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[1] Problem Statement :

- Time Based slicing to split Train Data(70%) and Test Data(30%).
- Appling Logistic Regression model to find the optimal hyperparameter(lambda) using 10 fold Cross Validation(both GridSearch and RandomSearch) in :
    1)Bag Of Words
    2)TF-IDF
    2)Average Word2Vec
    2)TF-IDF weighted Word2Vec
- Adding regularization(L1 and L2) to our logistic model.
- Checking the Accuracy and Sparsity of optimal weight vectors by increasing the value of lambda in L1 Regularization.
- Checking the Multicollinearity in weight vectors and finding the feature Importance.

[2] Overview of Dataset :

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective: Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A 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. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[3] Loading the Data :

In order to load the data, we have used the SQLITE dataset as it easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:

```
#Importing the necessary Packages
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import time
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from IPython.display import HTML
from collections import OrderedDict


from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
```

In [2]:

```
import pickle

#dumping an object to file object using dump method
def dumpfile(a,file_Name):
    fileObject = open(file_Name,"wb")
    pickle.dump(a,fileObject,protocol=2)
    fileObject.close()

#Loading an object from file object using Load method
def loadfile(file_Name):
    fileObject = open(file_Name,"rb")
    b = pickle.load(fileObject)
    return b
```

In [3]:

```
%%HTML
<style type="text/css">
table.dataframe td, table.dataframe th {
    border: 2px  black solid !important;
}
</style>
```

In [4]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')



#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)
```

In [7]:

```
# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative ra
ting.
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

In [8]:

```
print("Number of datapoints: ",filtered_data.shape[0])
print("Number of attributes/features: ",filtered_data.shape[1])
HTML(filtered_data.head().to_html(index=False))
```

```
Number of datapoints:  525814
Number of attributes/features:  10
```

Out[8]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulr
1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

[4] Exploratory Data Analysis :

[4.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

Deduplication 1:- As can be seen below the same user has multiple reviews of the with the same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [9]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[9]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

In [10]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
e, kind='quicksort', na_position='last')
```

In [11]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
'first', inplace=False)
final.shape
```

Out[11]:

(364173, 10)

Deduplication 2:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [12]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[12]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel
64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [13]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
print(final.shape)
```

(364171, 10)

Deduplication 3:- It was also seen that a same user has given different reviews for a same product at same time.I think it is normal for a user to give multiple reviews about a product,but that should be in diffrent time. So,all those rows with same user giving multiple reviews for a same product at same time are considered as duplicate and hence dropped.

In [14]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId= "A8891HVRDJAM6"
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[14]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfı
86221	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	33	33
86236	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	3	3

In [15]:

```
final=final.drop_duplicates(subset={"ProductId","UserId","ProfileName","Time"}, keep='f
irst', inplace=False)
print(final.shape)
```

(363633, 10)

Deduplication 4:- It was also seen that in few rows with Ids from 150493 to 150529 contain reviews regarding books,not fine foods.So I think these should be also removed from the dataset. After looking at the productid column, it can be noticed that all the observations for fine foods start with B followed by numbers except for Ids from 150493 to 150529. I suppose the reviews for book ‘Chicken soup for the soul’ have gotten into the datset mistakenly as they contain the words “chicken soup.

In [16]:

```
display = final[final.ProductId == "0006641040"]
HTML(display.head().to_html(index=False))
```

Out[16]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1
150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1
150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1
150509	0006641040	A3CMRKGE0P909G	Teresa	3	4

In [17]:

```
final = final[final.ProductId != "0006641040"]
```

In [18]:

```
print("Percentage  of data still remaining : ",(final['Id'].size*1.0)/(filtered_data['I
d'].size*1.0)*100)

#Before starting the next phase of preprocessing lets see the number of entries left
print("Number of reviews left after Data Cleaning and Deduplication :")
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
Percentage  of data still remaining :  69.14973735959865
Number of reviews left after Data Cleaning and Deduplication :
(363599, 10)
```

Out[18]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

Observation:-
It is an imbalanced dataset as the number of positive reviews are way high in number than negative reviews.

[5] Text Preprocessing Using NLTK :

In the Preprocessing phase we do the following in the order below:-

1. Removal of HTML Tags
2. Removal of any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Removal of Stopwords
7. Finally Snowball Stemming the word

After which we collect the words used to describe positive and negative reviews

In [19]:

```
# find sentences containing HTML tags
import re
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

```
10
I wanted a treat that was accepted and well liked for my rescue animals.<b
r />This is the only treat that is healthy and loved by all 4 legged being
s in my home!<br />It does not contain sugar or grains or silly vegetables
which virtually all treats contain. Dogs, cats and ferrets are carnivores
they are not cattle to eat grain or rabbits to eat vegetables, and WHYYYY
do companies add sugar,beet pulp or corn syrup to carnivore foods? It is d
angerous and can cause the death of an animal with diabetes.<br />It is pr
etty easy to break into smaller pieces for cats and kittens with weak jaws
and its wonderful to use as an aid to gain the trust of an abused dog as i
t will not cause stomach upset when given in common sense amounts.<br />I
like that it goes a long way as it costs alot to heal and maintain and tra
in abused and rescued dogs.<br />NO minus to this product other then the p
rice,I can not afford to use it as much as I would like.
```

[5.1] Removal of html Tags :

In [20]:

```
#function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

cleanhtml("<br />This is the only treat that is healthy and loved by all 4 legged being
s in my home!<br />It does not contain sugar or grains")
```

Out[20]:

```
' This is the only treat that is healthy and loved by all 4 legged beings
in my home! It does not contain sugar or grains'
```

[5.2] Removal of Punctuations and unecessary characters :

In [21]:

```
#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#|@|~|%|*]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned

cleanpunc("WHYYYY do companies add sugar,beet pulp or corn syrup to carnivore foods?")
```

Out[21]:

```
'WHYYYY do companies add sugar beet pulp or corn syrup to carnivore foods'
```

[5.3] StopWords :

In [22]:

```
import nltk
nltk.download('punkt')
nltk.download('stopwords')

stop = set(stopwords.words('english')) #set of stopwords
print(stop)
print("*********************************************************************")
print("No. of stop words: ",len(stop))
```

```
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
{'they', 'having', 'by', 'other', 'you', 'from', 'that', 'which', 'he', "n
eedn't", 'shan', "mightn't", 'd', 'me', 'wouldn', 'has', 'yourselves', 'he
re', 'both', "shan't", "doesn't", 'can', 'is', 'ain', 'into', 'or', 'sam
e', 't', 'again', "you're", 'are', 'mustn', 'under', 'further', 'hers', 'a
s', 'himself', "hadn't", 'few', 'have', 'below', 'hasn', 'off', 'until',
'my', 'she', 's', 'should', 'once', 'its', 'nor', 'where', 'haven', 'mor
e', 'how', 'too', 'just', 'were', "don't", 'of', "hasn't", 'before', "coul
dn't", 'm', "shouldn't", 'not', 'hadn', 'her', 'ourselves', "it's", 'our',
'but', 'after', 'did', "haven't", 'herself', 'am', 'themselves', 'be',
'a', "wasn't", 'ma', "weren't", 'own', 'these', 'yours', 'wasn', 'itself',
'an', 'your', 'shouldn', 'weren', 'being', 'out', 'to', 'their', 'him', 'y
ourself', "won't", "you'd", 've', 'only', 'aren', 'during', 'couldn', 'tho
se', 'isn', 're', 'against', 'all', "you've", 'at', 'some', "aren't", 'an
d', 'above', 'the', 'about', "wouldn't", 'over', 'because', 'was', 'does',
'will', 'what', 'no', 'who', 'most', 'very', 'up', "isn't", 'with', 'now',
"should've", 'won', 'y', 'needn', "you'll", 'his', 'why', 'theirs', 'who
m', 'don', 'it', 'doing', 'each', 'had', 'do', 'we', 'ours', 'while', 'i',
'myself', 'there', 'such', 'o', 'any', 'been', "she's", 'when', 'between',
'll', 'doesn', "didn't", "mustn't", 'than', 'through', 'on', 'then', 'the
m', 'so', 'didn', "that'll", 'down', 'this', 'for', 'mightn', 'if', 'in'}
*********************************************************************
No. of stop words:  179
```

In [23]:

```
exceptions = ["aren't","mightn","wasn","hadn","don't","against","hadn't","shan","were
n't","didn","don","hasn't", \
              "hasn","shouldn","didn't","wouldn","wasn't","needn't","shouldn't","would
n't","aren","isn't","doesn't", \
              "nor","not","needn","couldn't","mightn't","mustn","mustn't","ain","sha
n't","haven","won't","couldn","isn", \
              "weren","haven't","no","haven't"]
new_stop = []
for i in stop:
    if i not in exceptions:
        new_stop.append(i)


print("No. of stop words after removing exceptions: ",len(new_stop))
```

```
No. of stop words after removing exceptions:  140
```

[5.4] Stemming :

In [24]:

```
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

print("Orginal word: beautiful" + "|" +  "Stem word: " + sno.stem('beautiful'))
print("Orginal word: beauty" + "|" +  "Stem word: " + sno.stem('beauty'))
print("Orginal word: loved" + "|" +  "Stem word: " + sno.stem('loved'))
print("Orginal word: loving" + "|" +  "Stem word: " + sno.stem('loving'))
```

```
Orginal word: beautiful|Stem word: beauti
Orginal word: beauty|Stem word: beauti
Orginal word: loved|Stem word: love
Orginal word: loving|Stem word: love
```

Observation:-
We can see words like "beautiful" and "beauty" have their stem as "beauti","loved" and "loving" have their stem as "love".
Hence it helps in reducing the dimensions by taking the root stem of words.

[5.5] Implementing the preprocessing steps one by one on all the reviews of dataset :

In [22]:

```
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''

for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTML tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in new_stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describ
e positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describ
e negative reviews reviews
                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

    final_string.append(str1)
    i+=1
```

In [23]:

```
from nltk.probability import FreqDist
pdist = FreqDist(all_positive_words)
top_positive = pdist.most_common(20)
print("Top 20 Positive words ocuring frequenty in reviews:")
top_positive
```

```
Top 20 Positive words ocuring frequenty in reviews:
```

Out[23]:

```
[(b'not', 146568),
 (b'like', 139160),
 (b'tast', 128865),
 (b'good', 112601),
 (b'flavor', 109329),
 (b'love', 107172),
 (b'use', 103792),
 (b'great', 103670),
 (b'one', 96529),
 (b'product', 90912),
 (b'tri', 86683),
 (b'tea', 83699),
 (b'coffe', 78763),
 (b'make', 75004),
 (b'get', 71996),
 (b'food', 64539),
 (b'would', 55477),
 (b'time', 55184),
 (b'buy', 54137),
 (b'realli', 52657)]
```

In [24]:

```
ndist = FreqDist(all_negative_words)
top_negative = ndist.most_common(20)
print("Top 20 Negative words ocuring frequenty in reviews:")
top_negative
```

```
Top 20 Negative words ocuring frequenty in reviews:
```

Out[24]:

```
[(b'not', 54325),
 (b'tast', 34534),
 (b'like', 32271),
 (b'product', 28181),
 (b'one', 20544),
 (b'flavor', 19520),
 (b'would', 17947),
 (b'tri', 17718),
 (b'use', 15280),
 (b'good', 15024),
 (b'coffe', 14700),
 (b'get', 13775),
 (b'buy', 13742),
 (b'order', 12862),
 (b'food', 12720),
 (b'dont', 11865),
 (b'tea', 11646),
 (b'even', 11068),
 (b'box', 10833),
 (b'amazon', 10067)]
```

[5.6] Adding a new column of CleanedText which displays the data after pre-processing of the review :

In [27]:

```
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

In [26]:

```
final[['Text','CleanedText']].head(10)
```

Out[26]:

	Text	CleanedText
476617	This product by Arche...	product archer farm b...
22621	Our dogs just love th...	dog love saw pet stor...
22620	My dogs loves this ch...	dog love chicken prod...
284375	This book is easy to ...	book easi read ingred...
157850	I have been feeding m...	feed greyhound treat ...
157849	This is one product t...	one product welsh ter...
157833	This is the ONLY dog ...	dog treat lhasa apso ...
157832	These liver treas are...	liver trea phenomen r...
157837	This was the only tre...	treat dog like obedi ...
157831	No waste , even if sh...	wast even day goe hun...

[5.7] Using SQLite Table to load data after preprocessing of reviews :

In [ ]:

```
# store final result into an SQLLite table for future.
conn = sqlite3.connect('final.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn,  schema=None, if_exists='replace', index=True, index_labe
l=None, chunksize=None, dtype=None)
```

In [26]:

```
# using the SQLite Table to read data.
conn = sqlite3.connect('final.sqlite')

final = pd.read_sql_query(""" SELECT * FROM Reviews """,conn)
```

In [27]:

```
#Listing out the number of positive and negative reviews
final = final.reset_index(drop=True)
final['Score'].value_counts()
```

Out[27]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

In [28]:

```
(final['Score'].value_counts()/len(final['Score']))*100
```

Out[28]:

```
positive    84.314313
negative    15.685687
Name: Score, dtype: float64
```

[6] Train and Test Split of Data :

Sorting the data by Time :

In [29]:

```
final=final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort'
, na_position='last')
final.head()
```

Out[29]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNun
387	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0
293	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1
386	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0
209	346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2
271	346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19

Considering negative reviews to be 0 and positive reviews to be 1 :

In [31]:

```
def reviews(x):
    if x == "positive":
        return 1
    else:
        return 0

final['Score'] = final['Score'].map(reviews)
final.head()
```

Out[31]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessN
387	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0
293	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1
386	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0
209	346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2
271	346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19

Time Based Slicing :

- **Diving the data to Train set(first 70% ie older data) and Test Set(last 30% ie recent data)**

In [32]:

```
from sklearn.model_selection import train_test_split

X = final["CleanedText"].values
y = final["Score"].values
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size = 0.3,shuffle = False)
```

In [33]:

```
print("Shape of X_train: ",X_train.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of X_test: ",X_test.shape)
print("Shape of y_test: ",y_test.shape)
```

```
Shape of X_train:  (254519,)
Shape of y_train:  (254519,)
Shape of X_test:  (109080,)
Shape of y_test:  (109080,)
```

In [34]:

```
dumpfile(X,"X")
dumpfile(y,"y")
dumpfile(X_train,"X_train")
dumpfile(y_train,"y_train")
dumpfile(X_test,"X_test")
dumpfile(y_test,"y_test")
```

In [4]:

```
X = loadfile("X")
y = loadfile("y")
X_train = loadfile("X_train")
y_train = loadfile("y_train")
X_test = loadfile("X_test")
y_test = loadfile("y_test")
```

[7] Logistic Regression :

Grid Search Crossvalidation:

[7.1] Function to find the optimal hyperparameter(C = 1/λ) and error using K-fold cross-validation :

- **Taking C between range 0.0001 and 1000.**
- **Performing 10 fold cross validation on Train Data**
- **Finding the optimal C**
- **Plotting between CV error/CV Accuracy and C(1/λ)**

In [ ]:

```
from sklearn.model_selection import TimeSeriesSplit
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score as cv
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve,auc
import warnings
warnings.filterwarnings('ignore')
```

```
def LR_gridTrain(X_train,y_train,penalty):


    C_values = [0.0001,0.001, 0.01, 0.1, 1, 5 , 10, 50, 100, 1000]
    param_grid = dict(C = C_values)

    model = LogisticRegression(penalty = penalty)
    grid = GridSearchCV(model, param_grid, cv=10, scoring='accuracy')
    grid.fit(X_train, y_train)

    grid_mean_scores = [i.mean_validation_score for i in grid.grid_scores_]

    #Misclassification error
    MSE = [1 - x for x in grid_mean_scores]

    #Finding the optimal K
    optimal_C = grid.best_params_

    best_accuracy = np.round(grid.best_score_ * 100,3)

    print("\n\033[1mOptimal C:\033[0m ", optimal_C)
    print("\n\033[1mCrossValidation Error:\033[0m {}".format(np.round(min(MSE),3)))
    print("\n\033[1mCrossValidation Accuracy:\033[0m {} %\n\n".format(best_accuracy))

    plt.figure(figsize=(20,6))
    plt.style.use('fivethirtyeight')
    plt.subplot(121)
    plt.plot(C_values,MSE, 'r-o')
    for xy in zip(C_values, np.round(MSE,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Error vs C = 1/λ ")
    plt.xlabel("C = 1/λ")
    plt.ylabel("CV Error")
    plt.grid(True)

    plt.subplot(122)
    plt.plot(C_values,grid_mean_scores, 'g-o')
    for xy in zip(C_values, np.round(grid_mean_scores,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Accuracy vs C = 1/λ")
    plt.xlabel("C = 1/λ")
    plt.ylabel("CV Accuracy")
    plt.grid(True)
    plt.show()


    print("\n\033[1mCV Error for each value of C:\033[0m ",np.round(MSE,3))
    print("\n\033[1mCV Accuracy for each value of C:\033[0m ",np.round(grid_mean_scores
,3))
```

RandomSearch Crossvalidation: To find a better hyperparameter value in fewer number of experiments. Here the hyperparameter (C = 1/λ) is defined as a distribution rather than list of values.Here ,I use exponential distribution.

In [6]:

```
from sklearn.grid_search import RandomizedSearchCV
from scipy.stats import expon
import warnings
warnings.filterwarnings('ignore')

def LR_randomTrain(X_train,y_train,penalty):


    C_dist = expon(scale = 2)
    param_grid = dict(C = C_dist)

    model = LogisticRegression(penalty = penalty)
    random_grid = RandomizedSearchCV(model, param_grid, cv=10, scoring='accuracy')
    random_grid.fit(X_train, y_train)

    #Finding the optimal K
    optimal_C = random_grid.best_params_

    #Cv Accuracy
    best_accuracy = np.round(random_grid.best_score_ * 100,3)

    #Cv Error
    MSE = np.round((1 -random_grid.best_score_),3)


    print("\n\033[1mOptimal C:\033[0m ", optimal_C)
    print("\n\033[1mCrossValidation Error:\033[0m {}".format(MSE))
    print("\n\033[1mCrossValidation Accuracy:\033[0m {} %\n\n".format(best_accuracy))
```

[7.2] Function to predict on Test Data :

- **Plotting the Confusion matrix**
- **Plotting the ROC/AUC Curve**
- **Finding Acurracy,Precission,Recall and F1 Score on Test Data**

True Negative : Number of datapoints with class label "negative" correctly classified as "negative".
False Positive : Number of datapoints with class label "negative" misclassified as "positive".
False Negative : Number of datapoints with class label "positive" misclassified as "negative".
True Positive: Number of datapoints with class label "positive" correctly classified as "positive".
Precision : True Positive/(True Positive + False Positive)
Recall : True Positive/(True Positive + False Negative)

In [7]:

```
def LR_Test(X_train,X_test,y_train,y_test,penalty,optimal_C):

    optimal_model = LogisticRegression(C = optimal_C, penalty = penalty)
    optimal_model.fit(X_train, y_train)
    y_pred = optimal_model.predict(X_test)


    ##--------------Confusion Matrix and Performance metrics--------------##
    accuracy = accuracy_score(y_test,y_pred) * 100
    precision = precision_score(y_test,y_pred,average= 'macro')
    recall = recall_score(y_test,y_pred,average= 'macro')
    f1= f1_score(y_test,y_pred,average= 'macro')
    MSE = (1 - (accuracy/100))
    cm = confusion_matrix(y_test, y_pred)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    cm_df = pd.DataFrame(cm,
                     index = ['negative','positive'],
                     columns = ['negative','positive'])
    sns.heatmap(cm_df, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    print(cm)
    print("\n\033[1mTest Error :\033[0m {}".format(np.round(MSE,3)))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))
    print("\033[1mTrue Negative :\033[0m {}".format(tn))
    print("\033[1mFalse Positive :\033[0m {}".format(fp))
    print("\033[1mFalse Negative :\033[0m {}".format(fn))
    print("\033[1mTrue Positive :\033[0m {}".format(tp))
    print("\33[1mPrecission Score :\033[0m {}".format(np.round(precision,3)))
    print("\33[1mRecall Score :\033[0m {}".format(np.round(recall,3)))
    print("\33[1mF1 Score :\033[0m {}".format(np.round(f1,3)))

    print("\n\n")

    ##--------------ROC Curve--------------##
    fpr,tpr,thresholds = roc_curve(y_test,y_pred)
    roc_auc = auc(fpr,tpr)

    plt.figure(figsize=(8,6))
    plt.style.use('fivethirtyeight')
    plt.plot(fpr,tpr,'b',label="AUC = {}".format(roc_auc))
    plt.plot([0,1],[0,1],'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.title("Receiver Operating Characteristic")
    plt.legend()
    plt.grid(True)
    plt.show()
```

[7.3] Function to check the behaviour of sparsity on weight vectors on increasing C= 1/λ in L1 regularization :

In [8]:

```
def sparsity_check(X_train,X_test,y_train,y_test):
    C_values = [10,1,0.1,0.01,0.001,0.0001]

    for i in C_values :
        start = time.clock()
        print("\n\033[1mSparsity and Accuarcy when C = {}\033[0m".format(i))
        model = LogisticRegression(penalty = 'l1',C = i)
        model.fit(X_train,y_train)
        y_pred = model.predict(X_test)
        accuracy = accuracy_score(y_test,y_pred) * 100
        train_error = 1 - model.score(X_train,y_train)
        test_error = 1 - model.score(X_test,y_test)

        print("Number of non-zero weighhts: ",np.count_nonzero(model.coef_))
        print("Train Error: ",np.round(train_error,3))
        print("Test Error: ",np.round(test_error,3))
        print("Test Accuracy :",np.round(accuracy_score(y_test,y_pred),5))
        print("Run Time :{} sec".format(time.clock() - start))
```

[7.4] Multicollinearity Check (Pertubation Test) :

- **Finding the weight vector with X_train**
- **Adding a small random noise with X_train and finding the new weight vecor by fitting to logistic model**
- **Setting a threshold of 30%,if the difference between orginal weight vector and new weight vector is more than 30%,then said to be multicollinear**

In [9]:

```
from scipy.sparse import find

def multicollinear_check(X_train,X_test,y_train,y_test,optimal_C,threshold = 30):

    print("\033[1m-----------BEFORE PERTUBATION TEST------------\033[0m\n")


    model = LogisticRegression(C = optimal_C, penalty = 'l2')
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test,y_pred) * 100
    weights = model.coef_
    print("\033[1mSample Weights:\033[0m ",pd.DataFrame(weights))
    print("\033[1mSize of weight vector:\033[0m ",weights.size)
    print("\033[1mNon zero weights:\033[0m ",np.count_nonzero(model.coef_))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))


    #--------------------Adding a small random nosie(epsilon) to weight vector---------
---------#
    X_trainnew = X_train
    #contains the row indices, column indices and values of the nonzero matrixes
    row,column,values = find(X_trainnew)

    np.random.seed(0)
    noise = np.random.normal(loc = 0, scale = 0.01, size = (find(X_trainnew)[0].size,))
.astype(np.float16)
    X_trainnew[row,column] = noise + X_trainnew[row,column]


    print("\n\033[1m-----------AFTER PERTUBATION TEST------------\033[0m\n")


    model_new = LogisticRegression(C = optimal_C, penalty = 'l2')
    model_new.fit(X_trainnew, y_train)
    y_prednew = model_new.predict(X_test)
    accuracy_new = accuracy_score(y_test,y_prednew) * 100
    weights_new = model_new.coef_
    print("\033[1mSample Weights:\033[0m ",pd.DataFrame(weights_new))
    print("\033[1mSize of weight vector:\033[0m ",weights_new.size)
    print("\033[1mNon zero weights:\033[0m ",np.count_nonzero(model_new.coef_))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy_new,3)))


    weight_difference = abs((weights - weights_new)/weights) * 100
    total = (weight_difference > threshold).sum()
    print("\n\n\033[1mNumber of features with weights changing greater than 30% :\033[0
m",total)
    print("\n\033[1mFollowing are the {} features that are multicollinear\033[0m".forma
t(total))
    size = np.shape(weight_difference)[1]
    for i in range(size):
        if weight_difference[0][i] > threshold:
            print(i, end = ' ')
```

[7.4] Feature Importance :

- **Only finding the important features for each class in BOW and TFIDF**

In [10]:

```
def feature_imortance(X_train,X_test,y_train,y_test,optimal_C,vectorizer, n = 25):

    model = LogisticRegression(C = optimal_C, penalty = 'l2')
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    #------------------Feature Importance-------------------------------#
    class_labels = model.classes_
    feature_names = vectorizer.get_feature_names()
    top_negative = sorted(zip(model.coef_[0], feature_names))[:n]
    top_positive= sorted(zip(model.coef_[0], feature_names))[-n:]

    print("\n\n\033[1m------------Top {} Negative Words with high Importance-----------
-\033[0m".format(n))
    neg_featureimp_df = pd.DataFrame(top_negative, columns=['Coeficient Factor','Featur
es'])
    print(neg_featureimp_df.to_string(index=False))


    print("\n\033[1m------------Top {} Positive Words with high Importance------------
\033[0m".format(n))
    pos_featureimp_df = pd.DataFrame(top_positive, columns=['Coeficient Factor','Featur
es'],)
    print(pos_featureimp_df.to_string(index=False))
```

[8] Featurization Methods :

[8.1] Bag Of Words(unigram) :

In [46]:

```
%%time
bow_unigram = CountVectorizer(min_df = 0.0005)
X_train_bowuni = bow_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowuni))
print("The shape of text BOW vectorizer: ", X_train_bowuni.get_shape())
print("Number of unique word: ", X_train_bowuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 3878)
Number of unique word:  3878
CPU times: user 11.6 s, sys: 32 ms, total: 11.6 s
Wall time: 11.6 s
```

In [47]:

```
%%time
X_test_bowuni = bow_unigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowuni.get_shape())
print("Number of unique word: ", X_test_bowuni.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 3878)
Number of unique word:  3878
CPU times: user 5.53 s, sys: 4 ms, total: 5.54 s
Wall time: 5.54 s
```

In [48]:

```
dumpfile(X_train_bowuni,"X_train_bowuni")
dumpfile(X_test_bowuni,"X_test_bowuni")
```

In [11]:

```
X_train_bowuni = loadfile("X_train_bowuni")
X_test_bowuni = loadfile("X_test_bowuni")
```

In [12]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_bowuni_std = sc.fit_transform(X_train_bowuni)
```

In [13]:

```
X_test_bowuni_std = sc.transform(X_test_bowuni)
```

In [14]:

```
print("Shape of Training Data: ",X_train_bowuni_std.shape)
print("Shape of Test Data: ",X_test_bowuni_std.shape)
```

```
Shape of Training Data:  (254519, 3878)
Shape of Test Data:  (109080, 3878)
```

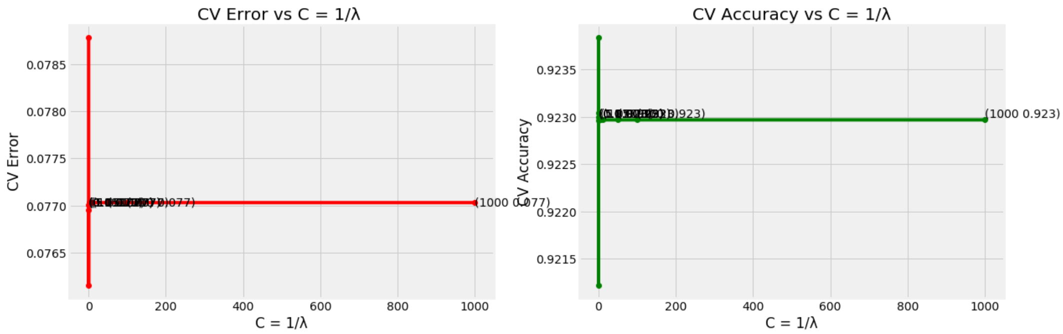
[8.1.1] Using GridSearch CV :

L2 Regularization :

In [15]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_bowuni_std, y_train, penalty = 'l2')
```

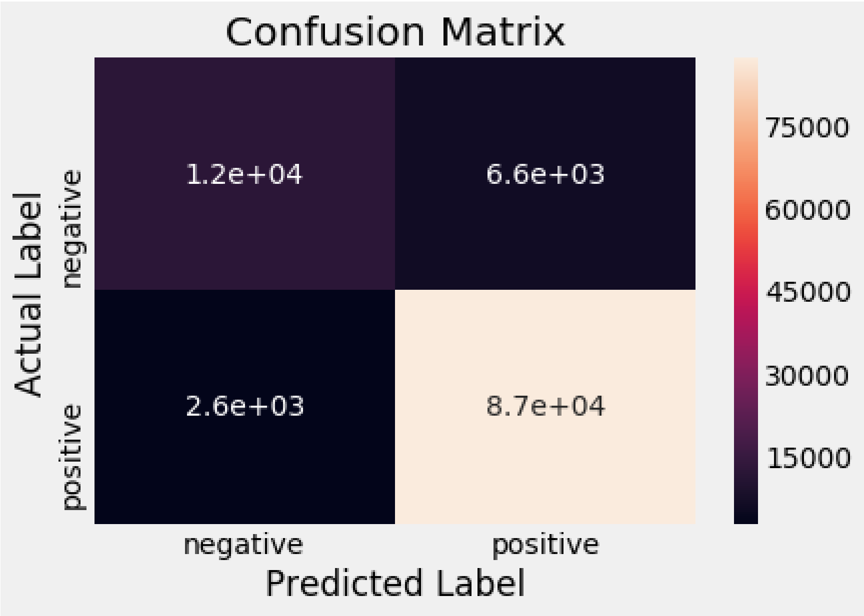
```
Optimal C:  {'C': 0.001}

CrossValidation Error: 0.076

CrossValidation Accuracy: 92.384 %
```



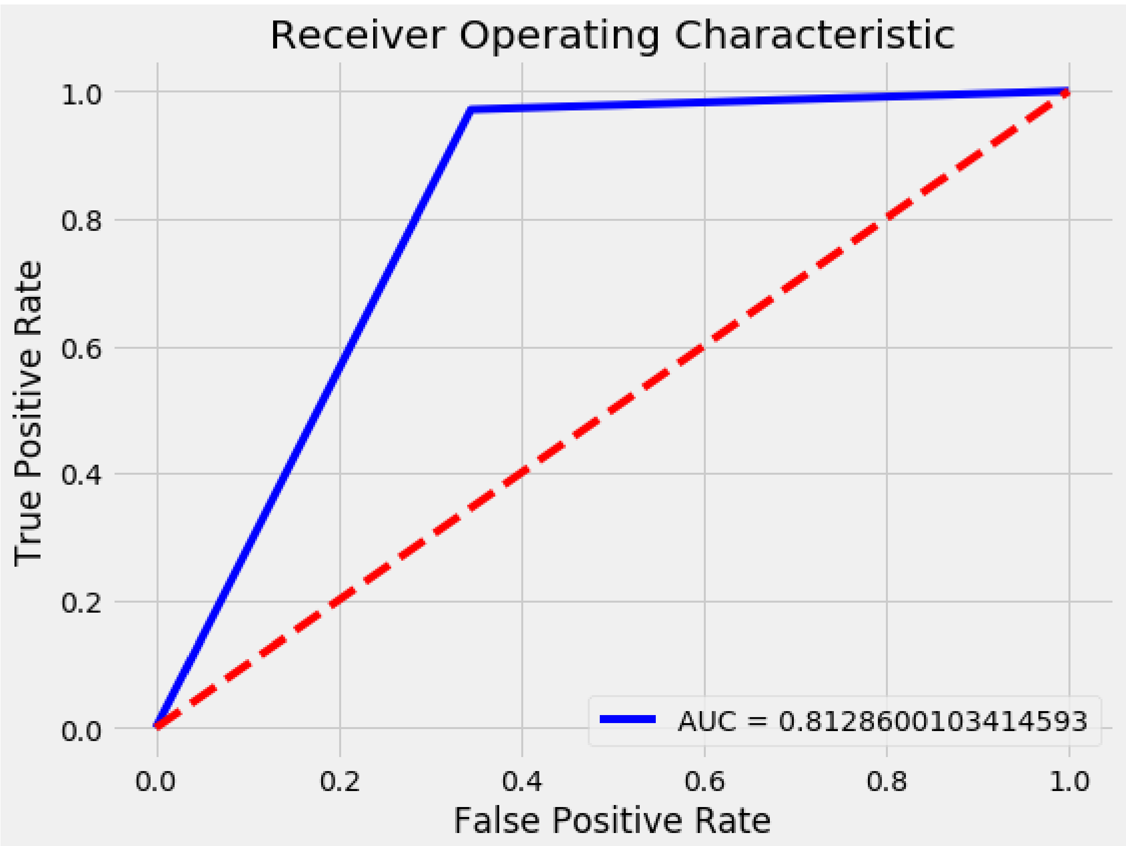

```
CV Error for each value of C:  [0.079 0.076 0.077 0.077 0.077 0.077 0.077
 0.077 0.077 0.077]

CV Accuracy for each value of C:  [0.921 0.924 0.923 0.923 0.923 0.923 0.9
23 0.923 0.923 0.923]
CPU times: user 9min 25s, sys: 2.56 s, total: 9min 27s
Wall time: 9min 27s
```

In [78]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowuni_std, X_test_bowuni_std, y_train, y_test, 'l2', 0.001)
```




```
[[12473  6574]
 [ 2623 87410]]

Test Error : 0.084
Test Accuracy : 91.569 %
True Negative : 12473
False Positive : 6574
False Negative : 2623
True Positive : 87410
Precission Score : 0.878
Recall Score : 0.813
F1 Score : 0.84
```



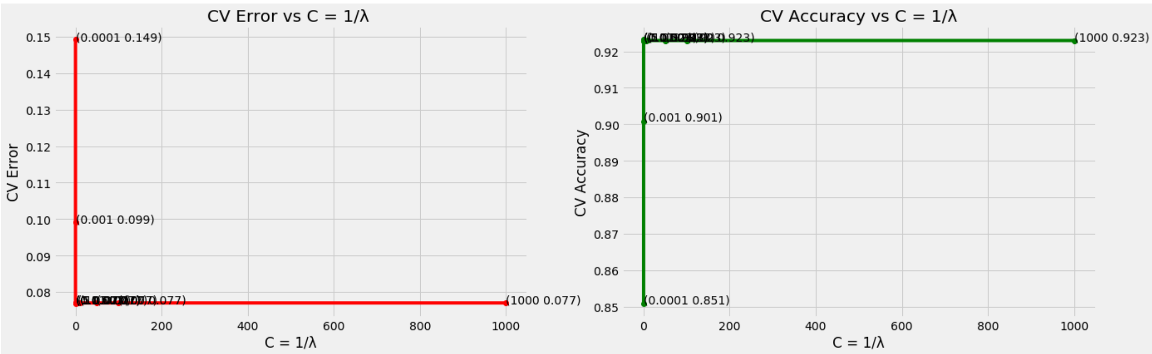
```
CPU times: user 3.68 s, sys: 8 ms, total: 3.69 s
Wall time: 3.33 s
```

L1 Regularization :

In [75]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_bowuni_std, y_train, penalty = 'l1')
```

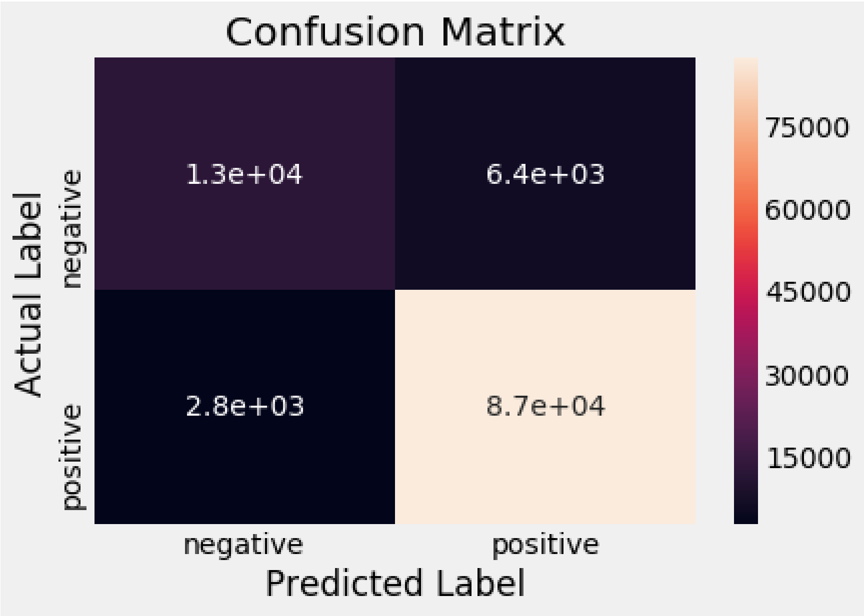
```
Optimal C:  {'C': 0.1}

CrossValidation Error: 0.077

CrossValidation Accuracy: 92.325 %
```



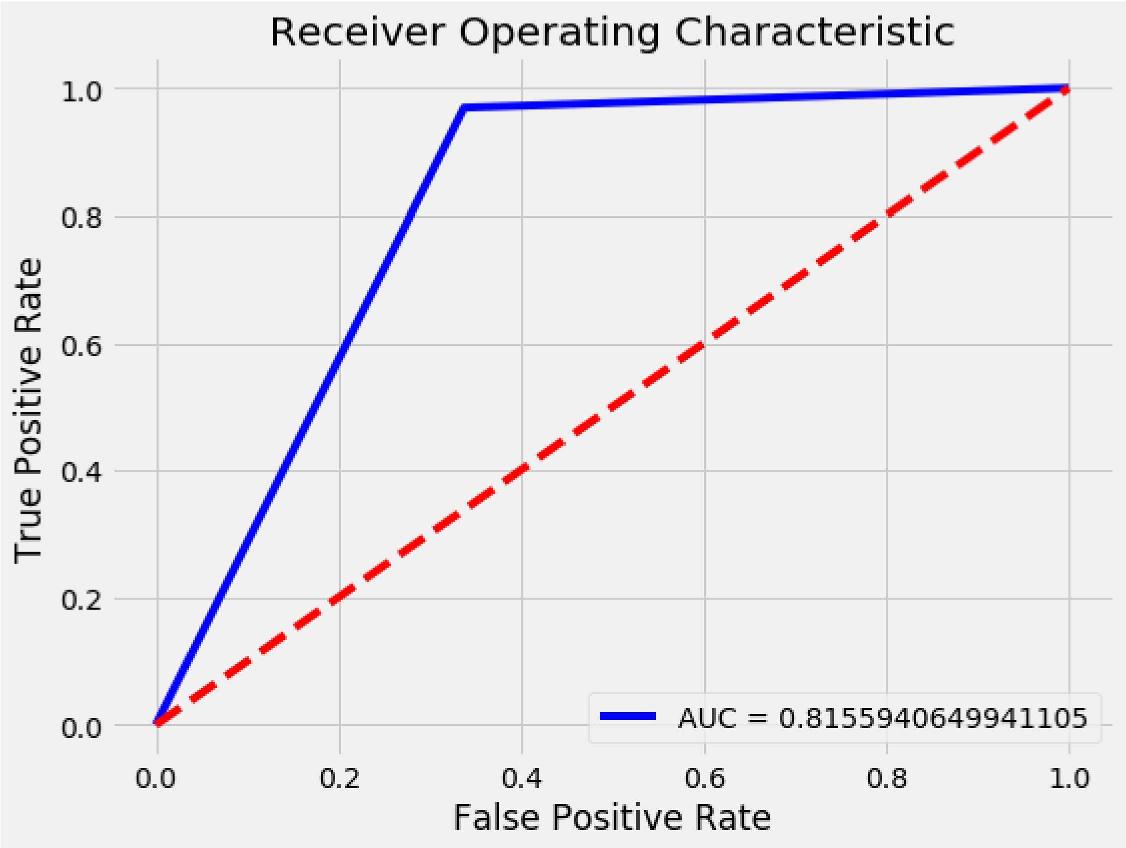

```
CV Error for each value of C:  [0.149 0.099 0.077 0.077 0.077 0.077 0.077
 0.077 0.077 0.077]

CV Accuracy for each value of C:  [0.851 0.901 0.923 0.923 0.923 0.923 0.9
23 0.923 0.923 0.923]
CPU times: user 3min 52s, sys: 2.01 s, total: 3min 54s
Wall time: 3min 54s
```

In [79]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowuni_std, X_test_bowuni_std, y_train, y_test, 'l1', 0.1)
```




```
[[12611  6436]
 [ 2783 87250]]

Test Error : 0.085
Test Accuracy : 91.548 %
True Negative : 12611
False Positive : 6436
False Negative : 2783
True Positive : 87250
Precission Score : 0.875
Recall Score : 0.816
F1 Score : 0.841
```




```
CPU times: user 3.9 s, sys: 28 ms, total: 3.92 s
Wall time: 3.61 s
```

[8.1.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [17]:

```
if __name__ == "__main__":
    sparsity_check(X_train_bowuni_std, X_test_bowuni_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  3876
Train Error:  0.069
Test Error:  0.084
Test Accuracy : 0.91569
Run Time :2.9262080000000004 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  3850
Train Error:  0.069
Test Error:  0.084
Test Accuracy : 0.91566
Run Time :2.668768 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  3714
Train Error:  0.069
Test Error:  0.085
Test Accuracy : 0.91547
Run Time :2.7338950000000004 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  2539
Train Error:  0.072
Test Error:  0.085
Test Accuracy : 0.91451
Run Time :2.7871330000000007 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  349
Train Error:  0.097
Test Error:  0.109
Test Accuracy : 0.891
Run Time :1.5401930000000004 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  11
Train Error:  0.149
Test Error:  0.174
Test Accuracy : 0.82554
Run Time :1.144057 sec
```

Observation : Here C= 1/λ, we can see as C decreases(λ increases)

- Sparsity Increases(Number of non zero elements decreases)
- Error increases and Performance accuarcy drops(model starts underfitting)
- Run Time is also fast as sparsity increases

[8.1.3] Using RandomSearch CV :

L2 Regularization :

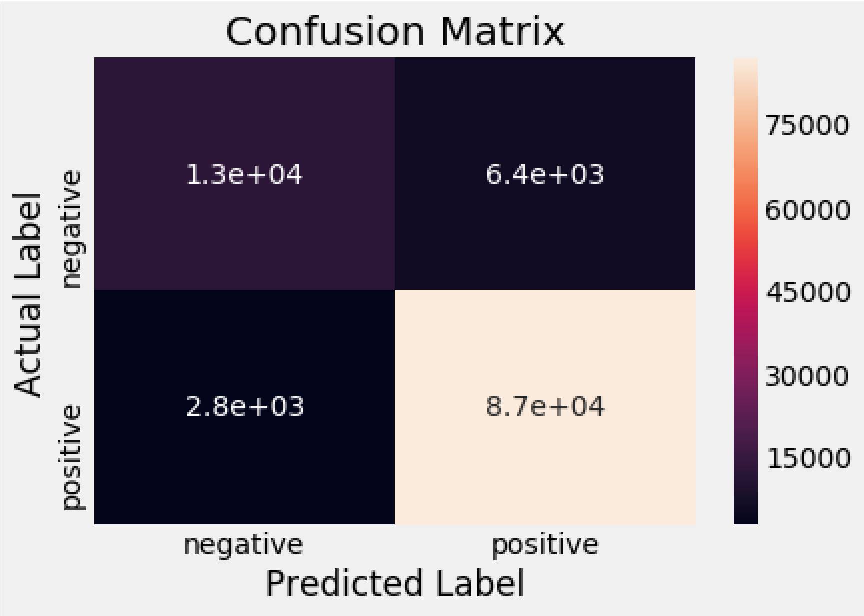
In [96]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_bowuni_std, y_train, penalty = 'l2')
```

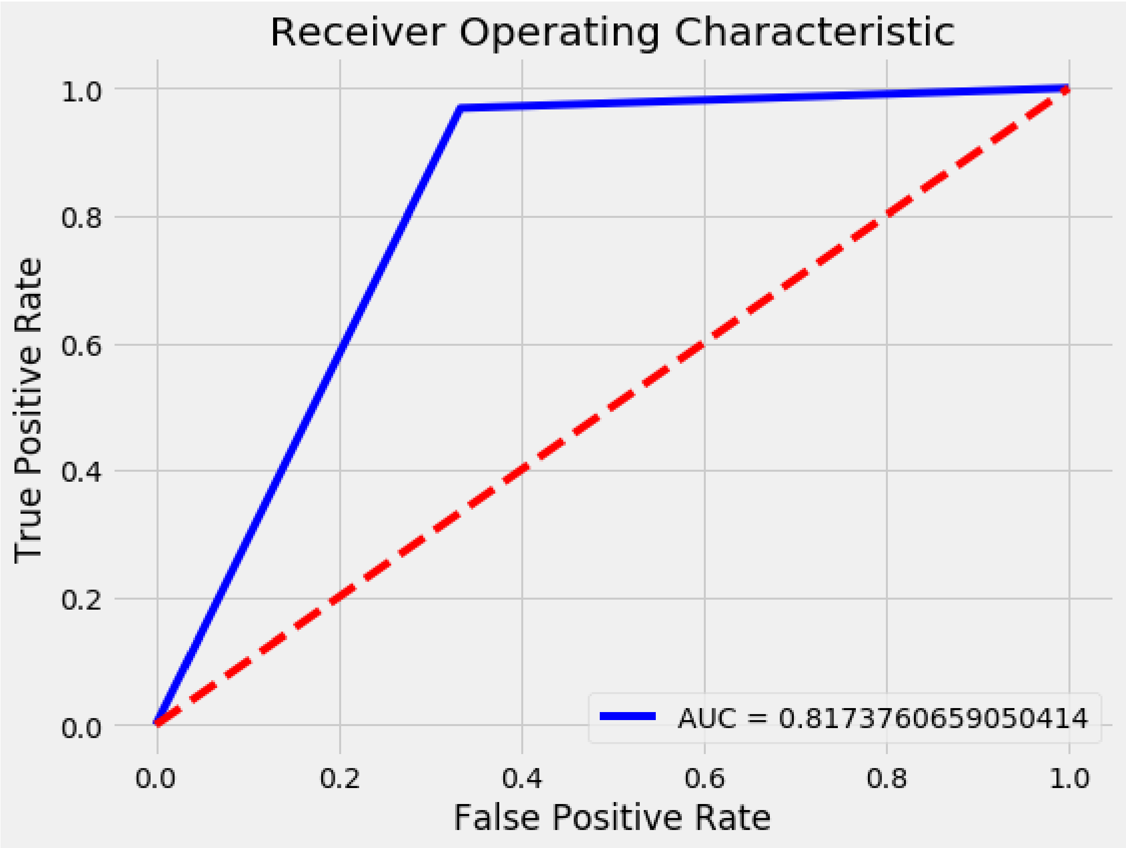
```
Optimal C:  {'C': 0.07806145232697875}

CrossValidation Error: 0.077

CrossValidation Accuracy: 92.299 %


CPU times: user 10min 47s, sys: 624 ms, total: 10min 48s
Wall time: 10min 48s
```

In [97]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowuni_std, X_test_bowuni_std, y_train, y_test, 'l2', 0.078)
```




```
[[12692  6355]
 [ 2845 87188]]

Test Error : 0.084
Test Accuracy : 91.566 %
True Negative : 12692
False Positive : 6355
False Negative : 2845
True Positive : 87188
Precission Score : 0.874
Recall Score : 0.817
F1 Score : 0.842
```




```
CPU times: user 5.82 s, sys: 12 ms, total: 5.83 s
Wall time: 5.46 s
```

L1 Regularization :

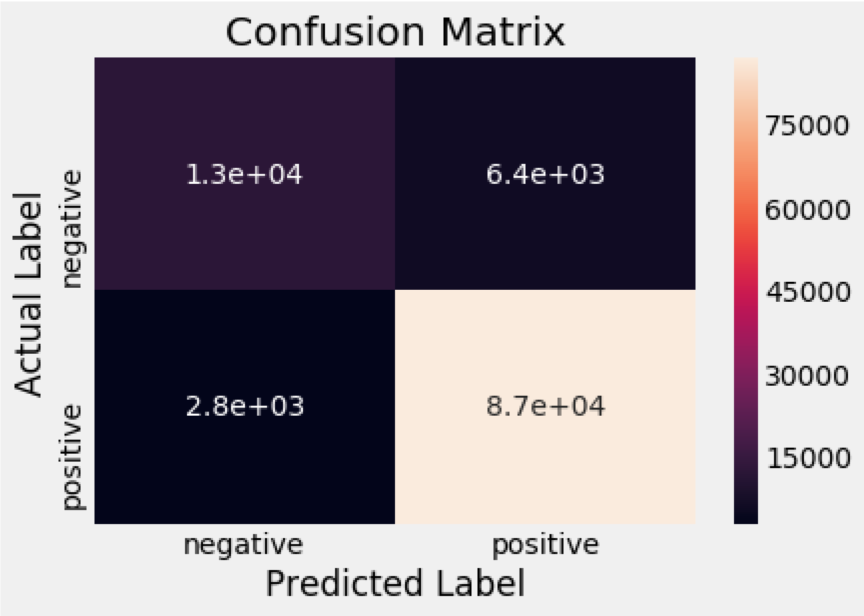
In [94]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_bowuni_std, y_train, penalty = 'l1')
```

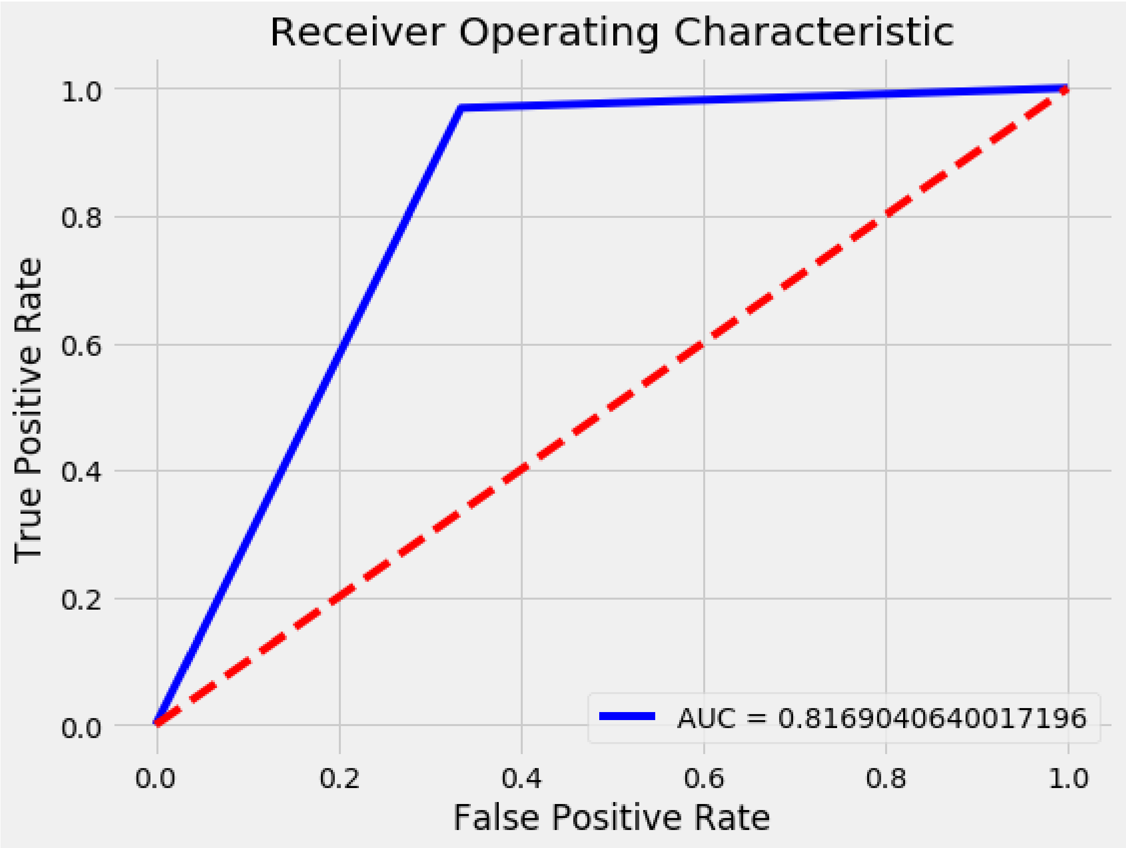
```
Optimal C:  {'C': 0.3521393406501542}

CrossValidation Error: 0.077

CrossValidation Accuracy: 92.3 %


CPU times: user 4min 31s, sys: 1.7 s, total: 4min 33s
Wall time: 4min 33s
```

In [95]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowuni_std, X_test_bowuni_std, y_train, y_test, 'l1', 0.352)
```




```
[[12670  6377]
 [ 2826 87207]]

Test Error : 0.084
Test Accuracy : 91.563 %
True Negative : 12670
False Positive : 6377
False Negative : 2826
True Positive : 87207
Precission Score : 0.875
Recall Score : 0.817
F1 Score : 0.842
```




```
CPU times: user 3.96 s, sys: 40 ms, total: 4 s
Wall time: 3.67 s
```

[8.1.4] MultiCollinearity :

In [49]:

```
if __name__ == "__main__":
    multicollinear_check(X_train_bowuni_std,X_test_bowuni_std,y_train,y_test,0.001)
```

```
-----------BEFORE PERTUBATION TEST------------

Sample Weights:         0         1         2         3         4
 5         6     \
0  0.000651  0.054345  0.037677  0.000138  0.004119 -0.008378  0.007636

       7        8         9      ...          3868      3869      3870  \
0 -0.012763  0.01727  0.022878    ...     0.012175  0.011759  0.004692

       3871      3872      3873      3874      3875      3876      3877
0 -0.017501  0.013488  0.025814  0.025312  0.010537  0.016239 -0.002453

[1 rows x 3878 columns]
Size of weight vector:  3878
Non zero weights:  3878
Test Accuracy : 91.574 %

-----------AFTER PERTUBATION TEST------------

Sample Weights:         0         1       2         3         4         5
        6     \
0  0.000654  0.054352  0.0377  0.000136  0.004148 -0.008354  0.007643

       7         8         9      ...          3868      3869      3870  \
0 -0.012724  0.017277  0.022884    ...     0.012187  0.011759  0.004678

       3871      3872      3873      3874      3875      3876     3877
0 -0.017495  0.013392  0.025791  0.025295  0.010553  0.016242 -0.00246

[1 rows x 3878 columns]
Size of weight vector:  3878
Non zero weights:  3878
Test Accuracy : 91.575 %


Number of features with weights changing greater than 30% : 11

Following are the 11 features that are multicollinear
11 479 1054 1626 1743 1797 1834 3007 3271 3495 3508
```

[8.1.5] FeatureImportance :

In [53]:

```
if __name__ == "__main__":
    feature_imortance(X_train_bowuni_std,X_test_bowuni_std,y_train,y_test,0.001,bow_uni
gram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor    Features
        -0.426936         not
        -0.281176  disappoint
        -0.209263       worst
        -0.171752          aw
        -0.171402     terribl
        -0.161840     horribl
        -0.157774        tast
        -0.157565      return
        -0.147626       money
        -0.144013    unfortun
        -0.136553     thought
        -0.132869       stale
        -0.129352       would
        -0.128290       bland
        -0.125914       threw
        -0.121448       didnt
        -0.121260        wast
        -0.118510        even
        -0.112495        weak
        -0.112317         bad
        -0.110978        mayb
        -0.110584        noth
        -0.110162        hope
        -0.108740     product
        -0.106904        yuck

------------Top 25 Positive Words with high Importance------------
Coeficient Factor Features
         0.148925     keep
         0.153824  satisfi
         0.154850     beat
         0.157583     glad
         0.161687   addict
         0.162531    enjoy
         0.163918    yummi
         0.167071   awesom
         0.170322   smooth
         0.176150     find
         0.183192    thank
         0.193714   wonder
         0.201873    happi
         0.202285     easi
         0.210035    tasti
         0.217571     amaz
         0.230436  favorit
         0.248848     nice
         0.297098    excel
         0.336582  perfect
         0.363671     good
         0.392887   delici
         0.439635     best
         0.443822     love
         0.604014    great
```

[8.2] Bag Of Words(bigram) :

In [13]:

```
%%time
bow_bigram = CountVectorizer(dtype='float', ngram_range=(1, 2), min_df = 0.0005)
X_train_bowbi = bow_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowbi))
print("The shape of text BOW vectorizer: ", X_train_bowbi.get_shape())
print("Number of unique word: ", X_train_bowbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 10711)
Number of unique word:  10711
CPU times: user 38.4 s, sys: 444 ms, total: 38.8 s
Wall time: 38.8 s
```

In [14]:

```
%%time
X_test_bowbi = bow_bigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowbi.get_shape())
print("Number of unique word: ", X_test_bowbi.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 10711)
Number of unique word:  10711
CPU times: user 11.3 s, sys: 36 ms, total: 11.4 s
Wall time: 11.4 s
```

In [15]:

```
dumpfile(X_train_bowbi,"X_train_bowbi")
dumpfile(X_test_bowbi,"X_test_bowbi")
```

In [137]:

```
X_train_bowbi = loadfile("X_train_bowbi")
X_test_bowbi = loadfile("X_test_bowbi")
```

In [138]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_bowbi_std = sc.fit_transform(X_train_bowbi)
```

In [139]:

```
X_test_bowbi_std = sc.transform(X_test_bowbi)
```

In [140]:

```
print("Shape of Training Data: ",X_train_bowbi_std.shape)
print("Shape of Test Data: ",X_test_bowbi_std.shape)
```

```
Shape of Training Data:  (254519, 10711)
Shape of Test Data:  (109080, 10711)
```

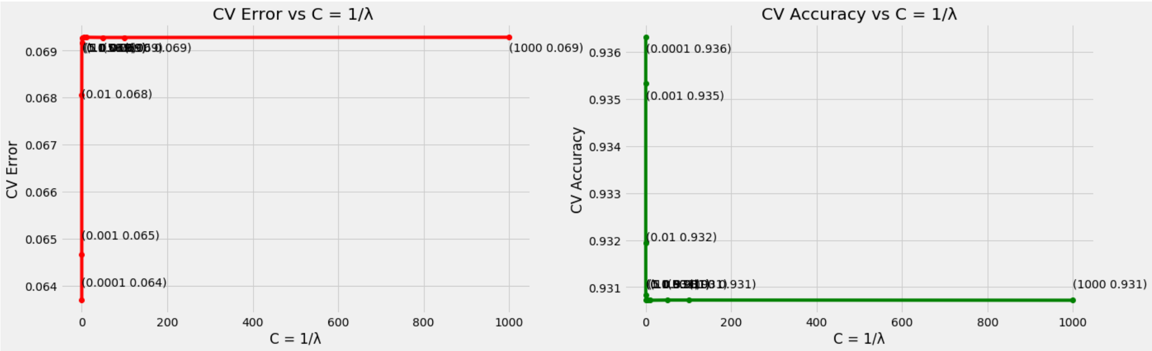
[8.2.1] Using GridSearch CV :

L2 Regularization :

In [124]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_bowbi_std, y_train, penalty = 'l2')
```

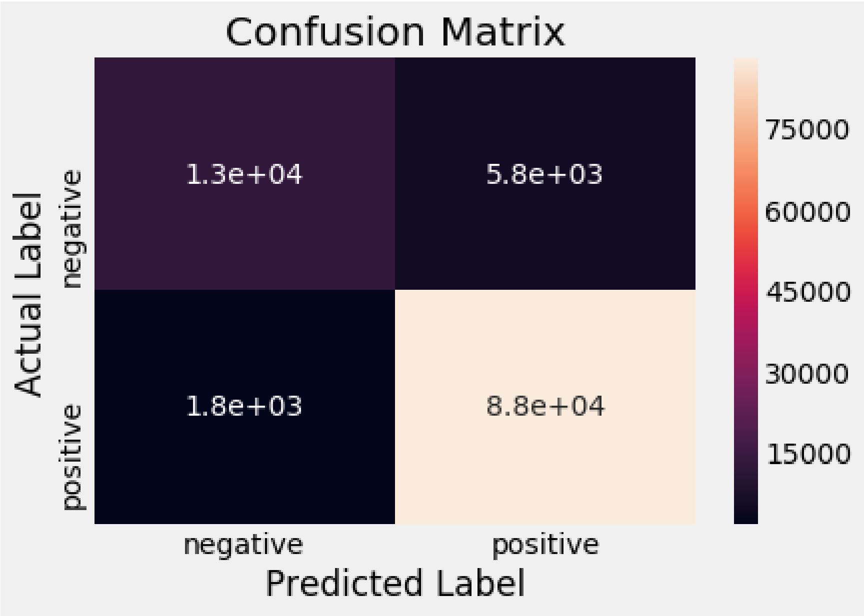
```
Optimal C:  {'C': 0.0001}

CrossValidation Error: 0.064

CrossValidation Accuracy: 93.631 %
```



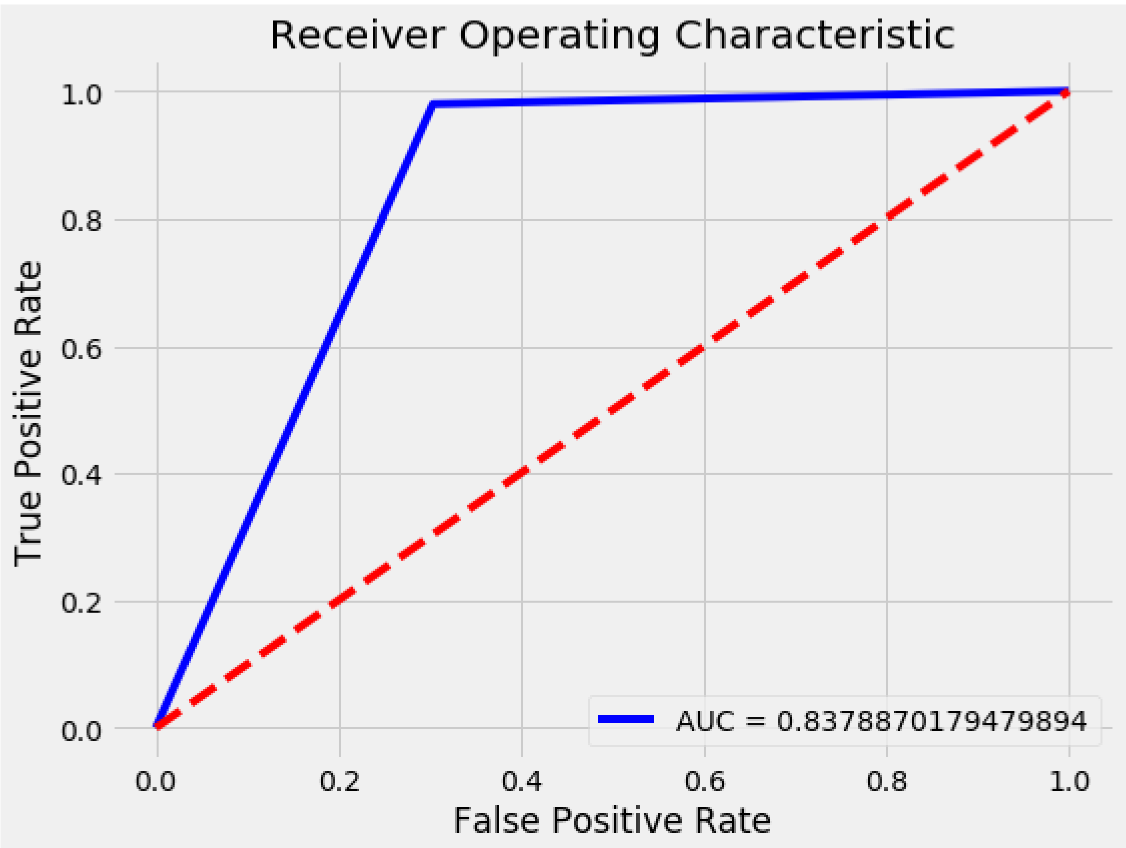

```
CV Error for each value of C:  [0.064 0.065 0.068 0.069 0.069 0.069 0.069
 0.069 0.069 0.069]

CV Accuracy for each value of C:  [0.936 0.935 0.932 0.931 0.931 0.931 0.9
31 0.931 0.931 0.931]
CPU times: user 1h 8min 23s, sys: 35.5 s, total: 1h 8min 59s
Wall time: 31min
```

In [126]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowbi_std, X_test_bowbi_std, y_train, y_test, 'l2', 0.0001)
```




```
[[13262  5785]
 [ 1846 88187]]

Test Error : 0.07
Test Accuracy : 93.004 %
True Negative : 13262
False Positive : 5785
False Negative : 1846
True Positive : 88187
Precission Score : 0.908
Recall Score : 0.838
F1 Score : 0.868
```



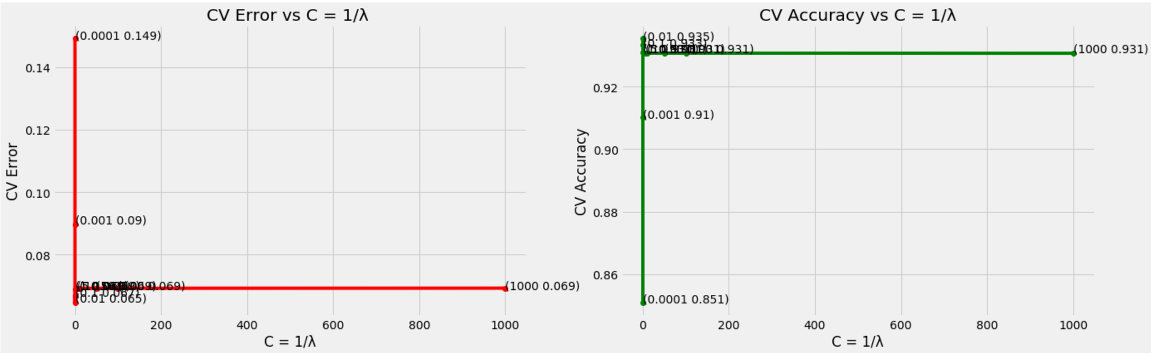
```
CPU times: user 7.15 s, sys: 48 ms, total: 7.2 s
Wall time: 3.9 s
```

L1 Regularization :

In [128]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_bowbi_std, y_train, penalty = 'l1')
```

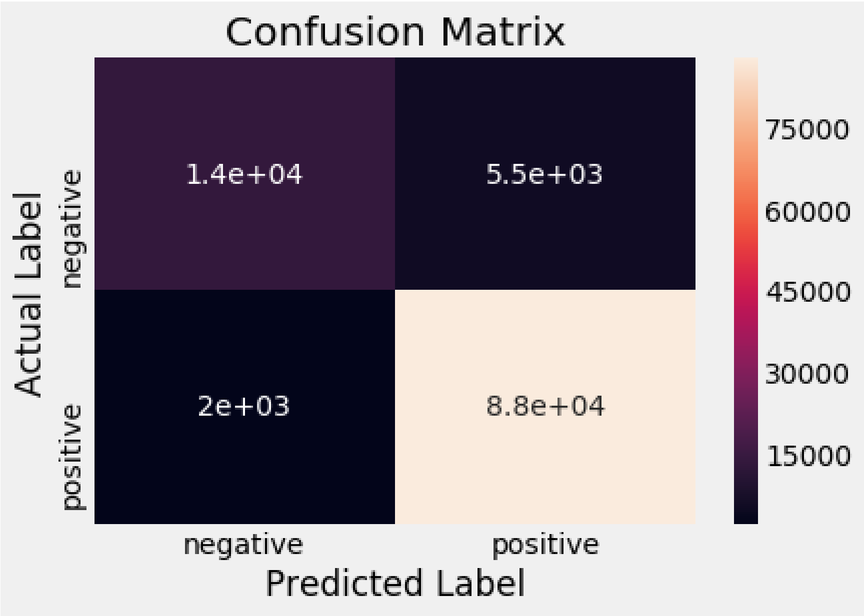
```
Optimal C:  {'C': 0.01}

CrossValidation Error: 0.065

CrossValidation Accuracy: 93.542 %
```



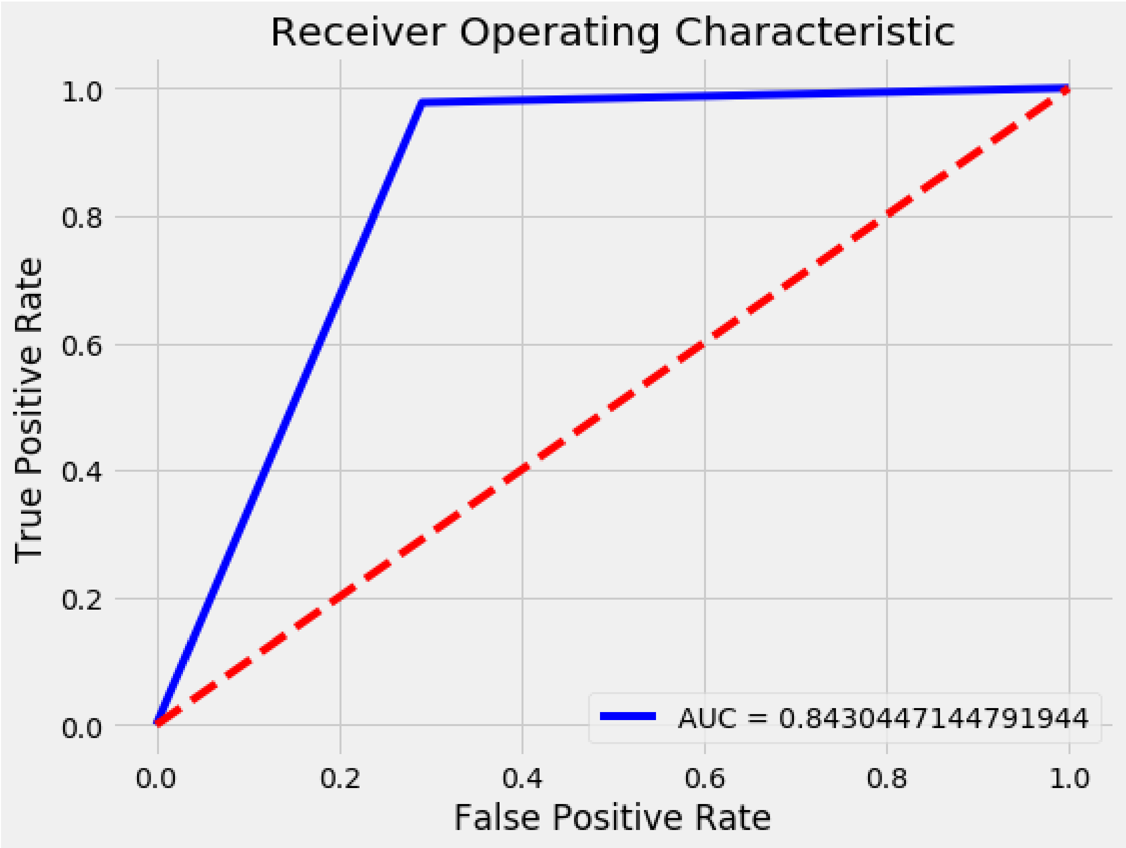

```
CV Error for each value of C:  [0.149 0.09  0.065 0.067 0.069 0.069 0.069
 0.069 0.069 0.069]

CV Accuracy for each value of C:  [0.851 0.91  0.935 0.933 0.931 0.931 0.9
31 0.931 0.931 0.931]
CPU times: user 9min 59s, sys: 3.12 s, total: 10min 2s
Wall time: 10min 2s
```

In [130]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowbi_std, X_test_bowbi_std, y_train, y_test, 'l1', 0.01)
```




```
[[13501  5546]
 [ 2047 87986]]

Test Error : 0.07
Test Accuracy : 93.039 %
True Negative : 13501
False Positive : 5546
False Negative : 2047
True Positive : 87986
Precission Score : 0.905
Recall Score : 0.843
F1 Score : 0.87
```




```
CPU times: user 4.68 s, sys: 48 ms, total: 4.73 s
Wall time: 4.39 s
```

[8.2.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [23]:

```
if __name__ == "__main__":
    sparsity_check(X_train_bowbi_std, X_test_bowbi_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  10700
Train Error:  0.046
Test Error:  0.072
Test Accuracy : 0.92789
Run Time :8.503957 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  10635
Train Error:  0.046
Test Error:  0.072
Test Accuracy : 0.92802
Run Time :8.91921 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  9917
Train Error:  0.047
Test Error:  0.07
Test Accuracy : 0.92952
Run Time :6.138832000000001 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  5251
Train Error:  0.055
Test Error:  0.07
Test Accuracy : 0.93036
Run Time :3.117297999999998 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  473
Train Error:  0.087
Test Error:  0.097
Test Accuracy : 0.90337
Run Time :1.7636930000000035 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  12
Train Error:  0.149
Test Error:  0.174
Test Accuracy : 0.82583
Run Time :1.483823000000001 sec
```

Observation : Here C= 1/λ, we can see as C decreases(λ increases)

- Sparsity Increases(Number of non zero elements decreases)
- Error increases and Performance accuarcy drops(model starts underfitting)
- Run Time is also fast as sparsity increases

[8.2.3] Using RandomSearch CV :

L2 Regularization :

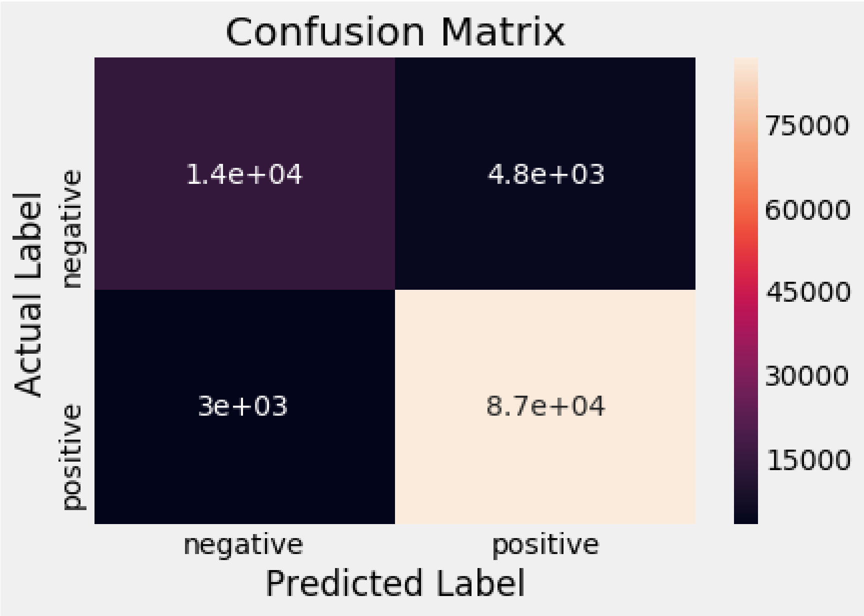
In [129]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_bowbi_std, y_train, penalty = 'l2')
```

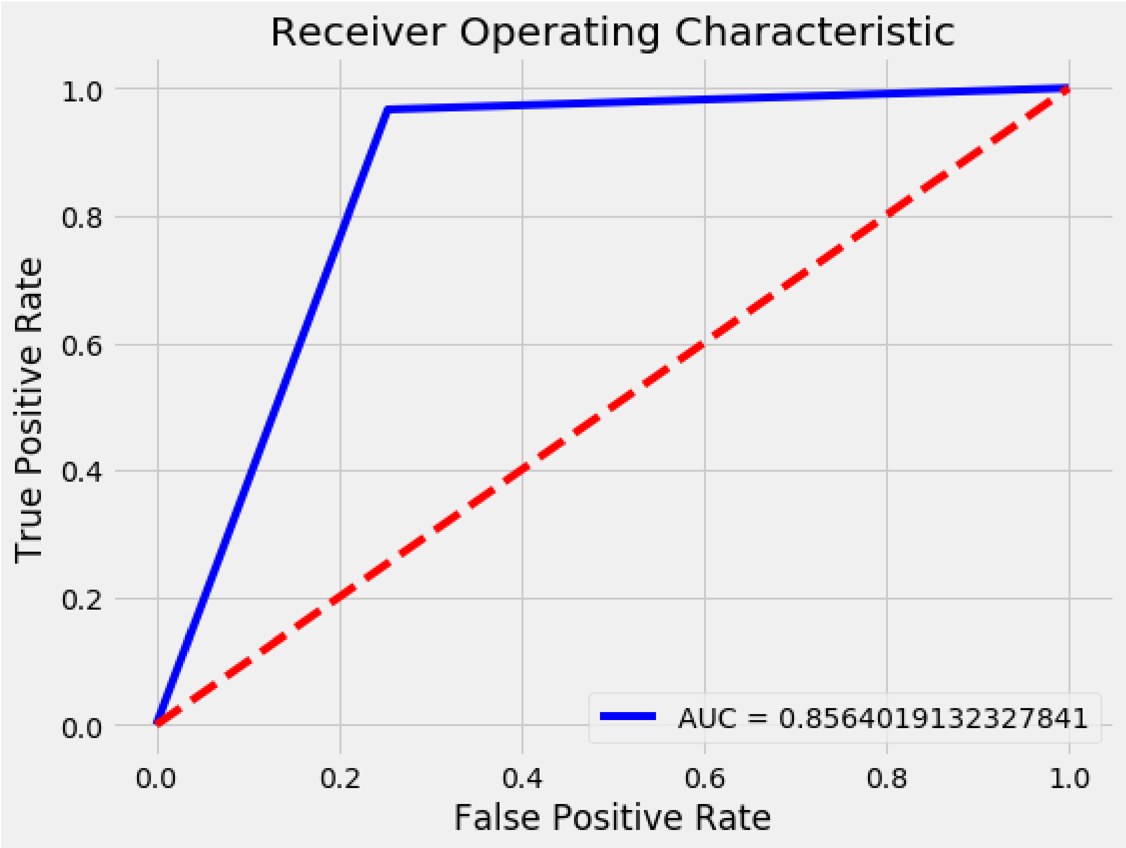
```
Optimal C:  {'C': 0.11828601922296544}

CrossValidation Error: 0.069

CrossValidation Accuracy: 93.079 %


CPU times: user 1h 28min 14s, sys: 39 s, total: 1h 28min 53s
Wall time: 39min 33s
```

In [131]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowbi_std, X_test_bowbi_std, y_train, y_test, 'l2', 0.118)
```




```
[[14218  4829]
 [ 3031 87002]]

Test Error : 0.072
Test Accuracy : 92.794 %
True Negative : 14218
False Positive : 4829
False Negative : 3031
True Positive : 87002
Precission Score : 0.886
Recall Score : 0.856
F1 Score : 0.87
```




```
CPU times: user 35.4 s, sys: 228 ms, total: 35.6 s
Wall time: 17.4 s
```

L1 Regularization :

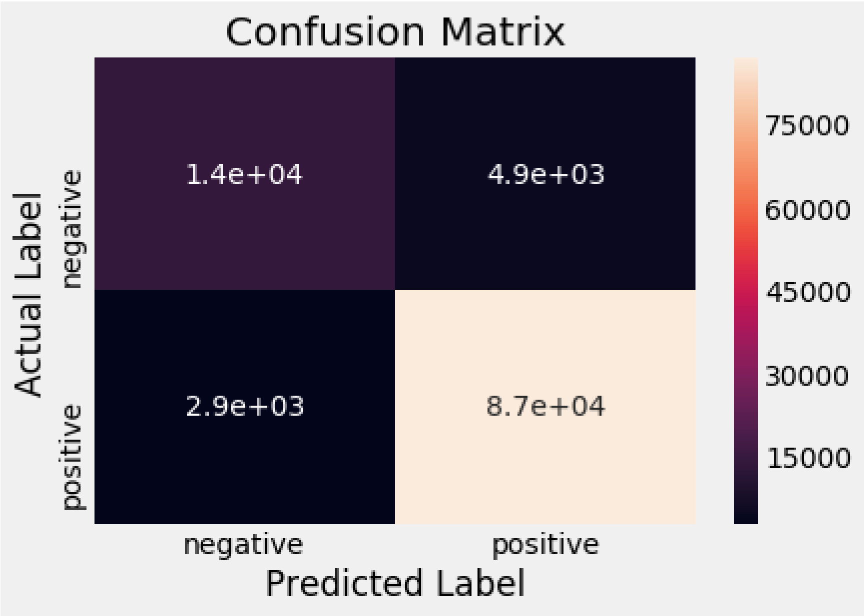
In [132]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_bowbi_std, y_train, penalty = 'l1')
```

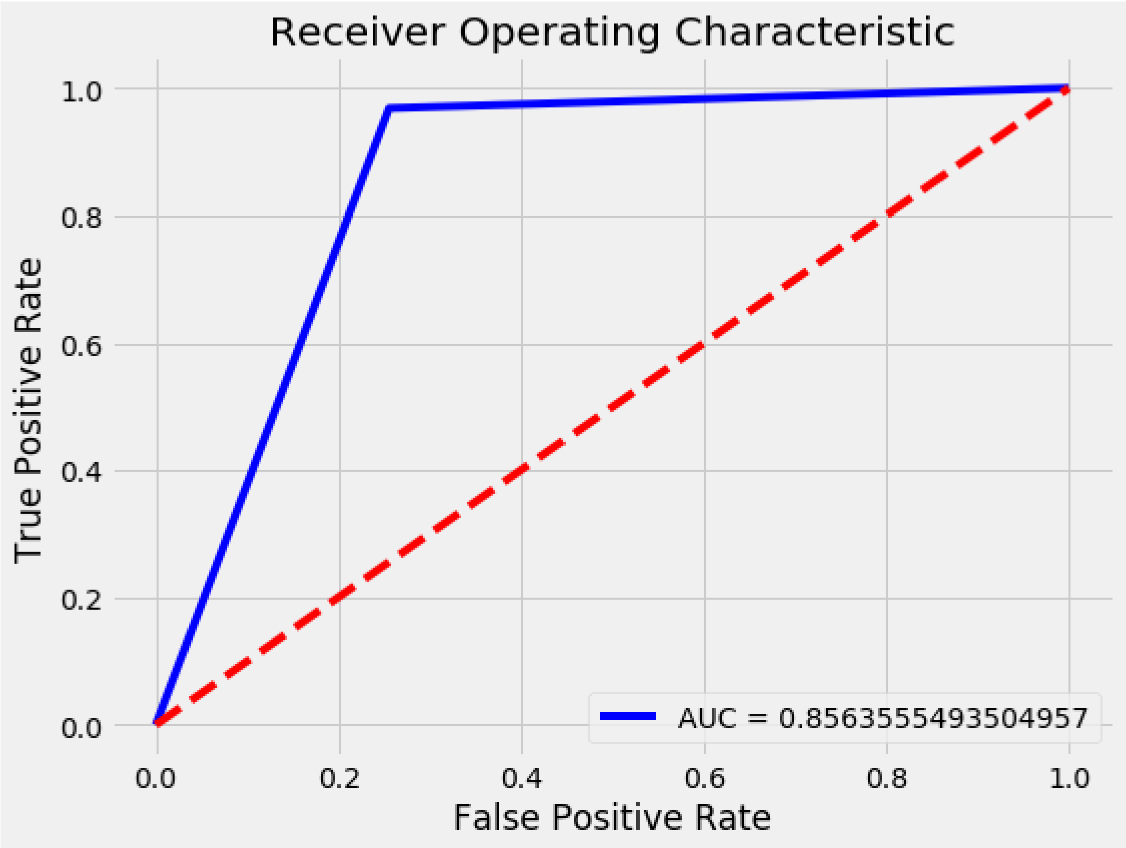
```
Optimal C:  {'C': 0.14447500879175584}

CrossValidation Error: 0.067

CrossValidation Accuracy: 93.257 %


CPU times: user 12min 6s, sys: 3.4 s, total: 12min 9s
Wall time: 12min 9s
```

In [133]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_bowbi_std, X_test_bowbi_std, y_train, y_test, 'l1', 0.144)
```




```
[[14179  4868]
 [ 2855 87178]]

Test Error : 0.071
Test Accuracy : 92.92 %
True Negative : 14179
False Positive : 4868
False Negative : 2855
True Positive : 87178
Precission Score : 0.89
Recall Score : 0.856
F1 Score : 0.872
```




```
CPU times: user 7.41 s, sys: 48 ms, total: 7.46 s
Wall time: 7.09 s
```

[8.2.4] MultiCollinearity :

In [141]:

```
if __name__ == "__main__":
    multicollinear_check(X_train_bowbi_std, X_test_bowbi_std, y_train, y_test,0.0001)
```

```
-----------BEFORE PERTUBATION TEST------------

Sample Weights:        0        1         2         3         4         5 
        6      \
0  0.001976  0.02532  0.017236 -0.007174  0.000338  0.021763  0.011046   

      7         8         9        ...         10701     10702     10703  \
0 -0.003079  0.020889  0.013498    ...    -0.009104  0.006508  0.012586   

      10704    10705    10706     10707     10708     10709     10710  
0  0.015023  0.00658  0.00078  0.006959  0.006199  0.004551 -0.001347  

[1 rows x 10711 columns]
Size of weight vector:  10711
Non zero weights:  10711
Test Accuracy : 93.004 %

-----------AFTER PERTUBATION TEST------------

Sample Weights:        0         1         2         3         4         5 
         6      \
0  0.001975  0.025319  0.017242 -0.007172  0.000351  0.021761  0.011045   

      7         8         9        ...        10701     10702     10703  \
0 -0.003079  0.020887  0.013507    ...    -0.00911  0.006512  0.012584   

     10704     10705    10706    10707     10708     10709     10710  
0  0.01502  0.006573  0.00078  0.00695  0.006194  0.004554 -0.001337  

[1 rows x 10711 columns]
Size of weight vector:  10711
Non zero weights:  10711
Test Accuracy : 93.005 %


Number of features with weights changing greater than 30% : 15

Following are the 15 features that are multicollinear
1158 1393 2595 3472 3842 3947 3980 4384 4702 6678 6916 7027 8211 8426 1023
3
```

[8.2.5] FeatureImportance :

In [143]:

```
if __name__ == "__main__":
    feature_imortance(X_train_bowbi_std,X_test_bowbi_std,y_train,y_test,0.0001,bow_bigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor       Features
        -0.187487     disappoint
        -0.112822          worst
        -0.106119      not worth
        -0.102862        not buy
        -0.097046       not good
        -0.094704  not recommend
        -0.094104             aw
        -0.092579        terribl
        -0.092061            not
        -0.087579        horribl
        -0.084748       unfortun
        -0.081491         return
        -0.078822       two star
        -0.077773          stale
        -0.076762       wont buy
        -0.073707          threw
        -0.073405          bland
        -0.072333           weak
        -0.072200     wast money
        -0.071753            bad
        -0.068186        disgust
        -0.067072           mayb
        -0.065819          sorri
        -0.062725      never buy
        -0.060210      tasteless

------------Top 25 Positive Words with high Importance------------
Coeficient Factor        Features
         0.070663            keep
         0.071755   great product
         0.073626         satisfi
         0.077443      tast great
         0.080625          addict
         0.081148           enjoy
         0.084625           yummi
         0.084781          awesom
         0.087047            easi
         0.092139  not disappoint
         0.093123            amaz
         0.094706          wonder
         0.096731           thank
         0.103235  high recommend
         0.103558            nice
         0.104545           happi
         0.107154         favorit
         0.116067           tasti
         0.126167           excel
         0.132739         perfect
         0.166082            good
         0.173295          delici
         0.174904            best
         0.209069            love
         0.233951           great
```

[8.3] TF-IDF(unigram) :

In [38]:

```
%%time
tfidf_unigram = TfidfVectorizer(dtype='float',min_df = 0.0005)
X_train_tfidfuni = tfidf_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfuni))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfuni.get_shape())
print("Number of unique word: ", X_train_tfidfuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 3878)
Number of unique word:  3878
CPU times: user 12 s, sys: 88 ms, total: 12.1 s
Wall time: 12.1 s
```

In [39]:

```
%%time
X_test_tfidfuni = tfidf_unigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfuni.get_shape())
print("Number of unique word: ", X_test_tfidfuni.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 3878)
Number of unique word:  3878
CPU times: user 5.6 s, sys: 16 ms, total: 5.62 s
Wall time: 5.62 s
```

In [40]:

```
dumpfile(X_train_tfidfuni,"X_train_tfidfuni")
dumpfile(X_test_tfidfuni,"X_test_tfidfuni")
```

In [144]:

```
X_train_tfidfuni = loadfile("X_train_tfidfuni")
X_test_tfidfuni = loadfile("X_test_tfidfuni")
```

In [145]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_tfidfuni_std = sc.fit_transform(X_train_tfidfuni)
```

In [146]:

```
X_test_tfidfuni_std = sc.transform(X_test_tfidfuni)
```

In [147]:

```
print("Shape of Training Data: ",X_train_tfidfuni_std.shape)
print("Shape of Test Data: ",X_test_tfidfuni_std.shape)
```

```
Shape of Training Data:  (254519, 3878)
Shape of Test Data:  (109080, 3878)
```

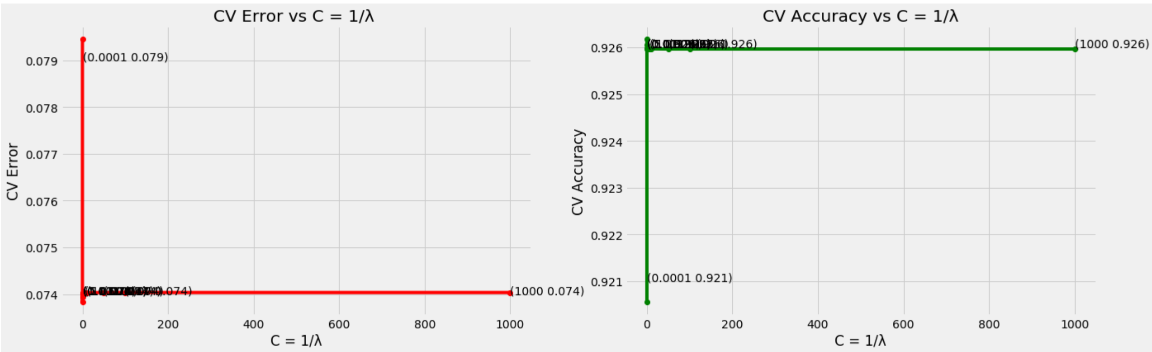
[8.3.1] Using GridSearch CV :

L2 Regularization :

In [141]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfuni_std, y_train, penalty = 'l2')
```

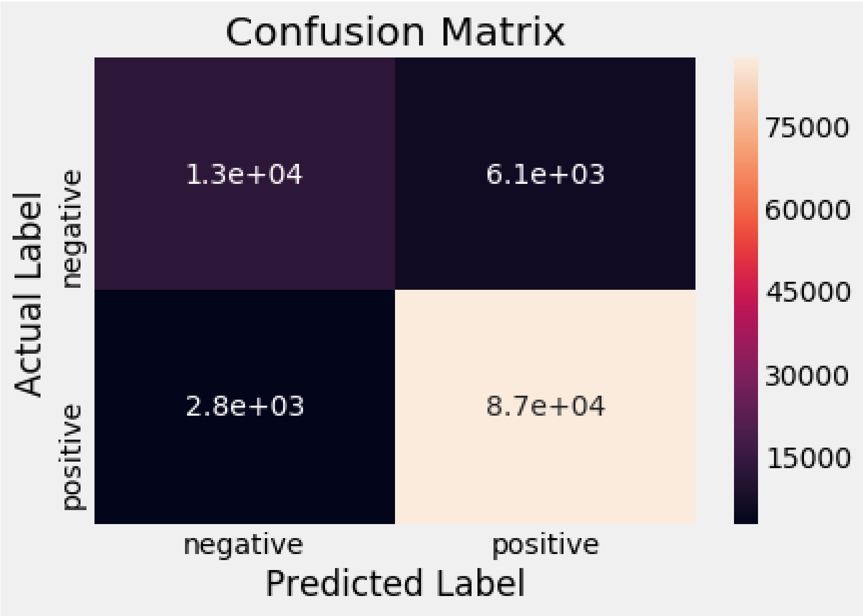
```
Optimal C:  {'C': 0.001}

CrossValidation Error: 0.074

CrossValidation Accuracy: 92.617 %
```



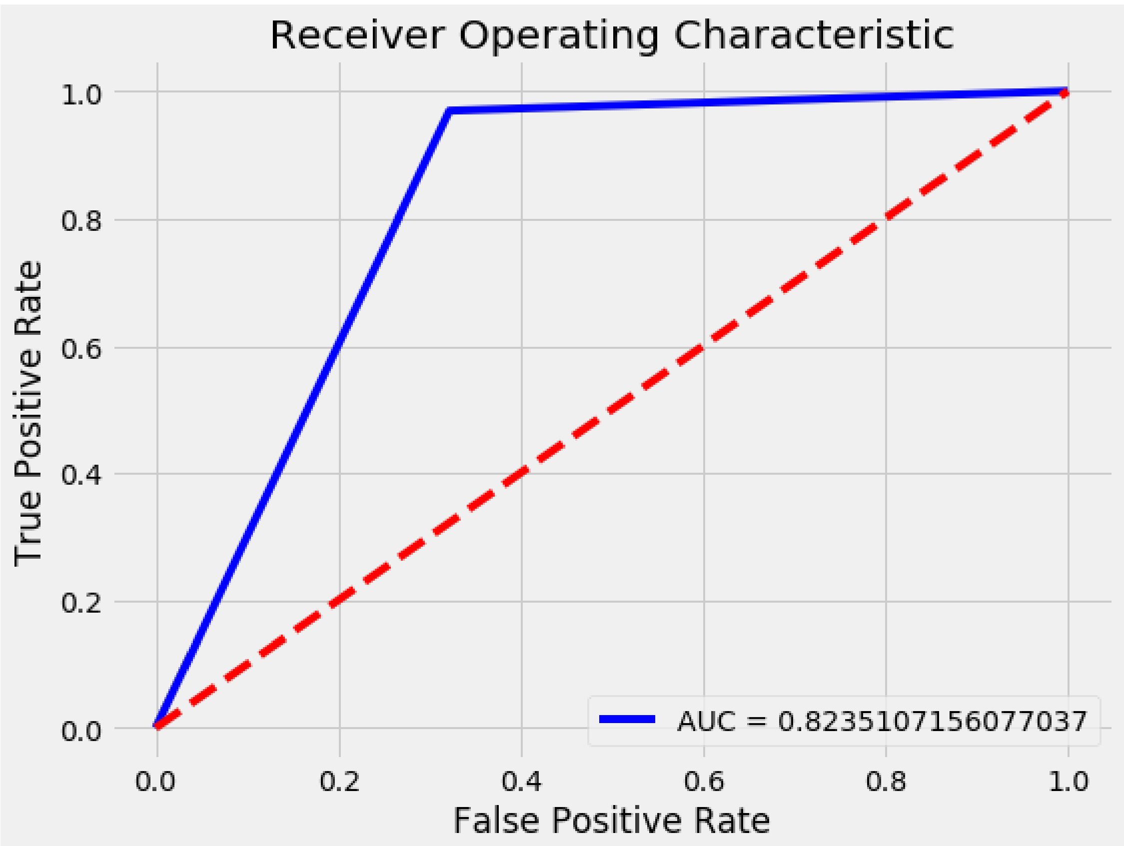

```
CV Error for each value of C:  [0.079 0.074 0.074 0.074 0.074 0.074 0.074
 0.074 0.074 0.074]

CV Accuracy for each value of C:  [0.921 0.926 0.926 0.926 0.926 0.926 0.9
26 0.926 0.926 0.926]
CPU times: user 6min 43s, sys: 436 ms, total: 6min 44s
Wall time: 6min 43s
```

In [145]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfuni_std, X_test_tfidfuni_std, y_train, y_test, 'l2', 0.001)
```




```
[[12913  6134]
 [ 2785 87248]]

Test Error : 0.082
Test Accuracy : 91.823 %
True Negative : 12913
False Positive : 6134
False Negative : 2785
True Positive : 87248
Precission Score : 0.878
Recall Score : 0.824
F1 Score : 0.847
```



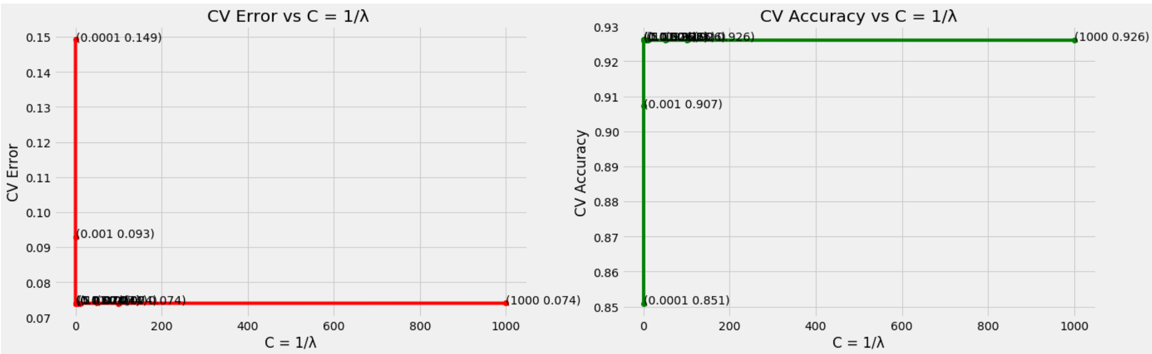
```
CPU times: user 3.66 s, sys: 4 ms, total: 3.66 s
Wall time: 3.3 s
```

L1 Regularization :

In [142]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfuni_std, y_train, penalty = 'l1')
```

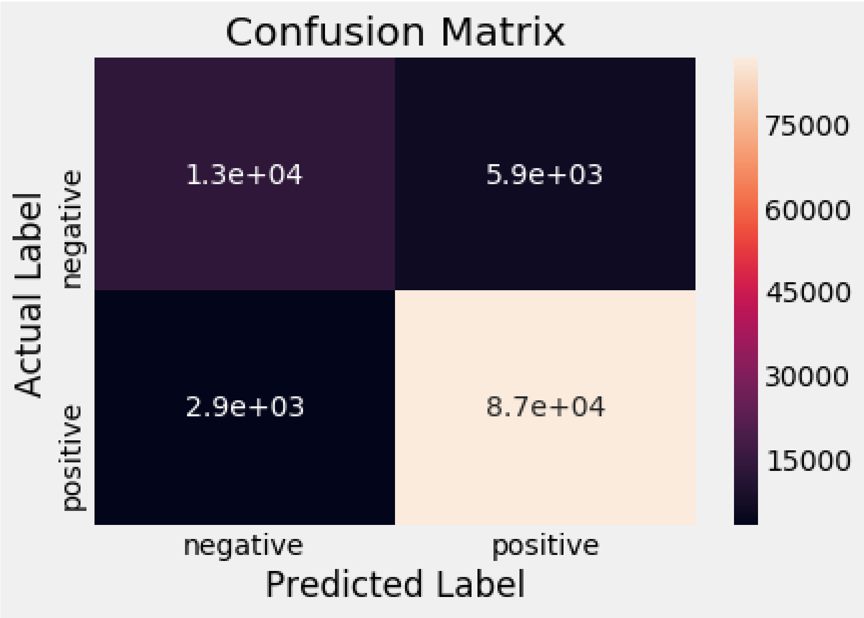
```
Optimal C:  {'C': 0.1}

CrossValidation Error: 0.074

CrossValidation Accuracy: 92.619 %
```



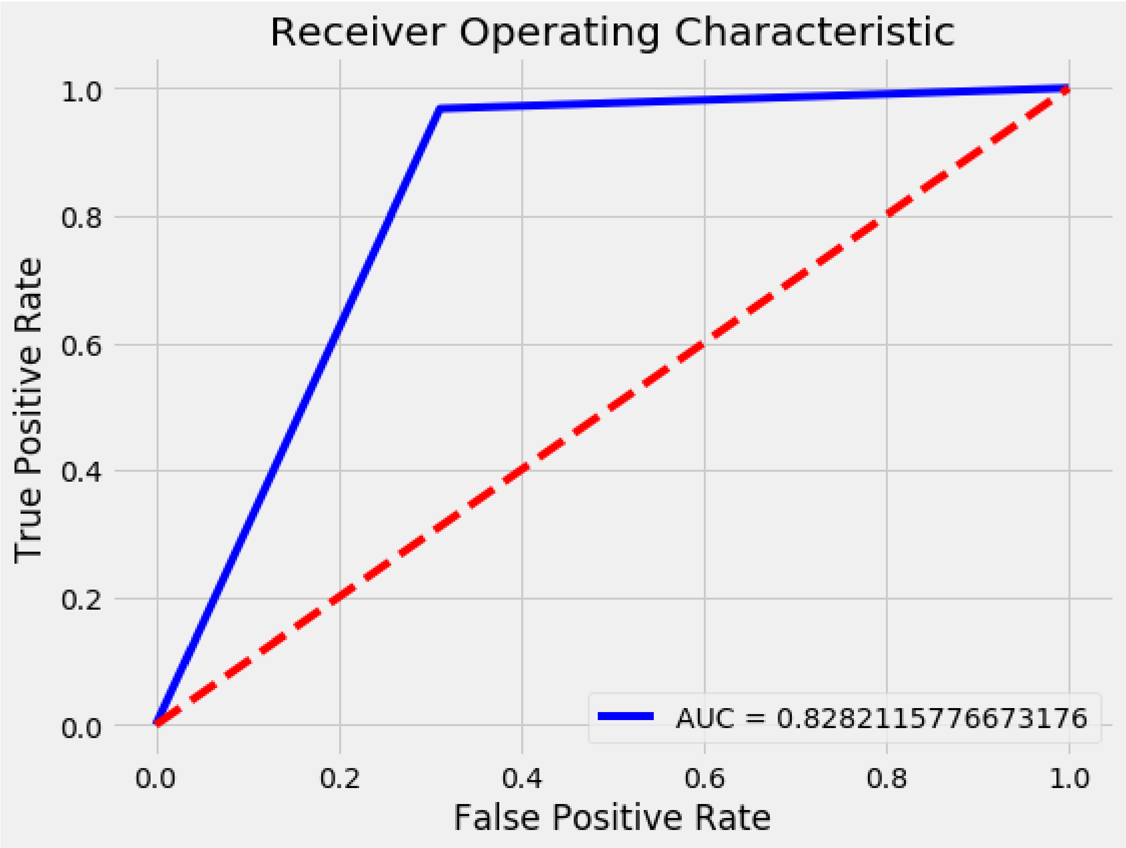

```
CV Error for each value of C:  [0.149 0.093 0.074 0.074 0.074 0.074 0.074
 0.074 0.074 0.074]

CV Accuracy for each value of C:  [0.851 0.907 0.926 0.926 0.926 0.926 0.9
26 0.926 0.926 0.926]
CPU times: user 7min 48s, sys: 1.98 s, total: 7min 50s
Wall time: 7min 50s
```

In [144]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfuni_std, X_test_tfidfuni_std, y_train, y_test, 'l1', 0.1)
```




```
[[13120  5927]
 [ 2917 87116]]

Test Error : 0.081
Test Accuracy : 91.892 %
True Negative : 13120
False Positive : 5927
False Negative : 2917
True Positive : 87116
Precission Score : 0.877
Recall Score : 0.828
F1 Score : 0.85
```




```
CPU times: user 7.09 s, sys: 20 ms, total: 7.11 s
Wall time: 6.72 s
```

[8.3.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [28]:

```
if __name__ == "__main__":
    sparsity_check(X_train_tfidfuni_std, X_test_tfidfuni_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  3875
Train Error:  0.066
Test Error:  0.081
Test Accuracy : 0.91856
Run Time :6.766615999999999 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  3853
Train Error:  0.066
Test Error:  0.081
Test Accuracy : 0.91868
Run Time :6.632743000000005 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  3747
Train Error:  0.066
Test Error:  0.081
Test Accuracy : 0.91891
Run Time :6.404086000000007 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  2682
Train Error:  0.068
Test Error:  0.081
Test Accuracy : 0.91913
Run Time :4.106678000000002 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  409
Train Error:  0.09
Test Error:  0.102
Test Accuracy : 0.89846
Run Time :2.20008 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  12
Train Error:  0.149
Test Error:  0.174
Test Accuracy : 0.8256
Run Time :1.175690000000003 sec
```

Observation : Here C= 1/λ, we can see as C decreases(λ increases)

- Sparsity Increases(Number of non zero elements decreases)
- Error increases and Performance accuarcy drops(model starts underfitting)
- Run Time is also fast as sparsity increases

[8.3.3] Using RandomSearch CV :

L2 Regularization :

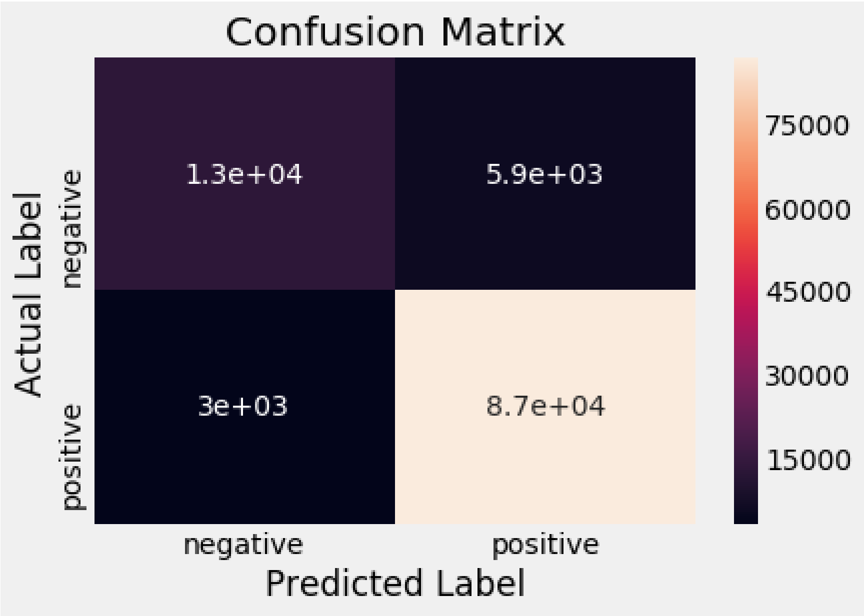
In [146]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfuni_std, y_train, penalty = 'l2')
```

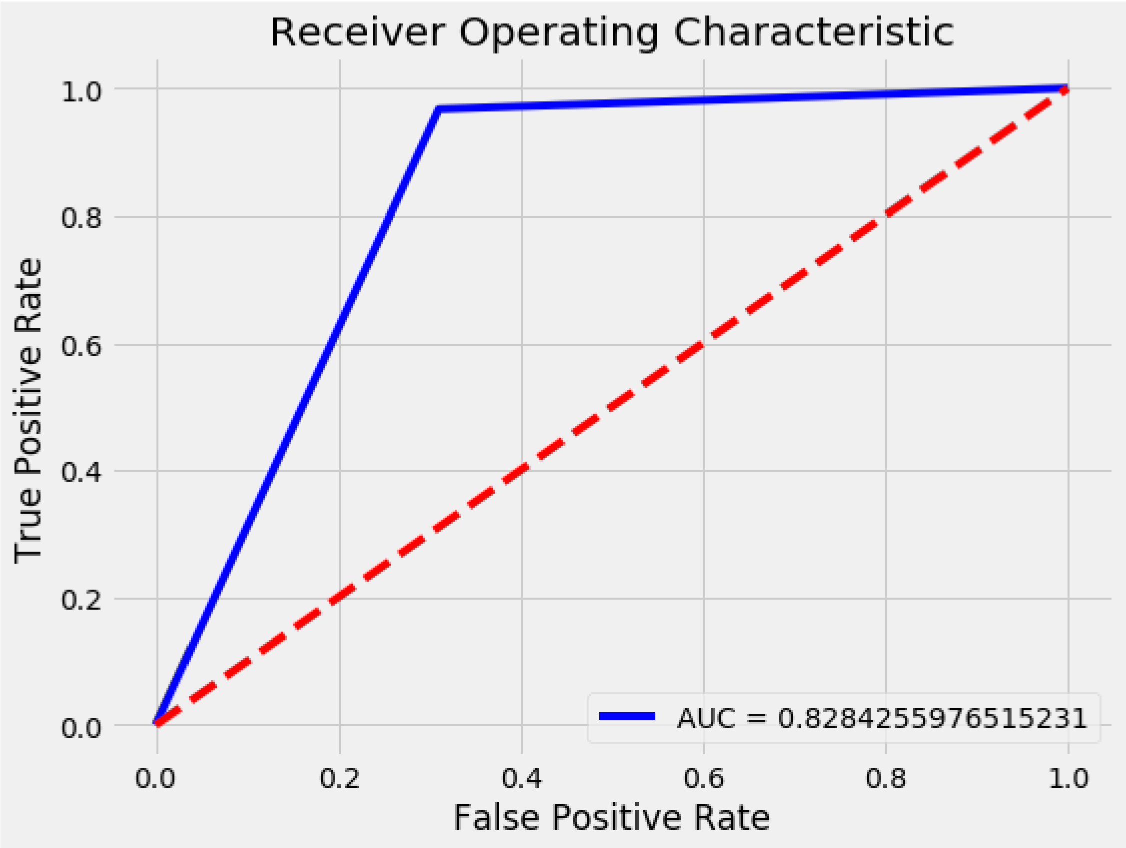
```
Optimal C:  {'C': 0.8189852652941816}

CrossValidation Error: 0.074

CrossValidation Accuracy: 92.598 %


CPU times: user 7min 51s, sys: 936 ms, total: 7min 52s
Wall time: 7min 52s
```

In [148]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfuni_std, X_test_tfidfuni_std, y_train, y_test, 'l2', 0.818)
```




```
[[13140  5907]
 [ 2973 87060]]

Test Error : 0.081
Test Accuracy : 91.859 %
True Negative : 13140
False Positive : 5907
False Negative : 2973
True Positive : 87060
Precission Score : 0.876
Recall Score : 0.828
F1 Score : 0.849
```




```
CPU times: user 6.42 s, sys: 32 ms, total: 6.45 s
Wall time: 6.1 s
```

L1 Regularization :

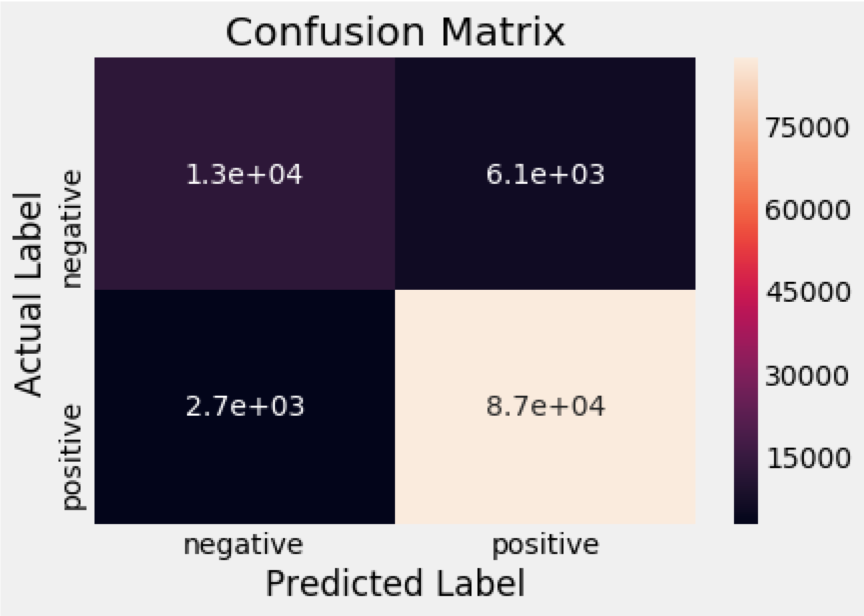
In [147]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfuni_std, y_train, penalty = 'l1')
```

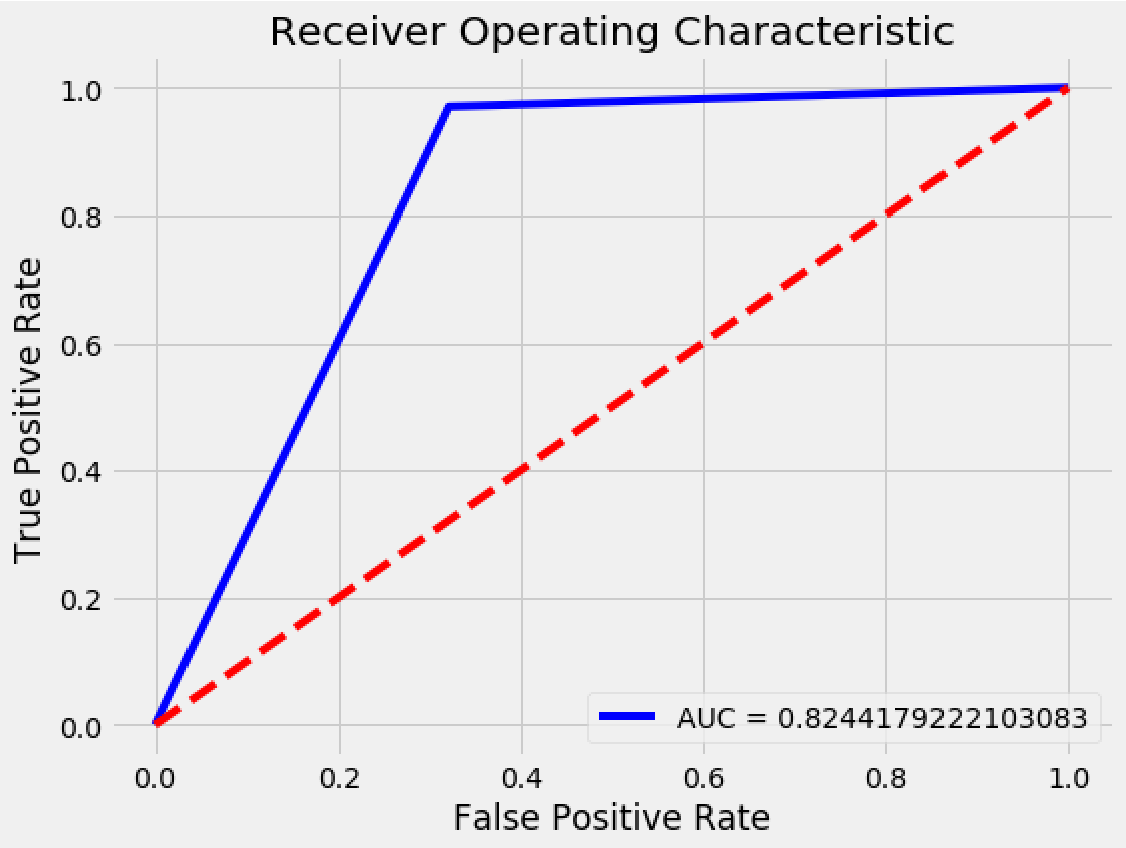
```
Optimal C:  {'C': 0.01676258606542679}

CrossValidation Error: 0.073

CrossValidation Accuracy: 92.681 %


CPU times: user 9min 15s, sys: 2.16 s, total: 9min 17s
Wall time: 9min 17s
```

In [149]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfuni_std, X_test_tfidfuni_std, y_train, y_test, 'l1', 0.016)
```




```
[[12930  6117]
 [ 2702 87331]]

Test Error : 0.081
Test Accuracy : 91.915 %
True Negative : 12930
False Positive : 6117
False Negative : 2702
True Positive : 87331
Precission Score : 0.881
Recall Score : 0.824
F1 Score : 0.849
```




```
CPU times: user 6.04 s, sys: 28 ms, total: 6.06 s
Wall time: 5.69 s
```

[8.3.4] MultiCollinearity :

In [150]:

```
if __name__ == "__main__":
    multicollinear_check(X_train_tfidfuni_std, X_test_tfidfuni_std, y_train, y_test,0.
001)
```

```
-----------BEFORE PERTUBATION TEST------------

Sample Weights:         0         1         2        3         4        5
        6    \
0  0.006177  0.054816  0.039201  0.00835  0.005969 -0.00787  0.009118

       7         8         9       ...         3868      3869      3870  \
0 -0.008688  0.008616  0.014231    ...     0.014822  0.010729  0.005334

       3871      3872      3873      3874      3875      3876      3877
0 -0.003729  0.006976  0.023702  0.023845  0.006898  0.018194 -0.002004

[1 rows x 3878 columns]
Size of weight vector:  3878
Non zero weights:  3878
Test Accuracy : 91.825 %

-----------AFTER PERTUBATION TEST------------

Sample Weights:         0         1         2         3         4
 5        6     \
0  0.006186  0.054843  0.039186  0.008354  0.005992 -0.007852  0.00912

       7         8         9       ...         3868      3869      3870  \
0 -0.008659  0.008639  0.014248    ...     0.014836  0.010734  0.005318

       3871      3872      3873      3874      3875     3876      3877
0 -0.003714  0.006912  0.023699  0.023831  0.006924  0.01818 -0.002012

[1 rows x 3878 columns]
Size of weight vector:  3878
Non zero weights:  3878
Test Accuracy : 91.828 %


Number of features with weights changing greater than 30% : 3

Following are the 3 features that are multicollinear
3154 3698 3828
```

[8.3.5] FeatureImportance :

In [149]:

```
if __name__ == "__main__":
    feature_imortance(X_train_tfidfuni_std,X_test_tfidfuni_std,y_train,y_test,0.001,tf
idf_unigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor    Features
        -0.347543         not
        -0.242920  disappoint
        -0.209474       worst
        -0.162968          aw
        -0.156885     terribl
        -0.145698     horribl
        -0.143453      return
        -0.134956        tast
        -0.126144       threw
        -0.119785       money
        -0.119123    unfortun
        -0.116417       stale
        -0.112915       didnt
        -0.111654        wast
        -0.110265       bland
        -0.108177     thought
        -0.106271     disgust
        -0.103017        even
        -0.099548       would
        -0.098077        hope
        -0.097126        weak
        -0.094650        mayb
        -0.094515        noth
        -0.093463        yuck
        -0.091183   tasteless

------------Top 25 Positive Words with high Importance------------
Coeficient Factor Features
         0.156612  fantast
         0.160048     beat
         0.160520  satisfi
         0.162330     glad
         0.167817    enjoy
         0.176734    yummi
         0.178656   smooth
         0.180394   addict
         0.182064   awesom
         0.191334    thank
         0.192106    happi
         0.195537     find
         0.201394   wonder
         0.201583     easi
         0.210871    tasti
         0.217372     amaz
         0.245529  favorit
         0.249742     nice
         0.310194    excel
         0.345013  perfect
         0.385975     good
         0.411531   delici
         0.459631     best
         0.489395     love
         0.660038    great
```

[8.4] TF-IDF(bigram) :

In [11]:

```
%%time
tfidf_bigram = TfidfVectorizer(ngram_range=(1, 2),min_df = 0.0005)
X_train_tfidfbi = tfidf_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfbi))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfbi.get_shape())
print("Number of unique word: ", X_train_tfidfbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 10711)
Number of unique word:  10711
CPU times: user 36.7 s, sys: 428 ms, total: 37.1 s
Wall time: 37.1 s
```

In [30]:

```
%%time
X_test_tfidfbi = tfidf_bigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfbi.get_shape())
print("Number of unique word: ", X_test_tfidfbi.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 10711)
Number of unique word:  10711
CPU times: user 11.2 s, sys: 28 ms, total: 11.2 s
Wall time: 11.2 s
```

In [152]:

```
dumpfile(X_train_tfidfbi,"X_train_tfidfbi")
dumpfile(X_test_tfidfbi,"X_test_tfidfbi")
```

In [151]:

```
X_train_tfidfbi = loadfile("X_train_tfidfbi")
X_test_tfidfbi = loadfile("X_test_tfidfbi")
```

In [152]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_tfidfbi_std = sc.fit_transform(X_train_tfidfbi)
```

In [153]:

```
X_test_tfidfbi_std = sc.transform(X_test_tfidfbi)
```

In [154]:

```
print("Shape of Training Data: ",X_train_tfidfbi_std.shape)
print("Shape of Test Data: ",X_test_tfidfbi_std.shape)
```

```
Shape of Training Data:  (254519, 10711)
Shape of Test Data:  (109080, 10711)
```

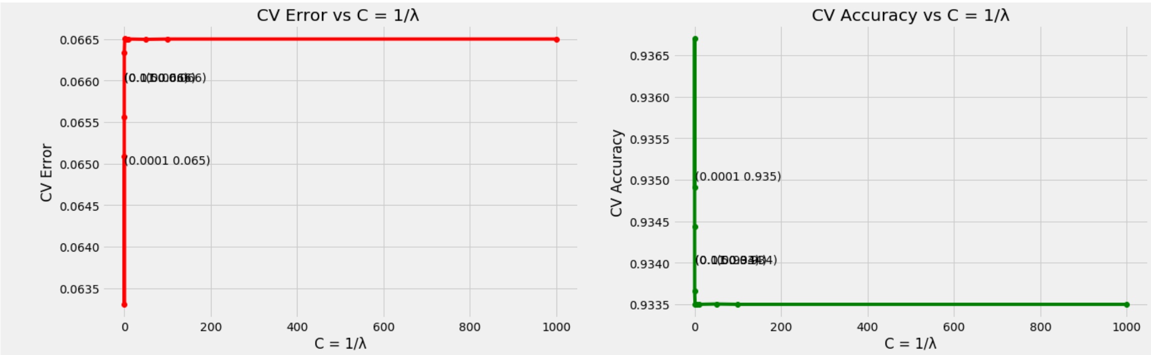
[8.4.1] Using GridSearch CV :

L2 Regularization :

In [157]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfbi_std, y_train, penalty = 'l2')
```

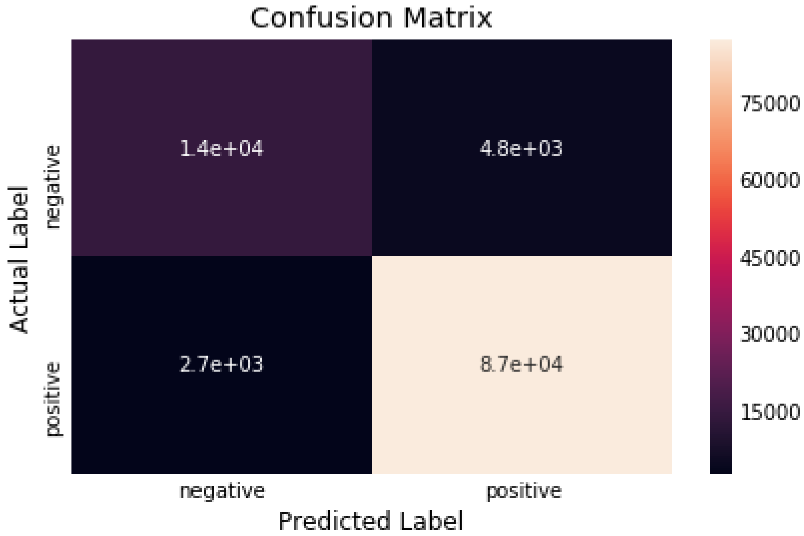
```
Optimal C:  {'C': 0.001}

CrossValidation Error: 0.063

CrossValidation Accuracy: 93.67 %
```



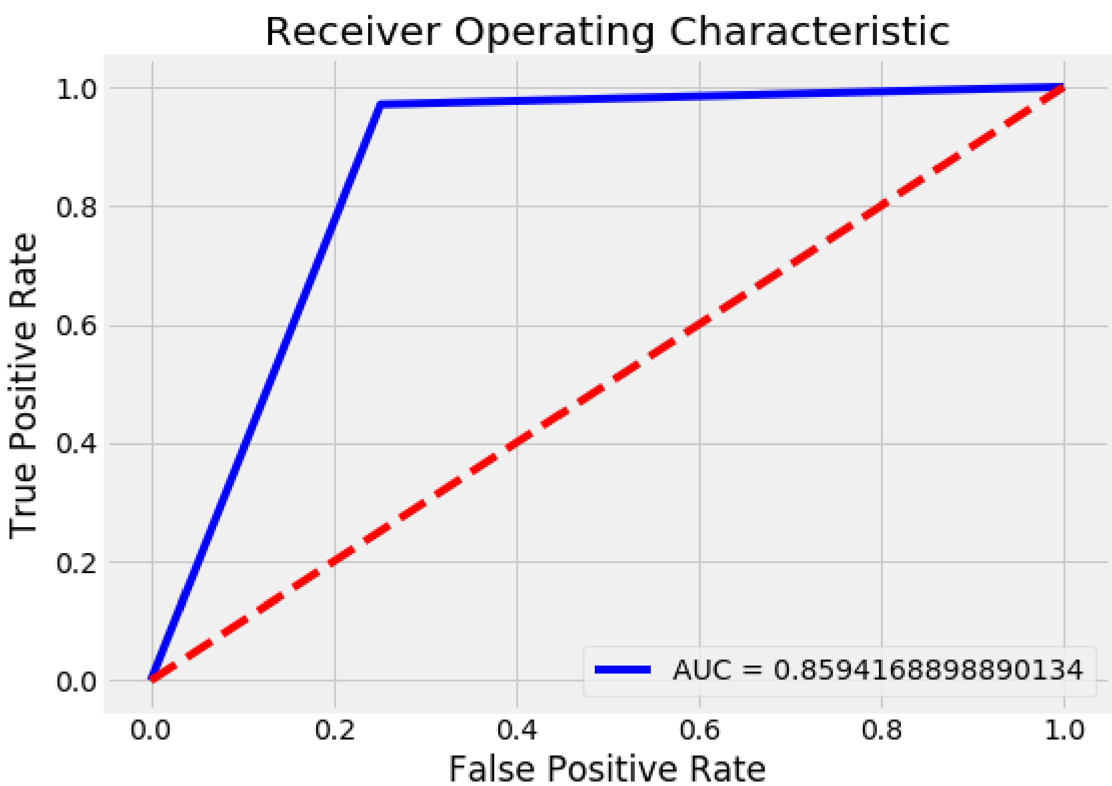

```
CV Error for each value of C:  [0.065 0.063 0.066 0.066 0.067 0.067 0.067
 0.066 0.067 0.067]

CV Accuracy for each value of C:  [0.935 0.937 0.934 0.934 0.933 0.933 0.9
33 0.934 0.933 0.933]
CPU times: user 1h 7min 34s, sys: 30 s, total: 1h 8min 4s
Wall time: 31min 42s
```

In [171]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfbi_std, X_test_tfidfbi_std, y_train, y_test, 'l2', 0.001)
```




```
[[14255  4792]
 [ 2663 87370]]

Test Error : 0.068
Test Accuracy : 93.166 %
True Negative : 14255
False Positive : 4792
False Negative : 2663
True Positive : 87370
Precission Score : 0.895
Recall Score : 0.859
F1 Score : 0.876
```



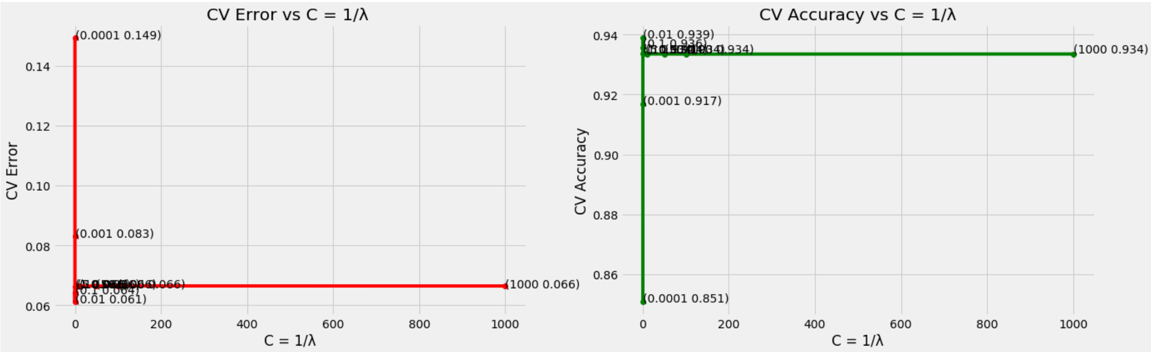

```
CPU times: user 11.6 s, sys: 104 ms, total: 11.7 s
Wall time: 6.09 s
```

L1 Regularization :

In [158]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfbi_std, y_train, penalty = 'l1')
```

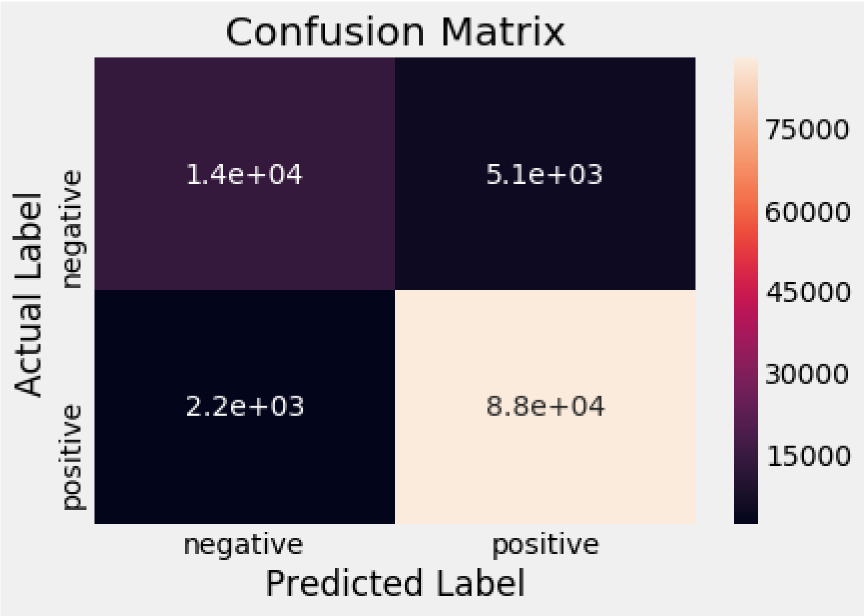
```
Optimal C:  {'C': 0.01}

CrossValidation Error: 0.061

CrossValidation Accuracy: 93.89 %
```



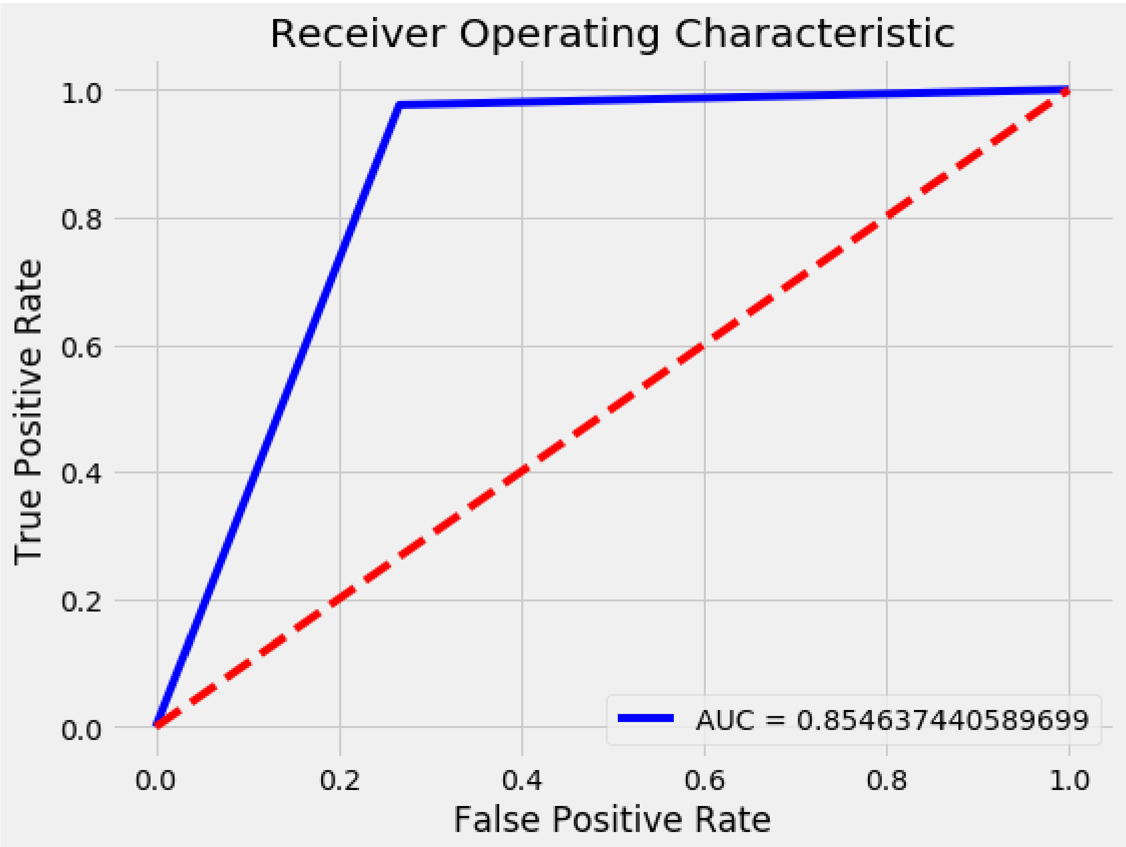

```
CV Error for each value of C:  [0.149 0.083 0.061 0.064 0.066 0.066 0.066
 0.066 0.066 0.066]

CV Accuracy for each value of C:  [0.851 0.917 0.939 0.936 0.934 0.934 0.9
34 0.934 0.934 0.934]
CPU times: user 11min 36s, sys: 5.46 s, total: 11min 42s
Wall time: 11min 41s
```

In [172]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfbi_std, X_test_tfidfbi_std, y_train, y_test, 'l1', 0.01)
```




```
[[13968  5079]
 [ 2167 87866]]

Test Error : 0.066
Test Accuracy : 93.357 %
True Negative : 13968
False Positive : 5079
False Negative : 2167
True Positive : 87866
Precission Score : 0.906
Recall Score : 0.855
F1 Score : 0.877
```



```
CPU times: user 6.5 s, sys: 48 ms, total: 6.54 s
Wall time: 6.14 s
```

[8.4.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [33]:

```
if __name__ == "__main__":
    sparsity_check(X_train_tfidfbi_std, X_test_tfidfbi_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  10698
Train Error:  0.045
Test Error:  0.07
Test Accuracy : 0.92995
Run Time :9.959680000000006 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  10608
Train Error:  0.045
Test Error:  0.07
Test Accuracy : 0.9301
Run Time :8.638589999999994 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  9956
Train Error:  0.046
Test Error:  0.069
Test Accuracy : 0.93129
Run Time :6.357533000000004 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  5396
Train Error:  0.052
Test Error:  0.066
Test Accuracy : 0.93356
Run Time :5.331001000000005 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  539
Train Error:  0.08
Test Error:  0.089
Test Accuracy : 0.91087
Run Time :2.64649399999999 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  14
Train Error:  0.149
Test Error:  0.174
Test Accuracy : 0.82603
Run Time :1.4733790000000084 sec
```

Observation : Here C= 1/λ, we can see as C decreases(λ increases)

```
- Sparsity Increases(Number of non zero elements decreases)
- Error increases and Performance accuarcy drops(model starts underfitting)
- Run Time is also fast as sparsity increases
```

[8.4.3] Using RandomSearch CV :

L2 Regularization :

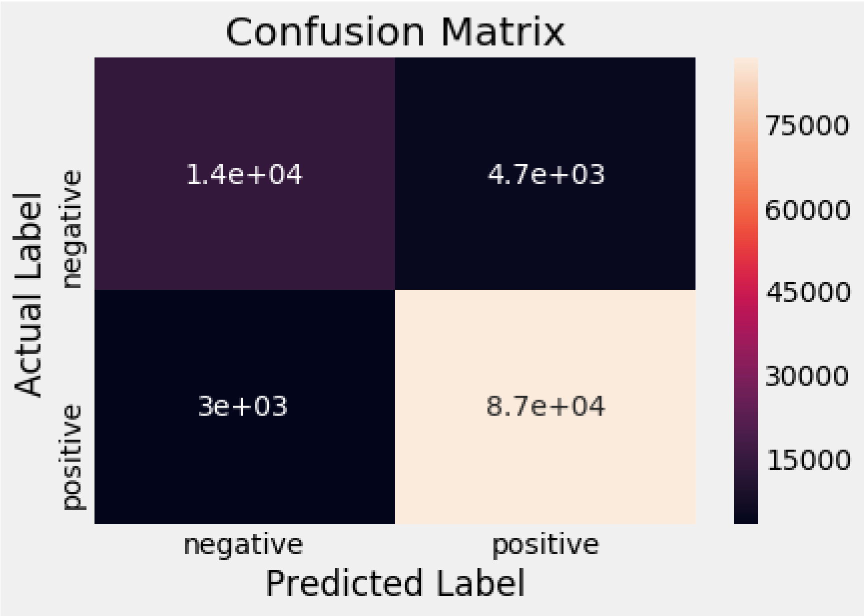
In [ ]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfbi_std, y_train, penalty = 'l2')
```

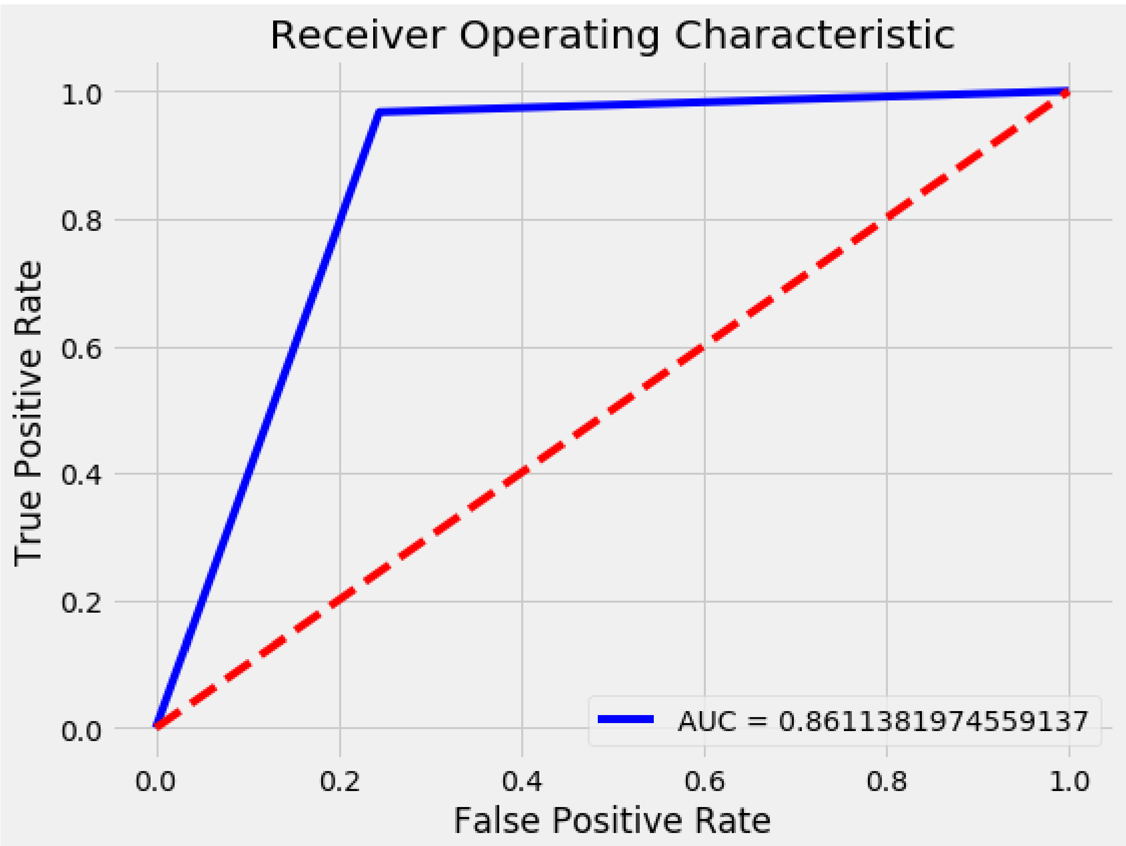
```
Optimal C:  {'C': 0.09716463627118838}

CrossValidation Error: 0.066

CrossValidation Accuracy: 93.366 %


CPU times: user 1h 24min 43s, sys: 35.6 s, total: 1h 25min 18s
Wall time: 39min 50s
```

In [36]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfbi_std, X_test_tfidfbi_std, y_train, y_test, 'l2',0.097)
```




```
[[14387  4660]
 [ 2977 87056]]

Test Error : 0.07
Test Accuracy : 92.999 %
True Negative : 14387
False Positive : 4660
False Negative : 2977
True Positive : 87056
Precission Score : 0.889
Recall Score : 0.861
F1 Score : 0.874
```



```
CPU times: user 30.9 s, sys: 200 ms, total: 31.1 s
Wall time: 15.5 s
```

L1 Regularization :

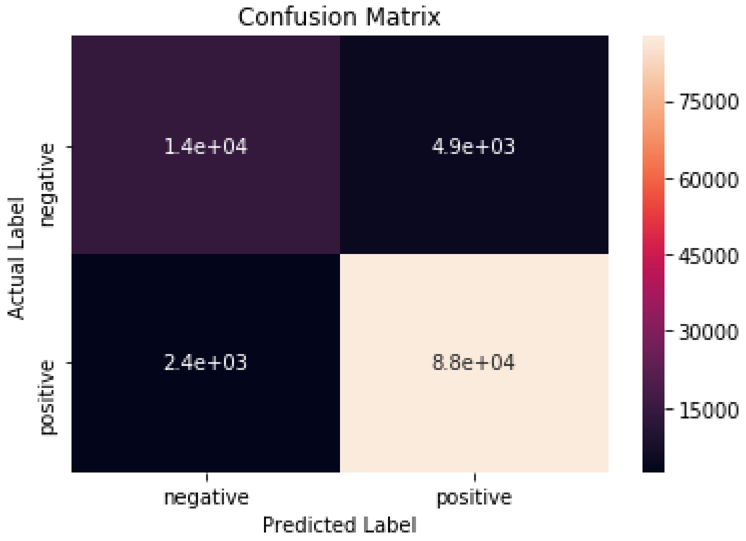
In [ ]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfbi_std, y_train, penalty = 'l1')
```

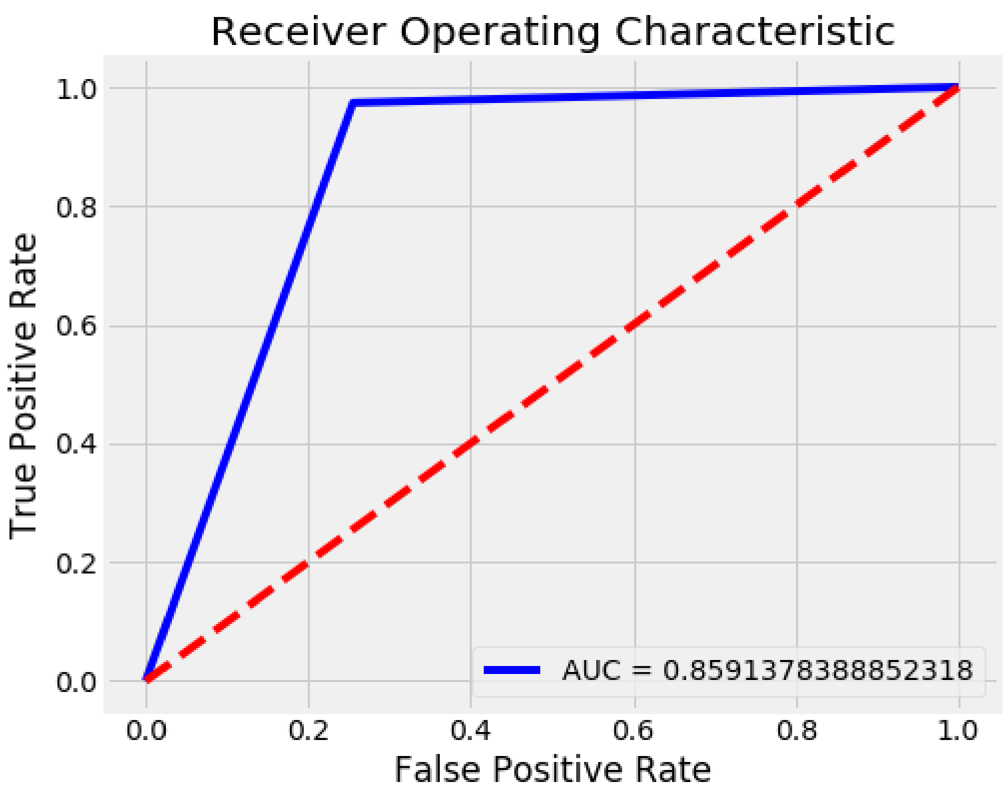
```
Optimal C:  {'C': 0.01845898506776376}

CrossValidation Error: 0.061

CrossValidation Accuracy: 93.904 %


CPU times: user 14min 6s, sys: 4.92 s, total: 14min 10s
Wall time: 14min 11s
```

In [34]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfbi_std, X_test_tfidfbi_std, y_train, y_test, 'l1', 0.018)
```




```
[[14190  4857]
 [ 2406 87627]]

Test Error : 0.067
Test Accuracy : 93.342 %
True Negative : 14190
False Positive : 4857
False Negative : 2406
True Positive : 87627
Precission Score : 0.901
Recall Score : 0.859
F1 Score : 0.878
```




```
CPU times: user 7.26 s, sys: 44 ms, total: 7.31 s
Wall time: 7.02 s
```

[8.4.4] MultiCollinearity :

In [155]:

```
if __name__ == "__main__":
    multicollinear_check(X_train_tfidfbi_std, X_test_tfidfbi_std, y_train, y_test,0.00
1)
```

```
-----------BEFORE PERTUBATION TEST------------

Sample Weights:        0         1        2        3         4         5
       6      \
0 -0.000201  0.039059  0.03512 -0.02023 -0.002252  0.035492  0.009385

     7         8         9       ...         10701     10702     10703  \
0 -0.01361  0.039944  0.014182   ...    -0.000493  0.011343  0.026953

      10704     10705     10706     10707     10708     10709    10710
0  0.030759  0.008869 -0.010293  0.024731  0.012831  0.008689 -0.00666

[1 rows x 10711 columns]
Size of weight vector:  10711
Non zero weights:  10711
Test Accuracy : 93.166 %

-----------AFTER PERTUBATION TEST------------

Sample Weights:        0         1         2         3         4         5
         6      \
0 -0.000221  0.039054  0.035148 -0.020233 -0.002193  0.035475  0.009385

      7         8         9        ...         10701    10702     10703  \
0 -0.013613  0.039935  0.014227    ...    -0.000511  0.01135  0.026948

      10704     10705     10706     10707     10708     10709     10710
0  0.030755  0.008834 -0.010282  0.024704  0.012802  0.008696 -0.006638

[1 rows x 10711 columns]
Size of weight vector:  10711
Non zero weights:  10711
Test Accuracy : 93.168 %


Number of features with weights changing greater than 30% : 33

Following are the 33 features that are multicollinear
379 759 781 991 1036 1572 1742 2069 2984 3017 3584 3974 3989 4728 4898 527
2 6226 6484 6650 7382 7920 8095 8323 8532 8645 8819 9052 9204 9255 9256 95
14 9560 10071
```

[8.4.5] FeatureImportance :

In [156]:

```
if __name__ == "__main__":
     feature_imortance(X_train_tfidfbi_std,X_test_tfidfbi_std,y_train,y_test,0.001,tfid
f_bigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor       Features
        -0.309475     disappoint
        -0.190949            not
        -0.179745          worst
        -0.168787      not worth
        -0.154740       not good
        -0.147985             aw
        -0.147965  not recommend
        -0.147495       two star
        -0.147186        terribl
        -0.137424        not buy
        -0.135074        horribl
        -0.120756          stale
        -0.118112         return
        -0.116322          threw
        -0.116124       unfortun
        -0.112878           weak
        -0.111305       wont buy
        -0.111163            bad
        -0.110713          bland
        -0.106437     wast money
        -0.104984        disgust
        -0.092486           mayb
        -0.091960          sorri
        -0.090592           tast
        -0.090431      tasteless

------------Top 25 Positive Words with high Importance------------
Coeficient Factor        Features
         0.133896            glad
         0.138518         fantast
         0.139108            hook
         0.140077           enjoy
         0.143920            easi
         0.156743           yummi
         0.163326          wonder
         0.163776           thank
         0.164907          addict
         0.165519          awesom
         0.167443         satisfi
         0.181310            amaz
         0.194191            nice
         0.196270         favorit
         0.211577  not disappoint
         0.216029  high recommend
         0.217148           tasti
         0.227297           happi
         0.243336           excel
         0.264744         perfect
         0.344418            best
         0.354443          delici
         0.360684            good
         0.382252            love
         0.453487           great
```

[8.5] Average Word2Vec :

In [13]:

```
i=0
list_of_sent_train=[]
for sent in X_train:
    list_of_sent_train.append(sent.split())
```

In [14]:

```
print(X_train[5])
print("****************************************************************************")
print(list_of_sent_train[5])
```

```
bought apart infest fruit fli hour trap mani fli within day practic gone m
ay not long term solut fli drive crazi consid buy one surfac sticki tri av
oid touch
**************************************************************************
**
['bought', 'apart', 'infest', 'fruit', 'fli', 'hour', 'trap', 'mani', 'fl
i', 'within', 'day', 'practic', 'gone', 'may', 'not', 'long', 'term', 'sol
ut', 'fli', 'drive', 'crazi', 'consid', 'buy', 'one', 'surfac', 'sticki',
'tri', 'avoid', 'touch']
```

In [15]:

```
%%time
## Word2Vec Model considering only those words that occur atleast 5 times in the corpus
min_count = 5
w2v_model = Word2Vec(list_of_sent_train, min_count = min_count, size = 50, workers = 4)
w2v_words = list(w2v_model.wv.vocab)
```

```
CPU times: user 2min 8s, sys: 240 ms, total: 2min 9s
Wall time: 36 s
```

In [16]:

```
i=0
list_of_sent_test=[]
for sent in X_test:
    list_of_sent_test.append(sent.split())
```

In [16]:

```
print(X_test[5])
print("****************************************************************************")
print(list_of_sent_test[5])
```

```
dog love love dog food say love twice dog food one dog favorit
**************************************************************************
**
['dog', 'love', 'love', 'dog', 'food', 'say', 'love', 'twice', 'dog', 'foo
d', 'one', 'dog', 'favorit']
```

In [37]:

```
%%time
X_train_avgw2v = [] # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_train:
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_train_avgw2v.append(sent_vec)
```

```
CPU times: user 7min 47s, sys: 64 ms, total: 7min 47s
Wall time: 7min 47s
```

In [38]:

```
%%time
X_test_avgw2v = [] # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_test:
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_test_avgw2v.append(sent_vec)
```

```
CPU times: user 3min 33s, sys: 12 ms, total: 3min 33s
Wall time: 3min 33s
```

In [68]:

```
#Checking NAN in test data if any
np.any(np.isnan(X_test_avgw2v))
```

Out[68]:

```
False
```

In [41]:

```
dumpfile(X_train_avgw2v,"X_train_avgw2v")
dumpfile(X_test_avgw2v,"X_test_avgw2v")
```

In [157]:

```
X_train_avgw2v = loadfile("X_train_avgw2v")
X_test_avgw2v = loadfile("X_test_avgw2v")
```

In [158]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_avgw2v_std = sc.fit_transform(X_train_avgw2v)
```

In [159]:

```
X_test_avgw2v_std = sc.transform(X_test_avgw2v)
```

In [160]:

```
print("Number of rows in Train Data: ",len(X_train_avgw2v_std))
print("Number of features in Train Data: ",len(X_train_avgw2v_std[0]))
print("Number of rows in Test Data: ",len(X_test_avgw2v_std))
print("Number of features in Test Data: ",len(X_test_avgw2v_std[0]))
```

```
Number of rows in Train Data:  254519
Number of features in Train Data:  50
Number of rows in Test Data:  109080
Number of features in Test Data:  50
```

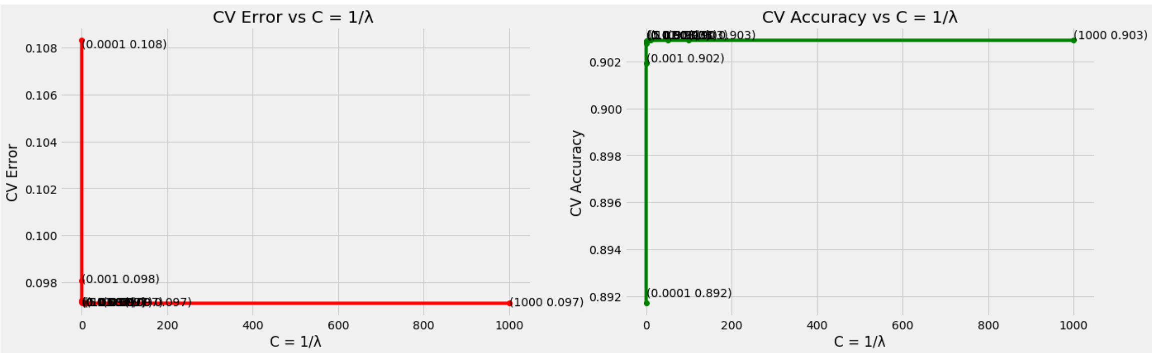
[8.5.1] Using GridSearch CV :

L2 Regularization :

In [49]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_avgw2v_std, y_train, penalty = 'l2')
```

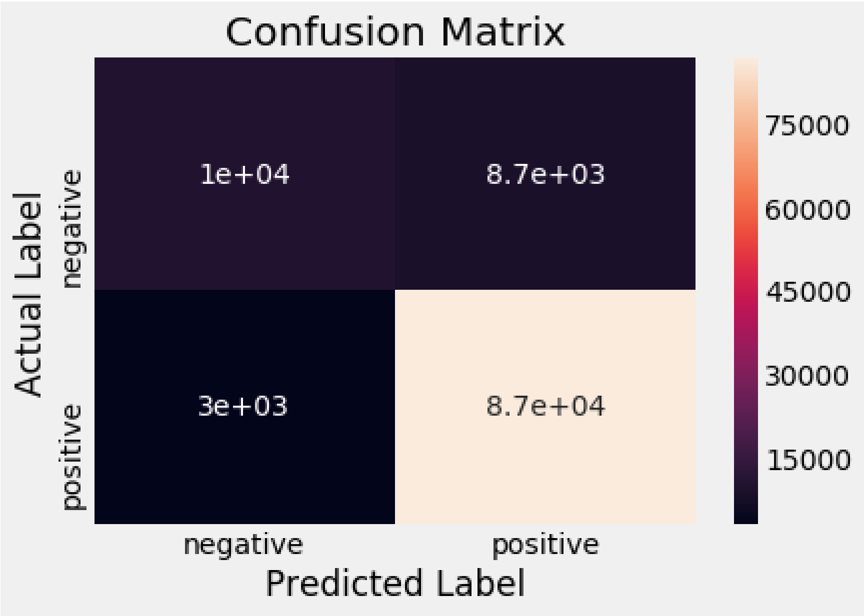
```
Optimal C:  {'C': 50}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.291 %
```



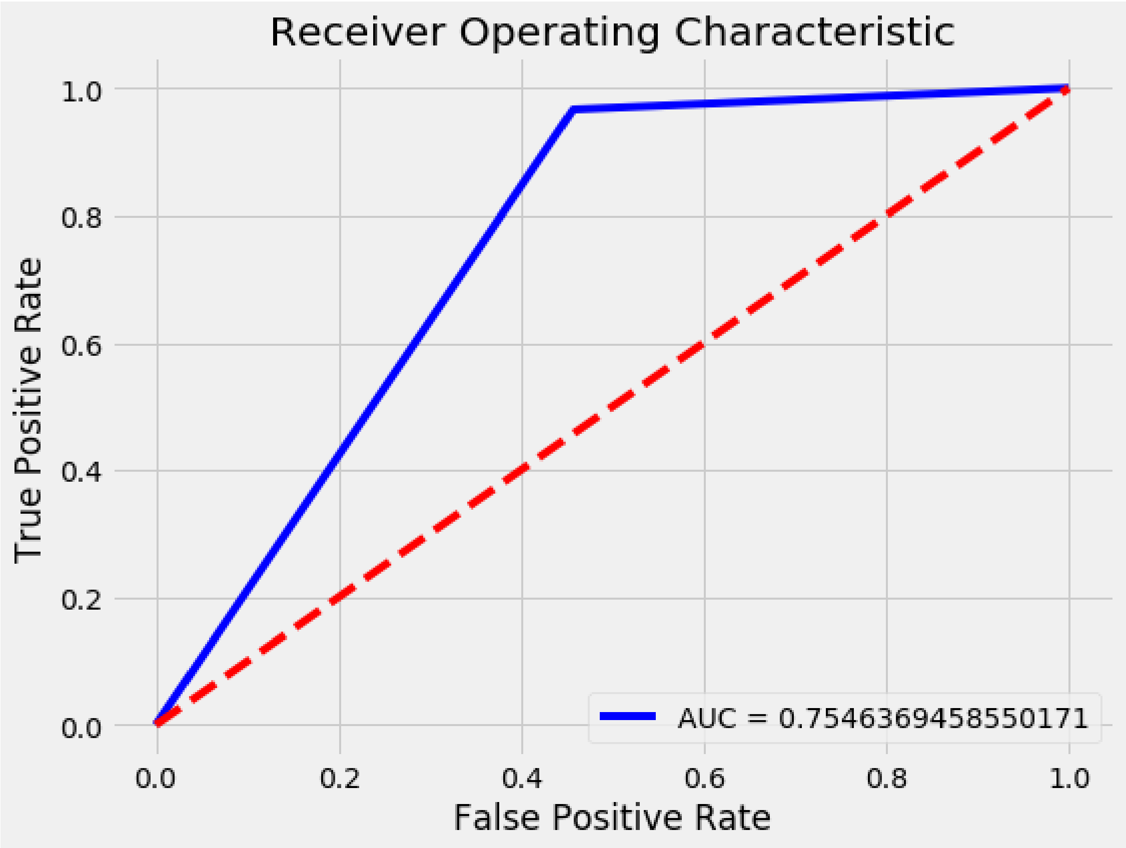

```
CV Error for each value of C:  [0.108 0.098 0.097 0.097 0.097 0.097 0.097
 0.097 0.097 0.097]

CV Accuracy for each value of C:  [0.892 0.902 0.903 0.903 0.903 0.903 0.9
03 0.903 0.903 0.903]
CPU times: user 8min 2s, sys: 1.04 s, total: 8min 3s
Wall time: 8min
```

In [50]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_avgw2v_std, X_test_avgw2v_std, y_train, y_test, 'l2', 50)
```




```
[[10342  8705]
 [ 3034 86999]]

Test Error : 0.108
Test Accuracy : 89.238 %
True Negative : 10342
False Positive : 8705
False Negative : 3034
True Positive : 86999
Precission Score : 0.841
Recall Score : 0.755
F1 Score : 0.787
```



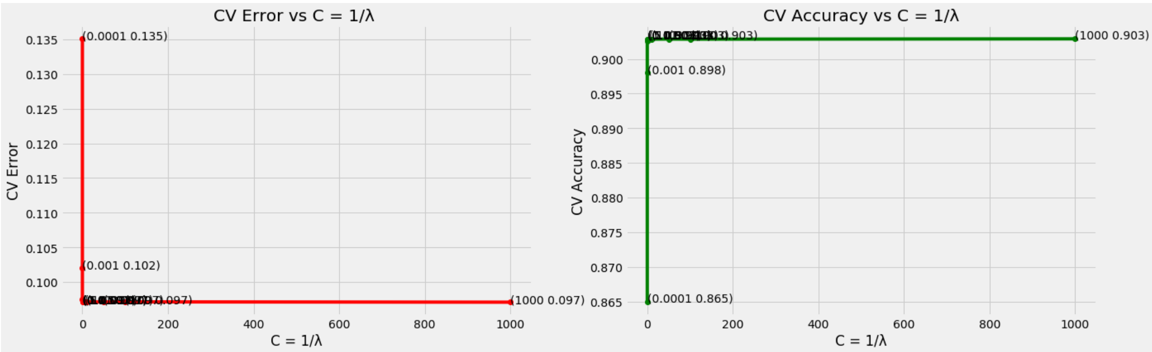

```
CPU times: user 7.46 s, sys: 12 ms, total: 7.47 s
Wall time: 7.03 s
```

L1 Regularization :

In [51]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_avgw2v_std, y_train, penalty = 'l1')
```

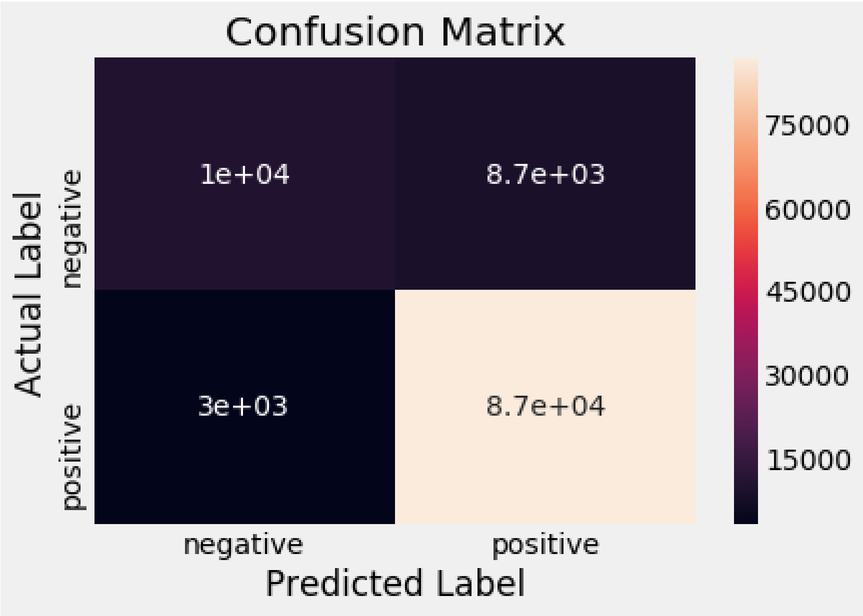
```
Optimal C:  {'C': 1000}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.29 %
```



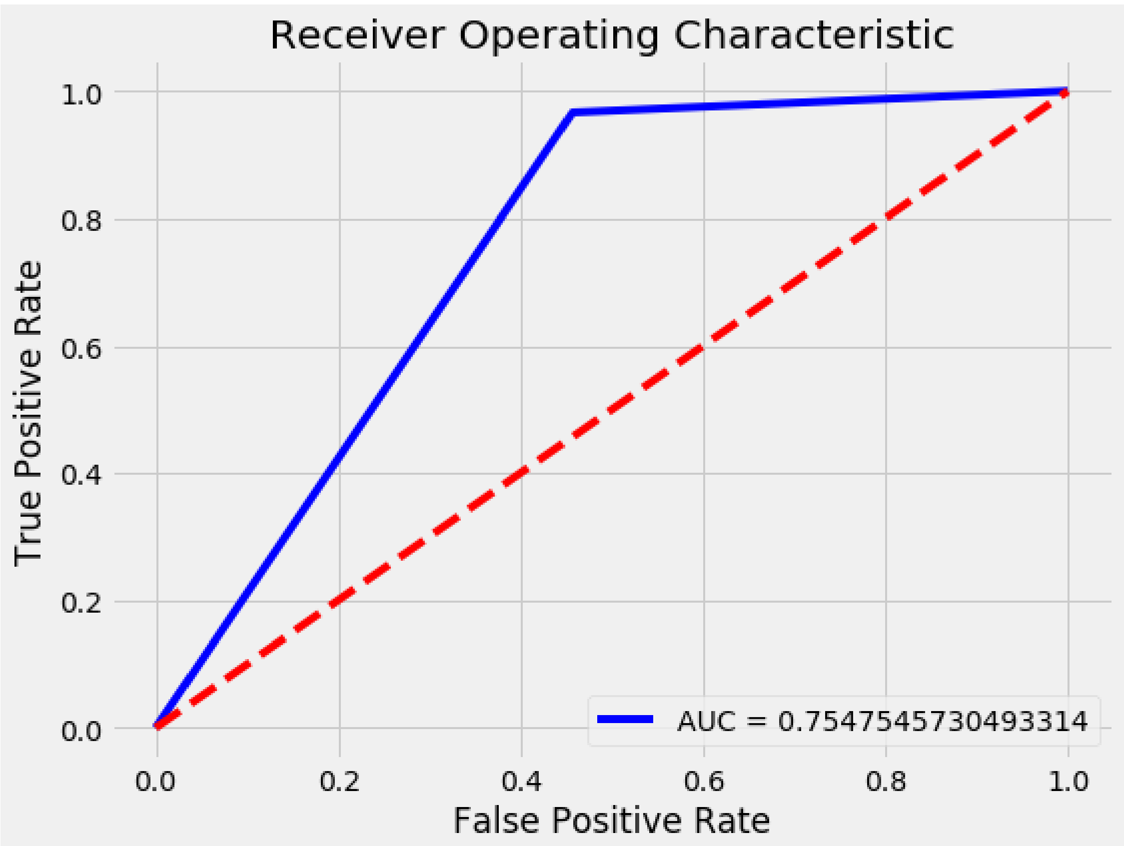

```
CV Error for each value of C:  [0.135 0.102 0.097 0.097 0.097 0.097 0.097
 0.097 0.097 0.097]

CV Accuracy for each value of C:  [0.865 0.898 0.903 0.903 0.903 0.903 0.9
03 0.903 0.903 0.903]
CPU times: user 1h 35min 19s, sys: 3.26 s, total: 1h 35min 22s
Wall time: 1h 35min 19s
```

In [53]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_avgw2v_std, X_test_avgw2v_std, y_train, y_test, 'l1',1000)
```




```
[[10345  8702]
 [ 3027 87006]]

Test Error : 0.108
Test Accuracy : 89.247 %
True Negative : 10345
False Positive : 8702
False Negative : 3027
True Positive : 87006
Precission Score : 0.841
Recall Score : 0.755
F1 Score : 0.788
```



```
CPU times: user 2min 18s, sys: 44 ms, total: 2min 18s
Wall time: 2min 18s
```

[8.5.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [52]:

```
if __name__ == "__main__":
    sparsity_check(X_train_avgw2v_std, X_test_avgw2v_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  50
Train Error:  0.097
Test Error:  0.107
Test Accuracy : 0.89251
Run Time :77.11510200000066 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  50
Train Error:  0.097
Test Error:  0.107
Test Accuracy : 0.8925
Run Time :76.87039000000004 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  50
Train Error:  0.097
Test Error:  0.108
Test Accuracy : 0.89241
Run Time :93.50651099999959 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  49
Train Error:  0.097
Test Error:  0.108
Test Accuracy : 0.89203
Run Time :30.468505000000732 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  38
Train Error:  0.101
Test Error:  0.113
Test Accuracy : 0.88731
Run Time :4.664448999999877 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  13
Train Error:  0.133
Test Error:  0.151
Test Accuracy : 0.84876
Run Time :1.6230040000009467 sec
```

Observation : Here C= 1/λ, we can see as C decreases(λ increases)

- Sparsity Increases(Number of non zero elements decreases)
- Error increases and Performance accuarcy drops(model starts underfitting)
- Run Time is also fast as sparsity increases

[8.5.3] Using RandomSearch CV :

L2 Regularization :

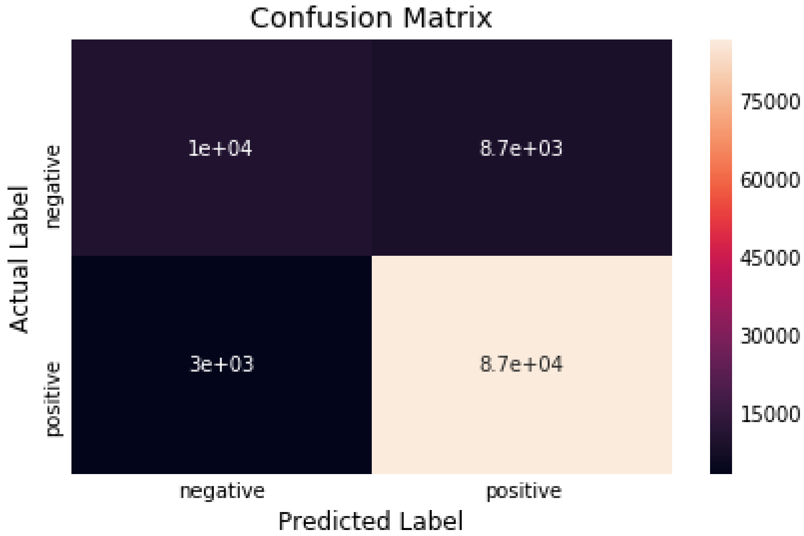
In [54]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_avgw2v_std, y_train, penalty = 'l2')
```

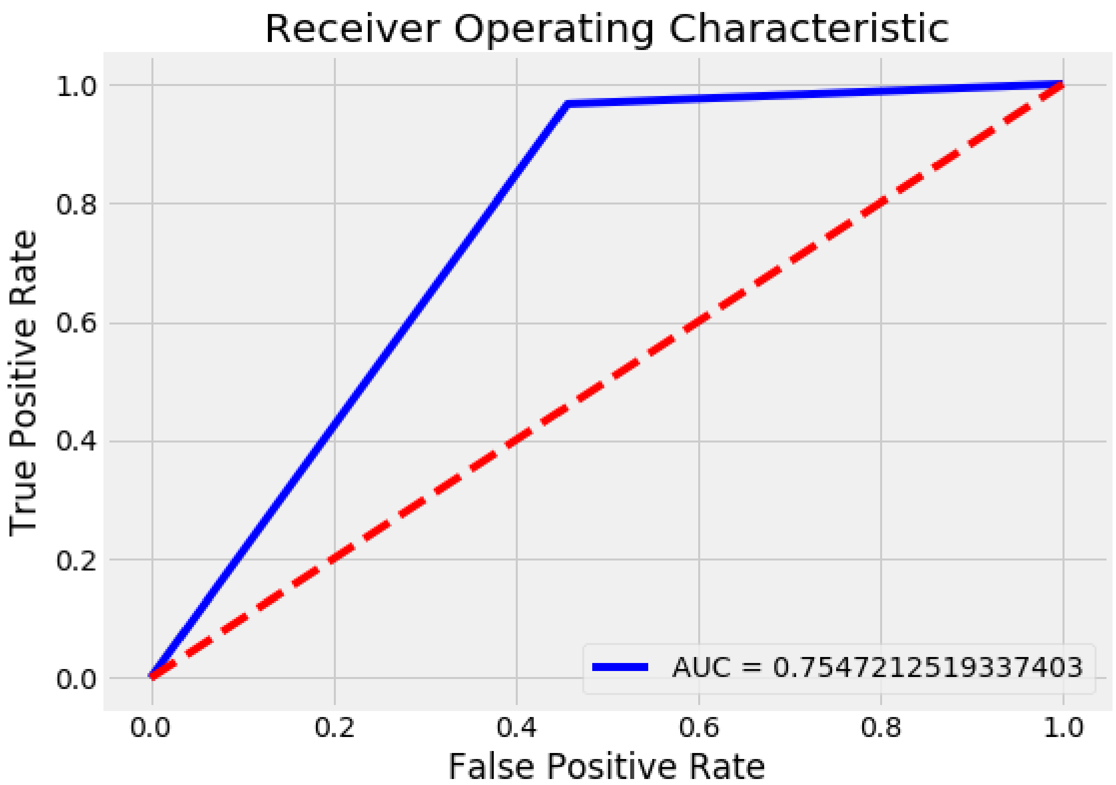
```
Optimal C:  {'C': 2.6804844914828405}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.293 %


CPU times: user 8min 47s, sys: 1.09 s, total: 8min 48s
Wall time: 8min 45s
```

In [72]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_avgw2v_std, X_test_avgw2v_std, y_train, y_test,'l2',2.680)
```




```
[[10345  8702]
 [ 3033 87000]]

Test Error : 0.108
Test Accuracy : 89.242 %
True Negative : 10345
False Positive : 8702
False Negative : 3033
True Positive : 87000
Precission Score : 0.841
Recall Score : 0.755
F1 Score : 0.787
```




```
CPU times: user 10 s, sys: 4 ms, total: 10 s
Wall time: 9.58 s
```

L1 Regularization :

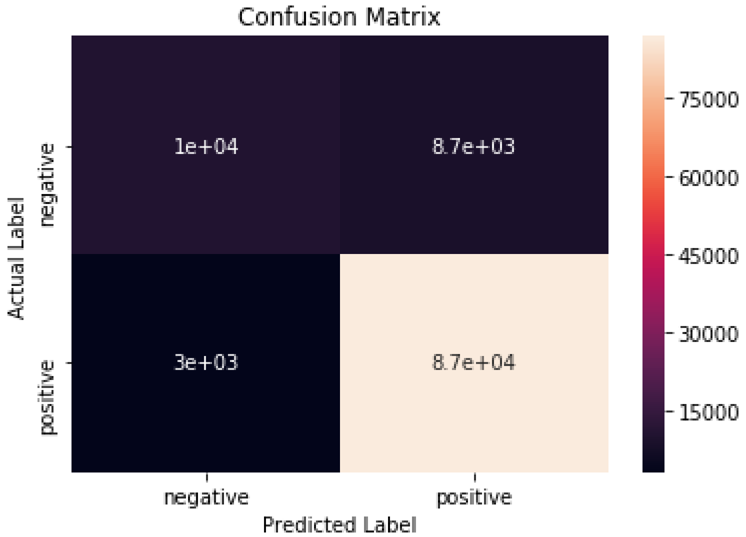
In [ ]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_avgw2v_std, y_train, penalty = 'l1')
```

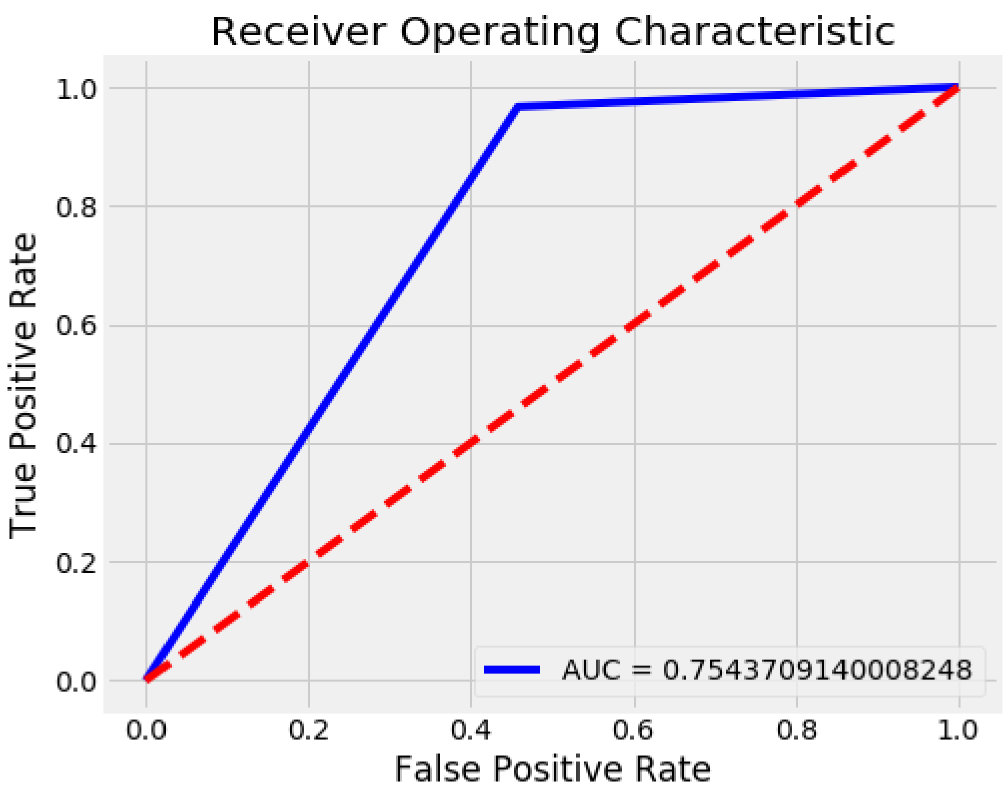
```
Optimal C:  {'C': 0.17690344265644772}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.288 %


CPU times: user 1h 53min 48s, sys: 5.83 s, total: 1h 53min 54s
Wall time: 1h 53min 51s
```

In [15]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_avgw2v_std, X_test_avgw2v_std, y_train, y_test, 'l1', 0.176)
```




```
[[10327  8720]
 [ 3011 87022]]

Test Error : 0.108
Test Accuracy : 89.246 %
True Negative : 10327
False Positive : 8720
False Negative : 3011
True Positive : 87022
Precission Score : 0.842
Recall Score : 0.754
F1 Score : 0.787
```



```
CPU times: user 1min 23s, sys: 148 ms, total: 1min 23s
Wall time: 1min 23s
```

[8.5.4] MultiCollinearity :

In [161]:

```
if __name__ == "__main__":
    multicollinear_check(X_train_avgw2v_std,X_test_avgw2v_std,y_train,y_test,50)
```

```
-----------BEFORE PERTUBATION TEST------------

Sample Weights:            0         1         2         3         4
  5         6   \
0 -0.588587  0.446414 -0.533977 -0.788838 -0.422129 -0.363002  0.372933

        7         8         9     ...            40        41        42  \
0  0.04856  0.144315 -0.020016    ...    -0.237664 -0.42991 -0.534093

         43        44        45        46        47        48        49
0 -0.174668 -0.363496  0.07075  0.365204 -0.169001 -0.25998 -0.458187

[1 rows x 50 columns]
Size of weight vector:  50
Non zero weights:  50
Test Accuracy : 89.238 %

-----------AFTER PERTUBATION TEST------------

Sample Weights:            0        1         2         3        4
 5        6   \
0 -0.576476  0.44317 -0.519533 -0.756785 -0.42583 -0.356126  0.35971

         7         8         9     ...            40        41        42  \
0  0.046812  0.136165 -0.012172    ...    -0.227333 -0.428892 -0.525311

         43        44        45        46        47        48        49
0 -0.188625 -0.345497  0.076696  0.360842 -0.160229 -0.258166 -0.440162

[1 rows x 50 columns]
Size of weight vector:  50
Non zero weights:  50
Test Accuracy : 89.248 %


Number of features with weights changing greater than 30% : 3

Following are the 3 features that are multicollinear
9 17 26
```

[8.6] TF-IDF Weighted Word2Vec :

In [17]:

```
%%time
tfidf_feat = tfidf_bigram.get_feature_names() # tfidf words/col-names
X_train_tfidfw2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in list_of_sent_train:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            tfidf = X_train_tfidfbi[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass

    if weight_sum != 0:
        sent_vec /= weight_sum
    X_train_tfidfw2v.append(sent_vec)
    row += 1
```

```
CPU times: user 29min 29s, sys: 876 ms, total: 29min 30s
Wall time: 29min 29s
```

In [37]:

```
%%time
X_test_tfidfw2v = [];
row=0;
for sent in list_of_sent_test:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            tfidf = X_train_tfidfbi[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass

    if weight_sum != 0:
        sent_vec /= weight_sum
    X_test_tfidfw2v.append(sent_vec)
    row += 1
```

```
CPU times: user 12min 57s, sys: 2.1 s, total: 13min
Wall time: 12min 59s
```

In [38]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean=False)
X_train_tfidfw2v_std = sc.fit_transform(X_train_tfidfw2v)
```

In [39]:

```
X_test_tfidfw2v_std = sc.transform(X_test_tfidfw2v)
```

In [40]:

```
print("Number of rows in Train Data: ",len(X_train_tfidfw2v_std))
print("Number of features in Train Data: ",len(X_train_tfidfw2v_std[0]))
print("Number of rows in Test Data: ",len(X_test_tfidfw2v_std))
print("Number of features in Test Data: ",len(X_test_tfidfw2v_std[0]))
```

```
Number of rows in Train Data:  254519
Number of features in Train Data:  50
Number of rows in Test Data:  109080
Number of features in Test Data:  50
```

In [41]:

```
dumpfile(X_train_tfidfw2v_std,"X_train_tfidfw2v_std")
dumpfile(X_test_tfidfw2v_std,"X_test_tfidfw2v_std")
```

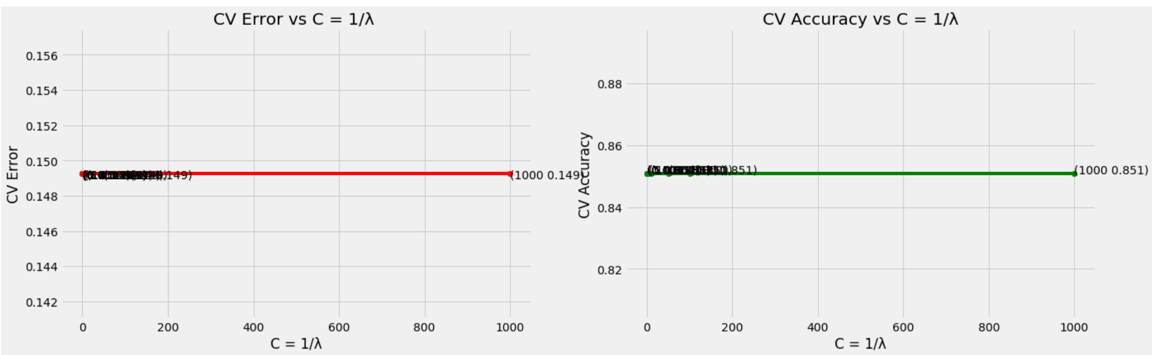
[8.6.1] Using GridSearch CV :

L2 Regularization :

In [42]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfw2v_std, y_train, penalty = 'l2')
```

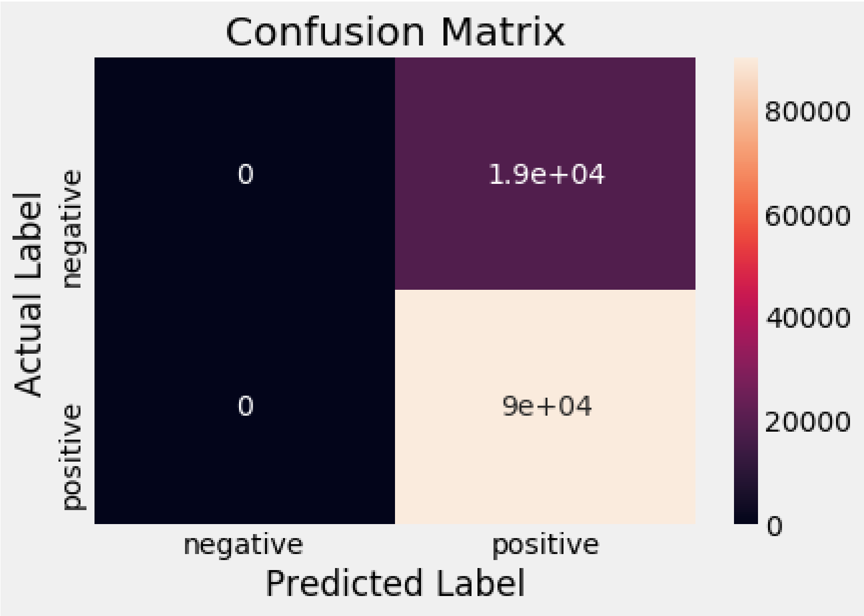
```
Optimal C:  {'C': 0.0001}

CrossValidation Error: 0.149

CrossValidation Accuracy: 85.075 %
```



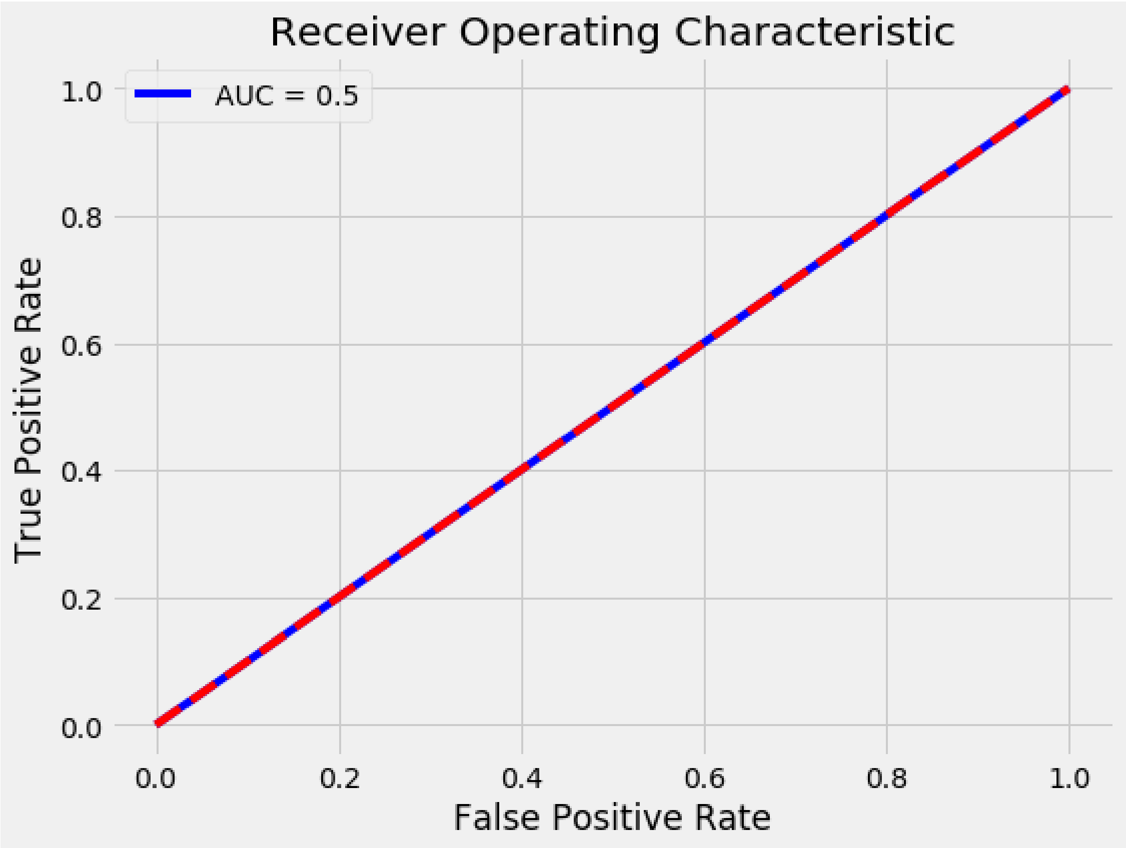

```
CV Error for each value of C:  [0.149 0.149 0.149 0.149 0.149 0.149 0.149
 0.149 0.149 0.149]

CV Accuracy for each value of C:  [0.851 0.851 0.851 0.851 0.851 0.851 0.8
51 0.851 0.851 0.851]
CPU times: user 32.8 s, sys: 1.21 s, total: 34 s
Wall time: 30.9 s
```

In [43]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfw2v_std, X_test_tfidfw2v_std, y_train, y_test, 'l2', 0.0001)
```




```
[[    0 19047]
 [    0 90033]]

Test Error : 0.175
Test Accuracy : 82.539 %
True Negative : 0
False Positive : 19047
False Negative : 0
True Positive : 90033
Precission Score : 0.413
Recall Score : 0.5
F1 Score : 0.452
```



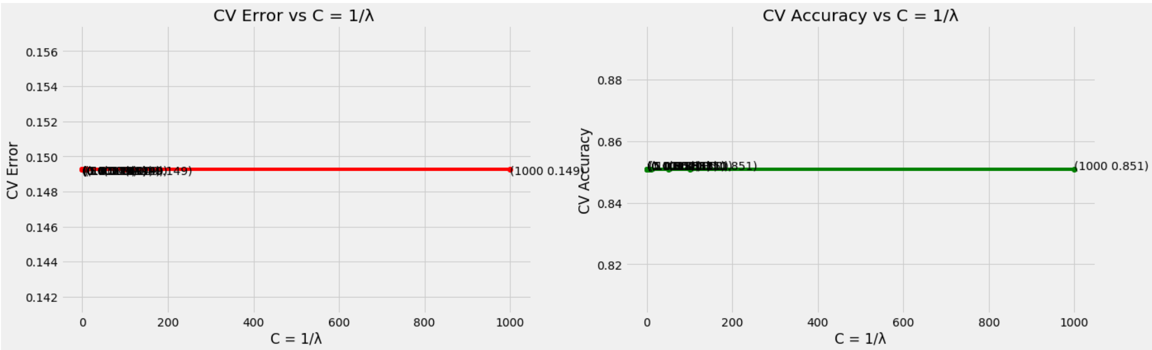

```
CPU times: user 1.41 s, sys: 8 ms, total: 1.42 s
Wall time: 990 ms
```

L1 Regularization :

In [47]:

```
%%time
if __name__ == "__main__":
    LR_gridTrain(X_train_tfidfw2v_std, y_train, penalty = 'l1')
```

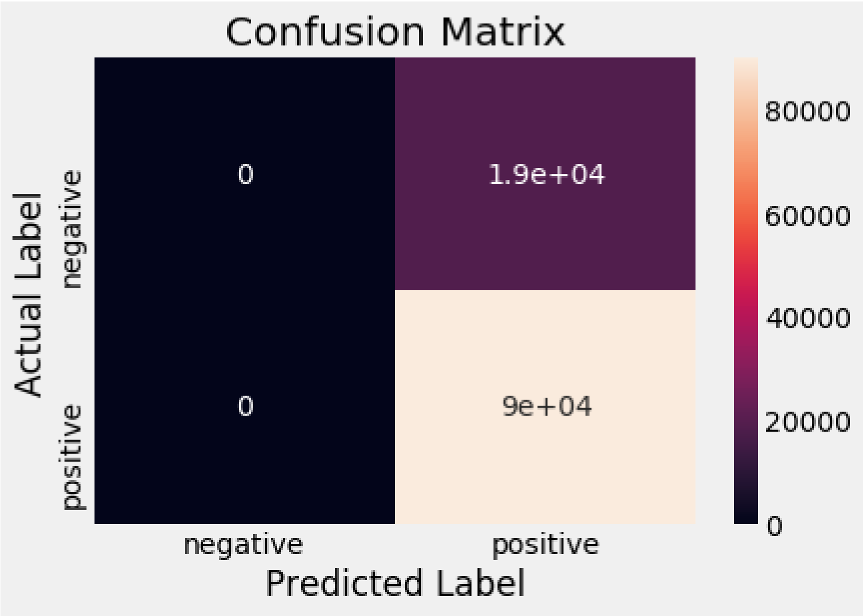
```
Optimal C:  {'C': 0.0001}

CrossValidation Error: 0.149

CrossValidation Accuracy: 85.075 %
```



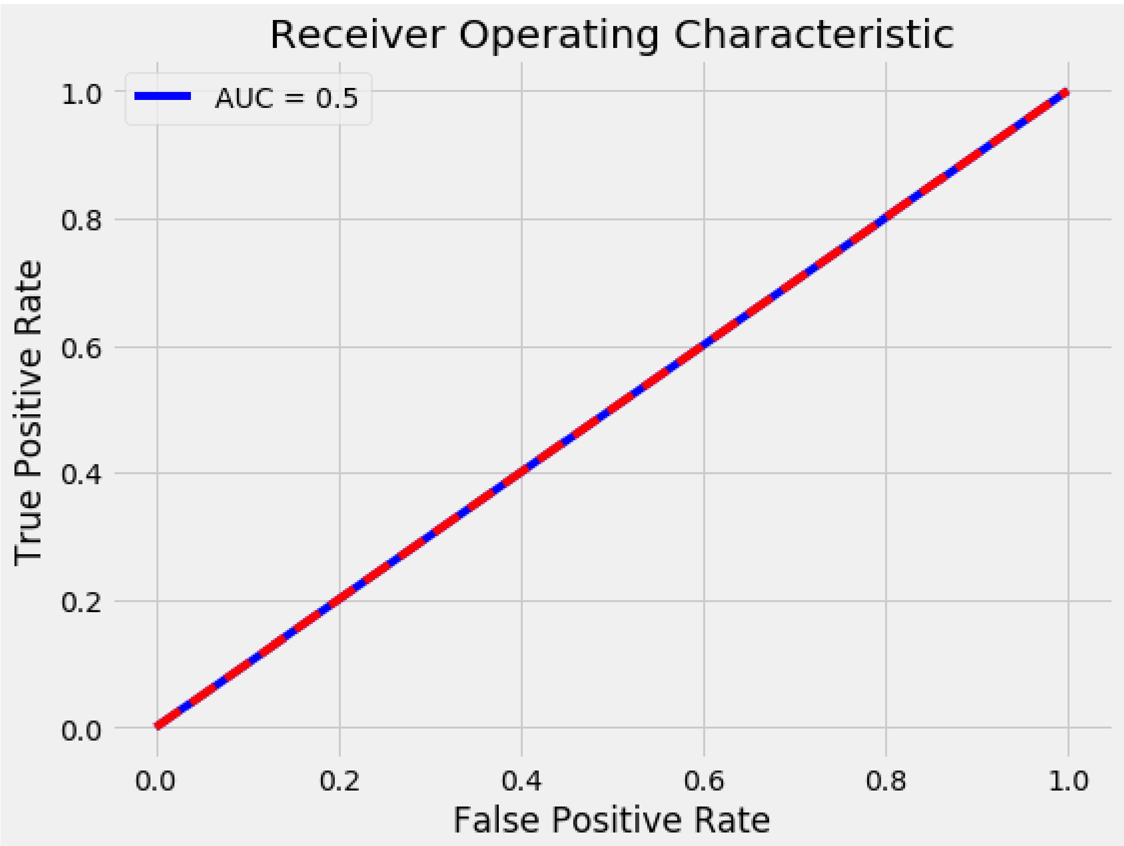

```
CV Error for each value of C:  [0.149 0.149 0.149 0.149 0.149 0.149 0.149
 0.149 0.149 0.149]

CV Accuracy for each value of C:  [0.851 0.851 0.851 0.851 0.851 0.851 0.8
51 0.851 0.851 0.851]
CPU times: user 28.1 s, sys: 1.07 s, total: 29.2 s
Wall time: 25.7 s
```

In [48]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfw2v_std, X_test_tfidfw2v_std, y_train, y_test, 'l1', 0.0001)
```




```
[[    0 19047]
 [    0 90033]]

Test Error : 0.175
Test Accuracy : 82.539 %
True Negative : 0
False Positive : 19047
False Negative : 0
True Positive : 90033
Precission Score : 0.413
Recall Score : 0.5
F1 Score : 0.452
```



```
CPU times: user 1.34 s, sys: 28 ms, total: 1.36 s
Wall time: 962 ms
```

[8.6.2] Sparsity And Accuracy on Weight Vectors(L1 Regularization) :

In [44]:

```
if __name__ == "__main__":
    sparsity_check(X_train_tfidfw2v_std, X_test_tfidfw2v_std ,y_train ,y_test)
```

```
Sparsity and Accuarcy when C = 10
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4394509999992806 sec

Sparsity and Accuarcy when C = 1
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4273480000001655 sec

Sparsity and Accuarcy when C = 0.1
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4278549999999086 sec

Sparsity and Accuarcy when C = 0.01
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4308789999995497 sec

Sparsity and Accuarcy when C = 0.001
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4345000000002983 sec

Sparsity and Accuarcy when C = 0.0001
Number of non-zero weighhts:  0
Train Error:  0.149
Test Error:  0.175
Test Accuracy : 0.82539
Run Time :0.4260019999992437 sec
```

[8.6.3] Using RandomSearch CV :

L2 Regularization :

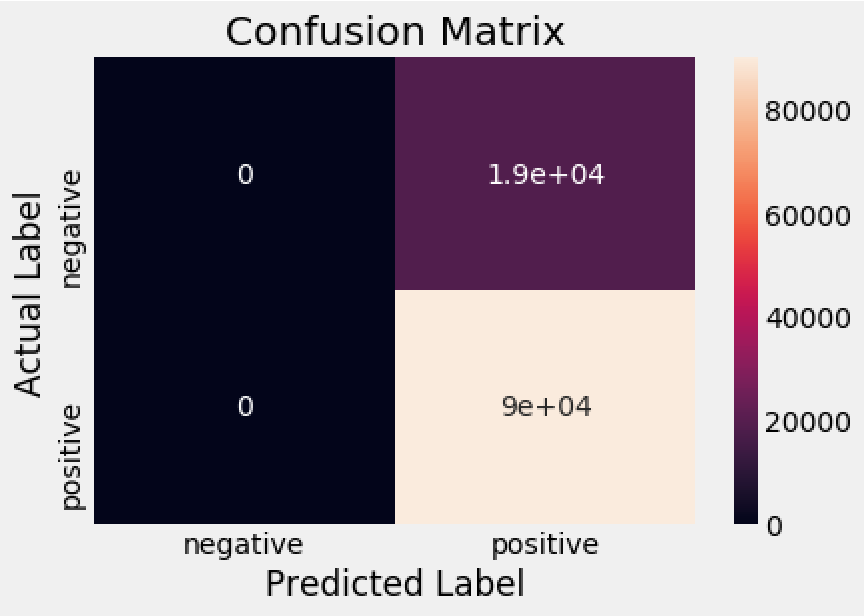
In [45]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfw2v_std, y_train, penalty = 'l2')
```

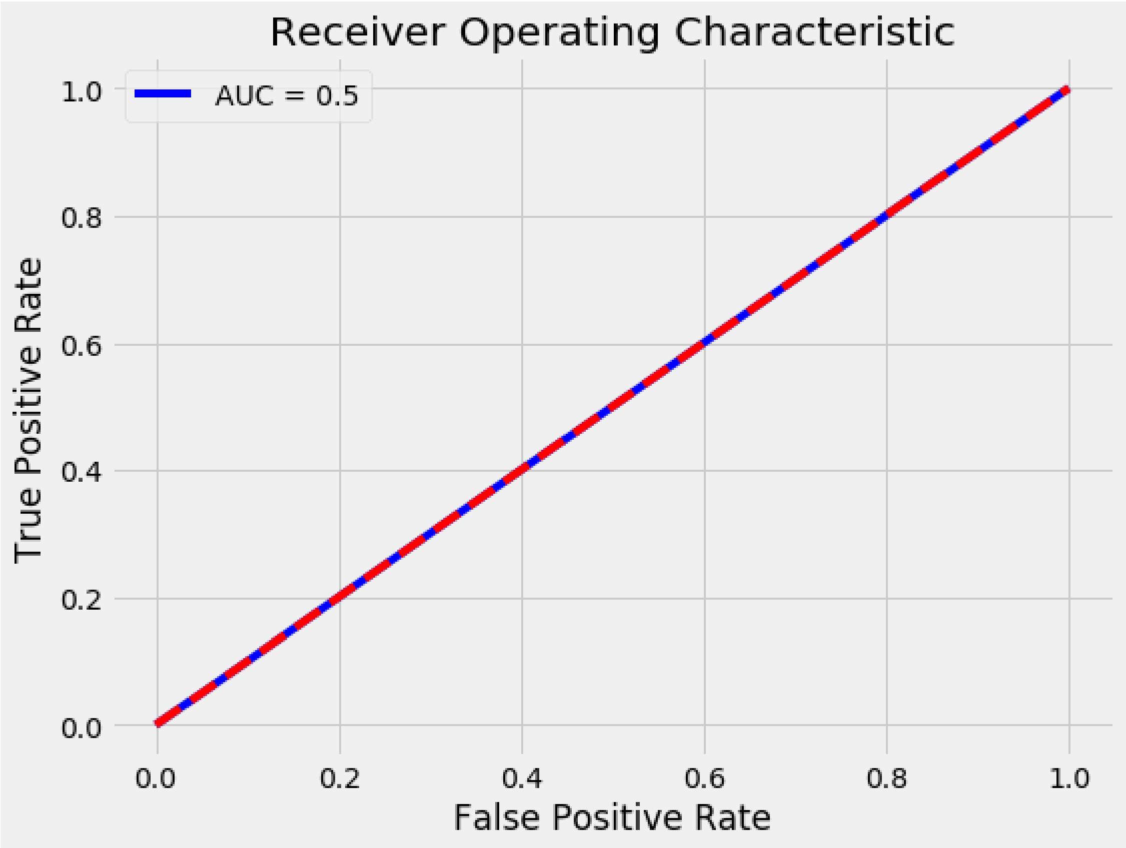
```
Optimal C:  {'C': 1.2928165589093843}

CrossValidation Error: 0.149

CrossValidation Accuracy: 85.075 %


CPU times: user 32.4 s, sys: 980 ms, total: 33.4 s
Wall time: 30.2 s
```

In [46]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfw2v_std, X_test_tfidfw2v_std, y_train, y_test, 'l2', 1.29)
```




```
[[    0 19047]
 [    0 90033]]

Test Error : 0.175
Test Accuracy : 82.539 %
True Negative : 0
False Positive : 19047
False Negative : 0
True Positive : 90033
Precission Score : 0.413
Recall Score : 0.5
F1 Score : 0.452
```




```
CPU times: user 1.36 s, sys: 8 ms, total: 1.36 s
Wall time: 981 ms
```

L1 Regularization :

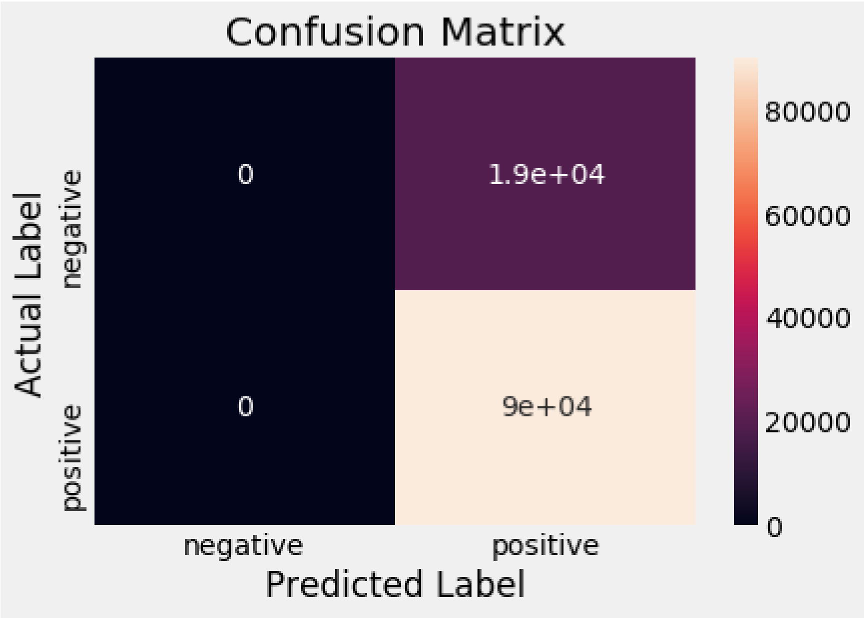
In [49]:

```
%%time
if __name__ == "__main__":
    LR_randomTrain(X_train_tfidfw2v_std, y_train, penalty = 'l1')
```

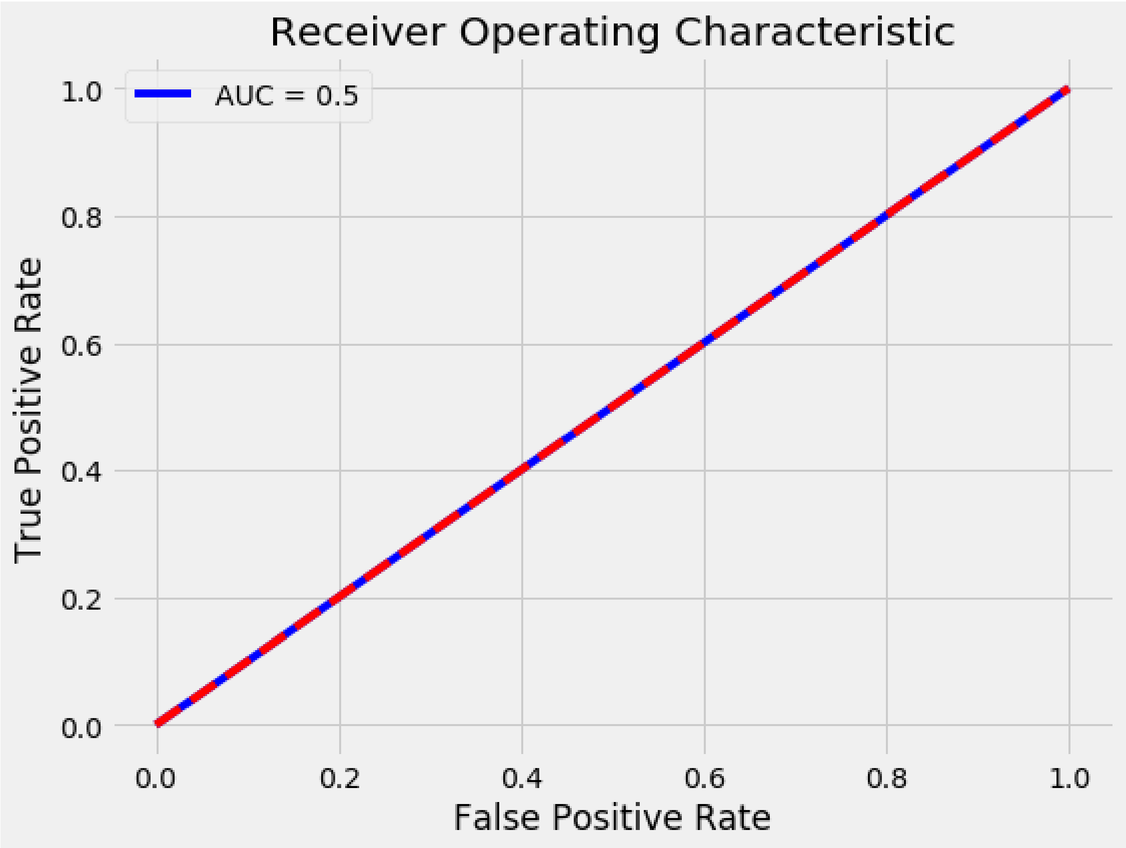
```
Optimal C:  {'C': 0.9964195542921448}

CrossValidation Error: 0.149

CrossValidation Accuracy: 85.075 %


CPU times: user 27.4 s, sys: 1.16 s, total: 28.5 s
Wall time: 25.4 s
```

In [51]:

```
%%time
if __name__ == "__main__":
    LR_Test(X_train_tfidfw2v_std, X_test_tfidfw2v_std, y_train, y_test, 'l1', 0.99)
```




```
[[    0 19047]
 [    0 90033]]

Test Error : 0.175
Test Accuracy : 82.539 %
True Negative : 0
False Positive : 19047
False Negative : 0
True Positive : 90033
Precission Score : 0.413
Recall Score : 0.5
F1 Score : 0.452
```




```
CPU times: user 1.34 s, sys: 28 ms, total: 1.37 s
Wall time: 954 ms
```

Observation : Tfidf Weighted Word2Vec classifies all the test data(unseen points) as Positive(majority class). It is like a dumb model as we can see from the ROC plot,it overlaps with simple model and True Negative is also zero.

[9] Conclusion :

Grid Search Cross Validation :

Featurization Model	L2 Regularization				L1 Regularization			
	Accuracy	Precission	Recall	F1 score	Accuracy	Precission	Recall	F1 score
BOW(unigram)	91.569 %	0.878	0.813	0.84	91.548 %	0.875	0.816	0.841
BOW(bigram)	93.004 %	0.908	0.838	0.868	93.039 %	0.905	0.843	0.87
TF-IDF(unigram)	91.823 %	0.878	0.824	0.847	91.892 %	0.877	0.828	0.85
TF-IDF(bigram)	93.166 %	0.895	0.859	0.876	93.357 %	0.906	0.855	0.877
Average Word2vec	89.238 %	0.841	0.755	0.787	89.247 %	0.841	0.755	0.788
TF-IDF Wweighted Word2Vec	82.539 %	0.413	0.5	0.452	82.539 %	0.413	0.5	0.452

Random Search Cross Validation :

Featurization Model	L2 Regularization				L1 Regularization			
	Accuracy	Precission	Recall	F1 score	Accuracy	Precission	Recall	F1 score
BOW(unigram)	91.566 %	0.874	0.817	0.842	91.563 %	0.875	0.817	0.842
BOW(bigram)	92.794 %	0.886	0.856	0.87	92.92 %	0.89	0.856	0.872
TF-IDF(unigram)	91.859 %	0.876	0.828	0.849	91.915 %	0.881	0.824	0.849
TF-IDF(bigram)	92.999 %	0.889	0.861	0.874	93.342 %	0.901	0.859	0.878
Average Word2vec	89.242 %	0.841	0.755	0.787	89.246 %	0.842	0.754	0.787
TF-IDF Wweighted Word2Vec	82.539 %	0.413	0.5	0.452	82.539 %	0.413	0.5	0.452

1 - Tfidf with bigram performed the best with all performance metrics having an accuracy of 93.166 % and F1 Score of .876 in L2 regularization, accuracy of 93.357 % and F1 Score of .877 in L1 regularization.

2 - Both Gridserach and Random Search Crossvalidation gave almost equal results.

3 - L1 regularization creates a sparse weight vector ie all the less impoartant features becomes zero.

4 - It is also observed that in L1 regularization, as hyperparameter C decreases(lambda increases),
(i) Sparsity Increases(Number of non zero elements decreases)
(ii)Error increases and Performance accuarcy drops(model starts underfitting)
(iii)Run Time is also fast as sparsity increases

5 - Logistic Regression gave better accuracies and results as compared to Naive Bayes model.

6 - Run Time Complexity of Logistic Regression is less. This model can be used for low latency applications.

7 - TF-IDF Wweighted Word2Vec performed worst in Logistic Regression model. It is like a dumb model as every unseen points gets classified as majority class(Positive).