Massachusetts Institute of Technology
Department of Electrical Engineering and Computer Science
6.863J/9.611J, Natural Language Processing
Assignment 5:

Handed out: October 29, 2012 **Due: November 14, 2012**

Last Updated: Monday 29th October, 2012 at 11:19

`http://web.mit.edu/6.863/www/fall2012/labs/assignment5.pdf`

Goals of the Assignment

Assignment 5 is an introduction to context-free parsing in a psycholinguistic context and computational context: learning how ambiguity makes natural language parsing difficult, and learning how this might relate to human algorithmic approaches to solving this problem, one that is stack-based. We also introduce you to probabilistic context-free parsing: how this speeds up sorting through the tremendous number of parses that can arise even with simple sentences when using more than a "toy" grammar; how to infer rules from already-parsed example sentences; and some of the strengths and weaknesses of this simple learning approach. In this Assignment, you'll have a chance to work with an actual, large-scale corpus, the Penn Treebank, which will give you familiarity with the data conventions commonly referenced in computational linguistics and NLP papers.

What you must turn in. Unlike previous assignments, we are NOT asking you to submit this as a PDF. Rather, you are to fill out the variables in the python template provided as per below. Comments are provided in the file itself explaining how you should fill it out, so **please consult these first if you have any question as to how you should write up your answer**.

`http://web.mit.edu/6.863/fall2012/writeups/assignment5/assignment5_template.py`

Once you have answered all questions and verified that your answers are in the correct format by running the script (it will report any format errors or questions you still have to fill out), email your filled-in assignment5_template.py file to `6.863-graders@mit.edu`, with the title "6.863 Assignment 5".

As usual, you may collaborate with whomever you wish; just please note the names of your collaborators (there is a variable for it in the template). Your report should be recognizably your own work.

Initial Preparation: This Assignment is designed to be done on Athena, because most of the tools needed run there. You can download software for this Assignment from here; this includes code and sample grammars that you will need later on:

`http://web.mit.edu/6.863/fall2012/code/assignment5.zip`

1 Context-free parsing and Stack-based parsing

Background reading: Read chapter 9 of the NLTK book that we have provided:

`http://web.mit.edu/~6.863/www/fall2012/labs/nltk-ch9.pdf`

Warning: please make sure you read the pdf of the NLTK chapter that we provide in the specific url specified above. Any newer online versions on the nltk.org site itself do not contain the material required for this assignment.

Additional reference material on context-free parsing is available in the Jurafsky and Martin textbook, chapter 13. If you do not have the textbook, you can read the draft here (there are some slight differences; e.g., this chapter is numbered chapter 12 in its draft form):

http://www.mit.edu/~6.863/fall2012/jmnew/12.pdf

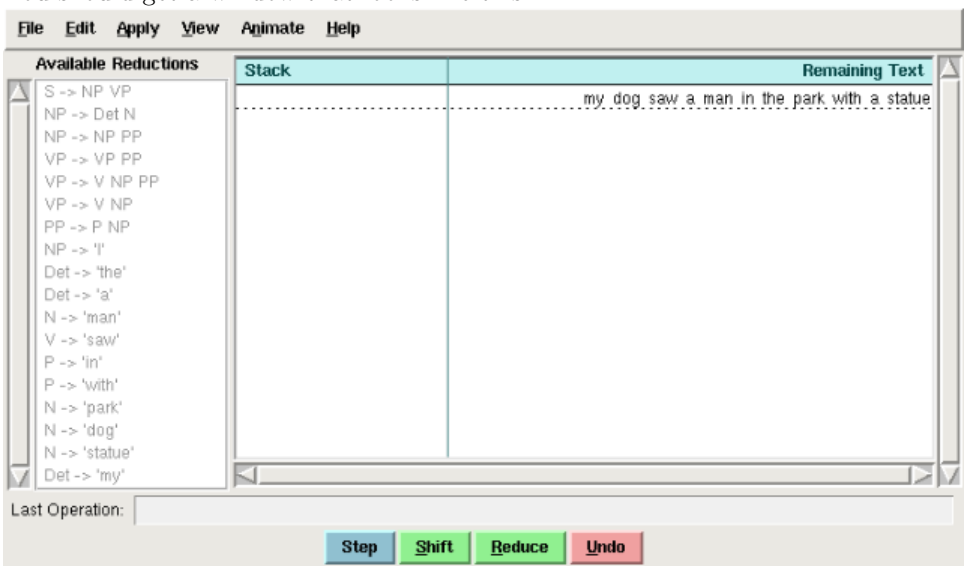
First, login at an Athena cluster (`ssh` will not easily work for the parts of the assignment that require you to use a GUI), and run the usual commands to set up and launch the 6.863-specific python environment:

```
add 6.863
source /mit/6.863/fall2012/bash_environment
python
```

The following python commands will bring up a GUI with a simple, interactive shift-reduce parser. (You may see a warning about pylab after the import line, but don't worry about it since it will not interfere with your ability to do this assignment.)

```
>>> from nltk.app import srparser_app
>>> srparser_app.app()
```

You should get a window that looks like this:



The pane on the right contains the stack and the remaining input. The pane on the left contains the entire grammar, as a list of production rules.

You can run the parser by clicking the button labeled "Step" repeatedly. Each step will animate one step of the parser, either shifting a word onto the stack or reducing two subtrees on the stack into a new subtree. Which action it has just carried out is displayed at the lower left, in the "Last Operation" panel.

Try stepping through the parser, using the provided example sentence, "my dog saw a man in the park with a statue". Click on "Step" until the parser gets stuck in a situation where it cannot shift, because the input has no tokens left, and it cannot reduce, because there is no production that involves the items on the stack. As we demonstrated in class, there is not really a way to get any thing parsed if you used a pure "always shift before reduce" policy in terms of this demo software. You get stuck immediately. For each symbol shifted you need to immediately reduce it to get the POS tag, otherwise the parse will guarantee to fail. In effect then, we should state that a "shift" operation really consists of two operations: a shift and an immediate reduce to get the part of speech tag. Even so, it is still easy to run into some state where the parser can no longer proceed, because of some incorrect choice between a **shift** and a **reduce** action. This is called a *shift-reduce conflict*. To get around this parsing misstep, you can now back up the parser by repeatedly hitting the "Undo" button.

Try this for yourself: making sure that you always follow a shift by a reduce in order to get a part of speech tag, see how to force the parser into some corner where neither a shift nor a reduce action will lead to

further processing and production of a parse tree that spans the entire sentence. Then, back up to the point at which the incorrect choice was made, and click "Shift" or "Reduce" yourself to make the correct choice.

Problem 1.1. By making manual decisions to shift or reduce when necessary, obtain a parse tree for the whole sentence.

We therefore see that context-free parsers in general must operate non-deterministically – that is, they must guess. This is a primary source of computational difficulty in natural language processing. Since no physical machine can operate non-deterministically, we must somehow either dodge this problem (use an oracle, order actions probabilistically, figure out how people operate...), or else simulate a nondeterministic machine.

For the moment, we will pursue another plan: developing a way to "always make the right choice" – that is, a parsing strategy that orders choices systematically when more than one action can apply at a given step. In a shift-reduce parser, there are only two possible such conflicts:

- A shift-reduce conflict, in which it is ambiguous whether the parser should shift a new word onto the stack or reduce two items on the stack
- A reduce-reduce conflict, in which there is more than one way to reduce the items on the stack into a new nonterminal

A **strategy** is a systematic resolution of these conflicts imposed on the parser's actions. For example, we could decide to always resolve shift-reduce conflicts in favor of **shift** actions – if a conflict occurs, always shift an item onto the stack, and do not reduce – or we could decide to do the opposite. We denote **shift** > **reduce** as the strategy in which shift takes precedence over reduce, and **reduce** > **shift** as the strategy in which reduce takes precedence over shift.

Problem 1.2. How would you characterize the strategy that the parser is automatically using? Is it **shift** > **reduce** or **reduce** > **shift**?

Problem 1.3. The choice of strategy affects the *shape* of the resulting parse tree. Parse trees can be **bushy** – flatter rather than deeper – or they can be **straggly** – branching deeply to the right or left. Which strategy leads to bushy parse trees? Which strategy leads to straggly parse trees?

Problem 1.4. The example sentence has multiple possible parses. Give a complete parse tree for the sentence that is as bushy as possible, and one that is as straggly as possible. You may, of course, use the shift-reduce parser to help you do this.

Problem 1.5. Putting aside issues about "meaning," people seem to have definite preferences in the way that they construct parse trees for sentences such as "my dog saw the man in the park with a statue on the grass behind the fence". (If you have a hard time with this sentence because of language difficulties, feel free to ask us or any native speaker what their preferred parse is.) Does this preference seem to more closely follow **shift** > **reduce** or **reduce** > **shift**? Can you justify this in terms of what they put on the stack?

While shift-reduce parsers are hindered by the ambiguity of natural language, they are often used to parse computer languages, where they are called LR parsers. (See `http://en.wikipedia.org/wiki/LR_parsing`.)

Parsers for computer languages still need to have strategies to resolve conflicts. A very common one is to decide based on the nonterminal on top of the stack and the next token of input that has not yet been shifted. This is known as *simple LR parsing with one token of lookahead*, or LALR(1), and it can be implemented very efficiently with lookup tables on computers. (The "LR" is an acronym invented by Donald Knuth, who first developed this approach: it stands for "parsing a sentence **L**eft to **R**ight, building a **L**eftmost derivation in **R**everse. The usual cute Knuthian puns appear.)

An example of using LALR(1) for parsing English might be that when you are parsing a noun phrase, you want to *reduce* (finishing the noun phrase) if the next word is a verb, but *shift* if the next word is a preposition (so it can be attached to the noun phrase).

Problem 1.6. Consider the following pair of sentences and desired parse trees:
a dog saw a dog

```
(S
  (NP (Det a) (N dog) )
  (VP (V saw)
    (NP (Det a) (N dog) ) ) )
```

a dog saw a dog in the park

```
(S
  (NP (Det a) (N dog) )
  (VP (V saw)
    (NP (Det a) (N dog)
      (PP (P in)
        (NP (Det the) (N park) ) ) ) ) )
```

Is it possible to write a standard LR parser without lookahead that will obtain the desired parses for both of these sentences, using our toy grammar? How about an LALR(1) parser? How about an LALR(2) parser (where we have 2 tokens of lookahead)?

Interesting generalizations of this strategy are possible. In his thesis work, Marcus (1980) suggested that this one token of lookahead be extended to lookahead for an entire *phrase*, and that the human sentence processor could be so characterized. Marcus's idea was that his method could distinguish between cases like the following, where the parser must decide whether *have* is an auxiliary verb or a main verb:

1. Have the students taken the exam (*Have* is an auxiliary verb, and the sentence is a Yes-No question)
2. Have the students take the exam (*Have* is a main verb, part of an imperative sentence, e.g., "You have the students take the exam.")

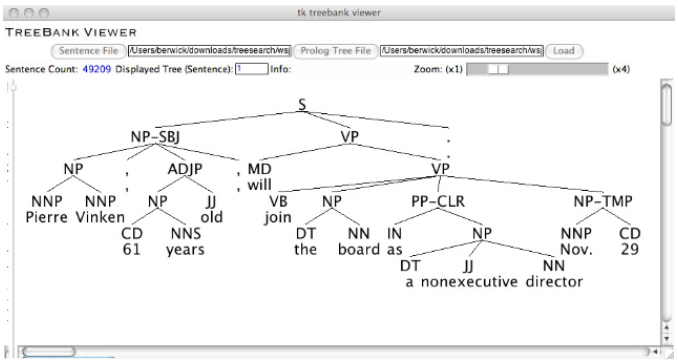
Note that the "disambiguating" material in this case could lie arbitrarily far ahead in terms of number of words: the information that a parser can use to figure out the correct way to proceed might be any number of words ahead, given on the tense of the verb (*taken* vs. *take*). However, this is still only one complete *phrase* ahead – if the parser could look past the next whole Noun phrase ("the students...") it could see this disambiguating cue. Marcus claimed this is how human parsing worked, in his book, *A Theory of Syntactic Recognition for Natural Language*, MIT Press, 1980.

2 Scaling up: Using Larger Grammars

Of course, this is all very well and good for "toy examples", but what about the real world? In this part of the Assignment, we will begin our exploration of the challenges faced when dealing with a fuller range of English, and so much larger grammars. As a resource we will use what has become something of a standard for testing (and machine learning) for parsing, the 49,208 sentences drawn from the Wall Street Journal in the late 1980s. These sentences were then (mostly) hand-parsed ("bracketed") and given annotated parse trees by a group at the University of Pennsylvania. This corpus is variously named "the Penn Treebank," (PTB) sometimes the "WSJ corpus" (after *Wall Street Journal*); or, as NLTK calls it, simply "treebank." For example, here is just one sentence from this corpus:

```
Pierre Vinken , 61 years old , will join the board as a nonexecutive director Nov. 29 .
```

And here is the corresponding hand-annotated parse tree for this sentence. The parse tree makes use of a standard set of phrase names (nonterminals) and categories for words (part of speech tags, abbreviated POS). Note that the POS tags are those symbols that immediately dominate the words. Here is a table of the phrase names and part of speech tags used in this example.



Phrase (nonterminal)	
S	Sentence or clause
NP-SBJ	Noun Phrase used as a Subject
NP	Noun Phrase
ADJP	Adjective Phrase
VP	Verb Phrase
PP-CLR	Prepositional phrase "closely related" to the higher phrase
NP-TMP	Noun Phrase indicating when, how often, how long
Part of speech tag	
NNP	Proper noun, singular
CD	Cardinal determiner (number)
NNS	Proper noun, plural
MD	Modal auxiliary verb
VB	Verb, root
DT	Determiner
NN	Noun, singular or mass
IN	Preposition
JJ	Adjective

And here is how you can access sentences in a 10% sample of this corpus from nltk (note that this, and other code in this section, will not work on your machine if you do not have the WSJ corpus - Athena is your safest bet):

```
>>> from nltk.corpus import treebank
>>> t = treebank.parsed_sents('wsj_0001.mrg')[0]
>>> print t
(S
  (NP-SBJ
    (NP (NNP Pierre) (NNP Vinken))
    (, ,)
    (ADJP (NP (CD 61) (NNS years)) (JJ old))
    (, ,))
  (VP
    (MD will)
    (VP
      (VB join)
      (NP (DT the) (NN board))
      (PP-CLR
        (IN as)
        (NP (DT a) (JJ nonexecutive) (NN director)))
      (NP-TMP (NNP Nov.) (CD 29))))
  (. .))
```

2.1 Running time, ambiguity, and grammar size

In class we showed that the worst-case running time of the CKY and similar parsers is $O(|G|^i n^3)$, where $|G|$ is the size of the grammar (simply a sum of all the symbols it takes to write down the grammar, see below), i is at most 2, and n is the length of the input sentence in tokens (or words).[1] Thus the running time is at worst quadratic in the grammar size and cubic in the sentence length. This means that the size of the grammar, though it is in fact a mere "constant", plays a crucial role in the running time of a parsing system for natural language as soon as we move to any kind of grammar that is more than a toy system. In fact, in practical parsing, constants like this are everywhere. The aim of the following problems is to give you some appreciation of such factors, to see why in practice one is almost forced to some method of probabilistic pruning, as described in the next section.

Let us now look more carefully at calculating grammar size. The size of the toy grammar "demo" used in section 1 of the Assignment for shift-reduce parsing can be calculated as follows, where the right-hand arrow `->` counts as one symbol, the vertical bar | counts as 1 symbol and means "or", and every other name made up of 1 or more characters, like `NP` or `'the'` counts as 1 symbol. Thus the first line in the grammar below uses 4 symbols, while the second uses 7. Continuing, the right hand number given below gives the number of symbols for that line:

```
S -> NP VP                     4
NP -> Det N | NP PP            7
VP -> VP PP | V NP PP | V NP  11
PP -> P NP                     4
Det -> 'the' | 'a'             5
N -> 'man'                     3
V -> 'saw'                     3
P -> 'in' | 'with'             5
N -> 'park' | 'dog' | 'statue' 7
Det -> 'my'                    3
```

If you add up the column of numbers, you get the total grammar size, which is 52.

Now let's experiment with a much larger grammar. We will use a grammar that has been trained on 50% of the Penn Treebank. (Sentences containing coordination words like "and" were excluded, because these increase the amount of ambiguity enormously.) This grammar file is available as the file `wsj.cfg` in the zip file package that you downloaded earlier. Here the "training" is very simple: we simply examined the parse trees to see which rules were ever used to build any part of any parse tree and added those to the grammar; you'll do something a bit smarter in the next section of the Assignment. To get some idea of this grammar's size, you can examine it using an editor like emacs and see that it contains approximately 10,000 individual rules. So this is orders of magnitude larger than the toy grammar you used earlier. But more precisely...

Problem 2.1. What is the `size` of the `wsj.cfg` grammar, using the calculation method we gave above? (Yes; this is a straightforward question, for warm-up. You can use any method you want to do this calculation. Hint: There is a simple 2-letter unix command that can tell you the number of symbols – or words – in a file.)

Now let's investigate how this larger grammar affects parsing. First, let's load the larger grammar and see how parsing time is affected for just a simple example sentence, *John is happy* . **IMPORTANT:** If you are using a newer version of nltk (>0.9.8) on your local machine, you will need to do the rest of this section on Athena. While there is a way to modify the code to use the new libraries, you will get different results if you do so.

To load the grammar and set up a simple Earley parser (without any tracing turned on) we simply do the following, making sure the `wsj.cfg` is in your current directory path. Note that even for this short sentence

[1] Here we use the standard "Big Oh" notation to say that the growth of some function is bounded "from above"; i.e., for real-valued functions f and g, $f(x) = O(g(x))$ as $x \to \infty$ iff there exists a positive real number M and a real number x_0 such that for $x > x_0$, $|f(x)| \leq M|g(x)|$. For additional details, see `http://en.wikipedia.org/wiki/Big_O_notation`.

you will have to wait a little while for the parse to finish – that is why we do not turn on any tracing, though you might want to set `trace=1` in the definition of the parser to see why we say "a little while."

We have provided you a script to run parses.

```
cfg_parse.py <cfg file> <sentence file> <sentence number> [verbose]
```

For example, running:

```
python cfg_parse.py wsj.cfg sentences.txt 0
```

will parse the first (0^{th}) sentence in `sentences.txt` using the `wsj.cfg` grammar file. and output the number of parses, and time taken to generate the parse. Running this script with the verbose option will also print out the parse trees. **But** before you print them out, you might want to try running the script without the verbose option to see how many there are. You might be surprised by this number.

Problem 2.2. How many parse trees are there for this first, simple sentence?

Problem 2.3. Are there *any* of the first 100 trees that correspond to what the "correct" parse for "John is happy" ought to be? This tree should be something like the following. (You might want to write a program to help with the search or modify `cfg_parse.py`.) If you can find this correct one, how far down the first 100 trees is it?

```
(S
  (NP (NPR (NNP John)))
  (VP (VBZ is) (ADJPPRD (JJ happy)))
  (PUNCpoint .))
```

3 Probabilistic context-free parsing

3.1 Using probabilistic context-free grammars

Preparation: Read section 9.3-9.4 of the NLTK book chapter, on how to define and use probabilistic context-free grammars using NLTK. For additional reference, see the J-M textbook, chapter 14 up through section 14.6.

Before trying your hand at a problem we would like you to appreciate that by assigning probabilities to context-free rules, one can construct a chart parser that works much faster than the "all possible parses" method, because one can prune away low probability rule combinations. As an example, the following code fragment is extracted from `pcfg-parse-wsj.py` in the package we have provided for this Assignment. It uses an A* parsing method, similar to the A* path finding methods you learned about in 6.034, and so finds a single, most likely ("optimal") parse of a sentence with respect to a given probabilistic context-free grammar. Since it does not have to keep all the parses around, it works much faster. As you may recall from 6.034, for this A* method to work, one needs two things: (1) a measure of 'distance so far', which in this case is just 'probability of the parse so far', which is measured just by multiplying together the individual rule probabilities that were used to build the parse so far; and (2) a (valid) estimate of the 'distance remaining', where a valid estimate must be an *underestimate* of the true distance – once again, we must map the notion of 'distance' somehow onto 'probability', a matter which we will not take up here. (There is one other condition to impose in order to have a *valid* estimate of the distance remaining – can you recall from 6.034 what this other condition is?)

In any event, this A* search method has been implemented in NLTK as a so-called `ViterbiParser`, like the Viterbi method in Assignment 4, this being simply another name for A*. You can invoke it this way.

```
>>> def pcfg_chartparser(grammarfile):
      f = open(grammarfile)
      grammar = f.read()
```

```
      f.close()
      return nltk.ViterbiParser(nltk.parse_pcfg(grammar))
>>> grammarp = pcfg_chartparser("wsjp.cfg")
>>> grammarp
<ViterbiParser for <Grammar with 10669 productions>>
>>> sent1 = 'John is happy .'.split()
>>> print grammarp.parse(sent1)
(S
  (NP (NPR (NNP John)))
  (VP (VBZ is) (ADJPPRD (JJ happy)))
  (PUNCpoint .)) (p=1.23978875209e-10)
```

3.2 Learning probabilistic context-free grammars

Preparation: Read section 9.5 of chapter 9 from the draft NLTK book on how to train probabilistic context-free grammars (PCFGs) from example parse trees.

We've written some utility functions for learning PCFGs; they're included in the package as `learn_pcfg.py`. You should read this file and its comments; it will make your life easier. This code can learn from a list of trees you provide, or from sections of the Penn Treebank.

Problem 3.1. Alyssa Hacker decides to build a treebank. She finally produces a corpus which contains the following three parse trees, all of which have the same structure as displayed in Figure 1.

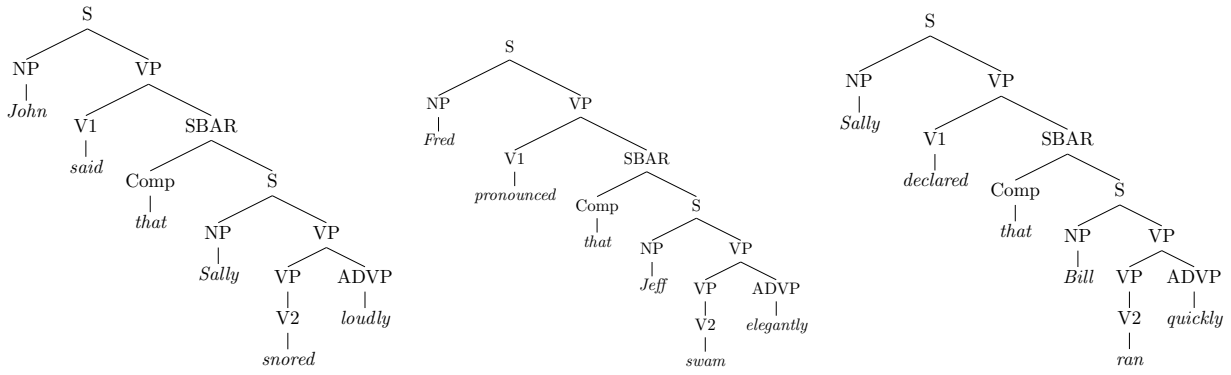


Figure 1: Three trees to put in a treebank, for problem 3.1.

Clearly, this is an important data resource and it deserves to be represented in NLTK. So we've defined these trees in the variable `three_trees` in `learn_pcfg.py`.

You decide to train a PCFG based on Alyssa's treebank, so that you can put in similar sentences and get similar parse trees. Use NLTK and our utility functions to train the maximum-likelihood PCFG for this treebank (leave the parameters *collapse* and *markov_order* as their defaults) and `print` it to see its rules. What are the rules for expanding the nonterminal `VP` and their associated probabilities?

Problem 3.2. Using this PCFG, find the **two** most likely parses for the sentence "Jeff pronounced that Fred snored loudly". What are their probabilities? (Hint: the Viterbi parser will only give you the most likely parse. Review section 9.4 of the NLTK book if stuck.)

Problem 3.3. You are surprised to find that this grammar produces ambiguous results, even though Alyssa's corpus was so consistent. One of the parse trees has a structure never seen in the three examples: the adverb *loudly* attaches to the "higher" verb, *pronounced*, instead of to *snored*.

You don't want this ambiguity; you want trees with high attachment to have zero probability, because they never appear in the corpus.

Make a small modification to the corpus, in a way that may slightly increase the number of non-terminals in the grammar, so that the resulting grammar will only give you parses with low attachment. What change did you make? What is the probability of the correct parse tree now?

3.3 Learning from a Large Corpus

Now it's time to move on to a bigger corpus. If you have imported the Treebank corpus with `from nltk.corpus import treebank`, the function `treebank.parsed_sents()` will give you parse trees for a (non-random) 10% sample of the Penn Treebank's *Wall Street Journal* training data.

Problem 3.4. Train a probabilistic grammar from this 10% sample. How many rules does the grammar have? (Using `print` on a grammar will display a count of the total number of rules, followed by all of the rules. You can also examine `len(grammar.productions())`.)

That's rather a lot of rules, and many of them are highly artificial rules that result from the Chomsky normal form translation (binary-branching form, aside from terminal, part of speech tags). If you used these in a parser, as we saw in the previous section, it would be bogged down in rules that were almost never used. A trick called *Markov smoothing*, however, can combine some of these artificial rules together. We described this briefly in lecture; you can read about it in the API documentation at the following url:

`http://nltk.googlecode.com/svn/trunk/doc/api/nltk.treetransforms-module.html`

Problem 3.5. Retrain your grammar using Markov order-1 smoothing. How many rules does the grammar have now?

For testing purposes, we will use four sentences that occur outside of this 10% sample. Figure 2, on page 10, shows the sentences in their gold-standard parse trees.

To use these sentences as input to a statistical parser, they need to be *tokenized*: there need to be spaces between everything that the parser considers as a separate token, not just where spaces would be used in natural English. For example, the tokenized version of sentence 3 is:

```
The dispute shows clearly the global power of Japan 's financial titans .
```

These four sentences appear, appropriately tokenized, as the variable `sentences` in `learn_pcfg.py`, so you can refer to them as `sentences[0]` through `sentences[3]`.

Problem 3.6. Use your smoothed grammar to parse these sentences (see Figure 2, on page 10). How many constituents does this parser correctly identify in the first three sentences? Count the number of constituents in the correct (reference) tree and the parsed tree, then identify how many constituents they have in common. A common constituent would have the same nonterminal spanning the same words. We have provided a small program `tree_eval.py` to help you compute this constituent set intersection:

```
python tree_eval.py <reference.txt> <parsed.txt>
```

Here, `reference.txt` is a text file containing the s-expression of the correct tree, sometimes called the "gold standard" tree, while `parsed.txt` is a text file containing the s-expression of the tree output by the parser. You may used functions in `tree_eval` directly to write a program that computes the precision and recall of the parsed trees relative to the correct trees.

Problem 3.7. Why can't the current grammar parse the fourth sentence? You should observe at least two problems. Suggest ways to fix each of these problems and make the parser less fragile. (Be brief; You do not need to implement your fixes.)

Figure 2: The parse trees for our four test sentences.

```
1. (S
    (NP-SBJ (DT The) (NN luxury) (NN auto) (NN maker) )
    (NP-TMP (JJ last) (NN year) )
    (VP (VBD sold)
      (NP (CD 1,000) (NNS cars) )
      (PP-LOC (IN in)
        (NP (DT the) (NNP U.S.) ))))


2. (S
    (NP-SBJ (NNP Bell) (NNP Industries) (NNP Inc.) )
    (VP (VBD increased)
      (NP (PRP$ its) (NN quarterly) )
      (PP-DIR (TO to)
        (NP (CD 10) (NNS cents) ))
      (PP-DIR (IN from)
        (NP
          (NP (CD seven) (NNS cents) )
          (NP-ADV (DT a) (NN share) ))))
    (. .) )

3. (S
    (NP-SBJ (DT The) (NN dispute) )
    (VP (VBZ shows)
      (ADVP-MNR (RB clearly) )
      (NP
        (NP (DT the) (JJ global) (NN power) )
        (PP (IN of)
          (NP
            (NP (NNP Japan) (POS 's) )
            (JJ financial) (NNS titans) ))))
    (. .) )

4. (SQ (VBD Was)
    (NP-SBJ (DT this) )
    (SBAR-PRD
      (WHADVP-1 (WRB why) )
      (S
        (NP-SBJ
          (NP (DT some) )
          (PP (IN of)
            (NP (DT the) (NN audience) )))
        (VP (VBD departed)
          (PP-TMP (IN before) (CC or) (IN during)
            (NP (DT the) (JJ second) (NN half) )))))
    (. ?) )
```

3.4 Optional: Accessing the entire corpus

If you want to experiment with the entire Wall Street Journal training set, instead of a 10% sample of it, we have this installed on Athena. You can access it as follows:

```
>>> trees = treebank.parsed_sents('wsj-02-21.mrg')
```

You can install the corpus on your own machine as well. Find the directory where your NLTK data is installed, such as `/usr/share/nltk/data`. That directory should have a subdirectory called `corpora/treebank`. Copy `/mit/6.863/tools/wsj-02-21.mrg` from Athena into that directory, and NLTK will then be able to find it.

However, you may find that using all this data in a simple NLTK parser makes it take a considerable amount of time to run.