Amazon Food Reviews - [Logistic Regression]

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

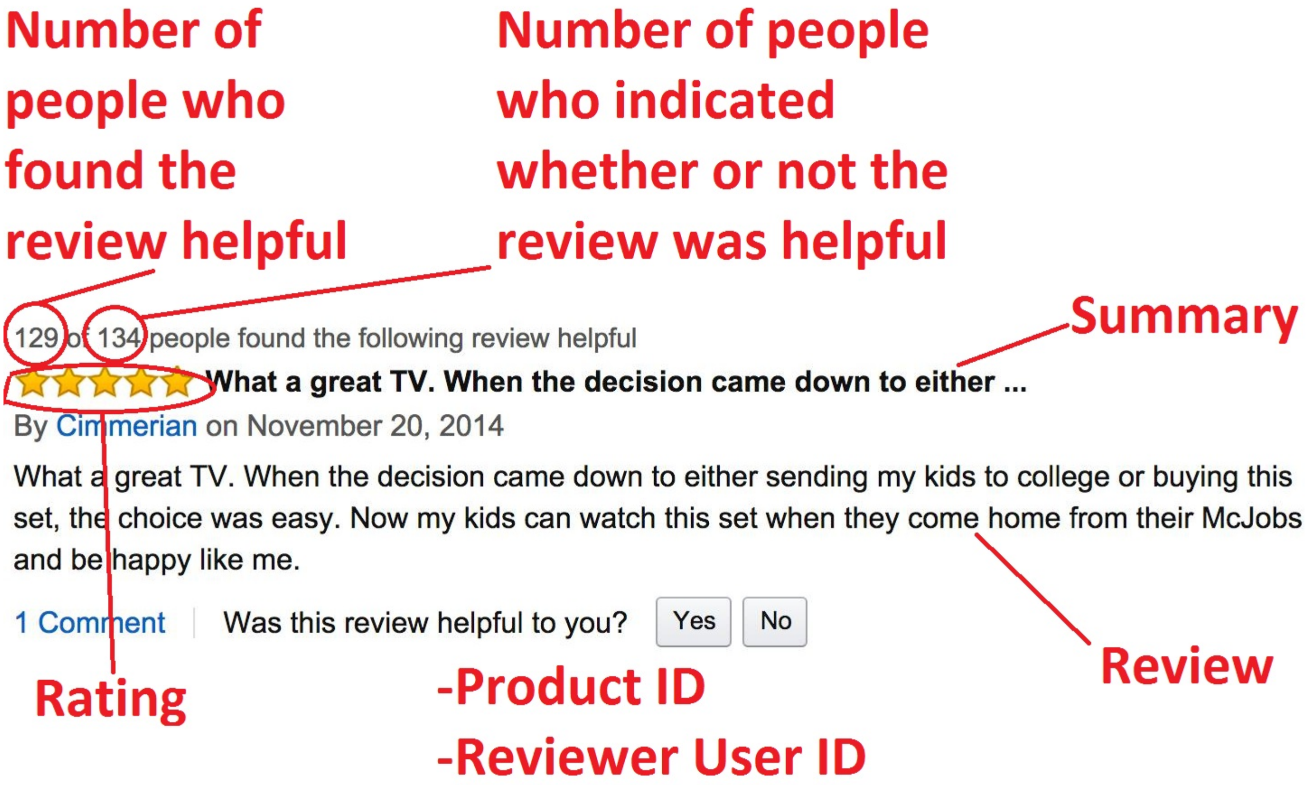
1. Applied Logistic Regression on Different Featurization of Data viz. BOW(uni-gram,bi-gram), tfidf, Avg-Word2Vec(using Word2Vec model pretrained on Google News) and tf-idf-Word2Vec
2. Used both Grid Search & Randomized Search Cross Validation
3. Evaluated the test data on various performance metrics like accuracy, f1-score, precision, recall,etc. also plotted Confusion matrix using seaborne
4. Showed How Sparsity increases as we increase lambda or decrease C when L1 Regularizer is used for each featurization
5. Did pertubation test to check whether the features are multi-collinear or not

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 [2]:

```
# !pip install --upgrade pip
# !pip install qtconsole ipywidgets widgetsnbextension
# !pip install seaborn
# !pip install nltk
# # import nltk
# # nltk.download("stopwords")
# !pip install gensim
```

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 frontends like the
Jupyter notebook,
#directly below the code cell that produced it. The resulting plots will then also be stored in th
e 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 [16]:

```
# !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" --h
eader="Accept:
text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,image/apng,*/*;q=0.8" --header="A
ccept-Language: en-US,en;q=0.9" --header="Cookie: _ga=GA1.2.1009651095.1527270727;
_xsrf=2|d66eb8d7|8e30b1015ec501038d0632ff567bddb6|1529904261;
session=.eJxVj9tugkAURX_FnGdi5FaBxKSgoiZKtYq0Ng0ZYIBRGBQGEY3_XjBt2r6us1f2PjdwjzhPEcWUgcbyEnOASha7Ll
oNOg3_gBoJaneSiIVh7x0UXf0wWsTyNNkZorCZKbm5Z6ZAgrAotpbZz3aC4fRn0vyqWFYujKlOp97YWF963kVdE10I-KoKzFLE
7OS9rtUzNmRnPlrOlq6a6Updnh00TspafjLEGJ18aSjtfRu4Zo0HGsD9885BgRL2GNiilX18tye70-
LNXLw4puw7vLzaWrWdxCN701OH0WAAjVQWOHcJDbPWxCkiSSPnxD_UKCCs-bLP889Ry7t-
lgIHIckL5lKU4iaoPzINTdAvnJRH1rJ_mc4PbQu_L39r2i2V55IANEWWROn-
BWX4gJ4.Dh00Fg.mP7VsxA46qaQLe4cyW_hdiRguhw" --header="Connection: keep-alive" "https://e-
2106e5ff6b.cognitiveclass.ai/files/Amazon%20Fine%20Food%20Reviews%20Dataset/GoogleNews-vectors-neg
ative300.bin?download=1" -O "GoogleNews-vectors-negative300.bin" -c
```

```
--2018-07-07 00:02:23--  https://e-
2106e5ff6b.cognitiveclass.ai/files/Amazon%20Fine%20Food%20Reviews%20Dataset/GoogleNews-vectors-neg
ative300.bin?download=1
Resolving e-2106e5ff6b.cognitiveclass.ai (e-2106e5ff6b.cognitiveclass.ai)... 169.53.184.237, 169.5
5.145.204
Connecting to e-2106e5ff6b.cognitiveclass.ai (e-
2106e5ff6b.cognitiveclass.ai)|169.53.184.237|:443... connected.
HTTP request sent, awaiting response... 416 Requested Range Not Satisfiable

    The file is already fully retrieved; nothing to do.
```

Loading the data

In [146]:

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

con = sql.connect("final.sqlite")#Loading Cleaned/ Preprocesed text that we did in Text
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[146]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	13
1									

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	13
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	12
3	3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	Negative	13
4	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	13

In [7]:

```
df.describe()
```

Out[7]:

	index	Id	HelpfulnessNumerator	HelpfulnessDenominator	Time
count	364171.000000	364171.000000	364171.000000	364171.000000	3.641710e+05
mean	241825.377603	261814.561014	1.739021	2.186841	1.296135e+09
std	154519.869452	166958.768333	6.723921	7.348482	4.864772e+07
min	0.000000	1.000000	0.000000	0.000000	9.393408e+08
25%	104427.500000	113379.500000	0.000000	0.000000	1.270858e+09
50%	230033.000000	249445.000000	0.000000	1.000000	1.311379e+09
75%	376763.500000	407408.500000	2.000000	2.000000	1.332893e+09
max	525813.000000	568454.000000	866.000000	878.000000	1.351210e+09

In [8]:

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

Out[8]:

```
364171
```

For EDA and Text Preprecessing Refer other ipynb notebook

In [9]:

```
#Score as positive/negative -> 0/1
def polarity(x):
    if x == "Positive":
        return 0
    else:
        return 1
```

```
        return 1
df["Score"] = df["Score"].map(polarity) #Map all the scores as the function polarity i.e. positive
or negative
df.head()
```

Out[9]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	0	130
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	134
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	0	121
3	3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	1	130
4	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	0	135

In [10]:

```
#Taking Sample Data
n_samples = 50000
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[10]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator
117924	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
117901	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2
298792							

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator
	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0
298791	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0
169342	212533	230348	B00004RYGX	A1048CYU0OV4O8	Judy L. Eans	2	2
169320	212511	230326	B00004RYGX	A2DEE7F9XKP3ZR	jerome	0	3
169366	212557	230375	B00004RYGX	A3K3YJWV0N54ZO	Joey	2	3
169303	212494	230308	B00004RYGX	A3C3BAQDZWH5YE	Kushana no shinryaku (Kushana's invasion)	0	1
117349	138016	149787	B00004S1C6	A2XZKD83G4N9Y5	Cindy Elliott	43	45
117266	137933	149701	B00006L2ZT	A2STZ646VQE8QI	anomalogue	1	3

In [11]:

```
#Saving 50000 samples in disk to as to test to test on the same sample for each of all Algo
savetofile(df_sample,"sample_lr")
```

In [4]:

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

Logistic Regression Model on Reviews using Different Vectorizing Techniques 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 [209]:

```
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,df_sample['Scor
e'].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:  (35000, 42387)
Test Data Size:  (15000, 42387)
```

Observed that Data Normalization gives better accuracy rather than Data Standardization.
Hence used Data Normalization

In [52]:

```
#To show how Time Series Split splits the data
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)
```

```
(3190, 42387) (3181, 42387)
(6371, 42387) (3181, 42387)
(9552, 42387) (3181, 42387)
(12733, 42387) (3181, 42387)
(15914, 42387) (3181, 42387)
(19095, 42387) (3181, 42387)
(22276, 42387) (3181, 42387)
(25457, 42387) (3181, 42387)
(28638, 42387) (3181, 42387)
(31819, 42387) (3181, 42387)
```

Finding the best "C" or "1/lambda" and regularizer [L1 or L2] using Forward Chaining Cross Validation or Time Series CV

On Whole Dataset

In [13]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'penalty':['l1','l2']}
```

```
                'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 7.63 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 201.6min finished
```

```
Best HyperParameter:  {'C': 0.05, 'penalty': 'l1'}
Best Accuracy: 91.37%
```

Note:As it took long hours for training on whole dataset, did modelling on sample 50000 points

On 50K points

In [7]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 11.9 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  2.5min finished
```

```
Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 90.94%
```

With 'C': 10 & 'penalty': 'l2' uni_gram has the highest accuracy of 90.94% in Cross Validation

In [54]:

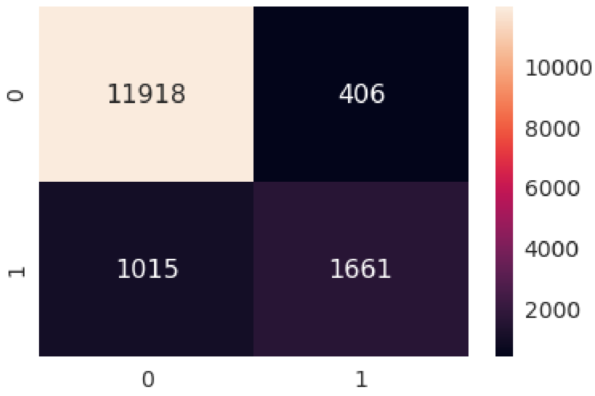
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 90.527%
Precision on test set: 0.804
Recall on test set: 0.621
F1-Score on test set: 0.700
Non Zero weights: 42387
```

```
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff2020d320>
```



Showing how sparsity increases as we increase lambda or decrease C when L1 Regularizer is used

In [9]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 86.487%
F1-Score on test set: 0.623
Non Zero weights: 7244
```

In [10]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.107%
F1-Score on test set: 0.657
Non Zero weights: 6599
```

In [11]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.100%
F1-Score on test set: 0.699
```

```
Non Zero weights: 3690
```

In [12]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.247%
F1-Score on test set: 0.681
Non Zero weights: 700
```

In [13]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 86.087%
F1-Score on test set: 0.417
Non Zero weights: 101
```

In [14]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.173%
F1-Score on test set: 0.001
Non Zero weights: 3
```

We can see how drastically the sparsity increases from 7244 non-zero weights(@ C=1000) to only 3 non-zero weights(@ C=0.01) when we use L1 Regularization

Using Randomized Search CV to find best parameters

In [16]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#params we need to try on classifier
param_grid = { 'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,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 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.2min finished
```

```
Best HyperParameter:  {'penalty': 'l2', 'C': 5}
Best Accuracy: 90.74%
```

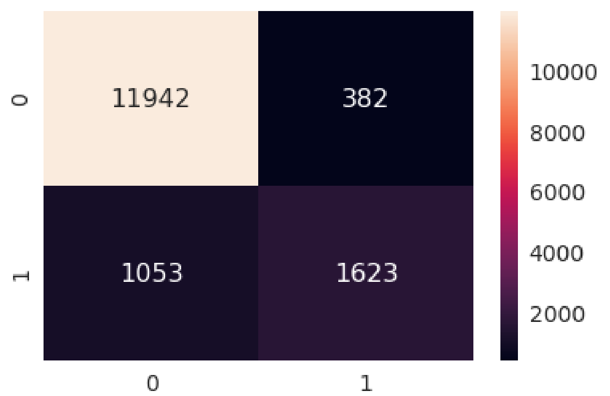
In [18]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 90.433%
Precision on test set: 0.809
Recall on test set: 0.607
F1-Score on test set: 0.693
Non Zero weights: 42387
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff1f2dab38>
```



Perturbation Test

In [210]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.527%
Non Zero weights: 42387
```

In [211]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[-1.89730274e-01 -3.15372263e-02 -6.76179169e-02 -5.11515825e-02
 -2.46214429e-02 -1.44501314e-02 -2.72618635e-01 -2.70065305e-01
 -6.28786581e-03 -6.11281646e-03 -9.66713082e-02  3.86776364e-01
  5.10933235e-01 -7.79666695e-03  1.21828724e-01  2.10066534e-01
  5.66267795e-01  1.24596872e-01 -2.44259460e-01 -1.32921619e-01
  1.70863867e-01 -1.16295181e-01 -5.53461924e-04  7.05172041e-02
  3.58983574e-02 -1.27481892e-01 -1.86824715e+00 -2.12679597e-02
 -6.81274598e-03 -2.29483656e-03 -8.37846437e-01 -8.11102012e-02
 -5.03645443e-02  2.04508909e+00  7.34631489e-01 -1.34789365e-01
 -1.04276355e-01 -1.43209680e-01 -2.29996110e-02 -2.41604628e-03
 -8.67516315e-03 -1.97463221e-01  1.07459896e-01 -3.35453349e-02
 -7.77627187e-03 -5.93428253e-03  3.20286868e-02  6.30952106e-01
 -8.58717575e-01  5.61936901e-01]
```

In [213]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [214]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.533%
Non Zero weights: 42387
```

In [215]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[-1.89950968e-01 -3.16337282e-02 -6.77317107e-02 -5.14557246e-02
 -2.46485012e-02 -1.45444516e-02 -2.72725882e-01 -2.70411219e-01
 -6.30040600e-03 -6.14559790e-03 -9.70617160e-02  3.86567619e-01
  5.10745146e-01 -7.79650378e-03  1.21740390e-01  2.10257183e-01
  5.66312396e-01  1.24363187e-01 -2.43903726e-01 -1.33243048e-01
  1.69985119e-01 -1.16127064e-01 -5.54595155e-04  7.05977955e-02
  3.59816819e-02 -1.27319420e-01 -1.86985598e+00 -2.13052554e-02
 -6.78135230e-03 -2.31172184e-03 -8.36409663e-01 -8.07220024e-02
 -5.04655554e-02  2.04163986e+00  7.34509011e-01 -1.34830819e-01
 -1.03999990e-01 -1.43578978e-01 -2.30018789e-02 -2.42712664e-03
 -8.71110442e-03 -1.97894906e-01  1.07495595e-01 -3.35448984e-02
 -7.77044764e-03 -5.91318255e-03  3.20063922e-02  6.30819931e-01
 -8.56312263e-01  5.60739271e-01]
```

In [216]:

```
print(weights2.size)
```

```
42387
```

In [217]:

```python
weights_diff = (abs(weights1 - weights2)/weights1) * 100
```

In [218]:

```python
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
7
```

7 features have weight changes greater than 30%. Hence the features are multicollinear

Feature Importance[Top 25]

The coef_ attribute of MultinomialNB is a re-parameterization of the naive Bayes model as a linear classifier model. For a binary classification problems this is basically the log of the estimated probability of a feature given the positive class. It means that higher values mean more important features for the positive class.

In [36]:

```python
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
print("________________________________________________________________________________________________
")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(uni_gram,clf)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-scikit-learn-classifiers
```

```
   Positive       Negative
________________________________________________________________________________________________
 -9.4336 delici              16.1592 worst
 -9.0718 amaz                11.6414 horribl
 -8.6047 perfect             10.6778 aw
 -8.4199 awesom              10.2086 bland
 -7.9709 excel               9.9958 disgust
 -7.6686 worri               9.7113 threw
 -7.4284 best                9.6797 rip
 -7.4061 addict              9.5185 weak
 -7.2919 complaint           9.1535 terribl
 -7.0809 beat                8.4418 unfortun
 -6.9148 great               8.2694 tasteless
 -6.6750 fantast             8.0384 sad
 -6.5800 thank               7.8580 cancel
 -6.1000 hook                7.6008 return
 -5.8641 easi                7.4167 disappoint
 -5.8585 happi               7.1576 wors
 -5.8395 satisfi             6.7185 gross
 -5.6925 nice                6.4584 stale
 -5.6883 delight             6.3680 progresso
 -5.5883 favorit             6.3099 flavorless
 -5.5788 glad                6.2643 concept
 -5.5442 smooth              6.1646 shame
 -5.5388 yummi               6.1612 refund
 -5.4953 uniqu               6.1435 stuck
 -5.4449 yum                 6.0197 china
```

bi-gram

In [74]:

```
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,df_sample['Scor
e'].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:  (35000, 644387)
Test Data Size:  (15000, 644387)
```

In [75]:

```
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)
```

```
(3190, 644387) (3181, 644387)
(6371, 644387) (3181, 644387)
(9552, 644387) (3181, 644387)
(12733, 644387) (3181, 644387)
(15914, 644387) (3181, 644387)
(19095, 644387) (3181, 644387)
(22276, 644387) (3181, 644387)
(25457, 644387) (3181, 644387)
(28638, 644387) (3181, 644387)
(31819, 644387) (3181, 644387)
```

In [72]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 13.8 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  7.8min finished
```

```
Best HyperParameter:  {'C': 1000, 'penalty': 'l2'}
Best Accuracy: 91.52%
```

In [76]:

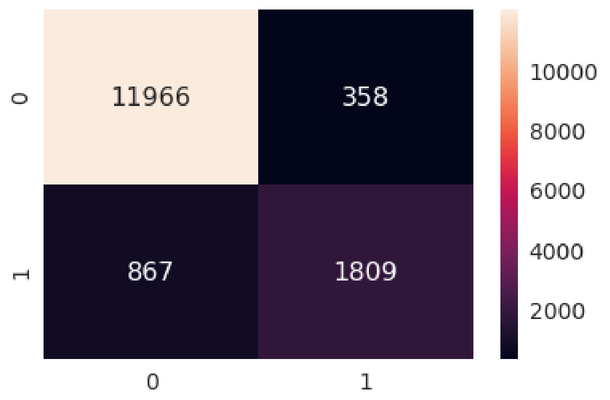
```
#Testing Accuracy on Test data
```

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 91.833%
Precision on test set: 0.835
Recall on test set: 0.676
F1-Score on test set: 0.747
Non Zero weights: 644387
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[76]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffde7daffd0>
```



Showing how sparsity increases as we increase lambda or decrease C when L1 Regularizer is used

In [77]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.140%
F1-Score on test set: 0.737
Non Zero weights: 8823
```

In [78]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.007%
F1-Score on test set: 0.734
Non Zero weights: 6708
```

In [79]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.347%
F1-Score on test set: 0.740
Non Zero weights: 4477
```

In [80]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.900%
F1-Score on test set: 0.706
Non Zero weights: 603
```

In [81]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 85.560%
F1-Score on test set: 0.381
Non Zero weights: 77
```

In [82]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.160%
F1-Score on test set: 0.000
Non Zero weights: 3
```

We can see how drastically the sparsity increases from 8823 non-zero weights(@ C=1000) to only 3 non-zero weights(@ C=0.01) when we use L1 Regularization

Using Randomized Search CV to find best parameters

In [73]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,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: 7.87 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  2.2min finished
```

```
Best HyperParameter:  {'penalty': 'l2', 'C': 500}
Best Accuracy: 91.49%
```

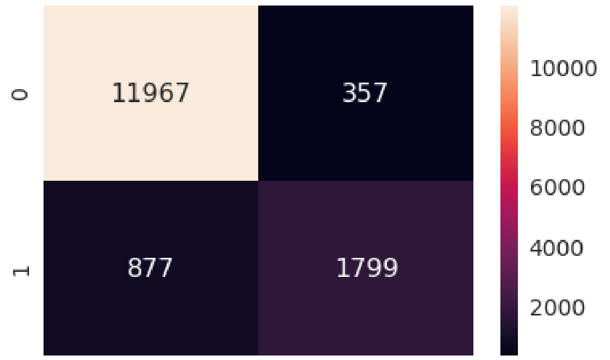
In [83]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 500, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 91.773%
Precision on test set: 0.834
Recall on test set: 0.672
F1-Score on test set: 0.745
Non Zero weights: 644387
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[83]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffde6f417f0>
```



0 1

Perturbation Test

In [84]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 500, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.773%
Non Zero weights: 644387
```

In [85]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[-4.97137908e-01 -4.97137908e-01 -5.84217060e-02 -5.84217060e-02
 -1.23929100e-01 -1.23929100e-01  4.38441778e-02 -1.07166825e-03
  3.30453714e-01 -1.07166825e-03 -6.83411769e-03 -7.17536471e-02
 -2.05878435e-01 -4.69698002e-02 -4.69698002e-02 -3.84751260e-02
 -3.15771985e-01 -2.56049922e-01 -4.12238618e-02 -1.84982012e-02
 -4.55092965e-01 -4.55092965e-01 -1.21459045e-02 -1.21459045e-02
 -4.34096846e-03 -2.86503408e-03 -1.47593438e-03 -3.44149642e-01
 -6.47980593e-04 -7.66443512e-03 -1.50013237e-02 -1.24062532e-02
 -3.08429649e-01  1.22563290e-01 -1.81367585e-01 -3.54951001e-03
 -9.13721821e-02  1.11686996e+00 -4.06404172e-01  2.02162972e-01
 -4.28554124e-01 -2.13171351e-04 -7.32671914e-02 -1.17417101e-02
  8.75326096e-01  8.75326096e-01 -4.30193168e-03 -4.30193168e-03
  2.61906723e-01 -2.45669888e-03]
```

In [87]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [88]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.633%
Non Zero weights: 644387
```

In [89]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(clf.coef_[0])[2]
```

```
print(weights2[:50])
```

```
[-1.24145710e-01 -1.24113896e-01 -3.21139353e-02 -3.20662337e-02
 -3.33904342e-02 -3.33695076e-02 -1.50775005e-02 -1.70652188e-03
  8.64015215e-02 -1.71544595e-03 -8.53974448e-03 -2.75940246e-02
 -6.28770794e-02 -1.95490165e-02 -1.95445236e-02 -2.31152193e-02
 -1.08878715e-01 -6.81260871e-02 -2.92657195e-02 -1.14572486e-02
 -1.12921661e-01 -1.12783705e-01 -9.94567724e-03 -9.95208209e-03
 -6.52260869e-03 -4.09800739e-03 -2.41567910e-03 -1.21254219e-01
 -1.06524044e-03 -1.15698582e-02 -1.24045561e-02 -6.52658745e-03
 -8.97176912e-02  8.33475329e-02 -7.22822623e-02 -3.81675413e-03
 -2.54951492e-02  3.70323277e-01 -8.04004336e-02  6.36101115e-02
 -1.17695636e-01 -1.45649578e-04 -4.31346004e-02 -7.93194596e-03
  2.83539371e-01  2.83508388e-01 -3.89563011e-03 -3.88617672e-03
  9.82629918e-02 -3.28661806e-03]
```

In [90]:

```
print(weights2.size)
```

```
644387
```

In [91]:

```
weights_diff = (abs(weights1 - weights2)/weights1) * 100
```

In [92]:

```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
429828
```

429828 features have weight changes greater than 30%. Hence the features are multicollinear

Feature Importance[Top 25]

In [93]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")

print("________________________________________________________________________________________________
")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(bi_gram,clf)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-scikit-learn-classifiers
```

```
   Positive       Negative
________________________________________________________________________________________________
 -10.9352 delici           15.1738 worst
 -10.3282 not disappoint   11.7104 horribl
 -10.0780 perfect          11.1874 aw
 -8.7928 amaz             10.9359 disappoint
 -8.6609 excel            10.8218 bland
 -8.6511 best             9.9192 terribl
 -8.4428 great            9.5863 weak
 -7.8331 awesom           9.2938 not worth
 -7.8283 high recommend   9.1916 not good
 -7.3019 happi            9.0991 unfortun
 -7.1258 thank            8.8704 threw
 -6.9936 wont disappoint  8.7462 disgust
 -6.9529 addict           8.7388 rip
 -6.8050 easi             8.3193 return
```

```
-6.7481 nice             7.9911 wont buy
-6.7082 not bad          7.6422 stale
-6.6801 favorit          7.6007 tasteless
-6.4899 complaint        7.5885 not buy
-6.4568 enjoy            6.8305 not recommend
-6.4429 love             6.6511 wast
-6.2228 fantast          6.5981 sad
-6.1705 without          6.5768 wors
-6.1258 worri            6.3138 poor
-5.9825 realli like      6.3032 nasti
-5.8626 wonder           6.2553 gross
```

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 [94]:

```
%%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=0.3,shuffle=Fa


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:  (35000, 644387)
Test Data Size:  (15000, 644387)
CPU times: user 8.26 s, sys: 8 ms, total: 8.27 s
Wall time: 8.26 s
```

In [42]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 7.87 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  4.8min finished
```

```
Best HyperParameter:  {'C': 5, 'penalty': 'l1'}
Best Accuracy: 91.41%
```

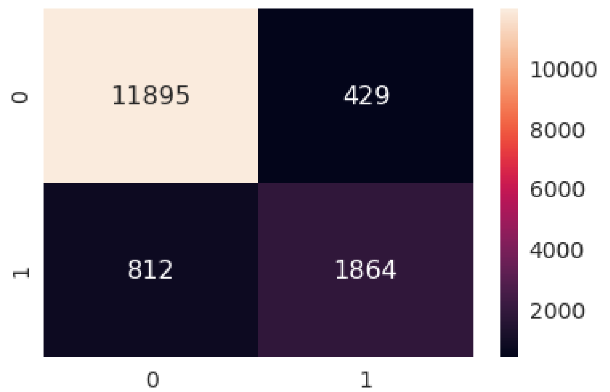
In [115]:

```python
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l1')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 91.727%
Precision on test set: 0.813
Recall on test set: 0.697
F1-Score on test set: 0.750
Non Zero weights: 3191
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[115]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffde6c3d080>
```



Showing how sparsity increases as we increase lambda or decrease C when L1 Regularizer is used

In [99]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.533%
F1-Score on test set: 0.747
Non Zero weights: 10783
```

In [100]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.427%
F1-Score on test set: 0.747
Non Zero weights: 7808
```

In [101]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.667%
F1-Score on test set: 0.751
Non Zero weights: 5296
```

In [102]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.920%
F1-Score on test set: 0.706
Non Zero weights: 531
```

In [103]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 84.220%
F1-Score on test set: 0.250
Non Zero weights: 34
```

In [104]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
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("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.160%
F1-Score on test set: 0.000
Non Zero weights: 0
```

We can see how drastically the sparsity increases from 10783 non-zero weights(@ C=1000) to only 0 non-zero weights(@ C=0.01) when we use L1 Regularization

Using Randomized Search CV to find best parameters

In [43]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
              ,'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,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 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.2min finished
```

```
Best HyperParameter:  {'penalty': 'l1', 'C': 5}
Best Accuracy: 91.41%
```

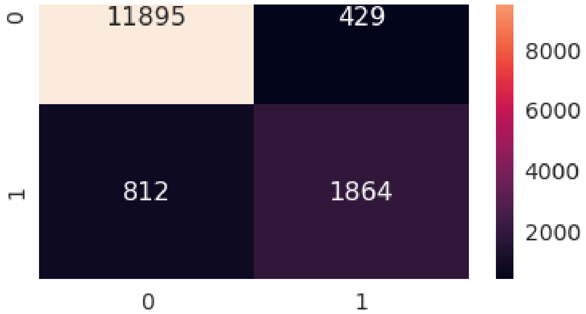
In [98]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l1')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 91.727%
Precision on test set: 0.813
Recall on test set: 0.697
F1-Score on test set: 0.750
Non Zero weights: 3209
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[98]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff14d50d68>
```



Perturbation Test

In [105]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 500, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.853%
Non Zero weights: 644387
```

In [106]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[-5.14122398e-01 -5.14122398e-01 -9.70979989e-02 -9.70979989e-02
 -1.49996430e-01 -1.49996430e-01 -2.54716375e-02 -2.81286695e-03
  2.94969888e-01 -2.81286695e-03 -1.28112759e-02 -1.27011618e-01
 -1.77886329e-01 -7.62921898e-02 -7.62921898e-02 -8.65406018e-02
 -4.15353324e-01 -3.35605681e-01 -7.92290143e-02 -2.90891981e-02
 -3.65625868e-01 -3.65625868e-01 -5.61273312e-02 -5.61273312e-02
 -1.16026156e-02 -8.70806203e-03 -3.34845356e-03 -3.31971561e-01
 -2.91935816e-03 -2.54206697e-02 -1.99292204e-02 -2.03068214e-02
 -3.01105552e-01  5.48047177e-02 -2.24344061e-01 -1.01005419e-02
 -1.18044621e-01  1.10187686e+00 -3.97504572e-01  2.95661236e-01
 -3.67844617e-01 -1.07900513e-03 -1.71205297e-01 -1.99941656e-02
  8.10552718e-01  8.10552718e-01 -1.04237166e-02 -1.04237166e-02
  4.33917837e-01 -1.63892098e-02]
```

In [107]:

```
print(weights1[weights1<=0.0001])
```

```
[-0.5141224  -0.5141224  -0.097098   ... -0.26021552 -0.01791669
 -0.01791669]
```

In [108]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [109]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 91.520%
Non Zero weights: 644387
```

In [110]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[-0.15587652 -0.15597608 -0.04543422 -0.04543933 -0.04754008 -0.0475538
 -0.0250883  -0.00373324  0.09970389 -0.00373599 -0.01280653 -0.04623585
 -0.06115771 -0.03279188 -0.03277948 -0.04007195 -0.14799953 -0.10177153
 -0.04003041 -0.01644891 -0.10673    -0.1067302  -0.03420053 -0.03419896
 -0.01520742 -0.01038264 -0.00541653 -0.13845381 -0.00472608 -0.02809518
 -0.01766471 -0.00828539 -0.09539501  0.05081769 -0.0779084  -0.00799419
 -0.04140253  0.40861503 -0.11099605  0.10783114 -0.11704848 -0.00118688
 -0.078718   -0.01259025  0.28945277  0.28964156 -0.00692778 -0.00691456
  0.16440902 -0.01437935]
```

In [111]:

```
print(weights2.size)
```

```
644387
```

In [112]:

```
weights_diff = (abs(weights1 - weights2)/weights1) * 100
```

In [113]:

```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
466374
```

466374 features have weight changes greater than 30%. Hence the features are multicollinear

Feature Importance[Top 25]

In [116]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")

print("_______________________________________________________________________________________________
")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(tfidf,clf)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-
for-scikit-learn-classifiers
```

```
   Positive       Negative
```

```
-37.4914 not disappoint      34.9910 worst
-30.1751 great               33.2723 two star
-28.4580 delici              25.0295 disappoint
-23.6620 wont disappoint     24.0939 horribl
-23.2881 perfect             22.8940 aw
-22.7462 best                22.8809 not worth
-22.1884 excel               22.4072 wont buy
-22.1436 amaz                21.5545 conglomer
-22.0387 love                21.4801 avail cup
-20.3228 month would         21.1732 threw
-19.5629 awesom              20.7827 bland
-19.0868 high recommend      19.7006 disgust
-18.0942 good                19.6385 terribl
-17.6643 happi               19.2560 almond still
-17.1094 complaint           19.0726 though purchas
-17.0805 thank               19.0681 deceiv
-16.8376 beat                19.0123 everyth better
-16.5115 worri               18.6616 rip
-16.4885 box disappoint      18.4955 great review
-16.3780 addict              17.6317 lack flavor
-15.9790 inform not          17.6239 may good
-15.4248 favorit             17.2773 wont purchas
-15.1369 nice                17.2308 elong
-15.0859 not overpow         17.2063 weak
-14.8947 not overwhelm       16.8209 quick cook
```

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 [44]:

```
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 [45]:

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

Out[45]:

```
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 [117]:

```
%%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 27.2 s, sys: 32 ms, total: 27.2 s
Wall time: 27.2 s
```

In [118]:

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

Out[118]:

```
False
```

In [119]:

```
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)
```

```
(50000, 300)
(50000,)
```

In [120]:

```
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
#Normalizing the data
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 [121]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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: 13.4 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 15.8min finished
```

```
Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 89.64%
```

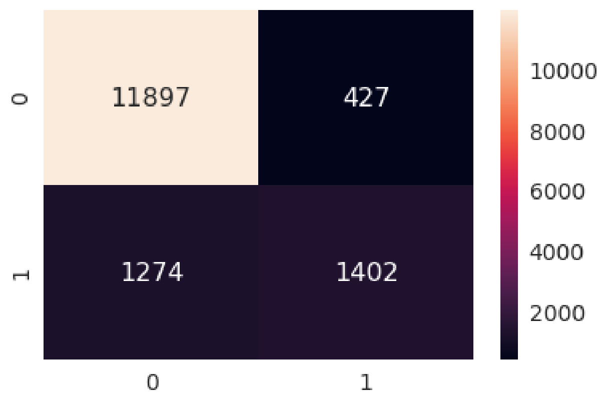
In [123]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 88.660%
Precision on test set: 0.767
Recall on test set: 0.524
F1-Score on test set: 0.622
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[123]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffe1957a2b0>
```



Using Randomized Search CV to find best parameters

In [122]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C': [1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
              ,'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,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 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  7.3min finished
```

```
Best HyperParameter:  {'penalty': 'l2', 'C': 10}
Best Accuracy: 89.64%
```

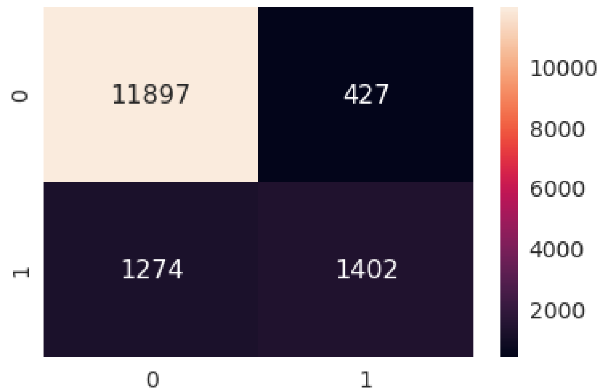
In [124]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 88.660%
Precision on test set: 0.767
Recall on test set: 0.524
F1-Score on test set: 0.622
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[124]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3ffde9ee6780>
```



Perturbation Test

In [134]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.660%
Non Zero weights:  300
```

In [135]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 4.26258629  0.12098269  7.08844436 -0.66706394 -3.22213119  0.83932454
 -1.06249836  0.33011011  0.31650731 -2.80676608  1.67766647 -2.10591555
 -1.97793342 -0.09013749 -1.51676614 -0.34577354 -0.25145424 -2.42067655
  0.15327152 -2.97624974 -0.99996899  5.10614554 -1.12699447 -2.44507472
  2.16794255  3.1501575   5.0282679   1.99578758  2.01132991 -0.14984294
 -0.49635989  1.92559871 -4.8872274  -2.94824343 -1.92820132  0.52873409
  0.75546695  3.78588235 -3.81553643 -0.92564545  0.40446639  4.31123745
  2.14691015 -6.52091446  0.65664225 -5.73615881 -2.12450831  1.62496885
 -3.75560091 -1.23236102]
```

In [137]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [138]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.607%
Non Zero weights:  300
```

In [139]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 4.00111359  0.27079926  6.90660173 -0.55721335 -2.78309505  0.84890116
 -0.84329924  0.66282238  0.76578684 -2.29616506  1.79098079 -2.0569662
 -1.70449602 -0.55047652 -1.36573252 -0.05028414 -0.73236221 -1.81448173
  0.20120897 -3.23117731 -0.73259299  4.50730526 -1.02399772 -2.495684
  2.76067807  2.96094362  5.07062685  1.44240433  1.98217538  0.23770079
 -1.02771496  1.99046737 -4.62283693 -3.04400302 -1.16898487  0.42481391
  0.27535089  3.5393455  -3.48742961 -1.0945706   0.28104383  3.80372019
  2.26410205 -6.28802575  0.60257142 -5.42097132 -1.89090069  1.59199664
 -3.69643383 -1.13076167]
```

In [140]:

```
print(weights2.size)
```

```
300
```

In [141]:

```
weights_diff = (abs(weights1 - weights2)/weights1) * 100
```

In [142]:

```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
41
```

41 features have weight changes greater than 30%. Hence the features are multicollinear

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 [220]:

```
%%time
###tf-idf with No Stemming
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from scipy.sparse import vstack

#Taking sample of only 25k points as it takes a huge amount of time ot compute
n_samples = 25000
df_sample_new = df_sample.sample(n_samples)
X_train, X_test, y_train, y_test =
train_test_split(df_sample_new['CleanedText_NoStem'].values,df_sample_new['Score'].values,test_size
,shuffle=False)

tfidf = TfidfVectorizer(ngram_range=(1,2)) #Using bi-grams
tfidf_vec_train = tfidf.fit_transform(X_train)
tfidf_vec_test = tfidf.transform(X_test)
print(tfidf_vec_train.shape)
print(tfidf_vec_test.shape)

#Concatenating sparse matrix vertically
tfidf_vec_new = vstack((tfidf_vec_train,tfidf_vec_test))
print(tfidf_vec.shape)
features = tfidf.get_feature_names()
```

In [219]:

```
savetofile(df_sample_new,"df_sample_new_tfidfw2vec")
```

In [179]:

```
%%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_new[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")
```

```
CPU times: user 4h 22min 47s, sys: 1.29 s, total: 4h 22min 48s
Wall time: 4h 22min 50s
```

In [180]:

```
#Precomputed File
tfidf_w2v_vec_google = openfromfile("tfidf_w2v_vec_google")
```

In [181]:

```
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'].value
s,test_size=0.3,shuffle=False)
```

In [182]:

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

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
             'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,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 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  5.4min finished
```

```
Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 87.74%
```

In [184]:

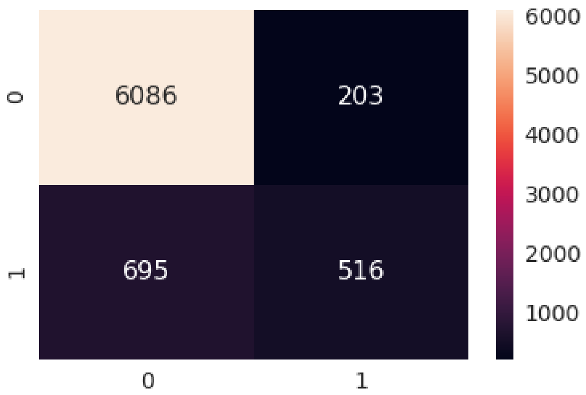
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 88.027%
Precision on test set: 0.718
Recall on test set: 0.426
F1-Score on test set: 0.535
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[184]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff13a0e4e0>
```



Using Randomized Search CV to find best parameters

In [185]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001],
              'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,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 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.8min finished
```

```
Best HyperParameter:  {'penalty': 'l2', 'C': 5}
Best Accuracy: 87.62%
```

In [196]:

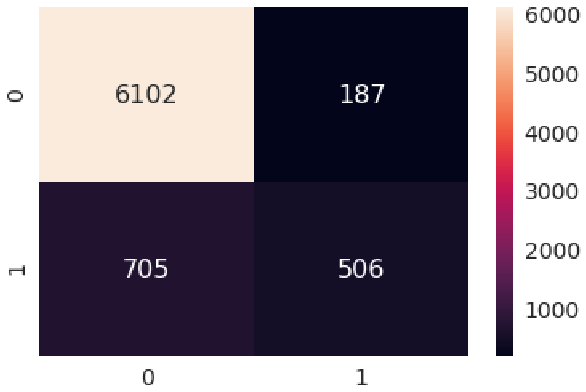
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
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: 88.107%
Precision on test set: 0.730
Recall on test set: 0.418
F1-Score on test set: 0.532
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[196]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x3fff13001ef0>
```



Perturbation Test

In [197]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
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("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.107%
Non Zero weights: 300
```

In [198]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 3.10151061  1.72523901  4.18887132  0.16375073 -2.51851256  0.97308008
  0.08162623  0.23531025  0.73570135 -1.95731002 -0.60585601 -1.26774866
 -2.10732433 -0.36280815 -0.61587658  0.52346719  1.65458894 -0.58372329
 -1.79489363 -2.15776457 -2.16090352  4.11836729 -1.37524263 -1.10998323
  2.02729197  2.75404629  2.49513363  1.75112354  1.55761229  1.71715067
  0.08938148  0.36730124 -4.24163495 -3.39895827 -0.88316211 -0.69113141
  1.0457133   1.93014494 -2.48846581 -2.15743005 -1.41559517  2.29019006
  2.10964695 -4.81383609  1.61361531 -4.61094159 -1.5392353   1.08822612
 -2.10770816 -0.45117846]
```

In [199]:

```
X_train_t = X_train
```

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [200]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.027%
Non Zero weights: 300
```

In [201]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 3.32863502e+00  1.91410599e+00  4.46057983e+00  3.22382231e-01
 -2.66805069e+00  9.30998893e-01 -2.68977922e-03  2.85652005e-01
  6.59404102e-01 -2.31390370e+00 -6.10943686e-01 -1.31754148e+00
 -2.27255672e+00 -4.20454187e-01 -6.27159405e-01  5.64817159e-01
  1.87802167e+00 -5.28205249e-01 -2.12069729e+00 -2.37449021e+00
 -2.42989600e+00  4.65303452e+00 -1.50391502e+00 -1.02257257e+00
  2.19813852e+00  3.16556827e+00  2.43228981e+00  2.20407793e+00
  1.67229306e+00  1.89214118e+00  1.13923914e-01  5.05650550e-01
 -4.81840445e+00 -3.57565679e+00 -1.07533604e+00 -9.62125001e-01
  9.49330453e-01  2.10268875e+00 -2.72864177e+00 -2.44466075e+00
 -1.64034258e+00  2.63342893e+00  2.24723645e+00 -5.40507517e+00
  1.78372197e+00 -5.18835798e+00 -1.91904475e+00  1.04447897e+00
 -2.18475429e+00 -4.78960953e-01]
```

In [202]:

```
print(weights2.size)
```

```
300
```

In [207]:

```
weights_diff = (abs(weights2 - weights1)/weights1) * 100
```

In [208]:

```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
22
```

22 features have weight changes greater than 30%. Hence the features are multicollinear

Performance Table

Logistic Regression (with 50k points)

Featurization	CV	Accuracy	F1-Score
Uni - gram	GridSearch CV	90.527	0.7
	Randomized Search CV	90.433	0.693
Bi -gram	GridSearch CV	88.63	0.554
	Randomized Search CV	88.68	0.542
tfidf	GridSearch CV	88.63	0.554
	Randomized Search CV	88.2	0.507
Avg Word2Vec	GridSearch CV	88.66	0.622
	Randomized Search CV	88.66	0.622
tfidf - Word2vec	GridSearch CV	88.027	0.535
	Randomized Search CV	88.107	0.532

Conclusion

1. **Features are multi-collinear i.e. they are co-related**
2. **Unigram Featurization performs best with accuracy of 90.527 and F1-Score of 0.7**
3. **Sparsity increases as we increase lambda or decrease C when L1 Regularizer is used**