Applying Logistic Regression on Amazon fine food reviews Dataset

Here we will be using Grid search CV for hyperparameter tuning.

Introduction to the 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.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
import sqlite3
import pandas as pd
import nltk
import string
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
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
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: Thi
s module was deprecated in version 0.18 in favor of the model_selection module into which all the re
factored classes and functions are moved. Also note that the interface of the new CV iterators are d
ifferent from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

2. Connecting to Amazon food review dataset

In [2]:
```
con=sqlite3.connect('./database.sqlite')
filtered_data=pd.read_sql_query("""select * from reviews where score!=3""",con)
def partition(x):
    if x<3:
        return 'negative'
    else:
        return 'positive'
actual_score=filtered_data['Score']
PositiveNegative=actual_score.map(partition)
filtered_data['Score']=PositiveNegative
print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	positive	1303862400
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	negative	1346976000
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	positive	1219017600
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	negative	1307923200
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	positive	1350777600

In [ ]:

3. Sorting our data on the basis of date and removing the Duplicate reviews

In [3]:
```
sorted_data=filtered_data.sort_values('ProductId',axis=0,ascending=True,inplace=False,kind='quicksort'
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},keep='first',inplace=F
print(final.shape)
```

```
(364173, 10)
```

4. we are also removing the rows which has HelpfulnessDenominator greater then HelpfulnessNumerator because its not practically possile

In [4]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [5]:
```
print(final.shape)
```

```
(364171, 10)
```

In [6]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

we are also cleaning our text of html tags , stop words, and puncuations

In [7]:
```
# 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;
```

```
6
I set aside at least an hour each day to read to my son (3 y/o). At this point, I consider myself a
connoisseur of children's books and this is one of the best. Santa Clause put this under the tree. S
ince then, we've read it perpetually and he loves it.<br /><br />First, this book taught him the mon
ths of the year.<br /><br />Second, it's a pleasure to read. Well suited to 1.5 y/o old to 4+.<br />
<br />Very few children's books are worth owning. Most should be borrowed from the library. This boo
k, however, deserves a permanent spot on your shelf. Sendak's best.
```

In [8]:
```
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
print(stop)
print('************************************')
print(sno.stem('tasty'))
```

```
{'being', 'to', 'more', 'this', 'those', "should've", 'itself', 'theirs', 'you', 'for', 'am', 'on',
'any', 'both', 'o', 'where', 'that', "that'll", 'these', "couldn't", 'only', 'but', 'can', 'was', 'h
e', 'ourselves', 'into', 'above', 'further', 'had', 'by', 'no', 'shouldn', 'some', 'what', 'been',
'against', 'does', 'until', 'during', 'm', "shouldn't", 'having', 'himself', 'a', 'there', 'hers',
'she', "haven't", "hadn't", "you're", 'we', "don't", 's', "isn't", 'd', 'doesn', 'up', 'couldn', 'he
re', 'ain', "mightn't", 'as', 'then', 'very', 'below', 'each', 'why', 'before', 'aren', 'mightn', 'a
nd', 'won', 'doing', 'who', 'yourself', 'the', 'how', 'most', 'hadn', 've', "shan't", 'than', "was
n't", 'same', 'which', 'after', 'my', 'too', 'weren', "won't", 'y', 'about', 'her', "it's", "need
n't", "she's", 'has', 'be', 'out', 'them', 'don', 'all', "hasn't", "wouldn't", 'or', 'an', "must
n't", 'themselves', 'now', 'other', 'down', 'yours', 'are', 'through', 'at', 'll', 'its', "you'll",
'herself', 'have', 'between', 'shan', 'under', 'off', 'i', 'his', 'once', "didn't", 'their', 'our',
"you'd", 'if', 'yourselves', 'were', 'it', 'wouldn', 'did', 'myself', 'not', 'haven', 'own', 't', 'h
asn', 'mustn', 'just', 'will', 'is', 'ours', 'such', 'few', 'nor', 'they', 'whom', 'him', 'needn',
'over', 'didn', 'with', 'do', 're', "aren't", 'me', 'your', 'of', 'from', 'ma', "weren't", 'while',
'so', 'in', 'should', 'when', "doesn't", 'again', 'because', "you've", 'isn', 'wasn'}
************************************
tasti
```

In [9]:
```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
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 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 describe positive revi
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe negative revi
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

In [10]:
```
final['CleanedText']=final_string #adding a column of CleanedText which displays the data after pre-pr
```

In [11]:
```
final.head(3) #below the processed review can be seen in the CleanedText Column


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

6. Here we are Seperating all the review information of user on the basis of their Score i.e positive or negative.

Then we are taking 306913 positive and 57087 negative reviews respectively from positive and negative data frame and we are concating them together in one data frame bigdata. We are also taking the scores of these 364000 reviews seperately in s1. We then divide 364000 reviews to train and test data, and we convert the text column of the test and train into BOW.

In [16]:
```
final.shape
```

Out[16]:
```
(364171, 11)
```

In [12]:
```
total_data=final.sample(364000)
```

In [18]:
```
#Again sorting our data in Ascending order
sorted_data=total_data.sort_values('Time',axis=0,ascending=True,inplace=False,kind='quicksort',na_posi
```

In [19]:
```
sorted_data[154:161]
```

Out[19]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
516061	557949	B0000DJDL4	A1Y20KNCR0SZA1	Dessartfamily "grandmasoven"	8	9	positive	1
152806	165713	B0000D9N59	A3FE2GUBM8JZ3G	TestMagic Inc.	26	31	positive	1
502441	543222	B0000D17HA	A2B7BUH8834Y6M	Shelley Gammon "Geek"	4	4	positive	1
295398	319992	B0000SX9U0	A2IF5C0I5BH11F	Kala	9	14	positive	1
333925	361312	B00005IX96	ANRV5VWOCM1Q2	M. Harvey	4	4	positive	1
347600	375994	B0000DBN1H	A281NPSIMI1C2R	Rebecca of Amazon "The Rebecca Review"	2	4	positive	1
347679	376089	B0000DBN1Q	A281NPSIMI1C2R	Rebecca of Amazon "The Rebecca Review"	7	7	positive	1

In [21]:
```
bigdata=sorted_data
s1=bigdata['Score']
print(s1.shape)
print(s1.head())
```

```
(364000,)
138706    positive
138683    positive
417839    positive
346055    positive
417838    positive
Name: Score, dtype: object
```

In [97]:
```
from sklearn import cross_validation
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
# split the data set into train and test
X_1, X_test, y_1, y_test = cross_validation.train_test_split(bigdata, s1, test_size=0.3, random_state=
```

In [103]:
```
#BOW for 254800 Train points
count_vect = CountVectorizer() #in scikit-learn
big_data = count_vect.fit_transform(X_1['Text'].values)
print(big_data.shape)
```

```
(254800, 95227)
```

In [104]:
```
#BOW for 109200 Test points
test_data = count_vect.transform(X_test['Text'].values)
print(test_data.shape)
```

```
(109200, 95227)
```

Standardizing our Train and Test BOW vectors

In [105]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
standardizedtest_data = StandardScaler(with_mean=False).fit_transform(test_data)
print(standardizedtest_data.shape)
test_data=standardizedtest_data
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning:
Data with input dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
(109200, 95227)
```

In [106]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler(with_mean=False).fit_transform(big_data)
print(standardized_data.shape)
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning:
Data with input dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
(254800, 95227)
```

In [107]:
```
big_data=standardized_data
```

Confusion Matrix Function

In [108]:

```python
import numpy as np


def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):
    """
    given a sklearn confusion matrix (cm), make a nice plot

    Arguments
    ---------
    cm:           confusion matrix from sklearn.metrics.confusion_matrix

    target_names: given classification classes such as [0, 1, 2]
                  the class names, for example: ['high', 'medium', 'low']

    title:        the text to display at the top of the matrix

    cmap:         the gradient of the values displayed from matplotlib.pyplot.cm
                  see http://matplotlib.org/examples/color/colormaps_reference.html
                  plt.get_cmap('jet') or plt.cm.Blues

    normalize:    If False, plot the raw numbers
                  If True, plot the proportions

    Usage
    -----
    plot_confusion_matrix(cm           = cm,                  # confusion matrix created by
                                                              # sklearn.metrics.confusion_matrix
                          normalize    = True,                # show proportions
                          target_names = y_labels_vals,       # list of names of the classes
                          title        = best_estimator_name) # title of graph

    Citiation
    ---------
    http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html

    """
    import matplotlib.pyplot as plt
    import numpy as np
    import itertools

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]


    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
```

```
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy, misclass))
    plt.show()
```

Using Logistic Regression now

In [32]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.naive_bayes import MultinomialNB
#code source: http://occam.olin.edu/sites/default/files/DataScienceMaterials/machine_learning_lecture_
from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\grid_search.py:42: DeprecationWarning: This mod
ule was deprecated in version 0.18 in favor of the model_selection module into which all the refacto
red classes and functions are moved. This module will be removed in 0.20.
  DeprecationWarning)
```

Logistic Regression With CLASS - BALANCING

In [109]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced'), param_search, scoring = 'accuracy'
gsearch.fit(X, y)
```

Out[109]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x000002158CA3BCA8>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [110]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

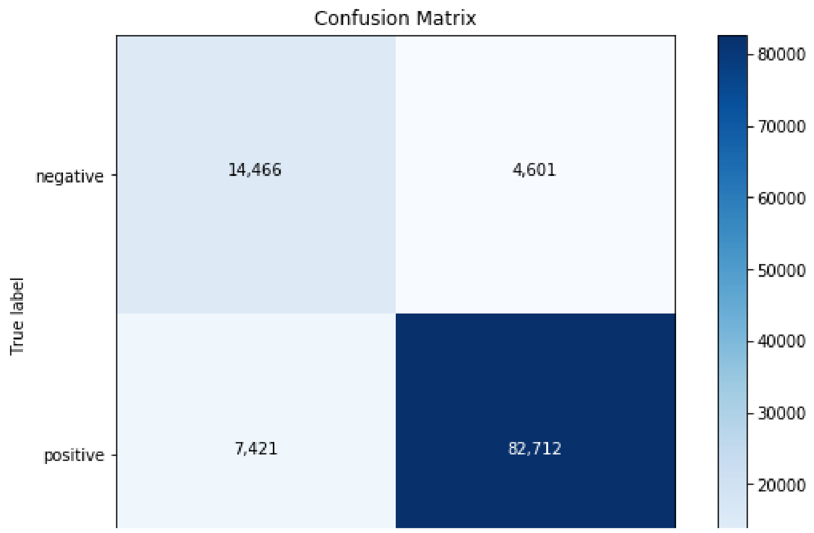
```
Test accuracy for best estimator is 88%
```

Confusion matrix , Precision, Recall, F-Score

In [113]:
```
# print the confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn import metrics
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[14466  4601]
 [ 7421 82712]]
Precision :- 0.9473045250993551
Recall    :- 0.9176661156291258
F1 Score  :- 0.9473045250993551
```

In [114]:
```
plot_confusion_matrix(cm           = np.array([[ 14466  ,4601],[7421 ,82712]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Logistic Regression L2 without Class balancing

In [115]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)
Cs = [10**-4, 10**-2, 10**0, 10**2, 10**4]
model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[115]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x000002156A24D360>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

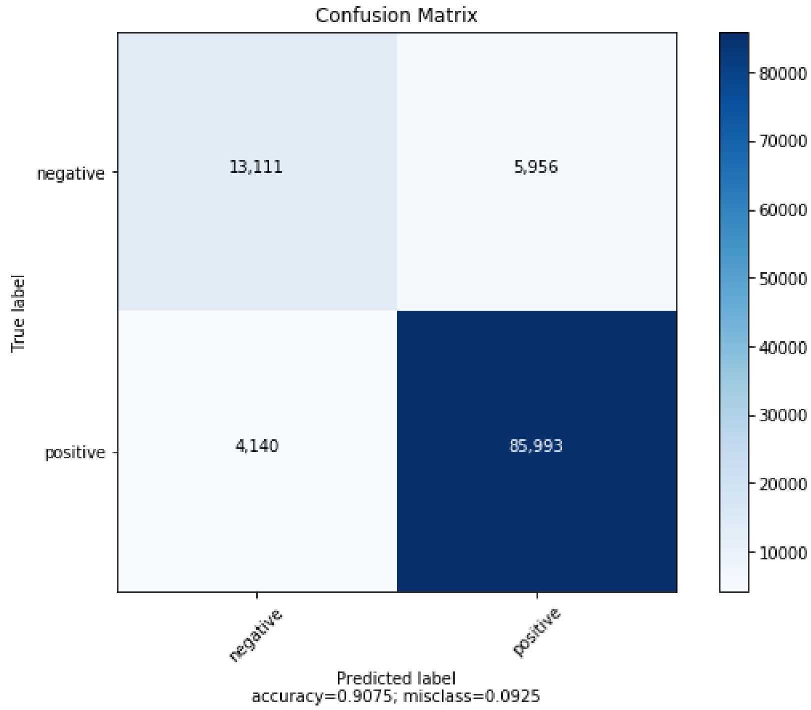
In [116]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```

Test accuracy for best estimator is 90%
```

In [117]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[13111  5956]
 [ 4140 85993]]
Precision :- 0.9352249616635309
Recall    :- 0.954067877469961
F1 Score  :- 0.9352249616635309
```

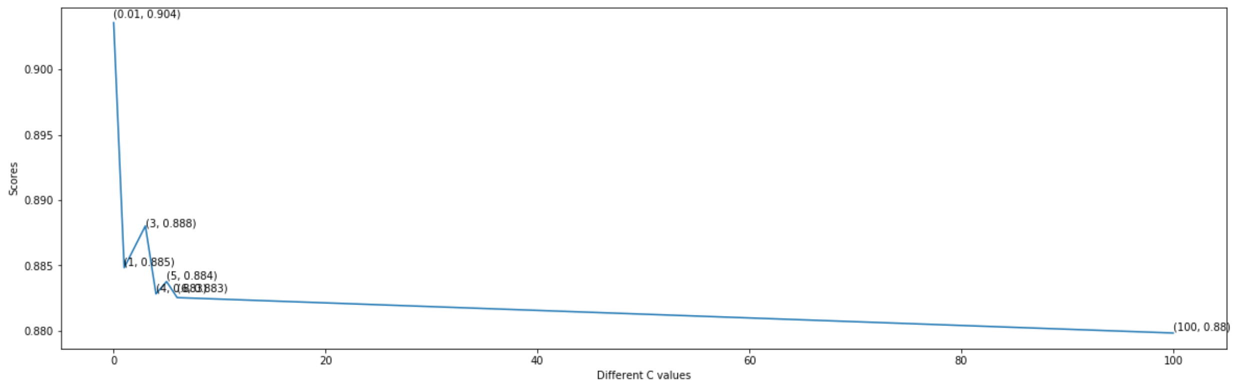
In [118]:
```
plot_confusion_matrix(cm           = np.array([[ 13111   ,5956],[4140   ,85993]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Misclassification error

In [128]:
```
Cs = [10**-2, 10**0, 3, 4, 5, 6 ,10**2]
scores = [x[1] for x in gsearch.grid_scores_]
scores = np.array(scores).reshape(len(Cs))
plt.figure(figsize=(20,6))
plt.plot(Cs, scores, label='C: ' )

for xy in zip(Cs, np.round(scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Different C values')
plt.ylabel('Scores')
plt.show()
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:762: DeprecationWarn
ing: The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate cv_res
ults_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



Now using L1 Regulariser in Logistic Regrression with class balancing

In [129]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l1'), param_search, scoring
gsearch.fit(X, y)
```

Out[129]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x000002156A24DD00>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

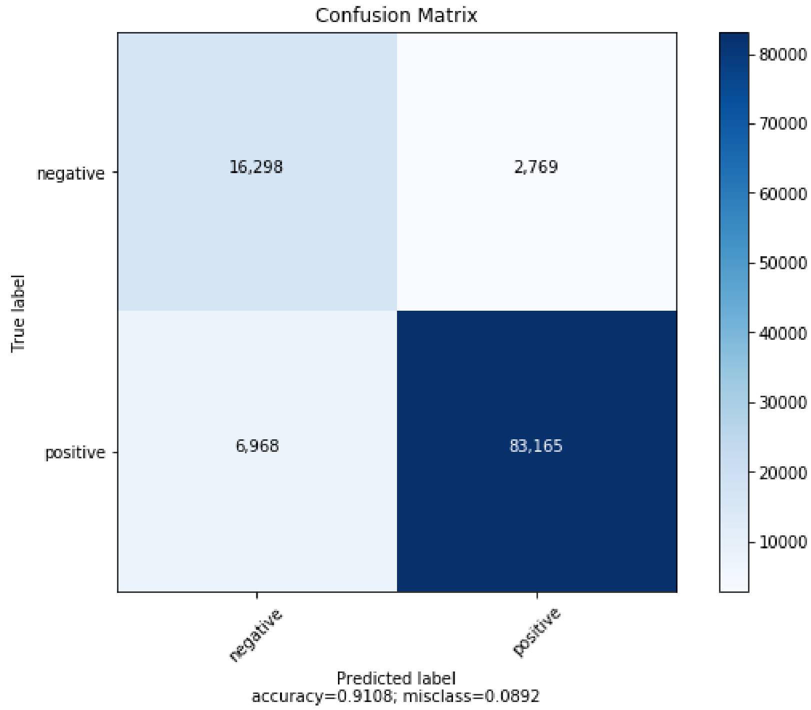
In [131]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```

Test accuracy for best estimator is 91%
```

In [132]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[16298  2769]
 [ 6968 83165]]
Precision :- 0.9677775967603044
Recall    :- 0.9226920217900214
F1 Score  :- 0.9677775967603044
```

In [133]:
```
plot_confusion_matrix(cm           = np.array([[ 16298  ,2769],[6968  ,83165]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Now using L1 Regulariser in Logistic Regrression without class balancing

In [134]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C':[10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(penalty='l1'), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[134]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x000002158CA4A200>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

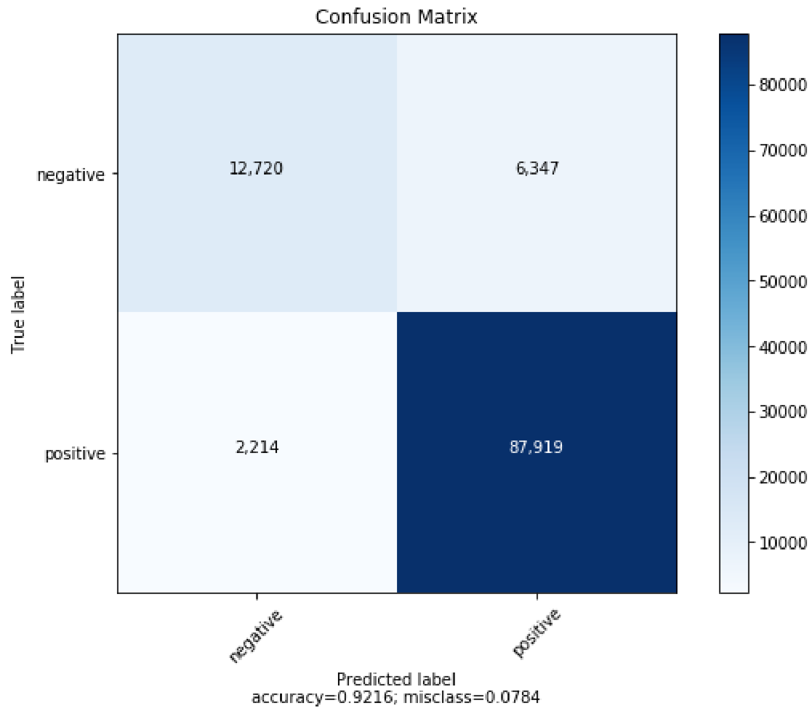
In [135]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 92%
```

In [138]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[12720  6347]
 [ 2214 87919]]
Precision :- 0.9326692550866696
Recall    :- 0.9754362996904574
F1 Score  :- 0.9326692550866696
```

In [137]:
```
plot_confusion_matrix(cm           = np.array([[ 12720   ,6347],[2214   ,87919]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Finding Sparsity of W vector for increasing values of C (Decreasing values of Lambda)

In [139]:
```
#http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_l1_l2_sparsity.html
l1_list=[0.01,0.05,0.08,1.2,2.0,10,20,30,40,70,150]
for item in l1_list:
    clf = LogisticRegression(random_state=0,penalty='l1',C=item).fit(big_data, y_1)
    #model = GridSearchCV(LogisticRegression(penalty='l1',C=item), tuned_parameters, scoring = 'accura
    #model.fit(big_data, y_1)
    coef = clf.coef_.ravel()
    sparsity_l1_LR = np.mean(coef == 0) * 100
    print("C=%.2f" % item)
    print("Sparsity with L1 penalty: %.2f%%" % sparsity_l1_LR)
    print('---------------------------------------------------------------')
```

```
C=0.01
Sparsity with L1 penalty: 83.42%
---------------------------------------------------------------
C=0.05
Sparsity with L1 penalty: 68.73%
---------------------------------------------------------------
C=0.08
Sparsity with L1 penalty: 65.77%
---------------------------------------------------------------
C=1.20
Sparsity with L1 penalty: 4.86%
---------------------------------------------------------------
C=2.00
Sparsity with L1 penalty: 3.26%
---------------------------------------------------------------
C=10.00
Sparsity with L1 penalty: 10.95%
---------------------------------------------------------------
C=20.00
Sparsity with L1 penalty: 48.23%
---------------------------------------------------------------
C=30.00
Sparsity with L1 penalty: 25.11%
---------------------------------------------------------------
C=40.00
Sparsity with L1 penalty: 2.78%
---------------------------------------------------------------
C=70.00
Sparsity with L1 penalty: 45.15%
---------------------------------------------------------------
C=150.00
Sparsity with L1 penalty: 0.01%
---------------------------------------------------------------
```

As we can see with different values of C i.e inverse of Lambda the sparsity of w* vector is changing.

1. as C increases (lambda decreases) the sparsity decreases. i.e as lambda increases the sparsity also increases
2. this proves the fact that in L1 regurarization when lambda increases the sparsity also increases

We are printing the top words which have the highest probablity in positive and negative reviews.

In [141]:
```
clf = LogisticRegression(C=5).fit(big_data, y_1)
clf.predict(test_data)
wv=clf.coef_
abs_weights = np.abs(wv)
```

In [142]:
```
sorted(wv)

hm=wv[-1:]
hm
```

Out[142]:
```
array([[-0.03763285,  0.0424076 ,  0.06205551, ...,  0.00851973,
         0.01122439,  0.00209671]])
```

In [147]:
```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tNEGATIVE\t\t\t\t\t\tPOSITIVE")
    print("_______________________________________________________________________________________________
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(count_vect,clf)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-
```

```
                        NEGATIVE                                                POSITIVE
________________________________________________________________________________________________
        -0.9690 not                                             1.1551  great
        -0.4221 worst                                           0.9005  best
        -0.3282 terrible                                        0.7989  delicious
        -0.3080 awful                                           0.7150  good
        -0.3035 horrible                                        0.6766  perfect
        -0.2932 disappointed                                    0.6101  love
        -0.2779 taste                                           0.5686  excellent
        -0.2492 mimalist                                        0.4906  nice
        -0.2492 roccoco                                         0.4859  highly
        -0.2491 unfortunately                                   0.4373  loves
        -0.2485 threw                                           0.4280  wonderful
        -0.2466 don                                             0.4167  tasty
        -0.2420 didn                                            0.3986  awesome
        -0.2416 worse                                           0.3948  smooth
        -0.2390 disappointing                                   0.3789  favorite
        -0.2386 even                                            0.3718  easy
        -0.2385 was                                             0.3705  amazing
        -0.2345 nothing                                         0.3565  pleased
        -0.2339 stale                                           0.3497  pleasantly
        -0.2299 disappointment                                  0.3277  happy
        -0.2269 earth                                           0.3254  yummy
        -0.2175 wouldn                                          0.3250  hooked
        -0.2122 money                                           0.3059  glad
        -0.2119 waste                                           0.2967  yum
        -0.2103 to                                              0.2930  find
```

Perturbation Test

In [163]:
```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 8, penalty= 'l2')
clf.fit(big_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.031%
Non Zero weights: 95227
```

In [172]:
```
from scipy.sparse import find
#Weights before adding random noise
w1 = find(clf.coef_[0])[2]
```

In [173]:
```
from scipy.sparse import find

#epsilon = np.random.normal(loc=0.0, scale=0.00000001)
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
new_data = big_data.copy()
#Random noise
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(new_data)

#Introducing random noise to non-zero datapoints
new_data[a,b] = epsilon + new_data[a,b]
```

In [174]:
```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 9, penalty= 'l2')
clf.fit(new_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.501%
Non Zero weights: 95227
```

In [175]:
```
w2.shape
```

Out[175]:
```
(95227,)
```

In [176]:
```
w1.shape
```

Out[176]:
```
(95227,)
```

In [177]:
```
#Weights after adding random noise
w2 = find(clf.coef_[0])[2]
```

In [178]:
```
diff = (abs(w1 - w2)/w1) * 100
```

In [179]:
```
print(diff[np.where(diff > 30)].size)
```

```
19475
```

""We have 19475 feature whose weight changed more then 30 percent""

In [181]:
```
from scipy.spatial import distance
from scipy import spatial
dst = distance.euclidean(w1, w2)
result = 1 - spatial.distance.cosine(w1,w2)
print("Euclidean distance between two vectors is:-",dst)
print("Cosine similarity between two vectors is:-",result)
```

```
Euclidean distance between two vectors is:- 3.3933380398798656
Cosine similarity between two vectors is:- 0.9640771628150064
```

Now Computing Using Tf-Idf Features

In [183]:
```
#Tf-IDF for 254800 Train points
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
big_data = tf_idf_vect.fit_transform(X_1['Text'].values)
print(big_data.shape)
```

```
(254800, 2301100)
```

In [184]:
```
#Tf-Idf for 109200 Test points
test_data = tf_idf_vect.transform(X_test['Text'].values)
print(test_data.shape)
```

```
(109200, 2301100)
```

Standardizing our Train and Test BOW vectors

In [185]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
standardizedtest_data = StandardScaler(with_mean=False).fit_transform(test_data)
print(standardizedtest_data.shape)
test_data=standardizedtest_data
```

```
(109200, 2301100)
```

In [186]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler(with_mean=False).fit_transform(big_data)
print(standardized_data.shape)
```

```
(254800, 2301100)
```

In [187]:
```
big_data=standardized_data
```

Logistic Regression With CLASS - BALANCING

In [188]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced'), param_search, scoring = 'accuracy'
gsearch.fit(X, y)
```

Out[188]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000215BC1D3F68>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [189]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

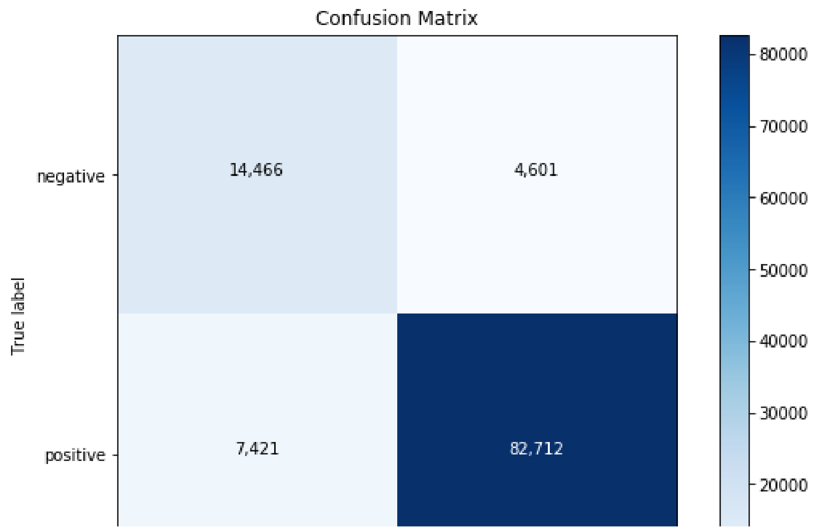
```

Test accuracy for best estimator is 90%
```

Confusion matrix , Precision, Recall, F-Score

In [190]:
```
# print the confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn import metrics
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[ 9697  9370]
 [  637 89496]]
Precision :- 0.9052252543847228
Recall    :- 0.9929326661711027
F1 Score  :- 0.9052252543847228
```

In [191]:
```
plot_confusion_matrix(cm           = np.array([[ 14466  ,4601],[7421 ,82712]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Logistic Regression L2 without Class balancing

In [192]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)
Cs = [10**-4, 10**-2, 10**0, 10**2, 10**4]
model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[192]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000215D9EC9780>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [193]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 90%
```

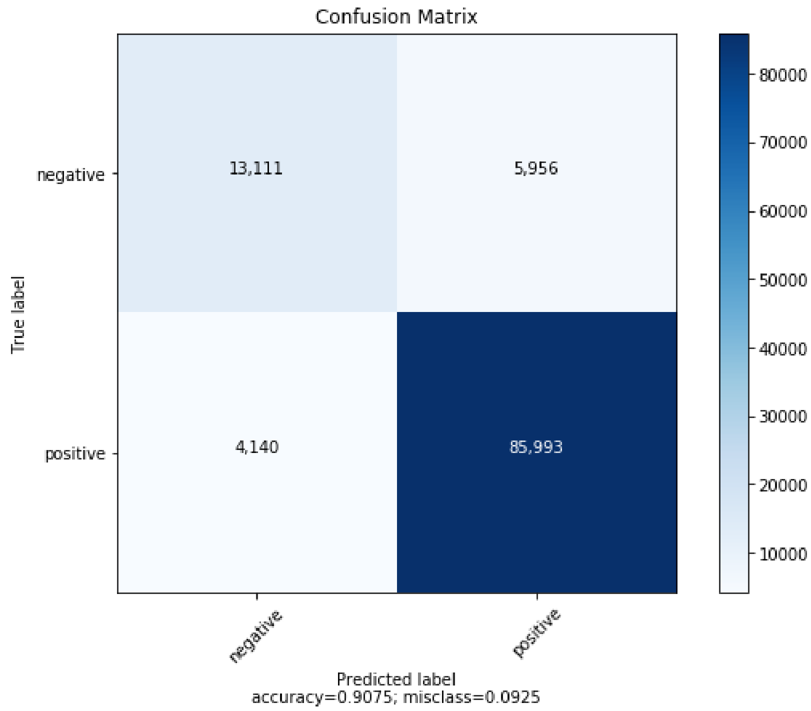
In [194]:

```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[ 9223  9844]
 [  577 89556]]
Precision :- 0.9009657947686117
Recall    :- 0.9935983491063206
F1 Score  :- 0.9009657947686117
```

In [195]:

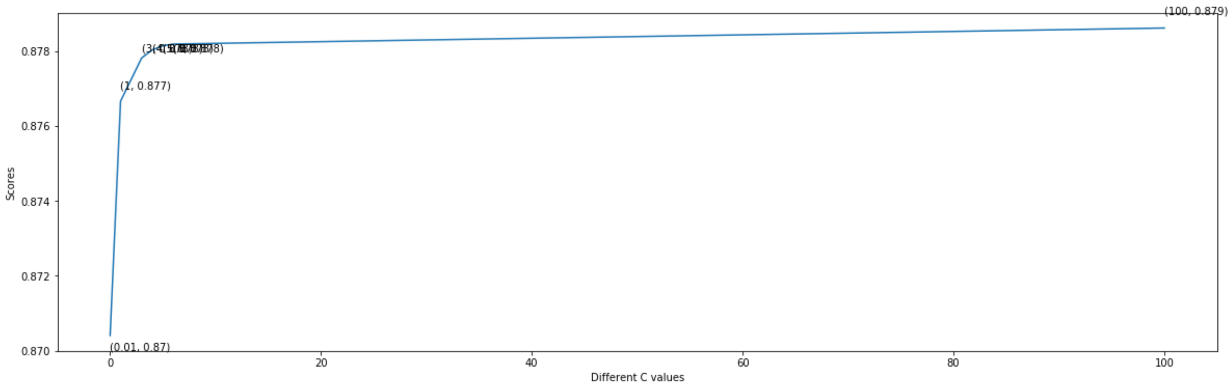
```
plot_confusion_matrix(cm           = np.array([[ 13111   ,5956],[4140  ,85993]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Misclassification error

In [196]:
```
Cs = [10**-2, 10**0, 3, 4, 5, 6 ,10**2]
scores = [x[1] for x in gsearch.grid_scores_]
scores = np.array(scores).reshape(len(Cs))
plt.figure(figsize=(20,6))
plt.plot(Cs, scores, label='C: ' )

for xy in zip(Cs, np.round(scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Different C values')
plt.ylabel('Scores')
plt.show()
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:762: DeprecationWarn
ing: The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate cv_res
ults_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



Now using L1 Regulariser in Logistic Regrression with class balancing

In [197]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l1'), param_search, scoring
gsearch.fit(X, y)
```

Out[197]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000215D9EC99E8>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

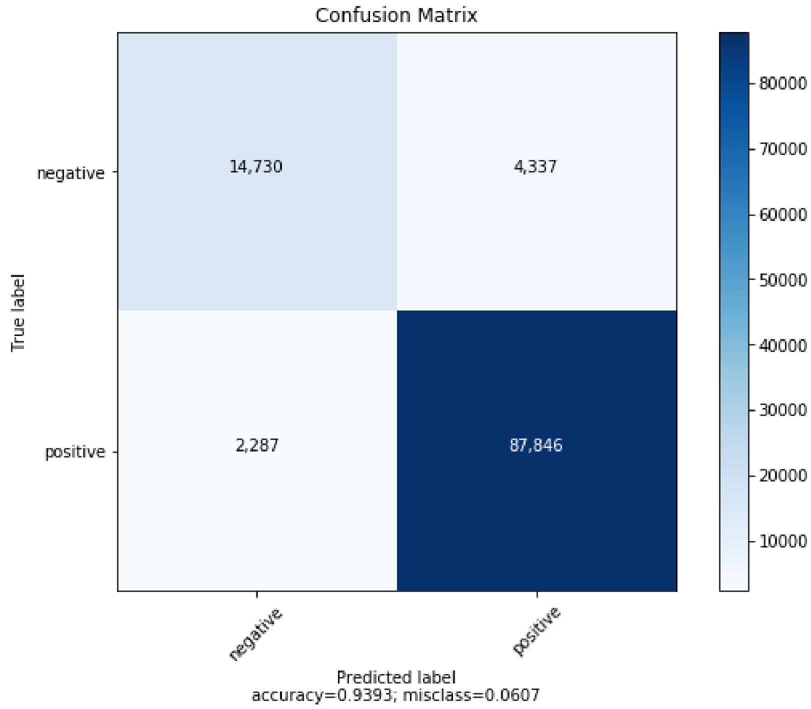
In [198]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 93%
```

In [199]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[14730  4337]
 [ 2287 87846]]
Precision :- 0.9529522797045008
Recall    :- 0.9746263854526089
F1 Score  :- 0.9529522797045008
```

In [221]:
```
plot_confusion_matrix(cm           = np.array([[ 14730 ,4337],[2287 ,87846]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Now using L1 Regulariser in Logistic Regrression without class balancing

In [201]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C':[10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(penalty='l1'), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[201]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x0000021526D1C048>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

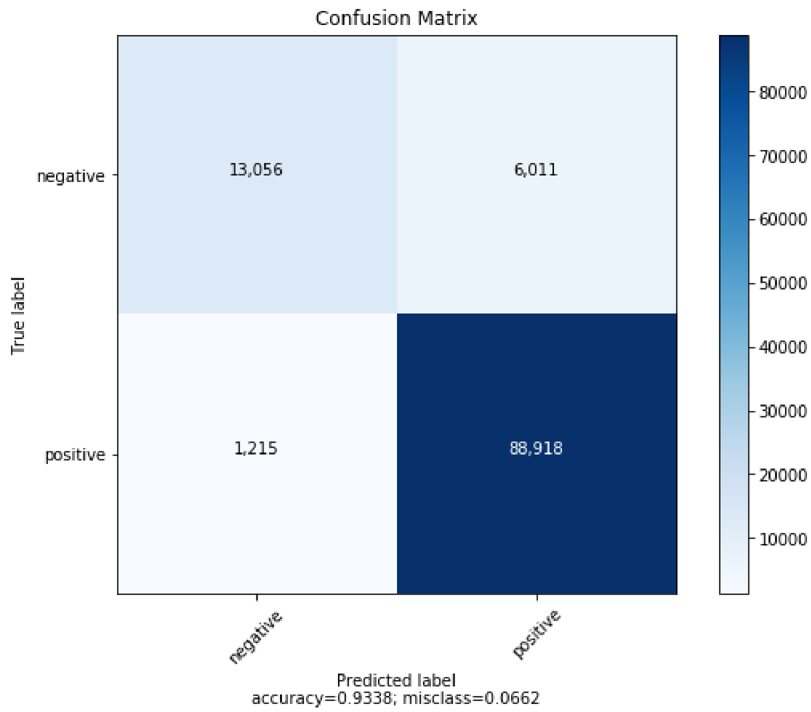
In [202]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 93%
```

In [203]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[13056  6011]
 [ 1215 88918]]
Precision :- 0.9366789916674567
Recall    :- 0.9865199205618363
F1 Score  :- 0.9366789916674567
```

In [220]:
```
plot_confusion_matrix(cm           = np.array([[ 13056     ,6011],[1215    ,88918]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Finding Sparsity of W vector for increasing values of C (Decreasing values of Lambda)

In [205]:
```
#http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_l1_l2_sparsity.html
l1_list=[0.01,0.05,0.08,1.2,2.0,10,20,30,40,70,150]
for item in l1_list:
    clf = LogisticRegression(random_state=0,penalty='l1',C=item).fit(big_data, y_1)
    #model = GridSearchCV(LogisticRegression(penalty='l1',C=item), tuned_parameters, scoring = 'accurc
    #model.fit(big_data, y_1)
    coef = clf.coef_.ravel()
    sparsity_l1_LR = np.mean(coef == 0) * 100
    print("C=%.2f" % item)
    print("Sparsity with L1 penalty: %.2f%%" % sparsity_l1_LR)
    print('---------------------------------------------------------------')
```

```
C=0.01
Sparsity with L1 penalty: 96.70%
---------------------------------------------------------------
C=0.05
Sparsity with L1 penalty: 95.11%
---------------------------------------------------------------
C=0.08
Sparsity with L1 penalty: 95.42%
---------------------------------------------------------------
C=1.20
Sparsity with L1 penalty: 94.74%
---------------------------------------------------------------
C=2.00
Sparsity with L1 penalty: 94.01%
---------------------------------------------------------------
C=10.00
Sparsity with L1 penalty: 91.82%
---------------------------------------------------------------
C=20.00
Sparsity with L1 penalty: 90.24%
---------------------------------------------------------------
C=30.00
Sparsity with L1 penalty: 86.19%
---------------------------------------------------------------
C=40.00
Sparsity with L1 penalty: 90.59%
---------------------------------------------------------------
C=70.00
Sparsity with L1 penalty: 88.96%
---------------------------------------------------------------
C=150.00
Sparsity with L1 penalty: 85.11%
---------------------------------------------------------------
```

As we can see with different values of C i.e inverse of Lambda the sparsity of w* vector is changing.

1. as C increases (lambda decreases) the sparsity decreases. i.e as lambda increases the sparsity also increases
2. this proves the fact that in L1 regurarization when lambda increases the sparsity also increases

We are printing the top words which have the highest probablity in positive and negative reviews.

In [206]:
```
clf = LogisticRegression(C=5).fit(big_data, y_1)
clf.predict(test_data)
wv=clf.coef_
abs_weights = np.abs(wv)
```

In [207]:
```
sorted(wv)

hm=wv[-1:]
hm
```

Out[207]:
```
array([[-0.01356872, -0.0006246 , -0.000544  , ...,  0.00082314,
         0.00072629,  0.00072629]])
```

In [208]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tNEGATIVE\t\t\t\t\t\tPOSITIVE")
    print("_______________________________________________________________________________________________
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(count_vect,clf)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-
```

```
                        NEGATIVE                                                POSITIVE
_______________________________________________________________________________________________
        -0.0325 drive                                           0.0518  yowie
        -0.0308 greenpowder                                     0.0353  lindas
        -0.0275 snackalicious                                   0.0339  greese
        -0.0271 stylish                                         0.0308  unfavorable
        -0.0245 017                                             0.0299  menial
        -0.0243 fancifully                                      0.0292  mcqueen
        -0.0243 ktoo                                            0.0281  flutterby2554
        -0.0239 leamonade                                       0.0265  fleisch
        -0.0238 familiar                                        0.0262  flipped
        -0.0236 primia                                          0.0245  grinz
        -0.0232 splashed                                        0.0242  street
        -0.0229 vinci                                           0.0234  whammy
        -0.0224 smothered                                       0.0232  mechs
        -0.0217 titch                                           0.0229  grubex
        -0.0217 snippit                                         0.0229  median
        -0.0213 8013                                            0.0221  sluicing
        -0.0208 rustica                                         0.0220  whow
        -0.0207 atlanta                                         0.0215  municipality
        -0.0206 b000f4f952                                      0.0199  envorment
        -0.0201 42bucks                                         0.0195  tropics
        -0.0201 grourmet                                        0.0193  squidgy
        -0.0199 seite                                           0.0192  zoomies
        -0.0196 lathers                                         0.0190  velva
        -0.0195 theanimal                                       0.0190  magnolia
        -0.0193 raison                                          0.0189  rainwater
```

Perturbation Test

In [209]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 8, penalty= 'l2')
clf.fit(big_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.470%
Non Zero weights: 2301100
```

In [210]:

```
from scipy.sparse import find
#Weights before adding random noise
w1 = find(clf.coef_[0])[2]
```

In [212]:

```
from scipy.sparse import find

#epsilon = np.random.normal(loc=0.0, scale=0.00000001)
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(big_data)[0].size,))
new_data = big_data.copy()
#Random noise
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(new_data)

#Introducing random noise to non-zero datapoints
new_data[a,b] = epsilon + new_data[a,b]
```

In [213]:
```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 9, penalty= 'l2')
clf.fit(new_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.233%
Non Zero weights: 2301100
```

In [214]:
```
w2.shape
```

Out[214]:
```
(95227,)
```

In [215]:
```
w1.shape
```

Out[215]:
```
(2301100,)
```

In [216]:
```
#Weights after adding random noise
w2 = find(clf.coef_[0])[2]
```

In [217]:
```
diff = (abs(w1 - w2)/w1) * 100
```

In [218]:
```
print(diff[np.where(diff > 30)].size)
```

```
287753
```

""We have 287753 feature whose beight changed more then 30 percent""

In [219]:
```
from scipy.spatial import distance
from scipy import spatial
dst = distance.euclidean(w1, w2)
result = 1 - spatial.distance.cosine(w1,w2)
print("Euclidean distance between two vectors is:-",dst)
print("Cosine similarity between two vectors is:-",result)
```

```
Euclidean distance between two vectors is:- 0.31236802981925144
Cosine similarity between two vectors is:- 0.9972256090202093
```

Now Trying on Word2Vec

In [228]:
```
# Train your own Word2Vec model using your own text corpus for train Data
import gensim
i=0
list_of_sent_train=[]
for sent in X_1['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent_train.append(filtered_sentence)
```

In [229]:
```
# min_count = 5 considers only words that occured atleast 5 times
import gensim
from gensim import models
from gensim.models import Word2Vec, KeyedVectors
w2v_model=Word2Vec(list_of_sent_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  28914
sample words  ['this', 'witty', 'little', 'book', 'makes', 'my', 'son', 'laugh', 'at', 'loud', 'i',
'it', 'in', 'the', 'car', 'as', 'were', 'driving', 'along', 'and', 'he', 'always', 'can', 'sing', 'r
efrain', 'hes', 'learned', 'about', 'whales', 'india', 'drooping', 'love', 'all', 'new', 'words', 'i
ntroduces', 'silliness', 'of', 'is', 'a', 'classic', 'am', 'willing', 'to', 'bet', 'will', 'still',
'be', 'able', 'from']
```

In [231]:
```

# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_train: # for each review/sentence
    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
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))
```

```
254800
50
```

In [230]:
```
# Train your own Word2Vec model using your own text corpus for test Data
import gensim
i=0
list_of_sent_test=[]
for sent in X_test['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent_test.append(filtered_sentence)
```

In [232]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sent_test,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  19804
sample words  ['the', 'only', 'good', 'comment', 'i', 'can', 'give', 'on', 'these', 'treats', 'is',
'that', 'my', 'cat', 'liked', 'them', 'when', 'they', 'were', 'fresh', 'and', 'are', 'really', 'inex
pensive', 'usually', 'find', 'for', 'under', 'two', 'dollars', 'at', 'grocery', 'or', 'pet', 'stor
e', 'even', 'occasion', 'dollar', 'as', 'this', 'treat', 'proves', 'often', 'with', 'a', 'low', 'pri
ce', 'comes', 'cheap', 'product']
```

In [234]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_test: # for each review/sentence
    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
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
109200
50
```

Standardizing our Train and Test word2vec vectors

In [235]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
#np.isnan(sent_vectors_train.values.any())
#Where sent_vectors_train is my pandas Dataframe
standardized_data_train = StandardScaler(with_mean=False).fit_transform(sent_vectors_train)
print(standardized_data_train.shape)
```

```
(254800, 50)
```

In [236]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
standardized_data_test = StandardScaler(with_mean=False).fit_transform(sent_vectors_test)
print(standardized_data_test.shape)
```

```
(109200, 50)
```

In [237]:
```
big_data=standardized_data_train
```

In [238]:
```
X=big_data
test_data=standardized_data_test
y=y_1
```

Logistic Regression With CLASS - BALANCING

In [239]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced'), param_search, scoring = 'accuracy'
gsearch.fit(X, y)
```

Out[239]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000216DD28EE08>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [240]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 82%
```

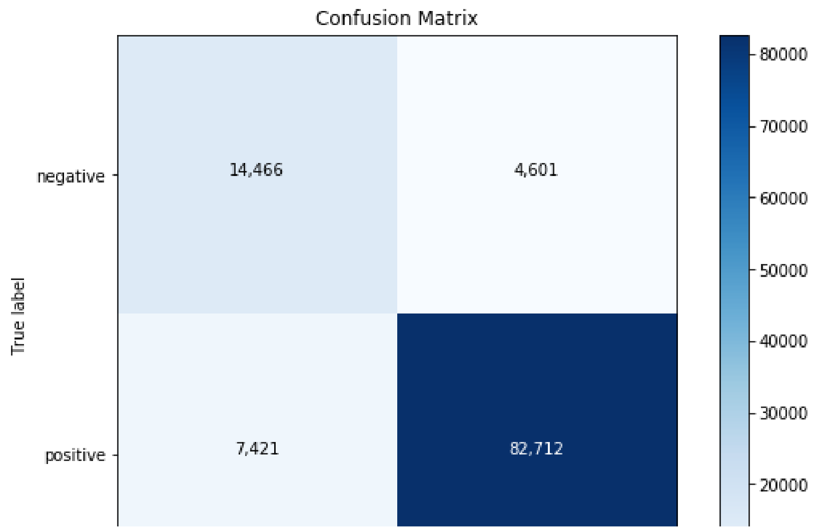
Confusion matrix , Precision, Recall, F-Score

In [241]:
```
# print the confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn import metrics
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[   12 19055]
 [   29 90104]]
Precision :- 0.8254381223719528
Recall    :- 0.999678253247978
F1 Score  :- 0.8254381223719528
```

In [242]:

```
plot_confusion_matrix(cm           = np.array([[ 14466  ,4601],[7421 ,82712]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Logistic Regression L2 without Class balancing

In [243]:

```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)
Cs = [10**-4, 10**-2, 10**0, 10**2, 10**4]
model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[243]:

```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000216DD28E888>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [244]:

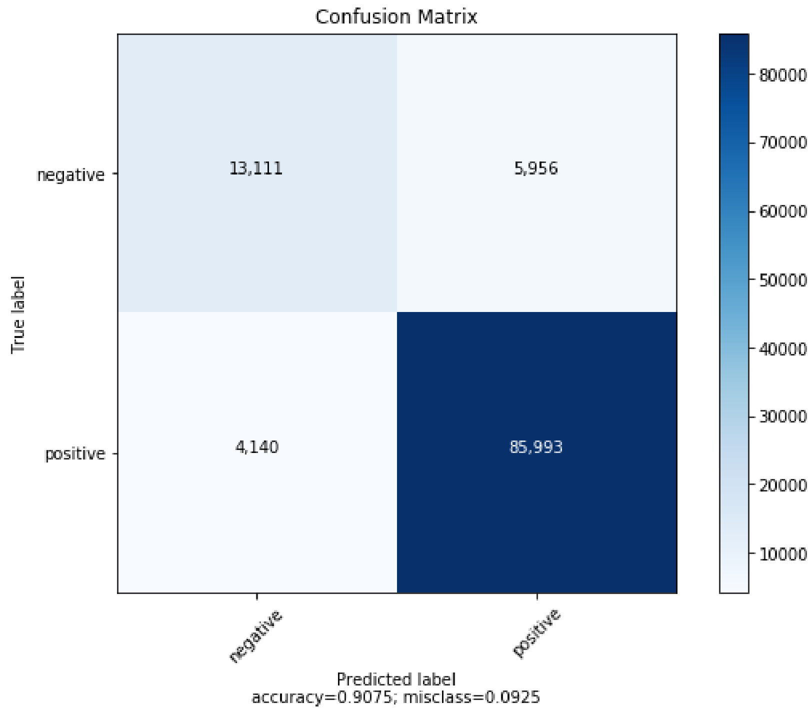
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 82%
```

In [245]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[    3 19064]
 [   25 90108]]
Precision :- 0.8253764701571832
Recall    :- 0.9997226321103259
F1 Score  :- 0.8253764701571832
```

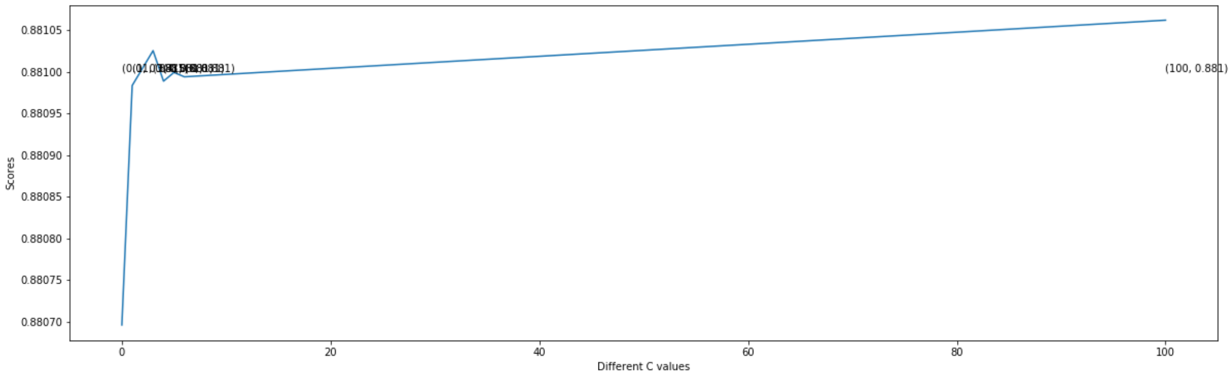
In [246]:
```
plot_confusion_matrix(cm           = np.array([[ 13111   ,5956],[4140  ,85993]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Misclassification error

In [247]:
```
Cs = [10**-2, 10**0, 3, 4, 5, 6 ,10**2]
scores = [x[1] for x in gsearch.grid_scores_]
scores = np.array(scores).reshape(len(Cs))
plt.figure(figsize=(20,6))
plt.plot(Cs, scores, label='C: ' )

for xy in zip(Cs, np.round(scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Different C values')
plt.ylabel('Scores')
plt.show()
```

```
C:\Users\Yaakuza\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:762: DeprecationWarn
ing: The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate cv_res
ults_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



Now using L1 Regulariser in Logistic Regrression with class balancing

In [248]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C': [10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l1'), param_search, scoring
gsearch.fit(X, y)
```

Out[248]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000216BC8CA0F8>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

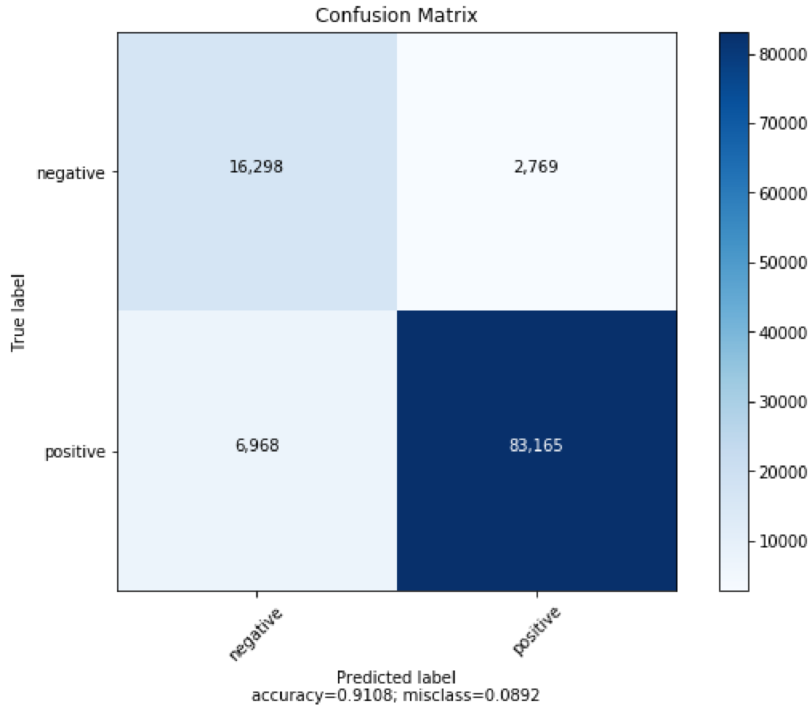
In [249]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 82%
```

In [250]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[   13 19054]
 [   29 90104]]
Precision :- 0.8254456842375273
Recall    :- 0.999678253247978
F1 Score  :- 0.8254456842375273
```

In [251]:
```
plot_confusion_matrix(cm           = np.array([[ 16298  ,2769],[6968  ,83165]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Now using L1 Regulariser in Logistic Regrression without class balancing

In [252]:
```
#https://stackoverflow.com/questions/46732748/how-do-i-use-a-timeseriessplit-with-a-gridsearchcv-objec
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV
import numpy as np
X = big_data
y = y_1
tscv = TimeSeriesSplit(n_splits=3)

model = xgb.XGBRegressor()
param_search = [{'C':[10**-2, 10**0, 3, 4, 5, 6 ,10**2]}]

my_cv = TimeSeriesSplit(n_splits=3).split(X)
gsearch = GridSearchCV(LogisticRegression(penalty='l1'), param_search, scoring = 'accuracy', cv=my_cv)
gsearch.fit(X, y)
```

Out[252]:
```
GridSearchCV(cv=<generator object TimeSeriesSplit.split at 0x00000216BC8CA570>,
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid=[{'C': [0.01, 1, 3, 4, 5, 6, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

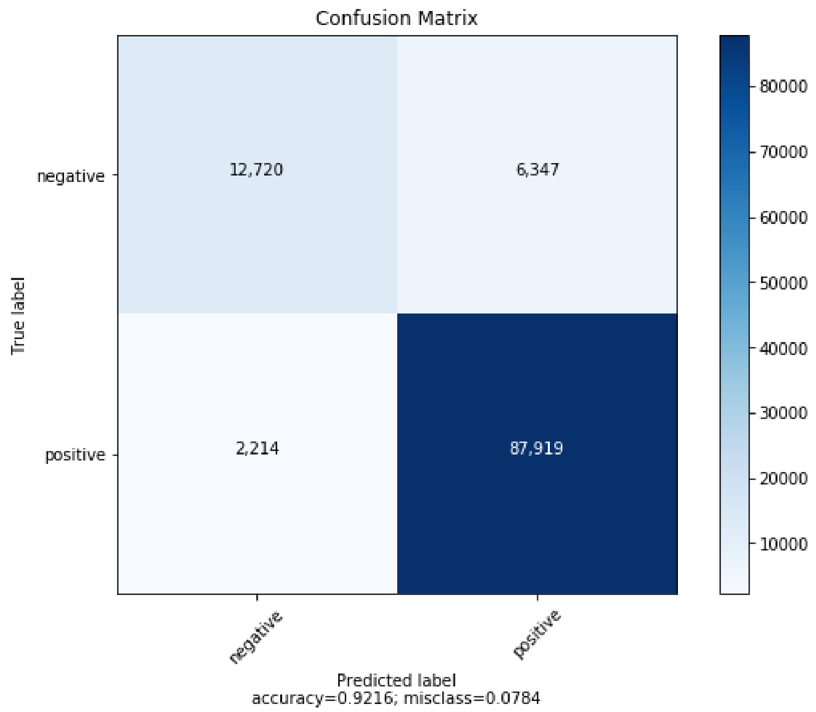
In [253]:
```
y_pred=gsearch.predict(test_data)
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\nTest accuracy for best estimator is %d%%' % ( acc))
```

```
Test accuracy for best estimator is 82%
```

In [254]:
```
gb=metrics.confusion_matrix(y_test,y_pred)
print(gb)
#plotting the confusion matrix
#Plot of Confusion Metric
#precision From above Confusion Metric
#Recall From above Confusion Metric
recall=(gb[1,1]+0.0)/sum(gb[1,:])
pre=(gb[1,1]+0.0)/sum(gb[:,1])
F1=(2*pre*recall)/(pre+recall)
print("Precision :-",pre)
print("Recall    :-",recall)
print("F1 Score  :-",pre)
```

```
[[    6 19061]
 [   25 90108]]
Precision :- 0.8253991517738553
Recall    :- 0.9997226321103259
F1 Score  :- 0.8253991517738553
```

In [255]:
```
plot_confusion_matrix(cm           = np.array([[ 12720   ,6347],[2214   ,87919]]),
                      normalize    = False,
                      target_names = ['negative', 'positive'],
                      title        = "Confusion Matrix")
```



Finding Sparsity of W vector for increasing values of C (Decreasing values of Lambda)

In [256]:
```
#http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_l1_l2_sparsity.html
l1_list=[0.01,0.05,0.08,1.2,2.0,10,20,30,40,70,150]
for item in l1_list:
    clf = LogisticRegression(random_state=0,penalty='l1',C=item).fit(big_data, y_1)
    #model = GridSearchCV(LogisticRegression(penalty='l1',C=item), tuned_parameters, scoring = 'accura
    #model.fit(big_data, y_1)
    coef = clf.coef_.ravel()
    sparsity_l1_LR = np.mean(coef == 0) * 100
    print("C=%.2f" % item)
    print("Sparsity with L1 penalty: %.2f%%" % sparsity_l1_LR)
    print('---------------------------------------------------------------')
```

```
C=0.01
Sparsity with L1 penalty: 6.00%
---------------------------------------------------------------
C=0.05
Sparsity with L1 penalty: 2.00%
---------------------------------------------------------------
C=0.08
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=1.20
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=2.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=10.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=20.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=30.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=40.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=70.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
C=150.00
Sparsity with L1 penalty: 0.00%
---------------------------------------------------------------
```

As we can see with different values of C i.e inverse of Lambda the sparsity of w* vector is changing.

1. as C increases (lambda decreases) the sparsity decreases. i.e as lambda increases the sparsity also increases
2. this proves the fact that in L1 regurarization when lambda increases the sparsity also increases

Perturbation Test

In [260]:
```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 8, penalty= 'l2')
clf.fit(big_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.519%
Non Zero weights: 50
```

In [261]:
```
from scipy.sparse import find
#Weights before adding random noise
w1 = find(clf.coef_[0])[2]
```

In [263]:
```
from scipy.sparse import find

#epsilon = np.random.normal(loc=0.0, scale=0.00000001)
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(big_data)[0].size,))
new_data = big_data.copy()
#Random noise
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(new_data)

#Introducing random noise to non-zero datapoints
new_data[a,b] = epsilon + new_data[a,b]
```

In [264]:
```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 9, penalty= 'l2')
clf.fit(new_data,y_1)
y_pred = clf.predict(test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.519%
Non Zero weights: 50
```

In [265]:
```
w2.shape
```

Out[265]:
```
(2301100,)
```

In [266]:
```
w1.shape
```

Out[266]:
```
(50,)
```

In [267]:
```
#Weights after adding random noise
w2 = find(clf.coef_[0])[2]
```

In [268]:
```
diff = (abs(w1 - w2)/w1) * 100
```

In [269]:
```
print(diff[np.where(diff > 30)].size)
```

```
0
```

""We have 0 feature whose beight changed more then 30 percent""

In [270]:
```
from scipy.spatial import distance
from scipy import spatial
dst = distance.euclidean(w1, w2)
result = 1 - spatial.distance.cosine(w1,w2)
print("Euclidean distance between two vectors is:-",dst)
print("Cosine similarity between two vectors is:-",result)
```

```
Euclidean distance between two vectors is:- 0.006495788187743015
Cosine similarity between two vectors is:- 0.9999998264554264
```

In [ ]:

Conclusion / Summary

```
(i) Sampled 364K reviews from our Dataset.
(ii) Then dividing our reviews into train and test.
(iii) Converting the text of reviews into vectors using both BOW .
(iv) Applying Logistic Regression with L2 regularizer with Grid search CV to find the best
C(1/lambda).
(v) Then we apply Logistic Regression using L1 Regulariser, we also check accuracy with different
values of
(vi) Also finding Confusion Matrix , Precision, Recall, F-Score.
(vii) Printing the TOP Words with highest probablities in our Positive and Negative Reviews.

1. Model :- Logistic Regression
   HyperParameter:- C (i.e  1/lambda)
```

	Regularizer	C	Test Accuracy	Precision	Recall	F-Score
BOW with CB	L2	1.0	88%	0.947	0.917	0.947
BOW without CB	L2	1.0	90%	0.935	0.954	0.935
BOW with CB	L1	1.0	91%	0.967	0.922	0.967
BOW without CB	L1	1.0	92%	0.932	0.975	0.932
Tf-Idf with CB	L2	1.0	90%	0.905	0.992	0.905
Tf-Idf without CB	L2	1.0	90%	0.900	0.993	0.900
Tf-Idf with CB	L1	1.0	93%	0.952	0.974	0.952
Tf-Idf without CB	L1	1.0	93%	0.936	0.986	0.936
Word2Vec with CB	L2	1.0	82%	0.825	0.999	0.825
Word2Vec without CB	l2	1.0	82%	0.825	0.999	0.825
Word2Vec with CB	l1	1.0	82%	0.825	0.999	0.825
Word2Vec without CB	l1	1.0	82%	0.825	0.999	0.825

```
2. L1 regularizer with different values of C(1/lambda) In BOW.

    C=0.01
    Sparsity with L1 penalty: 83.42%
-----------------------------------------------------------------
    C=0.05
    Sparsity with L1 penalty: 68.73%
---------------------------------------------------------------
    C=0.08
    Sparsity with L1 penalty: 65.77%
---------------------------------------------------------------
    C=1.20
    Sparsity with L1 penalty: 4.86%
---------------------------------------------------------------
    C=2.00
    Sparsity with L1 penalty: 3.26%
---------------------------------------------------------------

    Note := Same goes with other vectorizers also , the sparsity keeps increasing with increase in
lambda.

3. TOP Words with the highest weights

   (i) BOW:=      NEGATIVE                           POSITIVE

                -0.9690 not                         1.1551  great
                -0.4221 worst                       0.9005  best
                -0.3282 terrible                    0.7989  delicious
                -0.3080 awful                       0.7150  good
                -0.3035 horrible                    0.6766  perfect
                -0.2932 disappointed                0.6101  love

   (ii) Tf-Idf:=      NEGATIVE                           POSITIVE

               -0.0325  drive                       0.0518  yowie
               -0.0308  greenpowder                 0.0353  lindas
               -0.0275  snackalicious               0.0339  greese
               -0.0271  stylish                     0.0308  unfavorable
               -0.0245  017                         0.0299  menial
               -0.0243  fancifully                  0.0292  mcqueen
               -0.0243  ktoo                        0.0281  flutterby2554
```

```
             -0.0239  leamonade                    0.0265  fleisch
             -0.0238  familiar                     0.0262  flipped
```

4. (i) BOW:= We have 19475 feature whose weight changed more then 30 percent
   (ii) Tf-Idf:= We have 287753 feature whose weight changed more then 30 percent

__Final Conclusion:-__
(i) Logistic Regression Worked Fairly well Compared to all other models we have worked on before.
(ii)Best Model is Tf-Idf with L1 penalty with or without class balancing with the test accuracy of 93 Percent.
(iii)As we are increasing the value of lambda in using L1 regulariser the Sparsity also increases.
(iv)The features are multicollinear becoz so many of them have a weight change of more then 30 percent after perturbation test.