# Amazon Fine Food Reviews Analysis

Data Source: <a href="https://www.kaggle.com/snap/amazon-fine-food-reviews">https://www.kaggle.com/snap/amazon-fine-food-reviews</a>

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454

Number of users: 256,059 Number of products: 74,258

Timespan: Oct 1999 - Oct 2012

Number of Attributes/Columns in data: 10

Attribute Information:

ld

ProductId - unique identifier for the product

UserId - unqiue identifier for the user

ProfileName

HelpfulnessNumerator - number of users who found the review helpful

HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not

Score - rating between 1 and 5

Time - timestamp for the review

Summary - brief summary of the review

Text - text of the review

Objective: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import CountVectorizer #BOWs
from sklearn.feature_extraction.text import TfidfVectorizer #Tfidf
from sklearn import metrics
from sklearn.metrics import confusion_matrix
import nltk
from nltk.stem.porter import PorterStemmer
import re
```

### **→ 1. Reading Data**

```
con=sqlite3.connect("database.sqlite")
filtered_data=pd.read_sql_query("SELECT * FROM `Reviews` WHERE `Score` !=3",con)
filtered data.shape
filtered data.head()
С
         Ιd
                ProductId
                                        UserId ProfileName HelpfulnessNumerator Helpfuln
              B001E4KFG0 A3SGXH7AUHU8GW
                                                   delmartian
                                                        dll pa
             B00813GRG4
                             A1D87F6ZCVE5NK
                                                                                  0
                                                      Natalia
# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative rat
def partition(x):
    if x < 3:
       return 0
    return 1
actual_score=filtered_data['Score']
posnegative=actual_score.map(partition)
filtered_data['Score']=posnegative
filtered data.head(5)
\Box
```

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	

### 2. Exploratory Data Analysis

# 2.1 Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data.

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId',axis=0,ascending=True)
sorted_data.shape

□→ (525814, 10)

#Deduplication of entries
final=sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'},keep='first
final.shape

□→ (364173, 10)
```

**Observation**:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

### - 3. Preprocessing

In the Preprocessing phase we do the following in the order below:-

- 1. Begin by removing the linksand html tags
- 2.Expand English language contractions and Remove any punctuations or limited set of special characters like , or . or # etc.
- 3. Check if the word is made up of english letters and is not alpha-numeric
- 4.Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
- 5. Convert the word to lowercase
- 6. Remove Stopwords
- 7. Finally Snowball Stemming the word (it was observed to be better than Porter Stemming)

```
#print(link)
for i in range(0,1000):
  links=re.findall(r'http\S+',final['Text'].values[i])
  for link in links:
   print(link)
   http://www.amazon.com/gp/product/B0002DGRSY">Pro-Treat
    http://www.amazon.com/gp/product/B001905Z00">Charlee
    http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<br/>obr
    http://www.amazon.com/gp/product/B0088EDMMS">Hocus
    http://www.amazon.com/gp/product/B001AGXEAG">Beetlejuice
    http://www.amazon.com/gp/product/B001AGXEAG">here</a>.
    http://www.amazon.com/gp/product/B001AGXEA6">here</a>.
    http://www.amazon.com/gp/product/0790700506">Gremlins</a><br/>br
    http://www.amazon.com/gp/product/6301871952">Gremlins
    http://www.amazon.com/gp/product/6303347657">Mask</a><br/>br
    http://www.amazon.com/gp/product/6304826141">Rocketman</a><br/>br
    http://www.amazon.com/gp/product/B001B504LI">The
    http://www.amazon.com/gp/product/B001AGXEA6">Beetlejuice
    http://www.amazon.com/gp/product/B00004RAMX">Victor
    http://www.amazon.com/gp/product/B00004RAMY">Victor
    http://www.amazon.com/gp/product/B00004RAMY">Victor
    http://www.amazon.com/gp/product/B001VJ3FP6">SentryHOME
    http://www.amazon.com/gp/product/B0051GCTAW">Fiproguard
    http://www.amazon.com/gp/product/B000668Z96">Victor
    http://www.amazon.com/gp/product/B000668Z96">Victor
    http://www.amazon.com/gp/product/B000BQRQ8C">Rescue
    http://www.amazon.com/gp/product/B00004RBDZ">Victor
    http://www.amazon.com/gp/product/B00005344V">Traditional
    http://www.amazon.com/gp/product/B00005C2M2">Astronaut
for i in range(0,364171):
  final['Text'].values[i] = re.sub(r"http\S+", "", final['Text'].values[i])
#Remove HTML tags
from bs4 import BeautifulSoup
for i in range(1,364171):
```

```
soup = BeautifulSoup(final['Text'].values[i],'lxml')
   text = soup.get text()
   final['Text'].values[i]=text
#Expanding English language contractions
def decontracted(phrase):
   # specific
   phrase = re.sub(r"won\'t", "will not", phrase)
phrase = re.sub(r"can\'t", "can not", phrase)
   # general
   phrase = re.sub(r"n\'t", " not", phrase)
phrase = re.sub(r"\'re", " are", phrase)
  phrase = re.sub(r"\'t", " not", phrase)
phrase = re.sub(r"\'re", " are", phrase)
phrase = re.sub(r"\'s", " is", phrase)
phrase = re.sub(r"\'d", " would", phrase)
phrase = re.sub(r"\'ll", " will", phrase)
phrase = re.sub(r"\'t", " not", phrase)
phrase = re.sub(r"\'ve", " have", phrase)
phrase = re.sub(r"\'w", " am", phrase)
   return phrase
for i in range(0,364171):
   #print(final['Text'].values[i])
   final['Text'].values[i]=decontracted(final['Text'].values[i])
   #print(final['Text'].values[i])
#remove words with numbers python
for i in range(1,364171):
   #print(final['Text'].values[i])
   final['Text'].values[i] = re.sub("\S*\d\S*", "", final['Text'].values[i]).strip()
   #print(final['Text'].values[i])
#remove spacial character:
for i in range(1,364171):
   final['Text'].values[i]= re.sub('[^A-Za-z0-9]+', ' ', final['Text'].values[i])
#Remove punctution
for i in range(1,364171):
   final['Text'].values[i]= re.sub(r'[!|#|$\%|&|*|?|,|.\\'|/|"|)|(]',r'', final['Text'].valu
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step
'won', "won't", 'wouldn', "wouldn't"])
```

```
#tqdm
#Instantly make your loops show a smart progress meter
# just wrap any iterable with tqdm(iterable), and you're done!
from tqdm import tqdm
preprocessed reviews = []
for i in tqdm(range(0,364171)):
  sentence="
  #print(final['Text'].values[i])
  for word in final['Text'].values[i].split():
    #print(word)
    word =word.lower()
    if word not in stopwords:
     sentence+=" "+word
  #print(sentence)
  preprocessed_reviews.append(sentence.strip())
     100%| 364171/364171 [00:15<00:00, 23191.87it/s]
preprocessed reviews[364170]
     'purchased send son away college delivered right dorm room fast shipping loved much
final['Cleaned text']=preprocessed reviews
final.head()
С→
```

```
shari
      138706 150524 0006641040
                                        ACITT7DI6IDDL
                                                                                           0
                                                            zychinski
#Randomly sample Data 60k points
random sample data = final.sample(n=100000)
final sorted time=random sample data.sort values('Time',ascending=True,axis=0)
              AEDEDE DODEEAADAD ADIMADETIZOODDII
Data Splitting
v Train=final sorted time['Score'][0:70000]
y train=final sorted time['Score'][0:49000]
y_cv=final_sorted_time['Score'][49000:70000]
y_test=final_sorted_time['Score'][70000:100000]
                                                             Sally Suc
      420C00 150507 00066/10/0
                                     V161 12/1/3 UV 21/1/1
Train data=final sorted time['Cleaned text'][0:70000]
train data=final sorted time['Cleaned text'][0:49000]
cv data=final sorted time['Cleaned text'][49000:70000]
test data=final sorted time['Cleaned text'][70000:100000]
```

# - 4. Bag of Words

```
from sklearn.naive bayes import MultinomialNB
count vector=CountVectorizer()
train_bows=count_vector.fit_transform(train_data)
cv_bows=count_vector.transform(cv_data)
from sklearn.metrics import roc curve, auc
import math
#Simple CrossValidation
AUC_training=[]
AUC_cv=[]
ALPHA=[]
alpha=0.00001
while(alpha<1000000):
  ALPHA.append(math.ceil(math.log(alpha,10)))
  clf=MultinomialNB(alpha=alpha)
  clf.fit(train_bows , y_train)
  #Training Curve
  y predict training=clf.predict(train bows)
  fpr, tpr, thresholds = roc curve(y predict training, y train)
  AUC_training.append(metrics.auc(fpr, tpr))
```

```
#CV Curve
y_predict_cv=clf.predict(cv_bows)
fpr, tpr, thresholds = roc_curve(y_predict_cv, y_cv)
AUC_cv.append(metrics.auc(fpr, tpr))
alpha*=10

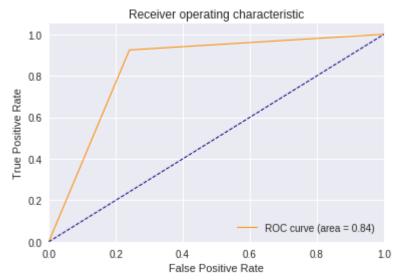
plt.plot(ALPHA[0:9],AUC_training[0:9],label='Training')
plt.plot(ALPHA[0:9],AUC_cv[0:9],label="CV")
plt.ylabel('AUC')
plt.ylabel('AUC')
plt.xlabel('Alpha')
plt.title('Alpha vs AUC ')
plt.legend()
plt.show()
```



Observation: Optimal Alpha value is 1 having AUC=0.88

```
#For Optimal on test data
count vectorizer=CountVectorizer()
Train_bows=count_vectorizer.fit_transform(Train_data)
test bows=count vectorizer.transform(test data)
clf=MultinomialNB(alpha=1.0)
clf.fit(Train_bows,y_Train)
y_pred=clf.predict(test_bows)
 #Drawing ROC curve
fpr, tpr, thresholds = roc_curve(y_pred, y_test)
roc_auc = auc(fpr, tpr)
print(' AUC = ', metrics.auc(fpr, tpr))
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
print("\n\n")
print(metrics.classification_report(y_test,y_pred))
```

#### C→ AUC = 0.8418896168504832



		precision	recall	f1-score	support
	0	0.76	0.63	0.69	5191
	1	0.92	0.96	0.94	24809
micro	avg	0.90	0.90	0.90	30000
macro	avg	0.84	0.79	0.81	30000
weighted	avg	0.90	0.90	0.90	30000

### Top Feature for negative

import operator

```
feature_names=count_vectorizer.get_feature_names()
a=getattr(clf, 'feature_log_prob_')
top =zip(a[0], feature_names)
top=list(top)
top.sort(key=lambda x: x[0])
l=len(top)
for i in range(1,20):
    print(top[l-i][1],end="\t")
```

r not like product would taste one good no coffee flavor tea

#### Top Feature for positive

```
feature_names=count_vectorizer.get_feature_names()
a=getattr(clf, 'feature_log_prob_')
top =zip(a[1], feature_names)
top=list(top)
top.sort(key=lambda x: x[0])
l=len(top)
for i in range(1,50):
    print(top[l-i][1],end="\t")
```

coffee would get amazon no really use food best also mu

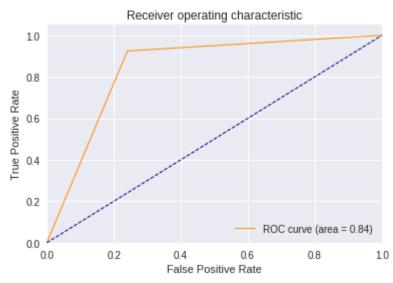
### TFIDF

```
tfidf_vector=TfidfVectorizer()
train_tfidf=tfidf_vector.fit_transform(train_data)
cv_tfidf=tfidf_vector.transform(cv_data)
#Simple CrossValidation
AUC_training=[]
AUC_cv=[]
ALPHA=[]
alpha=0.00001
while(alpha<1000000):
  ALPHA.append(math.ceil(math.log(alpha,10)))
  clf=MultinomialNB(alpha=alpha)
  clf.fit(train_tfidf , y_train)
  #Training Curve
  y_predict_training=clf.predict(train tfidf)
  fpr, tpr, thresholds = roc curve(y predict training, y train)
  AUC training.append(metrics.auc(fpr, tpr))
  #CV Cuve
  y_predict_cv=clf.predict(cv_tfidf)
  fpr, tpr, thresholds = roc_curve(y_predict_cv, y_cv)
  AUC cv.append(metrics.auc(fpr, tpr))
  alpha*=10
plt.plot(ALPHA[0:9],AUC training[0:9],label='Training')
plt.plot(ALPHA[0:9],AUC cv[0:9],label="CV")
plt.ylabel('AUC')
plt.xlabel('Alpha')
plt.title('ALpha vs AUC ')
plt.legend()
plt.show()
Гэ
                                ALpha vs AUC
        0.96
        0.94
        0.92
        0.90
        0.88
        0.86
        0.84
                                                        Training
              -5
                       -4
                                 -3
                                         -2
                                                   -1
                                                            0
                                    Alpha
```

Observation: Optimal Alpha value is 1 having AUC=0.89

```
#For Optimal on test data
tfidf vectorizer=CountVectorizer()
Train tfidf=tfidf vectorizer.fit transform(Train data)
test tfidf=tfidf vectorizer.transform(test data)
clf=MultinomialNB(alpha=1.0)
clf.fit(Train tfidf,y Train)
y_pred=clf.predict(test_tfidf)
 #Drawing ROC curve
fpr, tpr, thresholds = roc_curve(y_pred, y_test)
roc_auc = auc(fpr, tpr)
print(' AUC = ',metrics.auc(fpr, tpr))
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
print("\n\n")
print(metrics.classification_report(y_test,y_pred))
```

#### r→ AUC = 0.8418896168504832



		precision	recall	f1-score	support
	0	0.76	0.63	0.69	5191
	1	0.92	0.96	0.94	24809
micro	avg	0.90	0.90	0.90	30000
macro	avg	0.84	0.79	0.81	30000
weighted	avg	0.90	0.90	0.90	30000

#### Top Feature for positive

```
feature_names=count_vectorizer.get_feature_names()
a=getattr(clf, 'feature_log_prob_')
top =zip(a[1], feature_names)
top=list(top)
top.sort(key=lambda x: x[0])
l=len(top)
for i in range(1,50):
  print(top[l̄-i][1],end="\t")
                                                                                                        coff
               like
                                                       taste
                                                                tea
                                                                          flavor product love
С→
     not
                         good
                                   great
                                             one
```

### Top Feature for negative

```
feature_names=count_vectorizer.get_feature_names()
a=getattr(clf, 'feature_log_prob_')
top =zip(a[0], feature_names)
top=list(top)
top.sort(key=lambda x: x[0])
l=len(top)
for i in range(1,20):
 print(top[l-i][1],end="\t")
     not
             like
                      product would
                                       taste
                                                one
                                                         good
                                                                 no
                                                                          coffee flavor tea
Гэ
```