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
```

```python
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]:

```python
# 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
```

```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 50000""", 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 (50000, 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]:
```
(46072, 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]:
```
92.144
```

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()
```

```
(46071, 10)
```

Out[13]:

```
1    38479
0     7592
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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
```

ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==
this is yummy, easy and unusual. it makes a quick, delicous pie, crisp
or cobbler. home made is better, but a heck of a lot more work. this is
great to have on hand for last minute dessert needs where you really wa
nt to impress wih your creativity in cooking! recommended.
==
Great flavor, low in calories, high in nutrients, high in protein! Usua
lly protein powders are high priced and high in calories, this one is a
great bargain and tastes great, I highly recommend for the lady gym rat
s, probably not "macho" enough for guys since it is soy based...
==
For those of you wanting a high-quality, yet affordable green tea, you
should definitely give this one a try. Let me first start by saying tha
t everyone is looking for something different for their ideal tea, and
I will attempt to briefly highlight what makes this tea attractive to a
wide range of tea drinkers (whether you are a beginner or long-time tea
enthusiast). I have gone through over 12 boxes of this tea myself, and
highly recommend it for the following reasons:

-Quality: Fi
rst, this tea offers a smooth quality without any harsh or bitter after
tones, which often turns people off from many green teas. I've found m
y ideal brewing time to be between 3-5 minutes, giving you a light but
flavorful cup of tea. However, if you get distracted or forget about y
our tea and leave it brewing for 20+ minutes like I sometimes do, the q
uality of this tea is such that you still get a smooth but deeper flavo
r without the bad after taste. The leaves themselves are whole leaves
(not powdered stems, branches, etc commonly found in other brands), and
the high-quality nylon bags also include chunks of tropical fruit and o
ther discernible ingredients. This isn't your standard cheap paper bag
with a mix of unknown ingredients that have been ground down to a fine
powder, leaving you to wonder what it is you are actually drinking.

-Taste: This tea offers notes of real pineapple and other hint
s of tropical fruits, yet isn't sweet or artificially flavored. You ha
ve the foundation of a high-quality young hyson green tea for those tru
e "tea flavor" lovers, yet the subtle hints of fruit make this a truly
unique tea that I believe most will enjoy. If you want it sweet, you c

an add sugar, splenda, etc but this really is not necessary as this tea
offers an inherent warmth of flavor through it's ingredients.
<br

```
/>-Price:  This tea offers an excellent product at an exceptional price
(especially when purchased at the prices Amazon offers).  Compared to o
ther brands which I believe to be of similar quality (Mighty Leaf, Rish
i, Two Leaves, etc.), Revolution offers a superior product at an outsta
nding price.  I have been purchasing this through Amazon for less per b
ox than I would be paying at my local grocery store for Lipton, etc.<br
/><br />Overall, this is a wonderful tea that is comparable, and even b
etter than, other teas that are priced much higher.  It offers a well-b
alanced cup of green tea that I believe many will enjoy.  In terms of t
aste, quality, and price, I would argue you won't find a better combina
tion that that offered by Revolution's Tropical Green Tea.
==================================================
```

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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
```

In [16]:

```
# 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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==================================================
this is yummy, easy and unusual. it makes a quick, delicous pie, crisp
or cobbler. home made is better, but a heck of a lot more work. this is
great to have on hand for last minute dessert needs where you really wa
nt to impress wih your creativity in cooking! recommended.
==================================================
Great flavor, low in calories, high in nutrients, high in protein! Usua
lly protein powders are high priced and high in calories, this one is a
great bargain and tastes great, I highly recommend for the lady gym rat
s, probably not "macho" enough for guys since it is soy based...
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should definitely give this one a try. Let me first start by saying tha
t everyone is looking for something different for their ideal tea, and
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wide range of tea drinkers (whether you are a beginner or long-time tea
enthusiast).  I have gone through over 12 boxes of this tea myself, and
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a offers a smooth quality without any harsh or bitter after tones, whic
h often turns people off from many green teas.  I've found my ideal bre
wing time to be between 3-5 minutes, giving you a light but flavorful c
up of tea.  However, if you get distracted or forget about your tea and
leave it brewing for 20+ minutes like I sometimes do, the quality of th
```

```
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e bad after taste.  The leaves themselves are whole leaves (not powdere
d stems, branches, etc commonly found in other brands), and the high-qu
ality nylon bags also include chunks of tropical fruit and other discer
nible ingredients.  This isn't your standard cheap paper bag with a mix
of unknown ingredients that have been ground down to a fine powder, lea
ving you to wonder what it is you are actually drinking.-Taste:  This t
ea offers notes of real pineapple and other hints of tropical fruits, y
et isn't sweet or artificially flavored.  You have the foundation of a 
high-quality young hyson green tea for those true "tea flavor" lovers, 
yet the subtle hints of fruit make this a truly unique tea that I belie
ve most will enjoy.  If you want it sweet, you can add sugar, splenda, 
etc but this really is not necessary as this tea offers an inherent war
mth of flavor through it's ingredients.-Price:  This tea offers an exce
llent product at an exceptional price (especially when purchased at the
prices Amazon offers).  Compared to other brands which I believe to be 
of similar quality (Mighty Leaf, Rishi, Two Leaves, etc.), Revolution o
ffers a superior product at an outstanding price.  I have been purchasi
ng this through Amazon for less per box than I would be paying at my lo
cal grocery store for Lipton, etc.Overall, this is a wonderful tea that
is comparable, and even better than, other teas that are priced much hi
gher.  It offers a well-balanced cup of green tea that I believe many w
ill enjoy.  In terms of taste, quality, and price, I would argue you wo
n't find a better combination that that offered by Revolution's Tropica
l Green Tea.
```

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)
```

```
Great flavor, low in calories, high in nutrients, high in protein! Usua
lly protein powders are high priced and high in calories, this one is a
great bargain and tastes great, I highly recommend for the lady gym rat
s, probably not "macho" enough for guys since it is soy based...
==================================================
```

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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
```

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

```
Great flavor low in calories high in nutrients high in protein Usually
protein powders are high priced and high in calories this one is a grea
t bargain and tastes great I highly recommend for the lady gym rats pro
bably not macho enough for guys since it is soy based
```

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%|██████████| 46071/46071 [00:20<00:00, 2207.36it/s]
```

In [23]:

```
preprocessed_reviews[1500]
```

Out[23]:

```
'great flavor low calories high nutrients high protein usually protein
powders high priced high calories one great bargain tastes great highly
recommend lady gym rats probably not macho enough guys since soy based'
```

[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 [ ]:

```
# 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]
```

Obtaining the Required DataFrame:

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

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

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

```
(46071, 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 50K datapoints to work upon which got reduced to approx. 46K datapoints after all the text processing and data deduplication.

Out of these 46K datapoints in total we will consider only 25K points to be applied to the Random Forest & XGBoost Algorithms.

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	HelpfulnessDe
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
2546	2774	B00002NCJC	A196AJHU9EASJN	Alex Chaffee	0	
2547	2775	B00002NCJC	A13RRPGE79XFFH	reader48	0	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	

Now I have a total of approx. 46K rows in the dataframe called 'final', of which I will consider only 25K rows to be applied to the Random Forest Classifier & the XGBoost Algorithms. 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	H
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0	
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0	
38740	42069	B0000EIEQU	A1YMJX4YWCE6P4	Jim Carson "http://www.jimcarson.com"	12	

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
1146	1	really good idea final product outstanding use...
1145	1	received shipment could hardly wait try produc...
28086	1	nothing product bother link top page buy used ...
28087	1	love stuff sugar free not rot gums tastes good...
38740	1	fresh limes underappreciated joy kitchen squir...

[5.1] Applying Random Forest Classification :-

Obtaining Train, CV and Test Data :-

In [32]:
```
RF_df = df[:25000]
```

Basically we are taking a total of 25K 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 = 17500
    # of Datapoints in CV data = 2500
    # of Datapoints in Test data = 5000
```

In [33]:
```
Tr_RF_df = RF_df[:17500]
CV_RF_df = RF_df[17500:20000]
Te_RF_df = RF_df[20000:25000]
```

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

Out[34]:
```
(17500, 2)
```

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

Out[35]:
```
(2500, 2)
```

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

Out[36]:
```
(5000, 2)
```

Yes everything is working as expected: There are 17,500 points in the Training data, 2500 points in the CV data and 5K points in the Test data.

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

In [39]:
```
X_RFTrain = Tr_RF_df['Preprocessed_Reviews']
Y_RFTrain = Tr_RF_df['Score']

X_RFCV = CV_RF_df['Preprocessed_Reviews']
Y_RFCV = CV_RF_df['Score']

X_RFTest = Te_RF_df['Preprocessed_Reviews']
Y_RFTest = Te_RF_df['Score']
```

In [45]:
```
Y_RFTrain.value_counts()
```

Out[45]:
```
1    15008
0     2492
Name: Score, dtype: int64
```

In [46]:
```
Y_RFCV.value_counts()
```

Out[46]:
```
1    2074
0     426
Name: Score, dtype: int64
```

In [47]:
```
Y_RFTest.value_counts()
```

Out[47]:
```
1    4145
0     855
Name: Score, dtype: int64
```

As expected, this is an imbalanced real world dataset.

[5.1.1] SET 1 : Applying Random Forest on BOW :-

In [48]:
```
count_vect = CountVectorizer()
count_vect.fit(X_RFTrain) #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[48]:
```
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 [50]: X_RFTrain_BOW = count_vect.transform(X_RFTrain)
         X_RFCV_BOW = count_vect.transform(X_RFCV)
         X_RFTest_BOW = count_vect.transform(X_RFTest)
```

```
In [51]: print("Shapes before the BOW Vectorization was carried out:")

         print(X_RFTrain.shape,Y_RFTrain.shape)
         print(X_RFCV.shape,Y_RFCV.shape)
         print(X_RFTest.shape,Y_RFTest.shape)

         print("*"*100)

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

         print(X_RFTrain_BOW.shape,Y_RFTrain.shape)
         print(X_RFCV_BOW.shape,Y_RFCV.shape)
         print(X_RFTest_BOW.shape,Y_RFTest.shape)
```

```
Shapes before the BOW Vectorization was carried out:
(17500,) (17500,)
(2500,) (2500,)
(5000,) (5000,)
***********************************************************************
*****************************
Shapes after the BOW Vectorization was carried out:
(17500, 25012) (17500,)
(2500, 25012) (2500,)
(5000, 25012) (5000,)
```

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] }

- "n_estimators", which we would be considering in the range of (500,1200) in the interval of 100 and see how which value is ideal in our scenario.

According to "https://stackoverflow.com/questions/36107820/how-to-tune-parameters-in-random-forest-using-scikit-learn", the more the number of estimators or base learners present in the Random Forest the better it is and a value in the range of (500,1000) usually suffices in most scenarios.

I am basically considering the same Hyperparameter values as the ones that I tried for max_depth when we carried out Hyperparameter Tuning for Decision Trees. However, this is not the case for n_estimators.

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 [52]:

```
depth_hyperparameter = [4,6,8,9,10,12,14,17]
estimators_hyperparameter = []

for i in range(500,1300,100):
    estimators_hyperparameter.append(i)

print("The number of Estimators(Base Learners) for the Random Forest Cl
assification are considered in the following "
      "range:")
print(estimators_hyperparameter)
```

```
The number of Estimators(Base Learners) for the Random Forest Classific
ation are considered in the following range:
[500, 600, 700, 800, 900, 1000, 1100, 1200]
```

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

In [53]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.metrics import roc_auc_score
import numpy as np
import warnings
```

Again, the important fact to be noticed for the Random Forest Clasifier is the fact that Random Forests are made up of Decision Trees (of large depth) as the base learners and since for Decision Trees there was no need to carry out Standardization because we did not have any hyperplane in consideration, there is no need to carry out Standardization for Random Forests as well.

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

In [54]:

```python
def RFTrain_Heatmap(X_Train,Y_Train):

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

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

            Train_model = RandomForestClassifier(n_estimators=j,criteri
on='gini',max_depth=i,min_samples_split=2,
                                                   bootstrap=True,n_jobs=
-1,class_weight='balanced',random_state=0)
            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,'n_estimators':df2,'AUC_Score':Train_
AUC}
    train_dataframe = pd.DataFrame(train_data)
    train_dataframe = train_dataframe.pivot("max_depth","n_estimators",
"AUC_Score")
```

```
    return train_dataframe
```

Ideally speaking, the larger is the value of max_depth for Random Forests the better it is, because our job is to obtain our Base Learners (Decision Trees) with a high variance, which is achievable by a deep Decision Tree.

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

In [55]:
```
def RFCV_Heatmap(X_Train,Y_Train,X_CV,Y_CV):

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

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

            CV_model = RandomForestClassifier(n_estimators=j,criterion=
'gini',max_depth=i,min_samples_split=2,
                                                     bootstrap=True,n_jobs=-1,
class_weight='balanced',random_state=0)
            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,'n_estimators':df4,'AUC_Score':CV_AUC}
    cv_dataframe = pd.DataFrame(cv_data)
    cv_dataframe = cv_dataframe.pivot("max_depth","n_estimators","AUC_S
core")

    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 "estimators_hyperparameter" for the parameter "n_estimators" in the Random Forest 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 :-

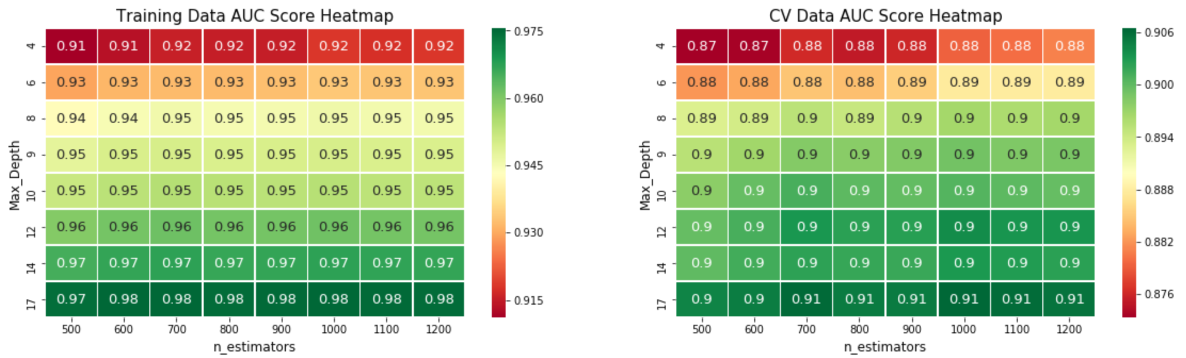
In [56]:
```
def rf_plotheatmaps(train_df,cv_df):
    fig, ax = plt.subplots(figsize=(30,5))

    plt.subplot(1, 3, 1)
    sns.heatmap(train_df, annot=True,cmap='RdYlGn',linewidths=0.5,annot_kws={"size": 13})
    plt.xlabel('n_estimators',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_kws={"size": 13})
    plt.xlabel('n_estimators',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 3-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 [58]:
```
import time
start = time.time()

BOW_Train_df = RFTrain_Heatmap(X_RFTrain_BOW,Y_RFTrain)
BOW_CV_df = RFCV_Heatmap(X_RFTrain_BOW,Y_RFTrain,X_RFCV_BOW,Y_RFCV)
rf_plotheatmaps(BOW_Train_df,BOW_CV_df)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for Simple CV S
earch for Random Forest Classifier on "
      "BOW Vectorizer (in minutes):", (end - start)/60)
```



```
Time Consumed to Complete  Hyperparameter tuning for Simple CV Search
for Random Forest Classifier on BOW Vectorizer (in minutes): 9.182292
783260346
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.90, and the minimum AUC Value on the Train Heatmap for the same combination is 0.95.
- Therefore the Best Combination of Max_Depth and n_estimators for the BOW Featurization is either of the following:

Max_Depth=9 or 10. n_estimators= 1100 or 1200.

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

In [59]:

```
warnings.filterwarnings('ignore')

#Carrying out 3-fold Cross Validation. class_weight is taken as 'balanc
ed' since the data that we originally had
#was an Imbalanced Real World Dataset.

start = time.time()

parameters= [{'max_depth':depth_hyperparameter,'n_estimators':estimator
s_hyperparameter}]
model1 = RandomForestClassifier(criterion='gini',class_weight='balance
d',min_samples_split=2,
                               bootstrap=True,n_jobs=-1)

RF_BOW = GridSearchCV(model1,parameters,scoring='roc_auc',cv=3)
RF_BOW.fit(X_RFTrain_BOW,Y_RFTrain)

print(RF_BOW.best_estimator_)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for GridSearchC
```

```
V for Random Forest Classifier on "
      "BOW Vectorizer (in minutes):", (end - start)/60)
```

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=12, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
Time Consumed to Complete  Hyperparameter tuning for GridSearchCV for R
andom Forest Classifier on BOW Vectorizer (in minutes): 38.917833316326
14
```

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

- max_depth = 12
- n_estimators = 1100

Testing with the Test Data on the BOW Representation:-

In [163]:
```
RFBOW_Test = RandomForestClassifier(criterion='gini',class_weight='bala
nced',min_samples_split=2,max_depth=12,
                                    n_estimators=1100,bootstrap=True,n_jo
bs=-1)
RFBOW_Test.fit(X_RFTrain_BOW,Y_RFTrain)
```

Out[163]:
```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=12, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

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 [61]:
```
Y_RFTrain.shape
```
Out[61]:
```
(17500,)
```

In [62]:
```
print(X_RFTrain_BOW.shape)
```
```
(17500, 25012)
```

In [63]:
```
print(Y_RFTest.shape)
```
```
(5000,)
```

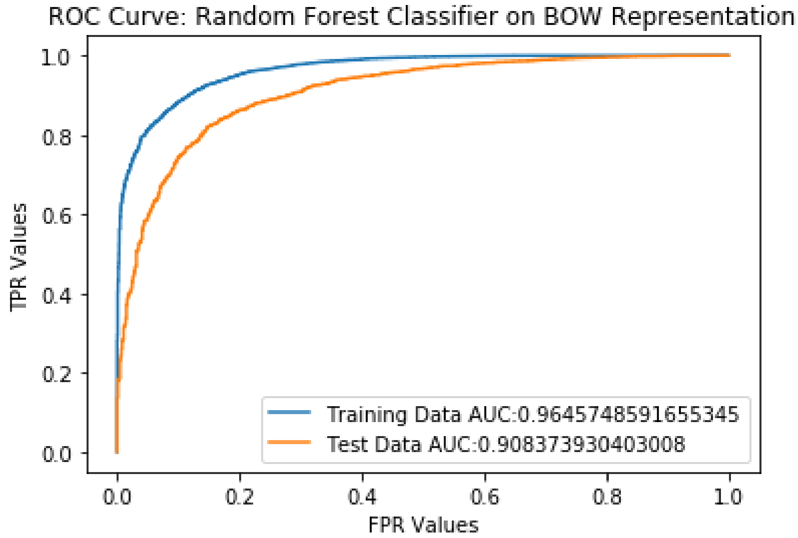
In [64]:
```
print(X_RFTest_BOW.shape)
```
```
(5000, 25012)
```

In [65]:
```
from sklearn.metrics import roc_curve, auc

train_fpr1,train_tpr1,threshold = roc_curve(Y_RFTrain,RFBOW_Test.predic
t_proba(X_RFTrain_BOW)[:,1])
test_fpr1,test_tpr1,threshold = roc_curve(Y_RFTest,RFBOW_Test.predict_p
roba(X_RFTest_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 [66]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr1,train_tpr1,label ='Training Data AUC:' + str(auc(tr
ain_fpr1,train_tpr1)))
plt.plot(test_fpr1,test_tpr1,label = 'Test Data AUC:' + str(auc(test_fp
r1,test_tpr1)))
```

```
plt.legend()

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

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



[5.1.2] Top 20 Important Features with Random Forest Implementation & BOW Featurization :-

In [166]:

```
BOW_feature_names = count_vect.get_feature_names()
BOW_feature_importances = RFBOW_Test.feature_importances_
BOW_feature_importances_sorted = np.argsort(BOW_feature_importances)
BOW_feature_importances_reverse = np.flip(BOW_feature_importances_sorte
d)
```

In [167]:
```
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      ---> 0.037
great    ---> 0.022
best     ---> 0.015
would    ---> 0.015
perfect          ---> 0.014
love     ---> 0.013
horrible         ---> 0.012
delicious        ---> 0.012
disappointed     ---> 0.012
bad      ---> 0.011
money    ---> 0.011
worst    ---> 0.01
thought          ---> 0.008
highly   ---> 0.008
easy     ---> 0.008
wonderful        ---> 0.007
favorite         ---> 0.007
terrible         ---> 0.007
snack    ---> 0.007
product          ---> 0.007
```

Wordcloud of Random Forest Implementation on BOW Featurization :-

As we have seen above, the first step of obtaining all the relevant features ie. the Top 20

Features is very straightforward and something that we have carried out in all of our Featurizations. Now the problem is that we need to obtain the same in the form of a String so as to input it to a WordCloud as an attribute. Following are the steps carried out in order to achieve the same :

1. Input these 20 Most Important Words into a List.(This has been carried out in the code snippet below)
2. Now convert this List into a String with each word separated by a Whitespace. This is carried out by joining an empty string with the string that we have obtained.
3. Now call the WordCloud with all its attributes defining on how we want the Word Cloud to be plotted.

In [224]:

```
from wordcloud import WordCloud

BOW_WC_Words = ' '
String_BOW_Words =[]
concat=''

j=0
while j <20:
    for i in BOW_feature_importances_reverse[0:j]:
        concat = BOW_WC_Words + BOW_feature_names[i]
    j=j+1
    String_BOW_Words.append(concat)
```

In [226]:

```
print(String_BOW_Words[1:])
```

```
[' not', ' great', ' best', ' would', ' perfect', ' love', ' horrible',
' delicious', ' disappointed', ' bad', ' money', ' worst', ' thought',
' highly', ' easy', ' wonderful', ' favorite', ' terrible', ' snack']
```

In [227]:

```
Final_BOW = BOW_WC_Words.join(String_BOW_Words[1:])
print(Final_BOW)
```

```
 not  great  best  would  perfect  love  horrible  delicious  disappoin
ted  bad  money  worst  thought  highly  easy  wonderful  favorite  ter
```

```
rible   snack
```

In [232]:
```
wordcloud_BOW = WordCloud(width = 1600, height = 800,
                background_color ='white',
                min_font_size = 10).generate(Final_BOW)

# Display the generated image:
plt.imshow(wordcloud_BOW, interpolation='bilinear')
plt.axis("off")
plt.show()
```

[5.1.3] SET 2 : Applying Random Forest on TFIDF :-

In [73]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_RFTrain)

# 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[73]:
```
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 [74]:
```
X_RFTrain_TFIDF = tf_idf_vect.transform(X_RFTrain)
X_RFCV_TFIDF = tf_idf_vect.transform(X_RFCV)
X_RFTest_TFIDF = tf_idf_vect.transform(X_RFTest)
```

In [75]:
```
print("Shapes before the TFIDF Vectorization was carried out:")

print(X_RFTrain.shape,Y_RFTrain.shape)
print(X_RFCV.shape,Y_RFCV.shape)
print(X_RFTest.shape,Y_RFTest.shape)

print("="*100)

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

print(X_RFTrain_TFIDF.shape,Y_RFTrain.shape)
print(X_RFCV_TFIDF.shape,Y_RFCV.shape)
print(X_RFTest_TFIDF.shape,Y_RFTest.shape)
```

```
Shapes before the TFIDF Vectorization was carried out:
(17500,) (17500,)
(2500,) (2500,)
(5000,) (5000,)
=======================================================================
=============================
Shapes after the TFIDF Vectorization was carried out:
(17500, 10508) (17500,)
(2500, 10508) (2500,)
(5000, 10508) (5000,)
```

Hyperparameter Tuning on the TFIDF Representation :-

Here we care about 2 hyperparameters :-

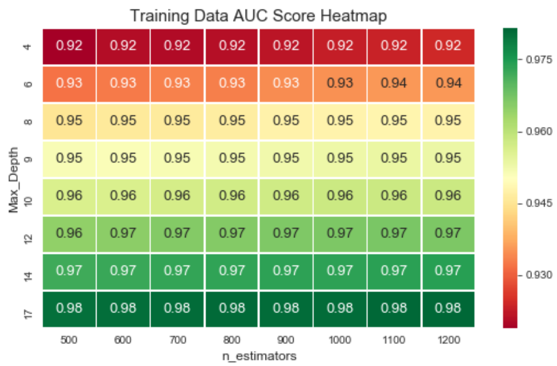
- "max_depth", which we would be considering in the range :- { [4,6,8,9,10,12,14,17] }
- "n_estimators", which we would be considering in the range of (500,1200) in the interval of 100 and see how which value is ideal in our scenario.

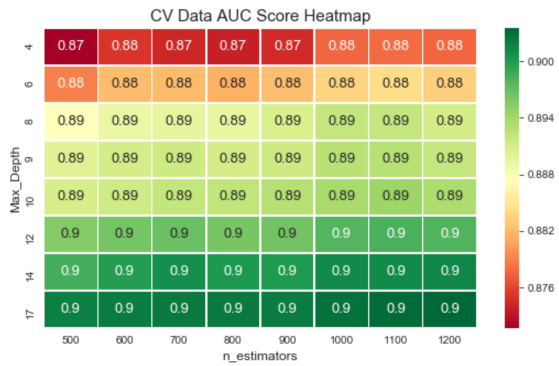
Again, the important fact to be noticed for the Random Forest Clasifier is the fact that Random Forests are made up of Decision Trees (of large depth) as the base learners and since for Decision Trees there was no need to carry out Standardization because we did not have any hyperplane in consideration, there is no need to carry out Standardization for Random Forests as well.

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

In [76]:

```
import time
start = time.time()

TFIDF_Train_df = RFTrain_Heatmap(X_RFTrain_TFIDF,Y_RFTrain)
TFIDF_CV_df = RFCV_Heatmap(X_RFTrain_TFIDF,Y_RFTrain,X_RFCV_TFIDF,Y_RFC
V)
rf_plotheatmaps(TFIDF_Train_df,TFIDF_CV_df)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for Simple CV S
earch for Random Forest Classifier on "
      "BOW Vectorizer (in minutes):", (end - start)/60)
```






```
Time Consumed to Complete  Hyperparameter tuning for Simple CV Search f
or Random Forest Classifier on BOW Vectorizer (in minutes): 11.21440651
4167786
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.90, and the minimum AUC Value on the Train Heatmap for the same combination is 0.97.
- Therefore the Best Combination of Max_Depth and n_estimators for the TFIDF Featurization is either of the following:

Max_Depth = 12 or 14. n_estimators = 1100 or 1200.

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

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

start = time.time()

#Carrying out 3-fold Cross Validation. class_weight is taken as 'balanc
ed' since the data that we originally had
#was an Imbalanced Real World Dataset.

parameters= [{'max_depth':depth_hyperparameter,'n_estimators':estimator
s_hyperparameter}]
```

```
model2 = RandomForestClassifier(criterion='gini',class_weight='balance
d',min_samples_split=2,
                               bootstrap=True,n_jobs=-1)

RF_TFIDF = GridSearchCV(model2,parameters,scoring='roc_auc',cv=3)
RF_TFIDF.fit(X_RFTrain_TFIDF,Y_RFTrain)

print(RF_TFIDF.best_estimator_)
print(" ")

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for GridSearchC
V for Random Forest Classifier on "
      "TFIDF Vectorizer (in minutes):", (end - start)/60)
```

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)

Time Consumed to Complete  Hyperparameter tuning for GridSearchCV for R
andom Forest Classifier on TFIDF Vectorizer (in minutes): 16.2044868151
34683
```

Testing with the Test Data on the TFIDF Representation:-

In [79]:

```
RFTFIDF_Test = RandomForestClassifier(criterion='gini',class_weight='ba
lanced',min_samples_split=2,max_depth=17,
                                  n_estimators=1100,bootstrap=True,n_jo
bs=-1)
RFTFIDF_Test.fit(X_RFTrain_TFIDF,Y_RFTrain)
```

Out[79]:

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, max_features='auto',
```

```
criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

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 [80]:
```
Y_RFTrain.shape
```
Out[80]:
```
(17500,)
```

In [81]:
```
print(X_RFTrain_TFIDF.shape)
```
```
(17500, 10508)
```

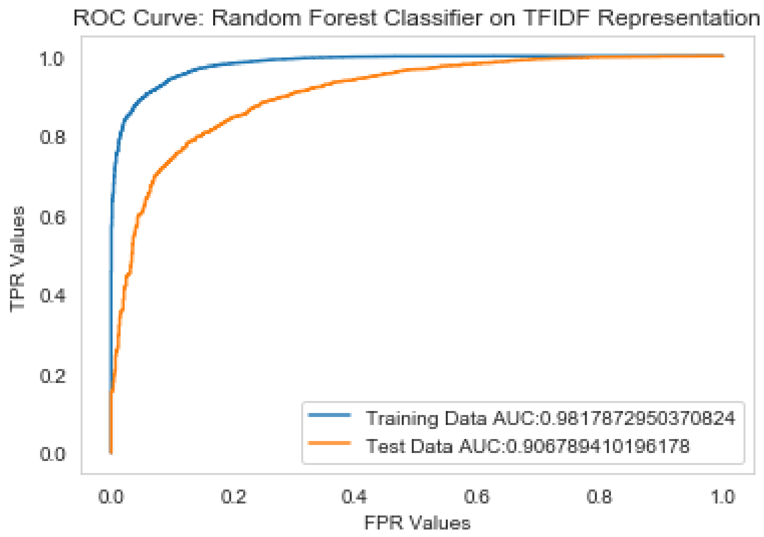
In [82]:
```
print(Y_RFTest.shape)
```
```
(5000,)
```

In [83]:
```
print(X_RFTest_TFIDF.shape)
```
```
(5000, 10508)
```

In [84]:
```
from sklearn.metrics import roc_curve, auc

train_fpr2,train_tpr2,threshold = roc_curve(Y_RFTrain,RFTFIDF_Test.pred
ict_proba(X_RFTrain_TFIDF)[:,1])
test_fpr2,test_tpr2,threshold = roc_curve(Y_RFTest,RFTFIDF_Test.predict
_proba(X_RFTest_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 [85]:
```
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: Random Forest Classifier on TFIDF Representation'
)

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



[5.1.4] Top 20 Important Features with Random Forest Implementation & BOW Featurization :-

In [234]:
```
RFTFIDF_feature_names = tf_idf_vect.get_feature_names()
RFTFIDF_feature_importances = RFTFIDF_Test.feature_importances_
RFTFIDF_feature_importances_sorted = np.argsort(RFTFIDF_feature_importa
nces)
RFTFIDF_feature_importances_reverse = np.flip(RFTFIDF_feature_importanc
es_sorted)
```

In [240]:
```
print("The Top 20 Important Features with TFIDF Featurization and their
 corresponding feature importances"
       "are as follows:")
print("="*100)

for i in RFTFIDF_feature_importances_reverse[:20]:
    print(RFTFIDF_feature_names[i],"\t", '--->',np.round(RFTFIDF_featur
e_importances[i],3))
```

```
The Top 20 Important Features with TFIDF Featurization and their corres
ponding feature importancesare as follows:
=======================================================================
=============================
not      ---> 0.037
great    ---> 0.029
best     ---> 0.017
would    ---> 0.017
love     ---> 0.016
delicious        ---> 0.014
bad      ---> 0.013
disappointed     ---> 0.013
perfect          ---> 0.012
would not        ---> 0.011
worst    ---> 0.011
money    ---> 0.01
thought          ---> 0.009
good     ---> 0.009
not buy          ---> 0.009
favorite         ---> 0.008
loves    ---> 0.008
easy     ---> 0.008
horrible         ---> 0.008
away     ---> 0.007
```

Wordcloud of Random Forest Implementation on TFIDF Featurization :-

In [236]:
```
from wordcloud import WordCloud

TFIDF_WC_Words = ' '
String_TFIDF_Words =[]
concat=''

j=0
while j <20:
    for i in RFTFIDF_feature_importances_reverse[0:j]:
        concat = TFIDF_WC_Words + RFTFIDF_feature_names[i]
    j=j+1
    String_TFIDF_Words.append(concat)
```

In [237]:
```
print(String_TFIDF_Words[1:])
```

```
[' not', ' great', ' best', ' would', ' love', ' delicious', ' bad', ' disappointed', ' perfect', ' would not', ' worst', ' money', ' thought', ' good', ' not buy', ' favorite', ' loves', ' easy', ' horrible']
```

In [238]:
```
Final_TFIDF = TFIDF_WC_Words.join(String_TFIDF_Words[1:])
print(Final_TFIDF)
```

```
 not  great  best  would  love  delicious  bad  disappointed  perfect  would not  worst  money  thought  good  not buy  favorite  loves  easy  horrible
```

In [239]:
```
wordcloud_TFIDF = WordCloud(width = 1600, height = 800,
                background_color ='white',
                min_font_size = 10).generate(Final_TFIDF)

# Display the generated image:
```

```
plt.imshow(wordcloud_TFIDF, interpolation='bilinear')
plt.axis("off")
plt.show()
```

[5.1.5] SET 3 : Applying Random Forest on Avg W2V :-

Converting Reviews into Numerical Vectors using W2V vectors :-

In [93]:
```
list_of_sentence_Train =[]

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

In [94]:
```
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 : 7984
Some of the sample words are as follows:  ['really', 'good', 'idea', 'f
inal', 'product', 'outstanding', 'use', 'car', 'window', 'everybody',
'asks', 'bought', 'made', 'two', 'thumbs', 'received', 'shipment', 'cou
ld', 'hardly', 'wait', 'try', 'love', 'call', 'instead', 'stickers', 'r
emoved', 'easily', 'daughter', 'designed', 'signs', 'printed', 'revers
e', 'windows', 'beautifully', 'print', 'shop', 'program', 'going', 'lo
t', 'fun', 'everywhere', 'like', 'tv', 'computer', 'nothing', 'bother',
'link', 'top', 'page', 'buy']
```

Converting the Train Data Text :-

In [95]:

```
# 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%|██████████| 17500/17500 [00:30<00:00, 564.83it/s]
```

```
(17500, 50)
[ 0.15220198  0.05576989 -0.07171854 -0.03404884  0.15028512  0.0287223
```

```
 -0.37607086 -0.39209854  0.11907352 -0.0339811  -0.22027381  0.5514338
 -0.14587451 -0.337997   -0.23680012  0.30940821 -0.5667558  -0.1244347
4
 -0.27543045  0.20164551  0.71283519 -0.53020276  0.3942512   0.0782334
1
  0.32314835 -0.03377031  0.34873995  0.2542308  -0.41922954 -0.1056303
  0.07678302 -0.26855448  0.01378719  0.41603668 -0.20859432 -0.0834522
1
 -0.2244219  -0.26578503 -0.45324875  0.15611992  0.45342708  0.0476327
6
  0.100735    0.46625714  0.14008529  0.2740927  -0.6588465   0.1194535
8
  0.04566242 -0.1905536 ]
```

Converting the CV Data Text :-

In [96]:

```
list_of_sentence_CV=[]

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

In [97]:

```
# 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%|██████████| 2500/2500 [00:05<00:00, 466.63it/s]
```

```
(2500, 50)
[ 0.08592392 -0.18178867 -0.45723418 -0.36011336  0.23976411  0.0472911
5
 -0.2077273   0.07959903  0.43789861 -0.14907607 -0.01379098  0.7042294
9
  0.04535472 -0.32398123 -0.51427877 -0.01735015 -0.92648441  0.1210871
6
 -0.17515983  0.13711045  0.63619954 -0.4865623   0.39375764 -0.0654601
2
  0.18935982  0.26766712  0.44931212 -0.41304849 -0.76575887 -0.5043167
4
  0.33818367 -0.27495907  0.07750371  0.7028081  -0.14046207 -0.3818203
1
 -0.0533286  -0.38390323 -0.46776722  0.11931604  0.54018443  0.4328251
7
  0.16000851  0.4001234   0.34865611  0.28761906 -0.23603271 -0.0829357
8
  0.19974293  0.00191084]
```

Converting the Test Dataset :-

In [98]:

```
list_of_sentence_Test=[]

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

In [99]:

```
# 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%|██████████| 5000/5000 [00:11<00:00, 444.77it/s]
```

```
(5000, 50)
[ 0.37846528  0.53107481 -0.33927674 -0.34418321  0.8389905  -0.0800654
4
 -0.85482396 -0.48786479  0.1053979  -0.18959435 -0.12634227  0.0464256
5
 -0.08181657 -0.07206561  0.52864775 -0.17352135 -0.70469238  0.1269889
6
 -0.31984442  0.32865084  1.81481743 -0.45717987  0.51690476 -0.2697234
8
  0.70017175  0.44684364  0.75821949  0.53982237 -0.1450845  -0.2144014
 -0.68760575 -0.33456707 -0.61569683  0.38886902 -0.80031829 -0.2552438
1
 -0.49219879 -0.14990563 -0.48235789  0.13019206  0.63653312  0.2021220
7
  0.23544724  0.34149272  0.24321884 -0.00277779 -0.07744593  0.2289454
4
  0.14697192 -0.74974837]
```

In [100]:
```
print("Shapes before the Avg W2V Vectorization was carried out:")

print(X_RFTrain.shape,Y_RFTrain.shape)
print(X_RFCV.shape,Y_RFCV.shape)
print(X_RFTest.shape,Y_RFTest.shape)

print("="*100)

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

print(sent_vectors_train.shape,Y_RFTrain.shape)
print(sent_vectors_cv.shape,Y_RFCV.shape)
print(sent_vectors_test.shape,Y_RFTest.shape)
```

```
Shapes before the Avg W2V Vectorization was carried out:
(17500,) (17500,)
(2500,) (2500,)
(5000,) (5000,)
========================================================================
=============================
Shapes after the Avg W2V Vectorization was carried out:
(17500, 50) (17500,)
(2500, 50) (2500,)
(5000, 50) (5000,)
```

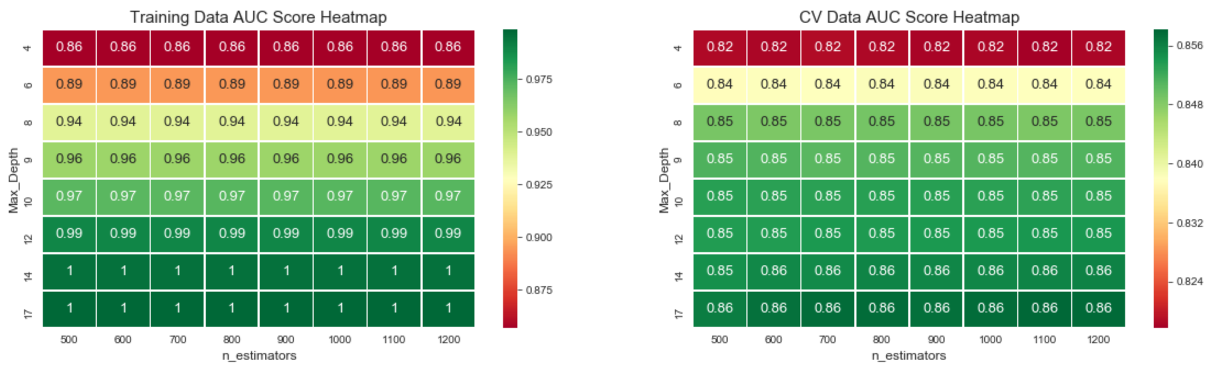
Hyperparameter Tuning on the Avg W2V Representation :-

Random Forests are made up of Decision Trees (of large depth) as the base learners and since for Decision Trees there was no need to carry out Standardization because we did not have any hyperplane in consideration, there is no need to carry out Standardization for Random Forests as well.

Calling the Different Functions to obtain the Train and CV Dataframes and Obtaining the

Seaborn HeatMaps for them :-

In [102]:
```python
import time
start = time.time()

AW2V_Train_df = RFTrain_Heatmap(sent_vectors_train,Y_RFTrain)
AW2V_CV_df = RFCV_Heatmap(sent_vectors_train,Y_RFTrain,sent_vectors_cv,
Y_RFCV)
rf_plotheatmaps(AW2V_Train_df,AW2V_CV_df)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for Simple CV S
earch for Random Forest Classifier on "
      "Avg W2V Vectorizer (in minutes):", (end - start)/60)
```




```
Time Consumed to Complete  Hyperparameter tuning for Simple CV Search f
or Random Forest Classifier on Avg W2V Vectorizer (in minutes): 55.4889
896829923
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.85, and the minimum AUC Value on the Train Heatmap for the same combination is 0.94.
- Therefore the Best Combination of Max_Depth and n_estimators for the Avg W2V Featurization is either of the following:

Max_Depth = 8. n_estimators = 1100 or 1200.

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

In [104]:
```
warnings.filterwarnings('ignore')

start = time.time()

#Carrying out 3-fold Cross Validation. class_weight is taken as 'balanc
ed' since the data that we originally had
#was an Imbalanced Real World Dataset.

parameters= [{'max_depth':depth_hyperparameter,'n_estimators':estimator
s_hyperparameter}]
model3 = RandomForestClassifier(criterion='gini',class_weight='balance
d',min_samples_split=2,
                               bootstrap=True,n_jobs=-1)

RF_AW2V = GridSearchCV(model3,parameters,scoring='roc_auc',cv=3)
RF_AW2V.fit(sent_vectors_train,Y_RFTrain)

print(RF_AW2V.best_estimator_)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for GridSearchC
V for Random Forest Classifier on "
      "Avg W2V (in minutes):", (end - start)/60)
```

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
Time Consumed to Complete  Hyperparameter tuning for GridSearchCV for R
andom Forest Classifier on Avg W2V (in minutes): 58.23843389749527
```

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

In [105]:
```
RFAW2V_Test = RandomForestClassifier(criterion='gini',class_weight='balanced',min_samples_split=2,max_depth=17,
                                  n_estimators=1100,bootstrap=True,n_jobs=-1)
RFAW2V_Test.fit(sent_vectors_train,Y_RFTrain)
```

Out[105]:
```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

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 [106]:
```
Y_RFTrain.shape
```

Out[106]:
```
(17500,)
```

In [107]:
```
print(sent_vectors_train.shape)
```

```
(17500, 50)
```

In [108]:
```
print(Y_RFTest.shape)
```

```
(5000,)
```

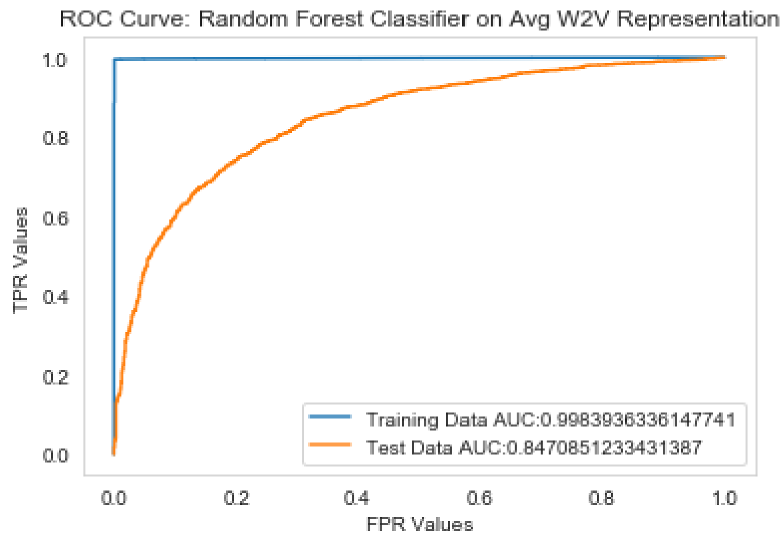
In [109]:
```
print(sent_vectors_test.shape)
```

```
(5000, 50)
```

In [110]:
```
from sklearn.metrics import roc_curve, auc

train_fpr3,train_tpr3,threshold = roc_curve(Y_RFTrain,RFAW2V_Test.predi
ct_proba(sent_vectors_train)[:,1])
test_fpr3,test_tpr3,threshold = roc_curve(Y_RFTest,RFAW2V_Test.predict_
proba(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 [111]:
```
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: Random Forest Classifier on Avg W2V Representatio
n')

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



[5.1.6] SET 4 : Applying Random Forest on TFIDF W2V :-

In [113]:
```
model_RF = TfidfVectorizer()
tf_idf_matrix = model_RF.fit_transform(X_RFTrain)

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

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

Out[114]:
```
(17500, 25012)
```

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 [115]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model_RF.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_RFTrain = []; # 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_RFTrain.append(sent_vec)
    row += 1
```

```
100%|██████████| 17500/17500 [04:13<00:00, 68.92it/s]
```

```
100%|██████████| 17500/17500 [04:13<00:00, 68.92it/s]
```

In [145]:
```
tfidf_sent_vectors_RFTrain[1]
```

Out[145]:
```
array([ 1.50340217e-01,  1.67166102e-01, -1.36324296e-01, -1.45961334e-
01,
        1.33451191e-01,  1.46271763e-01, -3.14017693e-01, -1.66337759e-
01,
        1.08598946e-01,  1.64667070e-01, -6.83528019e-02,  3.76364205e-
01,
       -1.75530195e-02, -7.73021945e-02, -1.04195482e-01,  1.45072052e-
01,
       -3.70068218e-01, -2.56753776e-02, -1.38101259e-01,  8.62671427e-
02,
        6.30486291e-01, -3.40259556e-01,  2.62683839e-01, -4.64388854e-
02,
        2.72424853e-01,  1.51372210e-01,  2.18428982e-01,  2.50856343e-
01,
       -2.71302702e-01,  4.54214941e-04,  1.00237904e-01, -2.84866885e-
01,
       -4.75550058e-02,  3.39206583e-01, -2.91306050e-01, -1.61539500e-
01,
       -2.68240473e-01, -1.11235975e-02, -4.65053555e-01,  1.70462975e-
01,
        4.72143572e-01, -1.23850753e-02,  4.22083580e-02,  3.93972935e-
01,
        1.53733760e-01,  3.13323776e-01, -3.27377919e-01,  1.16299442e-
02,
        4.32776899e-02, -2.16505219e-01])
```

Converting the CV Data Text :-

In [117]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model_RF.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_RFCV = []; # 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_RFCV.append(sent_vec)
    row += 1
```

```
100%|██████████| 2500/2500 [00:44<00:00, 56.66it/s]
```

Converting the Test Data Text :-

In [118]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = model_RF.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_RFTest = []; # 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_RFTest.append(sent_vec)
    row += 1
```

```
100%|██████████| 5000/5000 [01:19<00:00, 62.59it/s]
```

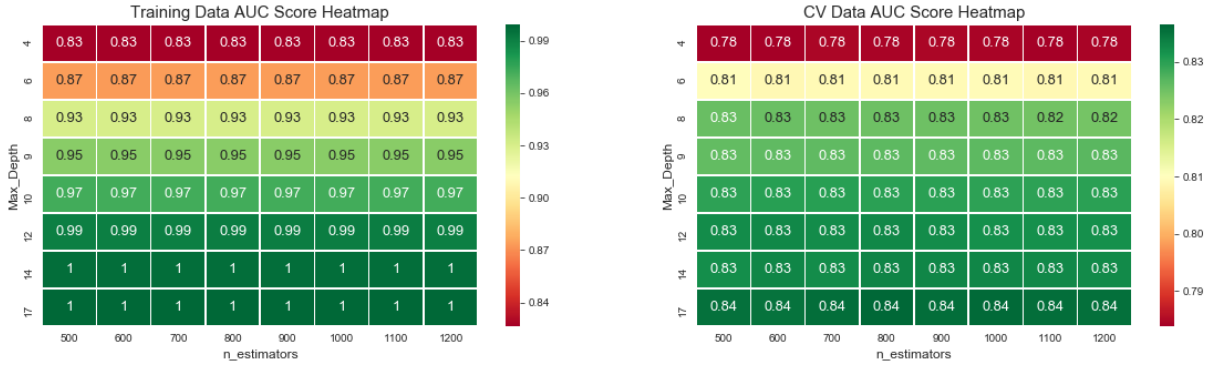
Hyperparameter Tuning on the TFIDF W2V Representation :-

Random Forests are made up of Decision Trees (of large depth) as the base learners and since for Decision Trees there was no need to carry out Standardization because we did not have any hyperplane in consideration, there is no need to carry out Standardization for Random Forests as well.

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

In [119]:
```
start = time.time()

TFIDFW2V_Train_df = RFTrain_Heatmap(tfidf_sent_vectors_RFTrain,Y_RFTrai
n)
```

```
TFIDFW2V_CV_df = RFCV_Heatmap(tfidf_sent_vectors_RFTrain,Y_RFTrain,tfid
f_sent_vectors_RFCV,Y_RFCV)
rf_plotheatmaps(TFIDFW2V_Train_df,TFIDFW2V_CV_df)

end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for Simple CV S
earch for Random Forest Classifier on "
      "TFIDF W2V (in minutes):", (end - start)/60)
```




```
Time Consumed to Complete  Hyperparameter tuning for Simple CV Search f
or Random Forest Classifier on TFIDF W2V (in minutes): 64.9894030650456
8
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.84, and the minimum AUC Value on the Train Heatmap for the same combination is 1.00.
- Therefore the Best Combination of Max_Depth and n_estimators for the TFIDF W2V Featurization is either of the following:

Max_Depth = 14 or 17. n_estimators = 1100 or 1200.

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

In [121]:
```
warnings.filterwarnings('ignore')
```

```
start = time.time()

#Carrying out 3-fold Cross Validation. class_weight is taken as 'balanc
ed' since the data that we originally had
#was an Imbalanced Real World Dataset.

parameters= [{'max_depth':depth_hyperparameter,'n_estimators':estimator
s_hyperparameter}]
model4 = RandomForestClassifier(criterion='gini',class_weight='balance
d',min_samples_split=2,
                               bootstrap=True,n_jobs=-1)

RF_TFIDFW2V = GridSearchCV(model4,parameters,scoring='roc_auc',cv=3)
RF_TFIDFW2V.fit(tfidf_sent_vectors_RFTrain,Y_RFTrain)

print(RF_TFIDFW2V.best_estimator_)

end = time.time()
print(" ")
print("Time Consumed to Complete  Hyperparameter tuning for GridSearchC
V for Random Forest Classifier on "
      "TFIDF W2V (in minutes):", (end - start)/60)
```

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)

Time Consumed to Complete  Hyperparameter tuning for GridSearchCV for R
andom Forest Classifier on TFIDF W2V (in minutes): 58.08252164920171
```

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

In [122]:
```
RFTFIDFW2V_Test = RandomForestClassifier(criterion='gini',class_weight=
'balanced',min_samples_split=2,max_depth=17,
                                  n_estimators=1100,bootstrap=True,n_jo
bs=-1)
RFTFIDFW2V_Test.fit(tfidf_sent_vectors_RFTrain,Y_RFTrain)
```

Out[122]:
```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=17, 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=1100, n_jobs=-1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

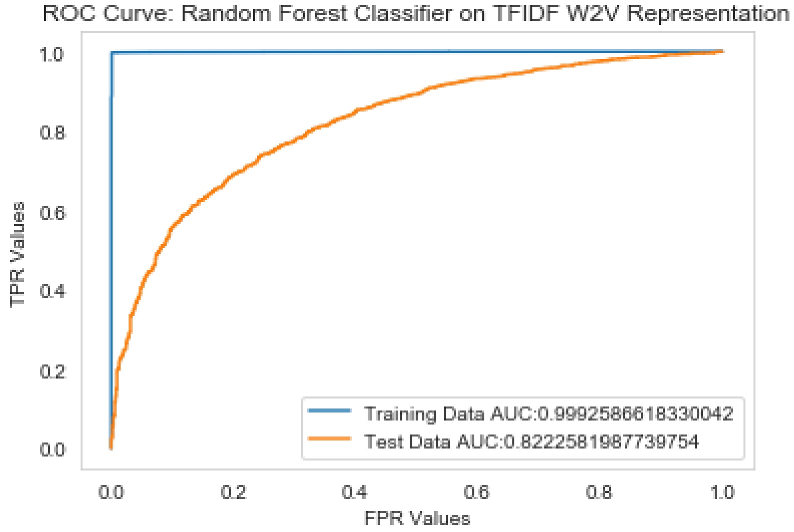
Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [123]:
```
from sklearn.metrics import roc_curve, auc

train_fpr4,train_tpr4,threshold = roc_curve(Y_RFTrain,RFTFIDFW2V_Test.p
redict_proba(tfidf_sent_vectors_RFTrain)[:,1])
test_fpr4,test_tpr4,threshold = roc_curve(Y_RFTest,RFTFIDFW2V_Test.pred
ict_proba(tfidf_sent_vectors_RFTest)[:,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 [124]:
```
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: Random Forest Classifier on TFIDF W2V Representat
ion')

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



[5.2] Applying GBDT using XGBOOST :-

[5.2.1] SET 1 : Applying XGBOOST on BOW Vectorization :-

Hyperparameter Tuning on the BOW Representation using XGBOOST :-

In [125]:
```
import xgboost as xgb
```

```
from xgboost.sklearn import XGBClassifier
from sklearn.metrics import roc_auc_score
```

In [126]:
```
GBDT_depth_hyperparameter = [2, 3, 4, 5, 6, 7, 8, 9, 10]
GBDT_estimators_hyperparameter = [5, 10, 50, 100, 200, 500, 1000]
```

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

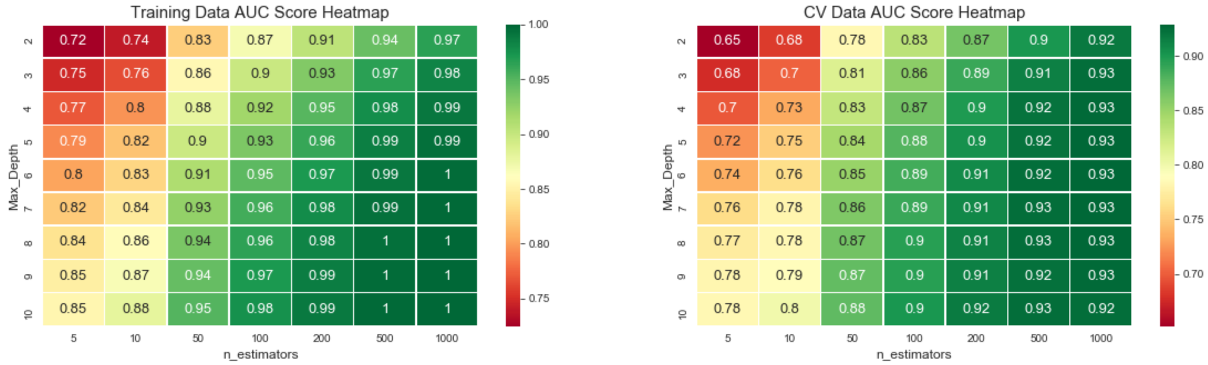
In [127]:
```
def GBDTTrain_Heatmap(X_Train,Y_Train):

    df5 = []
    df6 = []
    Train_AUC_XGB = []

    for i in GBDT_depth_hyperparameter:
        for j in GBDT_estimators_hyperparameter:
            df5.append(i)
            df6.append(j)

            Train_model = XGBClassifier(max_depth=i,subsample=0.7,colsa
mple_bytree=0.7,eval_metric='auc',
                                        n_estimators=j,learning_rate=0.
1,booster='gbtree')
            Train_model.fit(X_Train,Y_Train)

            Y_Train_XGB_pred = Train_model.predict_proba(X_Train)[:,1]
            Train_AUC_XGB.append(roc_auc_score(Y_Train,Y_Train_XGB_pred
))

    train_data_XGB = {'max_depth':df5,'n_estimators':df6,'AUC_Score':Tr
ain_AUC_XGB}
    train_dataframe_XGB = pd.DataFrame(train_data_XGB)
    train_dataframe_XGB = train_dataframe_XGB.pivot("max_depth","n_esti
mators","AUC_Score")

    return train_dataframe_XGB
```

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

In [128]:
```
def GBDTCV_Heatmap(X_Train,Y_Train,X_CV,Y_CV):

    df7 = []
    df8 = []
    CV_AUC_XGB = []

    for i in GBDT_depth_hyperparameter:
        for j in GBDT_estimators_hyperparameter:
            df7.append(i)
            df8.append(j)

            Train_model = XGBClassifier(max_depth=i,subsample=0.7,colsa
mple_bytree=0.7,eval_metric='auc',
                                        n_estimators=j,learning_rate=0.
1,booster='gbtree')
            Train_model.fit(X_Train,Y_Train)

            Y_CV_XGB_pred = Train_model.predict_proba(X_CV)[:,1]
            CV_AUC_XGB.append(roc_auc_score(Y_CV,Y_CV_XGB_pred))

    cv_data_XGB = {'max_depth':df7,'n_estimators':df8,'AUC_Score':CV_AU
C_XGB}
    cv_dataframe_XGB = pd.DataFrame(cv_data_XGB)
    cv_dataframe_XGB = cv_dataframe_XGB.pivot("max_depth","n_estimator
s","AUC_Score")

    return cv_dataframe_XGB
```

In [130]:
```
import time
start = time.time()

GBDTBOW_Train_df = GBDTTrain_Heatmap(X_RFTrain_BOW,Y_RFTrain)
GBDTBOW_CV_df = GBDTCV_Heatmap(X_RFTrain_BOW,Y_RFTrain,X_RFCV_BOW,Y_RFC
V)
rf_plotheatmaps(GBDTBOW_Train_df,GBDTBOW_CV_df)
```

```
end = time.time()
print("Time Consumed to Complete  Hyperparameter tuning for GBDT(XGBoos
t Implementation) Grid Search on"
      " BOW Vectorizer in minutes :",(end - start)/60)
```




```
Time Consumed to Complete  Hyperparameter tuning for GBDT(XGBoost Imple
mentation) Grid Search on BOW Vectorizer in minutes 177.28791013558705
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.93, and the minimum AUC Value on the Train Heatmap for the same combination is 0.98.
- Therefore the Best Combination of Max_Depth and n_estimators for the BOW Featurization is the following:

Max_Depth = 3. n_estimators= 1000.

Testing with the Test Data on the BOW Representation:-

In [156]:

```
GBDTBOW_Test = XGBClassifier(max_depth=3,subsample=0.7,colsample_bytree
=0.7,eval_metric='auc',
                                          n_estimators=1000,learning_rate
```

```
=0.1,booster='gbtree')
GBDTBOW_Test.fit(X_RFTrain_BOW,Y_RFTrain)
```

Out[156]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=0.7, eval_metric='auc',
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=1, missing=None, n_estimators=1000, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=0.7, verbosity=1)
```

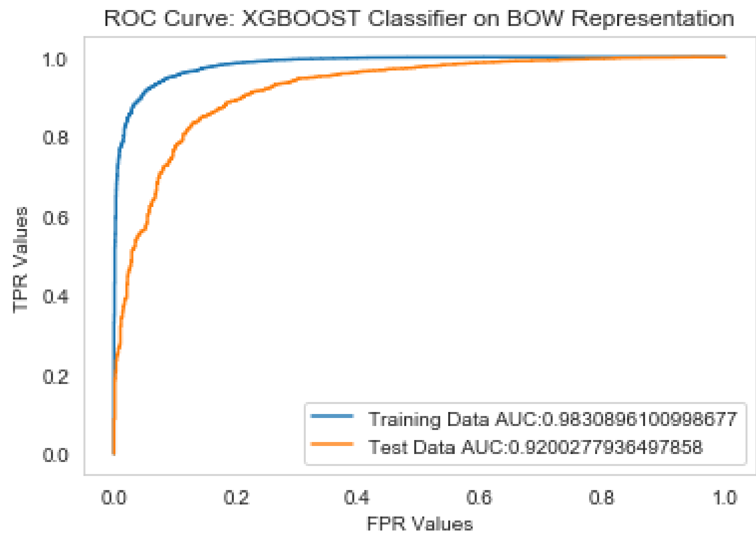
Therefore here we are basically creating a model (to Test the model on the Test Data) by applying the Best values of the Hyperparameters hence obtained.

In [157]:
```
from sklearn.metrics import roc_curve, auc

train_fpr5,train_tpr5,threshold = roc_curve(Y_RFTrain,GBDTBOW_Test.pred
ict_proba(X_RFTrain_BOW)[:,1])
test_fpr5,test_tpr5,threshold = roc_curve(Y_RFTest,GBDTBOW_Test.predict
_proba(X_RFTest_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 [158]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr5,train_tpr5,label ='Training Data AUC:' + str(auc(tr
ain_fpr5,train_tpr5)))
plt.plot(test_fpr5,test_tpr5,label = 'Test Data AUC:' + str(auc(test_fp
r5,test_tpr5)))
plt.legend()

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

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



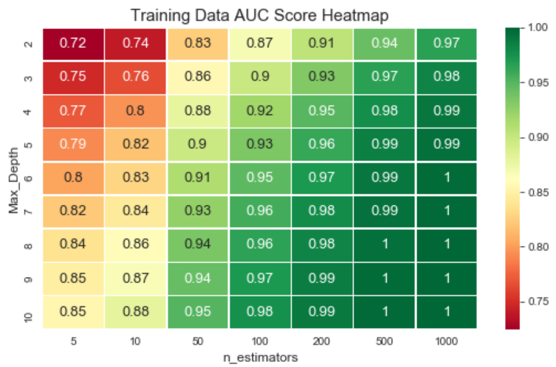
[5.2.2] SET 2 : Applying XGBOOST on TFIDF Vectorization :-

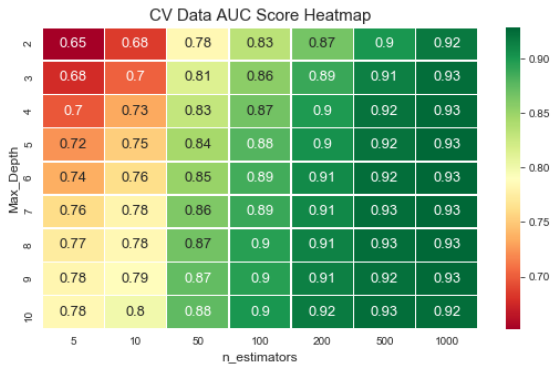
Hyperparameter Tuning on the TFIDF Representation using XGBOOST :-

In [134]:

```
import time
start = time.time()

GBDTTFIDF_Train_df = GBDTTrain_Heatmap(X_RFTrain_TFIDF,Y_RFTrain)
GBDTTFIDF_CV_df = GBDTCV_Heatmap(X_RFTrain_TFIDF,Y_RFTrain,X_RFCV_TFIDF
,Y_RFCV)
rf_plotheatmaps(GBDTBOW_Train_df,GBDTBOW_CV_df)

end = time.time()
```

```
print("Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost Implementation) Simple CV on"
      " TFIDF Vectorizer in minutes :",(end - start)/60)
```






```
Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost Implementation) Simple CV on TFIDF Vectorizer in minutes : 178.60421149730684
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.93, and the minimum AUC Value on the Train Heatmap for the same combination is 0.98.
- Therefore the Best Combination of Max_Depth and n_estimators for the TFIDF Featurization is the following:

Max_Depth=3. n_estimators= 1000.

Testing with the Test Data on the TFIDF Representation:-

In [135]:
```
GBDTTFIDF_Test = XGBClassifier(max_depth=3,subsample=0.7,colsample_bytree=0.7,eval_metric='auc',
                               n_estimators=1000,learning_rate=0.1,booster='gbtree')
GBDTTFIDF_Test.fit(X_RFTrain_TFIDF,Y_RFTrain)
```

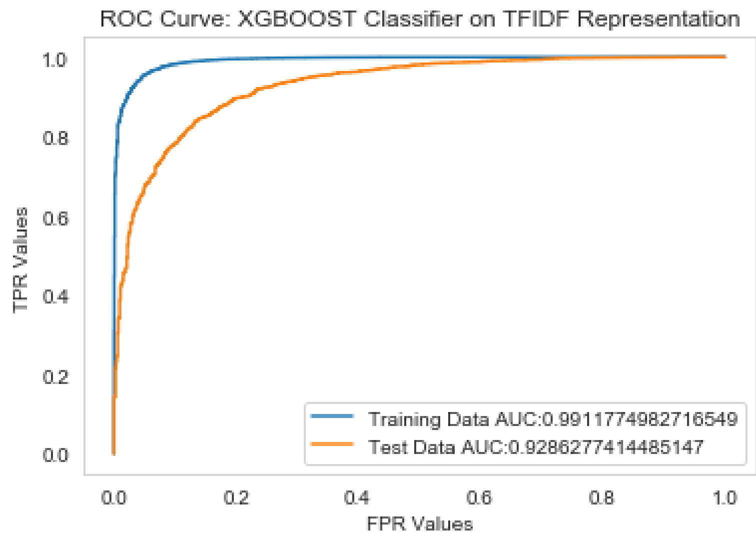
Out[135]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=0.7, eval_metric='auc',
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=1, missing=None, n_estimators=1000, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=0.7, verbosity=1)
```

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 [136]:
```
from sklearn.metrics import roc_curve, auc

train_fpr6,train_tpr6,threshold = roc_curve(Y_RFTrain,GBDTTFIDF_Test.pr
edict_proba(X_RFTrain_TFIDF)[:,1])
test_fpr6,test_tpr6,threshold = roc_curve(Y_RFTest,GBDTTFIDF_Test.predi
ct_proba(X_RFTest_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 [137]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr6,train_tpr6,label ='Training Data AUC:' + str(auc(tr
ain_fpr6,train_tpr6)))
plt.plot(test_fpr6,test_tpr6,label = 'Test Data AUC:' + str(auc(test_fp
r6,test_tpr6)))
plt.legend()

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

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

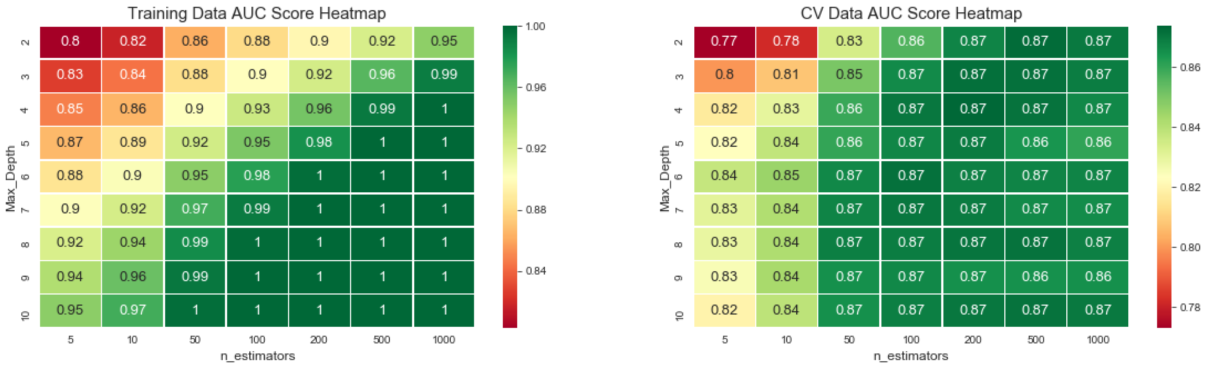


[5.2.3] SET 3 : Applying XGBOOST on Avg W2V Vectorization :-

Hyperparameter Tuning on the Avg W2V Representation using XGBOOST :-

In [138]:
```
import time
start = time.time()

GBDTAW2V_Train_df = GBDTTrain_Heatmap(sent_vectors_train,Y_RFTrain)
GBDTAW2V_CV_df = GBDTCV_Heatmap(sent_vectors_train,Y_RFTrain,sent_vecto
rs_cv,Y_RFCV)
rf_plotheatmaps(GBDTAW2V_Train_df,GBDTAW2V_CV_df)

end = time.time()
print("Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost
```

```
Implementation) Simple CV on"
      " Avg W2V in minutes :",(end - start)/60)
```




```
Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost Implem
entation) Simple CV on Avg W2V in minutes : 59.18065168857574
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.87, and the minimum AUC Value on the Train Heatmap for the same combination is 0.90.
- Therefore the Best Combination of Max_Depth and n_estimators for the Avg W2V Featurization is either of the following:

Max_Depth = 2. n_estimators = 200 .

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

In [159]:
```
GBDTAW2V_Test = XGBClassifier(max_depth=2,subsample=0.7,colsample_bytre
e=0.7,eval_metric='auc',
                                                  n_estimators=200,learning_rate=
0.1,booster='gbtree')
GBDTAW2V_Test.fit(sent_vectors_train,Y_RFTrain)
```

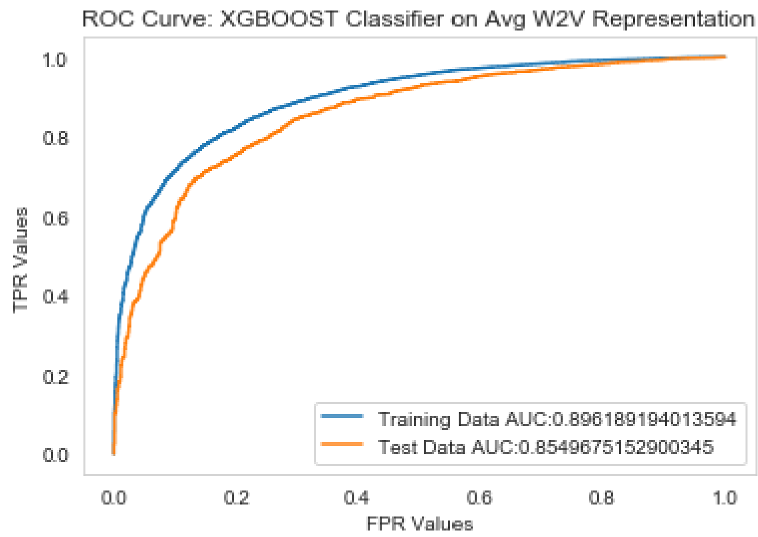
Out[159]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=0.7, eval_metric='auc',
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=2,
       min_child_weight=1, missing=None, n_estimators=200, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=0.7, verbosity=1)
```

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 [160]:
```
from sklearn.metrics import roc_curve, auc

train_fpr7,train_tpr7,threshold = roc_curve(Y_RFTrain,GBDTAW2V_Test.pre
dict_proba(sent_vectors_train)[:,1])
test_fpr7,test_tpr7,threshold = roc_curve(Y_RFTest,GBDTAW2V_Test.predic
t_proba(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 [161]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr7,train_tpr7,label ='Training Data AUC:' + str(auc(tr
ain_fpr7,train_tpr7)))
plt.plot(test_fpr7,test_tpr7,label = 'Test Data AUC:' + str(auc(test_fp
r7,test_tpr7)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: XGBOOST Classifier on Avg W2V Representation')

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

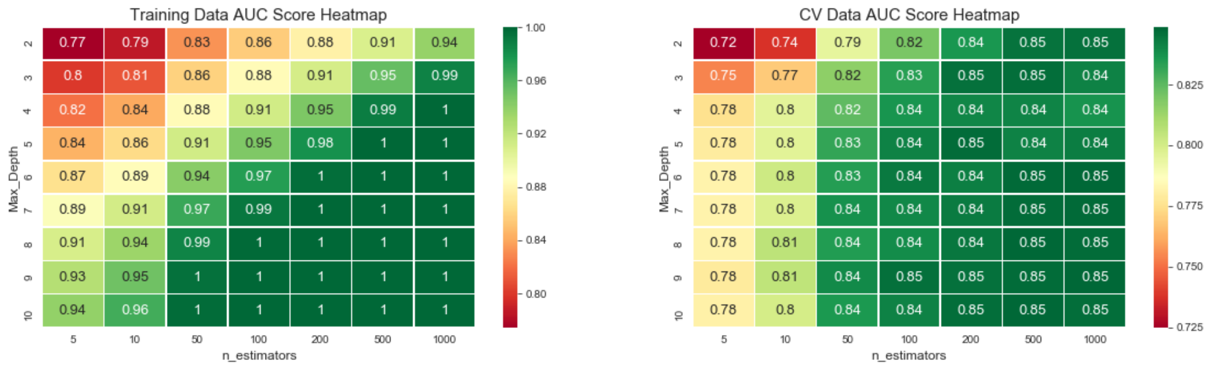


[5.2.4] SET 4 : Applying XGBOOST on TFIDF W2V Vectorization :-

Hyperparameter Tuning on the TFIDF W2V Representation using XGBOOST :-

In [151]:
```
import time
start = time.time()

GBDTTFIDFW2V_Train_df = GBDTTrain_Heatmap(np.array(tfidf_sent_vectors_R
FTrain),Y_RFTrain)
#We need to convert the X_Train to a numpy array because otherwise we g
et an error that says:- "List has no attribute"
#called shape

GBDTTFIDFW2V_CV_df = GBDTCV_Heatmap(np.array(tfidf_sent_vectors_RFTrain
```

```
),Y_RFTrain,tfidf_sent_vectors_RFCV,Y_RFCV)
rf_plotheatmaps(GBDTTFIDFW2V_Train_df,GBDTTFIDFW2V_CV_df)

end = time.time()
print("Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost
 Implementation) Simple CV on"
      " TFIDF W2V in minutes :",(end - start)/60)
```




```
Time Consumed to Complete Hyperparameter tuning for GBDT(XGBoost Implem
entation) Simple CV on TFIDF W2V in minutes : 61.93146287202835
```

With the Seaborn Heatmaps obtained, we see that :

- The maximum AUC Value on the CV Heatmap is 0.85, and the minimum AUC Value on the Train Heatmap for the same combination is 0.91.
- Therefore the Best Combination of Max_Depth and Min_samples_split for the BOW Featurization is either of the following:

Max_Depth=2. n_estimators= 500.

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

In [153]:
```
GBDTTFIDFW2V_Test = XGBClassifier(max_depth=2,subsample=0.7,colsample_b
```

```
ytree=0.7,eval_metric='auc',
                                        n_estimators=500,learning_rate=
0.1,booster='gbtree')
GBDTTFIDFW2V_Test.fit(np.array(tfidf_sent_vectors_RFTrain),Y_RFTrain)
```

Out[153]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=0.7, eval_metric='auc',
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=2,
       min_child_weight=1, missing=None, n_estimators=500, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=0.7, verbosity=1)
```

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 [154]:

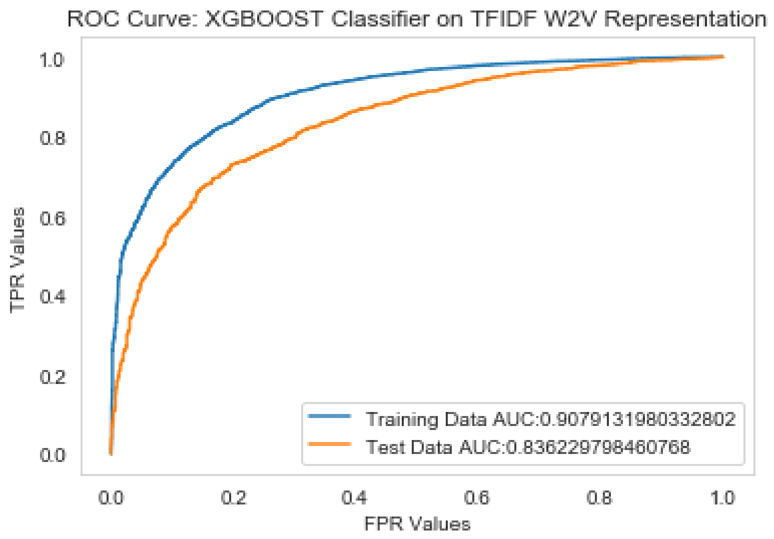
```
from sklearn.metrics import roc_curve, auc

train_fpr8,train_tpr8,threshold = roc_curve(Y_RFTrain,GBDTTFIDFW2V_Test
.predict_proba(tfidf_sent_vectors_RFTrain)[:,1])
test_fpr8,test_tpr8,threshold = roc_curve(Y_RFTest,GBDTTFIDFW2V_Test.pr
edict_proba(tfidf_sent_vectors_RFTest)[:,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 [155]:

```
import matplotlib.pyplot as plt

plt.plot(train_fpr8,train_tpr8,label ='Training Data AUC:' + str(auc(tr
ain_fpr8,train_tpr8)))
plt.plot(test_fpr8,test_tpr8,label = 'Test Data AUC:' + str(auc(test_fp
r8,test_tpr8)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: XGBOOST Classifier on TFIDF W2V Representation')
```

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



[6] Conclusions

In [241]:
```
from prettytable import PrettyTable

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

In [242]:
```
print("Top 20 Most Important Features with Random Forest Ensembling & B
OW Featurization:")
print(" "*100)

a.add_row(["1","not","0.037"])
a.add_row(["2","great","0.022"])
a.add_row(["3","best","0.015"])
a.add_row(["4","would","0.015"])
a.add_row(["5","perfect","0.014"])
```

```
a.add_row(["6","love","0.013"])
a.add_row(["7","horrible","0.012"])
a.add_row(["8","delicious","0.012"])
a.add_row(["9","disappointed","0.012"])
a.add_row(["10","bad","0.011"])
a.add_row(["11","money","0.011"])
a.add_row(["12","worst","0.01"])
a.add_row(["13","thought","0.008"])
a.add_row(["14","highly","0.008"])
a.add_row(["15","easy","0.008"])
a.add_row(["16","wonderful","0.007"])
a.add_row(["17","favorite","0.007"])
a.add_row(["18","terrible","0.007"])
a.add_row(["19","snack","0.007"])
a.add_row(["20","product","0.007"])

print(a)
```

```
Top 20 Most Important Features with Random Forest Ensembling & BOW Feat
urization:


+-------+--------------------------+--------+
| S No. | Top 20 Important Features | Weight |
+-------+--------------------------+--------+
|   1   |           not            | 0.037  |
|   2   |          great           | 0.022  |
|   3   |           best           | 0.015  |
|   4   |          would           | 0.015  |
|   5   |         perfect          | 0.014  |
|   6   |           love           | 0.013  |
|   7   |         horrible         | 0.012  |
|   8   |        delicious         | 0.012  |
|   9   |       disappointed       | 0.012  |
|   10  |           bad            | 0.011  |
|   11  |          money           | 0.011  |
|   12  |          worst           |  0.01  |
|   13  |         thought          | 0.008  |
|   14  |          highly          | 0.008  |
|   15  |           easy           | 0.008  |
```

```
|   16  |          wonderful          | 0.007  |
|   17  |           favorite          | 0.007  |
|   18  |           terrible          | 0.007  |
|   19  |            snack            | 0.007  |
|   20  |           product           | 0.007  |
+-------+---------------------------+--------+
```

In [243]:

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

In [244]:

```
print("Top 20 Most Important Features with Random Forest Ensembling & TFIDF Featurization:")
print(" "*100)

b.add_row(["1","not","0.037"])
b.add_row(["2","great","0.029"])
b.add_row(["3","best","0.017"])
b.add_row(["4","would","0.017"])
b.add_row(["5","love","0.016"])
b.add_row(["6","delicious","0.014"])
b.add_row(["7","bad","0.013"])
b.add_row(["8","disappointed","0.013"])
b.add_row(["9","perfect","0.012"])
b.add_row(["10","would not","0.011"])
b.add_row(["11","worst","0.011"])
b.add_row(["12","money","0.01"])
b.add_row(["13","thought","0.009"])
b.add_row(["14","good","0.009"])
b.add_row(["15","not buy","0.009"])
b.add_row(["16","favorite","0.008"])
b.add_row(["17","loves","0.008"])
b.add_row(["18","easy","0.008"])
b.add_row(["19","horrible","0.008"])
b.add_row(["20","away","0.007"])

print(b)
```

```
Top 20 Most Important Features with Random Forest Ensembling & TFIDF Fe
aturization:
```

```
+-------+-------------------------+--------+
| S No. | Top 20 Important Features | Weight |
+-------+-------------------------+--------+
|   1   |           not           | 0.037  |
|   2   |          great          | 0.029  |
|   3   |           best          | 0.017  |
|   4   |          would          | 0.017  |
|   5   |           love          | 0.016  |
|   6   |        delicious        | 0.014  |
|   7   |           bad           | 0.013  |
|   8   |       disappointed      | 0.013  |
|   9   |         perfect         | 0.012  |
|   10  |        would not        | 0.011  |
|   11  |          worst          | 0.011  |
|   12  |          money          |  0.01  |
|   13  |         thought         | 0.009  |
|   14  |           good          | 0.009  |
|   15  |         not buy         | 0.009  |
|   16  |         favorite        | 0.008  |
|   17  |          loves          | 0.008  |
|   18  |           easy          | 0.008  |
|   19  |         horrible        | 0.008  |
|   20  |           away          | 0.007  |
+-------+-------------------------+--------+
```

In [245]:

```
c = PrettyTable()
c.field_names=["Ensemble","Model","Ideal Max_Depth","Ideal n_estimator
s","Test AUC Score"]
```

In [246]:

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

c.add_row(["Random Forest","BOW","12","1100","0.91"])
c.add_row(["Random Forest","TFIDF","17","1100","0.91"])
c.add_row(["Random Forest","Avg W2V","17","1100","0.84"])
```

```
c.add_row(["Random Forest","TFIDF W2V","17","1100","0.82"])
c.add_row(["XGBoost","BOW","3","1000","0.92"])
c.add_row(["XGBoost","TFIDF","3","1000","0.93"])
c.add_row(["XGBoost","Avg W2V","2","200","0.85"])
c.add_row(["XGBoost","TFIDF W2V","2","500","0.84"])

print(c)
```

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


+---------------+-----------+----------------+--------------------+---
-------------+
|    Ensemble   |   Model   | Ideal Max_Depth | Ideal n_estimators | Te
st AUC Score |
+---------------+-----------+----------------+--------------------+---
-------------+
| Random Forest |    BOW    |       12       |        1100        |
   0.91        |
| Random Forest |   TFIDF   |       17       |        1100        |
   0.91        |
| Random Forest |  Avg W2V  |       17       |        1100        |
   0.84        |
| Random Forest | TFIDF W2V |       17       |        1100        |
   0.82        |
|    XGBoost    |    BOW    |       3        |        1000        |
   0.92        |
|    XGBoost    |   TFIDF   |       3        |        1000        |
   0.93        |
|    XGBoost    |  Avg W2V  |       2        |        200         |
   0.85        |
|    XGBoost    | TFIDF W2V |       2        |        500         |
   0.84        |
+---------------+-----------+----------------+--------------------+---
-------------+
```

Following are some Conclusions from the observations:-

- As far as the "Random Forest Ensemble" performance for the different featurizations is concerned, both BOW & TFIDF are the best across all the models since it has the highest Test AUC.
- As far as the "XGBoost Ensemble" performance for the different featurizations is concerned TFIDF are the best across all the models since it has the highest Test AUC of 0.93.
- Overall, when you compare the 2 Ensembles (ie Bagging & Boosting) in this scenario, TFIDF is the Best Algorithm with the Highest Test AUC Score of 0.93.

Note :- We have not computed the Accuracy on the Test Data here because our Dataset is Highly imbalanced and it makes no sense to obtain the Confusion Matrices & find the Test Accuracy. Instead ROC is a good metric where our Test AUC is not impacted by the Imbalanced data.