25.21.Amazon_food_review_naive_bayes

June 7, 2018

1 Amazon food review dataset apply naive bayes

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

2 Objective

- 1. Try predicting review using naive bayes and tunning alpha
- 2. Get important features of positive and negative review
- 3. Check accuracy using precision recall F1 score
- 4. Plot errors for train and CV

3 Import data and libraries

```
In [82]: from sklearn.manifold import TSNE
         import sqlite3
         import pandas as pd
         import numpy as np
         import nltk
         import string
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.feature_extraction.text import TfidfTransformer
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.feature_extraction.text import CountVectorizer
         from sklearn.metrics import confusion_matrix
         from sklearn import metrics
         from sklearn.metrics import roc_curve, auc
         from nltk.stem.porter import PorterStemmer
         con = sqlite3.connect('database.sqlite')
         #get only +ve and -ve review
         raw_data = pd.read_sql_query("""SELECT * FROM Reviews WHERE Score != 3""", con)
```

4 Data preprocessing

```
In [83]: filtered_data=raw_data
         # Score>3 a positive rating, and score<3 a negative rating.
         def partition(x):
             if x < 3:
                 return 'negative'
             return 'positive'
         #changing reviews with score less than 3 to be positive and vice-versa
         actualScore = filtered_data['Score']
         positiveNegative = actualScore.map(partition)
         filtered_data['Score'] = positiveNegative
         filtered_data.sample(5)
         filtered_data['Score'].value_counts()
         #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
         #Deduplication of entries for same profilename, userid, time, text and take first elem
         sorted_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}
In [117]: #take only 10000 + 10000 data
          #clean_data=sorted_data.sample(frac=1).groupby('Score').head(100)
          _ , clean_data = train_test_split(sorted_data, test_size = 20000, stratify = sorted_
          clean_data['Score'].value_counts()
Out[117]: positive
                      16864
                       3136
          negative
          Name: Score, dtype: int64
In [118]: # Clean html tag and punctuation
          import re
          import string
          from nltk.corpus import stopwords
          from nltk.stem import PorterStemmer
          from nltk.stem.wordnet import WordNetLemmatizer
          stop = set(stopwords.words('english')) #set of stopwords
          sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer
          #substitute html tag and punctuation
          def cleanhtml(sentence): #function to clean the word of any html-tags
              cleanr = re.compile('<.*?>')
              cleantext = re.sub(cleanr, ' ', sentence)
              return cleantext
          def cleanpunc(sentence): #function to clean the word of any punctuation or special c
```

```
cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
              cleaned = re.sub(r'[.|,|)|(||/|,r'',cleaned)
              return cleaned
          #print(sno.stem('tasty'))
In [119]: i=0
          str1=' '
          final_string=[]
          all_positive_words=[] # store words from +ve reviews here
          all_negative_words=[] # store words from -ve reviews here.
          S=11
          #Create new catagory as Cleanedtext after removing htmltag and punctuation and upper
          for sent in clean_data['Text'].values:
              filtered_sentence=[]
              #print(sent);
              sent=cleanhtml(sent) # remove HTMl tags
              for w in sent.split():
                  for cleaned_words in cleanpunc(w).split():
                      if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                          if(cleaned_words.lower() not in stop):
                              s=(sno.stem(cleaned_words.lower())).encode('utf8')
                              filtered_sentence.append(s)
                              if (clean_data['Score'].values)[i] == 'positive':
                                  all_positive_words.append(s) #list of all words used to desc
                              if(clean_data['Score'].values)[i] == 'negative':
                                  all_negative_words.append(s) #list of all words used to desc
                          else:
                              continue
                      else:
                          continue
              str1 = b" ".join(filtered_sentence) #final string of cleaned words
              final_string.append(str1)
              i+=1
In [120]: clean_data['CleanedText']=final_string
          #store for future use
          #conn = sqlite3.connect('clean_data.sqlite')
          #c=conn.cursor()
          \#conn.text\_factory = str
          #clean_data.to_sql('Reviews1', conn, flavor=None, schema=None, if_exists='replace',
          #con = sqlite3.connect('clean_data.sqlite')
          #clean_data = pd.read_sql_query("""SELECT * FROM Reviews1 WHERE Score != 3""", con)
          #clean_data['CleanedText'].sample(15)
          clean_data.shape
          #Sort data on timestamp
          clean_data=clean_data.sort_values(by=['Time'],ascending=False)
```

```
#clean_data
clean_data.sample(5)
```

```
Out[120]:
                      Ιd
                          ProductId
                                             UserId ProfileName HelpfulnessNumerator
         294199 318702 B001E5E33U
                                       AOWITT8WA9BME
                                                          scott
                                                                                    1
         316516 342683 B000FIY3FK A2RJKJCBQ9H62K Mary Dryer
                                                                                    0
          178608 193673 B005IW4WFY
                                      AOAOARIH72UWI
                                                                                    0
                                                                                    0
          148916 161584 B000GPM9IK
                                      A5G977UGFTVT1
                                                           Zach
         388286 419857 B00153Y3IQ A1Q0YMVAI71R20
                                                       S. Lewis
                                                                                    0
                 HelpfulnessDenominator
                                            Score
                                                         Time \
         294199
                                      2 negative 1325980800
         316516
                                         positive 1297209600
          178608
                                         positive 1321401600
          148916
                                        positive 1283990400
         388286
                                         positive 1342224000
                                                           Summary \
         294199
                          Packaging creates terrible tea leaf mess
         316516
                                                       Fructose-50
                                  Great Snack or Mixed with Yogurt
          178608
          148916
                                              Best pre-workout mix
         388286 This is a first - MY CATS ASKED ME TO SUBMIT T...
                                                              Text \
         294199 Every single K-cup I put in breaks open during...
         316516 I saddened by the fact I had to go to Amazon t...
         178608 This is a great tasting granola that can be ea...
         148916 I used to workout when i played baseball, but ...
         388286 WE (3 of us) love this stuff. The little mors...
                                                       CleanedText
         294199 b'everi singl put break open brew alway end ho...
         316516 b'sadden fact amazon get use purchas groceri s...
         178608 b'great tast granola easili enjoy great yogurt...
          148916 b'use workout play basebal stop play gain lot ...
         388286 b'love stuff littl morsel pretti small get the...
```

5 Model using BOW naive bayes

```
\#x = pd.DataFrame(final\_counts.toarray())\#this is stored like dataframe format all 0
          # sparse matrix in csr format works faster compare to dense format
          \#print(x.shape,x.loc[0])
(20000, 18058)
<class 'scipy.sparse.csr.csr_matrix'>
In [122]: #x = pd.DataFrame(final_counts.toarray())
          x=final_counts
          y = clean_data['Score']
          #time=time.reset_index(drop=True)
          n=x.shape[0]
          n1=int(n*.3)
          \#X_test = x[0:n1]
          \#X\_train=x[n1:n+1]
          X_{test} = x[0:n1,:]
          X_train= x[n1:n+1,:]
          y_test=y[0:n1]
          y_train=y[n1:n+1]
          print('size of X_train, X_test, y_train , y_test ',X_train.shape, X_test.shape,y_tra
          print("positive and negative review in train and test\n",y_train.value_counts(),"\n"
size of X_train, X_test, y_train , y_test (14000, 18058) (6000, 18058) (14000,) (6000,)
positive and negative review in train and test
positive
             11907
             2093
negative
Name: Score, dtype: int64
positive
             4957
           1043
negative
Name: Score, dtype: int64
In [123]: from sklearn.cross_validation import train_test_split,KFold
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.metrics import accuracy_score
          from sklearn.cross_validation import cross_val_score
          from collections import Counter
          from sklearn.metrics import accuracy_score
          from sklearn import cross_validation
          from sklearn.naive_bayes import MultinomialNB
In [124]: # Create 10 fold cross validation for different alpha
          cv_score=[]
          a = []
          for alphaval in range(1,30):
            clf = MultinomialNB(alpha=alphaval)
```

```
clf.fit(X_train,y_train)
                                 score= cross_val_score(clf, X_train, y_train, cv=10, scoring='accuracy')
                                 cv_score.append(score.mean())
                                 a.append(alphaval)
                                 #print('score with alpha=',alphaval,score.mean())
                           print('best score and alpha',cv_score[cv_score.index(max(cv_score))],a[cv_score.index
                           optimalpha=a[cv_score.index(max(cv_score))]
best score and alpha 0.889284048323 1
clf = MultinomialNB(alpha=optimalpha)
                           clf.fit(X_train,y_train)
                           # fitting the model
                           clf.fit(X_train, y_train)
                           print(clf)
                           clf1=clf
                           pred = clf.predict(X_train)
                           mat=pd.crosstab(y_train, pred, rownames=['Actual'], colnames=['Predicted'], margins='
                           tp=mat.iloc[1,1]; tn=mat.iloc[0,0]; fp=mat.iloc[0,1]; fn=mat.iloc[1,0]; precision=tp/(tp-mat.iloc[1,0]); fn=mat.iloc[1,0]; fn=mat.iloc[1
                           fscoretrain=2*precision*recall/(precision+recall)
                           # predict the response
                           pred = clf.predict(X_test)
                           # evaluate accuracy
                           acc = accuracy_score(y_test, pred) * 100
                           print('\nThe accuracy of the naive bayes classifier using alpha and accuracy respect
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

The accuracy of the naive bayes classifier using alpha and accuracy respectively become 188.

6 Check accuracy

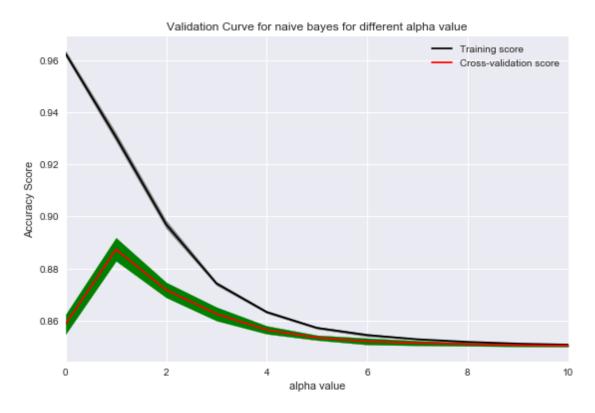
```
fn=mat.iloc[1,0]
          precision=tp/(tp+fp)
          recall=tp/(tp+fn)
          fscore=2*precision*recall/(precision+recall)
          print('precision, racall, f1score', precision, recall, fscore)
          aa=pd.DataFrame({'type':['BOW '],'train_score_accuracy':[clf.score(X_train,y_train)]
[[ 534 509]
 [ 183 4774]]
Predicted negative positive
                                All
Actual
                534
                          509 1043
negative
positive
                183
                         4774 4957
                         5283 6000
All
                717
precision, racall, f1score 0.903653227333 0.963082509582 0.932421875
```

7 Plot accuracy with train and CV error

plt.ylabel("Accuracy Score")

```
In [127]: import warnings
          warnings.filterwarnings('ignore')
          from sklearn.model_selection import validation_curve
          #create plot for training and test validation
          # Calculate accuracy on training and test set using range of parameter values
          alpha=[0,1,2,3,4,5,6,7,8,9,10]
          param_range=[0,1,2,3,4,5,6,7,8,9,10]
          train_scores, test_scores = validation_curve(clf1, X_train, y_train, param_name="alp:
          train_scores_mean = np.mean(train_scores, axis=1)
          train_scores_std = np.std(train_scores, axis=1)
          test_scores_mean = np.mean(test_scores, axis=1)
          test_scores_std = np.std(test_scores, axis=1)
          plt.plot(param_range, train_scores_mean, label="Training score", color="black")
          plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
          #Plot accurancy bands for training and test sets
          plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
          plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
          plt.title("Validation Curve for naive bayes for different alpha value")
          plt.xlabel("alpha value")
```

```
plt.xlim(0,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```



8 Show top 10 words in positive and negative review

```
print("\n")
              for coef, feat in reversed(topn_class2):
                  print (class_labels[1], coef, feat)
          print("Top 10 words for both review\n")
          most_informative_feature_for_binary_classification(count_vect, clf)
18058
(1, 18058)
['negative' 'positive']
[-12.3525943 \quad -12.3525943 \quad -13.04574148 \quad \dots, \quad -12.3525943 \quad -12.3525943
 -13.04574148]
Top 10 words for both review
negative -13.0457414788 aaah
negative -13.0457414788 aani
negative -13.0457414788 aappubl
negative -13.0457414788 abdomen
negative -13.0457414788 abit
negative -13.0457414788 ablaz
negative -13.0457414788 abomin
negative -13.0457414788 abot
negative -13.0457414788 abrotanum
negative -13.0457414788 abrupt
positive -4.48357492169 like
positive -4.52256621566 tast
positive -4.66574352651 good
positive -4.71898266424 flavor
positive -4.72480650987 great
positive -4.72919676082 love
positive -4.75997605824 use
positive -4.81276968816 one
positive -4.9392269625 product
positive -4.94436680752 tea
```

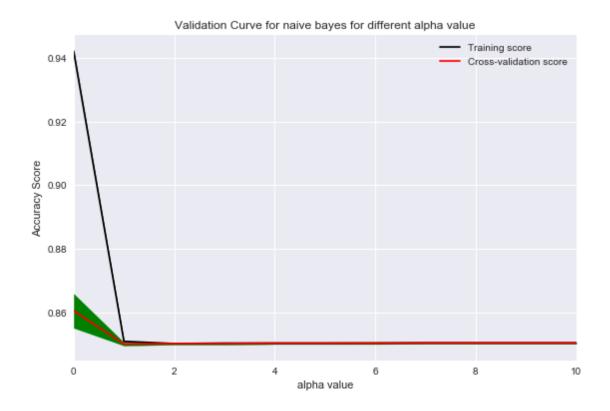
9 Use TFIDF and check performance

```
x=final_counts
y = clean_data['Score']
n=x.shape[0]
n1=int(n*.3)
X_{test} = x[0:n1,:]
X_train= x[n1:n+1,:]
y_{test=y[0:n1]}
y_train=y[n1:n+1]
print('size of X_train, X_test, y_train , y_test ',X_train.shape, X_test.shape,y_tra
print("positive and negative review in train and test\n",y_train.value_counts(),"\n"
# Create 10 fold cross validation for different alpha
cv_score=[]
a=[]
for alphaval in range(1,30):
    clf = MultinomialNB(alpha=alphaval)
    clf.fit(X_train,y_train)
    score= cross_val_score(clf, X_train, y_train, cv=10, scoring='accuracy')
    cv_score.append(score.mean())
    a.append(alphaval)
     #print('score with alpha=',alphaval,score.mean())
print('best score and alpha',cv_score[cv_score.index(max(cv_score))],a[cv_score.index
optimalpha=a[cv_score.index(max(cv_score))]
clf = MultinomialNB(alpha=optimalpha)
clf.fit(X_train,y_train)
pred = clf.predict(X_train)
mat=pd.crosstab(y_train, pred, rownames=['Actual'], colnames=['Predicted'], margins='
tp=mat.iloc[1,1]; tn=mat.iloc[0,0]; fp=mat.iloc[0,1]; fn=mat.iloc[1,0]; precision=tp/(tp-mat.iloc[1,0]; precision=tp/(tp-mat
fscoretrain=2*precision*recall/(precision+recall)
# fitting the model
clf.fit(X_train, y_train)
# predict the response
pred = clf.predict(X_test)
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the naive bayes classifier using alpha and accuracy respect
```

```
#Check accuracy
          print(confusion_matrix(y_test, pred))
          # try better way
          mat=pd.crosstab(y_test, pred, rownames=['Actual'], colnames=['Predicted'], margins=T:
          print(mat)
          #positive is fraud, negative is not fraud
          tp=mat.iloc[1,1]
          tn=mat.iloc[0,0]
          fp=mat.iloc[0,1]
          fn=mat.iloc[1,0]
          {\tt precision=tp/(tp+fp)}
          recall=tp/(tp+fn)
          fscore=2*precision*recall/(precision+recall)
          print('precision,racall,f1score',precision,recall,fscore)
          bb=pd.DataFrame({'type':['TFIDF '],'train_score_accuracy':[clf.score(X_train,y_train
          aa=aa.append(bb)
size of X_train, X_test, y_train , y_test (14000, 18058) (6000, 18058) (14000,) (6000,)
positive and negative review in train and test
positive
             11907
negative
             2093
Name: Score, dtype: int64
positive
             4957
negative
            1043
Name: Score, dtype: int64
best score and alpha 0.850500107252 7
The accuracy of the naive bayes classifier using alpha and accuracy respectively become 7 82.
ГΓ
    0 1043]
     0 4957]]
Predicted positive
                      All
Actual
negative
               1043 1043
               4957 4957
positive
All
               6000 6000
precision, racall, f1score 0.826166666667 0.5 0.622973482468
```

10 Plot accuracy with alpha

```
#create plot for training and test validation
alpha=[0,1,2,3,4,5,6,7,8,9,10]
param_range=[0,1,2,3,4,5,6,7,8,9,10]
train_scores, test_scores = validation_curve(MultinomialNB(), X_train, y_train, para
#print(train_scores, test_scores)
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve for naive bayes for different alpha value")
plt.xlabel("alpha value")
plt.ylabel("Accuracy Score")
plt.xlim(0,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
#plt.title("Validation Curve with NB")
#plt.xlabel("alpha")
#plt.ylabel("Score")
#plt.ylim(0.0, 1.1)
\#lw = 2
#plt.semilogx(param_range, train_scores_mean, label="Training score", color="darkora
#plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_me
#plt.semilogx(param_range, test_scores_mean, label="Cross-validation score", color="
#plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean
#plt.legend(loc="best")
#plt.show()
```



11 Here is the performance accuracy

Belo is the accuracy and f score of BOW and TFIDF

```
In [131]: aa
Out[131]:
             Alpha test_score_accuracy test_score_fscore train_score_accuracy
                                                  0.932422
                                                                         0.931857
                               0.884667
          0
                 7
                               0.826167
                                                  0.622973
                                                                         0.850500
             train_score_fscore
                                   type
          0
                       0.960815
                                   BOW
          0
                       0.629767 TFIDF
```