Amazon Food Reviews

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

This dataset consists of reviews of fine foods from Amazon. The data span a period of more than 10 years, including all ~500,000 reviews up to October 2012. Reviews include product and user information, ratings, and a plain text review. It also includes reviews from all other Amazon categories.

Excerpt

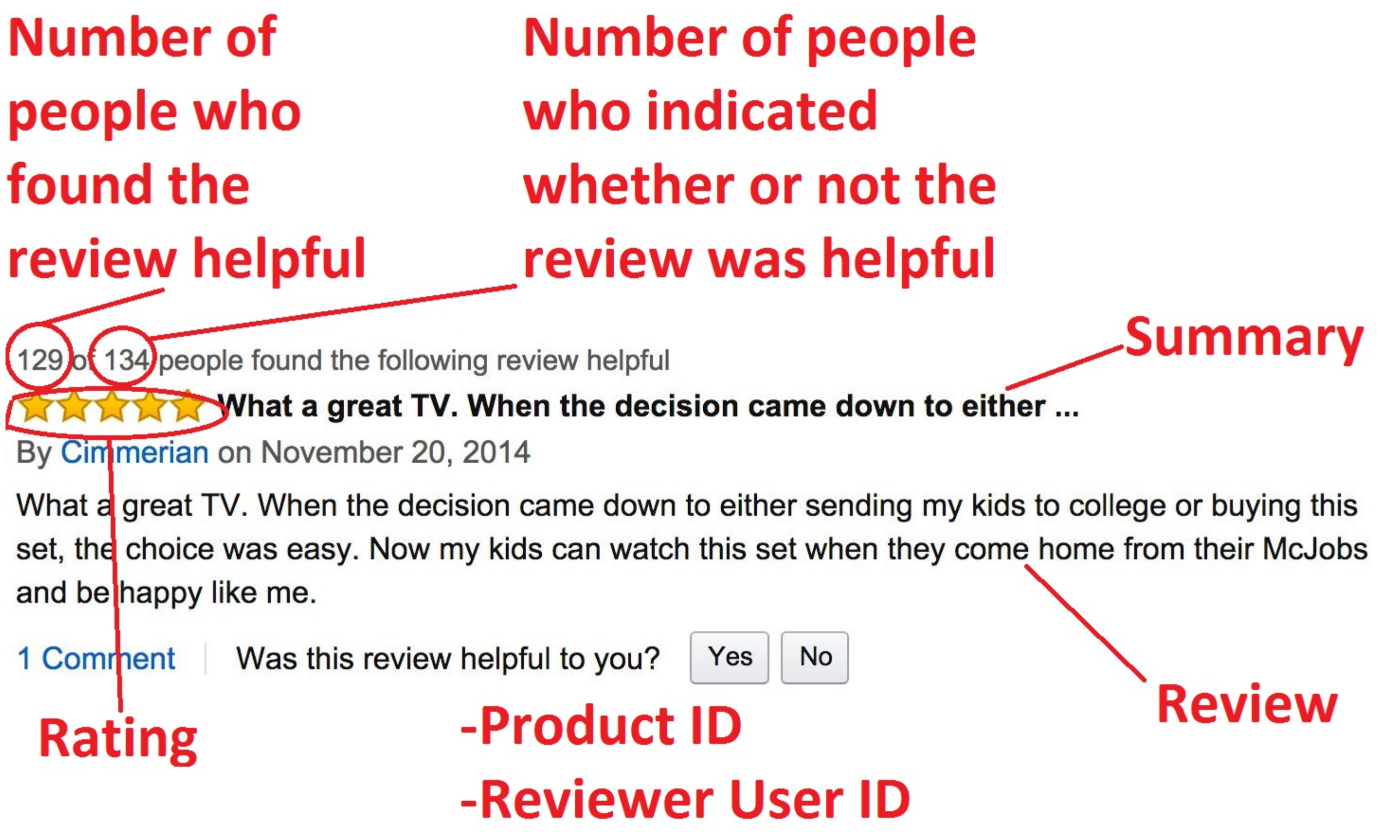
1. Applied K-Nearest Neighbour on Different Featurization of Data viz. BOW(uni-gram,bi-gram), tfidf, Avg-Word2Vec(using Word2Vec model pretrained on Google News) and tf-idf-Word2Vec
2. Used both brute & kd-tree implementation of KNN
3. Evaluated the test data on various performance metrics like accuracy, f1-score, precision, recall,etc. also plotted Confusion matrix using seaborne

Data includes:

- Reviews from Oct 1999 - Oct 2012
- 568,454 reviews
- 256,059 users
- 74,258 products
- 260 users with > 50 reviews

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:- Review Polarity

Given a review, determine the review is positive or neagative

Using text review to decide the polarity

Take the summary and text of review and analyze it using NLP whether the customer feedback/review is positive or negative

In [3]:

```
#Imports
import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt
import sqlite3 as sql
import seaborn as sns
from time import time
import random
import gensim
import warnings

#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 front
ends like the Jupyter notebook,
#directly below the code cell that produced it. The resulting plots will then also b
e stored in the notebook document.

#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 [4]:

```
# !wget --header="Host: storage.googleapis.com" --header="User-Agent: Mozilla/5.0 (Wi
ndows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/66.0.3359.139 Safari/537.36" --header="Accept:
text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,image/apng,*/*;q=0.8
--header="Accept-Language: en-US,en;q=0.9" "https://storage.googleapis.com/kaggle-da
tasets/18/2157/database.sqlite.zip?GoogleAccessId=web-data@kaggle-
161607.iam.gserviceaccount.com&Expires=1526375292&Signature=G95OD7LgGsnAoencBUsNHa3R2
IGiXOhdITLbhQVxqZ9IGS3JA9ETgbJRa3tHTguzL0ignoIz2sjQUxyY2YbcD98XR8immdcAmrFlQVA6Jm%2BE
u%2BpDGjF05FpW0wGeMq6utKq2Qy8eMtm3NW%2FA%2F7m557B%2Bi3kGcBP4uaEzMk6F%2BpGaZnxcroDAcjp
j9VzU03INKPwpkbxtM%2FrWCaX748Bpgx9uKqwfrRakGR%2BRCpnMHcUukj%2FhaKKRi9QoQaTNpdRjmVB%2F
ewKwDXTN8sr701yMkmqItQXBJI9Y312GqSP3Vd%2B3oleta5HZ2L9xlBFyUcLoyUEItOxI4pTjukwu1A%3D%3
" -O "database.sqlite.zip" -c
```

Loading the data

In [40]:

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

con = sql.connect("final.sqlite")#Loading Cleaned/ Preprocesed text that we did in T
ext Preprocessing

#Using pandas functions to query from sql table
df = pd.read_sql_query("""
SELECT * FROM Reviews
""",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
df.head()
```

Out[40]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
3	3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
4							

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel
	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

In [41]:

```
df.describe()
```

Out[41]:

	index	Id	HelpfulnessNumerator	HelpfulnessDenominator
count	364171.000000	364171.000000	364171.000000	364171.000000
mean	241825.377603	261814.561014	1.739021	2.186841
std	154519.869452	166958.768333	6.723921	7.348482
min	0.000000	1.000000	0.000000	0.000000
25%	104427.500000	113379.500000	0.000000	0.000000
50%	230033.000000	249445.000000	0.000000	1.000000
75%	376763.500000	407408.500000	2.000000	2.000000
max	525813.000000	568454.000000	866.000000	878.000000

In [42]:

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

Out[42]:

```
364171
```

-> For EDA and Text Preprecessing Refer other ipynb notebook

Score as positive or negative

In [43]:

```
def polarity(x):
    if x == "Positive":
        return 0
    else:
        return 1
df["Score"] = df["Score"].map(polarity) #Map all the scores as the function polarity i.e. positive or negative
df.head()
```

Out[43]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
3	3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
4	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

In [44]:

```
#Taking Sample Data
n_samples = 25000
df_sample = df.sample(n_samples)

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

Out[44]:

	index	Id	ProductId	UserId	ProfileName
117924	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski
1144	1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie
117265	137932	149700	B00006L2ZT	A19JWUIRF6DXLV	Andrew J Monzon
316048	443664	479725	B00005U2FA	A270SG4UVKEO3X	Susanna "suzattorney"
77727	87386	95119	B0000DIYIJ	A3S4XR84R8S0TV	Brook Lindquist
218787	284749	308481	B0000DIVUR	AAFD4W6P5XWNT	Nick Watson
334889	477821	516699	B0000DG87B	AF5EKQ4I9NHJ4	Smitty Peete
262407					

	index	Id	ProductId	UserId	ProfileName
	359912	389289	B0000DYZCG	A1U4PHVIQPBCD2	Dan Murphy
77127	86598	94281	B0000CNU2Q	A1NOWEOLKMRRXM	T. Reinhardt "olivia lee"
178039	224637	243579	B0000DIYKD	AYHW6HJSUCSAE	"insolent_shoeshine_grrl"

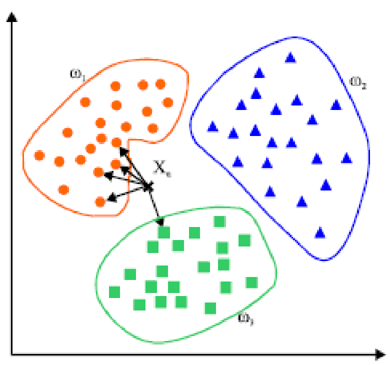
In [45]:

```
#Saving 25000 samples in disk to as to test to test on the same sample for each of a
ll Algo
savetofile(df_sample,"sample_25000_knn")
```

In [4]:

```
#Opening from samples from file
df_sample = openfromfile("sample_25000_knn")
```

KNN Models using Different Featurization in NLP



Bag of Words (BoW)

A commonly used model in methods of Text Classification. As part of the BOW model, a piece of text (sentence or a document) is represented as a bag or multiset of words, disregarding grammar and even word order and the frequency or occurrence of each

word is used as a feature for training a classifier.
OR
Simply,Converting a collection of text documents to a matrix of token counts

In [15]:

```
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(df_sample['CleanedText'].values,d
f_sample['Score'].values,test_size=0.3,shuffle=False)

#Text -> Uni gram Vectors
uni_gram = CountVectorizer()
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:  (17500, 26976)
Test Data Size:  (7500, 26976)
```

In [10]:

```
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)
```

```
(1600, 26976) (1590, 26976)
(3190, 26976) (1590, 26976)
(4780, 26976) (1590, 26976)
(6370, 26976) (1590, 26976)
(7960, 26976) (1590, 26976)
(9550, 26976) (1590, 26976)
(11140, 26976) (1590, 26976)
(12730, 26976) (1590, 26976)
(14320, 26976) (1590, 26976)
(15910, 26976) (1590, 26976)
```

Finding the best 'k' value using Forward Chaining Cross Validation or Time Series CV

1. Without Grid Search CV

In [11]:

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

#No of splits for Forward Chaining Cross Validation
n_splits = 10
#Max no. of neighbours for KNN
neigh_max = 100

tscv = TimeSeriesSplit(n_splits=n_splits)
#To store accuracy of different k values
k_acc = []

for k in range(1,neigh_max,2):
    #To store accuracy of different fold
    acc_list = []
    for train, cv in tscv.split(X_train):
          if(train.size > k):
            knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute',n_jobs=-1)
            knn.fit(X_train[train],y_train[train])
            acc_list.append(knn.score(X_train[cv],y_train[cv])*100)
    if(acc_list):
        acc_nparr = np.array(acc_list)
    k_acc.append(acc_nparr.mean())
k_acc = np.array(k_acc)
```

```
CPU times: user 2min 46s, sys: 1min 9s, total: 3min 56s
Wall time: 5min 57s
```

In [12]:

```
savetofile(k_acc,"k_acc_uni_gram")
```

In [13]:

```
k_acc_uni_gram = openfromfile("k_acc_uni_gram")
k_acc_uni_gram
```

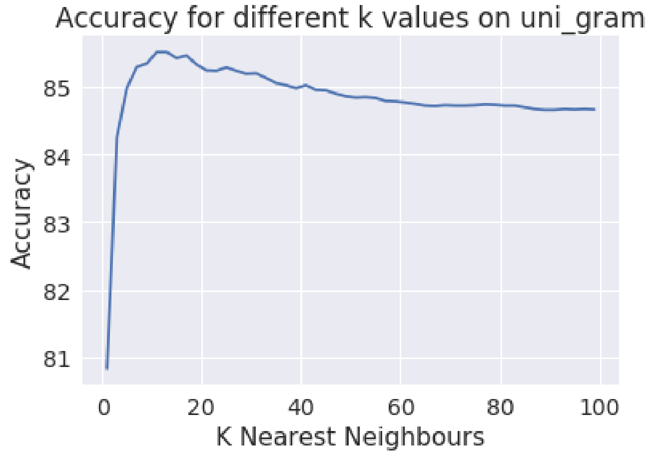
Out[13]:

```
array([ 80.83018868,  84.25786164,  84.98113208,  85.29559748,
        85.34591195,  85.51572327,  85.51572327,  85.42767296,
        85.46540881,  85.33333333,  85.24528302,  85.23899371,
        85.28930818,  85.23899371,  85.19496855,  85.20125786,
        85.13207547,  85.05660377,  85.02515723,  84.98113208,
        85.02515723,  84.95597484,  84.94968553,  84.89937107,
        84.86163522,  84.8427673 ,  84.8490566 ,  84.83647799,
        84.79245283,  84.78616352,  84.7672956 ,  84.74842767,
```

```
       84.72327044,  84.71698113,  84.72955975,  84.72327044,
       84.72327044,  84.72955975,  84.74213836,  84.73584906,
       84.72327044,  84.72327044,  84.69811321,  84.67295597,
       84.66037736,  84.66037736,  84.67295597,  84.66666667,
       84.67295597,  84.66666667])
```

In [14]:

```
sns.set_style("darkgrid")
plt.plot(np.arange(1,100,2),k_acc_uni_gram)
plt.xlabel("K Nearest Neighbours")
plt.ylabel("Accuracy")
plt.title("Accuracy for different k values on uni_gram")
plt.show()
```



With k=11-13 uni_gram has the highest accuracy of 86%
As we can see after a no. of neighbours the accuracy dips hence the no. of neighbours is restricted to 100 neighbours

2. With Grid Search CV

The above code for finding best value of 'k' can be condensed using Grid Search CV it tries all the possible params which tell it to try on and returns the best params and best accuracy

A.Brute Algorithm

In [16]:

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

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
```

```python
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 14.1 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.52%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 46.4min finished
```

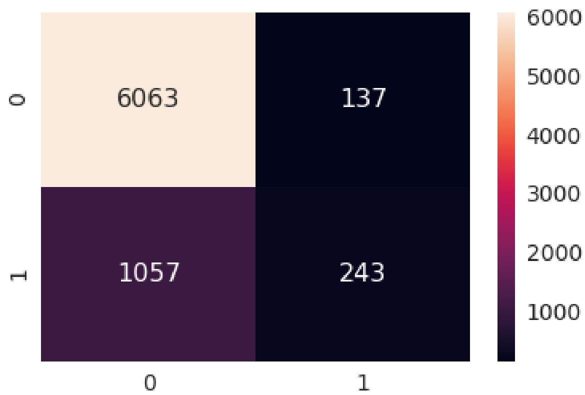
In [7]:

```python
#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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.080%
Precision on test set: 0.639
Recall on test set: 0.187
F1-Score on test set: 0.289
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff3d250eb8>
```



B. Kd tree Algorithm

In [17]:

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

knn = KNeighborsClassifier(algorithm='kd_tree')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.58 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.52%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 46.3min finished
```

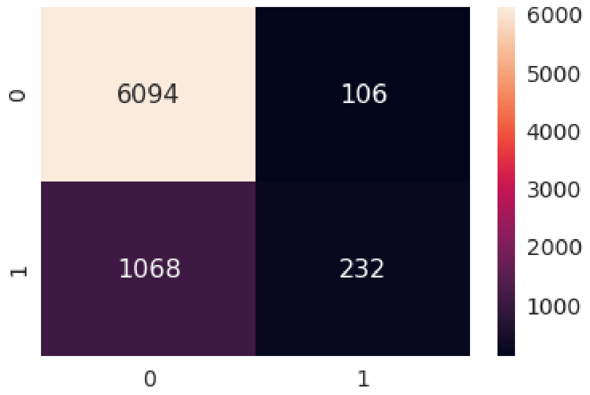
In [16]:

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

knn = KNeighborsClassifier(n_neighbors=11,algorithm='kd_tree')
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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.347%
Precision on test set: 0.686
Recall on test set: 0.178
F1-Score on test set: 0.283
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff1e5945f8>
```



bi-gram

In [17]:

```python
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(df_sample['CleanedText'].values,d
f_sample['Score'].values,test_size=0.3,shuffle=False)

#taking one words and two consecutive words together
bi_gram = CountVectorizer(ngram_range=(1,2))
X_train = bi_gram.fit_transform(X_train)
#Normalize Data
X_train = preprocessing.normalize(X_train)
print("Train Data Size: ",X_train.shape)
X_test = bi_gram.transform(X_test)
#Normalize Data
X_test = preprocessing.normalize(X_test)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (17500, 377282)
Test Data Size:  (7500, 377282)
```

A.Brute Algorithm

In [19]:

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

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,100,2)
```

```
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 9.06 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 17}
Best Accuracy: 85.77%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 47.3min finished
```

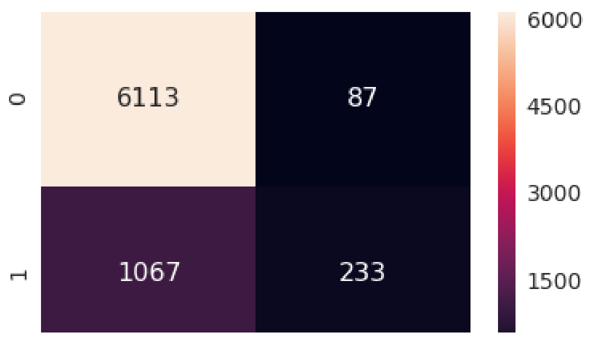
In [18]:

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

knn = KNeighborsClassifier(n_neighbors=17)
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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.613%
Precision on test set: 0.728
Recall on test set: 0.179
F1-Score on test set: 0.288
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2b13a278>
```



B. Kd tree Algorithm

In [20]:

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

knn = KNeighborsClassifier(algorithm='kd_tree')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.82 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 17}
Best Accuracy: 85.77%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 47.6min finished
```

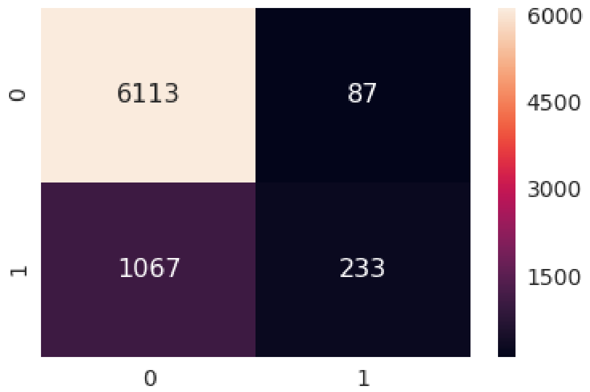
In [19]:

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

knn = KNeighborsClassifier(n_neighbors=17,algorithm='kd_tree')
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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.613%
Precision on test set: 0.728
Recall on test set: 0.179
F1-Score on test set: 0.288
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2b1c8c88>
```



tf-idf

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$ = number of occurrences of i in j
df_i = number of documents containing i
N = total number of documents

In [20]:

```
%%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(df_sample['CleanedText'].values,df_sample['Score'].values,test_size=
.3,shuffle=False)

tfidf = TfidfVectorizer(ngram_range=(1,2)) #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:  (17500, 377282)
Test Data Size:  (7500, 377282)
CPU times: user 3.88 s, sys: 16 ms, total: 3.89 s
```

Wall time: 3.89 s

A.Brute Algorithm

In [22]:

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

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.11 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 9}
Best Accuracy: 85.41%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 47.4min finished
```

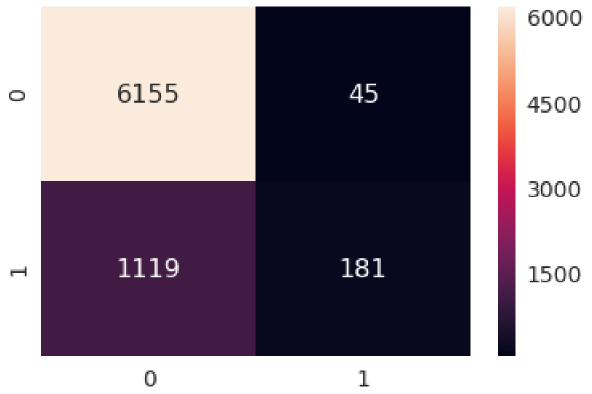
In [22]:

```
#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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.480%
Precision on test set: 0.801
Recall on test set: 0.139
F1-Score on test set: 0.237
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff1d1ff860>
```



B. Kd tree Algorithm

In [23]:

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

knn = KNeighborsClassifier(algorithm='kd_tree')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,100,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.58 µs
Fitting 10 folds for each of 50 candidates, totalling 500 fits
Best HyperParameter:  {'n_neighbors': 9}
Best Accuracy: 85.41%
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed: 47.5min finished
```

In [23]:

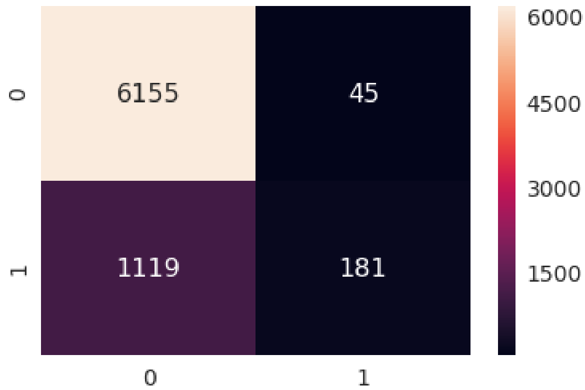
```
#Testing Accuracy on Test data
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=9,algorithm='kd_tree')
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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
```

```
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.480%
Precision on test set: 0.801
Recall on test set: 0.139
F1-Score on test set: 0.237
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff1d166080>
```



Gensim

Gensim is a robust open-source vector space modeling and topic modeling toolkit implemented in Python. It uses NumPy, SciPy and optionally Cython for performance. Gensim is specifically designed to handle large text collections, using data streaming and efficient incremental algorithms, which differentiates it from most other scientific software packages that only target batch and in-memory processing.

Word2Vec

[Refer Docs] :https://radimrehurek.com/gensim/models/word2vec.html

In [24]:

```
from gensim.models import KeyedVectors

#Loading the model from file in the disk
w2vec_model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin'
, binary=True)
```

In [25]:

```
w2v_vocub = w2vec_model.wv.vocab
len(w2v_vocub)
```

Out[25]:

```
3000000
```

Avg Word2Vec

- **One of the most naive but good ways to convert a sentence into a vector**
- **Convert all the words to vectors and then just take the avg of the vectors the resulting vector represent the sentence**

In [26]:

```
%%time
avg_vec_google = [] #List to store all the avg w2vec's
# no_datapoints = 364170
# sample_cols = random.sample(range(1, no_datapoints), 20001)
for sent in df_sample['CleanedText_NoStem']:
    cnt = 0 #to count no of words in each reviews
    sent_vec = np.zeros(300) #Initializing with zeroes
#     print("sent:",sent)
    sent = sent.decode("utf-8")
    for word in sent.split():
        try:
#             print(word)
            wvec = w2vec_model.wv[word] #Vector of each using w2v model
#             print("wvec:",wvec)
            sent_vec += wvec #Adding the vectors
#             print("sent_vec:",sent_vec)
            cnt += 1
        except:
            pass #When the word is not in the dictionary then do nothing
#     print(sent_vec)
    sent_vec /= cnt #Taking average of vectors sum of the particular review
#     print("avg_vec:",sent_vec)
    avg_vec_google.append(sent_vec) #Storing the avg w2vec's for each review
#     print("**********************************************************************")
# print(avg_vec_google)
avg_vec_google = np.array(avg_vec_google)
```

```
CPU times: user 12.1 s, sys: 160 ms, total: 12.3 s
Wall time: 12.3 s
```

In [27]:

```
np.isnan(avg_vec_google).any()
```

Out[27]:

False

In [28]:

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

avg_vec_norm = preprocessing.normalize(avg_vec_google)

#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,df_sample['Score'].v
alues,test_size=0.3,shuffle=False)
```

In [29]:

```
avg_vec_norm.shape
```

Out[29]:

```
(25000, 300)
```

In [30]:

```
avg_vec_norm.max()
```

Out[30]:

```
0.26854231895936098
```

A.Brute Algorithm

In [58]:

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

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,40,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 10 µs
Fitting 10 folds for each of 20 candidates, totalling 200 fits
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.61%
```

```
[Parallel(n_jobs=1)]: Done 200 out of 200 | elapsed: 14.0min finished
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed: [illegible]min finished
```

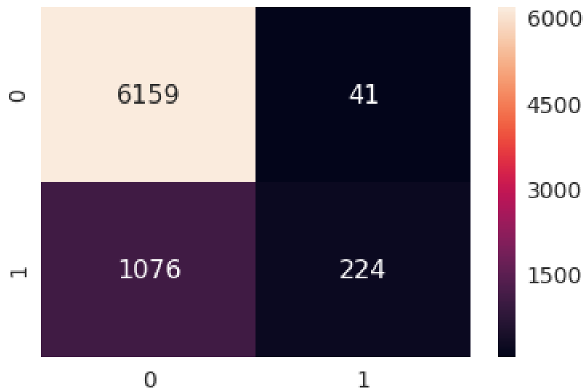
In [31]:

```python
#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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 85.107%
Precision on test set: 0.845
Recall on test set: 0.172
F1-Score on test set: 0.286
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffe2748fac8>
```



B. Kd tree Algorithm

In [33]:

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

knn = KNeighborsClassifier(algorithm='kd_tree')
# neigh = np.arange(1,100,2)
```

```
param_grid = {'n_neighbors':np.arange(1,40,2)} #params we need to try on classifier
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,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.82 µs
Fitting 10 folds for each of 20 candidates, totalling 200 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   21.1s
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 17.0min
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed: 24.8min finished
```

```
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.61%
```

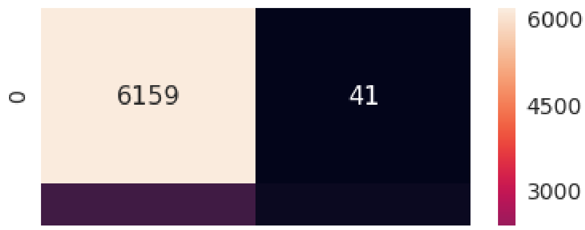
In [32]:

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

knn = KNeighborsClassifier(n_neighbors=11,algorithm='kd_tree')
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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 85.107%
Precision on test set: 0.845
Recall on test set: 0.172
F1-Score on test set: 0.286
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[32]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffe2748f080>
```



Tf-idf W2Vec

- **Another way to covert sentence into vectors**
- **Take weighted sum of the vectors divided by the sum of all the tfidf's i.e. (tfidf(word) x w2v(word))/sum(tfidf's)**

In [62]:

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

###tf-idf with No Stemming
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf = TfidfVectorizer(ngram_range=(1,2)) #Using bi-grams

tfidf_vec_new = tfidf.fit_transform(df_sample['CleanedText_NoStem'].values)

print(tfidf_vec_new.shape)

features = tfidf.get_feature_names()
```

```
(25000, 586319)
CPU times: user 6.37 s, sys: 92 ms, total: 6.46 s
Wall time: 6.93 s
```

In [67]:

```
%%time
tfidf_w2v_vec_google = []
review = 0

for sent in df_sample['CleanedText_NoStem'].values:
    cnt = 0
    weighted_sum  = 0
    sent_vec = np.zeros(300)
    sent = sent.decode("utf-8")
    for word in sent.split():
        try:
#              print(word)
            wvec = w2vec_model.wv[word] #Vector of each using w2v model
#              print("w2vec:",wvec)
#              print("tfidf:",tfidf_vec_ns[review,features.index(word)])
            tfidf_vec = tfidf_vec_new[review,features.index(word)]
            sent_vec += (wvec * tfidf_vec)
            weighted_sum += tfidf_vec
```

```
            weighted_sum += tfidf_vec
        except:
#              print(review)
            pass
    sent_vec /= weighted_sum
#     print(sent_vec)
    tfidf_w2v_vec_google.append(sent_vec)
    review += 1
tfidf_w2v_vec_google = np.array(tfidf_w2v_vec_google)
savetofile(tfidf_w2v_vec_google,"tfidf_w2v_vec_google")
```

```
CPU times: user 5h 58min 35s, sys: 2.69 s, total: 5h 58min 38s
Wall time: 5h 58min 39s
```

In [5]:

```
#Precomputed File
tfidf_w2v_vec_google = openfromfile("tfidf_w2v_vec_google")
#Loading the same samples as using precomuted file
df_sample_new = openfromfile("df_sample_new_tfidfw2vec")
```

In [6]:

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

tfidfw2v_vecs_norm = preprocessing.normalize(tfidf_w2v_vec_google)

#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,df_sample_new[
'Score'].values,test_size=0.3,shuffle=False)
```

A.Brute Algorithm

In [7]:

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

knn = KNeighborsClassifier(algorithm='brute')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,40,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 12.4 µs
Fitting 10 folds for each of 20 candidates, totalling 200 fits
```

```
Fitting 10 folds for each of 20 candidates, totalling 200 fits
Best HyperParameter:  {'n_neighbors': 9}
Best Accuracy: 85.08%
```

```
[Parallel(n_jobs=1)]: Done 200 out of 200 | elapsed: 14.0min finished
```

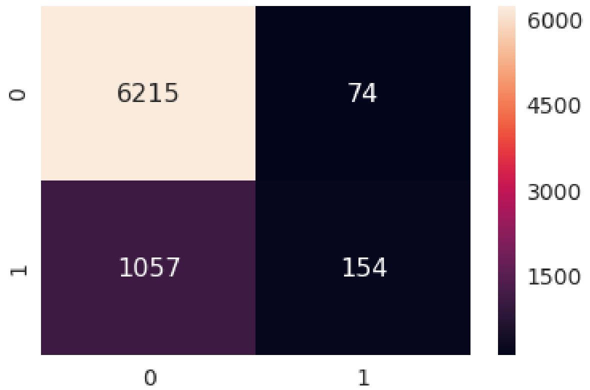
In [11]:

```
#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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.920%
Precision on test set: 0.675
Recall on test set: 0.127
F1-Score on test set: 0.214
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff3340c2e8>
```



B. Kd tree Algorithm

In [10]:

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

```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit

knn = KNeighborsClassifier(algorithm='kd_tree')
# neigh = np.arange(1,100,2)
param_grid = {'n_neighbors':np.arange(1,40,2)} #params we need to try on classifier
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))
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 8.34 µs
Fitting 10 folds for each of 20 candidates, totalling 200 fits
```

```
[Parallel(n_jobs=1)]: Done 200 out of 200 | elapsed: 380.7min finished
```

```
Best HyperParameter:  {'n_neighbors': 9}
Best Accuracy: 85.08%
```

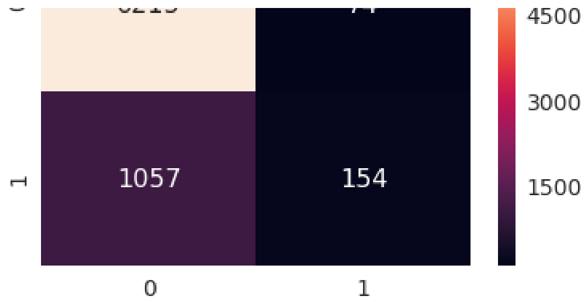
In [12]:

```python
#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)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
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: 84.920%
Precision on test set: 0.675
Recall on test set: 0.127
F1-Score on test set: 0.214
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff33419ef0>
```



KNN (with 25k points)			
Featurization	**Algo**	**Accuracy**	**F1-Score**
Uni - gram	brute	84.08	0.289
	kd-tree	84.347	0.283
Bi -gram	brute	84.613	0.288
	kd-tree	84.613	0.288
tfidf	brute	84.48	0.237
	kd-tree	84.48	0.237
Avg Word2Vec	brute	85.107	0.286
	kd-tree	85.107	0.286
tfidf - Word2vec	brute	84.92	0.214
	kd-tree	84.92	0.214

Conclusions

Note: As I have taken only 25k points(due to huge training time) the accuracy will not be the representive of the real accuracy

1. **Best Accuracy of 85.107% is achieved by Avg Word2Vec Featurization**
2. **The kd-tree and brute implementation of KNN gives relatively similar results**
3. **KNN is a very slow Algorithm compared to others takes alot of time to train**
4. **KNN did not fair in terms of precision and F1-score. Overall KNN was not that good for this dataset**