Natural Language Processing: Homework 3

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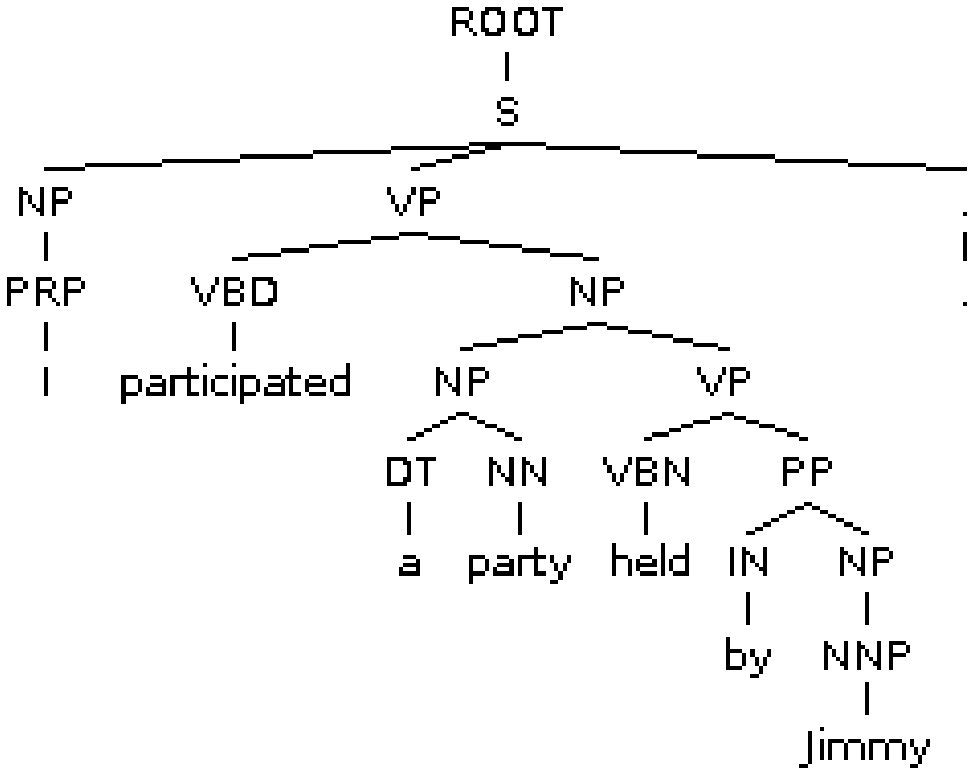
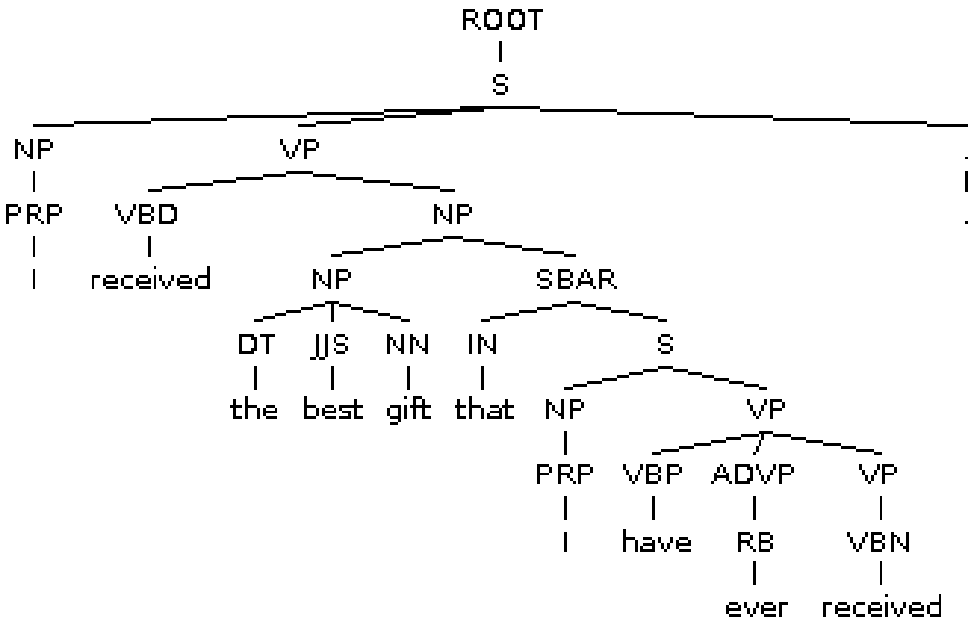
1 .

(a)
I tried the berkeley parser and got results as below:

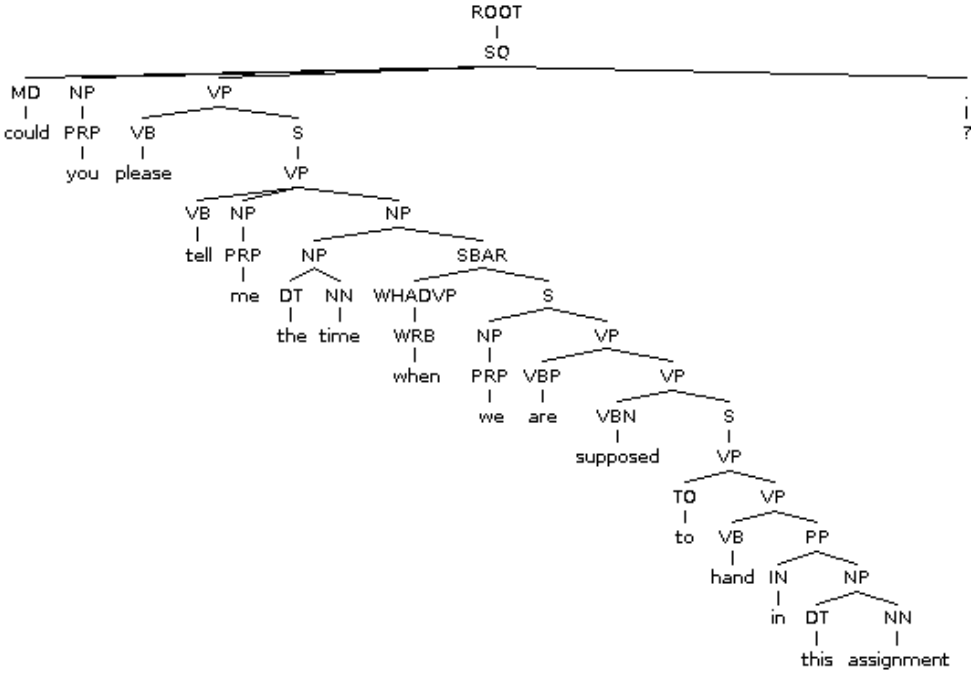
I participated a party held by Jimmy.



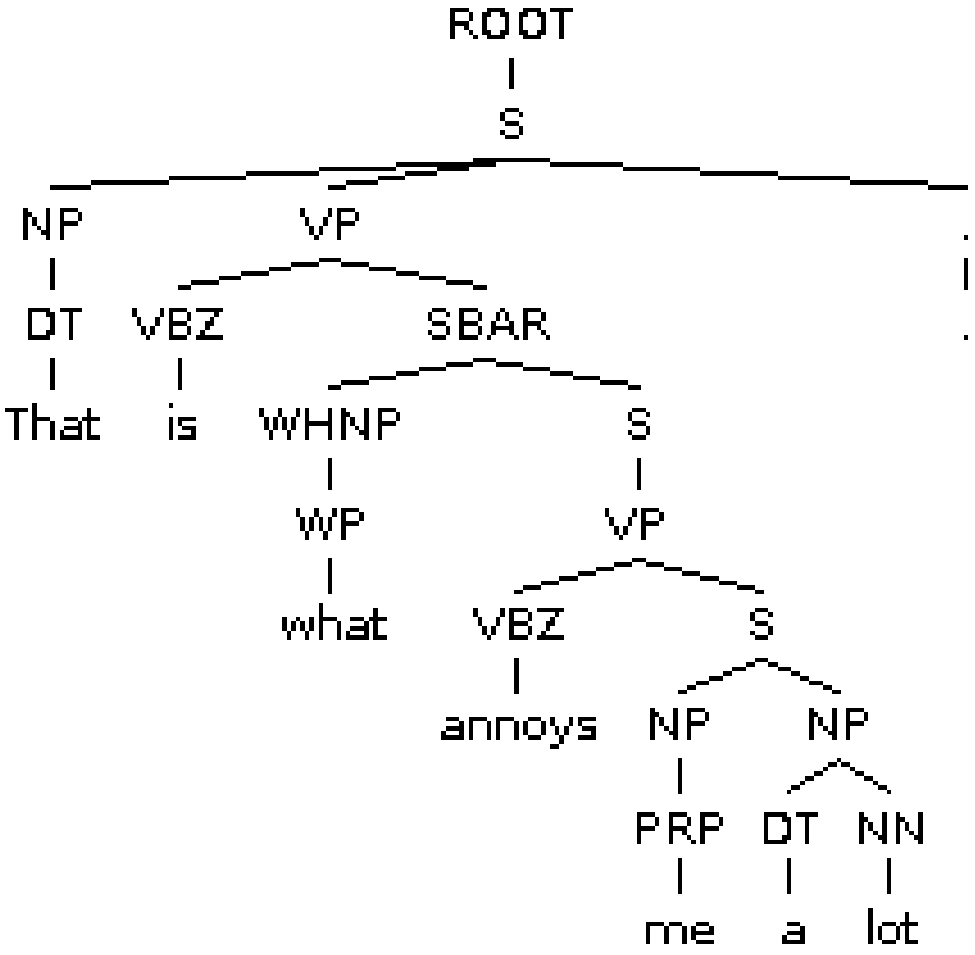
I received the best gift that I have ever received.



could you please tell me the time when we are supposed to hand in this assignment?



That is what annoys me a lot.



As we can see, there are more non-terminals than we previously learned, depending on the tenses, single or plural and so on. And there are lots of preterminals defined before the terminals come out.

(b)
There are also some places not satisfying. For example, in the fourth parsing, "me a lot" was parsed as a "S" which was composed of two NPs.

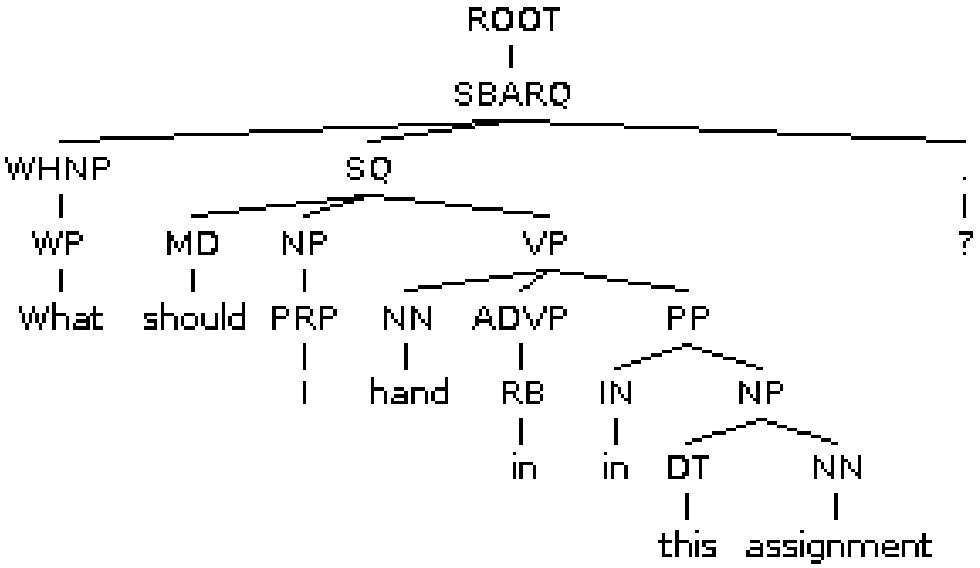
And there is a grammar NP $\rightarrow$ DT, which means a determiner itself could be a NP, just like "that" in the fourth parsing above.

Also, "hand in this assignment" is parsed as
VP (VB hand) (PP (IN in) (NP (DT this) (NN assignment))).
However, we know that "hand in" should be interpreted as a verb phrase.

The parser tried to recognize relative clauses in a relatively complex sentence.
In addition, it differentiates adjectives as normal, comparative and superlative. It also detects tenses of verbs.

(c)
example: What should I hand in in this assignment?

result:



As we can see, the parse still cannot parse the verb phrase "hand in". What's worse, "hand" is interpreted as a "NN"(Noun).

2 .

(a)
Link Grammar Parser:
Besides the parsed tree, this parser also shows linkages between constituents.
For example, when I parsed "I participated a party held by Jimmy.". It connected the "a" with "party" and the link between them is named as "Ds", which is used to connect determiners to nouns. And the link "Wd" is used to attach main clause to the beginning of the sentence. For example, "I participated a party" is the main clause in my sentence. I think those linkages help us to understand relationships between constituents.

(b)
I parsed Chinese sentence using Stanford parser. I found that before parsing Chinese sentence, it first segment the sentence into separate words. After the word-segmentation, it parsed Chinese sentence in a similar way as English sentence. It could get accurate results for some sentences. However, sometimes the error in word-segmentation would cause error in parsing.

(c)
I tried a neural network parser https://nlp.stanford.edu/software/nndep.shtml.
I got more satisfying parsing results on sentences in question 1. What's more, I think I was faster than CFG in question 1.

(e)
To solve this problem, I wrote a program named "sortOnLength.py". This program will will sort our classification result on dev set on lengths of files. For example, there are a few lines in our classification result of dev/spam/*:

gen ./gen_spam/dev/spam/spam.78.025.txt
spam ./gen_spam/dev/spam/spam.80.011.txt
spam ./gen_spam/dev/spam/spam.8.081.txt
spam ./gen_spam/dev/spam/spam.81.087.txt

Then my program will sort and print the result as:
(8,78) (80,81)
0.5 1.0
(8,78) means files of length from 8 to 78. And 0.5 means the classification accuracy on files of length from 8 to 78.
To run my program, I firstly output the classification results of dev/gen/* and dev/spam/* in result_gen and result_spam respectively. Then put those two results in the same directory as my program. Then, just run by typing "python3 ./sortOnLength.py".
In addition, the number of files in per length range to calculate the accuracy is 13. The table below describes the relationship between lengths and accuracies($\lambda = 0.01$, prior probability of gen is 0.7).

Length	Accuracy
(5, 20)	0.6
(22, 35)	0.875
(37, 55)	1.0
(57, 69)	0.929
(71, 89)	0.857
(91, 98)	0.857
(104, 118)	0.933
(121, 134)	0.929
(141, 161)	0.933
(164, 180)	0.929
(183, 211)	0.857
(218, 253)	0.786
(266, 290)	1.000
(299, 331)	0.929
(345, 449)	0.929
(457, 660)	0.786
(700, 1209)	0.786
(1355, 8185)	0.500

And the graph below is drawn based on the table.

(f)

4 .
(a)
If $V = 19999$, then in uniform estimate, $\sum_z \hat{p}(z \mid xy) = \frac{20000}{19999} > 1$,which is incorrect. Similarly, in ADDL estimate, $\sum_z \hat{p}(z \mid xy) = \frac{\sum_z (c(xyz)+\lambda)}{c(xy)+\lambda V} = \frac{c(xy)+20000\lambda}{c(xy)+19999\lambda} > 1$,which is incorrect too.
(b)
If $\lambda = 0$, then $\hat{p}(z \mid xy) = \frac{c(xyz)}{c(xy)}$, which has no smoothing at all. Without smoothing, the

probability of many files with unseen words will become zero.
(c)
In BACKOFF_ADDL, if $c(xyz) = c(xyz') = 0$, $\hat{p}(z \mid xy) = \frac{c(xyz)+\lambda V\hat{p}(z|y)}{c(xy)+\lambda V} = \frac{\lambda V\hat{p}(z|y)}{c(xy)+\lambda V}$.
Similarly, $\hat{p}(z' \mid xy) = \frac{\lambda V\hat{p}(z'|y)}{c(xy)+\lambda V}$.
if $\hat{p}(z \mid y) \neq \hat{p}(z' \mid y)$, then $\hat{p}(z \mid xy) \neq \hat{p}(z' \mid xy)$
When $c(xyz) = c(xyz') = 1$, $\hat{p}(z \mid xy) = \frac{1+\lambda V\hat{p}(z|y)}{c(xy)+\lambda V}$, $\hat{p}(z' \mid xy) = \frac{1+\lambda V\hat{p}(z'|y)}{c(xy)+\lambda V}$.
So, if $\hat{p}(z \mid y) \neq \hat{p}(z' \mid y)$, then $\hat{p}(z \mid xy) \neq \hat{p}(z' \mid xy)$

(d)
λ defines how much it smoothes the probabilities using $\hat{p}(z \mid y)$. Larger λ will make $\hat{p}(z \mid xy)$ closer to $\hat{p}(z \mid y)$

5 .
The λ^* I used here is 0.01

6 .
(c)

C	Cross-entropy	Accuracy
1	4.384	0.799
0.05	4.405	0.791
0.1	4.404	0.791
2	4.368	0.795
3	4.357	0.799
4	4.349	0.803
5	4.343	0.803
6	4.339	0.803
7	4.337	0.795
8	4.335	0.795
10	4.334	0.795

As we can see, when $C = 5$, the classification accuracy become the highest.
Thus, $C^* = 5$.

embeding	Cross-entropy	Accuracy
10	4.343	0.803
20	4.199	0.849
40	4.125	0.849

The more dimensions we have in our word embedding, the more information we can know about a word, which means we have more features to use. Thus, the accuracy increases and the cross entropy decreases.
I use training data to build my model, to tune parameters in matrices X, Y using SGD. And I use dev data to tune the hyperparameter C and also dimension of word embedding. And test data can be used to compare the accuracy of my loglinear model with that of the add-λ back-off model.

When I was tuning C, I found that when I got the C which could produce the highest accuracy, it was not the C that could produce the minimum cross-entropy.That is because in order to predict the correct label, your probability does not need to be very big. It just need to be bigger than the probability of the other label. So, the cross entropy may not be the minimum when the accuracy is the highest.

To compare the result with that of add_λ back-off,
I set $\lambda^* = 0.01, C = 5$, dimension=20. Below is the comparison.
Backoff_add:
Accuracy: 0.854
Cross-entropy per token: 5.148

Loglinear model: Accuracy: 0.849
Cross-entropy per token: 4.199

As we can see, the accuracy of backoff_addλ is a little bit higher. However the cross entropy of backoff_addλ is lower, which means even though it can predict the correct label, it is not so confident on that.

(d) I implemented the unigram log-probability.

7 .
Just find the $\vec{w'}$ that maximizes $P(\vec{w'} \mid U)$. And according to Bayes theorem, $P(\vec{w} \mid U) = \frac{P(\vec{w})P(U|\vec{w})}{P(U)}$. Since we already know $P(U \mid \vec{w})$ and we can estimate $P(\vec{w})$ using our language model. We don't need to know the denominator because we only need to find the $\vec{w'}$ that maximizes $P(\vec{w'})P(U \mid \vec{w'})$, which is equivalent to maximizing $P(\vec{w'} \mid U)$.