Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

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 Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is 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 is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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 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

from tqdm import tqdm
import os
```

In [2]:

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

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
```

```
 != 3""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#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
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (525814, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [5]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [6]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[6]:

UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	5

In [7]:
```
display['COUNT(*)'].sum()
```

Out[7]:
```
393063
```

[2] Exploratory Data Analysis

[2.1] 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:

In [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[8]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with 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) and so on

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

In [10]:
```
#Deduplication of entries
final_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final_data.shape
```

Out[10]: (364173, 10)

In [11]:
```
#Checking to see how much % of data still remains
(final_data['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[11]: 69.25890143662969

Observation:- 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)

display.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [13]:
```
final_data=final_data[final_data.HelpfulnessNumerator<=final_data.Helpf
ulnessDenominator]
```

In [14]:
```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final_data.shape)

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

```
(364171, 10)
```

Out[14]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

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

1. Begin by removing the html tags
2. Remove 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. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

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

In [15]:
```
import re
i=0;
for sent in final_data['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 thi
s point, I consider myself a connoisseur of children's books and this i
s one of the best. Santa Clause put this under the tree. Since then, w
e've read it perpetually and he loves it.<br /><br />First, this book t
aught him the months 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
book, however, deserves a permanent spot on your shelf. Sendak's best.
```

In [16]:
```
import nltk
from nltk.corpus import stopwords
```

```
nltk.download('stopwords')

stopwords = stopwords.words('english')
stop = set(stopwords)
sno = nltk.stem.SnowballStemmer('english')

def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned

if not os.path.isfile('final_data.sqlite'):
    i=0
    str1=' '
    final_string=[]
    all_positive_words=[]
    all_negative_words=[]
    s=''
    for sent in tqdm(final_data['Text'].values):
        filtered_sentence=[]
        sent=cleanhtml(sent)
        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('utf
8')
                        filtered_sentence.append(s)
                        if (final_data['Score'].values)[i] == 'positiv
e':
                            all_positive_words.append(s)
                        if(final_data['Score'].values)[i] == 'negative'
:
                            all_negative_words.append(s)
```

```
                        else:
                            continue
                    else:
                        continue
            str1 = b" ".join(filtered_sentence)

            final_string.append(str1)
            i+=1

    final_data['CleanedText']=final_string
    final_data['CleanedText']=final_data['CleanedText'].str.decode("utf
-8")
    conn = sqlite3.connect('final_data.sqlite')
    c=conn.cursor()
    conn.text_factory = str
    final_data.to_sql('Reviews', conn,  schema=None, if_exists='replac
e', \
                     index=True, index_label=None, chunksize=None, dtype=No
ne)
    conn.close()


    with open('positive_words.pkl', 'wb') as f:
        pickle.dump(all_positive_words, f)
    with open('negitive_words.pkl', 'wb') as f:
        pickle.dump(all_negative_words, f)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/chaitanyareddypatlolla/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [17]:

```
if os.path.isfile('final_data.sqlite'):
    conn = sqlite3.connect('final_data.sqlite')
    final = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !=
 3 """, conn)
    conn.close()
else:
    print("Please the above cell")
```

```
In [18]: final.shape
```

```
Out[18]: (364171, 12)
```

Sorting & Splitting the data:

```
In [19]: final = final.sort_values('Time') #Sorting based on time


         final= final[:100000] #After sorting data based on time, we're taking a
          sample of 100k points
```

```
In [20]: final['Score'].value_counts()
```

```
Out[20]: 1    87729
         0    12271
         Name: Score, dtype: int64
```

```
In [21]: from sklearn import model_selection
         from sklearn.model_selection import train_test_split

         final_points= final['CleanedText']
         labels = final['Score']

         X_1, X_test, y_1, y_test = model_selection.train_test_split(final, labe
         ls, test_size=0.3, random_state=0)

         X_tr, X_cv, y_tr, y_cv = model_selection.train_test_split(X_1, y_1, tes
         t_size=0.3)


         X_tr.shape, X_test.shape, X_cv.shape
```

```
Out[21]: ((49000, 12), (30000, 12), (21000, 12))
```

[4] Featurization

[4.1] BAG OF WORDS

In [22]:
```
#BoW
count_vect = CountVectorizer()
X_tr_bow = count_vect.fit_transform(X_tr['CleanedText'].values)
X_cv_bow = count_vect.transform(X_cv['CleanedText'].values)
X_test_bow = count_vect.transform(X_test['CleanedText'].values)
```

In [23]:
```
X_tr_bow.shape, X_cv_bow.shape,X_test_bow.shape
```

Out[23]:
```
((49000, 26617), (21000, 26617), (30000, 26617))
```

[4.2] Bi-Grams and n-Grams.

In [26]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html

# you can choose these numebrs min_df=10, max_features=5000, of your ch
oice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features
=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [98]:

```
tf_idf_vect = TfidfVectorizer(min_df= 10)
X_tr_tf_idf = tf_idf_vect.fit_transform(X_tr['CleanedText'].values)
X_cv_tf_idf = tf_idf_vect.transform(X_cv['CleanedText'].values)
X_test_tf_idf = tf_idf_vect.transform(X_test['CleanedText'].values)
```

[4.4] Word2Vec

In [123]:

```
# Train your own Word2Vec model using your own text corpus
i=0
train_sent_list=[]
for sent in X_tr['CleanedText'].values:
    train_sent_list.append(sent.split())

i=0
cv_sent_list=[]
for sent in X_cv['CleanedText'].values:
    cv_sent_list.append(sent.split())


i=0
test_sent_list=[]
for sent in X_test['CleanedText'].values:
    test_sent_list.append(sent.split())
```

In [124]:

```
from gensim.models import Word2Vec

train_w2v_model= Word2Vec(train_sent_list,min_count=5,size=50, workers=
4)
```

```python
train_w2v_words = list(train_w2v_model.wv.vocab)

cv_w2v_model= Word2Vec(cv_sent_list,min_count=5,size=50, workers=4)
cv_w2v_words = list(cv_w2v_model.wv.vocab)

test_w2v_model= Word2Vec(test_sent_list,min_count=5,size=50, workers=4)
test_w2v_words = list(test_w2v_model.wv.vocab)
```

[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [125]:

```python
#Training data for average w2v

train_sent_vectors = []
for sent in tqdm(train_sent_list):
    train_sent_vec = np.zeros(50)
    cnt_words =0
    for word in sent:
        if word in train_w2v_words:
            vec = train_w2v_model.wv[word]
            train_sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        train_sent_vec /= cnt_words
    train_sent_vectors.append(train_sent_vec)
print(len(train_sent_vectors))
print(len(train_sent_vectors[0]))
```

```
100%|██████████| 49000/49000 [05:20<00:00, 153.04it/s]
```

```
49000
50
```

In [126]:
```python
#CV data for average w2v

cv_sent_vectors = []
for sent in tqdm(cv_sent_list):
    cv_sent_vec = np.zeros(50)
    cnt_words =0
    for word in sent:
        if word in cv_w2v_words:
            vec = cv_w2v_model.wv[word]
            cv_sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        cv_sent_vec /= cnt_words
    cv_sent_vectors.append(cv_sent_vec)
print(len(cv_sent_vectors))
print(len(cv_sent_vectors[0]))
```

```
100%|██████████| 21000/21000 [01:09<00:00, 304.33it/s]
```

```
21000
50
```

In [127]:
```python
#Test data for average w2v

test_sent_vectors = []
for sent in tqdm(test_sent_list):
    test_sent_vec = np.zeros(50)
    cnt_words =0
    for word in sent:
        if word in test_w2v_words:
            vec = test_w2v_model.wv[word]
            test_sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        test_sent_vec /= cnt_words
    test_sent_vectors.append(test_sent_vec)
print(len(test_sent_vectors))
print(len(test_sent_vectors[0]))
```

```
100%|██████████| 30000/30000 [02:06<00:00, 237.16it/s]
```

```
30000
50
```

[4.4.1.2] TFIDF weighted W2v

In [133]:

```python
model = TfidfVectorizer()
train_matrix = model.fit_transform(X_tr['CleanedText'].values)
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

train_feat = model.get_feature_names()

train_vectors = [];
row=0;
for sent in tqdm(train_sent_list):
    train_sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in train_w2v_words:
            train_vec = train_w2v_model.wv[word]
            train_tf_idf = dictionary[word]*(sent.count(word)/len(sent
))
            train_sent_vec += (vec * train_tf_idf)
            weight_sum += train_tf_idf
    if weight_sum != 0:
        train_sent_vec /= weight_sum
    train_vectors.append(train_sent_vec)
    row += 1
```

```
100%|██████████| 49000/49000 [05:55<00:00, 137.78it/s]
```

In [134]:

```python
model = TfidfVectorizer()
cv_matrix = model.fit_transform(X_cv['CleanedText'].values)
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

cv_feat = model.get_feature_names()
```

```
cv_vectors = [];
row=0;
for sent in tqdm(cv_sent_list):
    cv_sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in cv_w2v_words:
            cv_vec = cv_w2v_model.wv[word]
            cv_tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            cv_sent_vec += (vec * cv_tf_idf)
            weight_sum += cv_tf_idf
    if weight_sum != 0:
        cv_sent_vec /= weight_sum
    cv_vectors.append(cv_sent_vec)
    row += 1
```

```
100%|██████████| 21000/21000 [01:18<00:00, 269.19it/s]
```

In [135]:

```
model = TfidfVectorizer()
test_matrix = model.fit_transform(X_test['CleanedText'].values)
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

test_feat = model.get_feature_names()

test_vectors = [];
row=0;
for sent in tqdm(test_sent_list):
    test_sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in test_w2v_words:
            test_vec = test_w2v_model.wv[word]
            test_tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            test_sent_vec += (vec * test_tf_idf)
            weight_sum += test_tf_idf
    if weight_sum != 0:
        test_sent_vec /= weight_sum
```

```
    test_vectors.append(train_sent_vec)
    row += 1
```

```
100%|██████████| 30000/30000 [02:30<00:00, 199.22it/s]
```

[5] Assignment 5: Apply Logistic Regression

1. **Apply Logistic Regression on these feature sets**
   - SET 1:Review text, preprocessed one converted into vectors using (BOW)
   - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
   - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
   - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

2. **Hyper paramter tuning (find best hyper parameters corresponding the algorithm that you choose)**
   - Find the best hyper parameter which will give the maximum AUC value
   - Find the best hyper paramter using k-fold cross validation or simple cross validation data
   - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Pertubation Test**
   - Get the weights W after fit your model with the data X.
   - Add a noise to the X (X' = X + e) and get the new data set X' (if X is a sparse matrix, X.data+=e)
   - Fit the model again on data X' and get the weights W'
   - Add a small eps value(to eliminate the divisible by zero error) to W and W’ i.e W=W+10^-6 and W’ = W’+10^-6
   - Now find the % change between W and W' (| (W-W') / (W) |)*100)
   - Calculate the 0th, 10th, 20th, 30th, ...100th percentiles, and observe any sudden rise in the values of percentage_change_vector

- Ex: consider your 99th percentile is 1.3 and your 100th percentiles are 34.6, there is sudden rise from 1.3 to 34.6, now calculate the 99.1, 99.2, 99.3,..., 100th percentile values and get the proper value after which there is sudden rise the values, assume it is 2.5
- Print the feature names whose % change is more than a threshold x(in our example it's 2.5)

4. **Sparsity**

- Calculate sparsity on weight vector obtained after using L1 regularization

NOTE: Do sparsity and multicollinearity for any one of the vectorizers. Bow or tf-idf is recommended.

5. **Feature importance**

- Get top 10 important features for both positive and negative classes separately.

6. **Feature engineering**

- To increase the performance of your model, you can also experiment with with feature engineering like :
  - Taking length of reviews as another feature.
  - Considering some features from review summary as well.

7. **Representation of results**

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure.
  Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
  Along with plotting ROC curve, you need to print the [confusion matrix]() with predicted and original labels of test data points. Please visualize your confusion matrices using [seaborn heatmaps.]()

8. **[Conclusion]**

- You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this link.

Applying Logistic Regression

[5.1] Logistic Regression on BOW, SET 1

[5.1.1] Applying Logistic Regression with L1 regularization on BOW, SET 1

In [24]:

```
#Performing Column standardization on train and cv data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler(copy=True, with_mean=False, with_std=True)

X_tr_bow= scaler.fit_transform(X_tr_bow)
```

```
X_tr_bow= scaler.fit_transform(X_tr_bow)
```

In [25]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score

c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

tr_list = []
for i in c:
    lr = LogisticRegression(penalty='l1', C=i, n_jobs=-1)
    lr.fit(X_tr_bow, y_tr)
    pred = lr.predict(X_tr_bow)
    auc = roc_auc_score(y_tr, pred)
    tr_list.append(auc.mean())
    print('\nTrain auc for C = %f is %f%%' % (i, auc))

print('*'*100)

cv_list = []
for j in c:
    lr = LogisticRegression(penalty='l1', C=j, n_jobs=-1)
    lr.fit(X_tr_bow, y_tr)
    pred = lr.predict(X_cv_bow)
    auc = roc_auc_score(y_cv, pred)
    cv_list.append(auc.mean())
    print('\nCV auc for C = %f is %f%%' % (j, auc))
```

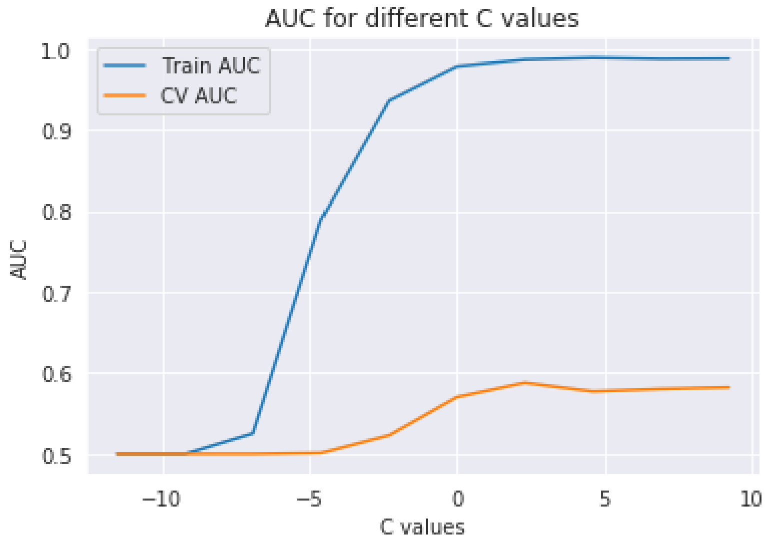
```
Train auc for C = 0.000010 is 0.500000%

Train auc for C = 0.000100 is 0.500000%

Train auc for C = 0.001000 is 0.525236%

Train auc for C = 0.010000 is 0.788717%

Train auc for C = 0.100000 is 0.936016%

Train auc for C = 1.000000 is 0.978040%
```

```
Train auc for C = 10.000000 is 0.986433%

Train auc for C = 100.000000 is 0.988744%

Train auc for C = 1000.000000 is 0.987271%

Train auc for C = 10000.000000 is 0.987659%
************************************************************************
*****************************

CV auc for C = 0.000010 is 0.500000%

CV auc for C = 0.000100 is 0.500000%

CV auc for C = 0.001000 is 0.500000%

CV auc for C = 0.010000 is 0.501176%

CV auc for C = 0.100000 is 0.522981%

CV auc for C = 1.000000 is 0.570328%

CV auc for C = 10.000000 is 0.587966%

CV auc for C = 100.000000 is 0.577359%

CV auc for C = 1000.000000 is 0.580360%

CV auc for C = 10000.000000 is 0.582294%
```

In [28]:

```
import math

c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

c =  [math.log(i) for i in c] #Applying log(alpha) for better visualiza
tion
```

```
In [29]: sns.set_style("darkgrid")
plt.plot(c, tr_list, label= 'Train AUC')
plt.plot(c, cv_list, label= 'CV AUC')
plt.xlabel("C values")
plt.ylabel("AUC")
plt.title("AUC for different C values")
plt.legend()
plt.show()
```



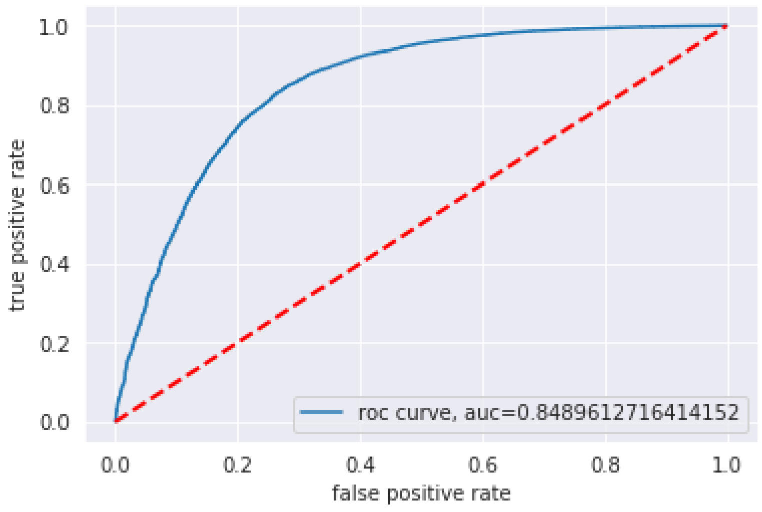
Observation:

From the above table and data we can observe that the optimal value of C is 10 with CV AUC score of 0.587

```
In [27]: lr = LogisticRegression(penalty='l1', C=10, n_jobs=-1)
lr.fit(X_tr_bow, y_tr)
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 10 is %f%%' % (auc))
```

```
****Test auc for C = 10 is 0.577235%
```

In [30]:
```
lw = 2
pred_proba = lr.predict_proba(X_test_bow)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  pred_proba)
auc = metrics.roc_auc_score(y_test, pred_proba)
plt.plot(fpr,tpr,label="roc curve, auc="+str(auc))
plt.plot([0, 1], [0, 1], color='red', lw=lw, linestyle='--')
plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
plt.legend(loc=4)
plt.show()
```

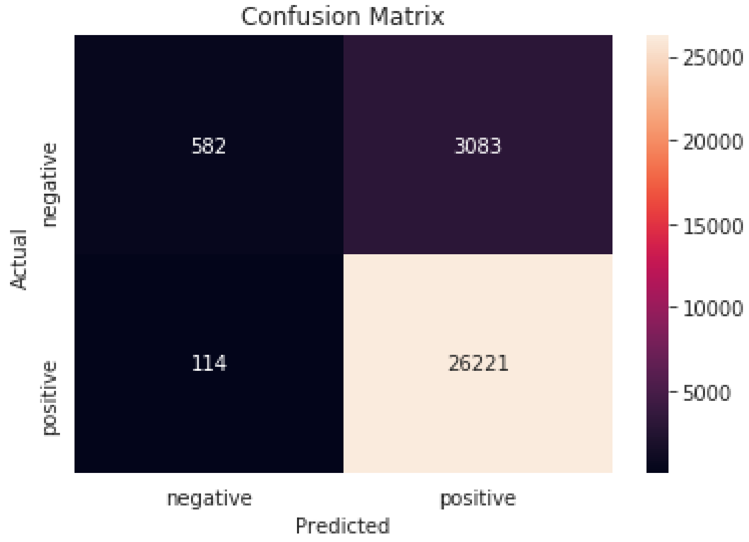


Obeservation:

The ROC curve of BOW with L1 regularizer is above the random line and seperated by a good distance

In [31]:
```
conf_matrix = confusion_matrix(y_test, pred)
class_label = ['negative', 'positive']
df_conf_matrix = pd.DataFrame(
    conf_matrix, index=class_label, columns=class_label)
```

```
sns.heatmap(df_conf_matrix, annot=True, fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Observation:

True Negative = 582, True Positive = 26221, False Negative = 114, False Positive = 3083

[5.1.1.1] Calculating sparsity on weight vector obtained using L1 regularization on BOW, SET 1

In [32]:
```
lr = LogisticRegression(penalty='l1', C=1, n_jobs=-1)
lr.fit(X_tr_bow, y_tr)
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 1 is %f%%' % (auc))
```

```
print("Non Zero weights at C=1 are:",np.count_nonzero(lr.coef_)) #Spars
ity on weight vector obtained by L1 on BoW
```

```
****Test auc for C = 1 is 0.566145%
Non Zero weights at C=1 are: 9352
```

In [33]:
```
lr = LogisticRegression(penalty='l1', C=10, n_jobs=-1)
lr.fit(X_tr_bow, y_tr)
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 10 is %f%%' % (auc))


print("Non Zero weights at C=10 are:",np.count_nonzero(lr.coef_))
```

```
****Test auc for C = 10 is 0.576962%
Non Zero weights at C=10 are: 12740
```

In [34]:
```
lr = LogisticRegression(penalty='l1', C=100, n_jobs=-1)
lr.fit(X_tr_bow, y_tr)
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 100 is %f%%' % (auc))


print("Non Zero weights at C=100 are:",np.count_nonzero(lr.coef_))
```

```
****Test auc for C = 100 is 0.576007%
Non Zero weights at C=100 are: 16355
```

Observation:

When L1 regularization is applied with BoW, the sparsity on weight vectors decreases i.e., the number of non zero values increases with the increase in the value of hyperparameter C.

[5.1.2] Applying Logistic Regression with L2 regularization on BOW,

SET 1

In [36]:
```
c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

tr_list = []
for i in c:
    lr = LogisticRegression(penalty='l2', C=i, n_jobs=-1)
    lr.fit(X_tr_bow, y_tr)
    pred = lr.predict(X_tr_bow)
    auc = roc_auc_score(y_tr, pred)
    tr_list.append(auc.mean())
    print('\nTrain auc for C = %f is %f%%' % (i, auc))

print('*'*100)

cv_list = []
for j in c:
    lr = LogisticRegression(penalty='l2', C=j, n_jobs=-1)
    lr.fit(X_tr_bow, y_tr)
    pred = lr.predict(X_cv_bow)
    auc = roc_auc_score(y_cv, pred)
    cv_list.append(auc.mean())
    print('\nCV auc for C = %f is %f%%' % (j, auc))
```

```
Train auc for C = 0.000010 is 0.544797%

Train auc for C = 0.000100 is 0.783663%

Train auc for C = 0.001000 is 0.902303%

Train auc for C = 0.010000 is 0.950860%

Train auc for C = 0.100000 is 0.973924%

Train auc for C = 1.000000 is 0.986493%

Train auc for C = 10.000000 is 0.993246%

Train auc for C = 100.000000 is 0.993870%
```

```
Train auc for C = 1000.000000 is 0.983440%

Train auc for C = 10000.000000 is 0.983487%
***********************************************************************
*****************************

CV auc for C = 0.000010 is 0.500000%

CV auc for C = 0.000100 is 0.500196%

CV auc for C = 0.001000 is 0.502941%

CV auc for C = 0.010000 is 0.521014%

CV auc for C = 0.100000 is 0.553953%

CV auc for C = 1.000000 is 0.583917%

CV auc for C = 10.000000 is 0.600985%

CV auc for C = 100.000000 is 0.603007%

CV auc for C = 1000.000000 is 0.575412%

CV auc for C = 10000.000000 is 0.575608%
```

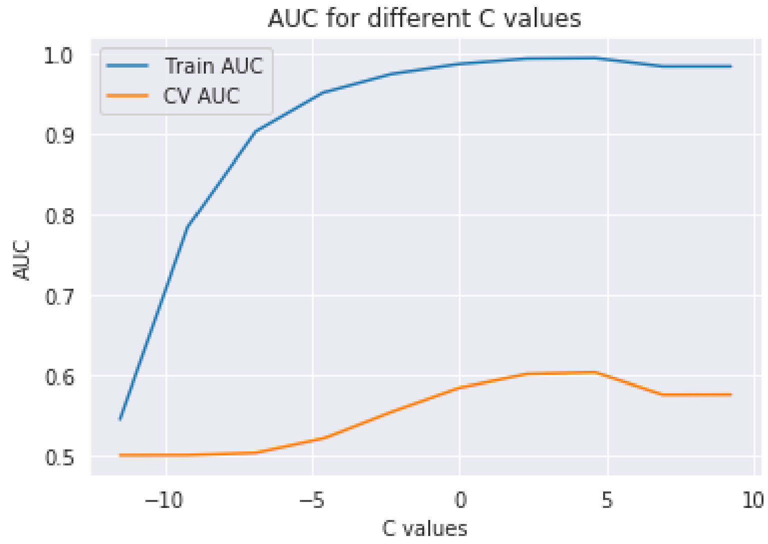
In [37]:

```
c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

c =  [math.log(i) for i in c] #Applying log(alpha) for better visualiza
tion
```

In [38]:

```
sns.set_style("darkgrid")
plt.plot(c, tr_list, label= 'Train AUC')
plt.plot(c,cv_list, label= 'CV AUC')
plt.xlabel("C values")
plt.ylabel("AUC")
plt.title("AUC for different C values")
```

```
plt.legend()
plt.show()
```



Observation:

From the above table and data we can observe that the optimalvalue of C is 100 with CV AUC score of 0.603

In [47]:
```
w= lr.coef_

lr = LogisticRegression(penalty='l2', C=100, n_jobs=-1)
lr.fit(X_tr_bow, y_tr)
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 100 is %f%%' % (auc))


print("Non Zero weights at C = 100 are:",np.count_nonzero(w)) #Sparsity
 on weight vector obtained by L2 on BoW
```

```
****Test auc for C = 100 is 0.582604%
```

```
Non Zero weights at C = 100 are: 26617
```

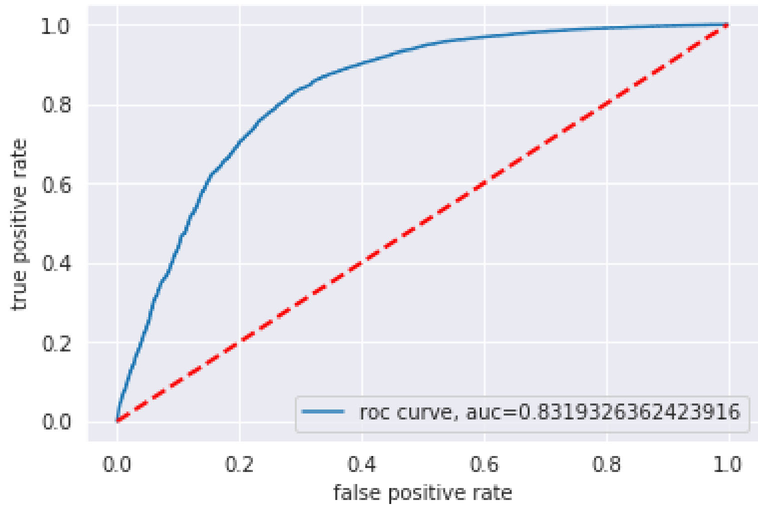
Observation:

The non-zero weights when L1 regularization applied on BoW with C as 100 = 16355

The non-zero weights when L2 regularization applied on BoW with C as 100 = 26617

There is a massive difference in the no. of zero values when L1 regularization and L2 regularizations are applied

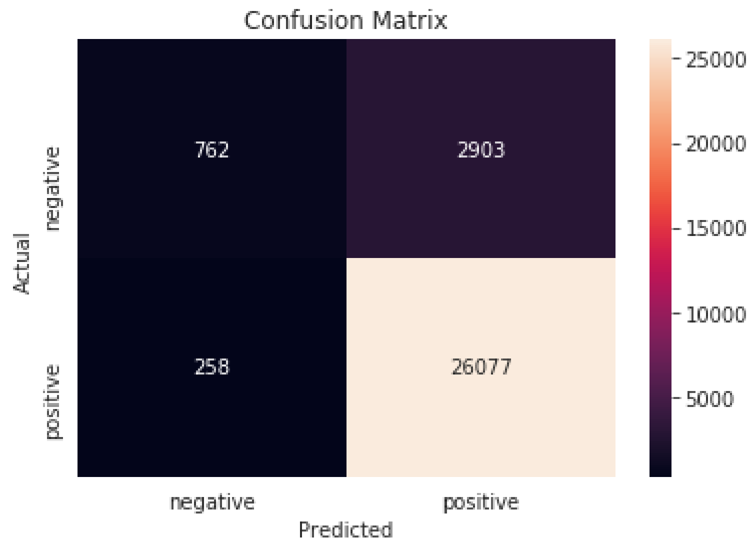
In [40]:
```
lw = 2
pred_proba = lr.predict_proba(X_test_bow)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  pred_proba)
auc = metrics.roc_auc_score(y_test, pred_proba)
plt.plot(fpr,tpr,label="roc curve, auc="+str(auc))
plt.plot([0, 1], [0, 1], color='red', lw=lw, linestyle='--')
plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
plt.legend(loc=4)
plt.show()
```



Obeservation:

The ROC curve of BOW with L2 regularization is above the random line and seperated by a good distance

In [41]:
```
conf_matrix = confusion_matrix(y_test, pred)
class_label = ['negative', 'positive']
df_conf_matrix = pd.DataFrame(
    conf_matrix, index=class_label, columns=class_label)
sns.heatmap(df_conf_matrix, annot=True, fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Observation:

True Negative = 762, True Positive = 26077, False Negative = 258, False Positive = 2903

[5.1.2.1] Performing pertubation test (multicollinearity check) on BOW, SET 1

In [48]:
```
#Reference: https://github.com/nishantml/Logistic-Regression-detailed-implementation/blob/master/Logistic%20Regression.ipynb (Performing perturbation test)

#After getting the weights W after fit your model with the train data.
#Adding noise to the X (X' = X + e) and get the new data set X' (if X is a sparse matrix, X.data+=e) that is e = 0.01

print(X_tr_bow.shape);
Standardize_x_tr_bow = X_tr_bow
Standardize_x_tr_bow.data = Standardize_x_tr_bow.data + 0.01
print(Standardize_x_tr_bow.shape)
```

```
(49000, 26617)
(49000, 26617)
```

In [49]:
```
#Training on train data having random noise

lr = LogisticRegression(penalty='l2', C=100, n_jobs=-1)
lr.fit(Standardize_x_tr_bow, y_tr)
w_dash = lr.coef_
pred = lr.predict(X_test_bow)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 100 is %f%%' % (auc))


print("Non Zero weights at C = 100 are:",np.count_nonzero(w_dash))
```

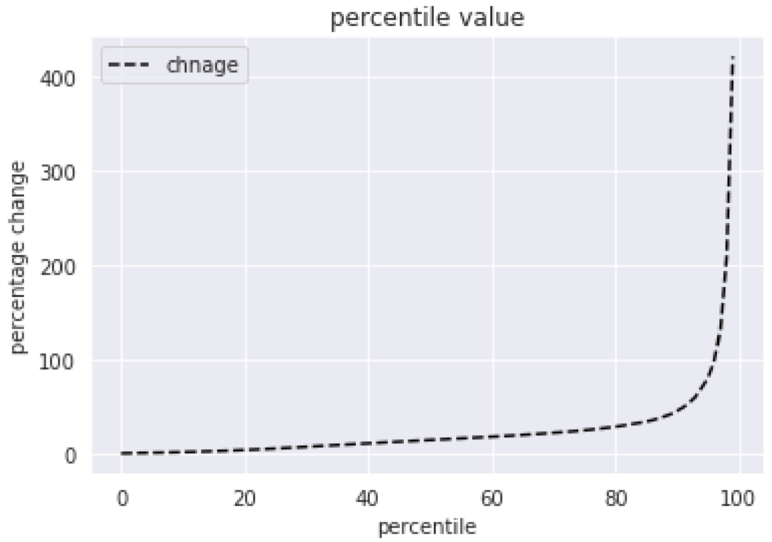
```
****Test auc for C = 100 is 0.574913%
Non Zero weights at C = 100 are: 26617
```

In [50]:
```
w = w[0] + 0.000001
w_dash = w_dash[0] +0.000001
W = list(w)
W_Dash = list(w_dash)
```

In [52]:
```python
#finding the % change between W and W' (| (W-W') / (W) |)*100)

change_vector_percentage = []
for i in tqdm(range(0,len(W))):
    change_vector = 0
    change_vector=(abs((W[i]-(W_Dash[i]))/(W[i])))*100
    change_vector_percentage.append(change_vector)
```

```
100%|██████████| 26617/26617 [00:00<00:00, 846840.19it/s]
```

In [53]:
```python
#calculating the 0th, 10th, 20th, 30th, ...100th percentiles, and obser
ving any sudden rise in the values of percentage_change_vector

percentile_value = []
percentile = []
i= 0
while i <100:
    percentile.append(i)
    percentile_value.append(np.percentile(change_vector_percentage,i))
    i = i+1;

# percentile_value
plt.plot(percentile, percentile_value, 'k--',label='chnage')
plt.xlabel('percentile')
plt.ylabel('percentage change')
plt.title("percentile value")
plt.legend()
plt.show()
```

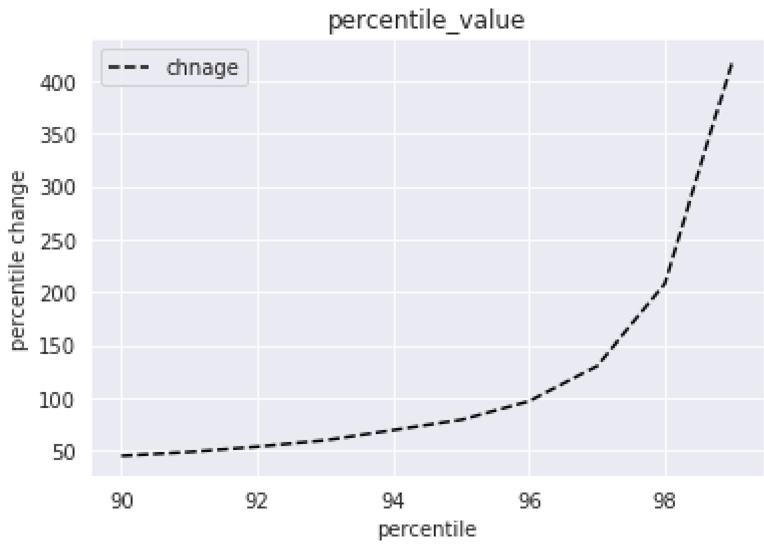


Observation:

As we can see above there is a sudden raise between 90 and 100

In [54]:
```
ninty_percentile_val = []
ninty_percentile = []
j= 90
while j <100:
    ninty_percentile.append(j)
    ninty_percentile_val.append(np.percentile(change_vector_percentage,
j))
    j = j+1;

plt.plot(ninty_percentile, ninty_percentile_val, 'k--',label='chnage')
plt.xlabel('percentile')
plt.ylabel('percentile change')
plt.title("percentile_value")
plt.legend()
plt.show()
```

```
print("Percentile value from 90 to 99\n")
print(ninty_percentile)
print(ninty_percentile_val)
```




```
Percentile value from 90 to 99

[90, 91, 92, 93, 94, 95, 96, 97, 98, 99]
[45.12079040719262, 48.75475219829979, 53.804963731631496, 59.865805395
308136, 69.52505304845418, 79.28111978015633, 96.87614829039795, 130.21
596933550035, 207.962728832516, 420.0449366403286]
```

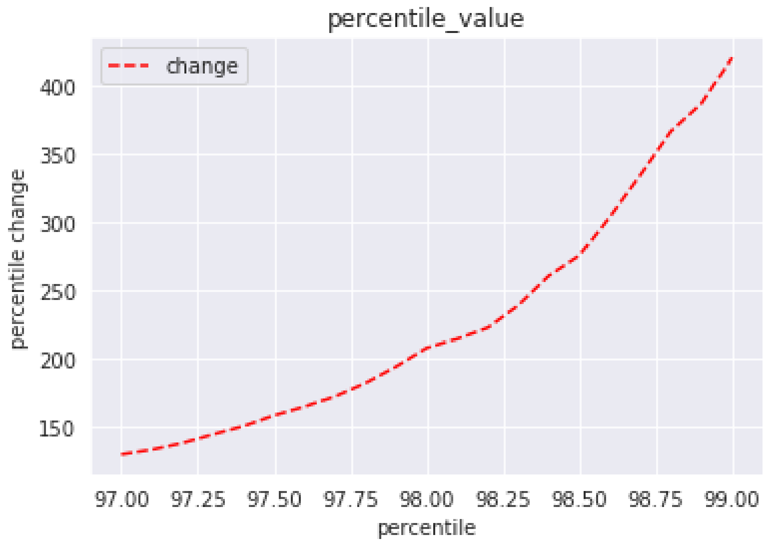
Observation:

From the above graph and data we can observe that there is a drastic change between 97 and 99

In [56]:

```
ninty_percentile_val = []
ninty_percentile = []
j= 97
while j <=99:
    ninty_percentile.append(j)
```

```
    ninty_percentile_val.append(np.percentile(change_vector_percentage,
j))
    j = j+0.1;

plt.plot(ninty_percentile, ninty_percentile_val, 'r--',label='change')
plt.xlabel('percentile')
plt.ylabel('percentile change')
plt.title("percentile_value")
plt.legend()
plt.show()

print("Percentile value from 97.0 to 99.0\n")
print(ninty_percentile)
print(ninty_percentile_val)
```




```
Percentile value from 97.0 to 99.0

[97, 97.1, 97.19999999999999, 97.29999999999998, 97.39999999999998, 97.
49999999999997, 97.59999999999997, 97.69999999999996, 97.7999999999999
5, 97.89999999999995, 97.99999999999994, 98.09999999999994, 98.19999999
999993, 98.29999999999993, 98.39999999999992, 98.49999999999991, 98.599
99999999991, 98.6999999999999, 98.7999999999999, 98.89999999999989, 98.
99999999999989]
```

```
[130.21596933550035, 133.66114912969564, 138.44242135646735, 144.863265
6030143, 150.8624240624944, 158.66705648382205, 165.09385082591214, 17
2.70640866539335, 182.41305679319797, 194.42593448469992, 207.962728832
516, 214.7137837327017, 222.77992653387287, 239.03564218737864, 260.656
02984735557, 275.4378850483848, 303.9338406386247, 334.2261994782286, 3
66.23207706797746, 386.49200542583276, 420.0449366401578]
```

Observation:

As we can see above at 98.3 percentile we got our elbow and the value at that is 239.0 and that is our thresold and after getting threshold the features I will print which has more than threshold why? -- they are the features which are affected by simple noise, so they are multicollinear with some other features if any of these features are in important features then we can't trust the top features.

In [57]:

```
w_with_greater_than_thresold = []
count = 0;
for i in range(0,len(change_vector_percentage)):
    if change_vector_percentage[i] > 239.03:
        count = count +1;
        w_with_greater_than_thresold.append(w[i])
    else:
        w_with_greater_than_thresold.append(0.0)

print(count)
```

```
453
```

In [59]:

```
def collinear_features(vectorizer, w):
    feature_names = vectorizer.get_feature_names()
    topn_class2 = sorted(zip(w, feature_names), reverse=True)[:]
    features_list = []
    for coef, feat in topn_class2:
        if coef != 0.0 :
            features_list.append(feat)
```

```
    collinear_features = features_list
    return collinear_features
```

In [60]:

```
features_with_greater_than_thresold = collinear_features(count_vect,w_with_greater_than_thresold)
print(features_with_greater_than_thresold)
```

```
['praiseworthi', 'overtook', 'curser', 'wireless', 'debut', 'crape', 'hiss', 'bouillion', 'pseudo', 'arrow', 'traditionalist', 'efagold', 'johanna', 'galt', 'further', 'catalyz', 'onboard', 'symbol', 'kindl', 'unintend', 'pardon', 'react', 'synergi', 'function', 'nutella', 'rico', 'financi', 'german', 'des', 'unseason', 'puerto', 'load', 'asset', 'mexican', 'whichev', 'mad', 'reduc', 'prune', 'partnership', 'asap', 'mere', 'extern', 'eschew', 'liaison', 'bolster', 'ecopod', 'tikka', 'cornucopia', 'mega', 'big', 'histori', 'las', 'regard', 'collin', 'underwhelm', 'winto', 'alberton', 'concret', 'someth', 'improv', 'job', 'lhasa', 'kit', 'spirulina', 'overproduc', 'litani', 'rancha', 'chopstickful', 'chocolati', 'domest', 'gimmicki', 'redirect', 'garganelli', 'forti', 'resourc', 'express', 'biloba', 'domata', 'candl', 'ohhh', 'sharki', 'gato', 'plenti', 'pile', 'fecal', 'breadman', 'flatten', 'reboot', 'defrag', 'condit', 'thinkof', 'tryin', 'lakesid', 'neoguri', 'koran', 'homegrown', 'ver', 'portland', 'prerequisit', 'definiteley', 'toaster', 'uncoop', 'halitosi', 'play', 'mull', 'instil', 'trendi', 'medley', 'hyperlink', 'chief', 'fuse', 'admonit', 'yamamotoyama', 'edibl', 'eversinc', 'jsut', 'ltd', 'reel', 'synagogu', 'arborio', 'toller', 'cranappl', 'rampant', 'sloooowwwli', 'belafont', 'collector', 'document', 'reconsid', 'rewar', 'phd', 'perus', 'lift', 'spackl', 'hoist', 'gump', 'diplomat', 'astut', 'gogo', 'handwash', 'album', 'wellington', 'daub', 'valerian', 'tradeoff', 'sml', 'cruz', 'rebar', 'grose', 'colgat', 'acn', 'rocher', 'subtract', 'peer', 'inadvert', 'spag', 'mozz', 'sunchip', 'fantstic', 'slope', 'tidal', 'halcyon', 'circumspect', 'becuz', 'abcstor', 'sfbc', 'phillip', 'sugur', 'whe', 'crispiest', 'aji', 'happybelli', 'maniac', 'insecticid', 'yore', 'ruptur', 'primordi', 'legion', 'jovial', 'counterattack', 'chum', 'boister', 'delightfuli', 'stire', 'fictiti', 'hom', 'reinact', 'pivot', 'mortifi', 'peppercini', 'spoonful', 'eva', 'noni', 'foodstor', 'guac', 'bayless', 'uncar', 'snowman', 'costo', 'dav', 'zig', 'zag', 'dubai', 'sanwich', 'futher', 'rochest', 'ringer', 'therel', 'ohao', 'mulholland', 'underweight', 'crumbi', 'delhi', 'cohen', 'publish', 'viewer', 'atleast', 'geek', 'downfal', 'sadd', 'anad', 'dazzl',
```

```
'startchi', 'uhmmmmm', 'jamba', 'amazonb', 'gasey', 'willett', 'laser',
'stickeri', 'goosebrri', 'cajum', 'scissorhand', 'precondit', 'sizzli
n', 'sexifi', 'diann', 'antonio', 'vacuvin', 'kunati', 'contradictori',
'nrg', 'moe', 'duff', 'lovlng', 'nector', 'guesswork', 'muh', 'mideas
t', 'eulog', 'ergonom', 'off', 'naval', 'tasmania', 'classi', 'delet',
'vulgar', 'cruch', 'woeber', 'tabouli', 'sinder', 'worldwid', 'potluc
k', 'shppping', 'schnauser', 'nnoth', 'minitur', 'intestsin', 'risc',
'housekeep', 'diamond', 'piquanc', 'ooomph', 'arab', 'aero', 'pupperon
i', 'briel', 'envor', 'ceral', 'citric', 'contraind', 'leaven', 'stra
y', 'sashimi', 'dunde', 'whistl', 'superpow', 'sandworm', 'po', 'pitt',
'oddest', 'interestng', 'cuss', 'afficionado', 'industr', 'accessori',
'dahh', 'munich', 'deliciousthi', 'unwil', 'carlson', 'whine', 'mestema
ch', 'stair', 'abscond', 'cheeseburg', 'colmbian', 'adobo', 'glycem',
'yoghourt', 'thym', 'protion', 'wholli', 'confectionari', 'stacey', 'ra
dioact', 'abrupt', 'messiah', 'donahu', 'bernard', 'keil', 'jolla', 'ji
mbo', 'escondido', 'clairemont', 'cerro', 'carlsbad', 'cardiff', 'footh
il', 'topnotch', 'jesus', 'demeanor', 'digust', 'viki', 'crabtre', 'mea
tti', 'esmal', 'bittersweet', 'headphon', 'smother', 'upss', 'loi', 'ra
pese', 'savi', 'semblanc', 'systemat', 'intrigu', 'conform', 'exhibit',
'writer', 'burrow', 'vietnam', 'hypocrit', 'pray', 'brais', 'molecula
r', 'jake', 'ref', 'moral', 'reggi', 'gastro', 'mgement', 'fus', 'ele
v', 'jerri', 'director', 'zaballion', 'docil', 'mamaeun', 'glucosim',
'bobolici', 'boblici', 'adminst', 'pack', 'gyokuro', 'swarm', 'given',
'garlicki', 'woman', 'acut', 'assign', 'ail', 'dessert', 'citadell', 's
weetgourmet', 'soar', 'frost', 'nebraska', 'mirror', 'institut', 'proba
bi', 'envis', 'senior', 'intimid', 'nathan', 'lotion', 'farm', 'own',
'spoonsful', 'btm', 'rusk', 'moonpi', 'templ', 'muffaletta', 'micro',
'carcass', 'aromat', 'barilla', 'swirl', 'ham', 'birch', 'section', 'go
odlif', 'regiment', 'tunisia', 'mezzogiorno', 'merum', 'hydraul', 'gazz
etta', 'chutney', 'carob', 'want', 'match', 'annalovesbook', 'book', 'c
onsumpt', 'panama', 'bean', 'marzipan', 'puriti', 'bariani', 'loooooon
g', 'onezip', 'pregnant', 'fife', 'spirit', 'spread', 'shelnutt', 'verm
outh', 'mind', 'gelatin', 'odwalla', 'briefli', 'butteri', 'brew', 'cam
pbel', 'spearhead', 'shortlist', 'moi', 'helm', 'dictat', 'yang', 'yuca
tan', 'buttinski']
```

[5.1.3] Feature Importance on BOW, SET 1

In [64]:
```
def show_most_informative_features(vectorizer, clf, n=10):
    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\tPositive\t\t\t\tNegative")
    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_2, fn_2, coef_
1, fn_1))
```

In [65]:
```
show_most_informative_features(count_vect,lr)
```

```
                        Positive                                Negativ
e
________________________________________________________________________
_________________________
        2.1095  great                                   -1.2972 worst
        1.8928  best                                    -1.1384 disappo
int
        1.8103  love                                    -0.9049 gram
        1.6242  delici                                  -0.8222 odor
        1.5050  favorit                                 -0.7930 would
        1.3707  addict                                  -0.7881 terribl
        1.3351  perfect                                 -0.7565 horribl
        1.3240  excel                                   -0.7366 slap
        1.3150  refresh                                 -0.7067 action
        1.2898  rooibo                                  -0.6926 protect
```

[5.2] Logistic Regression on TFIDF, SET 2

[5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

In [3]:
```
# Please write all the code with proper documentation
```

[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

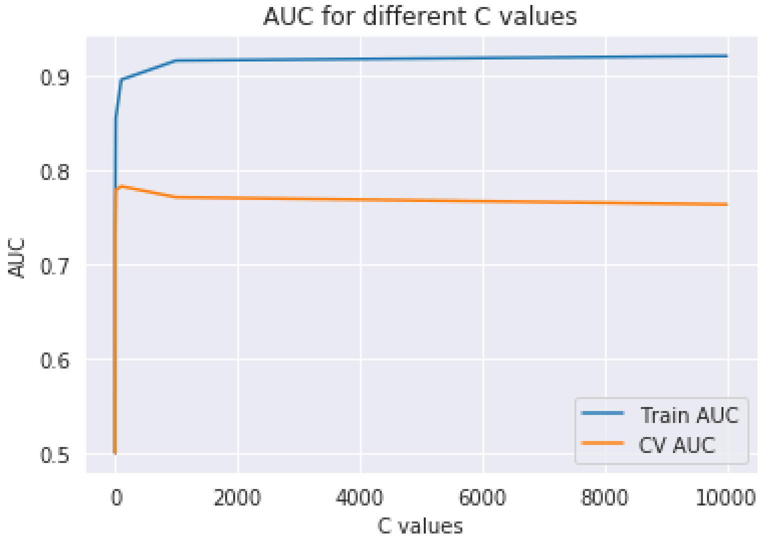
In [99]:
```
c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

tr_list = []
for i in c:
    lr = LogisticRegression(penalty='l2', C=i, n_jobs=-1)
    lr.fit(X_tr_tf_idf, y_tr)
    pred = lr.predict(X_tr_tf_idf)
    auc = roc_auc_score(y_tr, pred)
    tr_list.append(auc.mean())
    print('\nTrain auc for C = %f is %f%%' % (i, auc))

print('*'*100)

cv_list = []
for j in c:
    lr = LogisticRegression(penalty='l2', C=j, n_jobs=-1)
    lr.fit(X_tr_tf_idf, y_tr)
    pred = lr.predict(X_cv_tf_idf)
    auc = roc_auc_score(y_cv, pred)
    cv_list.append(auc.mean())
    print('\nCV auc for C = %f is %f%%' % (j, auc))
```

```
Train auc for C = 0.000010 is 0.500000%

Train auc for C = 0.000100 is 0.500000%
```

```
Train auc for C = 0.001000 is 0.500000%

Train auc for C = 0.010000 is 0.500000%

Train auc for C = 0.100000 is 0.563886%

Train auc for C = 1.000000 is 0.762529%

Train auc for C = 10.000000 is 0.855374%

Train auc for C = 100.000000 is 0.896405%

Train auc for C = 1000.000000 is 0.916842%

Train auc for C = 10000.000000 is 0.921722%
***********************************************************************
*****************************

CV auc for C = 0.000010 is 0.500000%

CV auc for C = 0.000100 is 0.500000%

CV auc for C = 0.001000 is 0.500000%

CV auc for C = 0.010000 is 0.500000%

CV auc for C = 0.100000 is 0.557072%

CV auc for C = 1.000000 is 0.735713%

CV auc for C = 10.000000 is 0.779325%

CV auc for C = 100.000000 is 0.783248%

CV auc for C = 1000.000000 is 0.771565%

CV auc for C = 10000.000000 is 0.763948%
```

In [100]:
```
sns.set_style("darkgrid")
```

```
plt.plot(c, tr_list, label= 'Train AUC')
plt.plot(c,cv_list, label= 'CV AUC')
plt.xlabel("C values")
plt.ylabel("AUC")
plt.title("AUC for different C values")
plt.legend()
plt.show()
```



Observation:

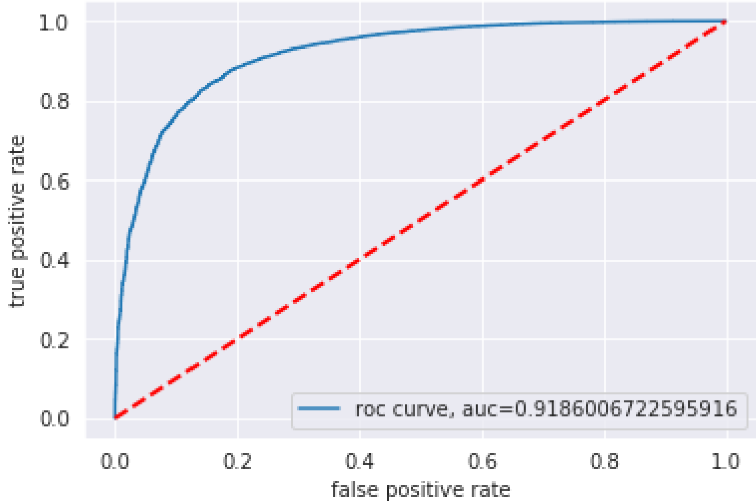
From the above table and data we can observe that the optimalvalue of C is 100 with CV AUC score of 0.783

In [102]:
```
lr = LogisticRegression(penalty='l2', C=100, n_jobs=-1)
lr.fit(X_tr_tf_idf, y_tr)
pred = lr.predict(X_test_tf_idf)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 10 is %f%%' % (auc))
```

```
****Test auc for C = 10 is 0.781207%
```

In [103]:

```
lw = 2
pred_proba = lr.predict_proba(X_test_tf_idf)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  pred_proba)
auc = metrics.roc_auc_score(y_test, pred_proba)
plt.plot(fpr,tpr,label="roc curve, auc="+str(auc))
plt.plot([0, 1], [0, 1], color='red', lw=lw, linestyle='--')
plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
plt.legend(loc=4)
plt.show()
```



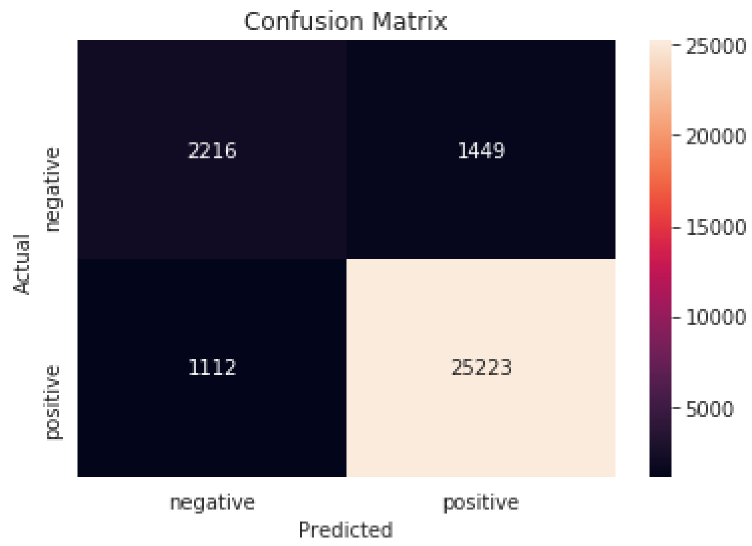
Obeservation:

The ROC curve of TF-IDF with L2 regularization is above the random line and seperated by a good distance

In [105]:

```
conf_matrix = confusion_matrix(y_test, pred)
class_label = ['negative', 'positive']
df_conf_matrix = pd.DataFrame(
    conf_matrix, index=class_label, columns=class_label)
sns.heatmap(df_conf_matrix, annot=True, fmt='d')
```

```
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Observation:

True Negative = 2216, True Positive = 25223, False Negative = 1112, False Positive = 1449

[5.2.3] Feature Importance on TFIDF, SET 2

In [121]:
```
show_most_informative_features(tf_idf_vect,lr)
```

```
                        Positive                                   Negativ
e
____________________________________________________________________________
_________________________
        -21.6668        great                                      17.9301
worst
```

```
        -19.4400        beat                                    16.9532
decept
        -15.4088        delici                                  16.5997
deceiv
        -15.3952        best                                    16.1349
colada
        -15.2241        aliv                                    15.7814
fragment
        -15.0372        danish                                  15.1607
margin
        -14.0747        mmmmm                                   14.9261
angri
        -14.0593        solv                                    14.8825
unaccept
        -13.6011        endless                                 14.8695
surf
        -13.4215        amaz                                    14.6899
unsatisfi
```

[5.3] Logistic Regression on AVG W2V, SET 3

[5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

In [3]:
```
# Please write all the code with proper documentation
```

[5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [128]:
```
c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

tr_list = []
for i in c:
    lr = LogisticRegression(penalty='l2', C=i, n_jobs=-1)
```

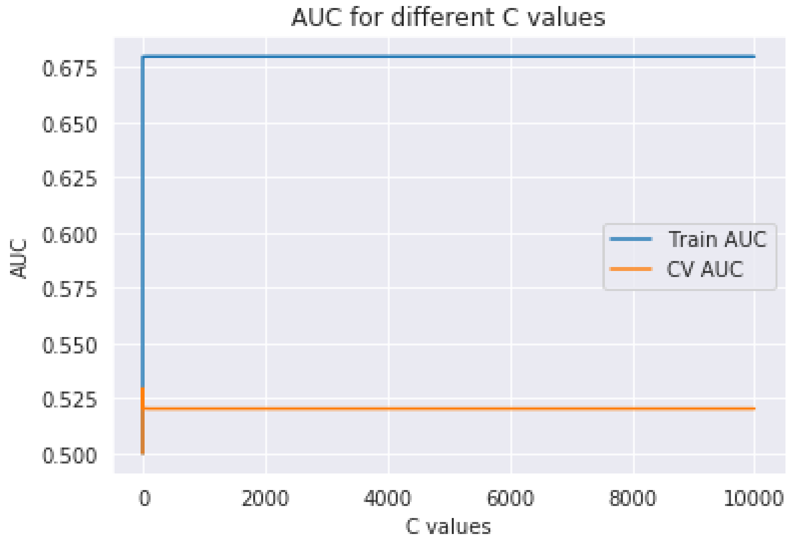
```
    lr.fit(train_sent_vectors, y_tr)
    pred = lr.predict(train_sent_vectors)
    auc = roc_auc_score(y_tr, pred)
    tr_list.append(auc.mean())
    print('\nTrain auc for C = %f is %f%%' % (i, auc))

print('*'*100)

cv_list = []
for j in c:
    lr = LogisticRegression(penalty='l2', C=j, n_jobs=-1)
    lr.fit(train_sent_vectors, y_tr)
    pred = lr.predict(cv_sent_vectors)
    auc = roc_auc_score(y_cv, pred)
    cv_list.append(auc.mean())
    print('\nCV auc for C = %f is %f%%' % (j, auc))
```

```
Train auc for C = 0.000010 is 0.500000%

Train auc for C = 0.000100 is 0.500000%

Train auc for C = 0.001000 is 0.533362%

Train auc for C = 0.010000 is 0.646439%

Train auc for C = 0.100000 is 0.674826%

Train auc for C = 1.000000 is 0.679452%

Train auc for C = 10.000000 is 0.679524%

Train auc for C = 100.000000 is 0.679607%

Train auc for C = 1000.000000 is 0.679595%

Train auc for C = 10000.000000 is 0.679595%
****************************************************************************************************

CV auc for C = 0.000010 is 0.500000%
```

```
CV auc for C = 0.000100 is 0.500000%

CV auc for C = 0.001000 is 0.502643%

CV auc for C = 0.010000 is 0.519242%

CV auc for C = 0.100000 is 0.529599%

CV auc for C = 1.000000 is 0.521442%

CV auc for C = 10.000000 is 0.520464%

CV auc for C = 100.000000 is 0.520297%

CV auc for C = 1000.000000 is 0.520297%

CV auc for C = 10000.000000 is 0.520297%
```

In [129]:

```
sns.set_style("darkgrid")
plt.plot(c, tr_list, label= 'Train AUC')
plt.plot(c,cv_list, label= 'CV AUC')
plt.xlabel("C values")
plt.ylabel("AUC")
plt.title("AUC for different C values")
plt.legend()
plt.show()
```



Observation:

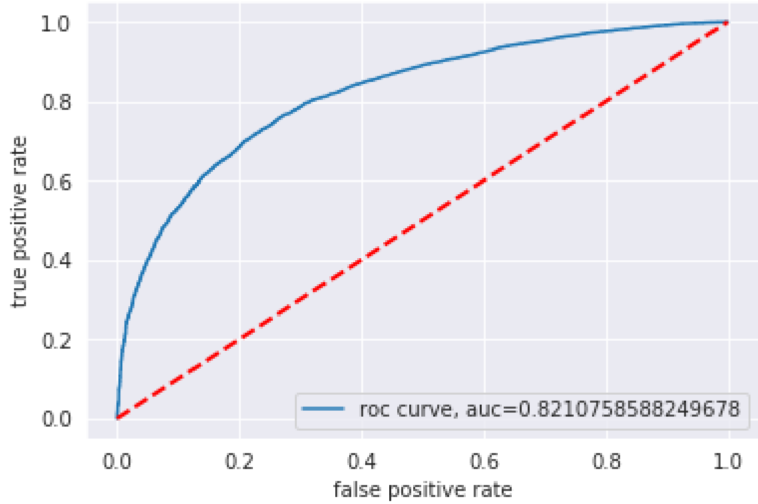
From the above table and data we can observe that the optimalvalue of C is 0.1 with CV AUC score of 0.529

In [130]:
```
lr = LogisticRegression(penalty='l2', C=0.1, n_jobs=-1)
lr.fit(train_sent_vectors, y_tr)
pred = lr.predict(test_sent_vectors)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 0.1 is %f%%' % (auc))
```

```
****Test auc for C = 0.1 is 0.577350%
```

In [131]:
```
lw = 2
pred_proba = lr.predict_proba(test_sent_vectors)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  pred_proba)
auc = metrics.roc_auc_score(y_test, pred_proba)
plt.plot(fpr,tpr,label="roc curve, auc="+str(auc))
plt.plot([0, 1], [0, 1], color='red', lw=lw, linestyle='--')
plt.xlabel("false positive rate")
```

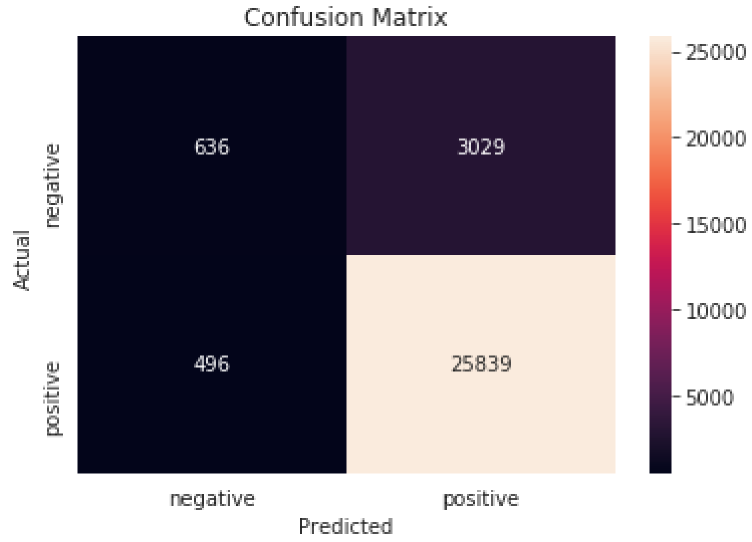
```
plt.ylabel("true positive rate")
plt.legend(loc=4)
plt.show()
```



Obeservation:

The ROC curve of Avg W2V is above the random line and seperated by a good margin

In [132]:
```
conf_matrix = confusion_matrix(y_test, pred)
class_label = ['negative', 'positive']
df_conf_matrix = pd.DataFrame(
    conf_matrix, index=class_label, columns=class_label)
sns.heatmap(df_conf_matrix, annot=True, fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Observation:

True Negative = 636, True Positive = 25839, False Negative = 496, False Positive = 3029

[5.4] Logistic Regression on TFIDF W2V, SET 4

[5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [3]:
```
# Please write all the code with proper documentation
```

[5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

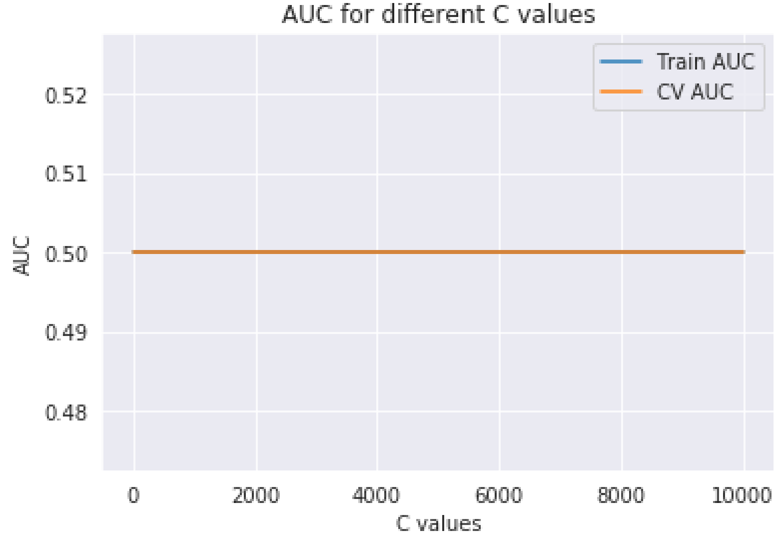
In [136]:
```
c = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
```

```
tr_list = []
for i in c:
    lr = LogisticRegression(penalty='l2', C=i, n_jobs=-1)
    lr.fit(train_vectors, y_tr)
    pred = lr.predict(train_vectors)
    auc = roc_auc_score(y_tr, pred)
    tr_list.append(auc.mean())
    print('\nTrain auc for C = %f is %f%%' % (i, auc))

print('*'*100)

cv_list = []
for j in c:
    lr = LogisticRegression(penalty='l2', C=j, n_jobs=-1)
    lr.fit(train_vectors, y_tr)
    pred = lr.predict(cv_vectors)
    auc = roc_auc_score(y_cv, pred)
    cv_list.append(auc.mean())
    print('\nCV auc for C = %f is %f%%' % (j, auc))
```

```
Train auc for C = 0.000010 is 0.500000%

Train auc for C = 0.000100 is 0.500000%

Train auc for C = 0.001000 is 0.500000%

Train auc for C = 0.010000 is 0.500000%

Train auc for C = 0.100000 is 0.500000%

Train auc for C = 1.000000 is 0.500000%

Train auc for C = 10.000000 is 0.500000%

Train auc for C = 100.000000 is 0.500000%

Train auc for C = 1000.000000 is 0.500000%

Train auc for C = 10000.000000 is 0.500000%
```

```
************************************************************************
*****************************

CV auc for C = 0.000010 is 0.500000%

CV auc for C = 0.000100 is 0.500000%

CV auc for C = 0.001000 is 0.500000%

CV auc for C = 0.010000 is 0.500000%

CV auc for C = 0.100000 is 0.500000%

CV auc for C = 1.000000 is 0.500000%

CV auc for C = 10.000000 is 0.500000%

CV auc for C = 100.000000 is 0.500000%

CV auc for C = 1000.000000 is 0.500000%

CV auc for C = 10000.000000 is 0.500000%
```

In [137]:
```
sns.set_style("darkgrid")
plt.plot(c, tr_list, label= 'Train AUC')
plt.plot(c,cv_list, label= 'CV AUC')
plt.xlabel("C values")
plt.ylabel("AUC")
plt.title("AUC for different C values")
plt.legend()
plt.show()
```



Observation:

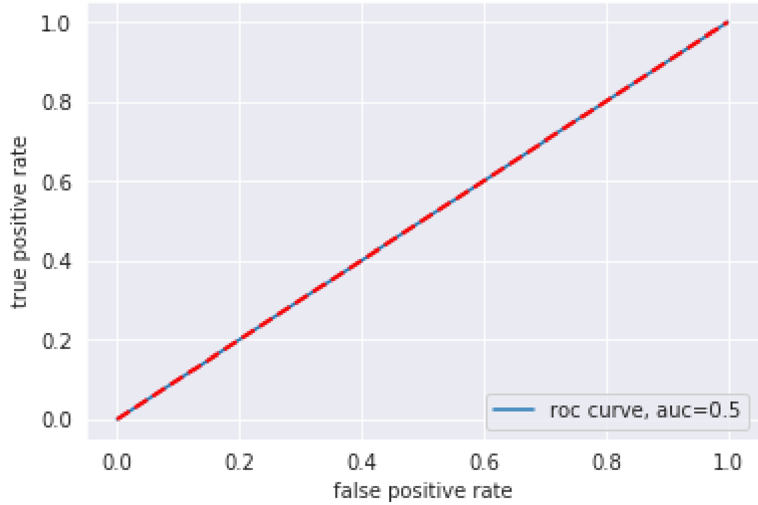
The AUC scores for all the values of C are same i.e., 0.50. Hence the optimal C = 0.000010

In [138]:
```
lr = LogisticRegression(penalty='l2', C=0.000010, n_jobs=-1)
lr.fit(train_sent_vectors, y_tr)
pred = lr.predict(test_sent_vectors)
auc = roc_auc_score(y_test, pred)
print('\n****Test auc for C = 0.000010 is %f%%' % (auc))
```

```
****Test auc for C = 0.000010 is 0.500000%
```

In [139]:
```
lw = 2
pred_proba = lr.predict_proba(test_vectors)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  pred_proba)
auc = metrics.roc_auc_score(y_test, pred_proba)
plt.plot(fpr,tpr,label="roc curve, auc="+str(auc))
plt.plot([0, 1], [0, 1], color='red', lw=lw, linestyle='--')
plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
```

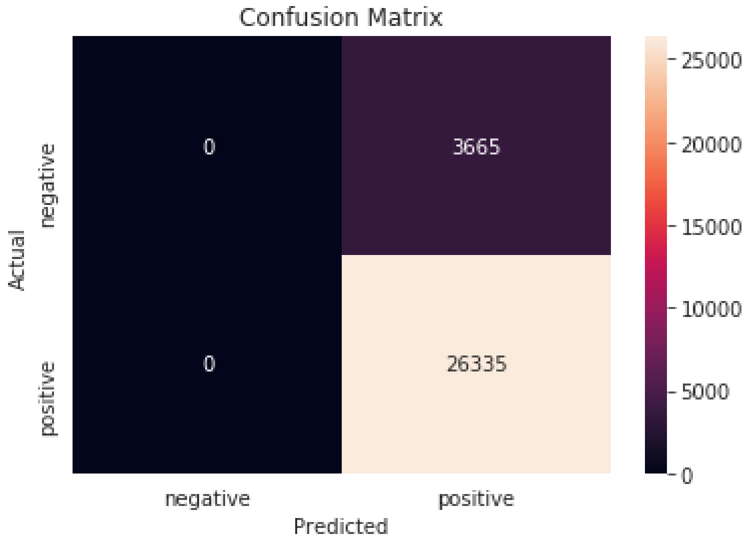
```
plt.legend(loc=4)
plt.show()
```



Obeservation:

The ROC curve of TF-IDF W2V is on the random line. Hence, this is a random model

In [140]:
```
conf_matrix = confusion_matrix(y_test, pred)
class_label = ['negative', 'positive']
df_conf_matrix = pd.DataFrame(
    conf_matrix, index=class_label, columns=class_label)
sns.heatmap(df_conf_matrix, annot=True, fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



[6] Conclusions

In [4]:
```
# Please compare all your models using Prettytable library
```