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June 29, 2001

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Efficient parsing of DOP with PCFG-reductions – DRAFT

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1.1 Introduction

While the Data-Oriented Parsing (DOP) approach has produced some extremely interesting and promising results (Bod 2000a, Bod 2000c, Bod 2000b, Bod 2001), its computational complexity has deterred its wider use, and made experiments with it more difficult. In particular, in its original form, sometimes called DOP-1 (Bod 1995a), the DOP model calls for using all possible subtrees in a training corpus. This leads to exponentially many trees, and thus both exponential time and space requirements. On top of this, the typical optimization criterion, most probable parse, is NP-complete to solve for, leading to an exponentially hard problem of exponential size. The solution has typically been various approximations, such as sampling from the set of all trees, to reduce the size of the grammar, or sampling from the set of all parses – Monte Carlo approximations – to reduce the difficulty of the search. In this chapter, we present two alternate solutions. The first removes the exponentiality of the grammar size, making it instead linear in the training data size,

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while producing an identical distribution over parse trees. The second removes the exponentiality of the search, making it instead $O(n^3)$, by changing slightly the search criterion, to one which is much easier, but gives almost identical performance. Our two new techniques can be used either separately, or together. Overall, together these techniques lead to a 500 times speedup over conventional DOP parsing.

1.1.1 Overview

In Section 1.2 we will show how to build a Probabilistic Context Free Grammar (PCFG) equivalent to the classic DOP model. Our model will only be linear in the size of each training tree, instead of the classic use of all possible subtrees, which produces a grammar that is typically exponential in the size of each training tree. Despite this drastically smaller size, we prove that the two models produce the same probability distributions over parse trees. This can lead to substantially faster parsing times. The grammars produced can be used with most of the typical parsing algorithms used for DOP, including an n-best parser; a monte-carlo parser; or the new parser introduced in this chapter.

We then continue more speculatively, showing variations on this efficient PCFG construction that have other desirable properties. For instance, we can build models that limit subtree depth, or that give a smaller weight to larger trees, or that give the same weight to each piece of training data, or that when parsed, return the shortest derivation. Our construction makes it easy to do a wide variety of experiments.

Next, we describe a different maximization criterion. The usual maximization criterion for DOP models is the most probable parse criterion, which selects the parse tree that has the highest probability of producing the sentence. However, finding the most probable parse is NP-hard. Instead, we argue for finding the maximum constituents parse, which can be done in $O(n^3)$ time. Theoretically, the maximum constituents parse performs at least as well as the most probable parse on measures like precision and recall, since it optimizes the number of correct pieces of a tree. We show that in practice, it also works as well as a Monte-Carlo parser on the exact match metric. We also describe some speedups for Monte-Carlo parsing, just in case someone wanted to use that technique.

Finally, we conclude with our own opinions about the usefulness of these techniques, and the prospects for DOP. While we think our techniques should be very useful for DOP research, we admit to skepticism about the overall potential of DOP.

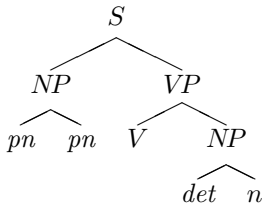


FIGURE 1 Training corpus tree for DOP example

1.1.2 The DOP-1 model

The DOP-1 model (Bod 1995a) was the first version of DOP, and most other versions of DOP are variations on it. We thus concentrate on that model. The model itself is extremely simple and can be described as follows: for every sentence in a parsed training corpus, extract *every subtree.* In general, the number of subtrees will be very large, typically exponential in sentence length. Now, use these trees to form a Stochastic Tree Substitution Grammar (STSG). Each tree is assigned a number of counts, one count for each time it occurred as a subtree of a tree in the training corpus. Each tree is then assigned a probability by dividing its number of counts by the total number of counts of trees with the same root nonterminal.

Given the tree of Figure 1, we can use the DOP model to convert it into the STSG of Figure 2. The numbers in parentheses represent the probabilities. To give one example, the tree

is assigned probability 0.5 because the tree occurs once in the training corpus, and there are two subtrees in the training corpus that are rooted in NP, so $\frac{1}{2} = 0.5$. The resulting STSG can be used for parsing.

In theory, the DOP model has several advantages over other models. In the conventional use of PCFGs (although not the use shown in this chapter), only a very small context is captured – perhaps a parent and its children. DOP's use of trees allows capturing large contexts, making the model more sensitive. Since every subtree is included, even trivial ones corresponding to rules in a conventional PCFG, novel sentences with unseen contexts may still be parsed.

Because every subtree is included, the number of subtrees is huge; therefore Bod (1995a) randomly samples 5% of the subtrees, throwing away the rest. This 95% reduction in grammar size significantly speeds up parsing.

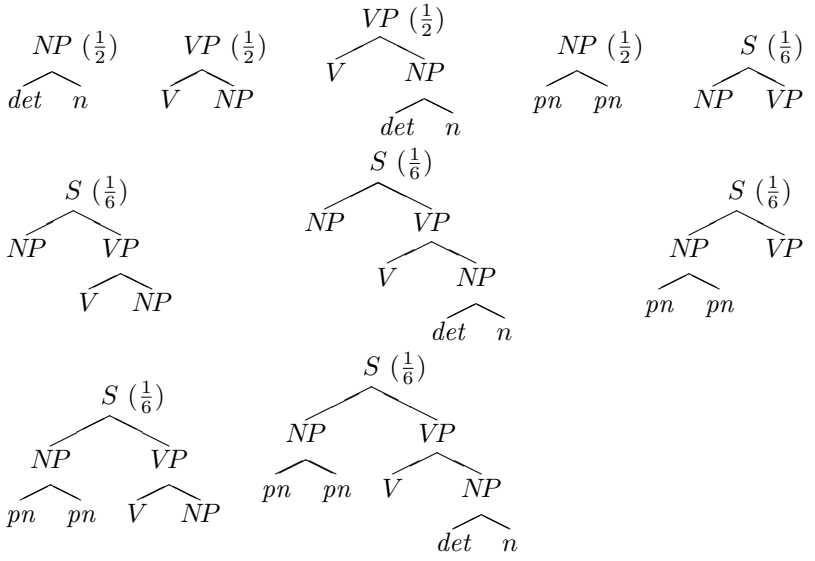


FIGURE 2 Sample STSG Produced from DOP Model

1.1.3 Different Criteria

Before our research, there were two existing ways to parse using the DOP model. First, one can find the most probable *derivation*. That is, there can be many ways a given sentence could be derived from an STSG. Using the most probable derivation criterion, one simply finds the most probable way that a sentence could be produced. Figure 3 shows a simple example STSG. For the string xx, what is the most probable derivation? The parse tree

has probability $\frac{3}{9}$ of being generated by the trivial derivation containing a single tree. This tree corresponds to the most probable derivation of xx.

One could try to find the most probable parse tree. For a given sentence and a given parse tree, there are many different derivations that could lead to that parse tree. The probability of the parse tree is the sum of the probabilities of the derivations. Given our example, there are two different ways to generate the parse tree

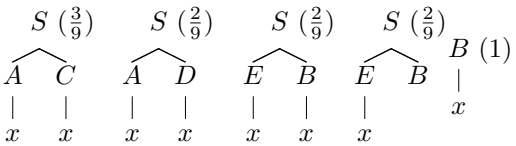
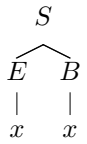


FIGURE 3 Simple Example STSG



each with probability $\frac{2}{9}$, so that the parse tree has probability $\frac{4}{9}$. This parse tree is most probable.

Bod (1993b) shows how to approximate this most probable parse using a Monte Carlo algorithm. The algorithm randomly samples possible derivations, then finds the tree with the most sampled derivations. Bod shows that the most probable parse yields better performance than the most probable derivation on the exact match criterion.

Sima'an (1996b, 1999) has discussed other ways of speeding up DOP parsing, mostly by limiting the sets of trees used, such as by limiting the number of substitution sites for the trees. Sima'an (1996a) shows that computing the most probable parse of a STSG is NP-Complete.

In Section 1.3 we will discuss a different way to speed up DOP parsing. We will show that there is a third criterion, in addition to the most probable parse and the most probable derivation, that can be used for parsing. In particular, we will find the parse with the largest number of expected correct parts: the maximum constituents parse. This criterion turns out to be much faster to maximize than the most probable parse: it can be found in time $O(n^3)$, instead of being NP-complete. As we will show, when tested on the ATIS corpus, it performs just as well. corpus.

1.2 Equivalent Grammar

1.2.1 PCFG for DOP-1

The classic reduction to a STSG is extremely expensive, even when throwing away 95% of the grammar. However, it is possible to find an equivalent PCFG that contains at most eight PCFG rules for each node in the training data; thus it is size $O(n)$. Because this reduction is so much smaller, we do not discard any of the grammar when using it. The PCFG is equivalent in two senses: first it generates the same strings with the same probabilities; second, using a homomorphism defined below, it

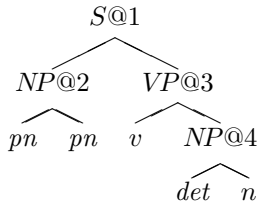


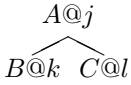
FIGURE 4 Example tree with addresses

generates the same trees with the same probabilities, although one must sum over several PCFG trees for each STSG tree.

To show this reduction and equivalence, we must first define some terminology. We assign every node in every tree a unique number, which we will call its address. Let $A@k$ denote the node at address k, where A is the non-terminal labeling that node. Figure 4 shows the example tree augmented with addresses. We will need to create one new non-terminal for each node in the training data. We will call this non-terminal A_k. We will call non-terminals of this form "interior" non-terminals, and the original non-terminals in the parse trees "exterior."

Let a_j represent the number of nontrivial subtrees headed by the node $A@j$. Let a represent the number of nontrivial subtrees headed by nodes with non-terminal A, that is $a = \sum_j a_j$.

Consider a node $A@j$ of the form:



How many nontrivial subtrees does it have? Consider first the possibilities on the left branch. There are b_k non-trivial subtrees headed by $B@k$, and there is also the trivial case where the left node is simply B. Thus there are $b_k + 1$ different possibilities on the left branch. Similarly, for the right branch there are $c_l + 1$ possibilities. We can create a subtree by choosing any possible left subtree and any possible right subtree. Thus, there are $a_j = (b_k + 1)(c_l + 1)$ possible subtrees headed by $A@j$. In our example tree of Figure 4, both noun phrases have exactly one subtree: $np_4 = np_2 = 1$; the verb phrase has 2 subtrees: $vp_3 = 2$; and the sentence has 6: $s_1 = 6$. These numbers correspond to the number of subtrees in Figure 2.

We will call a PCFG subderivation homomorphic to a STSG elementary tree if the subderivation begins with an external non-terminal, uses internal non-terminals for intermediate steps, and ends with external non-terminals. Figure 5 gives an example of an STSG elementary tree

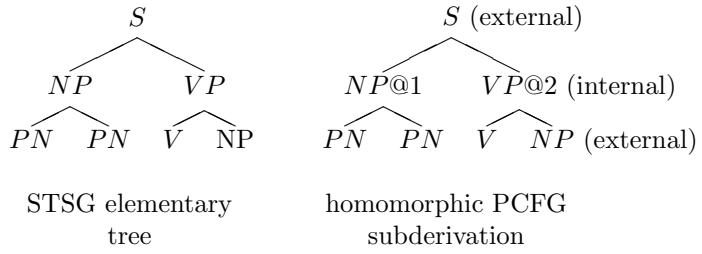
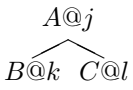


FIGURE 5 STSG elementary tree homomorphic to a PCFG subderivation

taken from Figure 2, and a homomorphic PCFG subderivation.

We will give a simple small PCFG with the following surprising property: for every subtree in the training corpus headed by A, the grammar will generate a homomorphic subderivation with probability $1/a$. In other words, rather than using the large, explicit STSG, we can use this small PCFG that generates homomorphic derivations, with identical probabilities.

The construction is as follows. For a node such as



we will generate the following eight PCFG rules, where the number in parentheses following a rule is its probability.

$$
\begin{array}{llll}
A_j \to BC & (1/a_j) & A \to BC & (1/a) \\
A_j \to B_k C & (b_k/a_j) & A \to B_k C & (b_k/a) \\
A_j \to BC_l & (c_l/a_j) & A \to BC_l & (c_l/a) \\
A_j \to B_k C_l & (b_k c_l/a_j) & A \to B_k C_l & (b_k c_l/a)
\end{array} \tag{1.1}
$$

Theorem 1 *Subderivations headed by A with external non-terminals at the roots and leaves and internal non-terminals elsewhere have probability $1/a$. Subderivations headed by A_j with external non-terminals only at the leaves and internal non-terminals elsewhere, have probability $1/a_j$.*

Proof The proof is by induction on the depth of the trees. For trees of depth 1, there are two cases:

Trivially, these trees have the required probabilities.

Now, assume that the theorem is true for trees of depth n or less. We show that it holds for trees of depth $n+1$. There are eight cases, one

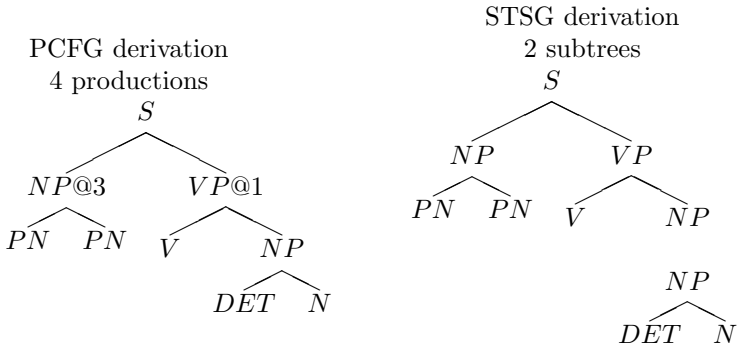


FIGURE 6 Example of Homomorphic Derivation

for each of the eight rules. We show two of them. Let $\overset{B@k}{\vdots}$ represent a tree of at most depth n with external leaves, headed by $B@k$, and with internal intermediate non-terminals. Then, for trees such as

$$\begin{array}{c} A@j \\ \diagup \quad \diagdown \\ B@k \quad C@l \\ \vdots \qquad \vdots \end{array}$$

the probability of the tree is $\frac{1}{b_k}\frac{1}{c_l}\frac{b_k c_l}{a_j} = \frac{1}{a_j}$. Similarly, for another case, trees headed by

$$\begin{array}{c} A \\ \diagup \quad \diagdown \\ B@k \quad C \end{array}$$

the probability of the tree is $\frac{1}{b_k}\frac{b_k}{a} = \frac{1}{a}$. The other six cases follow trivially with similar reasoning. □

We call a PCFG derivation homomorphic to a STSG derivation if for every substitution in the STSG there is a corresponding subderivation in the PCFG. Figure 6 contains an example of homomorphic derivations, using two subtrees in the STSG and four productions in the PCFG.

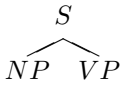
We call a PCFG tree homomorphic to a STSG tree if they are identical when internal non-terminals are changed to external non-terminals.

Theorem 2 *This construction produces PCFG trees homomorphic to the STSG trees with equal probability.*

Proof If every subtree in the training corpus occurred exactly once, the proof would be trivial. For every STSG subderivation, there

would be a homomorphic PCFG subderivation, with equal probability. Thus for every STSG derivation, there would be a homomorphic PCFG derivation, with equal probability. Thus every STSG tree would be produced by the PCFG with equal probability.

However, it is extremely likely that some subtrees, especially trivial ones like



will occur repeatedly.

If the STSG formalism were modified slightly, so that trees could occur multiple times, then our relationship could be made one-to-one. Consider a modified form of the DOP model, in which the counts of subtrees which occurred multiple times in the training corpus were not merged: both identical trees would be added to the grammar. Each of these trees will have a lower probability than if their counts were merged. This would change the probabilities of the derivations; however the probabilities of parse trees would not change, since there would be correspondingly more derivations for each tree. Now, the desired one-to-one relationship holds: for every derivation in the new STSG there is a homomorphic derivation in the PCFG with equal probability. Thus, summing over all derivations of a tree in the STSG yields the same probability as summing over all the homomorphic derivations in the PCFG. Thus, every STSG tree would be produced by the PCFG with equal probability.

It follows trivially from this that no extra trees are produced by the PCFG. Since the total probability of the trees produced by the STSG is 1, and the PCFG produces these trees with the same probability, no probability is "left over" for any other trees. □

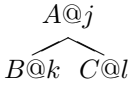
1.2.2 PCFGs for Other Versions of DOP

Since the time when this work was originally done, many variations on DOP have been introduced. While we have not performed experiments on any of these versions, we note that the techniques of this chapter can be used, sometimes quite easily, to produce similar or equivalent results for these variations. In particular, Bod has shown improved results both by limiting subtree depth (Bod 2001) and by using counting (Bod 2000c), rather than probabilities. We will show how to emulate both of these efficiently. We will also discuss interesting alternatives that could be tried, such as giving smaller weights to larger trees, or giving the same weight to each piece of training data, rather than each tree. We speculate that these techniques might also be helpful.

Most experiments in DOP have limited the subtree depth. This was originally done for efficiency, although more recent experiments (Sima'an 1999) have also shown improved accuracy. Ironically, limiting subtree depth using our model naively actually makes the grammar larger, by up to a factor of the maximum depth, but is still more efficient than the direct approach. The trick is to associate depth numbers with each new node we generate, keeping a count of how deep we are.

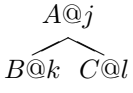
Assume we want to model subtrees of depth at most d. We use a variation on our previous technique. Let a_j^e represent the number of nontrivial subtrees headed by the node $A@j$ of depth at most e. Let a^d represent the number of nontrivial subtrees of depth at most d headed by nodes with non-terminal A, that is $a^d = \sum_j a_j^d$.

As before, consider a node $A@j$ of the form:



We now compute a_j^e. Following similar reasoning as before, there are b_k^{e-1} non-trivial subtrees of depth at most $e-1$ headed by $B@k$, plus the case where the left node is just B, leading to $b_k^{e-1}+1$ different possibilities on the left branch. Similarly, for the right branch there are $c_l^{e-1}+1$ possibilities. So, $a_j^e = (b_k^{e-1}+1)(c_l^{e-1}+1)$.

The construction with limited depth trees is as follows, similar to our previous construction, but with roughly $d/2$ times as many rules. For a node such as



we will generate the following rules:

$$
\begin{array}{ll}
A \rightarrow BC & (1/a^d) \\
A \rightarrow B_k^{d-1} C & (b_k^{d-1}/a^d) \\
A \rightarrow B C_l^{d-1} & (c_l^{d-1}/a^d) \\
A \rightarrow B_k^{d-1} C_l^{d-1} & (b_k^{d-1} c_l^{d-1}/a^d)
\end{array}
\tag{1.2}
$$

Now, for each $1 \leq e < d$ we need the following rules:

$$
\begin{array}{ll}
A_j^e \rightarrow BC & (1/a_j^e) \\
A_j^e \rightarrow B_k^{e-1} C & (b_k^{e-1}/a_j^e) \\
A_j^e \rightarrow B C_l^{e-1} & (c_l^{e-1}/a_j^e) \\
A_j^e \rightarrow B_k^{e-1} C_l^{e-1} & (b_k^{e-1} c_l^{e-1}/a_j^e)
\end{array}
\tag{1.3}
$$

We leave the proof of correctness to the reader; it follows the same reasoning as before.

Notice that if two nodes $A@j$ and $A@k$ have exactly the same subtrees of depth at most e, then the productions for A_j^e and A_k^e can be merged. For large trees, this is unlikely, but when the subtree depth is limited, this may be very common. (The set of all subtrees will be the same if and only if the trees are identical down to depth e. This can be detected efficiently with a good hash table.) Also, if a tree $A@j$ is of depth e, then for all $f > e$, the productions A_j^e can be merged with the productions for A_j^f.

These ideas can be extended even further. Sima'an (1999, page 133) notes that a variety of techniques can be used to limit the number of subtrees used: the depth, the number of substitution sites, the number of terminals, and the number of adjacent terminals. The first three can all be easily incorporated into our reduction technique, simply by adding limits analogous to the depth limit. There is also nothing to prevent these limits from also being used in combination. We could probably also apply the last technique, limiting the number of adjacent terminals, but it would be somewhat harder to do this, and probably not worth the effort.

Bod (2000c) shows that excellent results can be gotten from using the shortest derivation – smallest number of trees in the derivation – rather than the most probable parse. We can easily emulate this criterion, by simply giving the rules of Equation 1.1 headed by an external nonterminal a probability of 0.5, and internal nonterminal headed rules a probability of 1. The resulting grammar will, of course, not be a PCFG since the probabilities will sum to more than 1 – it might be better to think of these as weights, rather than probabilities – but the most probable derivation using this grammar has the following property: the probability of the parse is equal to 0.5^k where k is the number of external nonterminals used, which is exactly the number of trees that would be used in the corresponding STSG derivation. The highest probability parse will be the one corresponding to the shortest derivation. Bod (2000c) gives a moderately complex ranking technique to distinguish between ties; it would be necessary to use a different ranking technique in order to use our equivalence, or to break ties after the parsing step.

Bonnema *et al.* (1999) observes that one problem with the DOP model is that it provides more probability to nodes with more subtrees. The amount of probability given to two different training nodes depends critically on how many subtrees they have, and, given that the number of subtrees is an exponential function, this means that some training nodes could easily get hundreds or thousands of times the weight of others, even if both occur exactly once. We can easily fix this in a number of ways.

For instance, Bonnema *et al.* suggest using

$$P(\alpha) = 2^{-N(\alpha)} f(\alpha)/F(\alpha)$$

where α represents a tree, $N(\alpha)$ represents the number of non-root non-terminals in α, $f(\alpha)$ represents the number of times α occurs in the training data, and $F(\alpha)$ represents the number of times the root non-terminal of α occurs in the training data.

It turns out that we can create a PCFG equivalent to this model. Set $\overline{a}$ equal to the number of times nonterminals of type A occur in the training data, and use

$$\begin{array}{llll} A_j \rightarrow BC & (1/4) & A \rightarrow BC & (1/4\overline{a}) \\ A_j \rightarrow B_k C & (1/4) & A \rightarrow B_k C & (1/4\overline{a}) \\ A_j \rightarrow BC_l & (1/4) & A \rightarrow BC_l & (1/4\overline{a}) \\ A_j \rightarrow B_k C_l & (1/4) & A \rightarrow B_k C_l & (1/4\overline{a}) \end{array} \tag{1.4}$$

This grammar assigns the same probabilities to subtrees as the model of Bonnema *et al.* Bonnema *et al.* reduce the probability of a tree by a factor of two for each non-root non-terminal it contains. This is equivalent to reducing the probability of a tree by a factor of four for each pair of non-terminals it contains, which is exactly what we do. Note that Bod (2001) achieves excellent results while using a sampling technique that has the effect of assigning roughly equal weight to each node in the training data and very roughly exponentially less probability for larger trees, so techniques along these lines seem very promising.

Of course, there are many variations on these techniques that could be explored. For instance, an alternative that gives equal weight to each training data node, and equal weight to each subtree is:

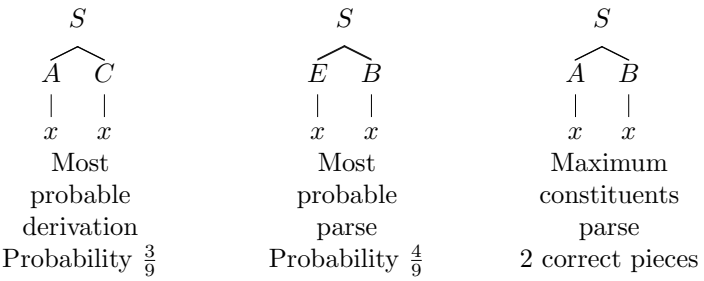
$$\begin{array}{llll} A_j \rightarrow BC & (1/a_j) & A \rightarrow BC & (1/a_j\overline{a}) \\ A_j \rightarrow B_k C & (b_k/a_j) & A \rightarrow B_k C & (b_k/a_j\overline{a}) \\ A_j \rightarrow BC_l & (c_l/a_j) & A \rightarrow BC_l & (c_l/a_j\overline{a}) \\ A_j \rightarrow B_k C_l & (b_k c_l/a_j) & A \rightarrow B_k C_l & (b_k c_l/a_j\overline{a}) \end{array} \tag{1.5}$$

While the only equivalence we have actually implemented is the first one (Equation 1.1), we find it very encouraging that so many interesting, different forms of DOP can all be transformed to PCFGs using variations on our technique. Since these transformations are so much smaller than the direct approach, we assume that others will be very interested in using them. Note that all of these equivalences can be used with either the conventional most probable parse criterion, or the parsing algorithm we describe in the next section. However, if used with the most probable derivation, they will lead to very different (and presumably worse) results than the corresponding STSG transformation, since each STSG derivation correspond to multiple PCFG derivations.

1.3 Parsing Algorithm

As we discussed in the introduction to this chapter, there are several different evaluation metrics one could use for finding the best parse. The two that have been used most are the most probable derivation, which can be found using the Viterbi algorithm, and the most probable parse, which can be approximated by random sampling. However, finding the most probable parse is NP-complete, and the most probable derivation has lower accuracy. In this section, we describe a third evaluation metric, the maximum constituents parse, which attempts to maximize the number of correct parts of the parse. We will show that this criterion can be maximized in $O(n^3)$ time, that in theory it is better for measures like precision and recall, and, in actual experiments on the ATIS corpus, performs at least as well as the most probable parse for precision, recall, and the exact match criteria.

Parsers are often evaluated on criteria such as precision and recall, or crossing brackets rate, that roughly count the number of correct parts of a parse tree. If our performance evaluation were based on such a measure, we would want the parse tree that was most likely to have the largest number of correct constituents. Consider this criterion and the example grammar of Figure 3. Here are the three best parses in this grammar, according to different criteria:



We previously analyzed the most probable derivation probability ($\frac{3}{9}$) and the most probable parse probability ($\frac{4}{9}$). For the maximum consituents parse, we want to know how many pieces we expect are correct. The probability that the S constituent is correct is 1.0, while the probability that the A constituent is correct is $\frac{5}{9}$, and the probability that the B constituent is correct is $\frac{4}{9}$. Thus, this tree has on average 2 constituents correct. All other trees will have fewer constituents correct on average. Notice that this parse tree cannot even be produced by the grammar: each of its constituents is good, but it is not necessarily good when considered as a full tree. In practice, however, the trees produced do tend to be both grammatical, and to score well on the exact match

criterion.

Bod (1993a, 1995a) shows that the most probable derivation does not perform nearly as well as the most probable parse for the DOP model. This is not surprising, since each parse tree can be derived by many different derivations; the most probable parse criterion takes all possible derivations into account. Similarly, the maximum constituents parse is also derived from the sum of many different derivations. Furthermore, although the maximum constituents parse should not do as well on the exact match criterion, it should perform even better on the percent constituents correct criterion, and presumably also work better on closely related criteria such as precision and recall. We have previously performed a detailed comparison between the most likely parse, and the maximum constituents parse for PCFGs (Goodman 1996b); we showed that the two have very similar performance on a broad range of measures, with at most a 10% relative difference in error rate (i.e., a change from 10% error rate to 9% error rate.) We therefore think that it is reasonable to use a maximum constituents parser to parse the DOP model.

The parsing algorithm is a variation on the Inside-Outside algorithm, developed by Baker (1979) and discussed in detail by Lari and Young (1990). However, while the Inside-Outside algorithm is a grammar re-estimation algorithm, the algorithm presented here is just a parsing algorithm. It is closely related to a similar algorithm (Rabiner 1989) used for Hidden Markov Models (HMMs) for finding the most likely state at each time. However, unlike in the HMM case where the algorithm produces a simple state sequence, in the PCFG case a parse tree is produced, resulting in additional constraints.

A formal derivation of a very similar algorithm is given elsewhere (Goodman 1996b); only the intuition is given here. The algorithm can be summarized as follows. First, for each potential constituent, where a constituent is a non-terminal, a start position, and an end position, find the probability that that constituent is in the parse. After that, put the most likely constituents together to form a parse tree, using dynamic programming.

The probability that a potential constituent occurs in the correct parse tree, $P(X \stackrel{*}{\Rightarrow} w_s...w_t | S \stackrel{*}{\Rightarrow} w_1...w_n)$, will be called $g(s,t,X)$. In words, it is the probability that, given the sentence $w_1...w_n$, a symbol X generates $w_s...w_t$. We can compute this probability using elements of the Inside-Outside algorithm. First, compute the inside probabilities, $e(s,t,X) = P(X \stackrel{*}{\Rightarrow} w_s...w_t)$. Second, compute the outside probabilities, $f(s,t,X) = P(S \stackrel{*}{\Rightarrow} w_1...w_{s-1}Xw_{t+1}...w_n)$. Third, compute the matrix

```
for length := 2 to n
   for s := 1 to n-length+1
      t := s + length - 1;
      for all non-terminals X
         sum[X] := g(s, t, X);
      loop over addresses k
         let X := non-terminal at k;
         let sum[X] := sum[X] + g(s,t,X_k);
      loop over non-terminals X
         let max_X := arg max of sum[X]
      loop over r such that s <= r < t
         let best_split :=
            max of maxc[s,r] + maxc[r+1,t];
      maxc[s,t] := sum[max_X] + best_split;
```

FIGURE 7 Maximum Constituents Data-Oriented Parsing Algorithm

$g(s,t,X)$:

$$\begin{aligned} g(s,t,X) &= \frac{P(S \stackrel{*}{\Rightarrow} w_1 ... w_{s-1} X w_{t+1} ... w_n) P(X \stackrel{*}{\Rightarrow} w_s ... w_t)}{P(S \stackrel{*}{\Rightarrow} w_1 ... w_n)} \\ &= f(s,t,X) \times e(s,t,X) / e(1,n,S) \end{aligned}$$

Once the matrix $g(s,t,X)$ is computed, a dynamic programming algorithm can be used to determine the best parse, in the sense of maximizing the number of constituents expected correct. Figure 7 shows pseudocode for a simplified form of this algorithm.

For a grammar with g nonterminals and training data of size T, the run time of the algorithm is $O(Tn^2 + gn^3 + n^3)$ since there are two layers of outer loops, each with run time at most n, and inner loops, over addresses (training data), nonterminals and n. However, this is dominated by the computation of the Inside and Outside probabilities, which takes time $O(rn^3)$, for a grammar with r rules. If we use the construction of section 1.2, there are eight rules for every node in the training data, making the overall runtime $O(Tn^3)$.

By modifying the algorithm slightly to record the actual split used at each node, we can recover the best parse. The entry `maxc[1, n]` contains the expected number of correct constituents, given the model.

1.4 Experimental Results and Discussion

We are grateful to Bod for supplying the data that he used for his ex-

Criteria	Min	Max	Mean	StdDev
Cross Brack DOP	86.53%	96.06%	90.15%	2.65%
Cross Brack P&S	86.99%	94.41%	90.18%	2.59%
Cross Brack DOP−P&S	-3.79%	2.87%	-0.03%	2.34%
Zero Cross Brack DOP	60.23%	75.86%	66.11%	5.56%
Zero Cross Brack P&S	54.02%	78.16%	63.94%	7.34%
Zero Cross Brack DOP−P&S	-5.68%	11.36%	2.17%	5.57%

TABLE 1 DOP versus Pereira and Schabes on Minimally Edited ATIS

Criteria	Min	Max	Mean	StdDev
Cross Brack DOP	95.63%	98.62%	97.16%	0.93%
Cross Brack P&S	94.08%	97.87%	96.11%	1.14%
Cross Brack DOP−P&S	-0.16%	3.03%	1.05%	1.04%
Zero Cross Brack DOP	78.67%	90.67%	86.13%	3.99%
Zero Cross Brack P&S	70.67%	88.00%	79.20%	5.97%
Zero Cross Brack DOP−P&S	-1.33%	20.00%	6.93%	5.65%
Exact Match DOP	58.67%	68.00%	63.33%	3.22%

TABLE 2 DOP versus Pereira and Schabes on Bod's Data

	Labelled Recall Parse	Most Probable Parse	Pereira and Schabes	Significant
Cross Brack	90.1	90.0	90.2	
0 Cross Brack	66.1	65.9	63.9	
Exact Match	40.0	39.2		

TABLE 3 Three way comparison on minimally edited ATIS data

	Labelled Recall Parse	Most Probable Parse	Pereira and Schabes	Significant
Cross Brack	97.2	97.1	96.1	$\surd$
0 Cross Brack	86.1	86.1	79.2	$\surd$
Exact Match	63.3	63.1		

TABLE 4 Three way comparison on ATIS data edited by Bod

periments (Bod 1995b, Bod 1995a, Bod 1993b). The original ATIS data from the Penn Tree Bank, version 0.5, is very noisy; it is difficult to even automatically read this data, due to inconsistencies between files. Researchers were thus left with the difficult decision as to how to clean the data. For this paper, we conducted two sets of experiments: one using a minimally cleaned set of data, making our results comparable to previous results; the other using the ATIS data prepared by Bod, which contained much more significant revisions.

Ten data sets were constructed by randomly splitting minimally edited ATIS (Hemphill et al., 1990) sentences into a 700 sentence training set, and 88 sentence test set, then discarding sentences of length > 30. For each of the ten sets, both the DOP algorithm outlined here and the grammar induction experiment of Pereira and Schabes (1992) were run. Crossing brackets, zero crossing brackets, and the paired differences are presented in Table 1. All sentences output by the parser were made binary branching (Goodman 1996a), since otherwise the crossing brackets measures are meaningless (Magerman 1994). A few sentences were not parsable; these were assigned right branching period high structure, a good heuristic (Brill 1993). Note that our comparison to Pereira and Schabes parsing is much outdated. While this was roughly state of the art at the time this work was done, much more advanced techniques have since become available (Charniak 2000).

We also ran experiments using Bod's data, 75 sentence test sets, and no limit on sentence length. However, while Bod provided us with his data, he did not provide us with the split into test and training that he used; as before we used ten random splits. The results are disappointing, as shown in Table 2. Note that they are noticeably worse than some previously reported results on this data set; elsewhere (Goodman 1996a, Goodman 1998), we examine this discrepancy more closely and show that the previous results are probably not reproducible.

DOP does do slightly better on most measures. We performed a statistical analysis using a t-test on the paired differences between DOP and Pereira and Schabes performance on each run. On the minimally edited ATIS data, the differences were statistically insignificant, while on Bod's data the differences were statistically significant beyond the 98'th percentile. Our technique for finding statistical significance is more strenuous than most: we assume that since all test sentences were parsed with the same training data, all results of a single run are correlated. Thus we compare paired differences of entire runs, rather than of sentences or constituents. This makes it harder to achieve statistical significance.

Notice also the minimum and maximum columns of the "DOP−P&S" lines, constructed by finding for each of the paired runs the difference

between the DOP and the Pereira and Schabes algorithms. Notice that the minimum is usually negative, and the maximum is usually positive, meaning that on some tests DOP did worse than Pereira and Schabes and on some it did better. It is important to run multiple tests, especially with small test sets like these, in order to avoid misleading results.

1.5 Timing and Optimization

In this section, we examine the empirical runtime of our algorithm, consider the run time of Monte Carlo parsing, and describe some optimizations that can be applied to a Monte Carlo parser.

It takes about 6 seconds per sentence to run our algorithm on an HP 9000/715[1], versus 3.5 hours to run a Monte Carlo parser using the STSG construction on a Sparc 2[1] (Bod 1995b). Factoring in that the HP is roughly four times faster than the Sparc, the new algorithm is about 500 times faster. Of course, some of this difference may be due to differences in implementation, so this estimate is fairly rough.

We also note that the run time for Monte-Carlo parsing is still exponential in the sentence length. Letting G represent grammar size, and ϵ represent maximum estimation error, the Monte Carlo run time is $O(Gn^2\epsilon^{-2})$. The ϵ^{-2} parameter is important; for this algorithm to have some reasonable chance of finding the most probable parse, the number of samples must be at least inversely proportional to the conditional probability of that parse. For instance, if the maximum probability parse had probability 1/50, then we need at least 50 samples to be reasonably sure of finding that parse.

Now, we note that the conditional probability of the most probable parse tree will in general decline exponentially with sentence length. We assume that the number of ambiguities in a sentence will increase linearly with sentence length; if a five word sentence has on average one ambiguity, then a ten word sentence will have two, etc. A linear increase in ambiguity will lead to an exponential decrease in probability of the most probable parse.

Since the probability of the most probable parse decreases exponentially in sentence length, the number of random samples needed to find this most probable parse increases exponentially in sentence length. Thus, when using the Monte Carlo algorithm, one is left with the uncomfortable choice of exponentially decreasing the probability of finding the most probable parse, or exponentially increasing the runtime. This is a somewhat informal argument, but seems reasonable. Note that our algorithm has true runtime $O(Tn^3)$, as shown previously.

[1] If you could still find one.

```
for k := 1 to n
  for i := 0 to n-k
    for chart-entry (i, i+k) do
      for each root-node X do
        select a random subderivation of root X
        eliminate the other subderivations
```

FIGURE 8 Bottom-up Sampling Algorithm for a Random Derivation

```
Sample(Chart_Address, Symbol)
{
   if Symbol is a terminal
      return Symbol;
   else
      select a random Entry for Symbol at Chart_Address;
      let Left := Sample(Entry's left address,
                         Entry's left symbol);
      let Right := Sample(Entry's right address,
                          Entry's right symbol);
      return MakeTree(Left, Right);
}
```

FIGURE 9 Top Down Algorithm for Sampling a Random Derivation

We present a more efficient top-down version of Monte-Carlo sampling that can lead to large speedups. Bod (1995b) gives the pseudocode in Figure 8 for how to sample a random derivation. This is essentially a bottom up sampling scheme. For a grammar with g non-terminals, it requires time $O(gn^2)$.[2] On the other hand, a top down sampling scheme such as Figure 9 would be faster. If we call `Sample((0,n), S)`, it finds a random entry for the root node, and then proceeds to recursively select random entries for each branch. Since the sampled tree will have $n-1$ nodes, this algorithm is $O(n)$. This would make Monte Carlo parsing significantly faster, although still not nearly as fast as a maximum constituents parser.

We mention another technique that can be used to potentially speed Monte-Carlo and n-best style parsers. The normal inside algorithm can be easily modified so that it finds only the sum of derivation probabilities

[2]This assumes that the selection of a random chart entry can be done in constant time. Bod (1995b) shows how to approximate this selection, by creating a large array with numbers of entries proportional to the probabilities.

consistent with a particular parse. While it is NP-complete to find the most probable parse, it is only $O(nP)$ to find the probability of any particular parse tree, where we define P to be the maximum number of productions consistent with a part of the tree. This means that if we are performing sampling, either Monte-Carlo or best first, we need only sample long enough to get a single instance of the most probable parse, rather than long enough to accurately estimate its probability.

1.6 Conclusion

In this paper we have described a large number of potential speedups for DOP parsing. Each of these techniques can be used either separately, or together. Combining our two favorite speedups, our grammar transformation, together with a maximum constituents parser, leads to a 500 times speedup over traditional DOP parsing. Given that the heavy resource usage of DOP is the biggest problem with the formalism, we believe our speedups will be very valuable to those implementing DOP models. Most of these techniques have not been widely used in the past. We know of no reason not to use maximum constituents parsing, and hope it will receive wide usage. The grammar transformation technique has not been widely used because prior to this publication, it was only available in the full form, rather than in the depth-limited form described in Equations 1.2 and 1.3. Hopefully, it will now be more widely used.

We note that we ourselves are not pursuing the DOP formalism any further. While there have been some promising recent results for DOP (Bod 2000a, Bod 2000c, Bod 2001) we personally prefer other recent techniques (Charniak 2000, Charniak 2001, Collins 2000). These other techniques tend to be easier to implement and more efficient than DOP-style models. Furthermore, by creating explicit probability models, the path to improvement is clearer: one can find unmodeled correlations or similar problems, and add these to the model. Also, we have been unable to get important details needed to replicate some DOP results. Given the computational complexity of DOP, even with the speedup techniques described here, we think other techniques are more promising.

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