Assignment - 5 (Applying Logistic Regression On Amazon Fine Food reviews)

September 6, 2018

1 Objective : - Applying Logistic Regression on Amazon Fine Food Reviews

```
In [2]: # Importing libraries
        import warnings
        warnings.filterwarnings("ignore")

        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        %matplotlib inline
        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 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
```

2 Loading Data

In [3]:
```
# using the SQLite Table to read data.
con1 = sqlite3.connect('database.sqlite')

# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def polarity(x):
    if x < 3:
        return 'negative'
    return 'positive'

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)

print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

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

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400
1                     0                       0  negative  1346976000
2                     1                       1  positive  1219017600
3                     3                       3  negative  1307923200
4                     0                       0  positive  1350777600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

3 Data Cleaning: Deduplication

In [4]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

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

#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

```
(364173, 10)
```

Out[4]: 69.25890143662969

In [5]:

```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[5]:

```
            Id   ProductId          UserId  \
138683  150501  0006641040   AJ46FKXOVC7NR
138676  150493  0006641040   AMXOPJKV4PPNJ
138682  150500  0006641040  A1IJKK6Q1GTEAY
138681  150499  0006641040  A3E7R866M94L0C
476617  515426  141278509X   AB1A5EGHHVA9M
22621    24751  2734888454  A1C298ITT645B6
22620    24750  2734888454  A13ISQV0U9GZIC
284375  308077  2841233731  A3QD68O22M2XHQ
157850  171161  7310172001   AFXMWPNS1BLU4
157849  171160  7310172001   A74C7IARQEM1R
157833  171144  7310172001  A1V5MY8V9AWUQB
157832  171143  7310172001  A2SW060IW01VPX
157837  171148  7310172001  A3TFTWTG2CC1GA
157831  171142  7310172001  A2ZO1AYFVQYG44
157830  171141  7310172001   AZ40270J4JBZN
157829  171140  7310172001   ADXXVGRCGQQUO
157828  171139  7310172001  A13MS1JQG2ADOJ
157827  171138  7310172001  A13LAE0YTXA11B
157848  171159  7310172001  A16GY2RCF410DT
157834  171145  7310172001  A1L8DNQYY69L2Z

                                  ProfileName  \
138683                      Nicholas A Mesiano
138676                E. R. Bird "Ramseelbird"
138682                              A Customer
138681                 L. Barker "simienwolf"
```

476617	CHelmic
22621	Hugh G. Pritchard
22620	Sandikaye
284375	LABRNTH
157850	H. Sandler
157849	stucker
157833	Cheryl Sapper "champagne girl"
157832	Sam
157837	J. Umphress
157831	Cindy Rellie "Rellie"
157830	Zhinka Chunmee "gamer from way back in the 70's"
157829	Richard Pearlstein
157828	C. Perrone
157827	Dita Vyslouzilova "dita"
157848	LB
157834	R. Flores

	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time \
138683	2	2	positive	940809600
138676	71	72	positive	1096416000
138682	2	2	positive	1009324800
138681	2	2	positive	1065830400
476617	1	1	positive	1332547200
22621	0	0	positive	1195948800
22620	1	1	negative	1192060800
284375	0	0	positive	1345852800
157850	0	0	positive	1229385600
157849	0	0	positive	1230076800
157833	0	0	positive	1244764800
157832	0	0	positive	1252022400
157837	0	0	positive	1240272000
157831	0	0	positive	1254960000
157830	0	0	positive	1264291200
157829	0	0	positive	1264377600
157828	0	0	positive	1265760000
157827	0	0	positive	1269216000
157848	0	0	positive	1231718400
157834	0	0	positive	1243728000

	Summary \
138683	This whole series is great way to spend time w...
138676	Read it once. Read it twice. Reading Chicken S...
138682	It Was a favorite!
138681	Can't explain why
476617	The best drink mix
22621	Dog Lover Delites
22620	made in china
284375	Great recipe book for my babycook

```
157850                                   Excellent treats
157849                                    Sophie's Treats
157833                         THE BEST healthy dog treat!
157832                    My Alaskan Malamute Loves Them!!
157837                                   Best treat ever!
157831       my 12 year old maltese has always loved these
157830                     Dogs, Cats, Ferrets all love this
157829                                          5 snouts!
157828                                Best dog treat ever
157827                           Great for puppy training
157848                                             Great!
157834                                    Terrific Treats

                                                    Text
138683  I can remember seeing the show when it aired o...
138676  These days, when a person says, "chicken soup"...
138682  This was a favorite book of mine when I was a ...
138681  This book has been a favorite of mine since I ...
476617  This product by Archer Farms is the best drink...
22621   Our dogs just love them.  I saw them in a pet ...
22620   My dogs loves this chicken but its a product f...
284375  This book is easy to read and the ingredients ...
157850  I have been feeding my greyhounds these treats...
157849  This is one product that my welsh terrier can ...
157833  This is the ONLY dog treat that my Lhasa Apso ...
157832  These liver treas are phenomenal. When i recei...
157837  This was the only treat my dog liked during ob...
157831  No waste , even if she is having a  day when s...
157830  I wanted a treat that was accepted and well li...
157829  My Westie loves these things!  She loves anyth...
157828  This is the only dog treat that my terrier wil...
157827  New puppy loves this, only treat he will pay a...
157848  My dog loves these treats!  We started using t...
157834  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

```
In [6]: final = final[final['ProductId'] != '2841233731']
        final = final[final['ProductId'] != '0006641040']
        final.shape
```

```
Out[6]: (364136, 10)
```

4 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

```
In [7]: #set of stopwords in English
        from nltk.corpus import stopwords
        stop = set(stopwords.words('english'))
        words_to_keep = set(('not'))
        stop -= words_to_keep
        #initialising the snowball stemmer
        sno = nltk.stem.SnowballStemmer('english')

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

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

In [8]: #Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
        # also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
        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 descri
                            if(final['Score'].values)[i] == 'negative':
                                all_negative_words.append(s) #list of all words used to descri
                        else:
                            continue
                    else:
```

```
                continue

        str1 = b" ".join(filtered_sentence) #final string of cleaned words


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

```
In [9]: #adding a column of CleanedText which displays the data after pre-processing of the re
        final['CleanedText']=final_string
        final['CleanedText']=final['CleanedText'].str.decode("utf-8")
        #below the processed review can be seen in the CleanedText Column
        print('Shape of final',final.shape)
        final.head()
```

```
Shape of final (364136, 11)
```

```
Out[9]:             Id   ProductId          UserId        ProfileName  \
        476617  515426  141278509X   AB1A5EGHHVA9M             CHelmic
        22621    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
        22620    24750  2734888454  A13ISQV0U9GZIC           Sandikaye
        157850  171161  7310172001   AFXMWPNS1BLU4         H. Sandler
        157849  171160  7310172001   A74C7IARQEM1R             stucker

                HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        476617                     1                       1  positive  1332547200
        22621                      0                       0  positive  1195948800
        22620                      1                       1  negative  1192060800
        157850                     0                       0  positive  1229385600
        157849                     0                       0  positive  1230076800

                           Summary                                               Text  \
        476617  The best drink mix  This product by Archer Farms is the best drink...
        22621    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
        22620        made in china  My dogs loves this chicken but its a product f...
        157850    Excellent treats  I have been feeding my greyhounds these treats...
        157849      Sophie's Treats  This is one product that my welsh terrier can ...

                                                      CleanedText
        476617  product archer farm best drink mix ever mix fl...
        22621   dog love saw pet store tag attach regard made ...
        22620   dog love chicken product china wont buy anymor...
        157850  feed greyhound treat year hound littl finicki ...
        157849  one product welsh terrier eat sophi food alerg...
```

TIME BASED SPLITTING OF SAMPLE DATASET

```
In [10]: from sklearn.model_selection import train_test_split
         ##Sorting data according to Time in ascending order for Time Based Splitting
```

```
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki

x = time_sorted_data['CleanedText'].values
y = time_sorted_data['Score']

# split the data set into train and test
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3, random_state=
```

5 (1). Bag of Words (BoW)

```
In [11]: #BoW
         count_vect = CountVectorizer(min_df = 50)
         X_train_vec = count_vect.fit_transform(X_train)
         X_test_vec = count_vect.transform(X_test)
         print("the type of count vectorizer :",type(X_train_vec))
         print("the shape of out text BOW vectorizer : ",X_train_vec.get_shape())
         print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (254895, 6098)
the number of unique words : 6098
```

```
In [12]: import warnings
         warnings.filterwarnings('ignore')
         # Data-preprocessing: Standardizing the data

         from sklearn.preprocessing import StandardScaler
         sc = StandardScaler(with_mean=False)
         X_train_vec_standardized = sc.fit_transform(X_train_vec)
         X_test_vec_standardized = sc.transform(X_test_vec)
```

6 (1.a) L2 Regularisation (Logistic Regression)

```
In [13]: # Importing libraries
         from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import GridSearchCV
         from sklearn.model_selection import RandomizedSearchCV
```

7 GridSearchCV Implementation

```
In [14]: # Importing libraries for accuracy metrics
         from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,r

         tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
         #Using GridSearchCV
         model = GridSearchCV(LogisticRegression(penalty='l2'), tuned_parameters, scoring = 'ac
```

```
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)
```

```
Model with best parameters :
 LogisticRegression(C=0.01, 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)
Accuracy of the model :  0.9220347671661738
The optimal value of C(1/lambda) is :  0.01
```

In [15]:
```
# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
bow_l2_grid_C = optimal_C
bow_l2_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
bow_l2_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

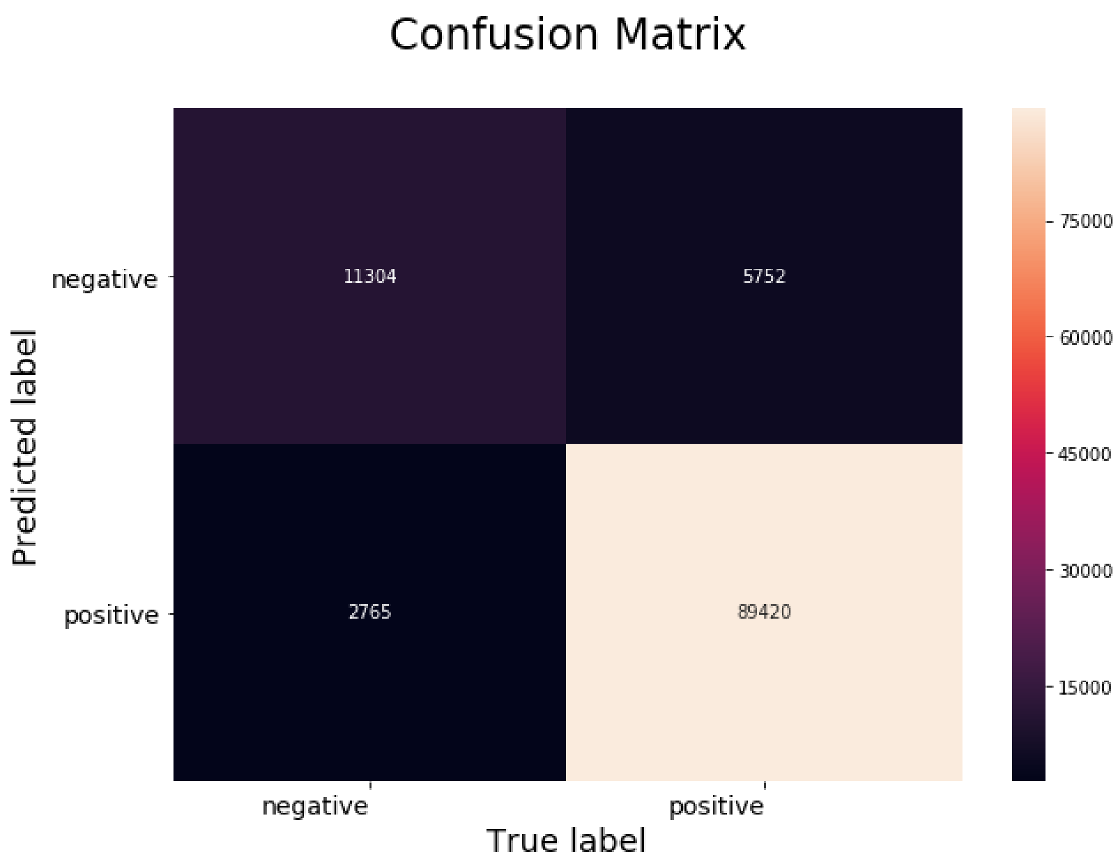
In [16]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.010 is 92.203477%

The Test Precision of the Logistic Regression classifier for C = 0.010 is 0.939562

The Test Recall of the Logistic Regression classifier for C = 0.010 is 0.970006
```

```
The Test F1-Score of the Logistic regression classifier for C = 0.010 is 0.954541
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [17]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, c
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [18]:
```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=fl

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
epsilon_train = X_train_vec_standardized + sparse_epsilon

print(X_train_vec_standardized.shape)
print(epsilon_train.shape)
```

```
(254895, 6098)
(254895, 6098)
```

In [20]:
```
# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon

# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[20]:
```
array([0.00159401, 0.0015377 , 0.0007778 , 0.00070106, 0.00067028,
```

```
0.00058177, 0.00053523, 0.00046506, 0.00038904, 0.00038481,
0.0003417 , 0.00030557, 0.00029905, 0.0002522 , 0.00024272,
0.00023424, 0.00021348, 0.00020301, 0.0002027 , 0.00020228])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

8 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

```
In [21]: absolute_weights = np.absolute(W_before_epsilon)
         sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
         top_index = sorted_absolute_index[0,0:20]

         all_features = count_vect.get_feature_names()
         weight_values = lr.coef_

         # Top 20 features are
         print("Top 20 features with their weight values :")

         for j in top_index:
             print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.730310
        love        -->         0.529931
        best        -->         0.522764
      delici        -->         0.505242
     perfect        -->         0.424769
        good        -->         0.412219
       excel        -->         0.361000
  disappoint        -->         -0.346830
        nice        -->         0.308957
     favorit        -->         0.271029
        amaz        -->         0.268661
       worst        -->         -0.238738
      awesom        -->         0.233476
        easi        -->         0.229080
       tasti        -->         0.227755
      wonder        -->         0.222639
       happi        -->         0.220394
        tast        -->         -0.216859
        find        -->         0.207083
     terribl        -->         -0.206875
```

9 RandomizedSearchCV Implementation

In [22]:
```
# Load libraries
from scipy.stats import uniform

# Create regularization hyperparameter distribution using uniform distribution
C = uniform(loc=0, scale=10)

# Create hyperparameter options
hyperparameters = dict(C=C)

#Using RandomizedSearchCV
model = RandomizedSearchCV(LogisticRegression(penalty='l2'), hyperparameters, scoring=
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
bow_l2_random_C = optimal_C
bow_l2_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
bow_l2_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=1.4275875917132186, 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)
Accuracy of the model :  0.9219798427330398
The optimal value of C(1/lambda) is :  1.4275875917132186
```

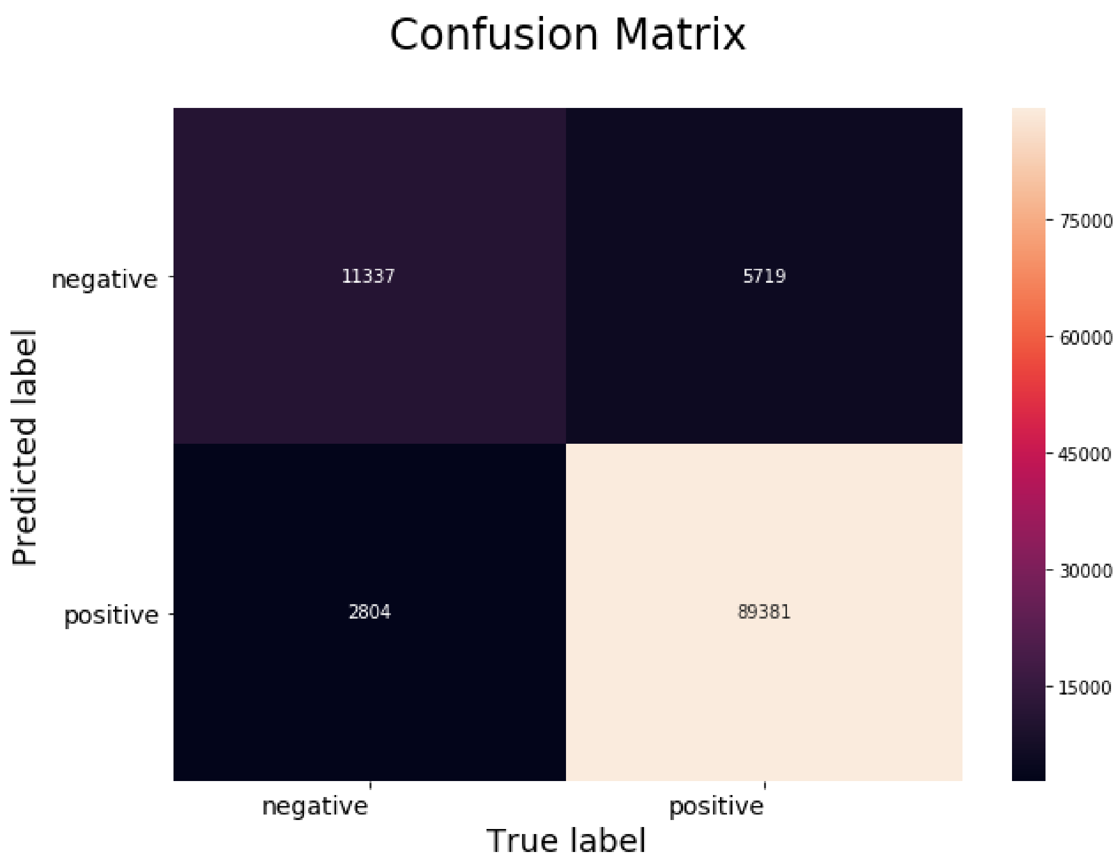
In [23]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %f is %f%%' %

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %f is %f' %

# evaluate recall
```

```
    acc = recall_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test Recall of the Logistic Regression classifier for C = %f is %f' % (op

    # evaluate f1-score
    acc = f1_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test F1-Score of the Logistic regression classifier for C = %f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 1.427588 is 92.197984%

The Test Precision of the Logistic Regression classifier for C = 1.427588 is 0.939863

The Test Recall of the Logistic Regression classifier for C = 1.427588 is 0.969583

The Test F1-Score of the Logistic regression classifier for C = 1.427588 is 0.954492
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [24]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [25]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()

# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=f

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
```

```
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[25]:
```
array([3.05209910e-03, 1.25906345e-03, 1.23313482e-03, 1.21377331e-03,
       1.09612039e-03, 1.02361241e-03, 8.56108561e-04, 8.35524152e-04,
       8.03491894e-04, 7.62642014e-04, 6.86882235e-04, 6.66070131e-04,
       4.38079401e-04, 2.89659297e-04, 2.86900927e-04, 1.02420820e-04,
       9.55668323e-05, 9.24656867e-05, 9.18820166e-05, 7.80115213e-05])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

10 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

In [26]:
```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.749685
        love        -->         0.540823
        best        -->         0.538182
      delici        -->         0.523692
     perfect        -->         0.441224
```

```
        good        -->         0.421720
       excel        -->         0.372815
  disappoint        -->        -0.352933
        nice        -->         0.317290
        muir        -->         0.301052
        moka        -->         0.278407
        amaz        -->         0.278136
     favorit        -->         0.277408
        glen        -->        -0.262062
       worst        -->        -0.243421
      awesom        -->         0.241359
         nom        -->         0.239984
        easi        -->         0.234943
       tasti        -->         0.232444
      wonder        -->         0.228119
```

11 (1.b) L1 Regularisation (Logistic regression)

12 GridSearchCV Implementation

In [27]:
```python
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l1'), tuned_parameters, scoring = 'a
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
bow_l1_grid_C = optimal_C
bow_l1_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
bow_l1_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=0.01, 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)
Accuracy of the model :  0.9224558544868685
```

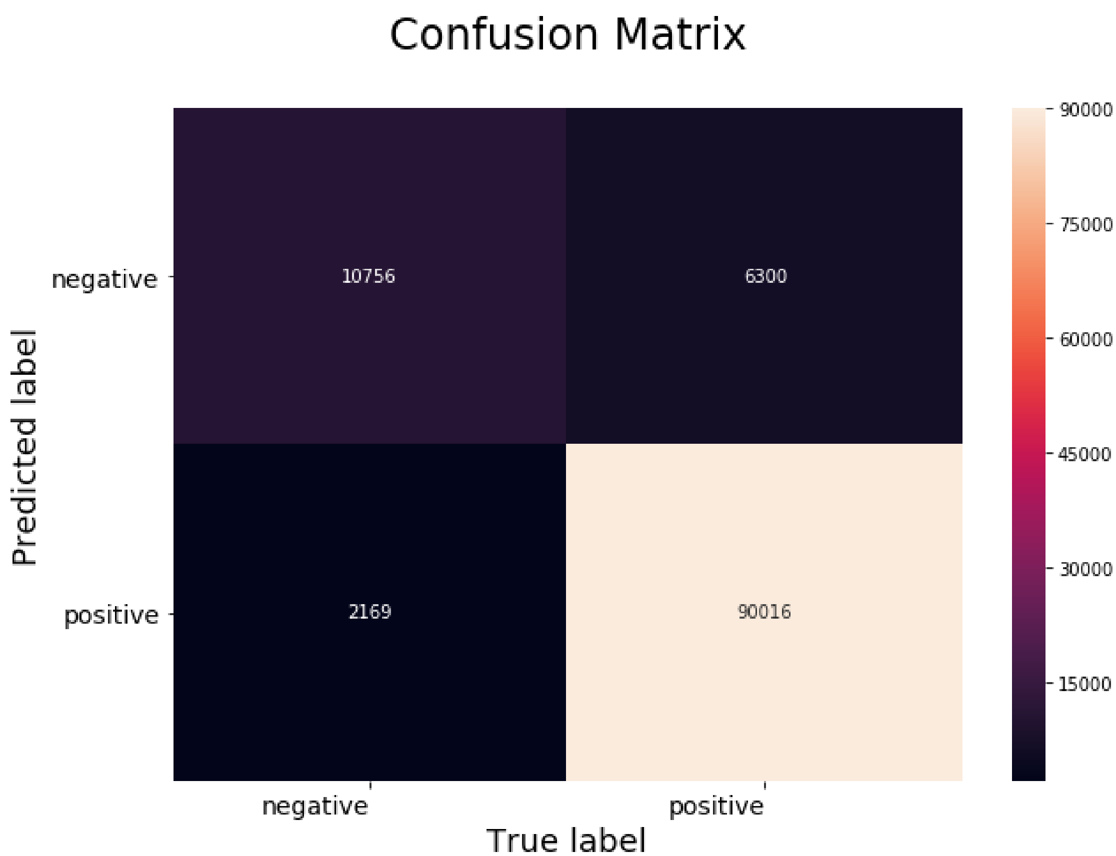
```
The optimal value of C(1/lambda) is :  0.01
```

```
In [28]: # evaluate accuracy
         acc = accuracy_score(Y_test, predictions) * 100
         print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

         # evaluate precision
         acc = precision_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

         # evaluate recall
         acc = recall_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

         # evaluate f1-score
         acc = f1_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.010 is 92.247416%

The Test Precision of the Logistic Regression classifier for C = 0.010 is 0.934590

The Test Recall of the Logistic Regression classifier for C = 0.010 is 0.976471

The Test F1-Score of the Logistic regression classifier for C = 0.010 is 0.955072
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [29]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [31]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()

# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=f

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
```

```
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
Out[31]: array([0.00579108, 0.00568539, 0.00039819, 0.00030376, 0.0002599 ,
                0.00022093, 0.00016221, 0.00016142, 0.00015442, 0.00015005,
                0.00014986, 0.0001476 , 0.00012443, 0.00011613, 0.0001115 ,
                0.00010834, 0.0001061 , 0.00010378, 0.00010375, 0.00010074])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

13 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

```
In [32]: absolute_weights = np.absolute(W_before_epsilon)
         sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
         top_index = sorted_absolute_index[0,0:20]

         all_features = count_vect.get_feature_names()
         weight_values = lr.coef_

         # Top 20 features are
         print("Top 20 features with their weight values :")

         for j in top_index:
             print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.671857
        love        -->         0.484587
        best        -->         0.471564
      delici        -->         0.451778
     perfect        -->         0.373985
        good        -->         0.358111
```

```
       excel          -->          0.322410
  disappoint          -->          -0.315437
        nice          -->          0.272810
     favorit          -->          0.242436
        amaz          -->          0.227471
       worst          -->          -0.214513
        easi          -->          0.203188
       tasti          -->          0.200469
      awesom          -->          0.199951
       happi          -->          0.193542
      wonder          -->          0.189211
        tast          -->          -0.188332
      return          -->          -0.184318
       thank          -->          0.183874
```

14 More Sparsity (Fewer elements of W* being non-zero) by increasing Lambda (decreasing C)

In [33]:
```python
# With lambda = 1
clf = LogisticRegression(C=1, penalty='l1',n_jobs=-1);
clf.fit(X_train_vec_standardized, Y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
6068
```

In [34]:
```python
# With lambda = 10
clf = LogisticRegression(C=0.1, penalty='l1',n_jobs=-1);
clf.fit(X_train_vec_standardized, Y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
5815
```

In [35]:
```python
# With lambda = 100
clf = LogisticRegression(C=0.01, penalty='l1',n_jobs=-1);
clf.fit(X_train_vec_standardized, Y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
3674
```

In [36]:
```python
# With lambda = 1000
clf = LogisticRegression(C=0.001, penalty='l1',n_jobs=-1);
```

```
clf.fit(X_train_vec_standardized, Y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
381
```

OBSERVATION :- From above we can see that the number of non-zero elements of W* is decreasing as we are increasing the value of lambda (C is decreasing) .

15 RandomizedSearchCV Implementation

```
In [37]: # Create regularization hyperparameter distribution using uniform distribution
         C = uniform(loc=0, scale=10)

         # Create hyperparameter options
         hyperparameters = dict(C=C)

         #Using RandomizedSearchCV
         model = RandomizedSearchCV(LogisticRegression(penalty='l1'), hyperparameters, scoring=
         model.fit(X_train_vec_standardized, Y_train)
         print("Model with best parameters :\n",model.best_estimator_)
         print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

         optimal_C = model.best_estimator_.C
         print("The optimal value of C(1/lambda) is : ",optimal_C)

         # Logistic Regression with Optimal value of C i.e.(1/lambda)
         lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
         lr.fit(X_train_vec_standardized,Y_train)
         predictions = lr.predict(X_test_vec_standardized)

         # Variables that will be used for  making table in Conclusion part of this assignment
         bow_l1_random_C = optimal_C
         bow_l1_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
         bow_l1_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=0.20062843367622873, 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)
Accuracy of the model :  0.9222361567543321
The optimal value of C(1/lambda) is :  0.20062843367622873
```

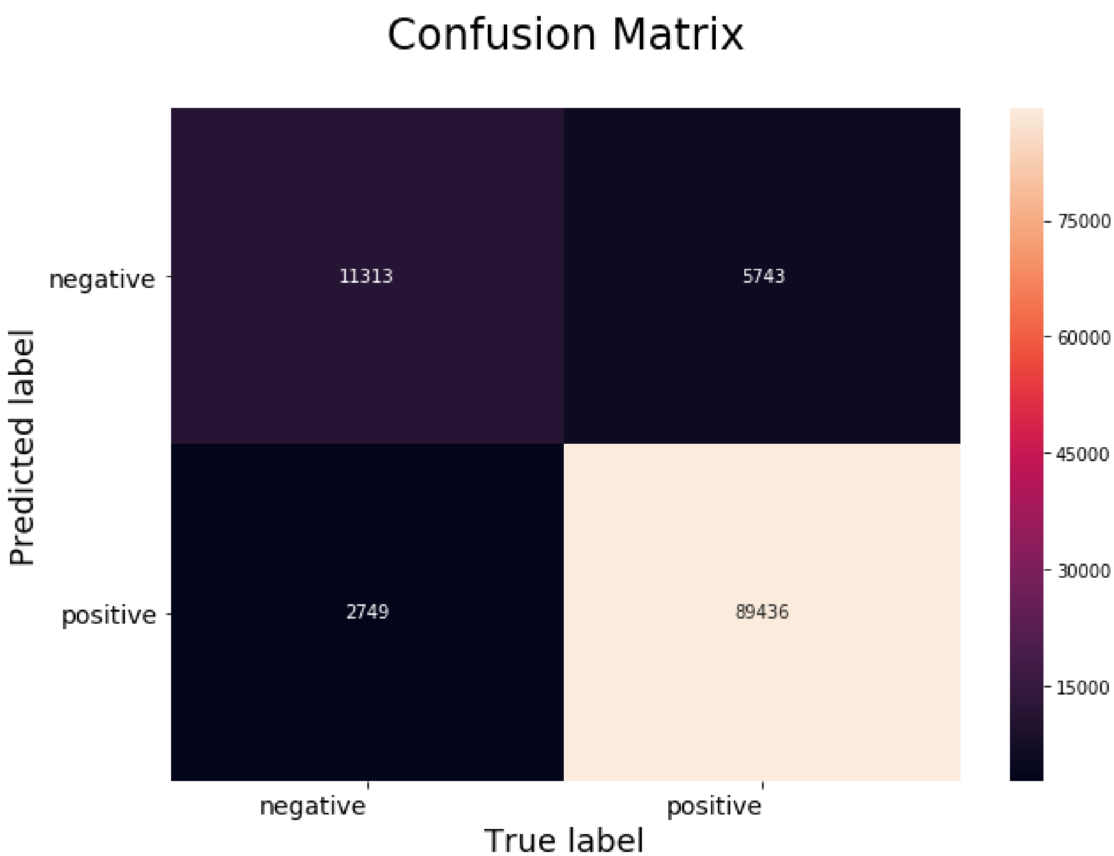
```
In [38]: # evaluate accuracy
         acc = accuracy_score(Y_test, predictions) * 100
```

```
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f'
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.201 is 92.226362%

The Test Precision of the Logistic Regression classifier for C = 0.201 is 0.939661

The Test Recall of the Logistic Regression classifier for C = 0.201 is 0.970180

The Test F1-Score of the Logistic regression classifier for C = 0.201 is 0.954676
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [39]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [40]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()

# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=fl

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
```

```
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[40]:
```
array([0.02237764, 0.02158832, 0.00169514, 0.00167163, 0.00088758,
       0.00088361, 0.00069944, 0.0006367 , 0.00063072, 0.00061668,
       0.00056487, 0.00054095, 0.00048238, 0.00043977, 0.00043314,
       0.00036974, 0.00036678, 0.00032307, 0.00028503, 0.00027125])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

16 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

In [41]:
```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.742383
        love        -->         0.535755
        best        -->         0.532161
      delici        -->         0.517292
     perfect        -->         0.435130
        good        -->         0.416290
```

```
      excel        -->        0.368052
 disappoint        -->        -0.349331
       nice        -->        0.313458
    favorit        -->        0.274382
       amaz        -->        0.273673
      worst        -->        -0.240574
     awesom        -->        0.237796
       easi        -->        0.232143
      tasti        -->        0.229744
     wonder        -->        0.224586
      happi        -->        0.222856
       tast        -->        -0.222744
      yummi        -->        0.209360
       find        -->        0.208743
```

17 (2) TFIDF

In [42]:
```python
tf_idf_vect = TfidfVectorizer(min_df=50)
X_train_vec = tf_idf_vect.fit_transform(X_train)
X_test_vec = tf_idf_vect.transform(X_test)
print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text TFIDF vectorizer : ",X_train_vec.get_shape())
print("the number of unique words :", X_train_vec.get_shape()[1])

# Data-preprocessing: Standardizing the data
sc = StandardScaler(with_mean=False)
X_train_vec_standardized = sc.fit_transform(X_train_vec)
X_test_vec_standardized = sc.transform(X_test_vec)
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (254895, 6098)
the number of unique words : 6098
```

18 (2.a) L2 Regularisation (Logistic Regression)

19 GridSearchCV Implementation

In [43]:
```python
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l2'), tuned_parameters, scoring = 'a
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
```

```
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_l2_grid_C = optimal_C
tfidf_l2_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_l2_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

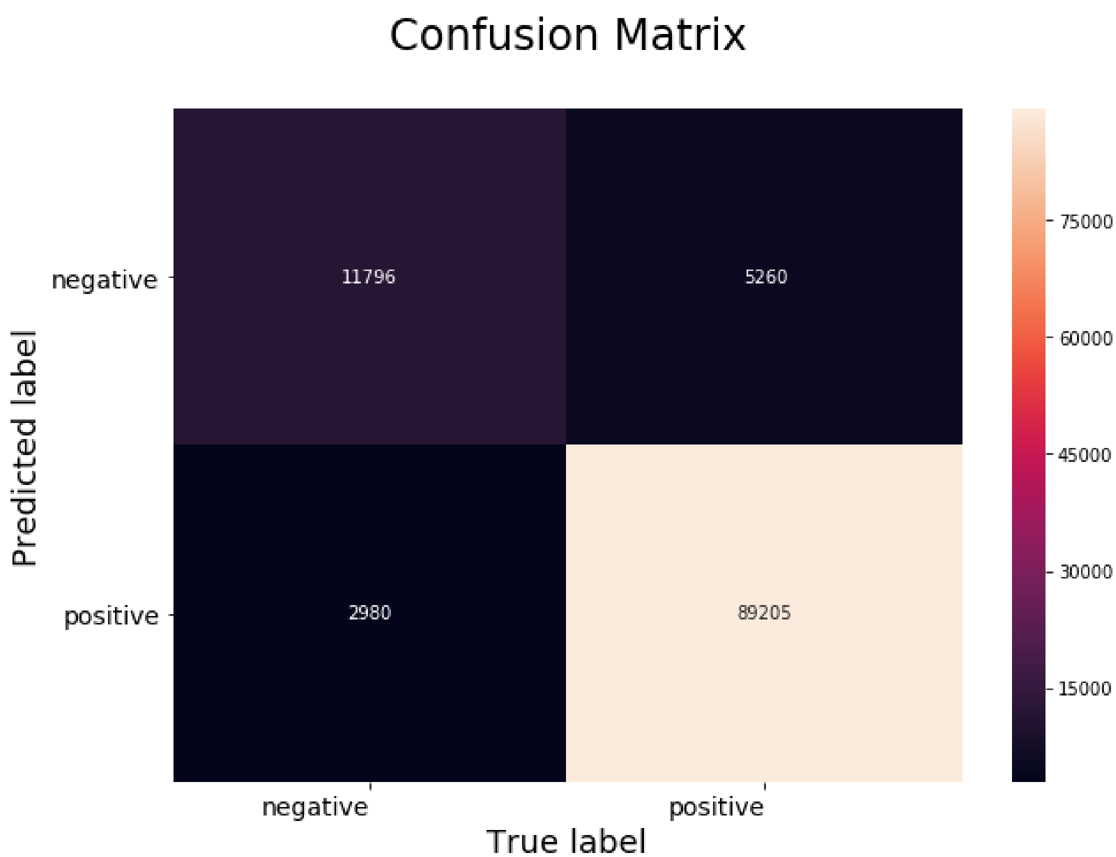
```
Model with best parameters :
 LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Accuracy of the model :  0.9245704451625305
The optimal value of C(1/lambda) is :  0.01
```

```
In [44]: # evaluate accuracy
         acc = accuracy_score(Y_test, predictions) * 100
         print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

         # evaluate precision
         acc = precision_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

         # evaluate recall
         acc = recall_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

         # evaluate f1-score
         acc = f1_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.010 is 92.457045%

The Test Precision of the Logistic Regression classifier for C = 0.010 is 0.944318

The Test Recall of the Logistic Regression classifier for C = 0.010 is 0.967674

The Test F1-Score of the Logistic regression classifier for C = 0.010 is 0.955853
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [45]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [46]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()
```

```
# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=fl

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[46]:
```
array([2.04264368e-04, 1.98353779e-04, 9.67404104e-05, 8.41218957e-05,
       6.98817831e-05, 5.89690569e-05, 5.87498048e-05, 5.43898704e-05,
       5.35128423e-05, 5.23590224e-05, 5.15183141e-05, 4.98570144e-05,
       4.33669317e-05, 3.83531952e-05, 3.71385635e-05, 3.71200760e-05,
       3.56373557e-05, 3.54688122e-05, 3.26788083e-05, 3.21656309e-05])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

20 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

In [47]:
```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
top_index = sorted_absolute_index[0,0:20]
```

```
all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.824989
        love        -->         0.590899
        best        -->         0.565669
      delici        -->         0.538336
     perfect        -->         0.443156
        good        -->         0.424295
       excel        -->         0.393403
  disappoint        -->         -0.305526
        nice        -->         0.302383
     favorit        -->         0.292604
        amaz        -->         0.270344
      awesom        -->         0.256720
        easi        -->         0.241699
       worst        -->         -0.237943
      wonder        -->         0.232105
       yummi        -->         0.230961
       tasti        -->         0.221280
       thank        -->         0.219595
        find        -->         0.215802
     fantast        -->         0.213699
```

21 RandomizedSearchCV Implementation

In [48]:
```
# Create regularization hyperparameter distribution using uniform distribution
C = uniform(loc=0, scale=10)

# Create hyperparameter options
hyperparameters = dict(C=C)

#Using RandomizedSearchCV
model = RandomizedSearchCV(LogisticRegression(penalty='l2'), hyperparameters, scoring
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
```

```
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_l2_random_C = optimal_C
tfidf_l2_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_l2_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

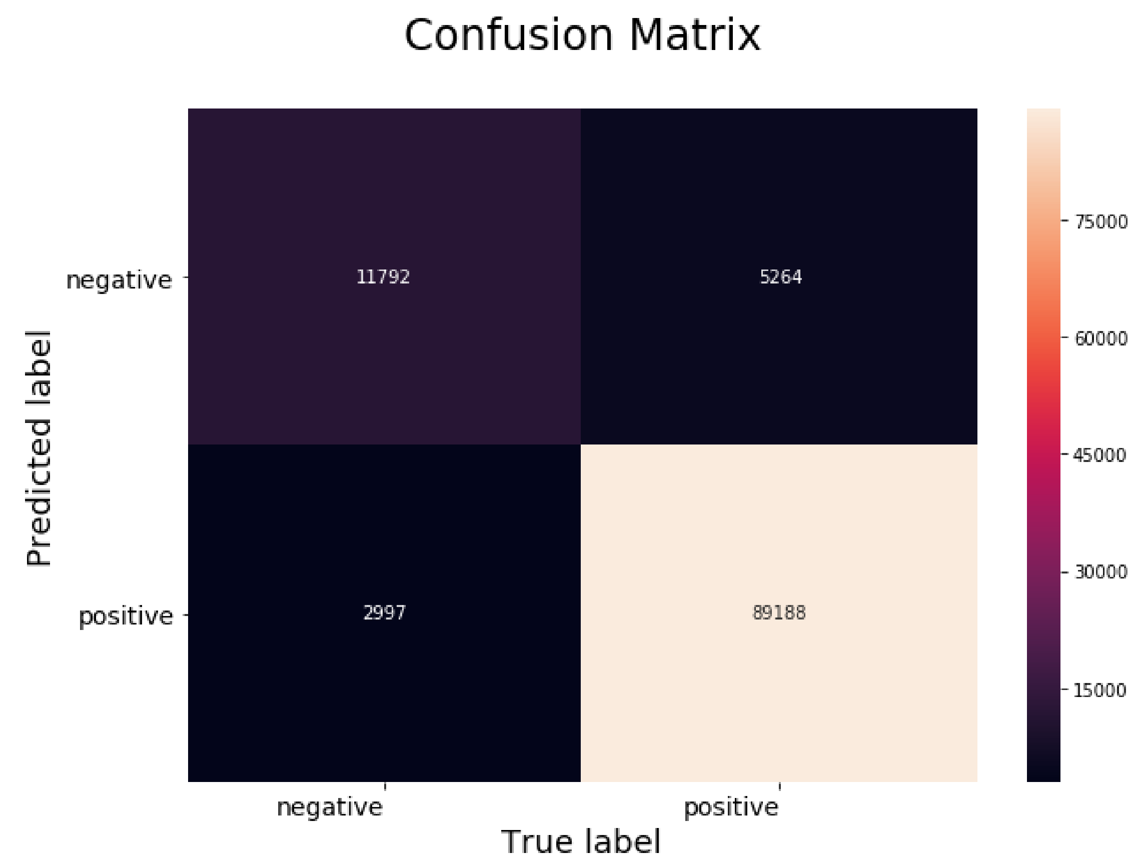
```
Model with best parameters :
 LogisticRegression(C=4.827593247007973, class_weight=None, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
Accuracy of the model :  0.9243782096465613
The optimal value of C(1/lambda) is :  4.827593247007973
```

In [49]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %f is %f%%' %

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %f is %f' %

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %f is %f' % (op

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 4.827593 is 92.437821%

The Test Precision of the Logistic Regression classifier for C = 4.827593 is 0.944268

The Test Recall of the Logistic Regression classifier for C = 4.827593 is 0.967489

The Test F1-Score of the Logistic regression classifier for C = 4.827593 is 0.955738
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [50]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [51]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()
```

```
# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=fl

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[51]:
```
array([8.87431952e-05, 6.30367082e-05, 6.29254718e-05, 6.27161106e-05,
       5.62670654e-05, 5.57362672e-05, 5.50217821e-05, 4.55021679e-05,
       4.46283845e-05, 4.28031537e-05, 4.24521546e-05, 4.19164487e-05,
       3.98683431e-05, 3.97135763e-05, 3.31797616e-05, 2.51553410e-05,
       1.91065413e-05, 1.75863252e-05, 1.72318094e-05, 1.69828696e-05])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

22 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

In [52]:
```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
top_index = sorted_absolute_index[0,0:20]
```

```
all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->          0.850204
        love        -->          0.603318
        best        -->          0.583994
      delici        -->          0.560556
     perfect        -->          0.462133
        good        -->          0.431604
       excel        -->          0.407692
  disappoint        -->          -0.311574
        nice        -->          0.310207
     favorit        -->          0.299839
        amaz        -->          0.279799
      awesom        -->          0.266254
        easi        -->          0.248024
       worst        -->          -0.242299
       yummi        -->          0.239338
      wonder        -->          0.237348
       tasti        -->          0.224943
       thank        -->          0.223960
     fantast        -->          0.221815
      addict        -->          0.220521
```

23 (2.b) L1 Regularisation (Logistic regression)

24 GridSearchCV Implementation

In [53]:
```
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l1'), tuned_parameters, scoring = 'a
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
```

```
lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_l1_grid_C = optimal_C
tfidf_l1_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_l1_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=0.01, 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)
Accuracy of the model :  0.9258886315577485
The optimal value of C(1/lambda) is :  0.01
```

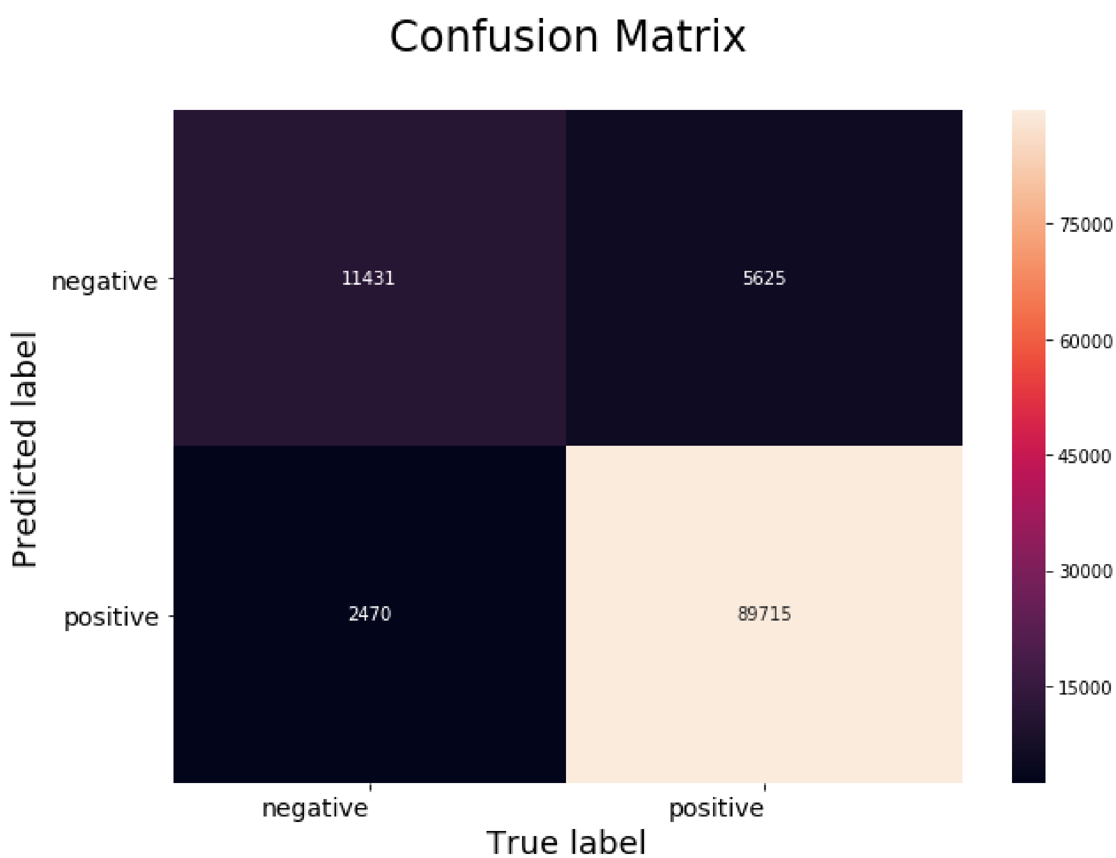
In [54]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %f is %f%%' %

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %f is %f' %

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %f is %f' % (op

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.010000 is 92.589779%

The Test Precision of the Logistic Regression classifier for C = 0.010000 is 0.941001

The Test Recall of the Logistic Regression classifier for C = 0.010000 is 0.973206

The Test F1-Score of the Logistic regression classifier for C = 0.010000 is 0.956832
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [55]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
```

```
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

In [56]:
```
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_
# Number of non zero elements in X_train_vec_standardized sparse matrix
no_of_non_zero = X_train_vec_standardized.count_nonzero()

# Creating new sparse matrix with epsilon at same position of non-zero elements of X_
indices_X_train = X_train_vec_standardized.indices
```

```
indptr_X_train = X_train_vec_standardized.indptr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = X_train_vec_standardized.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=fl

# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

Out[56]:
```
array([2.21733505e-04, 1.82563302e-04, 1.73249691e-04, 1.62491182e-04,
       1.28155685e-04, 1.12210395e-04, 1.07174428e-04, 1.01721274e-04,
       8.56302666e-05, 8.09102511e-05, 7.95781859e-05, 7.94541525e-05,
       7.84000199e-05, 7.78564244e-05, 6.79457968e-05, 6.73540266e-05,
       6.67539489e-05, 6.43223632e-05, 6.41916587e-05, 6.34377651e-05])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

25 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

In [57]:
```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
top_index = sorted_absolute_index[0,0:20]

all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_
```

```
# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.773984
        love        -->         0.555771
        best        -->         0.526791
      delici        -->         0.496685
     perfect        -->         0.408177
        good        -->         0.385962
       excel        -->         0.362690
  disappoint        -->         -0.285032
        nice        -->         0.276128
     favorit        -->         0.268575
        amaz        -->         0.239582
      awesom        -->         0.223106
        easi        -->         0.219676
       worst        -->         -0.218179
      wonder        -->         0.203090
       yummi        -->         0.201855
       tasti        -->         0.199293
        find        -->         0.196676
       thank        -->         0.195658
       happi        -->         0.191244
```

26 More Sparsity (Fewer elements of W* being non-zero) by increasing Lambda (decreasing C)

```
In [58]: # With lambda = 1
         clf = LogisticRegression(C=1, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
6061
```

```
In [59]: # With lambda = 10
         clf = LogisticRegression(C=0.1, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
5810
```

```
In [60]: # With lambda = 100
         clf = LogisticRegression(C=0.01, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
3903
```

```
In [61]: # With lambda = 1000
         clf = LogisticRegression(C=0.001, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
442
```

OBSERVATION :- From above we can see that the number of non-zero elements of W* is decreasing as we are increasing the value of lambda (C is decreasing) .

27 RandomizedSearchCV Implementation

```
In [62]: # Create regularization hyperparameter distribution using uniform distribution
         C = uniform(loc=0, scale=10)

         # Create hyperparameter options
         hyperparameters = dict(C=C)

         #Using RandomizedSearchCV
         model = RandomizedSearchCV(LogisticRegression(penalty='l1'), hyperparameters, scoring=
         model.fit(X_train_vec_standardized, Y_train)
         print("Model with best parameters :\n",model.best_estimator_)
         print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

         optimal_C = model.best_estimator_.C
         print("The optimal value of C(1/lambda) is : ",optimal_C)

         # Logistic Regression with Optimal value of C i.e.(1/lambda)
         lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
         lr.fit(X_train_vec_standardized,Y_train)
         predictions = lr.predict(X_test_vec_standardized)

         # Variables that will be used for  making table in Conclusion part of this assignment
         tfidf_l1_random_C = optimal_C
         tfidf_l1_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
         tfidf_l1_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=0.8718584489029746, 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)
Accuracy of the model :  0.9244697503684514
The optimal value of C(1/lambda) is :  0.8718584489029746
```

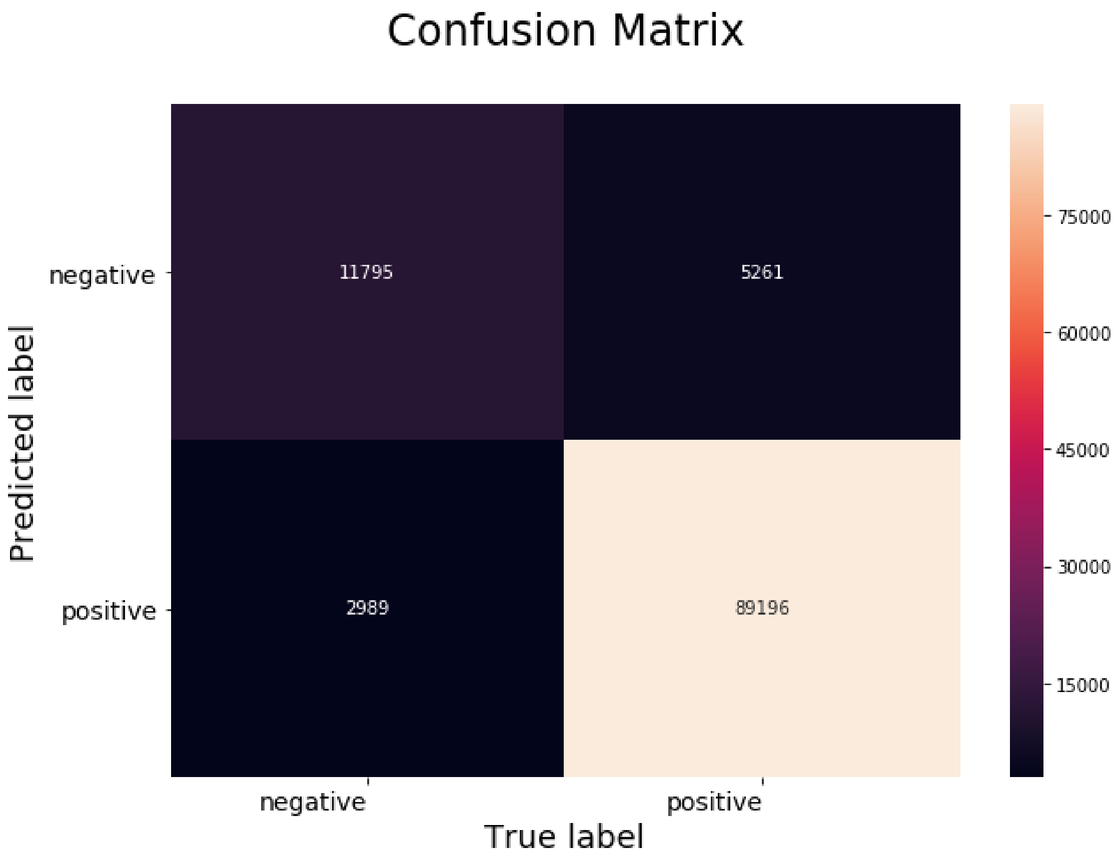
In [63]:
```python
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %f is %f%%' %

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %f is %f' %

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %f is %f' % (op

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 0.871858 is 92.447890%

The Test Precision of the Logistic Regression classifier for C = 0.871858 is 0.944303

The Test Recall of the Logistic Regression classifier for C = 0.871858 is 0.967576

The Test F1-Score of the Logistic regression classifier for C = 0.871858 is 0.955798
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [64]:
```python
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right',
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right',
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
```

```
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



MULTI-COLLINEARITY CHECK (PERTUBATION TECHNIQUE):

```
In [65]: epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
         # Vector before the addition of epsilon
         W_before_epsilon = lr.coef_
         # Number of non zero elements in X_train_vec_standardized sparse matrix
         no_of_non_zero = X_train_vec_standardized.count_nonzero()

         # Creating new sparse matrix with epsilon at same position of non-zero elements of X_
         indices_X_train = X_train_vec_standardized.indices
         indptr_X_train = X_train_vec_standardized.indptr

         # Creating a list of same element with repetition
         data = [epsilon] * no_of_non_zero
         Shape = X_train_vec_standardized.shape

         # Creating sparse matrix
         sparse_epsilon = csr_matrix((data,indices_X_train,indptr_X_train),shape=Shape,dtype=f
```

```
# Add sparse_epsilon and X-train_vec_standardized to get a new sparse matrix with eps
# non-zero element of X_train_vec_standardized
epsilon_train = X_train_vec_standardized + sparse_epsilon

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,Y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
# Sort this change_vector array after making all the elements positive in ascending o
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
Out[65]: array([0.00244115, 0.00241197, 0.00206425, 0.00173659, 0.00162052,
                0.00140127, 0.00135811, 0.00114338, 0.00103279, 0.00064469,
                0.00062623, 0.00062007, 0.00015853, 0.00014514, 0.00014103,
                0.00012394, 0.00012128, 0.00010544, 0.00010494, 0.00010258])
```

OBSERVATION :- From above we can see that there is no large change in the weights of the both vectors . So we will use absolute value of weights(|w|) of the feature to find important features

28 Selecting Top 20 Important Features Using Absolute Value of Weights (|w|)

```
In [66]: absolute_weights = np.absolute(W_before_epsilon)
         sorted_absolute_index = np.argsort(absolute_weights)[:,::-1]
         top_index = sorted_absolute_index[0,0:20]

         all_features = tf_idf_vect.get_feature_names()
         weight_values = lr.coef_

         # Top 20 features are
         print("Top 20 features with their weight values :")

         for j in top_index:
             print("%12s\t--> \t%f"%(all_features[j],weight_values[0,j]))
```

```
Top 20 features with their weight values :
       great        -->         0.849038
        love        -->         0.602777
        best        -->         0.583035
```

```
     delici          -->          0.559510
    perfect          -->          0.461114
       good          -->          0.431090
      excel          -->          0.406908
 disappoint          -->          -0.310883
       nice          -->          0.309608
    favorit          -->          0.299218
       amaz          -->          0.278982
     awesom          -->          0.265530
       easi          -->          0.247506
      worst          -->          -0.241804
      yummi          -->          0.238737
     wonder          -->          0.236777
      tasti          -->          0.224669
      thank          -->          0.223515
    fantast          -->          0.221172
     addict          -->          0.219877
```

29 Word2Vec

In [67]:
```
# List of sentence in X_train text
sent_of_train=[]
for sent in X_train:
    sent_of_train.append(sent.split())

# List of sentence in X_est text
sent_of_test=[]
for sent in X_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_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))
```

```
number of words that occured minimum 5 times  18825
```

30 (3). Avg Word2Vec

In [68]:
```
# compute average word2vec for each review for X_train .
train_vectors = [];
for sent in sent_of_train:
    sent_vec = np.zeros(50)
```

```
        cnt_words =0;
        for word in sent: #
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        train_vectors.append(sent_vec)

    # compute average word2vec for each review for X_test .
    test_vectors = [];
    for sent in sent_of_test:
        sent_vec = np.zeros(50)
        cnt_words =0;
        for word in sent: #
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        test_vectors.append(sent_vec)

    # Data-preprocessing: Standardizing the data
    sc = StandardScaler()
    X_train_vec_standardized = sc.fit_transform(train_vectors)
    X_test_vec_standardized = sc.transform(test_vectors)
```

31 (3.a) L2 Regularisation (Logistic Regression)

32 GridSearchCV Implementation

In [69]:
```
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l2'), tuned_parameters, scoring = 'a
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)
```

```
# Variables that will be used for  making table in Conclusion part of this assignment
avg_w2v_l2_grid_C = optimal_C
avg_w2v_l2_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
avg_w2v_l2_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=100, 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)
Accuracy of the model :  0.8996805228806034
The optimal value of C(1/lambda) is :  100
```

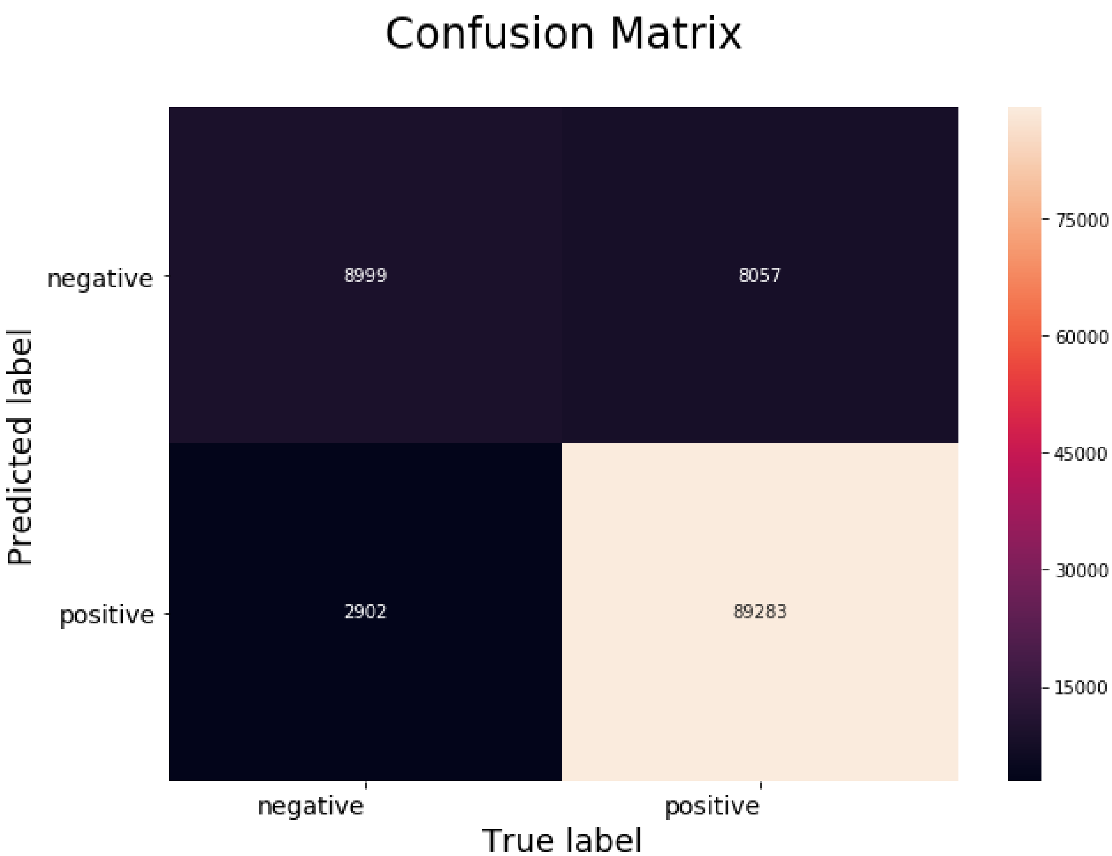
In [70]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 89.968052%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.917228

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.968520

The Test F1-Score of the Logistic regression classifier for C = 100.000 is 0.942176
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [71]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")
```

```
# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

33 RandomizedSearchCV Implementation

In [72]:
```
# Create regularization hyperparameter distribution using uniform distribution
C = uniform(loc=0, scale=10)

# Create hyperparameter options
hyperparameters = dict(C=C)
```

```
#Using RandomizedSearchCV
model = RandomizedSearchCV(LogisticRegression(penalty='l2'), hyperparameters, scoring=
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
avg_w2v_l2_random_C = optimal_C
avg_w2v_l2_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
avg_w2v_l2_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=3.4697855417732635, 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)
Accuracy of the model :  0.8996805228806034
The optimal value of C(1/lambda) is :  3.4697855417732635
```

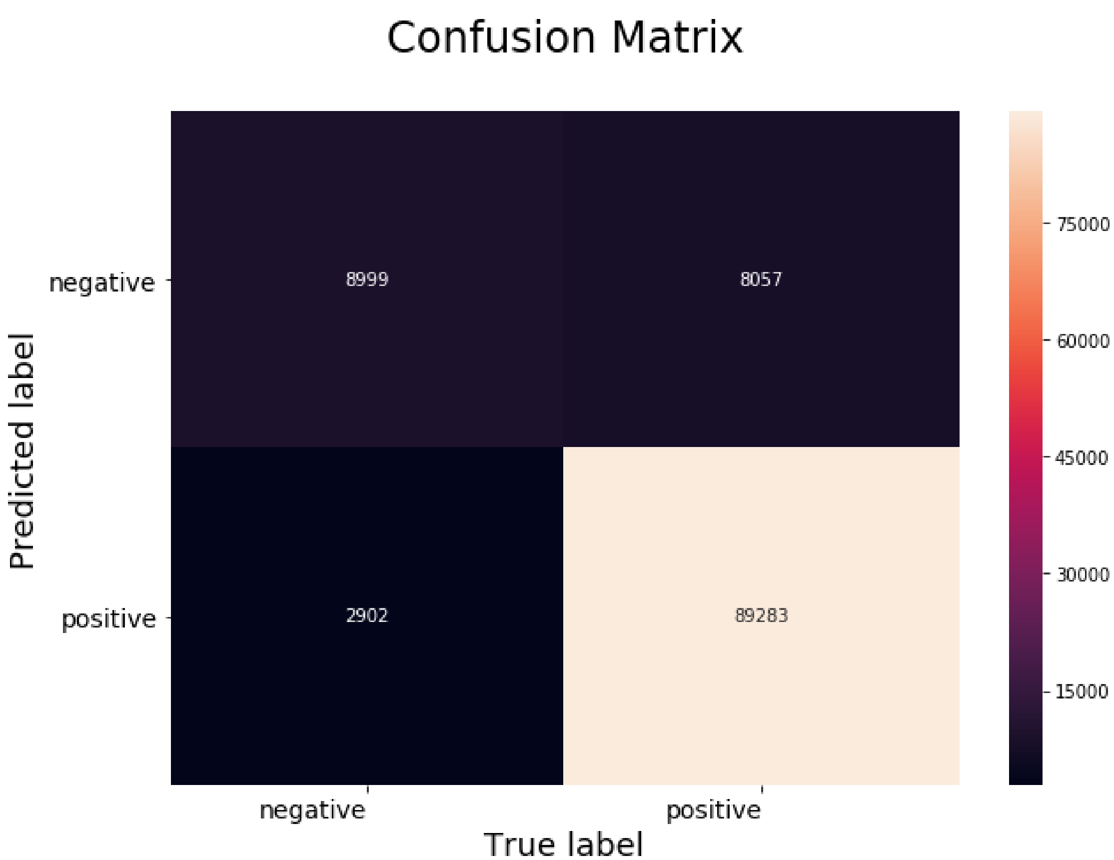
In [73]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 3.470 is 89.968052%

The Test Precision of the Logistic Regression classifier for C = 3.470 is 0.917228
```

```
The Test Recall of the Logistic Regression classifier for C = 3.470 is 0.968520

The Test F1-Score of the Logistic regression classifier for C = 3.470 is 0.942176
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [74]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

34 (3.b) L1 Regularisation (Logistic Regression)

35 GridSearchCV Implementation

In [75]:
```
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l1'), tuned_parameters, scoring = 'ac
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
avg_w2v_l1_grid_C = optimal_C
avg_w2v_l1_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
avg_w2v_l1_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=10000, 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)
Accuracy of the model :  0.8996713688084145
The optimal value of C(1/lambda) is :  10000
```

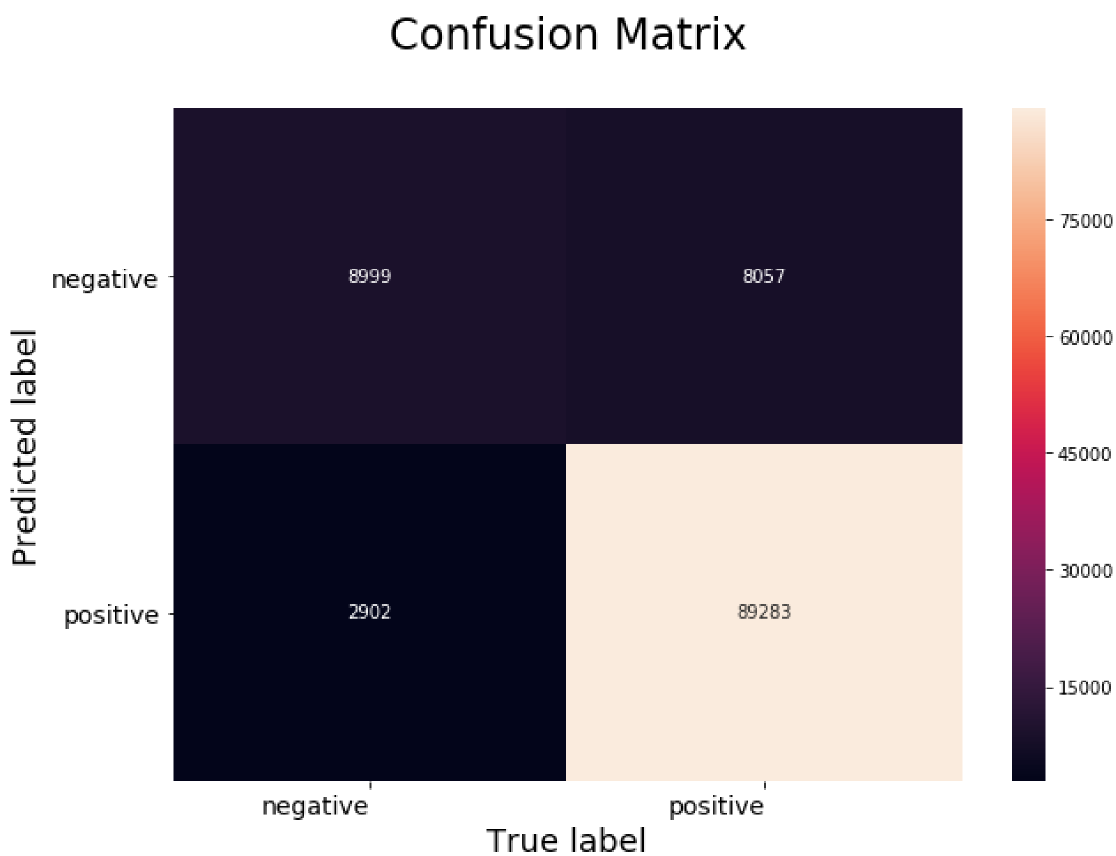
In [76]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
```

```
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 10000.000 is 89.968052%

The Test Precision of the Logistic Regression classifier for C = 10000.000 is 0.917228

The Test Recall of the Logistic Regression classifier for C = 10000.000 is 0.968520

The Test F1-Score of the Logistic regression classifier for C = 10000.000 is 0.942176
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [77]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

36 More Sparsity (Fewer elements of W* being non-zero) by increasing Lambda (decreasing C)

```
In [78]: # With lambda = 1
         clf = LogisticRegression(C=1, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
50
```

```
In [79]: # With lambda = 10
         clf = LogisticRegression(C=0.1, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
50
```

```
In [80]: # With lambda = 100
         clf = LogisticRegression(C=0.01, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
47
```

```
In [81]: # With lambda = 1000
         clf = LogisticRegression(C=0.001, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
40
```

```
In [82]: # With lambda = 10000
         clf = LogisticRegression(C=0.0001, penalty='l1',n_jobs=-1);
         clf.fit(X_train_vec_standardized, Y_train);
         w = clf.coef_
         print(np.count_nonzero(w))
```

```
11
```

OBSERVATION :- From above we can see that the number of non-zero elements of W* is decreasing as we are increasing the value of lambda (C is decreasing) .

37 RandomizedSearchCV Implementation

```
In [83]: # Create regularization hyperparameter distribution using uniform distribution
         C = uniform(loc=0, scale=10)

         # Create hyperparameter options
         hyperparameters = dict(C=C)

         #Using RandomizedSearchCV
         model = RandomizedSearchCV(LogisticRegression(penalty='l1'), hyperparameters, scoring
         model.fit(X_train_vec_standardized, Y_train)
         print("Model with best parameters :\n",model.best_estimator_)
         print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

         optimal_C = model.best_estimator_.C
```

```
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
avg_w2v_l1_random_C = optimal_C
avg_w2v_l1_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
avg_w2v_l1_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=8.218180574199001, 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)
Accuracy of the model :  0.8996622147362254
The optimal value of C(1/lambda) is :  8.218180574199001
```

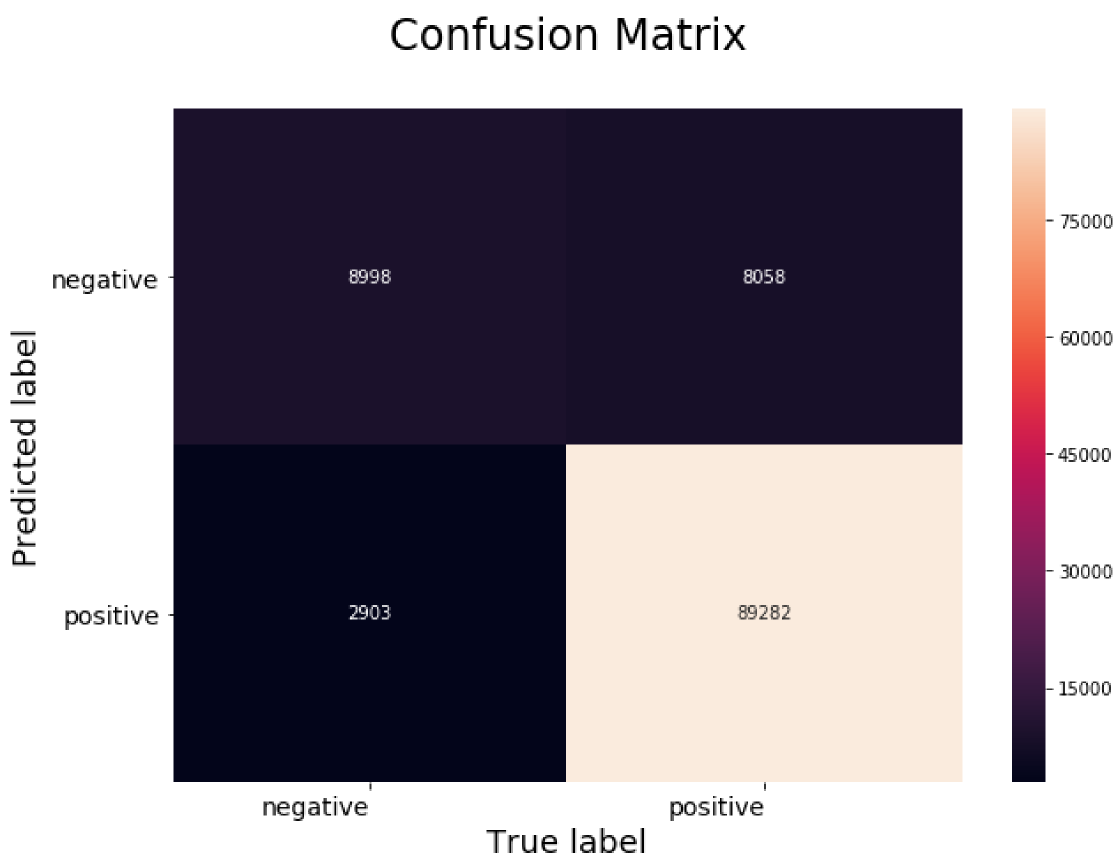
In [84]:

```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 8.218 is 89.966221%

The Test Precision of the Logistic Regression classifier for C = 8.218 is 0.917218

The Test Recall of the Logistic Regression classifier for C = 8.218 is 0.968509

The Test F1-Score of the Logistic regression classifier for C = 8.218 is 0.942166
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [85]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

38 (4). TFIDF-Word2Vec

NOTE :- It is taking a lot off time to perform TFIDF-Word2Vec on whole 364K rows of data . So , I am performing it with only 100K rows . Please don't mind because I am unable to perform it with whole data due to poor condition of my laptop . But I am completing all the steps as was asked .

RANDOMLY SAMPLING 100K POINTS OUT OF WHOLE DATASET

In [91]:
```
# We will collect different 100K rows without repetition from time_sorted_data datafr
my_final = time_sorted_data.take(np.random.permutation(len(final))[:100000])
print(my_final.shape)

x = my_final['CleanedText'].values
y = my_final['Score']

# split the data set into train and test
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3, random_state=

# List of sentence in X_train text
sent_of_train=[]
for sent in X_train:
    sent_of_train.append(sent.split())

# List of sentence in X_est text
sent_of_test=[]
for sent in X_test:
    sent_of_test.append(sent.split())

w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
```

```
(100000, 11)
```

In [92]:
```
# TF-IDF weighted Word2Vec
tf_idf_vect = TfidfVectorizer()

# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfid
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)

# tfidf words/col-names
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for each review for X_test .
tfidf_test_vectors = [];
row=0;
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
```

```
            if word in w2v_words:
                vec = w2v_model.wv[word]
                # obtain the tf_idfidf of a word in a sentence/review
                tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_test_vectors.append(sent_vec)
        row += 1
```

In [93]:
```
# compute TFIDF Weighted Word2Vec for each review for X_train .
tfidf_train_vectors = [];
row=0;
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_train_vectors.append(sent_vec)
    row += 1

# Data-preprocessing: Standardizing the data
sc = StandardScaler()
X_train_vec_standardized = sc.fit_transform(tfidf_train_vectors)
X_test_vec_standardized = sc.transform(tfidf_test_vectors)
```

39 (4.a) L2 Regularisation (Logistic Regression)

40 GridSearchCV Implementation

In [94]:
```
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
#Using GridSearchCV
model = GridSearchCV(LogisticRegression(penalty='l2'), tuned_parameters, scoring = 'a
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)
```

```
# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_w2v_l2_grid_C = optimal_C
tfidf_w2v_l2_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_w2v_l2_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=100, 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)
Accuracy of the model :  0.7401
The optimal value of C(1/lambda) is :  100
```

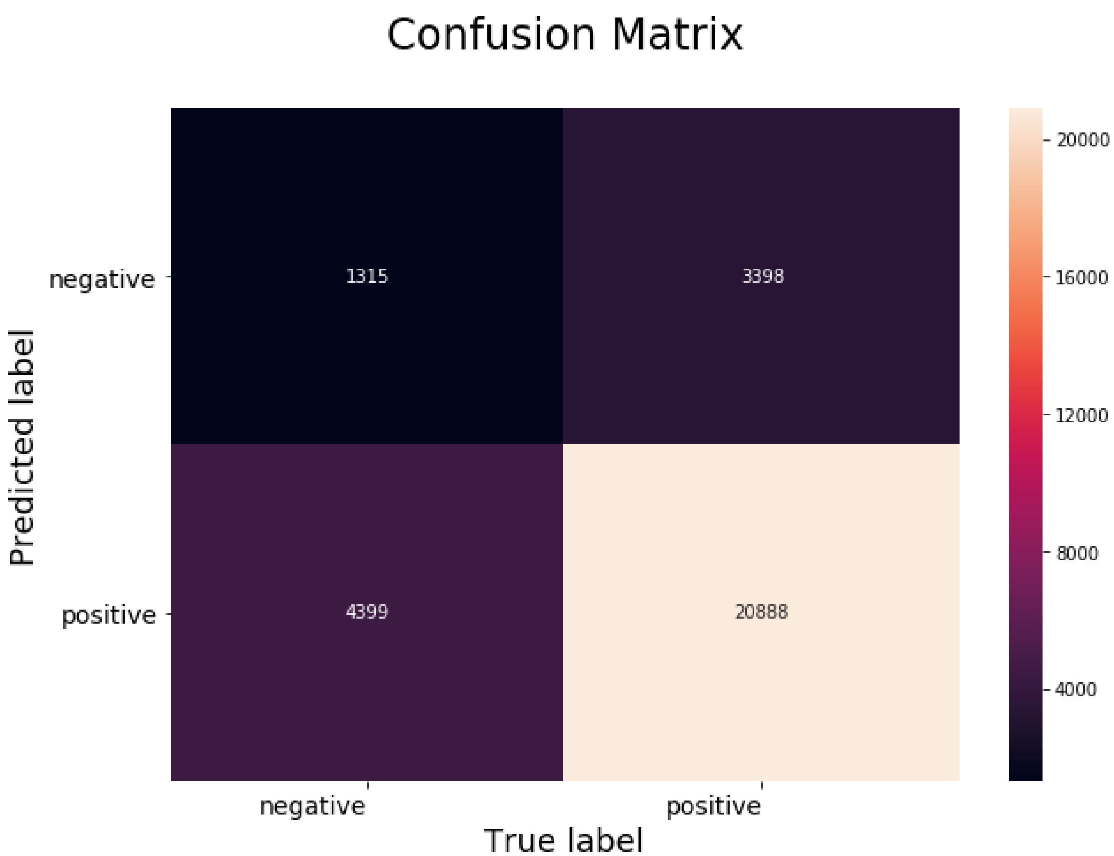
In [95]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 74.010000%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.860084

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.826037

The Test F1-Score of the Logistic regression classifier for C = 100.000 is 0.842717
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [96]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
```

```
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

41 RandomizedSearchCV Implementation

In [97]:
```
# Create regularization hyperparameter distribution using uniform distribution
C = uniform(loc=0, scale=10)
```

```
# Create hyperparameter options
hyperparameters = dict(C=C)

#Using RandomizedSearchCV
model = RandomizedSearchCV(LogisticRegression(penalty='l2'), hyperparameters, scoring=
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

optimal_C = model.best_estimator_.C
print("The optimal value of C(1/lambda) is : ",optimal_C)

# Logistic Regression with Optimal value of C i.e.(1/lambda)
lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
lr.fit(X_train_vec_standardized,Y_train)
predictions = lr.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_w2v_l2_random_C = optimal_C
tfidf_w2v_l2_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_w2v_l2_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=4.63926046784341, 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)
Accuracy of the model :  0.7401333333333333
The optimal value of C(1/lambda) is :  4.63926046784341
```

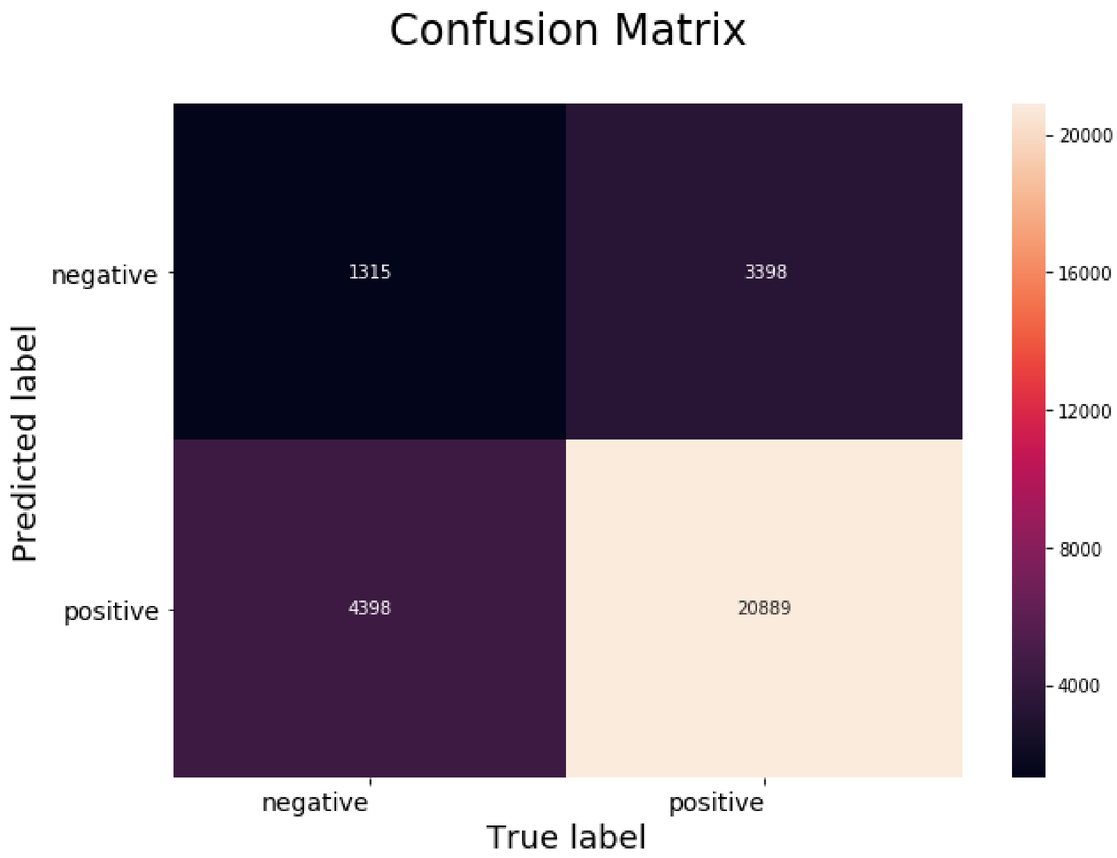
In [98]:

```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f'

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f' %
```

```
The Test Accuracy of the Logistic Regression classifier for C = 4.639 is 74.013333%

The Test Precision of the Logistic Regression classifier for C = 4.639 is 0.860090

The Test Recall of the Logistic Regression classifier for C = 4.639 is 0.826077

The Test F1-Score of the Logistic regression classifier for C = 4.639 is 0.842740
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [99]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

42 (4.b) L1 Regularisation (Logistic Regression)

43 GridSearchCV Implementation

```
In [100]: tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
          #Using GridSearchCV
          model = GridSearchCV(LogisticRegression(penalty='l1'), tuned_parameters, scoring = 'a
          model.fit(X_train_vec_standardized, Y_train)
          print("Model with best parameters :\n",model.best_estimator_)
          print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

          optimal_C = model.best_estimator_.C
          print("The optimal value of C(1/lambda) is : ",optimal_C)

          # Logistic Regression with Optimal value of C i.e.(1/lambda)
          lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
          lr.fit(X_train_vec_standardized,Y_train)
          predictions = lr.predict(X_test_vec_standardized)

          # Variables that will be used for  making table in Conclusion part of this assignmen
          tfidf_w2v_l1_grid_C = optimal_C
          tfidf_w2v_l1_grid_train_acc = model.score(X_test_vec_standardized, Y_test)*100
          tfidf_w2v_l1_grid_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=100, 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)
Accuracy of the model :  0.7401333333333333
The optimal value of C(1/lambda) is :  100
```

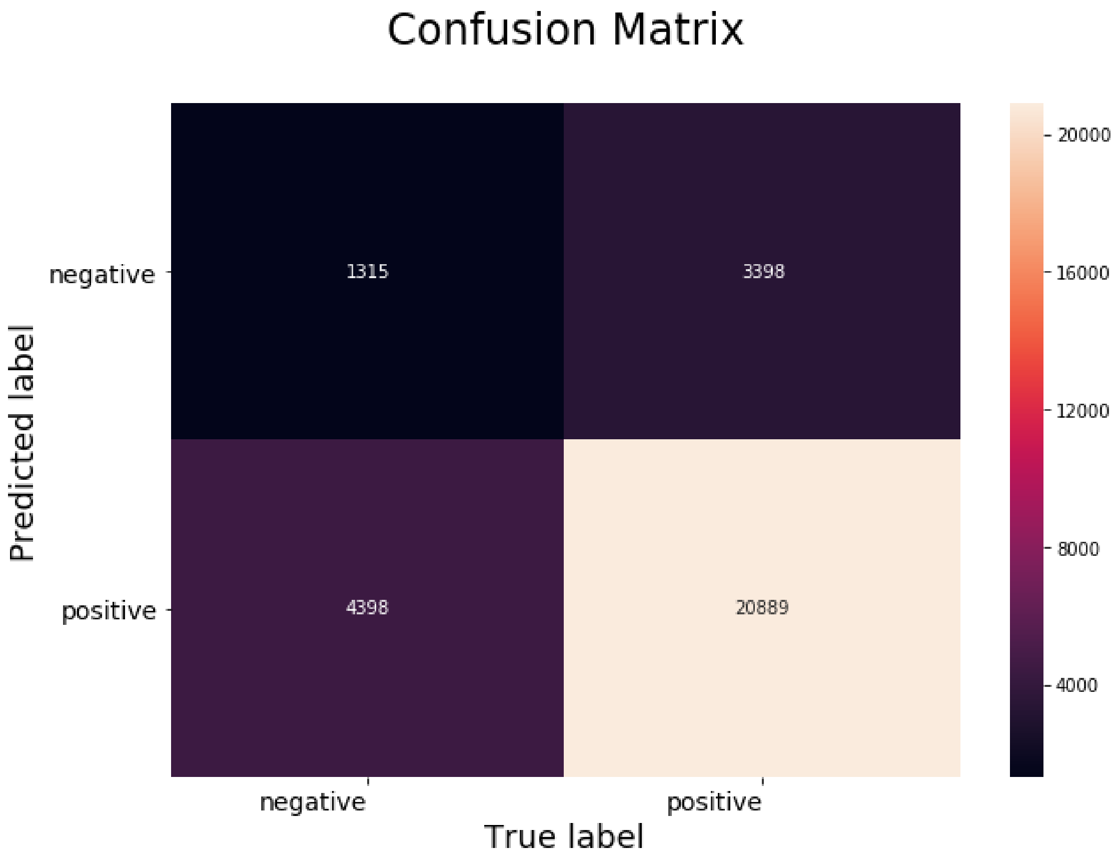
```
In [101]: # evaluate accuracy
          acc = accuracy_score(Y_test, predictions) * 100
          print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%

          # evaluate precision
          acc = precision_score(Y_test, predictions, pos_label = 'positive')
          print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f
```

```
    # evaluate recall
    acc = recall_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

    # evaluate f1-score
    acc = f1_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f'
```

```
The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 74.013333%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.860090

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.826077

The Test F1-Score of the Logistic regression classifier for C = 100.000 is 0.842740
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [102]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, c
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right',
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right',
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

44 More Sparsity (Fewer elements of W* being non-zero) by increasing Lambda (decreasing C)

```
In [103]: # With lambda = 1
          clf = LogisticRegression(C=1, penalty='l1',n_jobs=-1);
          clf.fit(X_train_vec_standardized, Y_train);
          w = clf.coef_
          print(np.count_nonzero(w))
```

```
50
```

```
In [104]: # With lambda = 10
          clf = LogisticRegression(C=0.1, penalty='l1',n_jobs=-1);
          clf.fit(X_train_vec_standardized, Y_train);
          w = clf.coef_
          print(np.count_nonzero(w))
```

50

```
In [105]: # With lambda = 100
          clf = LogisticRegression(C=0.01, penalty='l1',n_jobs=-1);
          clf.fit(X_train_vec_standardized, Y_train);
          w = clf.coef_
          print(np.count_nonzero(w))
```

45

```
In [106]: # With lambda = 1000
          clf = LogisticRegression(C=0.001, penalty='l1',n_jobs=-1);
          clf.fit(X_train_vec_standardized, Y_train);
          w = clf.coef_
          print(np.count_nonzero(w))
```

22

OBSERVATION :- From above we can see that the number of non-zero elements of W* is decreasing as we are increasing the value of lambda (C is decreasing) .

45 RandomizedSearchCV Implementation

```
In [108]: # Create regularization hyperparameter distribution using uniform distribution
          C = uniform(loc=0, scale=10)

          # Create hyperparameter options
          hyperparameters = dict(C=C)

          #Using RandomizedSearchCV
          model = RandomizedSearchCV(LogisticRegression(penalty='l1'), hyperparameters, scoring
          model.fit(X_train_vec_standardized, Y_train)
          print("Model with best parameters :\n",model.best_estimator_)
          print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y_test))

          optimal_C = model.best_estimator_.C
          print("The optimal value of C(1/lambda) is : ",optimal_C)

          # Logistic Regression with Optimal value of C i.e.(1/lambda)
          lr = LogisticRegression(penalty='l1', C=optimal_C, n_jobs=-1)
          lr.fit(X_train_vec_standardized,Y_train)
          predictions = lr.predict(X_test_vec_standardized)

          # Variables that will be used for  making table in Conclusion part of this assignmen
          tfidf_w2v_l1_random_C = optimal_C
```

```
tfidf_w2v_l1_random_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_w2v_l1_random_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 LogisticRegression(C=8.837472691586914, 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)
Accuracy of the model :  0.7401333333333333
The optimal value of C(1/lambda) is :  8.837472691586914
```

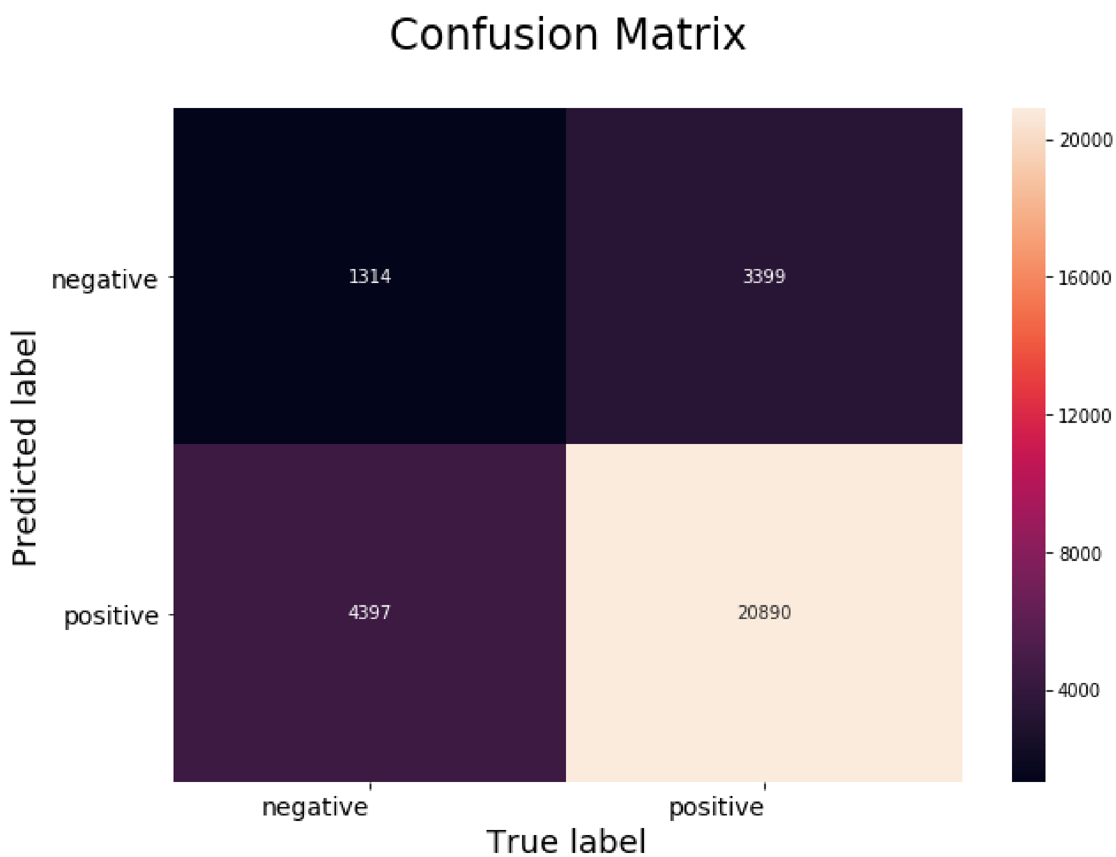
```
In [109]: # evaluate accuracy
          acc = accuracy_score(Y_test, predictions) * 100
          print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%

          # evaluate precision
          acc = precision_score(Y_test, predictions, pos_label = 'positive')
          print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f

          # evaluate recall
          acc = recall_score(Y_test, predictions, pos_label = 'positive')
          print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' %

          # evaluate f1-score
          acc = f1_score(Y_test, predictions, pos_label = 'positive')
          print('\nThe Test F1-Score of the Logistic regression classifier for C = %.3f is %f'
```

```
The Test Accuracy of the Logistic Regression classifier for C = 8.837 is 74.013333%

The Test Precision of the Logistic Regression classifier for C = 8.837 is 0.860060

The Test Recall of the Logistic Regression classifier for C = 8.837 is 0.826116

The Test F1-Score of the Logistic regression classifier for C = 8.837 is 0.842746
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [110]: # Code for drawing seaborn heatmaps
          class_names = ['negative','positive']
          df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, 
          fig = plt.figure(figsize=(10,7))
          heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

          # Setting tick labels for heatmap
          heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
          heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
```

```
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



NOTE :- Here we can find out important features but they are not related to any words so they are not interpretable . I am not performing Multicollinearity Check and also not finding important features because they are not interpretable and hence it is irrelevant to find important features .

46 CONCLUSION :-

47 (a). Procedure followed :

STEP 1 :- Text Preprocessing

STEP 2:- Time-based splitting of whole dataset into train_data and test_data

STEP 3:- Training the vectorizer on train_data and later applying same vectorizer on both train_data and test_data to transform them into vectors

STEP 4:- Using Logistic regression as an estimator in both GridSearchCV and RandomizedSearchCV in order to find optimal value of C i.e(1/lambda) with both L1 and L2 regularisation

STEP 5:- Once , we get optimal value of C then train Logistic Regression (both L1 and L2 regularisation) again with this optimal C and make predictions on test_data

STEP 6 :- Evaluate : Accuracy , F1-Score , Precision , Recall
STEP 7:- Draw Seaborn Heatmap for Confusion Matrix .
STEP 8:- Perform multicollinearity check and find important features (Only for BoW and TFIDF vectorizers)
STEP 9:- Creating more sparsity by increasing value of lambda i.e.(1/C) (Only for L1 regularisation)
Repeat from STEP 3 to STEP 9 for each of these two vectorizers : Bag Of Words(BoW), TFIDF
Repeat from STEP 3 to STEP 9 (except STEP 8) for each of these two vectorizers : Avg Word2Vec and TFIDF Word2Vec

48 (b). Table (Model Performances with their hyperparameters :

In [114]:
```
# Creating table using PrettyTable library
from prettytable import PrettyTable

# Names of models
names = ['LR(l2|GridSearchCV) for BoW','LR(l2|RandomizedSearchCV) for BoW','LR(l1|Gr
         'LR(l1|RandomizedSearchCV) for BoW','LR(l2|GridSearchCV) for TFIDF','LR(l2|R
         'LR(l1|GridSearchCV) for TFIDF','LR(l1|RandomizedSearchCV) for TFIDF','LR(l2
         'LR(l2|RandomizedSearchCV) for Avg_Word2Vec','LR(l1|GridSearchCV) for Avg_Wo
         'LR(l1|RandomizedSearchCV) for Avg_Word2Vec','LR(l2|GridSearchCV) for tfidf_
         'LR(l2|RandomizedSearchCV) for tfidf_Word2Vec','LR(l1|GridSearchCV) for tfid
         'LR(l1|RandomizedSearchCV) for tfidf_Word2Vec']

# Optimal values of C i.e. (1/lambda)
optimal_C = [bow_l2_grid_C,bow_l2_random_C,bow_l1_grid_C,bow_l1_random_C,\
             tfidf_l2_grid_C,tfidf_l2_random_C,tfidf_l1_grid_C,tfidf_l1_random_C,\
             avg_w2v_l2_grid_C,avg_w2v_l2_random_C,avg_w2v_l1_grid_C,avg_w2v_l1_rando
             tfidf_w2v_l2_grid_C,tfidf_w2v_l2_random_C,tfidf_w2v_l1_grid_C,tfidf_w2v_

# Training accuracies
train_acc = [bow_l2_grid_train_acc,bow_l2_random_train_acc,bow_l1_grid_train_acc,bow_
             tfidf_l2_grid_train_acc,tfidf_l2_random_train_acc,tfidf_l1_grid_train_ac
             avg_w2v_l2_grid_train_acc,avg_w2v_l2_random_train_acc,avg_w2v_l1_grid_tr
             tfidf_w2v_l2_grid_train_acc,tfidf_w2v_l2_random_train_acc,tfidf_w2v_l1_g
             tfidf_w2v_l1_random_train_acc]

# Test accuracies
test_acc = [bow_l2_grid_test_acc,bow_l2_random_test_acc,bow_l1_grid_test_acc,bow_l1_r
             tfidf_l2_grid_test_acc,tfidf_l2_random_test_acc,tfidf_l1_grid_test_acc,t
             avg_w2v_l2_grid_test_acc,avg_w2v_l2_random_test_acc,avg_w2v_l1_grid_test
             tfidf_w2v_l2_grid_test_acc,tfidf_w2v_l2_random_test_acc,tfidf_w2v_l1_gri

numbering = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16]

# Initializing prettytable
ptable = PrettyTable()
```

```python
# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
ptable.add_column("Best C(1/lambda)",optimal_C)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)


# Printing note regarding information of "MODEL" column in the table
print("NOTE:- In the Table below in 'MODEL' column :")
print("\t LR(l2|GridSearchCV) : Logistic Regression with L2 regularisation as an esti
print("\t LR(l1|GridSearchCV) : Logistic Regression with L1 regularisation as an esti
print("\t LR(l2|RandomizedSearchCV) : Logistic Regression with L2 regularisation as a
print("\t LR(l1|RandomizedSearchCV) : Logistic Regression with L1 regularisation as a
# Printing the Table
print(ptable)
```

```
NOTE:- In the Table below in 'MODEL' column :
         LR(l2|GridSearchCV) : Logistic Regression with L2 regularisation as an estimator in Gr
         LR(l1|GridSearchCV) : Logistic Regression with L1 regularisation as an estimator in Gr
         LR(l2|RandomizedSearchCV) : Logistic Regression with L2 regularisation as an estimato
         LR(l1|RandomizedSearchCV) : Logistic Regression with L1 regularisation as an estimato


+-------+----------------------------------------------+---------------------+-----------------
| S.NO. |                    MODEL                     |   Best C(1/lambda)  | Training Accura
+-------+----------------------------------------------+---------------------+-----------------
|   1   |         LR(l2|GridSearchCV) for BoW          |         0.01        | 92.203476716617
|   2   |      LR(l2|RandomizedSearchCV) for BoW       |  1.4275875917132186 | 92.197984273303
|   3   |         LR(l1|GridSearchCV) for BoW          |         0.01        | 92.245585448686
|   4   |      LR(l1|RandomizedSearchCV) for BoW       | 0.20062843367622873 | 92.223615675433
|   5   |        LR(l2|GridSearchCV) for TFIDF         |         0.01        | 92.457044516253
|   6   |     LR(l2|RandomizedSearchCV) for TFIDF      |  4.827593247007973  | 92.437820964656
|   7   |        LR(l1|GridSearchCV) for TFIDF         |         0.01        | 92.588863155774
|   8   |     LR(l1|RandomizedSearchCV) for TFIDF      |  0.8718584489029746 | 92.446975036845
|   9   |     LR(l2|GridSearchCV) for Avg_Word2Vec     |         100         | 89.968052288060
|   10  |  LR(l2|RandomizedSearchCV) for Avg_Word2Vec  |  3.4697855417732635 | 89.968052288060
|   11  |     LR(l1|GridSearchCV) for Avg_Word2Vec     |        10000        | 89.967136880841
|   12  |  LR(l1|RandomizedSearchCV) for Avg_Word2Vec  |  8.218180574199001  | 89.966221473622
|   13  |    LR(l2|GridSearchCV) for tfidf_Word2Vec    |         100         | 74.009999999999
|   14  | LR(l2|RandomizedSearchCV) for tfidf_Word2Vec |   4.63926046784341  | 74.013333333333
|   15  |    LR(l1|GridSearchCV) for tfidf_Word2Vec    |         100         | 74.013333333333
|   16  | LR(l1|RandomizedSearchCV) for tfidf_Word2Vec |  8.837472691586914  | 74.013333333333
+-------+----------------------------------------------+---------------------+-----------------
```