objective :

Applying knn to classify the amazon food reviews.

In [1]:
```
import sqlite3 as s
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.cross_validation import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import confusion_matrix
```

```
C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: D
eprecationWarning: This module was deprecated in version 0.18 in favor of the m
odel_selection module into which all the refactored classes and functions are m
oved. Also note that the interface of the new CV iterators are different from t
hat of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
con=s.connect("database.sqlite")
con
```

Out[2]:
```
<sqlite3.Connection at 0x1f20bf263b0>
```

In [3]:
```
data=pd.read_sql_query("SELECT * FROM Reviews WHERE Score!=3",con)
data.head(5)
```

Out[3]:

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

In [4]:
```
#function to change the score to positive/negative
def change(x):
    if x<3:
        return 'negative'
    else:
        return 'positive'
```

In [5]:
```
a_s=data.Score
a_s=a_s.map(change)
data.Score=a_s
data.Score.head(5)
```

Out[5]:
```
0    positive
1    negative
2    positive
3    negative
4    positive
Name: Score, dtype: object
```

Data cleaning

The data needs to get clean as it may have some unwanted things such as duplicates.

In [6]:
```
#sorting the values by product ids
data=data.sort_values("ProductId")
```

In [7]:
```
#removing the duplicates from the data
final_data=data.drop_duplicates(subset={"UserId","Text","ProfileName","Time"},kee
```

In [8]:
```
print(final_data.shape)
print(final_data.Score.value_counts())
```

```
(364173, 10)
positive    307063
negative     57110
Name: Score, dtype: int64
```

In [9]:
```
p_data=final_data[final_data.Score=="positive"]
n_data=final_data[final_data.Score=="negative"]
```

In [14]:
```
#randomly selecting points
p_data=p_data.sample(17000)
n_data=n_data.sample(3000)
p_8=p_data.head(8000)
n_8=n_data.head(2000)
```

In [15]:
```
print(p_data.shape,n_data.shape,p_8.shape,n_8.shape)
```

```
(17000, 10) (3000, 10) (8000, 10) (2000, 10)
```

In [16]:
```
#d is to use for brute force and kd is to use for kd_tree
d=pd.concat((p_data,n_data))
kd=pd.concat((p_8,n_8))
```

In [18]:
```
print(d.shape,kd.shape)
```

```
(20000, 10) (10000, 10)
```

In [19]:
```
#sorting according to time stamp
d=d.sort_values('Time')
kd=kd.sort_values('Time')
```

In [20]:
```
print(d.Score.value_counts(),kd.Score.value_counts())
```

```
positive    17000
negative     3000
Name: Score, dtype: int64 positive    8000
negative    2000
Name: Score, dtype: int64
```

Data preprocessing

The data should be preprocessed after cleaning it

In [21]:
```
import string
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
import re
```

In [22]:
```
#stopwords
stop_words=set(stopwords.words("english"))
#initializing snowball stemmer
sno=SnowballStemmer("english")
```

In [23]:
```
#function to remove html tags
def cleanhtml(s):
    cleanr=re.compile("<.*?>")
    cleant=re.sub(cleanr," ",s)
    return cleant
```

In [24]:
```
#funtion to remove punctuation and special character
def cleanpunc(s):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',s)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [25]:
```
i=0
final=[]

for s in d.Text.values:
    f=[]
    c=cleanhtml(s)
    for w in cleanpunc(c).split():
        if w.isalpha() and len(w)>2:
            if w not in stop_words:
                sne=(sno.stem(w.lower())).encode('utf-8')
                f.append(sne)

            else:
                continue
        else:
            continue
    te=b" ".join(f)
    final.append(te)
    i+=1
```

In [26]:
```
#adding the preprocessed data into another column
d["cleaned"]=final
```

In [27]:
```
i=0
kfinal=[]

for s in kd.Text.values:
    f=[]
    c=cleanhtml(s)
    for w in cleanpunc(c).split():
        if w.isalpha() and len(w)>2:
            if w not in stop_words:
                sne=(sno.stem(w.lower())).encode('utf-8')
                f.append(sne)

            else:
                continue
        else:
            continue
    te=b" ".join(f)
    kfinal.append(te)
    i+=1
```

In [28]:
```
kd["cleaned"]=kfinal
```

In [31]:
```
#checking if new column is added
d.columns
```

Out[31]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'cleaned'],
      dtype='object')
```

In [32]:
```
#checking if the column is added
kd.columns
```

Out[32]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'cleaned'],
      dtype='object')
```

In [33]:
```
import sqlite3
conn=sqlite3.connect("future.sqlite")
c=conn.cursor()
conn.text_factory=str
d.to_sql('Reviews',conn,if_exists='replace',index=True)
```

Lets create two functions for brute force and kd_tree,so, that we don't have to write it again and again

In [74]:
```
#function for brute force algorithm
def main(h,j,k,l):
    #gridsearchcv

    #params we need to try on classifier
    knn = KNeighborsClassifier(algorithm='brute')
    param_grid = {'n_neighbors':np.arange(1,40,2)}
    #For time based splitting
    t = TimeSeriesSplit(n_splits=5)
    gsv = GridSearchCV(knn,param_grid,cv=t)
    gsv.fit(h,j)
    print("Best HyperParameter: ",gsv.best_params_)
    print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
    print("best estimator: ",gsv.estimator)
    gsv.estimator.fit(h,j)
    pred=gsv.estimator.predict(k)
    #accuracy
    acc=accuracy_score(l,pred)*100
    print("the accuracy is %.2f%%"%acc)
    df_cm=pd.DataFrame(confusion_matrix(l,pred))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm,annot=True,fmt="d")
```

In [46]:
```
#function for kd_tree
def kmain(h,j,k,l):
    #gridsearchcv

    #params we need to try on classifier
    knn = KNeighborsClassifier(algorithm='kd_tree')
    param_grid = {'n_neighbors':np.arange(1,40,2)}
    #For time based splitting
    t = TimeSeriesSplit(n_splits=5)
    gsv = GridSearchCV(knn,param_grid,cv=t)
    gsv.fit(h,j)
    print("Best HyperParameter: ",gsv.best_params_)
    print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
    print("best estimator: ",gsv.estimator)
    gsv.estimator.fit(h,j)
    pred=gsv.estimator.predict(k)
    #accuracy
    acc=accuracy_score(l,pred)*100
    print("the accuracy is %.2f%%"%acc)
    df_cm=pd.DataFrame(confusion_matrix(l,pred))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm,annot=True,fmt="d")
```

Bag of words

Brute Force algorithm

In [107]:
```
x_1, x_test, y_1, y_test = train_test_split(d.cleaned.values, d.Score, test_size=(

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [108]:
```
print(x_1.shape,x_test.shape,y_1.shape,y_test.shape)
```

```
(14000,) (6000,) (14000,) (6000,)
```

In [109]:
```
from sklearn.feature_extraction.text import CountVectorizer
```

In [110]:
```
#bigrams
count_vect=CountVectorizer(ngram_range=(1,2))
```

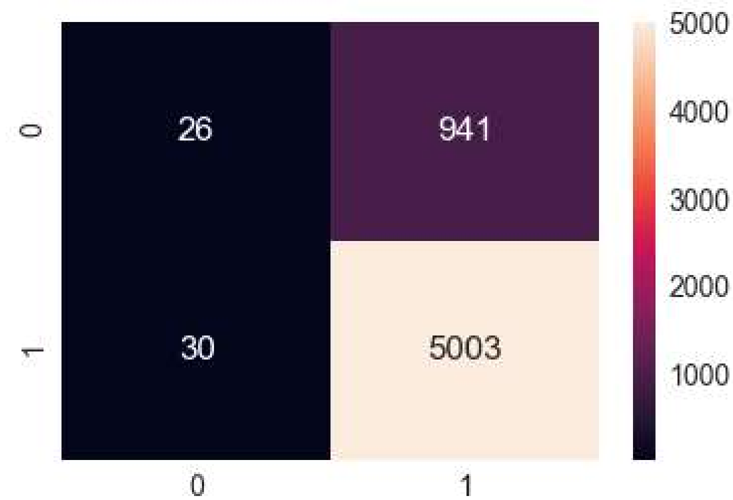
In [111]:
```
bdata=count_vect.fit_transform(x_1)

test_data=count_vect.transform(x_test)
print(bdata.shape,y_1.shape,test_data.shape,y_test.shape)
```

```
(14000, 308946) (14000,) (6000, 308946) (6000,)
```

In [112]:
```
%%time
main(bdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 7}
Best Accuracy: 84.62%
best estimator:  KNeighborsClassifier(algorithm='brute', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 83.82%
Wall time: 5min 6s
```



Kdtree algorithm

In [121]:
```
from sklearn.decomposition import TruncatedSVD
```

In [122]:
```
x_1, x_test, y_1, y_test = train_test_split(kd.cleaned.values, kd.Score, test_siz

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [123]:
```
#bigrams
count_vect=CountVectorizer(ngram_range=(1,2))
```

In [124]:
```
bdata=count_vect.fit_transform(x_1)

test_data=count_vect.transform(x_test)
print(bdata.shape,y_1.shape,test_data.shape,y_test.shape)
```

```
(7000, 181833) (7000,) (3000, 181833) (3000,)
```

In [117]:
```
#reducing dimension to 1500
T=TruncatedSVD(1500)
bdata=T.fit_transform(bdata)
bdata.shape
```

Out[117]:
```
(7000, 1500)
```

In [118]:
```
print(T.explained_variance_ratio_.sum())
```

```
0.7581585063506087
```

In [119]:
```
test_data=T.transform(test_data)
test_data.shape
```

Out[119]:
```
(3000, 1500)
```

In [120]:
```
%%time
#kd_tree with high dimensionality
kmain(bdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 7}
Best Accuracy: 80.09%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 79.20%
Wall time: 1h 32min 21s
```

In [125]:
```
#reducing dimendion to 5
T=TruncatedSVD(5)
bdata=T.fit_transform(bdata)
bdata.shape
```

Out[125]:
```
(7000, 5)
```

In [126]:
```
test_data=T.transform(test_data)
test_data.shape
```

Out[126]:
```
(3000, 5)
```

In [127]:
```
%%time
#kd_tree with small dimensionality
kmain(bdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 23}
Best Accuracy: 79.35%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 76.10%
Wall time: 7.73 s
```

Summary:
brute force : accuracy is 84.62 and TP is also high
kd_tree : with high dimension we got accuray as 80% and small dimension gave 79.35% but the thing to notice is that kd_tree with high dimension takes a lot of time than with smaller dimension.

Tfidf

In [94]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

brute force algorithm

In [95]:
```
x_1, x_test, y_1, y_test = train_test_split(d.cleaned.values, d.Score, test_size=(

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [96]:
```
#bigrams
tfidf=TfidfVectorizer(ngram_range=(1,2))
```

In [97]:
```
tdata=tfidf.fit_transform(x_1)
test_data=tfidf.transform(x_test)
print(tdata.shape,test_data.shape)
```

```
(14000, 308946) (6000, 308946)
```

In [98]:
```
%%time
main(tdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 7}
Best Accuracy: 85.43%
best estimator:  KNeighborsClassifier(algorithm='brute', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 84.85%
Wall time: 5min 25s
```

Kd tree

In [99]:
```
from sklearn.decomposition import TruncatedSVD
```

In [100]:
```
x_1, x_test, y_1, y_test = train_test_split(kd.cleaned.values, kd.Score, test_siz

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [101]:
```
#bigrams
tfidf=TfidfVectorizer(ngram_range=(1,2))
```

In [102]:
```
tdata=tfidf.fit_transform(x_1)
test_data=tfidf.transform(x_test)
print(tdata.shape,test_data.shape)
```

```
(7000, 181833) (3000, 181833)
```

In [103]:
```
#reducing the dimensionality to 5
T=TruncatedSVD(1500)
tdata=T.fit_transform(tdata)
tdata.shape
```

Out[103]:
```
(7000, 1500)
```

In [104]:
```
print(T.explained_variance_ratio_.sum())
```

```
0.41182636359860186
```

In [105]:
```
test_data=T.transform(test_data)
test_data.shape
```

Out[105]:
```
(3000, 1500)
```

In [106]:
```
%%time
#kd_tree with high dimensionality
kmain(tdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 7}
Best Accuracy: 80.55%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 79.77%
Wall time: 1h 24min 40s
```

In [90]:
```
#reducing the dimensionality to 5
T=TruncatedSVD(5)
tdata=T.fit_transform(tdata)
tdata.shape
```

Out[90]:
```
(7000, 5)
```

In [91]:
```
test_data=T.transform(test_data)
test_data.shape
```

Out[91]:
```
(3000, 5)
```

In [93]:
```
%%time
#kd_tree with small dimensionality
kmain(tdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 21}
Best Accuracy: 79.40%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 75.23%
Wall time: 7.8 s
```

Summary:
brute force : accuracy is 85.43 and TP is also high
kd_tree : with high dimension we got accuray as 80.55% and small dimension gave 79.40% but the thing to notice is that kd_tree with high dimension takes a lot of time than with smaller dimension.

Word2Vec

In [62]:
```
from gensim.models import Word2Vec
#making list of sentences
import string
i=0
list_s=[]
for s in d.Text.values:
    filtered=[]
    s=cleanhtml(s)
    for w in s.split():
        for c_w in cleanpunc(w).split():
            if c_w.isalpha():
                filtered.append(c_w.lower())
            else:
                continue
    list_s.append(filtered)
#training our own model
w2v_model=Word2Vec(list_s,min_count=5,size=50,workers=4)
```

```
C:\Users\himateja\Anaconda3\lib\site-packages\gensim\utils.py:1209: UserWarnin
g: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

Average word2vec

In [78]:
```
#creating avg word2vec
sv=[]
for s in list_s:
    sum=np.zeros(50)
    i=0
    for w in s:
        try:

            x=w2v_model.wv[w]
            sum+=x
            i+=1
        except:
            pass
    sum/=i
    sv.append(sum)

#cheking the dimension
print(len(sv))
print(len(sv[0]))
```

```
20000
50
```

In [79]:
```
x=np.asarray(sv)
y=d.Score
```

brute force algorithm

In [80]:
```
x_1, x_test, y_1, y_test = train_test_split(x, y, test_size=0.3, random_state=0,s

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [81]:
```
%%time
main(x_1,y_1,x_test,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.36%
best estimator:  KNeighborsClassifier(algorithm='brute', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 83.77%
Wall time: 3min 5s
```

kd_tree algorithm

In [82]:
```
%%time
kmain(x_1,y_1,x_test,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 11}
Best Accuracy: 85.36%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 83.77%
Wall time: 11min 36s
```

Summary:
brute force : accuracy is 85.36 and TP is also high .
kd_tree : with high dimension we got accuray as 85.36% .

Tfidf word2vec

In [68]:
```
tfidf_feat = tfidf.get_feature_names()
tf=tfidf.fit_transform(d.Text.values)
tfidfsv = []
row=0;
for s in list_s:
    sum = np.zeros(50)
    i=0;
    for word in s:
        try:
            vec = w2v_model.wv[word]
            tf_idf = tf[row, tfidf_feat.index(word)]
            sum += (vec * tf_idf)
            i += tf_idf
        except:
            pass
    sum /= i
    tfidfsv.append(sum)
    row += 1
```

```
C:\Users\himateja\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: Runtime
Warning: invalid value encountered in true_divide
  app.launch_new_instance()
```

In [70]:
```
x=np.asarray(tfidfsv)
y=d.Score
x
```

Out[70]:
```
array([[nan, nan, nan, ..., nan, nan, nan],
       [nan, nan, nan, ..., nan, nan, nan],
       [nan, nan, nan, ..., nan, nan, nan],
       ...,
       [nan, nan, nan, ..., nan, nan, nan],
       [nan, nan, nan, ..., nan, nan, nan],
       [nan, nan, nan, ..., nan, nan, nan]])
```

brute force algorithm

In [71]:
```
#splitting of the data
x_1, x_test, y_1, y_test = train_test_split(x, y, test_size=0.3,shuffle=False)

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

The 'x' array has 'NaN' values we have to change them .

In [72]:
```
# changing 'NaN' to numeric value
x_1=np.isnan(x_1)
np.where(np.isnan(x_1))
np.nan_to_num(x_1)

x_test=np.isnan(x_test)
np.where(np.isnan(x_test))
np.nan_to_num(x_test)
```

Out[72]:
```
array([[ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       ...,
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True]])
```

In [76]:
```
%%time
main(x_1,y_1,x_test,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 1}
Best Accuracy: 84.56%
best estimator:  KNeighborsClassifier(algorithm='brute', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 83.88%
Wall time: 2min 27s
```

kd_tree algorithm

In [77]:
```
%%time
kmain(x_1,y_1,x_test,y_test)
```

```
Best HyperParameter:  {'n_neighbors': 5}
Best Accuracy: 84.56%
best estimator:  KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric
='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
the accuracy is 83.88%
Wall time: 8min 50s
```

Summary:

brute force : accuracy is 83.88 and TP is also high .

kd_tree : with high dimension we got accuray as 83.88% .

Conclusion :

brute force

accuracy:

bag of words : 84.62%

tfidf :85.43%

avg word2vec :85.36%

tfidf word2vec:83.88%

the accuracy are good and even the TP of confusion matrix are high.so the model are doing good.

kd_tree:

bagofwords:

time for 1500 dimension = 1h 32min 21s

time for 5 dimension = 7.73s

tfidf:
time for 1500 dimension = 1h 24min 40s
time for 5 dimension = 7.8s

1.The more the data ,more will be the accuracy.
2.you cannot pass sparse matrix to the kdtree.
3.kd_tree works well with only when dimensionality is small.
4.doing cross validation can increase your train data which increases your accuracy as we know more the data more is the accuracy.

In [ ]:

```

```