TryingModels

July 15, 2019

1 Automatic Cancer Diagnosis

1.0.1 Assignments

```
<li> Apply All the models with tf-idf features (Replace CountVectorizer with tfidfVectorizer ar
<li> Instead of using all the words in the dataset, use only the top 1000 words based of idf va
<li>Apply Logistic regression with CountVectorizer Features, including both unigrams and bigran
<li> Try any of the feature engineering techniques discussed in the course to reduce the CV anc
```

```
In [1]: import pandas as pd
        import matplotlib.pyplot as plt
        import re
        import time
        import warnings
        import numpy as np
        from nltk.corpus import stopwords
        from sklearn.decomposition import TruncatedSVD
        from sklearn.preprocessing import normalize
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.manifold import TSNE
        import seaborn as sns
        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 sklearn.linear_model import SGDClassifier
        from imblearn.over_sampling import SMOTE
        from collections import Counter
        from scipy.sparse import hstack
        from sklearn.multiclass import OneVsRestClassifier
        from sklearn.svm import SVC
        from sklearn.model_selection import StratifiedKFold
        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
import math
from tqdm import tqdm
from tqdm import tqdm_pandas
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier
warnings.filterwarnings("ignore")

from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
```

1.0.2 1. Reading Data

```
In [2]: csv_path = '/home/monodeepdas112/Datasets/CancerDetection/training_variants'
        data = pd.read_csv(csv_path)
        print('Number of data points : ', data.shape[0])
        print('Number of features : ', data.shape[1])
        print('Features : ', data.columns.values)
        data.head()
```

```
Number of data points :  3321
Number of features :  4
Features :  ['ID' 'Gene' 'Variation' 'Class']
```

```
Out[2]:    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
```

```
training/training_variants is a comma separated file containing the description of the genetic
Fields are
<ul>
    <li><b>ID : </b>the id of the row used to link the mutation to the clinical evidence</li>
    <li><b>Gene : </b>the gene where this genetic mutation is located </li>
    <li><b>Variation : </b>the aminoacid change for this mutations </li>
    <li><b>Class :</b> 1-9 the class this genetic mutation has been classified on</li>
</ul>
```

1.0.3 2 Reading Text Data

```
In [3]: # note the seprator in this file
        text_path = '/home/monodeepdas112/Datasets/CancerDetection/training_text'
        data_text =pd.read_csv(text_path, sep="\|\|",engine="python",names=["ID","TEXT"],skipro
        print('Number of data points : ', data_text.shape[0])
```

```
        print('Number of features : ', data_text.shape[1])
        print('Features : ', data_text.columns.values)
        data_text.head()
```

```
Number of data points :  3321
Number of features :  2
Features :  ['ID' 'TEXT']
```

```
Out[3]:    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...
```

1.0.4 3. Preprocessing of text

```
In [4]: # 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
                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 [5]: #text processing stage.
        start_time = time.clock()
        for index, row in tqdm(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")
```

```
1126it [01:09, 17.07it/s]
```

```
there is no text description for id: 1109

1288it [01:19, 15.78it/s]

there is no text description for id: 1277

1428it [01:27, 16.92it/s]

there is no text description for id: 1407

1654it [01:41, 18.00it/s]

there is no text description for id: 1639

2767it [02:50, 15.06it/s]

there is no text description for id: 2755

3321it [03:24, 17.41it/s]

Time took for preprocessing the text : 206.059639 seconds
```

In [6]:
```
#merging both gene_variations and text data based on ID
result = pd.merge(data, data_text,on='ID', how='left')
result.head()
```

Out[6]:
```
   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

                                                TEXT
0  cyclin dependent kinases cdks regulate variety...
1  abstract background non small cell lung cancer...
2  abstract background non small cell lung cancer...
3  recent evidence demonstrated acquired uniparen...
4  oncogenic mutations monomeric casitas b lineag...
```

In [7]:
```
result[result.isnull().any(axis=1)]
```

```
Out[7]:         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 [8]: result.loc[result['TEXT'].isnull(),'TEXT'] = result['Gene'] +' '+result['Variation']
```

```
In [9]: result[result['ID']==1109]
```

```
Out[9]:         ID   Gene Variation  Class          TEXT
        1109  1109  FANCA    S1088F      1  FANCA S1088F
```

1.0.5 4. Test, Train and Cross Validation Split

4.1. Splitting data into train, test and cross validation (64:20:16)

```
In [10]: y_true = result['Class'].values
         result.Gene      = result.Gene.str.replace('\s+', '_')
         result.Variation = result.Variation.str.replace('\s+', '_')

         # split the data into test and train by maintaining same distribution of output varai
         X_train, test_df, y_train, y_test = train_test_split(result, y_true, stratify=y_true,
         # split the train data into train and cross validation by maintaining same distributi
         train_df, cv_df, y_train, y_cv = train_test_split(X_train, y_train, stratify=y_train,
```

```
In [11]: # cls_text is a data frame
         # for every row in dataframe consider the 'TEXT'
         # split the words by space
         # make a dict with those words
         # increment its count whenever we see that word

         def extract_dictionary_paddle(cls_text):
             dictionary = defaultdict(int)
             for index, row in cls_text.iterrows():
                 for word in row['TEXT'].split():
                     dictionary[word] +=1
             return dictionary
```

```
In [12]: import math
         #https://stackoverflow.com/a/1602964
         def get_text_responsecoding(df):
             text_feature_responseCoding = np.zeros((df.shape[0],9))
             for i in range(0,9):
                 row_index = 0
                 for index, row in df.iterrows():
                     sum_prob = 0
                     for word in row['TEXT'].split():
```

```
                sum_prob += math.log(((dict_list[i].get(word,0)+10 )/(total_dict.get(w
            text_feature_responseCoding[row_index][i] = math.exp(sum_prob/len(row['TE
            row_index += 1
    return text_feature_responseCoding
```

In [13]:
```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are pred

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

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in
    # 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]
    # 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, ytickla
    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, ytickla
    plt.xlabel('Predicted Class')
```

```python
    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, yticklabe
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

1.0.6 5. Featurizations

```python
In [14]: # code for response coding with Laplace smoothing.
         # alpha : used for laplace smoothing
         # feature: ['gene', 'variation']
         # df: ['train_df', 'test_df', 'cv_df']
         # algorithm
         # ----------
         # Consider all unique values and the number of occurances of given feature in train d
         # build a vector (1*9) , the first element = (number of times it occured in class1 + 
         # gv_dict is like a look up table, for every gene it store a (1*9) representation of 
         # for a value of feature in df:
         # if it is in train data:
         # we add the vector that was stored in 'gv_dict' look up table to 'gv_fea'
         # if it is not there is train:
         # we add [1/9, 1/9, 1/9, 1/9,1/9, 1/9, 1/9, 1/9, 1/9] to 'gv_fea'
         # return 'gv_fea'
         # ----------------------

         # get_gv_fea_dict: Get Gene varaition Feature Dict
         def get_gv_fea_dict(alpha, feature, df):
             # value_count: it contains a dict like
             # print(train_df['Gene'].value_counts())
             # output:
             #         {BRCA1      174
             #          TP53       106
             #          EGFR        86
             #          BRCA2       75
             #          PTEN        69
             #          KIT         61
             #          BRAF        60
             #          ERBB2       47
             #          PDGFRA      46
             #          ...}
             # print(train_df['Variation'].value_counts())
             # output:
             # {
```

```python
    # Truncating_Mutations                         63
    # Deletion                                     43
    # Amplification                                43
    # Fusions                                      22
    # Overexpression                                3
    # E17K                                          3
    # Q61L                                          3
    # S222D                                         2
    # P130S                                         2
    # ...
    # }
    value_count = train_df[feature].value_counts()

    # gv_dict : Gene Variation Dict, which contains the probability array for each ge
    gv_dict = dict()

    # denominator will contain the number of time that particular feature occured in t
    for i, denominator in value_count.items():
        # vec will contain (p(yi==1/Gi) probability of gene/variation belongs to pert
        # vec is 9 diamensional vector
        vec = []
        for k in range(1,10):
            # print(train_df.loc[(train_df['Class']==1) & (train_df['Gene']=='BRCA1')]
            #         ID   Gene             Variation  Class
            # 2470  2470  BRCA1                S1715C      1
            # 2486  2486  BRCA1                S1841R      1
            # 2614  2614  BRCA1                   M1R      1
            # 2432  2432  BRCA1                L1657P      1
            # 2567  2567  BRCA1                T1685A      1
            # 2583  2583  BRCA1                E1660G      1
            # 2634  2634  BRCA1                W1718L      1
            # cls_cnt.shape[0] will return the number of rows

            cls_cnt = train_df.loc[(train_df['Class']==k) & (train_df[feature]==i)]

            # cls_cnt.shape[0](numerator) will contain the number of time that partic
            vec.append((cls_cnt.shape[0] + alpha*10)/ (denominator + 90*alpha))

        # we are adding the gene/variation to the dict as key and vec as value
        gv_dict[i]=vec
    return gv_dict

# Get Gene variation feature
def get_gv_feature(alpha, feature, df):
    # print(gv_dict)
    #     {'BRCA1': [0.20075757575757575, 0.03787878787878788, 0.068181818181818177, 
    #      'TP53': [0.32142857142857145, 0.061224489795918366, 0.061224489795918366, 
    #      'EGFR': [0.056818181818181816, 0.21590909090909091, 0.0625, 0.068181818181818
```

```
        #      'BRCA2': [0.13333333333333333, 0.060606060606060608, 0.060606060606060608,
        #      'PTEN': [0.069182389937106917, 0.062893081761006289, 0.069182389937106917,
        #      'KIT': [0.066225165562913912, 0.25165562913907286, 0.072847682119205295, 0
        #      'BRAF': [0.066666666666666666, 0.17999999999999999, 0.073333333333333334,
        #      ...
        #     }
        gv_dict = get_gv_fea_dict(alpha, feature, df)
        # value_count is similar in get_gv_fea_dict
        value_count = train_df[feature].value_counts()

        # gv_fea: Gene_variation feature, it will contain the feature for each feature va
        gv_fea = []
        # for every feature values in the given data frame we will check if it is there i
        # if not we will add [1/9,1/9,1/9,1/9,1/9,1/9,1/9,1/9,1/9] to gv_fea
        for index, row in df.iterrows():
            if row[feature] in dict(value_count).keys():
                gv_fea.append(gv_dict[row[feature]])
            else:
                gv_fea.append([1/9,1/9,1/9,1/9,1/9,1/9,1/9,1/9,1/9])
    #             gv_fea.append([-1,-1,-1,-1,-1,-1,-1,-1,-1])
        return gv_fea
```

In [15]:
```
    # this function will be used just for naive bayes
    # for the given indices, we will print the name of the features
    # and we will check whether the feature present in the test point text or not
    def get_impfeature_names(indices, text, gene, var, no_features):
        gene_count_vec = CountVectorizer()
        var_count_vec = CountVectorizer()
        text_count_vec = CountVectorizer(min_df=3, ngram_range=[1,2])

        gene_vec = gene_count_vec.fit(train_df['Gene'])
        var_vec  = var_count_vec.fit(train_df['Variation'])
        text_vec = text_count_vec.fit(train_df['TEXT'])

        fea1_len = len(gene_vec.get_feature_names())
        fea2_len = len(var_count_vec.get_feature_names())

        word_present = 0
        for i,v in enumerate(indices):
            if (v < fea1_len):
                word = gene_vec.get_feature_names()[v]
                yes_no = True if word == gene else False
                if yes_no:
                    word_present += 1
                    print(i, "Gene feature [{}] present in test data point [{}]".format(wo
            elif (v < fea1_len+fea2_len):
                word = var_vec.get_feature_names()[v-(fea1_len)]
                yes_no = True if word == var else False
```

```
                if yes_no:
                    word_present += 1
                    print(i, "variation feature [{}] present in test data point [{}]".form
            else:
                word = text_vec.get_feature_names()[v-(fea1_len+fea2_len)]
                yes_no = True if word in text.split() else False
                if yes_no:
                    word_present += 1
                    print(i, "Text feature [{}] present in test data point [{}]".format(wo

        print("Out of the top ",no_features," features ", word_present, "are present in qu
```

In [16]:
```
#response-coding of the Gene and variation feature
# alpha is used for laplace smoothing
alpha = 1
# train gene feature
train_gene_feature_responseCoding = np.array(get_gv_feature(alpha, "Gene", train_df))
# train variation feature
train_variation_feature_responseCoding = np.array(get_gv_feature(alpha, "Variation", t

# test gene feature
test_gene_feature_responseCoding = np.array(get_gv_feature(alpha, "Gene", test_df))
# test variation feature
test_variation_feature_responseCoding = np.array(get_gv_feature(alpha, "Variation", te

# cross validation gene feature
cv_gene_feature_responseCoding = np.array(get_gv_feature(alpha, "Gene", cv_df))
# cross validation variation feature
cv_variation_feature_responseCoding = np.array(get_gv_feature(alpha, "Variation", cv_c
```

In [17]:
```
# building a CountVectorizer for gene
count_gene_vect = CountVectorizer()
count_gene_vect.fit(train_df['Gene'])

train_gene_feature_onehot = count_gene_vect.transform(train_df['Gene'])
test_gene_feature_onehot = count_gene_vect.transform(test_df['Gene'])
cv_gene_feature_onehot = count_gene_vect.transform(cv_df['Gene'])


# building a CountVectorizer for variation
count_var_vect = CountVectorizer()
count_var_vect.fit(train_df['Variation'])

train_variation_feature_onehot = count_var_vect.transform(train_df['Variation'])
test_variation_feature_onehot = count_var_vect.transform(test_df['Variation'])
cv_variation_feature_onehot = count_var_vect.transform(cv_df['Variation'])
```

```
# building a CountVectorizer for text
count_text_vect = CountVectorizer(min_df=3, ngram_range=[1,2])
count_text_vect.fit(train_df['TEXT'])

train_text_bow = count_text_vect.transform(train_df['TEXT'])
test_text_bow = count_text_vect.transform(test_df['TEXT'])
cv_text_bow = count_text_vect.transform(cv_df['TEXT'])


# building a CountVectorizer for text
tfidf_text_vect = TfidfVectorizer(min_df=3, ngram_range=[1,2])
tfidf_text_vect.fit(train_df['TEXT'])

train_text_tfidf = tfidf_text_vect.transform(train_df['TEXT'])
test_text_tfidf = tfidf_text_vect.transform(test_df['TEXT'])
cv_text_tfidf = tfidf_text_vect.transform(cv_df['TEXT'])
```

Stacking the three types of features

In [18]:
```
# stacking onehot gene with onehot variation with bow text
train_bow_onehot_features = hstack((train_gene_feature_onehot, train_variation_feature
test_bow_onehot_features = hstack((test_gene_feature_onehot, test_variation_feature_or
cv_bow_onehot_features = hstack((cv_gene_feature_onehot, cv_variation_feature_onehot,

# stacking onehot gene with onehot variation with tfidf text
train_tfidf_onehot_features = hstack((train_gene_feature_onehot, train_variation_featu
test_tfidf_onehot_features = hstack((test_gene_feature_onehot, test_variation_feature_
cv_tfidf_onehot_features = hstack((cv_gene_feature_onehot, cv_variation_feature_onehot

# stacking response gene with response variation with bow text
train_bow_response_features = hstack((train_gene_feature_responseCoding, train_variati
test_bow_response_features = hstack((test_gene_feature_responseCoding, test_variation_
cv_bow_response_features = hstack((cv_gene_feature_responseCoding, cv_variation_featu

# stacking response gene with response variation with tfidf text
train_tfidf_response_features = hstack((train_gene_feature_responseCoding, train_varia
test_tfidf_response_features = hstack((test_gene_feature_responseCoding, test_variatio
cv_tfidf_response_features = hstack((cv_gene_feature_responseCoding, cv_variation_fea
```

In [19]:
```
train_y = np.array(list(train_df['Class']))
test_y = np.array(list(test_df['Class']))
cv_y = np.array(list(cv_df['Class']))
```

1.0.7 6. Fitting models

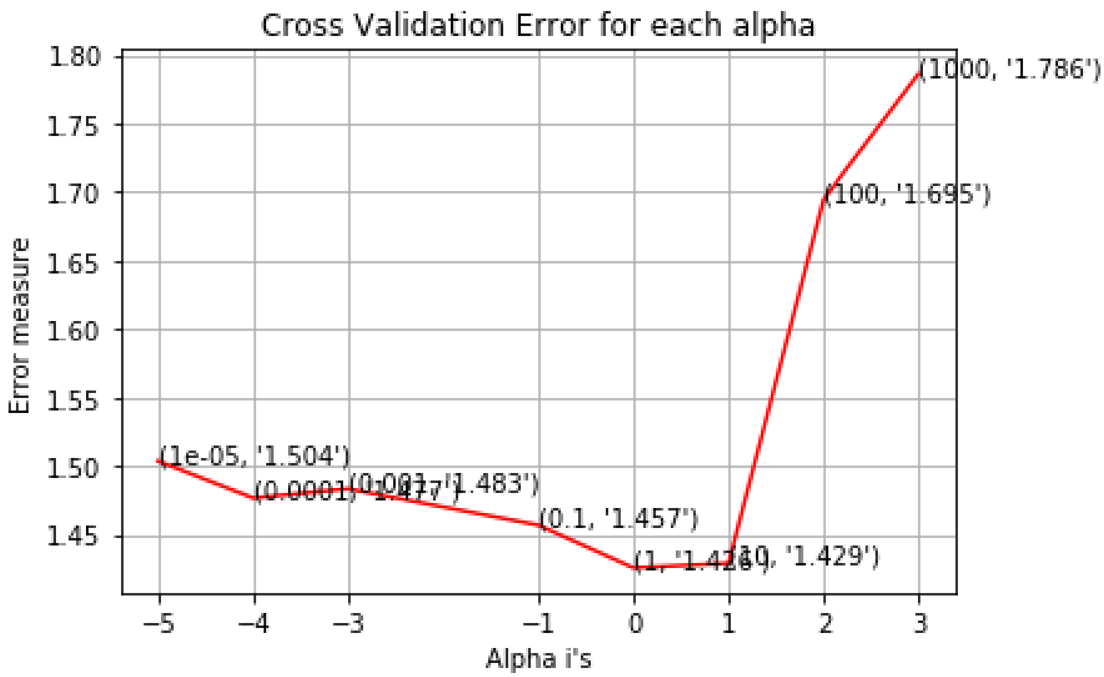
1.0.8 6.1 Baseline model - Naive Bayes

6.1.1 Feature - Onehot with BOW

```
In [20]: 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_bow_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')

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

         fig, ax = plt.subplots()
         ax.plot(np.log10(alpha), cv_log_error_array,c='r')
         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_bow_onehot_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')
         sig_clf.fit(train_bow_onehot_features, train_y)


         predict_y = sig_clf.predict_proba(train_bow_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
         predict_y = sig_clf.predict_proba(cv_bow_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
         predict_y = sig_clf.predict_proba(test_bow_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 1e-05
Log Loss : 1.5036069503758847
for alpha = 0.0001
Log Loss : 1.4766501833371857
for alpha = 0.001
Log Loss : 1.483410225538635
for alpha = 0.1
Log Loss : 1.4569644690739754
```

```
for alpha = 1
Log Loss : 1.4258124993942682
for alpha = 10
Log Loss : 1.4290711598552386
for alpha = 100
Log Loss : 1.6946426260067773
for alpha = 1000
Log Loss : 1.7859474881161315
```



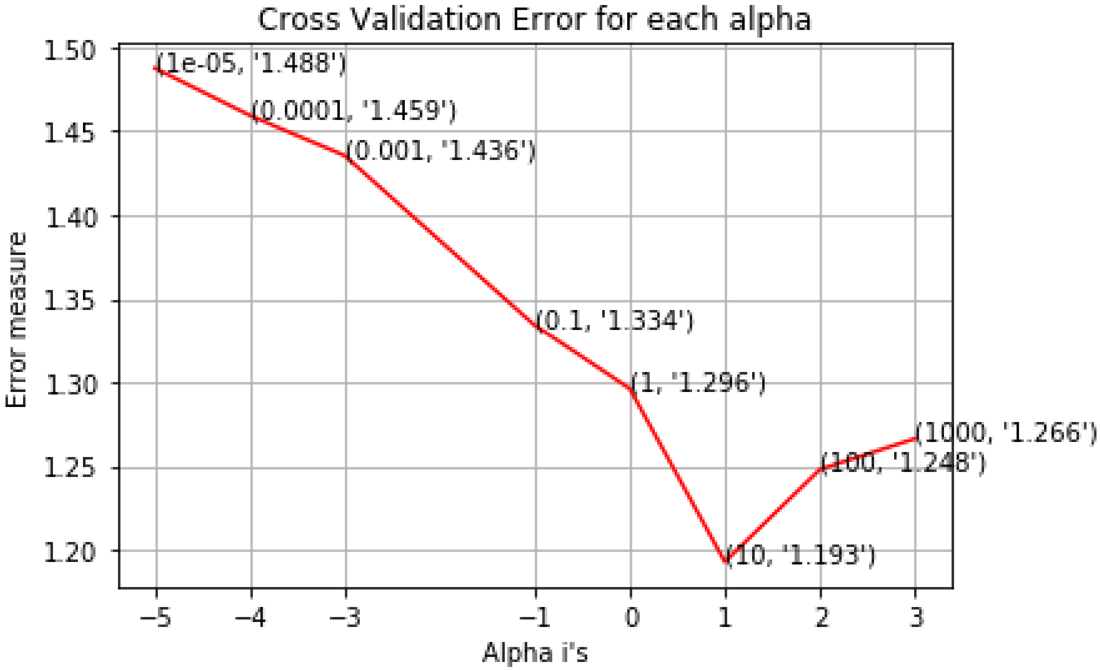

```
For values of best alpha =  1 The train log loss is: 0.9340638181654991
For values of best alpha =  1 The cross validation log loss is: 1.4258124993942682
For values of best alpha =  1 The test log loss is: 1.4401692121587184
```

6.1.2 Feature - Onehot with TFIDF

```
In [21]: 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_tfidf_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')
```

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

    fig, ax = plt.subplots()
    ax.plot(np.log10(alpha), cv_log_error_array,c='r')
    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_tfidf_onehot_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')
    sig_clf.fit(train_tfidf_onehot_features, train_y)


    predict_y = sig_clf.predict_proba(train_tfidf_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
    predict_y = sig_clf.predict_proba(cv_tfidf_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
    predict_y = sig_clf.predict_proba(test_tfidf_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 1e-05
Log Loss : 1.4876902150466456
for alpha = 0.0001
Log Loss : 1.4594526849319147
for alpha = 0.001
Log Loss : 1.4355370537110375
for alpha = 0.1
Log Loss : 1.3340974086798894
for alpha = 1
Log Loss : 1.296071274317102
for alpha = 10
Log Loss : 1.1926865603016439
for alpha = 100
Log Loss : 1.2478168339946871
for alpha = 1000
Log Loss : 1.2660961157000146
```

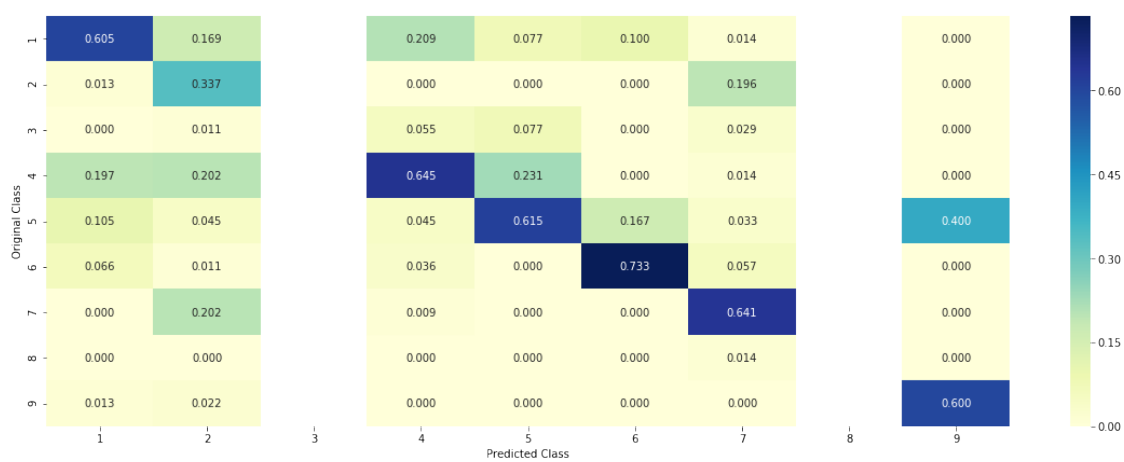



```
For values of best alpha =  10 The train log loss is: 1.0190340287801998
For values of best alpha =  10 The cross validation log loss is: 1.1926865603016439
For values of best alpha =  10 The test log loss is: 1.2611130595676376
```

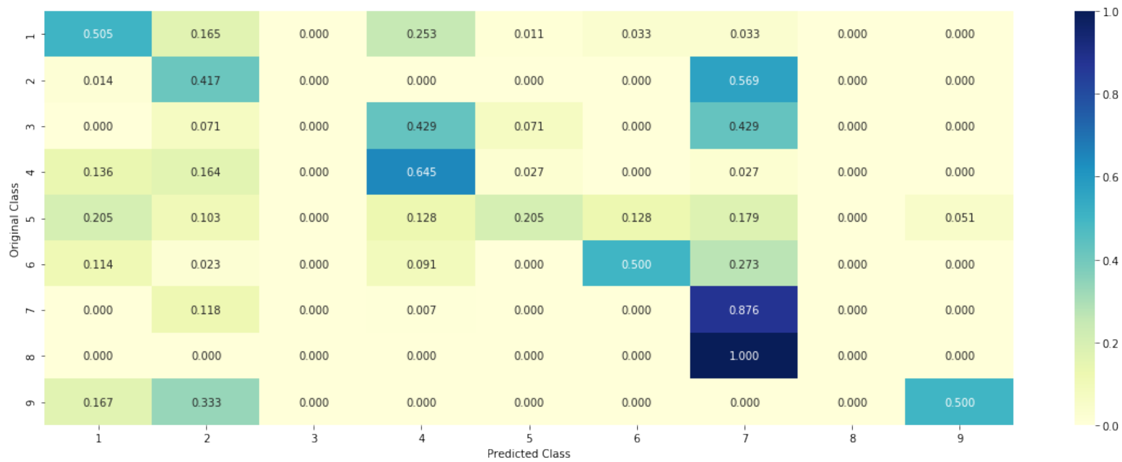
```
In [22]: # to avoid rounding error while multiplying probabilites we use log-probability estim
         print("Log Loss :",log_loss(cv_y, sig_clf_probs))
         print("Number of missclassified point :", np.count_nonzero((sig_clf.predict(cv_tfidf_
         plot_confusion_matrix(cv_y, sig_clf.predict(cv_tfidf_onehot_features.toarray()))
```

```
Log Loss : 1.2660961157000146
Number of missclassified point : 0.40977443609022557
-------------------- Confusion matrix --------------------
```

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



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



6.1.2.1. Feature Importance, Correctly classified point

In [23]:
```
test_point_index = 1
no_feature = 100
predicted_cls = sig_clf.predict(test_tfidf_onehot_features[test_point_index])
print("Predicted Class :", predicted_cls[0])
print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_onel
print("Actual Class :", test_y[test_point_index])
indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
print("-"*50)
get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 6
Predicted Class Probabilities: [[3.600e-02 1.340e-02 1.180e-02 2.290e-02 5.170e-02 8.588e-01 3
  1.100e-03 3.000e-04]]
Actual Class : 6
--------------------------------------------------
2 Text feature [brca1] present in test data point [True]
3 Text feature [variants] present in test data point [True]
4 Text feature [deleterious] present in test data point [True]
6 Text feature [brca2] present in test data point [True]
7 Text feature [vus] present in test data point [True]
8 Text feature [mutations] present in test data point [True]
9 Text feature [brca] present in test data point [True]
11 Text feature [odds] present in test data point [True]
14 Text feature [cancer] present in test data point [True]
15 Text feature [mutation] present in test data point [True]
16 Text feature [brct] present in test data point [True]
17 Text feature [vuss] present in test data point [True]
18 Text feature [neutral] present in test data point [True]
20 Text feature [variant] present in test data point [True]
21 Text feature [fig] present in test data point [True]
```

```
22 Text feature [bard1] present in test data point [True]
24 Text feature [history] present in test data point [True]
25 Text feature [family] present in test data point [True]
26 Text feature [data] present in test data point [True]
35 Text feature [causality] present in test data point [True]
40 Text feature [analysis] present in test data point [True]
41 Text feature [binding] present in test data point [True]
42 Text feature [breast] present in test data point [True]
43 Text feature [missense] present in test data point [True]
44 Text feature [00] present in test data point [True]
47 Text feature [cells] present in test data point [True]
49 Text feature [individuals] present in test data point [True]
50 Text feature [tumor] present in test data point [True]
51 Text feature [ovarian] present in test data point [True]
53 Text feature [protein] present in test data point [True]
55 Text feature [domain] present in test data point [True]
56 Text feature [classification] present in test data point [True]
57 Text feature [sequence] present in test data point [True]
62 Text feature [type] present in test data point [True]
63 Text feature [activity] present in test data point [True]
64 Text feature [classified] present in test data point [True]
65 Text feature [table] present in test data point [True]
68 Text feature [risk] present in test data point [True]
70 Text feature [used] present in test data point [True]
71 Text feature [figure] present in test data point [True]
72 Text feature [dna] present in test data point [True]
73 Text feature [using] present in test data point [True]
75 Text feature [et] present in test data point [True]
76 Text feature [al] present in test data point [True]
77 Text feature [favor] present in test data point [True]
78 Text feature [residues] present in test data point [True]
82 Text feature [two] present in test data point [True]
83 Text feature [likelihood] present in test data point [True]
84 Text feature [also] present in test data point [True]
87 Text feature [10] present in test data point [True]
88 Text feature [ligase] present in test data point [True]
90 Text feature [wild] present in test data point [True]
91 Text feature [associated] present in test data point [True]
92 Text feature [unclassified] present in test data point [True]
95 Text feature [structure] present in test data point [True]
98 Text feature [site] present in test data point [True]
Out of the top  100  features  56 are present in query point
```

6.1.2.2. Feature Importance, Incorrectly classified point

In [24]:
```
test_point_index = 100
no_feature = 100
```

```
predicted_cls = sig_clf.predict(test_tfidf_onehot_features[test_point_index])
print("Predicted Class :", predicted_cls[0])
print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_oneh
print("Actual Class :", test_y[test_point_index])
indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
print("-"*50)
get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 7
Predicted Class Probabilities: [[0.0242 0.1315 0.0212 0.0271 0.0481 0.0556 0.689  0.0025 0.0008
Actual Class : 6
--------------------------------------------------
1 Text feature [mutations] present in test data point [True]
4 Text feature [cells] present in test data point [True]
12 Text feature [cell] present in test data point [True]
14 Text feature [fig] present in test data point [True]
15 Text feature [ras] present in test data point [True]
16 Text feature [kinase] present in test data point [True]
17 Text feature [patients] present in test data point [True]
18 Text feature [mutation] present in test data point [True]
29 Text feature [raf] present in test data point [True]
30 Text feature [braf] present in test data point [True]
31 Text feature [cancer] present in test data point [True]
32 Text feature [mutant] present in test data point [True]
37 Text feature [tumor] present in test data point [True]
41 Text feature [tumors] present in test data point [True]
42 Text feature [activation] present in test data point [True]
44 Text feature [resistance] present in test data point [True]
45 Text feature [activity] present in test data point [True]
46 Text feature [exon] present in test data point [True]
50 Text feature [domain] present in test data point [True]
51 Text feature [expression] present in test data point [True]
53 Text feature [kras] present in test data point [True]
54 Text feature [signaling] present in test data point [True]
55 Text feature [also] present in test data point [True]
56 Text feature [using] present in test data point [True]
61 Text feature [10] present in test data point [True]
62 Text feature [protein] present in test data point [True]
63 Text feature [phosphorylation] present in test data point [True]
64 Text feature [growth] present in test data point [True]
66 Text feature [wt] present in test data point [True]
68 Text feature [type] present in test data point [True]
71 Text feature [treatment] present in test data point [True]
74 Text feature [inhibitors] present in test data point [True]
76 Text feature [tyrosine] present in test data point [True]
80 Text feature [table] present in test data point [True]
81 Text feature [analysis] present in test data point [True]
84 Text feature [two] present in test data point [True]
```

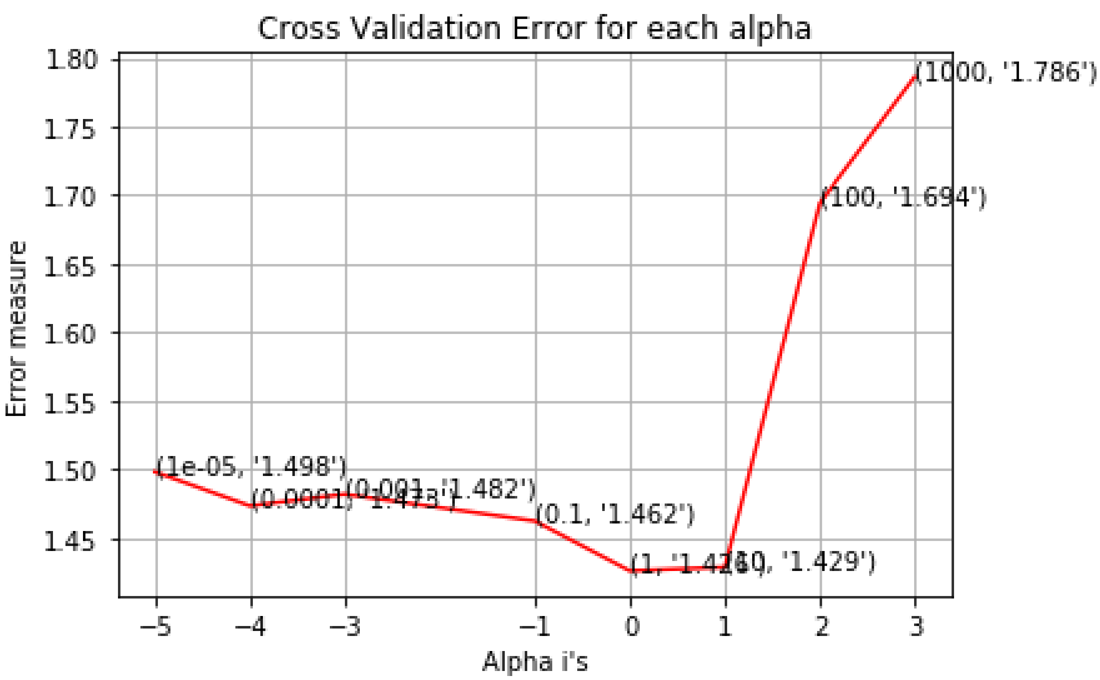
```
85 Text feature [may] present in test data point [True]
86 Text feature [lines] present in test data point [True]
87 Text feature [pathway] present in test data point [True]
89 Text feature [erk] present in test data point [True]
92 Text feature [melanoma] present in test data point [True]
94 Text feature [clinical] present in test data point [True]
95 Text feature [wild] present in test data point [True]
Out of the top  100  features  43 are present in query point
```

6.1.3 Feature - Response with BOW

In [25]:
```
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_bow_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')

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

fig, ax = plt.subplots()
ax.plot(np.log10(alpha), cv_log_error_array,c='r')
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_bow_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')
sig_clf.fit(train_bow_response_features, train_y)


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

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

```
for alpha = 1e-05
Log Loss : 1.498165222396136
for alpha = 0.0001
Log Loss : 1.473400719604246
for alpha = 0.001
Log Loss : 1.481898149175489
for alpha = 0.1
Log Loss : 1.462426475828153
for alpha = 1
Log Loss : 1.4261230019834117
for alpha = 10
Log Loss : 1.4287933391139205
for alpha = 100
Log Loss : 1.6941628604706906
for alpha = 1000
Log Loss : 1.7859385366733487
```



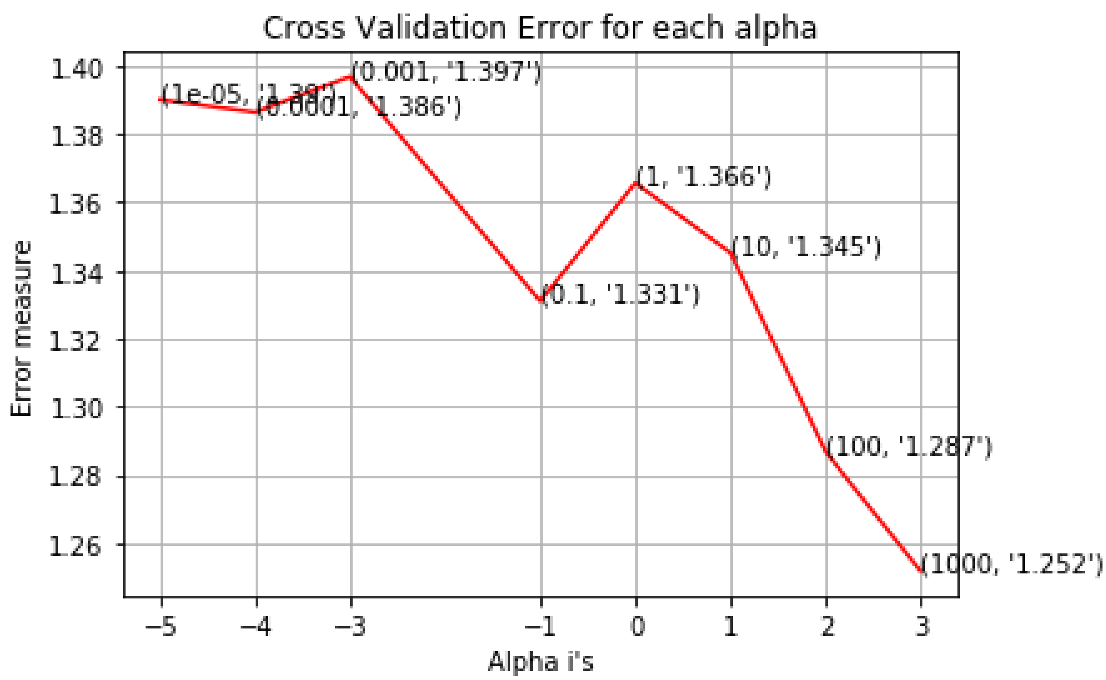

```
For values of best alpha =  1 The train log loss is: 0.9347008760644467
For values of best alpha =  1 The cross validation log loss is: 1.4261230019834117
For values of best alpha =  1 The test log loss is: 1.4398067239842225
```

6.1.1 Feature - Response with TFIDF

```
In [26]: 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_tfidf_response_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')

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

         fig, ax = plt.subplots()
         ax.plot(np.log10(alpha), cv_log_error_array,c='r')
         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_tfidf_response_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv='prefit')
         sig_clf.fit(train_tfidf_response_features, train_y)


         predict_y = sig_clf.predict_proba(train_tfidf_response_features)
         print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_
         predict_y = sig_clf.predict_proba(cv_tfidf_response_features)
         print('For values of best alpha = ', alpha[best_alpha], "The cross validation log los
         predict_y = sig_clf.predict_proba(test_tfidf_response_features)
         print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_l
```

```
for alpha = 1e-05
Log Loss : 1.390118730396215
for alpha = 0.0001
Log Loss : 1.3864561610373833
for alpha = 0.001
Log Loss : 1.3968535032533256
for alpha = 0.1
```

```
Log Loss : 1.3310559948175205
for alpha = 1
Log Loss : 1.3657216440036812
for alpha = 10
Log Loss : 1.3452272634602374
for alpha = 100
Log Loss : 1.2867785286181823
for alpha = 1000
Log Loss : 1.2518547876654251
```




```
For values of best alpha =  1000 The train log loss is: 1.1717410615702781
For values of best alpha =  1000 The cross validation log loss is: 1.2518547876654251
For values of best alpha =  1000 The test log loss is: 1.2884034784492435
```

1.0.9 6.2 K-Nearest Neighbours

Since dataset size is small and we do not have any response time limit requirements I am trying out OneHot Coding features with KNN as well and comparing all the possibilities

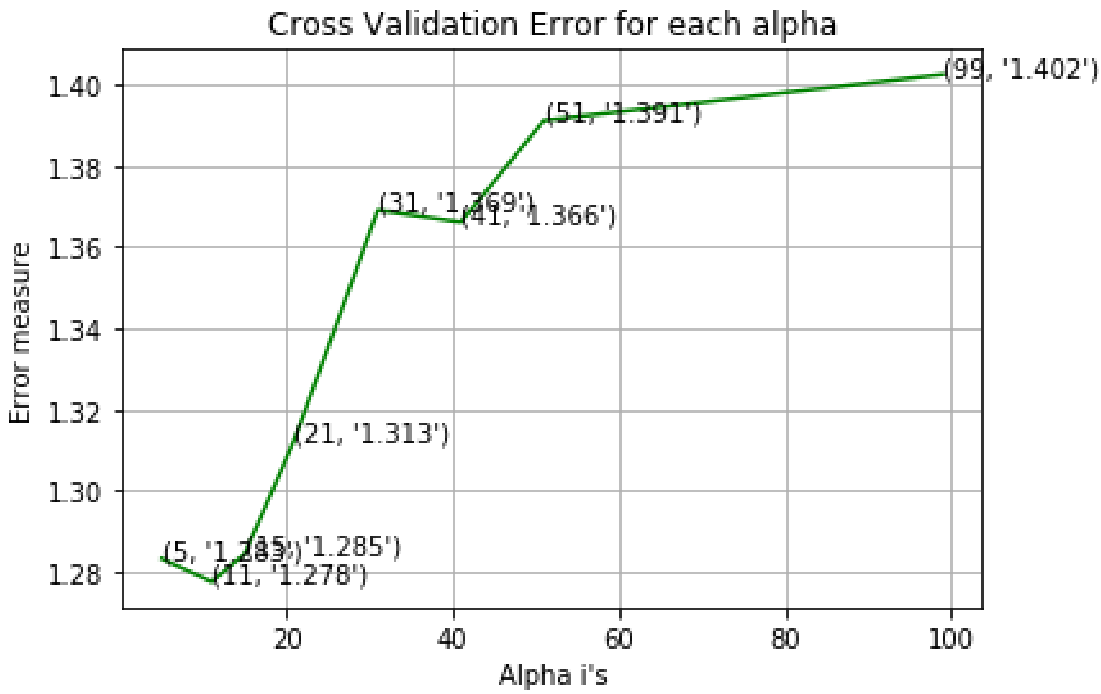
6.2.1 Feature - Onehot with BOW

In [27]:
```
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_bow_onehot_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_onehot_features, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_bow_onehot_features)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1
    # to avoid rounding error while multiplying probabilites we use log-probability e
    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_bow_onehot_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_bow_onehot_features, train_y)

predict_y = sig_clf.predict_proba(train_bow_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_bow_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_bow_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 5
Log Loss : 1.2832966661385778
for alpha = 11
Log Loss : 1.2775640381817417
for alpha = 15
Log Loss : 1.2845009820895326
for alpha = 21
Log Loss : 1.312643847727437
for alpha = 31
Log Loss : 1.3690153462534216
for alpha = 41
Log Loss : 1.3660797871428914
for alpha = 51
```

```
Log Loss : 1.39110166526791
for alpha = 99
Log Loss : 1.4023865732226706
```



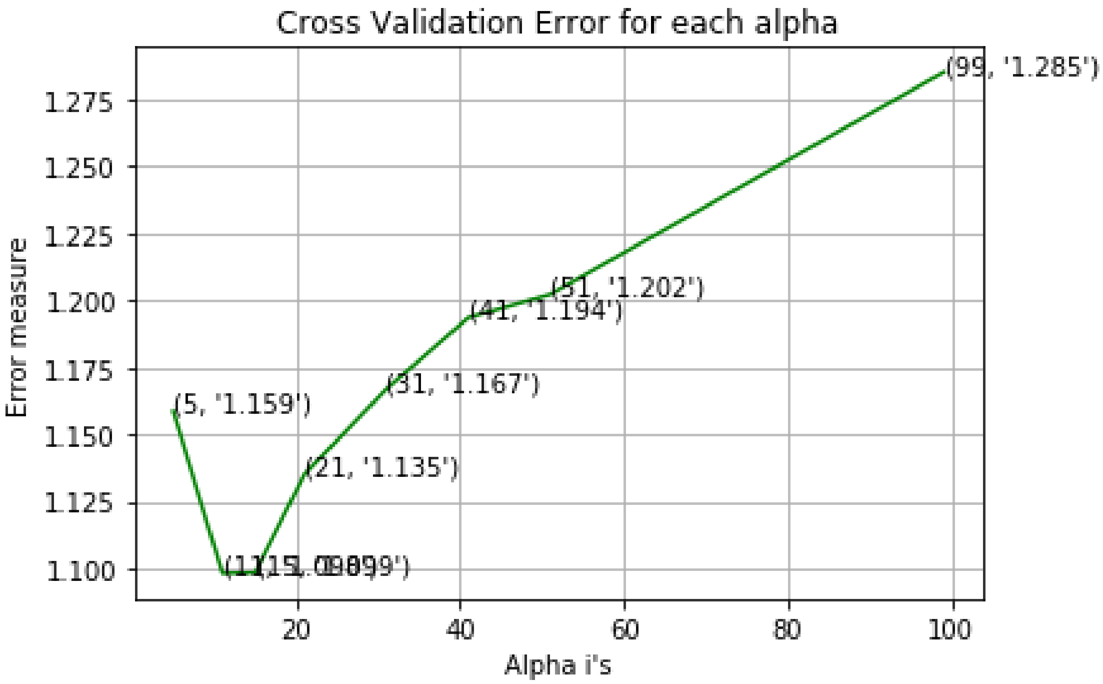

```
For values of best alpha =  11 The train log loss is: 0.9582566724999213
For values of best alpha =  11 The cross validation log loss is: 1.2775640381817417
For values of best alpha =  11 The test log loss is: 1.3043426701936207
```

6.2.2 Feature - Onehot with TFIDF

```
In [28]: 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_tfidf_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_tfidf_onehot_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_tfidf_onehot_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             # to avoid rounding error while multiplying probabilites we use log-probability e
             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_tfidf_onehot_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_onehot_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 5
Log Loss : 1.1587267805047112
for alpha = 11
Log Loss : 1.098273452178832
for alpha = 15
Log Loss : 1.0985360871430163
for alpha = 21
Log Loss : 1.135128008372018
for alpha = 31
Log Loss : 1.1669394047354755
for alpha = 41
Log Loss : 1.1936079675864641
for alpha = 51
Log Loss : 1.2023264138191208
for alpha = 99
Log Loss : 1.2852019098760887
```



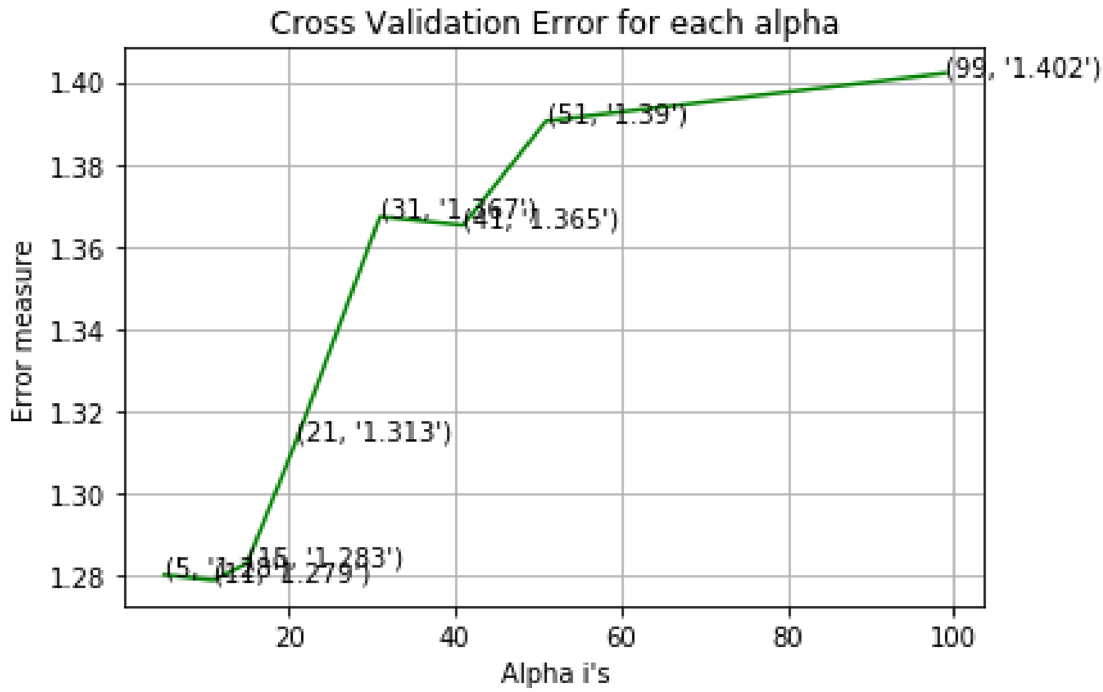

```
For values of best alpha =  11 The train log loss is: 0.87380967820423
For values of best alpha =  11 The cross validation log loss is: 1.098273452178832
For values of best alpha =  11 The test log loss is: 1.1751977255728103
```

6.2.3 Feature - Response with BOW

In [29]:
```python
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_bow_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_response_features, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_bow_response_features)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
    # to avoid rounding error while multiplying probabilites we use log-probability e
    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()
```

```python
    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_bow_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_response_features, train_y)

    predict_y = sig_clf.predict_proba(train_bow_response_features)
    print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
    predict_y = sig_clf.predict_proba(cv_bow_response_features)
    print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
    predict_y = sig_clf.predict_proba(test_bow_response_features)
    print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 5
Log Loss : 1.2803847624329263
for alpha = 11
Log Loss : 1.279103096793844
for alpha = 15
Log Loss : 1.2832353334475048
for alpha = 21
Log Loss : 1.313298977746649
for alpha = 31
Log Loss : 1.3672925694785742
for alpha = 41
Log Loss : 1.365165762930205
for alpha = 51
Log Loss : 1.3904637975835143
for alpha = 99
Log Loss : 1.4020254832484345
```



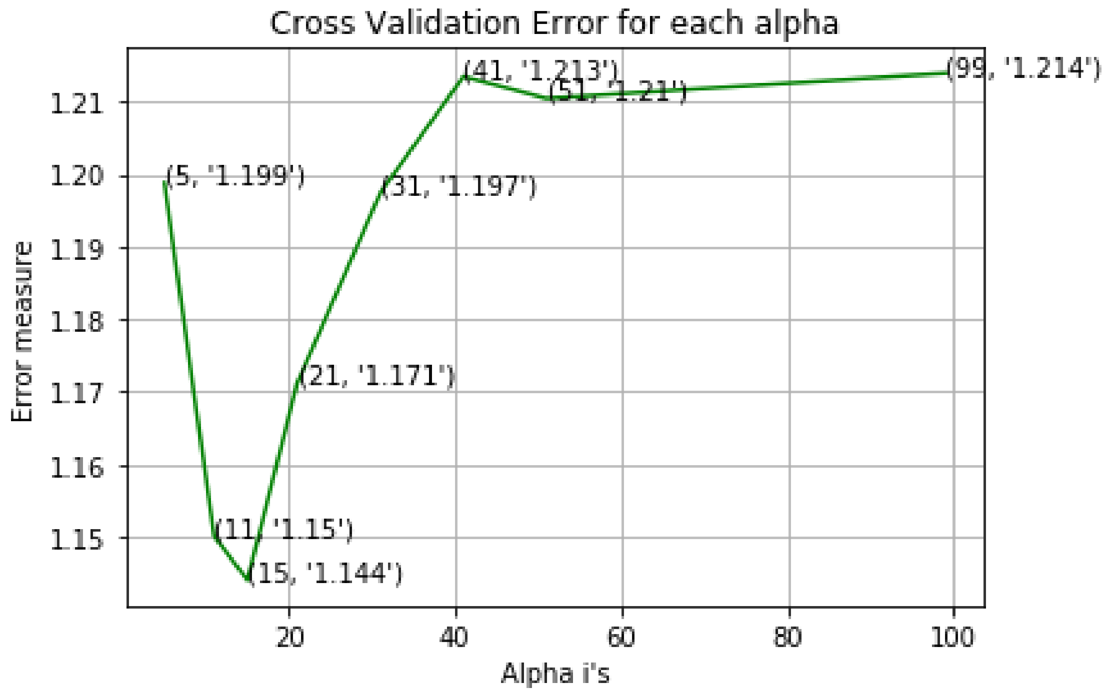

```
For values of best alpha =  11 The train log loss is: 0.9281210162923642
For values of best alpha =  11 The cross validation log loss is: 1.279103096793844
For values of best alpha =  11 The test log loss is: 1.3054637022002626
```

6.2.4 Feature - Response with TFIDF

```
In [30]: 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_tfidf_response_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_tfidf_response_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_tfidf_response_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1
             # to avoid rounding error while multiplying probabilites we use log-probability e
             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_tfidf_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_response_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 5
Log Loss : 1.198801127068247
for alpha = 11
Log Loss : 1.1501063993531673
for alpha = 15
Log Loss : 1.1440347820998134
for alpha = 21
Log Loss : 1.1711962369919213
for alpha = 31
Log Loss : 1.197417170667002
for alpha = 41
Log Loss : 1.2134419601176856
for alpha = 51
Log Loss : 1.2104115025133875
for alpha = 99
Log Loss : 1.2138858527231913
```




```
For values of best alpha =  15 The train log loss is: 0.9439439180685022
For values of best alpha =  15 The cross validation log loss is: 1.1440347820998134
For values of best alpha =  15 The test log loss is: 1.2206572717664992
```

6.2.4.1.Sample Query point -1

```
In [31]: clf = KNeighborsClassifier(n_neighbors=alpha[best_alpha])
         clf.fit(train_tfidf_response_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
         sig_clf.fit(train_tfidf_response_features, train_y)

         test_point_index = 1
         predicted_cls = sig_clf.predict(test_tfidf_response_features[0].reshape(1,-1))
         print("Predicted Class :", predicted_cls[0])
         print("Actual Class :", test_y[test_point_index])
         neighbors = clf.kneighbors(test_tfidf_response_features[test_point_index].reshape(1, -
         print("The ",alpha[best_alpha]," nearest neighbours of the test points belongs to clas
         print("Fequency of nearest points :",Counter(train_y[neighbors[1][0]]))
```

```
Predicted Class : 4
Actual Class : 6
The  15  nearest neighbours of the test points belongs to classes [6 6 6 6 6 6 6 6 6 6 6 6 6
Fequency of nearest points : Counter({6: 15})
```

6.2.4.2.Sample Query point -2

```
In [32]: clf = KNeighborsClassifier(n_neighbors=alpha[best_alpha])
         clf.fit(train_tfidf_response_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
         sig_clf.fit(train_tfidf_response_features, train_y)

         test_point_index = 100

         predicted_cls = sig_clf.predict(test_tfidf_response_features[test_point_index].reshape
         print("Predicted Class :", predicted_cls[0])
         print("Actual Class :", test_y[test_point_index])
         neighbors = clf.kneighbors(test_tfidf_response_features[test_point_index].reshape(1, 
         print("the k value for knn is",alpha[best_alpha],"and the nearest neighbours of the te
         print("Fequency of nearest points :",Counter(train_y[neighbors[1][0]]))
```

```
Predicted Class : 7
Actual Class : 6
the k value for knn is 15 and the nearest neighbours of the test points belongs to classes [6 
Fequency of nearest points : Counter({7: 9, 6: 3, 2: 2, 4: 1})
```

1.0.10 6.3 Logistic Regression

```
In [33]: 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
             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))/tes
             plot_confusion_matrix(test_y, pred_y)
```

```
In [34]: def get_imp_feature_names(text, indices, removed_ind = []):
             word_present = 0
             tabulte_list = []
             incresingorder_ind = 0
             for i in indices:
                 if i < train_gene_feature_onehotCoding.shape[1]:
                     tabulte_list.append([incresingorder_ind, "Gene", "Yes"])
                 elif i< 18:
                     tabulte_list.append([incresingorder_ind,"Variation", "Yes"])
                 if ((i > 17) & (i not in removed_ind)) :
                     word = train_text_features[i]
                     yes_no = True if word in text.split() else False
                     if yes_no:
```

```
                    word_present += 1
                tabulte_list.append([incresingorder_ind,train_text_features[i], yes_no])
            incresingorder_ind += 1
        print(word_present, "most importent features are present in our query point")
        print("-"*50)
        print("The features that are most importent of the ",predicted_cls[0]," class:")
        print (tabulate(tabulte_list, headers=["Index",'Feature name', 'Present or Not']))
```

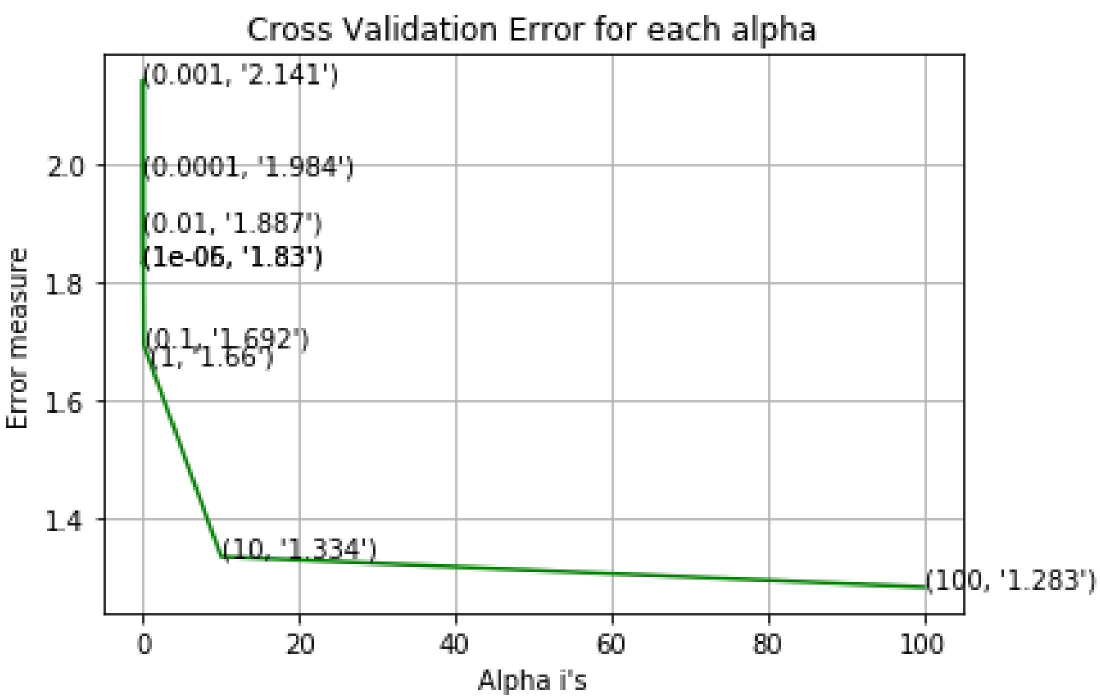
Trying out with Class Balancing only as it was seen earlier that class balancing gave better results

6.3.1 Feature - OneHot with BOW

```
In [35]: 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', ra
             clf.fit(train_bow_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_bow_onehot_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_bow_onehot_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             # to avoid rounding error while multiplying probabilites we use log-probability e
             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', random_state=42)
         clf.fit(train_bow_onehot_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
         sig_clf.fit(train_bow_onehot_features, train_y)

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

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

```
for alpha = 1e-06
Log Loss : 1.8302731648966806
for alpha = 1e-05
Log Loss : 1.8302731648966806
for alpha = 0.0001
Log Loss : 1.9841423580579787
for alpha = 0.001
Log Loss : 2.141058940033097
for alpha = 0.01
Log Loss : 1.8872864732217824
for alpha = 0.1
Log Loss : 1.6921852801078243
for alpha = 1
Log Loss : 1.6597797189325825
for alpha = 10
Log Loss : 1.3341653925274348
for alpha = 100
Log Loss : 1.2825385365922575
```




```
For values of best alpha =  100 The train log loss is: 1.0148728745422024
For values of best alpha =  100 The cross validation log loss is: 1.2825385365922575
```

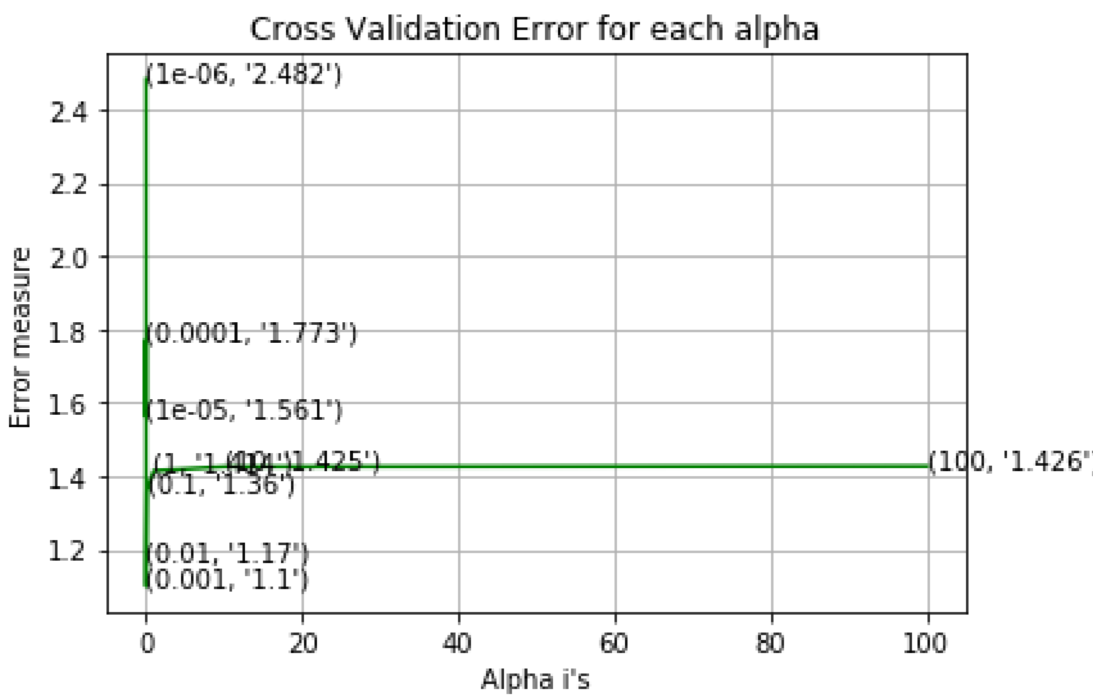
```
For values of best alpha =  100 The test log loss is: 1.3237591529785127
```

6.3.2 Feature - OneHot with TFIDF

```
In [36]: 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', ra
             clf.fit(train_tfidf_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_tfidf_onehot_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_tfidf_onehot_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             # to avoid rounding error while multiplying probabilites we use log-probability e
             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', random_state=42)
         clf.fit(train_tfidf_onehot_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
         sig_clf.fit(train_tfidf_onehot_features, train_y)

         predict_y = sig_clf.predict_proba(train_tfidf_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
         predict_y = sig_clf.predict_proba(cv_tfidf_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
         predict_y = sig_clf.predict_proba(test_tfidf_onehot_features)
         print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 1e-06
Log Loss : 2.4822222729504184
for alpha = 1e-05
Log Loss : 1.5612767692204501
```

```
for alpha = 0.0001
Log Loss : 1.7728773231757198
for alpha = 0.001
Log Loss : 1.0996036226418604
for alpha = 0.01
Log Loss : 1.1699586340875474
for alpha = 0.1
Log Loss : 1.3603890934785379
for alpha = 1
Log Loss : 1.4140882876756649
for alpha = 10
Log Loss : 1.4251175604935458
for alpha = 100
Log Loss : 1.426427773418946
```




```
For values of best alpha =  0.001 The train log loss is: 0.46761217352322295
For values of best alpha =  0.001 The cross validation log loss is: 1.0996036226418604
For values of best alpha =  0.001 The test log loss is: 1.1293319215819009
```

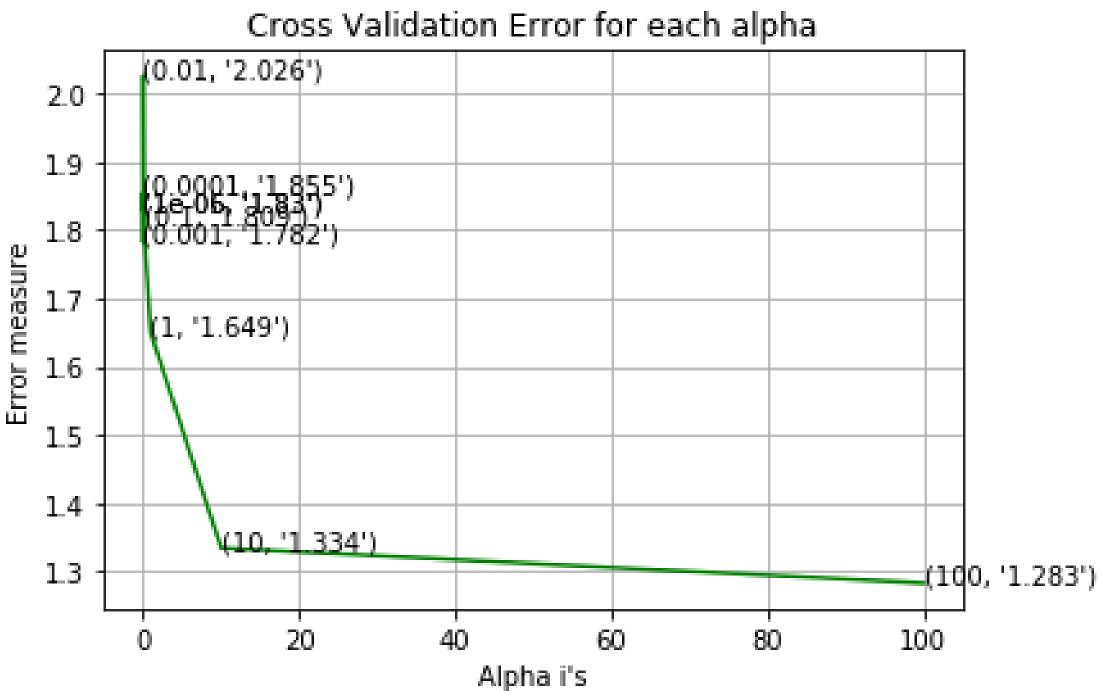
6.3.3 Feature - Respone with BOW

```
In [37]: 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', ra
    clf.fit(train_bow_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_response_features, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_bow_response_features)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
    # to avoid rounding error while multiplying probabilites we use log-probability e
    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', random_state=42)
clf.fit(train_bow_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_bow_response_features, train_y)

predict_y = sig_clf.predict_proba(train_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for alpha = 1e-06
Log Loss : 1.8302731648966806
for alpha = 1e-05
Log Loss : 1.8302731648966806
for alpha = 0.0001
Log Loss : 1.8546700364369344
for alpha = 0.001
Log Loss : 1.7822620996431209
for alpha = 0.01
Log Loss : 2.0264443272775634
for alpha = 0.1
```

```
Log Loss : 1.808521051561057
for alpha = 1
Log Loss : 1.649499195648993
for alpha = 10
Log Loss : 1.3340771496890087
for alpha = 100
Log Loss : 1.2825381422532185
```



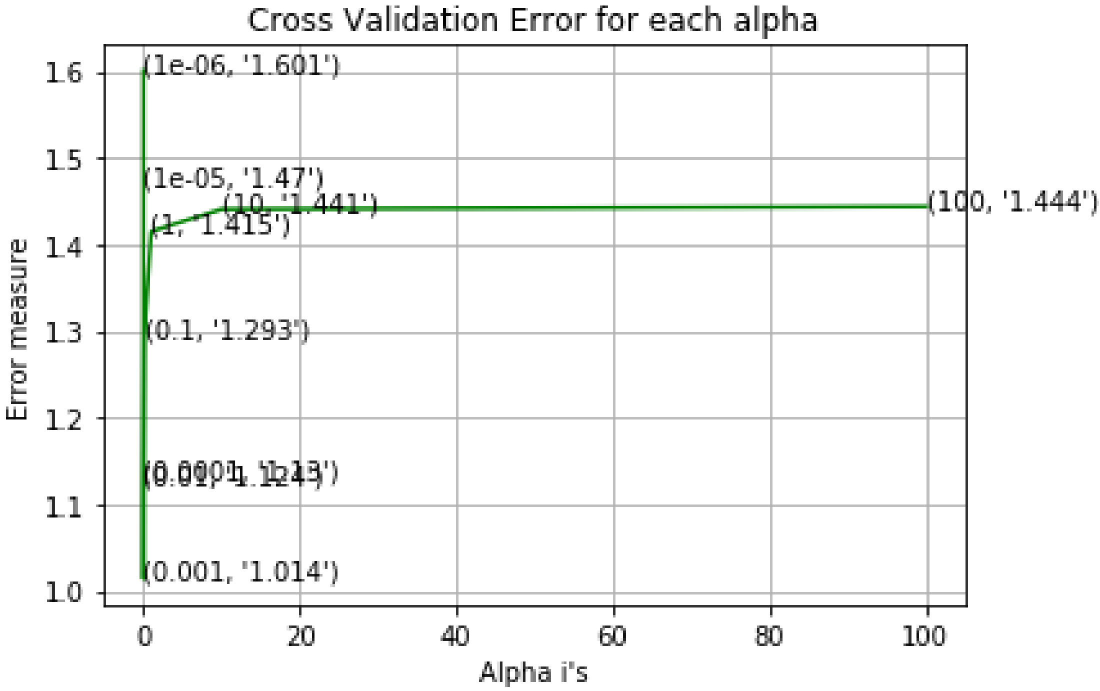

```
For values of best alpha =  100 The train log loss is: 1.014869525802214
For values of best alpha =  100 The cross validation log loss is: 1.2825381422532185
For values of best alpha =  100 The test log loss is: 1.3237569248761605
```

6.3.4 Feature - Response with TFIDF

In [38]:
```
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', ra
    clf.fit(train_tfidf_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_tfidf_response_features, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_tfidf_response_features)
```

```
            cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=1
            # to avoid rounding error while multiplying probabilites we use log-probability e
            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', random_state=42)
        clf.fit(train_tfidf_response_features, train_y)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
        sig_clf.fit(train_tfidf_response_features, train_y)

        predict_y = sig_clf.predict_proba(train_tfidf_response_features)
        print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
        predict_y = sig_clf.predict_proba(cv_tfidf_response_features)
        print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
        predict_y = sig_clf.predict_proba(test_tfidf_response_features)
        print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

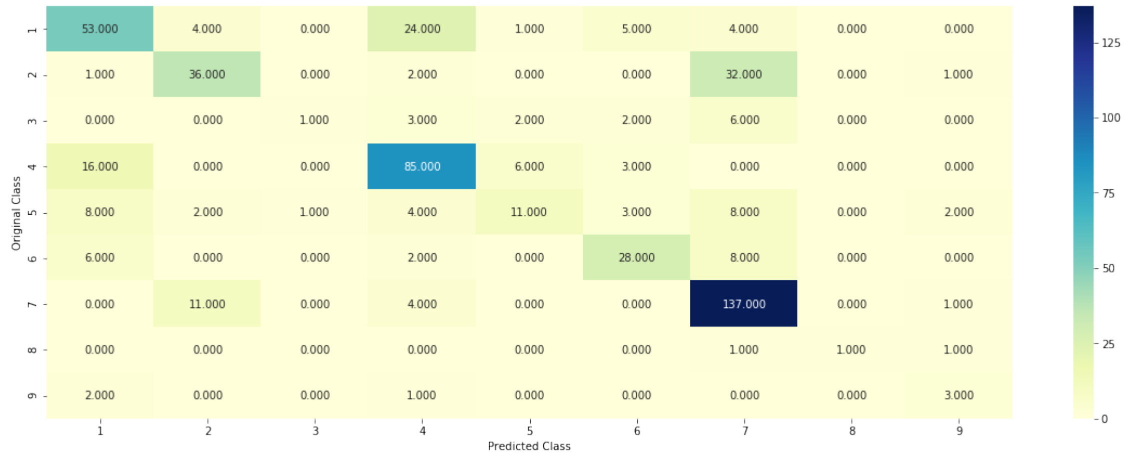
```
for alpha = 1e-06
Log Loss : 1.6007822786828285
for alpha = 1e-05
Log Loss : 1.4700865491813182
for alpha = 0.0001
Log Loss : 1.1298305169483192
for alpha = 0.001
Log Loss : 1.0139589374238192
for alpha = 0.01
Log Loss : 1.1241074023334088
for alpha = 0.1
Log Loss : 1.2927186206129584
for alpha = 1
Log Loss : 1.414950562050182
for alpha = 10
Log Loss : 1.4406786673269387
for alpha = 100
Log Loss : 1.4435569551732812
```




```
For values of best alpha =  0.001 The train log loss is: 0.7270445520060033
For values of best alpha =  0.001 The cross validation log loss is: 1.0139589374238192
For values of best alpha =  0.001 The test log loss is: 1.0524975290711158
```

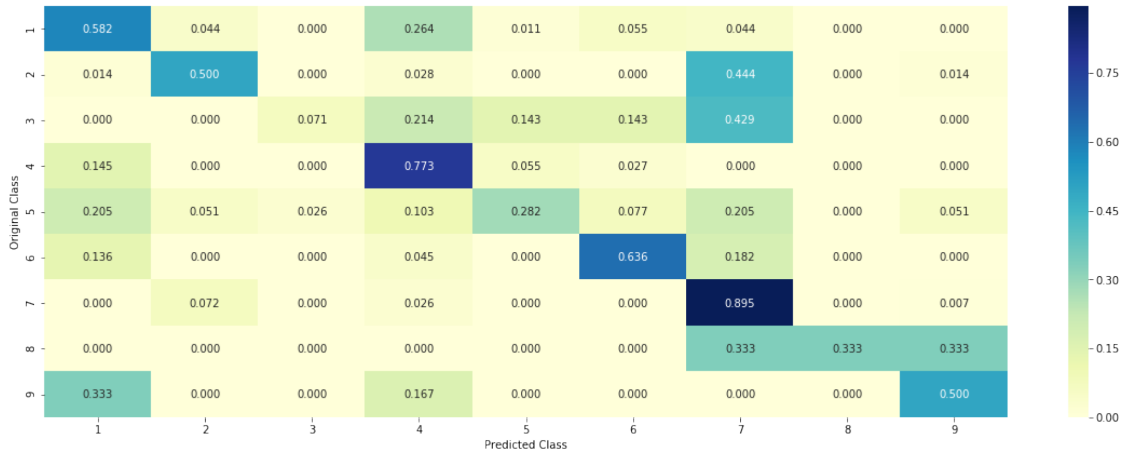
```
In [39]: clf = SGDClassifier(class_weight='balanced',
                             alpha=alpha[best_alpha], penalty='l2',
                             loss='log', random_state=42)
         predict_and_plot_confusion_matrix(train_tfidf_response_features, train_y, cv_tfidf_res
```

```
Log loss : 1.0298207114018774
Number of mis-classified points : 0.33270676691729323
-------------------- Confusion matrix --------------------
```



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

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



6.3.4.1. Correctly Classified point

```
In [40]: # from tabulate import tabulate
         clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', lo
         clf.fit(train_tfidf_response_features,train_y)
         test_point_index = 1
         no_feature = 500
         predicted_cls = sig_clf.predict(train_tfidf_response_features[test_point_index].todens
         print("Predicted Class :", predicted_cls[0])
         print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(train_tfidf_res
         print("Actual Class :", test_y[test_point_index])
         indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
         print("-"*50)
         get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 4
Predicted Class Probabilities: [[0.1161 0.0789 0.0057 0.6647 0.0317 0.0362 0.064  0.0007 0.0019
Actual Class : 6
--------------------------------------------------
285 Text feature [several] present in test data point [True]
Out of the top  500  features  1 are present in query point
```

6.3.4.2. In-correctly Classified point

```
In [41]: # from tabulate import tabulate
         clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty='l2', lo
         clf.fit(train_tfidf_response_features,train_y)
         test_point_index = 100
         no_feature = 500
         predicted_cls = sig_clf.predict(train_tfidf_response_features[test_point_index].todens
         print("Predicted Class :", predicted_cls[0])
         print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(train_tfidf_res
```

```
        print("Actual Class :", test_y[test_point_index])
        indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
        print("-"*50)
        get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 7
Predicted Class Probabilities: [[2.380e-02 7.590e-02 4.600e-03 5.790e-02 6.570e-02 1.183e-01 6
  6.000e-04 1.300e-03]]
Actual Class : 6
--------------------------------------------------
412 Text feature [disrupts] present in test data point [True]
Out of the top  500  features  1 are present in query point
```

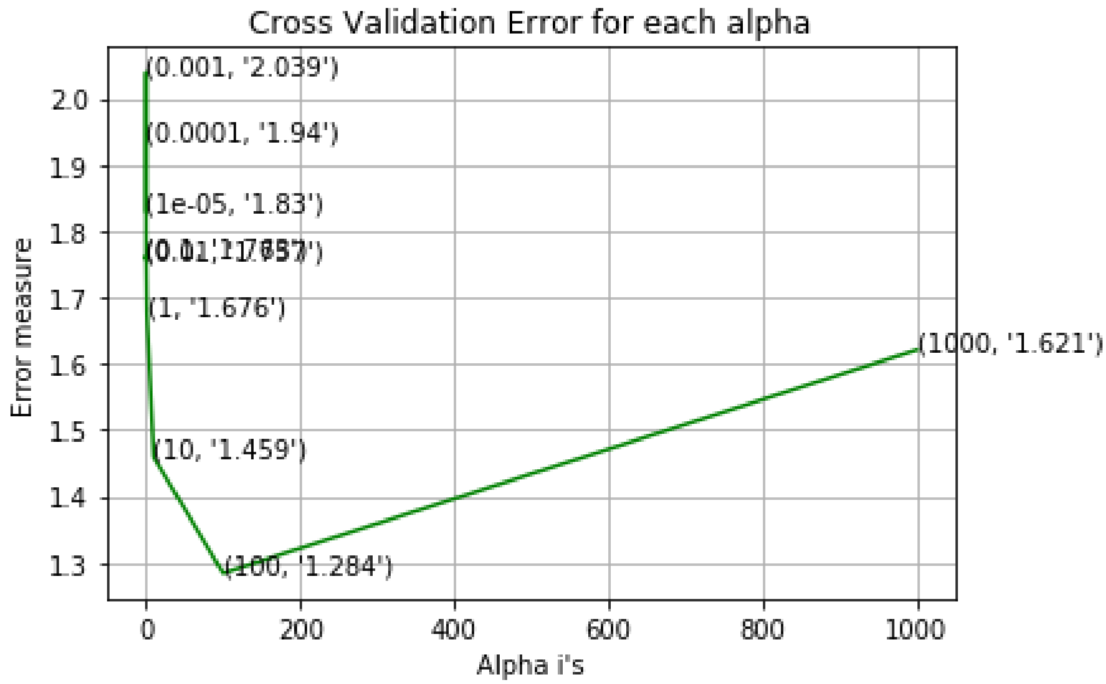
6.4. Linear Support Vector Machines

6.4.1 Feature - OneHot with BOW

```
In [42]: alpha = [10 ** x for x in range(-5, 4)]
         cv_log_error_array = []
         for i in alpha:
             print("for C =", i)
             clf = SGDClassifier(class_weight='balanced', alpha=i,
                                 penalty='l2', loss='hinge', random_state=42)
             clf.fit(train_bow_onehot_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_bow_onehot_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_bow_onehot_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             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', random_state=42)
         clf.fit(train_bow_onehot_features, train_y)
```

```
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_onehot_features, train_y)

    predict_y = sig_clf.predict_proba(train_bow_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
    predict_y = sig_clf.predict_proba(cv_bow_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
    predict_y = sig_clf.predict_proba(test_bow_onehot_features)
    print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for C = 1e-05
Log Loss : 1.8302731648966806
for C = 0.0001
Log Loss : 1.9397559017672599
for C = 0.001
Log Loss : 2.039294453630545
for C = 0.01
Log Loss : 1.7569326122001026
for C = 0.1
Log Loss : 1.7629881020121687
for C = 1
Log Loss : 1.6755308361593593
for C = 10
Log Loss : 1.4589179903167855
for C = 100
Log Loss : 1.283827703972858
for C = 1000
Log Loss : 1.6205476075813126
```



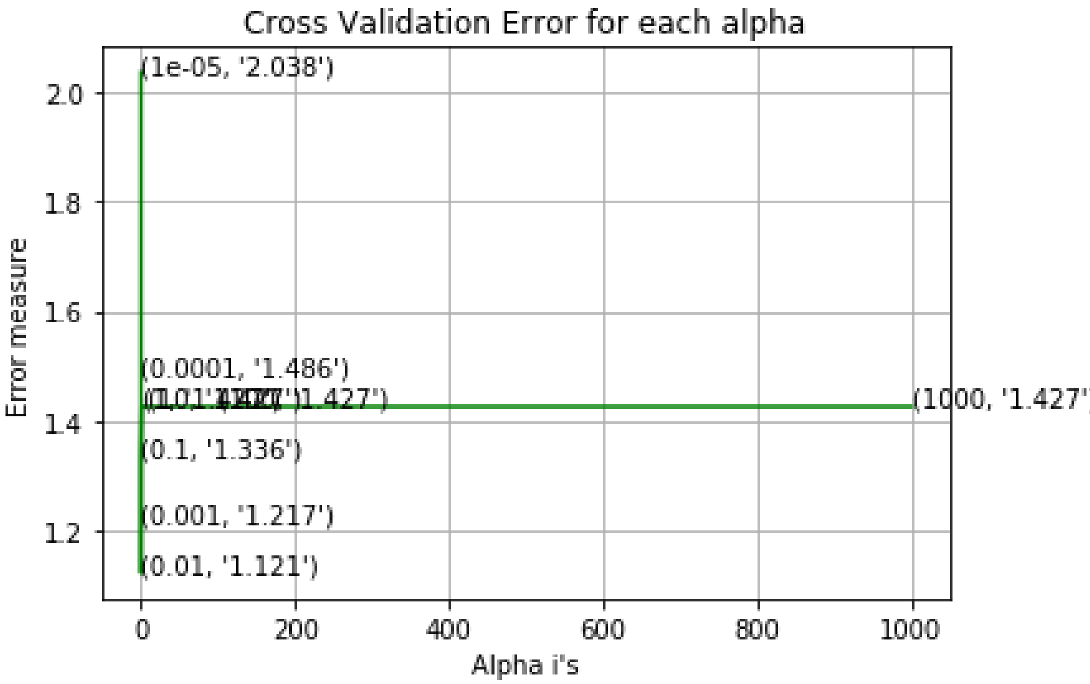

```
For values of best alpha =  100 The train log loss is: 0.9477136716956934
For values of best alpha =  100 The cross validation log loss is: 1.283827703972858
For values of best alpha =  100 The test log loss is: 1.308775678034629
```

6.4.2 Feature - OneHot with TFIDF

In [43]:
```
alpha = [10 ** x for x in range(-5, 4)]
cv_log_error_array = []
for i in alpha:
    print("for C =", i)
    clf = SGDClassifier(class_weight='balanced', alpha=i,
                        penalty='l2', loss='hinge', random_state=42)
    clf.fit(train_tfidf_onehot_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_tfidf_onehot_features, train_y)
    sig_clf_probs = sig_clf.predict_proba(cv_tfidf_onehot_features)
    cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
    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()
```

```python
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', random_state=42)
clf.fit(train_tfidf_onehot_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_onehot_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_tfidf_onehot_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for C = 1e-05
Log Loss : 2.037519032495875
for C = 0.0001
Log Loss : 1.48560519027176
for C = 0.001
Log Loss : 1.2172903358192992
for C = 0.01
Log Loss : 1.1212877961703323
for C = 0.1
Log Loss : 1.335757464816945
for C = 1
Log Loss : 1.4267454808673448
for C = 10
Log Loss : 1.426745476789236
for C = 100
Log Loss : 1.426745472635017
for C = 1000
Log Loss : 1.4267454755588407
```



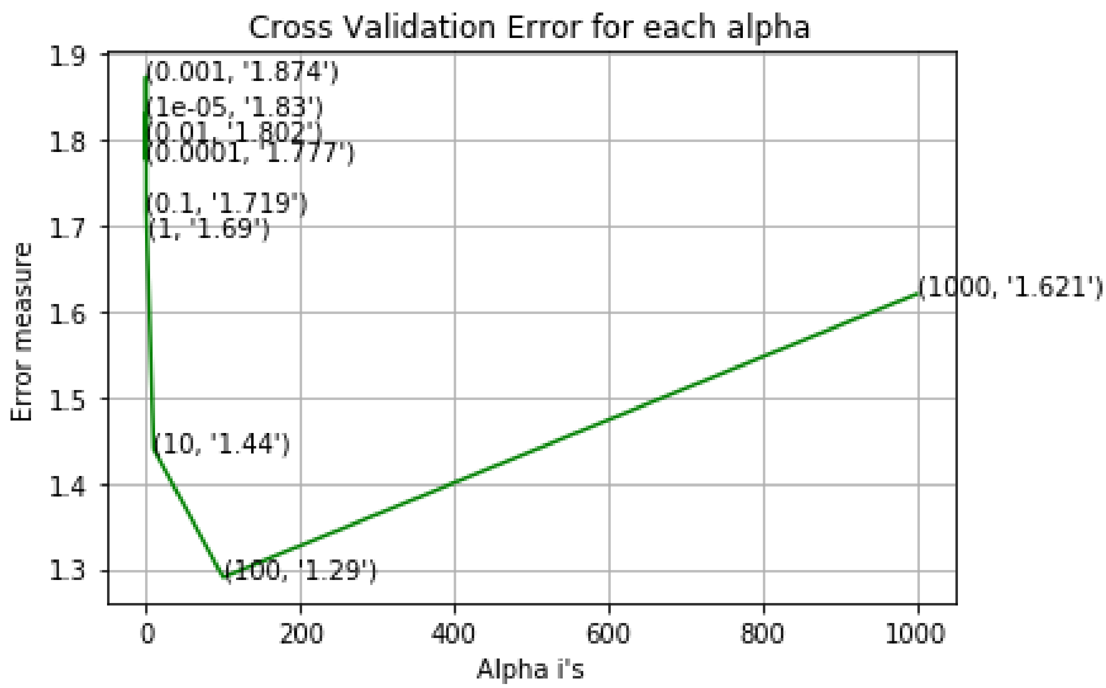

```
For values of best alpha =  0.01 The train log loss is: 0.6065499481942971
For values of best alpha =  0.01 The cross validation log loss is: 1.1212877961703323
For values of best alpha =  0.01 The test log loss is: 1.2237934559896593
```

6.4.3 Feature - Response Coding with BOW

```
In [44]: alpha = [10 ** x for x in range(-5, 4)]
         cv_log_error_array = []
         for i in alpha:
             print("for C =", i)
             clf = SGDClassifier(class_weight='balanced', alpha=i,
                                 penalty='l2', loss='hinge', random_state=42)
             clf.fit(train_bow_response_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_bow_response_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_bow_response_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             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', random_state=42)
clf.fit(train_bow_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_bow_response_features, train_y)

predict_y = sig_clf.predict_proba(train_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_bow_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

```
for C = 1e-05
Log Loss : 1.8302731648966806
for C = 0.0001
Log Loss : 1.776606782679195
for C = 0.001
Log Loss : 1.8736002210870573
for C = 0.01
Log Loss : 1.8022308121100141
for C = 0.1
Log Loss : 1.7186679784693701
for C = 1
Log Loss : 1.689733624451256
for C = 10
Log Loss : 1.4398716252498935
for C = 100
Log Loss : 1.2903508645726762
for C = 1000
Log Loss : 1.6205327573446544
```



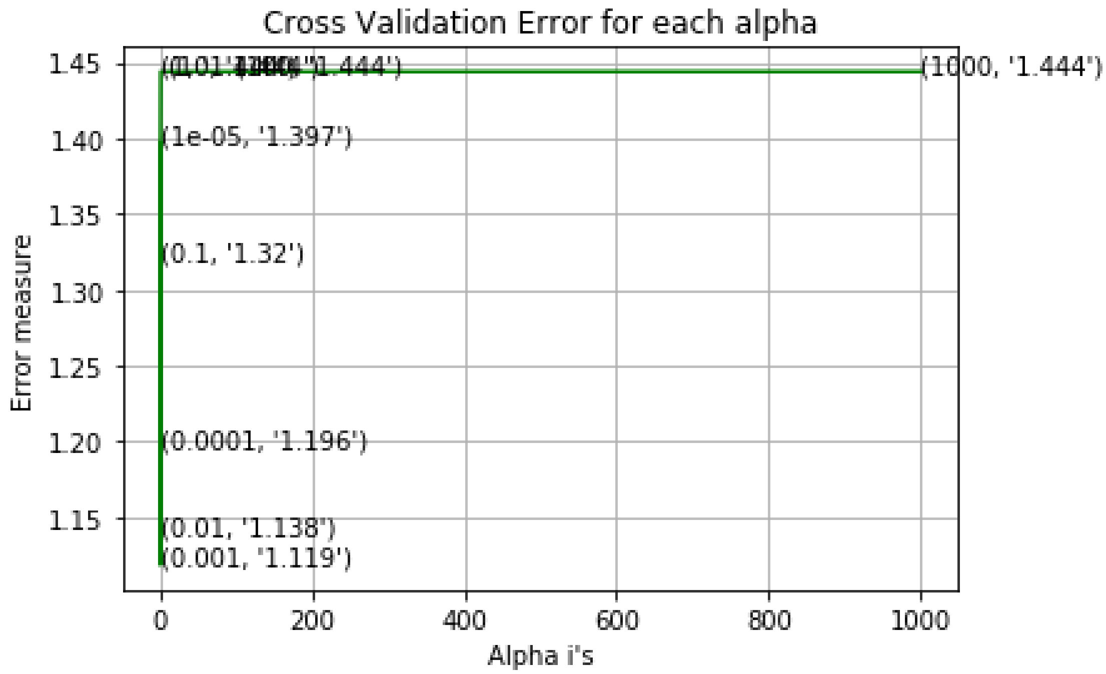

```
For values of best alpha =  100 The train log loss is: 0.9541811236127639
For values of best alpha =  100 The cross validation log loss is: 1.2903508645726762
For values of best alpha =  100 The test log loss is: 1.3121844483075165
```

6.4.4 Feature - Response Coding with TFIDF

```
In [45]: alpha = [10 ** x for x in range(-5, 4)]
         cv_log_error_array = []
         for i in alpha:
             print("for C =", i)
             clf = SGDClassifier(class_weight='balanced', alpha=i,
                                 penalty='l2', loss='hinge', random_state=42)
             clf.fit(train_tfidf_response_features, train_y)
             sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
             sig_clf.fit(train_tfidf_response_features, train_y)
             sig_clf_probs = sig_clf.predict_proba(cv_tfidf_response_features)
             cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, eps=
             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', random_state=42)
clf.fit(train_tfidf_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_response_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(cv_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss
predict_y = sig_clf.predict_proba(test_tfidf_response_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
```

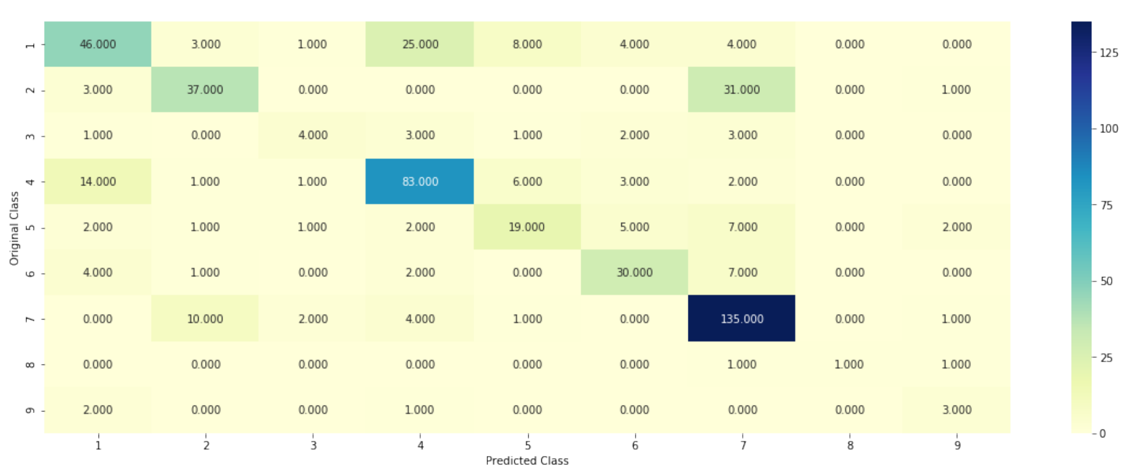
```
for C = 1e-05
Log Loss : 1.396567456591311
for C = 0.0001
Log Loss : 1.195661407301961
for C = 0.001
Log Loss : 1.1185347722719625
for C = 0.01
Log Loss : 1.137951179988843
for C = 0.1
Log Loss : 1.319939816514339
for C = 1
Log Loss : 1.4440524140821913
for C = 10
Log Loss : 1.4440523162763277
for C = 100
Log Loss : 1.4440523129539573
for C = 1000
Log Loss : 1.4440523593811712
```




```
For values of best alpha =  0.001 The train log loss is: 0.5801282028327186
For values of best alpha =  0.001 The cross validation log loss is: 1.1185347722719625
For values of best alpha =  0.001 The test log loss is: 1.1352617082330267
```

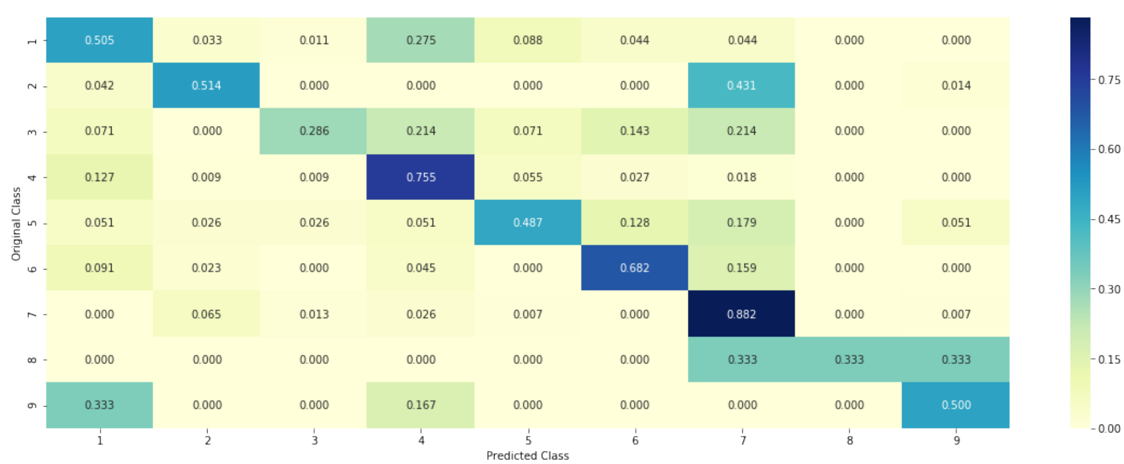
```
In [46]: clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='hinge', random_state=
         predict_and_plot_confusion_matrix(train_tfidf_response_features, train_y,cv_tfidf_resp
```

```
Log loss : 1.1514767056832687
Number of mis-classified points : 0.32706766917293234
-------------------- Confusion matrix --------------------
```



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


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



Feature Importance
6.4.4.1. For Correctly classified point

```
In [47]: clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='hinge', random_state
         clf.fit(train_tfidf_response_features,train_y)
         test_point_index = 1
         # test_point_index = 100
```

```
no_feature = 500
predicted_cls = sig_clf.predict(test_tfidf_response_features[test_point_index])
print("Predicted Class :", predicted_cls[0])
print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_res
print("Actual Class :", test_y[test_point_index])
indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
print("-"*50)
get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 6
Predicted Class Probabilities: [[5.450e-02 1.200e-02 4.000e-03 4.850e-02 2.370e-02 8.379e-01 1
  2.000e-04 2.000e-04]]
Actual Class : 6
--------------------------------------------------
287 Text feature [oophorectomy] present in test data point [True]
Out of the top  500  features  1 are present in query point
```

6.4.4.2. For Incorrectly classified point

```
In [48]: clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='hinge', random_state
         clf.fit(train_tfidf_response_features,train_y)
         test_point_index = 100
         # test_point_index = 100
         no_feature = 500
         predicted_cls = sig_clf.predict(test_tfidf_response_features[test_point_index])
         print("Predicted Class :", predicted_cls[0])
         print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_res
         print("Actual Class :", test_y[test_point_index])
         indices = np.argsort(-clf.coef_)[predicted_cls-1][:,:no_feature]
         print("-"*50)
         get_impfeature_names(indices[0], test_df['TEXT'].iloc[test_point_index],test_df['Gene
```

```
Predicted Class : 6
Predicted Class Probabilities: [[1.016e-01 2.800e-02 8.200e-03 7.090e-02 5.670e-02 5.092e-01 2
  6.000e-04 4.000e-04]]
Actual Class : 6
--------------------------------------------------
Out of the top  500  features  0 are present in query point
```

6.5 Random Forest Classifier
6.5.1. Features - OneHot with BOW

```
In [49]: 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, ra
            clf.fit(train_bow_onehot_features, train_y)
            sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
            sig_clf.fit(train_bow_onehot_features, train_y)
            sig_clf_probs = sig_clf.predict_proba(cv_bow_onehot_features)
            cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, e
            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_bow_onehot_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_onehot_features, train_y)

    predict_y = sig_clf.predict_proba(train_bow_onehot_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train log los
    predict_y = sig_clf.predict_proba(cv_bow_onehot_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross validat
    predict_y = sig_clf.predict_proba(test_bow_onehot_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test log loss
```

```
for n_estimators = 100 and max depth =  5
Log Loss : 1.2124122830515067
for n_estimators = 100 and max depth =  10
Log Loss : 1.1025529609311036
for n_estimators = 200 and max depth =  5
Log Loss : 1.195735411929411
for n_estimators = 200 and max depth =  10
Log Loss : 1.085164982453644
for n_estimators = 500 and max depth =  5
Log Loss : 1.1762609625786704
for n_estimators = 500 and max depth =  10
Log Loss : 1.0783883434104706
for n_estimators = 1000 and max depth =  5
Log Loss : 1.172353894424087
for n_estimators = 1000 and max depth =  10
Log Loss : 1.0793908282291136
for n_estimators = 2000 and max depth =  5
Log Loss : 1.1718554893729816
for n_estimators = 2000 and max depth =  10
Log Loss : 1.0696383055808654
For values of best estimator =  2000 The train log loss is: 0.5985458453387114
For values of best estimator =  2000 The cross validation log loss is: 1.0696383055808654
For values of best estimator =  2000 The test log loss is: 1.0952583634099629
```

6.5.2. Features - OneHot with TFIDF

In [50]:
```
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, ra
        clf.fit(train_tfidf_onehot_features, train_y)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
        sig_clf.fit(train_tfidf_onehot_features, train_y)
        sig_clf_probs = sig_clf.predict_proba(cv_tfidf_onehot_features)
        cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, e
        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_tfidf_onehot_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_onehot_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_onehot_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train log loss
predict_y = sig_clf.predict_proba(cv_tfidf_onehot_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross validati
predict_y = sig_clf.predict_proba(test_tfidf_onehot_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test log loss
```

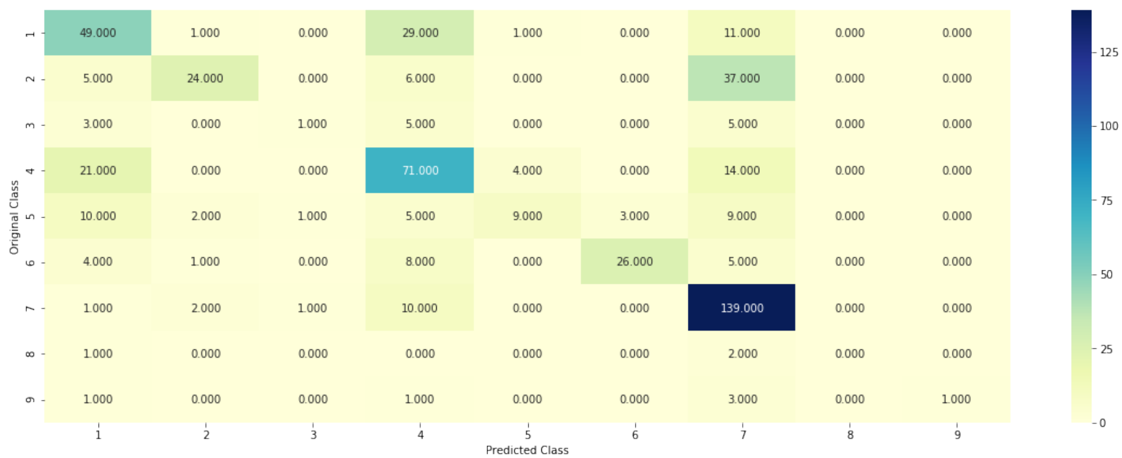
```
for n_estimators = 100 and max depth =  5
Log Loss : 1.1950933785496447
for n_estimators = 100 and max depth =  10
Log Loss : 1.0744465341090679
for n_estimators = 200 and max depth =  5
Log Loss : 1.1799077918750587
for n_estimators = 200 and max depth =  10
Log Loss : 1.0641194015081716
for n_estimators = 500 and max depth =  5
Log Loss : 1.165457296764393
for n_estimators = 500 and max depth =  10
Log Loss : 1.0454944074002903
for n_estimators = 1000 and max depth =  5
Log Loss : 1.1511568555449312
```

```
for n_estimators = 1000 and max depth =  10
Log Loss : 1.0397940509103574
for n_estimators = 2000 and max depth =  5
Log Loss : 1.1452244733653698
for n_estimators = 2000 and max depth =  10
Log Loss : 1.0335219796370754
For values of best estimator =  2000 The train log loss is: 0.5141384993956805
For values of best estimator =  2000 The cross validation log loss is: 1.0335219796370754
For values of best estimator =  2000 The test log loss is: 1.0754312756971138
```

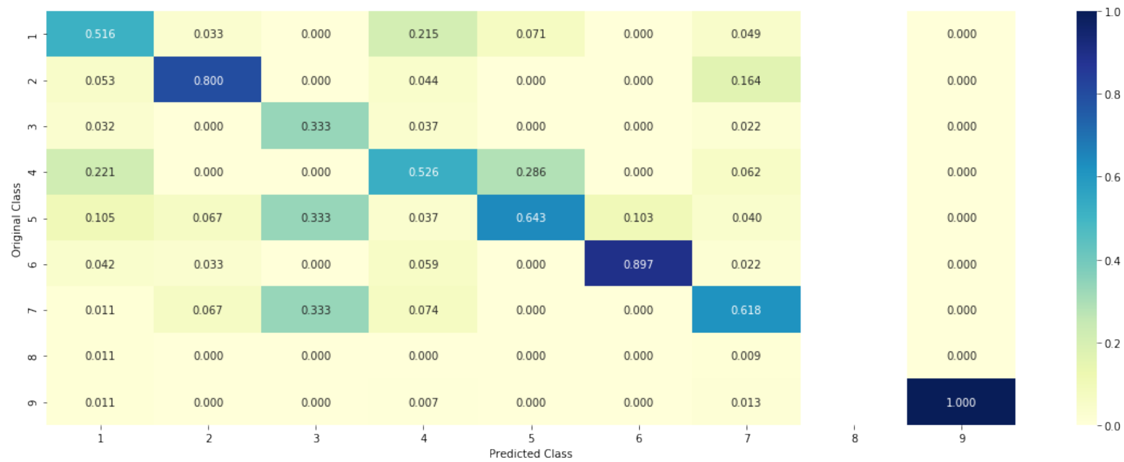
Testing the model with best hyperparameters

In [56]:
```
clf = RandomForestClassifier(n_estimators=int(best_alpha), criterion='gini', max_deptl
predict_and_plot_confusion_matrix(train_tfidf_onehot_features, train_y, cv_tfidf_oneho
```

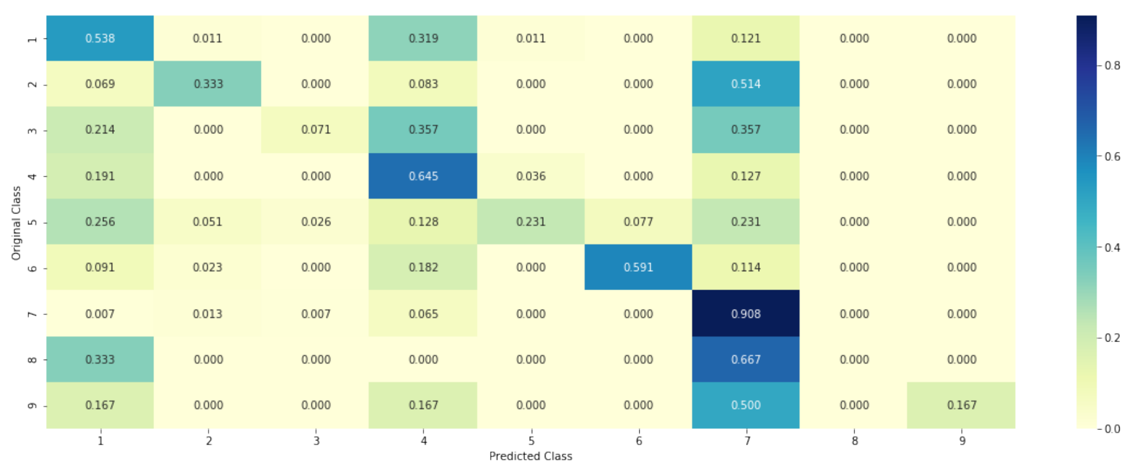
```
Log loss : 1.2240866157581334
Number of mis-classified points : 0.39849624060150374
-------------------- Confusion matrix --------------------
```




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




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



6.5.2.0. Feature Importance
6.5.2.1. Correctly Classified point

```
In [57]: # test_point_index = 10
         clf = RandomForestClassifier(n_estimators=int(best_alpha), criterion='gini', max_deptl
         clf.fit(train_tfidf_onehot_features, train_y)
         sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
         sig_clf.fit(train_tfidf_onehot_features, train_y)

         test_point_index = 1
         no_feature = 100
         predicted_cls = sig_clf.predict(train_tfidf_onehot_features[test_point_index])
         print("Predicted Class :", predicted_cls[0])
```

```
print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_onel
print("Actual Class :", test_y[test_point_index])
indices = np.argsort(-clf.feature_importances_)
print("-"*50)
get_impfeature_names(indices[:no_feature], test_df['TEXT'].iloc[test_point_index],tes
```

```
Predicted Class : 7
Predicted Class Probabilities: [[5.690e-02 1.400e-03 1.350e-02 1.760e-02 2.473e-01 6.618e-01 1
  0.000e+00 1.000e-04]]
Actual Class : 6
--------------------------------------------------
0 Text feature [transcriptional] present in test data point [True]
5 Text feature [polymorphisms] present in test data point [True]
8 Text feature [myriad] present in test data point [True]
Out of the top  100  features  3 are present in query point
```

6.5.2.2. Inorrectly Classified point

```
In [59]: test_point_index = 100
         no_feature = 100
         predicted_cls = sig_clf.predict(test_tfidf_onehot_features[test_point_index])
         print("Predicted Class :", predicted_cls[0])
         print("Predicted Class Probabilities:", np.round(sig_clf.predict_proba(test_tfidf_onel
         print("Actuall Class :", test_y[test_point_index])
         indices = np.argsort(-clf.feature_importances_)
         print("-"*50)
         get_impfeature_names(indices[:no_feature], test_df['TEXT'].iloc[test_point_index],tes
```

```
Predicted Class : 7
Predicted Class Probabilities: [[0.1819 0.124  0.0275 0.2609 0.055  0.0551 0.2704 0.0077 0.0174
Actuall Class : 6
--------------------------------------------------
Out of the top  100  features  0 are present in query point
```

6.5.3. Features - ResponseCoding with BOW

```
In [60]: 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, ra
                 clf.fit(train_bow_response_features, train_y)
                 sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
                 sig_clf.fit(train_bow_response_features, train_y)
                 sig_clf_probs = sig_clf.predict_proba(cv_bow_response_features)
```

```
            cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, e
            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_bow_response_features, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
    sig_clf.fit(train_bow_response_features, train_y)

    predict_y = sig_clf.predict_proba(train_bow_response_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train log los
    predict_y = sig_clf.predict_proba(cv_bow_response_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross validat
    predict_y = sig_clf.predict_proba(test_bow_response_features)
    print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test log loss
```

```
for n_estimators = 100 and max depth =  5
Log Loss : 1.1579080285828156
for n_estimators = 100 and max depth =  10
Log Loss : 1.0783618862339979
for n_estimators = 200 and max depth =  5
Log Loss : 1.1390945624895792
for n_estimators = 200 and max depth =  10
Log Loss : 1.0451797845321633
for n_estimators = 500 and max depth =  5
Log Loss : 1.1237258185812562
for n_estimators = 500 and max depth =  10
Log Loss : 1.0429844618362818
for n_estimators = 1000 and max depth =  5
Log Loss : 1.1215546611533405
for n_estimators = 1000 and max depth =  10
Log Loss : 1.047877847932957
for n_estimators = 2000 and max depth =  5
Log Loss : 1.1151147408835227
for n_estimators = 2000 and max depth =  10
Log Loss : 1.0480891168757336
For values of best estimator =  500 The train log loss is: 0.4592953746110341
For values of best estimator =  500 The cross validation log loss is: 1.0429844618362818
For values of best estimator =  500 The test log loss is: 1.0669229055804925
```

6.5.4. Features - ResponseCoding with TFIDF

In [61]:
```
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, ra
        clf.fit(train_tfidf_response_features, train_y)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
        sig_clf.fit(train_tfidf_response_features, train_y)
        sig_clf_probs = sig_clf.predict_proba(cv_tfidf_response_features)
        cv_log_error_array.append(log_loss(cv_y, sig_clf_probs, labels=clf.classes_, e
        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_tfidf_response_features, train_y)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid", cv="prefit")
sig_clf.fit(train_tfidf_response_features, train_y)

predict_y = sig_clf.predict_proba(train_tfidf_response_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train log loss
predict_y = sig_clf.predict_proba(cv_tfidf_response_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross validati
predict_y = sig_clf.predict_proba(test_tfidf_response_features)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test log loss
```

```
for n_estimators = 100 and max depth =  5
Log Loss : 1.1566838023029447
for n_estimators = 100 and max depth =  10
Log Loss : 1.0491504107179623
for n_estimators = 200 and max depth =  5
Log Loss : 1.1094981656886826
for n_estimators = 200 and max depth =  10
Log Loss : 1.024243704906568
for n_estimators = 500 and max depth =  5
Log Loss : 1.1045251569571664
for n_estimators = 500 and max depth =  10
Log Loss : 1.0231368898913296
for n_estimators = 1000 and max depth =  5
Log Loss : 1.1038931375072731
for n_estimators = 1000 and max depth =  10
Log Loss : 1.0136634349171492
for n_estimators = 2000 and max depth =  5
Log Loss : 1.0956845377742195
for n_estimators = 2000 and max depth =  10
Log Loss : 1.0091289534464267
```

```
For values of best estimator =  2000 The train log loss is: 0.36395064846069347
For values of best estimator =  2000 The cross validation log loss is: 1.0091289534464267
For values of best estimator =  2000 The test log loss is: 1.0674155456712104
```

6.6 Stack the models

Stacking up [RandomForest(n_estimators=500, depth=10), LinearSVM(alpha=0.0001), LogisticRegression(alpha=0.001)] as these got least log loss

6.6.1 Features - OneHot with BOW

In [62]:
```
clf1 = RandomForestClassifier(n_estimators=500, max_depth=10, class_weight='balanced'
clf1.fit(train_bow_onehot_features, train_y)
sig_clf1 = CalibratedClassifierCV(clf1, method="sigmoid")
sig_clf1.fit(train_bow_onehot_features, train_y)
print("RandomForest Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf1.predict_

clf2 = SGDClassifier(alpha=0.0001, penalty='l2', loss='hinge', random_state=42,class_w
clf2.fit(train_bow_onehot_features, train_y)
sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")
sig_clf2.fit(train_bow_onehot_features, train_y)
print("Linear SVM Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf2.predict_p

clf3 = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2',
                    loss='log', random_state=42)
clf3.fit(train_bow_onehot_features, train_y)
sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")
sig_clf3.fit(train_bow_onehot_features, train_y)
print("Logistic Regression Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf3.

alpha = [0.0001,0.001,0.01,0.1,1,10, 100, 1000]
best_alpha = 999
for i in alpha:
    lr = LogisticRegression(C=i)
    sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classi
    sclf.fit(train_bow_onehot_features, train_y)
    print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" % (i, log_
    log_error =log_loss(cv_y, sclf.predict_proba(cv_bow_onehot_features))
    if best_alpha > log_error:
        best_alpha = log_error
```

```
RandomForest Classifier :  Log Loss: 1.24
Linear SVM Classifier :  Log Loss: 1.83
Logistic Regression Classifier :  Log Loss: 1.36
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 2.182
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 2.076
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 1.688
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 1.237
```

```
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 1.135
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 1.246
Stacking Classifer : for the value of alpha: 100.000000 Log Loss: 1.348
Stacking Classifer : for the value of alpha: 1000.000000 Log Loss: 1.411
```

6.6.2 Features - OneHot with TFIDF

In [63]:
```
clf1 = RandomForestClassifier(n_estimators=500, max_depth=10, class_weight='balanced'
clf1.fit(train_tfidf_onehot_features, train_y)
sig_clf1 = CalibratedClassifierCV(clf1, method="sigmoid")
sig_clf1.fit(train_tfidf_onehot_features, train_y)
print("RandomForest Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf1.predict_

clf2 = SGDClassifier(alpha=0.0001, penalty='l2', loss='hinge', random_state=42,class_
clf2.fit(train_tfidf_onehot_features, train_y)
sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")
sig_clf2.fit(train_tfidf_onehot_features, train_y)
print("Linear SVM Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf2.predict_p

clf3 = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2',
                     loss='log', random_state=42)
clf3.fit(train_tfidf_onehot_features, train_y)
sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")
sig_clf3.fit(train_tfidf_onehot_features, train_y)
print("Logistic Regression Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf3.

alpha = [0.0001,0.001,0.01,0.1,1,10, 100, 1000]
best_alpha = 999
for i in alpha:
    lr = LogisticRegression(C=i)
    sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classi
    sclf.fit(train_tfidf_onehot_features, train_y)
    print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" % (i, log_
    log_error =log_loss(cv_y, sclf.predict_proba(cv_tfidf_onehot_features))
    if best_alpha > log_error:
        best_alpha = log_error
```

```
RandomForest Classifier :  Log Loss: 1.18
Linear SVM Classifier :  Log Loss: 1.05
Logistic Regression Classifier :  Log Loss: 1.02
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 2.175
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 2.010
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 1.426
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 1.020
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 1.111
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 1.477
Stacking Classifer : for the value of alpha: 100.000000 Log Loss: 2.023
```

```
Stacking Classifer : for the value of alpha: 1000.000000 Log Loss: 2.732
```

6.6.3 Features - Response with BOW

```
In [64]: clf1 = RandomForestClassifier(n_estimators=500, max_depth=10, class_weight='balanced'
         clf1.fit(train_bow_response_features, train_y)
         sig_clf1 = CalibratedClassifierCV(clf1, method="sigmoid")
         sig_clf1.fit(train_bow_response_features, train_y)
         print("RandomForest Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf1.predict_

         clf2 = SGDClassifier(alpha=0.0001, penalty='l2', loss='hinge', random_state=42,class_
         clf2.fit(train_bow_response_features, train_y)
         sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")
         sig_clf2.fit(train_bow_response_features, train_y)
         print("Linear SVM Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf2.predict_p

         clf3 = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2',
                             loss='log', random_state=42)
         clf3.fit(train_bow_response_features, train_y)
         sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")
         sig_clf3.fit(train_bow_response_features, train_y)
         print("Logistic Regression Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf3.

         alpha = [0.0001,0.001,0.01,0.1,1,10, 100, 1000]
         best_alpha = 999
         for i in alpha:
             lr = LogisticRegression(C=i)
             sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classi
             sclf.fit(train_bow_response_features, train_y)
             print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" % (i, log_
             log_error =log_loss(cv_y, sclf.predict_proba(cv_bow_response_features))
             if best_alpha > log_error:
                 best_alpha = log_error
```

```
RandomForest Classifier :  Log Loss: 1.10
Linear SVM Classifier :  Log Loss: 1.83
Logistic Regression Classifier :  Log Loss: 1.34
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 2.180
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 2.053
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 1.582
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 1.126
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 1.088
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 1.288
Stacking Classifer : for the value of alpha: 100.000000 Log Loss: 1.565
Stacking Classifer : for the value of alpha: 1000.000000 Log Loss: 1.777
```

6.6.4 Features - Response with TFIDF

```
In [65]: clf1 = RandomForestClassifier(n_estimators=500, max_depth=10, class_weight='balanced'
         clf1.fit(train_tfidf_response_features, train_y)
         sig_clf1 = CalibratedClassifierCV(clf1, method="sigmoid")
         sig_clf1.fit(train_tfidf_response_features, train_y)
         print("RandomForest Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf1.predict_

         clf2 = SGDClassifier(alpha=0.0001, penalty='l2', loss='hinge', random_state=42,class_
         clf2.fit(train_tfidf_response_features, train_y)
         sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")
         sig_clf2.fit(train_tfidf_response_features, train_y)
         print("Linear SVM Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf2.predict_p

         clf3 = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2',
                             loss='log', random_state=42)
         clf3.fit(train_tfidf_response_features, train_y)
         sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")
         sig_clf3.fit(train_tfidf_response_features, train_y)
         print("Logistic Regression Classifier :  Log Loss: %0.2f" % (log_loss(cv_y, sig_clf3.

         alpha = [0.0001,0.001,0.01,0.1,1,10, 100, 1000]
         best_alpha = 999
         for i in alpha:
             lr = LogisticRegression(C=i)
             sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classi
             sclf.fit(train_tfidf_onehot_features, train_y)
             print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" % (i, log_
             log_error =log_loss(cv_y, sclf.predict_proba(cv_tfidf_onehot_features))
             if best_alpha > log_error:
                 best_alpha = log_error
```

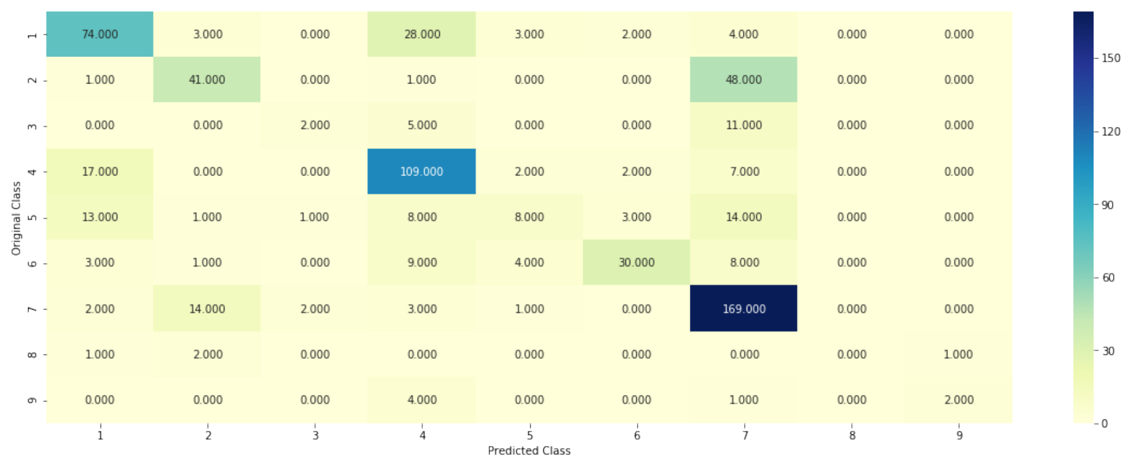
```
RandomForest Classifier :  Log Loss: 1.04
Linear SVM Classifier :  Log Loss: 1.09
Logistic Regression Classifier :  Log Loss: 1.03
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 2.175
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 2.010
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 1.426
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 1.020
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 1.111
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 1.477
Stacking Classifer : for the value of alpha: 100.000000 Log Loss: 2.023
Stacking Classifer : for the value of alpha: 1000.000000 Log Loss: 2.732
```

6.6.4.1 Testing the model with the best hyper parameters

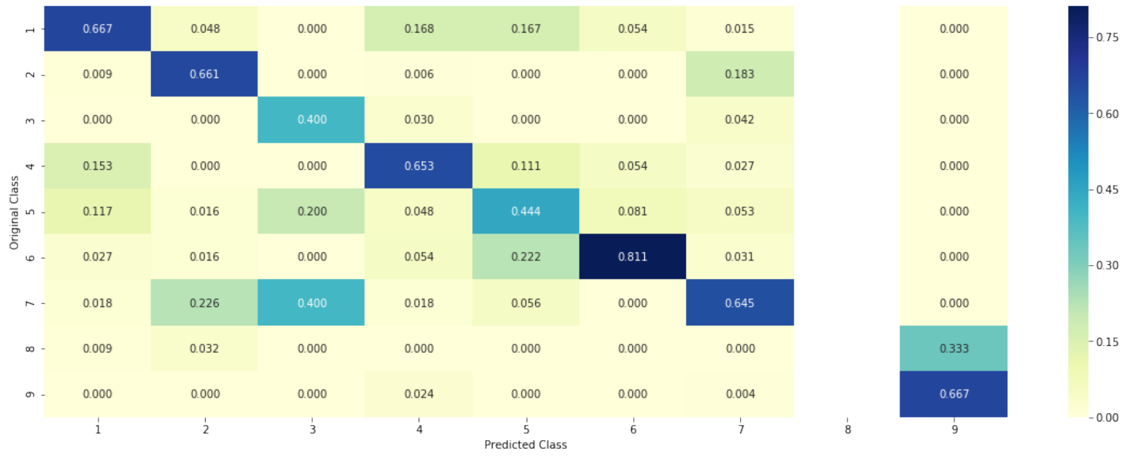
```
In [66]: lr = LogisticRegression(C=0.1)
         sclf = StackingClassifier(classifiers=[sig_clf1, sig_clf2, sig_clf3], meta_classifier
```

```python
sclf.fit(train_tfidf_onehot_features, train_y)

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

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

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

print("Number of missclassified point :", np.count_nonzero((sclf.predict(test_tfidf_or
plot_confusion_matrix(test_y=test_y, predict_y=sclf.predict(test_tfidf_onehot_features
```

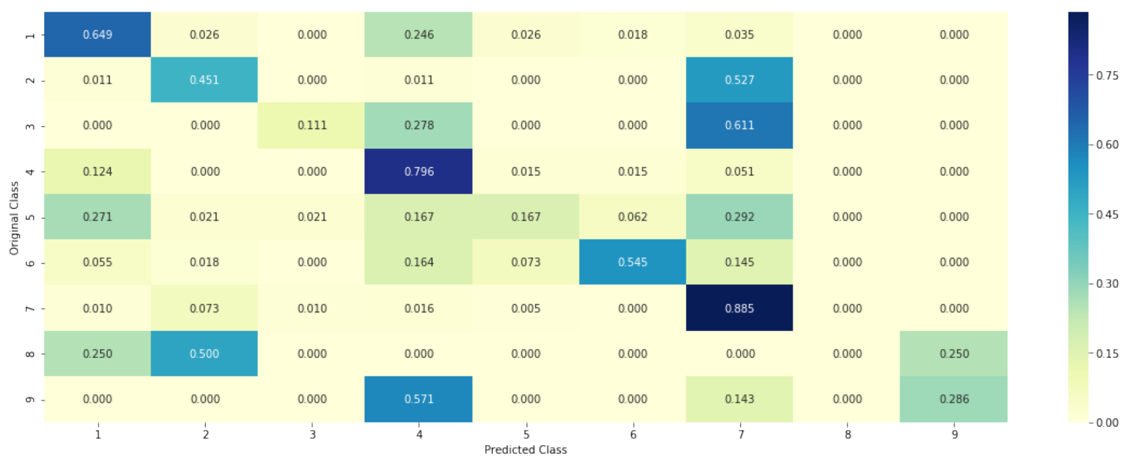
```
Log loss (train) on the stacking classifier : 0.4094484719965551
Log loss (CV) on the stacking classifier : 1.0199758344670404
Log loss (test) on the stacking classifier : 1.0615019072459961
Number of missclassified point : 0.3458646616541353
-------------------- Confusion matrix --------------------
```




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



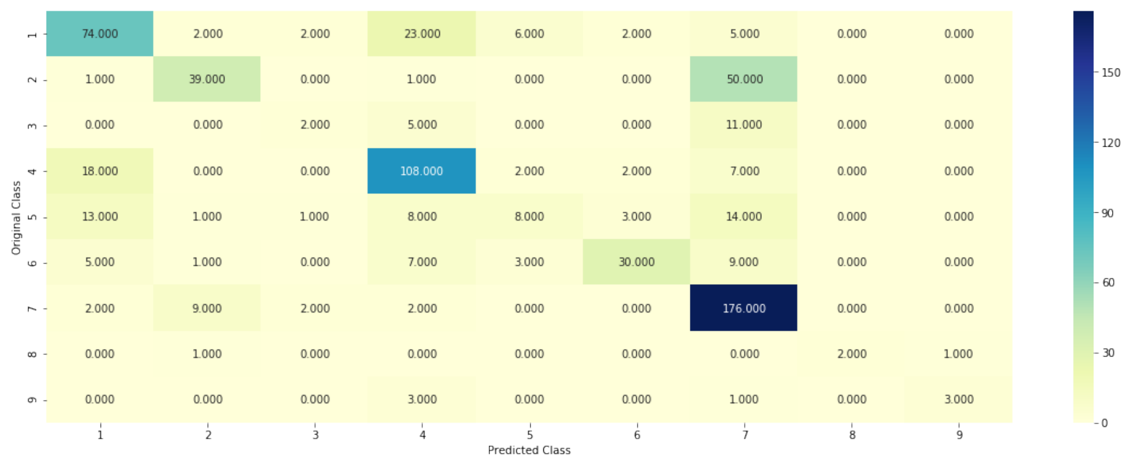

```
-------------------- Recall matrix (Row sum=1) --------------------
```



1.0.11 6.7. Maximum Voting Classifier

```
In [67]: #Refer:http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.VotingClassi
         from sklearn.ensemble import VotingClassifier
         vclf = VotingClassifier(estimators=[('rf', sig_clf1), ('lin', sig_clf2), ('logistic',
         vclf.fit(train_tfidf_onehot_features, train_y)
         print("Log loss (train) on the VotingClassifier :", log_loss(train_y, vclf.predict_pro
         print("Log loss (CV) on the VotingClassifier :", log_loss(cv_y, vclf.predict_proba(cv_
         print("Log loss (test) on the VotingClassifier :", log_loss(test_y, vclf.predict_proba
         print("Number of missclassified point :", np.count_nonzero((vclf.predict(test_tfidf_on
         plot_confusion_matrix(test_y=test_y, predict_y=vclf.predict(test_tfidf_onehot_features
```

```
Log loss (train) on the VotingClassifier : 0.5828435172445474
Log loss (CV) on the VotingClassifier : 1.0347273959826861
Log loss (test) on the VotingClassifier : 1.0550490439340257
Number of missclassified point : 0.33533834586466166
-------------------- Confusion matrix --------------------
```




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


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

1.1 7. Results

In [69]:
```
from prettytable import PrettyTable

print("Here I am only displaying the best result of each model that I tried with the f
x = PrettyTable()
x.field_names = ["Featurization", "Model", "Train log loss", "Test log loss", "CV log

prettytable_data = [
    ["gene(Onehot)+variantion(Onehot)+Text(TFIDF)", "MultinomialNB(alpha: 10)", 1.019
    ["gene(Response)+variantion(Response)+Text(TFIDF)","KNeighborsClassifier(n_neighbo
    ["gene(Response)+variantion(Response)+Text(TFIDF)","LogisticRegression(alpha=0.00
    ["gene(Response)+variantion(Response)+Text(TFIDF)","SupportVectorMachines(alpha=0
    ["gene(Onehot)+variantion(Onehot)+Text(TFIDF)","RandomForest(n_estimator=2000, max
    ["gene(Onehot)+variantion(Onehot)+Text(TFIDF)","RandomForest(n_estimator=2000, max
    ["gene(Onehot)+variantion(Onehot)+Text(TFIDF)","MaxVoteClf(RandomForest, LinearReg
]
[x.add_row(i) for i in prettytable_data]
print(x)
```

```
Here I am only displaying the best result of each model that I tried with the featurization tha
+---------------------------------------------------+-------------------------------------------
|                   Featurization                   |                       Model
+---------------------------------------------------+-------------------------------------------
|    gene(Onehot)+variantion(Onehot)+Text(TFIDF)    |          MultinomialNB(alpha: 10)
| gene(Response)+variantion(Response)+Text(TFIDF) |      KNeighborsClassifier(n_neighbors=15)
| gene(Response)+variantion(Response)+Text(TFIDF) |        LogisticRegression(alpha=0.001)
| gene(Response)+variantion(Response)+Text(TFIDF) |       SupportVectorMachines(alpha=0.001)
|    gene(Onehot)+variantion(Onehot)+Text(TFIDF)    |   RandomForest(n_estimator=2000, max_depth=
|    gene(Onehot)+variantion(Onehot)+Text(TFIDF)    |   RandomForest(n_estimator=2000, max_depth=
|    gene(Onehot)+variantion(Onehot)+Text(TFIDF)    | MaxVoteClf(RandomForest, LinearReg, Logisti
```

```
+-------------------------------------------------+--------------------------------------------
```

1.2 8. Conclusion

1.2.1 Step by step approach to the problem

1. We start of by loading the datasets of Gene and Variation, and text separately.
2. We preprocess the Text features by replacing the special character with a space and then followed by stop word removal.
3. Then we merge these two datasets to a single dataframe and then remove all the NaN rows.
4. Then we perform EDA upon the data.
5. Next we split the dataframe into 3 sections - Train, Test and CV in the ratio - 64:20:16
6. Now in this step we have 3 different sections that we featurize and form feature vectors by doing all possible combination of Gene(OneHot/Respone) with Variation(OneHot/Response) with Text(TFIDF).
7. Then we try upon various ml models upon the feature vectors and note down their corresponding log losses in Train, Test and CV respectively
8. We finally aggregate all the results into a tabular format.