[1] Amazon Fine Food Reviews Analysis

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

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

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

Attribute Information:

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

Objective:

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

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

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

[7.1] 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 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 id 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
#Metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score

warnings.filterwarnings("ignore")

%matplotlib inline
# sets the backend of matplotlib to the 'inline' backend:
#With this backend, the output of plotting commands is displayed inline within frontends li
#directly below the code cell that produced it. The resulting plots will then also be store

#Functions to save objects for later use and retireve it
import pickle
def savetofile(obj,filename):
    pickle.dump(obj,open(filename+".p","wb"))
def openfromfile(filename):
    temp = pickle.load(open(filename+".p","rb"))
    return temp
```

In [2]:

```
#Using sqlite3 to retrieve data from sqlite file

con = sqlite3.connect("final.sqlite")#Loading Cleaned/ Preprocesed text that we did in Text

#Using pandas functions to query from sql table
final = pd.read_sql_query("""
SELECT * FROM Reviews order by time
""",con)

#Reviews is the name of the table given
#Taking only the data where score != 3 as score 3 will be neutral and it won't help us much
final.head()
```

Out[2]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomina
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
2	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
3	346055	374359	B00004CI84	A344SMIA5LECCM	Vincent P.	1	

In [3]:

```
final.shape
final['Score'].size
```

Out[3]:

364171

Exploratory Data Analysis

[7.1.2] Data Cleaning: Deduplication

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

In [4]:

```
print(final.shape)
```

```
(364171, 12)
```

As can be seen above the same user has multiple reviews of the with the 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.

7.2.3 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

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

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

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

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

In [5]:

```
# find sentences containing HTML tags
import re
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

```
8
What happens when you say his name three times? Michael Keaten stars in this
comedy about two couples that live in an old two story house.  While coming
back from a supply store, the couple suddenly get caught inside of a  &quot;
broken-up&quot; bridge and then just before they start to tumble down  into
the lake, a board catches them.  But just when they've got their hopes  up,
and small dog steps on the board and the car starts to slide off the  bridge
and into the lake waters.  A few minutes later...<p>They find  themselves ba
ck into their home, they find that somehow somehad light the  fireplace, as
if done by magic.  From then on, they find a weird-looking  dead guy known a
s Bettlejuice.  The only way they can get him for help is  to call him by hi
s name three times and he will appear at their survice.  But they soon wish
that they have never called his name, because  Bettlejuice was once a troubl
emaker but he is the only one who can save  them, on the account that they s
aid his name three times.  They can't leave  their houses or else they will
find theirselves in another world with giant  sandworms.  This is a stellar
comedy that you should see! Michael Keaton is  awesome as he plays the leadi
ng role of Bettlejuice.
```

In [6]:

```
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special characte
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
print(stop)
print('************************************')
print(sno.stem('tasty'))
```

```
{'at', "you're", 'don', 'o', 'she', 'with', 'during', 'yourself', 'why', 'u
p', 'so', 'ourselves', 'been', 'were', "needn't", 'nor', 'very', 'again', 't
hrough', "weren't", 't', 'hers', 'their', 'your', 'herself', 'they', 'not',
'other', 'where', 'or', 'am', 'her', 'those', 'you', "couldn't", 'ours', 'a
s', 'into', 'mustn', 'only', 'each', 'a', "you've", 'have', 'by', 'mightn',
'under', 'm', 'y', "isn't", 'll', 'doing', 'his', 'd', 'than', 'haven', "tha
t'll", 'few', 'when', 're', 'before', 'for', 'about', 'being', 'couldn', 'so
me', 'our', 'them', 'what', "shouldn't", 'doesn', 'then', 'which', 'do', 'i
n', 'my', 'between', 'did', "mightn't", 'won', 'these', 'once', 'from', 'you
rselves', 'shouldn', 'over', 'are', "she's", 'no', 'does', 'after', 'too',
'off', 'can', 'myself', 'that', 'himself', 'of', "didn't", 'such', "hadn't",
'same', 'and', 'me', 'further', 'down', 'there', 'the', 'hadn', 've', "you'l
l", 'having', "shan't", 'wasn', 'now', "aren't", 'didn', 'but', 'to', 'had',
"hasn't", 'isn', "haven't", 'more', 's', "it's", 'whom', 'how', 'ain', 'on',
'weren', 'should', 'an', 'until', 'below', 'here', 'both', 'be', 'ma', 'woul
dn', "don't", 'if', "wasn't", 'who', 'themselves', 'has', 'while', 'out', 'b
ecause', 'most', 'it', 'itself', 'hasn', "won't", 'any', 'him', 'yours', 'ag
ainst', "wouldn't", 'own', 'was', "doesn't", "mustn't", 'above', 'he', "shou
ld've", 'needn', 'will', "you'd", 'we', 'its', 'aren', 'shan', 'all', 'jus
t', 'theirs', 'i', 'this', 'is'}
************************************
tasti
```

In [7]:

```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
if not os.path.isfile('final.sqlite'):
    final_string=[]
    all_positive_words=[] # store words from +ve reviews here
    all_negative_words=[] # store words from -ve reviews here.
    for i, sent in enumerate(tqdm(final['Text'].values)):
        filtered_sentence=[]
        #print(sent);
        sent=cleanhtml(sent) # remove HTML tags
        for w in sent.split():
            # we have used cleanpunc(w).split(), one more split function here because consi
            # if we dont use .split() function then we will be considring "abc def" as a si
            for cleaned_words in cleanpunc(w).split():
                if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                    if(cleaned_words.lower() not in stop):
                        s=(sno.stem(cleaned_words.lower())).encode('utf8')
                        filtered_sentence.append(s)
                        if (final['Score'].values)[i] == 1:
                            all_positive_words.append(s) #list of all words used to describ
                        if(final['Score'].values)[i] == 0:
                            all_negative_words.append(s) #list of all words used to describ
        str1 = b" ".join(filtered_sentence) #final string of cleaned words
        #print("***********************************************************************")
        final_string.append(str1)

    #############---- storing the data into .sqlite file ------########################
    final['CleanedText']=final_string #adding a column of CleanedText which displays the da
    final['CleanedText']=final['CleanedText'].str.decode("utf-8")
        # store final table into an SQLLite table for future.
    conn = sqlite3.connect('final.sqlite')
    c=conn.cursor()
    conn.text_factory = str
    final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
                 index=True, index_label=None, chunksize=None, dtype=None)
    conn.close()


    with open('positive_words.pkl', 'wb') as f:
        pickle.dump(all_positive_words, f)
    with open('negitive_words.pkl', 'wb') as f:
        pickle.dump(all_negative_words, f)
```

In [8]:

```
%%time
# Code takes a while to run as it needs to run on around 500k sentences.
i=0
str1=' '
final_string_nostem=[]
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)# remove HTML tags
    sent=cleanpunc(sent)# remove Punctuation Symbols
    for w in sent.split():
        if((w.isalpha()) and (len(w)>2)):#If it is a numerical value or character of lenght
            if(w.lower() not in stop):# If it is a stopword
                s=w.lower().encode('utf8') #encoding as byte-string/utf-8
            else:
                continue
        else:
            continue
    str1 = b" ".join(filtered_sentence)
    final_string_nostem.append(str1)
    i+=1
print("Preprocessing completed in ")
```

```
Preprocessing completed in
Wall time: 54 s
```

In [9]:

```
final=final[:20000]
```

In [10]:

```
final.shape
```

Out[10]:

```
(20000, 12)
```

In [11]:

```
###Sorting as we want according to time series
final.sort_values('Time',inplace=True)
final.head(10)
```

Out[11]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
2	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
3	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
4	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	
5	346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	
6	346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19	
7	70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
8	346141	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2	
9	346094	374400	B00004CI84	A2DEE7F9XKP3ZR	jerome	0	

In [12]:

```
savetofile(final,"sample_25000_knn")
```

In [13]:

```
final = openfromfile("sample_25000_knn")
```

In [14]:

```
final['Score'].value_counts()
```

Out[14]:

```
positive    17826
negative     2174
Name: Score, dtype: int64
```

In [15]:

```
final.shape
```

Out[15]:

```
(20000, 12)
```

[7.2.2] Bag of Words (BoW)

In [35]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(final['CleanedText'].values,final['Scor

#Text -> Uni gram Vectors
uni_gram = CountVectorizer(min_df = 10)
X_train = uni_gram.fit_transform(X_train)
#Normalize Data
X_train = preprocessing.normalize(X_train)
print("Train Data Size: ",X_train.shape)
X_test = uni_gram.transform(X_test)
#Normalize Data
X_test = preprocessing.normalize(X_test)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (14000, 3479)
Test Data Size:  (6000, 3479)
```

In [36]:

```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(X_train):
#     print("%s %s" % (train, cv))
    print(X_train[train].shape, X_train[cv].shape)
```

```
(1280, 3479) (1272, 3479)
(2552, 3479) (1272, 3479)
(3824, 3479) (1272, 3479)
(5096, 3479) (1272, 3479)
(6368, 3479) (1272, 3479)
(7640, 3479) (1272, 3479)
(8912, 3479) (1272, 3479)
(10184, 3479) (1272, 3479)
(11456, 3479) (1272, 3479)
(12728, 3479) (1272, 3479)
```

brute force

In [37]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,30,2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 14.8min finished

Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 89.10%
```

In [38]:

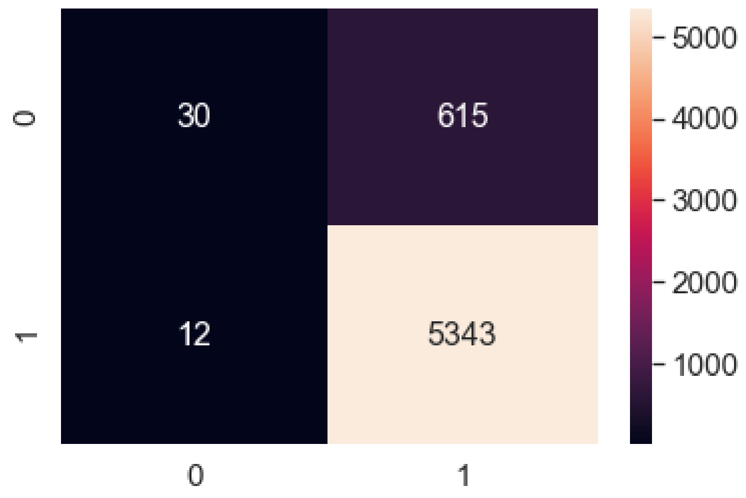
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=11)
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.550%
Precision on test set: 0.897
Recall on test set: 0.998
F1-Score on test set: 0.852
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa0096bf28>
```



KNN with Kd-tree Algorithm

In [39]:

```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=100)
X_train_vec_dense = svd.fit_transform(X_train)
X_test_vec_dense = svd.transform(X_test)


knn = KNeighborsClassifier(algorithm='kd_tree')
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train_vec_dense,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 49.4min finished

Best HyperParameter:  {'n_neighbors': 29}
Best Accuracy: 88.88%
```

In [40]:

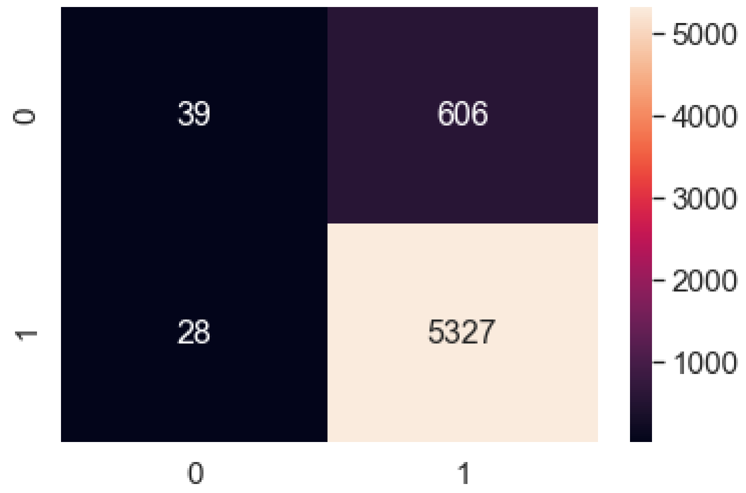
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=29,algorithm='kd_tree')
knn.fit(X_train_vec_dense,y_train)
y_pred = knn.predict(X_test_vec_dense)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.433%
Precision on test set: 0.898
Recall on test set: 0.995
F1-Score on test set: 0.854
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[40]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa008ae630>
```



[7.2.5] TF-IDF

In [51]:

```
%%time
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(final['CleanedText'].values,final['Scor

tfidf = TfidfVectorizer(min_df=10) #Using bi-grams
X_train = tfidf.fit_transform(X_train)
#Normalize Data
X_train = preprocessing.normalize(X_train)
print("Train Data Size: ",X_train.shape)
X_test = tfidf.transform(X_test)
#Normalize Data
X_test = preprocessing.normalize(X_test)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (14000, 3479)
Test Data Size:  (6000, 3479)
Wall time: 2.83 s
```

In [42]:

```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(X_train):
#     print("%s %s" % (train, cv))
    print(X_train[train].shape, X_train[cv].shape)
```

```
(1280, 3479) (1272, 3479)
(2552, 3479) (1272, 3479)
(3824, 3479) (1272, 3479)
(5096, 3479) (1272, 3479)
(6368, 3479) (1272, 3479)
(7640, 3479) (1272, 3479)
(8912, 3479) (1272, 3479)
(10184, 3479) (1272, 3479)
(11456, 3479) (1272, 3479)
(12728, 3479) (1272, 3479)
```

brute force

In [43]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit

knn = KNeighborsClassifier(algorithm='brute',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 24.7min finished

Best HyperParameter:  {'n_neighbors': 7}
Best Accuracy: 89.28%
```

In [ ]:

```

```

In [44]:

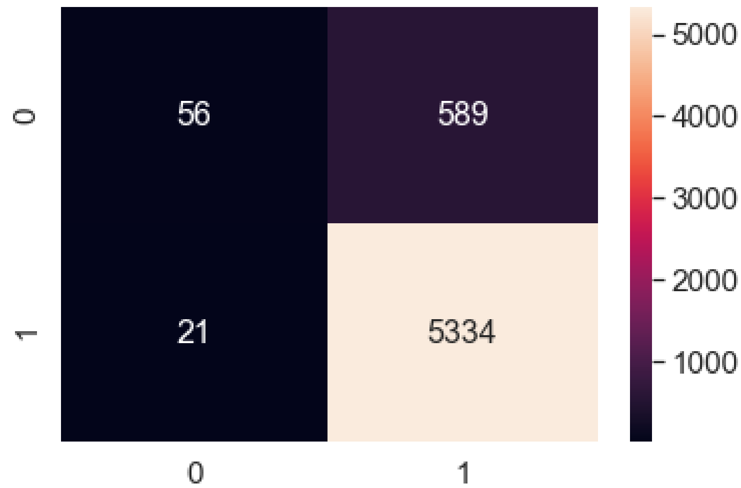
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.833%
Precision on test set: 0.901
Recall on test set: 0.996
F1-Score on test set: 0.861
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[44]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa0096cef0>
```



kd_tree implementation)

In [45]:

```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=100)
X_train_vec_dense = svd.fit_transform(X_train)
X_test_vec_dense = svd.transform(X_test)
```

In [46]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit
```

```
Wall time: 0 ns
```

In [47]:

```
knn = KNeighborsClassifier(algorithm='kd_tree',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train_vec_dense,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 25.8min finished

Best HyperParameter:  {'n_neighbors': 29}
Best Accuracy: 88.88%
```

In [48]:

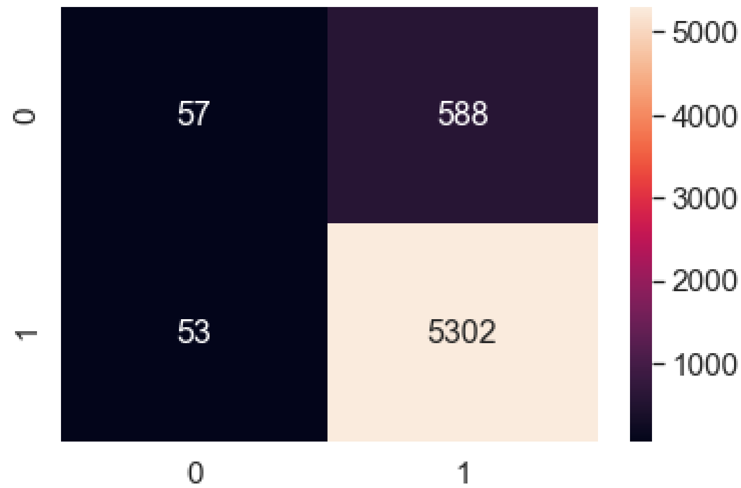
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=29,algorithm='kd_tree')
knn.fit(X_train_vec_dense,y_train)
y_pred = knn.predict(X_test_vec_dense)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.317%
Precision on test set: 0.900
Recall on test set: 0.990
F1-Score on test set: 0.858
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa005ab0f0>
```



In [ ]:

In [ ]:

[7.2.6] Word2Vec

In [16]:

```
import gensim
i=0
list_of_sent=[]
for sent in final['CleanedText'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent.append(filtered_sentence)
```

In [17]:

```
import gensim
model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50,workers=4)
#model = KeyedVectors.load_word2vec_format('amazon-fine-food-reviews/GoogleNews-vectors-neg
print(type(model))
#model_train=gensim.models.Word2Vec(final_train['CleanedText'].tolist(),min_count=5,size=50
#print(type(model_train)
```

```
<class 'gensim.models.word2vec.Word2Vec'>
```

In [18]:

```
words = list(model.wv.vocab)
print(len(words))
print(model)
```

```
6304
Word2Vec(vocab=6304, size=50, alpha=0.025)
```

In [20]:

```
# 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_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    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 words:
            vec = 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]))
```

```
20000
50
```

In [21]:

```
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

avg_vec_norm = preprocessing.normalize(sent_vectors)

#Not shuffling the data as we want it on time basis
X_train, X_test, y_train, y_test = train_test_split(avg_vec_norm,final['Score'].values,test
```

In [22]:

```
avg_vec_norm.shape
```

Out[22]:

```
(20000, 50)
```

In [23]:

```
avg_vec_norm.max()
```

Out[23]:

```
0.5498272102806953
```

In [24]:

```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
```

Brute force

In [25]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(algorithm='brute',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))}#params we need to t
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 29.8min finished

Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 89.38%
```

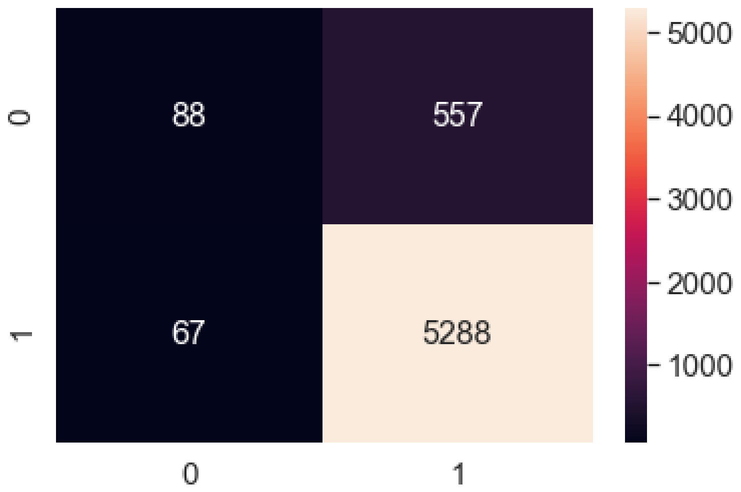
In [28]:

```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=11)
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.600%
Precision on test set: 0.905
Recall on test set: 0.987
F1-Score on test set: 0.866
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa003fb668>
```



Kd tree Algorithm

In [32]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=40)
X_train_vec_dense = svd.fit_transform(X_train)
X_test_vec_dense = svd.transform(X_test)

knn = KNeighborsClassifier(algorithm='kd_tree',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1,n_jobs=-1)
gsv.fit(X_train_vec_dense,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:  9.1min finished

Best HyperParameter:  {'n_neighbors': 13}
Best Accuracy: 89.34%
```

In [34]:

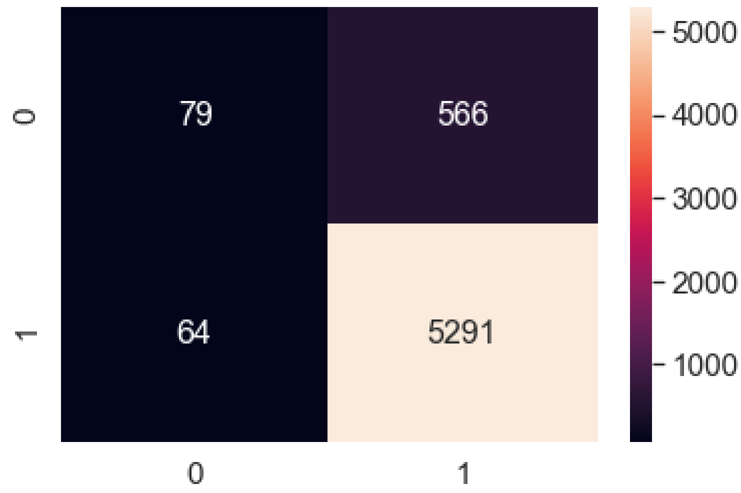
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=13,algorithm='kd_tree')
knn.fit(X_train_vec_dense,y_train)
y_pred = knn.predict(X_test_vec_dense)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.500%
Precision on test set: 0.903
Recall on test set: 0.988
F1-Score on test set: 0.864
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fa00095cc0>
```



In [ ]:

[7.2.7] Avg W2V, TFIDF-W2V

In [16]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sent=[]
for sent in final['CleanedText'].values:
    list_of_sent.append(sent.split())
```

In [18]:

```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [19]:

```
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  6304
sample words  ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'car', 'driv
e', 'along', 'alway', 'sing', 'hes', 'learn', 'india', 'love', 'new', 'wor
d', 'introduc', 'silli', 'classic', 'will', 'bet', 'still', 'abl', 'memori',
'colleg', 'rememb', 'see', 'show', 'air', 'televis', 'year', 'ago', 'child',
'sister', 'later', 'bought', 'day', 'thirti', 'someth', 'use', 'seri', 'son
g', 'student', 'teach', 'preschool', 'turn', 'whole', 'school', 'purchas']
```

In [22]:

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

```
100%|██████████| 20000/20000 [00:48<00:00, 415.28it/s]

20000
50
```

In [23]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(final['CleanedText'].values)
# 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 [24]:

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

```
100%|██████████| 20000/20000 [00:51<00:00, 390.88it/s]
```

In [25]:

```
tfidf_w2v_vec = np.array(tfidf_sent_vectors)
```

In [26]:

```
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

tfidfw2v_vecs_norm = preprocessing.normalize(tfidf_w2v_vec)

#Not shuffling the data as we want it on time basis
X_train, X_test, y_train, y_test = train_test_split(tfidfw2v_vecs_norm,final['Score'].value
```

Brute Algorithm

In [27]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit

knn = KNeighborsClassifier(algorithm='brute',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 37.4min finished

Best HyperParameter:  {'n_neighbors': 9}
Best Accuracy: 89.06%
```

In [28]:

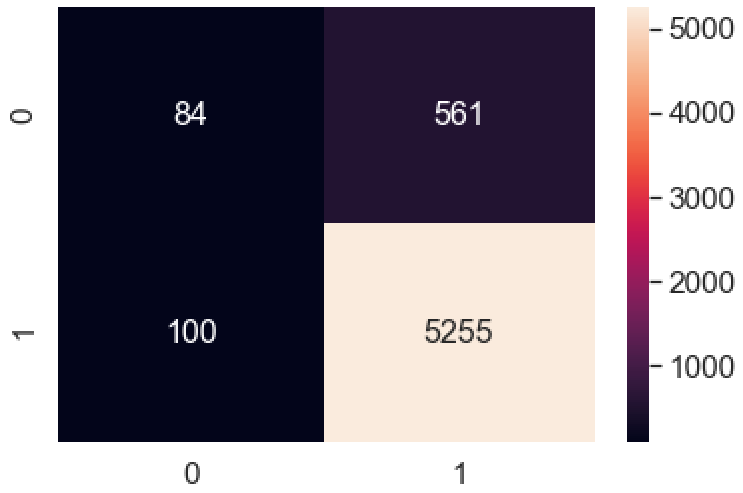
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 88.983%
Precision on test set: 0.904
Recall on test set: 0.981
F1-Score on test set: 0.861
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b0d1322e8>
```



Kd tree Algorithm

In [33]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD
X_train_vec_dense = svd.fit_transform(X_train)
X_test_vec_dense = svd.transform(X_test)

knn = KNeighborsClassifier(algorithm='kd_tree',n_jobs=2)
myList = list(range(0,30))
param_grid = {'n_neighbors':list(filter(lambda x: x % 2 != 0, myList))} #params we need to
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(knn,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train_vec_dense,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Wall time: 0 ns
Fitting 10 folds for each of 15 candidates, totalling 150 fits

[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 12.1min finished

Best HyperParameter:  {'n_neighbors': 13}
Best Accuracy: 89.07%
```

In [35]:

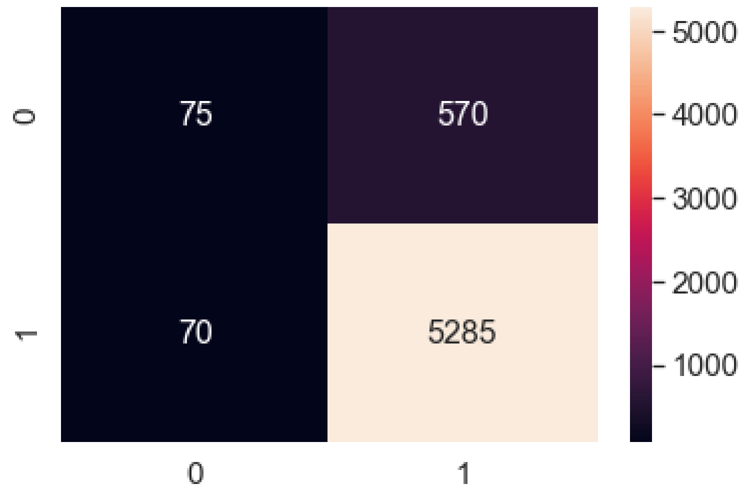
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=13)
knn.fit(X_train_vec_dense,y_train)
y_pred = knn.predict(X_test_vec_dense)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred,pos_label='positive'))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred,pos_label='positive')))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred,pos_label='positive',average='
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 89.333%
Precision on test set: 0.903
Recall on test set: 0.987
F1-Score on test set: 0.862
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[35]:

<matplotlib.axes._subplots.AxesSubplot at 0x20b0dbfac88>



In [14]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable
# Names of models
featurization = ['Bag of Words brute force','Bag of Words kd tree','Tf-Idf brute force',\
                'Tf-Idf kd tree','Avg word 2 vec brute force','Avg word 2 vec kd tree',\
                'TFIDF weighted w2vec brute force','TFIDF weighted w2vec kd tree']
# Training accuracies
accuracy = [89.10,88.88,89.28,88.88,89.38,89.34,89.06,89.07]
F1score = [0.852,0.854,0.861,0.858,0.866,0.864,0.861,0.862]
numbering = [1,2,3,4,5,6,7,8]
# Initializing prettytable
ptable = PrettyTable()
# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",featurization)
ptable.add_column("accuracy",accuracy)
ptable.add_column("F1 score",F1score)
# Printing the Table
print(ptable)
```

```
+-------+----------------------------------+----------+----------+
| S.NO. |              MODEL               | accuracy | F1 score |
+-------+----------------------------------+----------+----------+
|   1   |     Bag of Words brute force     |   89.1   |  0.852   |
|   2   |       Bag of Words kd tree       |  88.88   |  0.854   |
|   3   |        Tf-Idf brute force        |  89.28   |  0.861   |
|   4   |          Tf-Idf kd tree          |  88.88   |  0.858   |
|   5   |    Avg word 2 vec brute force    |  89.38   |  0.866   |
|   6   |      Avg word 2 vec kd tree      |  89.34   |  0.864   |
|   7   | TFIDF weighted w2vec brute force |  89.06   |  0.861   |
|   8   |   TFIDF weighted w2vec kd tree   |  89.07   |  0.862   |
+-------+----------------------------------+----------+----------+
```

In [ ]: