Amazon_Fine_Food_Reviews_Analysis_KNN

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1 Amazon Fine Food Reviews Analysis

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

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

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

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan:

Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

- 1. Id
- 2. ProductId unique identifier for the product
- 3. UserId unque 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.

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

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

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

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        from tqdm import tqdm
        import os
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.cross_validation import train_test_split
        from sklearn.model_selection import TimeSeriesSplit
        from sklearn.metrics import roc_auc_score
C:\Users\rites\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning:
```

In [2]: # using SQLite Table to read data.

"This module will be removed in 0.20.", DeprecationWarning)

```
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 point
        # 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 LIMIT 5
        filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 1000
        # Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negativ
        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 (100000, 10)
Out[2]:
           Id ProductId
                                   UserId
                                                               ProfileName \
           1 B001E4KFG0 A3SGXH7AUHU8GW
                                                                delmartian
           2 B00813GRG4 A1D87F6ZCVE5NK
                                                                    dll pa
           3 BOOOLQOCHO
                           ABXLMWJIXXAIN Natalia Corres "Natalia Corres"
           HelpfulnessNumerator HelpfulnessDenominator Score
                                                                      Time
        0
                                                             1 1303862400
                              1
                                                      1
        1
                              0
                                                      0
                                                             0 1346976000
        2
                              1
                                                      1
                                                             1 1219017600
                         Summary
                                                                               Text
        O Good Quality Dog Food I have bought several of the Vitality canned d...
               Not as Advertised Product arrived labeled as Jumbo Salted Peanut...
        1
           "Delight" says it all This is a confection that has been around a fe...
In [3]: display = pd.read_sql_query("""
        SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
       FROM Reviews
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
```

```
In [4]: print(display.shape)
        display.head()
(80668, 7)
Out [4]:
                       UserId
                                ProductId
                                                      ProfileName
                                                                         Time
                                                                               Score
          #oc-R115TNMSPFT9I7 B007Y59HVM
                                                          Breyton
                                                                   1331510400
                                                                                   2
        1 #oc-R11D9D7SHXIJB9 B005HG9ET0 Louis E. Emory "hoppy"
                                                                   1342396800
                                                                                   5
                                                 Kim Cieszykowski
        2 #oc-R11DNU2NBKQ23Z B007Y59HVM
                                                                   1348531200
                                                                                   1
        3 #oc-R1105J5ZVQE25C B005HG9ET0
                                                    Penguin Chick
                                                                   1346889600
                                                                                   5
         #oc-R12KPBODL2B5ZD B0070SBE1U
                                            Christopher P. Presta
                                                                   1348617600
                                                                                   1
                                                              COUNT(*)
                                                        Text
          Overall its just OK when considering the price...
        1 My wife has recurring extreme muscle spasms, u...
                                                                     3
        2 This coffee is horrible and unfortunately not ...
                                                                     2
        3 This will be the bottle that you grab from the...
                                                                     3
          I didnt like this coffee. Instead of telling y...
                                                                     2
In [5]: display[display['UserId']=='AZY10LLTJ71NX']
Out[5]:
                      UserId
                                                              ProfileName
                               ProductId
                                                                                 Time
        80638 AZY10LLTJ71NX B006P7E5ZI undertheshrine "undertheshrine"
                                                                           1334707200
               Score
                                                                   Text
                                                                         COUNT(*)
                     I was recommended to try green tea extract to ...
        80638
In [6]: display['COUNT(*)'].sum()
Out[6]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [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:

```
Out [7]:
               Ιd
                    ProductId
                                       UserId
                                                   ProfileName
                                                                HelpfulnessNumerator
        0
            78445
                   B000HDL1RQ
                               AR5J8UI46CURR Geetha Krishnan
                                                                                     2
        1
           138317
                   BOOOHDOPYC
                                AR5J8UI46CURR Geetha Krishnan
                                                                                    2
        2
           138277
                                                                                    2
                   BOOOHDOPYM
                               AR5J8UI46CURR Geetha Krishnan
                                                                                    2
        3
            73791
                   BOOOHDOPZG
                                AR5J8UI46CURR Geetha Krishnan
                                                                                    2
           155049
                   B000PAQ75C
                                AR5J8UI46CURR Geetha Krishnan
           HelpfulnessDenominator
                                    Score
                                                 Time
        0
                                 2
                                        5
                                           1199577600
                                 2
        1
                                        5
                                           1199577600
        2
                                 2
                                        5
                                           1199577600
        3
                                 2
                                           1199577600
                                 2
        4
                                           1199577600
                                      Summary
           LOACKER QUADRATINI VANILLA WAFERS
        0
        1
          LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
                                                          Text
           DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
          DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
          DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
           DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        3
           DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

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.

```
Out[9]: (87775, 10)
In [10]: #Checking to see how much % of data still remains
         (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
Out[10]: 87.775
  Observation:- It was also seen that in two rows given below the value of HelpfulnessNumera-
tor is greater than HelpfulnessDenominator which is not practically possible hence these two rows
too are removed from calcualtions
In [11]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND Id=44737 OR Id=64422
         ORDER BY ProductID
         """, con)
         display.head()
Out[11]:
               Ιd
                    ProductId
                                                             ProfileName \
                                        UserId
         O 64422 BOOOMIDROQ A161DK06JJMCYF J. E. Stephens "Jeanne"
         1 44737
                   B001EQ55RW A2V0I904FH7ABY
                                                                     Ram
            HelpfulnessNumerator HelpfulnessDenominator Score
                                                                         Time \
         0
                                3
                                                                  1224892800
                                3
         1
                                                                4 1212883200
                                                   Summary
                       Bought This for My Son at College
         1 Pure cocoa taste with crunchy almonds inside
                                                           Text
         O My son loves spaghetti so I didn't hesitate or...
         1 It was almost a 'love at first bite' - the per...
In [12]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]</pre>
In [13]: #Before starting the next phase of preprocessing lets see the number of entries left
         print(final.shape)
         #How many positive and negative reviews are present in our dataset?
         final['Score'].value_counts()
(87773, 10)
Out[13]: 1
              73592
              14181
         Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [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 observed to be better than Porter Stemming)

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

```
In [14]: # printing some random reviews
       sent_0 = final['Text'].values[0]
       print(sent_0)
       print("="*50)
       sent_1000 = final['Text'].values[1000]
       print(sent_1000)
       print("="*50)
       sent_1500 = final['Text'].values[1500]
       print(sent_1500)
       print("="*50)
       sent_4900 = final['Text'].values[4900]
       print(sent_4900)
       print("="*50)
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.
_____
The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
_____
was way to hot for my blood, took a bite and did a jig lol
_____
My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid
_____
```

sent_0 = re.sub(r"http\S+", "", sent_0)

In [15]: # remove urls from text python: https://stackoverflow.com/a/40823105/4084039

```
sent_150 = re.sub(r"http\S+", "", sent_1500)
        sent_{4900} = re.sub(r"http\S+", "", sent_{4900})
        print(sent_0)
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.
                                                                                    Its
In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
        from bs4 import BeautifulSoup
        soup = BeautifulSoup(sent_0, 'lxml')
        sent_0 = soup.get_text()
        print(sent_0)
        print("="*50)
        soup = BeautifulSoup(sent_1000, 'lxml')
        sent_1000 = soup.get_text()
        print(sent_1000)
        print("="*50)
        soup = BeautifulSoup(sent_1500, 'lxml')
        sent_1500 = soup.get_text()
        print(sent_1500)
        print("="*50)
        soup = BeautifulSoup(sent_4900, 'lxml')
        sent_4900 = soup.get_text()
        print(sent_4900)
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.
                                                                                    Its
_____
The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
_____
was way to hot for my blood, took a bite and did a jig lol
_____
My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid
In [17]: # 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)
            phrase = re.sub(r"wont", "will not", phrase) # in some words aposthepe is missing
            phrase = re.sub(r"its","it is",phrase)
            phrase = re.sub(r"Its","It is",phrase)
```

```
phrase = re.sub(r"isnt","is not",phrase)
             # general
            phrase = re.sub(r"n\'t", " not", phrase)
            phrase = re.sub(r"\'re", " are", phrase)
            phrase = re.sub(r"\'s", " is", phrase)
            phrase = re.sub(r"\'d", " would", phrase)
            phrase = re.sub(r"\'ll", " will", phrase)
            phrase = re.sub(r"\'t", " not", phrase)
            phrase = re.sub(r"\'ve", " have", phrase)
            phrase = re.sub(r"\'m", " am", phrase)
            return phrase
In [18]: sent_0 = decontracted(sent_0)
        print(sent_0)
        print("="*50)
My dogs loves this chicken but it is a product from China, so we will not be buying it anymore
_____
In [19]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_4900 = re.sub("\S*\d\S*", "", sent_4900).strip()
        print(sent_4900)
My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid
In [20]: #remove special character: https://stackoverflow.com/a/5843547/4084039
         sent_{4900} = re.sub('[^A-Za-z0-9]+', ' ', sent_{4900})
        print(sent_4900)
My dog LOVES these treats They tend to have a very strong fish oil smell So if you are afraid
In [21]: # https://qist.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 step
         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
                     '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', 'a
```

'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug' above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'e

```
'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                     "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                     'won', "won't", 'wouldn', "wouldn't"])
In [22]: # Combining all the above stundents
         import itertools
         from tqdm import tqdm
         preprocessed_reviews = []
         # tqdm is for printing the status bar
         for sentence in tqdm(final['Text'].values):
             sentence = re.sub(r"http\S+", "", sentence)
             sentence = BeautifulSoup(sentence, 'lxml').get_text()
             sentence = decontracted(sentence)
             sentence = re.sub("\S*\d\S*", "", sentence).strip()
             sentence = re.sub('[^A-Za-z]+', ' ', sentence)
             #https://www.analyticsvidhya.com/blog/2014/11/text-data-cleaning-steps-python/
             # This removes words such as aawwww or happpyyy or awsooommmee etc
             sentence = ''.join(''.join(s)[:2] for _, s in itertools.groupby(sentence))
             # https://gist.github.com/sebleier/554280
             sentence = ' '.join(e.lower() for e in sentence.split() if e.lower() not in stopwer
             preprocessed_reviews.append(sentence.strip())
100%|| 87773/87773 [01:07<00:00, 1301.29it/s]
In [23]: smpl = " aaaaww aaaww aaa aawwww"
         sent = ''.join(''.join(s)[:2] for _, s in itertools.groupby(smpl))
         print(sent)
aaww aaww aa aaww
In [24]: preprocessed_reviews[4900]
Out [24]: 'dog loves treats tend strong fish oil smell afraid fishy smell not get think dog lik
  [3.2] Preprocessing Review Summary
In [25]: ## Similartly performing preprocessing for review summary also.
         preprocessed_summary=[]
         for sent in tqdm(final['Summary'].values):
```

```
sent = re.sub(r"http\S+","",sent)
             sent = BeautifulSoup(sent,'lxml').get_text()
             sent = decontracted(sent)
             sent = re.sub(r"\S+\d\S+","",sent).strip()
             sent = re.sub(r"[^A-Za-z0]+"," ",sent)
             #https://www.analyticsvidhya.com/blog/2014/11/text-data-cleaning-steps-python/
             # This removes words such as aawwww or happpyyy or awsooommmee etc
             sent = ''.join(''.join(s)[:2] for _, s in itertools.groupby(sent))
             # https://qist.github.com/sebleier/554280
             sent = ' '.join(w.lower() for w in sent.split() if w.lower() not in stopwords)
             preprocessed_summary.append(sent.strip())
100%|| 87773/87773 [00:34<00:00, 2512.46it/s]
In [26]: preprocessed_summary[4900]
Out[26]: 'great value'
In [27]: final['Summary'].values[4900]
Out[27]: 'Great value'
In [28]: # Removing those words which are of length 2
         # This will remove non relevant words then we will perform featurization
         cleaned_reviews = []
         for sent in preprocessed_reviews:
             sentence = ' '.join(w for w in sent.split() if len(w)>2)
             cleaned_reviews.append(sentence.strip())
In [29]: print(cleaned_reviews[0])
dogs loves chicken product china not buying anymore hard find chicken products made usa one no
In [30]: final["Cleaned_review"] = cleaned_reviews
        final.head(5)
Out [30]:
                  Id ProductId
                                          UserId
                                                         ProfileName \
        22620 24750 2734888454 A13ISQV0U9GZIC
                                                           Sandikaye
        22621 24751 2734888454 A1C298ITT645B6 Hugh G. Pritchard
        70677 76870 B00002N8SM A19Q006CSFT011
                                                           Arlielle
        70676 76869 B00002N8SM A1FYH4S02BW7FN
                                                            wonderer
         70675 76868 B00002N8SM AUE8TB5VHS6ZV
                                                       eyeofthestorm
                HelpfulnessNumerator HelpfulnessDenominator Score
                                                                           Time \
         22620
                                   1
                                                           1
                                                                  0 1192060800
```

```
22621
                          0
                                                  0
                                                         1 1195948800
70677
                          0
                                                         0 1288396800
70676
                          0
                                                  0
                                                         0 1290038400
70675
                          0
                                                  0
                                                         0 1306972800
                                       Summary \
22620
                                 made in china
22621
                             Dog Lover Delites
70677
                      only one fruitfly stuck
70676 Doesn't work!! Don't waste your money!!
70675
                                 A big rip off
                                                    Text \
22620 My dogs loves this chicken but its a product f...
22621 Our dogs just love them. I saw them in a pet ...
70677 I had an infestation of fruitflies, they were ...
70676 Worst product I have gotten in long time. Woul...
70675 I wish I'd read the reviews before making this...
                                          Cleaned review
22620 dogs loves chicken product china not buying an...
22621 dogs love saw pet store tag attached regarding...
70677 infestation fruitflies literally everywhere fl...
70676 worst product gotten long time would rate star...
70675 wish would read reviews making purchase basica...
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

5.2 [4.2] Bi-Grams and n-Grams.

```
In [37]: #bi-gram, tri-gram and n-gram
         #removing stop words like "not" should be avoided before building n-grams
         # count_vect = CountVectorizer(ngram_range=(1,2))
        # please do read the CountVectorizer documentation http://scikit-learn.org/stable/mod
        # you can choose these numbers min_df=10, max_features=5000, of your choice
        count_vect2 = CountVectorizer(ngram_range=(1,2), min_df=5)
        final_bigram_counts = count_vect2.fit_transform(cleaned_reviews)
        print("the type of count vectorizer ",type(final_bigram_counts))
        print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
        print("the number of unique words including both unigrams and bigrams ", final_bigram
        bigram_features = count_vect2.get_feature_names()
        print(bigram_features[:10])
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (87773, 112780)
the number of unique words including both unigrams and bigrams 112780
['aafco', 'aback', 'abandon', 'abandoned', 'abc', 'abdomen', 'abdominal', 'abdominal pain', 'a
5.3 [4.3] TF-IDF
In [38]: # tfidf on unigrams
        tf_idf_vect1 = TfidfVectorizer()
        tf_idf_vect1.fit(cleaned_reviews)
        print("some sample features(unique words in the corpus)", tf_idf_vect1.get_feature_name
        print('='*50)
        final_tf_idf1 = tf_idf_vect1.transform(cleaned_reviews)
        print("the type of count vectorizer ",type(final_tf_idf1))
        print("the shape of out text TFIDF vectorizer ",final_tf_idf1.get_shape())
        print("the number of unique words including both unigrams and bigrams ", final_tf_idf
some sample features (unique words in the corpus) ['aaa', 'aaah', 'aaahh', 'aaaww', 'aachen', 'a
_____
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer (87773, 54095)
the number of unique words including both unigrams and bigrams 54095
In [39]: # Tfidf on bigrams
        tf_idf_vect2 = TfidfVectorizer(ngram_range=(1,2),min_df=3)
        tf_idf_vect2.fit(cleaned_reviews)
        print("some sample features(unique words in the corpus)",tf_idf_vect2.get_feature_name
        print('='*50)
```

```
final_tf_idf2 = tf_idf_vect2.transform(cleaned_reviews)
        print("the type of count vectorizer ",type(final_tf_idf2))
        print("the shape of out text TFIDF vectorizer ",final_tf_idf2.get_shape())
        print("the number of unique words including both unigrams and bigrams ", final_tf_idf
some sample features (unique words in the corpus) ['aafco', 'aafco dog', 'aah', 'aahs', 'aback'
_____
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer (87773, 213055)
the number of unique words including both unigrams and bigrams 213055
5.4 [4.4] Word2Vec
In [40]: # Train your own Word2Vec model using your own text corpus
        i=0
        list_of_sentence=[]
        for sentence in tqdm(cleaned_reviews):
            list_of_sentence.append(sentence.split())
100%|| 87773/87773 [00:00<00:00, 107758.27it/s]
In [32]: outfile = open("list_of_sentence","wb")
        pickle.dump(list_of_sentence,outfile)
        outfile.close()
In [41]: # 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
        # To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
         # from https://drive.google.com/file/d/OB7XkCwpI5KDYNlNUTTlSS21pQmM/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_sentence,min_count=5,size=50, workers=4)
            print(w2v_model.wv.most_similar('great'))
```

```
print('='*50)
            print(w2v_model.wv.most_similar('worst'))
        elif want_to_use_google_w2v and is_your_ram_gt_16g:
            if os.path.isfile('GoogleNews-vectors-negative300.bin'):
                w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.b
                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 = True,"
[('fantastic', 0.8564410209655762), ('good', 0.8339499235153198), ('terrific', 0.8293559551239
_____
[('greatest', 0.8057908415794373), ('tastiest', 0.7508324384689331), ('best', 0.71000838279724
In [42]: w2v_words = list(w2v_model.wv.vocab)
        print("number of words that occured minimum 5 times ",len(w2v_words))
        print("sample words ", w2v_words[0:50])
number of words that occured minimum 5 times 17061
sample words ['dogs', 'loves', 'chicken', 'product', 'china', 'not', 'buying', 'anymore', 'ha
5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V
[4.4.1.1] Avg W2v
```

```
In [52]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in list_of_sentence: # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             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]))
```

KeyboardInterrupt

Traceback (most recent call last)

KeyboardInterrupt:

[4.4.1.2] TFIDF weighted W2v

```
In [43]: \#S = ["abc\ def\ pqr",\ "def\ def\ def\ abc",\ "pqr\ pqr\ def"]
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(cleaned_reviews)
         # 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 [44]: # 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 = tfidf
         tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
         row=0:
         for sent in list_of_sentence: # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length
             weight_sum =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words and word in tfidf_feat:
                     vec = w2v_model.wv[word]
                     \#tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                     # to reduce the computation we are
                     # dictionary[word] = idf value of word in whole courpus
                     # sent.count(word) = tf values of word in this review
                     tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                     sent_vec += (vec * tf_idf)
                     weight_sum += 1
             if weight_sum != 0:
                 sent_vec /= weight_sum
             tfidf_sent_vectors.append(sent_vec)
             row += 1
```

 ${\tt KeyboardInterrupt}$

Traceback (most recent call last)

```
<ipython-input-44-acbebc07d9a9> in <module>()
                        # sent.count(word) = tf values of word in this review
         16
         17
                        tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                        sent_vec += (vec * tf_idf)
    ---> 18
                        weight_sum += 1
         19
         20
                if weight sum != 0:
        KeyboardInterrupt:
In [45]: print(len(tfidf_sent_vectors))
         print(len(tfidf_sent_vectors[0]))
64957
50
In [46]: # Function to plot confusion matrix
         def confusion_matrix_plot(test_y, predict_y):
             # C stores the confusion matrix
             C = confusion_matrix(test_y, predict_y)
             # Class labels
             labels_x = ["Predicted No", "Predicted Yes"]
             labels_y = ["Original No","Original Yes"]
             cmap=sns.light_palette("orange")
             print("Confusion matrix")
             plt.figure(figsize=(4,4))
             sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels_x, yticklabels
             plt.show()
In [47]: # Function to plot roc curve
         def plot_roc_curve(Y_test,predict_y_test,Y_train,predict_y_train):
             fpr1,tpr1,threshold1 = roc_curve(Y_test,predict_y_test) # For test dataset
             fpr2,tpr2,threshold2 = roc_curve(Y_train,predict_y_train) # For train dataset
             plt.plot([0,1],[0,1])
             plt.plot(fpr1,tpr1,label="Validation AUC")
             plt.plot(fpr2,tpr2,label="Train AUC")
             plt.xlabel("fpr")
             plt.ylabel("tpr")
             plt.legend()
             plt.show()
In [48]: # Plotting graph of auc and parameter for training and cross validation error
         param = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
```

```
def plot_knn_vs_auc(train_auc_list,cv_auc_list):
    plt.plot(param,train_auc_list,label="Train AUC")
    plt.xlabel("Parameter for K-NN")
    plt.ylabel("Area Under Curve")
    plt.plot(param,cv_auc_list,label="Validation AUC")
    plt.legend()
    plt.show()
```

6 [5] Assignment 3: KNN

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)

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 matrices. You can convert sparse matrices to dense using .toarray() attribute. For more information please visit this link

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

```
<font color='red'>SET 6:</font>Review text, preprocessed one converted into vectors
       tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
           tf_idf_vect.fit(preprocessed_reviews)
       <font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
       <font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
   <strong>The hyper paramter tuning(find best K)</strong>
   <l
Find the best hyper parameter which will give the maximum <a href='https://www.appliedaico</p>
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 to
   <br>
<
<strong>Representation of results
   ul>
```

You need to plot the performance of model both on train data and cross validation data for

```
<img src='train_cv_auc.JPG' width=300px>
Once after you found the best hyper parameter, you need to train your model with it, and f
<img src='train_test_auc.JPG' width=300px>
Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.</pre>
<img src='confusion_matrix.png' width=300px>
   <br>
<strong>Conclusion</strong>
   ul>
You need to summarize the results at the end of the notebook, summarize it in the table for
   <img src='summary.JPG' width=400px>
```

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.

6.1 [5.1] Applying KNN brute force

```
6.1.1 [5.1.1] Applying KNN brute force on BOW, SET 1
In [49]: from sklearn.cross_validation import train_test_split
         # cleaned_reviews contains all the required reviews
         # Splitting cleaned_reviews into train and test dataset
         X = cleaned_reviews
         Y = final['Score']
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=42)
         print(len(X_train),len(Y_train),len(X_test),len(Y_test))
61441 61441 26332 26332
In [50]: # Now we will vectorize train and test datasets separately using BagofWords
         # Use fit_transform to vectorize train dataset and transform to vectorize test datase
         count_vect2 = CountVectorizer(max_features=2000)
```

X_train = count_vect2.fit_transform(X_train)

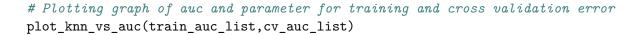
X_test = count_vect2.transform(X_test) print(X_train.shape, X_test.shape)

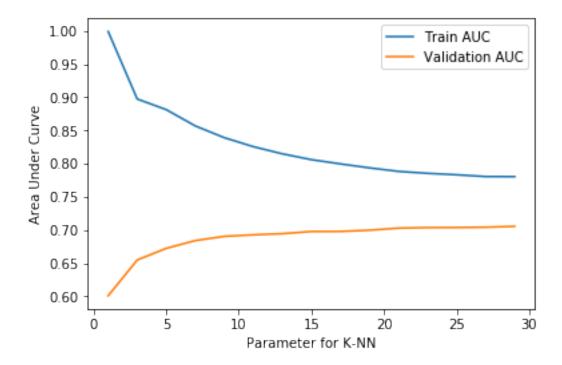
```
(61441, 2000) (26332, 2000)
```

```
In [52]: # In this section we will calculate training error.
         # To calculate training error you have to train model using training data and
         # Then test the same model on trainig data and compare the predicted labels with actu
        from sklearn.model_selection import TimeSeriesSplit
        from sklearn.metrics import roc_auc_score
        from sklearn.neighbors import KNeighborsClassifier
        param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
        train_auc_list1 = [] # This contains area under curve value of first batch correspo
        train_auc_list2 = [] # for second batch
        train_auc_list3 = [] # for third batch
         # Testing whole training data at once takes a lot of memory which takes a lot of time
         # There fore we are dividing training data into 3 parts and then we will calculate AU
        x_train_1 = X_train[0:20000][:] # Row 0 to 19999 and all columns
        x_train_2 = X_train[20000:40000][:]
        x_train_3 = X_train[40000:61441][:]
        y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
        y_train_2 = Y_train[20000:40000][:]
        y_train_3 = Y_train[40000:61441][:]
         # Calculating training error for first batch
        for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
             clf.fit(x_train_1,y_train_1)
            pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
             auc = roc_auc_score(y_train_1,pre_probab)
             train_auc_list1.append(auc)
         # Calculating training error for second batch
        for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
             clf.fit(x_train_2,y_train_2)
            pre_probab = clf.predict_proba(x_train_2)[:,1]
             auc = roc_auc_score(y_train_2,pre_probab)
             train_auc_list2.append(auc)
         # Calculating training error for third batch
```

```
for k in tqdm(range(1,30,2)):
                              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
                              clf.fit(x_train_3,y_train_3)
                              pre_probab = clf.predict_proba(x_train_3)[:,1]
                              auc = roc_auc_score(y_train_3,pre_probab)
                              train_auc_list3.append(auc)
100%|| 15/15 [10:10<00:00, 35.93s/it]
100%|| 15/15 [06:07<00:00, 24.80s/it]
100%|| 15/15 [06:35<00:00, 25.38s/it]
In [53]: # Combining training result of each batch together
                     train_auc_list = [(x+y+z)/3 \text{ for } x,y,z \text{ in } zip(train_auc_list1,train_auc_list2,train_auc_list2,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train
In [54]: # We will do time based splitting and do 10 fold cross validation
                     # This is done as reviews keeps changing with time and hence time based splitting is
                     # Time series object
                     tscv = TimeSeriesSplit(n_splits=10)
                     cv_auc_list = [] # will contain cross validation AUC corresponding to each k
                     for k in range(1,30,2):
                               # KNN Classifier
                              clf = KNeighborsClassifier(n_neighbors=k,algorithm='brute',leaf_size=30)
                              i=0
                              auc=0.0
                              for train_index,test_index in tscv.split(X_train):
                                        x_train = X_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                                        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                                        x_test = X_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                                        y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                                        clf.fit(x_train,y_train)
                                        predict_probab = clf.predict_proba(x_test)[:,1]
                                        i += 1
                                        auc += roc_auc_score(y_test,predict_probab)
                              cv_auc_list.append(auc/i) # Storing AUC value
```

In [55]: import matplotlib.pyplot as plt





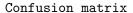
Observing the graph we will select a k for which AUC is not very high in training error plot to avoid overfitting and select a k for which AUC is not very low in Cross-validation error to avoid underfitting. Therefore we are selecting k=25.

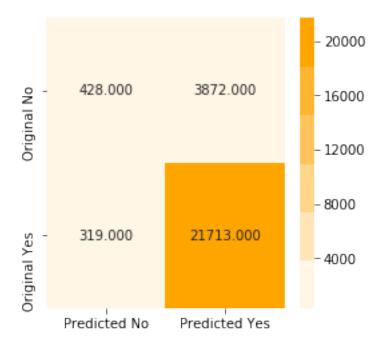
In [56]: # Training final model on best auc and taking k = 25

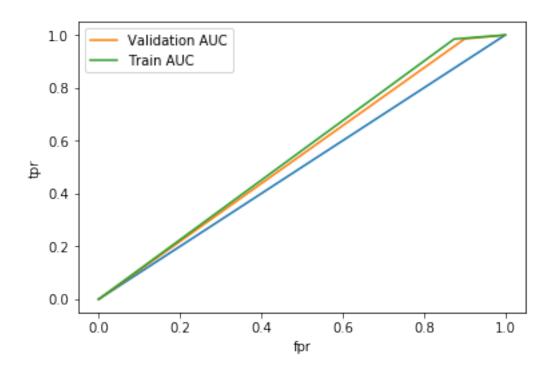
```
# Training one model with all the data hangs the PC .
# Therefore we will divide data into 3 parts and then train three seperate models.
final_clf1 = KNeighborsClassifier(n_neighbors=25,algorithm='brute',leaf_size=30)
final_clf1.fit(x_train_1,y_train_1)
predict_probab_1 = final_clf1.predict_proba(X_test)[:,1] # This returns only probabil
predict_y1 = final_clf1.predict(X_test)
predict_y_train1 = final_clf1.predict(x_train_1)

final_clf2 = KNeighborsClassifier(n_neighbors=25,algorithm='brute',leaf_size=30)
final_clf2.fit(x_train_2,y_train_2)
predict_probab_2 = final_clf2.predict_proba(X_test)[:,1] # This returns only probabil
predict_y2 = final_clf2.predict(X_test)
predict_y_train2 = final_clf2.predict(x_train_2)

final_clf3 = KNeighborsClassifier(n_neighbors=25,algorithm='brute',leaf_size=30)
final_clf3.fit(x_train_3,y_train_3)
predict_probab_3 = final_clf3.predict_proba(X_test)[:,1] # This returns only probabil
```







6.1.2 [5.1.2] Applying KNN brute force on TFIDF

```
In [99]: # In this section Tfidf will be used for vectorization
         # Splitting datasets into train and test datasets
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=42)
         # Initializinf TFidf
         tf_idf_vect2 = TfidfVectorizer(max_features=2000)
         # Now we will vectorize train and test datasets separately using Tfidf
         # Use fit_transform to vectorize train dataset and transform to vectorize test datase
         X_train = tf_idf_vect2.fit_transform(X_train)
         X_test = tf_idf_vect2.transform(X_test)
In [100]: param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
          train_auc_list1 = [] # This contains area under curve value of first batch corresp
          train_auc_list2 = []
                                 # for second batch
          train_auc_list3 = []
                                 # for third batch
          # Testing whole training data at once takes a lot of memory which takes a lot of tim
```

There fore we are dividing training data into 3 parts and then we will calculate A

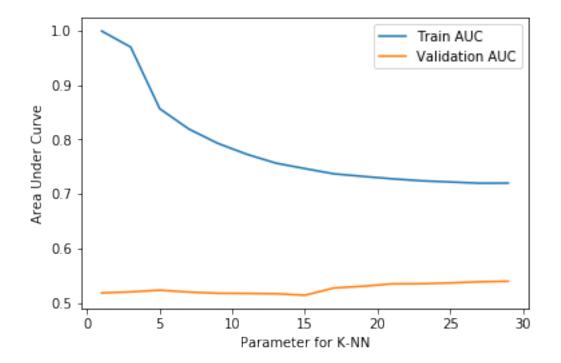
```
x_train_2 = X_train[20000:40000][:]
          x_train_3 = X_train[40000:61441][:]
          y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
          y_train_2 = Y_train[20000:40000][:]
          y_train_3 = Y_train[40000:61441][:]
          # Calculating training error for first batch
          for k in range(1,30,2):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
              clf.fit(x_train_1,y_train_1)
              pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
              auc = roc_auc_score(y_train_1,pre_probab)
              train_auc_list1.append(auc)
          # Calculating training error for second batch
          for k in range(1,30,2):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
              clf.fit(x_train_2,y_train_2)
              pre_probab = clf.predict_proba(x_train_2)[:,1]
              auc = roc_auc_score(y_train_2,pre_probab)
              train_auc_list2.append(auc)
          # Calculating training error for third batch
          for k in range(1,30,2):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute",leaf_size=30)
              clf.fit(x_train_3,y_train_3)
              pre_probab = clf.predict_proba(x_train_3)[:,1]
              auc = roc_auc_score(y_train_3,pre_probab)
              train_auc_list3.append(auc)
          # Combining training result of each batch together
          train_auc_list = [(x+y+z)/3 for x,y,z in zip(train_auc_list1,train_auc_list2,train_a
In [101]: # Performing time series split cross validation
          auc_list=[]
          for k in range(1,30,2):
              # KNN Classifier
```

x_train_1 = X_train[0:20000][:] # Row 0 to 19999 and all columns

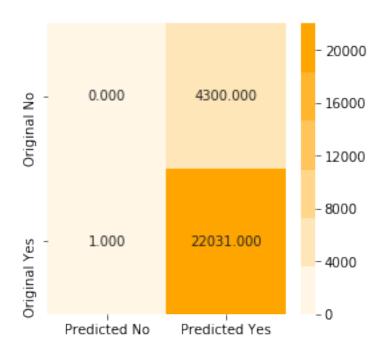
```
clf = KNeighborsClassifier(n_neighbors=k,algorithm='brute',leaf_size=30,n_jobs=3
i=0
auc=0.0
for train_index,test_index in tscv.split(X_train):
    x_train = X_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
    y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
    x_test = X_train[train_index[-1]]:test_index[-1]][:] # row from train_index t
    y_test = Y_train[train_index[-1]]:test_index[-1]][:] # row from train_index t
    clf.fit(x_train,y_train)
    predict_probab = clf.predict_proba(x_test)[:,1]
    i += 1
    auc += roc_auc_score(y_test,predict_probab)
auc_list.append(auc/i)
```

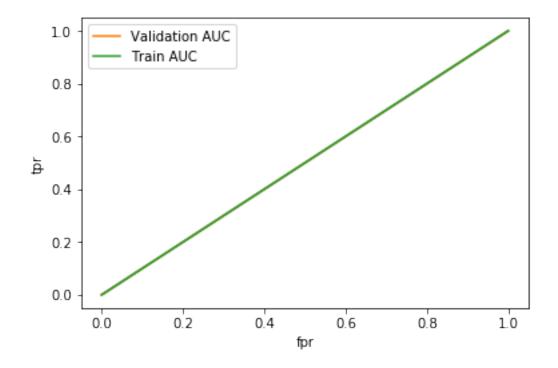
In [102]: import matplotlib.pyplot as plt

Plotting graph of auc and parameter for training and cross validation error
plot_knn_vs_auc(train_auc_list,auc_list)



```
In [103]: # Training final model on best auc and taking k = 21
          # Training one model with all the data hangs the PC .
          # Therefore we will divide data into 3 parts and then train three seperate models.
          final_clf1 = KNeighborsClassifier(n_neighbors=21,algorithm='brute',leaf_size=30)
          final_clf1.fit(x_train_1,y_train_1)
          predict_probab_1 = final_clf1.predict_proba(X_test)[:,1] # This returns only probabi
          predict_y1 = final_clf1.predict(X_test)
          predict_y_train1 = final_clf1.predict(x_train_1)
          final_clf2 = KNeighborsClassifier(n_neighbors=21,algorithm='brute',leaf_size=30)
          final_clf2.fit(x_train_2,y_train_2)
          predict_probab_2 = final_clf2.predict_proba(X_test)[:,1] # This returns only probabi
          predict_y2 = final_clf2.predict(X_test)
          predict_y_train2 = final_clf2.predict(x_train_2)
          final_clf3 = KNeighborsClassifier(n_neighbors=21,algorithm='brute',leaf_size=30)
          final_clf3.fit(x_train_3,y_train_3)
          predict_probab_3 = final_clf3.predict_proba(X_test)[:,1] # This returns only probabi
          predict_y3 = final_clf3.predict(X_test)
          predict_y_train3 = final_clf3.predict(x_train_3)
          # Now merging all the three probability scores into one
          predict_probab = [(x+y+z)/3 for x,y,z in zip(predict_probab_1,predict_probab_2,predict_probab_2)
          predict_y = [1 if(x+y+x>= 2) else 0 for x,y,z in zip(predict_y1,predict_y2,predict_y2
          {\it \# Combining results of train dataset evaluation}
          predict_y_train = np.concatenate((predict_y_train1,predict_y_train2),axis=None)
          predict_y_train = np.concatenate((predict_y_train,predict_y_train3),axis=None)
          auc = roc_auc_score(Y_test,predict_probab)
          print("Final AUC is ::{:.2f}".format(auc))
Final AUC is ::0.51
In [104]: # plotting confusion matrix
          confusion_matrix_plot(Y_test,predict_y)
Confusion matrix
```



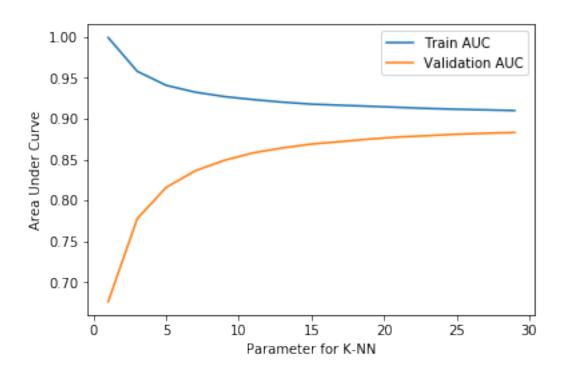


6.1.3 [5.1.3] Applying KNN brute force on AVG W2V, SET 3

```
In [106]: # In this section avg_w2v will be used for vectorization
          # Splitting datasets into train and test datasets
          Y = final['Score']
          X_train, X_test, Y_train, Y_test = train_test_split(list_of_sentence, Y, test_size=0.3, rain
          print(X train[0])
['use', 'beans', 'espresso', 'machine', 'love', 'taste', 'straight', 'espresso', 'coffee', 'fiz
In [107]: # Now we will vectorize train dataset usin avg_w2v
          train_sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
          for sent in X_train: # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need
              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
              train_sent_vectors.append(sent_vec)
          print(len(train_sent_vectors))
          print(len(train_sent_vectors[0]))
61441
50
In [108]: # Vectorization of test dataset using avg_w2v
          test_sent_vectors = []; # the avg-w2v for each sentence/review is stored in this lis
          for sent in X_test: # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need
              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
              test_sent_vectors.append(sent_vec)
          print(len(test_sent_vectors))
          print(len(test_sent_vectors[0]))
26332
50
```

```
In [109]: param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
          train_auc_list1 = [] # This contains area under curve value of first batch corresp
          train_auc_list2 = [] # for second batch
          train_auc_list3 = [] # for third batch
          # Testing whole training data at once takes a lot of memory which takes a lot of tim
          # There fore we are dividing training data into 3 parts and then we will calculate A
          x_train_1 = train_sent_vectors[0:20000][:] # Row 0 to 19999 and all columns
          x_train_2 = train_sent_vectors[20000:40000][:]
          x_train_3 = train_sent_vectors[40000:61441][:]
          y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
          y_train_2 = Y_train[20000:40000][:]
          y_train_3 = Y_train[40000:61441][:]
          # Calculating training error for first batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute")
              clf.fit(x_train_1,y_train_1)
              pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
              auc = roc_auc_score(y_train_1,pre_probab)
              train_auc_list1.append(auc)
          # Calculating training error for second batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute")
              clf.fit(x_train_2,y_train_2)
              pre_probab = clf.predict_proba(x_train_2)[:,1]
              auc = roc_auc_score(y_train_2,pre_probab)
              train_auc_list2.append(auc)
          # Calculating training error for third batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="brute")
              clf.fit(x_train_3,y_train_3)
              pre_probab = clf.predict_proba(x_train_3)[:,1]
              auc = roc_auc_score(y_train_3,pre_probab)
              train_auc_list3.append(auc)
100%|| 15/15 [02:54<00:00, 12.03s/it]
```

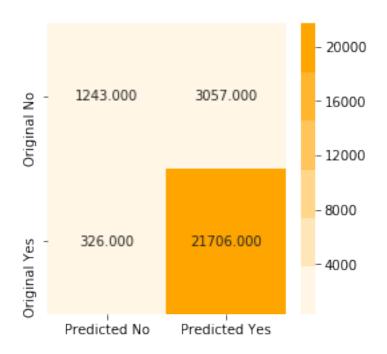
```
100%|| 15/15 [02:50<00:00, 11.73s/it]
100%|| 15/15 [03:19<00:00, 14.13s/it]
In [110]: # Combining training result of each batch together
                           train_auc_list = [(x+y+z)/3 for x,y,z in zip(train_auc_list1,train_auc_list2,train_auc_list2,train_auc_list2,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3
In [111]: # 10 fold cross validation using time series splitting
                           from sklearn.model_selection import TimeSeriesSplit
                           tscv = TimeSeriesSplit(n_splits=10)
                           auc_list=[]
                           for k in range(1,30,2):
                                      # KNN Classifier
                                      clf = KNeighborsClassifier(n_neighbors=k,algorithm='brute',leaf_size=30)
                                     i=0
                                     auc=0.0
                                     for train_index,test_index in tscv.split(train_sent_vectors):
                                                x_train = train_sent_vectors[0:train_index[-1]][:] # row 0 to train_index(ex
                                                y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                                                x_test = train_sent_vectors[train_index[-1]:test_index[-1]][:] # row from tr
                                                y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t
                                                clf.fit(x_train,y_train)
                                                predict_probab = clf.predict_proba(x_test)[:,1]
                                                i += 1
                                                auc += roc_auc_score(y_test,predict_probab)
                                      auc_list.append(auc/i)
In [113]: # Plotting graph of auc and parameter for training and cross validation error
                           plot_knn_vs_auc(train_auc_list,auc_list)
```

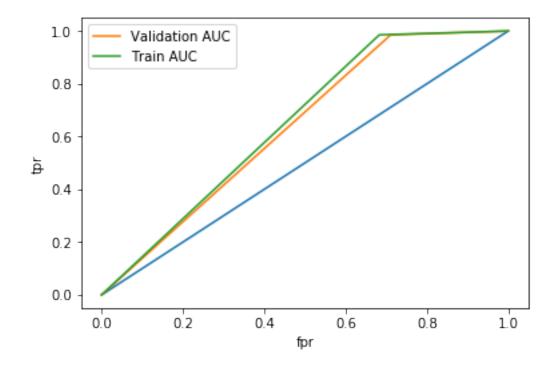


In [115]: # Training final model on best auc and taking k = 25

```
# Training one model with all the data hangs the PC .
# Therefore we will divide data into 3 parts and then train three seperate models.
final_clf1 = KNeighborsClassifier(n_neighbors=30,algorithm='brute',leaf_size=40)
final_clf1.fit(x_train_1,y_train_1)
predict_probab_1 = final_clf1.predict_proba(test_sent_vectors)[:,1] # This returns o
predict_y1 = final_clf1.predict(test_sent_vectors)
predict_y_train1 = final_clf1.predict(x_train_1)
final_clf2 = KNeighborsClassifier(n_neighbors=30,algorithm='brute',leaf_size=40)
final_clf2.fit(x_train_2,y_train_2)
predict_probab_2 = final_clf2.predict_proba(test_sent_vectors)[:,1] # This returns o
predict_y2 = final_clf2.predict(test_sent_vectors)
predict_y_train2 = final_clf2.predict(x_train_2)
final_clf3 = KNeighborsClassifier(n_neighbors=30,algorithm='brute',leaf_size=40)
final_clf3.fit(x_train_3,y_train_3)
predict_probab_3 = final_clf3.predict_proba(test_sent_vectors)[:,1] # This returns o
predict_y3 = final_clf3.predict(test_sent_vectors)
predict_y_train3 = final_clf3.predict(x_train_3)
# Now merging all the three probability scores into one
predict_probab = [(x+y+z)/3 for x,y,z in zip(predict_probab_1,predict_probab_2,predict_probab_2)
```

```
predict_y = [1 if(x+y+x>= 2) else 0 for x,y,z in zip(predict_y1,predict_y2,predict_y2
          auc = roc_auc_score(Y_test,predict_probab)
          print("Final AUC is ::{:.2f}".format(auc))
Final AUC is ::0.90
In [116]: predict_y_train = [] # will store predicted class labels of combined predicted label
          # Combining predicted labels of train dataset evaluation
          # Appending predicted labels of first model
          for i in predict_y_train1:
              predict_y_train.append(i)
          # Appending predicted labels of second model
          for i in predict_y_train2:
              predict_y_train.append(i)
          # Appending predicted labels of third model
          for i in predict_y_train3:
              predict_y_train.append(i)
          print(len(predict_y_train))
61441
In [117]: # Plotting confusion matrix
          confusion_matrix_plot(Y_test,predict_y)
Confusion matrix
```





6.1.4 [5.1.4] Applying KNN brute force on TFIDF W2V

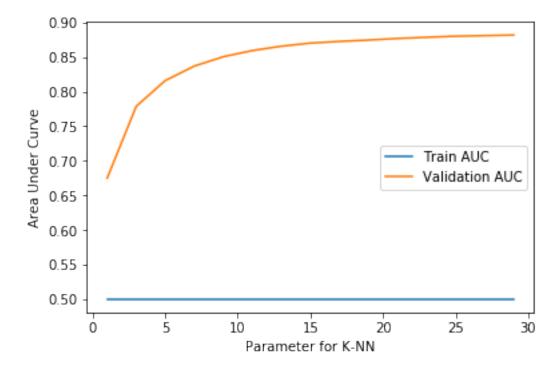
```
In [103]: Y = final['Score'] # Contains labels of data points
          X_train, X_test, Y_train, Y_test = train_test_split(cleaned_reviews, Y, test_size=0.3, rane
In [104]: # Vectorizing train dataset using tfidf
          model = TfidfVectorizer()
          model.fit_transform(X_train)
          tfidf_feat1 = model.get_feature_names()
          # This will map word with their tfidf only for train dataset
          dictionary1 = dict(zip(model.get_feature_names(), list(model.idf_)))
In [105]: # Vectorizing test dataset using tfidf
          model.transform(X_test)
          tfidf_feat2 = model.get_feature_names()
          # This will map word with their tfidf only for test dataset
          dictionary2 = dict(zip(model.get_feature_names(), list(model.idf_)))
In [106]: # Vectorizing train dataset
          # TF-IDF weighted Word2Vec
           # tfidf words/col-names
          # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfid
          train_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
          for sent in X_train: # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length
              weight_sum =0; # num of words with a valid vector in the sentence/review
              for word in sent: # for each word in a review/sentence
                  if word in w2v_words and word in tfidf_feat1:
                      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 values of word in this review
                      tf_idf = dictionary1[word]*(sent.count(word)/len(sent))
                      sent_vec += (vec * tf_idf)
                      weight_sum += 1
              if weight_sum != 0:
                  sent_vec /= weight_sum
              train_tfidf_sent_vectors.append(sent_vec)
In [107]: # TF-IDF weighted Word2Vec
          # Vectorizing test dataset.
          test_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
```

```
for sent in X_test: # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length
              weight_sum =0; # num of words with a valid vector in the sentence/review
              for word in sent: # for each word in a review/sentence
                  if word in w2v_words and word in tfidf_feat2:
                      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 values of word in this review
                      tf_idf = dictionary2[word]*(sent.count(word)/len(sent))
                      sent_vec += (vec * tf_idf)
                      weight_sum +=1
              if weight_sum != 0:
                  sent_vec /= weight_sum
              test_tfidf_sent_vectors.append(sent_vec)
In [108]: # Calculating training error .
          # Because of large amount of data. we are processing data into three batches here.
          # After processing all the results of these batches are merged into one .
          train_auc_list1 = [] # This contains area under curve value of first batch corresp
          train_auc_list2 = [] # for second batch
          train_auc_list3 = [] # for third batch
          # Testing whole training data at once takes a lot of memory which takes a lot of tim
          # There fore we are dividing training data into 3 parts and then we will calculate A
          x_train_1 = train_tfidf_sent_vectors[0:20000][:] # Row O to 19999 and all columns
          x_train_2 = train_tfidf_sent_vectors[20000:40000][:]
          x_train_3 = train_tfidf_sent_vectors[40000:61441][:]
          y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
          y_train_2 = Y_train[20000:40000][:]
          y_train_3 = Y_train[40000:61441][:]
          # Calculating training error for first batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs
              clf.fit(x_train_1,y_train_1)
              pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
              auc = roc_auc_score(y_train_1,pre_probab)
              train_auc_list1.append(auc)
          # Calculating training error for second batch
          for k in tqdm(range(1,30,2)):
```

```
clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs
                                   clf.fit(x_train_2,y_train_2)
                                  pre_probab = clf.predict_proba(x_train_2)[:,1]
                                   auc = roc_auc_score(y_train_2,pre_probab)
                                   train_auc_list2.append(auc)
                         # Calculating training error for third batch
                        for k in tqdm(range(1,30,2)):
                                   clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs
                                   clf.fit(x_train_3,y_train_3)
                                  pre_probab = clf.predict_proba(x_train_3)[:,1]
                                   auc = roc_auc_score(y_train_3,pre_probab)
                                  train_auc_list3.append(auc)
                         # Combining results together.
                        train_auc_list = [(x+y+z)/3 \text{ for } x,y,z \text{ in } zip(train_auc_list1,train_auc_list2,train_auc_list2,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train_auc_list3,train
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                                                                                                                                       | 6/15 [02:40<03:57, 26.41s/it]
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                                                                                                            | 8/15 [03:31<03:03, 26.15s/it]
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  67%1
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                                        | 13/15 [05:42<00:52, 26.32s/it]
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  27%|
  33%|
                                                                                                                                                       | 5/15 [02:04<04:09, 24.91s/it]
  40%1
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  47%|
                                                                                                                           | 7/15 [02:51<03:11, 23.99s/it]
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                                       | 9/15 [03:35<02:18, 23.07s/it]
                                 | 10/15 [04:05<02:05, 25.19s/it]
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80%1
                     | 12/15 [04:51<01:12, 24.14s/it]
87%1
                | 13/15 [05:12<00:46, 23.20s/it]
          | 14/15 [05:34<00:22, 22.71s/it]
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100%|| 15/15 [05:58<00:00, 23.11s/it]
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                          | 11/15 [04:43<01:40, 25.19s/it]
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87%1
                | 13/15 [05:31<00:49, 24.57s/it]
93%1
          | 14/15 [05:57<00:24, 24.78s/it]
100%|| 15/15 [06:24<00:00, 25.64s/it]
In [109]: # 10 fold cross validation using time series splitting
          auc_list = []
          for k in tqdm(range(1,30,2)):
              # KNN Classifier
              clf = KNeighborsClassifier(n_neighbors=k,algorithm='kd tree',leaf_size=30,n_jobs
              auc=0.0
              for train_index,test_index in tscv.split(train_tfidf_sent_vectors):
                  x_train = train_sent_vectors[0:train_index[-1]][:] # row 0 to train_index(ex
                  y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                  x_test = train_sent_vectors[train_index[-1]:test_index[-1]][:] # row from tr
                  y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t
                  clf.fit(x_train,y_train)
                  predict_probab = clf.predict_proba(x_test)[:,1] # Returns probability of for
                  auc += roc_auc_score(y_test,predict_probab)
```

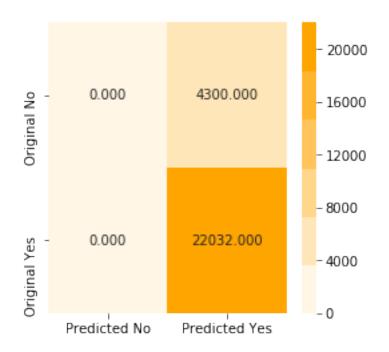
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                                 | 10/15 [29:36<15:47, 189.45s/it]
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                           | 11/15 [32:27<12:15, 183.88s/it]
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               | 13/15 [38:11<05:55, 177.94s/it]
          | 14/15 [41:06<02:57, 177.06s/it]
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```

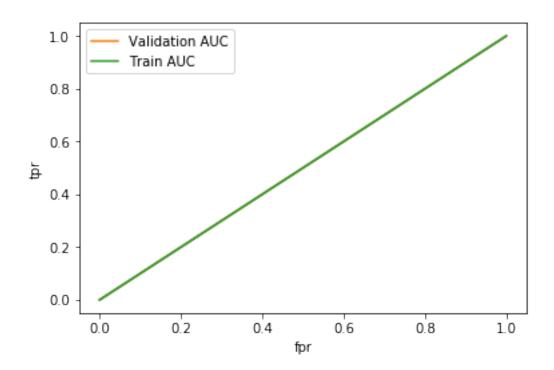


In [111]: 30# Training final model on best auc and taking k = 10

```
# Therefore we will divide data into 3 parts and then train three seperate models.
          x_train_1 = train_tfidf_sent_vectors[0:20000][:] # Row 0 to 19999 and all columns
          x_train_2 = train_tfidf_sent_vectors[20000:40000][:]
          x_train_3 = train_tfidf_sent_vectors[40000:61441][:]
          y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
          y_train_2 = Y_train[20000:40000][:]
          y_train_3 = Y_train[40000:61441][:]
          final_clf1 = KNeighborsClassifier(n_neighbors=30,algorithm='kd_tree',leaf_size=40,n_
          final_clf1.fit(x_train_1,y_train_1)
          predict_probab_1 = final_clf1.predict_proba(test_tfidf_sent_vectors)[:,1] # This ret
          predict_y_train1 = list(final_clf1.predict(x_train_1))
          final_clf2 = KNeighborsClassifier(n_neighbors=30,algorithm='kd_tree',leaf_size=40,n_
          final_clf2.fit(x_train_2,y_train_2)
          predict_probab_2 = final_clf2.predict_proba(test_tfidf_sent_vectors)[:,1] # This ret
          predict_y_train2 = list(final_clf1.predict(x_train_2))
          final_clf3 = KNeighborsClassifier(n_neighbors=30,algorithm='kd_tree',leaf_size=40,n_
          final_clf3.fit(x_train_3,y_train_3)
          predict_probab_3 = final_clf3.predict_proba(test_tfidf_sent_vectors)[:,1] # This ret
          predict_y_train3 = final_clf1.predict(x_train_3)
          # Now merging all the three probability scores into one
          predict_probab = [(x+y+z)/3 \text{ for } x,y,z \text{ in } zip(predict_probab_1,predict_probab_2,predict_probab_1)]
          predict_y = [1 if(x+y+z)=2) else 0 for x,y,z in zip(predict_probab_1,predict_probab_2)
          # Combining results for train dataset
          predict_y_train = np.concatenate((predict_y_train1,predict_y_train2),axis=None)
          predict_y_train = np.concatenate((predict_y_train,predict_y_train3),axis=None)
          auc = roc_auc_score(Y_test,predict_probab)
          print("Final AUC is ::{:.2f}".format(auc))
Final AUC is ::0.50
In [112]: # Plotting confusion matrix
          confusion_matrix_plot(Y_test,predict_y)
Confusion matrix
```

Training one model with all the data hangs the PC .





6.2 [5.2] Applying KNN kd-tree

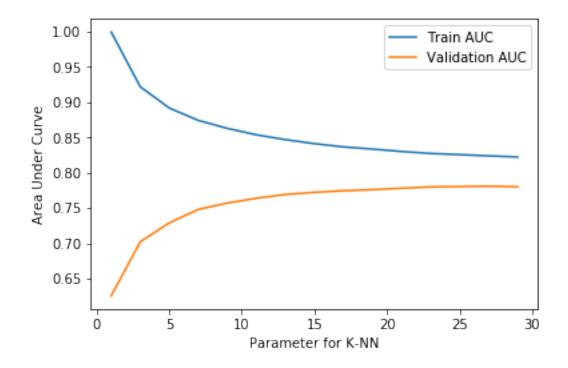
6.2.1 [5.2.1] Applying KNN kd-tree on BOW, SET 5

```
In [61]: # Kd tree works slow for high dimensional data.
         # Therefore taking top 5000 features
         from sklearn.cross_validation import train_test_split
         count_vect = CountVectorizer(max_features=5000)
         X = cleaned_reviews
         Y = final["Score"]
         # Splitting data into train and test dataset
         X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=42)
         print(len(X_train),len(X_test))
61441 26332
In [62]: # Vectorizing train and test dataset seperately
         X_train = count_vect.fit_transform(X_train)
         print(X_train.shape)
         X_test = count_vect.transform(X_test)
         print(X_test.shape)
(61441, 5000)
(26332, 5000)
In [63]: # Since kd Tree dont take sparse matrix .
         # Therefore we are converting sparse to dense matrxi using TruncatedSVD
         from sklearn.decomposition import TruncatedSVD
         # Initializing TruncatedSVD
         # Too many features takes a lot of time . Therefore taking 500 features only
         svd = TruncatedSVD(n_components=200,algorithm='randomized',n_iter=50,random_state=42)
         X_train = svd.fit_transform(X_train)
         X_test = svd.fit_transform(X_test)
         print(X_train.shape, X_test.shape)
(61441, 200) (26332, 200)
In [66]: # Calculating training error .
         # Because of large amount of data. we are processing data into three batches here.
         # After processing all the results of these batches are merged into one .
         param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
         train_auc_list1 = [] # This contains area under curve value of first batch correspo
         train_auc_list2 = [] # for stqdm(econd batch
```

```
# Testing whole training data at once takes a lot of memory which takes a lot of time
         # There fore we are dividing training data into 3 parts and then we will calculate AU
         x_train_1 = X_train[0:20000][:] # Row 0 to 19999 and all columns
         x_train_2 = X_train[20000:40000][:]
         x_train_3 = X_train[40000:61441][:]
         y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
         y_train_2 = Y_train[20000:40000][:]
         y_train_3 = Y_train[40000:61441][:]
         # Calculating training error for first batch
         for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40)
             clf.fit(x_train_1,y_train_1)
             pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
             auc = roc_auc_score(y_train_1,pre_probab)
             train_auc_list1.append(auc)
         # Calculating training error for second batch
         for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40)
             clf.fit(x_train_2,y_train_2)
             pre_probab = clf.predict_proba(x_train_2)[:,1]
             auc = roc_auc_score(y_train_2,pre_probab)
             train_auc_list2.append(auc)
         # Calculating training error for third batch
         for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40)
             clf.fit(x_train_3,y_train_3)
             pre_probab = clf.predict_proba(x_train_3)[:,1]
             auc = roc_auc_score(y_train_3,pre_probab)
             train_auc_list3.append(auc)
100%|| 15/15 [2:16:40<00:00, 595.11s/it]
100%|| 15/15 [1:52:25<00:00, 427.10s/it]
100%|| 15/15 [1:02:25<00:00, 273.88s/it]
```

train_auc_list3 = [] # for third batch

```
In [67]: train_auc_list = [(x+y+z)/3 \text{ for } x,y,z \text{ in } zip(train_auc_list1,train_auc_list2,train_auc_list2,train_auc_list3)
In [68]: # Performing 10 fold cross validation on time split data
         tscv = TimeSeriesSplit(n_splits=10)
         auc_list1 = []
         for k in range(1,30,2):
             clf1 = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree',leaf_size=40)
             auc1 = 0.0
             i1=0
             for train_index,test_index in tscv.split(X_train):
                  x_train = X_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = X_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                 y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                  clf1.fit(x_train,y_train)
                 predict_probab1 = clf1.predict_proba(x_test)[:,1]
                  i1 += 1
                  auc1 += roc_auc_score(y_test,predict_probab1)
             auc_list1.append(auc1/i1)
```



```
In [75]: # Training final model on best auc and taking k = 25

final_clf = KNeighborsClassifier(n_neighbors=25,algorithm='kd_tree',leaf_size=40)
    final_clf.fit(X_train,Y_train)
    predict_probab = final_clf.predict_proba(X_test)[:,1] # This returns only probability
    predict_y = final_clf.predict(X_test)

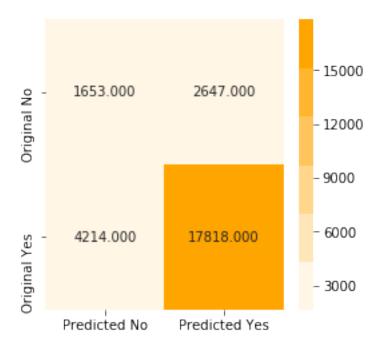
auc = roc_auc_score(Y_test,predict_probab)
    print("Final AUC is ::{:.2f}".format(auc))
Final AUC is ::0.63
```

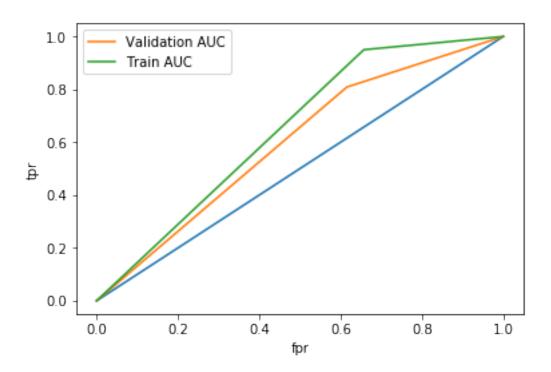
confusion_matrix_plot(Y_test,predict_y)

In [76]: # Plotting confusion matrix

In [72]: predict_y_train = final_clf.predict(X_train)

Confusion matrix





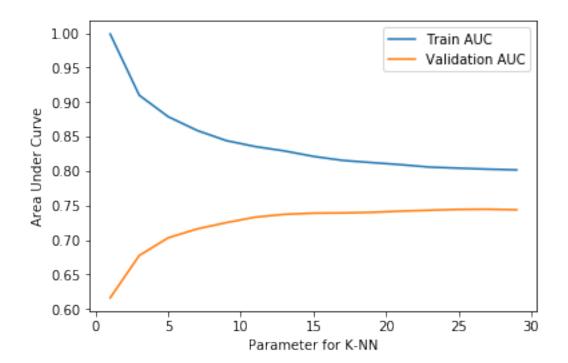
6.2.2 [5.2.2] Applying KNN kd-tree on TFIDF, SET 6

```
In [78]: # In this section Tfidf will be used for vectorization
         # Splitting datasets into train and test datasets
         X = final['Cleaned_review']
         Y = final['Score']
         tf_idf_vect = TfidfVectorizer(max_features=300)
         X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=42)
         # Now we will vectorize train and test datasets separately using Tfidf
         # Use fit_transform to vectorize train dataset and transform to vectorize test datase
         X_train = tf_idf_vect.fit_transform(X_train)
         X_test = tf_idf_vect.transform(X_test)
In [79]: from sklearn.decomposition import TruncatedSVD
         svd = TruncatedSVD(n_components=200,algorithm='randomized',n_iter=50,random_state=42)
         X_train = svd.fit_transform(X_train)
         X_test = svd.fit_transform(X_test)
         print(X_train.shape, X_test.shape)
(61441, 200) (26332, 200)
```

```
In [80]: param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
        train_auc_list1 = [] # This contains area under curve value of first batch correspo
        train_auc_list2 = [] # for second batch
        train_auc_list3 = [] # for third batch
         # Testing whole training data at once takes a lot of memory which takes a lot of time
         # There fore we are dividing training data into 3 parts and then we will calculate AU
        x_train_1 = X_train[0:20000][:] # Row 0 to 19999 and all columns
        x_train_2 = X_train[20000:40000][:]
        x_train_3 = X_train[40000:61441][:]
        y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
        y_train_2 = Y_train[20000:40000][:]
        y_train_3 = Y_train[40000:61441][:]
         # Calculating training error for first batch
        for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs=
             clf.fit(x_train_1,y_train_1)
            pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
             auc = roc_auc_score(y_train_1,pre_probab)
             train_auc_list1.append(auc)
         # Calculating training error for second batch
        for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs=
             clf.fit(x_train_2,y_train_2)
            pre_probab = clf.predict_proba(x_train_2)[:,1]
             auc = roc_auc_score(y_train_2,pre_probab)
             train_auc_list2.append(auc)
         # Calculating training error for third batch
        for k in tqdm(range(1,30,2)):
             clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs=
             clf.fit(x_train_3,y_train_3)
            pre_probab = clf.predict_proba(x_train_3)[:,1]
             auc = roc_auc_score(y_train_3,pre_probab)
             train_auc_list3.append(auc)
100%|| 15/15 [19:36<00:00, 84.13s/it]
```

```
100%|| 15/15 [20:11<00:00, 90.45s/it]
100%|| 15/15 [27:46<00:00, 117.68s/it]
In [81]: train_auc_list = [(x+y+z)/3 \text{ for } x,y,z \text{ in } zip(train_auc_list1,train_auc_list2,train_auc_list2,train_auc_list3)
In [84]: # Performing 10 fold cross validation on time split data
         tscv = TimeSeriesSplit(n_splits=10)
         auc_list1 = []
         for k in tqdm(range(1,30,2)):
             clf1 = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree',leaf_size=40,n_jobs:
             auc1 = 0.0
             i1=0
             for train_index,test_index in tscv.split(X_train):
                 x_train = X_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = X_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                 y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                 clf1.fit(x_train,y_train)
                 predict_probab1 = clf1.predict_proba(x_test)[:,1]
                 auc1 += roc_auc_score(y_test,predict_probab1)
             auc_list1.append(auc1/i1)
  0%1
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                                                                                   | 1/15 [07:01<1
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                                                                              | 2/15 [15:38<1:37:3
 20%|
                                                                         | 3/15 [23:22<1:30:51, 45
                                                                  | 4/15 [30:44<1:22:38, 450.80s/
 27%|
                                                             | 5/15 [38:05<1:14:37, 447.76s/it]
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 40%1
                                                        | 6/15 [45:23<1:06:43, 444.88s/it]
 47%|
                                                  | 7/15 [52:40<59:00, 442.60s/it]
                                             | 8/15 [59:58<51:27, 441.07s/it]
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                                       | 9/15 [1:07:20<44:08, 441.48s/it]
 67%1
                                 | 10/15 [1:14:42<36:48, 441.66s/it]
 73%|
                           | 11/15 [1:22:05<29:27, 442.00s/it]
80%1
                     | 12/15 [1:29:51<22:27, 449.24s/it]
                | 13/15 [1:37:14<14:54, 447.18s/it]
87%1
93%1
          | 14/15 [1:45:34<07:43, 463.07s/it]
100%|| 15/15 [1:52:53<00:00, 455.96s/it]
```

In [85]: # Plotting graph of auc and parameter for training and cross validation error plot_knn_vs_auc(train_auc_list,auc_list1)



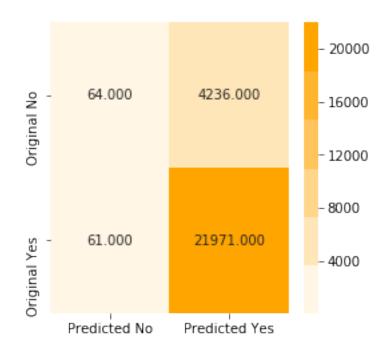
```
In [86]: # Training final model on best auc and taking k = 11
         final_clf = KNeighborsClassifier(n_neighbors=24,algorithm='kd_tree',leaf_size=30,n_jo')
         final_clf.fit(X_train,Y_train)
         predict_probab = final_clf.predict_proba(X_test)[:,1] # This returns only probability
         predict_y = final_clf.predict(X_test)
         auc = roc_auc_score(Y_test,predict_probab)
         print("Final AUC is {:.2f}".format(auc))
```

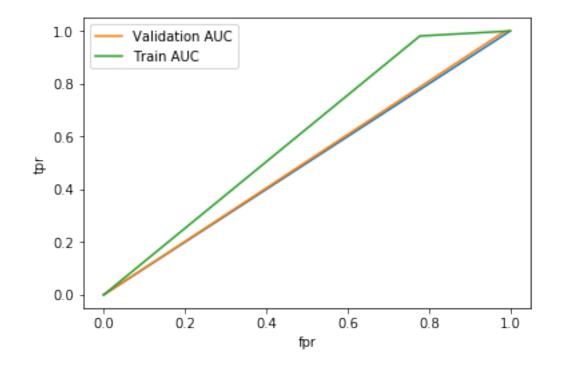
Final AUC is 0.57

In [89]: predict_y_train = final_clf.predict(X_train)

In [87]: # Plotting confusion matrix confusion_matrix_plot(Y_test,predict_y)

Confusion matrix





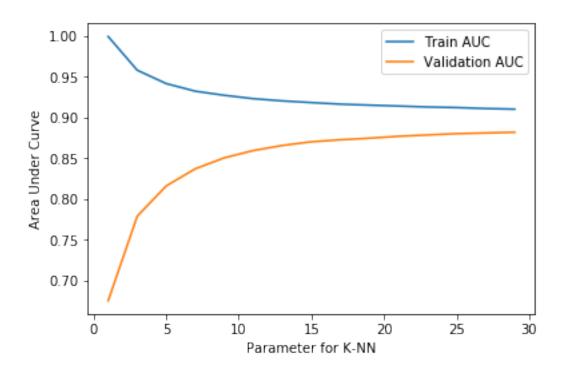
6.2.3 [5.2.3] Applying KNN kd-tree on AVG W2V, SET 3

```
In [91]: # Splitting data into train and test.
         Y = final['Score']
         X_train,X_test,Y_train,Y_test = train_test_split(list_of_sentence,Y,test_size=0.3,rane)
In [92]: # Now we will vectorize train dataset usin avg\_w2v
         train_sent_vectors = []; # the avg-w2v for each sentence/review is stored in this lis
         for sent in X_train: # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             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
             train_sent_vectors.append(sent_vec)
         print(len(train_sent_vectors))
         print(len(train_sent_vectors[0]))
61441
50
In [93]: # Vectorization of test dataset using avg_w2v
         test_sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in X_test: # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             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
             test_sent_vectors.append(sent_vec)
         print(len(test_sent_vectors))
         print(len(test_sent_vectors[0]))
26332
50
In [94]: param_list = [1,3,5,7,9,11,13,15,17,19,21,23,25,27,29]
         train_auc_list1 = [] # This contains area under curve value of first batch correspo
```

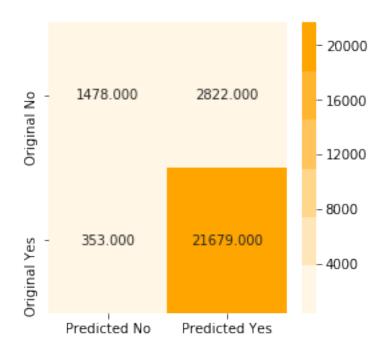
```
train_auc_list2 = [] # for second batch
train_auc_list3 = [] # for third batch
# Testing whole training data at once takes a lot of memory which takes a lot of time
# There fore we are dividing training data into 3 parts and then we will calculate AU
x_train_1 = train_sent_vectors[0:20000][:] # Row 0 to 19999 and all columns
x_train_2 = train_sent_vectors[20000:40000][:]
x_train_3 = train_sent_vectors[40000:61441][:]
y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
y_train_2 = Y_train[20000:40000][:]
y_train_3 = Y_train[40000:61441][:]
# Calculating training error for first batch
for k in tqdm(range(1,30,2)):
    clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs=
    clf.fit(x_train_1,y_train_1)
   pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
    auc = roc_auc_score(y_train_1,pre_probab)
    train_auc_list1.append(auc)
# Calculating training error for second batch
for k in tqdm(range(1,30,2)):
    clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs=
    clf.fit(x_train_2,y_train_2)
   pre_probab = clf.predict_proba(x_train_2)[:,1]
    auc = roc_auc_score(y_train_2,pre_probab)
    train_auc_list2.append(auc)
# Calculating training error for third batch
for k in tqdm(range(1,30,2)):
    clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=30,n_jobs=
    clf.fit(x_train_3,y_train_3)
   pre_probab = clf.predict_proba(x_train_3)[:,1]
    auc = roc_auc_score(y_train_3,pre_probab)
    train_auc_list3.append(auc)
# Combining the result into one.
train_auc_list = [(x+y+z)/3 for x,y,z in zip(train_auc_list1,train_auc_list2,train_auc_
```

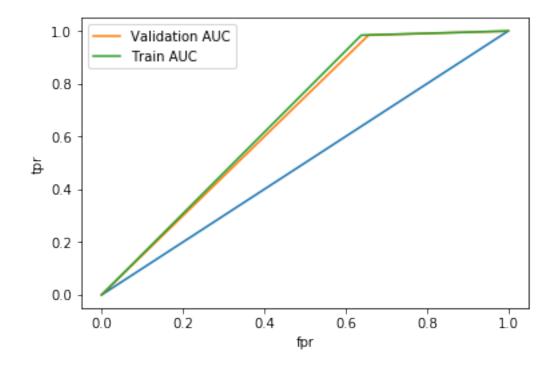
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In [95]: # 10 fold cross validation using time series splitting
         \# Here X_train is train_sent_vectors and X_test is test_sent_vectors
         # Here vectorization results of previous section is used . Only KNN algorithm is chan
         tscv = TimeSeriesSplit(n_splits=10)
         auc list=[]
         for k in range(1,30,2):
             # KNN Classifier
             clf = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree',leaf_size=40,n_jobs=
             i=0
             auc=0.0
             for train_index,test_index in tscv.split(train_sent_vectors):
                 x_train = train_sent_vectors[0:train_index[-1]][:] # row 0 to train_index(exc
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = train_sent_vectors[train_index[-1]:test_index[-1]][:] # row from tra
                 y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to
                 clf.fit(x_train,y_train)
                 predict_probab = clf.predict_proba(x_test)[:,1]
                 #print(len(x_test), len(y_test), len(predict_probab))
                 i += 1
                 auc += roc_auc_score(y_test,predict_probab)
             auc_list.append(auc/i)
In [96]: # Plotting graph of auc and parameter for training and cross validation error
        plot_knn_vs_auc(train_auc_list,auc_list)
```



Confusion matrix





6.2.4 [5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

```
In [114]: # Using vectorized data from previous section
          # Calculating training error .
          # Because of large amount of data. we are processing data into three batches here.
          # After processing all the results of these batches are merged into one .
          train_auc_list1 = [] # This contains area under curve value of first batch corresp
          train_auc_list2 = [] # for second batch
          train_auc_list3 = [] # for third batch
          # Testing whole training data at once takes a lot of memory which takes a lot of tim
          # There fore we are dividing training data into 3 parts and then we will calculate A
          x_train_1 = train_tfidf_sent_vectors[0:20000][:] # Row 0 to 19999 and all columns
          x_train_2 = train_tfidf_sent_vectors[20000:40000][:]
          x_train_3 = train_tfidf_sent_vectors[40000:61441][:]
          y_train_1 = Y_train[0:20000][:] # Row 0 to 19999 and all columns
          y_train_2 = Y_train[20000:40000][:]
          y_train_3 = Y_train[40000:61441][:]
          # Calculating training error for first batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs
              clf.fit(x_train_1,y_train_1)
              pre_probab = clf.predict_proba(x_train_1)[:,1] # Returns probability of positive
              auc = roc_auc_score(y_train_1,pre_probab)
              train_auc_list1.append(auc)
          # Calculating training error for second batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs
              clf.fit(x_train_2,y_train_2)
              pre_probab = clf.predict_proba(x_train_2)[:,1]
              auc = roc_auc_score(y_train_2,pre_probab)
              train_auc_list2.append(auc)
          # Calculating training error for third batch
          for k in tqdm(range(1,30,2)):
              clf = KNeighborsClassifier(n_neighbors=k,algorithm="kd_tree",leaf_size=40,n_jobs=
              clf.fit(x_train_3,y_train_3)
```

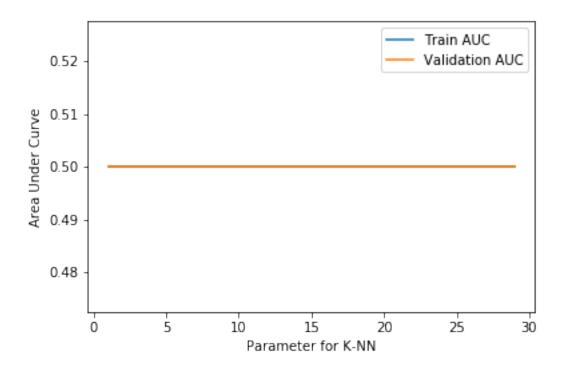
```
auc = roc_auc_score(y_train_3,pre_probab)
              train auc list3.append(auc)
          # Combining results together.
          train_auc_list = [(x+y+z)/3 for x,y,z in zip(train_auc_list1,train_auc_list2,train_a
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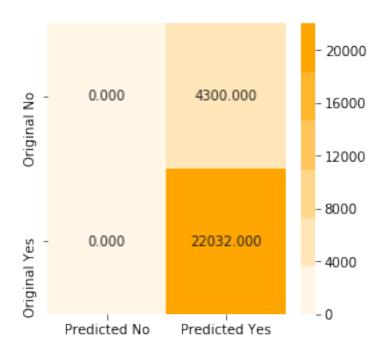
pre_probab = clf.predict_proba(x_train_3)[:,1]

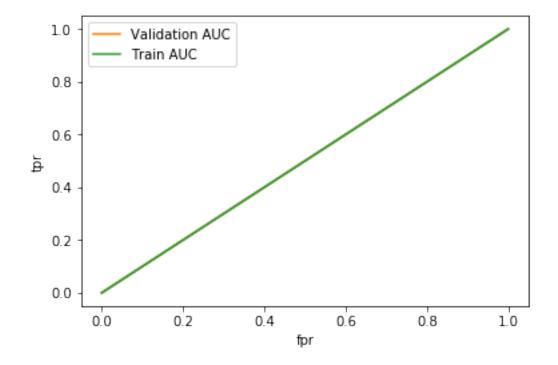
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          | 14/15 [06:21<00:27, 27.05s/it]
100%|| 15/15 [06:50<00:00, 27.43s/it]
In [115]: # 10 fold cross validation using time series splitting
          from sklearn.model_selection import TimeSeriesSplit
          tscv = TimeSeriesSplit()
          auc_list = []
          for k in range(1,30,2):
              # KNN Classifier
              clf = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree',leaf_size=40,n_jobs
              i=0
              auc=0.0
              for train_index,test_index in tscv.split(train_tfidf_sent_vectors):
                  x_train = train_tfidf_sent_vectors[0:train_index[-1]][:] # row 0 to train_in
                  y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                  x_test = train_tfidf_sent_vectors[train_index[-1]:test_index[-1]][:] # row f
                  y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t
                  clf.fit(x_train,y_train)
                  predict_probab = clf.predict_proba(x_test)[:,1] # Returns probability of for
                  auc += roc_auc_score(y_test,predict_probab)
              auc_list.append(auc/i) # Averaging auc for all 10 folds .
In [117]: # Plotting graph of auc and parameter for training and cross validation error
          plot_knn_vs_auc(train_auc_list,auc_list)
```

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27%|







7 [6] Conclusions

```
In [1]: from prettytable import PrettyTable
      x = PrettyTable()
      x.field_names = ["Model Type", "Best K", "AUC",]
      x.add_row(["BOW","21","0.67"])
      x.add_row(["TfIdf","25","0.51"])
      x.add_row(["Avg W2V","17","0.87"])
      x.add_row(["TfIdf Weighted W2V","21","0.50"])
      print(x)
+----+
    Model Type | Best K | AUC |
+----+
       BOW
                | 21 | 0.67 |
     BOW | 21 | 0.67 |
TfIdf | 25 | 0.51 |
Avg W2V | 17 | 0.87 |
| TfIdf Weighted W2V | 21 | 0.50 |
+----+
```