Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (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 [149]:

```
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

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

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

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

from tqdm import tqdm
import os
```

In [150]:
```
# 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 500000 data p
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIM
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMI

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a neg
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[150]:

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

In [151]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [152]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[152]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [153]:
```
display['COUNT(*)'].sum()
```

Out[153]: 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 [154]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[154]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
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 [155]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplac
```

In [156]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
final.shape
```

Out[156]:
```
(46072, 10)
```

In [157]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[157]:
```
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 [158]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[158]:

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

In [159]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [160]:
```
#Before starting the next phase of preprocessing lets see the number of entries le
print(final.shape)

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

```
(46071, 10)
```

Out[160]:
```
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 [161]:

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

sent_1000 = final['Text'].values[0]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4]
print(sent_4900)
print("="*50)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
==================================================
My dogs loves this chicken but its a product from China, so we wont be buying i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
==================================================
Our dogs just love them.  I saw them in a pet store and a tag was attached rega
rding them being made in China and it satisfied me that they were safe.
==================================================
I just received my shipment and could hardly wait to try this product. We love
&quot;slickers&quot; which is what we call them, instead of stickers because th
ey can be removed so easily. My daughter designed signs to be  printed in rever
se to use on her car windows. They printed beautifully (we  have 'The Print Sho
p' program). I am going to have a lot of fun with this  product because there a
re windows everywhere and other surfaces like tv  screens and computer monitor
s.
==================================================
```

In [162]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_1500 = 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 i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
```

In [163]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove
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 i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
==================================================
My dogs loves this chicken but its a product from China, so we wont be buying i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
==================================================
Our dogs just love them.  I saw them in a pet store and a tag was attached rega
rding them being made in China and it satisfied me that they were safe.
==================================================
I just received my shipment and could hardly wait to try this product. We love
"slickers" which is what we call them, instead of stickers because they can be
removed so easily. My daughter designed signs to be  printed in reverse to use
on her car windows. They printed beautifully (we  have 'The Print Shop' progra
m). I am going to have a lot of fun with this  product because there are window
s everywhere and other surfaces like tv  screens and computer monitors.
```

In [164]:
```
# 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 [165]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Our dogs just love them.  I saw them in a pet store and a tag was attached rega
rding them being made in China and it satisfied me that they were safe.
==================================================
```

In [166]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
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 i
t 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 because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
```

In [167]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Our dogs just love them I saw them in a pet store and a tag was attached regard
ing them being made in China and it satisfied me that they were safe
```

In [168]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <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 ste

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'our
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', '
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itsel
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because'
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'th
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all'
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "di
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn'
            'won', "won't", 'wouldn', "wouldn't"])
```

In [169]:
```
# Combining all the above stundents

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 s
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████
| 46071/46071 [00:22<00:00, 2078.72it/s]
```

In [170]:
```
print(" size of a Data set" , final['Text'].size , ", length of reviews : ",len(p
```

```
 size of a Data set 46071 , length of reviews :  46071   46071
```

In [171]:
```
#final['Score'][final['Score']==1] = "Positive"
#final['Score'][final['Score']==0] = "Negative"
```

In [172]:
```
#final['Score'][final['Score']==1] = "Positive"
#final['Score'][final['Score']==0] = "Negative"

#final['Score'][final['Score']==1] = "Positive"
#final['Score'][final['Score']==0] = "Negative"
```

[3.2] Preprocessing Review Summary

In [173]:
```
## Similartly you can do preprocessing for review summary also.
```

Split the Data

In [174]:
```
X = preprocessed_reviews
Y = final['Score']
```

In [175]:
```
from sklearn.cross_validation import train_test_split
X_1 , X_test , Y_1 , Y_test  = train_test_split(X,Y,test_size=0.3,random_state=0)
X_tr , X_cv , Y_tr , Y_cv  = train_test_split(X_1,Y_1,test_size=0.3,random_state=
```

We Split the Data for Train, Test and CrossValidation.

Train Data is to Train the Model. Where as Cross validation is to understand the Over/Under fit of a model.

Majorly The Cross Validation will be usefull to figureout the best no of nearest neibhours, It helps the model to Test With.

Test Data is exclusively for testing the trained Model. where we predict the Outcomes.

[4] Featurization

[4.1] BAG OF WORDS

In [176]:
```
#BoW
count_vect = CountVectorizer(min_df=30, max_features=70) #in scikit-learn  max no
count_vect.fit(X_tr)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

X_Bow_Tr = count_vect.transform(X_tr)
X_Bow_Cv = count_vect.transform(X_cv)
X_Bow_Test = count_vect.transform(X_test)

print("the type of count vectorizer ",type(X_Bow_Tr))
print("the shape of out text BOW vectorizer ",X_Bow_Tr.get_shape())
print("the number of unique words ", X_Bow_Tr.get_shape()[1])
```

```
some feature names  ['also', 'amazon', 'bag', 'best', 'better', 'bit', 'bough
t', 'box', 'buy', 'chocolate']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (22574, 70)
the number of unique words  70
```

In [177]:
```
X_Bow_Tr = X_Bow_Tr.toarray()
X_Bow_Cv = X_Bow_Cv.toarray()
X_Bow_Test = X_Bow_Test.toarray()
```

We got the Bag of words vector for each review

Each vectore is of 100 Dimensions.

We have Converted the Train data, Cross Validation Data and the Test to an Identical form, that is Bag Of Words

Also converted the sparse matrixes to dense matrixes

[4.2] Bi-Grams and n-Grams.

Reduced max_features size,due to computationl issues

[4.3] TF-IDF

In [178]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=30, max_features=70)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_
print('='*50)

X_Tfidf_Tr = tf_idf_vect.transform(X_tr)
X_Tfidf_Cv = tf_idf_vect.transform(X_cv)
X_Tfidf_Test = tf_idf_vect.transform(X_test)

print("the type of count vectorizer ",type(X_Tfidf_Tr))
print("the shape of out text TFIDF vectorizer ",X_Tfidf_Tr.get_shape())
print("the number of unique words including both unigrams and bigrams ", X_Tfidf_
```

```
some sample features(unique words in the corpus) ['also', 'amazon', 'bag', 'bes
t', 'better', 'bit', 'bought', 'box', 'buy', 'chocolate']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (22574, 70)
the number of unique words including both unigrams and bigrams  70
```

In [179]:
```
X_Tfidf_Tr = X_Tfidf_Tr.toarray()
X_Tfidf_Cv = X_Tfidf_Cv.toarray()
X_Tfidf_Test = X_Tfidf_Test.toarray()
```

We got the TfIdf s vector for each review

Each vectore is of 100 Dimensions.

We have Converted the Train data, Cross Validation Data and the Test to an Identical form, that is TfIdf-vector

Also converted the sparse matrixes to dense matrixes

[4.4] Word2Vec

In [180]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in X_tr :
    list_of_sentance.append(sentance.split())
```

In [181]:
```
# 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 values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# 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=30,size=70, 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-negative3
        #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_train_w2v = Tr
```

```
==================================================
```

We have created the Word2Vec Model with the Training Data Corpus.

In [182]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 1 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 1 times  3166
sample words  ['favorite', 'nut', 'snacks', 'sunflower', 'absolute', 'almond',
'buttery', 'rich', 'really', 'great', 'given', 'gifts', 'everyone', 'ask', 'bu
y', 'stay', 'long', 'hours', 'school', 'looking', 'bring', 'not', 'unhealthy',
'found', 'pretty', 'excited', 'since', 'absolutely', 'love', 'full', 'size', 's
maller', 'course', 'much', 'less', 'fruit', 'filling', 'still', 'delicious', 's
nack', 'individual', 'bag', 'quite', 'small', 'little', 'hunger', 'helps', 'rep
eat', 'purchase', 'used']
```

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

[4.4.1.1] Avg W2v

average Word2Vec

compute average word2vec for each review.

In [183]:
```
# average Word2Vec
# compute average word2vec for each review.

#def getAvgWordToVector(x):
#    if x < 3:
#        return 0
#    return 1

def getAvgWordToVector(list_of_sentance):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this l
    for sentence in list_of_sentance: # for each review/sentence
        sent = sentence.split()
        sent_vec = np.zeros(70) # as word vectors are of zero length 50, you migh
        cnt_words =0; # num of words with a valid vector in the sentence/review
        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]))
    return sent_vectors
```

In [184]:
```
X_AvgW2V_Tr     = getAvgWordToVector(X_tr)
X_AvgW2V_Cv     = getAvgWordToVector(X_cv)
X_AvgW2V_Test   = getAvgWordToVector(X_test)
```

```
22574
70
9675
70
13822
70
```

We have created the Average WordtoVec Vectors for each review in the Train Data

[4.4.1.2] TFIDF weighted W2v

In [185]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer(min_df=1, max_features=70)
tf_idf_matrix = model.fit(X_tr)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [186]:
```
# 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 cell_val = t

def getAvgW2VtfIdfToVector(list_of_sentance):
    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored i
    row=0;
    for sentence in list_of_sentance: # for each review/sentence
        sent = []
        sent_vec = np.zeros(70) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        sent = sentence.split()
        for word in sent: # for each word in a review/sentence3
            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
    return tfidf_sent_vectors
```

In [187]:
```
X_AvgW2VtfIdf_Tr     = getAvgW2VtfIdfToVector(X_tr)
X_AvgW2VtfIdf_Cv     = getAvgW2VtfIdfToVector(X_cv)
X_AvgW2VtfIdf_Test   = getAvgW2VtfIdfToVector(X_test)
```

In [188]:
```
X_AvgW2VtfIdf_Tr[0]
```

Out[188]:
```
array([ 0.12421825, -0.96347333,  1.27903725,  1.02377459, -0.07715738,
        0.45785842,  0.00763287, -0.39731525, -1.03407082, -0.23909475,
        0.5594552 , -0.79354915,  0.26635891,  0.58160582,  0.03707935,
       -0.24100805, -0.55271607, -0.04885027,  0.12132413, -0.57295137,
       -0.17638869,  0.25682716,  0.13558562, -0.31369082, -0.36007373,
       -0.45052612,  1.02519157, -0.37695714, -0.6061574 ,  0.22376945,
       -0.81491955, -0.48295462,  0.43720743, -0.70331514, -0.57756556,
       -0.16003028,  0.51863033, -0.9103166 , -0.94457474,  0.05190576,
       -0.01670023,  0.06648053, -0.13083925, -0.82293201,  0.82290824,
        0.5256388 , -0.53291657, -0.39139237, -0.34614278,  0.51781061,
       -0.15311419,  0.06597874,  0.68958409, -0.06948233, -0.15222518,
       -0.77651263, -0.29069334,  1.16683331, -0.54262205, -0.48582012,
       -0.55259421, -0.74967218,  0.07608354, -0.43342726, -0.273494  ,
        0.88578205,  0.6737901 ,  1.56796923, -0.48675159,  0.67705026])
```

[5] Assignment 3: KNN

1. **Apply Knn(brute force version) on these feature sets**
   - SET 1:Review text, preprocessed one converted into vectors using (BOW)
   - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
   - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
   - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

2. **Apply Knn(kd tree version) on these feature sets**
   NOTE: sklearn implementation of kd-tree accepts only dense matrices, you need to convert the sparse matrices of CountVectorizer/TfidfVectorizer into dense matices. You can convert sparse matrices to dense using .toarray() attribute. For more information please visit this [link (https://docs.scipy.org/doc/scipy-0.18.1/reference/generated/scipy.sparse.csr_matrix.toarray.html)](https://docs.scipy.org/doc/scipy-0.18.1/reference/generated/scipy.sparse.csr_matrix.toarray.html)

   - SET 5:Review text, preprocessed one converted into vectors using (BOW) but with restriction on maximum features generated.

     ```
     count_vect = CountVectorizer(min_df=10, max_features=500)
     count_vect.fit(preprocessed_reviews)
     ```

   - SET 6:Review text, preprocessed one converted into vectors using (TFIDF) but with restriction on maximum features generated.

     ```
     tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
     tf_idf_vect.fit(preprocessed_reviews)
     ```

   - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
   - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

3. **The hyper paramter tuning(find best K)**

   - Find the best hyper parameter which will give the maximum [AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/)](https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
   - Find the best hyper paramter using k-fold cross validation or simple cross validation data
   - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

4. **Representation of results**

   - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure
     Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
     Along with plotting ROC curve, you need to print the [confusion matrix (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/)](https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points

5. **Conclusion**

   - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library [link (http://zetcode.com/python/prettytable/)](http://zetcode.com/python/prettytable/)

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this [link. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)](https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

In [189]:
```
Total_AUC = {}
```

```
#cv = Y_cv.apply(lambda x : 1 if x=="Positive" else 0)
#test = Y_test.apply(lambda x : 1 if x=="Positive" else 0)
#tr = Y_tr.apply(lambda x : 1 if x=="Positive" else 0
#Y_cv = cv
#Y_test = test
#Y_tr = tr
```

In [190]:
```
from sklearn.cross_validation import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KDTree
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.metrics import confusion_matrix
```

[5.1] Applying KNN brute force

[5.1.1] Applying KNN brute force on BOW, SET 1

In [191]:
```
neighbors = np.arange(3,32,2)
neighbors
```

Out[191]:
```
array([ 3,  5,  7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31])
```

We have taken a list of Odd numbers from 1 to 29 for finding out the best nearest neibhour for each type dataset

The reason behind we chosing the odd numbers is for simplifying the voting process between the classes.

We Split the Data for Train, Test and CrossValidation.

Train Data is to Train the Model. Wherase Cross validation is to understand the Over/Under fit of a model.

Majorly The Cross Validation will be usefull to figureout the best no of nearest neibhours, It helps the model to Test With.

Test Data is exclusively for testing the trained Model. where we predict the Outcomes.

Hyper Parametre Tuning with 20% of Cross Validation Data

In [192]:

```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set1_Acc_Tr     = []
Set1_Acc_Cv     = []
Set1_Train_Auc = []
Set1_Cv_Auc     = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    knn.fit(X_Bow_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Bow_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Bow_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_Bow_Tr)    # Probablity of TRAIN-Valid
    Cv_pred_prob     =  knn.predict_proba(X_Bow_Cv)

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob[:,1])
    Cv_Auc     = roc_auc_score(Y_cv,Cv_pred_prob[:,1])

    Set1_Train_Auc.append(Train_Auc)
    Set1_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9074287409914582
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.674012538699690
4
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8815581211848615
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.705214318885448
9
 AUC for the  TRAIN Data at nearest neibour  7  is  0.863751525333031
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.718558900928792
5
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8505493011812338
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.729477902476780
1
 AUC for the  TRAIN Data at nearest neibour  11  is  0.8419509317694495
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.73696056501547
98
 AUC for the  TRAIN Data at nearest neibour  13  is  0.834457957433172
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.74176358359133
12
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8297382682403005
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.74370030959752
32
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8250728102780943
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.74977523219814
23
 AUC for the  TRAIN Data at nearest neibour  19  is  0.8214345589586742
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.74946904024767
79
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8172610344868563
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.75145642414860
68
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8147975429470912
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.75148192724458
22
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8129604369929624
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.75400158668730
64
```

```
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8108462546310234
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.755408088235294
2
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8089048573039505
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.756229373065015
4
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8070822687202661
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.758821710526315
8
```

Here, we are trianing the KNN-Model with the Bag of words.

We do not know what is the best nearest neibhour to train the Model.

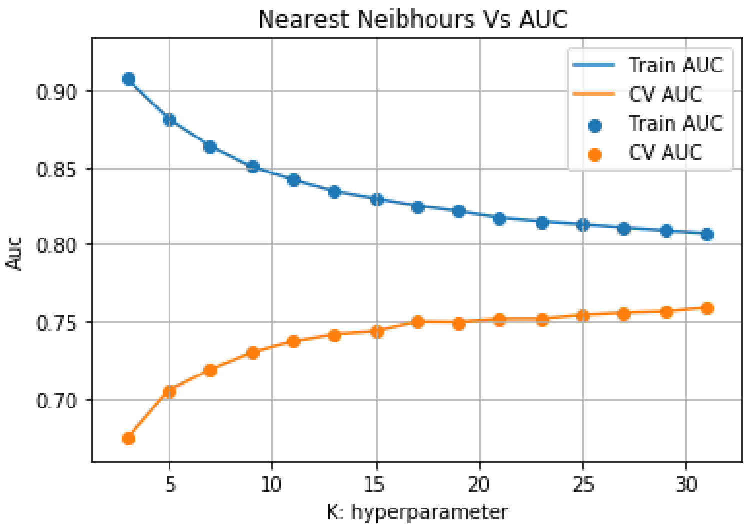
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We get the AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data.

Plot AUC Curves for the Train and CrossValidation

In [193]:
```
#set1_train_auc,set1_cv_auc
plt.grid()
plt.scatter(neighbors, Set1_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set1_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set1_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set1_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```




```
AUC for both CrossValidation  and  Training Data Getting Closer/Converging at
Neibhour 31

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that
31-nearest neibhours will be the best fit.

Let us figure out, which hyper parameter can yeild the  the Highest AUC.
```

```
Average the accruacis from the Hyper parameters, the value we get is the one we
expect on top of test data.
```

In [194]:
```
print("Train AUC: ",neighbors[Set1_Train_Auc.index(min(Set1_Train_Auc))] )  # Bes
print("Cross Validation AUC: ",neighbors[Set1_Cv_Auc.index(max(Set1_Cv_Auc))])
```

```
Train AUC:  31
Cross Validation AUC:  31
```

In [195]:
```
Optimal_N = neighbors[Set1_Cv_Auc.index(max(Set1_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest AUC at Neigherest Neibhour value is at 31.

Hence, we can expext the test data AUc near around the same.

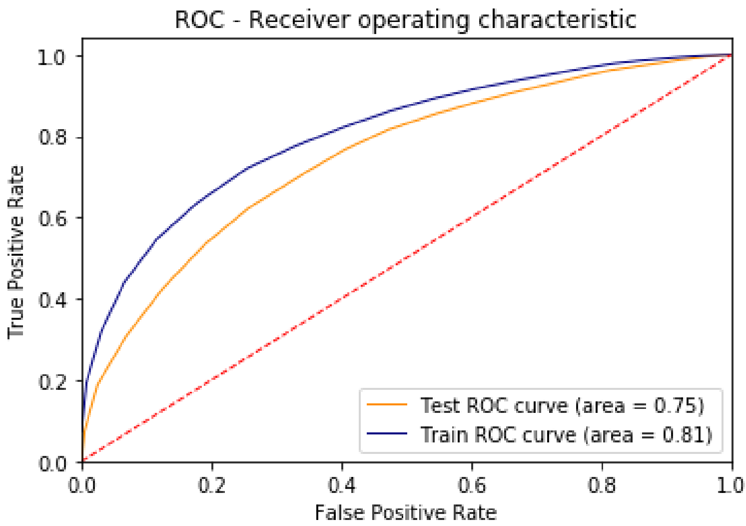
In case we we have the CrossValidation AUC High and Test Accruacy is High, then we can consider it as a Over Fitting.

In case we we have the CrossValidation AUC Low and Test Accruacy is also Low, then we can consider it as a Under Fitting.

In [196]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.h
#Set1_Train_Pred =  knn.predict(X_Bow_Tr)
#Set1_Train_Acc  = accuracy_score(Y_tr,Set1_Train_Pred,normalize=True)

Set1_Train_Auc = []
Set1_Tst_Auc   = []
Set1_Train_Prb = []
Set1_Tst_Prb   = []
Set1_Train_Predict = []
Set1_Tst_Predict   = []

knn =  KNeighborsClassifier(n_neighbors = Optimal_N, algorithm = 'brute')
knn.fit(X_Bow_Tr,Y_tr)
Train_Predict =  knn.predict(X_Bow_Tr)
Tst_Predict    =  knn.predict(X_Bow_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidation
Train_pred_prob    =  knn.predict_proba(X_Bow_Tr)# Probablity of TRAIN-Validation
Tst_pred_prob      =  knn.predict_proba(X_Bow_Test)

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob[:,1])
Test_Auc   = roc_auc_score(Y_test,Tst_pred_prob[:,1])

#Probablity Scores
Set1_Train_Prb = Train_pred_prob[:,1]
Set1_Tst_Prb=Tst_pred_prob[:,1]

#AUC
Set1_Train_Auc=Train_Auc
Set1_Tst_Auc=Test_Auc

#MOdel Predictions
Set1_Train_Predict=Train_Predict
Set1_Tst_Predict=Tst_Predict

print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

```
 AUC for the  Train Data at nearest neibour  31  is  0.8070822687202661
 AUC for the Test-Validation Data at nearest neibour  31  is  0.749035613233619
3
```

In [197]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set1_tst_fpr, set1_tst_tpr, thresholds = roc_curve(Y_test,Set1_Tst_Prb)
set1_tst_roc_auc = auc(set1_tst_fpr, set1_tst_tpr)


set1_train_fpr, set1_train_tpr, thresholds = roc_curve(Y_tr,Set1_Train_Prb)
set1_train_roc_auc = auc(set1_train_fpr, set1_train_tpr)

lw=1
plt.figure()
plt.plot(set1_tst_fpr, set1_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set1_train_fpr, set1_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Test Results of the Model with Neigherest Neibhour value is at 25. Area Under Curve = "0.66"

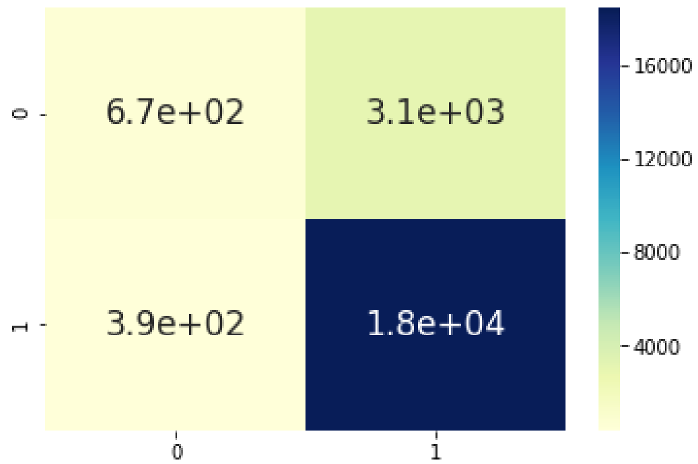
In [198]:
```
Total_AUC['set1']=[Optimal_N , set1_tst_roc_auc]
```

Train Confusion Matrix

In [199]:
```
Train_CM= confusion_matrix(Y_tr, Set1_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  670  3081]
 [  393 18430]]
```

Out[199]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30b8f3c8>



In [200]:
```
Y_tr.value_counts()
```

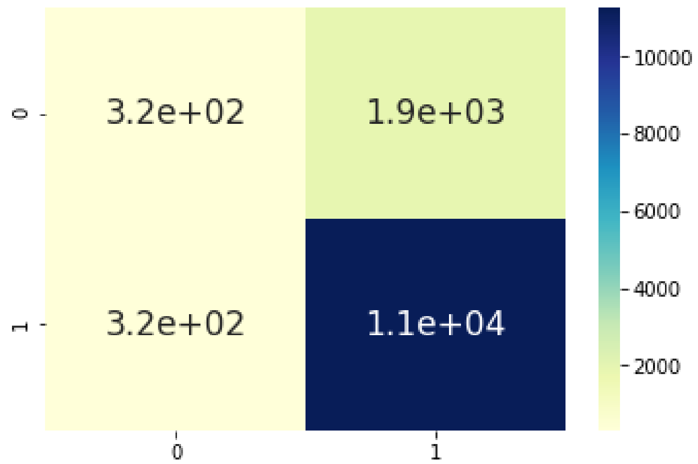
Out[200]:
```
1    18823
0     3751
Name: Score, dtype: int64
```

Test Confusion Matrix

In [201]:
```
Test_CM= confusion_matrix(Y_test, Set1_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  318  1923]
 [  320 11261]]
```

Out[201]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30c640b8>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Thus in binary classification, the count of

true negatives is 318 at C(0,0) ,

false negatives is 320 C(1,0),

true positives is 11261 at C(1,1)

and false positives is 1923 at C(0,1).

[5.1.2] Applying KNN brute force on TFIDF, SET 2

In [202]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set2_Train_Auc = []
Set2_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    knn.fit(X_Tfidf_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set2_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set2_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_Tfidf_Tr)[:,1]    # Probablity of TRAI
    Cv_pred_prob    =  knn.predict_proba(X_Tfidf_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set2_Train_Auc.append(Train_Auc)
    Set2_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9074856490836005
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.658779102167182
6
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8780214348054
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.691084984520123
9
 AUC for the  TRAIN Data at nearest neibour  7  is  0.860786440940299
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.708558281733746
1
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8485149431118072
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.724525928792569
7
 AUC for the  TRAIN Data at nearest neibour  11  is  0.8385591358286677
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.72941900154798
77
 AUC for the  TRAIN Data at nearest neibour  13  is  0.8303952536101763
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.73627972136222
92
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8266847482758072
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.74330874613003
11
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8221367039730983
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.74822956656346
75
 AUC for the  TRAIN Data at nearest neibour  19  is  0.8215859503466557
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.75255963622291
02
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8189682135163291
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.75671327399380
8
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8171004865330287
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.76111130030959
75
 AUC for the  TRAIN Data at nearest neibour  25  is  0.814422214534075
```

```
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.76413061145510
84
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8145281288782181
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.76665638544891
63
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8142264720836703
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.76672801857585
14
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8141215008728906
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.76837886996904
03
```

Here, we are trianing the KNN-Model with the Bag of words.

We do not know what is the best nearest neibhour to train the Model.

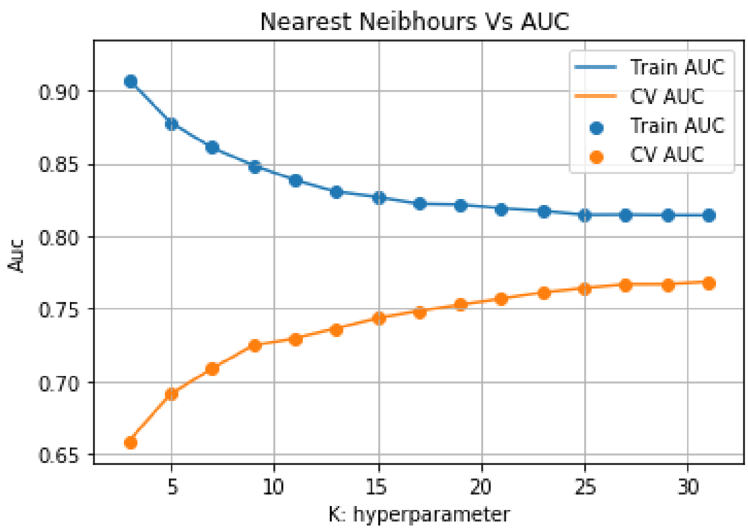
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the AUC, Error and AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data at each k.

AUC Curves for the Train and CrossValidation Data

In [203]:
```
#set2_train_auc,set2_cv_auc
plt.grid()
plt.scatter(neighbors, Set2_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set2_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set2_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set2_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```




```
Both AUC for CrossValidation  and  Training Data Getting Closer/Converging at
Neibhour 31

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that
19-nearest neibhours will be the best fit.
```

Let us figure out, which hyper parameter can yeild the the Highest AUC.

Average the accruacis from the Hyper parameters, the value we get is the one we expect on top of test data.

In [204]:
```
Optimal_N = neighbors[Set2_Cv_Auc.index(max(Set2_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest AUC at Neigherest Neibhour value is at 31.

Hence, we can expext the test data AUC near around the same.

In case we have the CrossValidation AUC High and Test AUC is High, then we can consider it as a Over Fitting.

In case we have the CrossValidation AUC Low and Test AUc is also Low, then we can consider it as a Under Fitting.

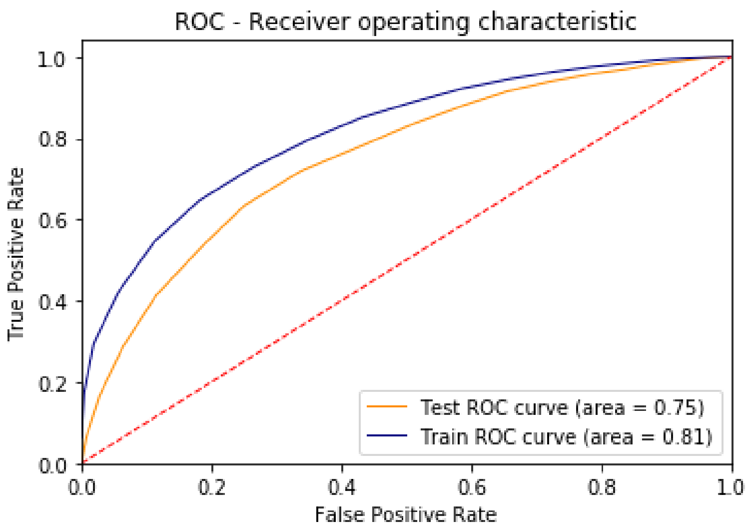
In [205]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.
#Set2_Train_Pred =  knn.predict(X_Bow_Tr)
#Set2_Train_Acc  = accuracy_score(Y_tr,Set2_Train_Pred,normalize=True)

Set2_Train_Auc = []
Set2_Tst_Auc   = []
Set2_Train_Prb = []
Set2_Tst_Prb   = []
Set2_Train_Predict = []
Set2_Tst_Predict   = []

knn =  KNeighborsClassifier(n_neighbors = Optimal_N, algorithm = 'brute')
knn.fit(X_Tfidf_Tr,Y_tr)

Train_Predict =  knn.predict(X_Tfidf_Tr)
Tst_Predict   =  knn.predict(X_Tfidf_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidatio
Train_pred_prob    =  knn.predict_proba(X_Tfidf_Tr)[:,1] # Probablity of TRAIN-Val
Tst_pred_prob      =  knn.predict_proba(X_Tfidf_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc  = roc_auc_score(Y_test,Tst_pred_prob)

#Probablity Scores
Set2_Train_Prb = Train_pred_prob
Set2_Tst_Prb =Tst_pred_prob

#AUC
Set2_Train_Auc= Train_Auc
Set2_Tst_Auc=Test_Auc

#MOdel Predictions
Set2_Train_Predict = Train_Predict
Set2_Tst_Predict = Tst_Predict


print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

```
 AUC for the  Train Data at nearest neibour  31  is  0.8141215008728906
 AUC for the Test-Validation Data at nearest neibour  31  is  0.752584101866214
4
```

AUC and ROC for Knn-bruteforce on top BagOfWords

In [206]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set2_tst_fpr, set2_tst_tpr, thresholds = roc_curve(Y_test,Tst_pred_prob)
set2_tst_roc_auc = auc(set2_tst_fpr, set2_tst_tpr)


set2_train_fpr, set2_train_tpr, thresholds = roc_curve(Y_tr,Train_pred_prob)
set2_train_roc_auc = auc(set2_train_fpr, set2_train_tpr)

lw=1
plt.figure()
plt.plot(set2_tst_fpr, set2_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set2_train_fpr, set2_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Test Results of the Model with Neigherest Neibhour value is at 31.

Auc is = "0.72"

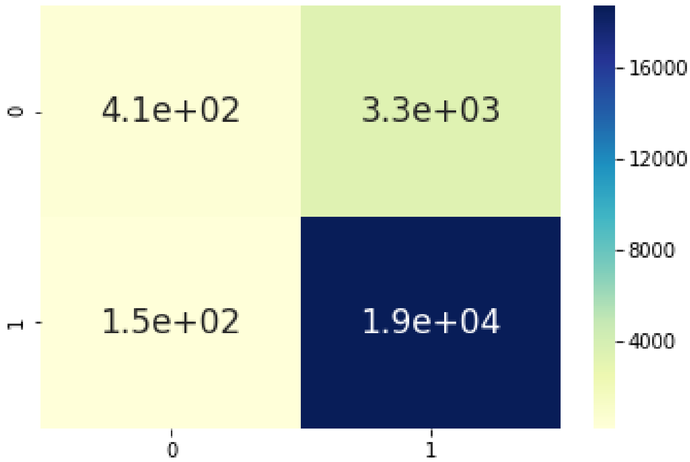
In [207]:
```
Total_AUC['set2']=[Optimal_N , set2_tst_roc_auc]
```

Train Confusion Matrix

In [208]:
```
Train_CM= confusion_matrix(Y_tr, Set2_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  412  3339]
 [  150 18673]]
```

Out[208]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30d56fd0>

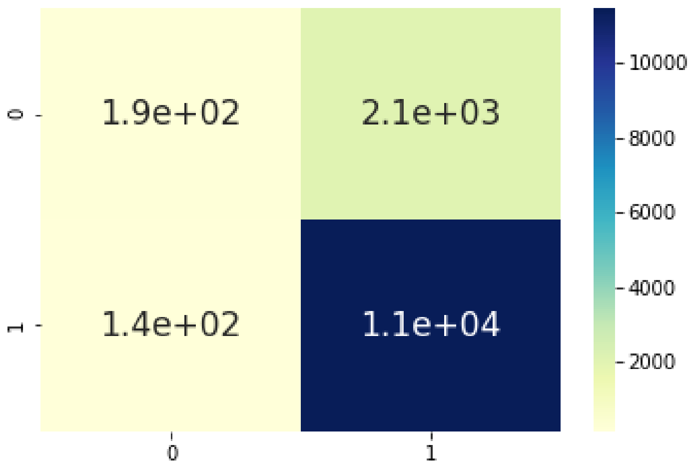


Test Confusion Matrix

In [209]:
```
Test_CM= confusion_matrix(Y_test, Set2_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  189  2052]
 [  143 11438]]
```

Out[209]: <matplotlib.axes._subplots.AxesSubplot at 0x20d23a8c128>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Thus in binary classification, the count of

true negatives is 189 at C(0,0) ,

false negatives is 143 C(1,0),

true positives is 11438 at C(1,1)

and false positives is 2052 at C(0,1).

[5.1.3] Applying KNN brute force on AVG W2V, SET 3

```
Below Model is Knn Brute on top of Average Word2Vec Data
```

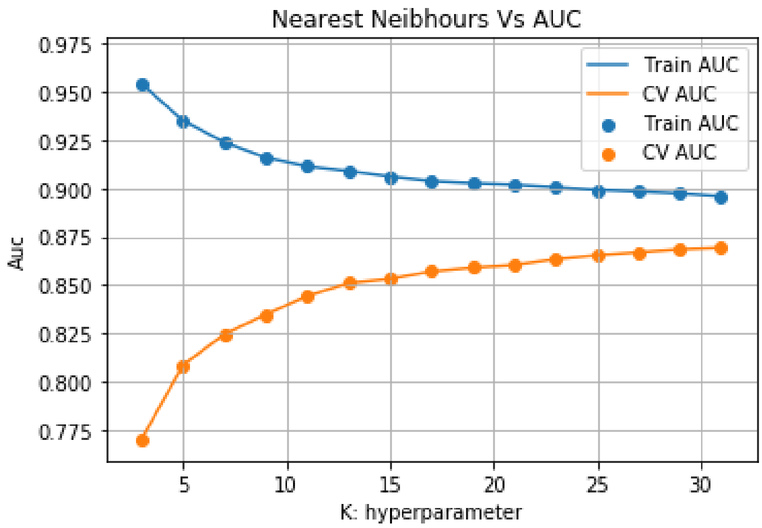
In [210]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set3_Train_Auc = []
Set3_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    knn.fit(X_AvgW2V_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set3_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set3_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_AvgW2V_Tr)[:,1]    # Probablity of TRA
    Cv_pred_prob    =  knn.predict_proba(X_AvgW2V_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set3_Train_Auc.append(Train_Auc)
    Set3_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9538551146317772
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.770594195046439
7
 AUC for the  TRAIN Data at nearest neibour  5  is  0.9349450711565725
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.808668962848297
3
 AUC for the  TRAIN Data at nearest neibour  7  is  0.9237257852562522
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.824726625386996
9
 AUC for the  TRAIN Data at nearest neibour  9  is  0.9158371240548111
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.834849767801857
6
 AUC for the  TRAIN Data at nearest neibour  11  is  0.9113497906871366
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.84439775541795
68
 AUC for the  TRAIN Data at nearest neibour  13  is  0.9089620302495828
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.85105491486068
11
 AUC for the  TRAIN Data at nearest neibour  15  is  0.9060312635042527
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.85326277089783
28
 AUC for the  TRAIN Data at nearest neibour  17  is  0.903733595743184
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.85705541795665
63
 AUC for the  TRAIN Data at nearest neibour  19  is  0.9026606487610317
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.85908026315789
48
 AUC for the  TRAIN Data at nearest neibour  21  is  0.9018980760773377
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.86036420278637
78
 AUC for the  TRAIN Data at nearest neibour  23  is  0.9005894873871174
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.86339740712074
32
```

```
 AUC for the  TRAIN Data at nearest neibour  25  is  0.899145405599963
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.86541714396284
83
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8982966138991174
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.86695553405572
76
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8973328941958604
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.86849969040247
68
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8958472148311497
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.86930580495356
02
```

Plot AUC Curves for the Train and CrossValidation

In [211]:
```
#set3_train_auc,set3_cv_auc
plt.grid()
plt.scatter(neighbors, Set3_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set3_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set3_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set3_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```



Here, we are trianing the KNN-Model with the Average Woork2Vec.

We do not know what is the best nearest neibhour to train the Model.

To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the AUC, Error and AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data at each k.

In [212]:
```
Optimal_N = neighbors[Set3_Cv_Auc.index(max(Set3_Cv_Auc))]
print("Best nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Best nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest AUC at Neigherest Neibhour value is at 31.

Hence, we can expext the test data AUC near around the same.

In case we have the CrossValidation AUC High and Test AUC is High, then we can consider it as a Over Fitting.

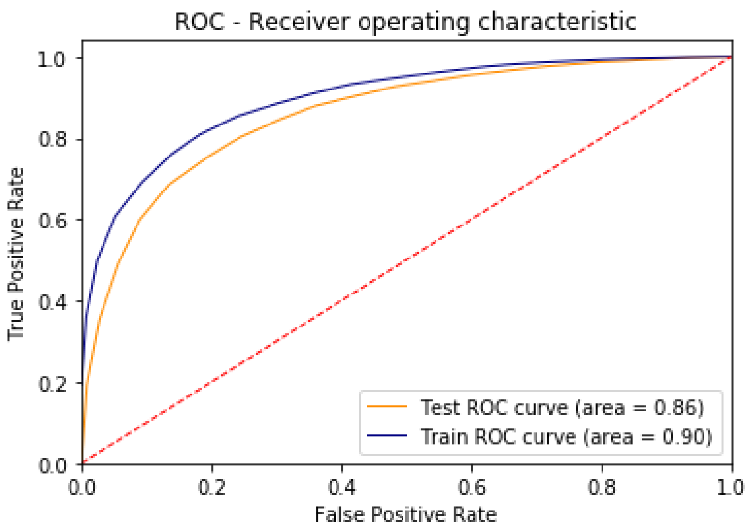
In case we have the CrossValidation AUC Low and Test AUc is also Low, then we can consider it as a Under Fitting.

In [213]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.
#Set3_Train_Pred =  knn.predict(X_Bow_Tr)
#Set3_Train_Acc  = accuracy_score(Y_tr,Set3_Train_Pred,normalize=True)

Set3_Train_Auc = []
Set3_Tst_Auc   = []
Set3_Train_Prb = []
Set3_Tst_Prb   = []
Set3_Train_Predict = []
Set3_Tst_Predict   = []


knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
knn.fit(X_AvgW2V_Tr,Y_tr)

Train_Predict =  knn.predict(X_AvgW2V_Tr)
Tst_Predict   =  knn.predict(X_AvgW2V_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidatio
Train_pred_prob    =  knn.predict_proba(X_AvgW2V_Tr)[:,1] # Probablity of TRAIN-Va
Tst_pred_prob      =  knn.predict_proba(X_AvgW2V_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc  = roc_auc_score(Y_test,Tst_pred_prob)

#Probablity Scores
Set3_Train_Prb = Train_pred_prob
Set3_Tst_Prb = Tst_pred_prob

#AUC
Set3_Train_Auc= Train_Auc
Set3_Tst_Auc = Test_Auc

#MOdel Predictions
Set3_Train_Predict= Train_Predict
Set3_Tst_Predict=Tst_Predict


print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

```
 AUC for the  Train Data at nearest neibour  31  is  0.8958472148311497
 AUC for the Test-Validation Data at nearest neibour  31  is  0.859170152099056
2
```

In [214]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set3_tst_fpr, set3_tst_tpr, thresholds = roc_curve(Y_test,Set3_Tst_Prb)
set3_tst_roc_auc = auc(set3_tst_fpr, set3_tst_tpr)


set3_train_fpr, set3_train_tpr, thresholds = roc_curve(Y_tr,Set3_Train_Prb)
set3_train_roc_auc = auc(set3_train_fpr, set3_train_tpr)

lw=1
plt.figure()
plt.plot(set3_tst_fpr, set3_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set3_train_fpr, set3_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



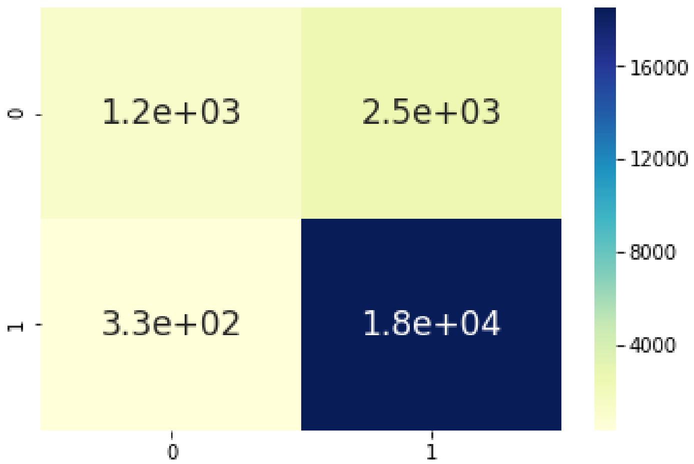
In [215]:
```
Total_AUC['set3']=[Optimal_N , set3_tst_roc_auc]
```

Confusion Matrix

In [216]:
```
Train_CM= confusion_matrix(Y_tr, Set3_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[ 1237  2514]
 [  334 18489]]
```

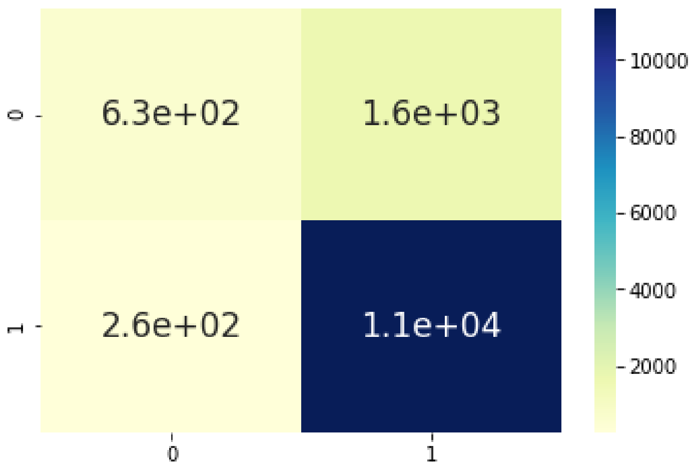
Out[216]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30b71550>



In [217]:
```
Test_CM= confusion_matrix(Y_test, Set3_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  628  1613]
 [  265 11316]]
```

Out[217]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30b99048>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of

true negatives is 628 at C(0,0) ,

false negatives is 265 C(1,0),

true positives is 11316 at C(1,1)

and false positives is 1613 at C(0,1).

[5.1.4] Applying KNN brute force on TFIDF W2V, SET 4

In [218]:
```
# Please write all the code with proper documentation
#Bag_O_W_Dense,Tfidf_Data_Dense,Total_W2V_Vecors,Tfidf_W2V_vectors
```

In [219]:

```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set4_Train_Auc = []
Set4_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    knn.fit(X_AvgW2VtfIdf_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set4_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set4_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_AvgW2VtfIdf_Tr)[:,1]    # Probablity o
    Cv_pred_prob    =  knn.predict_proba(X_AvgW2VtfIdf_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set4_Train_Auc.append(Train_Auc)
    Set4_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9134352144923071
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.660923877708978
3
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8806625906328289
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.682425735294117
7
 AUC for the  TRAIN Data at nearest neibour  7  is  0.8626597270142331
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.699152825077399
5
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8489262237573213
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.708897484520123
9
 AUC for the  TRAIN Data at nearest neibour  11  is  0.8378836107144879
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.71876280959752
31
 AUC for the  TRAIN Data at nearest neibour  13  is  0.8330921490584678
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.72400472136222
9
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8276535384362538
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.72883839009287
91
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8236618068506211
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.73149682662538
71
 AUC for the  TRAIN Data at nearest neibour  19  is  0.8221111321561837
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.73491590557275
54
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8202145474730973
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.73885793343653
25
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8169293586028867
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.73969512383900
94
```

```
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8153131999452787
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.74065681114551
09
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8130296388192956
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.73943003095975
23
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8103444280838007
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.74171706656346
76
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8083128247739366
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.74312743808049
54
```

Here, we are trianing the KNN-Model with the Tf-Idf values.

We do not know what is the best nearest neibhour to train the Model.

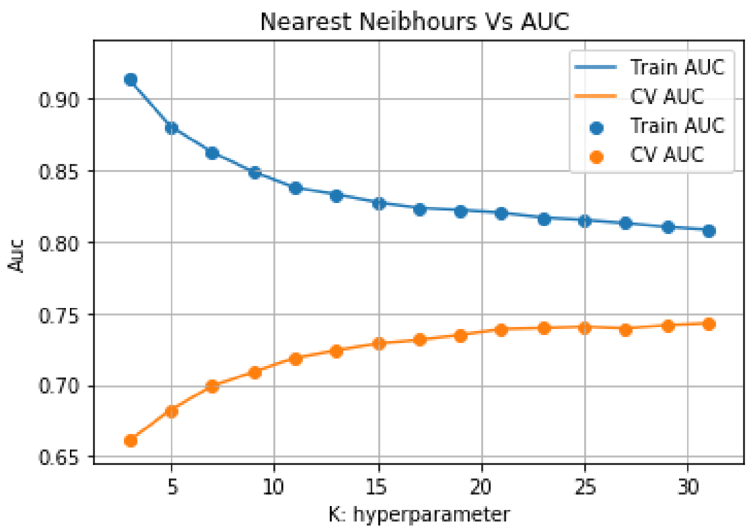
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the Error and AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data.

AUC Vs KNN - for the Train and CrossValidation Data

In [220]:
```
#set4_train_auc,set4_cv_auc
plt.grid()
plt.scatter(neighbors, Set4_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set4_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set4_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set4_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```




```
AUC for Both CrossValidation  and  Training Data Getting Closer/Converging at
Neibhour 9
```

```
Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that 
9-nearest neibhours will be the best fit.

Let us figure out, which hyper parameter can yeild the  the Highest AUC
.

Average the AUc from the Hyper parameters, the value we get is the one we expect 
on top of test data.
```

In [221]:
```
Optimal_N = neighbors[Set4_Cv_Auc.index(max(Set4_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

Nearest Neibhours we have at highest AUC is = 31

Hence, we can expect the test data AUC near around the same.

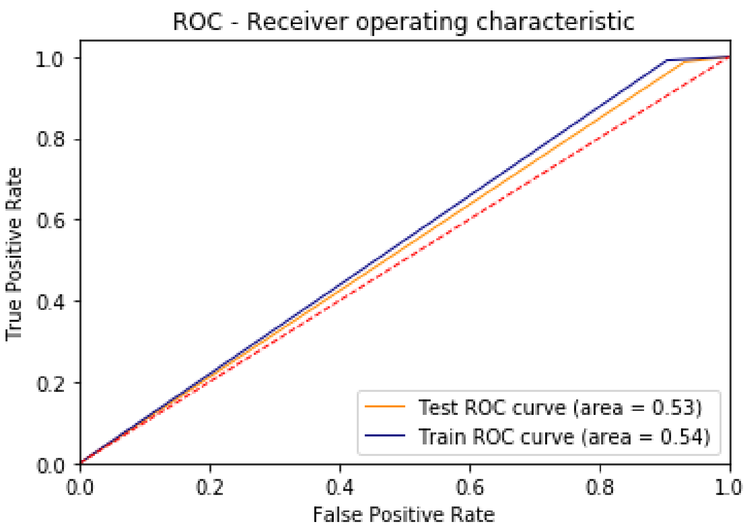
In case we we have the CrossValidation AUC High and Test AUC is High, then we can consider it as a Over Fitting.

In case we we have the CrossValidation AUC Low and Test AUC is also Low, then we can consider it as a Under Fitting

In [ ]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.l
#Set4_Train_Pred =  knn.predict(X_Bow_Tr)
#Set4_Train_Acc  = accuracy_score(Y_tr,Set4_Train_Pred,normalize=True)

Set4_Train_Auc = []
Set4_Tst_Auc   = []
Set4_Train_Prb = []
Set4_Tst_Prb   = []
Set4_Train_Predict = []
Set4_Tst_Predict   = []


knn =  KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
knn.fit(X_AvgW2VtfIdf_Tr,Y_tr)

Train_Predict =  knn.predict(X_AvgW2VtfIdf_Tr)
Tst_Predict   =  knn.predict(X_AvgW2VtfIdf_Test)

   # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValida
Train_pred_prob    =  knn.predict_proba(X_AvgW2VtfIdf_Tr)[:,1] # Probablity of TRA
Tst_pred_prob      =  knn.predict_proba(X_AvgW2VtfIdf_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc   = roc_auc_score(Y_test,Tst_pred_prob)

    #Probablity Scores
Set4_Train_Prb=Train_pred_prob
Set4_Tst_Prb=Tst_pred_prob

    #AUC
Set4_Train_Auc=Train_Auc
Set4_Tst_Auc=Test_Auc

    #MOdel Predictions
Set4_Train_Predict=Train_Predict
Set4_Tst_Predict=Tst_Predict

print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

In [223]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set4_tst_fpr, set4_tst_tpr, thresholds = roc_curve(Y_test,Set4_Tst_Predict)
set4_tst_roc_auc = auc(set4_tst_fpr, set4_tst_tpr)


set4_train_fpr, set4_train_tpr, thresholds = roc_curve(Y_tr,Set4_Train_Predict)
set4_train_roc_auc = auc(set4_train_fpr, set4_train_tpr)

lw=1
plt.figure()
plt.plot(set4_tst_fpr, set4_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set4_train_fpr, set4_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



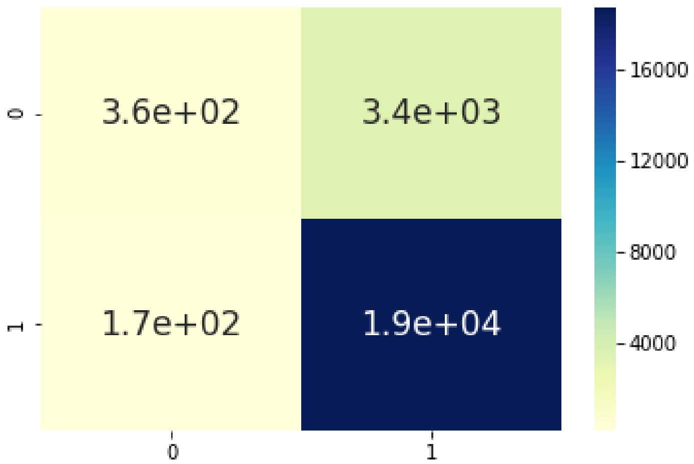
In [224]:
```
Total_AUC['set4']=[Optimal_N , set4_tst_roc_auc]
```

Confusion Matrix

In [225]:
```
Train_CM= confusion_matrix(Y_tr, Set4_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  360  3391]
 [  170 18653]]
```

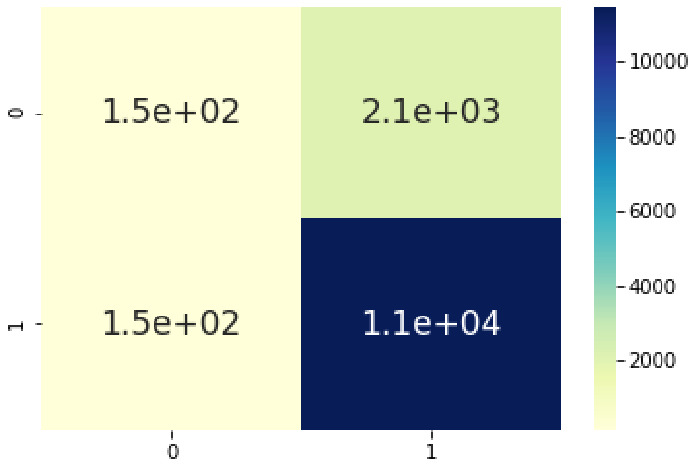
Out[225]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30e37470>



In [226]:
```
Test_CM= confusion_matrix(Y_test, Set4_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  154  2087]
 [  147 11434]]
```

Out[226]: <matplotlib.axes._subplots.AxesSubplot at 0x20d30f12860>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of

true negatives is 154 at C(0,0) ,

false negatives is 147 C(1,0),

true positives is 11434 at C(1,1)

and false positives is 2087 at C(0,1).

In [227]:
```
# Please write all the code with proper documentation
```

[5.2] Applying KNN kd-tree

[5.2.1] Applying KNN kd-tree on BOW, SET 5

In [228]:
```
# Please write all the code with proper documentation
```

```
Applying the KD-Tree on BagOfWords
```

In [229]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set5_Train_Auc = []
Set5_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i,leaf_size=30 , algorithm= 'kd_tre
    knn.fit(X_Bow_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set5_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set5_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_Bow_Tr)[:,1]    # Probablity of TRAIN-
    Cv_pred_prob    =  knn.predict_proba(X_Bow_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set5_Train_Auc.append(Train_Auc)
    Set5_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv_
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9075206111606173
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.672968227554179
6
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8759118838387151
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.697959249226006
2
 AUC for the  TRAIN Data at nearest neibour  7  is  0.856668330333714
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.714804024767801
8
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8477760160378278
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.723773103715170
2
 AUC for the  TRAIN Data at nearest neibour  11  is  0.837892221993737
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.73085607585139
31
 AUC for the  TRAIN Data at nearest neibour  13  is  0.8335559825849908
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.74155189628482
98
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8284478298039575
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.74542759287925
71
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8240504970513947
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.74670046439628
49
 AUC for the  TRAIN Data at nearest neibour  19  is  0.819365231730587
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.75109361455108
35
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8149123505615524
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.75225789473684
21
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8133218770271649
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.75214667182662
54
```

```
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8131101287863551
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.75177260061919
49
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8102964003733839
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.75468424922600
62
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8089596904743659
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.75443610681114
55
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8064759666773519
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.75590727554179
56
```

Here, we are trianing the KD-Tree Model with the Bag of words values.

We do not know what is the best nearest neibhour to train the Model.

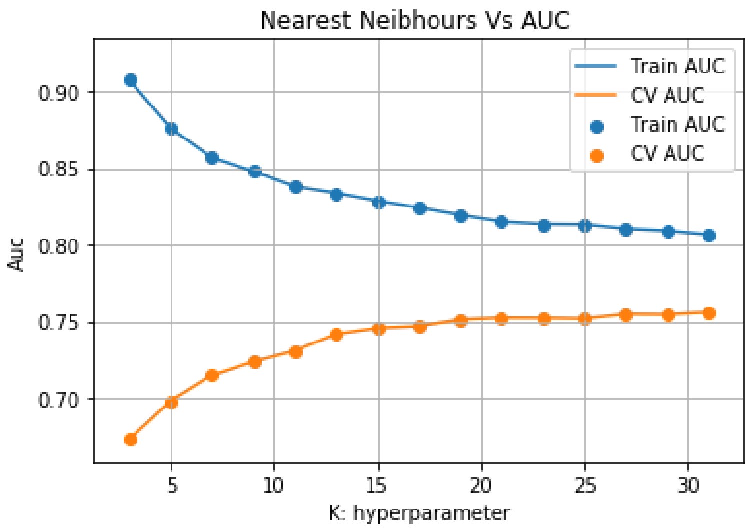
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data

Plot KNN VS AUC

In [230]:
```
#set5_train_auc,set5_cv_auc
plt.grid()
plt.scatter(neighbors, Set5_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set5_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set5_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set5_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```



Both AUC for CrossValidation and Training Data Getting Closer/Converging at Neibhour 23

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that 23-nearest neibhours will be the best fit.

Let us figure out, which hyper parameter can yeild the the Highest accuracy.

Average the accruacis from the Hyper parameters, the value we get is the one we expect on top of test data.

In [231]:
```
#set1_tst_fpr, set1_tst_tpr, set1_tst_thresholds = roc_curve(set1_tst_pred, Y_tes
#set1_cv_roc_auc = auc(set1_tst_fpr, set1_tst_fpr)

#https://qiita.com/bmj0114/items/460424c110a8ce22d945

Optimal_N = neighbors[Set5_Cv_Auc.index(max(Set5_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

Hence, we can expext the test data AUC near around the same.

In case we we have the CrossValidation AUC High and Test Accruacy is High, then we can consider it as a Over Fitting.

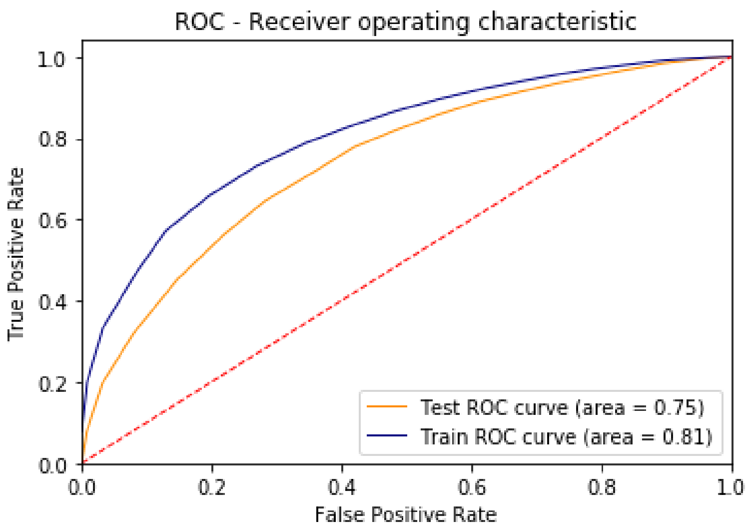
In case we we have the CrossValidation AUC Low and Test Accruacy is also Low, then we can consider it as a Under Fitting

In [232]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.l
#Set5_Train_Pred =  knn.predict(X_Bow_Tr)
#Set5_Train_Acc  = accuracy_score(Y_tr,Set5_Train_Pred,normalize=True)

Set5_Train_Auc = []
Set5_Tst_Auc   = []
Set5_Train_Prb = []
Set5_Tst_Prb   = []
Set5_Train_Predict = []
Set5_Tst_Predict   = []

knn =  KNeighborsClassifier(n_neighbors = i,leaf_size=30 , algorithm= 'kd_tree')
knn.fit(X_Bow_Tr,Y_tr)

Train_Predict =  knn.predict(X_Bow_Tr)
Tst_Predict   =  knn.predict(X_Bow_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidatio
Train_pred_prob    =  knn.predict_proba(X_Bow_Tr)[:,1] # Probablity of TRAIN-Valid
Tst_pred_prob      =  knn.predict_proba(X_Bow_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc  = roc_auc_score(Y_test,Tst_pred_prob)

    #Probablity Scores
Set5_Train_Prb = Train_pred_prob
Set5_Tst_Prb = Tst_pred_prob

    #AUC
Set5_Train_Auc=Train_Auc
Set5_Tst_Auc=Test_Auc

    #MOdel Predictions
Set5_Train_Predict=Train_Predict
Set5_Tst_Predict=Tst_Predict

print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is \n", Train_
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is \n
```

```
 AUC for the  Train Data at nearest neibour  31  is 
 0.8064759666773519
 AUC for the Test-Validation Data at nearest neibour  31  is 
 0.745163983029182
```

In [233]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set5_tst_fpr, set5_tst_tpr, thresholds = roc_curve(Y_test,Set5_Tst_Prb)
set5_tst_roc_auc = auc(set5_tst_fpr, set5_tst_tpr)


set5_train_fpr, set5_train_tpr, thresholds = roc_curve(Y_tr,Set5_Train_Prb)
set5_train_roc_auc = auc(set5_train_fpr, set5_train_tpr)

lw=1
plt.figure()
plt.plot(set5_tst_fpr, set5_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set5_train_fpr, set5_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



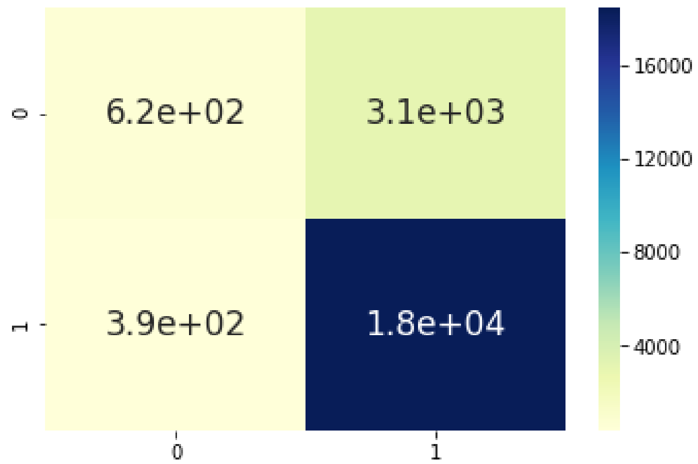
In [234]:
```
Total_AUC['set5']=[Optimal_N , set5_tst_roc_auc]
```

Confusion Matrix

In [235]:
```
Train_CM= confusion_matrix(Y_tr, Set5_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  621  3130]
 [  391 18432]]
```

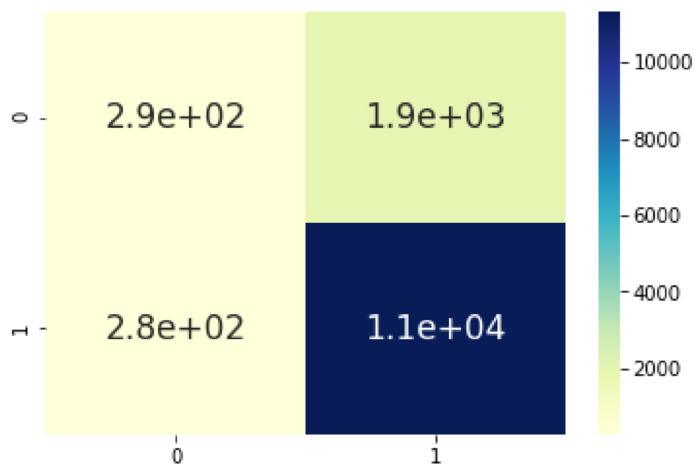
Out[235]: <matplotlib.axes._subplots.AxesSubplot at 0x20d35893c88>



In [236]:
```
Test_CM= confusion_matrix(Y_test, Set5_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  293  1948]
 [  277 11304]]
```

Out[236]: <matplotlib.axes._subplots.AxesSubplot at 0x20d3590dc18>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of

true negatives is 293 at C(0,0) ,

false negatives is 277 C(1,0),

true positives is 11304 at C(1,1),

and false positives is 1948 at C(0,1).

[5.2.2] Applying KNN kd-tree on TFIDF, SET 6

```
Applying the Kd-Tree on Tf-Idf
```

In [237]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set6_Train_Auc = []
Set6_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, leaf_size=30 , algorithm= 'kd_tr
    knn.fit(X_Tfidf_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set6_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set6_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_Tfidf_Tr)[:,1]    # Probablity of TRAI
    Cv_pred_prob    =  knn.predict_proba(X_Tfidf_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set6_Train_Auc.append(Train_Auc)
    Set6_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.907740892782591
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.659072639318885
5
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8764307771482652
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.686204992260061
8
 AUC for the  TRAIN Data at nearest neibour  7  is  0.8600517203629263
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.706562151702786
4
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8497561287133009
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.723213506191950
5
 AUC for the  TRAIN Data at nearest neibour  11  is  0.8392996279459977
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.72918467492260
06
 AUC for the  TRAIN Data at nearest neibour  13  is  0.8316465730444043
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.73466114551083
6
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8278961059922706
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.74292945046439
64
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8226376382331622
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.74726342879256
97
 AUC for the  TRAIN Data at nearest neibour  19  is  0.8208253251150948
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.75084651702786
38
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8183011863750923
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.75594535603715
17
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8168165621753554
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.76124268575851
4
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8152455631622958
```

```
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.76437906346749
23
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8137823326094431
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.76629013157894
72
 AUC for the  TRAIN Data at nearest neibour  29  is  0.812706864561984
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.76600955882352
94
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8132762004225956
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.76890394736842
1
```

Here, we are trianing the KD-Tree Model with the Tf-Idf values.

We do not know what is the best nearest neibhour to train the Model.

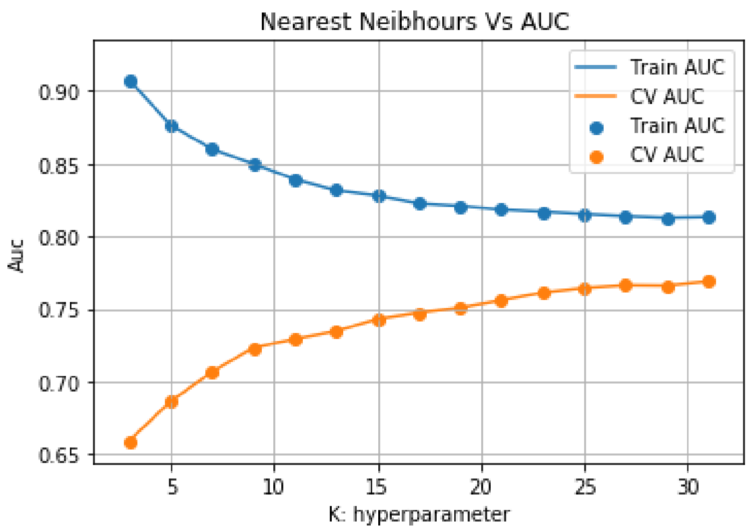
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the AUC , Error and AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data.

Plot K-NN Vs AUC

In [238]:
```
#set6_train_auc,set6_cv_auc
plt.grid()
plt.scatter(neighbors, Set6_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set6_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set6_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set6_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```




```
Both  AUC  for CrossValidation  and  Training Data Getting Closer/Converging at
Neibhour 25

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that
25-nearest neibhours will be the best fit.
```

```
Let us figure out, which hyper parameter can yeild the  the Highest accuracy.

Average the accruacis from the Hyper parameters, the value we get is the one we
expect on top of test data.
```

In [239]:

```python
Optimal_N = neighbors[Set6_Cv_Auc.index(max(Set6_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest Accuacy at Neigherest Neibhour value is at 31.

In case we we have the CrossValidation AUC High and Test Accruacy is High, then we can consider it as a Over Fitting.

In case we we have the CrossValidation AUC Low and Test Accruacy is also Low, then we can consider it as a Under Fitting

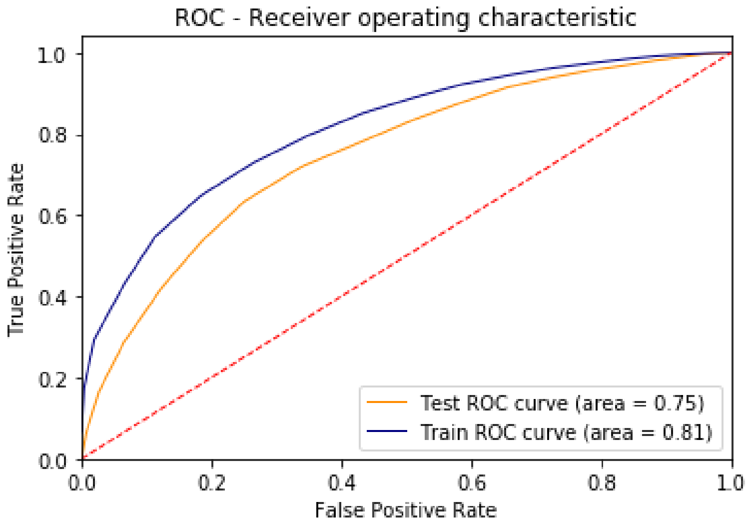
In [240]:

```
Hence, we can expext the test data Accuracy near around the same.
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.h
#Set6_Train_Pred =  knn.predict(X_Bow_Tr)
#Set6_Train_Acc  = accuracy_score(Y_tr,Set6_Train_Pred,normalize=True)

Set6_Train_Auc = []
Set6_Tst_Auc   = []
Set6_Train_Prb = []
Set6_Tst_Prb   = []
Set6_Train_Predict = []
Set6_Tst_Predict   = []


knn =  KNeighborsClassifier(n_neighbors = i, leaf_size=30 , algorithm= 'kd_tree')
knn.fit(X_Tfidf_Tr,Y_tr)

Train_Predict =  knn.predict(X_Tfidf_Tr)
Tst_Predict   =  knn.predict(X_Tfidf_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidation
Train_pred_prob    =  knn.predict_proba(X_Tfidf_Tr)[:,1] # Probablity of TRAIN-Val
Tst_pred_prob      =  knn.predict_proba(X_Tfidf_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc   = roc_auc_score(Y_test,Tst_pred_prob)

    #Probablity Scores
Set6_Train_Prb=Train_pred_prob
Set6_Tst_Prb=Tst_pred_prob

    #AUC
Set6_Train_Auc=Train_Auc
Set6_Tst_Auc=Test_Auc

    #MOdel Predictions
Set6_Train_Predict=Train_Predict
Set6_Tst_Predict=Tst_Predict


print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is \n", Train_A
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is \n
```

```
 AUC for the  Train Data at nearest neibour  31  is
 0.8132762004225956
 AUC for the Test-Validation Data at nearest neibour  31  is
 0.7518026128827161
```

In [241]:

```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set6_tst_fpr, set6_tst_tpr, thresholds = roc_curve(Y_test,Set6_Tst_Prb)
set6_tst_roc_auc = auc(set6_tst_fpr, set6_tst_tpr)


set6_train_fpr, set6_train_tpr, thresholds = roc_curve(Y_tr,Set6_Train_Prb)
set6_train_roc_auc = auc(set6_train_fpr, set6_train_tpr)

lw=1
plt.figure()
plt.plot(set6_tst_fpr, set6_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set6_train_fpr, set6_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [242]:

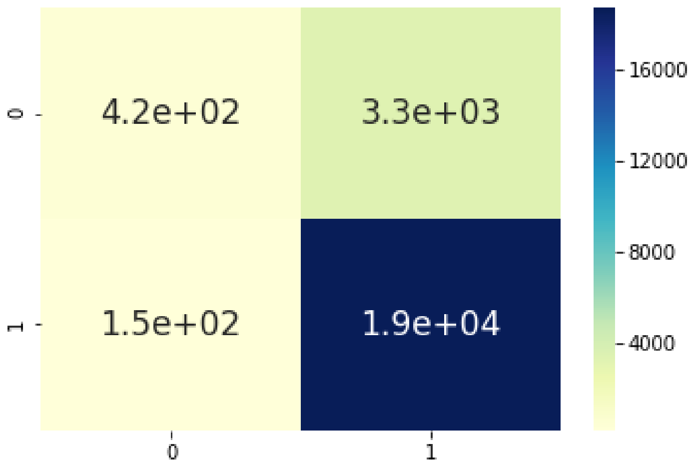
```
Total_AUC['set6']=[Optimal_N , set6_tst_roc_auc]
```

Train Confusion Matrix

In [243]:
```
Train_CM= confusion_matrix(Y_tr, Set6_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  416  3335]
 [  150 18673]]
```

Out[243]: <matplotlib.axes._subplots.AxesSubplot at 0x20d339bf860>

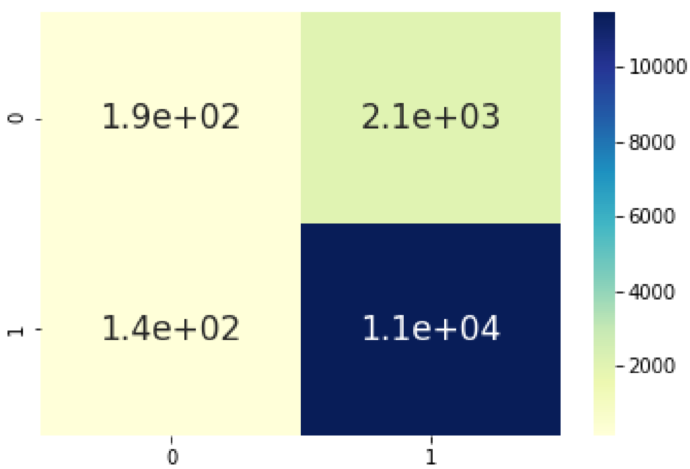


Test Confusion Matrix

In [244]:
```
Test_CM= confusion_matrix(Y_test, Set6_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  187  2054]
 [  145 11436]]
```

Out[244]: <matplotlib.axes._subplots.AxesSubplot at 0x20d3392c278>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of

true negatives is 187 at C(0,0) ,

false negatives is 145 C(1,0),

true positives is 11436 at C(1,1)

false positives is 2054 at C(0,1).

Accuracy : 0.8632153882688198

[5.2.3] Applying KNN kd-tree on AVG W2V, SET 7

```
Applying the Kd-Tree on AvgW2v Data
```

In [245]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set7_Train_Auc = []
Set7_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, leaf_size=30 , algorithm= 'kd_tr
    knn.fit(X_AvgW2V_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set7_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set7_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_AvgW2V_Tr)[:,1]    # Probablity of TRA
    Cv_pred_prob    =  knn.predict_proba(X_AvgW2V_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set7_Train_Auc.append(Train_Auc)
    Set7_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9538099195790082
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.771640170278637
7
 AUC for the  TRAIN Data at nearest neibour  5  is  0.9349450711565725
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.808668962848297
3
 AUC for the  TRAIN Data at nearest neibour  7  is  0.9237257852562522
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.824726625386996
9
 AUC for the  TRAIN Data at nearest neibour  9  is  0.9161226771906319
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.834490634674922
7
 AUC for the  TRAIN Data at nearest neibour  11  is  0.9116351809451427
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.84412952786377
72
 AUC for the  TRAIN Data at nearest neibour  13  is  0.9089894574572567
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.85073057275541
79
 AUC for the  TRAIN Data at nearest neibour  15  is  0.9060901119668838
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.85298556501547
98
 AUC for the  TRAIN Data at nearest neibour  17  is  0.9038141919349053
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.85683432662538
69
 AUC for the  TRAIN Data at nearest neibour  19  is  0.9027622774357871
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.85889620743034
06
 AUC for the  TRAIN Data at nearest neibour  21  is  0.9018980760773377
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.86036420278637
78
 AUC for the  TRAIN Data at nearest neibour  23  is  0.9005894873871174
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.86339740712074
```

```
32
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8991897933453025
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.86524992260061
92
 AUC for the  TRAIN Data at nearest neibour  27  is  0.898341306155154
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.86662445820433
43
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8973989305272725
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.86821350619195
05
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8959334763381663
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.86905441176470
58
```

Here, we are trianing the KD-Tree Model with the Avg W2V values.

We do not know what is the best nearest neibhour to train the Model.

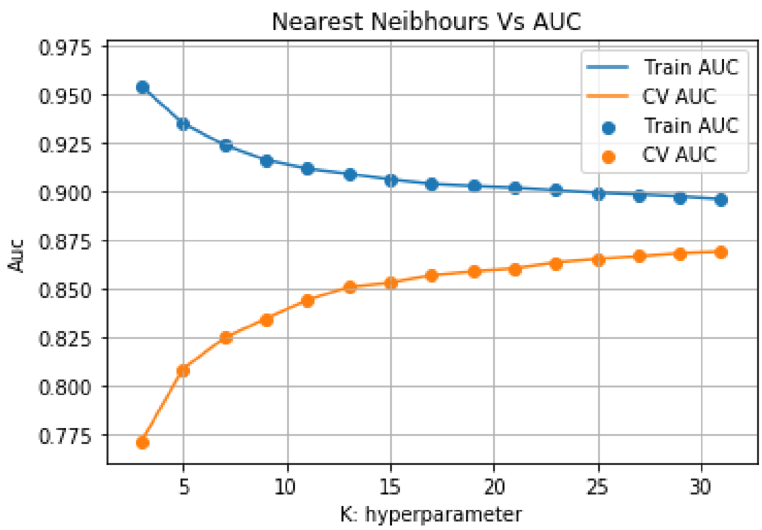
To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

We got the AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data

Plot K-nn Vs AUC

In [246]:
```
#set7_train_auc,set7_cv_auc
plt.grid()
plt.scatter(neighbors, Set7_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set7_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set7_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set7_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```



AUC for both CrossValidation and Training Data Getting Closer/Converging at Neibhour 29

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that 29-nearest neibhours will be the best fit.

Let us figure out, which hyper parameter can yeild the the Highest accuracy.

Average the accruacis from the Hyper parameters, the value we get is the one we expect on top of test data.

In [247]:
```
Optimal_N = neighbors[Set7_Cv_Auc.index(max(Set7_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest Accuacy at Neigherest Neibhour value is at 31.

Hence, we can expext the test data AUC near around the same.

In case we we have the CrossValidation AUC High and Test Accruacy is High, then we can consider it as a Over Fitting.

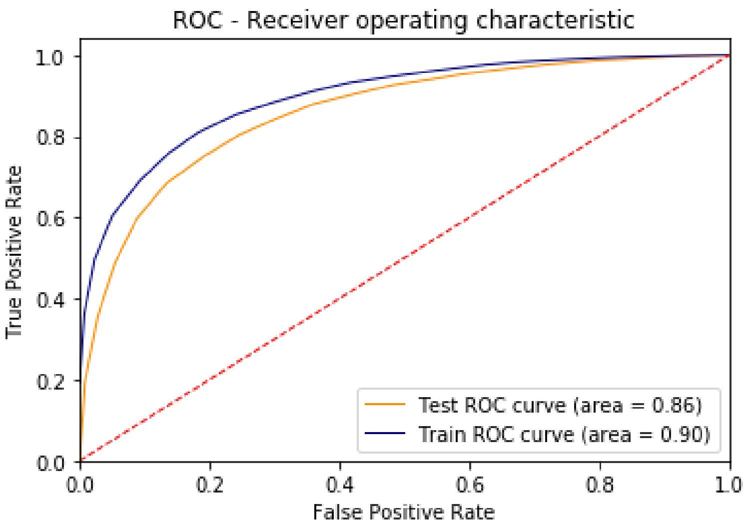
In case we we have the CrossValidation AUC Low and Test Accruacy is also Low, then we can consider it as a Under Fitting

In [248]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.
#Set7_Train_Pred =  knn.predict(X_Bow_Tr)
#Set7_Train_Acc  = accuracy_score(Y_tr,Set7_Train_Pred,normalize=True)

Set7_Train_Auc = []
Set7_Tst_Auc   = []
Set7_Train_Prb = []
Set7_Tst_Prb   = []
Set7_Train_Predict = []
Set7_Tst_Predict   = []


knn =  KNeighborsClassifier(n_neighbors = Optimal_N, leaf_size=30 , algorithm= 'k
knn.fit(X_AvgW2V_Tr,Y_tr)

Train_Predict =  knn.predict(X_AvgW2V_Tr)
Tst_Predict   =  knn.predict(X_AvgW2V_Test)

# Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValidatio
Train_pred_prob    =  knn.predict_proba(X_AvgW2V_Tr)[:,1] # Probablity of TRAIN-Va
Tst_pred_prob      =  knn.predict_proba(X_AvgW2V_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc  = roc_auc_score(Y_test,Tst_pred_prob)

#Probablity Scores
Set7_Train_Prb=Train_pred_prob
Set7_Tst_Prb=Tst_pred_prob

    #AUC
Set7_Train_Auc=Train_Auc
Set7_Tst_Auc=Test_Auc

    #MOdel Predictions
Set7_Train_Predict=Train_Predict
Set7_Tst_Predict=Tst_Predict

print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

```
 AUC for the  Train Data at nearest neibour  31  is  0.8959334763381663
 AUC for the Test-Validation Data at nearest neibour  31  is  0.859338841516754
4
```

In [249]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set7_tst_fpr, set7_tst_tpr, thresholds = roc_curve(Y_test,Set7_Tst_Prb)
set7_tst_roc_auc = auc(set7_tst_fpr, set7_tst_tpr)


set7_train_fpr, set7_train_tpr, thresholds = roc_curve(Y_tr,Set7_Train_Prb)
set7_train_roc_auc = auc(set7_train_fpr, set7_train_tpr)

lw=1
plt.figure()
plt.plot(set7_tst_fpr, set7_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set7_train_fpr, set7_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



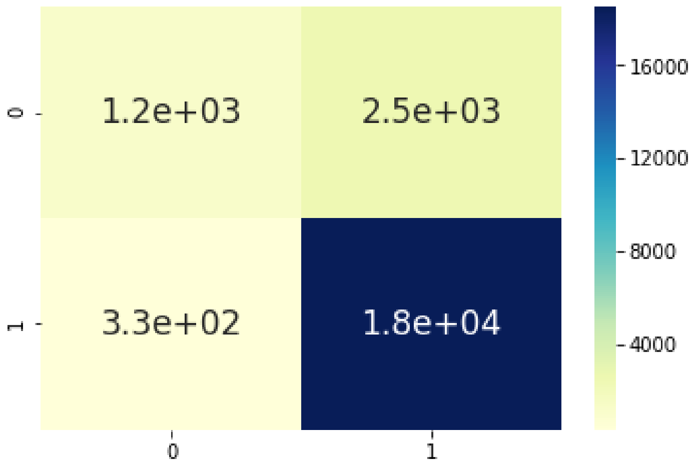
In [250]:
```
Total_AUC['set7']=[Optimal_N , set7_tst_roc_auc]
```

Confusion Matrix

In [251]:
```
Train_CM= confusion_matrix(Y_tr, Set7_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[ 1237  2514]
 [  334 18489]]
```

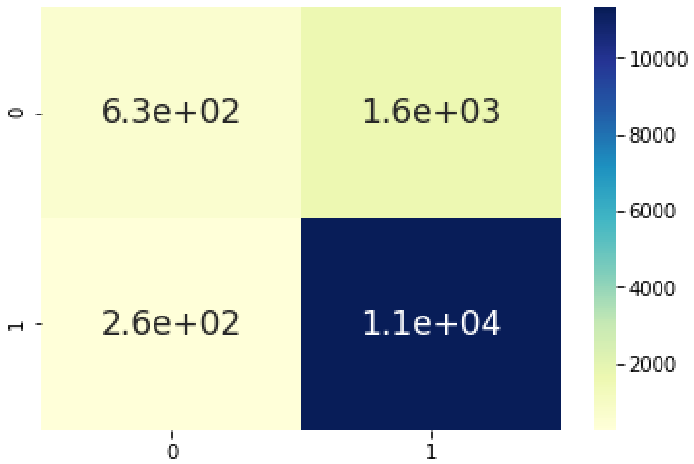
Out[251]: <matplotlib.axes._subplots.AxesSubplot at 0x20d33bf0e10>



In [252]:
```
Test_CM= confusion_matrix(Y_test, Set7_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  628  1613]
 [  265 11316]]
```

Out[252]: <matplotlib.axes._subplots.AxesSubplot at 0x20d33cc9ba8>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of

true negatives is 628 at C(0,0) ,

false negatives is 265 C(1,0),

true positives is 11316 at C(1,1)

and false positives is 1613 at C(0,1).

AUC and ROC for Kd-Tree on top Tf-IDF

[5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 8

```
Applying the Kd-tree on Average Tf-idf,W2V
```

In [253]:
```
#https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
Set8_Train_Auc = []
Set8_Cv_Auc    = []
for i in neighbors:
    knn =  KNeighborsClassifier(n_neighbors = i, leaf_size=30 , algorithm= 'kd_tr
    knn.fit(X_AvgW2VtfIdf_Tr,Y_tr)

    #pred_tr =  knn.predict(X_Tfidf_Tr) # Class-Predictions of TRAIN-Validation
    #pred_cv =  knn.predict(X_Tfidf_Cv) # Class-Predictions of Cross-Validation
    #Y_train_acc  = accuracy_score(Y_tr,pred_tr,normalize=True)    # Accuracy of
    #Y_cv_acc  = accuracy_score(Y_cv,pred_cv,normalize=True)     # Accuracy of TR

    #Set8_Acc_Tr.append(Y_train_acc)   #Accuracy
    #Set8_Acc_Cv.append(Y_cv_acc)      #Accuracy


    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
    Train_pred_prob =  knn.predict_proba(X_AvgW2VtfIdf_Tr)[:,1]    # Probablity o
    Cv_pred_prob    =  knn.predict_proba(X_AvgW2VtfIdf_Cv)[:,1]

    Train_Auc = roc_auc_score(Y_tr,Train_pred_prob)
    Cv_Auc    = roc_auc_score(Y_cv,Cv_pred_prob)

    Set8_Train_Auc.append(Train_Auc)
    Set8_Cv_Auc.append(Cv_Auc)

    print(" AUC for the  TRAIN Data at nearest neibour ",i,  " is ", Train_Auc)
    print(" AUC for the Cross-Validation Data at nearest neibour ",i,  " is ", Cv
```

```
 AUC for the  TRAIN Data at nearest neibour  3  is  0.9153320257880053
 AUC for the Cross-Validation Data at nearest neibour  3  is  0.659335332817337
4
 AUC for the  TRAIN Data at nearest neibour  5  is  0.8817401548469471
 AUC for the Cross-Validation Data at nearest neibour  5  is  0.679647329721362
2
 AUC for the  TRAIN Data at nearest neibour  7  is  0.8644229785018422
 AUC for the Cross-Validation Data at nearest neibour  7  is  0.697580456656346
8
 AUC for the  TRAIN Data at nearest neibour  9  is  0.8509692285142173
 AUC for the Cross-Validation Data at nearest neibour  9  is  0.708086803405572
7
 AUC for the  TRAIN Data at nearest neibour  11  is  0.8403287324694076
 AUC for the Cross-Validation Data at nearest neibour  11  is  0.71857697368421
06
 AUC for the  TRAIN Data at nearest neibour  13  is  0.8355394236331999
 AUC for the Cross-Validation Data at nearest neibour  13  is  0.72420166408668
72
 AUC for the  TRAIN Data at nearest neibour  15  is  0.8303192321605559
 AUC for the Cross-Validation Data at nearest neibour  15  is  0.72844767801857
58
 AUC for the  TRAIN Data at nearest neibour  17  is  0.8264534051257195
 AUC for the Cross-Validation Data at nearest neibour  17  is  0.73147128482972
13
 AUC for the  TRAIN Data at nearest neibour  19  is  0.823495062458189
 AUC for the Cross-Validation Data at nearest neibour  19  is  0.73413374613003
1
 AUC for the  TRAIN Data at nearest neibour  21  is  0.8200344825080771
 AUC for the Cross-Validation Data at nearest neibour  21  is  0.73778498452012
38
 AUC for the  TRAIN Data at nearest neibour  23  is  0.8169868261449145
 AUC for the Cross-Validation Data at nearest neibour  23  is  0.73873196594427
25
```

```
 AUC for the  TRAIN Data at nearest neibour  25  is  0.8152832516722983
 AUC for the Cross-Validation Data at nearest neibour  25  is  0.74015452786377
71
 AUC for the  TRAIN Data at nearest neibour  27  is  0.8130022682647747
 AUC for the Cross-Validation Data at nearest neibour  27  is  0.73940255417956
65
 AUC for the  TRAIN Data at nearest neibour  29  is  0.8102929445310537
 AUC for the Cross-Validation Data at nearest neibour  29  is  0.74175743034055
74
 AUC for the  TRAIN Data at nearest neibour  31  is  0.8078603502045809
 AUC for the Cross-Validation Data at nearest neibour  31  is  0.74229253095975
23
```

Here, we are trianing the KD-Tree Model with the Avg of Tf-Idf values.

We do not know what is the best nearest neibhour to train the Model.

To find out this, we are trying to train the model on top of Cross-Validation Data with different neighrest neibhours.

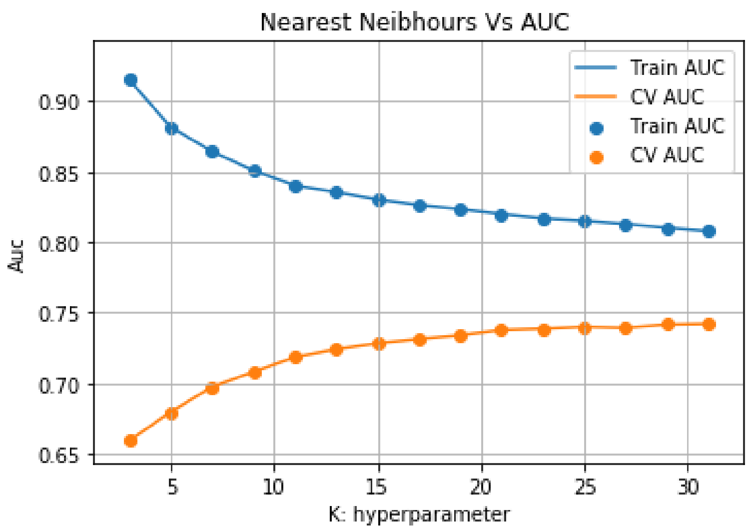
We got the AUC, Error and AUC/ROC which helps to judge a Model performance.

Let us see the AUC values for Cross Validation Data and Training Data

Plot K-nn Vs AUC

In [254]:

```
#set8_train_auc,set8_cv_auc
plt.grid()
plt.scatter(neighbors, Set8_Train_Auc, label='Train AUC')
plt.plot(neighbors, Set8_Train_Auc, label='Train AUC')
plt.scatter(neighbors, Set8_Cv_Auc, label='CV AUC')
plt.plot(neighbors, Set8_Cv_Auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("Auc")
plt.title(" Nearest Neibhours Vs AUC  ")
plt.show()
```



Both AUC for CrossValidation and Training Data Getting Closer/Converging at Neibhour 31

Accoring to analysis of Train-AUC and CrosValidation-AUC,we can Uderstand that 31-nearest neibhours will be the best fit.

Let us figure out, which hyper parameter can yeild the the Highest accuracy.

Average the accruacis from the Hyper parameters, the value we get is the one we expect on top of test data.

In [255]:
```
Optimal_N = neighbors[Set8_Cv_Auc.index(max(Set8_Cv_Auc))]
print("Highest nearest neighbors of CrosValidation: ", Optimal_N  )
```

```
Highest nearest neighbors of CrosValidation:  31
```

According to the CrossValidation, we are getting the Highest auc at Neigherest Neibhour value is at 31.

Hence, we can expext the test data AUC near around the same.

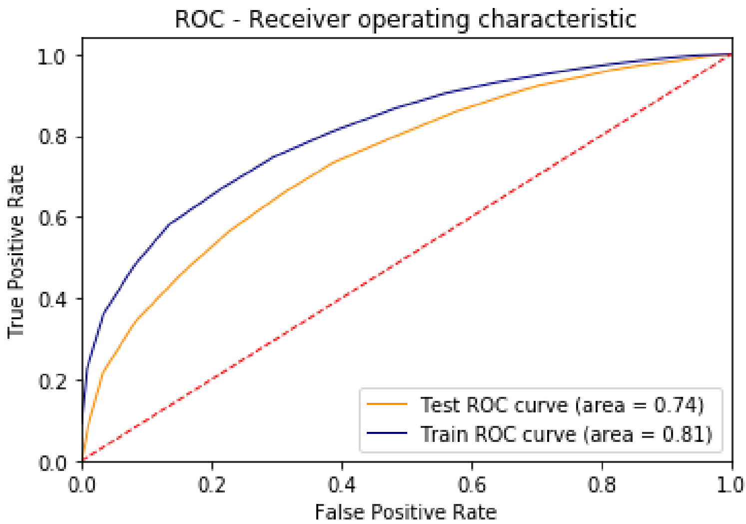
In case we we have the CrossValidation AUC High and Test Accruacy is High, then we can consider it as a Over Fitting.

In case we we have the CrossValidation AUC Low and Test Accruacy is also Low, then we can consider it as a Under Fitting

In [256]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.
#Set8_Train_Pred =  knn.predict(X_Bow_Tr)
#Set8_Train_Acc  = accuracy_score(Y_tr,Set8_Train_Pred,normalize=True)

Set8_Train_Auc = []
Set8_Tst_Auc   = []
Set8_Train_Prb = []
Set8_Tst_Prb   = []
Set8_Train_Predict = []
Set8_Tst_Predict   = []

knn =  KNeighborsClassifier(n_neighbors = i, leaf_size=30 , algorithm= 'kd_tree')
knn.fit(X_AvgW2VtfIdf_Tr,Y_tr)

Train_Predict =  knn.predict(X_AvgW2VtfIdf_Tr)
Tst_Predict   =  knn.predict(X_AvgW2VtfIdf_Test)

    # Let PLOT  AUC-socre Vs each nearest neibhours  for both Test and CrossValid
Train_pred_prob    =  knn.predict_proba(X_AvgW2VtfIdf_Tr)[:,1] # Probablity of TRA
Tst_pred_prob      =  knn.predict_proba(X_AvgW2VtfIdf_Test)[:,1]

Train_Auc=  roc_auc_score(Y_tr,Train_pred_prob)
Test_Auc  = roc_auc_score(Y_test,Tst_pred_prob)

    #Probablity Scores
Set8_Train_Prb=Train_pred_prob
Set8_Tst_Prb=Tst_pred_prob

    #AUC
Set8_Train_Auc=Train_Auc
Set8_Tst_Auc=Test_Auc

    #MOdel Predictions
Set8_Train_Predict=Train_Predict
Set8_Tst_Predict=Tst_Predict

print(" AUC for the  Train Data at nearest neibour ",Optimal_N,  " is ", Train_Au
print(" AUC for the Test-Validation Data at nearest neibour ",Optimal_N,  " is ",
```

```
 AUC for the  Train Data at nearest neibour  31  is  0.8078603502045809
 AUC for the Test-Validation Data at nearest neibour  31  is  0.738990578399331
6
```

In [257]:
```
#https://qiita.com/bmj0114/items/460424c110a8ce22d945
set8_tst_fpr, set8_tst_tpr, thresholds = roc_curve(Y_test,Tst_pred_prob)
set8_tst_roc_auc = auc(set8_tst_fpr, set8_tst_tpr)


set8_train_fpr, set8_train_tpr, thresholds = roc_curve(Y_tr,Train_pred_prob)
set8_train_roc_auc = auc(set8_train_fpr, set8_train_tpr)

lw=1
plt.figure()
plt.plot(set8_tst_fpr, set8_tst_tpr, color='darkorange', lw=1, label='Test ROC cu
plt.plot(set8_train_fpr, set8_train_tpr, color='navy', lw=1, label='Train ROC cur
plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.04])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



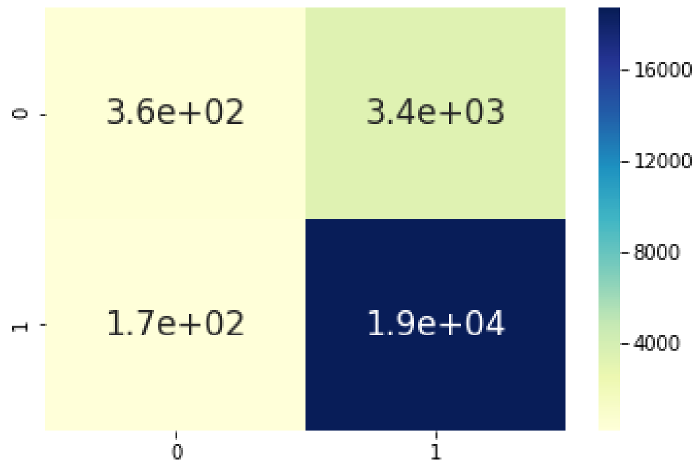
In [258]:
```
Total_AUC['set8']=[Optimal_N , set8_tst_roc_auc]
```

Confusion Matrix

In [259]:
```
Train_CM= confusion_matrix(Y_tr, Set8_Train_Predict, labels=None, sample_weight=N
print("Train Confusion Matrix::\n",Train_CM,"\n")
sns.heatmap(Train_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Train Confusion Matrix::
 [[  363  3388]
 [  173 18650]]
```

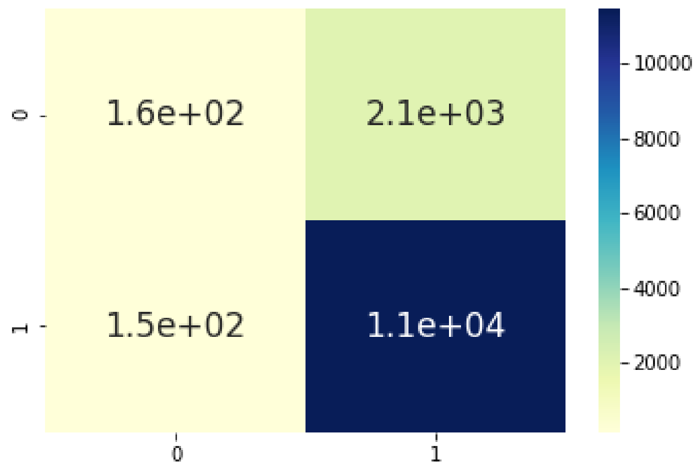
Out[259]: <matplotlib.axes._subplots.AxesSubplot at 0x20d339ddd30>



In [260]:
```
Test_CM= confusion_matrix(Y_test, Set8_Tst_Predict, labels=None, sample_weight=No
print("Test Confusion Matrix::\n",Test_CM,"\n")
sns.heatmap(Test_CM, cmap="YlGnBu"  ,annot=True,annot_kws={"size": 17})
```

```
Test Confusion Matrix::
 [[  155  2086]
 [  148 11433]]
```

Out[260]: <matplotlib.axes._subplots.AxesSubplot at 0x20d3100f7f0>



By definition a confusion matrix C is such that C-ij is equal to the number of observations known to be in group i but predicted to be in group j .

Horizantal Lines are Predictions and the Verticals are Acutuals

Thus in binary classification, the count of true

negatives is 154 at C(0,0) ,

false negatives is 148 C(1,0),

true positives is 11433 at C(1,1),

false positives is 2086 at C(0,1).

[6] Conclusions

In [261]:

```
#Letus check all the neibours
from prettytable import PrettyTable
```

In [262]:

```
#http://zetcode.com/python/prettytable/
x = PrettyTable()
x.clear_rows()
sets = ["BOW","TFIDF","W2V","TFIDFW2V"]
x.field_names = ["SET","Vectorizer", "Model", "Best Hyper parameter", "Test AUC"]
for i,j in enumerate(Total_AUC) :
    #print(j,sets[(i%4)],"Brute",Total_ACU[j][0],Total_ACU[j][1])
    x.add_row([ j, sets[(i%4)], ("Brute") if (i < 3) else ("KD-Tree") ,Total_AUC[
print(x)
```

```
+------+------------+---------+----------------------+--------------------+
| SET  | Vectorizer |  Model  | Best Hyper parameter |      Test AUC      |
+------+------------+---------+----------------------+--------------------+
| set1 |    BOW     |  Brute  |          31          | 0.7490356132336193 |
| set2 |   TFIDF    |  Brute  |          31          | 0.7525841018662144 |
| set3 |    W2V     |  Brute  |          31          | 0.8591701520990562 |
| set4 |  TFIDFW2V  | KD-Tree |          31          | 0.5280130586724374 |
| set5 |    BOW     | KD-Tree |          31          | 0.745163983029182  |
| set6 |   TFIDF    | KD-Tree |          31          | 0.7518026128827161 |
| set7 |    W2V     | KD-Tree |          31          | 0.8593388415167544 |
| set8 |  TFIDFW2V  | KD-Tree |          31          | 0.7389905783993316 |
+------+------------+---------+----------------------+--------------------+
```

Area Under the Curve is the best Metrice to understand or to compare the Models.

In the Above table, we can see each model with its Hyper parameter and corresponding the Test AUC.

By Observing the above Auc fOR each Model we can conclude Highest Test Area under the curve is 0.8593388415167544.

And we are acheiving the High AUC with AVg Tf-idf for KD-Tree Algorithms.