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PRODUCT CATEGORY:BABY PRODUCTS REVIEWS

DATASET:

I chose the baby dataset to run my experiment.

I downloaded the dataset and then load the dataset into “baby’” dataframe and continue to experiment from that.

```
def parse_gz(path):
   g = gzip.open(path, 'rb')
   for l in g:
      yield eval(l)


def convert_to_DF(path):
   i = 0
   df = {}
   for d in parse_gz(path):
      df[i] = d
      i += 1
   return pd.DataFrame.from_dict(df, orient='index')


baby= convert_to_DF('reviews_Baby_5.json.gz')
print('Dataset size: {:,} words'.format(len(baby)))
```

This code only give us the REVIEWS from the baby dataframe.

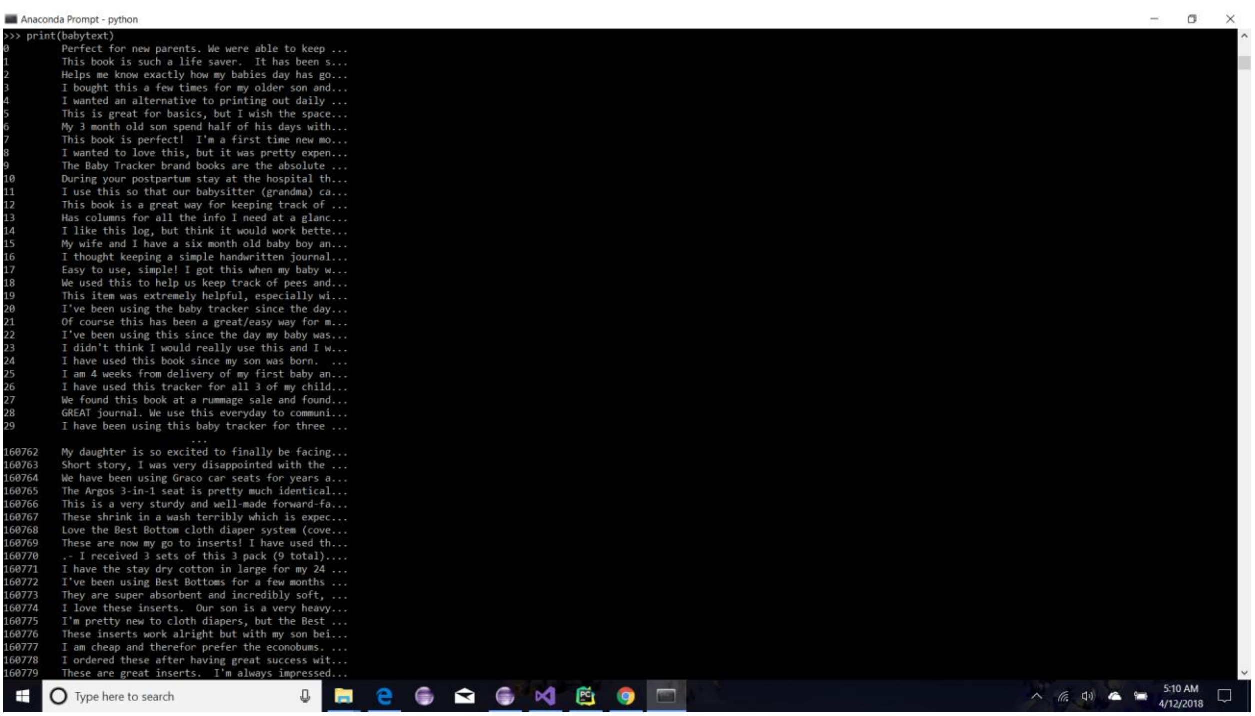
```
reviews = baby['reviewText']
```

Preprocessing:

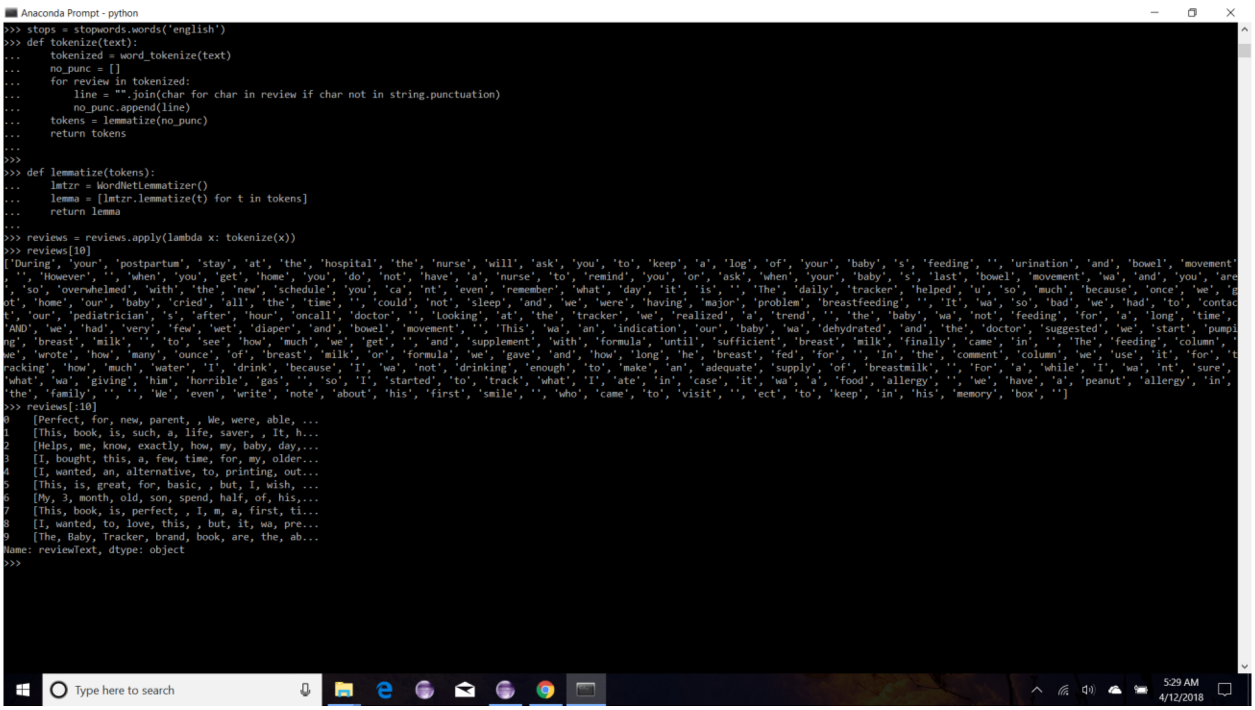
Now we do some preprocessing. I ran some pre processing on my data like removing some of the stop words ,lemmatization.

```python
stops = stopwords.words('english')

def tokenize(text):

    tokenized = word_tokenize(text)

    no_punc = []

    for review in tokenized:

        line = "".join(char for char in review if char not in string.punctuation)

        no_punc.append(line)

    tokens = lemmatize(no_punc)

    return tokens

#lemmatization
def lemmatize(tokens):

    lmtzr = WordNetLemmatizer()

    lemma = [lmtzr.lemmatize(t) for t in tokens]

    return lemma

reviews = reviews.apply(lambda x: tokenize(x))
```

BEFORE PREPROCESSING



AFTER PREPROCESSING



RESULTS:

0 [Perfect, for, new, parent, , We, were, able, ...

1 [This, book, is, such, a, life, saver, , It, h...

2 [Helps, me, know, exactly, how, my, baby, day,...

3 [I, bought, this, a, few, time, for, my, older...

4 [I, wanted, an, alternative, to, printing, out...

5 [This, is, great, for, basic, , but, I, wish, ...

6 [My, 3, month, old, son, spend, half, of, his,...

7 [This, book, is, perfect, , I, m, a, first, ti...

8 [I, wanted, to, love, this, , but, it, wa, pre...

9 [The, Baby, Tracker, brand, book, are, the, ab...

10 [During, your, postpartum, stay, at, the, hosp...

Name: reviewText, dtype: object

Experiment:

Now we explore the sentiment of the comments at the 3 sentence level. This includes how to process the words and how to conduct the sentiment analysis using classifiers.

We collect all the words in the sentence_polarity corpus and select some number of most frequent words to be the word features.

```
reviews = reviews.apply(lambda x: tokenize(x))

from nltk.corpus import sentence_polarity

import random

sentences = sentence_polarity.sents()

documents = [(sent, reviews) for reviews in sentence_polarity.categories()

    for sent in sentence_polarity.sents(categories=reviews)]

random.shuffle(documents)

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

all_words = nltk.FreqDist(all_words_list)

import nltk

all_words = nltk.FreqDist(all_words_list)

word_items = all_words.most_common(100)

word_features = [word for (word, freq) in word_items]

def document_features(document, word_features):

    document_words = set(document)

    features = {}

    for word in word_features:

        features['contains({})'.format(word)] = (word in document_words)

    return features


featuresets = [(document_features(d,word_features), c) for (d,c) in documents]

train_set, test_set = featuresets[50:], featuresets[:50]
```

classifier = nltk.NaiveBayesClassifier.train(train_set)

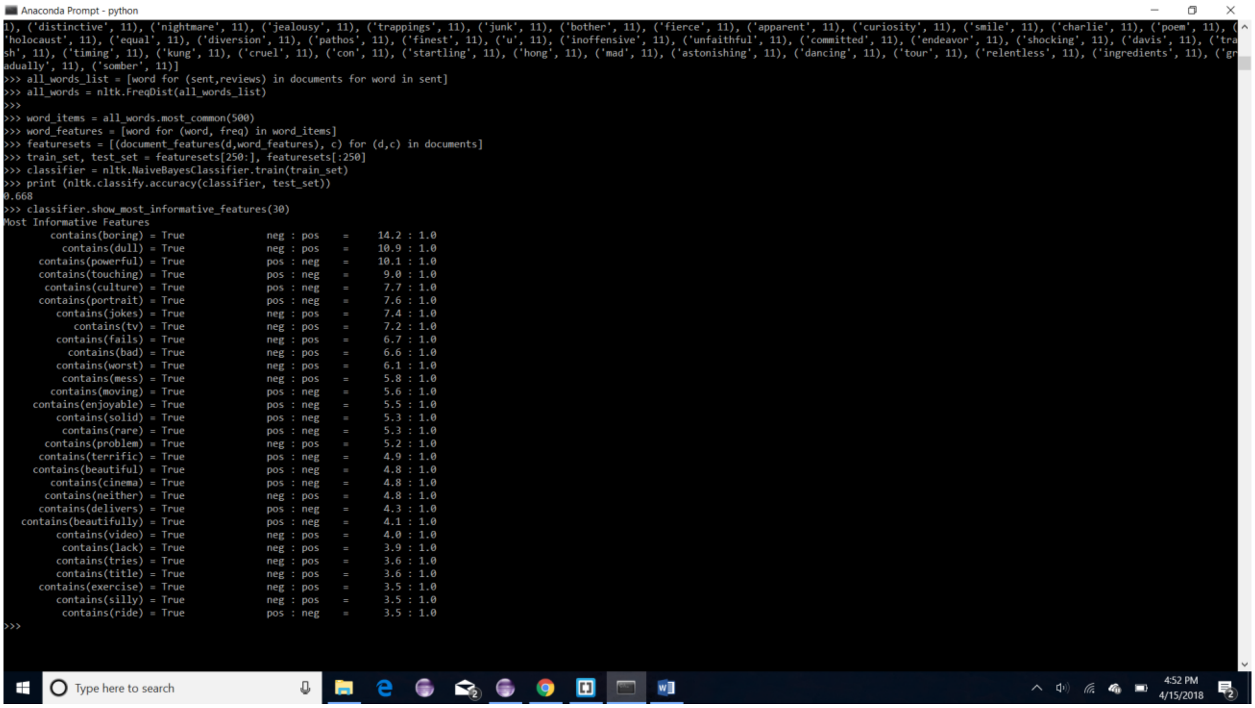
print (nltk.classify.accuracy(classifier, test_set))

0.668

classifier.show_most_informative_features(20)

Before implementing ANY lexicons features the accuracy rate is coming as 0.66.

Here is the sentence list with Negative and Positive features.



Now we implement Subjectivity Lexicon and run the same classifier.

def SL_features(document, word_features, reviews):

...   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 reviews:
...             strength, posTag, isStemmed, polarity = reviews[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
>>> SL_featuresets = [(SL_features(d, word_features, reviews), c) for (d,c) in documents]
>>> train_set, test_set = SL_featuresets[100:], SL_featuresets[:100]
>>> classifier = nltk.NaiveBayesClassifier.train(train_set)
>>> print (nltk.classify.accuracy(classifier, test_set))
0.61
```

RESULTS:

```
Most Informative Features
           contains(bad) = True              neg : pos    =      6.3 : 1.0
           contains(too) = True              neg : pos    =      3.6 : 1.0
             contains(?) = True              neg : pos    =      2.7 : 1.0
          contains(best) = True              pos : neg    =      2.4 : 1.0
            contains(no) = True              neg : pos    =      2.2 : 1.0
```

```
contains(doesn't) = True          neg : pos    =      2.1 : 1.0
contains(was) = True              neg : pos    =      2.0 : 1.0
contains(only) = True             neg : pos    =      1.9 : 1.0
contains(just) = True             neg : pos    =      1.9 : 1.0
contains(would) = True            neg : pos    =      1.9 : 1.0
contains(there's) = True          neg : pos    =      1.8 : 1.0
contains(love) = True             pos : neg    =      1.8 : 1.0
contains(us) = True               pos : neg    =      1.8 : 1.0
contains(life) = True             pos : neg    =      1.8 : 1.0
contains(been) = True             neg : pos    =      1.8 : 1.0
contains(funny) = True            pos : neg    =      1.8 : 1.0
contains(or) = True               neg : pos    =      1.6 : 1.0
contains(so) = True               neg : pos    =      1.6 : 1.0
contains(much) = True             neg : pos    =      1.6 : 1.0
contains(i) = True                neg : pos    =      1.5 : 1.0
```

We see improvement in accuracy.

The other strategy with negation words is to negate the word following the negation word ow we try the negation stratergy .We build a negation word features on top of SL word features to improve the accuracy.

```
for sent in list(sentences)[:50]:
    for word in sent:
      if (word.endswith("n't")):
          print(sent)
```

['there', 'is', 'a', 'difference', 'between', 'movies', 'with', 'the', 'courage', 'to', 'go', 'over', 'the', 'top', 'and', 'movies', 'that', "don't", 'care', 'about', 'being', 'stupid']

['a', 'farce', 'of', 'a', 'parody', 'of', 'a', 'comedy', 'of', 'a', 'premise', ',', 'it', "isn't", 'a', 'comparison', 'to', 'reality', 'so', 'much', 'as', 'it', 'is', 'a', 'commentary', 'about', 'our', 'knowledge', 'of', 'films', '.']

['i', "didn't", 'laugh', '.', 'i', "didn't", 'smile', '.', 'i', 'survived', '.']

['i', "didn't", 'laugh', '.', 'i', "didn't", 'smile', '.', 'i', 'survived', '.']

['most', 'of', 'the', 'problems', 'with', 'the', 'film', "don't", 'derive', 'from', 'the', 'screenplay', ',', 'but', 'rather', 'the', 'mediocre', 'performances', 'by', 'most', 'of', 'the', 'actors', 'involved']

['the', 'lack', 'of', 'naturalness', 'makes', 'everything', 'seem', 'self-consciously', 'poetic', 'and', 'forced', '.', '.', '.', "it's", 'a', 'pity', 'that', "[nelson's]", 'achievement', "doesn't", 'match', 'his', 'ambition', '.']

```
negationwords = ['no', 'not', 'never', 'none', 'nowhere', 'nothing', 'noone', 'rather', 'hardly', 'scarcely', 'rarely', 'seldom', 'neither', 'nor']

def NOT_features(document, word_features, negationwords):
    features = {}
    for word in SL_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 SL_features)
        else:
            features['contains({})'.format(word)] = (word in SL_features)
    return features


NOT_featuresets = [(NOT_features(d, SL_features, negationwords), c) for (d, c) in documents]
```

train_set, test_set = NOT_featuresets[50:], NOT_featuresets[:50]

classifier = nltk.NaiveBayesClassifier.train(train_set)

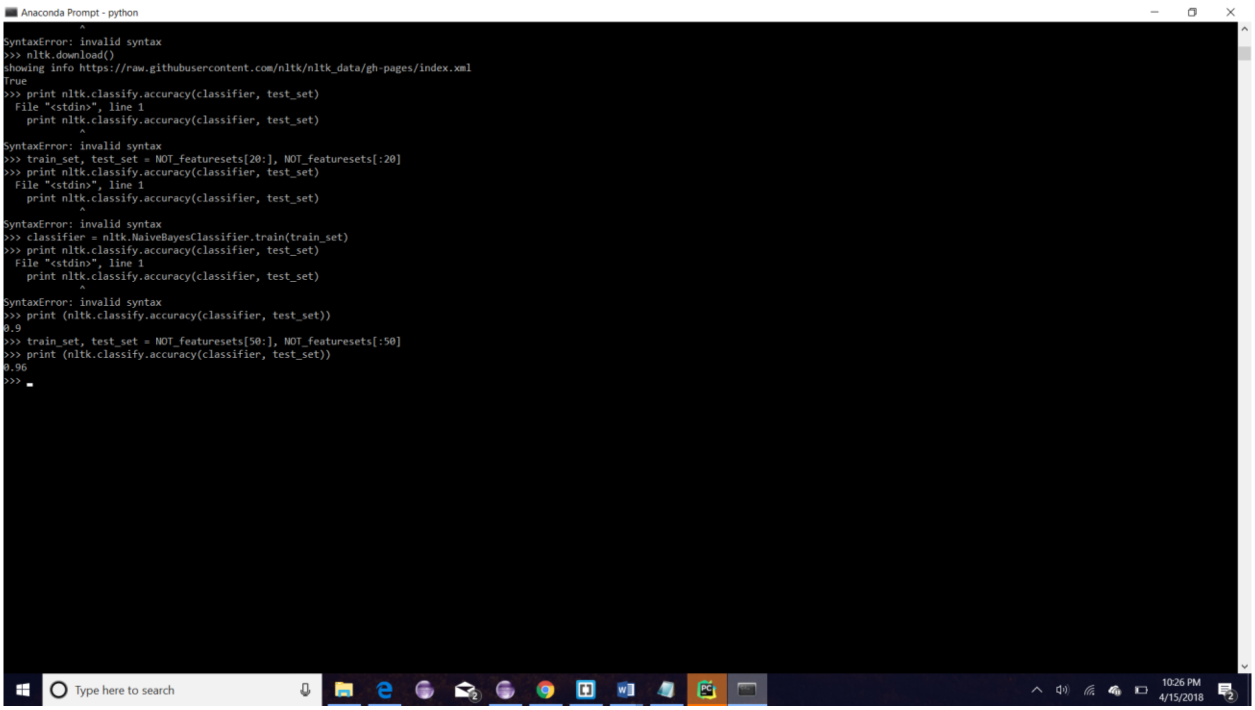
We define the negation words and then convert the double negation into positives.

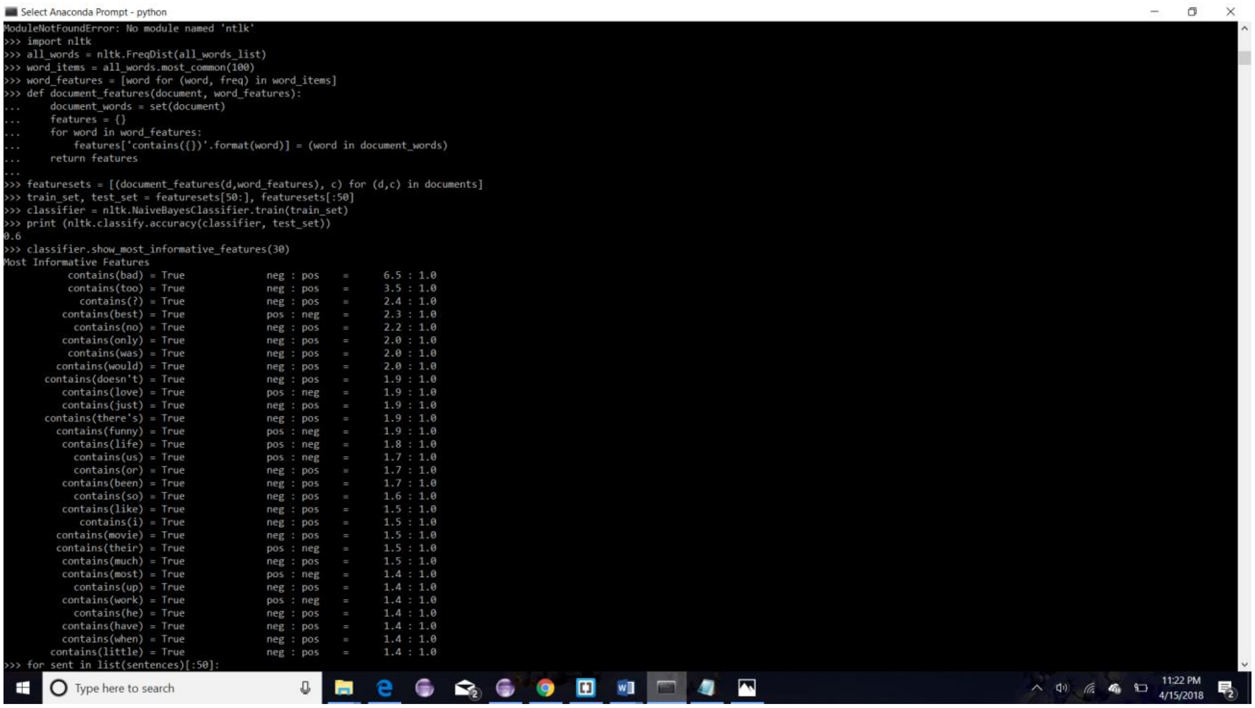
print (nltk.classify.accuracy(classifier, test_set))

0.78

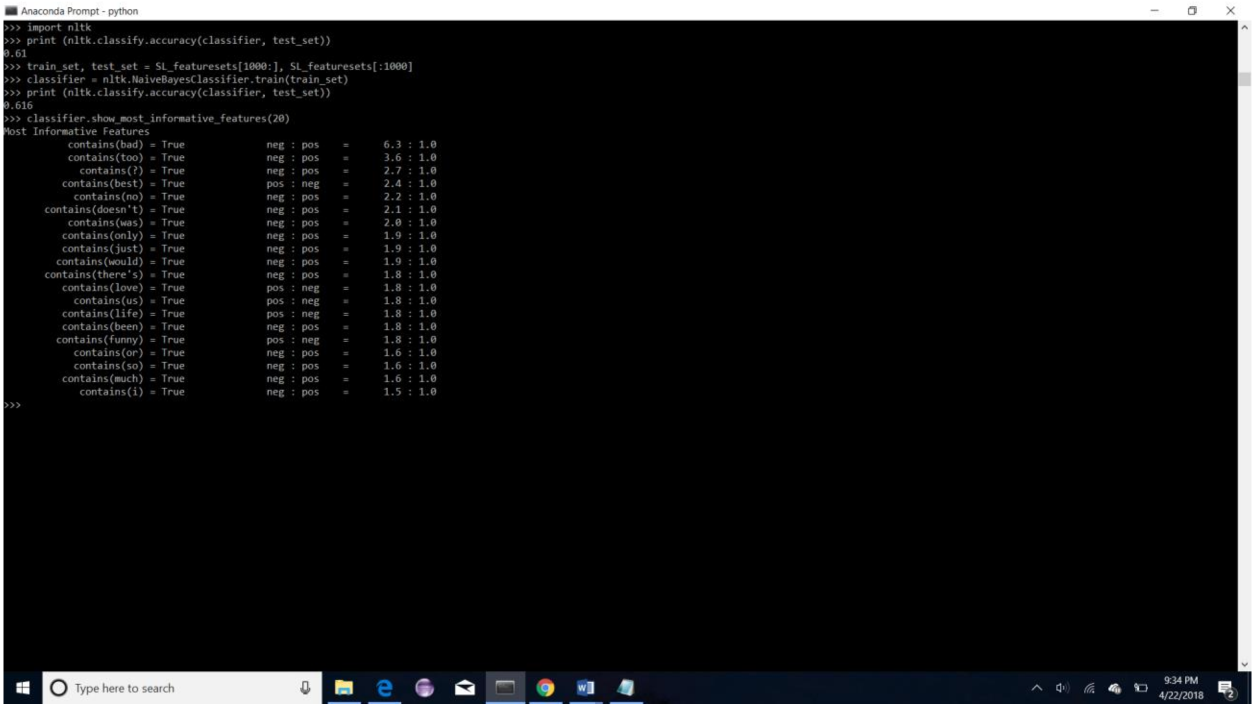
classifier.show_most_informative_features(20)

Now our accuracy is increased a lot.

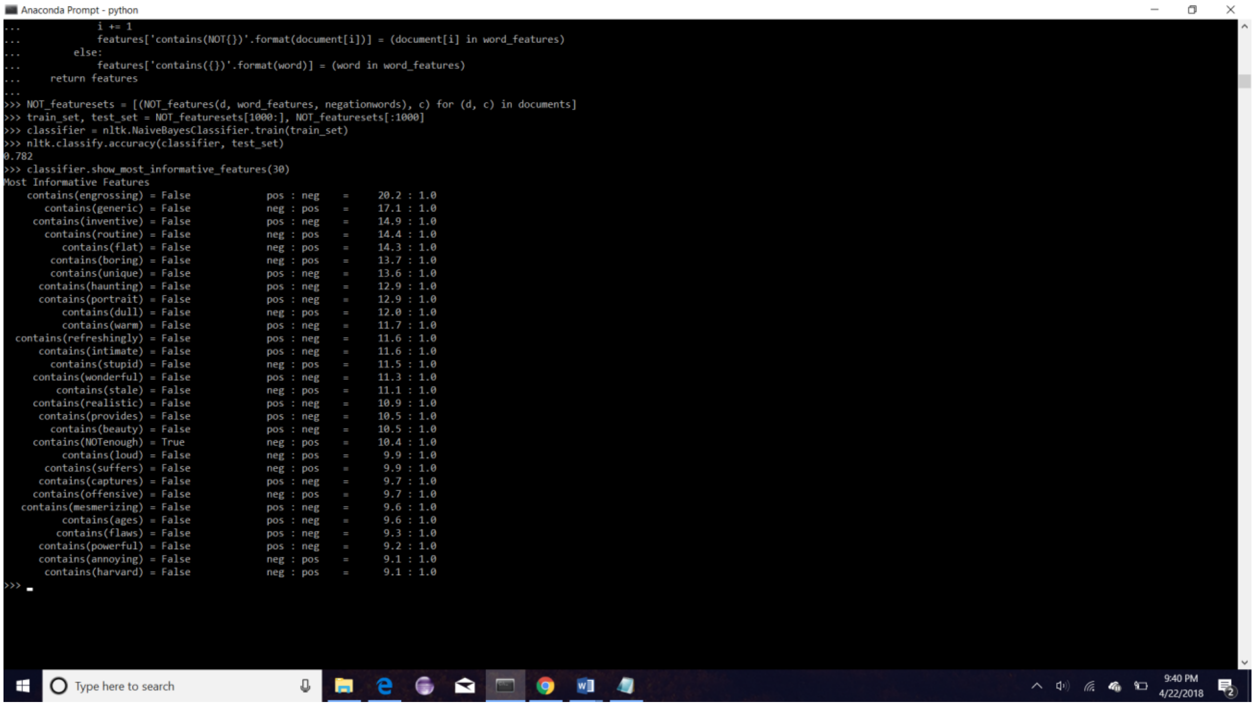




AFTER SUBJECTIVITY:



AFTER NEGATION:



```
Anaconda Prompt - python
...             i += 1
...             features['contains(NOT{})'.format(document[i])] = (document[i] in word_features)
...         else:
...             features['contains({})'.format(word)] = (word in word_features)
...     return features
...
>>> NOT_featuresets = [(NOT_features(d, word_features, negationwords), c) for (d, c) in documents]
>>> train_set, test_set = NOT_featuresets[1000:], NOT_featuresets[:1000]
>>> classifier = nltk.NaiveBayesClassifier.train(train_set)
>>> nltk.classify.accuracy(classifier, test_set)
0.782
>>> classifier.show_most_informative_features(30)
Most Informative Features
    contains(engrossing) = False           pos : neg    =     20.2 : 1.0
       contains(generic) = False           neg : pos    =     17.1 : 1.0
     contains(inventive) = False           pos : neg    =     14.9 : 1.0
       contains(routine) = False           neg : pos    =     14.4 : 1.0
          contains(flat) = False           neg : pos    =     14.3 : 1.0
        contains(boring) = False           neg : pos    =     13.7 : 1.0
        contains(unique) = False           pos : neg    =     13.6 : 1.0
      contains(haunting) = False           pos : neg    =     12.9 : 1.0
      contains(portrait) = False           pos : neg    =     12.9 : 1.0
          contains(dull) = False           neg : pos    =     12.0 : 1.0
          contains(warm) = False           pos : neg    =     11.7 : 1.0
  contains(refreshingly) = False           pos : neg    =     11.6 : 1.0
      contains(intimate) = False           pos : neg    =     11.6 : 1.0
        contains(stupid) = False           neg : pos    =     11.5 : 1.0
     contains(wonderful) = False           pos : neg    =     11.3 : 1.0
         contains(stale) = False           neg : pos    =     11.1 : 1.0
     contains(realistic) = False           pos : neg    =     10.9 : 1.0
      contains(provides) = False           pos : neg    =     10.5 : 1.0
        contains(beauty) = False           pos : neg    =     10.5 : 1.0
     contains(NOTenough) = True            neg : pos    =     10.4 : 1.0
          contains(loud) = False           neg : pos    =      9.9 : 1.0
       contains(suffers) = False           neg : pos    =      9.9 : 1.0
      contains(captures) = False           pos : neg    =      9.7 : 1.0
     contains(offensive) = False           neg : pos    =      9.7 : 1.0
   contains(mesmerizing) = False           pos : neg    =      9.6 : 1.0
          contains(ages) = False           pos : neg    =      9.6 : 1.0
         contains(flaws) = False           pos : neg    =      9.3 : 1.0
      contains(powerful) = False           pos : neg    =      9.2 : 1.0
      contains(annoying) = False           neg : pos    =      9.1 : 1.0
       contains(harvard) = False           neg : pos    =      9.1 : 1.0
>>>
```

COMPARISON: We saw that after implementing negation on top of subjectivity gave us a good performance and accuracy.

RESULTS:

Most Informative Features

contains(engrossing) = False pos : neg = 20.2 : 1.0

contains(generic) = False neg : pos = 17.1 : 1.0

contains(inventive) = False pos : neg = 14.9 : 1.0

contains(routine) = False neg : pos = 14.4 : 1.0

contains(flat) = False neg : pos = 14.3 : 1.0

contains(boring) = False neg : pos = 13.7 : 1.0

contains(unique) = False pos : neg = 13.6 : 1.0

contains(haunting) = False pos : neg = 12.9 : 1.0

contains(portrait) = False pos : neg = 12.9 : 1.0

contains(dull) = False neg : pos = 12.0 : 1.0

contains(warm) = False pos : neg = 11.7 : 1.0

contains(refreshingly) = False pos : neg = 11.6 : 1.0

```
contains(intimate) = False            pos : neg    =     11.6 : 1.0
contains(stupid) = False              neg : pos    =     11.5 : 1.0
contains(wonderful) = False           pos : neg    =     11.3 : 1.0
contains(stale) = False               neg : pos    =     11.1 : 1.0
contains(realistic) = False           pos : neg    =     10.9 : 1.0
contains(provides) = False            pos : neg    =     10.5 : 1.0
contains(beauty) = False              pos : neg    =     10.5 : 1.0
contains(NOTenough) = True            neg : pos    =     10.4 : 1.0
contains(loud) = False                neg : pos    =      9.9 : 1.0
contains(suffers) = False             neg : pos    =      9.9 : 1.0
contains(captures) = False            pos : neg    =      9.7 : 1.0
contains(offensive) = False           neg : pos    =      9.7 : 1.0
contains(mesmerizing) = False         pos : neg    =      9.6 : 1.0
contains(ages) = False                pos : neg    =      9.6 : 1.0
contains(flaws) = False               pos : neg    =      9.3 : 1.0
contains(powerful) = False            pos : neg    =      9.2 : 1.0
contains(annoying) = False            neg : pos    =      9.1 : 1.0
```

ADDITIONAL LEXICON:

I took the bigram word features as a baseline and see if the features you designed improve the accuracy of the classification.

```
import collections

import nltk.classify.util, nltk.metrics

from nltk.classify import NaiveBayesClassifier


def evaluate_classifier(featx):

    negids = reviews.fileids('neg')

    posids = reviews.fileids('pos')
```

```
    negfeats = [(featx(reviews.words(fileids=[f])), 'neg') for f in negids]
    posfeats = [(featx(reviews.words(fileids=[f])), 'pos') for f in posids]

    negcutoff = len(negfeats)*3/4
    poscutoff = len(posfeats)*3/4

    trainfeats = negfeats[:negcutoff] + posfeats[:poscutoff]
    testfeats = negfeats[negcutoff:] + posfeats[poscutoff:]

    classifier = NaiveBayesClassifier.train(trainfeats)
    refsets = collections.defaultdict(set)
    testsets = collections.defaultdict(set)

    for i, (feats, label) in enumerate(testfeats):
        refsets[label].add(i)
        observed = classifier.classify(feats)
        testsets[observed].add(i)

    print 'accuracy:', nltk.classify.util.accuracy(classifier, testfeats)
    print 'pos precision:', nltk.metrics.precision(refsets['pos'], testsets['pos'])
    print 'pos recall:', nltk.metrics.recall(refsets['pos'], testsets['pos'])
    print 'neg precision:', nltk.metrics.precision(refsets['neg'], testsets['neg'])
    print 'neg recall:', nltk.metrics.recall(refsets['neg'], testsets['neg'])
    classifier.show_most_informative_features()
```

For reviews:

```
def word_feats(reviewss):
```

```
    return dict([(reviews, True) for word in words])


evaluate_classifier(word_feats)
accuracy: 0.66
pos precision: 0.651595744681
pos recall: 0.98
neg precision: 0.959677419355
neg recall: 0.476
from nltk.corpus import stopwords
stopset = set(stopwords.words('english'))
```

Stopword Filtering

```
def stopword_filtered_word_feats(reviews):
    return dict([(reviews, True) for reviews in words if reviews not in stopset])


evaluate_classifier(stopword_filtered_word_feats)
accuracy: 0.726
pos precision: 0.649867374005
pos recall: 0.98
neg precision: 0.959349593496
neg recall: 0.472
```

ADDITIONAL FEATURES:

I used LDA AND NMP for topic modelling to see which are most discussed topics in Baby products reviews.

```
>>> review_text = baby["reviewText"]
>>> tfidf = tfidf_vectorizer.fit_transform(review_text)
>>> tf_vectorizer = CountVectorizer(stop_words=stops)
>>> tf = tf_vectorizer.fit_transform(review_text)
```

>>> tfidf_feature_names = tfidf_vectorizer.get_feature_names()

>>> print("Number of total features: {}".format(len(tfidf_feature_names)))

Number of total features: 63483

I created a TERM FREQUENCY DOCUMENST MATRIX and loaded the vectorize text into my TFIDF.

Then We build clustering model Using **Nonnegative Matrix Factorization.**

nmf_tf = nmf.fit(tf)

nmf_ = nmf_tf.transform(tf)

Counter([np.argmax(i) for i in nmf_])

retrieve_top_words(nmf_tf, tfidf_feature_names, num_top_words)

Topic #0:

would great use old son little months get easy love time well still daughter put

Topic #1:

seat car seats britax facing child back rear straps easy infant use get base fit

Topic #2:

baby carrier use put also time back babies months ergo used much around first bjorn

Topic #3:

stroller easy strollers wheels basket fold city canopy great back handle love also easily bag

Topic #4:

bottles bottle nipple nipples use milk avent water clean formula cup flow dr brush breast

Topic #5:

bag diaper diapers use cloth bags wipes changing size fit pad pocket pockets pail small

Topic #6:

one little two bought another gate side first get new hand buy got second different

Topic #7:

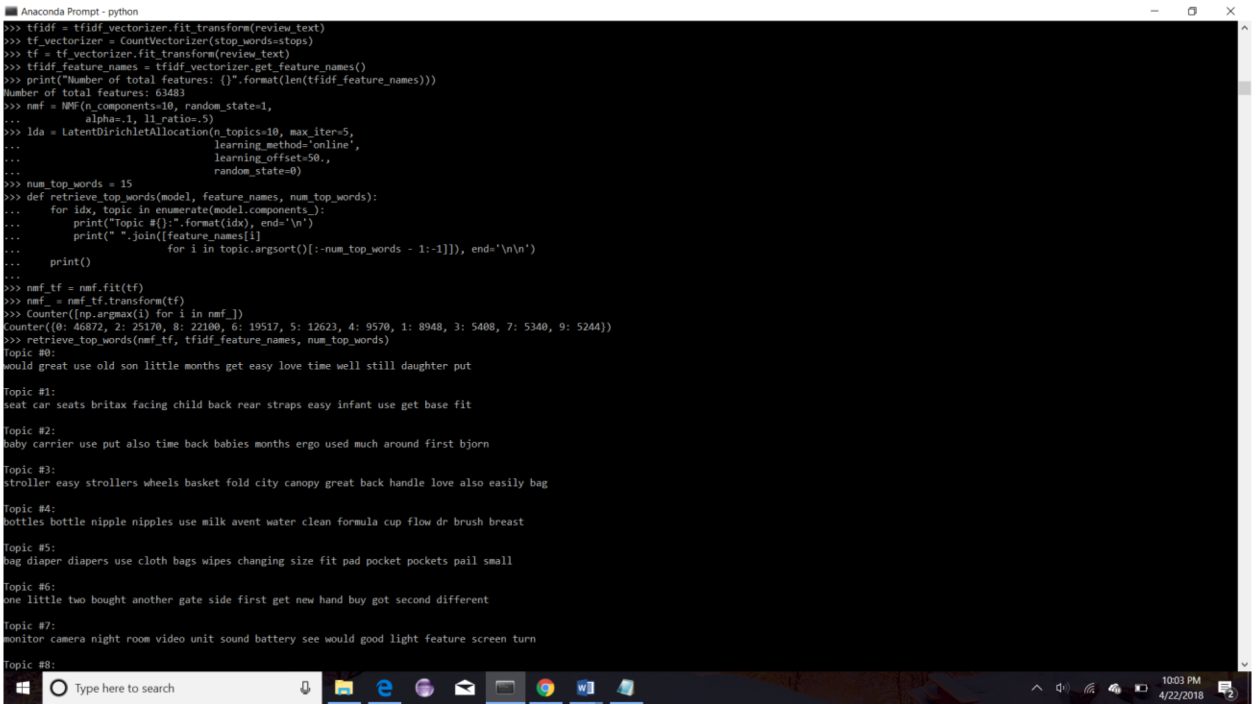
monitor camera night room video unit sound battery see would good light feature screen turn

Topic #8:

like really would also much think get nice seems good better feel little thing well

Topic #9:

pump milk medela pumping use get work breast time suction parts much would used pumps.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```
>>> tfidf = tfidf_vectorizer.fit_transform(review_text)
>>> tf_vectorizer = CountVectorizer(stop_words=stops)
>>> tf = tf_vectorizer.fit_transform(review_text)
>>> tfidf_feature_names = tfidf_vectorizer.get_feature_names()
>>> print("Number of total features: {}".format(len(tfidf_feature_names)))
Number of total features: 63483
>>> nmf = NMF(n_components=10, random_state=1,
...           alpha=.1, l1_ratio=.5)
>>> lda = LatentDirichletAllocation(n_topics=10, max_iter=5,
...                                 learning_method='online',
...                                 learning_offset=50.,
...                                 random_state=0)
>>> num_top_words = 15
>>> def retrieve_top_words(model, feature_names, num_top_words):
...     for idx, topic in enumerate(model.components_):
...         print("Topic #{}:".format(idx), end='\n')
...         print(" ".join([feature_names[i]
...                         for i in topic.argsort()[:-num_top_words - 1:-1]]), end='\n\n')
...     print()
...
>>> nmf_tf = nmf.fit(tf)
>>> nmf_ = nmf_tf.transform(tf)
>>> Counter([np.argmax(i) for i in nmf_])
Counter({0: 46872, 2: 25170, 8: 22100, 6: 19517, 5: 12623, 4: 9570, 1: 8948, 3: 5408, 7: 5340, 9: 5244})
>>> retrieve_top_words(nmf_tf, tfidf_feature_names, num_top_words)
Topic #0:
would great use old son little months get easy love time well still daughter put

Topic #1:
seat car seats britax facing child back rear straps easy infant use get base fit

Topic #2:
baby carrier use put also time back babies months ergo used much around first bjorn

Topic #3:
stroller easy strollers wheels basket fold city canopy great back handle love also easily bag

Topic #4:
bottles bottle nipple nipples use milk avent water clean formula cup flow dr brush breast

Topic #5:
bag diaper diapers use cloth bags wipes changing size fit pad pocket pockets pail small

Topic #6:
one little two bought another gate side first get new hand buy got second different

Topic #7:
monitor camera night room video unit sound battery see would good light feature screen turn

Topic #8:
```


LDA:

We do the same thing for LDA modelling.

lda_tf = lda.fit(tf)

In [145]:

lda_ = lda_tf.transform(tf)

Counter([np.argmax(i) **for** i **in** lda_])

retrieve_top_words(lda_tf, tfidf_feature_names, num_top_words)

Topic #0:

baby monitor night sleep room carrier looks back bed light video sound sleeping crib see

Topic #1:

food chair tray high table clean bibs bib eat eating chairs prefolds highchair plate dishwasher

Topic #2:

diaper soft diapers baby cover great well use cloth love crib wash pad changing mattress

Topic #3:

water tub bath open gate door wall bottom top temperature lock install plastic place wood

Topic #4:

seat car straps back seats britax strap child potty kid front carseat rear infant easy

Topic #5:
pump pillow medela milk nursing pumping breast work use back time day service customer freezer

Topic #6:

bottles bottle cup cups nipple sippy clean nipples milk straw leak avent brush baby formula

Topic #7:

one would like get baby use really little much well time good old great still

Topic #8:

stroller bag easy use great love one baby also clean small easily diaper well put

Topic #9:

baby loves old toy toys little great love son play cute months daughter one like