CS6120 Assignment 1

October 11, 2018

1 Naive Bayes Document Classification

We must compute several values,

Priors:

 $P(c) = \frac{N_c}{N}$ where N_c is just number of documents with class and N number of documents

We will calculate the conditional probabilities of each word in the document. For the purposes of this calculation we will not calculate conditional probabilities for every single word, but only the words in D1 and D2

Using

$$P(w|c) = \frac{count(w,c) + \lambda}{count(c) + |V| \cdot \lambda}$$

Using $\lambda = 0.1$ Example calculation:

 $P(rose|vegetable) = \frac{0+0.1}{8+7\cdot0.1}$ Other calculations outlined below

We then find the maximum probablity of a document being in a class by using Where c is class and d document $P(c|d) = P(c) \cdot \prod_{i=1}^{n} P(d_i|c)$

Example calculation: $P(flower|D1) = P(flower) \cdot P(rose|flower) \cdot P(lily|flower) \cdot P(apple|flower) \cdot P(carrot|flower)$

```
P[('carrot', 'fruit')] = p(1, 14, 2)
        #Priors
        P['vegetable'] = 1/4
        P['flower'] = 3/8
        P['fruit'] = 3/8
        D1_flower = P['flower']*P[('rose', 'flower')]*P[('lily', 'flower')]*P[('apple', 'flower'
        print("D1_flower", D1_flower)
        D1_fruit = P['fruit']*P[('rose', 'fruit')]*P[('lily', 'fruit')]*P[('apple', 'fruit')]*P[
        print("D1_fruit", D1_fruit)
        D1_vegetable = P['vegetable']*P[('rose', 'vegetable')]*P[('lily', 'vegetable')]*P[('appl
        print("D1_vegetable", D1_vegetable)
D1_flower 7.985671244629444e-07
D1_fruit 2.490268929586247e-05
D1_vegetable 5.732867232465228e-08
   We take the argmax of these values and find that the fruit class is the most probable.
   Similarly for D2
In [2]: P[('pea', 'vegetable')] = p(2, 8, 3)
        P[('lotus', 'vegetable')] = p(1, 8, 2)
```

```
In [2]: P[('pea', 'vegetable')] = p(2, 8, 3)
    P[('lotus', 'vegetable')] = p(1, 8, 2)
    P[('grape', 'vegetable')] = p(0, 8, 2)

P[('pea', 'flower')] = p(1, 13, 3)
    P[('lotus', 'flower')] = p(0, 13, 2)

P[('grape', 'fruit')] = p(0, 14, 3)
    P[('lotus', 'fruit')] = p(1, 14, 2)
    P[('grape', 'fruit')] = p(2, 14, 2)

D2_flower = P['flower']*(P[('pea', 'flower')]**2)*P[('lotus', 'flower')]*P[('grape', 'flower')]*P[('grape', 'fuit')]*P[('grape', 'fruit')]*P[('grape', 'grape', 'grape')]*P[('grape', 'grape', 'grape')]*P[('grape', 'grape
```

D2_flower 1.47219552641001e-07 D2_fruit 2.1008472857159783e-07 D2_vegetable 2.618107011591733e-05

We find that D2 is classed as vegetable

2 Word Sense Disambiguation

Counting all the senses will be done by putting each word through wordnet

In the cold weather, they started to the city. They were least worried protecting themselves against the common cold. After she signed the agreement, a cold chill crept up her spine. "Chill, its not that serious," her husband assured and left to deposit cash at the bank.

```
In [3]: from nltk import download
        download('wordnet')
        download('punkt')
[nltk_data] Downloading package wordnet to
                C:\Users\cdilg\AppData\Roaming\nltk_data...
[nltk_data]
[nltk_data]
             Package wordnet is already up-to-date!
[nltk_data] Downloading package punkt to
                C:\Users\cdilg\AppData\Roaming\nltk_data...
[nltk_data]
[nltk_data]
             Package punkt is already up-to-date!
Out[3]: True
In [228]: from nltk.corpus import wordnet as wn
          import numpy as np
          import string
          raw = "In the cold weather, they started to the city. They were least worried protecti
          sents = [s.translate(str.maketrans('','', string.punctuation)).lower() for s in raw.st
          sentence_senses = []
          word_senses = {}
          for s in sents:
              sentencecount = 1
              for word in s.split(' '):
                  syns = max([len(wn.synsets(word)), 1])
                  sentencecount *= syns
                  word_senses[word] = syns
              sentence_senses += [sentencecount]
          total = 1
          for sentence in sentence_senses:
              total *= sentence
          print("Total senses: ", total)
          print("Distinct combinations of senses per sentence: ", sentence_senses)
          #print(word_senses)
Total senses: 4654630885130005118976000
Distinct combinations of senses per sentence: [28224, 149760, 39513600, 27869184]
```

Here we see how many different ways all of the senses could be combined, broken down by sentence. These numbers are extremely large for a relatively short sentence of only around 10 words.

Language Modelling
Implement a 4 gram language model

```
In [77]: from os import listdir
         from nltk import word_tokenize
         import pickle
         from collections import Counter
         def save(corpus, file):
             with open(file, 'wb') as f:
                 pickle.dump(corpus, f, pickle.HIGHEST_PROTOCOL)
         def read(file):
             with open(file, 'rb') as f:
                 return pickle.load(f)
         def read_dir(directory, cachefile):
             try:
                 text = read(cachefile)
             except(FileNotFoundError):
                 corpus = ""
                 base = directory
                 for file in listdir(base):
                     for line in open(base + "/" + file):
                         corpus += ' ' + line.strip().lower().replace(' ', ' ')
                 text = word_tokenize(corpus)
                 save(text, cachefile)
             finally:
                 return text
         # we need to remove words that occur less than 5 times and replace with UNK
         # count the items in the list. Figure out which ones are greater
         # unkwords = [w for w in [w for w in wordcount.keys() if wordcount[w] <= unk_threshold]
         # we want a list of indices for which to replace with 'UNK'
         # go through the list, keep an index of where each word ocurrs.
         # at the end, count all of the lengths of these lists
         # for each list which is less than 5. go to the text list and replace each element with
         def replace_unk(text, threshold, savefile):
             try:
                 return read(savefile)
             except(FileNotFoundError):
                 counterdict = {}
                 for i, t in enumerate(text):
```

```
if t in counterdict.keys():
                           counterdict[t].append(i)
                       else:
                           counterdict[t] = [i]
                  for locations in counterdict:
                       #print(locations, len(counterdict[locations]))
                       if len(counterdict[locations]) <= threshold:</pre>
                           for loc in counterdict[locations]:
                                text[loc] = 'UNK'
                  save(text, savefile)
                  return text
          #find out the definition of 4 gram counts
          #probably count all of the ways 3 previous words occur
          #make a big table
          def ngram(n, text, outfile):
              ngrams = {}
              for i in range(n, len(text)+1):
                   #get the previous n words.
                  gram = tuple(text[i-n:i])
                   if gram in ngrams.keys():
                       ngrams[gram] += 1
                  else:
                        ngrams[gram] = 1
              #save a textual representation of the dict to file
              with open(outfile, 'w') as f:
                  for line in sorted(ngrams, key=ngrams.get, reverse=True):
                       f.write(' '.join(line) + ' ' + str(ngrams[line]) + '\n')
              return ngrams
In [78]: text = read_dir('gutenberg', 'gutenberg-corpus.txt')
          text = replace_unk(text, 5, 'gutenberg-unk.txt')
          guten4 = ngram(4, text, 'gutenberg-4grams.txt')
          guten3 = ngram(3, text, 'gutenberg-3grams.txt')
   Perplexity formula: PP(W) = \left(\prod_{i=1}^{N} \frac{1}{P(w|w_{n-1},w_{n-2},w_{n-3},w_{n-4})}\right)
                                               numcounts
   Probability of words:
                                P(w)
                                                         P(w_n|w_{n-1},w_{n-2},w_{n-3},w_{n-4})
 C(w_{n-4}w_{n-3}w_{n-2}w_{n-1}w)+0.1
C(w_{n-4}w_{n-3}w_{n-2}w_{n-1}) + |V| \times 0.1
In [79]: imdb = read_dir('imdb_data', 'imdb-corpus.txt')
          imdb = replace_unk(imdb, 5, 'imdb-unk.txt')
          #imdbmodel = ngram(4, imdb, 'imdb-ngrams.txt')
          #imdbmodel3 = ngram(3, imdb, 'imdb-3grams.txt')
          import math
```

```
def calculate_probability(model, onelessmodel, word, context, n = 4, lam = 0.1):
             #for each of the words, we need the prior 4 words. We will look this up and find wh
                 ret = (model[(context[0], context[1], context[2], word)] + lam)/(onelessmodel[(
             except:
                 ret = lam/(len(model)*lam)
             #here v is a vocabulary of n-grams, so will be the count of the ngrams
             return ret
         def perplexity(model, onelessmodel, text, n = 4):
             #this takes in text, which the existing probabilities and counts are used to
             #come up with a number, all of the probabilities multiplied together. We probably of
             #Perplexity is a measure of how probable the model is at generating a sentence
             #Perplexity is an integer - lower better
             pp = 1
             V = len(model)
             for i, word in enumerate(text):
                 #calculate the probability of this word
                 #TODO implement log sum instead
                 pp *= 1/calculate_probability(model, onelessmodel, word, text[i-n:i-1])
             return math.pow(pp, 1/V)
         def wikiperplexity(model, onelessmodel, text, n=4):
             pp = 0
             V = len(model)
             for i, word in enumerate(text):
                 pp -= math.log(2, calculate_probability(model, onelessmodel, word, text[i-n:i-1
             return math.pow(2, pp/V)
         #Currently, this works:
         #print(guten4[('the', 'children', 'of', 'israel')])
         print(calculate_probability(guten4, guten3, 'israel', ['the', 'children', 'of']))
         print(calculate_probability(guten4, guten3, 'were', ['children', 'of', 'israel']))
         print(wikiperplexity(guten4, guten3, ['the', 'children', 'of', 'israel', 'were', 'off',
         print(perplexity(guten4, guten3, ['the', 'children', 'of', 'israel', 'were', 'off', 'or
         #perplexity(quten4, guten3, ["the", "children", "of", "israel", "are", "well"])
0.0030798517076259754
7.797958291094393e-05
1.0000001605774118
1.000070634697219
In [80]: news = read_dir('news_data', 'news-corpus.txt')
         news = replace_unk(news, 5, 'news-unk.txt')
```

```
news4 = ngram(4, news, 'news-4grams.txt')
news3 = ngram(3, news, 'news-3grams.txt')

print(wikiperplexity(news4, news3, ['the', 'children', 'of', 'israel', 'were', 'off', 'print(perplexity(news4, news3, ['the', 'children', 'of', 'israel', 'were', 'off', 'on',
1.0000033056111426
1.0009467110114756
```

2.1 POS Tagging HMM

First find the tag unigram and tag bigram counts from the corpus

```
In [115]: import operator
          import random
          #read in the file/s?
          import nltk
          from nltk.corpus import brown
          #nltk.download('brown')
          def read_brown(directory, cachefile):
                   text = read(cachefile)
              except(FileNotFoundError):
                  corpus = []
                  base = directory
                  for file in listdir(base):
                       #print(file)
                       for sent in open(base + "/" + file):
                           if sent == "\n": continue
                           wordlist = []
                           for word in sent.strip().split(' '):
                               #split the word and it's tag
                               if word == '':
                                   continue
                               wordlist.append(word.split('/'))
                           corpus += [[' < s > ', ' < s > ']] + wordlist + [[' < / s > ', ' < / s > ']]
                  text = corpus
                   save(text, cachefile)
              finally:
                  return text
          brown = read_brown('brown', 'brown-cache.txt')
          #calculate the word-tag counts
          #lets do this in the same dictionary way we did earlier
```

```
def wordtag(text, outfile):
   pairs = {}
    for word in text:
        #ignore the sentence tags
        if (word == [' < s >', ' < s >'] or word == [' < / s >', ' < / s >']): continue
        tagpair = tuple(word)
        if tagpair in pairs.keys():
            pairs[tagpair] += 1
        else:
             pairs[tagpair] = 1
    #save a textual representation of the dict to file
    with open(outfile, 'w') as f:
        for word in sorted(pairs, key=pairs.get, reverse=True):
            f.write(' '.join(word) + ' ' + str(pairs[word]) + '\n')
    return pairs
def tagunigram(text, outfile):
    '''This is literally a unigram of the tag, t_n. That is we
    will not consider the word association and will instead just
    consider the impact of the counts of tags themselves.'''
    unigrams = {}
    for word in text:
        #ignore the sentence tags
        if (word == [' < s >', ' < s >'] or word == [' < / s >', ' < / s >']): continue
        tag = word[1]
        if tag in unigrams.keys():
            unigrams[tag] += 1
        else:
             unigrams[tag] = 1
    #save a textual representation of the dict to file
    with open(outfile, 'w') as f:
        #TODO there is a problem with the way this joins - it's assuming a tuple
        for word in sorted(unigrams, key=unigrams.get, reverse=True):
            f.write(' '.join(word) + ' ' + str(unigrams[word]) + '\n')
    return unigrams
def savecounts(d, file):
    with open(file, 'w') as f:
        for token in sorted(d, key=d.get, reverse=True):
            f.write(' '.join(token) + ' ' + str(d[token]) + ' 'n')
def tagbigram(text, outfile):
    '''Here we consider both t_n and t_{n-1} and report the counts.
    Again we do not stop to consider the effects of the word association'''
    bigrams = {}
    for i in range(len(text)):
```

```
if (\text{text}[i] == [' < s >', ' < s >'] or \text{text}[i] == [' < / s >', ' < / s >']): continue
                  t = text[i][1]
                  t1 = text[i-1][1]
                  if (t, t1) in bigrams.keys():
                      bigrams[(t, t1)] += 1
                  else:
                       bigrams[(t, t1)] = 1
              savecounts(bigrams, outfile)
              return bigrams
              #save a textual representation of the dict to file
          def transition(bigramtags, unigramtags):
              probabilities = {}
              for bigram in bigramtags.keys():
                  probabilities[bigram] = bigramtags[bigram]/unigramtags[bigram[0]]
              savecounts(probabilities, 'brownmeta/transition-probabilities.txt')
              return probabilities
          def emission(wordtags, unigramtags):
              emissionprob = {}
              for wordpair in wordtags.keys():
                  emissionprob[wordpair] = wordtags[wordpair]/unigramtags[wordpair[1]]
              savecounts(emissionprob, 'brownmeta/emission-probabilities.txt')
              return emissionprob
          tags = wordtag(brown, 'brownmeta/brownwordtag.txt')
          unitags = tagunigram(brown, 'brownmeta/brownuni.txt')
          bitags = tagbigram(brown, 'brownmeta/brownbigrams.txt')
          #These are both saved to file
          transitionprobs = transition(bitags, unitags)
          emissionprobs = emission(tags, unitags)
In [187]: from collections import defaultdict
          class postagger:
              def default(self):
                  return 0.0001
              def __init__(self, wordtags, unigramprobabilities, bigramprobabilities):
                  #Emission probabilities
                  self.wt = defaultdict(self.default, wordtags)
                  self.up = defaultdict(self.default, unigramprobabilities)
```

#ignore the sentence tags

```
\#Transition\ probabilities
    self.bp = defaultdict(self.default, bigramprobabilities)
def nextword(self, dct):
    #select a next item based on a random number which is weighted by the probabil
    #sum all of the probabilities and normalize
    for value in dct.keys():
        tot += dct[value]
    normalised = {}
    index = random.random()
    for pair in dct.keys():
        index -= dct[pair] / tot
        if index <= 0.0:</pre>
            return pair
def predictSentence(self):
    '''Will generate a sentence, with associated tags.
    Output will contain sentence and sentence probability in a dict'''
    sent = []
    humansent = []
    priortag = '<s>'
    sentp = 0
    while(priortag != '</s>' and priortag != '.'):
        subset = {}
        for tags in self.bp.keys():
            if priortag == tags[1]:
                subset[tags] = self.bp[tags]
        selectedbigram = self.nextword(subset)
        #capture tag probability
        sentp -= math.log(subset[selectedbigram], 2)
        currenttag = selectedbigram[0]
        potentialwordtags = {}
        for wordtag in self.wt.keys():
            if currenttag == wordtag[1]:
                potentialwordtags[wordtag] = self.wt[wordtag]
        currentword = self.nextword(potentialwordtags)
        #capture word probability
        sentp -= math.log(potentialwordtags[currentword], 2)
        sent.append('/'.join(currentword))
        #humansent.append(currentword[0])
        priortag = currenttag
```

```
return({'sentence': sent, 'probability': math.pow(2, sentp)})
def viterbi(self, sentence):
    '''Takes a tokenised sentence and will then apply some tags to it.'''
    #remember states are the wordtags
    startp = {}
    for tags in self.bp.keys():
            if '<s>' == tags[1]:
                startp[tags[0]] = self.bp[tags]
    viterbim = [{}]
    #we will keep track of the backpointers using a list of dicts, with probabilit
    #this will make the backtracing easy
    #Essentially the up.tags gives us a list of all of the POS tags
    for state in startp.keys():
        #Create the first column of the viterbi
        #TODO implement lambda smoothing. It will require changing how the probabil
        #and will require a return here for the unknowns which is calculated in pl
        viterbim[0][state] = {'prev': None, 'probability': startp[state]*self.wt[(
    for i in range(1, len(sentence)):
        #Find the maximum transition probability from the previous state to the cu
        viterbim.append({})
        for state in self.up.keys():
            viterbim[i][state] = {'probability': 0, 'prev': None}
            listofstateprobs = []
            for prevstate in viterbim[i-1].keys():
                #TODO Lambda smoothing
                currentprob = viterbim[i-1][prevstate]['probability']*self.bp[(prevstate)]
                currentmax = viterbim[i][state]['probability']
                if (currentprob > currentmax):
                    #This is basically saying, set the probability to the probabil
                    #and multiply (by markov assumption) the emission probability
                    viterbim[i][state] = {'probability': currentprob*self.wt[(sent
    #now find the highest probability state
    taggedsentence = []
    maxprob = max(prob['probability'] for prob in viterbim[-1].values())
    #backtrack on this state
   prevstate = None
    #iterate through backwards through viterbim
    for state, prob in viterbim[i].items():
            if prob['probability'] == maxprob:
```

```
prevstate = prob['prev']
                              taggedsentence.append('/'.join([sentence[i], state]))
                  for i in range(len(viterbim)-1, 0, -1):
                      prevstate = viterbim[i][prevstate]['prev']
                      taggedsentence.insert(0, '/'.join([sentence[i-1], prevstate]))
                  return taggedsentence
          pos = postagger(tags, unitags, bitags)
          sents = []
          with open('brownmeta/generatedsentences.txt', 'w') as f:
              for i in range(5):
                  sents.append(pos.predictSentence())
                  f.write('{} Probability: {}\n'.format(' '.join(sents[i]['sentence']), sents[i]
          with open('brownmeta/human-readablesentences.txt', 'w') as f:
              for sent in sents:
                  f.write(' '.join([word.split('/')[0] for word in sent['sentence']]) + '\n')
          pos.viterbi(['The', 'cat', 'sat'])
maxprob: 79410481308774000
Out[187]: ['The/at', 'cat/nn-nc', 'sat/vbd']
In [214]: import re
          with open('brownmeta/science_sample.txt') as f:
              sentencecounter = 0
              sentence = False
              words = [[]]
              for line in f:
                  if line != '\n':
                      if re.match('<.*>', line):
                          if sentence:
                              words.append([])
                              sentencecounter += 1
                          sentence = not sentence
                          words[sentencecounter].append(line.strip())
          tags = []
          for sentence in words:
              try:
                  tags.append(pos.viterbi(sentence))
              except:
```

```
tags.append(['error'])
          with open('brownmeta/science-tagged.txt', 'w') as f:
              for sent in tags:
                  f.write(' '.join(sent) + '\n')
maxprob: 2.0080252384283956e+42
maxprob: 3.1477207761221576e+97
maxprob: 3.021324982380108e+109
maxprob: 2.1955339299622646e+239
maxprob: 3.7176547643644863e+59
13
maxprob: 3.365011980748336e+52
maxprob: 9.942807467315857e+33
maxprob: 1.5800078389366676e+245
maxprob: 7.275540136710308e+34
maxprob: 4.654784038470841e+39
maxprob: 3.310088804696931e+100
maxprob: 6.820221933502801e+34
maxprob: 1.3794921079771193e+108
maxprob: 2.740226758248556e+25
maxprob: 2.3085513786579857e+85
maxprob: 7.977017574726705e+25
maxprob: 3.183289012453947e+49
13
maxprob: 1.5337830574162862e+38
maxprob: 1.8049563962042477e+107
20
maxprob: 3.748864718831112e+110
maxprob: 8.428131337233712e+59
12
```

maxprob: 1.3450249446538133e+109

25

maxprob: 4.28122840840757e+201

44

maxprob: 6.49513912383942e+61

15

maxprob: 1.5928714459221863e+107

19

maxprob: 5.729089095576724e+143

30

maxprob: 1.510424638859083e+67

16

maxprob: 1.8316315259107136e+31

7

maxprob: 3.191219054616047e+51

11

maxprob: 2.26263753523917e+145

28

maxprob: 2.960978726747843e+57

15

maxprob: 7.746246496695334e+46

12

maxprob: 2.3341782509392293e+113

23

maxprob: 3.713256797713509e+43

11

maxprob: 5.519938228928071e+54

10

maxprob: 1.7046322881813378e+16

5

maxprob: 3.6537752263632495e+43

10

maxprob: 3.954091780817073e+44

10

maxprob: 4.31954834752815e+84

17

maxprob: 2.8280124839255855e+133

29

maxprob: 5.3407547374234453e+154

31

maxprob: 3.380948357661286e+107

21

maxprob: 3.581773588317232e+44

10

maxprob: 1.305793203418419e+116

26

maxprob: 1.3771973742082674e+36

maxprob: 1.4775691065458468e+28

8

maxprob: 9.440871938310182e+110

24

maxprob: 5.617373723191542e+144

28

maxprob: 7.741484732284823e+93

19

maxprob: 4.001593671241936e+107

24

maxprob: 1.7360063135753248e+89

22

maxprob: 212661603.8753472

4

maxprob: 4.931295792322579e+90

23

maxprob: 1.6368997960539327e+97

21

maxprob: 1.7204832369954207e+129

27

maxprob: 6.2979961160194436e+134

28

maxprob: 2.8544055782657124e+126

26

maxprob: 9.823541967650845e+136

28

maxprob: 5.697256678785799e+193

44

maxprob: 1.0446060398764055e+131

26

maxprob: 2.175320936354649e+160

36

maxprob: 7.695136981167532e+120

27

maxprob: 9.921333325221339e+104

22

maxprob: 3.0017683212328973e+61

12

maxprob: 1.0838893083876078e+161

34

maxprob: 2.867499351537756e+121

27

maxprob: 3.2040299577198434e+130

32

maxprob: 8.954832599396884e+79

18

maxprob: 4.336372238683612e+52

maxprob: 3.251500483195947e+179

38

maxprob: 5.674241268504574e+119

24

maxprob: 1.775344888957056e+53

14

maxprob: 5.502641123237151e+152

31

maxprob: 1.883915522329825e+51

12

maxprob: 2.4678066890219872e+94

23

maxprob: 3.0105336171173067e+128

27

maxprob: 3.701778982837172e+125

25

maxprob: 1.0976713275912227e+74

19

maxprob: 1604918.259

2

maxprob: 8.975327625602733e+29

9

maxprob: 5.26543346877114e+44

10

maxprob: 1.574792699541144e+55

14

maxprob: 1107886.8360000001

2

maxprob: 8.02678948239168e+116

26

maxprob: 2.51938296116893e+68

13

maxprob: 2.326874629022499e+55

13

maxprob: 2.5357280929575984e+61

15

maxprob: 1.599239186634182e+79

17

maxprob: 2.2500717676208848e+95

23

maxprob: 3.963044357286545e+33

8

maxprob: 3.171678480247068e+77

16

maxprob: 9.444038584823708e+38

9

maxprob: 2.1360312867866232e+60

maxprob: 4.487991509940431e+149

30

maxprob: 3.8800517533478456e+101

23

maxprob: 9.148845091120974e+54

11

maxprob: 2.72577046913966e+90

22

maxprob: 3.164706296162717e+129

26

maxprob: 4.2589190093272573e+155

33

maxprob: 9.234051881128154e+103

25

maxprob: 1.039126474489869e+66

15

maxprob: 4.772271343840981e+71

17

maxprob: 1.897406793038261e+46

13

maxprob: 3.2126857694855814e+51

11

maxprob: 2.3967301677703837e+101

21

maxprob: 5.1337339554480445e+72

19

maxprob: 1.5444110521454043e+91

18

maxprob: 2.865100930704463e+60

12

maxprob: 1.1409053959390534e+96

22

maxprob: 3.068452702552526e+43

10

maxprob: 4.067703096288416e+70

13

maxprob: 4.84859722293412e+23

О

maxprob: 3.013171453407726e+99

22

maxprob: 4.364355347705655e+93

22

maxprob: 1.1893513596223013e+49

10

maxprob: 1.1676331294179756e+142

30

maxprob: 2.0451236070539533e+100

maxprob: 6.715470073878611e+20

5

maxprob: 5.404497491073148e+114

24

maxprob: 1.0974788953983454e+139

29

maxprob: 1.170530852206504e+69

15

maxprob: 1.6357992787059615e+145

33

maxprob: 1.315581953515767e+89

21

maxprob: 1.2413454568060485e+48

10

maxprob: 1.2996764365558676e+132

26

2.2 Discussion of Viterbi HMM POS Tagger

It is acknowledged that the smoothing function employed in this implementation of the veterbi algorithm is incorrect, and simply adds a constant to all unknown values. This will have a definite negative impact on performance, where unknown bigrams will have higher probability than infrequent but known bigrams.

Look in the folder brownmeta/science-tagged.txt for the sentences and their associated tags.