Logistic Regression to Amazon Fine Food Reviews Dataset

Exercise :

1. Download Amazon Fine Food Reviews dataset from Kaggle. You may have to create a Kaggle account to download data. (https://www.kaggle.com/snap/amazon-fine-food-reviews)
2. Split data into train and test using time based slicing as 70% train & 30% test.
3. Perform featurization, BoW, tf-idf,Avg Word2Vec, tf-idf-Word2Vec.
4. Apply GridsearchCV and RandomsearchCV on train data to find optimal lambda.
5. Implement L1 and L2 regularizer to avoid overfitting or underfitting.
6. Try L1 regularization, and keep increasing lambda, to calculate error and sparsity.
7. Perform Multicollinearity-(Pertubation test) on features and show feature importance.(Add small epsilon to perform perturbation test)
8. To test the performance of the model, calculate test error, train error, accuracy,precision,recall,F1-score,confusion matrix(TPR,TNR,FPR,FNR)
9. Write your observations in English as crisply and unambiguously as possible. Always quantify your results.

Information regarding data set :

1. **Title**: Amazon Fine Food Reviews Data
2. **Sources**: Stanford Network Analysis Project(SNAP)
3. **Relevant Information**: This dataset consists of reviews of fine foods from amazon. The data span a period of more than 10 years, including all ~568,454 reviews up to October 2012(Oct 1999 - Oct 2012). Reviews include product and user information, ratings, and a plain text review.
4. **Attribute Information**:
   ProductId - unique identifier for the product
   UserId - unqiue identifier for the user
   ProfileName - name of the user
   HelpfulnessNumerator - number of users who found the review helpful
   HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
   Score - rating between 1 and 5.(rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored)
   Time - timestamp for the review
   Summary - brief summary of the review
   Text - text of the review

Objective :

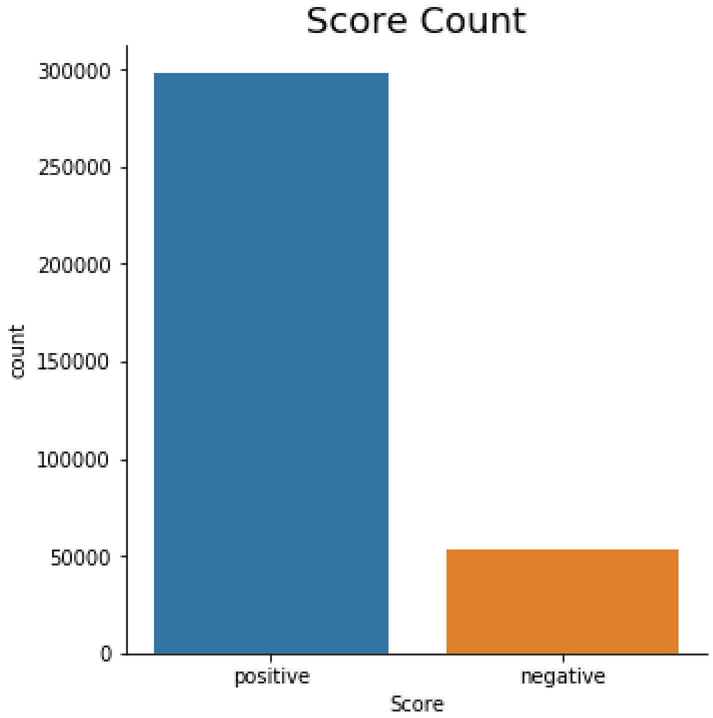
> It is a 2-class classification task, where we have to analyze, transform(BoW,TF-IDF) and calculate probabilistic class label values using logistic regression, which evaluates whether a review is positive or negative.

In [2]:
```
import warnings
from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)
warnings.filterwarnings(action='ignore', category=UserWarning)
warnings.filterwarnings(action='ignore', category=FutureWarning)

import math
import random
import traceback
import sqlite3
import itertools
import datetime as dt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
from tqdm import tqdm
from sklearn import preprocessing
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from prettytable import PrettyTable
from sklearn.metrics import accuracy_score,precision_score,recall_score,confusion_matrix,classificatio
n_report
from sklearn.metrics import make_scorer
from scipy.stats import uniform
from scipy.sparse import find
from sklearn.externals import joblib
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import TimeSeriesSplit
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
from gensim.models import word2vec
```

(1) Load dataset :

In [4]:
```
# This dataset is already gone through data deduplication and text preprocessing, so it is approx ~364
K

# For Data Cleaning Steps follow this link -
# ipython notebook - https://drive.google.com/open?id=1JXCva5vXdIPgHbfNdD9sgnySqELoVtpy
# dataset - https://drive.google.com/open?id=1IoDoTT8TfDu53N6cyKg6xVCU-FDPHyIF

# For Text Preporcessing Steps follow this link -
# ipython notebook - https://drive.google.com/open?id=18-AkTzzEhCwM_hflIbDNBMAP-imX4k4i
# dataset - https://drive.google.com/open?id=1SfDwwXFhDpjgtfIE5O_E80SO89xRc8Sa

# Load 'finalDataSet.sqlite' in panda's daraframe.
reviews_df = load_review_dataset()

# Split data into train and test
x_train, x_test, y_train, y_test = perform_splitting(reviews_df['CleanedText'].values,reviews_df['Scor
e'].values,0.3)

# Save data to disk for future reference
# joblib.dump(x_train, './raw_data/x_train_351237_X_1_by_7.joblib')
# joblib.dump(x_test, './raw_data/x_test_351237_X_1_by_3.joblib')
# joblib.dump(y_train, './raw_data/y_train_351237_X_1_by_7.joblib')
# joblib.dump(y_test, './raw_data/y_test_351237_X_1_by_3.joblib')
```

```
Dataset Shape :
 (351237, 11)

Column Names:
 Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText'],
      dtype='object')

Target Class label :
positive    297807
negative     53430
Name: Score, dtype: int64
```


Score Count
300000
250000
200000
150000
100000
50000
0
count
positive
negative
Score

In [9]:
```
###--- All utility variables and functions(After importing all the necessary packages, always run this
 cell first.) ---###

# Regularization term : L1 and L2 Norm
norms = ["L1","L2"]

# Values for hyperparameter lambda : C = 1 / lambda
tuned_parameters = {'C': [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,0.5,1,5,10,50,100,500,1000]}

# Training Error
train_error = []

# Test Error
test_error = []

# Test Error
list_lambda = []

# Target Classes
target_classes = ["negative", "positive"]

def perform_splitting(train,test,test_size):
    '''
    This function splits data into given test_size
    '''
    # Split data into training and testing.
    return train_test_split(train,test,test_size=test_size,shuffle=False,random_state=0)

def load_review_dataset():
    # Create connection object to load sqlite dataset
    connection = sqlite3.connect('finalDataSet.sqlite')

    # Load data into pandas dataframe.
    reviews_df = pd.read_sql_query(""" SELECT * FROM Reviews """,connection)

    # Drop index column
    reviews_df = reviews_df.drop(columns=['index'])

    # Take sample of reviews
    # reviews_df = reviews_df.sample(3000)

    # Convert timestamp to datetime.
    reviews_df['Time'] = reviews_df[['Time']].applymap(lambda x: dt.datetime.fromtimestamp(x))

    # Sort the data on the basis of time.
    reviews_df = reviews_df.sort_values(by=['Time'])

    print("Dataset Shape : \n",reviews_df.shape)
    print("\nColumn Names: \n",reviews_df.columns)
    print("\nTarget Class label : ")
    print(reviews_df['Score'].value_counts())
    print()

    # Plot review counts
    plot_count_values(reviews_df)

    return reviews_df

def get_most_common_words(classifier,vectorizer,top_n=None):
    ''' Get top n values in row and return them with their corresponding feature names.'''
    print()
    class_labels = classifier.classes_
    feature_names =vectorizer.get_feature_names()
    top_positive_negative = sorted(zip(classifier.coef_[0], feature_names))
    top_values = zip(top_positive_negative[:top_n], top_positive_negative[:-(top_n+1):-1])

    complete_list = list()
    for (p_value,p_word),(n_value,n_word) in top_values:
        holder = []
        holder.append(n_word)
        holder.append(n_value)
        holder.append(p_word)
        holder.append(p_value)
        complete_list.append(holder)

    df = pd.DataFrame(complete_list,columns=['feature_positive', 'value_positive','feature_negative',
'value_negative'])

    ptable = PrettyTable()
    ptable.title = "Feature Importance - {0} Most Common Features using absolute value of W".format(to
p_n)
    ptable.field_names = ['Feature (+ve)', '|W| (+ve)','Feature (-ve)', '|W| (-ve)']

    for row in df.itertuples():
        ptable.add_row([row.feature_positive,abs(row.value_positive),row.feature_negative,abs(row.valu
e_negative)])
```

```python
    print(ptable)
    print()


def perform_featurization(vectorizer_name, train=None, test=None):
    if vectorizer_name == "bow":
        # Instantiate CountVectorizer
        bow_count_vectorizer = CountVectorizer()

        # Tokenize and build vocab
        bow_count_vectorizer.fit(train)

        # Encode document
        x_train_matrix = bow_count_vectorizer.transform(train)
        x_test_matrix = bow_count_vectorizer.transform(test)

        # Save data and bow vectorizer for later use.
        # joblib.dump(x_train_matrix, './matrix_data/bow/x_train_matrix_351237_X_1_by_7.joblib')
        # joblib.dump(x_test_matrix, './matrix_data/bow/x_test_matrix_351237_X_1_by_3.joblib')
        # joblib.dump(bow_count_vectorizer, './matrix_data/bow/bow_vectorizer_351237.joblib')

        return x_train_matrix,x_test_matrix,bow_count_vectorizer

    if vectorizer_name == "tf-idf":
        # Instantiate TfidfVectorizer
        tfidf_vectorizer = TfidfVectorizer(min_df = 3,ngram_range=(1,2))

        # Tokenize and build vocab
        tfidf_vectorizer.fit(train)

        # Encode document
        x_train_matrix = tfidf_vectorizer.transform(train)
        x_test_matrix = tfidf_vectorizer.transform(test)

        # Save data and tf-idf vectorizer for later use.
        # joblib.dump(x_train_matrix, './matrix_data/tfidf/x_train_matrix_351237_X_1_by_7.joblib')
        # joblib.dump(x_test_matrix, './matrix_data/tfidf/x_test_matrix_351237_X_1_by_3.joblib')
        # joblib.dump(tfidf_vectorizer, './matrix_data/tfidf/tf_idf_vectorizer_351237.joblib')

        return x_train_matrix,x_test_matrix,tfidf_vectorizer

    if vectorizer_name == "avg-w2v":
        # Create our own Word2Vec model from training data.

        # Make list of list from training data
        list_of_sentences_in_train=[]
        for sentence in train:
            list_of_sentences_in_train.append(sentence.split())

        # Make list of list from testing data - this will be useful when vectorizing testing data.
        list_of_sentences_in_test=[]
        for sentence in test:
            list_of_sentences_in_test.append(sentence.split())

        print("Shape of training data : ",train.shape)
        print("Shape of testing data : ",test.shape)
        print("Number of sentences present in training data : ",len(list_of_sentences_in_train))
        print("Number of sentences present in testing data : ",len(list_of_sentences_in_test))

        # Generate model
        w2v_model = Word2Vec(list_of_sentences_in_train,min_count=3,size=50, workers=6)

        # Train model on training dataset
        # w2v_model_train.train(list_of_sentences_in_train,total_examples=len(list_of_sentences_in_tra
in), epochs=10)

        # List of word in vocabulary
        w2v_words = list(w2v_model.wv.vocab)
        print("Length of vocabulary : ",len(w2v_words))

        # Save  Word2vec model to disk
        # w2v_model_train.wv.save_word2vec_format('./matrix_data/avgw2v/word2vec_vectorizer_351237_X_1
_by_7.bin', binary=True)

        # Load Word2vec from disk
        # w2v_model = KeyedVectors.load_word2vec_format('./matrix_data/avgw2v/word2vec_vectorizer_3512
37_X_1_by_7.bin', binary=True)
```

```
        # Prepare train vectorizer using trained word2vec model
        train_list = []
        for sentence in tqdm(list_of_sentences_in_train,unit=" sentence",desc='Average Word2Vec - Trai
n data'):
            word_2_vec = np.zeros(50)
            cnt_words = 0
            for word in sentence:
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    word_2_vec += vec
                    cnt_words += 1
            if cnt_words != 0 :
                word_2_vec /= cnt_words
            train_list.append(word_2_vec)

        # Prepare test vectorizer using trained word2vec model
        test_list = []
        for sentence in tqdm(list_of_sentences_in_test,unit=" sentence",desc='Average Word2Vec - Test
 data'):
            word_2_vec = np.zeros(50)
            cnt_words = 0
            for word in sentence:
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    word_2_vec += vec
                    cnt_words += 1
            if cnt_words != 0 :
                word_2_vec /= cnt_words
            test_list.append(word_2_vec)

        avg_w2v_train = np.array(train_list)
        avg_w2v_test = np.array(test_list)

        # Save data for later use.
        # joblib.dump(avg_w2v_train, './matrix_data/avgw2v/x_train_matrix_351237_X_1_by_7.joblib')
        # joblib.dump(avg_w2v_test, './matrix_data/avgw2v/x_test_matrix_351237_X_1_by_3.joblib')

        return avg_w2v_train,avg_w2v_test

    if vectorizer_name == "tf-idf-w2v":
        # Make list of list from training data.
        sentences_in_train=[]
        for sentence in train:
            sentences_in_train.append(sentence.split())

        # Make list of list from testing data - this will be useful when vectorizing testing data.
        sentences_in_test=[]
        for sentence in test:
            sentences_in_test.append(sentence.split())

        # Generate model
        w2v_model = Word2Vec(sentences_in_train,min_count=3,size=50, workers=6)

        # Instantiate TfidfVectorizer
        tfidf_vectorizer = TfidfVectorizer(min_df = 3,ngram_range=(1,2))

        # Tokenize and build vocab
        tfidf_vectorizer.fit(train)

        # Encode document
        x_train_matrix = tfidf_vectorizer.transform(train)

        # Dictionary with word as a key, and the idf as a value
        dict_word_idf = dict(zip(tfidf_vectorizer.get_feature_names(), list(tfidf_vectorizer.idf_)))

        # Get feature names
        features = tfidf_vectorizer.get_feature_names()

        # Load Word2vec from disk that we have already trained(on training data) and stored.
        # w2v_model = KeyedVectors.load_word2vec_format('./matrix_data/avgw2v/word2vec_vectorizer_3512
37_X_1_by_7.bin', binary=True)
```

```
        # Prepare train vectorizer using trained word2vec model
        train_list = []
        row = 0
        for sentence in tqdm(sentences_in_train,unit=" sentence",desc='TF-IDF Weighted Word2Vec - Trai
n data'):
            word_2_vec = np.zeros(50)
            weight_tfidf_sum = 0
            for word in sentence:
                try:
                    vec = w2v_model.wv[word]
                    # dict_word_idf[word] = idf value of word in whole courpus
                    # sentence.count(word) = tf valeus of word in this review
                    tfidf_value =  dict_word_idf[word]*sentence.count(word)
                    word_2_vec += (vec * tfidf_value)
                    weight_tfidf_sum += tfidf_value
                except:
                    pass
            if weight_tfidf_sum != 0:
                word_2_vec /= weight_tfidf_sum
            train_list.append(word_2_vec)
            row += 1

        # Prepare test vectorizer using trained word2vec model
        test_list = []
        row = 0
        for sentence in tqdm(sentences_in_test, unit=" sentebce",desc='TF-IDF Weighted Word2Vec - Test
 data'):
            word_2_vec = np.zeros(50)
            weight_tfidf_sum = 0
            for word in sentence:
                try:
                    vec = w2v_model.wv[word]
                    # dict_word_idf[word] = idf value of word in whole courpus
                    # sentence.count(word) = tf valeus of word in this review
                    tfidf_value =  dict_word_idf[word]*sentence.count(word)
                    word_2_vec += (vec * tfidf_value)
                    weight_tfidf_sum += tfidf_value
                except:
                    pass
            if weight_tfidf_sum != 0:
                word_2_vec /= weight_tfidf_sum
            test_list.append(word_2_vec)
            row += 1

        tfidf_w2v_train = np.array(train_list)
        tfidf_w2v_test = np.array(test_list)

        # Save data for later use.
        # joblib.dump(tfidf_w2v_train, './matrix_data/tfidf-w2v/x_train_matrix_351237_X_1_by_7.jobli
b')
        # joblib.dump(tfidf_w2v_test, './matrix_data/tfidf-w2v/x_test_matrix_351237_X_1_by_3.joblib')

        return tfidf_w2v_train,tfidf_w2v_test

def generate_report(optimal_alpha,testing_target,predicted_testing_target):
    '''
    This funtion generate reports like recall,precision,f1-score,confusion matrix.
    '''
    print()
    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Classification Report with alpha = {0}".format(optimal_alpha)
    ptable.field_names = ["Class Lable/Averages","Precision", "Recall","F1-Score","Support"]
    report_dict = classification_report(testing_target, predicted_testing_target,output_dict = True)
    for key , value in report_dict.items():
        inner_dict = value
        ptable.add_row([key,inner_dict['precision'],inner_dict['recall'],inner_dict['f1-score'],inner_
dict['support']])

    # Print pretty table values
    print(ptable)

    print()
    print("\nAccuracy Score: ",accuracy_score(testing_target, predicted_testing_target))
    test_error.append(1-accuracy_score(testing_target, predicted_testing_target))
    print()
    cnf_mat = confusion_matrix(testing_target, predicted_testing_target)
    plt.figure()
    plot_confusion_matrix(cnf_mat, classes=target_classes,title='Confusion Matrix')
    TN = cnf_mat[0,0]
    FP = cnf_mat[0,1]
    FN = cnf_mat[1,0]
    TP = cnf_mat[1,1]
```

```
    # Sensitivity, hit rate, recall, or true positive rate
    TPR = TP/(TP+FN)

    # Specificity or true negative rate
    TNR = TN/(TN+FP)

    # Fall out or false positive rate
    FPR = FP/(FP+TN)

    # False negative rate
    FNR = FN/(TP+FN)

    # Overall accuracy
    ACC = (TP+TN)/(TP+FP+FN+TN)

    print()
    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Confusion Matrix Report"
    ptable.field_names = ['Term','Value']
    ptable.add_row(["TP (True Positive)",TP])
    ptable.add_row(["TN (True Negative)",TN])
    ptable.add_row(["FP (False Positive)",FP])
    ptable.add_row(["FN (False Negative)",FN])
    ptable.add_row(["TPR (True Positive Rate)= TP/(TP+FN))",TPR])
    ptable.add_row(["TNR (True Negative Rate)= TN/(TN+FP))",TNR])
    ptable.add_row(["FPR (False Positive Rate)= FP/(FP+TN))",FPR])
    ptable.add_row(["FNR (False Negative Rate)= FN/(TP+FN))",FNR])
    ptable.add_row(["ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))",ACC])

    # Print pretty table values
    print(ptable)

def plot_x_vs_y(x,y,x_label=None,y_label=None,title_name=None):
    plt.plot(x,
             y,
             color='green',
             linestyle='dashed',
             linewidth = 3,
             marker='o',
             markerfacecolor='blue',
             markersize=12)

    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title_name)
    plt.show()

def plot_count_values(reviews_df):
    sn.catplot(x ="Score",kind='count',data=reviews_df,height=5)
    plt.title("Score Count", fontsize=18)
    plt.show()

def plot_scoring_hyperparameter(scores):
    # Plot the value of lambda's(x-axis) and crosss validation scoring(accuracy,precision,recall)(y-ax
is)
    plt.plot(scores.keys(),scores.values())
    plt.xlabel("C")
    plt.ylabel("Accuracy")
    plt.show()

def plot_report_confusion_matrix(confusion_matrix, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    plt.figure()
    plt.imshow(confusion_matrix, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = confusion_matrix.max() / 2.
    for i, j in itertools.product(range(confusion_matrix.shape[0]), range(confusion_matrix.shape[1])):
        plt.text(j, i, format(confusion_matrix[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if confusion_matrix[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
    plt.show()
```

```python
    TN = confusion_matrix[0,0]
    FP = confusion_matrix[0,1]
    FN = confusion_matrix[1,0]
    TP = confusion_matrix[1,1]


    # Sensitivity, hit rate, recall, or true positive rate
    TPR = TP/(TP+FN)

    # Specificity or true negative rate
    TNR = TN/(TN+FP)

    # Fall out or false positive rate
    FPR = FP/(FP+TN)

    # False negative rate
    FNR = FN/(TP+FN)

    # Overall accuracy
    ACC = (TP+TN)/(TP+FP+FN+TN)

    print()
    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Confusion Matrix Report"
    ptable.field_names = ['Term','Value']
    ptable.add_row(["TP (True Positive)",TP])
    ptable.add_row(["TN (True Negative)",TN])
    ptable.add_row(["FP (False Positive)",FP])
    ptable.add_row(["FN (False Negative)",FN])
    ptable.add_row(["TPR (True Positive Rate)= TP/(TP+FN))","{0:.2f}".format(TPR)])
    ptable.add_row(["TNR (True Negative Rate)= TN/(TN+FP))","{0:.2f}".format(TNR)])
    ptable.add_row(["FPR (False Positive Rate)= FP/(FP+TN))","{0:.2f}".format(FPR)])
    ptable.add_row(["FNR (False Negative Rate)= FN/(TP+FN))","{0:.2f}".format(FNR)])
    ptable.add_row(["ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))","{0:.2f}%".format(ACC*100)])

    # Print pretty table values
    print(ptable)

def perform_sparsity_testing(classifier, bow_train_features):

  # List of values to test C
    new_c_values =  [10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3]

    # Data normalization
    x_train_normalized = preprocessing.normalize(bow_train_features)


    # For tabular report
    ptable = PrettyTable()
    ptable.title = "Sparsity Testing Report"
    ptable.field_names = ["Hyperparameter(C)","Sparsity","Training Error"]

    list_w_vactor = []
    list_training_error = []
    for value in new_c_values:
        classifier.C = value
        classifier.fit(x_train_normalized, y_train);
        w_nonzero =  np.count_nonzero(classifier.coef_)
        list_w_vactor.append(w_nonzero)
        predicted_y_train = classifier.predict(x_train_normalized)
        accuracy = accuracy_score(y_train,predicted_y_train)
        list_training_error.append(1 - accuracy)
        ptable.add_row([value, w_nonzero, "{0:.02f}".format(1 - accuracy)])


    print()

    # Plot Sparsity vs Hyperparameter values
    plot_x_vs_y(list_w_vactor,
                new_c_values,
                x_label="Non Zero Values in W",
                y_label="C",
                title_name="Non Zero Values in W versus 'C'")
    print()

    # Plot Training Error vs Hyperparameter values
    plot_x_vs_y(list_training_error,
                new_c_values,
                x_label="Training error",
                y_label="C",
                title_name="Training error versus 'C'")
```

```
    print()
    print()
    print(ptable)
    print()

def perform_pertubation_test(x_train, x_test, y_train, y_test, c,penalty_value):
    # Data normalization
    x_train_normalized = preprocessing.normalize(x_train)
    x_test_normalized = preprocessing.normalize(x_test)

    # Logistic regression before pertubation
    classifier_before_pertubation = LogisticRegression(C= c, penalty= penalty_value,class_weight ="bal
anced")
    classifier_before_pertubation.fit(x_train_normalized,y_train)
    predicted_y_test = classifier_before_pertubation.predict(x_test_normalized)
    weight_before_pertubation = find(classifier_before_pertubation.coef_[0])[2]
    print("------------------ Before Pertubation Test ------------------")
    print("Accuracy on testing data: %0.2f%%"%(accuracy_score(y_test, predicted_y_test)*100))
    print("Number of non zero weights in weight vector 'w': ",np.count_nonzero(classifier_before_pertu
bation.coef_))
    print()
    print()

    # Contains the row indices, column indices, and values of the nonzero matrix entries
    row_index, column_index, values_nnz = find(x_train_normalized)

    # Create random noise
    epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(row_index.size,))

    # Add noise to non zero elements in sparse matrix
    x_train_normalized[row_index,column_index] = epsilon + x_train_normalized[row_index,column_index]

    # Logistic regression after pertubation
    classifier_after_pertubation = LogisticRegression(C= c, penalty= penalty_value,class_weight ="bala
nced")
    classifier_after_pertubation.fit(x_train_normalized,y_train)
    predicted_y_test = classifier_after_pertubation.predict(x_test_normalized)
    weight_after_pertubation = find(classifier_after_pertubation.coef_[0])[2]
    print("------------------ After Pertubation Test ------------------")
    print("Accuracy on testing data: %0.2f%%"%(accuracy_score(y_test, predicted_y_test)*100))
    print("Number of non zero weights in weight vector 'w': ",np.count_nonzero(classifier_after_pertub
ation.coef_))

    return weight_before_pertubation,weight_after_pertubation,classifier_before_pertubation



def compare_weight_vectors(weight_before_pertubation, weight_after_pertubation, tolerance):

    # Returns a boolean array where two arrays are element-wise equal within a tolerance.
    difference = np.isclose(weight_before_pertubation, weight_after_pertubation, atol=tolerance)
    false_size = difference[np.where(difference == False)].size
    percentage = (false_size / difference.size)*100
    print()
    print()
    print("{0:.2f}% value changes with tolerence value of {1} between two weight vectors".format(perce
ntage,tolerance))
    print()




def get_cross_validation_models(x_train =None, y_train=None):

    # Create dictionary to hold GridSearchCV and RandomizedSearchCV objects
    model_gs_rs = dict()

    cv_time_splits = TimeSeriesSplit(n_splits = 5)

    for penalty_name in norms:
        # Instantiate LogisticRegression
        lr_classifier_gs = LogisticRegression()
        lr_classifier_gs.penalty = penalty_name.lower()

        # Instantiate GridSearchCV
        gs_model = GridSearchCV(lr_classifier_gs,
                                tuned_parameters,
                                scoring = "accuracy",
                                cv = cv_time_splits,
                                n_jobs = -1)

        # Fit feature matrix with all sets of parameters
        gs_model.fit(x_train, y_train)
```

```
        # Instantiate LogisticRegression
        lr_classifier_rs = LogisticRegression()
        lr_classifier_rs.penalty = penalty_name.lower()

        # Instantiate RandomizedSearchCV
        rs_model = RandomizedSearchCV(lr_classifier_rs,
                                      tuned_parameters,
                                      scoring = "accuracy",
                                      cv = cv_time_splits,
                                      n_jobs = -1)

        # Fit feature matrix with all sets of parameters
        rs_model.fit(x_train, y_train)

        # Add models to model_dict
        model_gs_rs[penalty_name] = (gs_model,rs_model)

    return model_gs_rs

def performance_measure(gs_rs_model,x_train_normalized, original_y_train, x_test_normalized,original_y
_test):
    for norm_name, model in gs_rs_model.items():
        print()
        print("\n*****************************************************************************")
        print("---------------------------- {0} Regularizaion ----------------------------".format(n
orm_name))
        print("*****************************************************************************\n")
        print()
        for classifier in list(model):
            print("-------------------------- {0} --------------------------".format(type(classifier).
__name__))

            # Predict target class label
            predicted_y_test = classifier.predict(x_test_normalized)

            # Predict train class label
            predicted_y_train = classifier.predict(x_train_normalized)

            ptable = PrettyTable()
            if type(classifier) is GridSearchCV:
                ptable.title = "{0} Regularization with 'GridSearchCV'".format(norm_name)
            else:
                ptable.title = "{0} Regularization with 'RandomizedSearchCV'".format(norm_name)

            ptable.field_names = ["Hyperparameter (C)","Scoring","Mean","Variance"]

            list_means = classifier.cv_results_['mean_test_score']
            list_stds = classifier.cv_results_['std_test_score']
            list_params = classifier.cv_results_['params']
            scores = dict()
            for mean, std, params in zip(list_means, list_stds, list_params):
                scores[params['C']] = "{0:.2f}".format(mean)
                ptable.add_row([params['C'], "Accuracy", "{0:.2f}".format(mean), "{0:.2f}".format(std*
2)])

            print()
            plot_scoring_hyperparameter(scores)
            print()

            print()
            print(ptable)
            print()

            optimal_lambda = classifier.best_params_['C']
            train_accuracy = accuracy_score(original_y_train, predicted_y_train)
            test_accuracy = accuracy_score(original_y_test, predicted_y_test)
            list_lambda.append(optimal_lambda)
            test_error.append(1 - test_accuracy)
            train_error.append(1 - train_accuracy)

            # Print Optimal hyperparameter and corresponding accuracy
            ptable = PrettyTable()
            ptable.title = "Optimal hyperparameter & Testing accuracy score"
            ptable.field_names=["Regularization","Cross Validation","Optimal Hyperparameter (C)","Accu
racy(%)"]
            ptable.add_row([norm_name , type(classifier).__name__ ,optimal_lambda,"{0:.2f}".format(tes
t_accuracy*100)])
            print(ptable)
```

```
            # Print classification report
            print()
            ptable = PrettyTable()
            ptable.title = "Classification Report with lambda = {0}".format(optimal_lambda)
            ptable.field_names = ["Class Lable/Averages","Precision", "Recall","F1-Score","Support"]
            report_dict = classification_report(original_y_test, predicted_y_test,output_dict = True)
            for key , value in report_dict.items():
                inner_dict = value
                ptable.add_row([key,
                                "{0:.2f}".format(inner_dict['precision']),
                                "{0:.2f}".format(inner_dict['recall']),
                                "{0:.2f}".format(inner_dict['f1-score']),
                                "{0:.2f}".format(inner_dict['support'])])

            print(ptable)

            # Calculate and plot confusion matrix
            cnf_mat = confusion_matrix(original_y_test, predicted_y_test)
            plot_report_confusion_matrix(cnf_mat, classes=target_classes,title='Confusion Matrix')
            print()
            print()
        print()
        print()


def run_logistic_regression(vectorizer_name, x_train=None, x_test=None,y_train=None,y_test=None):

        # Data Normalization
        x_train = preprocessing.normalize(x_train)
        x_test = preprocessing.normalize(x_test)

        # Get GridSearchCV and RandomizedSearchCV models
        gs_rs_model = get_cross_validation_models(x_train = x_train,y_train = y_train)

        # Generate Reports and plot scoring values
        performance_measure(gs_rs_model,x_train,y_train,x_test,y_test)


def conclude():
    ptable=PrettyTable()
    ptable.title = "***Conclusion***"
    ptable.field_names=["Penalty-CV","Model","Hyperparameter","Train Error","Test Error"]
    ptable.add_row(["L1\nGridSearchCV","BOW\nLogistic Regression",list_lambda[0],str(round(train_error[0], 2)*100)+"%",str(round(test_error[0], 2)*100)+"%"])
    ptable.add_row(["L1\nRandomizedSearchCV","BOW\nLogistic Regression",list_lambda[1],str(round(train_error[1], 2)*100)+"%",str(round(test_error[1], 2)*100)+"%"])
    ptable.add_row(["L2\nGridSearchCV","BOW\nLogistic Regression",list_lambda[2],str(round(train_error[2], 2)*100)+"%",str(round(test_error[2], 2)*100)+"%"])
    ptable.add_row(["L2\nRandomizedSearchCV","BOW\nLogistic Regression",list_lambda[3],str(round(train_error[3], 2)*100)+"%",str(round(test_error[3], 2)*100)+"%"])

    ptable.add_row(["L1\nGridSearchCV","TFIDF\nLogistic Regression",list_lambda[4],str(round(train_error[4], 2)*100)+"%",str(round(test_error[4], 2)*100)+"%"])
    ptable.add_row(["L1\nRandomizedSearchCV","TFIDF\nLogistic Regression",list_lambda[5],str(round(train_error[5], 2)*100)+"%",str(round(test_error[5], 2)*100)+"%"])
    ptable.add_row(["L2\nGridSearchCV","TFIDF\nLogistic Regression",list_lambda[6],str(round(train_error[6], 2)*100)+"%",str(round(test_error[6], 2)*100)+"%"])
    ptable.add_row(["L2\nRandomizedSearchCV","TFIDF\nLogistic Regression",list_lambda[7],str(round(train_error[7], 2)*100)+"%",str(round(test_error[7], 2)*100)+"%"])

    ptable.add_row(["L1\nGridSearchCV","AVG-W2V\nLogistic Regression",list_lambda[8],str(round(train_error[8], 2)*100)+"%",str(round(test_error[8], 2)*100)+"%"])
    ptable.add_row(["L1\nRandomizedSearchCV","AVG-W2V\nLogistic Regression",list_lambda[9],str(round(train_error[9], 2)*100)+"%",str(round(test_error[9], 2)*100)+"%"])
    ptable.add_row(["L2\nGridSearchCV","AVG-W2V\nLogistic Regression",list_lambda[10],str(round(train_error[10], 2)*100)+"%",str(round(test_error[10], 2)*100)+"%"])
    ptable.add_row(["L2\nRandomizedSearchCV","AVG-W2V\nLogistic Regression",list_lambda[11],str(round(train_error[11], 2)*100)+"%",str(round(test_error[11], 2)*100)+"%"])

    ptable.add_row(["L1\nGridSearchCV","TFIDF-W2V\nLogistic Regression",list_lambda[12],str(round(train_error[12], 2)*100)+"%",str(round(test_error[12], 2)*100)+"%"])
    ptable.add_row(["L1\nRandomizedSearchCV","TFIDF-W2V\nLogistic Regression",list_lambda[13],str(round(train_error[13], 2)*100)+"%",str(round(test_error[13], 2)*100)+"%"])
    ptable.add_row(["L2\nGridSearchCV","TFIDF-W2V\nLogistic Regression",list_lambda[14],str(round(train_error[14], 2)*100)+"%",str(round(test_error[14], 2)*100)+"%"])
    ptable.add_row(["L2\nRandomizedSearchCV","TFIDF-W2V\nLogistic Regression",list_lambda[15],str(round(train_error[15], 2)*100)+"%",str(round(test_error[15], 2)*100)+"%"])
    print(ptable)
```

(2) Convert review text to vector representation :

(2.1) Bag of Words (BoW) :

In [5]:
```
%%time

# Perofrm Bag of Words
bow_train_features, bow_test_features, bow_vectorizer = perform_featurization(vectorizer_name="bow",
                                                                              train = x_train,
                                                                              test = x_test)

print("\nThe type of count vectorizer ",type(bow_train_features))
print("The shape of BOW vectorizer ",bow_train_features.get_shape())
print("The number of unique words ", bow_train_features.get_shape()[1])
```

```
The type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
The shape of BOW vectorizer  (245865, 74398)
The number of unique words  74398
Wall time: 15.5 s
```

(2.2) Term Frequency - Inverse Document Frequency (TF-IDF) :

In [6]:
```
%%time

# Perofrm TF-IDF
tf_idf_train_features, tf_idf_test_features, tfidf_vectorizer = perform_featurization(vectorizer_name
="tf-idf",
                                                                                      train = x_train,
                                                                                      test = x_test)

print("\nThe type of count vectorizer ",type(tf_idf_train_features))
print("The shape of TF-IDF vectorizer ",tf_idf_train_features.get_shape())
print("The number of unique words ", tf_idf_train_features.get_shape()[1])
```

```
The type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
The shape of TF-IDF vectorizer  (245865, 487621)
The number of unique words  487621
Wall time: 47.4 s
```

(2.3) Average Word2Vec :

In [7]:
```
%%time

# Perofrm Average Word2Vec
avg_w2v_train,avg_w2v_test = perform_featurization(vectorizer_name="avg-w2v",
                                                              train = x_train,
                                                              test= x_test)
print("\nShape of training vectorizer : ",avg_w2v_train.shape)
print("Shape of testing vectorizer : ",avg_w2v_test.shape)
```

```
Shape of training data :  (245865,)
Shape of testing data :  (105372,)
Number of sentences present in training data :  245865
Number of sentences present in testing data :  105372
Length of vocabulary :  24460
```

```
Average Word2Vec - Train data: 100%|██████████| 245865/245865 [04:28<00:00, 9
14.93 sentence/s]
Average Word2Vec - Test data: 100%|██████████| 105372/105372 [02:03<00:00, 8
55.08 sentence/s]
```

```
Shape of training vectorizer :  (245865, 50)
Shape of testing vectorizer :  (105372, 50)
Wall time: 6min 46s
```

(2.4) Term Frequency - Inverse Document Frequency Weighted Word2Vec(TF-IDF Word2Vec) :

In [11]:
```
%%time

# Perofrm TF-IDF Weighted Word2Vec
tfidf_w2v_train,tfidf_w2v_test = perform_featurization(vectorizer_name="tf-idf-w2v",
                                                                  train = x_train,
                                                                  test= x_test)
print("\nShape of training vectorizer : ",tfidf_w2v_train.shape)
print("Shape of testing vectorizer : ",tfidf_w2v_test.shape)
```

```
TF-IDF Weighted Word2Vec - Train data: 100%|██████████| 245865/245865 [01:05<00:00, 37
32.49 sentence/s]
TF-IDF Weighted Word2Vec - Test data: 100%|██████████| 105372/105372 [00:27<00:00, 37
76.57 sentebce/s]
```

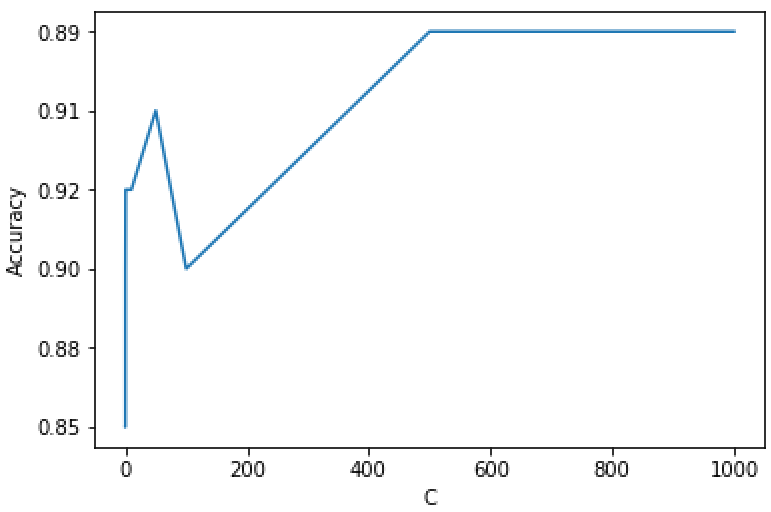
```
Shape of training vectorizer :  (245865, 50)
Shape of testing vectorizer :  (105372, 50)
Wall time: 2min 30s
```

(3) Apply logistic regression :

(3.1) Logistic regression on BoW :

In [12]:
```
%%time

# Perform logistic regression with l1 and l2 as a penalty, on bow
try:
    run_logistic_regression("bow",
                            x_train = bow_train_features,
                            x_test = bow_test_features,
                            y_train = y_train,
                            y_test = y_test)
except Exception:
    traceback.print_exc()
```

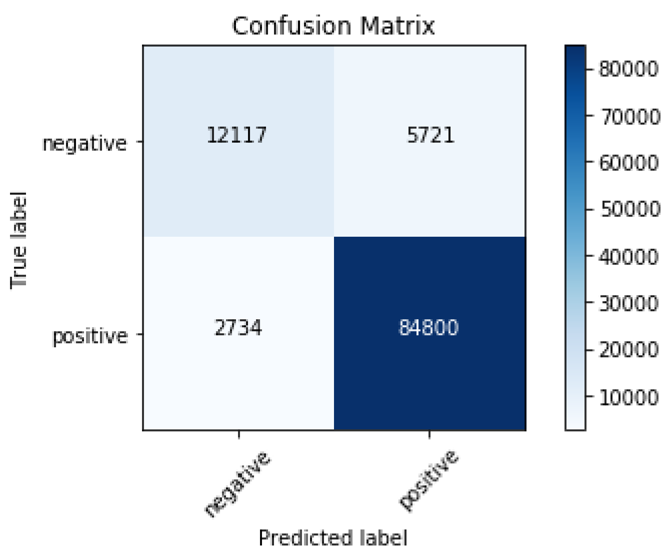
```
*****************************************************************************
----------------------------- L1 Regularizaion -----------------------------
*******************************************************************************


-------------------------- GridSearchCV --------------------------
```



L1 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.85	0.03
0.01	Accuracy	0.85	0.02
0.05	Accuracy	0.88	0.01
0.1	Accuracy	0.90	0.01
0.5	Accuracy	0.92	0.00
1	Accuracy	0.92	0.00
5	Accuracy	0.92	0.00
10	Accuracy	0.92	0.00
50	Accuracy	0.91	0.01
100	Accuracy	0.90	0.01
500	Accuracy	0.89	0.02
1000	Accuracy	0.89	0.02

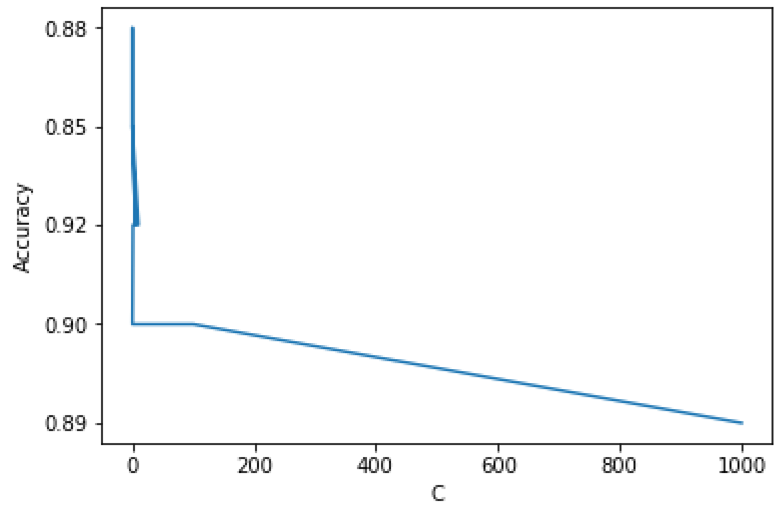
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	GridSearchCV	5	91.98

Classification Report with lambda = 5				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.82	0.68	0.74	17838.00
positive	0.94	0.97	0.95	87534.00
micro avg	0.92	0.92	0.92	105372.00
macro avg	0.88	0.82	0.85	105372.00
weighted avg	0.92	0.92	0.92	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84800
TN (True Negative)	12117
FP (False Positive)	5721
FN (False Negative)	2734
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.68
FPR (False Positive Rate)= FP/(FP+TN))	0.32
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	91.98%

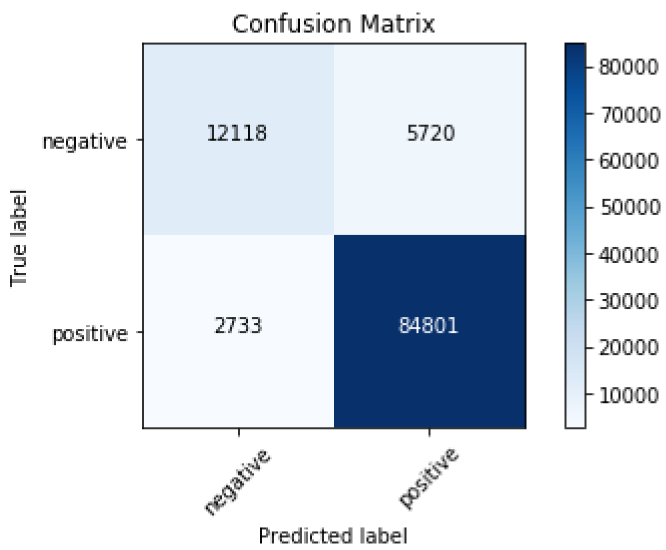
------------------------- RandomizedSearchCV -------------------------



L1 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
1000	Accuracy	0.89	0.02
100	Accuracy	0.90	0.01
0.1	Accuracy	0.90	0.01
1	Accuracy	0.92	0.00
10	Accuracy	0.92	0.00
0.0005	Accuracy	0.85	0.03
5	Accuracy	0.92	0.00
0.001	Accuracy	0.85	0.03
0.05	Accuracy	0.88	0.01
0.01	Accuracy	0.85	0.02

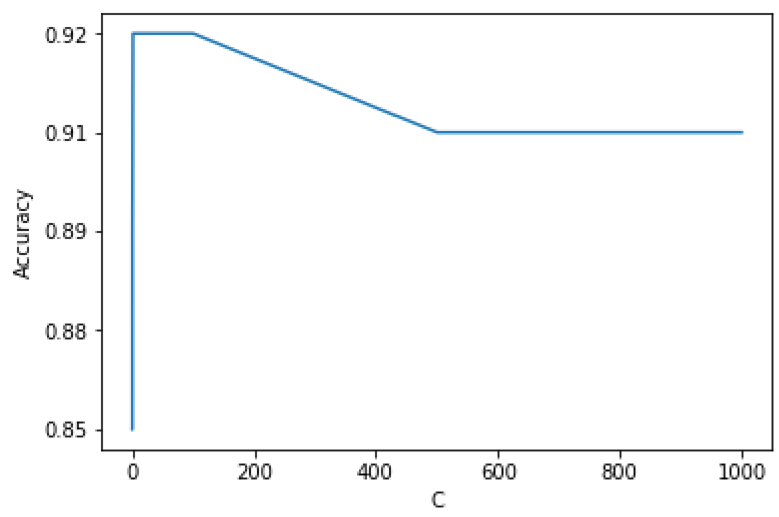
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	RandomizedSearchCV	5	91.98

Classification Report with lambda = 5				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.82	0.68	0.74	17838.00
positive	0.94	0.97	0.95	87534.00
micro avg	0.92	0.92	0.92	105372.00
macro avg	0.88	0.82	0.85	105372.00
weighted avg	0.92	0.92	0.92	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84801
TN (True Negative)	12118
FP (False Positive)	5720
FN (False Negative)	2733
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.68
FPR (False Positive Rate)= FP/(FP+TN))	0.32
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	91.98%

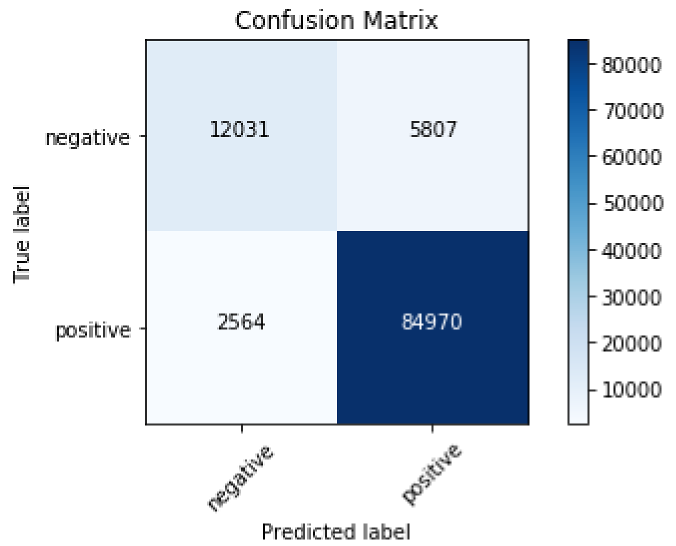
```
********************************************************************************
---------------------------- L2 Regularizaion ----------------------------
********************************************************************************


------------------------- GridSearchCV -------------------------
```



L2 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.85	0.03
0.01	Accuracy	0.85	0.02
0.05	Accuracy	0.88	0.01
0.1	Accuracy	0.89	0.01
0.5	Accuracy	0.91	0.01
1	Accuracy	0.92	0.00
5	Accuracy	0.92	0.00
10	Accuracy	0.92	0.00
50	Accuracy	0.92	0.00
100	Accuracy	0.92	0.00
500	Accuracy	0.91	0.01
1000	Accuracy	0.91	0.01

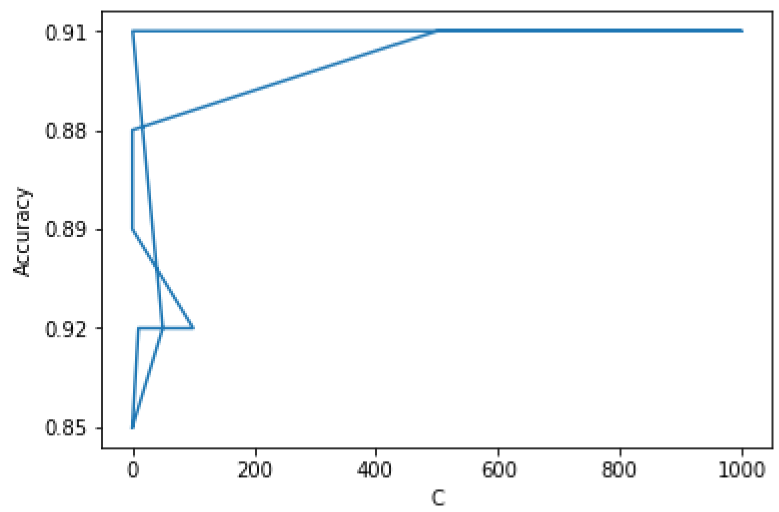
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	GridSearchCV	10	92.06

Classification Report with lambda = 10				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.82	0.67	0.74	17838.00
positive	0.94	0.97	0.95	87534.00
micro avg	0.92	0.92	0.92	105372.00
macro avg	0.88	0.82	0.85	105372.00
weighted avg	0.92	0.92	0.92	105372.00




```
+------------------------------------------------+
|             Confusion Matrix Report             |
+------------------------------------------------+---------+
|                   Term                 | Value   |
+----------------------------------------+---------+
|            TP (True Positive)          | 84970   |
|            TN (True Negative)          | 12031   |
|           FP (False Positive)          |  5807   |
|           FN (False Negative)          |  2564   |
| TPR (True Positive Rate)= TP/(TP+FN))  |  0.97   |
| TNR (True Negative Rate)= TN/(TN+FP))  |  0.67   |
| FPR (False Positive Rate)= FP/(FP+TN)) |  0.33   |
| FNR (False Negative Rate)= FN/(TP+FN)) |  0.03   |
| ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN)) | 92.06%  |
+----------------------------------------+---------+
```

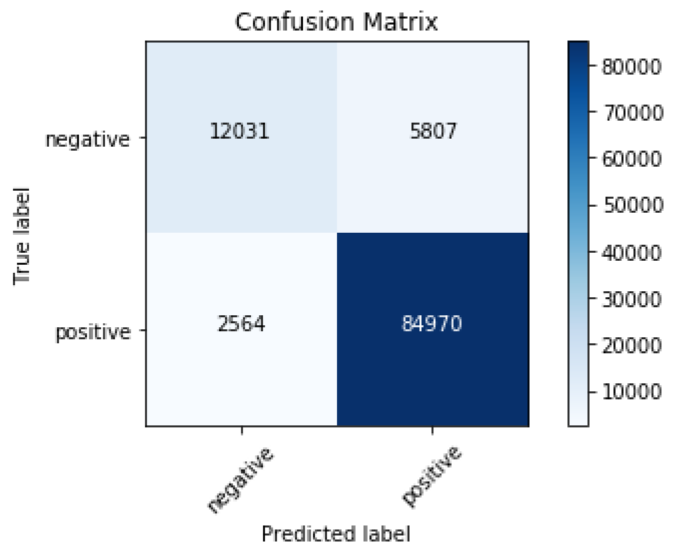
```
------------------------- RandomizedSearchCV -------------------------
```



L2 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
10	Accuracy	0.92	0.00
100	Accuracy	0.92	0.00
0.1	Accuracy	0.89	0.01
0.05	Accuracy	0.88	0.01
500	Accuracy	0.91	0.01
1000	Accuracy	0.91	0.01
0.5	Accuracy	0.91	0.01
50	Accuracy	0.92	0.00
0.0005	Accuracy	0.85	0.03

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	RandomizedSearchCV	10	92.06

Classification Report with lambda = 10				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.82	0.67	0.74	17838.00
positive	0.94	0.97	0.95	87534.00
micro avg	0.92	0.92	0.92	105372.00
macro avg	0.88	0.82	0.85	105372.00
weighted avg	0.92	0.92	0.92	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84970
TN (True Negative)	12031
FP (False Positive)	5807
FN (False Negative)	2564
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.67
FPR (False Positive Rate)= FP/(FP+TN))	0.33
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	92.06%

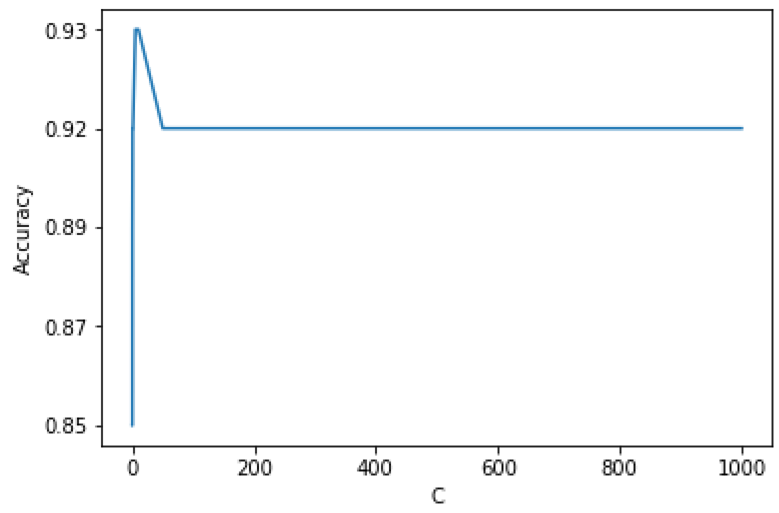
```
Wall time: 10min 44s
```

(3.2) Logistic regression on TF-IDF :

In [13]:

```
%%time

# Perform logistic regression with l1 and l2 as a penalty, on TF-IDF
try:
    run_logistic_regression("tf-idf",
                            x_train = tf_idf_train_features,
                            x_test = tf_idf_test_features,
                            y_train = y_train,
                            y_test = y_test)
except Exception:
    traceback.print_exc()
```

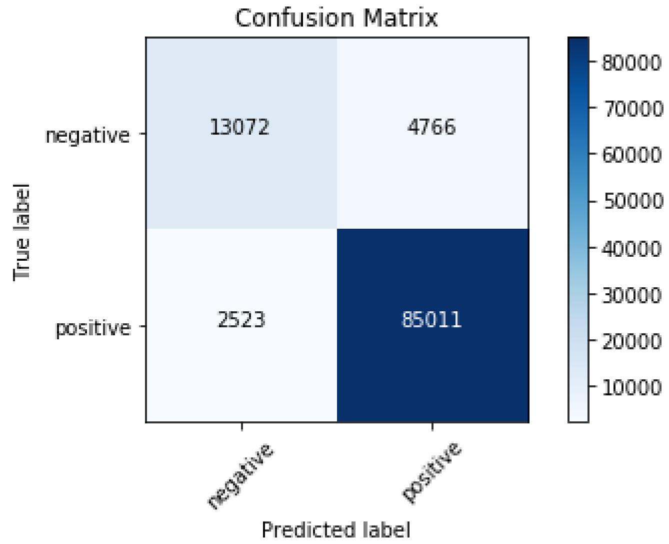
```
*****************************************************************************
---------------------------- L1 Regularizaion ----------------------------
*******************************************************************************


------------------------- GridSearchCV -------------------------
```



L1 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.85	0.03
0.01	Accuracy	0.85	0.03
0.05	Accuracy	0.87	0.01
0.1	Accuracy	0.89	0.02
0.5	Accuracy	0.92	0.01
1	Accuracy	0.92	0.01
5	Accuracy	0.93	0.00
10	Accuracy	0.93	0.00
50	Accuracy	0.92	0.00
100	Accuracy	0.92	0.00
500	Accuracy	0.92	0.00
1000	Accuracy	0.92	0.00

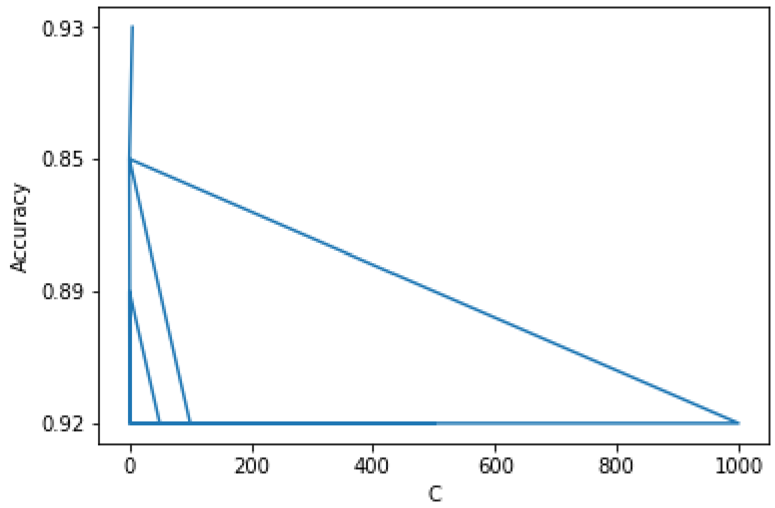
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	GridSearchCV	5	93.08

Classification Report with lambda = 5				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.84	0.73	0.78	17838.00
positive	0.95	0.97	0.96	87534.00
micro avg	0.93	0.93	0.93	105372.00
macro avg	0.89	0.85	0.87	105372.00
weighted avg	0.93	0.93	0.93	105372.00




```
+-----------------------------------------------------+
|               Confusion Matrix Report               |
+---------------------------------------+-------------+
|                 Term                  |    Value    |
+---------------------------------------+-------------+
|           TP (True Positive)          |    85011    |
|           TN (True Negative)          |    13072    |
|           FP (False Positive)         |     4766    |
|           FN (False Negative)         |     2523    |
| TPR (True Positive Rate)= TP/(TP+FN)) |     0.97    |
| TNR (True Negative Rate)= TN/(TN+FP)) |     0.73    |
| FPR (False Positive Rate)= FP/(FP+TN))|     0.27    |
| FNR (False Negative Rate)= FN/(TP+FN))|     0.03    |
| ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))|    93.08%   |
+---------------------------------------+-------------+
```

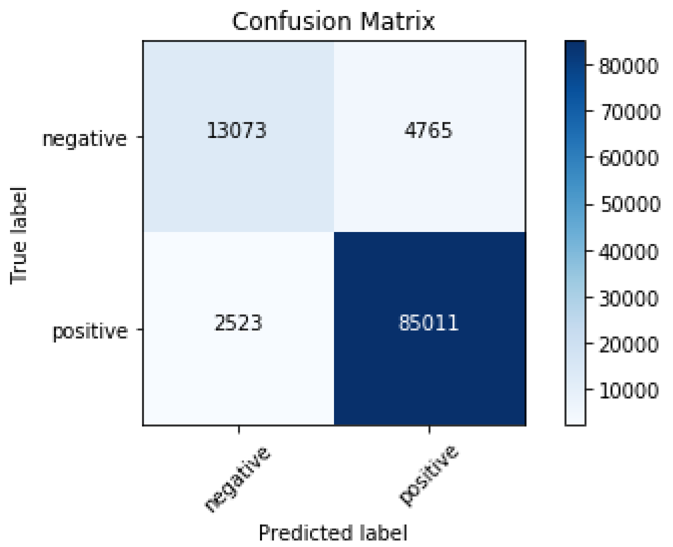
```
-------------------------- RandomizedSearchCV --------------------------
```



L1 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
50	Accuracy	0.92	0.00
0.1	Accuracy	0.89	0.02
0.5	Accuracy	0.92	0.01
1000	Accuracy	0.92	0.00
0.0005	Accuracy	0.85	0.03
100	Accuracy	0.92	0.00
500	Accuracy	0.92	0.00
1	Accuracy	0.92	0.01
0.0001	Accuracy	0.85	0.03
5	Accuracy	0.93	0.00

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	RandomizedSearchCV	5	93.08

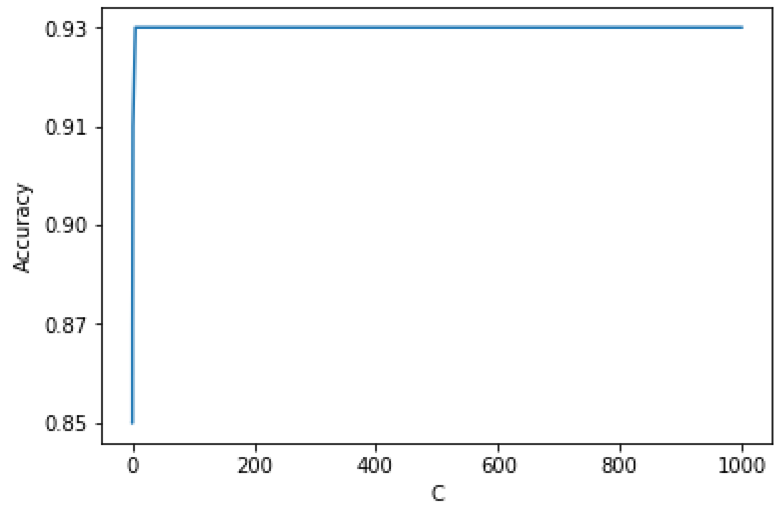
Classification Report with lambda = 5				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.84	0.73	0.78	17838.00
positive	0.95	0.97	0.96	87534.00
micro avg	0.93	0.93	0.93	105372.00
macro avg	0.89	0.85	0.87	105372.00
weighted avg	0.93	0.93	0.93	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	85011
TN (True Negative)	13073
FP (False Positive)	4765
FN (False Negative)	2523
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.73
FPR (False Positive Rate)= FP/(FP+TN))	0.27
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	93.08%

****
---------------------------- L2 Regularizaion ----------------------------
****

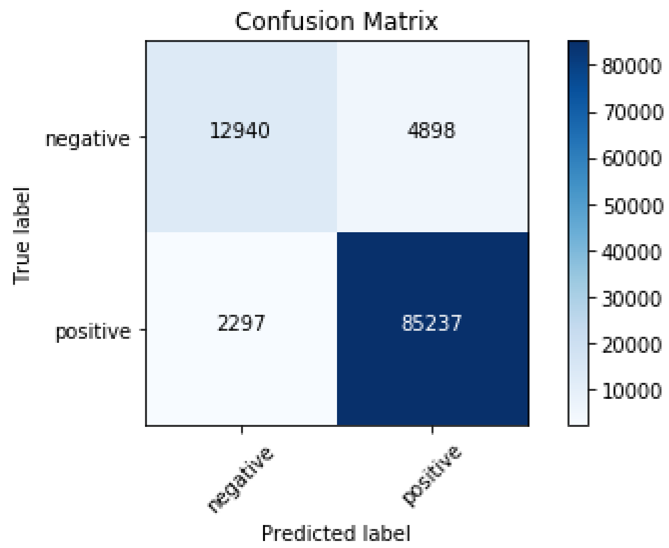
------------------------- GridSearchCV -------------------------



L2 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.85	0.03
0.01	Accuracy	0.85	0.03
0.05	Accuracy	0.85	0.02
0.1	Accuracy	0.87	0.02
0.5	Accuracy	0.90	0.02
1	Accuracy	0.91	0.02
5	Accuracy	0.93	0.01
10	Accuracy	0.93	0.01
50	Accuracy	0.93	0.00
100	Accuracy	0.93	0.00
500	Accuracy	0.93	0.00
1000	Accuracy	0.93	0.00

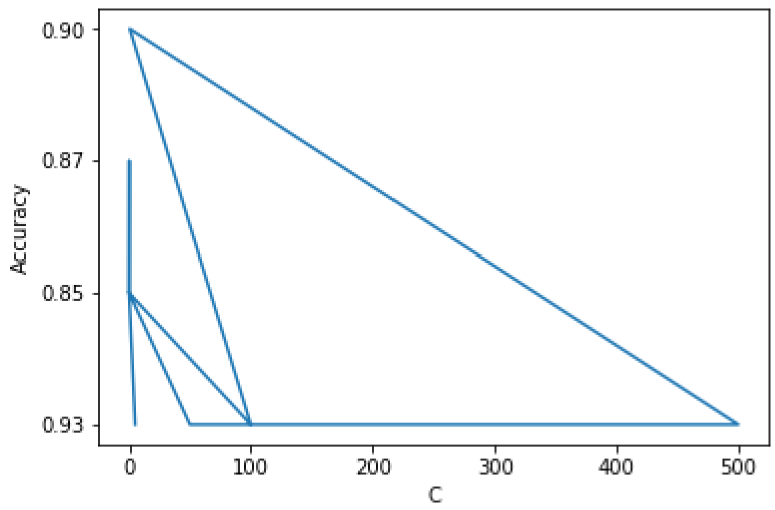
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	GridSearchCV	100	93.17

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.85	0.73	0.78	17838.00
positive	0.95	0.97	0.96	87534.00
micro avg	0.93	0.93	0.93	105372.00
macro avg	0.90	0.85	0.87	105372.00
weighted avg	0.93	0.93	0.93	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	85237
TN (True Negative)	12940
FP (False Positive)	4898
FN (False Negative)	2297
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.73
FPR (False Positive Rate)= FP/(FP+TN))	0.27
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	93.17%

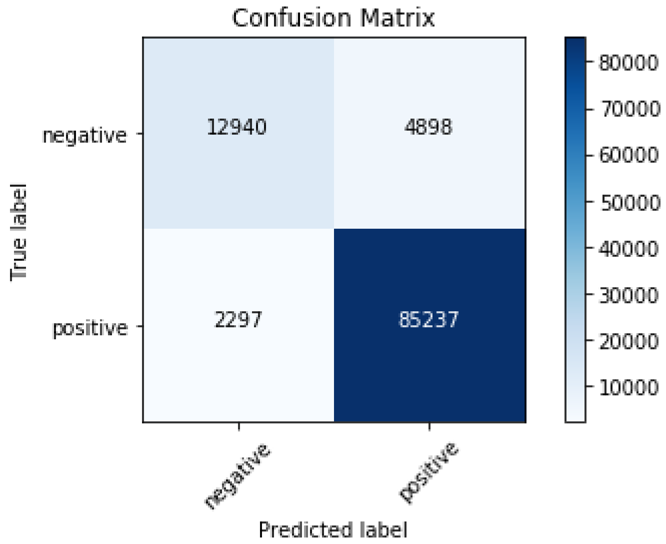
------------------------- RandomizedSearchCV -------------------------



L2 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
5	Accuracy	0.93	0.01
0.001	Accuracy	0.85	0.03
0.01	Accuracy	0.85	0.03
0.1	Accuracy	0.87	0.02
0.005	Accuracy	0.85	0.03
100	Accuracy	0.93	0.00
0.5	Accuracy	0.90	0.02
500	Accuracy	0.93	0.00
50	Accuracy	0.93	0.00
0.0005	Accuracy	0.85	0.03

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	RandomizedSearchCV	100	93.17

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.85	0.73	0.78	17838.00
positive	0.95	0.97	0.96	87534.00
micro avg	0.93	0.93	0.93	105372.00
macro avg	0.90	0.85	0.87	105372.00
weighted avg	0.93	0.93	0.93	105372.00



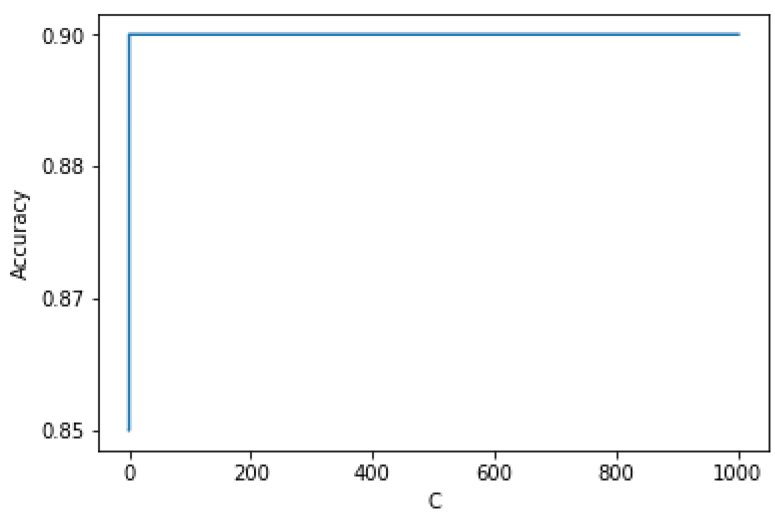

```
+-----------------------------------------------------+
|              Confusion Matrix Report                 |
+--------------------------------------+--------+
|                Term                  | Value  |
+--------------------------------------+--------+
|          TP (True Positive)          | 85237  |
|          TN (True Negative)          | 12940  |
|         FP (False Positive)          |  4898  |
|         FN (False Negative)          |  2297  |
| TPR (True Positive Rate)= TP/(TP+FN))  |  0.97  |
| TNR (True Negative Rate)= TN/(TN+FP))  |  0.73  |
| FPR (False Positive Rate)= FP/(FP+TN)) |  0.27  |
| FNR (False Negative Rate)= FN/(TP+FN)) |  0.03  |
| ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN)) | 93.17% |
+--------------------------------------+--------+
```

```
Wall time: 11min 7s
```

(3.3) Logistic regression on Average Word2Vec :

In [14]:
```
%%time

# Perform logistic regression with l1 and l2 as a penalty, on average word2vec
try:
    run_logistic_regression("avg-w2v",
                            x_train = avg_w2v_train,
                            x_test = avg_w2v_test,
                            y_train = y_train,
                            y_test = y_test)
except Exception:
    traceback.print_exc()
```

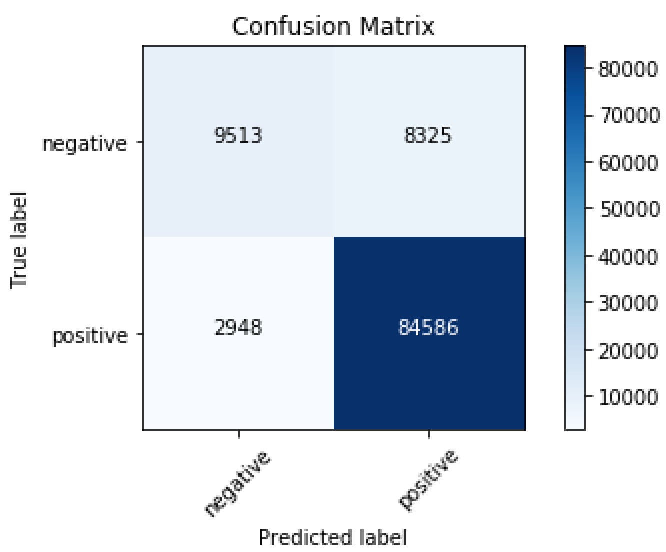
```
****************************************************************************
----------------------------- L1 Regularizaion -----------------------------
******************************************************************************


------------------------- GridSearchCV -------------------------
```



L1 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.87	0.01
0.01	Accuracy	0.88	0.00
0.05	Accuracy	0.90	0.01
0.1	Accuracy	0.90	0.01
0.5	Accuracy	0.90	0.01
1	Accuracy	0.90	0.01
5	Accuracy	0.90	0.01
10	Accuracy	0.90	0.01
50	Accuracy	0.90	0.01
100	Accuracy	0.90	0.01
500	Accuracy	0.90	0.01
1000	Accuracy	0.90	0.01

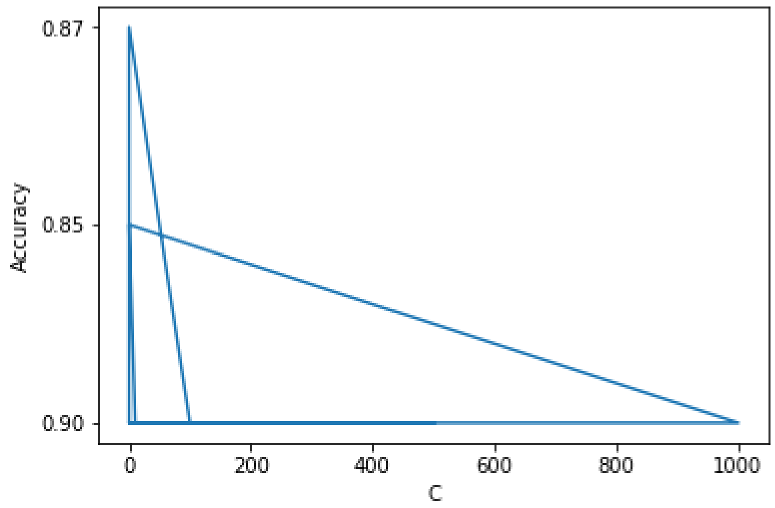
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	GridSearchCV	50	89.30

Classification Report with lambda = 50				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.76	0.53	0.63	17838.00
positive	0.91	0.97	0.94	87534.00
micro avg	0.89	0.89	0.89	105372.00
macro avg	0.84	0.75	0.78	105372.00
weighted avg	0.89	0.89	0.89	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84586
TN (True Negative)	9513
FP (False Positive)	8325
FN (False Negative)	2948
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.53
FPR (False Positive Rate)= FP/(FP+TN))	0.47
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	89.30%

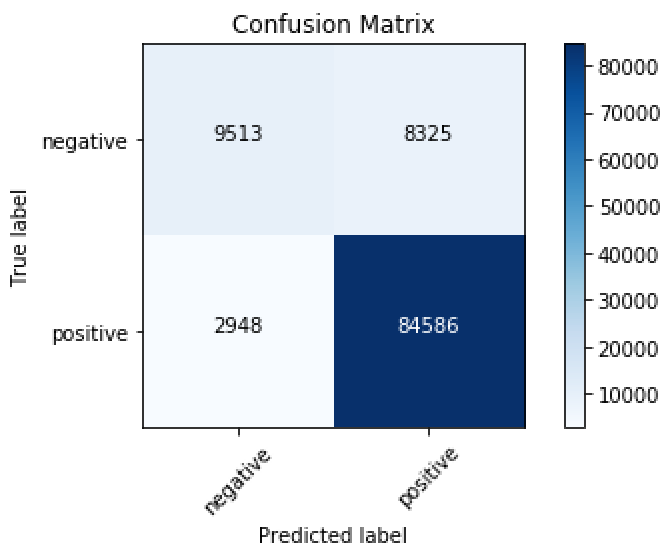
------------------------- RandomizedSearchCV -------------------------



L1 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.5	Accuracy	0.90	0.01
500	Accuracy	0.90	0.01
50	Accuracy	0.90	0.01
10	Accuracy	0.90	0.01
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
1000	Accuracy	0.90	0.01
0.1	Accuracy	0.90	0.01
0.005	Accuracy	0.87	0.01
100	Accuracy	0.90	0.01

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	RandomizedSearchCV	100	89.30

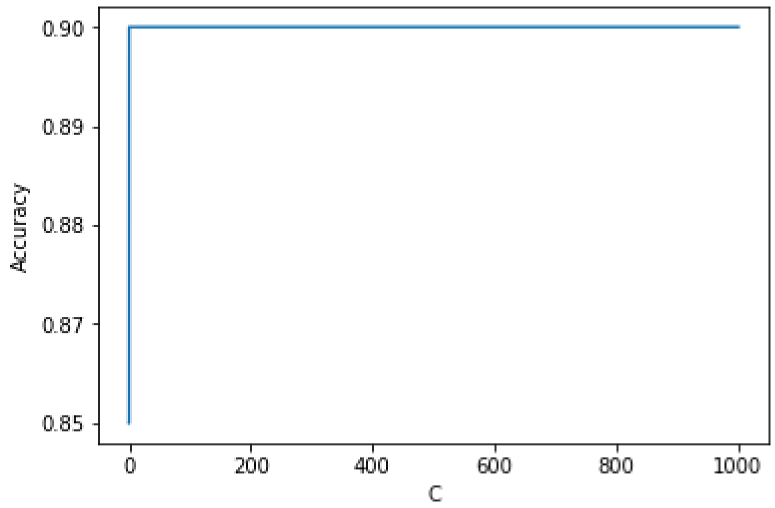
Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.76	0.53	0.63	17838.00
positive	0.91	0.97	0.94	87534.00
micro avg	0.89	0.89	0.89	105372.00
macro avg	0.84	0.75	0.78	105372.00
weighted avg	0.89	0.89	0.89	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84586
TN (True Negative)	9513
FP (False Positive)	8325
FN (False Negative)	2948
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.53
FPR (False Positive Rate)= FP/(FP+TN))	0.47
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	89.30%

```
******************************************************************************
---------------------------- L2 Regularizaion ----------------------------
******************************************************************************
```

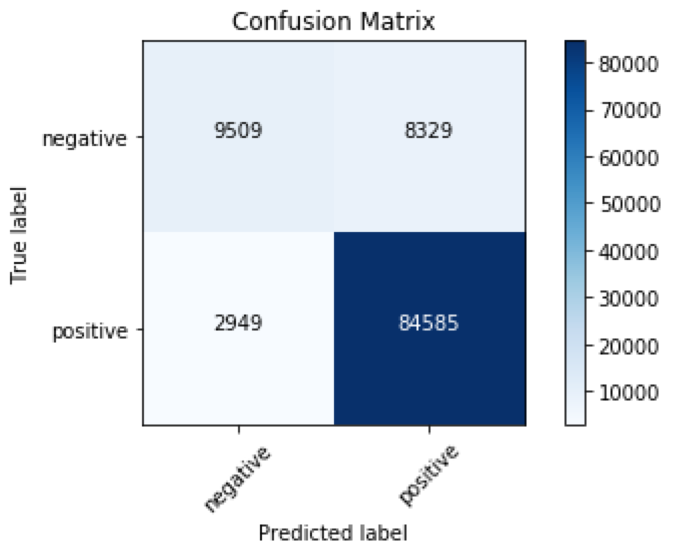
```
------------------------- GridSearchCV -------------------------
```



L2 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.87	0.01
0.01	Accuracy	0.88	0.00
0.05	Accuracy	0.89	0.01
0.1	Accuracy	0.90	0.01
0.5	Accuracy	0.90	0.01
1	Accuracy	0.90	0.01
5	Accuracy	0.90	0.01
10	Accuracy	0.90	0.01
50	Accuracy	0.90	0.01
100	Accuracy	0.90	0.01
500	Accuracy	0.90	0.01
1000	Accuracy	0.90	0.01

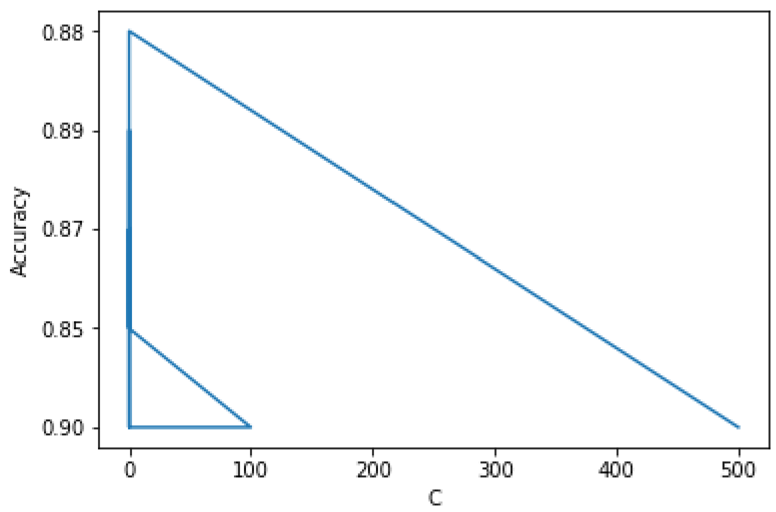
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	GridSearchCV	100	89.30

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.76	0.53	0.63	17838.00
positive	0.91	0.97	0.94	87534.00
micro avg	0.89	0.89	0.89	105372.00
macro avg	0.84	0.75	0.78	105372.00
weighted avg	0.89	0.89	0.89	105372.00




```
+---------------------------------------------------------+
|                 Confusion Matrix Report                 |
+---------------------------------------------+-----------+
|                    Term                     |  Value    |
+---------------------------------------------+-----------+
|            TP (True Positive)               |  84585    |
|            TN (True Negative)               |   9509    |
|            FP (False Positive)              |   8329    |
|            FN (False Negative)              |   2949    |
| TPR (True Positive Rate)= TP/(TP+FN))       |   0.97    |
| TNR (True Negative Rate)= TN/(TN+FP))       |   0.53    |
| FPR (False Positive Rate)= FP/(FP+TN))      |   0.47    |
| FNR (False Negative Rate)= FN/(TP+FN))      |   0.03    |
| ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))      |  89.30%   |
+---------------------------------------------+-----------+
```

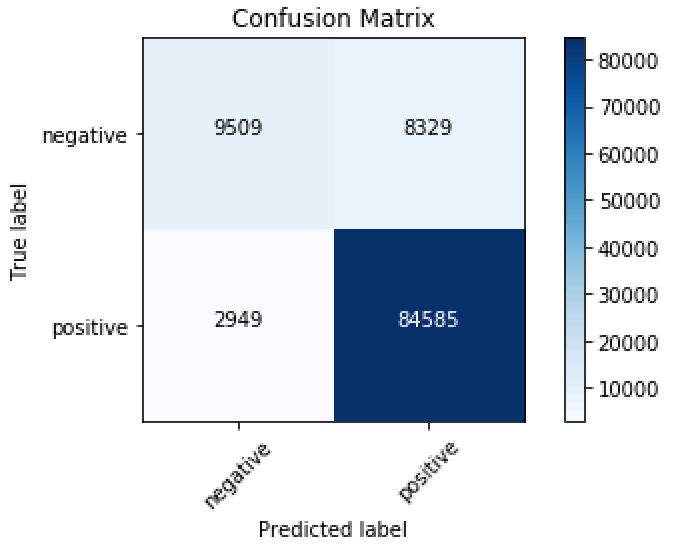
```
-------------------------- RandomizedSearchCV --------------------------
```



L2 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.5	Accuracy	0.90	0.01
100	Accuracy	0.90	0.01
0.001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.005	Accuracy	0.87	0.01
0.1	Accuracy	0.90	0.01
0.05	Accuracy	0.89	0.01
0.0001	Accuracy	0.85	0.03
0.01	Accuracy	0.88	0.00
500	Accuracy	0.90	0.01

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	RandomizedSearchCV	100	89.30

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.76	0.53	0.63	17838.00
positive	0.91	0.97	0.94	87534.00
micro avg	0.89	0.89	0.89	105372.00
macro avg	0.84	0.75	0.78	105372.00
weighted avg	0.89	0.89	0.89	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84585
TN (True Negative)	9509
FP (False Positive)	8329
FN (False Negative)	2949
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.53
FPR (False Positive Rate)= FP/(FP+TN))	0.47
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	89.30%

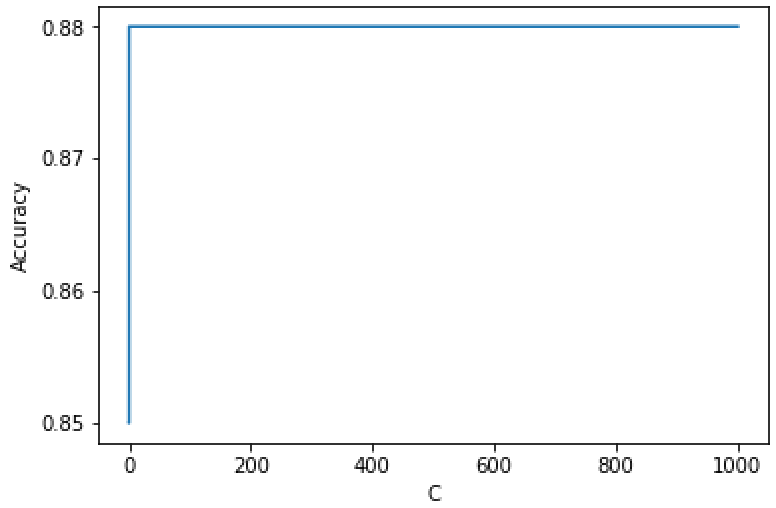
```
Wall time: 6min 46s
```

(3.4) Logistic regression on TF-IDF weighted Word2Vec :

In [15]:

```
%%time

# Perform logistic regression with l1 and l2 as a penalty, on tf-idf weighted Word2Vec
try:
    run_logistic_regression("tf-idf-w2v",
                            x_train = tfidf_w2v_train,
                            x_test = tfidf_w2v_test,
                            y_train = y_train,
                            y_test = y_test)
except Exception:
    traceback.print_exc()
```

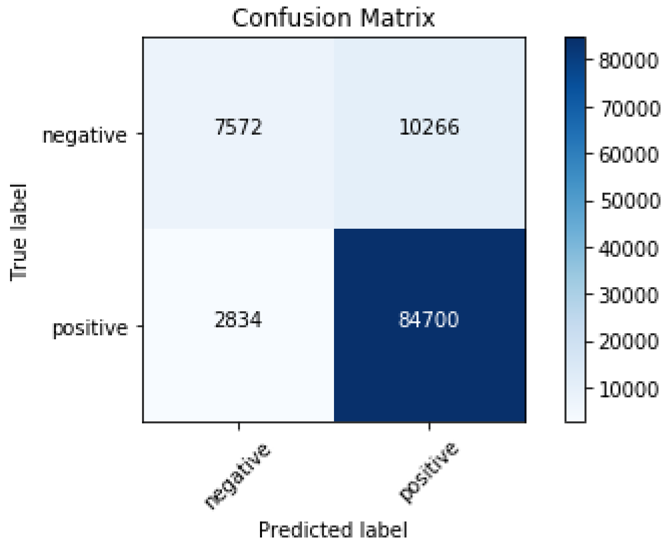
```
******************************************************************************
---------------------------- L1 Regularizaion ----------------------------
********************************************************************************


------------------------- GridSearchCV -------------------------
```



L1 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.86	0.01
0.01	Accuracy	0.87	0.00
0.05	Accuracy	0.88	0.01
0.1	Accuracy	0.88	0.02
0.5	Accuracy	0.88	0.02
1	Accuracy	0.88	0.02
5	Accuracy	0.88	0.02
10	Accuracy	0.88	0.02
50	Accuracy	0.88	0.02
100	Accuracy	0.88	0.02
500	Accuracy	0.88	0.02
1000	Accuracy	0.88	0.02

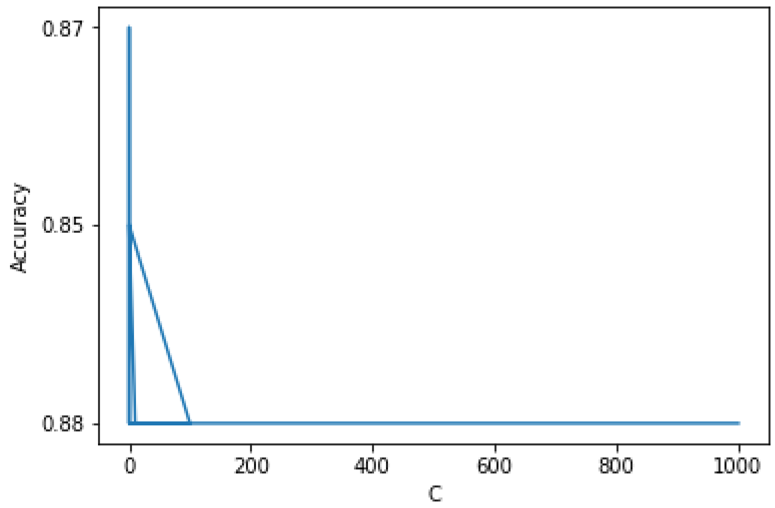
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	GridSearchCV	50	87.57

Classification Report with lambda = 50				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.73	0.42	0.54	17838.00
positive	0.89	0.97	0.93	87534.00
micro avg	0.88	0.88	0.88	105372.00
macro avg	0.81	0.70	0.73	105372.00
weighted avg	0.86	0.88	0.86	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84700
TN (True Negative)	7572
FP (False Positive)	10266
FN (False Negative)	2834
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.42
FPR (False Positive Rate)= FP/(FP+TN))	0.58
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	87.57%

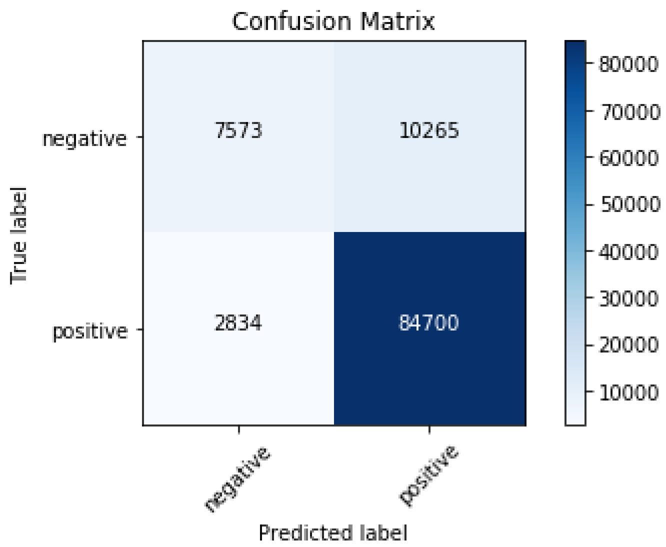
------------------------- RandomizedSearchCV -------------------------



L1 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
50	Accuracy	0.88	0.02
1	Accuracy	0.88	0.02
100	Accuracy	0.88	0.02
0.001	Accuracy	0.85	0.03
0.0001	Accuracy	0.85	0.03
10	Accuracy	0.88	0.02
0.1	Accuracy	0.88	0.02
0.01	Accuracy	0.87	0.00
0.05	Accuracy	0.88	0.01
1000	Accuracy	0.88	0.02

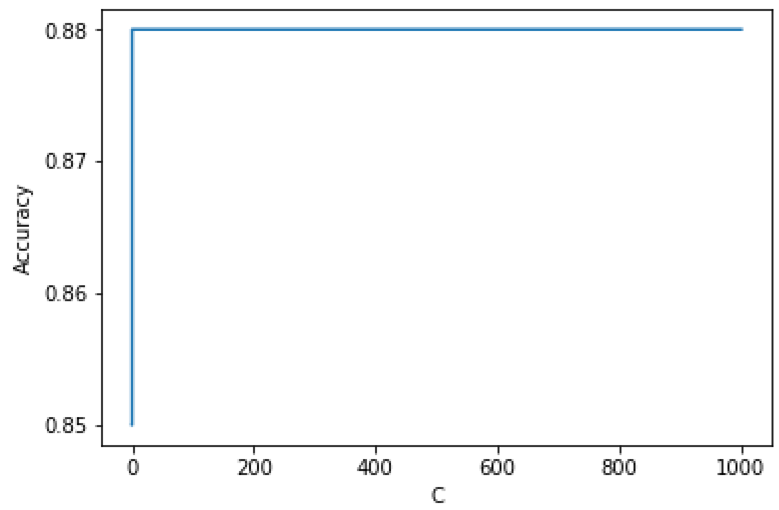
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L1	RandomizedSearchCV	100	87.57

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.73	0.42	0.54	17838.00
positive	0.89	0.97	0.93	87534.00
micro avg	0.88	0.88	0.88	105372.00
macro avg	0.81	0.70	0.73	105372.00
weighted avg	0.86	0.88	0.86	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84700
TN (True Negative)	7573
FP (False Positive)	10265
FN (False Negative)	2834
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.42
FPR (False Positive Rate)= FP/(FP+TN))	0.58
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	87.57%

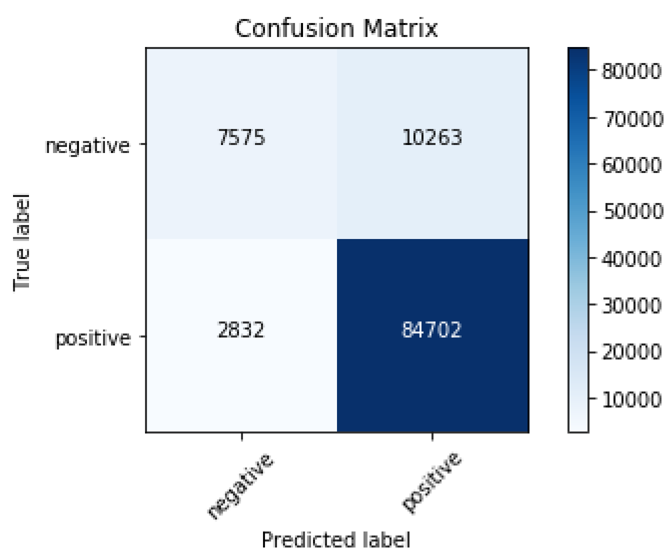
```
*****************************************************************************
---------------------------- L2 Regularizaion ----------------------------
*****************************************************************************


------------------------- GridSearchCV -------------------------
```



L2 Regularization with 'GridSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
0.001	Accuracy	0.85	0.03
0.005	Accuracy	0.86	0.01
0.01	Accuracy	0.87	0.01
0.05	Accuracy	0.88	0.01
0.1	Accuracy	0.88	0.01
0.5	Accuracy	0.88	0.02
1	Accuracy	0.88	0.02
5	Accuracy	0.88	0.02
10	Accuracy	0.88	0.02
50	Accuracy	0.88	0.02
100	Accuracy	0.88	0.02
500	Accuracy	0.88	0.02
1000	Accuracy	0.88	0.02

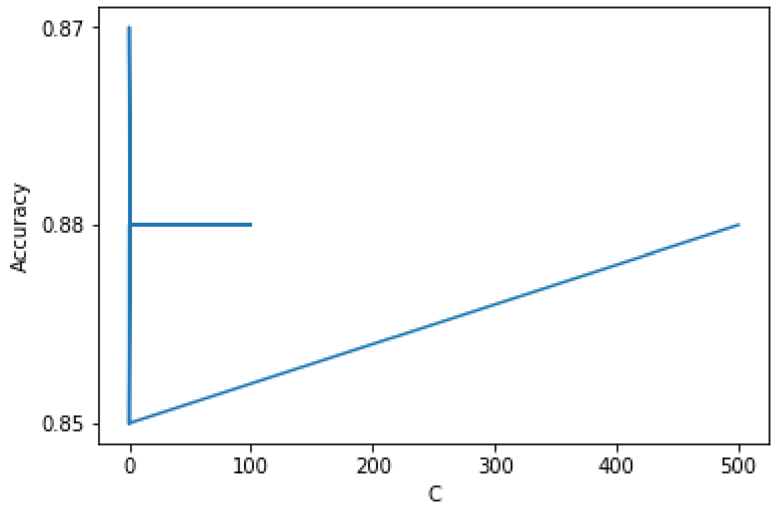
Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	GridSearchCV	1000	87.57

Classification Report with lambda = 1000				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.73	0.42	0.54	17838.00
positive	0.89	0.97	0.93	87534.00
micro avg	0.88	0.88	0.88	105372.00
macro avg	0.81	0.70	0.73	105372.00
weighted avg	0.86	0.88	0.86	105372.00



Confusion Matrix Report	
Term	Value
TP (True Positive)	84702
TN (True Negative)	7575
FP (False Positive)	10263
FN (False Negative)	2832
TPR (True Positive Rate)= TP/(TP+FN))	0.97
TNR (True Negative Rate)= TN/(TN+FP))	0.42
FPR (False Positive Rate)= FP/(FP+TN))	0.58
FNR (False Negative Rate)= FN/(TP+FN))	0.03
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	87.57%

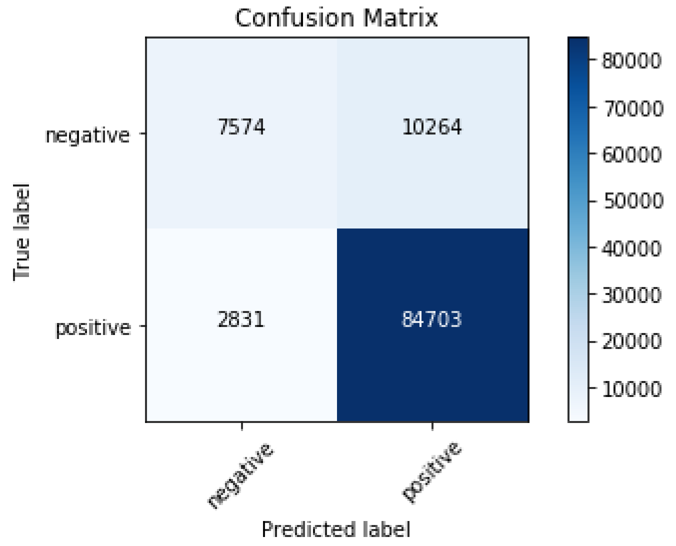
------------------------- RandomizedSearchCV -------------------------



L2 Regularization with 'RandomizedSearchCV'			
Hyperparameter (C)	Scoring	Mean	Variance
0.001	Accuracy	0.85	0.03
1	Accuracy	0.88	0.02
0.01	Accuracy	0.87	0.01
0.5	Accuracy	0.88	0.02
100	Accuracy	0.88	0.02
0.1	Accuracy	0.88	0.01
0.05	Accuracy	0.88	0.01
0.0001	Accuracy	0.85	0.03
0.0005	Accuracy	0.85	0.03
500	Accuracy	0.88	0.02

Optimal hyperparameter & Testing accuracy score			
Regularization	Cross Validation	Optimal Hyperparameter (C)	Accuracy(%)
L2	RandomizedSearchCV	100	87.57

Classification Report with lambda = 100				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.73	0.42	0.54	17838.00
positive	0.89	0.97	0.93	87534.00
micro avg	0.88	0.88	0.88	105372.00
macro avg	0.81	0.70	0.73	105372.00
weighted avg	0.86	0.88	0.86	105372.00




```
+-------------------------------------------------+
|              Confusion Matrix Report            |
+----------------------------------------+--------+
|                  Term                  | Value  |
+----------------------------------------+--------+
|            TP (True Positive)          | 84703  |
|            TN (True Negative)          |  7574  |
|           FP (False Positive)          | 10264  |
|           FN (False Negative)          |  2831  |
| TPR (True Positive Rate)= TP/(TP+FN))  |  0.97  |
| TNR (True Negative Rate)= TN/(TN+FP))  |  0.42  |
| FPR (False Positive Rate)= FP/(FP+TN)) |  0.58  |
| FNR (False Negative Rate)= FN/(TP+FN)) |  0.03  |
| ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN)) | 87.57% |
+----------------------------------------+--------+
```

```
Wall time: 6min 26s
```

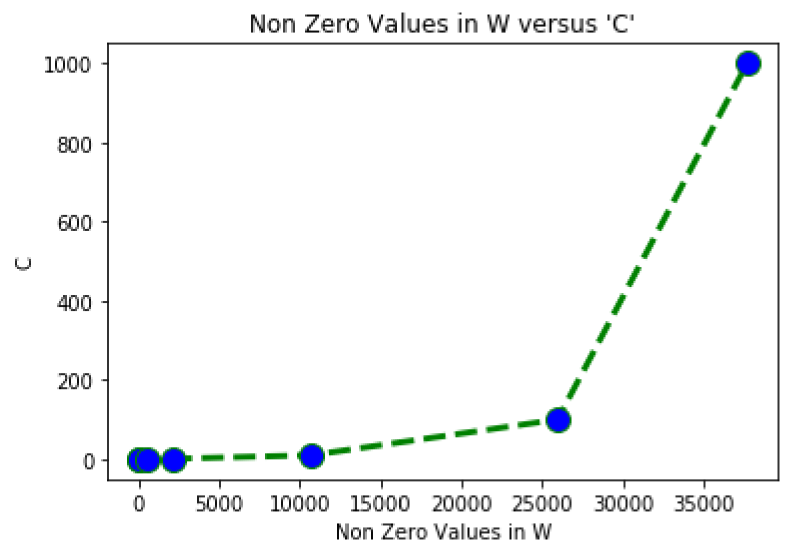
(3) Calculate sparsity on weight vector using L1 regularization :

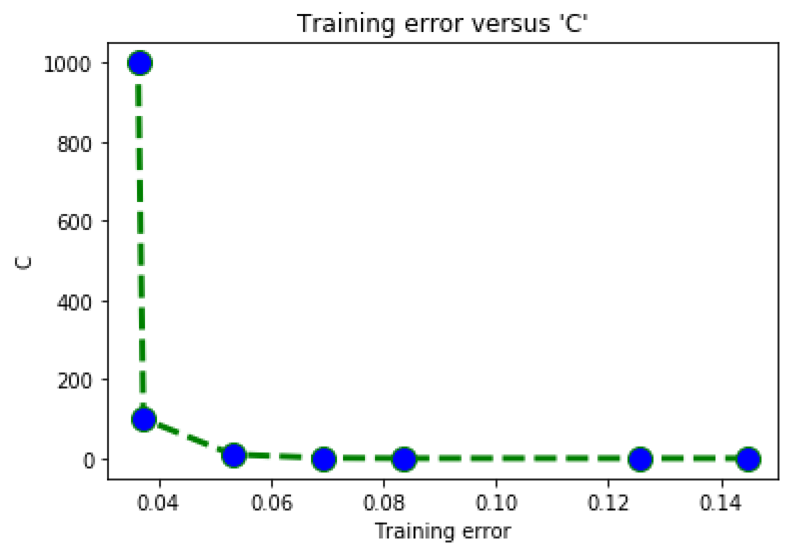
In [16]:
```
classifier = LogisticRegression()
classifier.penalty = 'l1'
```

(3.1) Sparsity testing using BoW :

Task : Keep increasing and decreasing lambda(1 / C), to calculate error and sparsity.

In [17]:
```
%%time

# perform sparsity testing on bow
perform_sparsity_testing(classifier,bow_train_features)
```






```
+-------------------------------------------------+
|             Sparsity Testing Report             |
+------------------+----------+-----------------+
| Hyperparameter(C) | Sparsity | Training Error |
+------------------+----------+-----------------+
|       0.001      |    2     |      0.14       |
|        0.01      |    72    |      0.13       |
|       0.1        |   505    |      0.08       |
|        1         |   2166   |      0.07       |
|        10        |  10720   |      0.05       |
|       100        |  25947   |      0.04       |
|        1000      |  37703   |      0.04       |
+------------------+----------+-----------------+

Wall time: 36.4 s
```

As we can observe from the table that,when we increase hyperparameter's value, sparsity of weight vector increases drastically.

(4) Perform multicollinearity (pertubation test) on features and show feature importance :

(4.1) Pertubation test using BoW:

In [18]:

```
# Check for multicollinearity on Bow
weight_before_pertubation,weight_after_pertubation,clf_bow = perform_pertubation_test(bow_train_featur
es,
                                                                                     bow_test_feature
s,
                                                                                     y_train,
                                                                                     y_test,
                                                                                     10,
                                                                                     "l2")

count_nnz_w1 = np.count_nonzero(weight_before_pertubation != 0)
count_nnz_w2 = np.count_nonzero(weight_after_pertubation != 0)

if(count_nnz_w1 == 0):
    print("\nWeight vector has 0 number of non zero alements.")
    print("Features are highly collinear in nature.")
elif(count_nnz_w1 == count_nnz_w2 and count_nnz_w1 != 0):
    # Compare weight vectors for tolerence value
    # For tolerence value check for numpy.isclose() documentation
    compare_weight_vectors(weight_before_pertubation, weight_after_pertubation, 0.001)
    print("\nFeatures are non collinear for tolerence value 0.001")
    print("As we decrease tolerence value and increase noise, features may become multicollinear.")
else:
    print("\nFeatures are highly collinear in nature.")
    print("After adding the noise, {0} of non zero elements changes drastically.".format(abs(count_nnz
_w1 - count_nnz_w2)))
```

```
------------------ Before Pertubation Test ------------------
Accuracy on testing data: 88.54%
Number of non zero weights in weight vector 'w':  74398


------------------ After Pertubation Test ------------------
Accuracy on testing data: 88.54%
Number of non zero weights in weight vector 'w':  74398


5.01% value changes with tolerence value of 0.001 between two weight vectors


Features are non collinear for tolerence value 0.001
As we decrease tolerence value and increase noise, features may become multicollinear.
```

Feature importance for BoW:

In [19]:
```
# Get most common features based on absolute value of weight vectors for positive and negative reviews.
get_most_common_words(clf_bow, bow_vectorizer, top_n=25)
```

Feature Importance - 25 Most Common Features using absolute value of W

Feature (+ve)	|W| (+ve)	Feature (-ve)	|W| (-ve)
skeptic	14.093841521131703	worst	18.622891313261203
downsid	12.4193682373266	undrink	13.921291319297751
hook	11.8752691044259	mediocr	13.404212464786815
drawback	10.739237103699683	aw	12.548249483460532
yum	10.133941063043544	disgust	12.212535927662982
beat	9.950258878259177	terribl	11.930148162984606
addict	9.933788089974016	flavorless	11.704998305667674
yay	9.853897813765265	yuck	11.487647957905772
delici	9.805674502886099	unaccept	11.474091074920668
perfect	9.595107673448034	horribl	11.371041360463323
deduct	9.095812358443766	tasteless	11.208470614702401
easiest	8.939129758658733	concept	11.0221789267423
sinus	8.89617865464568	redeem	11.002946119554673
terrif	8.870329580835953	decept	10.665117184977944
excel	8.85514656401629	unpleas	10.33364628676511
amaz	8.741291078303824	threw	10.229094669074406
delish	8.71239027395237	disapoint	10.123567171189285
awesom	8.624387204585492	ugh	10.07084938051702
fantast	8.44486204588827	disappoint	9.988457730781597
steal	8.379929531491548	opposit	9.856156211867225
uniqu	8.261437635215401	unimpress	9.835947787084702
sooth	8.23331829397752	useless	9.676382531835438
outstand	8.10598488911242	gross	9.647285908375853
gripe	8.004045288186761	unapp	9.543947571257203
whim	8.000506092619151	ruin	9.538845465313683

(4.2) Pertubation test using TF-IDF:

In [20]:
```
# Check for multicollinearity on TF-IDF
weight_before_pertubation,weight_after_pertubation,clf_tfidf = perform_pertubation_test(tf_idf_train_f
eatures,
                                                                                              tf_idf_test_fe
atures,
                                                                                              y_train,
                                                                                              y_test,
                                                                                              100,
                                                                                              "l2")


count_nnz_w1 = np.count_nonzero(weight_before_pertubation != 0)
count_nnz_w2 = np.count_nonzero(weight_after_pertubation != 0)

if(count_nnz_w1 == 0):
    print("\nWeight vector has 0 number of non zero alements.")
    print("Features are highly collinear in nature.")
elif(count_nnz_w1 == count_nnz_w2 and count_nnz_w1 != 0):
    # Compare weight vectors for tolerence value
    # For tolerence value check for numpy.isclose() documentation
    compare_weight_vectors(weight_before_pertubation, weight_after_pertubation, 0.001)
    print("\nFeatures are non collinear for tolerence value 0.001")
    print("As we decrease tolerence value and increase noise, features may become multicollinear.")
else:
    print("\nFeatures are highly collinear in nature.")
    print("After adding the noise, {0} of non zero elements changes drastically.".format(abs(count_nnz
_w1 - count_nnz_w2)))
```

```
------------------ Before Pertubation Test ------------------
Accuracy on testing data: 92.97%
Number of non zero weights in weight vector 'w':  487621


------------------ After Pertubation Test ------------------
Accuracy on testing data: 92.97%
Number of non zero weights in weight vector 'w':  487621


18.49% value changes with tolerence value of 0.001 between two weight vectors


Features are non collinear for tolerence value 0.001
As we decrease tolerence value and increase noise, features may become multicollinear.
```

Feature importance for TF-IDF:

In [21]:
```
# Get most common features based on absolute value of weight vectors for positive and negative review
s.
get_most_common_words(clf_tfidf, tfidf_vectorizer, top_n=25)
```

Feature Importance - 25 Most Common Features using absolute value of W

Feature (+ve)	|W| (+ve)	Feature (-ve)	|W| (-ve)
great	35.71753722234398	two star	36.03427893987466
delici	33.90030035531667	worst	33.408742132252534
high recommend	31.948761537248355	disappoint	30.34677939920822
best	28.740551312314132	aw	24.97421765228579
perfect	28.608983960336065	terribl	24.703196603437235
love	28.15723999115403	horribl	22.67822522092035
excel	26.266356006723967	disgust	21.02086539348089
wont disappoint	24.801194120737186	bland	19.88532717278006
amaz	22.237633250446308	return	19.825226082195247
four star	20.819931052090144	wont buy	19.487666207955403
pleasant surpris	19.867399577174446	threw	19.25031685869836
addict	19.697245290413917	undrink	18.859931089890907
good	19.162054868947763	unfortun	18.688573672995823
awesom	19.157362231884832	want like	18.502619195665268
nice	18.892239330841864	yuck	18.145175720454436
tasti	18.47867364418753	tasteless	17.93166870075845
favorit	17.98397296071259	way sweet	17.81746214146594
never disappoint	17.940140777548216	great review	17.63678820654511
well worth	17.842058507929625	least favorit	17.411385228541313
yummi	17.701792619433775	dont recommend	17.294841069641297
hook	17.638951791890946	stale	17.29080491202529
fantast	17.532167783684322	flavorless	17.07461636718377
skeptic	17.371940251543162	never buy	16.989249909302213
even better	16.924082041358822	weak	16.947999930246677
glad	16.49084579632252	unpleas	16.93511034003923

(4.3) Pertubation test using Average Word2Vec:

In [22]:
```
# Check for multicollinearity on Bow
weight_before_pertubation,weight_after_pertubation,ignore = perform_pertubation_test(avg_w2v_train,
                                                                                      avg_w2v_test,
                                                                                      y_train,
                                                                                      y_test,
                                                                                      100,
                                                                                      "l2")


count_nnz_w1 = np.count_nonzero(weight_before_pertubation != 0)
count_nnz_w2 = np.count_nonzero(weight_after_pertubation != 0)

if(count_nnz_w1 == 0):
    print("\nWeight vector has 0 number of non zero alements.")
    print("Features are highly collinear in nature.")
elif(count_nnz_w1 == count_nnz_w2 and count_nnz_w1 != 0):
    # Compare weight vectors for tolerence value
    # For tolerence value check for numpy.isclose() documentation
    compare_weight_vectors(weight_before_pertubation, weight_after_pertubation, 0.001)
else:
    print("\nFeatures are highly collinear in nature.")
    print("After adding the noise, {0} of non zero elements changes drastically.".format(abs(count_nnz
_w1 - count_nnz_w2)))
```

```
------------------ Before Pertubation Test ------------------
Accuracy on testing data: 82.66%
Number of non zero weights in weight vector 'w':  50


------------------ After Pertubation Test ------------------
Accuracy on testing data: 82.66%
Number of non zero weights in weight vector 'w':  50


0.00% value changes with tolerence value of 0.001 between two weight vectors
```

(4.4) Pertubation test using TF-IDF Weighted Word2Vec:

In [24]:
```
# Check for multicollinearity on Bow
weight_before_pertubation,weight_after_pertubation,ignore = perform_pertubation_test(tfidf_w2v_train,
                                                                                      tfidf_w2v_test,
                                                                                      y_train,
                                                                                      y_test,
                                                                                      50,
                                                                                      "l1")


count_nnz_w1 = np.count_nonzero(weight_before_pertubation != 0)
count_nnz_w2 = np.count_nonzero(weight_after_pertubation != 0)

if(count_nnz_w1 == 0):
    print("\nWeight vector has 0 number of non zero alements.")
    print("Features are highly collinear in nature.")
elif(count_nnz_w1 == count_nnz_w2 and count_nnz_w1 != 0):
    # Compare weight vectors for tolerence value
    # For tolerence value check for numpy.isclose() documentation
    compare_weight_vectors(weight_before_pertubation, weight_after_pertubation, 0.001)
else:
    print("\nFeatures are highly collinear in nature.")
    print("After adding the noise, {0} of non zero elements changes drastically.".format(abs(count_nnz
_w1 - count_nnz_w2)))
```

```
------------------ Before Pertubation Test ------------------
Accuracy on testing data: 80.00%
Number of non zero weights in weight vector 'w':  50


------------------ After Pertubation Test ------------------
Accuracy on testing data: 80.00%
Number of non zero weights in weight vector 'w':  50


0.00% value changes with tolerence value of 0.001 between two weight vectors
```

Conclusion :

In [25]:
```
conclude()
```

Conclusion

Penalty-CV	Model	Hyperparameter	Train Error	Test Error
L1 GridSearchCV	BOW Logistic Regression	5	6.0%	8.0%
L1 RandomizedSearchCV	BOW Logistic Regression	5	6.0%	8.0%
L2 GridSearchCV	BOW Logistic Regression	10	6.0%	8.0%
L2 RandomizedSearchCV	BOW Logistic Regression	10	6.0%	8.0%
L1 GridSearchCV	TFIDF Logistic Regression	5	2.0%	7.000000000000001%
L1 RandomizedSearchCV	TFIDF Logistic Regression	5	2.0%	7.000000000000001%
L2 GridSearchCV	TFIDF Logistic Regression	100	0.0%	7.000000000000001%
L2 RandomizedSearchCV	TFIDF Logistic Regression	100	0.0%	7.000000000000001%
L1 GridSearchCV	AVG-W2V Logistic Regression	50	10.0%	11.0%
L1 RandomizedSearchCV	AVG-W2V Logistic Regression	100	10.0%	11.0%
L2 GridSearchCV	AVG-W2V Logistic Regression	100	10.0%	11.0%
L2 RandomizedSearchCV	AVG-W2V Logistic Regression	100	10.0%	11.0%
L1 GridSearchCV	TFIDF-W2V Logistic Regression	50	11.0%	12.0%
L1 RandomizedSearchCV	TFIDF-W2V Logistic Regression	100	11.0%	12.0%
L2 GridSearchCV	TFIDF-W2V Logistic Regression	1000	11.0%	12.0%
L2 RandomizedSearchCV	TFIDF-W2V Logistic Regression	100	11.0%	12.0%

Observations :

> 1. Here, Logistic Regression classifier is applied on complete dataset(~364K).
> 2. Given dataset is imbalanced in nature (postive reviews:negative reviews = 5.57/1).
> 3. Grid search and Randomized search cross validation with 5-fold technique is applied to calculate optimal hyperparameter 'C'= 1/lambda.
> 4. Logistic regression produces very good result and sensible models on BoW & TF-IDF with ~92 and ~93 % accuracy.
> 5. For this dataset, it is observed that logistic regression does not perform well with Average Word2Vec and TF-IDF weighted Word2Vec, but accuracy can be increased by introducing rigorous topic modeling or trying out different classification techniques.
> 6. Sparsity testing is done, which evaluates that as you incease the values of 'C', number of zero values in the weight vector increases drastically.
> 7. Multicollinearity testing(Pertubation technique) is done, which evaluates that ,BoW produces good result and it is non collinear in nature.
> 8. for more information you can always refer to conclusion table above.