Amazon Fine Food Reviews Analysis

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

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

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

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

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

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


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

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

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
```

In [2]:

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

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

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

```python
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 150000""", con)

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

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (150000, 10)
```

Out[2]:

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

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

In [4]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [6]:
```
display['COUNT(*)'].sum()
```

Out[6]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [7]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [8]:

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

In [9]:

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

Out[9]:

```
(126359, 10)
```

In [10]:

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

Out[10]:

```
84.23933333333333
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [11]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)
```

```
display.head()
```

Out[11]:

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

In [12]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:

```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

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

```
(126357, 10)
```

Out[13]:

```
1    106326
0     20031
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

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

In [14]:

```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
I grew up reading these Sendak books, and watching the Really Rosie mov
ie that incorporates them, and love them. My son loves them too. I do h
owever, miss the hard cover version. The paperbacks seem kind of flimsy
```

```
and it takes two hands to keep the pages open.
==================================================
Its about time Spanish products started getting their due.. The most fa
mous (rightly so) Spanish cheese, Manchego, is world class, and is real
ly tough to beat.  Try some with some fig cake, or some quince paste, o
r drizzled with olive oil garnished with rosemary..  Serve with a fino 
sherry, manzanilla, or any number of red wines (depending on age of che
ese), and you are guaranteed a winning combination..  Sliced, melted ov
er a great burger, with a roasted red pepper and a hearty glass of eart
hy zinfandel = heavenly joy..  Cube and marinate in Spanish olive oil i
s also a treat... I have had no problems with iGourmet so far, so I ca
n't comment on their customer service - all of my orders have been ship
ped quickly (1-3 business days), without issue.  Their Manchego is much
better than I can get at the local gourmet grocery stores.  They have g
reat specials and offers, so I have to count myself as a big iGourmet f
an.  Regardless, Manchego cheese is so good, you'll undoubtedly be back
for more.. and more..  and more.
==================================================
I love this stuff.  I nuke a mug a milk until it's very hot, drop in 2
of the triangles, stir until the chocolate melts, then froth it with my
Aerolatte.  Simple and tasty.
==================================================
There's nothing like the scent of real lavender! Just a whiff smells so
good. Besides enjoying the fragrance, I've only used a small amount a f
ew times to make some tea but it is wonderful! Can't wait to try it in
ice cubes, add a pinch on top of a dessert, throw a little into homemad
e laundry soap, or whatever else comes to mind. Would definitely buy mo
re!
==================================================
```

In [15]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
I grew up reading these Sendak books, and watching the Really Rosie mov
```

```
I grew up reading these Sendak books, and watching the Really Rosie mov
ie that incorporates them, and love them. My son loves them too. I do h
owever, miss the hard cover version. The paperbacks seem kind of flimsy
and it takes two hands to keep the pages open.
```

In [16]:

```python
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
I grew up reading these Sendak books, and watching the Really Rosie mov
ie that incorporates them, and love them. My son loves them too. I do h
owever, miss the hard cover version. The paperbacks seem kind of flimsy
and it takes two hands to keep the pages open.
==================================================
Its about time Spanish products started getting their due.. The most fa
mous (rightly so) Spanish cheese, Manchego, is world class, and is real
ly tough to beat.  Try some with some fig cake, or some quince paste, o
r drizzled with olive oil garnished with rosemary..  Serve with a fino
sherry, manzanilla, or any number of red wines (depending on age of che
ese), and you are guaranteed a winning combination..  Sliced, melted ov
er a great burger, with a roasted red pepper and a hearty glass of cart
```

```
er a great burger, with a roasted red pepper and a hearty glass of eart
hy zinfandel = heavenly joy..  Cube and marinate in Spanish olive oil i
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ped quickly (1-3 business days), without issue.  Their Manchego is much
better than I can get at the local gourmet grocery stores.  They have g
reat specials and offers, so I have to count myself as a big iGourmet f
an.  Regardless, Manchego cheese is so good, you'll undoubtedly be back
for more.. and more..  and more.
==================================================
I love this stuff.  I nuke a mug a milk until it's very hot, drop in 2
of the triangles, stir until the chocolate melts, then froth it with my
Aerolatte.  Simple and tasty.
==================================================
There's nothing like the scent of real lavender! Just a whiff smells so
good. Besides enjoying the fragrance, I've only used a small amount a f
ew times to make some tea but it is wonderful! Can't wait to try it in
ice cubes, add a pinch on top of a dessert, throw a little into homemad
e laundry soap, or whatever else comes to mind. Would definitely buy mo
re!
```

In [17]:

```python
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
I love this stuff.  I nuke a mug a milk until it is very hot, drop in 2
of the triangles, stir until the chocolate melts, then froth it with my
Aerolatte.  Simple and tasty.
==================================================
```

In [19]:
```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I grew up reading these Sendak books, and watching the Really Rosie mov
ie that incorporates them, and love them. My son loves them too. I do h
owever, miss the hard cover version. The paperbacks seem kind of flimsy
and it takes two hands to keep the pages open.
```

In [20]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
I love this stuff I nuke a mug a milk until it is very hot drop in 2 of
the triangles stir until the chocolate melts then froth it with my Aero
latte Simple and tasty
```

In [21]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in
 the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
```

```
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
```

```
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 126357/126357 [00:56<00:00, 2252.69it/s]
```

In [23]:
```
preprocessed_reviews[1500]
```

Out[23]:
```
'love stuff nuke mug milk hot drop triangles stir chocolate melts froth
aerolatte simple tasty'
```

Obtaining the Required DataFrame:

In [24]:
```
type(preprocessed_reviews)
```

Out[24]:
```
list
```

In [25]:
```
print(final.shape)
```

```
(126357, 10)
```

We obtain a list at the end of all the Preprocessing whereas the data frame that we obtained at the end was named 'final'. Initially I considered 150K datapoints to work upon which got reduced to approx. 126K datapoints after all the text processing and data deduplication.

Out of these 126K datapoints in total we will consider only 100K to be applied to the Decision Tree Algorithm.

In [26]:
```
final['Preprocessed_Reviews'] = preprocessed_reviews
```

Basically I have taken the entire list and added the list as a column to the entire dataframe, such that each value corresponds to a row in the dataframe.

In [27]:
```
final.head()
```

Out[27]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
138699	150517	0006641040	ABW4IC5G5G8B5	kevin clark	0	
138698	150516	0006641040	A3OI7ZGH6WZJ5G	Mary Jane Rogers "Maedchen"	0	
138696	150514	0006641040	A2ONB6ZA292PA	Rosalind Matzner	0	
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0	

Now I have a total of approx. 126K rows in the dataframe called 'final', of which I will consider only 100K rows to be applied to the Decision Tree Classifier. Also here you have the Unix Timestamp in the data, which is basically the time when the review was posted.

This makes it possible to carry out Time Based Split of the data instead of random splitting of the data into Train, CV and Test Datasets. For Time Based Split I will take the oldest of the reviews as the Training Data, the intermediate reviews as the CV data and the latest reviews as the Test data.

In [28]:
```
final_TBS = final.sort_values('Time')
```

In [29]:
```
final_TBS.head()
```

Out[29]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	

Now the values are sorted on the basis of Time. We know that by default the values are sorted in ascending order.

Further Data Processing :-

First I will remove all the useless columns from my dataframe. The only columns that we are concerned about here in this case are the 'Score' & 'Preprocessed_Reviews' (Without carrying out any Feature Engineering). Remaining columns in the dataframe are of no use to us.

In [30]:
```
df = final_TBS[['Score','Preprocessed_Reviews']]
```

In [31]:
```
df.head()
```

Out[31]:

	Score	Preprocessed_Reviews
138706	1	witty little book makes son laugh loud recite ...
138683	1	remember seeing show aired television years ag...
70688	1	bought apartment infested fruit flies hours tr...
1146	1	really good idea final product outstanding use...
1145	1	received shipment could hardly wait try produc...

Applying Decision Trees :-

Obtaining Train, CV and Test Data :-

In [32]:
```
Dec_treedf = df[:100000]
```

Basically we are taking a total of 100K reviews for the model. Since I am carrying out Time Based Splitting into Train, CV and Test datasets, I will split them in 70:10:20 ratio respectively.

```
So, # of Datapoints in Train data = 70,000
    # of Datapoints in CV data = 10,000
    # of Datapoints in Test data = 20,000
```

In [33]:
```
Tr_dectree_df = Dec_treedf[:70000]
CV_dectree_df = Dec_treedf[70000:80000]
Te_dectree_df = Dec_treedf[80000:100000]
```

In [34]:
```
Tr_dectree_df.shape
```

Out[34]:
```
(70000, 2)
```

In [35]:
```
CV_dectree_df.shape
```

Out[35]:
```
(10000, 2)
```

In [36]:
```
Te_dectree_df.shape
```

Out[36]:
```
(20000, 2)
```

Yes everything is working as expected: There are 70K points in the Training data, 10K points in the CV data and 20K points in the Test data.

Now we can split the data as features in X and the class label in Y.

In [37]:
```
X_DTTrain = Tr_dectree_df['Preprocessed_Reviews']
Y_DTTrain = Tr_dectree_df['Score']

X_DTCV = CV_dectree_df['Preprocessed_Reviews']
Y_DTCV = CV_dectree_df['Score']

X_DTTest = Te_dectree_df['Preprocessed_Reviews']
Y_DTTest = Te_dectree_df['Score']
```

In [38]:
```
Y_DTTrain.value_counts()
```

Out[38]:
```
1    59861
0    10139
Name: Score, dtype: int64
```

In [39]:
```
Y_DTCV.value_counts()
```

Out[39]:
```
1    8241
0    1759
Name: Score, dtype: int64
```

In [40]:
```
Y_DTTest.value_counts()
```

Out[40]:
```
1    16305
0     3695
Name: Score, dtype: int64
```

As expected, this is an imbalanced real world dataset.

[4] Featurization

[4.1] BAG OF WORDS

In [0]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abb
```

```
ott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [0]:

```
#bi-gram, tri-gram and n-gram

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

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

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

[4.3] TF-IDF

In [0]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
```

```
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble find', 'able get', 'absolute', 'absolutely', 'absolutely deliciou
s', 'absolutely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [0]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [0]:

```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
```

```
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors
-negative300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wond
erful', 0.9946032166481018), ('excellent', 0.9944332838058472), ('espec
ially', 0.9941144585609436), ('baked', 0.9940600395202637), ('salted',
0.994047224521637), ('alternative', 0.9937226176261902), ('tasty', 0.99
36816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('p
opcorn', 0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.99
92451071739197), ('melitta', 0.999218761920929), ('choice', 0.999210238
```

```
4567261), ('american', 0.9991837739944458), ('beef', 0.999178051948547
4), ('finish', 0.9991567134857178)]
```

In [0]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

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

[4.4.1.1] Avg W2V

In [0]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
```

```
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████████████████████████
████████| 4986/4986 [00:03<00:00, 1330.47it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [0]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is st
ored in this list
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
```

```
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████
███████████| 4986/4986 [00:20<00:00, 245.63it/s]
```

[5.1] SET 1 : Applying Decision Trees on BOW :-

In [41]:
```
count_vect = CountVectorizer()
count_vect.fit(X_DTTrain) #Again the fit function is applied only on th
e Train data.

#fit internally stores the parameters that will be used for transformin
g the data from the text to a numerical vector
```

Out[41]:
```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

In [42]:
```
X_DTTrain_BOW = count_vect.transform(X_DTTrain)
X_DTCV_BOW = count_vect.transform(X_DTCV)
X_DTTest_BOW = count_vect.transform(X_DTTest)
```

In [43]:
```
print("Shapes before the BOW Vectorization was carried out:")
```

```python
print(X_DTTrain.shape,Y_DTTrain.shape)
print(X_DTCV.shape,Y_DTCV.shape)
print(X_DTTest.shape,Y_DTTest.shape)

print("*"*100)

print("Shapes after the BOW Vectorization was carried out:")

print(X_DTTrain_BOW.shape,Y_DTTrain.shape)
print(X_DTCV_BOW.shape,Y_DTCV.shape)
print(X_DTTest_BOW.shape,Y_DTTest.shape)
```

```
Shapes before the BOW Vectorization was carried out:
(70000,) (70000,)
(10000,) (10000,)
(20000,) (20000,)
************************************************************************
****************************
Shapes after the BOW Vectorization was carried out:
(70000, 49207) (70000,)
(10000, 49207) (10000,)
(20000, 49207) (20000,)
```

Hyperparameter Tuning on the BOW Representation :-

Here we care about 2 hyperparameters :-

- "max_depth", which we would be considering in the range :- { [4,6, 8, 9,10,12,14,17] }
- "min_samples_split", which we would be considering in the range :- { [2,10,20,30,40,50] }

We can easily apply GridSearchCV in this case since we are only focused on 2 Hyperparameters. If we had to obtain the best values for a lot of hyperparameters, GridSearchCV won't have been the best option considering its time complexity.

In [44]:
```
depth_hyperparameter = [4,6,8,9,10,12,14,17]
samples_hyperparameter = [2,10,20,30,40,50]
```

Here we have generated a list with the required values of the 2 hyperparameters. The necessary packages are imported as follows:-

In [45]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score
import numpy as np
import warnings
```

However in this case for the Decision Tree Classification there is no need to carry out Standardization because we do not have any hyperplane in consideration over here unlike the other algorithms that we have encountered previously.

Function to obtain the DataFrame for the AUC Metric Calculation from the Training Data :-

In [46]:
```
def train_heatmap(X_Train,Y_Train):

    df1 = []
    df2 = []
    Train_AUC = []

    for i in depth_hyperparameter:
        for j in samples_hyperparameter:
            df1.append(i)
            df2.append(j)

            Train_model = DecisionTreeClassifier(criterion='gini',split
ter='best',class_weight='balanced',
                                                 min_samples_split=j,max_depth=
i)
            Train_model.fit(X_Train,Y_Train)

            Y_Train_pred = Train_model.predict_proba(X_Train)[:,1]
```

```
            Train_AUC.append(roc_auc_score(Y_Train,Y_Train_pred))

    train_data = {'max_depth':df1,'min_samples_split':df2,'AUC_Score':T
rain_AUC}
    train_dataframe = pd.DataFrame(train_data)
    train_dataframe = train_dataframe.pivot("max_depth","min_samples_sp
lit","AUC_Score")

    return train_dataframe
```

Function to obtain the DataFrame for the AUC Metric Calculation from the CV Data :-

In [47]:
```
def cv_heatmap(X_Train,Y_Train,X_CV,Y_CV):

    df3 = []
    df4 = []
    CV_AUC = []

    for i in depth_hyperparameter:
        for j in samples_hyperparameter:
            df3.append(i)
            df4.append(j)

            CV_model = DecisionTreeClassifier(criterion='gini',splitter
='best',class_weight='balanced',
                                              min_samples_split=j,max_depth=
i)
            CV_model.fit(X_Train,Y_Train)

            Y_CV_pred = CV_model.predict_proba(X_CV)[:,1]
            CV_AUC.append(roc_auc_score(Y_CV,Y_CV_pred))

    cv_data = {'max_depth':df3,'min_samples_split':df4,'AUC_Score':CV_A
UC}
    cv_dataframe = pd.DataFrame(cv_data)
    cv_dataframe = cv_dataframe.pivot("max_depth","min_samples_split",
"AUC_Score")
```

```
    return cv_dataframe
```

What I have carried out in both of these functions is as follows :-

- We have already initialized 2 Lists for each of the 2 Hyperparameters :- "depth_hyperparameter" for the parameter "max_depth" and "samples_hyperparameter" for the parameter "min_samples_split" in the Decision Tree Classifier.
- Now basically we are trying to obtain a dataframe with all the possible combinations of the 2 Hyperparameters to obtain the corresponding Heatmap with the AUC Scores for that particular combination shown as an annotation in the Heatmap.
- Remember that even in the case to obtain the Cross Validation DataFrame, we are supposed to fit() only on the Train dataset. We give column headers to each of the columns in the DataFrame which we consequently pivot to obtain the data in the dataframe in the required format so that the Heatmap is plotted as expected.
- Basically, at the end of calling each of these functions, we obtain the corresponding dataframe, whether that be for the Training Data or the CV Data.

Function to plot the Seaborn HeatMaps for the Train & CV Dataframes obtained :-

In [48]:
```
def plot_heatmaps(train_df,cv_df):
    fig, ax = plt.subplots(figsize=(30,5))

    plt.subplot(1, 3, 1)
    sns.heatmap(train_df, annot=True,cmap='RdYlGn',linewidths=0.5,annot
_kws={"size": 13})
    plt.xlabel('Min_samples_split',fontsize=12)
    plt.ylabel('Max_Depth',fontsize=12)
    plt.title("Training Data AUC Score Heatmap",fontsize=15)

    plt.subplot(1, 3, 2)
    sns.heatmap(cv_df, annot=True,cmap='RdYlGn',linewidths=0.5,annot_kw
s={"size": 13})
    plt.xlabel('Min_samples_split',fontsize=12)
    plt.ylabel('Max_Depth',fontsize=12)
```

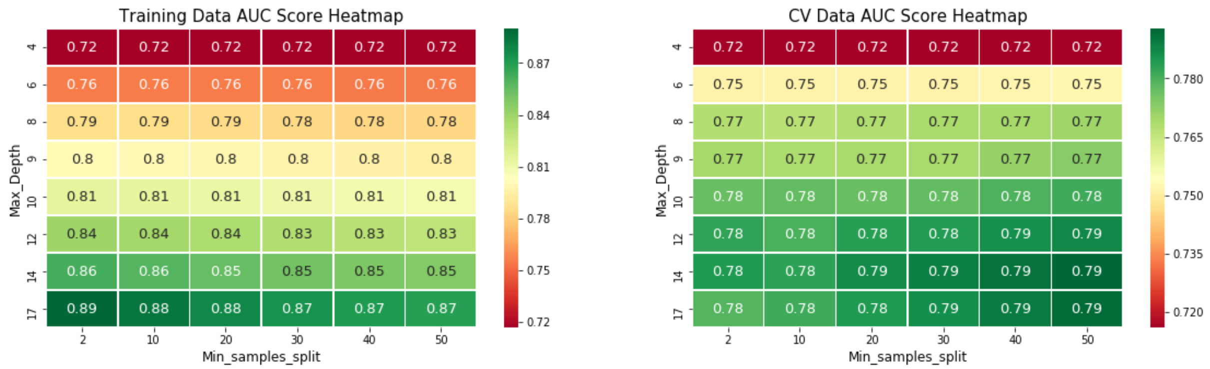
```
    plt.title("CV Data AUC Score Heatmap",fontsize=15)

    plt.show()
```

- In the function above, we are plotting the Seaborn HeatMaps for the Train and CV Dataframes next to each other as subplots for easier comparison of the AUC Values.
- Note that we could have carried out the same with the help of a 3-D plot of the 2 Hyperparameters. However, the issue with this approach is the fact that it becomes difficult to visualise the right combination of the 2 Hyperparameters.
- Again, our aim in choosing the Best Hyperparameters is the same as before : The AUC Value on the CV Dataset be the maximum and the gap between the Train and CV AUC values be low, which we obtain with the help of the Heatmaps obtained below. The same is confirmed by carrying out the GridSearchCV with 10-fold Cross Validation and obtaining the best*estimator*.

Calling the Different Functions to obtain the Train and CV Dataframes and Obtaining the Seaborn HeatMaps for them :-

In [52]:
```
BOW_Train_df = train_heatmap(X_DTTrain_BOW,Y_DTTrain)
BOW_CV_df = cv_heatmap(X_DTTrain_BOW,Y_DTTrain,X_DTCV_BOW,Y_DTCV)
plot_heatmaps(BOW_Train_df,BOW_CV_df)
```



With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.79, and the minimum AUC Value on the Train Heatmap for the same combination is 0.83.
- Therefore the Best Combination of Max_Depth and Min_samples_split for the BOW Featurization is either of the following:

Max_Depth=17. Min_samples_split= 50 or 40 or 30.

- Therefore the best of these values is obtained by GridSearchCV below.

In [53]:

```
warnings.filterwarnings('ignore')

#Carrying out 10-fold Cross Validation. class_weight is taken as 'balan
ced' since the data that we originally had
#was an Imbalanced Real World Dataset.

parameters= [{'max_depth':depth_hyperparameter, 'min_samples_split':sam
ples_hyperparameter}]
model1 = DecisionTreeClassifier(criterion='gini',splitter='best',class_
weight='balanced')

DT_BOW = GridSearchCV(model1,parameters,scoring='roc_auc',cv=10)
DT_BOW.fit(X_DTTrain_BOW,Y_DTTrain)

print(DT_BOW.best_estimator_)
```

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=17, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

Therefore obtaining the Best Hyperparameters of the model after carrying out Hyperparameter tuning via GridSearchCV, we obtain the following Best values :-

- max_depth = 17

- min_samples_split = 50

Testing with the Test Data on the BOW Representation:-

In [68]:
```
BOW_Test = DecisionTreeClassifier(criterion='gini',splitter='best',clas
s_weight='balanced',max_depth=17,
                                  min_samples_split=50)
BOW_Test.fit(X_DTTrain_BOW,Y_DTTrain)
```

Out[68]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=17, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [55]:
```
Y_DTTrain.shape
```

Out[55]:
```
(70000,)
```

In [56]:
```
print(X_DTTrain_BOW.shape)
```

```
(70000, 49207)
```

In [57]:
```
print(Y_DTTest.shape)
```

```
(20000,)
```

In [58]:
```
print(X_DTTest_BOW.shape)
```

```
(20000, 49207)
```

In [59]:

```
from sklearn.metrics import roc_curve, auc

train_fpr1,train_tpr1,threshold = roc_curve(Y_DTTrain,BOW_Test.predict_proba(X_DTTrain_BOW)[:,1])
test_fpr1,test_tpr1,threshold = roc_curve(Y_DTTest,BOW_Test.predict_proba(X_DTTest_BOW)[:,1])
```

Plotting the graph between the FPR Values as well as the TPR values for the Training Data as well as the Test data we obtain the ROC Curve as follows:

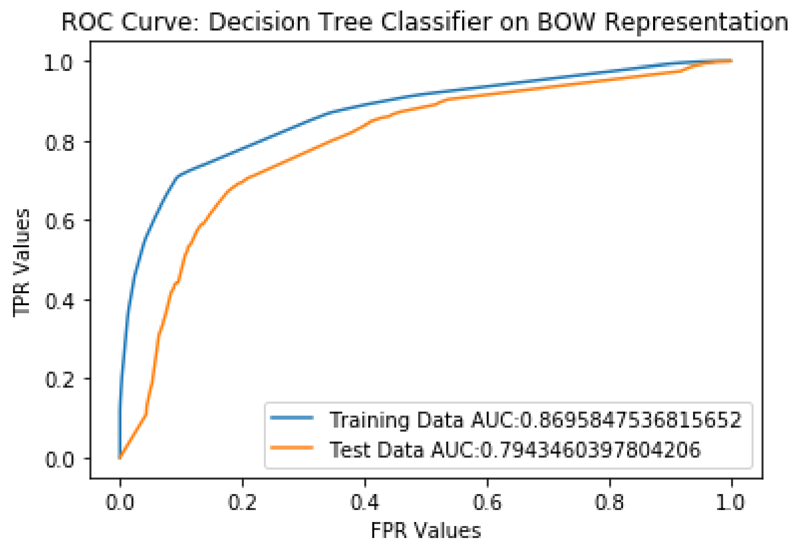
In [60]:

```
import matplotlib.pyplot as plt

plt.plot(train_fpr1,train_tpr1,label ='Training Data AUC:' + str(auc(train_fpr1,train_tpr1)))
plt.plot(test_fpr1,test_tpr1,label = 'Test Data AUC:' + str(auc(test_fpr1,test_tpr1)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Decision Tree Classifier on BOW Representation')

plt.grid(False)
plt.show()
```



In [61]:
```
Y_Train_pred1 = BOW_Test.predict_proba(X_DTTrain_BOW)[:,1]
Y_Test_pred1 = BOW_Test.predict_proba(X_DTTest_BOW)[:,1]
```

Function to Obtain the Best Threshold & Predictions:-

In [62]:
```
def matrixpredict(data,thresholds,tpr,fpr):
    matrixpredict.best_tradeoff = tpr*(1-fpr)
    matrixpredict.ideal_threshold = thresholds[matrixpredict.best_trade
off.argmax()]

    predictions=[]

    for i in data:
        if i>= matrixpredict.ideal_threshold:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Function to Plot the Training Confusion Matrix HeatMap:-

In [63]:
```
import seaborn as sns

def plottrainmatrix (train_matrix):
    sns.set_style("whitegrid")

    labels = [0,1]

    print("-"*20, "Training Confusion Matrix", "-"*20)
    print(" ")
    print("The Training Data Confusion Matrix is as follows:")
    print(" ")
    print("The maximum value of tpr*(1-fpr) :", max(matrixpredict.best_
tradeoff))
    print("Threshold for Maximum Value of tpr*(1-fpr) :",round(matrixpr
edict.ideal_threshold,3))

    plt.figure(figsize=(10,7))

    sns.heatmap(train_matrix,
                annot=True, cmap="YlGnBu",fmt=".0f", xticklabels=labels
, yticklabels=labels,
                annot_kws={"size": 15})
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

Function to Plot the Test Confusion Matrix HeatMap:-

In [64]:
```
import seaborn as sns

def plottestmatrix (test_matrix):
    labels = [0,1]

    print("-"*20, "Test Data Confusion Matrix", "-"*20)
    print(" ")
    print("The Test Data Confusion Matrix is as follows:")
```

```
    print(" ")
    print("The maximum value of tpr*(1-fpr) :", max(matrixpredict.best_
tradeoff))
    print("Threshold for Maximum Value of tpr*(1-fpr) :",round(matrixpr
edict.ideal_threshold,3))

    plt.figure(figsize=(10,7))

    sns.heatmap(test_matrix,annot=True, cmap="YlGnBu",fmt=".0f", xtickl
abels=labels,
                ytickllabels=labels,annot_kws={"size": 15})
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

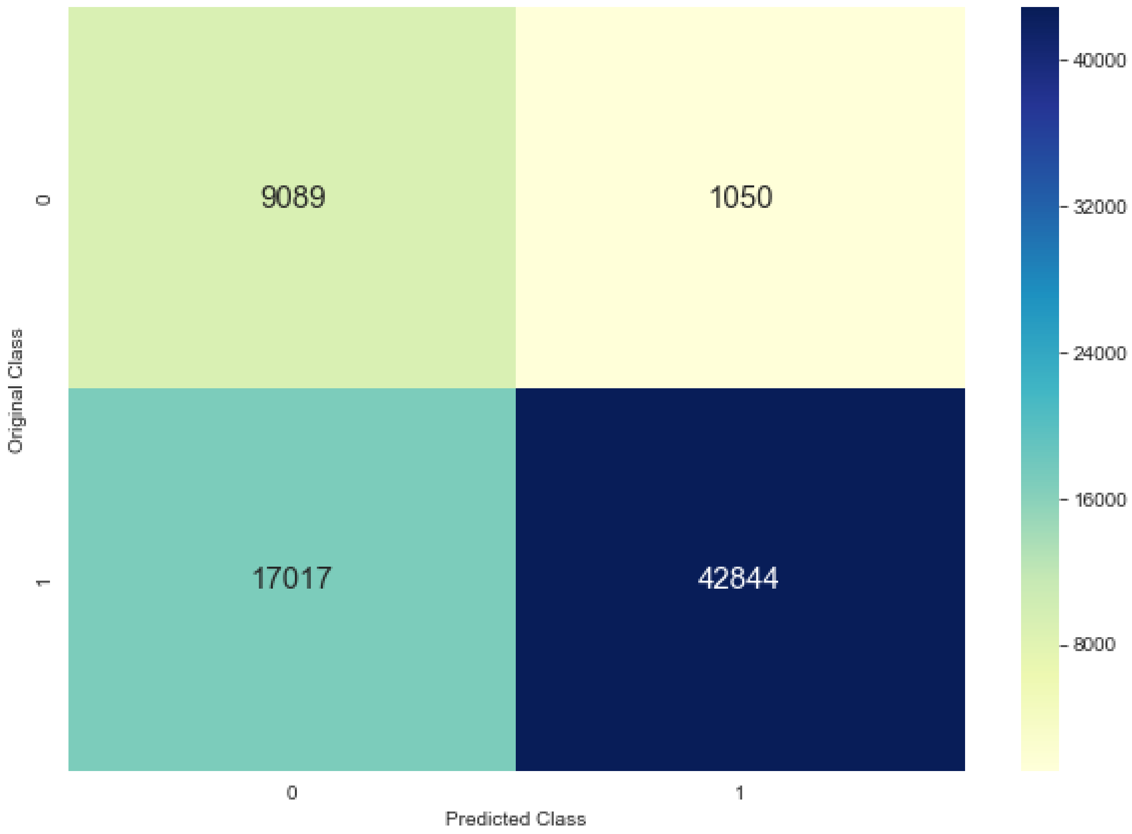
Calling the Different Functions and Obtaining Confusion Matrices for the Ideal Threshold Value:-

In [65]:
```
BOW_Train = confusion_matrix(Y_DTTrain,matrixpredict(Y_Train_pred1,thre
shold,train_tpr1,train_fpr1))
plottrainmatrix(BOW_Train)
```

```
-------------------- Training Confusion Matrix --------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.6416039417246199
Threshold for Maximum Value of tpr*(1-fpr) : 0.444
```



Accuracy on the Training Data => (42844+9089)/70000 = 74.19%

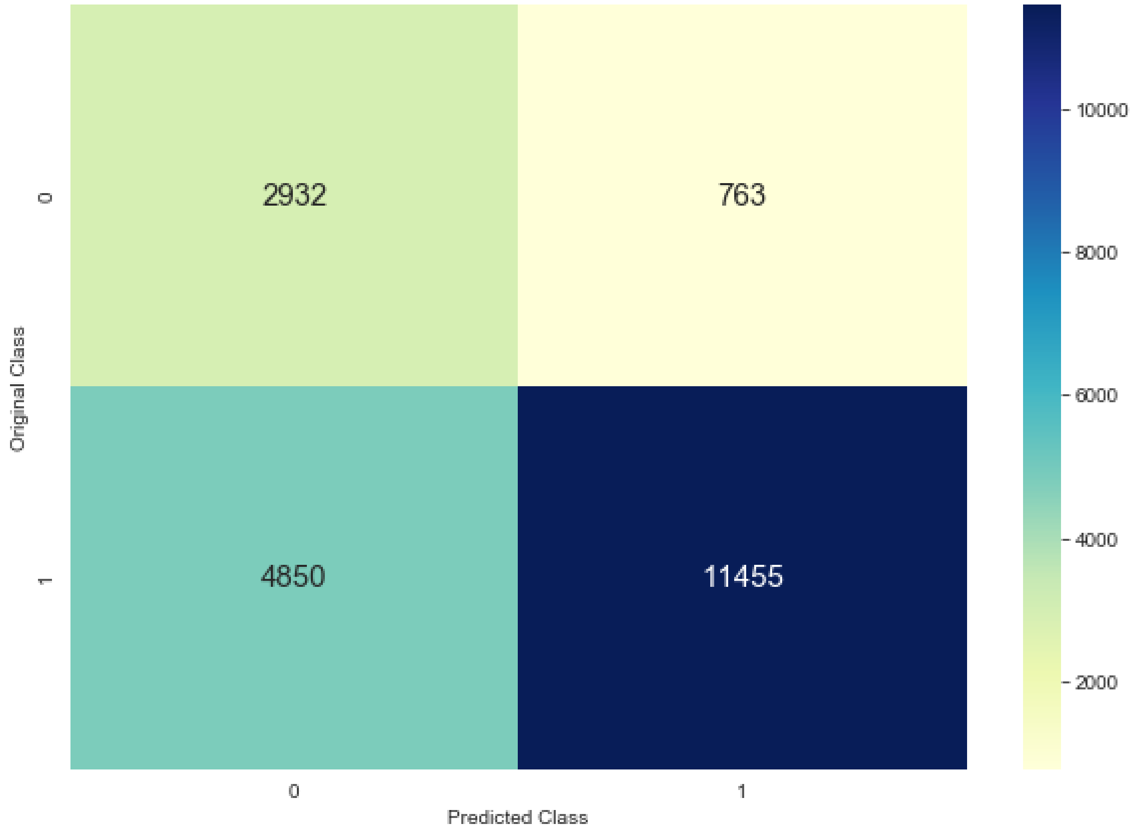
The Test Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottestmatrix() that were defined previously:

In [66]:
```
BOW_Test = confusion_matrix(Y_DTTest,matrixpredict(Y_Test_pred1,thresho
ld,test_tpr1,test_fpr1))
plottestmatrix(BOW_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:
```

```
The maximum value of tpr*(1-fpr) : 0.5574729685598322
Threshold for Maximum Value of tpr*(1-fpr) : 0.404
```



Accuracy on the Test Data => (11443+2931)/20000 = 71.93%

[5.1.1] Top 20 Important Features with Decision Tree Implementation & BOW Featurization :-

In [69]:
```
BOW_feature_names = count_vect.get_feature_names()
```

```
BOW_feature_importances = BOW_Test.feature_importances_
BOW_feature_importances_sorted = np.argsort(BOW_feature_importances)
BOW_feature_importances_reverse = np.flip(BOW_feature_importances_sorte
d)
```

In [158]:
```
print("The Top 20 Important Features with BOW Featurization and their c
orresponding feature "
      "importances are as follows:")
print("="*100)
for i in BOW_feature_importances_reverse[:20]:
    print(BOW_feature_names[i],"\t", '--->',np.round(BOW_feature_import
ances[i],3))
```

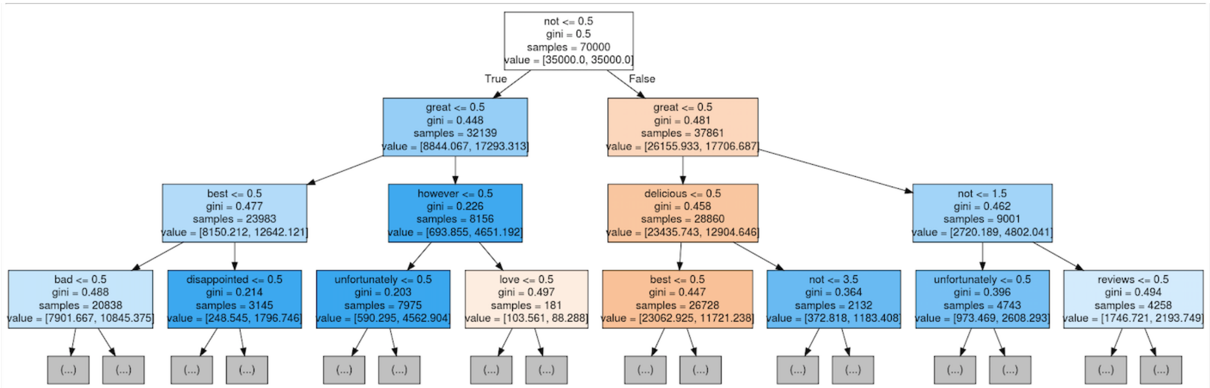
```
The Top 20 Important Features with BOW Featurization and their correspo
nding feature importances are as follows:
========================================================================
=============================
not      ---> 0.174
great    ---> 0.103
best     ---> 0.054
delicious        ---> 0.049
love     ---> 0.035
perfect          ---> 0.032
good     ---> 0.029
loves    ---> 0.028
bad      ---> 0.024
disappointed     ---> 0.019
nice     ---> 0.018
favorite         ---> 0.017
excellent        ---> 0.015
wonderful        ---> 0.015
unfortunately    ---> 0.014
easy     ---> 0.013
thought          ---> 0.012
money    ---> 0.011
highly   ---> 0.009
awful    ---> 0.008
```

[5.1.2] Graphviz visualization of Decision Tree on BOW Featurization :-

In [72]:
```
from sklearn import tree
BOW_tree = tree.export_graphviz(decision_tree=BOW_Test,max_depth=3,feat
ure_names = BOW_feature_names,
                                  filled = True)
```

In [73]:
```
from IPython.display import Image
Image(filename='BOW_DT_filled.png')
```

Out[73]:



Following is what I have carried out in this scenario :-

- Initially the variable BOW_Tree is declared to be equal to the value obtained when export_graphviz is called. Here, 'decision_tree' parameter has the 'BOW_Test' ie the decision tree where the Hyperparameter Tuning has been successfully carried out.
- Then 'feature_names' parameter has been provided with the variable called 'BOW_feature_names' which has all the feature names obtained by the BOW Representation. Similarly, for the ease of visualization, max_depth has been provided only with a value of 3.
- Also the parameter called 'filled' has been set a Boolean Value of 'True' :- This basically means that when it's set to 'True' it paints nodes to indicate majority class for classification and the extremity of values in case of regression.

- Now, since we have not assigned any particular value to the parameter 'out_file' it takes the default value of String and returns a String output. Now, when this output is passed to the following website link :- 'http://webgraphviz.com/', we obtain the HTML link of the Decision Tree.
- Now this HTML Link is converted to a png image online, downloaded and then copied to the Current Working Directory in order to be uploaded to the Jupyter Notebook with the help of the code block stated above.

[5.2] SET 2 : Applying Decision Trees on TFIDF :-

In [74]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_DTTrain)

# Again fit is carried out only on the Training data. fit() internally
 stores the parameters that will be used to
#convert the Text to a numerical vector.
```

Out[74]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='conten
t',
        lowercase=True, max_df=1.0, max_features=None, min_df=10,
        ngram_range=(1, 2), norm='l2', preprocessor=None, smooth_idf=Tr
ue,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=Tru
e,
        vocabulary=None)
```

In [75]:
```
X_DTTrain_TFIDF = tf_idf_vect.transform(X_DTTrain)
X_DTCV_TFIDF = tf_idf_vect.transform(X_DTCV)
X_DTTest_TFIDF = tf_idf_vect.transform(X_DTTest)
```

In [76]:
```
print("Shapes before the TFIDF Vectorization was carried out:")
```

```python
print(X_DTTrain.shape,Y_DTTrain.shape)
print(X_DTCV.shape,Y_DTCV.shape)
print(X_DTTest.shape,Y_DTTest.shape)

print("="*100)

print("Shapes after the TFIDF Vectorization was carried out:")

print(X_DTTrain_TFIDF.shape,Y_DTTrain.shape)
print(X_DTCV_TFIDF.shape,Y_DTCV.shape)
print(X_DTTest_TFIDF.shape,Y_DTTest.shape)
```

```
Shapes before the TFIDF Vectorization was carried out:
(70000,) (70000,)
(10000,) (10000,)
(20000,) (20000,)
====================================================================================================
Shapes after the TFIDF Vectorization was carried out:
(70000, 41297) (70000,)
(10000, 41297) (10000,)
(20000, 41297) (20000,)
```

Hyperparameter Tuning on the TFIDF Representation :-

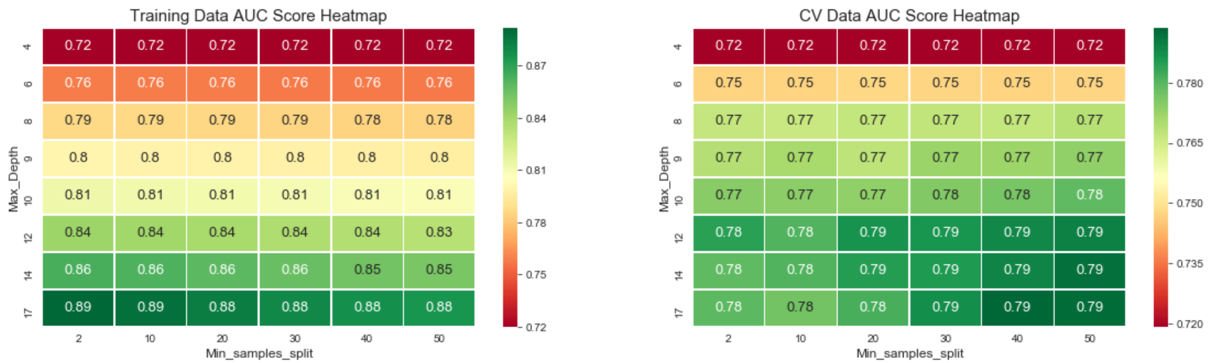
Again, all that we care about are 2 hyperparameters :-

- "max_depth", which we would be considering in the range :- { [4,6, 8, 9,10,12,14,17] }
- "min_samples_split", which we would be considering in the range :- { [2,10,20,30,40,50] }

However in this case for the Decision Tree Classification there is no need to carry out Standardization because we do not have any hyperplane in consideration over here unlike the other algorithms that we have encountered previously.

Calling the Different Functions to obtain the Train and CV Dataframes and Obtaining the Seaborn HeatMaps for them :-

In [77]:
```
TFIDF_Train_df = train_heatmap(X_DTTrain_TFIDF,Y_DTTrain)
TFIDF_CV_df = cv_heatmap(X_DTTrain_TFIDF,Y_DTTrain,X_DTCV_TFIDF,Y_DTCV)
plot_heatmaps(TFIDF_Train_df,TFIDF_CV_df)
```



With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.79, and the minimum AUC Value on the Train Heatmap for the same combination is 0.88.
- Therefore the Best Combination of Max_Depth and Min_samples_split for the BOW Featurization is either of the following:

Max_Depth=12 or 17. Min_samples_split= 50 or 40 or 30.

- Therefore the best of these values is obtained by GridSearchCV below.

In [78]:
```
warnings.filterwarnings('ignore')

#Carrying out 10-fold Cross Validation. class_weight is taken as 'balan
ced' since the data that we originally had
#was an Imbalanced Real World Dataset.

model2 = DecisionTreeClassifier(criterion='gini',splitter='best',class_
```

```
weight='balanced')

DT_TFIDF = GridSearchCV(model2,parameters,scoring='roc_auc',cv=10)
DT_TFIDF.fit(X_DTTrain_TFIDF,Y_DTTrain)

print(DT_TFIDF.best_estimator_)
```

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=17, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

Therefore, according to the Hyperparameter Tuning and obtaining the Best Hyperparameters of the model after carrying out Hyperparameter tuning via GridSearchCV, we obtain the following Best values :-

- max_depth = 17
- min_samples_split = 50

Testing with the Test Data on the TFIDF Representation:-

In [113]:
```
TFIDF_Test = DecisionTreeClassifier(criterion='gini',splitter='best',cl
ass_weight='balanced',max_depth=17,
                                  min_samples_split=50)
TFIDF_Test.fit(X_DTTrain_TFIDF,Y_DTTrain)
```

Out[113]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=17, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
```

```
one,
              splitter='best')
```

Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [114]:
```
Y_DTTrain.shape
```

Out[114]:
```
(70000,)
```

In [115]:
```
print(X_DTTrain_TFIDF.shape)
```

```
(70000, 41297)
```

In [116]:
```
print(Y_DTTest.shape)
```

```
(20000,)
```

In [117]:
```
print(X_DTTest_TFIDF.shape)
```

```
(20000, 41297)
```

In [118]:
```
from sklearn.metrics import roc_curve, auc

train_fpr2,train_tpr2,threshold = roc_curve(Y_DTTrain,TFIDF_Test.predic
t_proba(X_DTTrain_TFIDF)[:,1])
test_fpr2,test_tpr2,threshold = roc_curve(Y_DTTest,TFIDF_Test.predict_p
roba(X_DTTest_TFIDF)[:,1])
```

Plotting the graph between the FPR Values as well as the TPR values for the Training Data as well as the Test data we obtain the ROC Curve as follows:

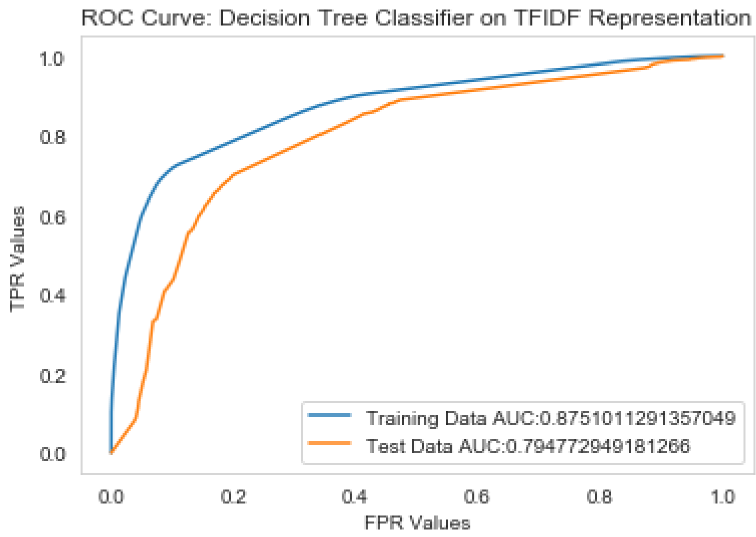
In [119]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr2,train_tpr2,label ='Training Data AUC:' + str(auc(tr
ain_fpr2,train_tpr2)))
```

```
plt.plot(test_fpr2,test_tpr2,label = 'Test Data AUC:' + str(auc(test_fp
r2,test_tpr2)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Decision Tree Classifier on TFIDF Representation'
)

plt.grid(False)
plt.show()
```



In [86]:
```
Y_Train_pred2 = TFIDF_Test.predict_proba(X_DTTrain_TFIDF)[:,1]
Y_Test_pred2 = TFIDF_Test.predict_proba(X_DTTest_TFIDF)[:,1]
```

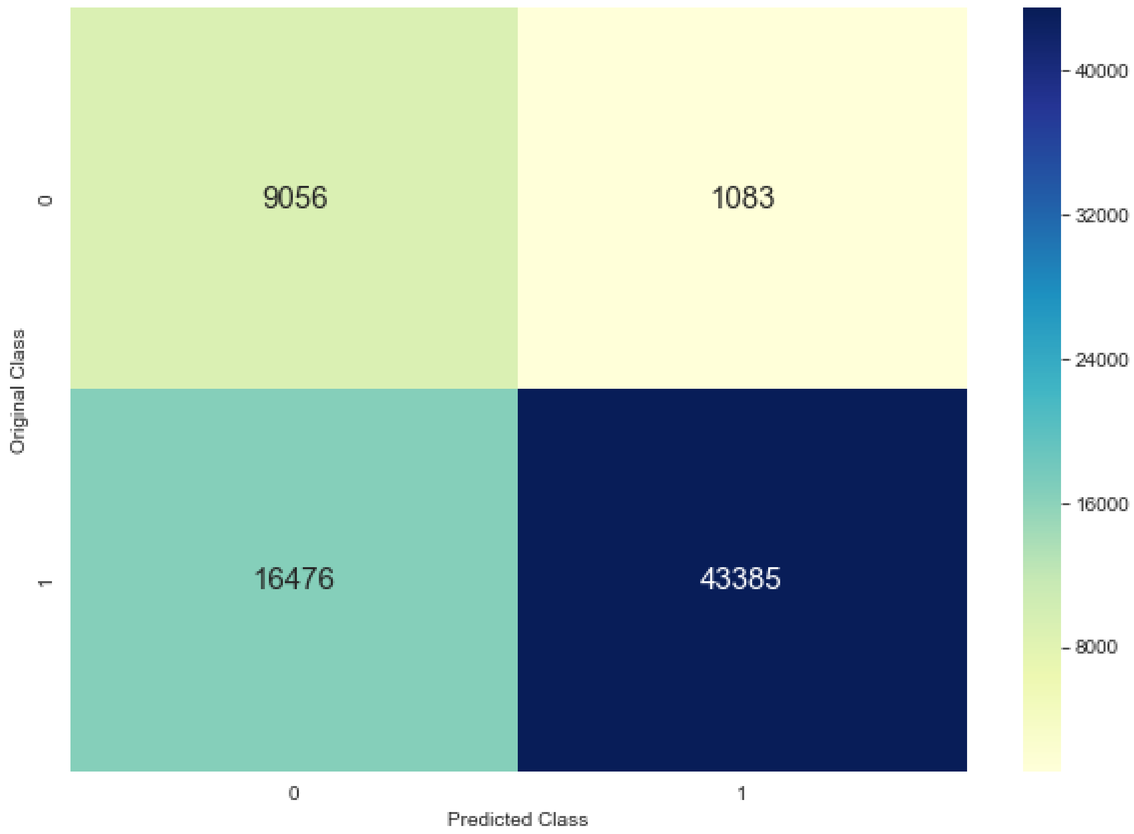
Calling the Different Functions and Obtaining Confusion Matrices for the Ideal Threshold Value:-

In [87]:
```
TFIDF_Train = confusion_matrix(Y_DTTrain,matrixpredict(Y_Train_pred2,th
reshold,train_tpr2,train_fpr2))
plottrainmatrix(TFIDF_Train)
```

```
------------------- Training Confusion Matrix -------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.6473521649084408
Threshold for Maximum Value of tpr*(1-fpr) : 0.441
```



Accuracy on the Training Data => (43385+9056)/70000 = 74.91%

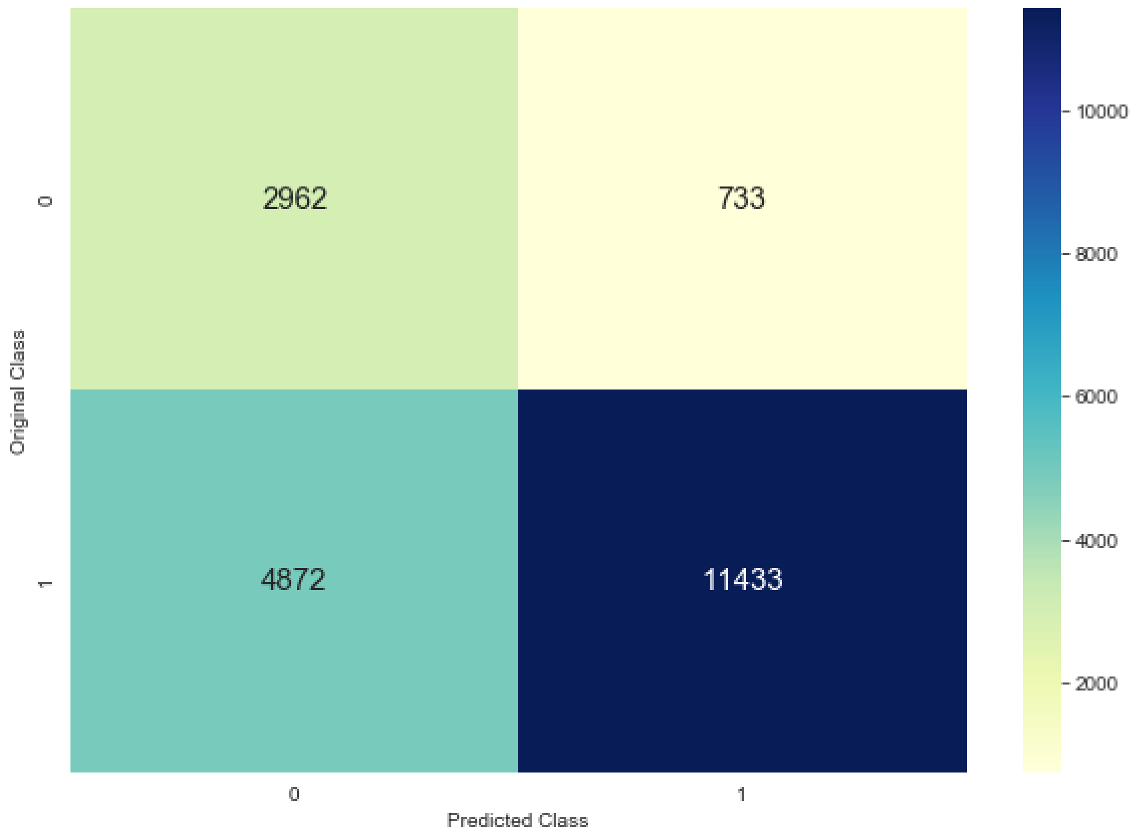
The Test Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottestmatrix() that were defined previously:

In [88]:
```
TFIDF_Test = confusion_matrix(Y_DTTest,matrixpredict(Y_Test_pred2,thres
hold,test_tpr2,test_fpr2))
plottestmatrix(TFIDF_Test)
```

```
------------------- Test Data Confusion Matrix -------------------

The Test Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.5620953749130144
Threshold for Maximum Value of tpr*(1-fpr) : 0.438
```



Accuracy on the Test Data => (11433+2962)/20000 = 71.97%

[5.2.1] Top 20 Important Features with Decision Tree Implementation & TFIDF Featurization :-

In [91]:
```
TFIDF_feature_names = tf_idf_vect.get_feature_names()
TFIDF_feature_importances = TFIDF_Test.feature_importances_
TFIDF_feature_importances_sorted = np.argsort(TFIDF_feature_importances
)
TFIDF_feature_importances_reverse = np.flip(TFIDF_feature_importances_s
orted)
```

In [159]:
```
print("The Top 20 Important Features with TFIDF Featurization and their
 corresponding feature importances"
       "are as follows:")
print("="*100)
for i in TFIDF_feature_importances_reverse[:20]:
    print(TFIDF_feature_names[i],"\t", '--->',np.round(TFIDF_feature_im
portances[i],3))
```

```
The Top 20 Important Features with TFIDF Featurization and their corres
ponding feature importancesare as follows:
=======================================================================
=============================
not	 ---> 0.155
great	 ---> 0.104
best	 ---> 0.051
delicious	 ---> 0.049
love	 ---> 0.038
perfect	 ---> 0.032
good	 ---> 0.03
loves	 ---> 0.028
bad	 ---> 0.026
disappointed	 ---> 0.024
nice	 ---> 0.021
wonderful	 ---> 0.017
excellent	 ---> 0.017
favorite	 ---> 0.016
thought	 ---> 0.014
easy	 ---> 0.013
```

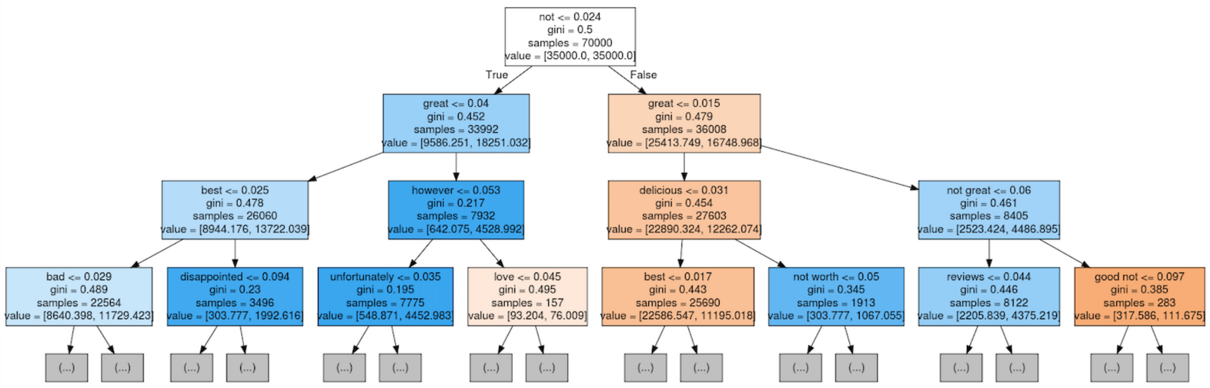
```
awful         ---> 0.01
unfortunately      ---> 0.009
reviews            ---> 0.009
not great          ---> 0.009
```

[5.2.2] Graphviz visualization of Decision Tree on TFIDF Featurization :-

In [94]:
```python
from sklearn import tree
TFIDF_tree = tree.export_graphviz(decision_tree=TFIDF_Test,max_depth=3,
feature_names = TFIDF_feature_names,
                                  filled = True)
```

In [95]:
```python
from IPython.display import Image
Image(filename='TFIDF_DT_filled.png')
```

Out[95]:



[5.3] SET 3 : Applying Decision Trees on Avg W2V :-

Converting Reviews into Numerical Vectors

using W2V vectors :-

In [96]:
```
list_of_sentence_Train =[]

for sentence in X_DTTrain:
    list_of_sentence_Train.append(sentence.split())
```

In [97]:
```
w2v_model=Word2Vec(list_of_sentence_Train,min_count=5,size=50, workers=
4)

w2v_words = list(w2v_model.wv.vocab)
print("Number of words that occur a minimum 5 times :",len(w2v_words))
print("Some of the sample words are as follows: ", w2v_words[0:50])
```

```
Number of words that occur a minimum 5 times : 15838
Some of the sample words are as follows:  ['witty', 'little', 'book',
'makes', 'son', 'laugh', 'loud', 'car', 'driving', 'along', 'always',
'sing', 'refrain', 'learned', 'india', 'roses', 'love', 'new', 'words',
'introduces', 'classic', 'willing', 'bet', 'still', 'able', 'memory',
'college', 'remember', 'seeing', 'show', 'television', 'years', 'ago',
'child', 'sister', 'later', 'bought', 'day', 'thirty', 'something', 'us
ed', 'series', 'books', 'songs', 'student', 'teaching', 'turned', 'whol
e', 'school', 'purchasing']
```

Converting the Train Data Text :-

In [98]:
```
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sent in tqdm(list_of_sentence_Train): # for each review/sentence fo
r Training Dataset
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
```

```
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|██████████| 70000/70000 [03:33<00:00, 327.71it/s]
```

```
(70000, 50)
[ 0.08374445  0.11358148 -0.6424285   0.16594547 -0.39580159 -0.2171652
1
  0.47262891 -0.09081476  0.29330332  0.33274209 -0.26223407 -0.1544759
  0.34929812  0.4287227  -0.02432394 -0.15540102  0.03349705  0.1309566
9
  0.26310493 -0.12339989 -0.03462045  0.31852649  0.42437512  0.5757571
8
  0.01906831 -0.10361083 -0.14755479 -0.18972265 -0.01085083  0.3759519
7
  0.22245147  0.14201182 -0.16854957  0.24117232  0.08469833 -0.1693630
1
 -0.03763765 -0.120778   -0.15587337 -0.05331916 -0.00095392  0.6558541
2
  0.23179963  0.34926485  0.22673576  0.07569735 -0.09777285  0.1840643
7
 -0.04635285  0.00166602]
```

Converting the CV Data Text :-

In [99]:
```
list_of_sentence_CV=[]

for sentence in X_DTCV:
    list_of_sentence_CV.append(sentence.split())
```

In [100]:
```python
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored
 in this list
for sent in tqdm(list_of_sentence_CV): # for each review/sentence in th
e CV Dataset.
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|██████████| 10000/10000 [00:39<00:00, 337.10it/s]
```

```
(10000, 50)
[-0.47151479  0.73292572 -1.17230538 -0.95917967  0.16429216 -0.26138
154
  0.0709977   0.18353182  1.33657234 -0.19855433 -0.68216277  0.56530
448
 -0.17059103 -0.22029708  1.04768221 -0.3022164   0.5177164  -0.28265
206
 -0.22390601  0.05136999 -0.15793241  0.10684319  1.2002637   0.47628
892
  0.14220972  0.09045629 -0.36286917 -0.46014813 -0.09175275 -0.13922
263
 -0.21393081  0.01136041 -0.44154121 -0.7144757  -0.57291803  1.06928
191
  0.98161294 -0.39739939 -0.83762413 -1.07666478  1.0026014   0.11726
452
```

```
 -0.03397764 -0.16374966  0.80529435  0.75766442 -0.59692761  0.07479
387
 -0.0576688   0.3231994 ]
```

Converting the Test Dataset :-

In [101]:
```python
list_of_sentence_Test=[]

for sentence in X_DTTest:
    list_of_sentence_Test.append(sentence.split())
```

In [102]:
```python
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d in this list
for sent in tqdm(list_of_sentence_Test): # for each review/sentence in
 the Test Dataset
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
print(sent_vectors_test.shape)
print(sent_vectors_test[0])
```

```
100%|██████████| 20000/20000 [01:18<00:00, 255.44it/s]
```

```
(20000, 50)
[ 0.41770288  0.50655313 -0.22420099 -0.03307324 -0.47707725 -0.3272628
7
  0.35200297 -0.11341446 -0.07472366  0.02816265 -0.0302562   0.0728236
4
  0.29646624 -0.22758231 -0.37472965 -0.46324453 -0.06229151  0.1165891
5
  0.21160062 -0.69033039  0.05002348  0.040887    0.47897451  0.3765551
  0.65207949  0.03952411 -0.25902525  0.04207033 -0.46113494  0.5453338
3
  0.40216599 -0.12814072  0.09710253  0.11077926  0.09974643 -0.2173569
9
  0.1146471  -0.04855074 -0.45418426  0.17501483 -0.14482127  0.2056824
4
  0.10788081  0.05281569  0.01160476  0.11674235  0.21745085  0.0739488
2
 -0.00847296 -0.16166151]
```

In [103]:
```
print("Shapes before the Avg W2V Vectorization was carried out:")

print(X_DTTrain.shape,Y_DTTrain.shape)
print(X_DTCV.shape,Y_DTCV.shape)
print(X_DTTest.shape,Y_DTTest.shape)

print("="*100)

print("Shapes after the Avg W2V Vectorization was carried out:")

print(sent_vectors_train.shape,Y_DTTrain.shape)
print(sent_vectors_cv.shape,Y_DTCV.shape)
print(sent_vectors_test.shape,Y_DTTest.shape)
```

```
Shapes before the Avg W2V Vectorization was carried out:
(70000,) (70000,)
(10000,) (10000,)
(20000,) (20000,)
========================================================================
=============================
Shapes after the Avg W2V Vectorization was carried out:
```

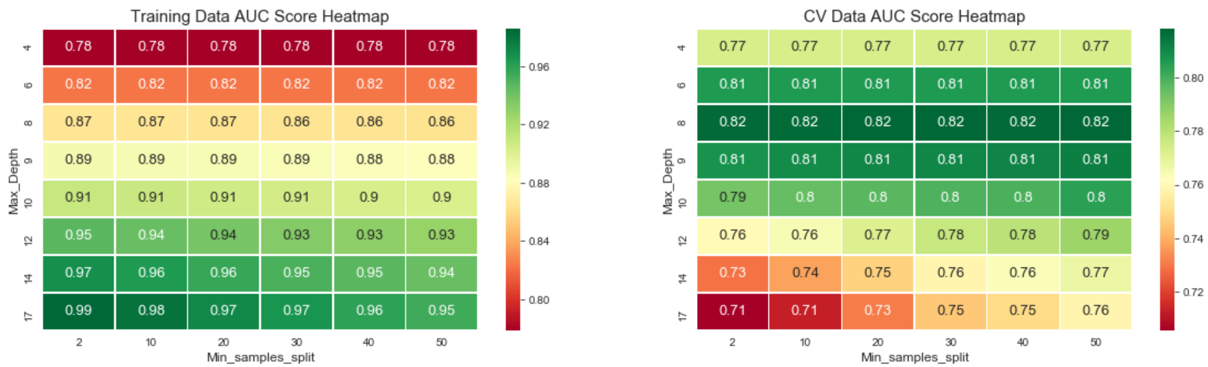
```
(70000, 50) (70000,)
(10000, 50) (10000,)
(20000, 50) (20000,)
```

Hyperparameter Tuning on the Avg W2V Representation :-

Again, there is no need to carry out Standardization for Decision Tree Classification because we do not have any hyperplane in consideration over here unlike the other algorithms that we have encountered previously.

Calling the Different Functions to obtain the Train and CV Dataframes and Obtaining the Seaborn HeatMaps for them :-

In [104]:
```
AW2V_Train_df = train_heatmap(sent_vectors_train,Y_DTTrain)
AW2V_CV_df = cv_heatmap(sent_vectors_train,Y_DTTrain,sent_vectors_cv,Y_
DTCV)
plot_heatmaps(AW2V_Train_df,AW2V_CV_df)
```



With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.82, and the minimum AUC Value on the Train Heatmap for the same combination is 0.86.
- Therefore the Best Combination of Max_Depth and Min_samples_split for the BOW Featurization is either of the following:

Max_Depth=8. Min_samples_split= 30 or 40 or 50.

- Therefore the best of these values is obtained by GridSearchCV below.

In [105]:
```
warnings.filterwarnings('ignore')

#Carrying out 10-fold Cross Validation. class_weight is taken as 'balan
ced' since the data that we originally had
#was an Imbalanced Real World Dataset.

model3 = DecisionTreeClassifier(criterion='gini',splitter='best',class_
weight='balanced')

DT_AW2V = GridSearchCV(model3,parameters,scoring='roc_auc',cv=10)
DT_AW2V.fit(sent_vectors_train,Y_DTTrain)

print(DT_AW2V.best_estimator_)
```

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_d
epth=8,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

Therefore, according to the Hyperparameter Tuning and obtaining the Best Hyperparameters of the model after carrying out Hyperparameter tuning via GridSearchCV, we obtain the following Best values :-

- max_depth = 8

- min_samples_split = 50

Testing with the Test Data on the AW2V Representation:-

In [120]:
```
AW2V_Test = DecisionTreeClassifier(criterion='gini',splitter='best',class_weight='balanced',max_depth=8,
                                    min_samples_split=50)
AW2V_Test.fit(sent_vectors_train,Y_DTTrain)
```

Out[120]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_depth=8,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=50,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [121]:
```
Y_DTTrain.shape
```

Out[121]:
```
(70000,)
```

In [122]:
```
print(sent_vectors_train.shape)
```

```
(70000, 50)
```

In [123]:
```
print(Y_DTTest.shape)
```

```
(20000,)
```

```
In [124]: print(sent_vectors_test.shape)
```

```
(20000, 50)
```

```
In [125]: from sklearn.metrics import roc_curve, auc

train_fpr3,train_tpr3,threshold = roc_curve(Y_DTTrain,AW2V_Test.predict
_proba(sent_vectors_train)[:,1])
test_fpr3,test_tpr3,threshold = roc_curve(Y_DTTest,AW2V_Test.predict_pr
oba(sent_vectors_test)[:,1])
```

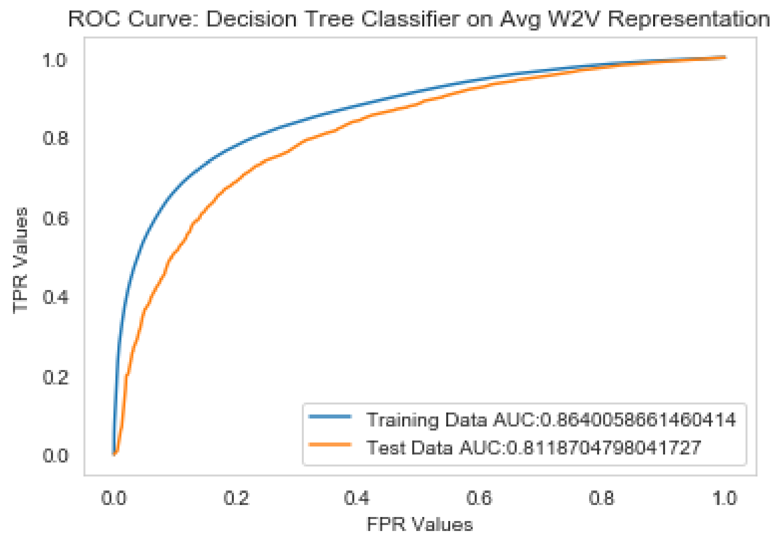
Plotting the graph between the FPR Values as well as the TPR values for the Training Data as well as the Test data we obtain the ROC Curve as follows:

```
In [126]: import matplotlib.pyplot as plt

plt.plot(train_fpr3,train_tpr3,label ='Training Data AUC:' + str(auc(tr
ain_fpr3,train_tpr3)))
plt.plot(test_fpr3,test_tpr3,label = 'Test Data AUC:' + str(auc(test_fp
r3,test_tpr3)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Decision Tree Classifier on Avg W2V Representatio
n')

plt.grid(False)
plt.show()
```



In [127]:
```
Y_Train_pred3 = AW2V_Test.predict_proba(sent_vectors_train)[:,1]
Y_Test_pred3 = AW2V_Test.predict_proba(sent_vectors_test)[:,1]
```

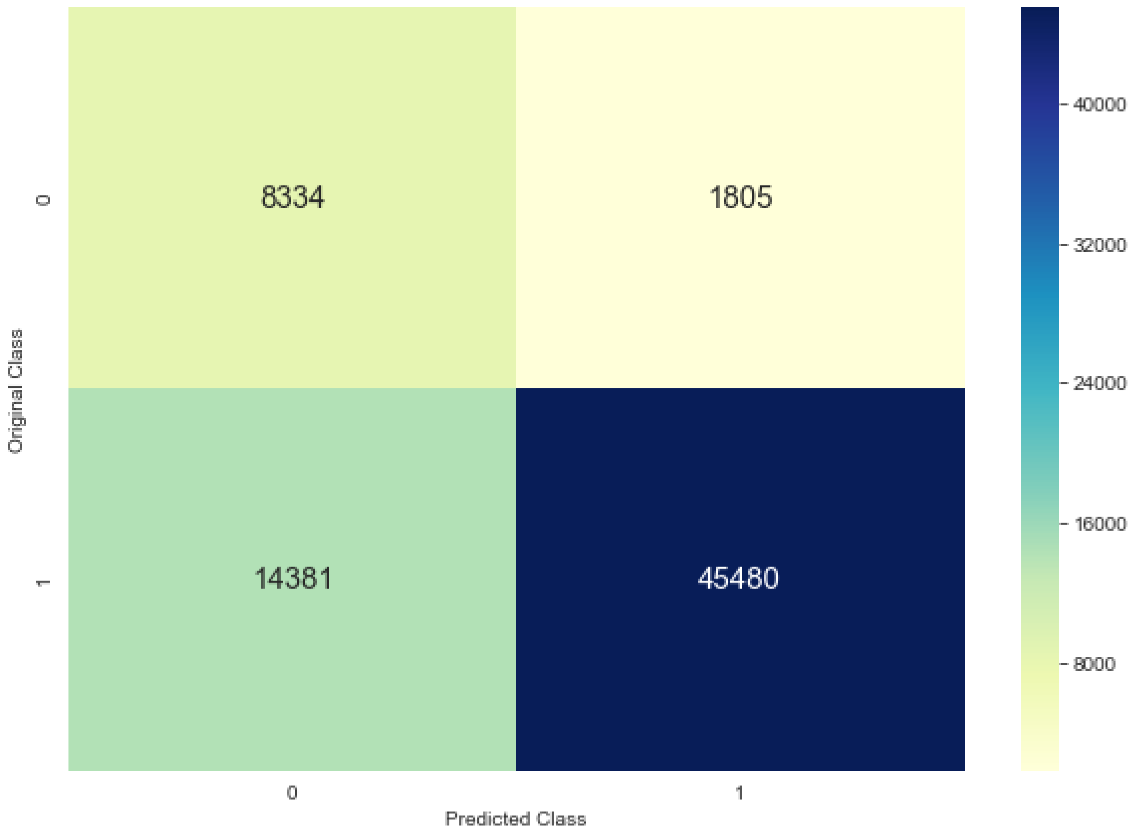
Calling the Different Functions and Obtaining Confusion Matrices for the Ideal Threshold Value:-

In [128]:
```
AW2V_Train = confusion_matrix(Y_DTTrain,matrixpredict(Y_Train_pred3,thr
eshold,train_tpr3,train_fpr3))
plottrainmatrix(AW2V_Train)
```

```
-------------------- Training Confusion Matrix --------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.6245034780981965
Threshold for Maximum Value of tpr*(1-fpr) : 0.48
```



Accuracy on the Training Data => (45480+8334)/70000 = 76.87%

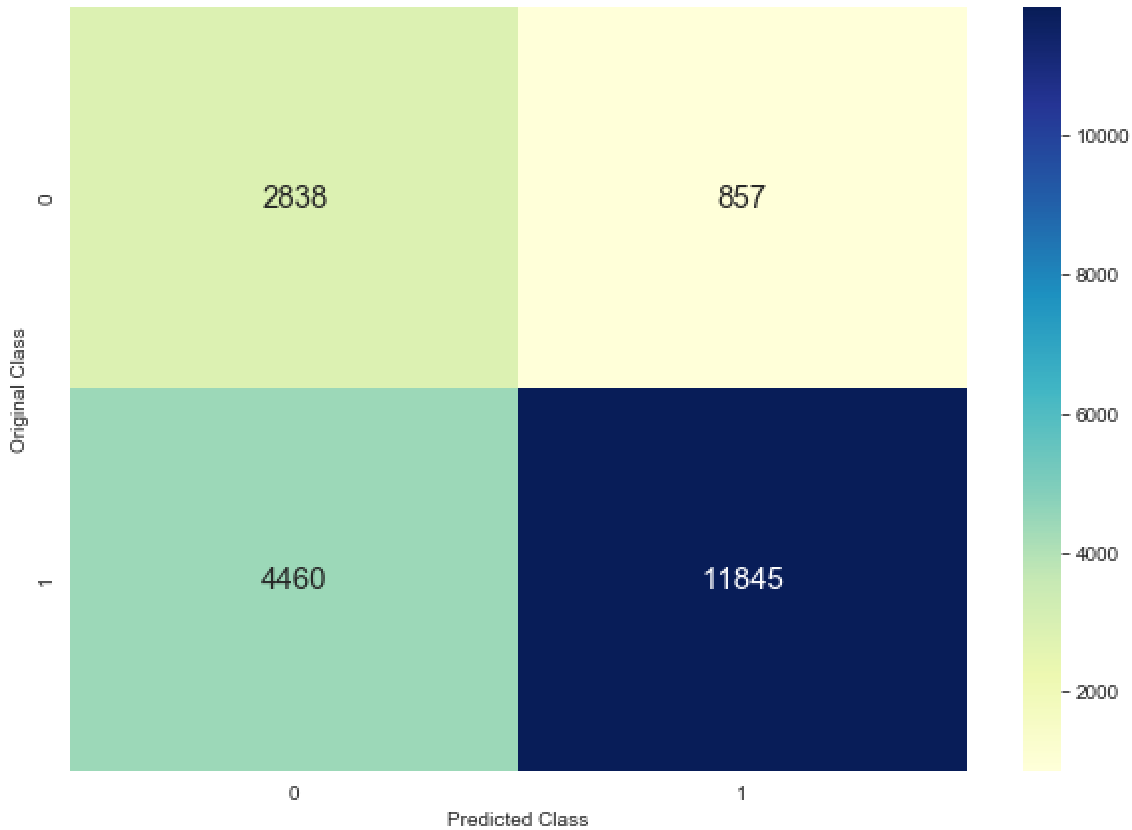
The Test Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottestmatrix() that were defined previously:

In [129]:
```
AW2V_Test = confusion_matrix(Y_DTTest,matrixpredict(Y_Test_pred3,thresh
old,test_tpr3,test_fpr3))
plottestmatrix(AW2V_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:
```

```
The maximum value of tpr*(1-fpr) : 0.5579717487890471
Threshold for Maximum Value of tpr*(1-fpr) : 0.459
```



Accuracy on the Test Data => (11845+2838)/20000 = 73.41%

[5.4] SET 4 : Applying Decision Trees on TFIDF W2V :-

In [130]:
```
model_DT = TfidfVectorizer()
```

```
tf_idf_matrix = model_DT.fit_transform(X_DTTrain)

# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model_DT.get_feature_names(), list(model_DT.idf_
)))
```

In [131]:
```
tf_idf_matrix.shape
```

Out[131]:
```
(70000, 49207)
```

So basically tf_idf_matrix has learnt the vocabulary from X_Train and now we will apply the same on the Cross Validation as well as the Test Datasets.

Converting Reviews into Numerical Vectors using W2V vectors :-

Converting the Train Data Text :-

In [132]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model_DT.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_DTTrain = []; # the tfidf-w2v for each sentence/revi
ew from Training Data is stored in this list
row=0;
for sent in tqdm(list_of_sentence_Train): # for each review/sentence in
 Training Data
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
```

```
            vec = w2v_model.wv[word]
            #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_DTTrain.append(sent_vec)
    row += 1
```

```
100%|██████████| 70000/70000 [50:38<00:00, 22.25it/s]
```

In [133]:
```
tfidf_sent_vectors_DTTrain[1]
```

Out[133]:
```
array([ 0.1304704 ,  0.57015529, -1.18922956,  0.13974138, -0.47373454,
        0.27974984,  0.419855  , -0.39407225,  0.21986594,  0.31392055,
       -0.1326052 , -0.27810041,  0.38461409,  0.12793856, -0.06008979,
        0.03570792, -0.21453964, -0.13601   ,  0.38189914,  0.12709805,
        0.20247222, -0.07358603,  0.25436161,  0.80897751,  0.00290538,
       -0.0022254 , -0.08372897, -0.29064979,  0.16774149,  0.26040704,
        0.34987317,  0.13962634, -0.52824507,  0.22459052,  0.1349742 ,
       -0.39915374, -0.25944629, -0.00642681,  0.09301739, -0.26557113,
        0.03964491,  0.33693007,  0.1457974 , -0.02743263,  0.03908711,
       -0.05679933,  0.26705852,  0.49281824, -0.33163641, -0.1649227
1])
```

Converting the CV Data Text :-

In [134]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model_DT.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_DTCV = []; # the tfidf-w2v for each sentence/review
```

```
 from the CV Dataset is stored in this list
row=0;
for sent in tqdm(list_of_sentence_CV): # for each review/sentence in th
e Cross Validation Dataset
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            # tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_DTCV.append(sent_vec)
    row += 1
```

```
100%|██████████| 10000/10000 [07:10<00:00, 23.24it/s]
```

Converting the Test Data Text :-

In [135]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = model_DT.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_DTTest = []; # the tfidf-w2v for each sentence/revie
w from the Test Dataset is stored in this list
row=0;
for sent in tqdm(list_of_sentence_Test): # for each review/sentence in
 the Test Dataset
    sent_vec = np.zeros(50) # as word vectors are of zero length
```

```
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            # tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_DTTest.append(sent_vec)
    row += 1
```

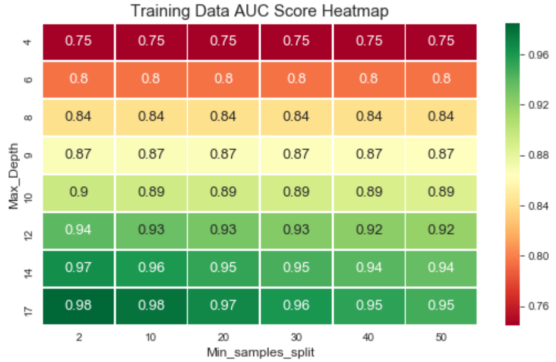
```
100%|██████████| 20000/20000 [17:55<00:00, 18.60it/s]
```

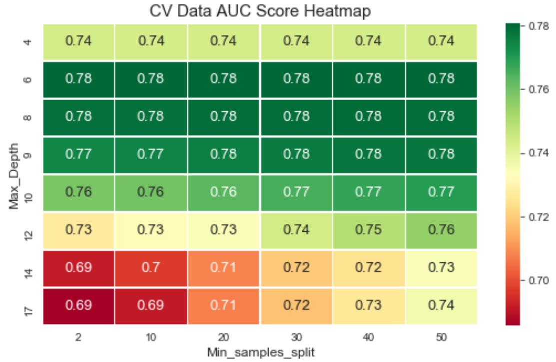
Hyperparameter Tuning on the TFIDF W2V Representation :-

Again, there is no need to carry out Standardization for Decision Tree Classification because we do not have any hyperplane in consideration over here unlike the other algorithms that we have encountered previously.

Calling the Different Functions to obtain the Train and CV Dataframes and Obtaining the Seaborn HeatMaps for them :-

In [136]:
```
TFIDFW2V_Train_df = train_heatmap(tfidf_sent_vectors_DTTrain,Y_DTTrain)
TFIDFW2V_CV_df = cv_heatmap(tfidf_sent_vectors_DTTrain,Y_DTTrain,tfidf_
sent_vectors_DTCV,Y_DTCV)
plot_heatmaps(TFIDFW2V_Train_df,TFIDFW2V_CV_df)
```





With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.78, and the minimum AUC Value on the Train Heatmap for the same combination is 0.84.
- Therefore the Best Combination of Max_Depth and Min_samples_split for the BOW Featurization is either of the following:

Max_Depth=8. Min_samples_split= 30 or 40 or 50.

- Therefore the best of these values is obtained by GridSearchCV below.

In [137]:
```
warnings.filterwarnings('ignore')

#Carrying out 10-fold Cross Validation. class_weight is taken as 'balan
ced' since the data that we originally had
#was an Imbalanced Real World Dataset.

model4 = DecisionTreeClassifier(criterion='gini',splitter='best',class_
weight='balanced')

DT_TFIDFW2V = GridSearchCV(model4,parameters,scoring='roc_auc',cv=10)
DT_TFIDFW2V.fit(tfidf_sent_vectors_DTTrain,Y_DTTrain)

print(DT_TFIDFW2V.best_estimator_)
```

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_d
```

```
epth=8,
                max_features=None, max_leaf_nodes=None,
                min_impurity_decrease=0.0, min_impurity_split=None,
                min_samples_leaf=1, min_samples_split=40,
                min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
                splitter='best')
```

Therefore, according to the Hyperparameter Tuning and obtaining the Best Hyperparameters of the model after carrying out Hyperparameter tuning via GridSearchCV, we obtain the following Best values :-

- max_depth = 8
- min_samples_split = 40

Testing with the Test Data on the TFIDF W2V Representation:-

In [138]:

```
TFIDFW2V_Test = DecisionTreeClassifier(criterion='gini',splitter='best'
,class_weight='balanced',max_depth=8,
                                      min_samples_split=40)
TFIDFW2V_Test.fit(tfidf_sent_vectors_DTTrain,Y_DTTrain)
```

Out[138]:

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_d
epth=8,
                max_features=None, max_leaf_nodes=None,
                min_impurity_decrease=0.0, min_impurity_split=None,
                min_samples_leaf=1, min_samples_split=40,
                min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
                splitter='best')
```

Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [139]:
```
from sklearn.metrics import roc_curve, auc

train_fpr4,train_tpr4,threshold = roc_curve(Y_DTTrain,TFIDFW2V_Test.pre
dict_proba(tfidf_sent_vectors_DTTrain)[:,1])
test_fpr4,test_tpr4,threshold = roc_curve(Y_DTTest,TFIDFW2V_Test.predic
t_proba(tfidf_sent_vectors_DTTest)[:,1])
```

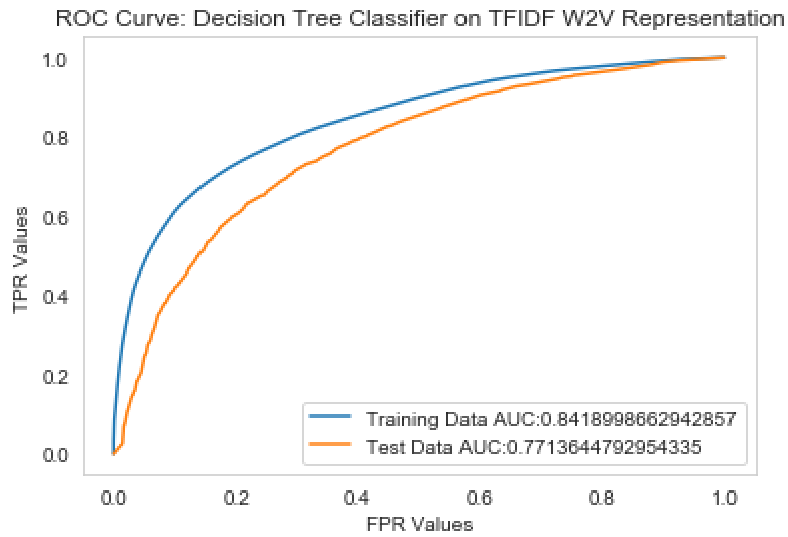
Plotting the graph between the FPR Values as well as the TPR values for the Training Data as well as the Test data we obtain the ROC Curve as follows:

In [140]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr4,train_tpr4,label ='Training Data AUC:' + str(auc(tr
ain_fpr4,train_tpr4)))
plt.plot(test_fpr4,test_tpr4,label = 'Test Data AUC:' + str(auc(test_fp
r4,test_tpr4)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Decision Tree Classifier on TFIDF W2V Representat
ion')

plt.grid(False)
plt.show()
```



In [141]:
```
Y_Train_pred4 = TFIDFW2V_Test.predict_proba(tfidf_sent_vectors_DTTrain)
[:,1]
Y_Test_pred4 = TFIDFW2V_Test.predict_proba(tfidf_sent_vectors_DTTest)
[:,1]
```

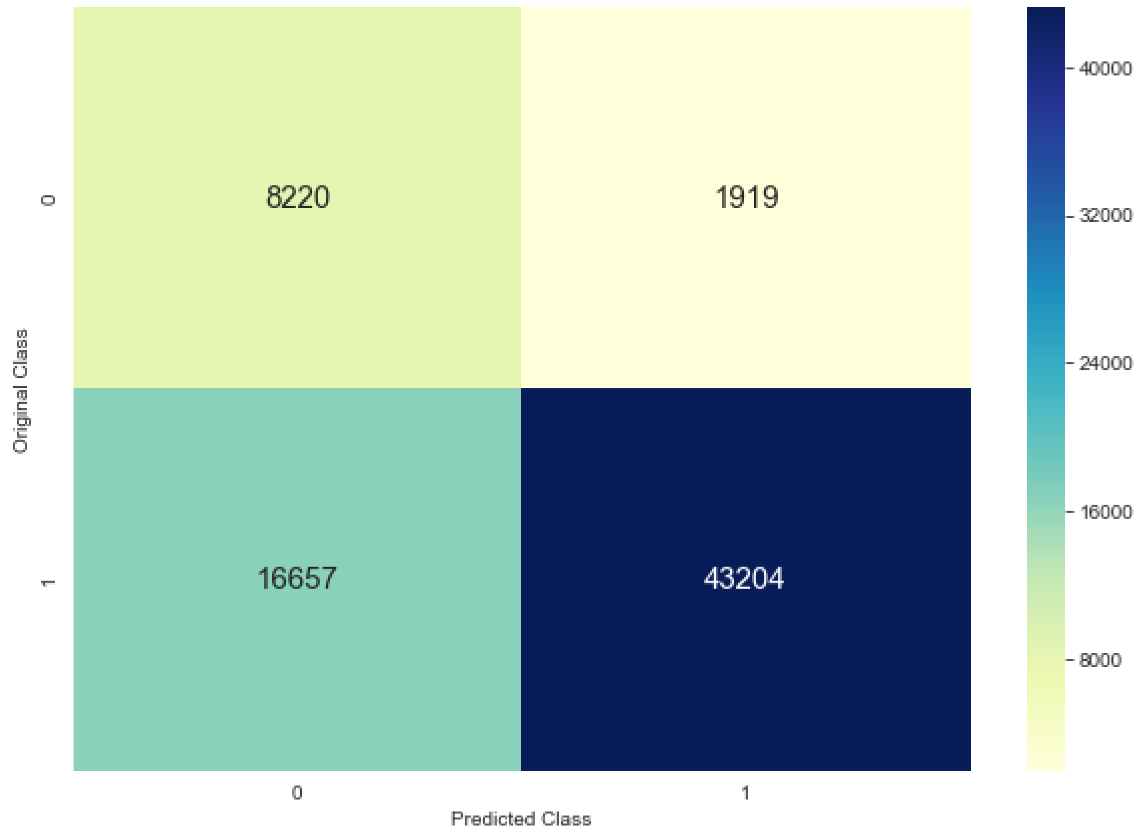
Calling the Different Functions and Obtaining Confusion Matrices for the Ideal Threshold Value:-

In [142]:
```
TFIDFW2V_Train = confusion_matrix(Y_DTTrain,matrixpredict(Y_Train_pred4
,threshold,train_tpr4,train_fpr4))
plottrainmatrix(TFIDFW2V_Train)
```

```
-------------------- Training Confusion Matrix --------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.585135819110571
Threshold for Maximum Value of tpr*(1-fpr) : 0.475
```



Accuracy on the Training Data => (44976+8216)/70000 = 73.46%

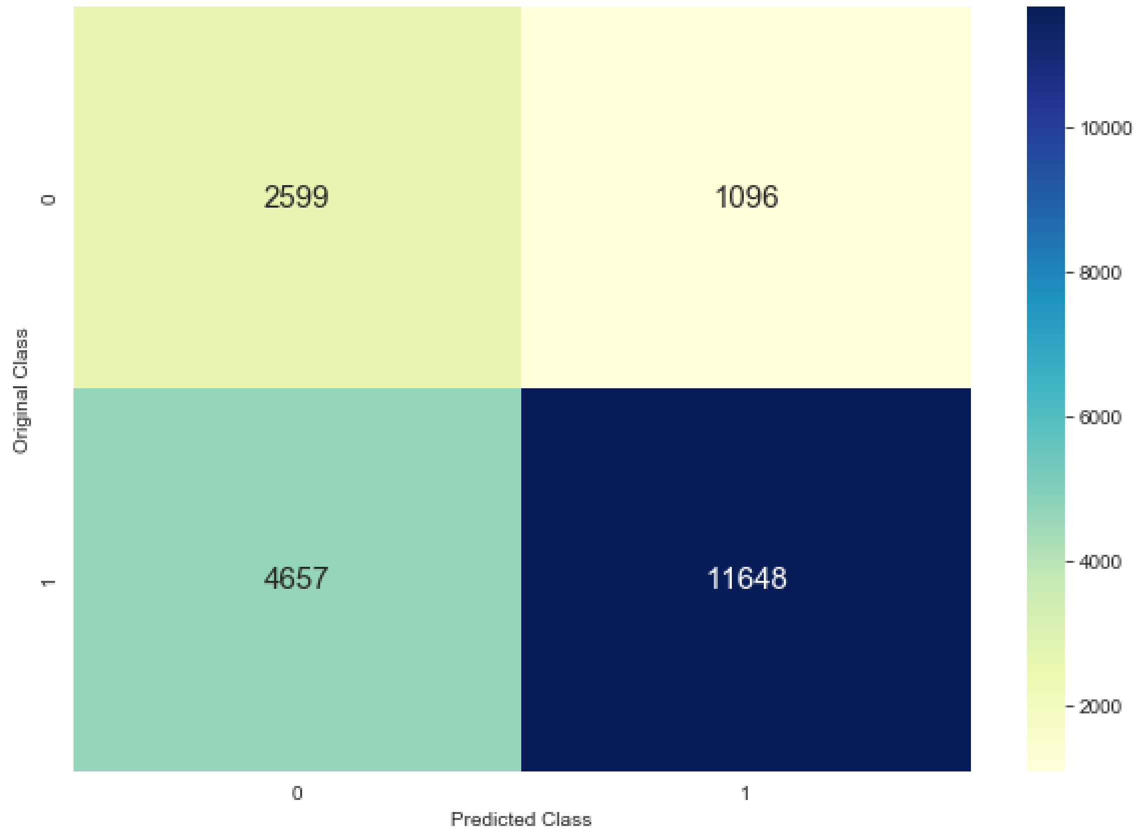
The Test Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottestmatrix() that were defined previously:

In [143]:
```
TFIDFW2V_Test = confusion_matrix(Y_DTTest,matrixpredict(Y_Test_pred4,th
reshold,test_tpr4,test_fpr4))
plottestmatrix(TFIDFW2V_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:
```

```
The maximum value of tpr*(1-fpr) : 0.5024841828158176
Threshold for Maximum Value of tpr*(1-fpr) : 0.431
```



Accuracy on the Test Data => (11983+2643)/20000 = 71.23%

[6] Conclusions

In [160]:
```python
from prettytable import PrettyTable
```

In [163]:

```
a=PrettyTable()
a.field_names=["S No.","Top 20 Important Features","Weight"]
```

In [164]:

```
print("Top 20 Most Important Features with Decision Trees & BOW Featuri
zation:")
print(" "*100)

a.add_row(["1","not","0.174"])
a.add_row(["2","great","0.103"])
a.add_row(["3","best","0.054"])
a.add_row(["4","delicious","0.049"])
a.add_row(["5","love","0.035"])
a.add_row(["6","perfect","0.032"])
a.add_row(["7","good","0.029"])
a.add_row(["8","loves","0.028"])
a.add_row(["9","bad","0.024"])
a.add_row(["10","disappointed","0.019"])
a.add_row(["11","nice","0.018"])
a.add_row(["12","favorite","0.017"])
a.add_row(["13","excellent","0.015"])
a.add_row(["14","wonderful","0.015"])
a.add_row(["15","unfortunately","0.014"])
a.add_row(["16","easy","0.013"])
a.add_row(["17","thought","0.012"])
a.add_row(["18","money","0.011"])
a.add_row(["19","highly","0.009"])
a.add_row(["20","awful","0.008"])

print(a)
```

```
Top 20 Most Important Features with Decision Trees & BOW Featurization:


+-------+---------------------------+--------+
| S No. | Top 20 Important Features | Weight |
+-------+---------------------------+--------+
|   1   |            not            | 0.174  |
|   2   |           great           | 0.103  |
|   3   |            best           | 0.054  |
|   4   |         delicious         | 0.049  |
```

```
|   5   |          love          | 0.035  |
|   6   |        perfect         | 0.032  |
|   7   |          good          | 0.029  |
|   8   |         loves          | 0.028  |
|   9   |          bad           | 0.024  |
|   10  |      disappointed      | 0.019  |
|   11  |          nice          | 0.018  |
|   12  |        favorite        | 0.017  |
|   13  |       excellent        | 0.015  |
|   14  |       wonderful        | 0.015  |
|   15  |     unfortunately      | 0.014  |
|   16  |          easy          | 0.013  |
|   17  |        thought         | 0.012  |
|   18  |         money          | 0.011  |
|   19  |         highly         | 0.009  |
|   20  |         awful          | 0.008  |
+-------+------------------------+--------+
```

In [165]:

```
b=PrettyTable()
b.field_names=["S No.","Top 20 Important Features","Weight"]
```

In [166]:

```
print("Top 20 Most Important Features with Decision Trees & TFIDF Featu
rization:")
print(" "*100)

b.add_row(["1","not","0.155"])
b.add_row(["2","great","0.104"])
b.add_row(["3","best","0.051"])
b.add_row(["4","delicious","0.049"])
b.add_row(["5","love","0.038"])
b.add_row(["6","perfect","0.032"])
b.add_row(["7","good","0.03"])
b.add_row(["8","loves","0.028"])
b.add_row(["9","bad","0.026"])
b.add_row(["10","disappointed","0.024"])
b.add_row(["11","nice","0.021"])
b.add_row(["12","wonderful","0.017"])
```

```python
b.add_row(["13","excellent","0.017"])
b.add_row(["14","favorite","0.016"])
b.add_row(["15","thought","0.014"])
b.add_row(["16","easy","0.013"])
b.add_row(["17","awful","0.01"])
b.add_row(["18","unfortunately","0.009"])
b.add_row(["19","reviews","0.009"])
b.add_row(["20","not great","0.009"])

print(b)
```

```
Top 20 Most Important Features with Decision Trees & TFIDF Featurizatio
n:


+--------+--------------------------+--------+
| S No.  | Top 20 Important Features | Weight |
+--------+--------------------------+--------+
|   1    |           not            | 0.155  |
|   2    |          great           | 0.104  |
|   3    |           best           | 0.051  |
|   4    |        delicious         | 0.049  |
|   5    |           love           | 0.038  |
|   6    |         perfect          | 0.032  |
|   7    |           good           |  0.03  |
|   8    |          loves           | 0.028  |
|   9    |           bad            | 0.026  |
|   10   |       disappointed       | 0.024  |
|   11   |           nice           | 0.021  |
|   12   |        wonderful         | 0.017  |
|   13   |        excellent         | 0.017  |
|   14   |         favorite         | 0.016  |
|   15   |         thought          | 0.014  |
|   16   |           easy           | 0.013  |
|   17   |          awful           |  0.01  |
|   18   |      unfortunately       | 0.009  |
|   19   |         reviews          | 0.009  |
|   20   |        not great         | 0.009  |
+--------+--------------------------+--------+
```

In [167]:
```
c = PrettyTable()
c.field_names=["Model","Ideal Max_Depth","Ideal Min_Samples_Split","Ide
al Threshold Test Accuracy",
               "Test AUC Score"]
```

In [168]:
```
print("Performance on Test Data using different Featurizations using De
cision Trees:")
print(" "*100)

c.add_row(["BOW","17","50","71.93%","0.79"])
c.add_row(["TFIDF","17","50","71.97%","0.79"])
c.add_row(["Avg W2V","8","50","73.41%","0.81"])
c.add_row(["TFIDF W2V","8","40","71.23%","0.77"])

print(c)
```

```
Performance on Test Data using different Featurizations using Decision
Trees:


+-----------+----------------+-------------------------+--------------
----------------+----------------+
|   Model   | Ideal Max_Depth | Ideal Min_Samples_Split | Ideal Thresho
ld Test Accuracy | Test AUC Score |
+-----------+----------------+-------------------------+--------------
----------------+----------------+
|    BOW    |        17       |            50           |             7
1.93%           |      0.79      |
|   TFIDF   |        17       |            50           |             7
1.97%           |      0.79      |
|  Avg W2V  |        8        |            50           |             7
3.41%           |      0.81      |
| TFIDF W2V |        8        |            40           |             7
1.23%           |      0.77      |
+-----------+----------------+-------------------------+--------------
----------------+----------------+
```

Following are some Conclusions from the observations:-

- As far as the "Decision Tree" performance for the different featurizations is concerned, Avg W2V is the best across all the models since it has the highest Test Accuracy and Test AUC. This is followed by the TFIDF model.
- Overall, "Decision Tree" is not a very good model in this scenario as compared to the models that we saw previously because the "Ideal Threshold Test Accuracy" for all the 4 Featurizations is only around 72 % which is not very high.