
CIS 668 Assignment #3

*Sentiment Analysis of Amazon Product
Reviews*

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Data Pre-processing

1. Retrieve the data needed.

- Extract the text content from the text file. (rawtextSplit)

The second figure shows the first 20 words in the original file.

```
import nltk
import re
from nltk import FreqDist
from nltk import pos_tag
from nltk.corpus import stopwords
from nltk.corpus import wordnet as wn
from nltk.corpus import PlaintextCorpusReader
from nltk.tokenize import word_tokenize
from collections import defaultdict
from nltk.collocations import *

#Open the original file
path = "/Users/LXIN/Desktop/T/clothing_shoes_jewelry.txt"
textfile = open(path, "r")
rawtext = textfile.read()
textfile.close()
rawtextSplit = rawtext.splitlines()
#Original text content
print(rawtextSplit[:20])
```

```
['reviewerID:A1KLRMW2FWPL4', 'asin:0000031887', 'reviewerName:Amazon Customer "cameramom"', 'helpful:[0, 0]', 'reviewText:This is a great tutu and at a really great price. It doesn't look cheap at all. I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly. A++', 'overall:5.0', 'summary:Great tutu- not cheaply made', 'unixReviewTime:1297468800', 'reviewTime:02 12, 2011', '', 'reviewerID:A2G5TCU2WDFZ65', 'asin:0000031887', 'reviewerName:Amazon Customer', 'helpful:[0, 0]', 'reviewText:I bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable. I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great. Price was very good too since some of these go for over $15.00 dollars.', 'overall:5.0', 'summary:Very Cute!!', 'unixReviewTime:1358553600', 'reviewTime:01 19, 2013', '']
```

- Create a document to save the extracted text, which contains only the reviews contents (reviews.txt)

The second figure shows the first 20 words in the new file.

```
#Extract only the reviewText from the file
def extract(files):
    f = open("/Users/LXIN/Desktop/T/reviews.txt", 'w+')
    for var in files:
        if "reviewText" in var:
            varwrite = re.sub("reviewText:", "", var)
            f.write(varwrite+"\n")
    f.close()
extract(rawtextSplit)

textfile2 = open("/Users/LXIN/Desktop/T/reviews.txt")
reviewText = textfile2.read()
print(reviewText[:20])
```

```
This is a great tutu
```

2. Pre-processing the data

- a. Tokenization. Open the new text file *reviews*. Separate the file content into tokens with sentence tokenizer.

The second figure shows the first 20 tokenized words in the file.

```
#Tokenize
from nltk import tokenize
tokensen = tokenize.sent_tokenize(reviewText)
print(len(tokensen))
print(tokensen[:20])
```

1140642

['This is a great tutu and at a really great price.', 'It doesn't look cheap at all.', 'I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly.', 'A++\nI bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.', 'I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great.', 'Price was very good too since some of these go for over \$15.00 dollars.', 'What can I say... my daughters have it in orange, black, white and pink and I am thinking to buy for they the fuccia one.', 'It is a very good way for exalt a dancer outfit: great colors, comfortable, looks great, easy to wear, durables and little girls love it.', 'I think it is a great buy for costumer and play too.', 'We bought several tutus at once, and they are got high reviews.', 'Sturdy and seemingly well-made.', 'The girls have been wearing them regularly, including out to play, and the tutus have stood up well.', 'Fits the 3-yr old & the 5-yr old well.', 'Clearly plenty of room to grow.', 'Only con is that when the kids pull off the tutus, the waste band gets twisted, and an adult has to un-tangle.', 'But this is not difficult.', 'Thank you Halo Heaven great product for Little Girls.', 'My Great Grand Daughters Love these Tutu's.', 'Will buy more from this seller.', 'Made well and cute on the girls.']

- b. Note that since we are going to explore the sentiment of the comments at sentence level, we won't do much pre-processing for the Amazon reviews. Instead, we will have a new step for this assignment, which is creating the word feature for training and testing.

Word Set

We are going to download the corpus and do the pre-processing before defining feature sets.

- a. Download and load the sentence_polarity corpus.

Note: this corpus of sentences are from the Movie Review corpus, and all the sentences are already labeled with tags ('positive' or 'negative').

```
import nltk
# nltk.download('sentence_polarity')
from nltk.corpus import sentence_polarity
import random
sentences = sentence_polarity.sents()

print(len(sentences))
print(sentence_polarity.categories())
```

```
10662
['neg', 'pos']
```

- b. Create a list of documents and each document is a sentence with the words and the label ('positive' or 'negative').

```
from nltk.corpus import sentence_polarity
import random

documents = [(sent, cat) for cat in sentence_polarity.categories()
              for sent in sentence_polarity.sents(categories=cat)]
print(documents[:2])

[(['simplistic', ',', 'silly', 'and', 'tedious', '.'], 'neg'), ([ 'it's", 'so', 'laddish', 'and', 'juvenile', ',', 'on ly', 'teenage', 'boys', 'could', 'possibly', 'find', 'it', 'funny', '.'], 'neg')]
```

- c. Import random and use it to mix up the documents.

Why: The documents are sorted by label, we will need to mix them up so that both training and test sets have sentences from two categories.

```
random.shuffle(documents)
print(documents[0])

([ 'if', 'hill', "isn't", 'quite', 'his', "generation's", 'don', 'siegel', '(', 'or', 'robert', 'aldrich', ')', ',', ' ', 'it's", 'because', "there's", 'no', 'discernible', 'feeling', 'beneath', 'the', 'chest', 'hair', ';', "it's", 'all', 'bluster', 'and', 'cliché', '.'], 'neg')
```

- d. Create a list named “all_words_list”, which includes all the words in the document collection we created in last step.

```
all_words_list = [word for (sent,cat) in documents for word in sent]

print(all_words_list[:10])
print(len(all_words_list))

['still', 'rapturous', 'after', 'all', 'these', 'years', ',', 'cinema', 'paradiso', 'stands']
224073
```

- e. Apply the lower() and isalpha() functions to the word list, to lower all the characters that are alphabetic.

```
#Filters: isalpha() and lower()
wordLower = [w for w in all_words_list if w.isalpha()]
print(len(wordLower))
print(wordLower[:20])

187486
['still', 'rapturous', 'after', 'all', 'these', 'years', 'cinema', 'paradiso', 'stands', 'as', 'one', 'of', 'the', 'g reat', 'films', 'about', 'movie', 'love', 'be', 'left']
```

Sentiment Classification

Note: Two different feature sets will be defined in this section, for the sentiment classification.

1. Feature Set #1 (Subjectivity Count Features)

- a. Remove all the stopwords and define it as a new words-set.

Why: to prune the word features

```
# Set 1: Remove stopwords
stopwords = nltk.corpus.stopwords.words('english')
wordRmStop = [w for w in wordLower if not w in stopwords]
print("-----")
print(len(wordRmStop))
print(wordRmStop[:20])
```

```
-----
105085
['still', 'rapturous', 'years', 'cinema', 'paradiso', 'stands', 'one', 'great', 'films', 'movie', 'love', 'left', 'se
nsation', 'witnessed', 'great', 'performance', 'perhaps', 'give', 'urge', 'get']
```

- b. Call FreqDist to limit the collection to 2000 most frequent words.

```
# word_features 1 (without stopwords)
all_words = nltk.FreqDist(wordRmStop)
word_items = all_words.most_common(2000)
word_features = [word for (word, count) in word_items]
print(word_features[:20])
```

```
['film', 'movie', 'one', 'like', 'story', 'much', 'even', 'good', 'comedy', 'time', 'characters', 'little', 'way', 'f
unny', 'make', 'enough', 'never', 'makes', 'may', 'us']
```

- c. I'll choose to read in the subjectivity words from the subjectivity lexicon file first. I'll create two features that involve counting the positive and negative subjectivity words present.

I'll use just the words (also called “unigram features”).

Create a path variable, copy and paste the definition of the readSbjectivity function from the Subjectivity.py module.

Note: this subjectivity lexicon file is created by Janyce Wiebe and her group at the University of Pittsburgh in MPQA project.

```
# Feature 1
SLpath = 'subjclueslen1-HLTEMNLP05.tff'
def readSubjectivity(path):
    flexicon = open(path, 'r')
    # initialize an empty dictionary
    sldict = { }
    for line in flexicon:
        fields = line.split() # default is to split on whitespace
        # split each field on the '=' and keep the second part as the value
        strength = fields[0].split("=")[1]
        word = fields[2].split("=")[1]
        posTag = fields[3].split("=")[1]
        stemmed = fields[4].split("=")[1]
        polarity = fields[5].split("=")[1]
        if (stemmed == 'y'):
            isStemmed = True
        else:
            isStemmed = False
        # put a dictionary entry with the word as the keyword
        # and a list of the other values
        sldict[word] = [strength, posTag, isStemmed, polarity]
    return sldict
SL = readSubjectivity(SLpath)
```

- d. Define a function named “SL_features” to extract all the words has two features “positivecount” and “negativecount”. The “positivecount” and “negativecount” features counts for all the positive and negative subjectivity words. Counting method differs, depending on how strongly the subjective word is.

```
def SL_features(document, word_features, SL):
    document_words = set(document)
    features = {}
    for word in word_features:
        features['contains({})'.format(word)] = (word in document_words)
    # count variables for the 4 classes of subjectivity
    weakPos = 0
    strongPos = 0
    weakNeg = 0
    strongNeg = 0
    for word in document_words:
        if word in SL:
            strength, posTag, isStemmed, polarity = SL[word]
            if strength == 'weaksubj' and polarity == 'positive':
                weakPos += 1
            if strength == 'strongsubj' and polarity == 'positive':
                strongPos += 1
            if strength == 'weaksubj' and polarity == 'negative':
                weakNeg += 1
            if strength == 'strongsubj' and polarity == 'negative':
                strongNeg += 1
            features['positivecount'] = weakPos + (2 * strongPos)
            features['negativecount'] = weakNeg + (2 * strongNeg)
    return features
```

- e. Apply the feature extraction function to all the words.

```
SL_featuresets = [(SL_features(d, word_features, SL), c) for (d, c) in documents]
```

- f. Create the training and test sets, train the Naïve Bayes classifier, and get the accuracy. The length of the documents is around 10500.

```
train_set, test_set = SL_featuresets[1000:], SL_featuresets[:1000]
classifier = nltk.NaiveBayesClassifier.train(train_set)
nltk.classify.accuracy(classifier, test_set)
# classifier.show_most_informative_features(30)
```

0.76

- g. Call the show_most_informative_features function to show the top 30 ranked features, according to the ratio of one label ('pos' / 'neg') to another.

```
classifier.show_most_informative_features(30)
```

```
Most Informative Features
contains(boring) = True          neg : pos = 18.9 : 1.0
contains(engrossing) = True     pos : neg = 18.4 : 1.0
contains(stupid) = True         neg : pos = 18.3 : 1.0
contains(provides) = True       pos : neg = 17.7 : 1.0
contains(mediocre) = True       neg : pos = 16.3 : 1.0
contains(inventive) = True      pos : neg = 15.7 : 1.0
contains(flat) = True           neg : pos = 13.8 : 1.0
contains(generic) = True        neg : pos = 13.6 : 1.0
contains(refreshing) = True     pos : neg = 13.0 : 1.0
contains(routine) = True        neg : pos = 13.0 : 1.0
contains(warm) = True           pos : neg = 12.6 : 1.0
contains(wonderful) = True      pos : neg = 11.8 : 1.0
contains(haunting) = True       pos : neg = 11.7 : 1.0
contains(refreshingly) = True   pos : neg = 11.7 : 1.0
contains(captures) = True       pos : neg = 11.4 : 1.0
contains(realistic) = True      pos : neg = 11.0 : 1.0
contains(ages) = True           pos : neg = 10.4 : 1.0
contains(mesmerizing) = True    pos : neg = 10.4 : 1.0
contains(mindless) = True       neg : pos = 10.3 : 1.0
contains(offensive) = True      neg : pos = 10.3 : 1.0
contains(dull) = True           neg : pos = 10.0 : 1.0
contains(wry) = True            pos : neg = 9.7 : 1.0
contains(bears) = True          neg : pos = 9.6 : 1.0
contains(powerful) = True       pos : neg = 9.2 : 1.0
contains(playful) = True        pos : neg = 9.0 : 1.0
contains(intimate) = True       pos : neg = 9.0 : 1.0
contains(chilling) = True       pos : neg = 9.0 : 1.0
contains(unexpected) = True     pos : neg = 9.0 : 1.0
contains(tiresome) = True       neg : pos = 9.0 : 1.0
contains(loud) = True           neg : pos = 9.0 : 1.0
```

h. Precision, Recall and F-measure score on test-set

```
# Build the reference and test lists from the classifier on the test set:
reflist = []
testlist = []
for (features, label) in test_set:
    reflist.append(label)
    testlist.append(classifier.classify(features))

reflist[:30]
testlist[:30]

reffemale = set([i for i,label in enumerate(reflist) if label == 'pos'])
refmale = set([i for i,label in enumerate(reflist) if label == 'neg'])

testfemale = set([i for i,label in enumerate(testlist) if label == 'pos'])
testmale = set([i for i,label in enumerate(testlist) if label == 'neg'])

from nltk.metrics import *

# compute precision, recall and F-measure for each label
def printmeasures(label, refset, testset):
    print(label, 'precision:', precision(refset, testset))
    print(label, 'recall:', recall(refset, testset))
    print(label, 'F-measure:', f_measure(refset, testset))

printmeasures('pos', reffemale, testfemale)
print("-----")
printmeasures('neg', refmale, testmale)

pos precision: 0.7718940936863544
pos recall: 0.747534516765286
pos F-measure: 0.7595190380761523
-----
neg precision: 0.7485265225933202
neg recall: 0.7728194726166329
neg F-measure: 0.7604790419161678
```

2. Feature Set #2 (Negation Features)

a. Create a list of negation words.

```
# Feature 2 (Not Feature)

# Negation Words
# this list of negation words includes some "approximate negators" like hardly and rarely
negationwords = ['no', 'not', 'never', 'none', 'nowhere', 'nothing', 'noone', 'rather', 'hardly', 'scarcely',
                 'rarely', 'seldom', 'neither', 'nor', 'ain', 'aren', 'couldn', 'didn', 'doesn', 'hadn', 'hasn',
                 'haven', 'isn', 'ma', 'mightn', 'mustn', 'needn', 'shan', 'shouldn', 'wasn', 'weren', 'won', 'wouldn']
```

b. Remove stopwords, but reserve the negation words (or parts of words)

Why: the negation filter will need them

```
# Remove stop words
newstopwords = [word for word in stopwords if word not in negationwords]
stop_words_list = [word for word in wordLower if word not in newstopwords]
len(stop_words_list)
```

106321

c. Call FreqDist to limit the collection to 2000 most frequent words.

```
all_words = nltk.FreqDist(stop_words_list)
word_items = all_words.most_common(2000)
word_features = [word for (word,count) in word_items]
print(word_features[:20])

['film', 'movie', 'not', 'one', 'like', 'story', 'no', 'much', 'even', 'good', 'comedy', 'time', 'characters', 'littl
e', 'way', 'funny', 'make', 'enough', 'never', 'makes']
```

d. Define the feature function named "NOT_features". Two feature sets are defined:
2000 word features and 2000 Not word features sets.

How it works: if a negation occurs, add the following word as a Not word feature; else add it as a regular feature word.

```
def NOT_features(document, word_features, negationwords):
    features = {}
    for word in word_features:
        features['contains({})'.format(word)] = False
        features['contains(NOT{})'.format(word)] = False
    # go through document words in order
    for i in range(0, len(document)):
        word = document[i]
        if ((i + 1) < len(document)) and ((word in negationwords) or (word.endswith("n't"))):
            i += 1
            features['contains(NOT{})'.format(document[i])] = (document[i] in word_features)
        else:
            features['contains({})'.format(word)] = (word in word_features)
    return features
```

e. Apply the NOT_features extraction function to words.

```
# Not Feature Sets
NOT_featuresets = [(NOT_features(d, word_features, negationwords), c) for (d, c) in documents]
NOT_featuresets[0][0]['contains(NOTlike)']
```

False

f. Create the training and test sets, train the Naïve Bayes classifier, and get the accuracy.

```
# Accuracy
train_set3, test_set3 = NOT_featuresets[1000:], NOT_featuresets[:1000]
classifier3 = nltk.NaiveBayesClassifier.train(train_set3)
nltk.classify.accuracy(classifier3, test_set3)
```

0.791

g. Call the show_most_informative_features function to show the top 30 ranked features, according to the ratio of one label ('pos' / 'neg') to another.

```
# Most informative features
classifier3.show_most_informative_features(30)
```

```
Most Informative Features
contains(engrossing) = True      pos : neg = 19.1 : 1.0
contains(captures) = True       pos : neg = 17.7 : 1.0
contains(mediocre) = True       neg : pos = 16.3 : 1.0
contains(generic) = True        neg : pos = 14.9 : 1.0
contains(routine) = True        neg : pos = 14.9 : 1.0
contains(flat) = True           neg : pos = 13.7 : 1.0
contains(imax) = True           pos : neg = 13.1 : 1.0
contains(refreshing) = True     pos : neg = 13.1 : 1.0
contains(powerful) = True       pos : neg = 12.5 : 1.0
contains(dull) = True           neg : pos = 12.4 : 1.0
contains(inventive) = True      pos : neg = 12.4 : 1.0
contains(boring) = True         neg : pos = 12.4 : 1.0
contains(wonderful) = True      pos : neg = 12.3 : 1.0
contains(warm) = True           pos : neg = 12.3 : 1.0
contains(refreshingly) = True   pos : neg = 11.7 : 1.0
contains(stale) = True          neg : pos = 11.6 : 1.0
contains(realistic) = True      pos : neg = 11.0 : 1.0
contains(stupid) = True         neg : pos = 11.0 : 1.0
contains(mesmerizing) = True    pos : neg = 10.4 : 1.0
contains(ages) = True           pos : neg = 10.4 : 1.0
contains(delicate) = True       pos : neg = 10.4 : 1.0
contains(NOTenough) = True      neg : pos = 10.3 : 1.0
contains(provides) = True       pos : neg = 10.2 : 1.0
contains(wry) = True            pos : neg = 9.7 : 1.0
contains(apparently) = True     neg : pos = 9.6 : 1.0
contains(unless) = True         neg : pos = 9.6 : 1.0
contains(mindless) = True       neg : pos = 9.6 : 1.0
contains(intimate) = True       pos : neg = 9.0 : 1.0
contains(chilling) = True       pos : neg = 9.0 : 1.0
contains(tender) = True         pos : neg = 9.0 : 1.0
```

h. Precision, Recall and F-measure score on test-set

```

# Build the reference and test lists from the classifier on the test set:
reflist = []
testlist = []
for (features, label) in test_set3:
    reflist.append(label)
    testlist.append(classifier3.classify(features))

reflist[:30]
testlist[:30]

reffemale = set([i for i, label in enumerate(reflist) if label == 'pos'])
refmale = set([i for i, label in enumerate(reflist) if label == 'neg'])

testfemale = set([i for i, label in enumerate(testlist) if label == 'pos'])
testmale = set([i for i, label in enumerate(testlist) if label == 'neg'])

from nltk.metrics import *

# compute precision, recall and F-measure for each label
def printmeasures(label, refset, testset):
    print(label, 'precision:', precision(refset, testset))
    print(label, 'recall:', recall(refset, testset))
    print(label, 'F-measure:', f_measure(refset, testset))

printmeasures('pos', reffemale, testfemale)
print("-----")
printmeasures('neg', refmale, testmale)

pos precision: 0.8003992015968064
pos recall: 0.7862745098039216
pos F-measure: 0.7932739861523244
-----
neg precision: 0.781563126252505
neg recall: 0.7959183673469388
neg F-measure: 0.788675429726997

```

Sentiment Analysis

Note: From the previous section we find out that **Subjectivity Count Features is less accurate than Negation Features**. But I'll apply both the Subjectivity Count Feature and Negation Feature on the Amazon reviews data.

1. Subjectivity Count Feature

a. Running result.

There are 463424 sentences tagged as negative and 444152 sentences tagged as positive.

```
print("neg-----")
print(len(neg2))
print(neg2[:5])

print("\npos-----")
print(len(pos2))
print(pos2[:5])
```

```
neg-----
463424
```

```
["It doesn't look cheap at all.", "I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly.", 'Price was very good too since some of these go for over $15.00 dollars.,What can I say... my daughters have it in orange, black, white and pink and I am thinking to buy for they the fuccia one.', 'I think it is a great buy for costumer and play too.,We bought several tutus at once, and they are got high reviews.', 'Sturdy and seemingly well-made.']
```

```
pos-----
444152
```

```
['This is a great tutu and at a really great price.', 'A++,I bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.', 'I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great.', 'It is a very good way for exalt a dancer outfit: great colors, comfortable, looks great, easy to wear, durables and little girls love it.', 'The girls have been wearing them regularly, including out to play, and the tutus have stood up well.']
```

b. Store the two sets of sentences in two files.

```
# pos into file
posFile = open('/Users/LXIN/Desktop/posSL.txt', 'w')
for r in posSL:
    posFile.write(r + '\n')
posFile.close()

# neg into file
negFile = open('/Users/LXIN/Desktop/negSL.txt', 'w')
for r in negSL:
    negFile.write(r + '\n')
negFile.close()
```

c. Create a table for sample result. (100 for each in this case).

```
# pos into file
posFile = open('/Users/LXIN/Desktop/posSL.txt', 'w')
for r in posSL:
    posFile.write(r + '\n')
posFile.close()

# neg into file
negFile = open('/Users/LXIN/Desktop/negSL.txt', 'w')
for r in negSL:
    negFile.write(r + '\n')
negFile.close()
```

[illegible]

2. Negation Features

a. Running result.

There are 724380 sentences tagged as negative and 415262 sentences tagged as positive.

```
# Reviews NOT
posNOT = []
negNOT = []

for s in tokens:
    wordToken = nltk.word_tokenize(s)
    getFeature = NOT_features(wordToken, word_features, negationwords)
    if classifier3.classify(getFeature) == 'pos':
        posNOT.append(s)
    elif classifier3.classify(getFeature) == 'neg':
        negNOT.append(s)

print("neg -----")
print(len(negNOT))
print(negNOT[:5])

print("\npos -----")
print(len(posNOT))
print(posNOT[:5])
```

```
neg -----
725380
["I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly.", 'Price was very good too since some of these go for over $15.00 dollars.', 'What can I say... my daughters have it in orange, black, white and pink and I am thinking to buy for they the fuccia one.', 'I think it is a great buy for costumer and play too.', 'The girls have been wearing them regularly, including out to play, and the tutus have stood up well.']

pos -----
415262
['This is a great tutu and at a really great price.', "It doesn't look cheap at all.", 'A++\nI bought this for my 4 y r old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.', 'I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great.', 'It is a very good way for exalt a dancer outfit: great colors, comfortable, looks great, easy to wear, durables and little girls love it.']
```

b. Store the two sets of sentences in two files.

```
# pos into file
posFile = open('/Users/LXIN/Desktop/posNOT.txt', 'w')
for r in posNOT:
    posFile.write(r + '\n')
posFile.close()

# neg into file
negFile = open('/Users/LXIN/Desktop/negNOT.txt', 'w')
for r in negNOT:
    negFile.write(r + '\n')
negFile.close()
```

c. Create a table for sample result. (100 for each in this case).

```
import pandas as pd
import os
col = ['Positive', 'Negative']
define = pd.DataFrame(columns = col)

define['Positive'] = posNOT[:100]
define['Negative'] = negNOT[:100]

file = "/Users/LXIN/Desktop/table.csv"

if not os.path.isfile(file):
    define.to_csv(file, header = True, index = False, encoding = 'utf-8')
print(define)
```

```

                                Positive \
0  This is a great tutu and at a really great price.
1                                It doesn't look cheap at all.
2  A++\nI bought this for my 4 yr old daughter fo...
3  I bought this to go with a light blue long sle...
4  It is a very good way for exalt a dancer outfi...
..                                ...
95 This is a better way to learn to make the asso...
96 However, it is still nice to have some feedbac...
97 However, how much would it cost to take a fore...
98 Rosetta Stone Italiano Level 1Rosetta Stone It...
99 The included instructions are simple and strai...

                                Negative
0  I'm so glad I looked on Amazon and found such ...
1  Price was very good too since some of these go...
2  What can I say... my daughters have it in oran...
3  I think it is a great buy for costumer and pla...
4  The girls have been wearing them regularly, in...
..                                ...
95 This wasn't a problem for me yet it's somethin...
96 * Lack of matching supplemental physical mater...
97                                Okay, I admit it.
98 I have recently returned to college to finish ...
99                                Ugh.

[100 rows x 2 columns]
```

table	
Question	Response
This is a great tute and at a really great price.	I'm so glad I looked on Amazon and found such an affordable tute that isn't made poorly.
I haven't took cheap at all.	Price was very good too since some of these go for over \$15.00 dollars.
As I bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.	What can I say... my daughter loves it in orange, black, white and pink and I am thinking to buy for my the dance one.
I bought this to go with a light blue long sleeve topband and was happy the colors matched up great.	I think it is a great buy for costume and play too.
It is a very good way for what a dancer needs great colors, comfortable, looks great, easy to wear, durable and little girls love it.	The girls have been wearing them regularly, including out to play, and the tutes have stand up well.
We bought several tutes at once, and they are got high reviews.	Cheerly plenty of room to grow.
Sturdy and certainly well made.	But this is not difficult.
For the 4 yr old it fits 4 yr old well.	Thank you have always great product for little girls.
Only con is that when this tute put off the tute, the waist band gets twisted, and an adult has to untangle.	My Great Grand Daughters love these Tute's.
Made well and cute on the girls.	Will buy more from this seller.
Thanks for a great product!NEVER BUY FROM DRESS UP DREAMS.....I will buy more as long as I don't buy from DressUp Dreams!NE, I never rec'd or order in FL.	Only one tip, the people are was missing.
definitely to make good on purchase.....Real cheap.	Company is so good.
So far, she's using it to play out her Christmas dreams but I am sure we'll be able to use it for a while sometime soon.	I received this today and I'm not at all if I had my daughter's I thought it would be perfect as it looks in the pic but it's not and the one they sent me is pink underneath and the waist band is pink which is not what I needed.
Great tute for a great price.	Bought this as a backup to the regular baller outfit my daughter has to wear.
It isn't a substitute or high quality item, but it is perfect for my daughter to wear over leggings for her little outfit.	The quality is just fine for the price we paid.
My daughter liked this, and it with her costume, but she would have liked it to be a bit taller.	I was not expecting a designer shirt for this price and got exactly what I paid for.
I ordered a pink and turquoise and they are vibrant and beautiful.	For what I paid for two tutes is unbeatable anywhere!
Awesome idea!	The tute is very full.
Wears size 4t and this shirt (one size) fit perfect and will probably be able to accommodate her quickly growing waist for some time!	Not cheaply made.
It's amazing quality!	Not cheap material.
It fit nicely with room to grow in.	Obviously someone made these with love and care!
I'm very please with it and will purchase more in varying colors in the future.	I paid less than 7 Bucks for a tute I am not the proud of my self for researching to the point of finding good!Recommended 2-4 year old daughter is best!
Full and well stitched.	Wonder my niece wears it every single day, yellow is her favorite color right now so this cute little tute made her day.
This tute is a beautiful purple color that looks just like the picture.	It is well built and we hope she gets lots of wear out of it.
It looks just adorable on our little thing.	My daughter has worn this shirt almost every day since she received it and it's made been through the washer along with the other clothes.
This was a gift for a two year old and a five year old.	She fits it 4T and it's just above her knee, another benefit of growing room, although I'm not so sure as much as others are saying.
The tute seem to be well made, and can stand up to handling by little princesses.	But considering how often she wears it, I'm not worried!
My 4yr old loved this tute (she is pink)	I purchased this tute for my granddaughter's first birthday.
Beautiful vibrant color.	The girls happened upon opening the box, they grabbed the tute, put them on, and wore them the rest of the day.
I'm great and easy to clean.	I recommend these tute.
I bought several more colors!	Was hoping to order more in different colors, she had hardly used this one, stitching came apart in 2 weeks, now it's lying in her closet. Altogether she wore it 5 times for 20 mins or so when the stitching was of better quality.
Nice and pretty tute shirt.	Can't recommend.
Bought this for my niece as part of her tiny outfit.	Perfect for my budding grand daughter ballerina!
I bought this for her for Christmas and she never wanted to take it off.	Have 4QT this tute - had given a 1 QT because the quality from the SUPPLIER was GREAT. They tried to send that but more than once, my \$ was refunded in a timely manner too. It was a shame I never got it for my daughter.
It is almost a year later and she still has it!	I would recommend this for girls under 10 yrs old.
Great color and fit for a 4 year old as well as her aunt who is 50!	It will be too short and small for older girls.
The elastic waist will expand with her as she grows.	She looks it and wears it all the time.
You will love this color too.	Well made for the price.
If this is a gift do not hesitate.	My 4 year old daughter always wants to take dress up.
It is suitable for an adult though.	I am not sure how many times I have had up this tute with nothing wrong with it!
Buy it...	I would recommend it.
Love this jewelry box, so well put together looks plenty... Love the pink & looks so nice on my vanity.	Our granddaughters are all very girls, so when the youngest one received this for Christmas, they all wanted it!
My granddaughter loves the looking image jewelry box given to her for birthday gift box. Genuine.	I would recommend this tute for all the girls.
Really nice box, a lot cheaper made.	prompt delivery, and it is exactly as described.
Every inch is made space for jewelry & very compact, which is a nice feature.	The only reason I did not give it 5 stars is because I haven't washed it yet, so I don't know how it will hold up... Other than that my little girl LOVES her tute (we got one in light pink color, especially spinning and twirling in it).
While a clear endowment might work better for some, there's not always time for that either.	The jewelry case for my heart shipped a year.
The software comes with a headset and microphone so that while you are learning, you also speak into the headset and respond to questions.	What a nice case to sort my collection.
Unlike a classroom environment, you can work at this at your own pace, which I appreciate.	I love all the compartments and the layout too.
I'm more comfortable learning from the program as well than in front of a group of strangers. While going to France and living there for a while is probably the easiest and fastest way to learn French, Rosetta Stone is a great alternative.	I will please even the most busy, on the go.
I own both an iPhone and an iPad so with the Rosetta Stone app that link directly to my account I could learn and practice whenever I needed to.	The price is fair if you check around on other sites.
For three months I made great progress whether at home, in the background or at work on my lunch hour.	Seems well made too.
If I want to continue learning this way I need to purchase a very expensive subscription.	Not meant as a tip.
I want to continue to learn on my iPad!	This is for without jewelry box's.
Three month access included with purchase.*	This product is great for anyone with a lot of jewelry, my girlfriend has a lot and this gift for her was one of my best ideas!
The first question was which computer to install this program - Rosetta Stone has a two seat minimum.	I recommend this to any one with a lot of jewelry.
* There are learning sessions in this software to allow speaking with native French speakers.	Already own this particular jewelry, I hope jewelry box is better, so this was my second buy.
"The one on an individual, this is better way to learn than a formal classroom course." The instruction is the number of words (5).	Finished with some of the leather scratched, even though it looked like I was the first one opening the box.
I fear the need for this and can't wait to see it, but again I prefer to learn outside a formal classroom.	The jewelry case color was also loved pretty hard in person.
"Lack of simple visuals to help with identifying grammatical patterns.	The quality of this box seemed better than the others and I was informed this pink case for a refund without a problem.
I'm one of the millions of Americans that routinely struggle with any language other than English.	Got another brown looking large jewelry case and it's fine!
The university I'm enrolled in requires two years of a foreign language.	I wanted to have the life insurance my thoughts if you decided not to read the entire review.
They had that happen contact her often and have them remove the link! Apparently in the key 4-point font disclaimer on the package it says that the license is not transferable, so you can't sell it as a used item.	I wish the drawers were deeper for holding her many necklaces.
The Rosetta Stone "Spoken immersion" method is different than traditional methods where you use a word in English and then use a word in the new language to memorize.	Also, with the drawers had a stop, preventing the drawers from tipping contents out when trying to remove one piece of jewelry.
You will feel confident with the basics after this.	My granddaughter is only five years old, so having the background knowledge of knowing when to stop the action of pulling the drawer from the base requires practice.
I think that means the gift works.	On the other hand, from hundreds of years of practice with jewelry drawers, but also struggle with removing the drawer without spilling the contents.
They really did one heck of a job making learning fun and easy.	It is made of different with jewelry.
	Although the suggestion for all your jewelry is great, I'm not so sure how I will stand up to my seven daughter's son.
	Once having a language from software is not exactly the same as learning a language from going to live in the country itself, I suggest picking up the Rosetta Stone software I level at a time, like the French level 1.

Bonus (Different Word Set & Additional Feature)

A brief description: A different dataset is used in this part. It is a dataset of sample tweets from NLTK package. I'll download it and apply some data cleaning methods on it (stopwords, etc..) I'll train a model on pre-classified tweets, and use this model to classify the Amazon reviews into positive and negative sentiments.

Reference: < <https://www.digitalocean.com/community/tutorials/how-to-perform-sentiment-analysis-in-python-3-using-the-natural-language-toolkit-nltk>>

1. Download Data

a. Download the sample tweets from NLTK package

```
import nltk

# Download the sample tweets from the NLTK package
nltk.download('twitter_samples')

[nltk_data] Downloading package twitter_samples to
[nltk_data] /Users/LXIN/nltk_data...
[nltk_data] Unzipping corpora/twitter_samples.zip.

True
```

b. Download

```
nltk.download('punkt')

[nltk_data] Downloading package punkt to /Users/LXIN/nltk_data...
[nltk_data] Package punkt is already up-to-date!

True
```

2. Pre-processing Data

a. There are 3 datasets from NLTK which contain tweets to train and test the model:

Negative_tweets.json: 5000 tweets with negative sentiments

Positive_tweets.json: 5000 tweets with positive sentiments

Tweets.20150430-223406: 20000 tweets with no sentiments

```
from nltk.corpus import twitter_samples

# negative_tweets.json: 5000 tweets with negative sentiments
# positive_tweets.json: 5000 tweets with positive sentiments
# tweets.20150430-223406.json: 20000 tweets with no sentiments

positive_tweets = twitter_samples.strings('positive_tweets.json')
negative_tweets = twitter_samples.strings('negative_tweets.json')
text = twitter_samples.strings('tweets.20150430-223406.json')
tweet_tokens = twitter_samples.tokenized('positive_tweets.json')

print(tweet_tokens[0])

['#FollowFriday', '@France_Inte', '@PKuchly57', '@Milipol_Paris', 'for', 'being', 'top', 'engaged', 'members', 'in', 'my', 'community', 'this', 'week', ':)']
```

b. Tokenization

```
# Normalizing the Data
nltk.download('wordnet')
nltk.download('averaged_perceptron_tagger')

from nltk.tag import pos_tag
from nltk.corpus import twitter_samples
tweet_tokens = twitter_samples.tokenized('positive_tweets.json')
print(pos_tag(tweet_tokens[0]))

[nltk_data] Downloading package wordnet to /Users/LXIN/nltk_data...
[nltk_data] Package wordnet is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data] /Users/LXIN/nltk_data...
[nltk_data] Package averaged_perceptron_tagger is already up-to-
[nltk_data] date!

[(('#FollowFriday', 'JJ'), ('@France_Inte', 'NNP'), ('@PKuchly57', 'NNP'), ('@Milipol_Paris', 'NNP'), ('for', 'IN'), ('being', 'VBG'), ('top', 'JJ'), ('engaged', 'VBN'), ('members', 'NNS'), ('in', 'IN'), ('my', 'PRP$'), ('community', 'NN'), ('this', 'DT'), ('week', 'NN'), (':)', 'NN'))]
```

c. Normalizing the data


```

from nltk.tag import pos_tag
from nltk.stem.wordnet import WordNetLemmatizer

# This code imports the WordNetLemmatizer class and initializes it to a variable, lemmatizer
def lemmatize_sentence(tokens):
    lemmatizer = WordNetLemmatizer()
    lemmatized_sentence = []
    for word, tag in pos_tag(tokens):
        if tag.startswith('NN'):
            pos = 'n'
        elif tag.startswith('VB'):
            pos = 'v'
        else:
            pos = 'a'
        lemmatized_sentence.append(lemmatizer.lemmatize(word, pos))
    return lemmatized_sentence

print(lemmatize_sentence(tweet_tokens[0]))

['#FollowFriday', '@France_Inte', '@PKuchly57', '@Milipol_Paris', 'for', 'be', 'top', 'engage', 'member', 'in', 'my',
'community', 'this', 'week', ':)']

```

d. Remove noise

Use regular expressions in Python to search for and remove these items:

Hyperlinks - All hyperlinks in Twitter are converted to the URL shortener t.co.

Twitter handles in replies

Punctuation and special characters

```

# Removing Noise from the Data

# Use regular expressions in Python to search for and remove these items:
# Hyperlinks - All hyperlinks in Twitter are converted to the URL shortener t.co.
# Twitter handles in replies
# Punctuation and special characters

import re, string

def remove_noise(tweet_tokens, stop_words = ()):

    cleaned_tokens = []

    for token, tag in pos_tag(tweet_tokens):
        token = re.sub('http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|![*(){}]|\'|\"
        '(?:%[0-9a-fA-F][0-9a-fA-F]))+', '', token)
        token = re.sub('@([A-Za-z0-9_]+)', '', token)

        if tag.startswith("NN"):
            pos = 'n'
        elif tag.startswith('VB'):
            pos = 'v'
        else:
            pos = 'a'

        lemmatizer = WordNetLemmatizer()
        token = lemmatizer.lemmatize(token, pos)

        if len(token) > 0 and token not in string.punctuation and token.lower() not in stop_words:
            cleaned_tokens.append(token.lower())
    return cleaned_tokens

```

e. Remove stopwords

```

# Remove stopwords
from nltk.corpus import stopwords
stop_words = stopwords.words('english')

#print(remove_noise(tweet_tokens[0], stop_words))

positive_tweet_tokens = twitter_samples.tokenized('positive_tweets.json')
negative_tweet_tokens = twitter_samples.tokenized('negative_tweets.json')

positive_cleaned_tokens_list = []
negative_cleaned_tokens_list = []

for tokens in positive_tweet_tokens:
    positive_cleaned_tokens_list.append(remove_noise(tokens, stop_words))

for tokens in negative_tweet_tokens:
    negative_cleaned_tokens_list.append(remove_noise(tokens, stop_words))

```

3. Word set

- a. Take a list of tweets as an argument to provide a list of words in all of the tweet tokens joined


```
# Determining Word Density
# Take a list of tweets as an argument to provide a list of words in all of the tweet tokens joined
def get_all_words(cleaned_tokens_list):
    for tokens in cleaned_tokens_list:
        for token in tokens:
            yield token

all_pos_words = get_all_words(positive_cleaned_tokens_list)
```

b. Get the most common words

```
from nltk import FreqDist

freq_dist_pos = FreqDist(all_pos_words)
print(freq_dist_pos.most_common(10))
```

c. Creating training and test set for model

A label (“positive” or “negative”) is labeled to each tweet. A dataset is created then by joining the positive and negative tweets

```
# Preparing Data for the Model

# Converting Tokens to a Dictionary
def get_tweets_for_model(cleaned_tokens_list):
    for tweet_tokens in cleaned_tokens_list:
        yield dict([token, True] for token in tweet_tokens)

positive_tokens_for_model = get_tweets_for_model(positive_cleaned_tokens_list)
negative_tokens_for_model = get_tweets_for_model(negative_cleaned_tokens_list)

# Splitting the Dataset for Training and Testing the Model
import random

positive_dataset = [(tweet_dict, "Positive")
                    for tweet_dict in positive_tokens_for_model]

negative_dataset = [(tweet_dict, "Negative")
                    for tweet_dict in negative_tokens_for_model]

dataset = positive_dataset + negative_dataset

random.shuffle(dataset)

train_data = dataset[:7000]
test_data = dataset[7000:]
```

4. Building and training the model

a. Build and train the model

```
# Building and Testing the Model
from nltk import classify
from nltk import NaiveBayesClassifier

classifier = NaiveBayesClassifier.train(train_data)
```

b. Get the accuracy

```
print("Accuracy is:", classify.accuracy(classifier, test_data))

print(classifier.show_most_informative_features(10))

Accuracy is: 0.9976666666666667
Most Informative Features
              :( = True               Negati : Positi =   2085.4 : 1.0
              :) = True               Positi : Negati =   1650.9 : 1.0
              sad = True              Negati : Positi =    24.8 : 1.0
              glad = True             Positi : Negati =    22.7 : 1.0
              bam = True              Positi : Negati =    22.0 : 1.0
      follower = True                Positi : Negati =    21.9 : 1.0
      welcome = True                 Positi : Negati =    20.3 : 1.0
              x15 = True              Negati : Positi =    17.2 : 1.0
      followed = True                Negati : Positi =    14.8 : 1.0
      appreciate = True              Positi : Negati =    14.8 : 1.0

None
```

5. Apply on the Amazon Review

a. Retrieve data and tokenize it

```
# Retrieve text file
textfile = open("/Users/LXIN/Desktop/reviews.txt")
reviewText = textfile.read()
print(reviewText[:20])

#Tokenize
from nltk import tokenize
tokensen = tokenize.sent_tokenize(reviewText)
print(len(tokensen))
print(tokensen[:20])
```

This is a great tutu
1140642
['This is a great tutu and at a really great price.', "It doesn't look cheap at all.", "I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly.", 'A++\nI bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.', 'I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great.', 'Price was very good too since some of these go for over \$15.00 dollars.', 'What can I say... my daughters have it in orange, black, white and pink and I am thinking to buy for they the fuccia one.', 'It is a very good way for exalt a dancer outfit: great colors, comfortable, looks great, easy to wear, durables and little girls love it.', 'I think it is a great buy for costumer and play too.', 'We bought several tutus at once, and they are got high reviews.', 'Sturdy and seemingly well-made.', 'The girls have been wearing them regularly, including out to play, and the tutus have stood up well.', 'Fits the 3-yr old & the 5-yr old well.', 'Clearly plenty of room to grow.', 'Only con is that when the kids pull off the tutus, the waste band gets twisted, and an adult has to un-tangle.', 'But this is not difficult.', 'Thank you Halo Heaven great product for Little Girls.', 'My Great Grand Daughters Love these Tutu's.', 'Will buy more from this seller.', 'Made well and cute on the girls.']

b. Perform the model on all comments

```
# Reviews
posBouns = []
negBouns = []

from nltk.tokenize import word_tokenize

for s in tokensen:
    wordToken = remove_noise(word_tokenize(s))

    if classifier.classify(dict([token, True] for token in wordToken)) == 'Positive':
        posBouns.append(s)
    elif classifier.classify(dict([token, True] for token in wordToken)) == 'Negative':
        negBouns.append(s)

print("neg -----")
print(len(negBouns))
print(negBouns[:5])

print("\npos -----")
print(len(posBouns))
print(posBouns[:5])
```

neg -----
495485
['A++\nI bought this for my 4 yr old daughter for dance class, she wore it today for the first time and the teacher thought it was adorable.', 'Price was very good too since some of these go for over \$15.00 dollars.', 'We bought several tutus at once, and they are got high reviews.', 'Fits the 3-yr old & the 5-yr old well.', 'Clearly plenty of room to grow.']

pos -----
645157
['This is a great tutu and at a really great price.', "It doesn't look cheap at all.", "I'm so glad I looked on Amazon and found such an affordable tutu that isn't made poorly.", 'I bought this to go with a light blue long sleeve leotard and was happy the colors matched up great.', 'What can I say... my daughters have it in orange, black, white and pink and I am thinking to buy for they the fuccia one.']

c. Save the two sets into files

```
# pos into file
posFile = open('/Users/LXIN/Desktop/posBonus.txt', 'w')
for r in posBouns:
    posFile.write(r + '\n')
posFile.close()

# neg into file
negFile = open('/Users/LXIN/Desktop/negBonus.txt', 'w')
for r in negBouns:
    negFile.write(r + '\n')
negFile.close()
```

d. Save the sample result in form of table to another file (100 sentences from each set)

```

import pandas as pd
import os
col = ['Positive', 'Negative']
define = pd.DataFrame(columns = col)

define['Positive'] = posBouns[:100]
define['Negative'] = negBouns[:100]

file = "/Users/LXIN/Desktop/tableBonus.csv"

if not os.path.isfile(file):
    define.to_csv(file, header = True, index = False, encoding = 'utf-8')
print(define)

```

Positive \

```

0 This is a great tutu and at a really great price.
1 It doesn't look cheap at all.
2 I'm so glad I looked on Amazon and found such ...
3 I bought this to go with a light blue long sle...
4 What can I say... my daughters have it in oran...
..
95 Okay, I admit it.
96 The university I'm enrolled in requires two ye...
97 I never thought that was a possibility.
98 I'm not ready to jet off to France or anything...
99 I'm calling that a huge success.

```

Negative

```

0 A++\nI bought this for my 4 yr old daughter fo...
1 Price was very good too since some of these go...
2 We bought several tutus at once, and they are ...
3 Fits the 3-yr old & the 5-yr old well.
4 Clearly plenty of room to grow.
..
95 Neither do I.
96 I've taken college/high school and even junior...
97 But by far, the fastest way to a new language ...
98 Plus iphone apps and internet based learning.
99 I understand the need to prevent software theft.

```

[100 rows x 2 columns]

Positive	Negative
This is a great tutu and at a really great price.	It doesn't look cheap at all.
I'm so glad I looked on Amazon and found such ...	I bought this to go with a light blue long sle...
What can I say... my daughters have it in oran...	Okay, I admit it.
The university I'm enrolled in requires two ye...	I never thought that was a possibility.
I'm not ready to jet off to France or anything...	I'm calling that a huge success.
A++\nI bought this for my 4 yr old daughter fo...	Price was very good too since some of these go...
We bought several tutus at once, and they are ...	Fits the 3-yr old & the 5-yr old well.
Clearly plenty of room to grow.	Neither do I.
I've taken college/high school and even junior...	But by far, the fastest way to a new language ...
Plus iphone apps and internet based learning.	I understand the need to prevent software theft.

Conclusion

1. **A brief description of how I conducted this assignment:** I used tokenization (sentence-level) to split the reviews into single sentence first. I believe no more cleaning or pre-processing is needed for the data in this assignment. I downloaded the sentence_polarity to create a word_list for training and test then, which needs to eliminate non-alphabet characters and stopwords. Note that some stopwords need to be kept for the Not_feature.

An additional step for Not_feature is a list of negation words which is defined by ourselves.

These two features are implemented to train the unigram word_features.

A comparison of accuracy between these two features was conducted then, and both were used to analyze the review contents from Amazon Product Data. In other word, exploring the sentiment of the comments at sentence level.

The results of the sentiment analysis are very different, which will be discussed later. I also downloaded another dataset from NLTK and applied different features on it, in order to build a different model (Bonus part).

2. Result

- a. **Not_feature and SL_feature.** Both Not_feature and SL_feature have an accuracy lower than 0.8, an improvement should be considered therefore. For Not_feature, there are 415262 positive comments and 725380 negative comments, the ratio of positive comments is only 36%. This indicates that many customers who left comments on Amazon have negative attitude towards what they bought, in other word, they are not that satisfied. The conclusion implies that Amazon shall try to find out why most customers were not happy with the products bought and improve more on the quality.
- b. Another feature I applied on the different dataset has an accuracy of 0.997, which is much more higher than the Not_feature and SL_feature. Using the classifier trained by this feature, the result shows that there are 495485 negative comments and 645157 positive sentences, the ratio of positive comments is 56%. We could conclude that the comments are half positive and half negative, but more customers are satisfied with the products overall.
- c. The accuracy of Not_feature and SL_feature is less than 80%, while the other is 99.7%.

3. Improvement

Though the feature I chose is the higher one, the accuracy is still lower than 0.8, and it's much lower than the feature I chose in the Bonus part.

Possible measures to improve the accuracy include improving the accuracy of Not_feature by adding more (possible) negation words into the list and trying other advanced features.