2. Post_Clean_RF_GBDT

October 19, 2018

1 GBDT & RF on Amazon Reviews Dataset (Part II)

1.1 Data Source:

The preprocessing step has produced final.sqlite file after doing the data preparation & cleaning. The review text is now devoid of punctuations, HTML markups and stop words.

1.2 Objective:

To find number of trees of Random Forest Classifier using GridSearchCV or iterated cross validation on standardized feature vectors obtained from BoW, tf-idf, W2V and tf-idf weighted W2V featurizations.

Use Gradient Boosted Decision Trees alongsize RF for comparison. GridSearchCV is to be done in order to tune 3 hyperparameters: # of trees, depth of the tree as well as learning rate

Find Precision, Recall, F1 Score, Confusion Matrix, Accuracy of the optimal model obstained with GridSearch or Cross Validation, on vectorized input data, for BoW, tf-idf, W2V and tf-idf weighted W2V featurizations. TPR, TNR, FPR and FNR is calculated for all.

1.3 At a glance:

Tail end data is taken after sorting the data, to conserve the timing info & time Series based cross validation is done, as it is time series data. **The optimal number of trees for Random Forest Classifier is found using GridSearchCV (wrote code for cross validation also), by searching for # of trees between 9 - 135, with step size 9.**

GBDT is also done along with RF. The **optimal parameters for GBDT is found using GridSearchCV. Parameter tuning of 3 hyperparameters is done**: # of trees between 20-81 (with step size 10), max_depth between 5-16 (with step size 2) & learning_rate between 0.05 - 0.2 (with step size 0.05).

The Precision, Recall, F1 Score, Confusion Matrix, Accuracy metrics are found out for all 4 featurizations.

2 Preprocessed Data Loading

```
In [11]: #loading libraries for LR
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
```

```python
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
# from sklearn.cross_validation import cross_val_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
#from sklearn import cross_validation

#loading libraries for scikit learn, nlp, db, plot and matrix.
import sqlite3
import pdb
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn import tree

from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer


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

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

print(final.head(2))
```

```
    index      Id   ProductId          UserId      ProfileName  \
0  138706  150524  0006641040   ACITT7DI6IDDL  shari zychinski
1  138688  150506  0006641040  A2IW4PEEKO2R0U            Tracy

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     0                       0  positive   939340800
1                     1                       1  positive  1194739200
```

```
                                     Summary  \
0                   EVERY book is educational
1  Love the book, miss the hard cover version

                                              Text  \
0  this witty little book makes my son laugh at l...
1  I grew up reading these Sendak books, and watc...

                                       CleanedText
0  b'witti littl book make son laugh loud recit c...
1  b'grew read sendak book watch realli rosi movi...
```

3 Random Sampling & Time Based Slicing

In [12]:
```
# To randomly sample the data and sort based on time before doing train/ test split.
# The slicing into train & test data is done thereafter.

num_points = 20000

# used to format headings
bold = '\033[1m'
end = '\033[0m'

# you can use random_state for reproducibility
# sampled_final = final.sample(n=num_points, random_state=2)

#Sorting data according to Time in ascending order
sorted_final = final.sort_values('Time', axis=0,
                ascending=True, inplace=False, kind='quicksort', na_position='first')

selected_final = sorted_final.tail(num_points)

# fetching the outcome class
y = selected_final['Score']

def class2num(response):
    if (response == 'positive'):
        return 1
    else:
        return 0

y_bin = list(map(class2num, y))

X_train, X_test, y_train, y_test = train_test_split(
            selected_final, y_bin, test_size=0.3, random_state=42)
```

4 Custom Defined Functions

4 user defined functions are written to

```
a) Random Forest Hyperparameter Tuning

b) Gradient Boosted Decision Tree (GBDT) Hyperparameter Tuning

c) Compute Performance Metrics for RF & GBDT

d) Generate Word Cloud based on Feature Importance
```

4.1 a) Random Forest Hyperparameter Tuning

In [16]:
```python
# source: https://chrisalbon.com/machine_learning/
# model_selection/hyperparameter_tuning_using_random_search/
# some parts of the below code are from the above link.

# Part of Decision tree code is taken from here.
# https://towardsdatascience.com/random-useful-scikit-learn-methods-a032f78e1ec3

# Cross Validation using GridSearchCV

import numpy
import math
from scipy.stats import uniform
import matplotlib.pyplot as plt
# from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV, RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
# from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
import scipy

def rfGridCV(X_train_vect, X_test_vect, genCloud = False, title_cf=''):

    # empty list that will hold cv scores
    cv_scores = []

    # search for trees between 9 - 135, step size 9
    n_trees = list(range(9, 136, 9))

    # to do time_series based CV, as it is time series data.
    tscv = TimeSeriesSplit(n_splits=10)

    # Use a grid over parameters of interest
    param_grid = {"n_estimators" : n_trees}
```

```
CV_rfc = GridSearchCV(estimator=RandomForestClassifier(),
                          param_grid=param_grid, cv=tscv)
CV_rfc.fit(X_train_vect, y_train)
print (CV_rfc.best_params_)

print("**RF Grid Search Results**")
print("Best Training Accuracy:\t", CV_rfc.best_score_)
print("Best Parameters:\t", CV_rfc.best_params_)
print("Best Estimator:\t", CV_rfc.best_estimator_)
print("CV Results:\t", CV_rfc.cv_results_.keys())
means = CV_rfc.cv_results_['mean_test_score']

optimal_ntrees   = CV_rfc.cv_results_[
                    'params'][means.argmax()].get('n_estimators')

# Hyperparameters
    #     depth_range = range(1, 25)
    #     param_grid = dict(max_depth=depth_range)


    #     # perform 10-fold cross validation
    #     for d in depth_range:

    #         dt = tree.DecisionTreeClassifier(max_depth=d)

    #         scores = cross_val_score(dt,
    #                         X_train_vect, y_train, cv=tscv, scoring='accuracy')
    #         cv_scores.append(scores.mean())
    #         print(scores.mean())

    #     # changing to misclassification error
    #     MSE = [1 - x for x in cv_scores]

    #     print(MSE.index(min(MSE)))
    #     # determining best k
    #     optimal_d = depth_range[MSE.index(min(MSE))]
    #     print('\nThe optimal depth is %d.' % optimal_d)

    #     plt.figure()
    #     plt.title('Cross Validation Plot: Depth vs CV Error')
    #     plt.plot(depth_range, MSE)
    #     plt.show()

optimal_clf = RandomForestClassifier(n_estimators=optimal_ntrees)
optimal_clf.fit(X_train_vect, y_train)

compute_metrics(optimal_clf, X_test_vect,
                title_cf="Confusion Matrix: GridSearchCV")
```

```
    if genCloud:
        return optimal_clf
```

5 b) GBDT Hyperparameter Tuning

In [17]:
```
# source: got from below link and modified.
# https://www.analyticsvidhya.com/blog/2016/02/complete-guide-parameter-tuning-gradie

from sklearn.ensemble import GradientBoostingClassifier

def gbdtGridCV(X_train_vect, X_test_vect, genCloud = False, title_cf=''):

    # empty list that will hold cv scores
    cv_scores = []

    # to do time_series based CV, as it is time series data.
    tscv = TimeSeriesSplit(n_splits=10)

    param_test = {'n_estimators':range(20,81,10),
                  'max_depth':range(5,16,2),
                  'learning_rate': list(np.arange(0.05,0.2,0.05))}

    gbSearch = GridSearchCV(estimator = GradientBoostingClassifier(
                min_samples_split=500,min_samples_leaf=50,max_features='sqrt'),
                param_grid = param_test, scoring='roc_auc', cv=10)

    gbSearch.fit(X_train_vect, y_train)
    optimal_ntrees   = gbSearch.best_params_.get('n_estimators')
    optimal_max_depth = gbSearch.best_params_.get('max_depth')
    optimal_learning_rate = gbSearch.best_params_.get('learning_rate')

    print("**GBDT Grid Search Results**")
    print("Optimal Number of Trees:\t", optimal_ntrees)
    print("Optimal Max Depth:\t", optimal_max_depth)
    print("Optimal Learning Rate:\t", optimal_learning_rate)

    # Hyperparameters
        #     depth_range = range(1, 25)
        #     param_grid = dict(max_depth=depth_range)


        #     # perform 10-fold cross validation
        #     for d in depth_range:

        #         dt = tree.DecisionTreeClassifier(max_depth=d)
```

```
    #         scores = cross_val_score(dt,
    #                         X_train_vect, y_train, cv=tscv, scoring='accuracy')
    #         cv_scores.append(scores.mean())
    #         print(scores.mean())

    #     # changing to misclassification error
    #     MSE = [1 - x for x in cv_scores]

    #     print(MSE.index(min(MSE)))
    #     # determining best k
    #     optimal_d = depth_range[MSE.index(min(MSE))]
    #     print('\nThe optimal depth is %d.' % optimal_d)

    #     plt.figure()
    #     plt.title('Cross Validation Plot: Depth vs CV Error')
    #     plt.plot(depth_range, MSE)
    #     plt.show()

    optimal_clf = GradientBoostingClassifier(learning_rate = optimal_learning_rate,
                                max_depth = optimal_max_depth,
                                n_estimators = optimal_ntrees,
                                min_samples_split=500,
                                min_samples_leaf=50,max_features='sqrt')
    optimal_clf.fit(X_train_vect, y_train)

    compute_metrics(optimal_clf, X_test_vect,
                    title_cf="Confusion Matrix: GridSearchCV")

    if genCloud:
        return optimal_clf
```

5.1 c) Compute Performance Metrics for RF & GBDT

In [18]:
```
# ========================= LR with alpha = optimal_alpha ==========================
#To compute the performance metrics for RF & GBDT

import seaborn as sn
from sklearn.metrics import *

def compute_metrics(dt_optimal, X_test_vect, title_cf="Confusion Matrix"):

    # predict the response
    pred = dt_optimal.predict(X_test_vect)

    print(bold + '\n\nMetric Analysis of DT Classifier' + end)
```

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nAccuracy \t= %f' % acc)

precision = precision_score(y_test, pred) * 100
print('Precision \t= %f' % precision)

recall = recall_score(y_test, pred) * 100
print('Recall \t\t= %f' % recall)

f1score = f1_score(y_test, pred) * 100
print('F1 Score \t= %f' % f1score)

confusion = confusion_matrix(y_test, pred)
print(bold + "\n\nConfusion Matrix" + end)

plt.figure()
plt.title(title_cf)
df_cm = pd.DataFrame(confusion, range(2), range(2))
sn.set(font_scale=1.4)#for label size
sn.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt="d")# font size

(tn, fp, fn, tp) = confusion.ravel()
print("\nTrue Negatives = " + str(tn))
print("True Positives = " + str(tp))
print("False Negatives = " + str(fn))
print("False Positives = " + str(fp))

actual_positives = tp+fn
actual_negatives = tn+fp
print("\nTotal Actual Positives = " + str(actual_positives))
print("Total Actual Negatives = " + str(actual_negatives))

print("\nTrue Positive Rate(TPR) = " + str(round(tp/actual_positives, 2)))
print("True Negative Rate(TNR) = " + str(round(tn/actual_negatives, 2)))
print("False Positive Rate(FPR) = " + str(round(fp/actual_negatives, 2)))
print("False Negative Rate(FNR) = " + str(round(fn/actual_positives, 2)))
```

6 d) Generate Word Cloud based on Feature Importance

In [20]:
```
# taken word cloud src from here:
# https://stackoverflow.com/questions/43043437/wordcloud-python-with-generate-from-fr
# modified for creating the dictionary of importance.

from wordcloud import WordCloud
```

```
def generateCloud(clf, vect):

    clf.fit(X_train_vect, y_train)

    feature_importances = pd.DataFrame(clf.feature_importances_,
                                       index = vect.get_feature_names(),
                                        columns=['importance']).sort_values(
                                                 'importance',ascending=False)

    print(feature_importances.size)
    # remove features with importance = 0
    feature_importances = feature_importances.loc[
                               ~(feature_importances==0).all(axis=1)]

    # create the word cloud with feature importance as the scaling factor
    wordcloud = WordCloud(width=2200,height=1200,
                  max_words=2000,relative_scaling=1,
                  normalize_plurals=False).generate_from_frequencies(
                                dict(feature_importances)['importance'])

    plt.figure(figsize =[16, 12])
    plt.title('Most Important Features in Amazon Reviews')
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

7 BoW

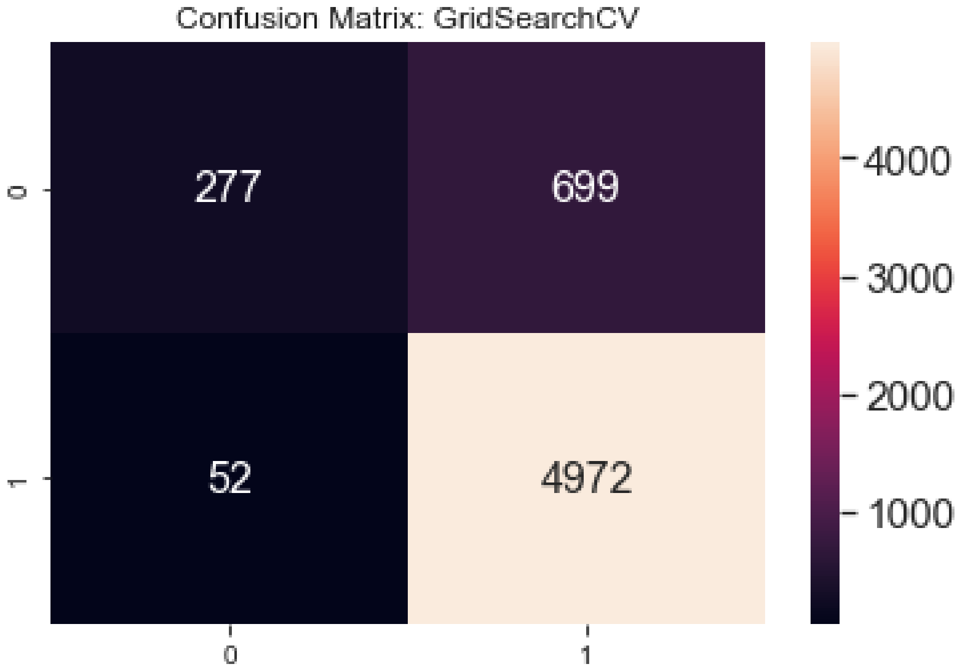
BoW will result in a **sparse matrix with huge number of features** as it creates a feature for each unique word in the review.

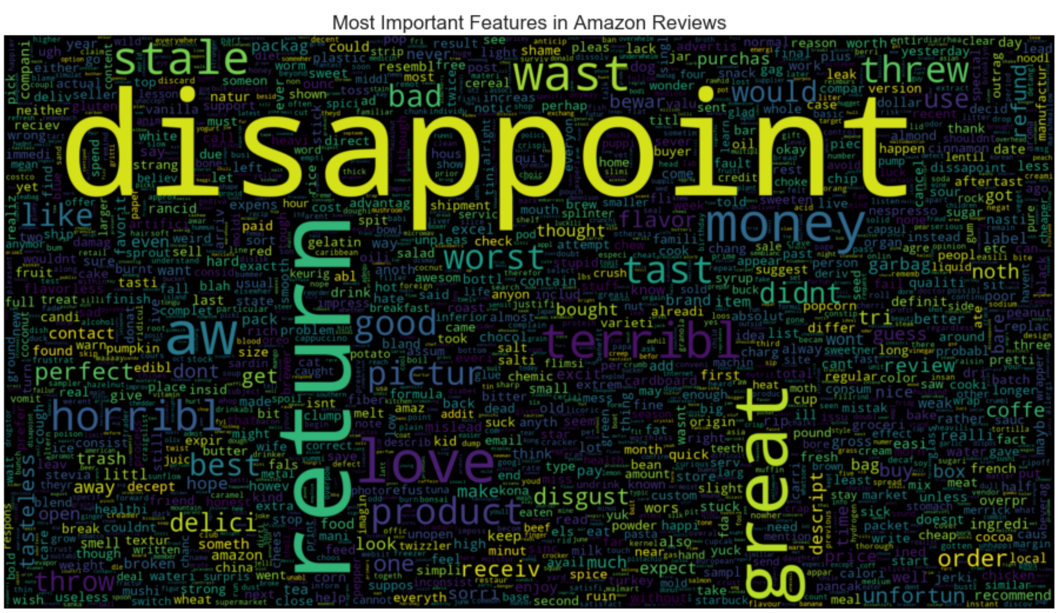
For Binary BoW feature representation, CountVectorizer is declared as float, as the values can take non-integer values on further processing.

```
In [7]: # BoW Featurisation, Standardisation, Grid Search

        from sklearn.random_projection import sparse_random_matrix

        #BoW
        count_vect = CountVectorizer(dtype="float") #in scikit-learn
        X_train_vect = count_vect.fit_transform(X_train['CleanedText'].values)
        X_train_vect.get_shape()

        #BoW Test
        X_test_vect = count_vect.transform(X_test['CleanedText'].values)

        # Standardisation is not required for DTs, GBDTs & RF
```

```python
print(bold + "\n\n1) Grid Search CV using RF Classifier on BoW"+ end)

# Do grid Search using Random Forest Classifier.
# The function computes the performance metrics also
clf = rfGridCV(X_train_vect, X_test_vect, genCloud=True)
generateCloud(clf, count_vect)

print(bold + "\n\n2) Grid Search CV using GBDT Classifier on BoW"+ end)

# Do grid Search using GBDT Classifier.
# The function computes the performance metrics also
clf = gbdtGridCV(X_train_vect, X_test_vect, genCloud=True)
generateCloud(clf, count_vect)
```

```
1) Grid Search CV using RF Classifier on BoW
{'n_estimators': 36}
**RF Grid Search Results**
Best Training Accuracy:         0.8679245283018868
Best Parameters:        {'n_estimators': 36}
Best Estimator:         RandomForestClassifier(bootstrap=True, class_weight=None, criterion='g
            max_depth=None, max_features='auto', 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, n_estimators=36, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
CV Results:         dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_
Metric Analysis of DT Classifier

Accuracy         = 87.483333
Precision         = 87.674132
Recall                = 98.964968
F1 Score         = 92.978027
Confusion Matrix

True Negatives = 277
True Positives = 4972
False Negatives = 52
False Positives = 699

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.99
True Negative Rate(TNR) = 0.28
False Positive Rate(FPR) = 0.72
False Negative Rate(FNR) = 0.01
14494
```



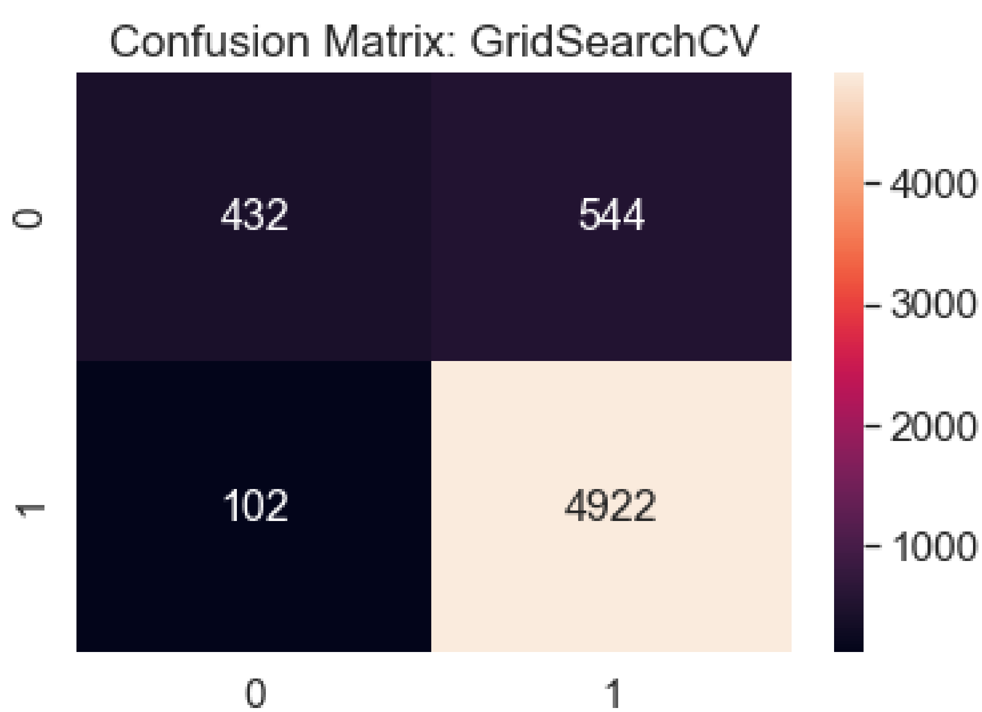



```
2) Grid Search CV using GBDT Classifier on BoW
**GBDT Grid Search Results**
```

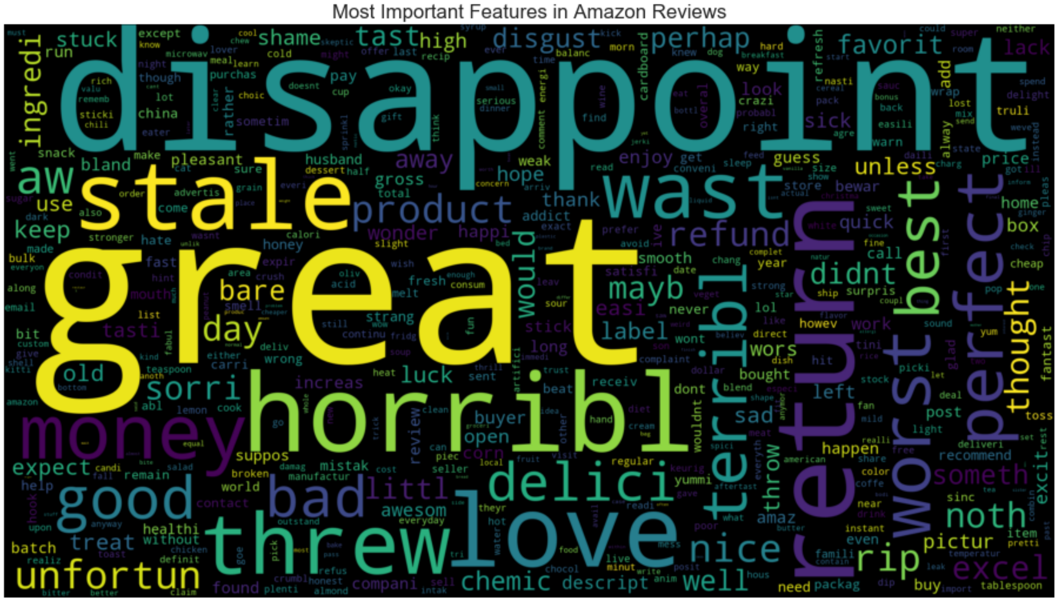
```
Optimal Number of Trees:         70
Optimal Max Depth:         15
Optimal Learning Rate:         0.2
```
Metric Analysis of DT Classifier

```
Accuracy          = 89.233333
Precision          = 90.047567
Recall                 = 97.969745
F1 Score          = 93.841754
```
Confusion Matrix

```
True Negatives = 432
True Positives = 4922
False Negatives = 102
False Positives = 544

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.98
True Negative Rate(TNR) = 0.44
False Positive Rate(FPR) = 0.56
False Negative Rate(FNR) = 0.02
14494
```



Most Important Features in Amazon Reviews



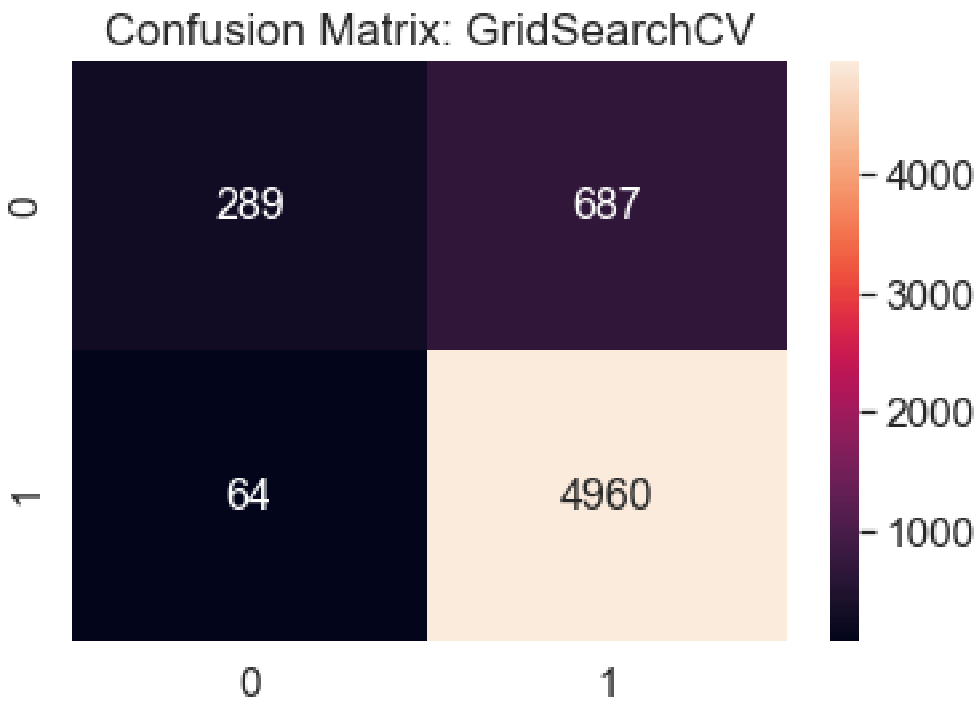
8 tf-IDF

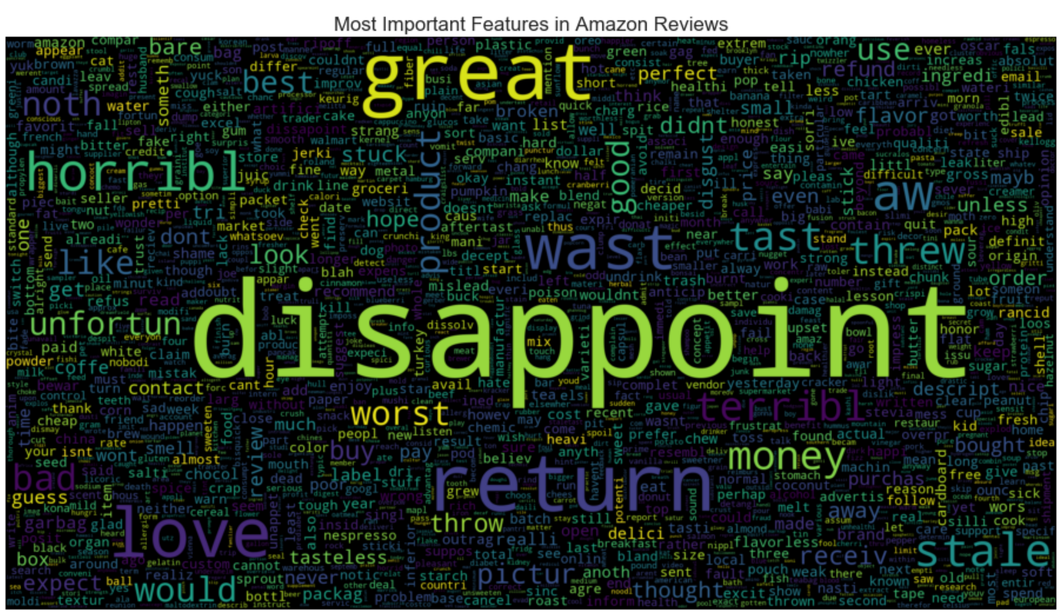
Sparse matrix generated from tf-IDF is fed in to GridSearch GBDT Cross Validator & RF Cross Validator to find the optimal depth value. Performance metrics of optimal GBDT with tf-idf featurization is found.

```
In [8]: # TFID Featurisation, Standardisation, Grid Search

        from sklearn.random_projection import sparse_random_matrix

        # TFID
        count_vect = TfidfVectorizer(dtype="float") #in scikit-learn
        X_train_vect = count_vect.fit_transform(X_train['CleanedText'].values)
        X_train_vect.get_shape()

        # TFID Test
        X_test_vect = count_vect.transform(X_test['CleanedText'].values)

        # Standardisation is not required for DTs, GBDTs & RF

        print(bold + "\n\n1) Grid Search CV using RF Classifier on tf-idf"+ end)

        # Do grid Search using Random Forest Classifier.
        # The function computes the performance metrics also
```

```python
clf = rfGridCV(X_train_vect, X_test_vect, genCloud=True)
generateCloud(clf, count_vect)

print(bold + "\n\n2) Grid Search CV using GBDT Classifier on tf-idf"+ end)

# Do grid Search using GBDT Classifier.
# The function computes the performance metrics also
clf = gbdtGridCV(X_train_vect, X_test_vect, genCloud=True)
generateCloud(clf, count_vect)
```

```
1) Grid Search CV using RF Classifier on tf-idf
{'n_estimators': 18}
**RF Grid Search Results**
Best Training Accuracy:         0.8647012578616352
Best Parameters:         {'n_estimators': 18}
Best Estimator:         RandomForestClassifier(bootstrap=True, class_weight=None, criterion='g
            max_depth=None, max_features='auto', 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, n_estimators=18, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
CV Results:         dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_
Metric Analysis of DT Classifier

Accuracy         = 87.483333
Precision         = 87.834248
Recall                  = 98.726115
F1 Score         = 92.962234
Confusion Matrix

True Negatives = 289
True Positives = 4960
False Negatives = 64
False Positives = 687

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.99
True Negative Rate(TNR) = 0.3
False Positive Rate(FPR) = 0.7
False Negative Rate(FNR) = 0.01
14494
```



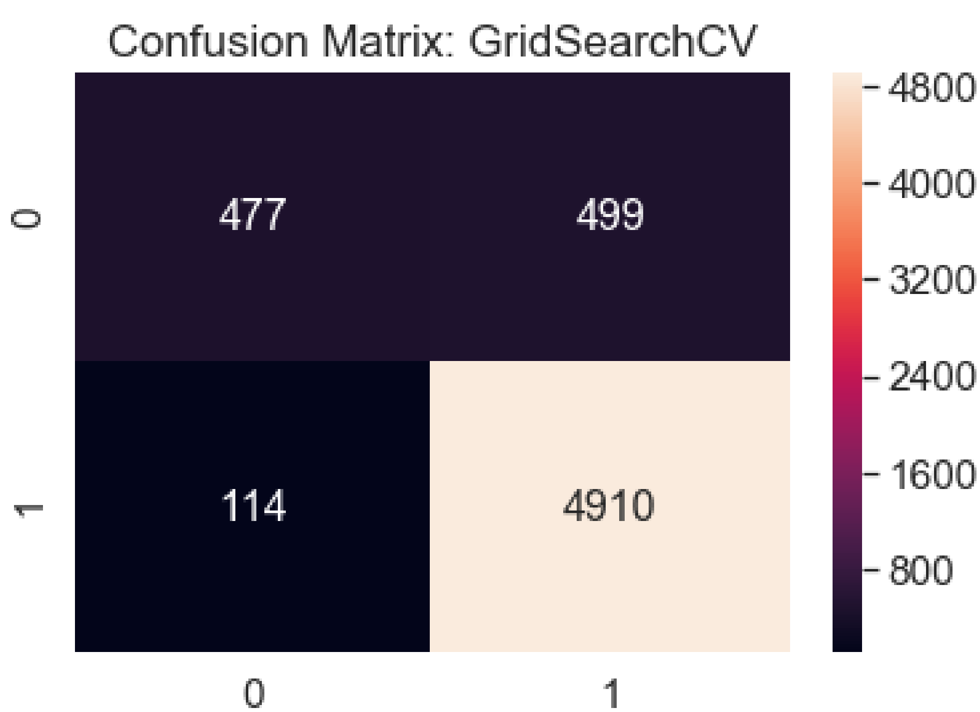


2) Grid Search CV using GBDT Classifier on tf-idf
****GBDT Grid Search Results****

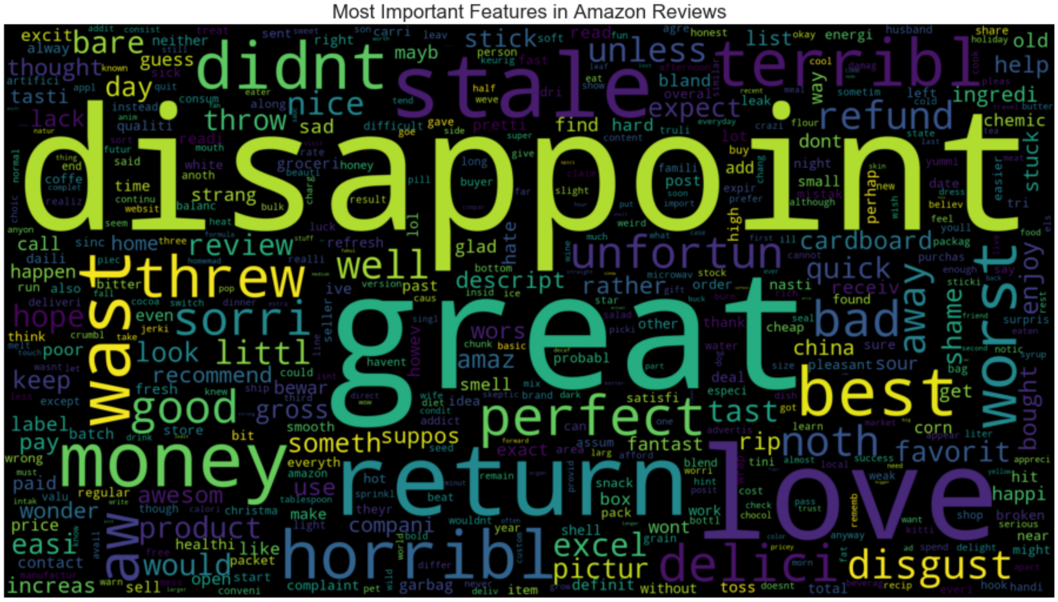
```
Optimal Number of Trees:         80
Optimal Max Depth:         15
Optimal Learning Rate:         0.2
```
Metric Analysis of DT Classifier

```
Accuracy          = 89.783333
Precision          = 90.774635
Recall                 = 97.730892
F1 Score          = 94.124413
```
Confusion Matrix

```
True Negatives = 477
True Positives = 4910
False Negatives = 114
False Positives = 499

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.98
True Negative Rate(TNR) = 0.49
False Positive Rate(FPR) = 0.51
False Negative Rate(FNR) = 0.02
14494
```



Most Important Features in Amazon Reviews



9 Word2Vec

Dense matrix generated from Word2Vec is fed in to GridSearch GBDT Cross Validator & RF Cross Validator to find the optimal depth value. Performance metrics of GBDT and RF with W2V featurization is found.

```
In [21]: # Train your own Word2Vec model using your own text corpus
         import gensim
         import re

         w2v_dim = 300

         def cleanhtml(sentence): #function to clean the word of any html-tags
             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

         def trainW2V_model(reviewText):
```

```
    #select subset of points for fast execution
    i=0
    list_of_sent=[]

    for sent in reviewText:
        sent = str(sent, 'utf-8')
        filtered_sentence=[]
        sent=cleanhtml(sent)
        for w in sent.split():
            for cleaned_words in cleanpunc(w).split():
                if(cleaned_words.isalpha()):
                    filtered_sentence.append(cleaned_words.lower())
                else:
                    continue
        list_of_sent.append(filtered_sentence)

    w2v_model=gensim.models.Word2Vec(list_of_sent,
                                     min_count=5,size=w2v_dim, workers=4)

    return w2v_model
```

In [22]:
```
# average Word2Vec
# compute average word2vec for each review.

def computeAvgW2V(w2vTrained_model, reviewText):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list

    for sent in reviewText: # for each review/sentence
        sent_vec = np.zeros(w2v_dim) # as word vectors are of zero length
        cnt_words =0; # num of words with a valid vector in the sentence/review
        sent = str(sent, 'utf-8')
        sent = re.sub("[^\w]", " ",  sent).split()

        for word in sent: # for each word in a review/sentence
            try:
                vec = w2vTrained_model.wv[word]
                sent_vec += vec
                cnt_words += 1
            except:
                pass
        sent_vec /= cnt_words
        sent_vectors.append(sent_vec)

    return np.nan_to_num(sent_vectors)
```

In [23]:
```
# W2V Main Function
# W2V Featurisation, Standardisation, Grid Search and Random Search,
# Perturbation test to remove multicollinear features
```

```python
from sklearn.preprocessing import StandardScaler

# W2V Train
w2v_trainModel = trainW2V_model(X_train['CleanedText'].values)
X_train_vect = computeAvgW2V(w2v_trainModel, X_train['CleanedText'].values)

# W2V Test
w2v_testModel = trainW2V_model(X_test['CleanedText'].values)
X_test_vect = computeAvgW2V(w2v_testModel, X_test['CleanedText'].values)

# Standardisation is not required for DTs

# Do grid Search using RF & GBDT Classifier.
# The function computes the performance metrics also
print(bold + "\n\n1) Grid Search CV using RF Classifier"+ end)
rfGridCV(X_train_vect, X_test_vect)

print(bold + "\n\n2) Grid Search CV using GBDT Classifier"+ end)
gbdtGridCV(X_train_vect, X_test_vect)
```

```
C:\Users\Anand\Anaconda3\envs\myenv\lib\site-packages\ipykernel_launcher.py:20: RuntimeWarning


1) Grid Search CV using RF Classifier
{'n_estimators': 108}
**RF Grid Search Results**
Best Training Accuracy:         0.8585691823899371
Best Parameters:         {'n_estimators': 108}
Best Estimator:         RandomForestClassifier(bootstrap=True, class_weight=None, criterion='g
            max_depth=None, max_features='auto', 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, n_estimators=108, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
CV Results:         dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_
Metric Analysis of DT Classifier

Accuracy         = 82.966667
Precision         = 83.800676
Recall                 = 98.746019
F1 Score         = 90.661550
Confusion Matrix

True Negatives = 17
True Positives = 4961
False Negatives = 63
```

```
False Positives = 959

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.99
True Negative Rate(TNR) = 0.02
False Positive Rate(FPR) = 0.98
False Negative Rate(FNR) = 0.01
```

2) Grid Search CV using GBDT Classifier

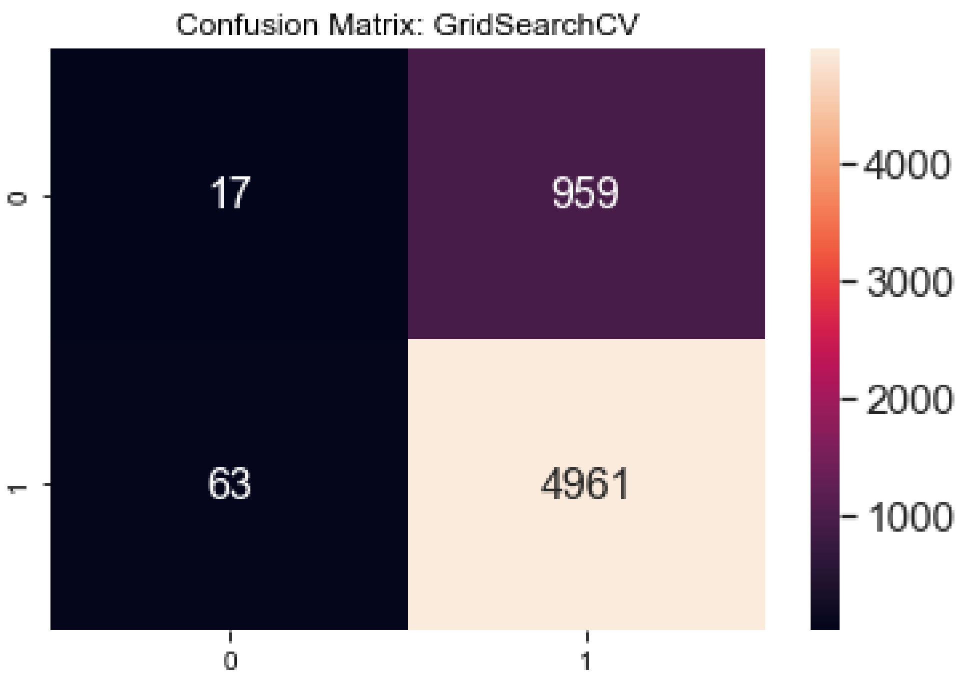
```
**GBDT Grid Search Results**
Optimal Number of Trees:         80
Optimal Max Depth:         7
Optimal Learning Rate:         0.1
```

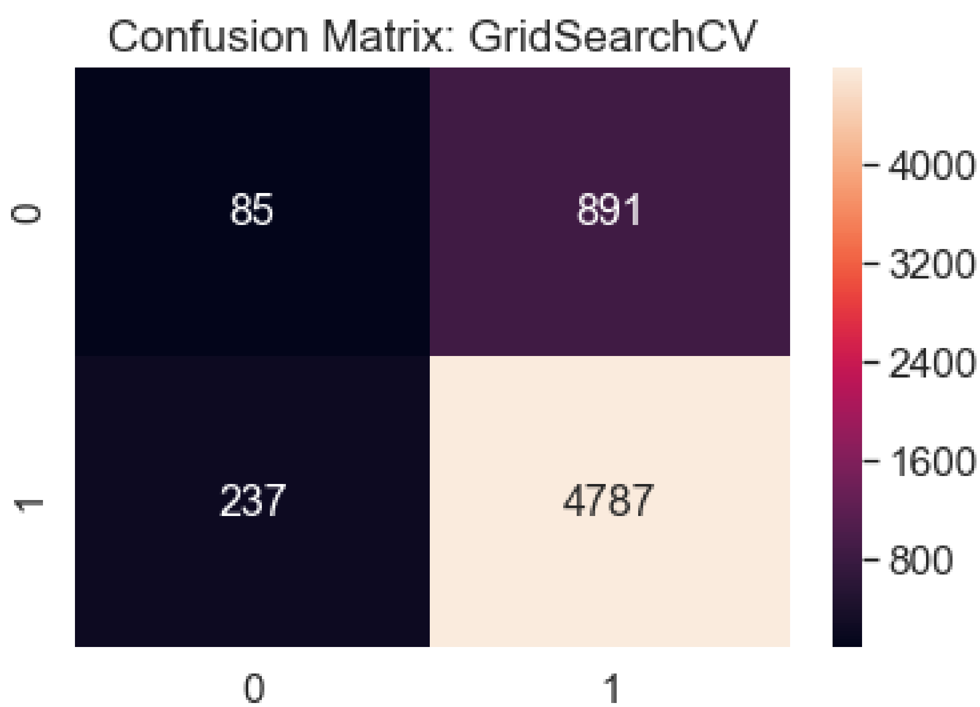
Metric Analysis of DT Classifier

```
Accuracy         = 81.200000
Precision         = 84.307855
Recall                 = 95.282643
F1 Score         = 89.459914
```

Confusion Matrix

```
True Negatives = 85
True Positives = 4787
False Negatives = 237
False Positives = 891

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.95
True Negative Rate(TNR) = 0.09
False Positive Rate(FPR) = 0.91
False Negative Rate(FNR) = 0.05
```


Confusion Matrix: GridSearchCV
17
959
63
4961
0
1
0
1
4000
3000
2000
1000


Confusion Matrix: GridSearchCV
85
891
237
4787
0
1
0
1
4000
3200
2400
1600
800

10 TF-ID Weighted W2V

In [24]:
```
# average Word2Vec
# compute average word2vec for each review.

def compute_tfidW2V(w2v_model, model_tf_idf, count_vect, reviewText):

    # the tfidf-w2v for each sentence/review is stored in this list
    tfidf_sent_vectors = [];
    row=0;

    # TF-IDF weighted Word2Vec
    tfidf_feats = count_vect.get_feature_names() # tfidf words/col-names

    # iterate for each review/sentence
    for sent in reviewText:
        sent_vec = np.zeros(w2v_dim) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        sent = str(sent, 'utf-8')
        sent = re.sub("[^\w]", " ",  sent).split()

        for word in sent: # for each word in a review/sentence
            try:
                vec = w2v_model.wv[word]
                # obtain the tf_idfidf of a word in a sentence/review
                tfidf = model_tf_idf[row, tfidf_feats.index(word)]
                sent_vec += (vec * tfidf)
                weight_sum += tfidf
            except:
                pass
        sent_vec /= weight_sum

        tfidf_sent_vectors.append(sent_vec)
        row += 1

    return np.nan_to_num(tfidf_sent_vectors)
```

In [25]:
```
# tf-df weighted W2V Main Function
# tfidf and W2V Featurisation, Standardisation, Grid Search
# Perturbation test to remove multicollinear features

from sklearn.preprocessing import StandardScaler

# TFID
count_vect = TfidfVectorizer(dtype="float") #in scikit-learn
X_train_tfid_vect = count_vect.fit_transform(X_train['CleanedText'].values)

# TFID Test
```

```
X_test_tfid_vect = count_vect.transform(X_test['CleanedText'].values)


X_train_vect = compute_tfidW2V(w2v_trainModel, X_train_tfid_vect,
                                count_vect, X_train['CleanedText'].values)
X_test_vect = compute_tfidW2V(w2v_testModel, X_test_tfid_vect,
                               count_vect, X_test['CleanedText'].values)

# Standardisation is not required for DTs

# Do both grid Search and Random Search.
# The function computes the performance metrics also
print(bold + "\n\n1) Grid Search CV using RF Classifier"+ end)
rfGridCV(X_train_vect, X_test_vect)

print(bold + "\n\n2) Grid Search CV using GBDT Classifier"+ end)
gbdtGridCV(X_train_vect, X_test_vect)
```

```
C:\Users\Anand\Anaconda3\envs\myenv\lib\site-packages\sklearn\feature_extraction\text.py:1547:
  UserWarning)
C:\Users\Anand\Anaconda3\envs\myenv\lib\site-packages\ipykernel_launcher.py:29: RuntimeWarning
```

1) Grid Search CV using RF Classifier

```
{'n_estimators': 90}
**RF Grid Search Results**
Best Training Accuracy:         0.8481132075471698
Best Parameters:         {'n_estimators': 90}
Best Estimator:         RandomForestClassifier(bootstrap=True, class_weight=None, criterion='g
            max_depth=None, max_features='auto', 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, n_estimators=90, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
CV Results:         dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_
```

Metric Analysis of DT Classifier

```
Accuracy         = 81.850000
Precision         = 83.998618
Recall                  = 96.755573
F1 Score         = 89.926926
```

Confusion Matrix

```
True Negatives = 50
True Positives = 4861
False Negatives = 163
False Positives = 926
```

```
Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.97
True Negative Rate(TNR) = 0.05
False Positive Rate(FPR) = 0.95
False Negative Rate(FNR) = 0.03
```

1) Grid Search CV using GBDT Classifier

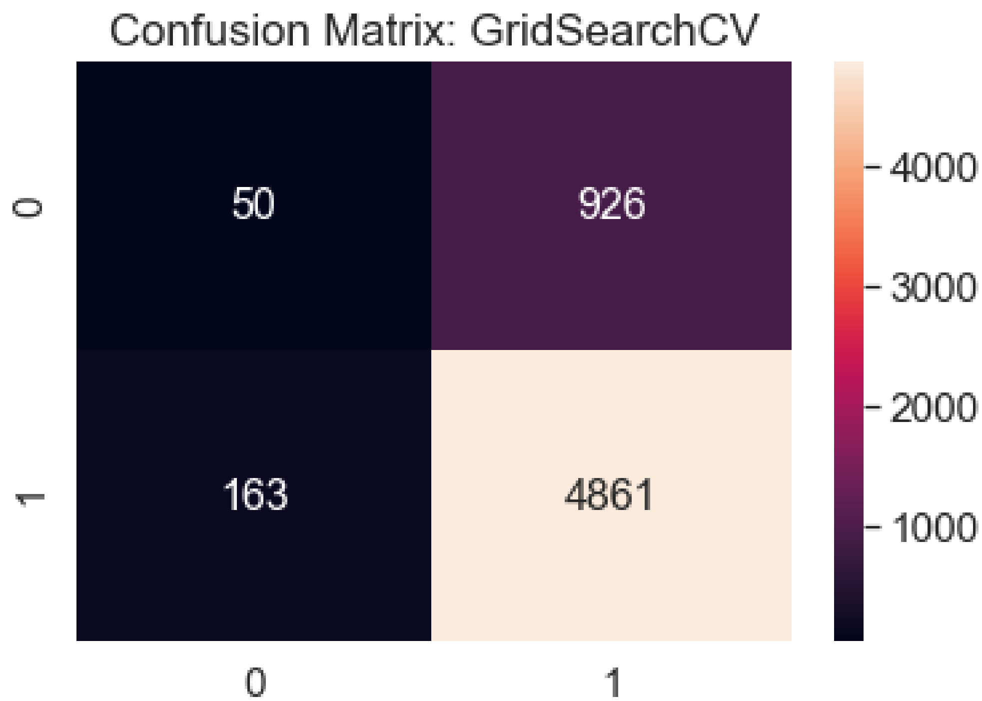
```
**GBDT Grid Search Results**
Optimal Number of Trees:        70
Optimal Max Depth:        13
Optimal Learning Rate:        0.1
```

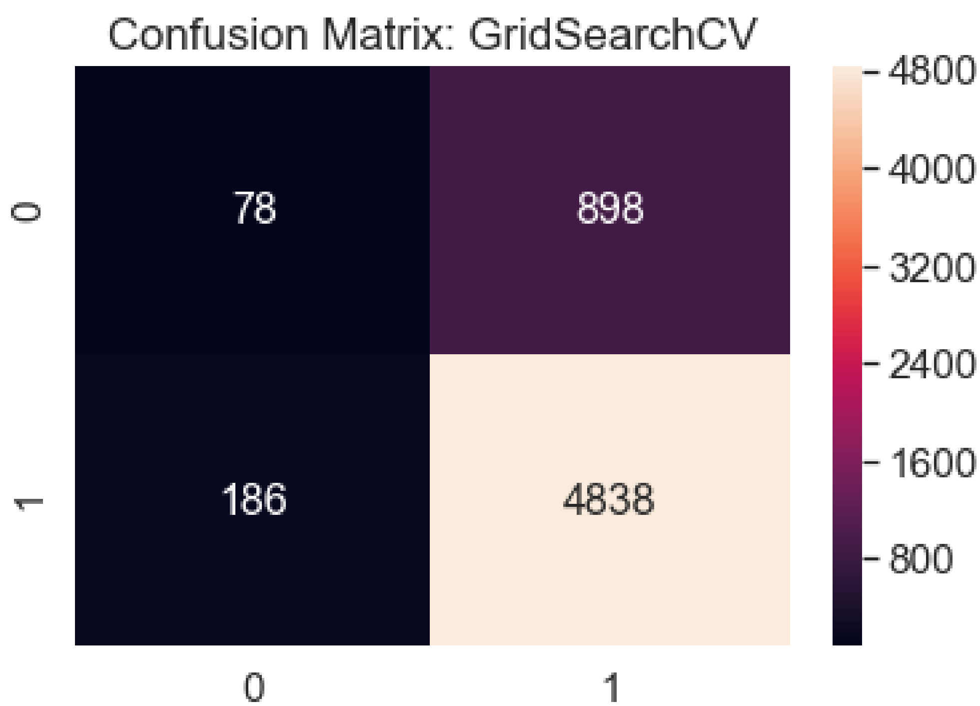
Metric Analysis of DT Classifier

```
Accuracy        = 81.933333
Precision        = 84.344491
Recall                = 96.297771
F1 Score        = 89.925651
```

Confusion Matrix

```
True Negatives = 78
True Positives = 4838
False Negatives = 186
False Positives = 898

Total Actual Positives = 5024
Total Actual Negatives = 976

True Positive Rate(TPR) = 0.96
True Negative Rate(TNR) = 0.08
False Positive Rate(FPR) = 0.92
False Negative Rate(FNR) = 0.04
```


Confusion Matrix: GridSearchCV
0
1
50
926
163
4861
0
1
4000
3000
2000
1000


Confusion Matrix: GridSearchCV
0
1
78
898
186
4838
0
1
4800
4000
3200
2400
1600
800

11 Summary Statistics

Model	Optimal Parameters	Test Metric
RF on BoW	Number of trees: 36	**Accuracy = 87.48, F1 Score = 92.97** TPR = 0.99, TNR = 0.28, FPR = 0.72, FNR = 0.01
GBDT on BoW	Number of Trees: 70, Max Depth: 15, Learning Rate: 0.2	**Accuracy = 89.23, F1 Score = 93.84** TPR = 0.98, TNR = 0.44, FPR = 0.56, FNR = 0.02
RF on tf-idf	Number of trees: 18	**Accuracy = 87.48, F1 Score = 92.96** TPR = 0.99, TNR = 0.3, FPR = 0.7, FNR = 0.01
GBDT on tf-idf	Number of Trees: 80, Max Depth: 15, Learning Rate: 0.2	**Accuracy = 89.78, F1 Score = 94.12** **TPR = 0.98, TNR = 0.49, FPR = 0.51, FNR = 0.02**
RF on W2V	Number of trees: 108	**Accuracy = 82.96, F1 Score = 90.66** TPR = 0.99, TNR = 0.02, FPR = 0.98, FNR = 0.01
GBDT on W2V	Number of Trees: 80, Max Depth: 7, Learning Rate: 0.1	**Accuracy = 81.2, F1 Score = 89.46** TPR = 0.95, TNR = 0.09, FPR = 0.91, FNR = 0.05
RF on tf-idf W2V	Number of trees: 90	**Accuracy = 82.96, F1 Score = 90.66** TPR = 0.99, TNR = 0.02, FPR = 0.98, FNR = 0.01
GBDT on tf-idf W2V	Number of Trees: 90, Max Depth: 7, Learning Rate: 0.1	**Accuracy = 81.85, F1 Score = 89.93** TPR = 0.97, TNR = 0.05, FPR = 0.95, FNR = 0.03

12 Observations

1) The **best model** based on test metrics is found to be **GBDT on tf-idf**. The F1 Score is **94.12**, while **98% of positive points and around 50% of negative points** are detected correctly.

2) The **classification accuracy of GBDT and RF is found to be less than linear models** like logistic regression. This is possibly because the **separation at high dimensional space using hyperplanes is easier** than doing a decision tree based approach.

3) **GBDT consistently performs better than RF** for Amazon review classiciation problem.

4) The **wordcloud figure of GBDT is much clearer than RF**. RF wordcloud is too cluttered and hence less suitable.

5) **Words such as "dissapoint", "horrible" etc have high feature importance**, as evident from the wordcloud. While these words are important **to classify negative reviews, words like "love", "good", "best" etc. also have high feature importance, as they intuitively denote positive reviews.**