Homework 2 - Types, tokens and Zipf's law; sentiment analysis with naive Bayes

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CSCI 4140: Natural Language Processing

CSCI/DASC 6040: Computational Analysis of Natural Languages

Spring 2023

Homework 2 - Types, tokens and Zipf's law; sentiment analysis with naive Bayes

Due Sunday, February 12, at 11:59 PM

[150]:
```
# Run this cell! It sets some things up for you.

from __future__ import division  # this line is important to avoid unexpected
 ↪behavior from division
import matplotlib.pyplot as plt
import os
import zipfile
import math
import time
import operator
from collections import defaultdict, Counter

%matplotlib inline
plt.rcParams['figure.figsize'] = (5, 4) # set default size of plots

if not os.path.isdir('data'):
    os.mkdir('data')  # make the data directory

# Extract the data from the zipfile and put it into the data directory
with zipfile.ZipFile('large_movie_review_dataset.zip', 'r') as zip_ref:
    zip_ref.extractall('data')
print("IMDb data extracted!")

PATH_TO_DATA = 'data/large_movie_review_dataset'  # path to the data directory
POS_LABEL = 'pos'
NEG_LABEL = 'neg'
TRAIN_DIR = os.path.join(PATH_TO_DATA, "train")
```

```
TEST_DIR = os.path.join(PATH_TO_DATA, "test")

for label in [POS_LABEL, NEG_LABEL]:
    if len(os.listdir(TRAIN_DIR + "/" + label)) == 12500:
        print ("Great! You have 12500 {} reviews in {}".format(label, TRAIN_DIR␣
 ↪+ "/" + label))
    else:
        print ("Oh no! Something is wrong. Check your code which loads the␣
 ↪reviews")
```

```
IMDb data extracted!
Great! You have 12500 pos reviews in data/large_movie_review_dataset\train/pos
Great! You have 12500 neg reviews in data/large_movie_review_dataset\train/neg
```

[151]:
```
# Actually reading the data you are working with is an important part of NLP!␣
 ↪Let's look at one of these reviews

print (open(TRAIN_DIR + "/neg/98_1.txt").read())
```

```
I received this movie as a gift, I knew from the DVD cover, this movie are going
to be bad.After not watching it for more than a year I finally watched it. what
a pathetic movieÃ….<br /><br />I almost didn't finish watching this bad
movie,but it will be unfair of me to write a review without watching the
complete movie.<br /><br />Trust me when I say " this movie sucks" I am truly
shocked that some bad filmmaker wane bee got even financed to make this pathetic
movie, But it couldn't have cost more than $20 000 to produce this movie. all
you need are a cheap camcorder or a cell phone camera .about 15 people with no
acting skills, a scrip that were written by a couple of drunk people.<br /><br
/>In the fist part of this ultra bad move a reporter (Tara Woodley )run a
suppose to be drunk man over on her way to report on a hunted town. He are
completely unharmed. They went to a supposed to be abandon house ,but luckily
for the it almost complete furnished and a bottle of liquor on the door step
happens to be there. just for the supposed to be drunk man but all is not what
it seems.<br /><br />Then the supposed drunk man start telling Tara
ghost/zombies stories.<br /><br />The fist of his stupid lame stories must be
the worst in history.<br /><br />his story<br /><br />Sgt. Ben Draper let one of
his soldiers die of complete exhaustion (I think this is what happens)after
letting the poor soldier private Wilson do sit ups he let him dig a grave and
then the soldier collapse ,Ben Draper<br /><br />buries him in a shallow
grave.<br /><br />But Sgt. Ben Draper are in for n big surprise. his wife/girl
fiend knows about this and she and her lover kills Sgt. Ben Draper to take
revenge on private Wilson.(next to the grave of the soldier he sort off
murdered) The soldier wakes up from his grave in the form of zombie and kill
them for taking revenge on his behalf.<br /><br />The twist ending were so
lame.<br /><br />Even if you like B HORROR movies, don't watch this movie
```

1 Preprocessing Block

The following cell contains code that will be referred to as the `Preprocessing Block` from now on. It contains a function that tokenizes the document passed to it, and functions that return counts of word types and tokens.

[152]:
```
###### PREPROCESSING BLOCK ######

###### DO NOT MODIFY THIS FUNCTION #####
def tokenize_doc(doc):
    """
    Tokenize a document and return its bag-of-words representation.
    doc - a string representing a document.
    returns a dictionary mapping each word to the number of times it appears in␣
 ↪doc.
    """
    bow = defaultdict(float)
    tokens = doc.split()
    lowered_tokens = map(lambda t: t.lower(), tokens)
    for token in lowered_tokens:
        bow[token] += 1.0
    return dict(bow)
###### END FUNCTION #####

def n_word_types(word_counts):
    '''
    Implement Me!
    return a count of all word types in the corpus
    using information from word_counts
    '''
    return len(word_counts)


def n_word_tokens(word_counts):
    '''
    Implement Me!
    return a count of all word tokens in the corpus
    using information from word_counts
    '''
    return sum(word_counts.values())
```

2 Naive Bayes Block

This next block of code (referred to as `Naive Bayes Block` from now on) is something you will keep coming back to throughout the course of the assignment. There are several functions you need to implement here, that will be called in later parts of the assignment. Familiarize yourself with what each function does, as well as how everything comes together.

[153]:
```
###### NAIVE BAYES BLOCK ######

class NaiveBayes:
    """A Naive Bayes model for text classification."""

    def __init__(self, path_to_data, tokenizer):
        # Vocabulary is a set that stores every word seen in the training data
        self.vocab = set()
        self.path_to_data = path_to_data
        self.tokenize_doc = tokenizer
        self.train_dir = os.path.join(path_to_data, "train")
        self.test_dir = os.path.join(path_to_data, "test")
        # class_total_doc_counts is a dictionary that maps a class (i.e., pos/
 ↪neg) to
        # the number of documents in the trainning set of that class
        self.class_total_doc_counts = { POS_LABEL: 0.0,
                                        NEG_LABEL: 0.0 }

        # class_total_word_counts is a dictionary that maps a class (i.e., pos/
 ↪neg) to
        # the number of words in the training set in documents of that class
        self.class_total_word_counts = { POS_LABEL: 0.0,
                                         NEG_LABEL: 0.0 }

        # class_word_counts is a dictionary of dictionaries. It maps a class (i.
 ↪e.,
        # pos/neg) to a dictionary of word counts. For example:
        #    self.class_word_counts[POS_LABEL]['awesome']
        # stores the number of times the word 'awesome' appears in documents
        # of the positive class in the training documents.
        self.class_word_counts = { POS_LABEL: defaultdict(float),
                                   NEG_LABEL: defaultdict(float) }

    def train_model(self):
        """
        This function processes the entire training set using the global PATH
        variable above.  It makes use of the tokenize_doc and update_model
        functions you will implement.
        """

        pos_path = os.path.join(self.train_dir, POS_LABEL)
        neg_path = os.path.join(self.train_dir, NEG_LABEL)
        for (p, label) in [ (pos_path, POS_LABEL), (neg_path, NEG_LABEL) ]:
            for f in os.listdir(p):
                with open(os.path.join(p,f),'r',encoding='utf-8') as doc:
                    content = doc.read()
                    self.tokenize_and_update_model(content, label)
```

```
        self.report_statistics_after_training()

    def report_statistics_after_training(self):
        """
        Report a number of statistics after training.
        """

        print ("REPORTING CORPUS STATISTICS")
        print ("NUMBER OF DOCUMENTS IN POSITIVE CLASS:", self.
↪class_total_doc_counts[POS_LABEL])
        print ("NUMBER OF DOCUMENTS IN NEGATIVE CLASS:", self.
↪class_total_doc_counts[NEG_LABEL])
        print ("NUMBER OF TOKENS IN POSITIVE CLASS:", self.
↪class_total_word_counts[POS_LABEL])
        print ("NUMBER OF TOKENS IN NEGATIVE CLASS:", self.
↪class_total_word_counts[NEG_LABEL])
        print ("VOCABULARY SIZE: NUMBER OF UNIQUE WORDTYPES IN TRAINING CORPUS:
↪", len(self.vocab))

    def update_model(self, bow, label):
        """
        Implement me!

        Update internal statistics given a document represented as a␣
↪bag-of-words
        bow - a map from words to their counts
        label - the class of the document whose bag-of-words representation was␣
↪input
        This function doesn't return anything but should update a number of␣
↪internal
        statistics. Specifically, it updates:
          - the internal map the counts, per class, how many times each word was
            seen (self.class_word_counts)
          - the number of words seen for each label (self.
↪class_total_word_counts)
          - the vocabulary seen so far (self.vocab)
          - the number of documents seen of each label (self.
↪class_total_doc_counts)
        """
        for words in bow:
         self.class_word_counts[label][words]+=bow[words]
         self.class_total_word_counts[label]+=bow[words]
         self.vocab.add(words)

        self.class_total_doc_counts[label]+=1.0
```

```
    def tokenize_and_update_model(self, doc, label):
        """
        Implement me!

        Tokenizes a document doc and updates internal count statistics.
        doc - a string representing a document.
        label - the sentiment of the document (either postive or negative)
        stop_word - a boolean flag indicating whether to stop word or not

        Make sure when tokenizing to lower case all of the tokens!
        """
        bow = self.tokenize_doc(doc)
        self.update_model(bow, label)

    def top_n(self, label, n):
        """
        Implement me!

        Returns the most frequent n tokens for documents with class 'label'.
        """
        return sorted(self.class_word_counts[label].items(), key=lambda wc:␣
↪wc[1], reverse=True)[:n]

    def p_word_given_label(self, word, label):
        """
        Implement me!

        Returns the probability of word given label
        according to this NB model.
        """
        word_counts = self.class_word_counts[label]
        total_word_count = self.class_total_word_counts[label]
        return (word_counts[word] + 1) / (total_word_count + len(self.vocab))

    def p_word_given_label_and_alpha(self, word, label, alpha):
        """
        Implement me!

        Returns the probability of word given label wrt psuedo counts.
        alpha - pseudocount parameter
        """
        word_counts = self.class_word_counts[label]
        total_word_count = self.class_total_word_counts[label]
        return (word_counts.get(word, 0) + alpha) / (total_word_count + alpha *␣
↪len(self.vocab))

    def log_likelihood(self, bow, label, alpha):
```

```
        """
        Implement me!

        Computes the log likelihood of a set of words given a label and␣
↪pseudocount.
        bow - a bag of words (i.e., a tokenized document)
        label - either the positive or negative label
        alpha - float; pseudocount parameter
        """
        log_likelihood = 0
        for word, count in bow.items():
            p_word = self.p_word_given_label_and_alpha(word, label, alpha)
            log_likelihood += count * math.log(p_word)
        return log_likelihood

    def log_prior(self, label):
        """
        Implement me!

        Returns the log prior of a document having the class 'label'.
        """
        total_docs = sum(self.class_total_doc_counts.values())
        p_label = self.class_total_doc_counts[label] / total_docs
        return math.log(p_label)

    def unnormalized_log_posterior(self, bow, label, alpha):
        """
        Implement me!

        Computes the unnormalized log posterior (of doc being of class 'label').
        bow - a bag of words (i.e., a tokenized document)
        """
        return self.log_prior(label)+self.log_likelihood(bow, label, alpha)

    def classify(self, bow, alpha):
        """
        Implement me!

        Compares the unnormalized log posterior for doc for both the positive
        and negative classes and returns the either POS_LABEL or NEG_LABEL
        (depending on which resulted in the higher unnormalized log posterior)
        bow - a bag of words (i.e., a tokenized document)
        """
        pos=self.unnormalized_log_posterior(bow,POS_LABEL,alpha)
        neg=self.unnormalized_log_posterior(bow,NEG_LABEL,alpha)
        if pos>neg:
         return POS_LABEL
```

```
        else:
         return NEG_LABEL

    def likelihood_ratio(self, word, alpha):
        """
        Implement me!

        Returns the ratio of P(word|pos) to P(word|neg).
        """
        pos_likelihood = self.p_word_given_label_and_alpha(word, POS_LABEL,␣
↪alpha)
        neg_likelihood = self.p_word_given_label_and_alpha(word, NEG_LABEL,␣
↪alpha)
        return pos_likelihood / neg_likelihood

    def evaluate_classifier_accuracy(self, alpha):
        """
        DO NOT MODIFY THIS FUNCTION

        alpha - pseudocount parameter.
        This function should go through the test data, classify each instance␣
↪and
        compute the accuracy of the classifier (the fraction of classifications
        the classifier gets right.
        """
        correct = 0.0
        total = 0.0

        pos_path = os.path.join(self.test_dir, POS_LABEL)
        neg_path = os.path.join(self.test_dir, NEG_LABEL)
        for (p, label) in [ (pos_path, POS_LABEL), (neg_path, NEG_LABEL) ]:
            for f in os.listdir(p):
                with open(os.path.join(p,f),'r',encoding="utf-8") as doc:
                    content = doc.read()
                    bow = self.tokenize_doc(content)
                    if self.classify(bow, alpha) == label:
                        correct += 1.0
                    total += 1.0
        return 100 * correct / total

    def highest_lr_word(self, alpha):
        """
        Finds the word in the vocabulary with the highest likelihood ratio␣
↪(P(word|pos) / P(word|neg)).
        """
        highest_lr = -1
        highest_lr_word = None
```

```
        for word in self.vocab:
            lr = self.likelihood_ratio(word, alpha)
            if lr > highest_lr:
                highest_lr = lr
                highest_lr_word = word
        return highest_lr_word
```

3 Part One: Intro to NLP in Python: types, tokens and Zipf's law

3.1 Types and tokens

One major part of any NLP project is word tokenization. Word tokenization is the task of segmenting text into individual words, called tokens. In this assignment, we will use simple whitespace tokenization. Take a look at the `tokenize_doc` function in the Preprocessing Block above. **You should not modify tokenize_doc** but make sure you understand what it is doing.

[154]:
```
d1 = "This SAMPLE doc has   words tHat  repeat repeat"
bow = tokenize_doc(d1)

assert bow['this'] == 1
assert bow['sample'] == 1
assert bow['doc'] == 1
assert bow['has'] == 1
assert bow['words'] == 1
assert bow['that'] == 1
assert bow['repeat'] == 2

bow2 = tokenize_doc("NLP is my favorite class this semester!")
for b in bow2:
    print (b)
```

```
nlp
is
my
favorite
class
this
semester!
```

Now we are going to look at the word types and word tokens in the corpus. Use the `word_counts` dictionary variable to store the count of each word in the corpus. Use the `tokenize_doc` function to break documents into tokens. **You should not modify tokenize_doc** but make sure you understand what it is doing.

3.1.1 Question 1.1 (5 points)

Complete the cell below to fill out the `word_counts` dictionary variable. `word_counts` keeps track of how many times a word type appears across the corpus. For instance, `word_counts["movie"]` should store the number 61492, the count of how many times the word `movie` appears in the corpus.

[155]:
```
import glob
import codecs
import re
word_counts = Counter() # Counters are often useful for NLP in python

for label in [POS_LABEL, NEG_LABEL]:
    for directory in [TRAIN_DIR, TEST_DIR]:
        for fn in glob.glob(directory + "/" + label + "/*txt"):
            doc = codecs.open(fn, 'r', 'utf8') # Open the file with UTF-8␣
 ↪encoding
            contents = doc.read()
            tokens = tokenize_doc(contents)
            word_counts.update(tokens)
```

[156]:
```
if word_counts["movie"] == 61492:
    print ("yay! there are {} total instances of the word type movie in the␣
 ↪corpus".format(word_counts["movie"]))
else:
    print ("hmm. Something seems off. Double check your code")
```

```
yay! there are 61492.0 total instances of the word type movie in the corpus
```

3.1.2 Question 1.2 (5 points)

Fill out the functions `n_word_types`, `n_word_tokens` in the Preprocessing Block.

Note: you will have to rerun the `Preprocessing Block` cell every time you change its code for it to have any effect!

[157]:
```
print ("there are {} word types in the corpus".
 ↪format(n_word_types(word_counts)))
print ("there are {} word tokens in the corpus".
 ↪format(n_word_tokens(word_counts)))
```

```
there are 390931 word types in the corpus
there are 11557847.0 word tokens in the corpus
```

What is the difference between word types and tokens? Why are the number of tokens much higher than the number of types?

Answer in one or two lines here.

`n_word_types` function counts the number of unique words in the corpus.

`n_word_tokens` function counts the total number of words in the corpus.

3.1.3 Question 1.3 (5 points)

Using the `word_counts` dictionary you just created, make a new dictionary called `sorted_dict` where the words are sorted according to their counts, in decending order:

[158]:
```
sorted_dict = dict(sorted(word_counts.items(), key=lambda item: item[1],␣
↪reverse=True))
```

Now print the first 30 values from sorted_dict.

[159]:
```
for i, (word, count) in enumerate(sorted_dict.items()):
    if i == 30:
        break
    print(f"{word}: {count}")
```

```
the: 638861.0
a: 316615.0
and: 313637.0
of: 286661.0
to: 264573.0
is: 204876.0
in: 179807.0
i: 141587.0
this: 138483.0
that: 130140.0
it: 129614.0
/><br: 100974.0
was: 93258.0
as: 88242.0
with: 84590.0
for: 84510.0
but: 77864.0
on: 62890.0
movie: 61492.0
are: 57009.0
his: 56870.0
not: 56765.0
you: 55600.0
film: 55086.0
have: 54423.0
he: 51062.0
be: 50901.0
at: 45259.0
one: 44983.0
by: 43359.0
```

3.2 Zipf's Law

3.2.1 Question 1.4 (10 points)

In this section, you will verify a key statistical property of text: Zipf's Law.

Zipf's Law describes the relations between the frequency rank of words and frequency value of words. For a word w, its frequency is inversely proportional to its rank:

$$count_w = K\frac{1}{rank_w}$$

K is a constant, specific to the corpus and how words are being defined.

What would this look like if you took the log of both sides of the equation?

Answer in one or two lines here.

Therefore, if Zipf's Law holds, after sorting the words descending on frequency, word frequency decreases in an approximately linear fashion under a log-log scale.

Now, please make such a log-log plot by plotting the rank versus frequency

Hint: Make use of the sorted dictionary you just created. Use a scatter plot where the x-axis is the *log(rank)*, and y-axis is *log(frequency)*. You should get this information from `word_counts`; for example, you can take the individual word counts and sort them. dict methods `.items()` and/or `values()` may be useful. (Note that it doesn't really matter whether ranks start at 1 or 0 in terms of how the plot comes out.) You can check your results by comparing your plots to ones on Wikipedia; they should look qualitatively similar.

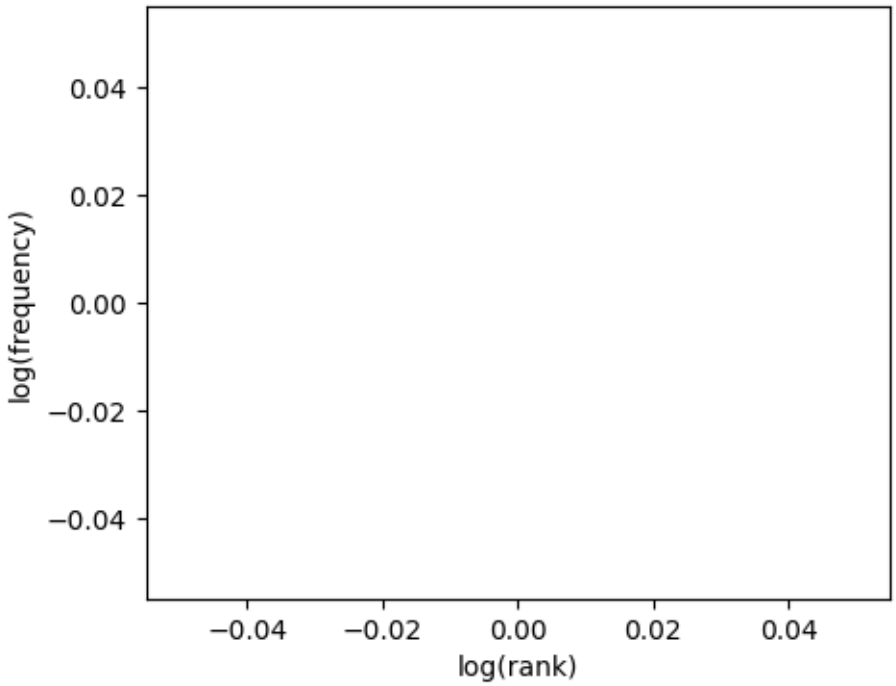
Please remember to label the meaning of the x-axis and y-axis.

[160]:
```
import math
import operator
x = []
y = []
X_LABEL = "log(rank)"
Y_LABEL = "log(frequency)"

# Add your code here
# You should fill the x and y arrays.
# Running this cell should produce your plot below.

plt.scatter(x, y)
plt.xlabel(X_LABEL)
plt.ylabel(Y_LABEL)
```

[160]:
```
Text(0, 0.5, 'log(frequency)')
```



4 Part Two: Naive Bayes

This section of the homework will walk you through coding a Naive Bayes classifier that can distinguish between positive and negative reviews (with some level of accuracy).

4.1 Question 2.1 (10 pts)

To start, implement the `update_model` and `tokenize_and_update_model` functions in the Naive Bayes Block. Make sure to read the functions' comments so you know what to update. Also review the `NaiveBayes` class variables in the `def __init__` method of the `NaiveBayes class` to get a sense of which statistics are important to keep track of. Once you have implemented `update_model`, run the train model function using the code below.

[161]:
```
nb = NaiveBayes(PATH_TO_DATA, tokenizer=tokenize_doc)
nb.train_model()

if len(nb.vocab) == 251637:
    print ("Great! The vocabulary size is {}".format(251637))
else:
    print ("Oh no! Something seems off. Double check your code before␣
 ↪continuing. Maybe a mistake in update_model?")
```

```
REPORTING CORPUS STATISTICS
NUMBER OF DOCUMENTS IN POSITIVE CLASS: 12500.0
NUMBER OF DOCUMENTS IN NEGATIVE CLASS: 12500.0
```

```
NUMBER OF TOKENS IN POSITIVE CLASS: 2958832.0
NUMBER OF TOKENS IN NEGATIVE CLASS: 2885848.0
VOCABULARY SIZE: NUMBER OF UNIQUE WORDTYPES IN TRAINING CORPUS: 251637
Great! The vocabulary size is 251637
```

4.2 Exploratory analysis

Let's begin to explore the count statistics stored by the update model function. Implement the provided `top_n` function in the Naive Bayes Block to find the top 10 most common words in the positive class and top 10 most common words in the negative class.

[162]:
```
print ("TOP 10 WORDS FOR CLASS " + POS_LABEL + ":")
for tok, count in nb.top_n(POS_LABEL, 10):
    print ('', tok, count)
print ()

print ("TOP 10 WORDS FOR CLASS " + NEG_LABEL + ":")
for tok, count in nb.top_n(NEG_LABEL, 10):
    print ('', tok, count)
print ()
```

```
TOP 10 WORDS FOR CLASS pos:
 the 165805.0
 and 87029.0
 a 82055.0
 of 76155.0
 to 65869.0
 is 55785.0
 in 48422.0
 i 33143.0
 it 32802.0
 that 32705.0

TOP 10 WORDS FOR CLASS neg:
 the 156393.0
 a 77898.0
 and 71543.0
 of 68307.0
 to 68098.0
 is 48386.0
 in 42105.0
 i 37337.0
 this 37301.0
 that 33587.0
```

4.2.1 Question 2.2 (5 points)

What is the first thing that you notice when you look at the top 10 words for the 2 classes? Are these words helpful for discriminating between the two classes? Do you imagine that processing other English text will result in a similar phenomenon? What about other languages?

Answer in one or two lines here.

4.2.2 Question 2.3 (5 points)

The Naive Bayes model assumes that all features are conditionally independent given the class label. For our purposes, this means that the probability of seeing a particular word in a document with class label y is independent of the rest of the words in that document. Implement the `p_word_given_label` function in the Naive Bayes Block. This function calculates P (w|y) (i.e., the probability of seeing word w in a document given the label of that document is y).

Use your `p_word_given_label` function to compute the probability of seeing the word "amazing" given each sentiment label. Repeat the computation for the word "dull."

[163]:
```
print ("P('amazing'|pos):",  nb.p_word_given_label("amazing", POS_LABEL))
print ("P('amazing'|neg):",  nb.p_word_given_label("amazing", NEG_LABEL))
print ("P('dull'|pos):",  nb.p_word_given_label("dull", POS_LABEL))
print ("P('dull'|neg):",  nb.p_word_given_label("dull", NEG_LABEL))
```

```
P('amazing'|pos): 0.000241397752166428
P('amazing'|neg): 6.661386428939103e-05
P('dull'|pos): 3.0525135112658e-05
P('dull'|neg): 0.00013195282208520518
```

Which word has a higher probability, given the positive class? Which word has a higher probability, given the negative class? Is this behavior expected?

Answer in one or two lines here.

4.2.3 Question 2.4 (5 points)

In the next cell, compute the probability of the word "car-thievery" in the positive training data and negative training data.

[164]:
```
print ("P('car-thievery'|pos):",  nb.p_word_given_label("car-thievery",␣
 ↪POS_LABEL))
print ("P('car-thievery'|neg):",  nb.p_word_given_label("car-thievery",␣
 ↪NEG_LABEL))
```

```
P('car-thievery'|pos): 6.229619410746529e-07
P('car-thievery'|neg): 3.187266233942154e-07
```

What is unusual about P('car-thievery'|neg)? What would happen if we took the log of "P('car-thievery'|neg)"? What would happen if we multiplied "P('car-thievery'|neg)" by "P('dull'|neg)"? Why might these operations cause problems for a Naive Bayes classifier?

Answer in one or two lines here.

4.2.4 Question 2.5 (5 points)

We can address the issues from question 2.4 with add-α smoothing (like add-1 smoothing except instead of adding 1 we add α). Implement `p_word_given_label_and_alpha` in the Naive Bayes Block and then run the next cell.

Hint: look at the slides from the lecture on add-1 smoothing.

[165]:
```
print ("P('stop-sign.'|pos):",  nb.p_word_given_label_and_alpha("stop-sign.",␣
↪POS_LABEL, 0.2))
```

```
P('stop-sign.'|pos): 6.646374399441918e-08
```

4.2.5 Question 2.6 (5 points)

Prior and Likelihood

As noted before, the Naive Bayes model assumes that all words in a document are independent of one another given the document's label. Because of this we can write the likelihood of a document as:

$P(w_{d1}, \cdots, w_{dn}|y_d) = \prod_{i=1}^{n} P(w_{di}|y_d)$

However, if a document has a lot of words, the likelihood will become extremely small and we'll encounter numerical underflow. Underflow is a common problem when dealing with probabilistic models; if you are unfamiliar with it, you can get a brief overview on Wikipedia. To deal with underflow, a common transformation is to work in log-space.

$\log[P(w_{d1}, \cdots, w_{dn}|y_d)] = \sum_{i=1}^{n} \log[P(w_{di}|y_d)]$

Implement the `log_likelihood` function in the Naive Bayes Block. **Hint:** it should make calls to the p word given label and alpha function.

Implement the `log_prior` function in the Naive Bayes Block. This function takes a class label and returns the log of the fraction of the training documents that are of that label.

4.2.6 Question 2.7 (5 points)

Naive Bayes is a model that tells us how to compute the posterior probability of a document being of some label (i.e., $P(y_d|\mathbf{w_d})$). Specifically, we do so using bayes rule:

$P(y_d|\mathbf{w_d}) = \frac{P(y_d)P(\mathbf{w_d}|y_d)}{P(\mathbf{w_d})}$

In the previous section you implemented functions to compute both the log prior ($\log[P(y_d)]$) and the log likelihood ($\log[P(\mathbf{w_d}|y_d)]$). Now, all you're missing is the *normalizer*, $P(\mathbf{w_d})$.

Derive the normalizer by expanding $P(\mathbf{w_d})$.

Answer in one or two lines here. Provide the formula and define each term in this formula.

4.2.7 Question 2.8 (5 points)

One way to classify a document is to compute the unnormalized log posterior for both labels and take the argmax (i.e., the label that yields the higher unnormalized log posterior). The unnormal-

ized log posterior is the sum of the log prior and the log likelihood of the document. Why don't we need to compute the log normalizer here?

Answer in one or two lines here.

4.2.8 Question 2.9 (10 points)

As we saw earlier, the top 10 words from each class do not give us much to go on when classifying a document. A much more powerful metric is the likelihood ratio, which is defined as

$LR(w) = \frac{P(w|y=\text{pos})}{P(w|y=\text{neg})}$

A word with LR 3 is 3 times more likely to appear in the positive class than in the negative. A word with LR 0.3 is one-third as likely to appear in the positive class as opposed to the negative class.

[166]:
```
# Implement the nb.likelihod_ratio function and use it to investigate the␣
↪likelihood ratio of "amazing" and "dull"
print ("LIKELIHOOD RATIO OF 'amazing':", nb.likelihood_ratio('amazing', 0.2))
print ("LIKELIHOOD RATIO OF 'dull':", nb.likelihood_ratio('dull', 0.2))
print ("LIKELIHOOD RATIO OF 'and':", nb.likelihood_ratio('and', 0.2))
print ("LIKELIHOOD RATIO OF 'to':", nb.likelihood_ratio('to', 0.2))
```

```
LIKELIHOOD RATIO OF 'amazing': 3.628350587556548
LIKELIHOOD RATIO OF 'dull': 0.22953174277018223
LIKELIHOOD RATIO OF 'and': 1.1869527527674362
LIKELIHOOD RATIO OF 'to': 0.9438077915764572
```

What is the minimum and maximum possible values the likelihood ratio can take? Does it make sense that $LR('amazing') > LR('to')$?

Answer in one or two lines here.

Find the word in the vocabulary with the highest liklihood ratio below.

[167]:
```
print("WORD WITH HIGHEST LIKELIHOOD RATIO:", nb.highest_lr_word(0.2))
```

```
WORD WITH HIGHEST LIKELIHOOD RATIO: edie
```

4.2.9 Question 2.10 (5 points)

The unnormalized log posterior is the sum of the log prior and the log likelihood of the document. Implement the `unnormalized_log_posterior` function and the `classify` function in the Naive Bayes Block. The `classify` function should use the unnormalized log posteriors but should not compute the normalizer. Once you implement the `classify` function, we'd like to evaluate its accuracy.

[168]:
```
print (nb.evaluate_classifier_accuracy(0.2))
```

```
81.668
```

4.2.10 Question 2.11 (5 points)

Try evaluating your model again with a smoothing parameter of 1000.

[169]:
```
print (nb.evaluate_classifier_accuracy(1000.0))
```

```
75.9
```

Does the accuracy go up or down when alpha is raised to 1000? Why do you think this is?

The accuracy of the model goes down when the alpha is raised to 1000. The accuracy went down when the alpha was raised to 1000 because the alpha was set too high, causing the model to place too much weight on the prior probabilities and not enough on the likelihoods.

4.2.11 Question 2.12 (5 points)

Find a review that your classifier got wrong.

[170]:
```
# In this cell, print out a review your classifier got wrong, along with its␣
↪label.
```

What are two reasons your system might have misclassified this example? What improvements could you make that may help your system classify this example correctly?

There could be 2 major issues ambiguity of the text and lack of training data.

4.2.12 Question 2.13 (5 points)

Often times we care about multi-class classification rather than binary classification.

How many counts would we need to keep track of if the model were modified to support 5-class classification?

Five we need to keep track of the following Total number of documents for each class (i.e., the number of training examples that belong to each class). Total number of words for each class (i.e., the sum of the word counts for all training examples that belong to each class). Word counts for each class and each word (i.e., the number of times each word appears in training examples for each class).

4.3 Extra Credit (Up to 10 points)

If you don't want to do the extra credit, you can stop here! Otherwise... keep reading... In this assignment, we use whitespace tokenization to create a bag-of-unigrams representation for the movie reviews. It is possible to improve this represetation to improve your classifier's performance. Use your own code or an external library such as nltk to perform tokenization, text normalization, word filtering, etc. Fill out your work in `def tokenize_doc_and_more` (below) and then show improvement by running the cells below.

Roughly speaking, the larger performance improvement, the more extra credit. We will also give points for the effort in the evaluation and analysis process. For example, you can split the training data into training and validation set to prevent overfitting, and report results from trying different versions of features. You can also provide some qualitative examples you found in the dataset to support your choices on preprocessing steps. Whatever you choose to try, make sure to describe

your method and the reasons that you hypothesize for why the method works. Be sure to explain what your code is doing.

[ ]:
```
def tokenize_doc_and_more(doc):
    """
    Return some representation of a document.
    At a minimum, you need to perform tokenization, the rest is up to you.
    """
    # Implement me!
    bow = defaultdict(float)
    # your code goes here

    return bow
```

[ ]:
```
nb = NaiveBayes(PATH_TO_DATA, tokenizer=tokenize_doc_and_more)
nb.train_model()
nb.evaluate_classifier_accuracy(1.0)
```

Use cells at the bottom of this notebook to explain what you did in `tokenize_doc_and_more`. Include any experiments or explanations that you used to decide what goes in your function. Doing a good job examining, explaining and justifying your work with small experiments and comments is as important as making the accuracy number go up!

Explain what you did here.

5 How to submit this problem set:

- Write all the answers in this iPython notebook. Once you are finished (1) generate the PDF file (`File -> Print Preview`, and print to PDF), 2) ZIP the PDF and this Jupyter Notebook (.ipynb), and 3) upload the ZIP file to Canvas.
- **Important:** check your PDF before you turn it in to Canvas to make sure it exported correctly.
- When creating your final version of the PDF to hand in, please do a fresh restart and execute every cell in order. Then you'll be sure it's actually right. One handy way to do this is by clicking `Runtime -> Run All` in the notebook menu.