

Statistical Techniques for Natural Language Parsing

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■ I review current statistical work on syntactic parsing and then consider part-of-speech tagging, which was the first syntactic problem to successfully be attacked by statistical techniques and also serves as a good warm-up for the main topic—statistical parsing. Here, I consider both the simplified case in which the input string is viewed as a string of parts of speech and the more interesting case in which the parser is guided by statistical information about the particular words in the sentence. Finally, I anticipate future research directions.

Syntactic parsing is the process of assigning a phrase marker to a sentence, that is, the process that given a sentence such as “the dog ate” produces a structure like that in figure 1. In this example, I adopt the standard abbreviations: s for sentence, np for noun phrase, vp for verb phrase, and det for determiner.

It is generally accepted that finding the sort of structure shown in figure 1 is useful in determining the meaning of a sentence. Consider a sentence such as “salespeople sold the dog biscuits.” Figure 2 shows two structures for this sentence. Note that the two have different meanings: On the left, the salespeople are selling dog biscuits, but on the right, they are selling biscuits to dogs. Thus, finding the correct parse corresponds to determining the correct meaning.

Figure 2 also exemplifies a major problem in parsing, *syntactic ambiguity*—sentences with two or more parses. In such cases, it is necessary for the parser (or the understanding system in which the parser is embedded) to choose the correct one among the possible parses.

However, this example is misleading in a fundamental respect: It implies that we can assign at least a semiplausible meaning to all the possible parses. For most grammars (certainly for the ones statistical parsers typically deal with), this is not the case. Such grammars would as-

sign dozens, possibly hundreds, of parses to this sentence, ranging from the reasonable to the uninterpretable, with the majority at the uninterpretable end of things. To take but one example, a grammar I have been using has the rule

$$\text{np} \rightarrow \text{np np} .$$

This rule would be used in the analysis of a noun phrase such as “10 dollars a share,” where the two nps *10 dollars* and *a share* are part of the same np. The point here is that this rule would allow the third parse of the sentence shown in figure 3, and this parse has no obvious meaning associated with it—the best I can do is an interpretation in which *biscuits* is the name of the dog. In fact, most of the parses that wide-coverage grammars find are like this one—pretty senseless.

A usually unstated, but widely accepted, assumption in the nonstatistical community has it that some comparatively small set of parses for a sentence are legitimate ambiguities and that these parses have interpretations associated with them, albeit pretty silly ones sometimes. Furthermore, it is assumed that deciding between the legitimate parses is the responsibility not of the parser but, rather, of some syntactic disambiguation unit working either in parallel with the parser or as a postparsing process. Thus, our hypothetical nonstatistical traditionalist might say that the parser must rule out the structure in figure 3 but would be within its rights to remain undecided between those in figure 2.

By contrast, statistical parsing researchers assume that there is a continuum and that the only distinction to be drawn is between the correct parse and all the rest. The fact that we were able to find some interpretation for the parse in figure 3 supports this continuum view. To put it another way, in this view of the problem, there is no difference between parsing on

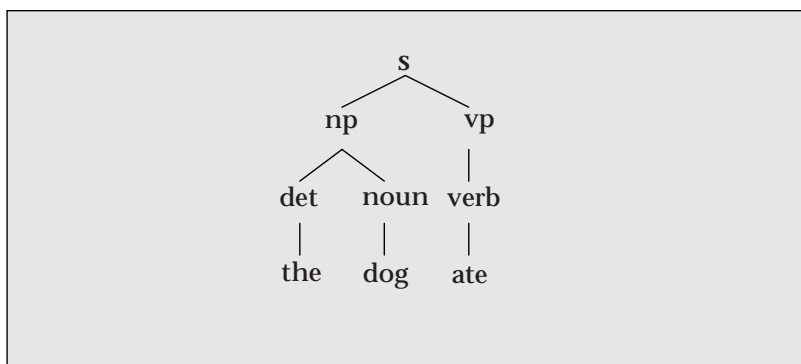


Figure 1. A Simple Parse.

the one hand and syntactic disambiguation on the other: it's parsing all the way down.

Part-of-Speech Tagging

The view of disambiguation as inseparable from parsing is well illustrated by the first natural language-processing task to receive a thoroughgoing statistical treatment—part-of-speech tagging (henceforth, just tagging). A tagger assigns to each word in a sentence the part of speech that it assumes in the sentence. Consider the following example:

The	can	will	rust
det	modal-verb	modal-verb	noun
	noun	noun	verb
	verb	verb	

Under each word, I give some of its possible parts of speech in order of frequency; the correct tag appears in bold. Typically, for English, there will be somewhere between 30 and 150 different parts of speech, depending on the tagging scheme. Although most English words have only one possible part of speech (thus it is impossible to get them wrong), many words have multiple possible parts of speech, and it is the responsibility of a tagger to choose the correct one for the sentence at hand.

Suppose you have a 300,000-word training corpus in which all the words are already marked with their parts of speech. (At the end of this section, we consider the case when no corpus is available.) You can parlay this corpus into a tagger that achieves 90-percent accuracy using a simple algorithm. Record for each word its most common part of speech in the training corpus. To tag a new text, simply assign each word its most common tag. For words that do not appear in the training corpus, guess proper-noun. (Although 90 percent might sound high, it is worth remembering that if we restricted consideration to words that have tag ambiguity, the accuracy figures would be much lower.)

Let us now express our algorithm in more mathematical terms, not so much to illuminate the algorithm as to introduce some mathematical notation. We ignore for the moment the possibility of seeing a new word. Let t vary over all possible tags. Then the most common tag for the i th word of a sentence, w_i , is the one that maximizes the probability $p(t | w_i)$. To put it another way, this algorithm solves the tagging problem for a single word by finding

$$\arg \max_t p(t | w_i). \quad (1)$$

Here, $\arg \max_t$ says “find the t that maximizes the following quantity,” in this case, the probability of a tag given the word. We could extend this scheme to an entire text by looking for the sequence of tags that maximize the product of the individual word probabilities:

$$\arg \max_{t_{1:n}} \prod_{i=1}^n p(t_i | w_i). \quad (2)$$

Here, we are looking for the sequence of n tags $t_{1:n}$ that maximizes the probabilities.

As I said, this simple algorithm achieves 90-percent accuracy; although this accuracy rate is not bad, it is not too hard to get as high as 96 percent, and the best taggers are now creeping toward 97 percent.¹ The basic problem with this algorithm is that it completely ignores a word's context, so that in “the can will rust,” the word *can* is tagged as a modal rather than a noun, even though it follows the word *the*.

To allow a bit of context, suppose we collect statistics on the probability of tag t_i following tag t_{i-1} . Now consider a tagger that follows the equation

$$\arg \max_{t_{1:n}} \prod_i p(t_i | t_{i-1}) p(w_i | t_i). \quad (3)$$

As before, we are taking the product over the probabilities for each word, but where before we considered the probability of each word out of context, here we use two probabilities: (1) $p(t_i | t_{i-1})$ is the probability of a tag (t_i) given the previous tag (t_{i-1}) as context and (2) $p(w_i | t_i)$ relates the word to its possible tags. This second probability, the probability of a word given a possible tag, might look odd, but it is correct. Many would assume that we would want $p(t_i | w_i)$, the probability of the tag given the word, but if we were to derive equation 3 from first principles, we would see that the less intuitive version shown here is correct. It is also the case that if you try the system with both equations, equation 3 outperforms the seemingly more intuitive one by about 1 percent in accuracy. I note this difference because of the moral that a bit of mathematical care can improve program performance, not merely impress journal referees.

Expressions such as equation 3 correspond to a well-understood mathematical construct,

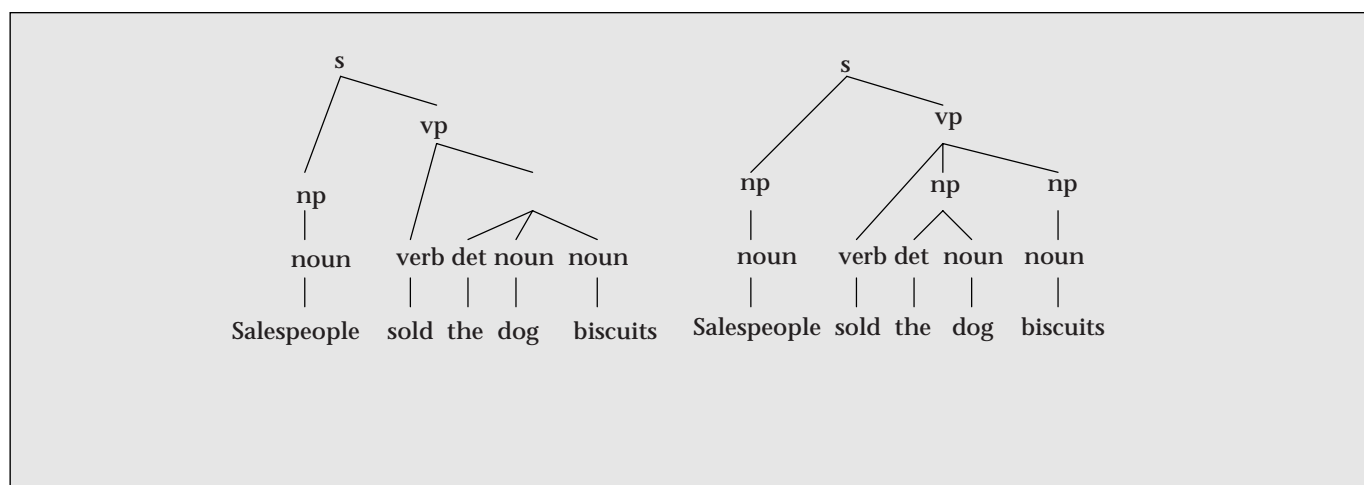


Figure 2. Two Structures for an Ambiguous Sentence.

hidden Markov models (HMMs) (Levinson, Rabiner, and Sondhi 1983). Basically, an HMM is a finite automaton in which the state transitions have probabilities and whose output is also probabilistic. For the tagging problem as defined in equation 3, there is one state for each part of speech, and the output of the machine is the words of the sentence. Thus, the probability of going from one state to another is given by $p(t_i | t_{i-1})$, and for state t_i the probabilistic output of the machine is governed by $p(w_i | t_i)$.

Figure 4 shows a fragment of an HMM for tagging. We see the state for *det* and from it transitions to adjective (*adj*) and noun with relatively high probabilities (.218 and .475, respectively) and a transition returning to *det* with fairly low probability (.0016), the latter reflecting that two determiners in a row are unusual in English. We also see some possible output of each state, along with their probabilities.

From this point of view, the tagging problem is simply this: Given a string of words, find the sequence of states the machine went through to output the sentence at hand. The HMM is hidden in the sense that the machine could have gone through many possible state sequences to produce the output, and thus, we want to find the set of states with the highest probability. Again, this state sequence is exactly what is required in equation 3.

The important point here is that there are many well-understood algorithms for dealing with HMMs. I note two of them: First, there is a simple algorithm for solving equation 3 in linear time (the Viterbi algorithm), even though the number of possible tag sequences to be evaluated goes up exponentially in the length of the text. Second, there is an algorithm (the forward-backward algorithm) for

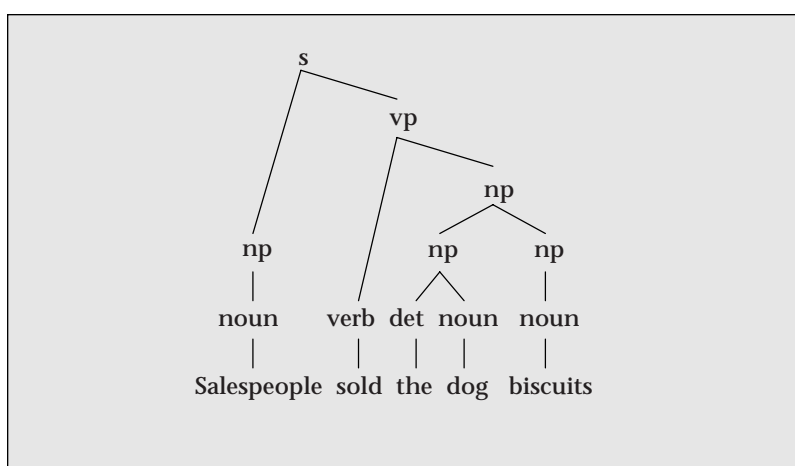


Figure 3. A Third Structure for an Ambiguous Sentence.

adjusting the probabilities on the states and output to better reflect the observed data.

It is instructive to consider what happens in this model when we allow unknown words in the input. For such words, $p(w_i | t_i)$ is zero for all possible tags, which is not good. This is a special case of the *sparse-data problem*—what to do when there is not enough training data to cover all possible cases. As a practical issue, simply assigning unknown words some low probability for any possible tag lets the tagger at least process the sentence. It is better to base one's statistics on less detailed information. For example, word endings in English give part-of-speech clues; for example, words ending in *ing* are typically progressive verbs. One can collect statistics on, say, the last two letters of the word and use them. More generally, this process is called *smoothing*, and it is a major research problem in its own right.

The tagger we just outlined is close to what might be called the canonical statistical tagger

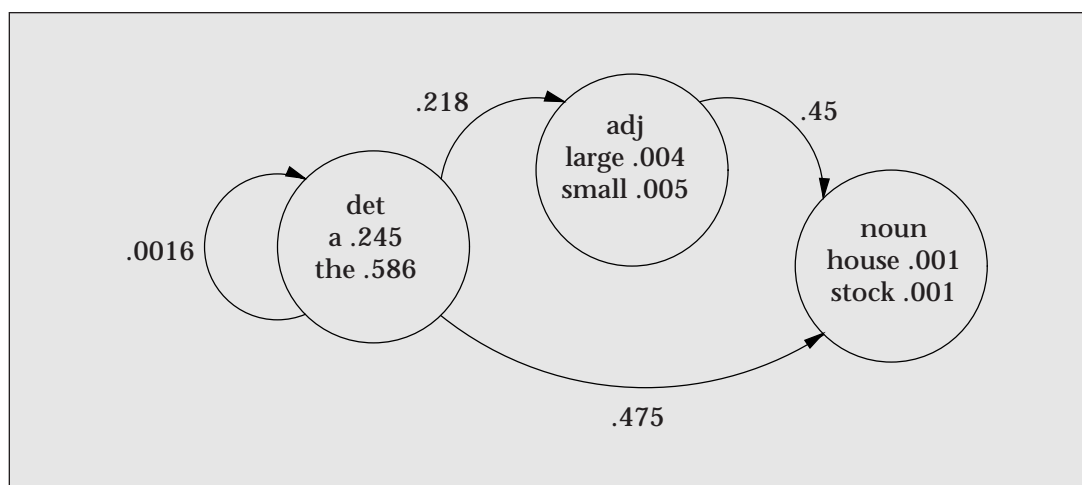


Figure 4. A Fragment of a Hidden Markov Model for Tagging.

(Weischedel 1993; Church 1988). There are, however, many different ways of using statistical information to make part-of-speech tagging decisions. Let us consider a second such method, *transformational tagging*. It loosens the grip of this first example on our imagination, and it also has interesting properties of its own. (An analogous transformational approach to parsing [Brill 1993] is not covered here.)

The transformational scheme takes as its starting point the observation that a simple method, such as choosing the most common tag for each word, does well. It then proposes and evaluates rules for altering the tags to others we hope are more accurate. Rule formats are kept simple to make them easy to learn. For example, in Brill (1995), one of the formats is

Change the tag of a word from *X* to *Y* if
the tag of the previous word is *Z*.

We already noted that in “the can will rust,” the trivial algorithm chooses the modal meaning of *can*. A rule in the previous format that would fix this problem is “change modal-verb to noun after det.” More generally, if we have, say, 40 possible parts of speech (a common number), then this rule format would correspond to $40^3 = 6.4 \times 10^4$ possible rules if we substitute each possible part of speech for *X*, *Y*, and *Z*. (In fact, all possible rules need not be created.)

The system then uses the training data as follows: It measures the initial accuracy (about 90 percent, as noted previously) and then tries each possible rule on the training data, measuring the accuracy that would be achieved by applying the rule across the board. Some rules make things worse, but many make things better, and we pick the rule that makes the accuracy the highest. Call this rule 1.

Next we ask, given that we have already ap-

plied rule 1, which of the other rules does the best job of correcting the remaining mistakes. This is rule 2. We keep doing this until the rules have little effect. The result is an ordered list of rules, typically numbering 200 or so, to apply to new examples we want tagged.

Besides illustrating the diversity of statistical parsers, transformation tagging has several nice properties that have not been duplicated in the conventional version. One is speed. Roche and Schabes (1995) report a method for turning the transformational tagger’s rule list into a finite automaton and compiling the automaton into efficient code. This tagger can tag at the rate of about 11,000 words/second—effectively the speed at which the program is able to look up words in its dictionary. This rate contrasts with 1200 words/second for Roche and Schabes’s implementation of the standard HMM tagger. (From my experience, 1200 words/second is a fast implementation indeed of an HMM tagger.)

Another way in which the transformational version seems superior has to do with the assumption I made at the outset, that we have at our disposal a 300,000-word hand-tagged corpus. Is it possible to do without such a corpus? The current answer to this question is confusing. As already noted, the standard tagger uses HMM technology, and there are standard techniques for training HMMs, that is, for adjusting their parameters to fit the data better even when the data are not marked with the answers (the tags). Unfortunately, Merialdo (1994) reports that HMM training does not seem to improve HMM taggers. For example, suppose you start out with a dictionary for the language but no statistics. Thus, you know the possible parts of speech for the words but know neither their relative frequency nor probabilities such as $p(t_i$

| t_{i-1}). With this information, HMM training gets little higher than the 90 percent achieved by the trivial algorithm. However, Brill (1995) reports on a learning mechanism for a transformational tagger using untagged data that achieve a 95-percent to 96-percent level of performance. At first glance, the algorithm looks a lot like the traditional HMM training algorithm adapted to a transformational milieu. Why it works, although training the statistic version with standard HMM training does not, is currently unexplained.

Statistical Parsing

We started our discussion of statistical taggers by assuming we had a corpus of hand-tagged text. For our statistical parsing work, we assume that we have a corpus of hand-parsed text. Fortunately, for English there are such corpora, most notably the Penn tree bank (Marcus 1993). In this article, I concentrate on statistical parsers that use such corpora to produce parses mimicking the tree-bank style. Although some work has used tree banks to learn a grammar that is reasonably different from that used in the corpus (Briscoe and Waegner 1993; Pereira and Schabes 1992), this has proved more difficult and less successful than the tree-bank-mimicking variety.

Deciding to parse in the tree-bank style obviously makes testing a program's behavior easier—just compare the program output to the reserved testing portion from the tree bank. However, we still need to define precisely how to measure accuracy. In this article, I concentrate on two such measures: (1) labeled precision and (2) labeled recall. *Precision* is the number of correct constituents found by the parser (summed over all the sentences in the test set) divided by the total number of nonterminal constituents the parser postulated. *Recall* is the number correct divided by the number found in the tree-bank version. (We consider the parts of speech to be the terminal symbols in this counting and, thus, ignore them. Otherwise, we would be conflating parsing accuracy with part-of-speech tagging accuracy.) A constituent is considered correct if it starts in the right place, ends in the right place, and is labeled with the correct nonterminal.

For example, suppose our tree bank has the following parse:

```
(s (np (det The) (noun stranger))
  (vp (verb ate)
      (np (det the) (noun doughnut))
      (pp (prep with) (np (det a) (noun fork))))),
```

and our parser instead comes up with

```
(s (np (det The) (noun stranger))
  (vp (verb ate)
```

```
(np (det the) (noun doughnut)
  (pp (prep with) (np (det a) (noun fork)))))).
```

The parser has postulated six nonterminals (1 s, 3 nps, 1 vp, and 1 prepositional phrase [pp]), of which all are correct except the np headed by *doughnut*, which should have ended after *doughnut* but instead ends after *fork*. Thus, the precision is 5/6, or .83. Because the tree-bank version also has 6 nonterminals, the recall is also .83.

To give some idea of how good current parsers are according to these measures, if we give a parser just the parts of speech and ask it to parse the sentence (that is, if it does not see the actual words in the sentence), a good statistical parser that does not try to do anything too fancy can achieve about 75-percent-average precision-recall. However, a state-of-the-art parser that has access to the actual words and makes use of fine-grained statistics on how particular English words fit into parses achieves labeled precision-recall rates of about 87 percent to 88 percent. These figures are for the Penn *Wall Street Journal* corpus mentioned earlier. This corpus contains the text of many articles taken from the *Wall Street Journal* without modification, except for the separation of punctuation marks from the words they adjoin. The average sentence length is 23 words and punctuation. I have not measured how many parses there typically are for these sentences, and of course, it would depend on the grammar. However, I would guess that for the kinds of grammar we discuss in the following pages, a million parses to a sentence would be conservative. At any rate, we are not talking about toy examples.

Statistical parsers work by assigning probabilities to possible parses of a sentence, locating the most probable parse, and then presenting the parse as the answer. Thus, to construct a statistical parser, one must figure out how to (1) find possible parses, (2) assign probabilities to them, and (3) pull out the most probable one.

One of the simplest mechanisms for this is based on *probabilistic context-free grammars* (PCFGs), context-free grammars in which every rule is assigned a probability (Charniak 1993). The probabilities are to be interpreted as the probability of expanding a constituent, say an np, using this particular rule, as opposed to any of the other rules that could be used to expand this kind of constituent. For example, this toy PCFG generates the three parses for our ambiguous sentence from figures 2 and 3 (figure 5). Note, for example, how the probabilities of all the rules for np sum to one.

Given the probability of individual rules, we calculate the probability of an entire parse by taking the product of the probabilities for each

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of a
sentence,
locating
the most
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parse,
and then
presenting
the parse
as the
answer.*

s	→	np vp	(1.00)	np	→	det noun	(0.5)
vp	→	verb np	(0.8)	np	→	noun	(0.3)
vp	→	verb np np	(0.2)	np	→	det noun noun	(0.15)
				np	→	np np	(0.05)

Figure 5. The Three Parses for the Ambiguous Sentence from Figures 2 and 3.

of the rules used therein. That is, if s is the entire sentence, π is a particular parse of s , c ranges over the constituents of π , and $r(c)$ is the rule used to expand c , then

$$p(s, \pi) = \prod_c p(r(c)). \quad (4)$$

In discussing the parses for “the salespeople sold the dog biscuits,” we were particularly concerned about the nonsensical parse that considered *the dog biscuits* to be a single noun phrase containing two completely distinct noun phrases inside. Note that if, as in the previous grammar, the rule $np \rightarrow np\ np$ has a fairly low probability, this parse would be ranked low. According to our PCFG fragment, the leftmost parse of figure 2 has probability $1.0 \times .3 \times .8 \times .15 = .036$, whereas that of figure 3 has probability .0018.

PCFGs have many virtues. First and foremost, they are the obvious extension in the statistical domain of the ubiquitous context-free grammars that most computer scientists and linguists are already familiar with. Second, the parsing algorithms used for context-free parsing carry over to PCFGs (in particular, all possible parses can be found in n^3 time, where n is the length of the sentence). Also, given the standard compact representation of CFG parses, the most probable parse can be found in n^3 time as well, so PCFGs have the same time complexity as their nonprobabilistic brethren. There are more complicated but potentially useful algorithms as well (Goodman 1996b; Stolcke 1995; Jelinek 1991). Nevertheless, as we see in the following sections, PCFGs by themselves do not make particularly good statistical parsers, and many researchers do not use them.

Obtaining a Grammar

Suppose that we do want to use a PCFG as our statistical parsing mechanism and that, as we said earlier, we have a tree bank. To parse a new sentence, we need the following: (1) an actual

grammar in PCFG form such that new (presumably novel) sentences have parses according to the grammar, (2) a parser that applies the PCFG to a sentence and finds some or all of the possible parses for the sentence, and (3) the ability to find the parses with the highest probability according to equation 4.

As noted at the end of the last section, there are well-understood and reasonably efficient algorithms for points 2 and 3, so these are not pressing problems. This leaves point 1.

There is a trivial way to solve point 1. Suppose we are not concerned about parsing novel sentences and only want to make sure that we produce a grammar capable of assigning one or more parses to all the training data. This is easy. All we need do is read in the parses and record the necessary rules. For example, suppose the leftmost parse in figure 2 is in our tree bank. Because this parse has an s node with np and vp immediately below it, our grammar must therefore have the rule $s \rightarrow np\ vp$. Similarly, because there are three noun phrases, two consisting of a det followed by a $noun$ and one with a det $noun\ pp$, our grammar would need the rules $np \rightarrow det\ noun$ and $np \rightarrow det\ noun\ pp$.

It is possible to read off all the necessary rules in this fashion. Furthermore, we can assign probabilities to the rules by counting how often each rule is used. For example, if the rule $np \rightarrow det\ noun$ is used, say, 1,000 times, and overall np rules are used 60,000 times, then we assign this rule the probability $1,000/60,000 = .017$.

I evaluate tree-bank grammars of this sort in Charniak (1996), and a generalization of them is used in Bod (1993). They seem to be reasonably effective. That is to say, grammars of this sort achieve an average of about 75-percent labeled precision and recall, the percentage mentioned previously as pretty good for grammars that only look at the parts of speech for the words.

In some respects, this result is surprising. It was widely assumed that reading off a gram-

```

(s (np The (adjp most troublesome) report)
  (vp may
    (vp be
      (np (np the August merchandise trade deficit)
        (adjp due (advp out) (np tomorrow))))))
(. .))

(s (np The (adjp most troublesome) report)
  (vp may
    (vp be
      (adjp (np the August merchandise trade deficit)
        due)
      (pp out (np tomorrow))))
(. .))

```

Figure 6. A Real Tree-Bank Example and the Parse Found by a Tree-Bank Grammar.

mar in this fashion would not lead to accurate parsing. The number of possible grammatical constructions is large, and even the Penn tree bank, with its nearly 50,000 hand-parsed sentences, is not large enough to contain them all, especially because the tree-bank style is relatively flat (constituents often contain little substructure). Thus, one would expect new sentences to require rules not in the derived grammar. Although this indeed happens, the rules not in the tree bank are so rare that missing them has little effect on parsing, and when the tree-bank grammar is missing a rule used in the correct parse, the ambiguity we talked about earlier ensures that there will be lots of incorrect parses that are just a little off. Thus, the missing rules have little effect on statistical measures such as average precision-recall.

To get some idea of how these grammars perform, we give a real example in figure 6 cleaned up only by removing all the parts of speech from the words to concentrate our attention on the nonterminals. The parser gets things correct except for the area around the phrase *due out tomorrow*, which seems to confuse it, leading to the unintuitive adjectival phrase (adjp) “the August merchandise trade deficit due.” In terms of precision-recall, the parse got 7 constituents correct of the 9 it proposed (precision = 7/9) and of the 10 found in the tree-bank version (recall = 7/10).

Nevertheless, it is troubling that a tree-bank grammar is doomed from the start to misparse certain sentences simply because it does not have the correct rule. An alternative that has been used in two state-of-the-art sta-

tistical parsers (Collins 1996; Magerman 1995) are Markov grammars. (I made up this term; neither Magerman [1995] nor Collins [1996] uses it.)

Rather than storing explicit rules, a Markov grammar stores probabilities that allow it to invent rules on the fly. For example, to invent np rules, we might know the probability that an np starts with a determiner (high) or a preposition (low). Similarly, if we are creating a noun phrase, and we have seen a determiner, we might know what the probability is that the next constituent is an adjective (high) or another determiner (low). It should be clear that we can collect such statistics from the tree bank in much the same way as we collected statistics about individual rules. Having collected these statistics, we can then assign a probability that any sequence of constituents is any part of speech. Some of these probabilities will be high (for example, $np \rightarrow det\ adj\ noun$), but most of them will be low (for example, $np \rightarrow preposition$).

To formalize this idea slightly, we capture the idea of using the probability of adj appearing after det inside an np with probabilities of the form $p(t_i | l, t_{i-1})$, where t_{i-1} is the previous constituent, and l is the constituent type we are expanding. Naturally, this is but one way to try to capture the regularities; we could condition instead on l and the two previous constituents.

We can relate this scheme to our more traditional rule-based version by noting that the probability of a rule is the product of the probabilities of its individual components.

Rather than storing explicit rules, a Markov grammar stores probabilities that allow it to invent rules on the fly.

*Lexicalized
statistical
parsers
collect,
to a first
approxima-
tion, two
kinds of
statistics.
One relates
the head
of a phrase
to the rule
used to
expand
the phrase,
and the
other
relates the
head of a
phrase
to the
head
of a
subphrase
....*

$$p(r | l) = \prod_{t \in r} p(t_i | l, t_{i-1}). \quad (5)$$

There are no formal studies on how well different Markov grammars perform or how they compare to tree-bank grammars. I have looked at this some, and found that for nonlexicalized parsers (that is, parsers that do not use information about the words, just about the parts of speech), tree-bank grammars seem to work slightly better, though my colleague Mark Johnson found a Markov scheme that worked ever so slightly better than the tree-bank grammar. Either way, the parsers that have used Markov grammars have mostly been lexicalized, which is where the real action is.

Lexicalized Parsing

The biggest change in statistical parsing over the last few years has been the introduction of statistics on the behavior of individual words. As noted earlier, rather than the 75-percent precision-recall accuracy of parsers that use statistics based only on a word's part of speech, lexicalized parsers now achieve 87-percent to 88-percent precision-recall.

Gathering statistics on individual words immediately brings to the fore the sparse data problems I first mentioned in our discussion of tagging. Some words we will have never seen before, and even if we restrict ourselves to those we have already seen, if we try to collect statistics on detailed combinations of words, the odds of seeing the combination in our training data become increasingly remote. Consider again the noun phrase from figure 6, "the August merchandise trade deficit." This combination does not seem terribly unusual (at least not for text from the *Wall Street Journal*), but it does not appear in our 900,000-word training set.

To minimize the combinations to be considered, a key idea is that each constituent has a *head*, its most important lexical item. For example, the head of a noun phrase is the main noun, which is typically the rightmost. More generally, heads are computed bottom up, and the head of a constituent c is a deterministic function of the rule used to expand c . For example, if the c is expanded using $s \rightarrow np\ vp$, the function would indicate that one should find the head of the c by looking for the head of the vp . In "the August merchandise trade deficit," the head is *deficit*, and even though this noun phrase does not appear in the training set, all the words in the noun phrase do appear under the head *deficit*. Thus, if we restrict ourselves to statistics on at most pairs of words, the best ones to gather would relate the

heads of phrases to the heads of all their subphrases. (A different scheme for lexicalization is proposed by Bod [1993], but its efficacy is still under debate [Goodman 1996a].)

Lexicalized statistical parsers collect, to a first approximation, two kinds of statistics. One relates the head of a phrase to the rule used to expand the phrase, which we denote $p(r | h)$, and the other relates the head of a phrase to the head of a subphrase, which we denote $p(h | m, t)$, where h is the head of the subphrase, m the head of the mother phrase, and t the type of subphrase. For example, consider the vp "be ... tomorrow" from figure 6. Here, the probability $p(h | m, t)$ would be $p(be | may, vp)$, but $p(r | h)$ would be $p(vp \rightarrow aux\ np | be)$. Parsers that use Markov grammars do not actually have $p(r | h)$ because they have no rules as such. Rather, this probability is spread out, just as in equation 5, except now each of the probabilities is to be conditioned on the head of the constituent h . In what follows, we talk as if all the systems used rules because the differences do not seem crucial.

Thus, for a lexicalized parser, equation 4 is replaced by

$$p(s, \pi) = \prod_c p(h(c) | m(c)) \cdot p(r(c) | h(c)). \quad (6)$$

Here, we first find the probability of the head of the constituent $h(c)$ given the head of the mother $m(c)$ and then the probability of the rule $r(c)$ given the head of c .

In general, conditioning on heads tightens up the probabilities considerably. For example, consider the probability of our noun phrase "the August merchandise trade deficit." In table 1, I give the probabilities for the word *August* given (1) no prior information (that is, what percentage of all words are *August*), (2) the part of speech (what percentage of all proper nouns are *August*), and (3) the part of speech and the head of the previous phrase (*deficit*). We do the same for the rule used in this noun phrase: $np \rightarrow det\ propernoun\ noun\ noun\ noun$ (table 1). In both cases, the probabilities increase as the conditioning events get more specific.

Another good example of the utility of lexical head information is the problem of pp attachment. Consider the following example from Hindle and Rooth (1991):

Moscow sent more than 100,000 soldiers into Afghanistan.

The problem for a parser is deciding if the pp *into Afghanistan* should be attached to the verb *sent* or the noun phrase *more than 100,000 soldiers*. Hindle and Rooth (1991) suggest basing this decision on the compatibility of the preposition *into* with the respective heads of the vp (*sent*) and the np (*soldiers*). They measure this

Conditioning events	$p(\text{August})$	$p(\text{rule})$
Nothing	2.7×10^{-4}	3.8×10^{-5}
Part of speech	2.8×10^{-3}	9.4×10^{-5}
Also $h(c)$ is deficit	1.9×10^{-1}	6.3×10^{-3}

Table 1. Probabilities for the Word August.

compatibility by looking at $p(\text{into} \mid \text{sent})$ (the probability of seeing a pp headed by *into* given it is under a vp headed by *sent*) and $p(\text{into} \mid \text{soldiers})$ (its probability given it is inside an np headed by *soldiers*). The pp is attached to the constituent for which this probability is higher. In this case, the probabilities match our intuition that it should be attached to *sent* because $p(\text{into} \mid \text{sent}) = .049$, whereas $p(\text{into} \mid \text{soldiers}) = .0007$. Note that the probabilities proposed here are exactly those used in the parsing model based on equation 6, where the probability of a constituent c incorporates the probability $p(h(c) \mid m(c))$, the probability of the head of c given the head of the parent of c . For the two pp analyses, these would be the probability of the head of the pp (for example, *into*) given the head of the mother (for example, *sent* or *soldiers*).

Figure 7 shows our lexicalized parser's parse of the sentence in figure 6. Note that this time, the parser is not as confused by the expression *due out tomorrow*, although it makes it a prepositional phrase, not an adjectival phrase. These improvements can be traced to the variety of ways in which the probabilities conditioned on heads better reflect the way English works. For example, consider the bad adjp from figure 6. The probability of the rule $\text{adjp} \rightarrow \text{np adj}$ is .0092, but the observed probability of this rule given that the head of the phrase is *due* is zero—this combination does not occur in the training corpus.

There is one somewhat sobering fact about this last example. Even though the parse in figure 7 is much more plausible than that in figure 6, the precision and recall figures are much the same: in both cases, the parser finds seven correct constituents. Obviously, the number of constituents in the tree-bank parse stays the same (10), so the recall remains 70 percent. In the lexically based version, the number of constituents proposed by the parser decreases from 9 to 8, so the precision goes up from 78 percent to 87 percent. This modest improvement hardly reflects our intuitive idea that the second parse is much better than the first.

Thus, the precision-recall figures do not completely capture our intuitive ideas about the goodness of a parse. However, quantification of intuitive ideas is always hard, and most researchers are willing to accept some artificiality in exchange for the boon of being able to measure what they are talking about.

Conditioning on lexical heads, although important, is not the end of the line in what current parsers use to guide their decisions. Also considered are (1) using the type of the parent to condition the probability of a rule (Charniak 1997), (2) using information about the immediate left context of a constituent (Collins 1996), (3) using the classification of noun phrases inside a vp as optional or required (Collins 1997), and (4) considering a wide variety of possible conditioning information and using a decision tree-learning scheme to pick those that seem to give the most purchase (Magerman 1995). I expect this list to increase over time.

Future Research

The precision and recall measures of the best statistical parsers have been going up year by year for several years now, and as I have noted, the best of them is now at 88 percent. How much higher can these numbers be pushed? To answer this question, one thing we should know is how well people do on this task. I know of no published figures on this question, but the figure that is bandied about in the community is 95 percent. Given that people achieve 98 percent at tagging, and parsing is obviously more complicated, 95 percent has a reasonable ring to it, and it is a nice round number.

Although there is room for improvement, I believe for several reasons that it is now (or will soon be) time to stop working on improving labeled precision-recall as such. We have already noted the artificiality that can accompany these measurements, and we should always keep in mind that parsing is a means to an end, not an end in itself. At some point, we should move on. In addition, many of the

```

(s (np The (adp most troublesome) report)
  (vp may
    (vp be
      (np the August merchandise trade deficit)
      (pp due out (np tomorrow))))
  (. .))

```

Figure 7. The Example Tree-Bank Sentence Parsed Using Word Statistics.

tasks we could move on to might themselves improve parsing accuracy as a by-product.

One area that deserves more research is statistical parsers that produce trees unlike those in extant tree banks. We have already noted that this is a tough problem because in this circumstance, the tree bank provides only approximate information about what rules are needed in the grammar and when they should be applied. For this reason, tree-bank-style parsers typically perform better than those that aim for a style further from the parent tree. Nevertheless, eventually we must move beyond tree-bank styles. Anyone who studies, say, the Penn tree bank will have objections to some of its analyses, and many of these objections will prove correct. However, producing a new tree bank for each objection is impossible: Tree banks are much too labor intensive for this to be practicable. Rather, we must find ways to move beyond, using the tree bank as a first step.

For example, look again at figure 6, in particular at the np *the August merchandise trade deficit*. Notice how flat it is, particularly with regard to the sequence of nouns *August merchandise trade deficit*. The problem of noun-noun compounds is an old one. Lauer (1995) suggests statistical techniques for attacking this problem. Interestingly, he also recommends looking at head-head relations. However, nobody has yet incorporated his suggestions into a complete parser, and this is but one of many things that could be improved about the trees produced by tree-bank-style parsers.

However, the most important task to be tackled now is parsing into a semantic representation, many aspects of which are covered in the accompanying article by Hwee Tou Ng and John Zelle on semantic processing. One of these aspects, null elements, deserves special attention here because of its close relation to

parsing. A standard example of a null element is in relative clauses, for example, “the bone that the dog chewed,” where we should recognize that “the dog chewed the bone.” At least one statistical parser has attacked this problem (Collins 1997). Another example of null elements is gapping, as in “Sue ate an apple and Fred a pear.” Here, there is a gap in the phrase “Fred a pear,” which obviously should be understood as “Fred ate a pear.” Although there have been numerous theoretical studies of gapping, to the best of my knowledge, there has been no statistical work on the topic.

Other aspects of parsing also deserve attention. One is speed. Some of the best statistical parsers are also fast (Collins 1996), and there are the beginnings of theory and practice on how to use statistical information to better guide the parsing process (Caraballo and Charniak 1998). I would not be surprised if the statistical information at hand could be parlayed into something approaching deterministic parsing.

Before closing, I should at least briefly mention applications of parsing technology. Unfortunately, most natural language applications do not use parsing, statistical or otherwise. Although some statistical parsing work has been aimed directly at particular applications (for example, parsing for machine translation [Wu 1995]) and applications such as speech recognition require parsers with particular features not present in current statistical models (for example, fairly strict left-to-right parsing), I believe that the greatest impetus to parsing applications will be the natural course of things toward better; faster; and, for parsing, deeper.

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Notes

1. Human taggers are consistent with one another at the 98-percent level, which gives an upper bound on the sort of performance one can expect.

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