Amazon Food Reviews - [SVM]

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

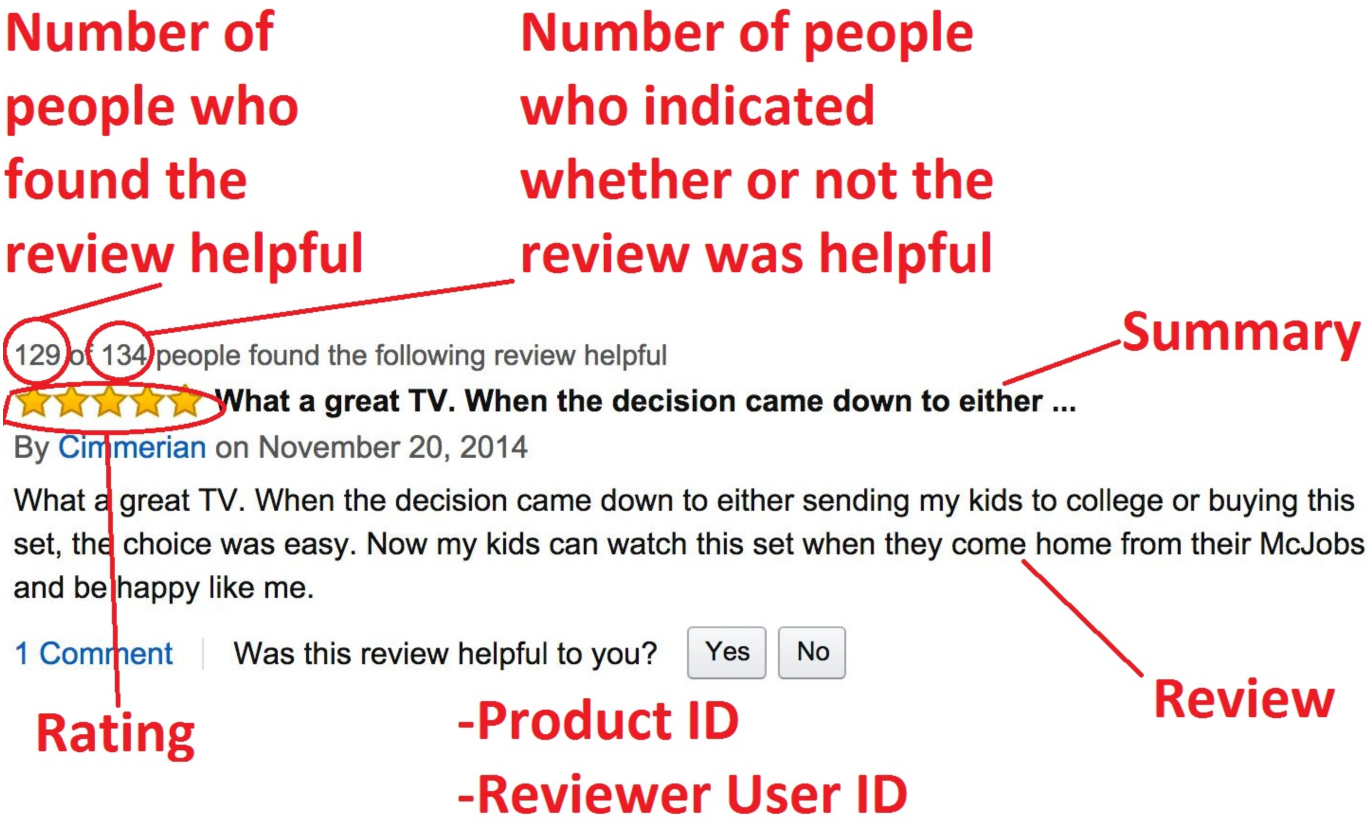
1. Applied SVM with rbf(radial basis function) kernel on Different Featurization of Data viz. BOW(uni-gram,bi-gram), tfidf, Avg-Word2Vec(using Word2Vec model pretrained on Google News) and tf-idf-Word2Vec
2. Used both Grid Search & Randomized Search Cross Validation
3. Evaluated the test data on various 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 negative

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 [10]:

```
# !pip install --upgrade pip
# !pip install qtconsole ipywidgets widgetsnbextension
```

```
# !pip install nltk
# # import nltk
# # nltk.download("stopwords")
# !pip install seaborn
# !pip install gensim
!pip install sklearn-evaluation
```

```
Collecting sklearn-evaluation
  Downloading
https://files.pythonhosted.org/packages/51/cb/797d9ccb9de85fed54bd418b4e726fb8d14450c
c1a9251f444bb4e5e3b3/sklearn-evaluation-0.4.tar.gz
Requirement already satisfied: scikit-learn in /opt/conda/envs/py3.6/lib/python3.6/si
te-packages (from sklearn-evaluation) (0.19.0)
Requirement already satisfied: matplotlib in /opt/conda/envs/py3.6/lib/python3.6/site
-packages (from sklearn-evaluation) (2.1.2)
Requirement already satisfied: six in /opt/conda/envs/py3.6/lib/python3.6/site-packag
es (from sklearn-evaluation) (1.11.0)
Requirement already satisfied: decorator in /opt/conda/envs/py3.6/lib/python3.6/site-
packages (from sklearn-evaluation) (4.3.0)
Requirement already satisfied: numpy>=1.7.1 in /opt/conda/envs/py3.6/lib/python3.6/si
te-packages (from matplotlib->sklearn-evaluation) (1.12.1)
Requirement already satisfied: python-dateutil>=2.1 in /opt/conda/envs/py3.6/lib/pyth
on3.6/site-packages (from matplotlib->sklearn-evaluation) (2.7.3)
Requirement already satisfied: pytz in /opt/conda/envs/py3.6/lib/python3.6/site-packa
ges (from matplotlib->sklearn-evaluation) (2018.4)
Requirement already satisfied: cycler>=0.10 in /opt/conda/envs/py3.6/lib/python3.6/si
te-packages (from matplotlib->sklearn-evaluation) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /opt/conda
/envs/py3.6/lib/python3.6/site-packages (from matplotlib->sklearn-evaluation) (2.2.0)
Building wheels for collected packages: sklearn-evaluation
  Running setup.py bdist_wheel for sklearn-evaluation ... done
  Stored in directory:
/home/jovyan/.cache/pip/wheels/be/3c/51/97b3f06627b632815707e6f9dd71fa2744ef8f1ef4005
a5ed
Successfully built sklearn-evaluation
ipywidgets 7.0.3 has requirement widgetsnbextension~=3.0.0, but you'll have widgetsnb
extension 3.2.1 which is incompatible.
Installing collected packages: sklearn-evaluation
Successfully installed sklearn-evaluation-0.4
```

In [7]:

```
#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 [28]:

```
# !wget --header="Host: e-2106e5ff6b.cognitiveclass.ai" --header="User-Agent: Mozilla
/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/67.
0.3396.99 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" --header="Cookie:
_ga=GA1.2.1009651095.1527270727;
_xsrf=2|d66eb8d7|8e30b1015ec501038d0632ff567bddb6|1529904261;
session=.eJxVj9tugkAURX_FnGdi5FaBxKSgoiZKtYq0Ng0ZYIBRGBQGEY3_XjBt2r6us1f2PjdwjzhPEcWU
cbyEnOASha7LDtgCtoNOg3_gBoJaneSiIVh7x0UXf0wWsTyNNkZorCZKbm5Z6ZAgrAotpbZz3aC4fRn0vyqWF
ujKlOp97YWF963kVdE10I-
KoKzFLE7OS9rtUzNmRnPlrOlq6a6Updnh00TspafjLEGJ18aSjtfRu4Zo0HGsD9885BgRL2GNiilX18tye70-
LNXLw4puw7vLzaWrWdxCN701OH0WAAjVQWOHcJDbPWxCkiSSPnxD_UKCCs-bLP889Ry7t-
lgIHIckL5lKU4iaoPzINTdAvnJRH1rJ_mc4PbQu_L39r2i2V55IANEWWROn-BWX4gJ4.Dh-
C7A.53fm96PBqDQvenTjy0oa1UWqE_8" --header="Connection: keep-alive" "https://e-
2106e5ff6b.cognitiveclass.ai/files/Amazon%20Fine%20Food%20Reviews%20Dataset/tfidf_w2v
vec_google.p?download=1" -O "tfidf_w2v_vec_google.p" -c
```

Loading the data

In [13]:

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

con = sql.connect("final.sqlite")#Loading Cleaned/ Preprocessed 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[13]:

	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

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel

In [14]:

```
df.describe()
```

Out[14]:

	index	Id	HelpfulnessNumerator	HelpfulnessDenominator	
count	364171.000000	364171.000000	364171.000000	364171.000000	3
mean	241825.377603	261814.561014	1.739021	2.186841	1
std	154519.869452	166958.768333	6.723921	7.348482	4
min	0.000000	1.000000	0.000000	0.000000	9
25%	104427.500000	113379.500000	0.000000	0.000000	1
50%	230033.000000	249445.000000	0.000000	1.000000	1
75%	376763.500000	407408.500000	2.000000	2.000000	1
max	525813.000000	568454.000000	866.000000	878.000000	1

In [15]:

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

Out[15]:

```
364171
```

For EDA and Text Preprecessing Refer other ipynb notebook

In [16]:

```
#Score as positive/negative -> 0/1
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[16]:

	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 [17]:

```
#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[17]:

	index	Id	ProductId	UserId	ProfileName	Helpfulness

169263	index	Id	ProductId	UserId	ProfileName	Helpfulness
	212454	230265	B00004RYGX	AZRJH4JFB59VC	Lynwood E. Hines	21
169255	212446	230257	B00004RYGX	A1OP3SQP78M1PP	James Gowen	0
316046	443662	479723	B00005U2FA	A3TO9GEQEGKFDC	N. Smith "emerald999"	35
178946	226060	245108	B001O8NLV2	A356HBGSVZ5NRH	B.P. "tilley_traveler"	14
280071	388413	419994	B0000A0BS5	A238V1XTSK9NFE	Andrew Lynn	46
55686	61299	66610	B0000SY9U4	A3EEDHNHI4WNSH	Joanna J. Young	23
36307	38888	42226	B0000A0BS8	A23GFTVIETX7DS	Debbie Lee Wesselmann	5
10496						

	Index	Id	ProductId	UserId	ProfileName	Helpfulness
	10992	11991	B0000T15M8	A2928LJN5IISB4	chatchi	5
199797	255320	276802	B0000DCXFY	AQFIH82DRPMW	Patrick O'Brien	5
208301	267390	289844	B0000E5JRW	A12PEEUG7CN2BO	B. Kalafut	6

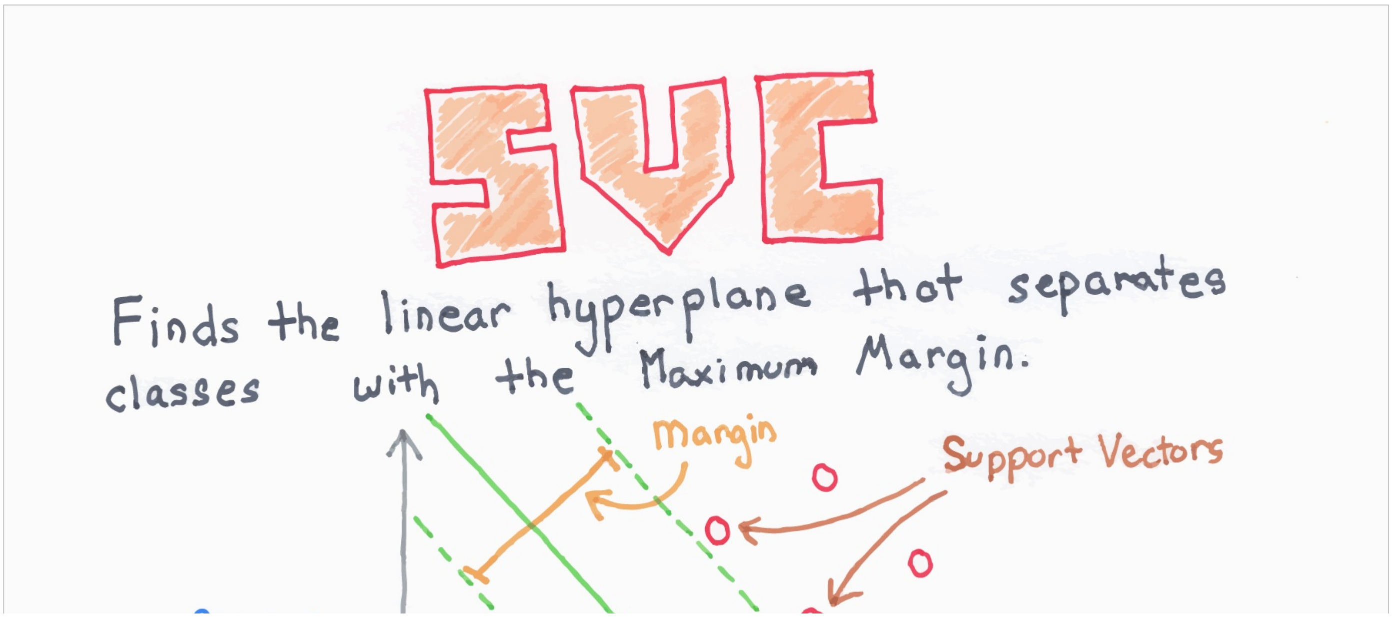
In [18]:

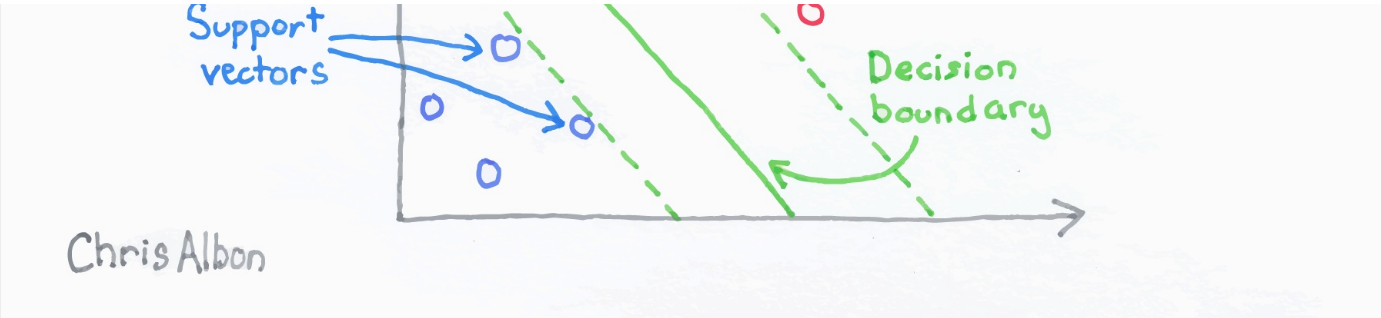
```
#Saving all samples in disk to as to test to test on the same sample for each of all Algo
savetofile(df_sample,"sample_svm")
```

In [15]:

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

Support Vector Machine Model 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 [16]:

```
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)
```

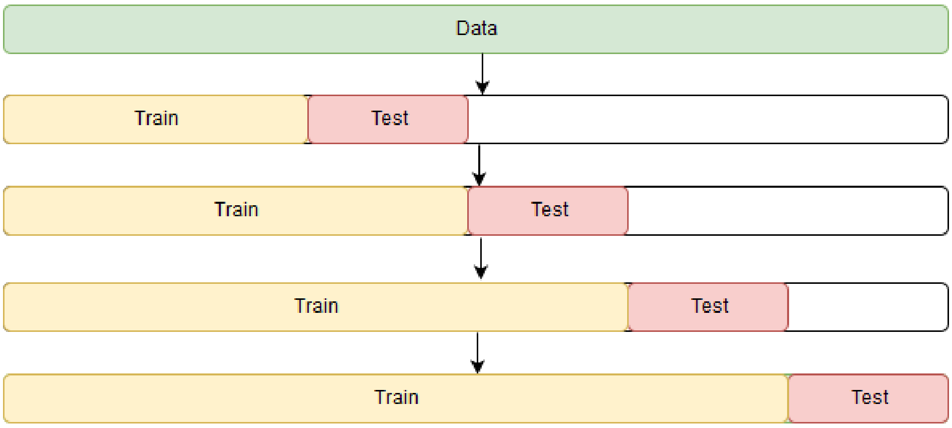
```
Train Data Size:  (17500, 27066)
Test Data Size:  (7500, 27066)
```

In [7]:

```
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, 27066) (1590, 27066)
```

```
(1600, 27066) (1590, 27066)
(3190, 27066) (1590, 27066)
(4780, 27066) (1590, 27066)
(6370, 27066) (1590, 27066)
(7960, 27066) (1590, 27066)
(9550, 27066) (1590, 27066)
(11140, 27066) (1590, 27066)
(12730, 27066) (1590, 27066)
(14320, 27066) (1590, 27066)
(15910, 27066) (1590, 27066)
```



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

In [8]:

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

clf = SVC()
param_grid = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 7.39 µs
Fitting 10 folds for each of 225 candidates, totalling 2250 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   29.3s
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 12.8min
[Parallel(n_jobs=-1)]: Done 410 tasks      | elapsed: 34.6min
[Parallel(n_jobs=-1)]: Done 760 tasks      | elapsed: 59.6min
```

```
[Parallel(n_jobs=-1)]: Done 1210 tasks      | elapsed: 89.3min
[Parallel(n_jobs=-1)]: Done 1760 tasks      | elapsed: 114.9min
[Parallel(n_jobs=-1)]: Done 2250 out of 2250 | elapsed: 123.5min finished
```

```
Best HyperParameter:  {'C': 10, 'gamma': 0.5}
Best Accuracy: 90.30%
```

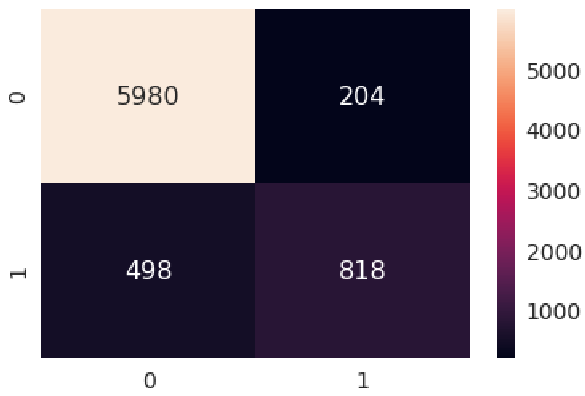
In [18]:

```python
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=10,gamma=0.5)
clf.fit(X_train,y_train)
y_pred = clf.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: 90.640%
Precision on test set: 0.800
Recall on test set: 0.622
F1-Score on test set: 0.700
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2efb5630>
```



Using Randomized Search CV to find best parameters

In [9]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from scipy.stats import uniform as sp_rand

clf = SVC()
#params we need to try on classifier
param_dist = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
              'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_dist,cv=tscv,verbose=1,n_iter=15)
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: 7.39 µs
Fitting 10 folds for each of 15 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 155.2min finished
```

```
Best HyperParameter:  {'gamma': 0.05, 'C': 50}
Best Accuracy: 89.96%
```

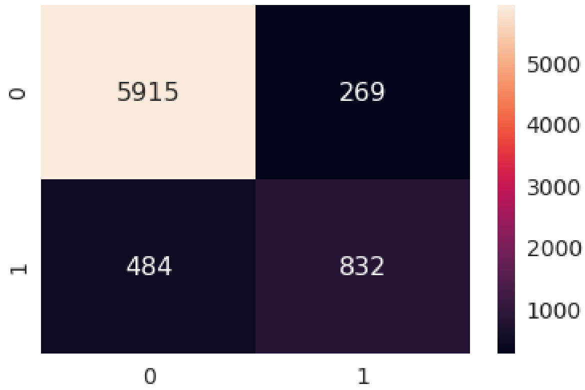
In [19]:

```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=50,gamma=0.05)
clf.fit(X_train,y_train)
y_pred = clf.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: 89.960%
Precision on test set: 0.756
Recall on test set: 0.632
F1-Score on test set: 0.688
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2efb0860>
```



bi-gram

In [21]:

```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()
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, 27066)
Test Data Size:  (7500, 27066)
```

In [11]:

```python
%time
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

clf = SVC()
param_grid = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 7.87 µs
Fitting 10 folds for each of 225 candidates, totalling 2250 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   26.7s
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 12.3min
[Parallel(n_jobs=-1)]: Done 410 tasks      | elapsed: 33.9min
[Parallel(n_jobs=-1)]: Done 760 tasks      | elapsed: 59.0min
[Parallel(n_jobs=-1)]: Done 1210 tasks      | elapsed: 88.7min
[Parallel(n_jobs=-1)]: Done 1760 tasks      | elapsed: 114.4min
[Parallel(n_jobs=-1)]: Done 2250 out of 2250 | elapsed: 123.3min finished
```

```
Best HyperParameter:  {'C': 10, 'gamma': 0.5}
Best Accuracy: 90.30%
```

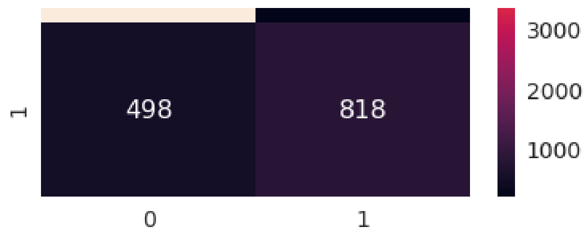
In [23]:

```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=10,gamma=0.5)
clf.fit(X_train,y_train)
y_pred = clf.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: 90.640%
Precision on test set: 0.800
Recall on test set: 0.622
F1-Score on test set: 0.700
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2eb09dd8>
```



Using Randomized Search CV to find best parameters

In [12]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from scipy.stats import uniform as sp_rand

clf = SVC()
#params we need to try on classifier
param_dist = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_dist,cv=tscv,verbose=1,n_iter=15)
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: 7.87 µs
Fitting 10 folds for each of 15 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 126.9min finished
```

```
Best HyperParameter:  {'gamma': 0.5, 'C': 5}
Best Accuracy: 90.29%
```

In [24]:

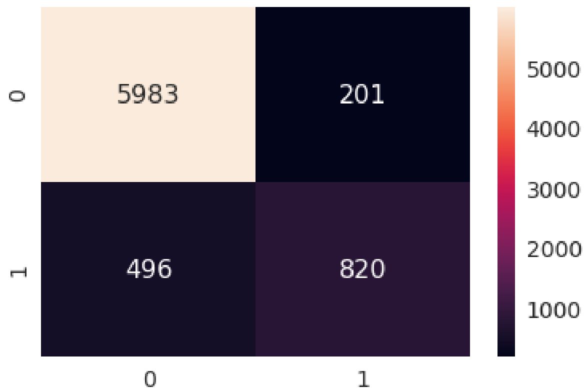
```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=5,gamma=0.5)
clf.fit(X_train,y_train)
y_pred = clf.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: 90.707%
Precision on test set: 0.803
Recall on test set: 0.623
F1-Score on test set: 0.702
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2eb05eb8>
```



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 [25]:

```
%%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, 378093)
Test Data Size:  (7500, 378093)
CPU times: user 3.78 s, sys: 32 ms, total: 3.81 s
Wall time: 3.81 s
```

In [14]:

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

clf = SVC()
param_grid = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 6.91 µs
Fitting 10 folds for each of 225 candidates, totalling 2250 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   47.2s
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 26.9min
[Parallel(n_jobs=-1)]: Done 410 tasks      | elapsed: 72.6min
[Parallel(n_jobs=-1)]: Done 760 tasks      | elapsed: 123.9min
[Parallel(n_jobs=-1)]: Done 1210 tasks      | elapsed: 180.8min
[Parallel(n_jobs=-1)]: Done 1760 tasks      | elapsed: 227.8min
[Parallel(n_jobs=-1)]: Done 2250 out of 2250 | elapsed: 241.7min finished
```

```
Best HyperParameter:  {'C': 1000, 'gamma': 0.005}
Best Accuracy: 89.87%
```

In [26]:

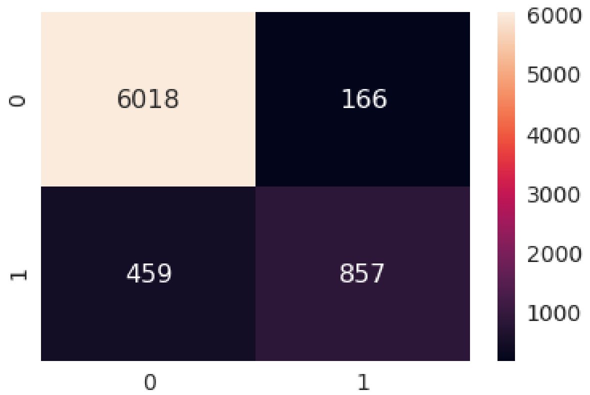
```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=1000,gamma=0.005)
clf.fit(X_train,y_train)
y_pred = clf.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: 91.667%
Precision on test set: 0.838
Recall on test set: 0.651
F1-Score on test set: 0.733
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff27f7cef0>
```



Using Randomized Search CV to find best parameters

In [15]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from scipy.stats import uniform as sp_rand

clf = SVC()
#params we need to try on classifier
param_dist = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_dist,cv=tscv,verbose=1,n_iter=15)
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
```

```
CPU times: user 0 ns, sys: 0 ns, total: 0 ns
Wall time: 7.63 µs
Fitting 10 folds for each of 15 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 327.5min finished
```

```
Best HyperParameter:  {'gamma': 0.01, 'C': 1000}
Best Accuracy: 89.86%
```

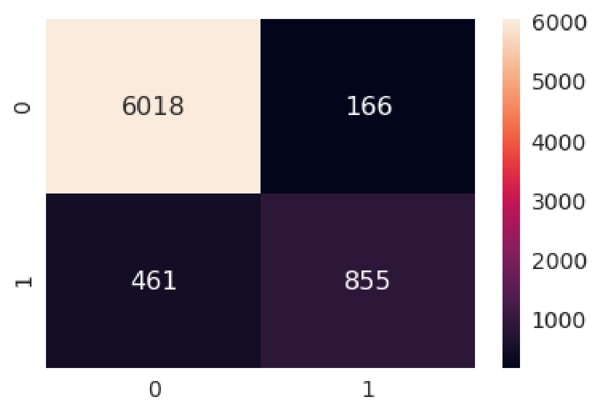
In [27]:

```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=1000,gamma=0.01)
clf.fit(X_train,y_train)
y_pred = clf.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: 91.640%
Precision on test set: 0.837
Recall on test set: 0.650
F1-Score on test set: 0.732
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff27d0e7b8>
```



Gensim

Gensim is a robust open-source vector space modeling and topic modeling toolkit

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 [28]:

```
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 [29]:

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

Out[29]:

```
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 [30]:

```
%%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 11.9 s, sys: 40 ms, total: 11.9 s
Wall time: 11.9 s
```

In [31]:

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

Out[31]:

```
False
```

In [32]:

```
mask = ~np.any(np.isnan(avg_vec_google), axis=1)
# print(mask)
avg_vec_google_new = avg_vec_google[mask]
df_sample_new = df_sample['Score'][mask]
print(avg_vec_google_new.shape)
print(df_sample_new.shape)
```

```
(25000, 300)
(25000,)
```

In [33]:

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

avg_vec_norm = preprocessing.normalize(avg_vec_google_new)

#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_new.values
,test_size=0.3,shuffle=False)
```

In [15]:

```
%time
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

clf = SVC()
```

```
param_grid = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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 225 candidates, totalling 2250 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 21.4min
[Parallel(n_jobs=-1)]: Done 410 tasks      | elapsed: 57.5min
[Parallel(n_jobs=-1)]: Done 760 tasks      | elapsed: 100.5min
[Parallel(n_jobs=-1)]: Done 1210 tasks      | elapsed: 150.8min
[Parallel(n_jobs=-1)]: Done 1760 tasks      | elapsed: 194.6min
[Parallel(n_jobs=-1)]: Done 2250 out of 2250 | elapsed: 211.4min finished
```

```
Best HyperParameter:  {'C': 5, 'gamma': 1}
Best Accuracy: 90.00%
```

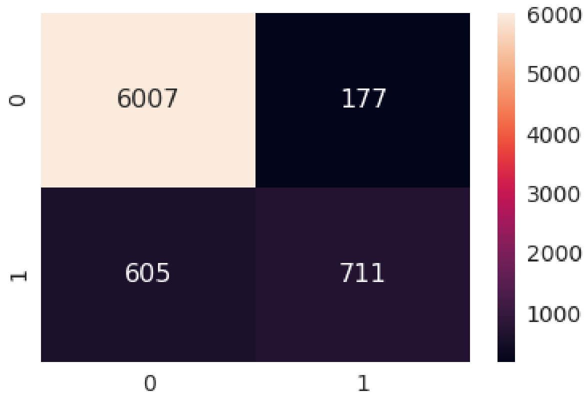
In [34]:

```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=5,gamma=1)
clf.fit(X_train,y_train)
y_pred = clf.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: 89.573%
Precision on test set: 0.801
Recall on test set: 0.540
F1-Score on test set: 0.645
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fffa111edd8>
```



Using Randomized Search CV to find best parameters

In [24]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from scipy.stats import uniform as sp_rand

clf = SVC()
#params we need to try on classifier
param_dist = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_dist,cv=tscv,verbose=1,n_iter=15)
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 15 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 294.9min finished
```

```
Best HyperParameter:  {'gamma': 0.005, 'C': 500}
Best Accuracy: 89.19%
```

In [35]:

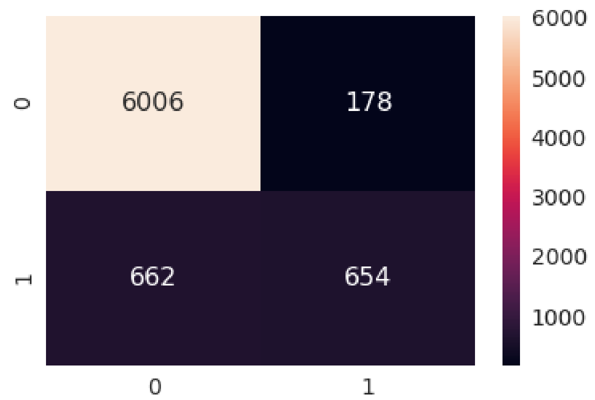
```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=500,gamma=0.005)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
```

```python
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: 88.800%
Precision on test set: 0.786
Recall on test set: 0.497
F1-Score on test set: 0.609
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[35]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffe14311ef0>
```



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 [11]:

```python
%%time
#Taking Sample Data as it was taking more that 10 hours to computer this block
n_samples = 25000
df_sample_new = df_sample.sample(n_samples)

###Sorting as we want according to time series
df_sample_new.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_new['CleanedText_NoStem'].values)

print(tfidf_vec_new.shape)

# tf-idf came up with 2.9 million features for the data corpus
# from sklearn.decomposition import TruncatedSVD

# tsvd_tfidf_ns = TruncatedSVD(n_components=300)#No of components as total
dimensions
# tsvd_tfidf_vec_ns = tsvd_tfidf_ns.fit_transform(tfidf_vec_ns)
# print(tsvd_tfidf_ns.explained_variance_ratio_[:].sum())
features = tfidf.get_feature_names()
```

```
(25000, 589499)
CPU times: user 6.15 s, sys: 16 ms, total: 6.16 s
Wall time: 6.16 s
```

In [ ]:

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

for sent in df_sample_new['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
        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")
```

In [2]:

```
#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 [3]:

```
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)
```

In [8]:

```
%time
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

clf = SVC()
param_grid = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
} #params we need to try on classifier
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 13.1 µs
Fitting 10 folds for each of 225 candidates, totalling 2250 fits
```

```
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   57.9s
[Parallel(n_jobs=-1)]: Done 160 tasks      | elapsed: 24.2min
[Parallel(n_jobs=-1)]: Done 410 tasks      | elapsed: 65.3min
[Parallel(n_jobs=-1)]: Done 760 tasks      | elapsed: 112.6min
[Parallel(n_jobs=-1)]: Done 1210 tasks      | elapsed: 163.2min
[Parallel(n_jobs=-1)]: Done 1760 tasks      | elapsed: 214.0min
[Parallel(n_jobs=-1)]: Done 2250 out of 2250 | elapsed: 235.1min finished
```

```
Best HyperParameter:  {'C': 5, 'gamma': 0.5}
Best Accuracy: 88.08%
```

In [13]:

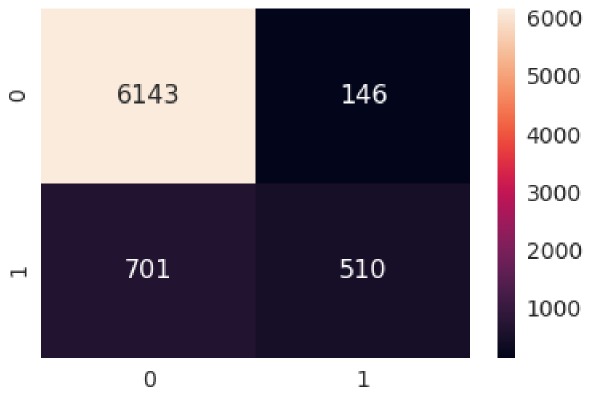
```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=5,gamma=0.5)
clf.fit(X_train,y_train)
```

```
y_pred = clf.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: 88.707%
Precision on test set: 0.777
Recall on test set: 0.421
F1-Score on test set: 0.546
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2d37d390>
```



Using Randomized Search CV to find best parameters

In [9]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC

clf = SVC()
#params we need to try on classifier
param_dist = {'gamma':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
0001],
             'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_dist,cv=tscv,verbose=1,n_iter=15)
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: 7.63 µs
Fitting 10 folds for each of 15 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed: 224.7min finished
```

```
Best HyperParameter:  {'gamma': 0.05, 'C': 1000}
Best Accuracy: 87.45%
```

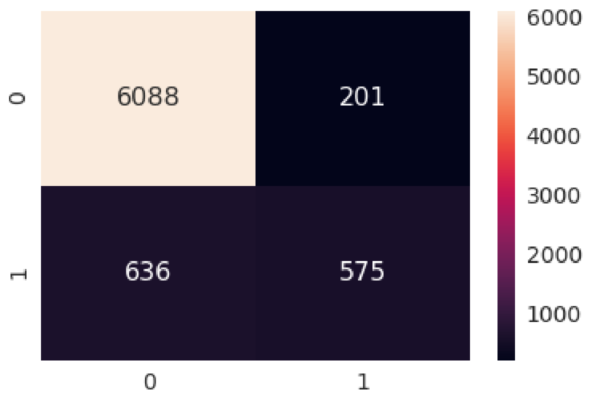
In [12]:

```
#Testing Accuracy on Test data
from sklearn.svm import SVC

clf = SVC(C=1000,gamma=0.05)
clf.fit(X_train,y_train)
y_pred = clf.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: 88.840%
Precision on test set: 0.741
Recall on test set: 0.475
F1-Score on test set: 0.579
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2dc43748>
```



Conclusions

Conclusions

1. Support Vector Machine(SVM) gave the best result better than other algos close to Logistic Regression
2. Tf-idf Featurization(C=1000,gamma=0.005) gave the best results with accuracy of 91.667% and F1-score of 0.733
3. SVM with RBF kernel the separating plane exists in another space - a result of kernel transformation of the original space. Its coefficients are not directly related to the input space. Hence we can't get the feature importance