In [3]:

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np

import pickle
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV

from sklearn.metrics import accuracy_score
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import label_binarize
from sklearn.metrics.classification import log_loss
from sklearn.metrics import confusion_matrix
```

In [4]:

```
# function to load the pickle data
def loadPickleData(filename):
    pickle_off = open(filename,"rb")
    final = pickle.load(pickle_off)
    return final
```

In [5]:

```
# load the y values because they are common across all feature engineering
y_train = loadPickleData('y_train.pickle')
y_test = loadPickleData('y_test.pickle')
y_cv = loadPickleData('y_cv.pickle')
```

In [6]:

```
# Encode labels

encoded_column_vector = label_binarize(y_train, classes=['negative','positive'])
 # ham will be 0 and spam will be 1
y_train = np.ravel(encoded_column_vector)

encoded_column_vector = label_binarize(y_test, classes=['negative','positive'])
# ham will be 0 and spam will be 1
y_test = np.ravel(encoded_column_vector)

encoded_column = label_binarize(y_cv, classes=['negative','positive']) # ham wil
l be 0 and spam will be 1
y_cv = np.ravel(encoded_column)
```

In [7]:

```
len(y_train)
```

Out[7]:

```
69920
```

In [8]:

```
# 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)
    labels = [0,1]
    # 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, yti
cklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [9]:

```
def calculateMetricC(X,y,alpha,train,y_train):
    fpr_array = []
    sparsity_array = []
    for i in alpha:
            print("for alpha =", i)
            clf = SGDClassifier(class_weight='balanced', alpha=i, penalty='l1',
loss='log', random_state=42)
            clf.fit(train, y_train)
            sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
            sig_clf.fit(train, y_train)
            pred = sig_clf.predict(X)
            tn, fp, fn, tp = confusion_matrix(y, pred,labels=[0,1]).ravel()
            if fp == 0 and tp ==0:
                fpr = np.inf
            else:
                fpr = fp/(fp+tn)
            fpr_array.append(fpr)
            sparsity = findSparsity(clf)
            sparsity_array.append(sparsity)
            print("Fpr :",fpr)
            print("Sparsity :",sparsity)
    return fpr_array,sparsity_array
```

In [10]:

```
def drawplots(alpha,cv_log_error_array,sparsity_array,train_log_error_array):
    fig, ax = plt.subplots(2,1,figsize=(15,15))
    a = np.arange(len(alpha))
    ax[0].plot(a, cv_log_error_array,c='g')
    for i, txt in enumerate(np.round(cv_log_error_array,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],cv_log_error_array[i]))

    ax[0].plot(a, train_log_error_array,c='r')
    for i, txt in enumerate(np.round(train_log_error_array,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],train_log_error_array[i]),(a[i]+0.
005,train_log_error_array[i]+0.015))

    ax[0].set_xticks(a)
    ax[0].set_xticklabels(alpha)
    plt.grid()
    ax[0].set_title("Cross Validation Error for each alpha")
    ax[0].set_xlabel("Alpha i's")
    ax[0].set_ylabel("Error measure")
#    ax[0].set_legend(loc= 4)


    ax[1].plot(a, sparsity_array,c='b')
    for i, txt in enumerate(sparsity_array):
        ax[1].annotate((alpha[i],str(txt)), (a[i],sparsity_array[i]))
    ax[1].set_xticks(a)
    ax[1].set_xticklabels(alpha)
    ax[1].set_title("Non zero values for each alpha")
    ax[1].set_xlabel("Alpha i's")
    plt.show()
```

In [11]:

```
# performs hyperparameter tuning for logistic regression
def performHyperParameterTuningC(train,cv,test):
    alpha = [10 ** x for x in range(-14, 3)]
    fpr_array = []
    sparsity_array = []
    fpr_error_array,sparsity_array = calculateMetricC(cv,y_cv,alpha,train,y_trai
n)
    fpr_error_array_train,train_sparsity_array = calculateMetricC(train,y_train,
alpha,train,y_train)

    drawplots(alpha,fpr_error_array,sparsity_array,fpr_error_array_train)
    best_alpha = np.argmin(fpr_error_array)
    clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalt
y='l1', loss='log', random_state=42)
    clf.fit(train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train, y_train)

    predict_y = sig_clf.predict(train)
    tn, fp, fn, tp = confusion_matrix(y_train, predict_y,labels=[0,1]).ravel()
    plot_confusion_matrix(y_train,predict_y)
    print('For values of best alpha = ', alpha[best_alpha], "The train fpr is:",
fp/(fp+tn))
    predict_y = sig_clf.predict(cv)
    tn, fp, fn, tp = confusion_matrix(y_cv, predict_y,labels=[0,1]).ravel()
    print('For values of best alpha = ', alpha[best_alpha], "The cross validatio
n fpr is:",fp/(fp+tn))
    predict_y = sig_clf.predict(test)
    tn, fp, fn, tp = confusion_matrix(y_test, predict_y,labels=[0,1]).ravel()
    plot_confusion_matrix(y_test,predict_y)
    print('For values of best alpha = ', alpha[best_alpha], "The test fpr is:",f
p/(fp+tn))
    return clf,alpha[best_alpha]
```

In [12]:

```
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 bel
ongs to each class
#     print("Log loss :",log_loss(test_y, sig_clf.predict_proba(test_x)))
#     # calculating the number of data points that are misclassified
#     print("Number of mis-classified points :", np.count_nonzero((pred_y- test_
y))/test_y.shape[0])
    plot_confusion_matrix(test_y, pred_y)
```

In [13]:

```
def plot(data):
    fig = plt.figure(figsize=(15,15))
    ax1 = fig.add_subplot(1,1,1)
    ax1.plot(data)
```

In [14]:

```
def findPercentageDifference(w,w_new):
    z =np.subtract(w,w_new)
    q = np.linalg.norm(w)
    a = abs(np.divide(z,q))*100
    return a
```

In [15]:

```
def doPertubation(train):
    e = np.random.normal(0,0.1)
    #train_1 = np.add(train,e)
    train_1 = train.data + e
    train.data = train_1
    return train
```

In [16]:

```
# def findSparsity(clf):
#     coef_list =  clf.coef_.ravel()
#     sparsity_LR = np.mean(coef_list == 0) * 100
#     print("Sparsity is :" ,sparsity_LR)
```

In [17]:

```
def findSparsity(clf):
    coef_list =  clf.coef_.ravel()
    non_sparse = coef_list[coef_list !=0]
    return non_sparse.size
```

In [18]:

```
def getImportantFeatures(indices,feature_names):
    words =[]
    for x in indices:
        words.append(feature_names[x])
    return words
```

BOW

In [19]:

```
train = loadPickleData("bow_train.pickle")
test = loadPickleData('bow_test.pickle')
cv = loadPickleData('bow_cv.pickle')
```

In [20]:

```
count_vect = loadPickleData('count_vect.pickle')
feature_names = count_vect.get_feature_names()
```

In [21]:

```
cv.shape
```

Out[21]:

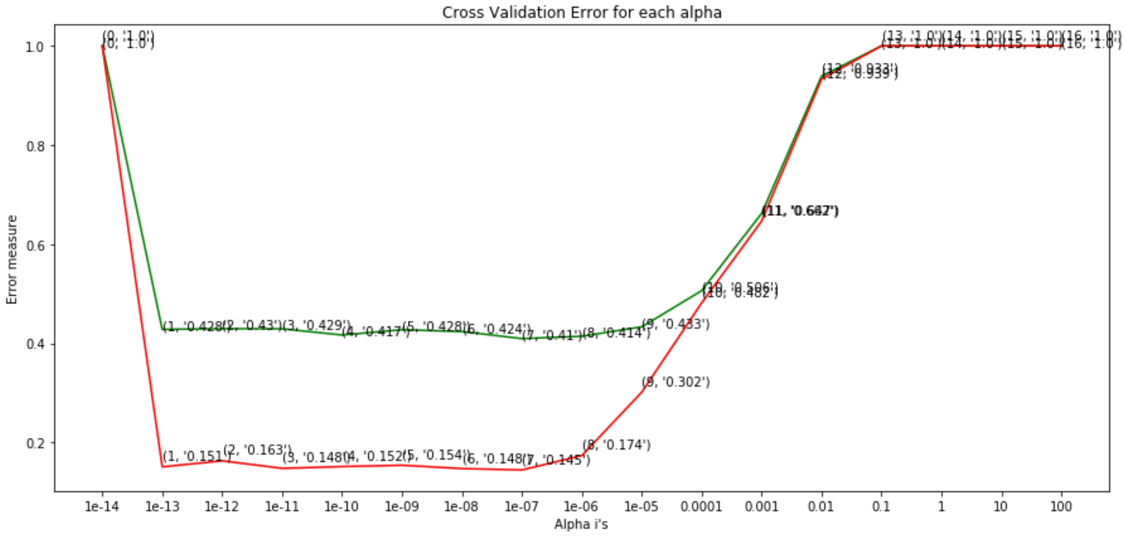
```
(17480, 3185692)
```

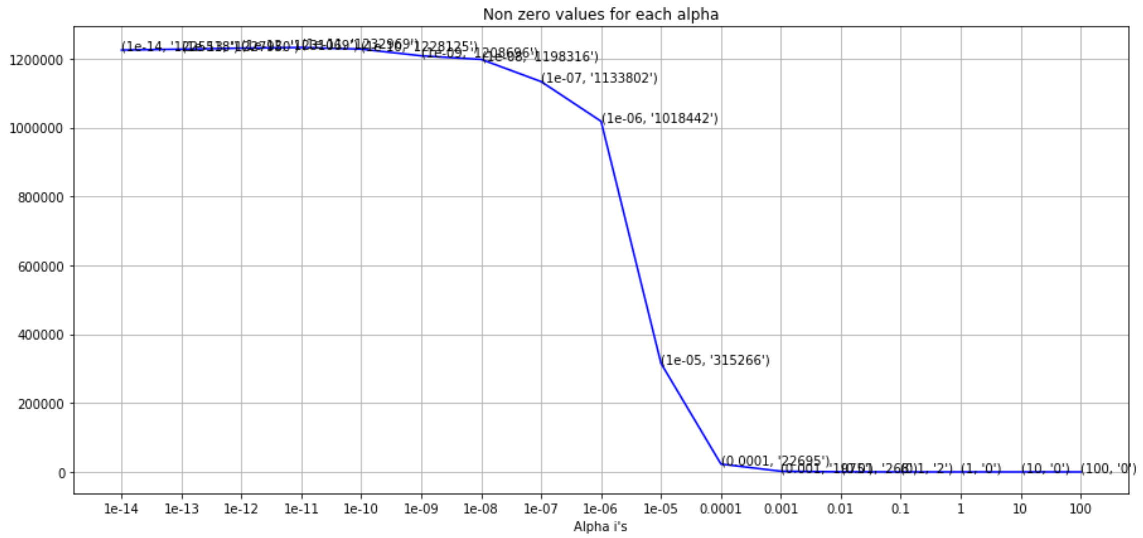
In [22]:

```
clf,alph = performHyperParameterTuningC(train,cv,test)
```

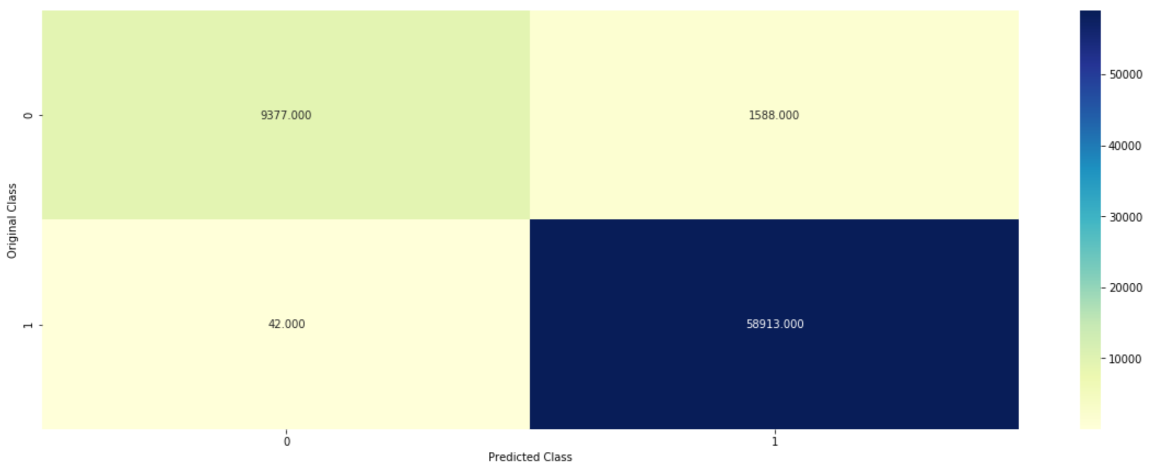
```
for alpha = 1e-14
Fpr : 1.0
Sparsity : 1225518
for alpha = 1e-13
Fpr : 0.4283108354615104
Sparsity : 1227950
for alpha = 1e-12
Fpr : 0.42977015687705217
Sparsity : 1231069
for alpha = 1e-11
Fpr : 0.4294053265231667
Sparsity : 1232969
for alpha = 1e-10
Fpr : 0.41700109449106165
Sparsity : 1228125
for alpha = 1e-09
Fpr : 0.4275811747537395
Sparsity : 1208696
for alpha = 1e-08
Fpr : 0.4239328712148851
Sparsity : 1198316
for alpha = 1e-07
Fpr : 0.4097044874133528
Sparsity : 1133802
for alpha = 1e-06
Fpr : 0.41444728201386355
Sparsity : 1018442
for alpha = 1e-05
Fpr : 0.4334184604159066
Sparsity : 315266
for alpha = 0.0001
Fpr : 0.5063845311929952
Sparsity : 22695
for alpha = 0.001
Fpr : 0.6621670923020795
Sparsity : 1975
for alpha = 0.01
Fpr : 0.939073330901131
Sparsity : 268
for alpha = 0.1
Fpr : 1.0
Sparsity : 2
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
for alpha = 1e-14
Fpr : 1.0
Sparsity : 1225518
for alpha = 1e-13
Fpr : 0.15102599179206566
Sparsity : 1227950
for alpha = 1e-12
Fpr : 0.1632466940264478
Sparsity : 1231069
for alpha = 1e-11
```

```
Fpr : 0.14801641586867306
Sparsity : 1232969
for alpha = 1e-10
Fpr : 0.15166438668490653
Sparsity : 1228125
for alpha = 1e-09
Fpr : 0.15430916552667578
Sparsity : 1208696
for alpha = 1e-08
Fpr : 0.14756041951664386
Sparsity : 1198316
for alpha = 1e-07
Fpr : 0.14482444140446876
Sparsity : 1133802
for alpha = 1e-06
Fpr : 0.17382580939352485
Sparsity : 1018442
for alpha = 1e-05
Fpr : 0.301687186502508
Sparsity : 315266
for alpha = 0.0001
Fpr : 0.4818969448244414
Sparsity : 22695
for alpha = 0.001
Fpr : 0.6468764249886001
Sparsity : 1975
for alpha = 0.01
Fpr : 0.9330597355221159
Sparsity : 268
for alpha = 0.1
Fpr : 1.0
Sparsity : 2
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
```

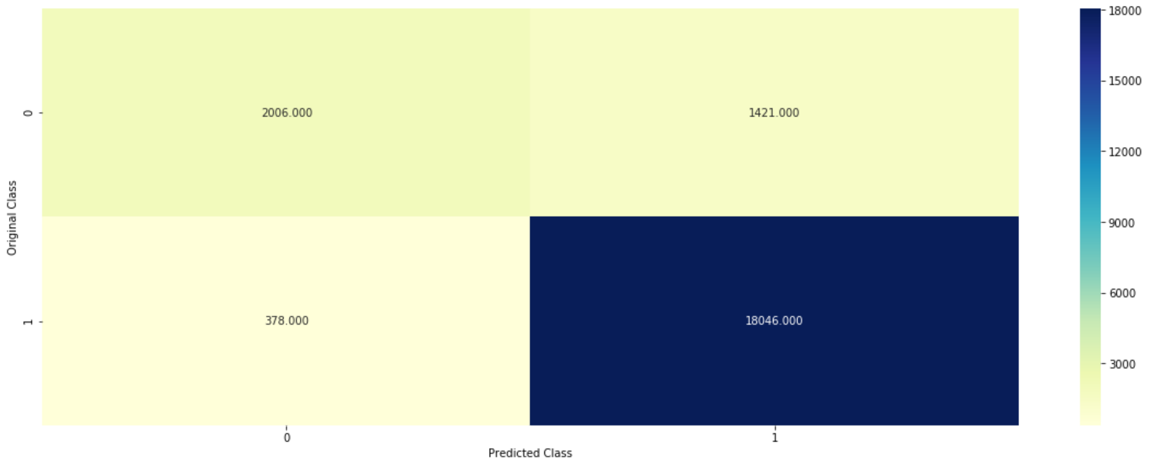




------------------- Confusion matrix -------------------



```
For values of best alpha =  1e-07 The train fpr is: 0.14482444140446
876
For values of best alpha =  1e-07 The cross validation fpr is: 0.409
7044874133528
-------------------- Confusion matrix --------------------
```

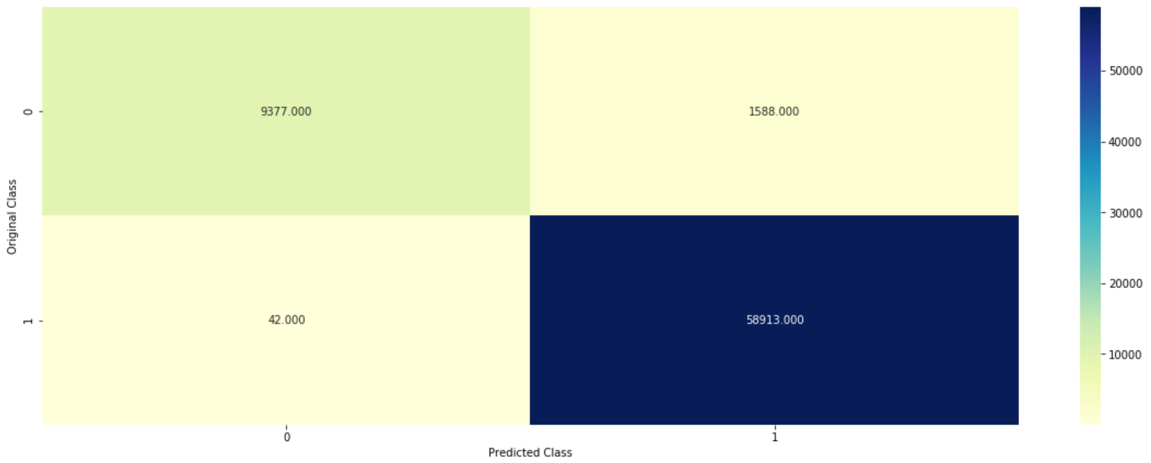



```
For values of best alpha =  1e-07 The test fpr is: 0.414648380507732
73
```

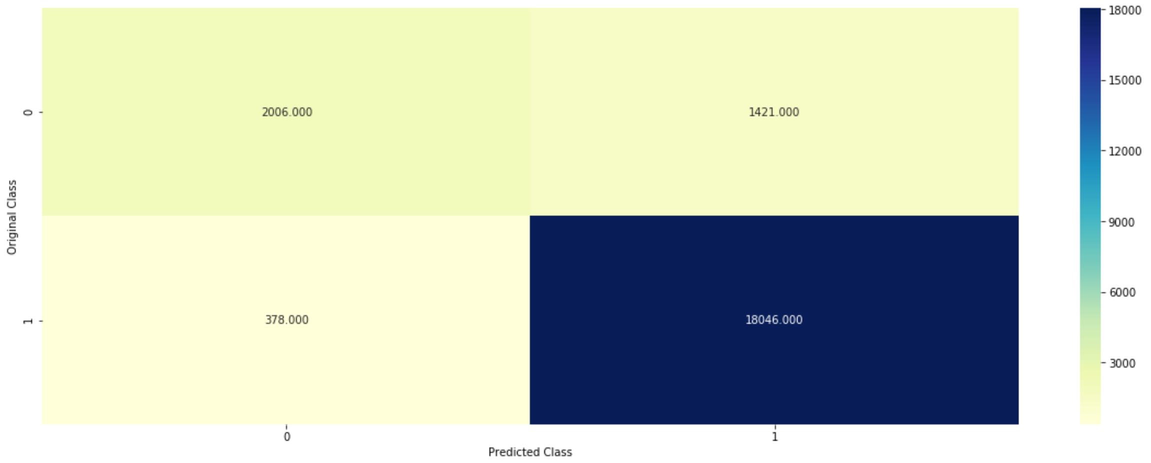
In [23]:

```
clf = SGDClassifier(class_weight='balanced', alpha=alph, penalty='l1', loss='lo
g', random_state=42)
print("Train")
predict_and_plot_confusion_matrix(train, y_train,train, y_train, clf)
print("Test")
predict_and_plot_confusion_matrix(train, y_train,test, y_test, clf)
```

```
Train
-------------------- Confusion matrix --------------------
```




```
Test
-------------------- Confusion matrix --------------------
```



In [24]:

```
x = clf.coef_
```

Sparsity

In [25]:

```
findSparsity(clf)
```

Out[25]:

```
1133802
```

Pertubation

In [26]:

```
train_1 = doPertubation(train)
```

In [27]:

```
clf = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l1',loss='lo
g', random_state=42)
clf.fit(train_1, y_train)
```

Out[27]:

```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=Tr
ue,
       l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=
None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=42, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [28]:

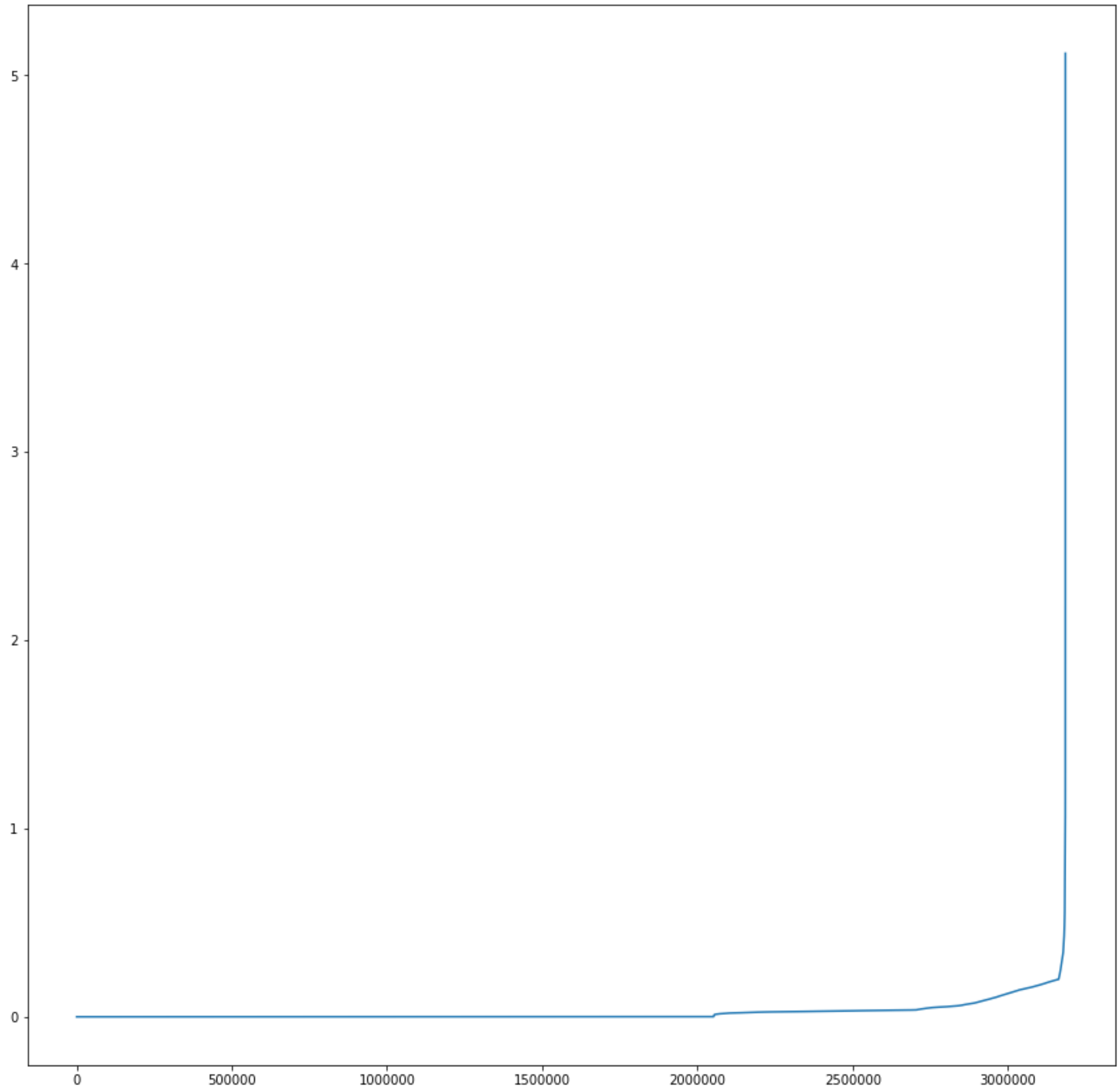
```
y = clf.coef_
```

In [29]:

```
a = findPercentageDifference(x,y)
```

In [30]:

```
b = np.sort(a.ravel())
plot(b)
```



Features whose % change is above threshold

In [31]:

```
percentage_change_flattened = a.ravel()
c = b>0.01
indices = np.where(c)
words = getImportantFeatures(indices[0],feature_names)
print(len(words))
print(words[:20])
```

```
1131227
['perfect thank ami', 'perfect thank ever', 'perfect thank gift', 'p
erfect thank god', 'perfect thank thank', 'perfect thanksgiv', 'perf
ect thanksgiv here', 'perfect there', 'perfect there doubt', 'perfec
t there much', 'perfect therefor', 'perfect therefor quench', 'perfe
ct theyr', 'perfect theyr carbon', 'perfect theyr crunchi', 'perfect
theyr cute', 'perfect theyr hard', 'perfect theyr sturdi', 'perfect
thick', 'perfect thick bite']
```

Important Features

In [32]:

```
indices = np.argsort(-clf.coef_)[0][:]
positive_indices = indices[:20]
words = getImportantFeatures(positive_indices,feature_names)
print(words)
```

```
['delici', 'favorit', 'keep', 'high recommend', 'perfect', 'easi',
'happi', 'excel', 'glad', 'best', 'help', 'nice', 'run', 'alway', 'g
reat', 'wonder', 'sometim', 'shake', 'amaz', 'muffin']
```

In [33]:

```
negative_indices = indices[-20:]
words = getImportantFeatures(negative_indices,feature_names)
print(words)
```

```
['gross', 'safeti seal cap', 'differ food', 'olli', 'under kidney di
seas', 'under kidney', 'safeti', 'salsa garden', 'pgpr', 'caus', 'li
me juic', 'key lime', 'refus', 'multipl', 'diseas', 'kidney diseas',
'under', 'lime', 'key', 'kidney']
```

In [33]:

```
print(clf.coef_.shape)
```

```
(1, 3185692)
```

TFIDF

In [29]:

```
train = loadPickleData("tfidf_train.pickle")
test = loadPickleData('tfidf_test.pickle')
cv = loadPickleData('tfidf_cv.pickle')
```

In [30]:

```
train.shape
```

Out[30]:

```
(69920, 42422)
```

In [31]:

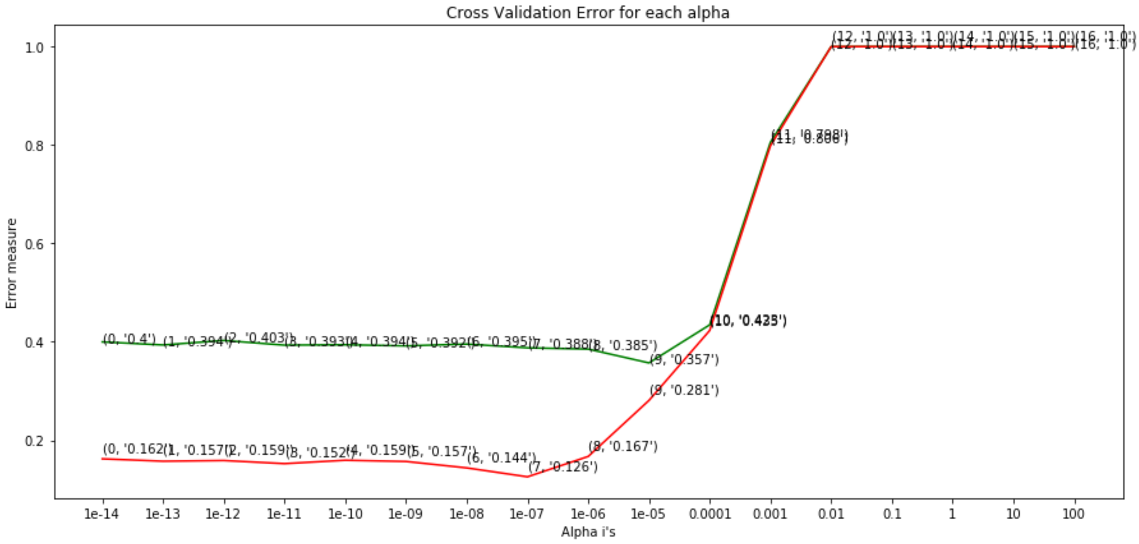
```
tf_idf_vect = loadPickleData('tf_idf_vect.pickle')
feature_names = tf_idf_vect.get_feature_names()
```

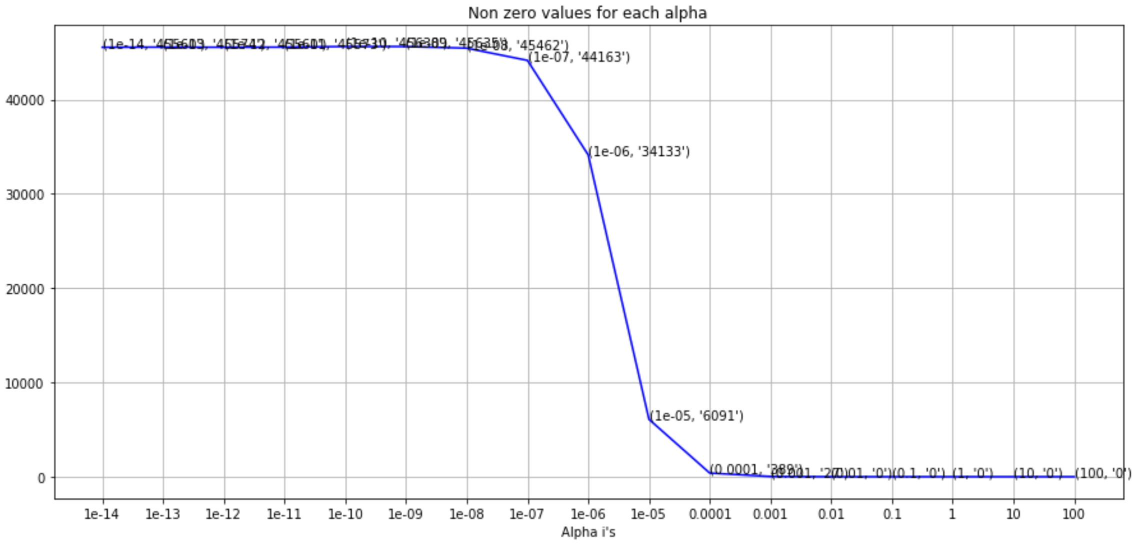
In [46]:

```
clf,alph = performHyperParameterTuningC(train,cv,test)
```

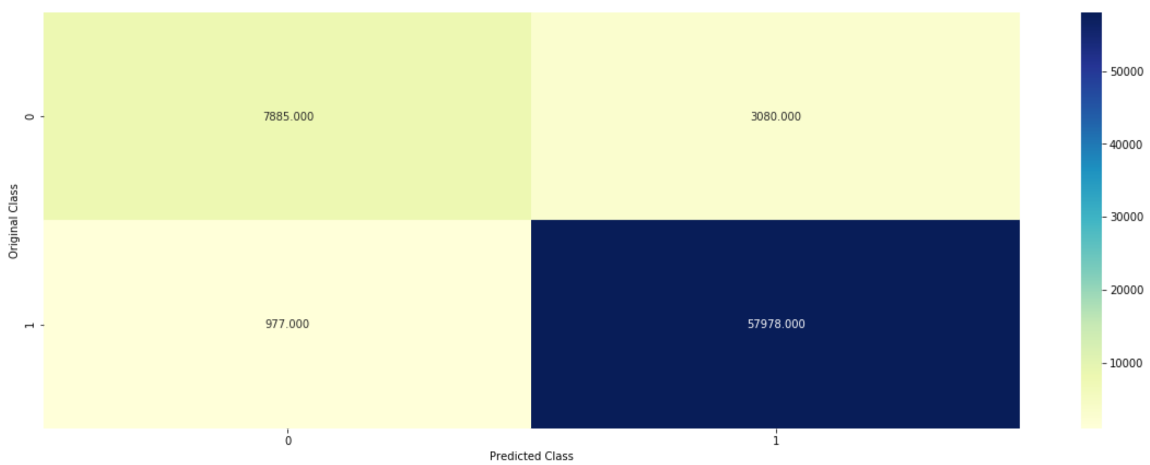
```
for alpha = 1e-14
Fpr : 0.39985406785844585
Sparsity : 45560
for alpha = 1e-13
Fpr : 0.39365195184239327
Sparsity : 45574
for alpha = 1e-12
Fpr : 0.40277271068952936
Sparsity : 45560
for alpha = 1e-11
Fpr : 0.39328712148850786
Sparsity : 45573
for alpha = 1e-10
Fpr : 0.3940167821962787
Sparsity : 45638
for alpha = 1e-09
Fpr : 0.3918278000729661
Sparsity : 45635
for alpha = 1e-08
Fpr : 0.3954761036118205
Sparsity : 45462
for alpha = 1e-07
Fpr : 0.3878146661802262
Sparsity : 44163
for alpha = 1e-06
Fpr : 0.3852608537030281
Sparsity : 34133
for alpha = 1e-05
Fpr : 0.35716891645384896
Sparsity : 6091
for alpha = 0.0001
Fpr : 0.4345129514775629
Sparsity : 389
for alpha = 0.001
Fpr : 0.8055454213790587
Sparsity : 27
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
for alpha = 1e-14
Fpr : 0.1622435020519836
Sparsity : 45560
for alpha = 1e-13
Fpr : 0.15740994072047423
Sparsity : 45574
for alpha = 1e-12
Fpr : 0.1587779297765618
Sparsity : 45560
for alpha = 1e-11
```

```
Fpr : 0.15248518011855905
Sparsity : 45573
for alpha = 1e-10
Fpr : 0.15932512539899682
Sparsity : 45638
for alpha = 1e-09
Fpr : 0.1568627450980392
Sparsity : 45635
for alpha = 1e-08
Fpr : 0.14382124943000457
Sparsity : 45462
for alpha = 1e-07
Fpr : 0.12567259461924304
Sparsity : 44163
for alpha = 1e-06
Fpr : 0.16707706338349293
Sparsity : 34133
for alpha = 1e-05
Fpr : 0.2808937528499772
Sparsity : 6091
for alpha = 0.0001
Fpr : 0.4230734154126767
Sparsity : 389
for alpha = 0.001
Fpr : 0.7984496124031008
Sparsity : 27
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
```

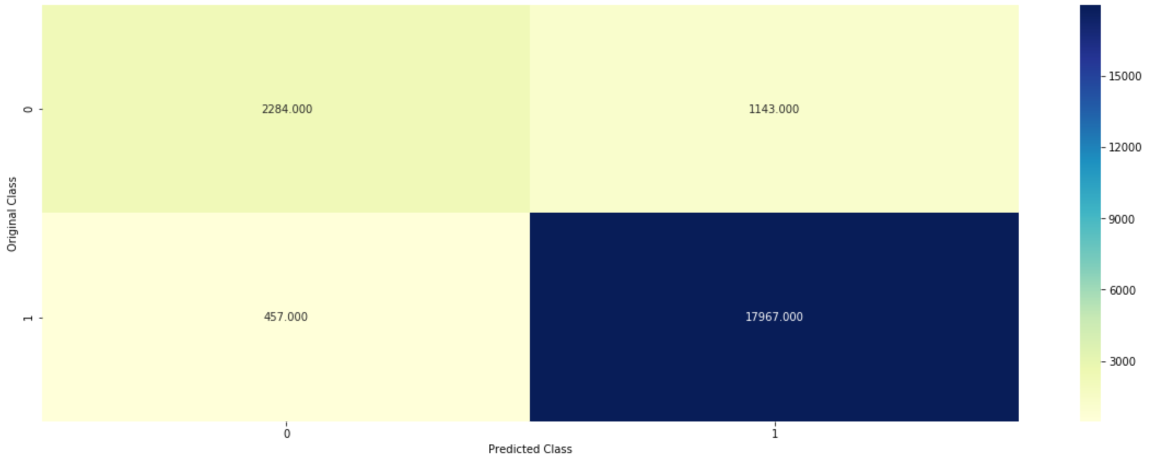




------------------- Confusion matrix -------------------




```
For values of best alpha =  1e-05 The train fpr is: 0.28089375284997
72
For values of best alpha =  1e-05 The cross validation fpr is: 0.357
16891645384896
------------------- Confusion matrix -------------------
```




```
For values of best alpha =  1e-05 The test fpr is: 0.333527866939013
7
```

In [31]:

```
clf = SGDClassifier(class_weight='balanced', alpha=alph, penalty='l2', loss='lo
g', random_state=42)
clf.fit(train, y_train)
```

```
/home/admin1/anaconda3/lib/python3.7/site-packages/sklearn/linear_mo
del/stochastic_gradient.py:166: FutureWarning: max_iter and tol para
meters have been added in SGDClassifier in 0.19. If both are left un
set, they default to max_iter=5 and tol=None. If tol is not None, ma
x_iter defaults to max_iter=1000. From 0.21, default max_iter will b
e 1000, and default tol will be 1e-3.
  FutureWarning)
```

Out[31]:

```
SGDClassifier(alpha=1e-05, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=Tr
ue,
       l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=
None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=42, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Important Features

In [33]:

```
indices = np.argsort(-clf.coef_)[0][:]
positive_indices = indices[:20]
words = getImportantFeatures(positive_indices,feature_names)
print(words)
```

```
['delici', 'perfect', 'high recommend', 'great', 'wont disappoint',
'best', 'awesom', 'excel', 'love', 'fantast', 'yummi', 'nice', 'well
worth', 'smooth', 'satisfi', 'worri', 'hook', 'amaz', 'terrif', 'won
der']
```

In [34]:

```
negative_indices = indices[-20:]
words = getImportantFeatures(negative_indices,feature_names)
print(words)
```

```
['tasteless', 'ruin', 'red dye', 'crappi', 'sad', 'box broken', 'ine
d', 'trash', 'devil', 'bland', 'unfortun', 'wont buy', 'return', 'di
sgust', 'chickpea', 'terribl', 'horribl', 'aw', 'disappoint', 'wors
t']
```

AvgW2V

In [39]:

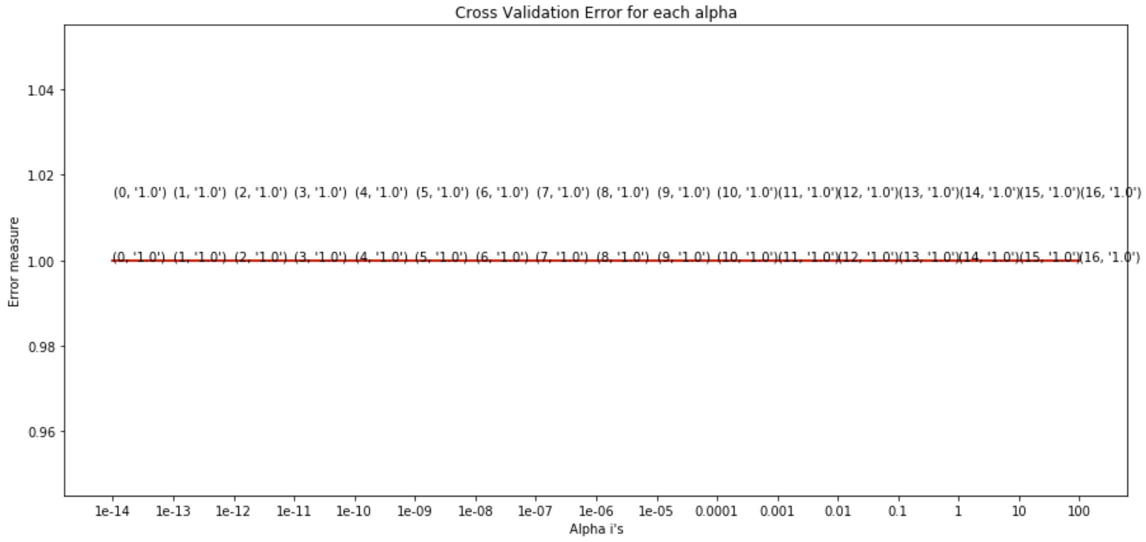
```
train = loadPickleData("avg_w2v_train.pickle")
test = loadPickleData('avg_w2v_test.pickle')
cv = loadPickleData('avg_w2v_cv.pickle')
```

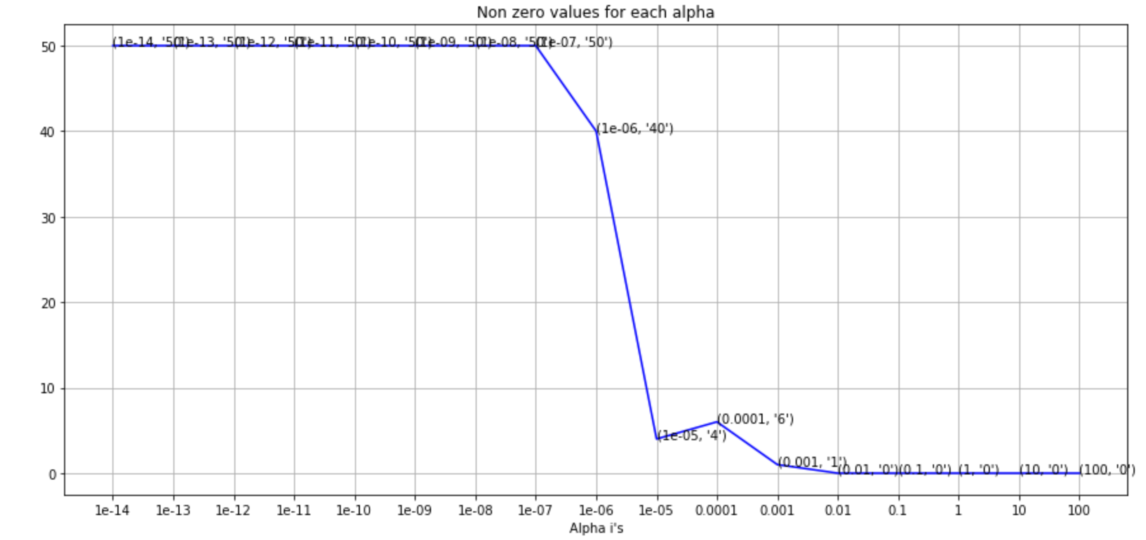
In [40]:

```
clf,alph = performHyperParameterTuningC(train,cv,test)
```

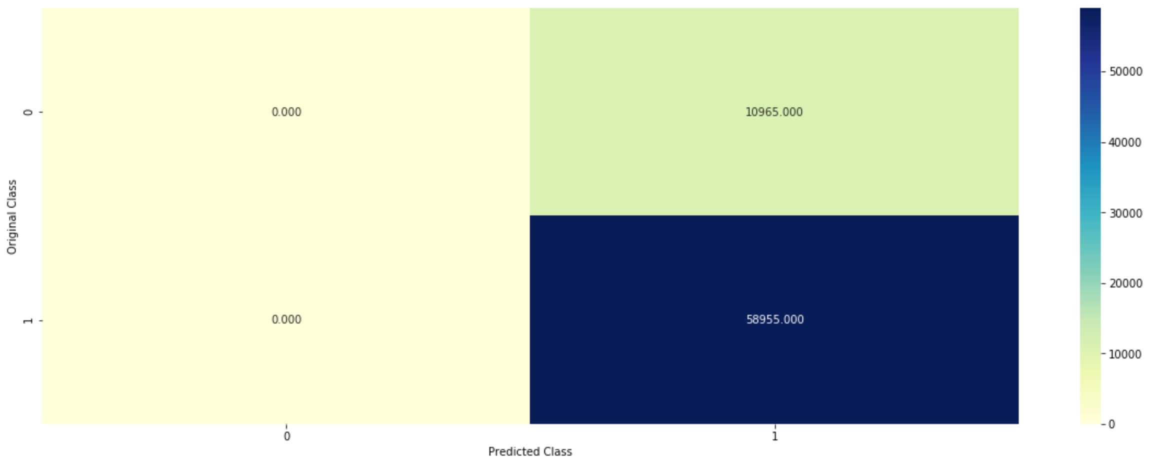
```
for alpha = 1e-14
Fpr : 1.0
Sparsity : 50
for alpha = 1e-13
Fpr : 1.0
Sparsity : 50
for alpha = 1e-12
Fpr : 1.0
Sparsity : 50
for alpha = 1e-11
Fpr : 1.0
Sparsity : 50
for alpha = 1e-10
Fpr : 1.0
Sparsity : 50
for alpha = 1e-09
Fpr : 1.0
Sparsity : 50
for alpha = 1e-08
Fpr : 1.0
Sparsity : 50
for alpha = 1e-07
Fpr : 1.0
Sparsity : 50
for alpha = 1e-06
Fpr : 1.0
Sparsity : 40
for alpha = 1e-05
Fpr : 1.0
Sparsity : 4
for alpha = 0.0001
Fpr : 1.0
Sparsity : 6
for alpha = 0.001
Fpr : 1.0
Sparsity : 1
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
for alpha = 1e-14
Fpr : 1.0
Sparsity : 50
for alpha = 1e-13
Fpr : 1.0
Sparsity : 50
for alpha = 1e-12
Fpr : 1.0
Sparsity : 50
for alpha = 1e-11
```

```
Fpr : 1.0
Sparsity : 50
for alpha = 1e-10
Fpr : 1.0
Sparsity : 50
for alpha = 1e-09
Fpr : 1.0
Sparsity : 50
for alpha = 1e-08
Fpr : 1.0
Sparsity : 50
for alpha = 1e-07
Fpr : 1.0
Sparsity : 50
for alpha = 1e-06
Fpr : 1.0
Sparsity : 40
for alpha = 1e-05
Fpr : 1.0
Sparsity : 4
for alpha = 0.0001
Fpr : 1.0
Sparsity : 6
for alpha = 0.001
Fpr : 1.0
Sparsity : 1
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
```

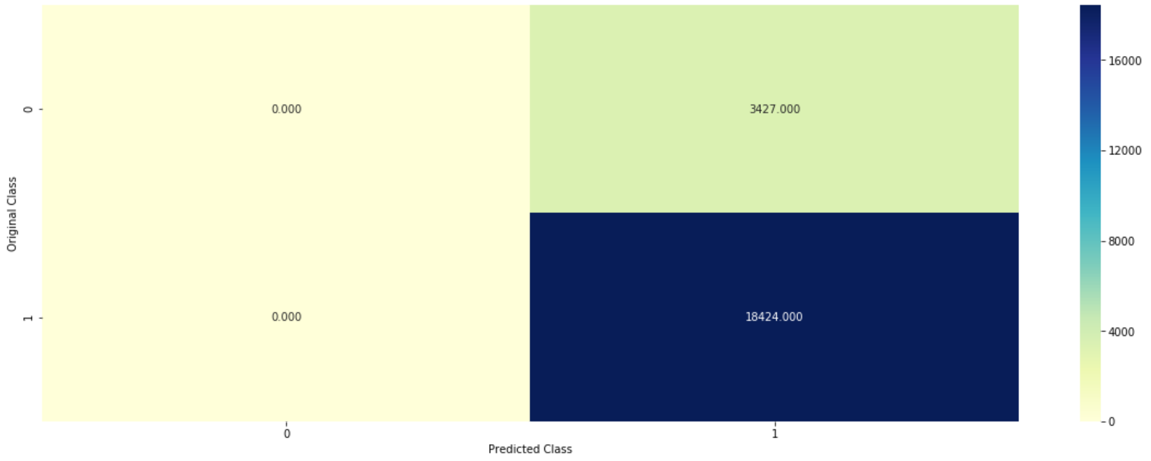





```
-------------------- Confusion matrix --------------------
```




```
For values of best alpha =  1e-14 The train fpr is: 1.0
For values of best alpha =  1e-14 The cross validation fpr is: 1.0
-------------------- Confusion matrix --------------------
```




```
For values of best alpha =  1e-14 The test fpr is: 1.0
```

TFIDF-W2V

In [41]:

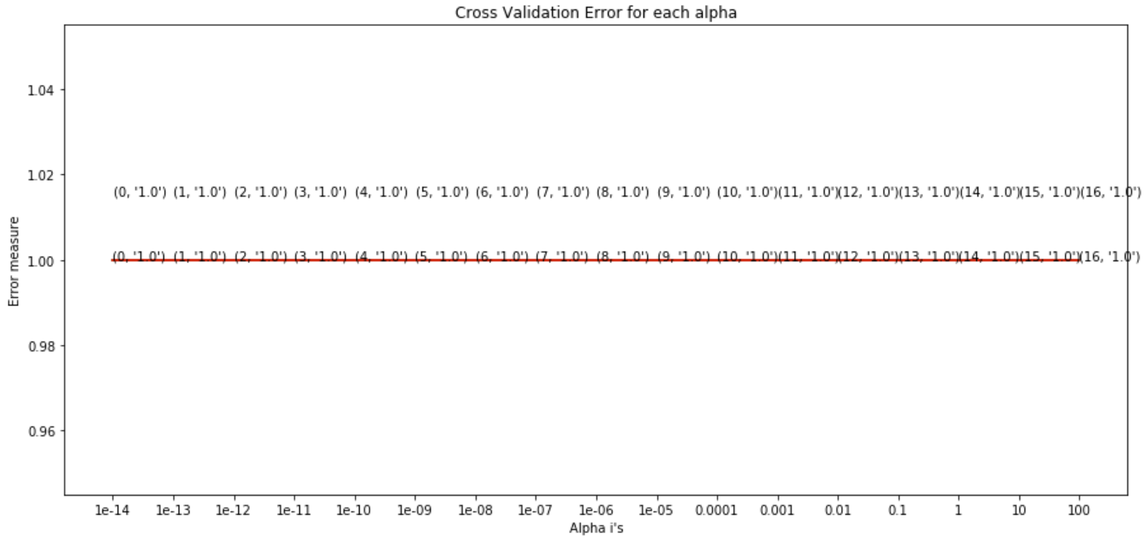
```
train = loadPickleData("tfidf_w2v_train.pickle")
test = loadPickleData('tfidf_w2v_test.pickle')
cv = loadPickleData('tfidf_w2v_cv.pickle')
```

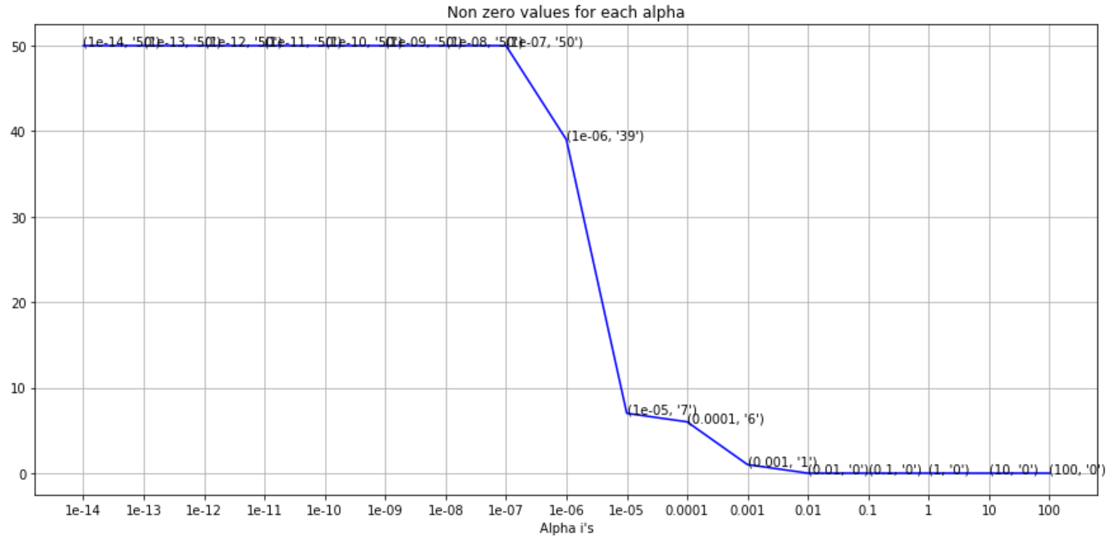
In [26]:

```
clf,alph = performHyperParameterTuningC(train,cv,test)
```

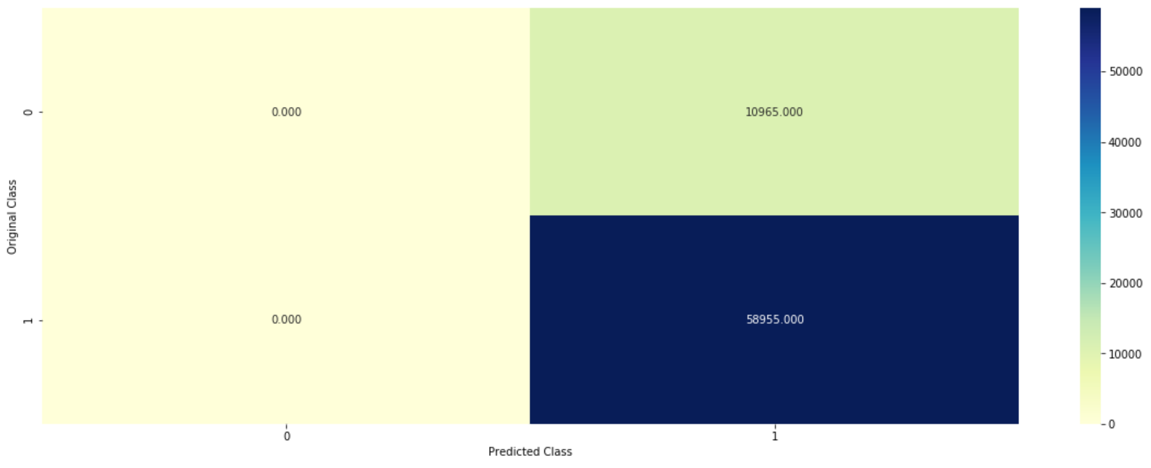
```
for alpha = 1e-14
Fpr : 1.0
Sparsity : 50
for alpha = 1e-13
Fpr : 1.0
Sparsity : 50
for alpha = 1e-12
Fpr : 1.0
Sparsity : 50
for alpha = 1e-11
Fpr : 1.0
Sparsity : 50
for alpha = 1e-10
Fpr : 1.0
Sparsity : 50
for alpha = 1e-09
Fpr : 1.0
Sparsity : 50
for alpha = 1e-08
Fpr : 1.0
Sparsity : 50
for alpha = 1e-07
Fpr : 1.0
Sparsity : 50
for alpha = 1e-06
Fpr : 1.0
Sparsity : 39
for alpha = 1e-05
Fpr : 1.0
Sparsity : 7
for alpha = 0.0001
Fpr : 1.0
Sparsity : 6
for alpha = 0.001
Fpr : 1.0
Sparsity : 1
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
for alpha = 1e-14
Fpr : 1.0
Sparsity : 50
for alpha = 1e-13
Fpr : 1.0
Sparsity : 50
for alpha = 1e-12
Fpr : 1.0
Sparsity : 50
for alpha = 1e-11
```

```
Fpr : 1.0
Sparsity : 50
for alpha = 1e-10
Fpr : 1.0
Sparsity : 50
for alpha = 1e-09
Fpr : 1.0
Sparsity : 50
for alpha = 1e-08
Fpr : 1.0
Sparsity : 50
for alpha = 1e-07
Fpr : 1.0
Sparsity : 50
for alpha = 1e-06
Fpr : 1.0
Sparsity : 39
for alpha = 1e-05
Fpr : 1.0
Sparsity : 7
for alpha = 0.0001
Fpr : 1.0
Sparsity : 6
for alpha = 0.001
Fpr : 1.0
Sparsity : 1
for alpha = 0.01
Fpr : 1.0
Sparsity : 0
for alpha = 0.1
Fpr : 1.0
Sparsity : 0
for alpha = 1
Fpr : 1.0
Sparsity : 0
for alpha = 10
Fpr : 1.0
Sparsity : 0
for alpha = 100
Fpr : 1.0
Sparsity : 0
```

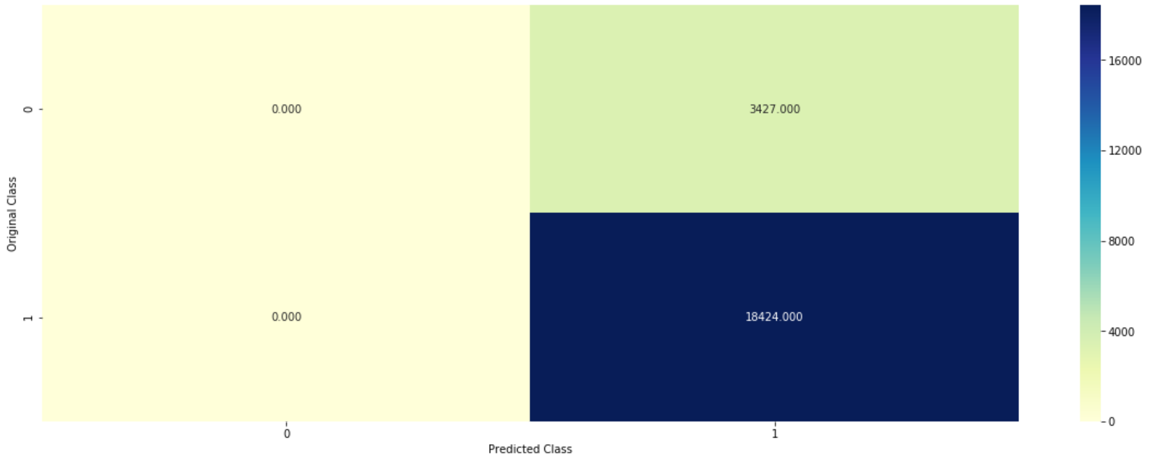





```
-------------------- Confusion matrix --------------------
```




```
For values of best alpha =  1e-14 The train fpr is: 1.0
For values of best alpha =  1e-14 The cross validation fpr is: 1.0
-------------------- Confusion matrix --------------------
```




```
For values of best alpha =  1e-14 The test fpr is: 1.0
```

Summary

Vectorizer	Alpha	Fpr - train	Fpr -test
BOW	0.001	0.14	0.41
TFIDF	0.00001	0.33	0.28
AvgW2V	0.0001	1	1
TFIDFW2V	0.001	1	1