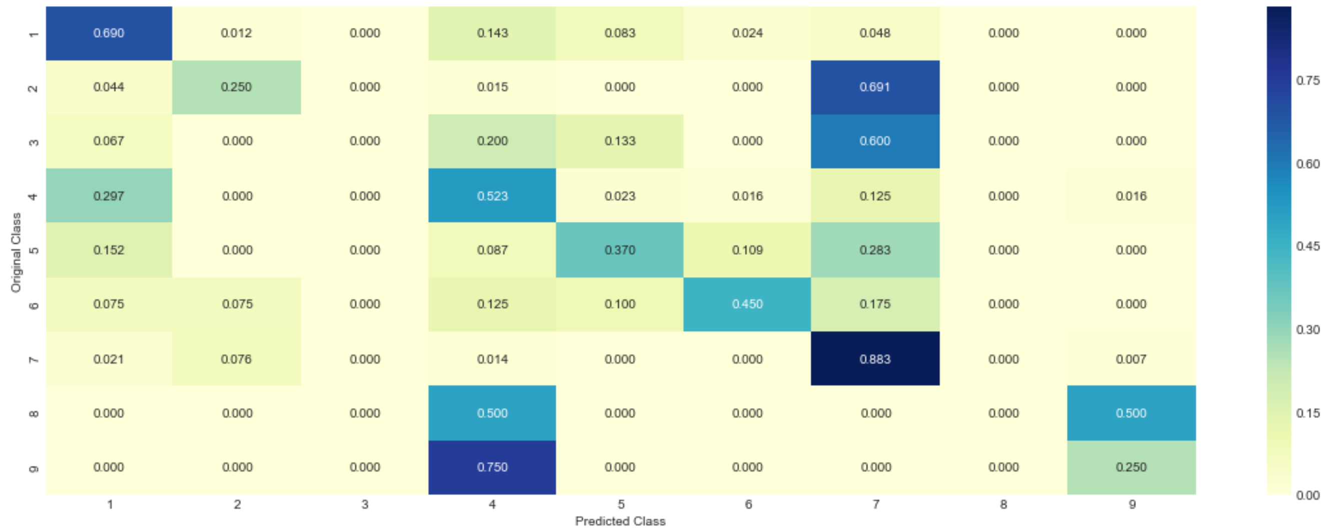





```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [56]:

```
result1 = result1.append(pd.DataFrame([["K-NN", 1.1171, 1.2019, 1.2438, "42.48%",  "GoodFit"]],
                                      columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

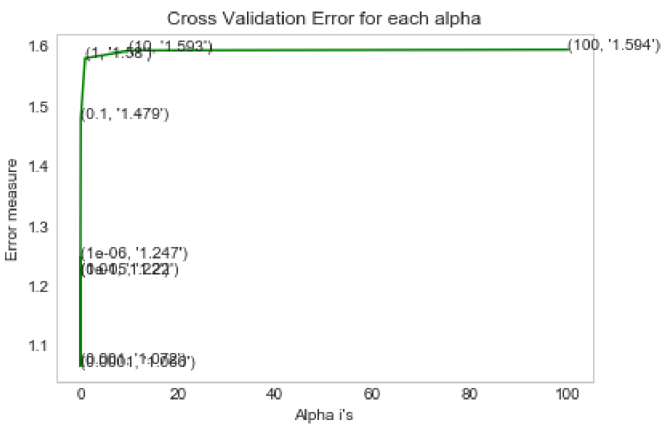
8.3 Logistic Regression

In [57]:

```
alpha = [10 ** x for x in range(-6, 3)]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = SGDClassifier(class_weight='balanced', alpha=i, penalty='l2', loss='log', random_state=42
)
    clf.fit(train_x_tfidf, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x_tfidf, train_y)
```

```
    sig_clf.fit(train_x_tfidf, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_x_tfidf)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probability estimates
    print("Log Loss :",log_loss(cv_y, sig_clf_probs))

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],str(txt)), (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()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', loss='log', ran
dom_state=42)
clf.fit(train_x_tfidf, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_tfidf, train_y)

predict_y = sig_clf.predict_proba(train_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_lo
ss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_y, labels=clf.classes_, eps=1e-15))
```

```
for alpha = 1e-06
Log Loss : 1.2465364219282533
for alpha = 1e-05
Log Loss : 1.2201730586306971
for alpha = 0.0001
Log Loss : 1.065528182075855
for alpha = 0.001
Log Loss : 1.0716527120866841
for alpha = 0.01
Log Loss : 1.2203815235147992
for alpha = 0.1
Log Loss : 1.4792062606778265
for alpha = 1
Log Loss : 1.5796221907695527
for alpha = 10
Log Loss : 1.5925190888839187
for alpha = 100
Log Loss : 1.5939764196845596
```

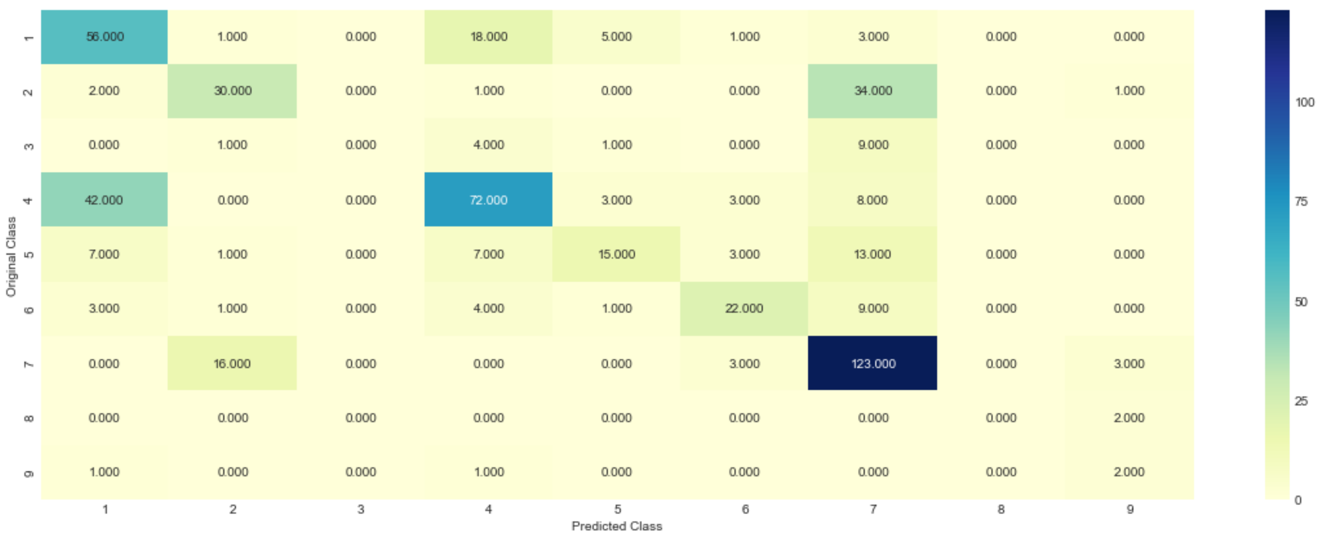



```
For values of best alpha =  0.0001 The train log loss is: 0.6123928658234737
For values of best alpha =  0.0001 The cross validation log loss is: 1.065528182075855
For values of best alpha =  0.0001 The test log loss is: 1.071597764315154
```

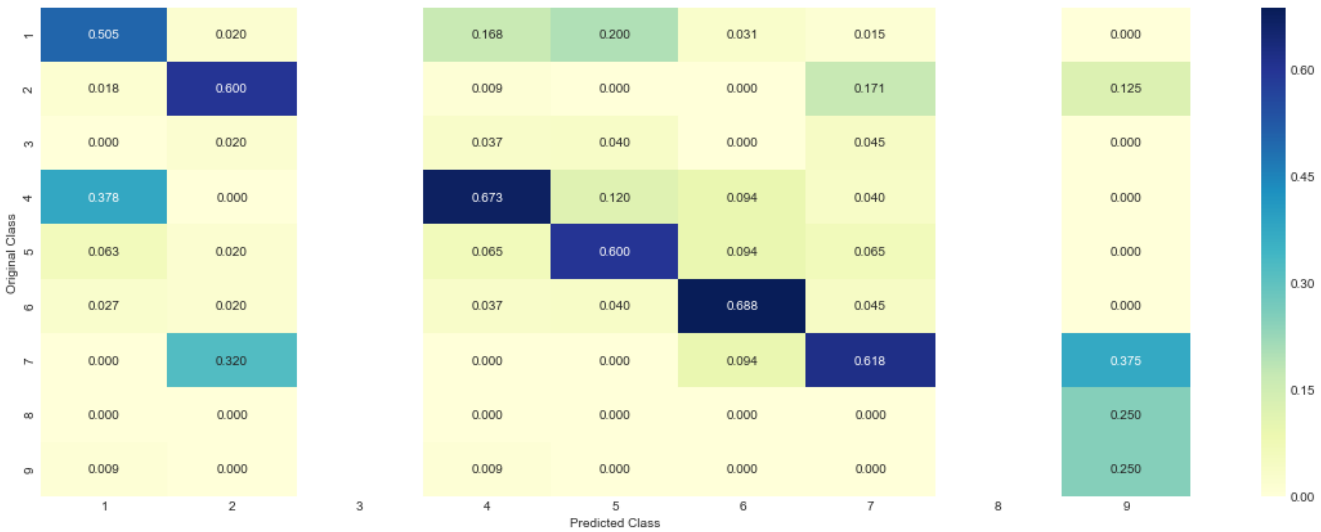
In [58]:

```
predict_and_plot_confusion_matrix(train_x_tfidf, train_y, cv_x_tfidf, cv_y, clf)
```

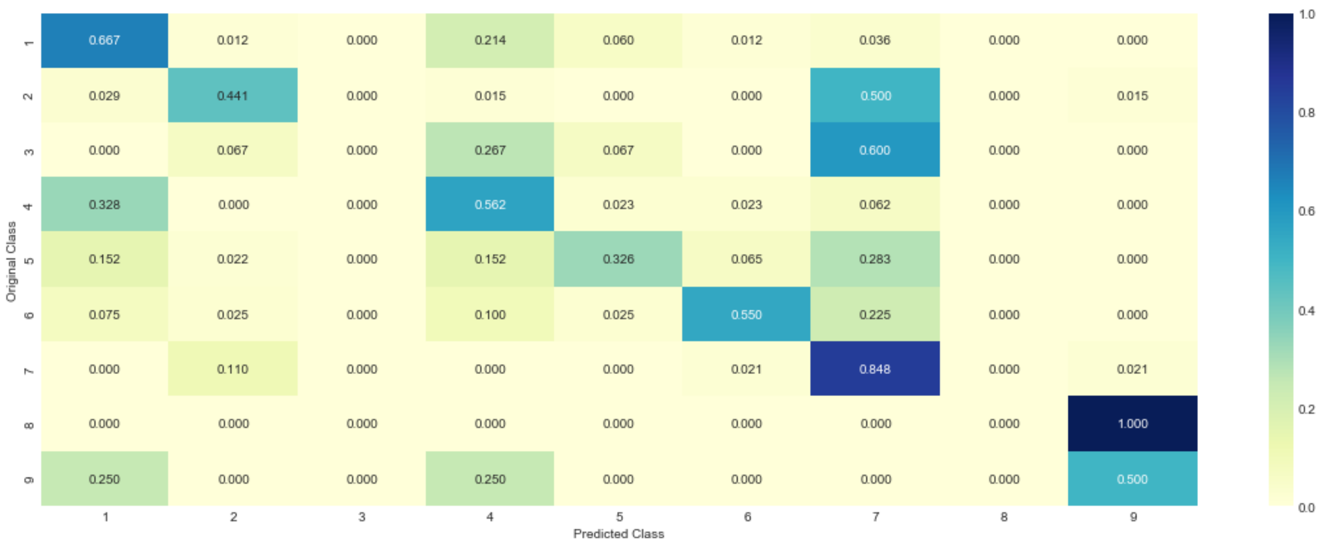
```
Log loss : 1.065528182075855
Number of mis-classified points : 0.39849624060150374
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [59]:

```
result1 = result1.append(pd.DataFrame([["Logistic-Regression",0.6123, 1.0655, 1.0715, "39.84%",  "G
oodFit"]],
                                      columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

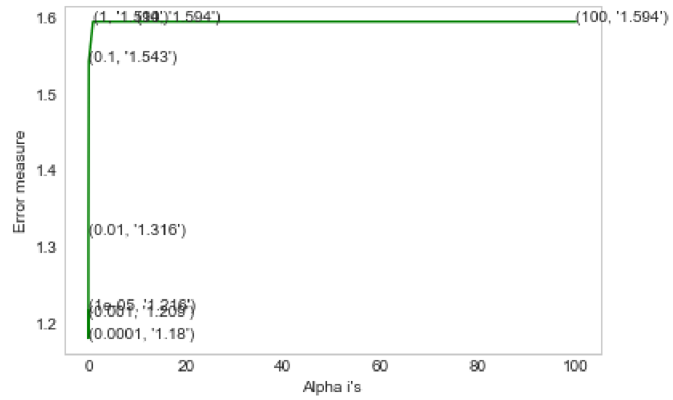
8.4 Linear Support Vector Machines

In [60]:

```
alpha = [10 ** x for x in range(-5, 3)]
cv_log_error_array = []
for i in alpha:
    print("for C =", i)
#     clf = SVC(C=i,kernel='linear',probability=True, class_weight='balanced')
    clf = SGDClassifier( class_weight='balanced', alpha=i, penalty='l2', loss='hinge', random_state
=42)
    clf.fit(train_x_tfidf, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x_tfidf, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_x_tfidf)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
    print("Log Loss :",log_loss(cv_y, sig_clf_probs))

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],str(txt)), (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()


best_alpha = np.argmin(cv_log_error_array)
# clf = SVC(C=i,kernel='linear',probability=True, class_weight='balanced')
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', loss='hinge', r
andom_state=42)
clf.fit(train_x_tfidf, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_tfidf, train_y)

predict_y = sig_clf.predict_proba(train_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_lo
ss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_tfidf)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_y, labels=clf.classes_, eps=1e-15))
```

```
for C = 1e-05
Log Loss : 1.2160797388003899
for C = 0.0001
Log Loss : 1.1797621743575233
for C = 0.001
Log Loss : 1.2091867797280327
for C = 0.01
Log Loss : 1.3156285445438407
for C = 0.1
Log Loss : 1.5426932155396316
for C = 1
Log Loss : 1.594298631721724
for C = 10
Log Loss : 1.5942985842074928
for C = 100
Log Loss : 1.5942986294512307
```

Cross Validation Error for each alpha

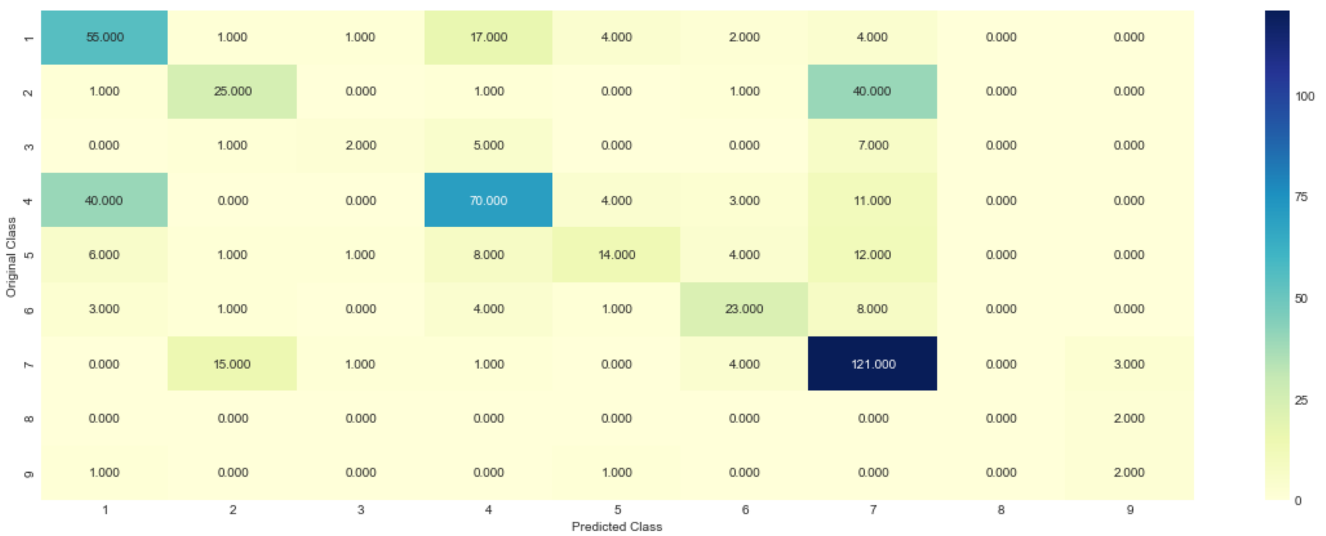



```
For values of best alpha =  0.0001 The train log loss is: 0.718759251019382
For values of best alpha =  0.0001 The cross validation log loss is: 1.1797621743575233
For values of best alpha =  0.0001 The test log loss is: 1.1754326810083873
```

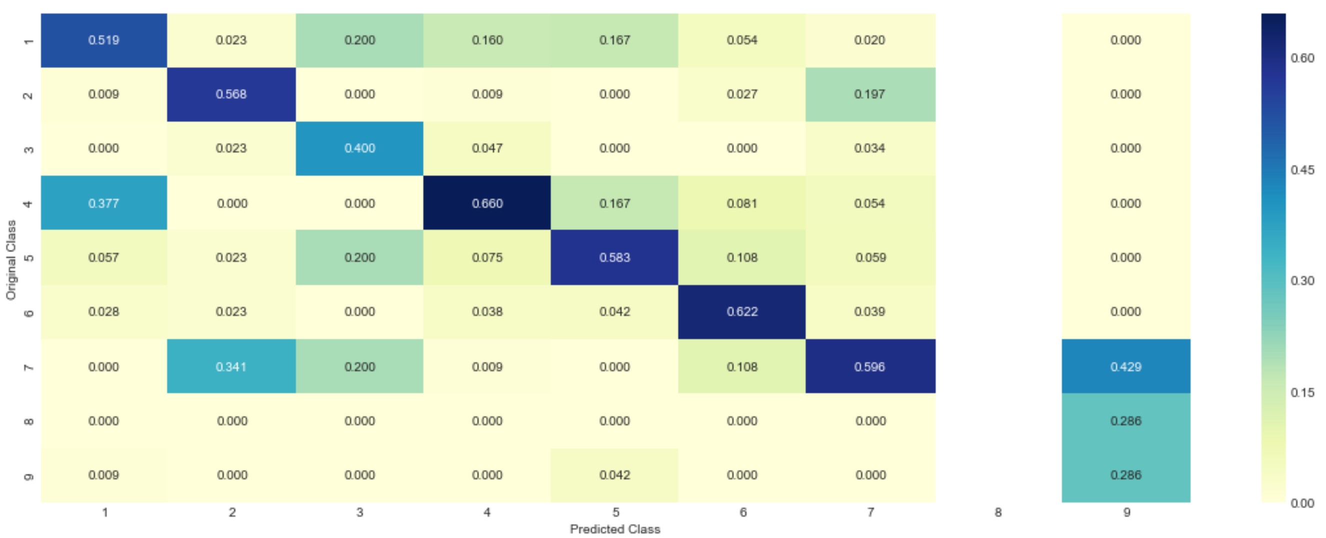
In [61]:

```
predict_and_plot_confusion_matrix(train_x_tfidf, train_y, cv_x_tfidf, cv_y, clf)
```

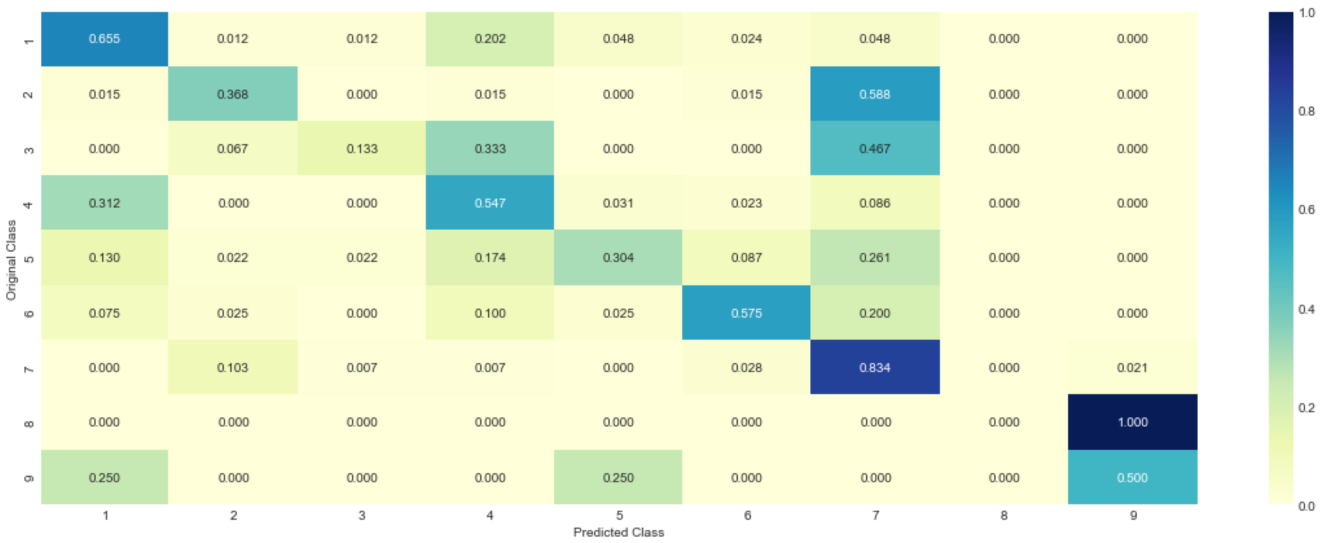
```
Log loss : 1.1797621743575233
Number of mis-classified points : 0.41353383458646614
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [62]:

```
result1 = result1.append(pd.DataFrame([["Linear-SVM", 0.7187, 1.1797, 1.1754, "41.35%",  "GoodFit"]
],
                                  columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

8.5 Random Forest Classifier

In [63]:

```
alpha = [100,200,500,1000,2000]
max_depth = [5, 10]
cv_log_error_array = []
for i in alpha:
    for j in max_depth:
        print("for n_estimators =", i,"and max depth = ", j)
        clf = RandomForestClassifier(n_estimators=i, criterion='gini', max_depth=j, random_state=42
, n_jobs=-1)
        clf.fit(train_x_tfidf, train_y)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
        sig_clf.fit(train_x_tfidf, train_y)
        sig_clf_probs = sig_clf.predict_proba(cv_x_tfidf)
        cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
        print("Log Loss :",log_loss(cv_y, sig_clf_probs))


best_alpha = np.argmin(cv_log_error_array)
clf = RandomForestClassifier(n_estimators=alpha[int(best_alpha/2)], criterion='gini', max_depth=max
_depth[int(best_alpha%2)], random_state=42, n_jobs=-1)
clf.fit(train_x_tfidf, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x_tfidf, train_y)

predict_y = sig_clf.predict_proba(train_x_tfidf)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train log loss
is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x_tfidf)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross validation log loss
is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_x_tfidf)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test log loss
is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

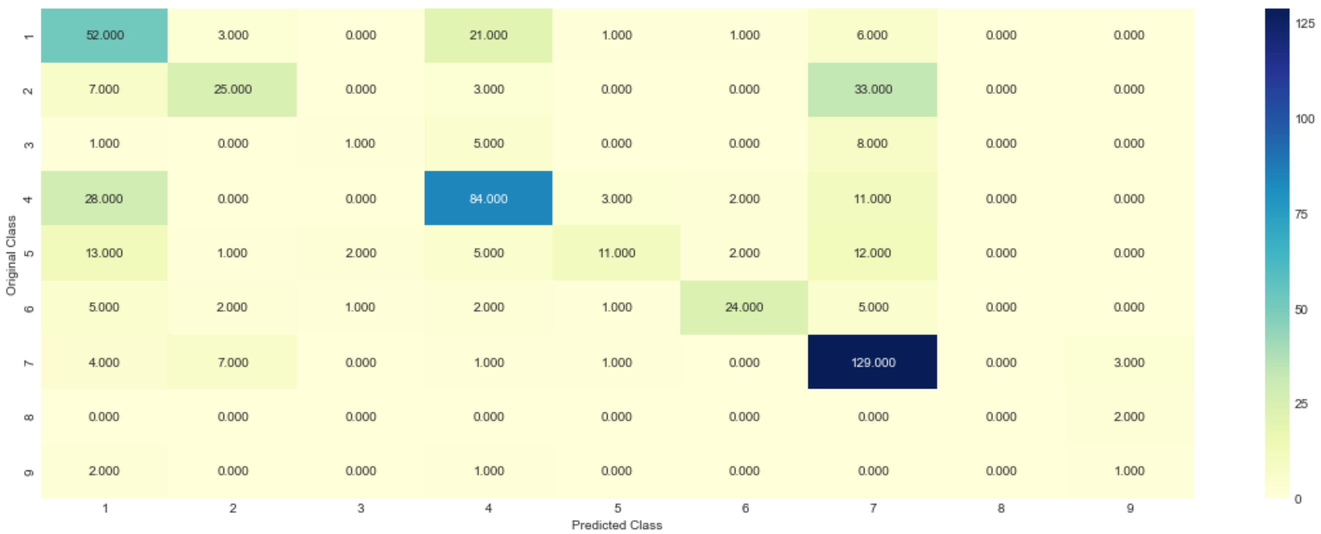
```
for n_estimators = 100 and max depth =  5
Log Loss : 1.1215962772043093
for n_estimators = 100 and max depth =  10
Log Loss : 1.1304681961756393
for n_estimators = 200 and max depth =  5
Log Loss : 1.1193874277647333
```

```
for n_estimators = 200 and max depth =  10
Log Loss : 1.1198270324301776
for n_estimators = 500 and max depth =  5
Log Loss : 1.123549800737744
for n_estimators = 500 and max depth =  10
Log Loss : 1.1160243335958873
for n_estimators = 1000 and max depth =  5
Log Loss : 1.1185785179998853
for n_estimators = 1000 and max depth =  10
Log Loss : 1.1121676779838399
for n_estimators = 2000 and max depth =  5
Log Loss : 1.1185803217258512
for n_estimators = 2000 and max depth =  10
Log Loss : 1.1130772557334192
For values of best estimator =  1000 The train log loss is: 0.5580987476285331
For values of best estimator =  1000 The cross validation log loss is: 1.1121676779838399
For values of best estimator =  1000 The test log loss is: 1.1063957192253842
```

In [64]:

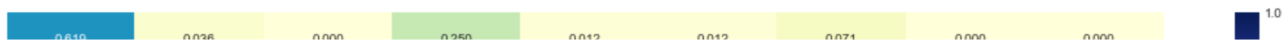
```
predict_and_plot_confusion_matrix(train_x_tfidf, train_y, cv_x_tfidf, cv_y, clf)
```

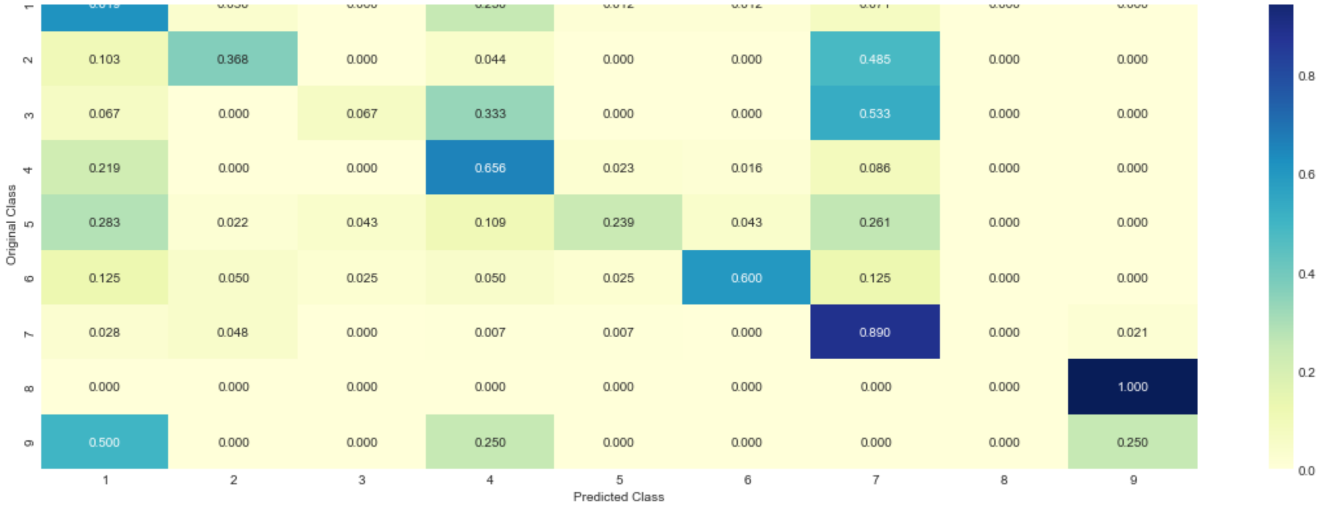
```
Log loss : 1.1121676779838399
Number of mis-classified points : 0.38533834586466165
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```


```
-------------------- Recall matrix (Row sum=1) --------------------
```





In [65]:

```
result1 = result1.append(pd.DataFrame([["Random-Forest",0.5580, 1.1121, 1.1063, "38.53%",  "BestFit
"]],
                                  columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

8.6 Stack the models

In [66]:

```
clf1 = SGDClassifier(alpha=0.001, penalty='l2', loss='log', class_weight='balanced', random_state=0
)
clf1.fit(train_x_tfidf, train_y)
sig_clf1 = CalibratedClassifierCV(clf1, method="sigmoid")

clf2 = SGDClassifier(alpha=1, penalty='l2', loss='hinge', class_weight='balanced', random_state=0)
clf2.fit(train_x_tfidf, train_y)
sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")


clf3 = MultinomialNB(alpha=0.001)
clf3.fit(train_x_tfidf, train_y)
sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")

sig_clf1.fit(train_x_tfidf, train_y)
print("Logistic Regression :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf1.predict_proba(cv_x_tfidf)
)))
sig_clf2.fit(train_x_tfidf, train_y)
print("Support vector machines : Log Loss: %0.2f" % (log_loss(cv_y,
sig_clf2.predict_proba(cv_x_tfidf))))
sig_clf3.fit(train_x_tfidf, train_y)
print("Naive Bayes : Log Loss: %0.2f" % (log_loss(cv_y, sig_clf3.predict_proba(cv_x_tfidf))))
print("-"*50)
alpha = [0.0001,0.001,0.01,0.1,1,10]

for i in alpha:
    lr = LogisticRegression(C=i)
    sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classifier=lr, use_p
robas=True)
    sclf.fit(train_x_tfidf, train_y)
    print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" % (i, log_loss(cv_y, sc
lf.predict_proba(cv_x_tfidf))))
    log_error =log_loss(cv_y, sclf.predict_proba(cv_x_tfidf))
    if best_alpha > log_error:
        best_alpha = log_error
```

```
Logistic Regression :  Log Loss: 1.06
Support vector machines : Log Loss: 1.59
Naive Bayes : Log Loss: 1.23
--------------------------------------------------
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 2.179
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 2.048
```

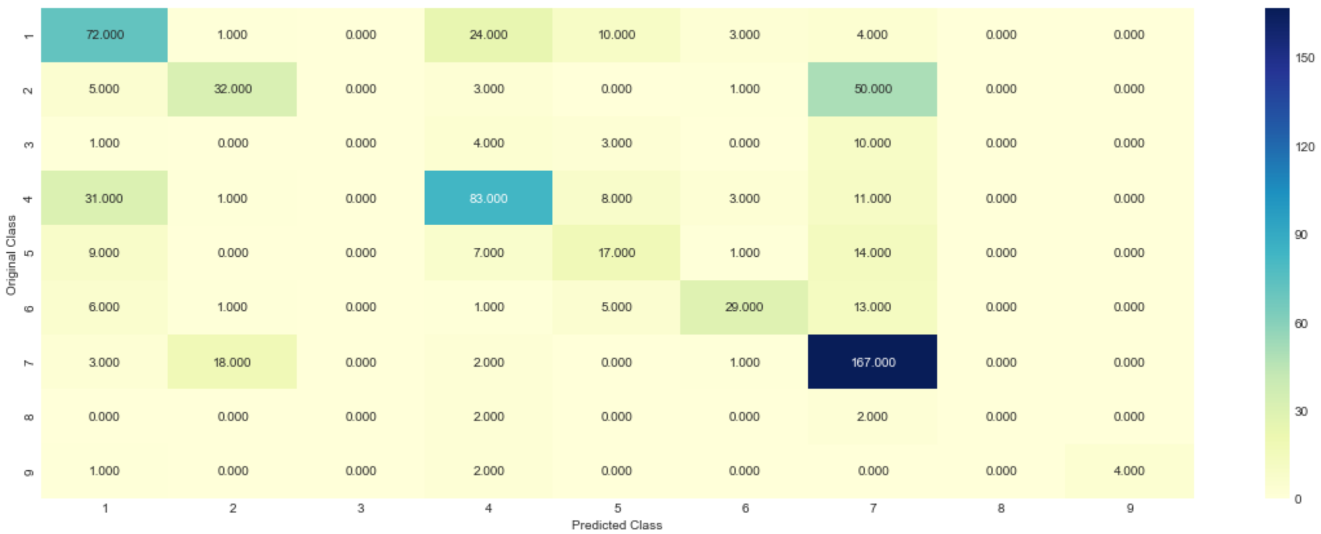
```
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 1.568
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 1.176
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 1.163
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 1.201
```

testing the model with the best hyper parameters

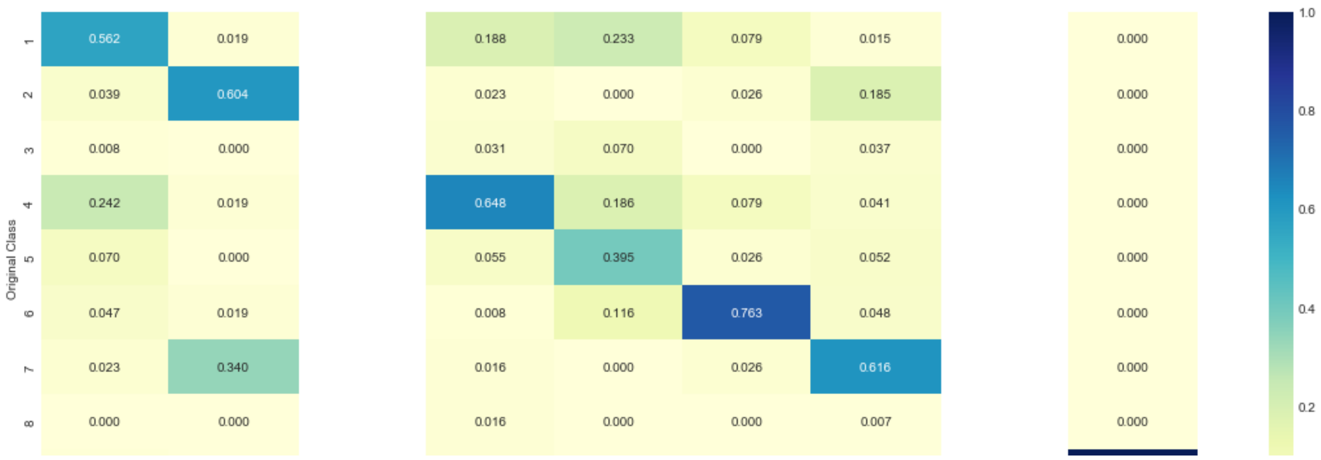
In [67]:

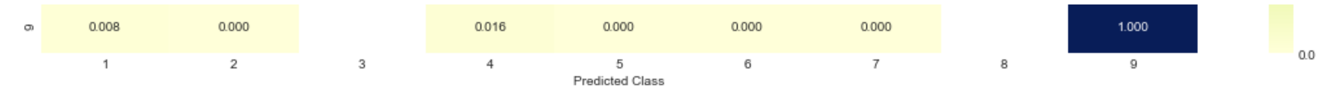
```python
lr = LogisticRegression(C=0.1)
sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classifier=lr, use_proba
s=True)
sclf.fit(train_x_tfidf, train_y)

log_error = log_loss(train_y, sclf.predict_proba(train_x_tfidf))
print("Log loss (train) on the stacking classifier :",log_error)

log_error = log_loss(cv_y, sclf.predict_proba(cv_x_tfidf))
print("Log loss (CV) on the stacking classifier :",log_error)

log_error = log_loss(test_y, sclf.predict_proba(test_x_tfidf))
print("Log loss (test) on the stacking classifier :",log_error)

print("Number of missclassified point :", np.count_nonzero((sclf.predict(test_x_tfidf)- test_y))/t
est_y.shape[0])
plot_confusion_matrix(test_y=test_y, predict_y=sclf.predict(test_x_tfidf))
```

```
Log loss (train) on the stacking classifier : 0.8166620953107279
Log loss (CV) on the stacking classifier : 1.1756872281645971
Log loss (test) on the stacking classifier : 1.19587295751898
Number of missclassified point : 0.3924812030075188
-------------------- Confusion matrix --------------------
```

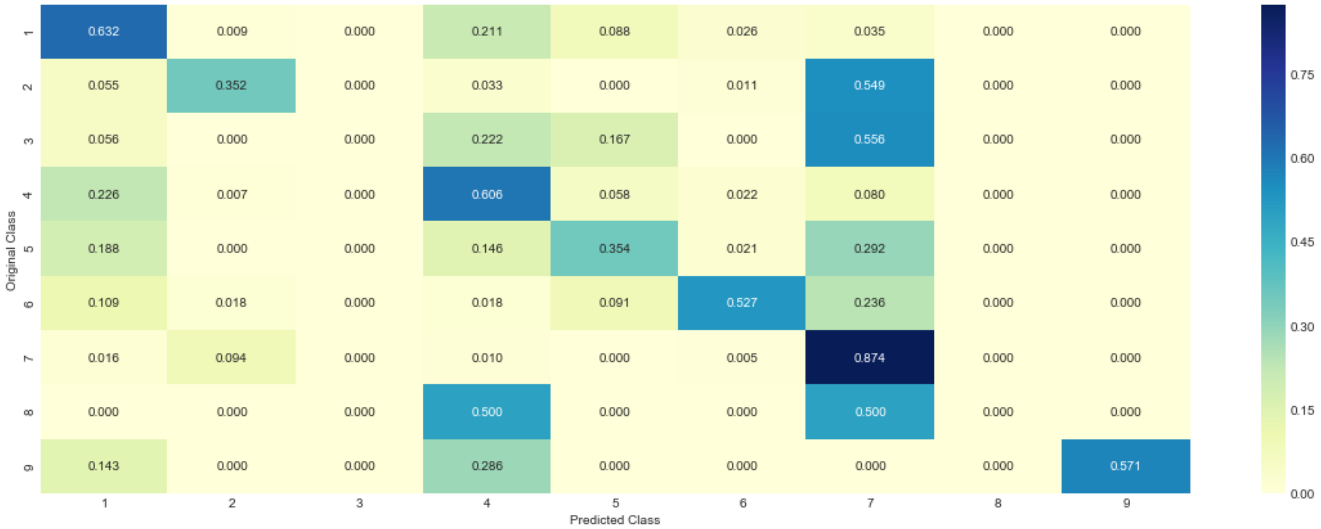



```
-------------------- Precision matrix (Columm Sum=1) --------------------
```






```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [68]:

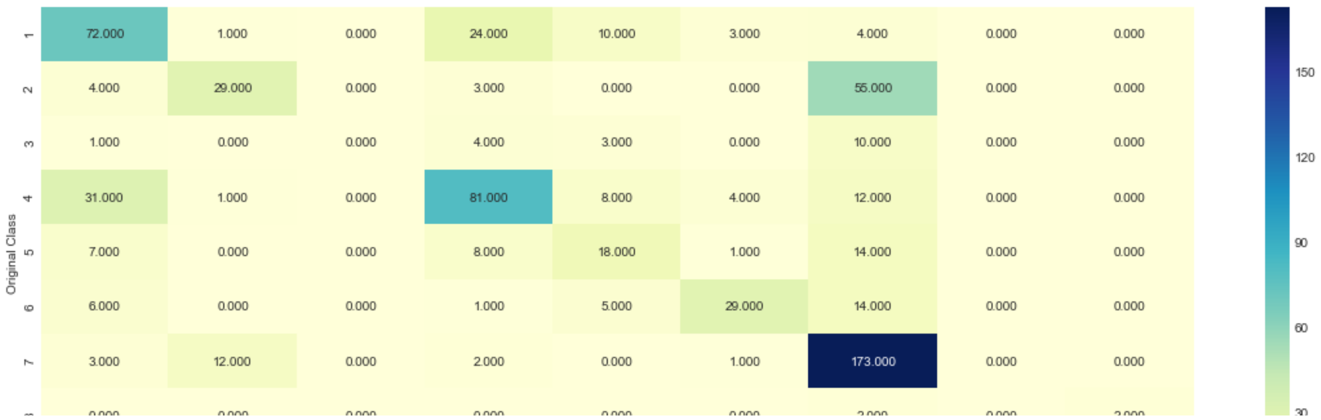
```
result1 = result1.append(pd.DataFrame([["stacking-classifier",0.8166,1.1756, 1.1958, "39.24%",  "GoodFit"]],
                                columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-loss", "Mis-Classified CV", "Remarks"]))
```

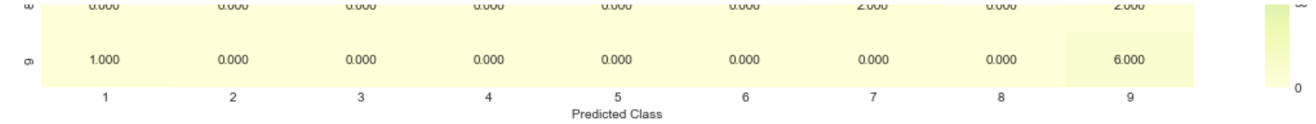
8.7 Maximum Voting classifier

In [69]:

```
vclf = VotingClassifier(estimators=[('lr', sig_clf1), ('svc', sig_clf2), ('rf', sig_clf3)], voting='soft')
vclf.fit(train_x_tfidf, train_y)
print("Log loss (train) on the VotingClassifier :", log_loss(train_y, vclf.predict_proba(train_x_tfidf)))
print("Log loss (CV) on the VotingClassifier :", log_loss(cv_y, vclf.predict_proba(cv_x_tfidf)))
print("Log loss (test) on the VotingClassifier :", log_loss(test_y, vclf.predict_proba(test_x_tfidf)))
print("Number of missclassified point :", np.count_nonzero((vclf.predict(test_x_tfidf)- test_y))/test_y.shape[0])
plot_confusion_matrix(test_y=test_y, predict_y=vclf.predict(test_x_tfidf))
```

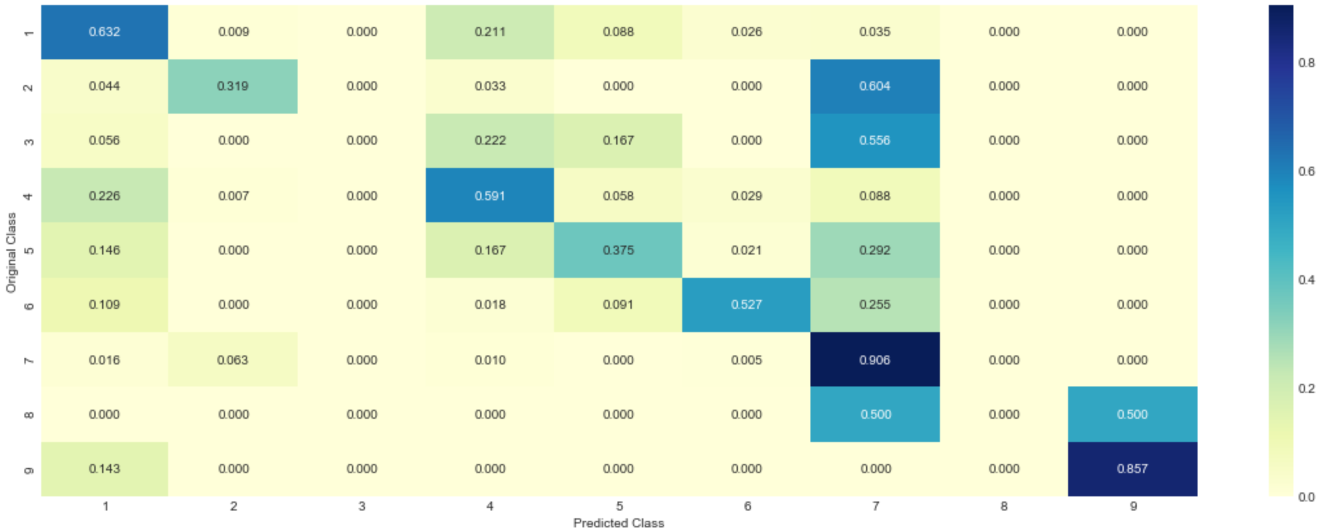
```
Log loss (train) on the VotingClassifier : 0.9406402937098679
Log loss (CV) on the VotingClassifier : 1.2165903525810051
Log loss (test) on the VotingClassifier : 1.2421220869729934
Number of missclassified point : 0.38646616541353385
-------------------- Confusion matrix --------------------
```






```
-------------------- Precision matrix (Columm Sum=1) --------------------
```


```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [70]:

```
result1 = result1.append(pd.DataFrame([["Maximum voting classifier",0.9406, 1.2165, 1.2421, "38.64%
",  "GoodFit"]],
                                       columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-lo
s", "Mis-Classified CV", "Remarks"]))
```

Conclusions:

In [71]:

```
(result1)
```

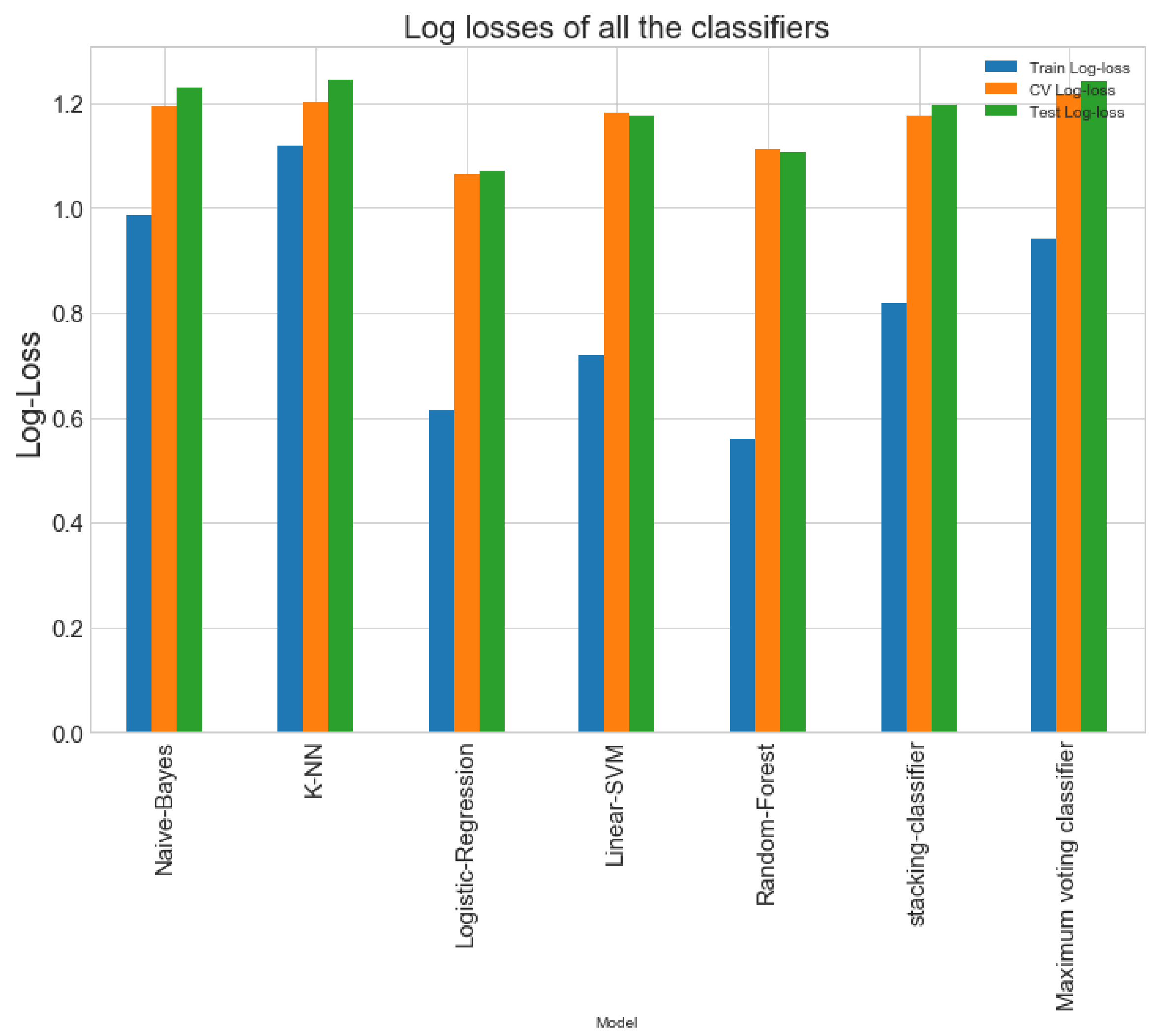
Out[71]:

	Model	Train Log-loss	CV Log-loss	Test Log-loss	Mis-Classified CV	Remarks
0	Naive-Bayes	0.9870	1.1936	1.2304	40.60%	GoodFit

	Model	Train Log-loss	CV Log-loss	Test Log-loss	Mis-Classified CV	Remarks
0	K-NN	1.1171	1.2019	1.2438	42.48%	GoodFit
0	Logistic-Regression	0.6123	1.0655	1.0715	39.84%	GoodFit
0	Linear-SVM	0.7187	1.1797	1.1754	41.35%	GoodFit
0	Random-Forest	0.5580	1.1121	1.1063	38.53%	BestFit
0	stacking-classifier	0.8166	1.1756	1.1958	39.24%	GoodFit
0	Maximum voting classifier	0.9406	1.2165	1.2421	38.64%	GoodFit

In [72]:

```
result2 = result1.drop(["Mis-Classified CV", "Remarks"], axis = 1)
result2.plot(x = "Model", kind = "bar", figsize = (12, 8), grid = True, fontsize = 15)
plt.title("Log losses of all the classifiers", fontsize = 20)
plt.ylabel("Log-Loss", fontsize = 20)
plt.show()
```



In [73]:

```
#getting the data
data_no_preprocess.head(5)
```

Out[73]:

	ID	Gene	Variation	Class	TEXT
0	0	FAM58A	Truncating Mutations	1	Cyclin-dependent kinases (CDKs) regulate a var...
1	1	CBL	W802*	2	Abstract Background Non-small cell lung canc...
2	2	CBL	Q249E	2	Abstract Background Non-small cell lung canc...
3	3	CBL	N454D	3	Recent evidence has demonstrated that acquired...

	ID	Gene	Variation	Class	TEXT
4	4	CBL	L399V	4	Oncogenic mutations in the monomeric Casitas B...

In [ ]:

```
train_gene_var_onehotCoding =
hstack((train_gene_feature_onehotCoding,train_variation_feature_onehotCoding))
test_gene_var_onehotCoding =
hstack((test_gene_feature_onehotCoding,test_variation_feature_onehotCoding))
cv_gene_var_onehotCoding = hstack((cv_gene_feature_onehotCoding,cv_variation_feature_onehotCoding)
)

train_x_onehotCoding = hstack((train_gene_var_onehotCoding, train_text_feature_onehotCoding)).tocs
r()
train_y = np.array(list(y_train))

test_x_onehotCoding = hstack((test_gene_var_onehotCoding, test_text_feature_onehotCoding)).tocsr()
test_y = np.array(list(y_test))

cv_x_onehotCoding = hstack((cv_gene_var_onehotCoding, cv_text_feature_onehotCoding)).tocsr()
cv_y = np.array(list(y_cv))
```

In [75]:

```
#importing required libraries
import re

#pre-defined finctions to remove html tags ,punctuations, special characters

#function fro removing html tags
def remove_html (sentence):
    cleanhtml = re.compile('<.*?>')
    clean_text = re.sub(cleanhtml,' ',str(sentence))
    return clean_text

#function for removing punctuations and special characters
def remove_punc(sentence):
    cleanpunc = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleanpunc = re.sub(r'[.|,|)|(|\|/]',r' ',cleanpunc)
    cleanpunc = cleanpunc.strip()
    cleanpunc = cleanpunc.replace("\n" ,'')
    return cleanpunc


#function for keeping only alphabets
def keep_alpha(sentence):
    alpha_sentence = ""
    for word in sentence.split():
        alpha_word = re.sub('[^a-z A-Z]+', ' ', word)
        alpha_sentence += alpha_word
        alpha_sentence += " "
    alpha_sentence = alpha_sentence.strip()
    return alpha_sentence



#removing stopwords with some exceptions and do stemmming
#initializing stopwords with some exceptions words like not and very and stemming
import nltk
#nltk.download("stopwords")

from nltk.corpus import stopwords

exceptions = set(("very","not","few","against","more" ,"between",))

stop_words = set(stopwords.words('english')) - exceptions
stop_words.update(['zero','one','two','three','four','five','six','seven','eight',
                   'nine','ten','may','also','however','yet'])
print(stop_words)

#function for removing stopwords

def remove_stopwords(sentence):
    no_stopword_review = ""
    for word in sentence.split():
```

```
        if word not in stop_words:
            no_stopword_review += word
            no_stopword_review += " "
    no_stopword_review = no_stopword_review.strip()
    return no_stopword_review


#stemming
sno = nltk.stem.SnowballStemmer('english')

#function to do stemming
def stem_remove(sentence):
    stem_sentence = ""
    for word in sentence.split():
        stem_word = sno.stem(word)
        stem_sentence += stem_word
        stem_sentence += " "
    stem_sentence = stem_sentence.strip()
    return stem_sentence
```

```
{'couldn', 'mustn', 'themselves', 'hasn', 'shan', "mustn't", "weren't", 'hadn', "hadn't", 're',
'were', 'an', 'again', 'are', 'yourself', 'who', 'herself', 'hers', "should've", 'here',
'ourselves', "you'll", 'out', 've', 'be', 'can', "you're", 'she', "haven't", 'during', 'her', 'abo
ve', "couldn't", 'ain', 'as', 't', 'at', 'through', 'ours', 'a', 'theirs', 'its', 'that', 'you', '
do', 'why', "mightn't", 'same', "doesn't", "that'll", 'how', 'down', 'should', 'after', 'whom', 'f
urther', 'some', 'but', 'before', 'eight', 'other', 'doesn', 'he', 'itself', 'in', "don't", 'their
', "didn't", 'no', 'am', 'than', 'weren', 'under', 'yourselves', "wouldn't", 'was', 'being', 'when
', "wasn't", 'isn', 'on', 'however', 'it', 'this', 'there', 'only', 'me', 'or', 'because',
"hasn't", 'wouldn', 'four', 'may', 'zero', 'too', 'of', 'where', 'into', 'own', 'about', 'needn',
'what', 'nine', 'once', "aren't", 'has', 'my', 'them', 'did', 'won', 'your', 'from', 'wasn',
"she's", 'aren', 'is', 'll', 'ten', 'yet', 'his', 'having', 'such', 'ma', 'these', 'shouldn',
'three', 'himself', 'does', 'him', 'nor', 'off', 'just', 'with', 'd', 'seven', 'i', "isn't", 'whil
e', "needn't", 'so', 'yours', 'and', 's', 'each', 'had', 'will', 'our', 'all', 'most', 'by',
'then', 'have', 'if', 'y', 'for', 'o', 'haven', 'now', 'also', 'those', 'they', "you've", 'm', 'do
ing', "shan't", 'up', 'the', 'five', 'which', 'been', 'both', 'don', "you'd", 'until', 'we', 'six'
, 'any', "shouldn't", 'two', 'over', 'to', 'didn', "won't", "it's", 'myself', 'one', 'below', 'mig
htn'}
```

In [77]:

```
#applying all pre-processing functions on the text to get cleaned text
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].str.lower()
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].apply(remove_html)
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].apply(remove_punc)
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].apply(keep_alpha)
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].apply(remove_stopwords)
data_no_preprocess['TEXT'] = data_no_preprocess['TEXT'].apply(stem_remove)
```

AvgW2Vec

In [79]:

```
#importing required libraries
import warnings
warnings.filterwarnings(action='ignore', category=UserWarning, module='gensim')
from gensim.models import Word2Vec

#spliting the text review into sentences
list_of_sentences=[]
for sent in data_no_preprocess['TEXT'].values:
    list_of_sentences.append(sent.split())

#initiating word2vec with required parameters like minimum count for any word to be considered
word2vec_model = Word2Vec(list_of_sentences,min_count=5,size=50, workers=4)
word2vec_words = list(word2vec_model.wv.vocab)

#getting avgw2vec  for each review
avgw2vec_vectors = []; #list of avgw2vec vectors
for sent in list_of_sentences:
    sent_vectors = np.zeros(50)
    count_words =0;
    for word in sent:
        if word in word2vec_words:
```

```
        if word in word2vec_words:
            vec = word2vec_model.wv[word]
            sent_vectors += vec
            count_words += 1 #number of words in the sentence vector
    if count_words != 0:
        sent_vectors /= count_words #taking the average
    avgw2vec_vectors.append(sent_vectors)
```

In [80]:

```
#splitting data into 64% train-20% test-16% CV data
y = merge_data["Class"].values
X = avgw2vec_vectors

X_train_cv,X_test ,y_train_cv ,y_test = train_test_split(X,y,test_size = 0.2 ,random_state = 123,st
ratify = y )
X_train ,X_cv ,y_train ,y_cv = train_test_split (X_train_cv,y_train_cv,test_size = 0.2 , random_sta
te = 123 )
```

In [81]:

```
train_gene_var_onehotCoding =
hstack((train_gene_feature_onehotCoding,train_variation_feature_onehotCoding))
test_gene_var_onehotCoding =
hstack((test_gene_feature_onehotCoding,test_variation_feature_onehotCoding))
cv_gene_var_onehotCoding = hstack((cv_gene_feature_onehotCoding,cv_variation_feature_onehotCoding)
)

train_x = hstack((train_gene_var_onehotCoding, X_train)).tocsr()
train_y = np.array(list(y_train))

test_x = hstack((test_gene_var_onehotCoding, X_test)).tocsr()
test_y = np.array(list(y_test))

cv_x = hstack((cv_gene_var_onehotCoding,X_cv)).tocsr()
cv_y = np.array(list(y_cv))
```

Random-Forest

In [88]:

```
esti = [10,20,30,40,50,80,100]
max_depth = [5, 10,15,20]
cv_log_error_array = []
for i in esti:
    for j in max_depth:
        print("for n_estimators =", i,"and max depth = ", j)
        clf = RandomForestClassifier(n_estimators=i, criterion='gini', max_depth=j, random_state=42
, n_jobs=-1)
        clf.fit(train_x, train_y)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
        sig_clf.fit(train_x, train_y)
        sig_clf_probs = sig_clf.predict_proba(cv_x)
        cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1e-15))
        print("Log Loss :",log_loss(cv_y, sig_clf_probs))
```

```
for n_estimators = 10 and max depth =  5
Log Loss : 1.2935362160633879
for n_estimators = 10 and max depth =  10
Log Loss : 1.1589219508159014
for n_estimators = 10 and max depth =  15
Log Loss : 1.1701017900217459
for n_estimators = 10 and max depth =  20
Log Loss : 1.1611010916058804
for n_estimators = 20 and max depth =  5
Log Loss : 1.2492523025714375
for n_estimators = 20 and max depth =  10
Log Loss : 1.1383195752780166
for n_estimators = 20 and max depth =  15
Log Loss : 1.1365768663376945
for n_estimators = 20 and max depth =  20
Log Loss : 1.1424313966094788
```

```
for n_estimators = 30 and max depth =  5
Log Loss : 1.2252174721176432
for n_estimators = 30 and max depth =  10
Log Loss : 1.13331450689948
for n_estimators = 30 and max depth =  15
Log Loss : 1.1257953350723306
for n_estimators = 30 and max depth =  20
Log Loss : 1.1294379760171616
for n_estimators = 40 and max depth =  5
Log Loss : 1.216923135607606
for n_estimators = 40 and max depth =  10
Log Loss : 1.1266039470444331
for n_estimators = 40 and max depth =  15
Log Loss : 1.1155454366506332
for n_estimators = 40 and max depth =  20
Log Loss : 1.1248129424868747
for n_estimators = 50 and max depth =  5
Log Loss : 1.221921207410648
for n_estimators = 50 and max depth =  10
Log Loss : 1.1227755640759773
for n_estimators = 50 and max depth =  15
Log Loss : 1.110500608147484
for n_estimators = 50 and max depth =  20
Log Loss : 1.117375622482576
for n_estimators = 80 and max depth =  5
Log Loss : 1.2249892500636514
for n_estimators = 80 and max depth =  10
Log Loss : 1.1192208290341212
for n_estimators = 80 and max depth =  15
Log Loss : 1.1067640641066834
for n_estimators = 80 and max depth =  20
Log Loss : 1.110342192227
for n_estimators = 100 and max depth =  5
Log Loss : 1.221182258258214
for n_estimators = 100 and max depth =  10
Log Loss : 1.1185915428932391
for n_estimators = 100 and max depth =  15
Log Loss : 1.102602844779191
for n_estimators = 100 and max depth =  20
Log Loss : 1.1090108483597056
```

In [91]:

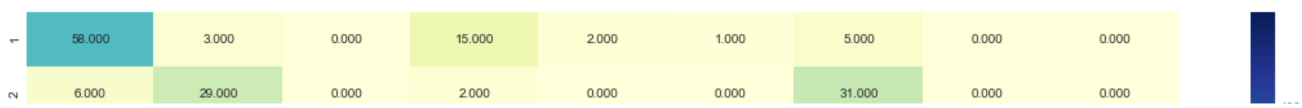
```python
best_alpha = np.argmin(cv_log_error_array)
clf = RandomForestClassifier(n_estimators=100, criterion='gini', max_depth=15, random_state=42, n_j
obs=-1)
clf.fit(train_x, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_x, train_y)

predict_y = sig_clf.predict_proba(train_x)
print( "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(cv_x)
print("The cross validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15)
)
predict_y = sig_clf.predict_proba(test_x)
print( "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

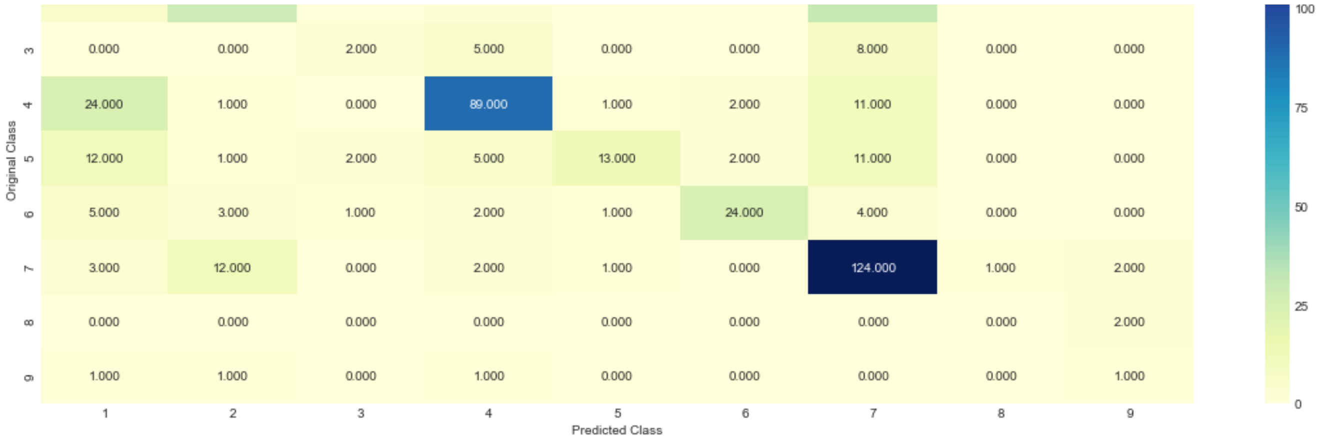
```
The train log loss is: 0.5241995297319304
The cross validation log loss is: 1.102602844779191
The test log loss is: 1.1068232673038858
```

In [92]:

```python
predict_and_plot_confusion_matrix(train_x, train_y, cv_x, cv_y, clf)
```

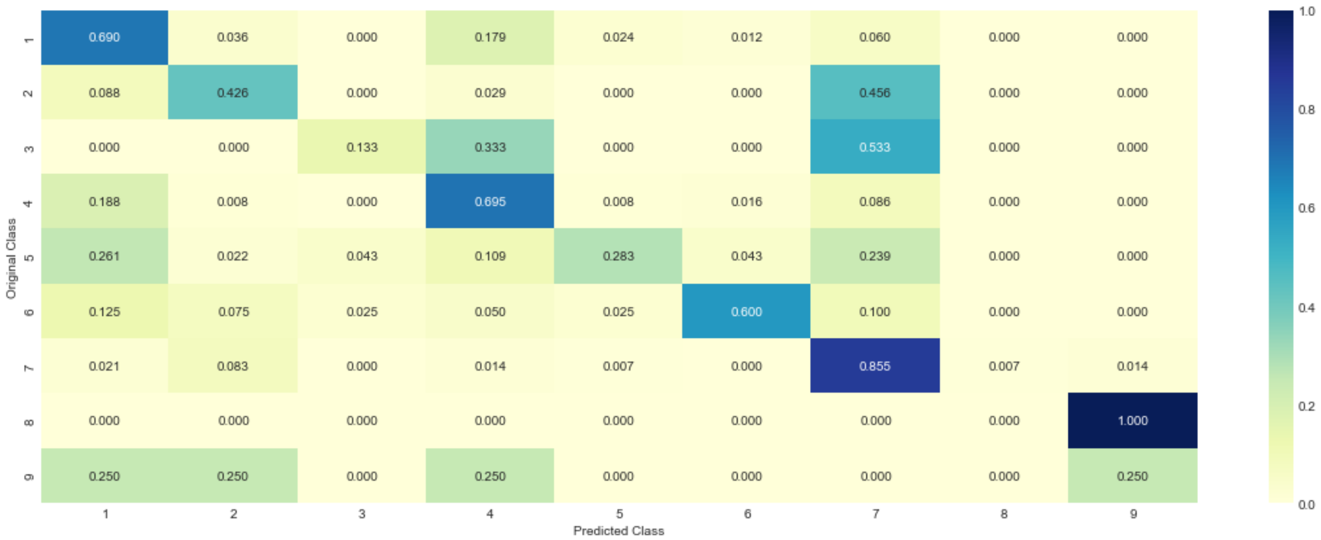
```
Log loss : 1.102602844779191
Number of mis-classified points : 0.3609022556390977
-------------------- Confusion matrix --------------------
```






```
-------------------- Precision matrix (Columm Sum=1) --------------------
```


```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [95]:

```
result2 = pd.DataFrame(columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-loss", "Mis-Classified CV", "Remarks"])
result2 = result2.append(pd.DataFrame([["Random-Forest",0.5241, 1.1026, 1.1068, "36.09%",  "BestFit"]],
                                      columns = ["Model", "Train Log-loss", "CV Log-loss", "Test Log-loss", "Mis-Classified CV", "Remarks"]))
```

In [96]:

```
result2
```

Out[96]:

	Model	Train Log-loss	CV Log-loss	Test Log-loss	Mis-Classified CV	Remarks
0	Random-Forest	0.5241	1.1026	1.1068	36.09%	BestFit