Assignment - 8 (Apply Decision Tree on Amazon Food Reviews)

September 7, 2018

1 OBJECTIVE :- Apply Decision Tree on Amazon Fine Food Reviews Dataset

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  A2SWO60IW01VPX
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]:
```python
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 Word2Vec

```
In [11]: # 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
```

6 (1). Avg Word2Vec

```
In [12]: # 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)

import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train_vec_standardized = sc.fit_transform(train_vectors)
X_test_vec_standardized = sc.transform(test_vectors)
```

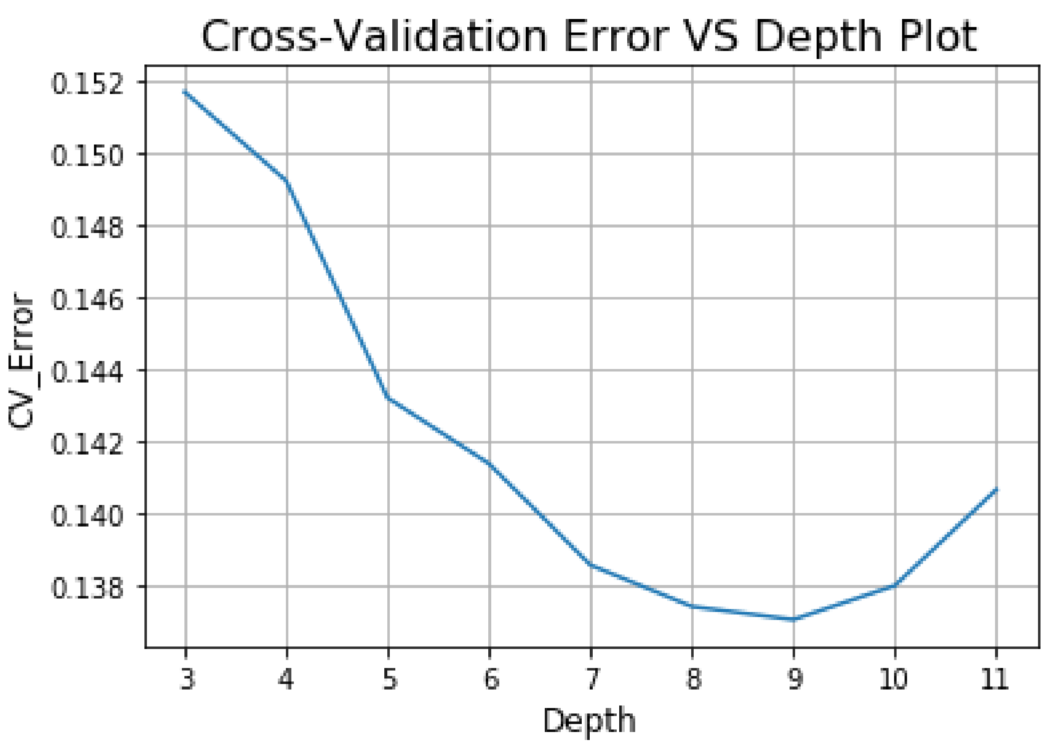
7 GridSearchCV Implementation (Decision Tree)

```
In [13]: # Importing libraries
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.model_selection import GridSearchCV
         from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,:

         Depths = [3,4,5,6,7,8,9,10,11]

         param_grid = {'max_depth': Depths}
         model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'accuracy', cv=3
         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))

         # Cross-Validation errors
         cv_errors = [1-i for i in model.cv_results_['mean_test_score']]

         # Optimal value of depth
         optimal_depth = model.best_estimator_.max_depth
         print("The optimal value of depth is : ",optimal_depth)

         # DecisionTreeClassifier with Optimal value of depth
         dt = DecisionTreeClassifier(max_depth=optimal_depth)
         dt.fit(X_train_vec_standardized,Y_train)
         predictions = dt.predict(X_test_vec_standardized)
```

```
# Variables that will be used for  making table in Conclusion part of this assignment
avg_w2v_depth = optimal_depth
avg_w2v_train_acc = model.score(X_test_vec_standardized, Y_test)*100
avg_w2v_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=9,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
Accuracy of the model :  0.8662773134628939
The optimal value of depth is :  9
```

In [14]:
```
# plotting Cross-Validation Error vs Depth graph
plt.plot(Depths, cv_errors)
plt.xlabel('Depth',size=12)
plt.ylabel('CV_Error',size=12)
plt.title('Cross-Validation Error VS Depth Plot',size=16)
plt.grid()
plt.show()
```



```
In [15]: # evaluate accuracy
         acc = accuracy_score(Y_test, predictions) * 100
         print('\nThe Test Accuracy of the DecisionTreeClassifier for depth = %d is %f%%' % (op

         # evaluate precision
         acc = precision_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Precision of the DecisionTreeClassifier for depth = %d is %f' % (opt

         # evaluate recall
         acc = recall_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test Recall of the DecisionTreeClassifier for depth = %d is %f' % (optima

         # evaluate f1-score
         acc = f1_score(Y_test, predictions, pos_label = 'positive')
         print('\nThe Test F1-Score of the DecisionTreeClassifier for depth = %d is %f' % (opti
```

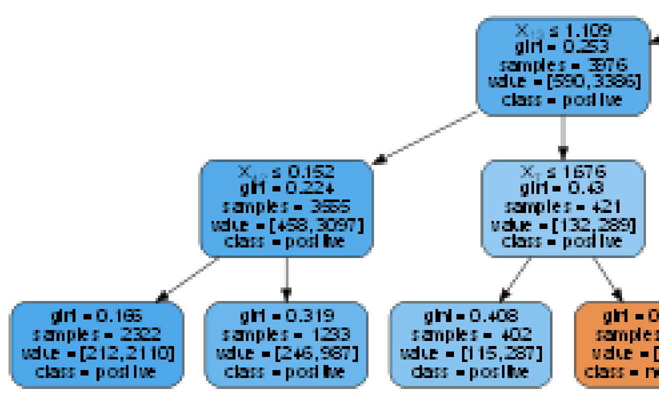
```
The Test Accuracy of the DecisionTreeClassifier for depth = 9 is 86.622239%

The Test Precision of the DecisionTreeClassifier for depth = 9 is 0.886291

The Test Recall of the DecisionTreeClassifier for depth = 9 is 0.965320

The Test F1-Score of the DecisionTreeClassifier for depth = 9 is 0.924119
```

8 Visualize Decision Tree

```
In [16]: # Importing libraries
         from sklearn import tree
         import pydotplus
         from IPython.display import Image
         from IPython.display import SVG
         from graphviz import Source
         from IPython.display import display

         target = ['negative','positive']
         # Create DOT data
         data = tree.export_graphviz(dt,out_file=None,class_names=target,filled=True,rounded=Tr

         # Draw graph
         graph = pydotplus.graph_from_dot_data(data)
         #graph = Source(data)

         # Show graph
         Image(graph.create_png())
         #display(SVG(graph.pipe(format='svg')))
```

```
dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.35064 to fit
```

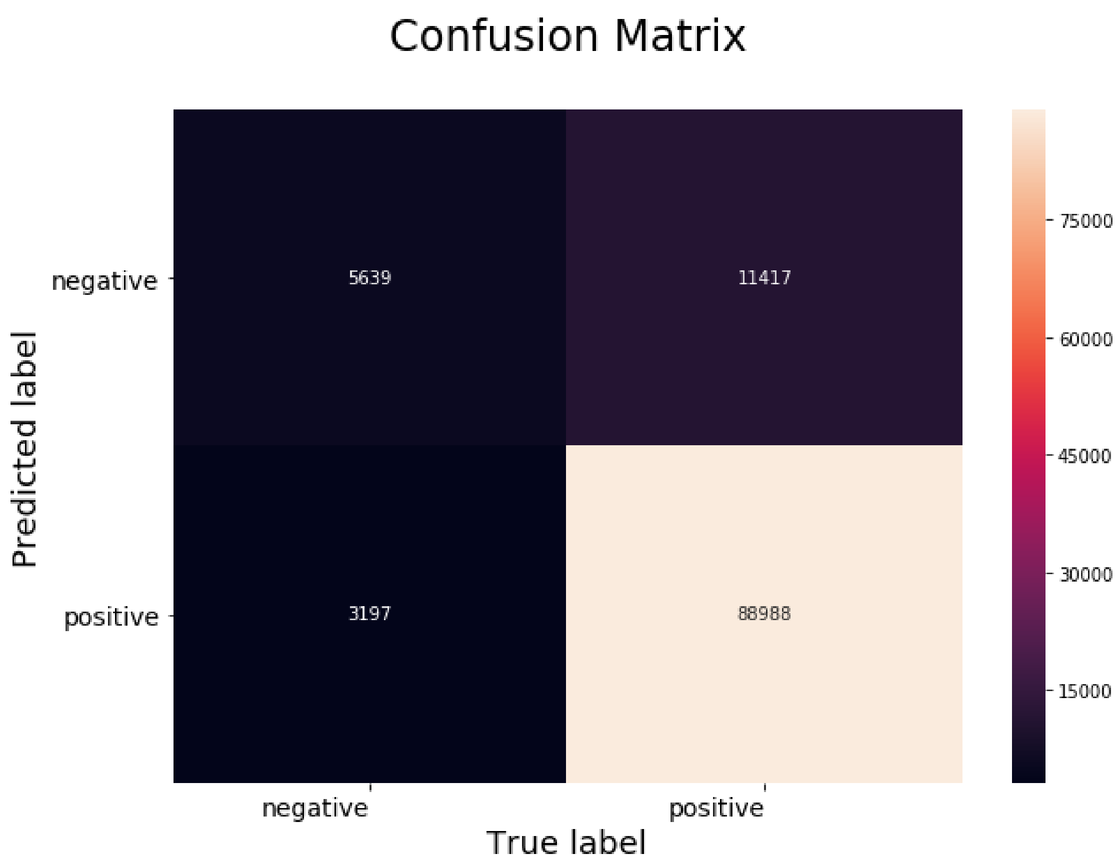
Out[16]:



NOTE :- Decision Tree is very large to visualize . Later in the end we will visualize it with small sample dataset

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, 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()
```



9 (2). 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 [18]:
```
# 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 [19]:
```
# 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 [20]: # 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)
```

10 GridSearchCV Implementation (Decision Tree)

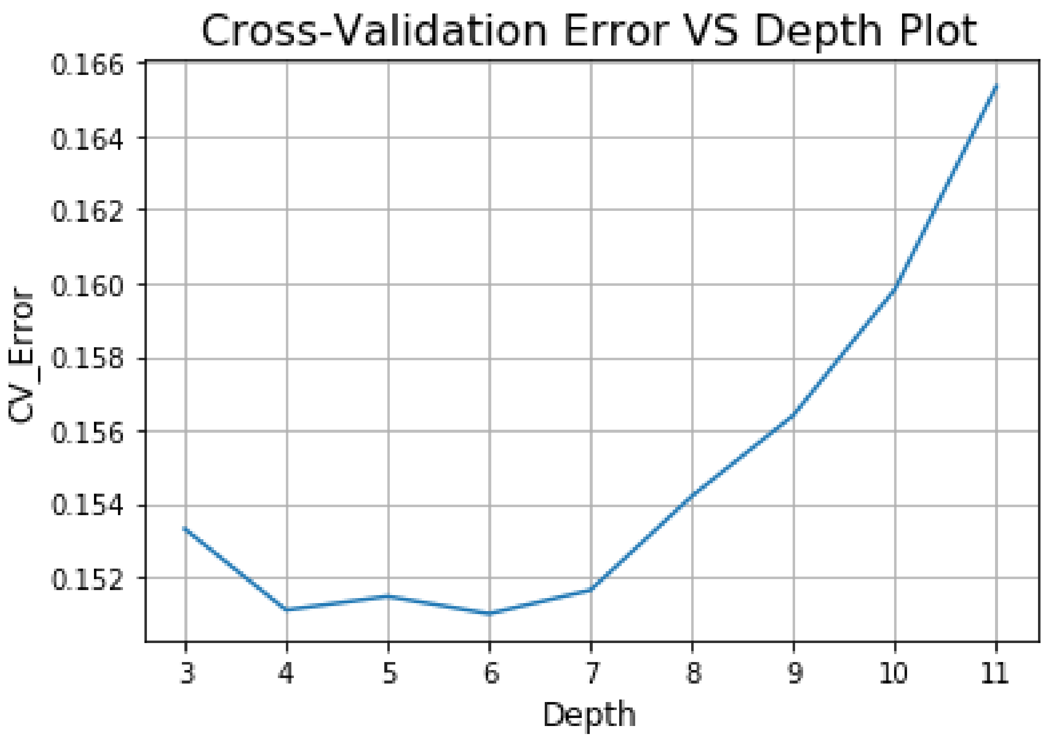
```
In [21]: Depths = [3,4,5,6,7,8,9,10,11]

         param_grid = {'max_depth': Depths}
         model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'accuracy', cv=3
         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))

         # Cross-Validation errors
         cv_errors = [1-i for i in model.cv_results_['mean_test_score']]
```

```
# Optimal value of depth
optimal_depth = model.best_estimator_.max_depth
print("The optimal value of depth is : ",optimal_depth)

# DecisionTreeClassifier with Optimal value of depth
dt = DecisionTreeClassifier(max_depth=optimal_depth)
dt.fit(X_train_vec_standardized,Y_train)
predictions = dt.predict(X_test_vec_standardized)

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_w2v_depth = optimal_depth
tfidf_w2v_train_acc = model.score(X_test_vec_standardized, Y_test)*100
tfidf_w2v_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=6,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
Accuracy of the model :  0.8101333333333334
The optimal value of depth is :  6
```

In [22]:

```
# plotting Cross-Validation Error vs Depth graph
plt.plot(Depths, cv_errors)
plt.xlabel('Depth',size=12)
plt.ylabel('CV_Error',size=12)
plt.title('Cross-Validation Error VS Depth Plot',size=16)
plt.grid()
plt.show()
```



In [23]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the DecisionTreeClassifier for depth = %d is %f%%' % (op

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the DecisionTreeClassifier for depth = %d is %f' % (op

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the DecisionTreeClassifier for depth = %d is %f' % (optim

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the DecisionTreeClassifier for depth = %d is %f' % (opt
```

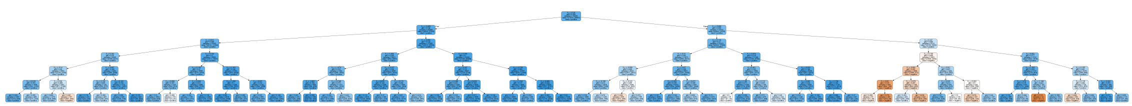
```
The Test Accuracy of the DecisionTreeClassifier for depth = 6 is 81.013333%

The Test Precision of the DecisionTreeClassifier for depth = 6 is 0.845783

The Test Recall of the DecisionTreeClassifier for depth = 6 is 0.946889
```

```
The Test F1-Score of the DecisionTreeClassifier for depth = 6 is 0.893485
```

11 Visualize Decision Tree

In [24]:
```
target = ['negative','positive']
# Create DOT data
data = tree.export_graphviz(dt,out_file=None,class_names=target,filled=True,rounded=T

# Draw graph
graph = pydotplus.graph_from_dot_data(data)

# Show graph
Image(graph.create_png())
```

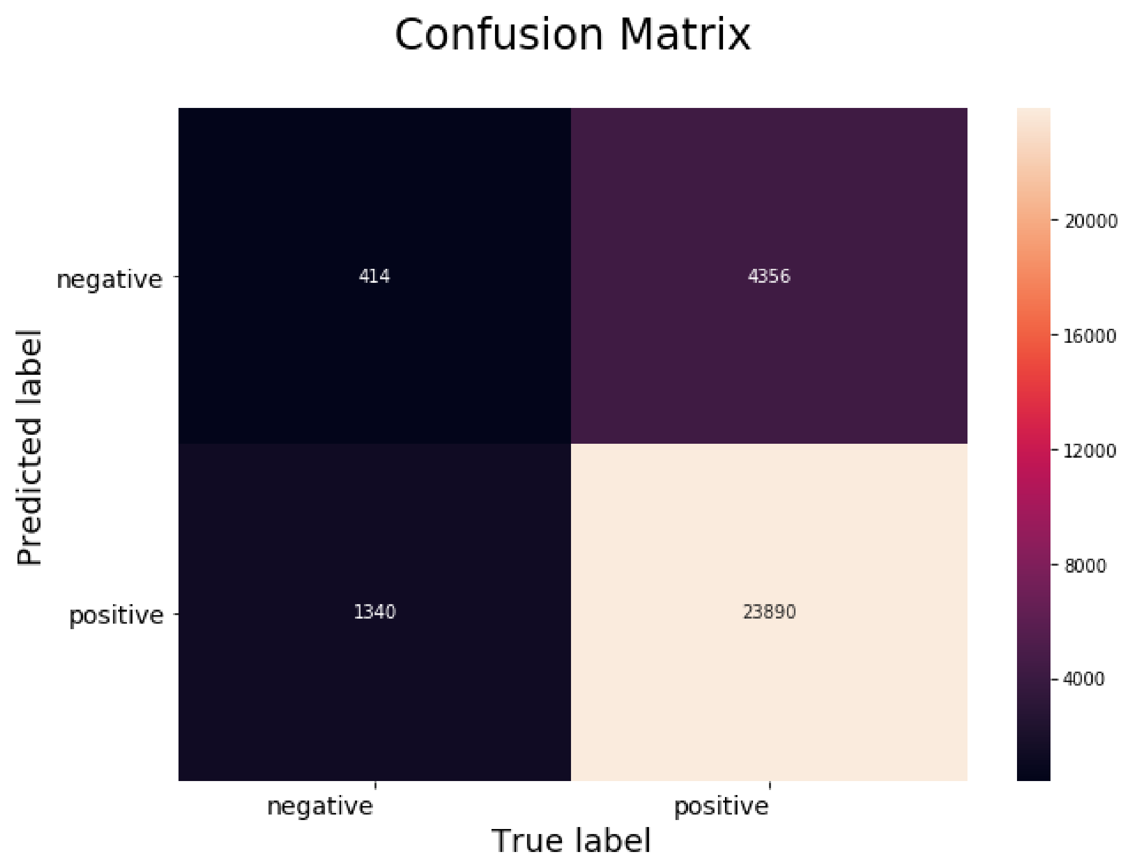
Out[24]:



NOTE :- Decision Tree is very large to visualize . Later in the end we will visualize it with small sample dataset

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

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



12 Implementing Decision Tree on Small Sample for BoW and TFIDF

RANDOMLY SAMPLING 40K POINTS OUT OF WHOLE DATASET

```
In [26]: # We will collect different 40K rows without repetition from time_sorted_data datafra
         my_final = time_sorted_data.take(np.random.permutation(len(final))[:40000])
         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=
```

```
(40000, 11)
```

13 (3). Bag of Words (BoG)

```
In [27]: #BoW
         count_vect = CountVectorizer(min_df = 1000)
         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 :  (28000, 174)
the number of unique words : 174
```

```
In [28]: sc = StandardScaler(with_mean=False)
         X_train_vec_standardized = sc.fit_transform(X_train_vec)
         X_test_vec_standardized = sc.transform(X_test_vec)
```

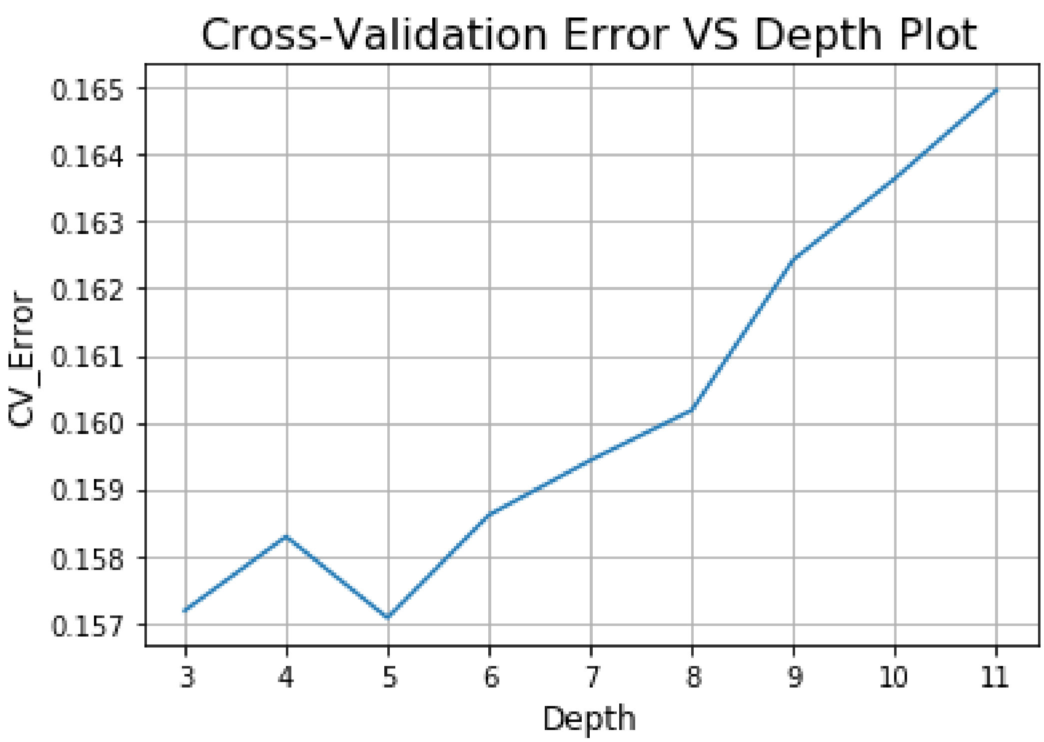
14 GridSearchCV Implementation (Decision Tree)

```
In [29]: Depths = [3,4,5,6,7,8,9,10,11]

         param_grid = {'max_depth': Depths}
         model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'accuracy', cv=3
         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))

         # Cross-Validation errors
         cv_errors = [1-i for i in model.cv_results_['mean_test_score']]

         # Optimal value of depth
         optimal_depth = model.best_estimator_.max_depth
         print("The optimal value of depth is : ",optimal_depth)

         # DecisionTreeClassifier with Optimal value of depth
         dt = DecisionTreeClassifier(max_depth=optimal_depth)
         dt.fit(X_train_vec_standardized,Y_train)
         predictions = dt.predict(X_test_vec_standardized)

         # Variables that will be used for  making table in Conclusion part of this assignment
         bow_depth = optimal_depth
         bow_train_acc = model.score(X_test_vec_standardized, Y_test)*100
         bow_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=5,
```

```
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
Accuracy of the model :  0.8413333333333334
The optimal value of depth is :  5
```

In [30]:
```
# plotting Cross-Validation Error vs Depth graph
plt.plot(Depths, cv_errors)
plt.xlabel('Depth',size=12)
plt.ylabel('CV_Error',size=12)
plt.title('Cross-Validation Error VS Depth Plot',size=16)
plt.grid()
plt.show()
```



In [31]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the DecisionTreeClassifier for depth = %d is %f%%' % (op

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
```

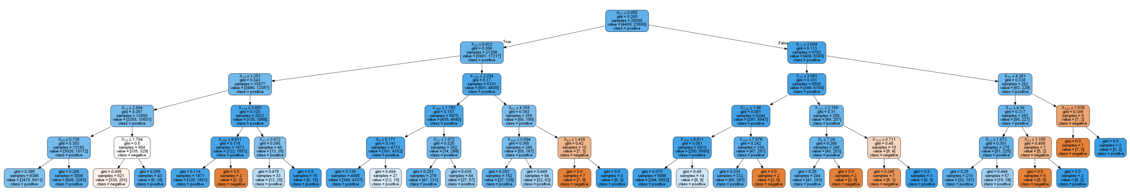
```
print('\nThe Test Precision of the DecisionTreeClassifier for depth = %d is %f' % (opt

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the DecisionTreeClassifier for depth = %d is %f' % (optima

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the DecisionTreeClassifier for depth = %d is %f' % (opti
```

```
The Test Accuracy of the DecisionTreeClassifier for depth = 5 is 84.166667%

The Test Precision of the DecisionTreeClassifier for depth = 5 is 0.849957

The Test Recall of the DecisionTreeClassifier for depth = 5 is 0.985836

The Test F1-Score of the DecisionTreeClassifier for depth = 5 is 0.912868
```

15 Visualize Decision Tree

In [32]:
```
target = ['negative','positive']
# Create DOT data
data = tree.export_graphviz(dt,out_file=None,class_names=target,filled=True,rounded=T

# Draw graph
graph = pydotplus.graph_from_dot_data(data)

# Show graph
Image(graph.create_png())
```

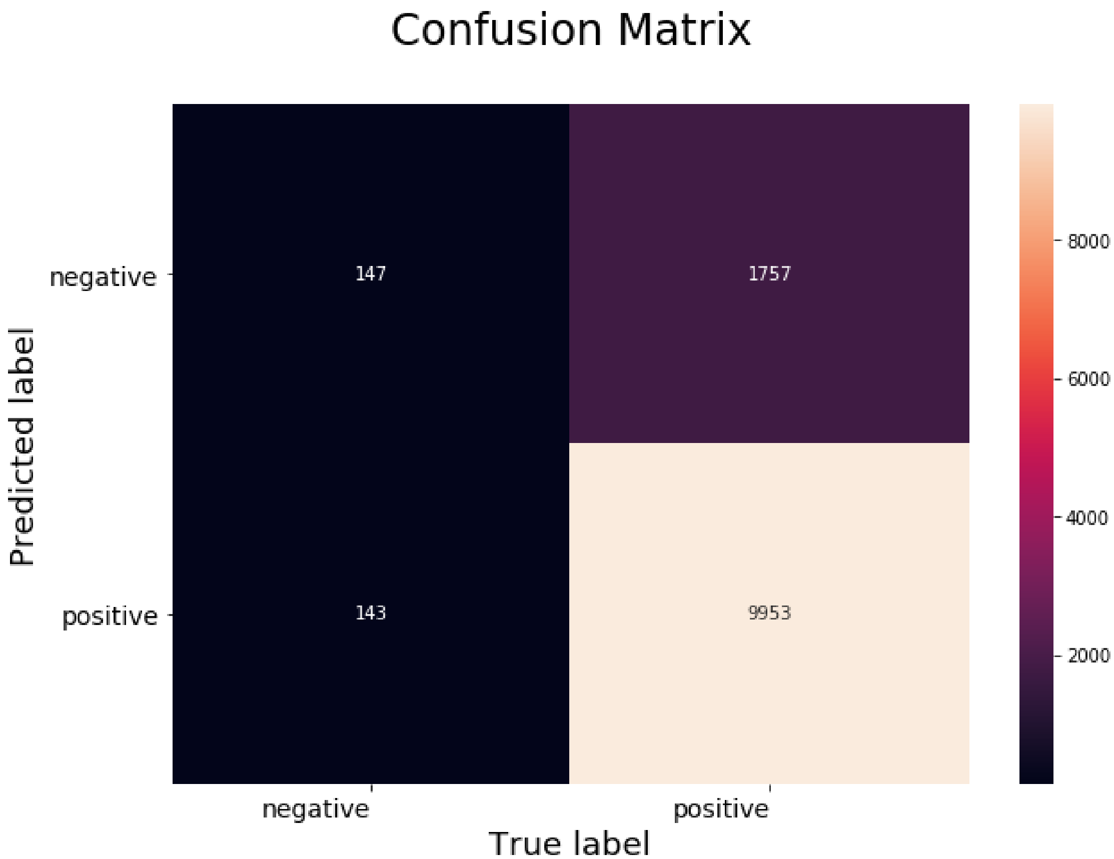
Out[32]:



SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [33]:
```
# 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()
```



16 (4). TFIDF

In [34]:
```
tf_idf_vect = TfidfVectorizer(min_df=1000)
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)
```

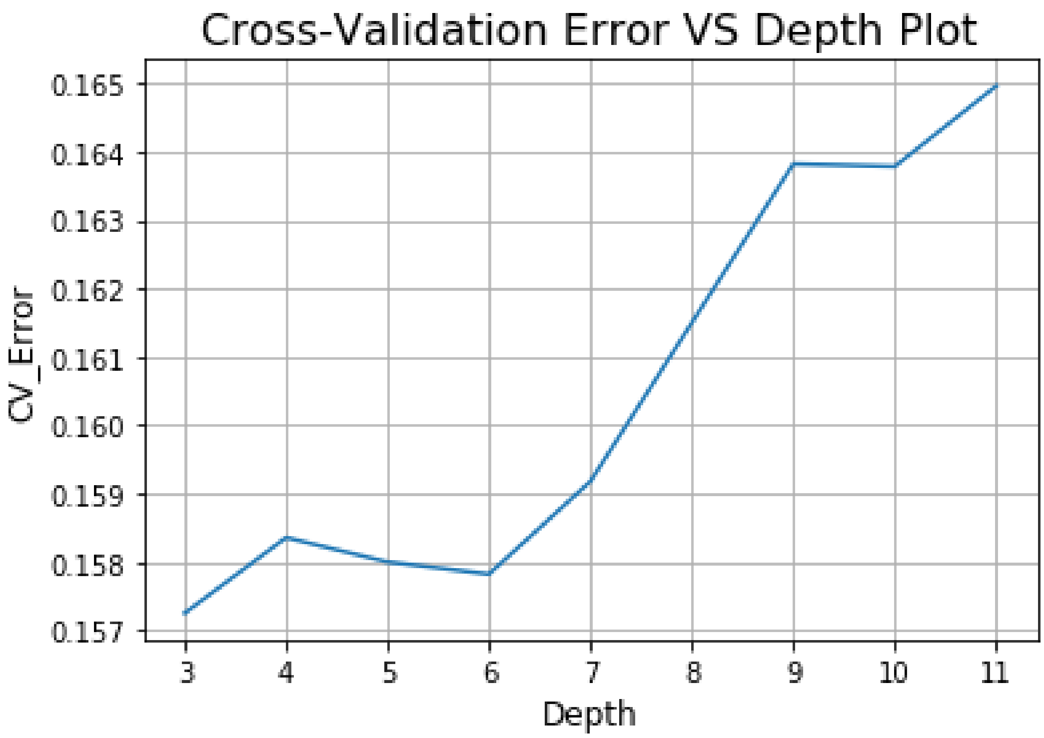
```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (28000, 174)
the number of unique words : 174
```

17 GridSearchCV Implementation (Decision Tree)

```
In [35]: Depths = [3,4,5,6,7,8,9,10,11]

         param_grid = {'max_depth': Depths}
         model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'accuracy', cv=3
         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))

         # Cross-Validation errors
         cv_errors = [1-i for i in model.cv_results_['mean_test_score']]

         # Optimal value of depth
         optimal_depth = model.best_estimator_.max_depth
         print("The optimal value of depth is : ",optimal_depth)

         # DecisionTreeClassifier with Optimal value of depth
         dt = DecisionTreeClassifier(max_depth=optimal_depth)
         dt.fit(X_train_vec_standardized,Y_train)
         predictions = dt.predict(X_test_vec_standardized)

         # Variables that will be used for  making table in Conclusion part of this assignment
         tfidf_depth = optimal_depth
         tfidf_train_acc = model.score(X_test_vec_standardized, Y_test)*100
         tfidf_test_acc = accuracy_score(Y_test, predictions) * 100
```

```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
Accuracy of the model :  0.8410833333333333
The optimal value of depth is :  3
```

In [36]:
```
# plotting Cross-Validation Error vs Depth graph
plt.plot(Depths, cv_errors)
plt.xlabel('Depth',size=12)
plt.ylabel('CV_Error',size=12)
plt.title('Cross-Validation Error VS Depth Plot',size=16)
plt.grid()
plt.show()
```



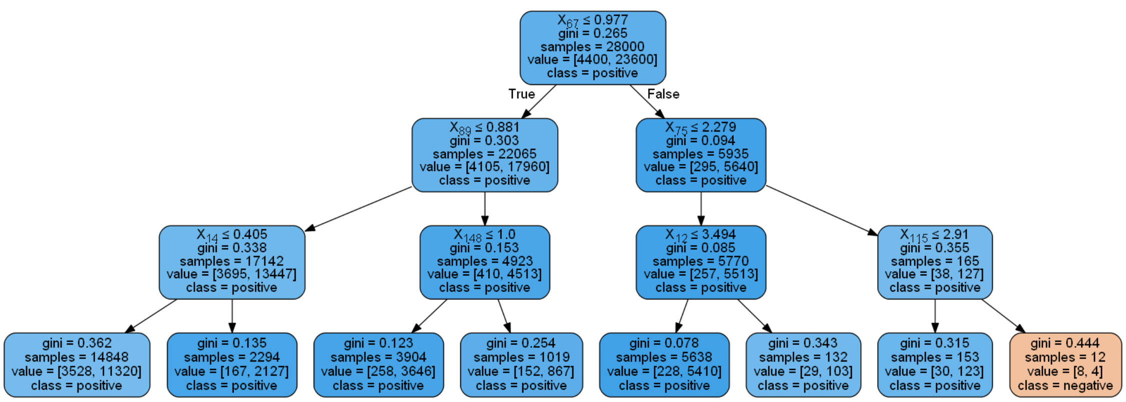
In [37]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the DecisionTreeClassifier for depth = %d is %f%%' % (op

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the DecisionTreeClassifier for depth = %d is %f' % (opt

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the DecisionTreeClassifier for depth = %d is %f' % (optima

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test F1-Score of the DecisionTreeClassifier for depth = %d is %f' % (opti
```

```
The Test Accuracy of the DecisionTreeClassifier for depth = 3 is 84.108333%

The Test Precision of the DecisionTreeClassifier for depth = 3 is 0.841351

The Test Recall of the DecisionTreeClassifier for depth = 3 is 0.999604

The Test F1-Score of the DecisionTreeClassifier for depth = 3 is 0.913675
```

18 Visualize Decision Tree

In [38]:
```python
target = ['negative','positive']
# Create DOT data
data = tree.export_graphviz(dt,out_file=None,class_names=target,filled=True,rounded=T

# Draw graph
graph = pydotplus.graph_from_dot_data(data)

# Show graph
Image(graph.create_png())
```

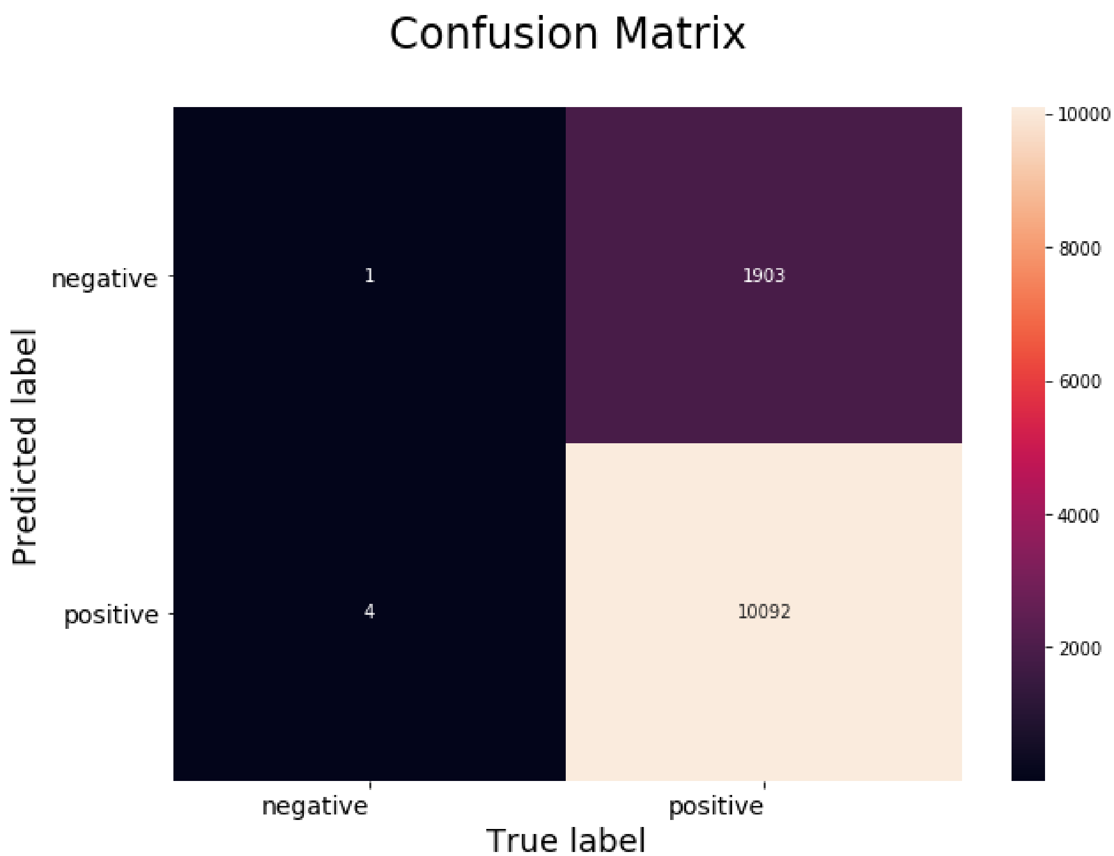
Out[38]:



SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [39]:
```python
# 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', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



19 CONCLUSION :-

20 (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 Decision_Tree as an estimator in GridSearchCV in order to find optimal value of depth of the tree

STEP 5:- Once , we get optimal value of depth then train Decision_Tree again with this optimal depth and make predictions on test_data

STEP 6:- Draw Cross-Validation Error vs Depth graph

STEP 7 :- Evaluate : Accuracy , F1-Score , Precision , Recall
STEP 8:- Visualizing the Decision Tree using Graphviz
STEP 9:- Draw Seaborn Heatmap for Confusion Matrix .
Repeat from STEP 3 to STEP 9 for each of these four vectorizers : BoW, TFIDF, Avg Word2Vec and TFIDF Word2Vec

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

In [41]:
```
# Creating table using PrettyTable library
from prettytable import PrettyTable

# Names of the models
names =['Decision_Tree for BoW','Decision_Tree for TFIDF','Decision_Tree for Avg_Word2

# Values of optimal depth
optimal_depth = [bow_depth, tfidf_depth,avg_w2v_depth, tfidf_w2v_depth]

# Training Accuracies
train_acc = [bow_train_acc,tfidf_train_acc,avg_w2v_train_acc, tfidf_w2v_train_acc]

# Test Accuracies
test_acc = [bow_test_acc,tfidf_test_acc,avg_w2v_test_acc, tfidf_w2v_test_acc]
numbering = [1,2,3,4]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
ptable.add_column("Optimal Depth",optimal_depth)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)

# Printing the Table
print(ptable)
```

```
+--------+-----------------------------------+---------------+-------------------+---------------
| S.NO. |               MODEL               | Optimal Depth | Training Accuracy |   Test Accura
+--------+-----------------------------------+---------------+-------------------+---------------
|   1    |       Decision_Tree for BoW       |       5       | 84.13333333333334 | 84.1666666666
|   2    |      Decision_Tree for TFIDF      |       3       | 84.10833333333333 | 84.1083333333
|   3    |   Decision_Tree for Avg_Word2Vec  |       9       |  86.6277313462894 |  86.622238902
|   4    | Decision_Tree for tfidf_Word2Vec |       6       | 81.01333333333334 | 81.0133333333
+--------+-----------------------------------+---------------+-------------------+---------------
```