Abstract
We perform Noun Phrase Bracketing by using a local, maximum entropy-based tagging model, which produces bracketing hypotheses. These hypotheses are subsequently fed into a reranking framework based on support vector machines. We solve the problem of hierarchical structure in our tagging model by modeling underspecified tags, which are fully determined only at decoding time. The tagging model performs comparably to competing approaches and the subsequent reranking increases our system’s performance from an f-score of 81.7 to 86.1, surpassing the best reported results to date of 83.8.

1 Introduction and Prior Work
Noun Phrase Bracketing (NP Bracketing) is the task of identifying any and all noun phrases in a sentence. It is a strictly more difficult problem than NP Chunking (Ramshaw and Marcus, 1995), in which only non-recursive (or “base”) noun phrases are identified. It is simultaneously strictly more simple than either full parsing (Collins, 2003; Charniak, 2000) or supertagging (Bangalore and Joshi, 1999). NP Bracketing is both a useful first step toward full parsing and also a meaningful task in its own right; for instance as an initial step toward co-reference resolution and noun-phrase translation.

While existing NP Bracketers (including the one described in this paper) tend to achieve worse overall F-measures than a full statistical parser (e.g., (Collins, 2003; Charniak, 2000)), they can be significantly more computationally efficient. Statistical parsers tend to scale exponentially in sentence length, unless a narrow beam is employed, which leads to globally poorer parses. In contrast, the bracketer described in this paper scales linearly in

Figure 1: Sample sentence with NPs bracketed.

the length of the sentence to find the globally optimal solution. This trade-off is depicted graphically in Figure 2. This figure shows the amount of time (excluding any startup overhead) spent parsing or bracketing using this system (the two lowest lines) versus the parsers of Collins (2003) and Charniak (2000) run with default settings.

NP Bracketing was the shared task of the Computational Natural Language Learning workshop in 1999 (CoNLL-99). In this competition, NP Bracketing systems were trained on sections 15-18 of the Wall Street Journal corpus, while section 20 was used for testing. The bracketing information was extracted directly from the Penn Treebank, essentially disregarding all non-NP brackets. An example bracketed sentence is in Figure 1.

There have been several successful approaches reported in the literature to solve this task. Tjong Kim Sang (1999) first used repeated chunking to attain an f-score of 82.98 during the CoNLL competition and subsequently (Sang, 2002) an f-score of 83.79 using a combination of two different systems. Krymolowski and Dagan (2000) have obtained similar results using more training data and lexicalization. Brandts (1999) has used cascaded HMMs to solve the NP Bracketing problem; however, he evaluated his system only on German NPs, so his results cannot be directly compared.

Obviously, the difficulty that arises in NP Bracketing that differentiates it from NP Chunking is the issue of embedded NPs, thus requiring output in the
form of a tree structure. Most solutions to problems involving building trees from sequences build in to the model a concept of depth (in parsing, this is typically in the form of a chart; in bracketing and shallow parsing, this is typically in the form of embedded finite-state automata). We elect to take a completely different approach. The model we use is agnostic to any sort of depth: it hypothesizes underspecified tags and allows the matching bracket constraint to select a solution.

Specifically, we approach the NP Bracketing problem as a tagging and reranking problem. We use an efficient maximum entropy-based tagger to hypothesize possible bracketings (see Section 2) and then rerank these hypotheses using a support vector reranking system (see Section 3). Using only the tagger (without reranking), we achieve comparable results to those referenced above and, with the addition of the reranking system, achieve, to our knowledge, the best reported results to date.

2 Bracketing as a Tagging Problem

In any tagging problem, the task is to associate each word in the input with a single tag. There are many competing approaches to tagging problems including Hidden Markov Models (HMMs), Maximum Entropy Markov Models (MEMMs) and Conditional Random Fields (CRFs). We adopt a slight variant of the MEMM framework.

2.1 Maximum Entropy Tagging Model

In the formulation of the maximum entropy tagging model, we assume that the probability distribution of tags takes the form of an exponential distribution, parameterized by a sequence of feature weights, $\lambda_i^m$, where there are $m$-many features. Thus, we obtain a distribution for $Pr_{\lambda_i^m} (t_i | t_{i-1}, \bar{w})$ of the form:

$$
\frac{1}{Z_{t_{i-1}, \bar{w}}} \exp \left[ \sum_{j=1}^{m} \lambda_j f_j(t_i, t_{i-1}, \bar{w}) \right]
$$

(1)

where $Z_{t_{i-1}, \bar{w}}$ is a normalizing factor.

Like other maximum entropy approaches, this distribution is unimodal and optimal values for the $\lambda$s can be found through various algorithms; we use GIS. A good introduction to maximum entropy models can be found in (Berger et al., 1996).

In our approach, we use a tag set of exactly five tags: \{open, close, in, out, sing\}. An open tag is assigned to all words that open a bracketing (regardless of the number of brackets opened) and do not also close a bracketing. A close tag is assigned to all words that close a bracketing and do not also open one. An in tag is assigned to all words enclosed in an NP, but which neither open nor close one. An out tag is assigned to all words which are not enclosed in an NP. A sing(leton) tag is assigned to all words that both open and close a bracketing (regardless of whether they open or close more than just their own bracketing).

Note that such a tagging does not uniquely determine a bracketing. For instance, the tag sequence \{open, sing\} could correspond either to \([[w_1] [w_2]]\) or to \([w_1] [w_2]\). Nevertheless, due to the constraints involved in the tagging process (namely that a close tag cannot appear unless one is already within an NP and that one cannot have two close tags when the corresponding open tags appear at the same location\(^1\)), we hope that our system will be able to disambiguate sufficiently. In other words, although our taggings are under-specified, we hope that the additional constraints that we subsequently associate with these tags will yield high quality bracketings.

2.2 Feature Functions

The probability distribution shown in Equation 1 is based on $m$-many real-valued feature functions, $f_j$. We use two classes of features, closed features and open features (these roughly correspond to whether they look at closed class elements or open class elements). The open features for position $i$ are applied at positions $i$, $i - 1$ and $i + 1$. The closed features are applied at $i$, $i - 1$, $i - 2$, $i - 3$ and $i + 1$, $i + 2$ and $i + 3$.

\(^1\)For instance, the bracketing \([[w_1 \ldots w_j]]\) is disallowed; this bracketing must appear simply as \([w_1 \ldots w_j]\).
2.3 Maximum Entropy Training

We used generalized iterative scaling to train the maximum entropy model\(^2\) on 929,921 features and 211,728 training instances from sections 15-18 of the Penn Treebank (20\% of which was set aside as a validation set). Training was run for ten thousand iterations and, at convergence, achieved a tagging error rate of 2.1\% on the training data and 6.9\% on the validation data.

2.4 Decoding Algorithm

We use a Viterbi-like dynamic programming decoding algorithm, where transition probabilities are governed by the discriminative tagging model. However, the tags generated by our decoder are not the same as those predicted by the maximum entropy model. Our decoder does not search in the original space of tags (\textit{sing}, \textit{in}, \textit{out}, \ldots) but rather in a new space that yields only well-formed bracketings. In the secondary search space, the algorithm is guaranteed to find the most likely well-formed bracketing, even though this might not correspond to the most likely tag sequence. While it would be possible to simply tag using the original tag set and allow the reranker (see Section 3) to select a well-formed bracketing, it is unlikely that this will lead to improved performance: the complexity of the decoders will be the same, yet the bracketer would have to wade through significantly more bad taggings to find a good solution.

Our decoding tags take one of five forms, capitalized to distinguish them from the maximum entropy tags: \(O_n\), \(C_n\), \(N\), \(O_nC\), \(OC_n\) where \(n \geq 1\) for all but \(OC_n\) where \(n \geq 2\). The meaning of the tags is: \(O_n\) means \(n\) simultaneous open brackets; \(C_n\) means \(n\) simultaneous close brackets; \(N\) means that no brackets appear at this position. \(O_nC\) corre-

\(^2\)Using the YASMET maximum entropy training package: http://www.isi.edu/~och/YASMET/.

Figure 3: Plot of \(n\) versus maximal f-score (and associated precision and recall) for test data.

\(A_{i,d,t} = P_{\lambda}(\hat{t}_0)\)

\(A_{p,d,t} = \max_{t'} A_{p-1,d-\Delta t,p} \cdot P_{\lambda}(\hat{t}_d | t')\)

where

\[
\hat{t}_d = \begin{cases}
  \text{\textit{out}} & t = N \land d = 0 \\
  \text{\textit{in}} & t = N \land d > 0 \\
  \text{\textit{sing}} & t \in \{O_nC, OC_n\} \\
  \text{\textit{begin}} & t = O_n \\
  \text{\textit{end}} & t = C_n
\end{cases}
\]

\(\Delta t = \begin{cases}
  n & t = O_n \\
  n - 1 & t = O_nC \\
  -n & t = C_n \\
  -n + 1 & t = OC_n \\
  0 & t = N
\end{cases}\)

The intuition for calculating the value of \(A_{p,d,t}\) for \(p > 1\) (see Equation 3) is that we first choose the optimal previous tag, \(t'\). Furthermore, based on
Equation 5) we must have been at previously. Thus, we have the possibility of improving our system’s f-score for the best tag. For instance, it must assign precisely good ones. For instance, it must assign precisely the same probability to both of the following bracketings, since the maximum entropy tags (shown beneath) are identical:

\[
\text{[John, [president] of [the company]] ]}
\]

\[
\text{[John, [president] of [the company]] ]}
\]

\[
sing \quad sing \quad in \quad open \quad close \quad close
\]

This limitation causes the model to make consistent mistakes distinguishing between, for example, lists and appositional phrases. To solve these problems in the tagging model would be nearly impossible, without giving up on efficiency. However, our decoder is able to produce n-best lists using exact A* search that very frequently contain globally superior taggings, even though the simple tagging model cannot recognize them as such.

In Figure 3, we show the maximal f-score (and corresponding precision and recall) for the best bracketing chosen out of the n-best, as we let n range from 1 to 400 for both the validation data and the test data. As we can see from these graphs, we have the possibility of improving our system’s f-score performance by about ten points – from 82% to 93%, simply by being able to choose the correct hypothesis from the n-best list; also working with 100-best lists is likely sufficient.

3 Hypothesis Reranking

In the previous section, we described a tagging model for NP Bracketing that can produce n-best lists. In this section, we describe a machine learning method for reranking these lists in an attempt to choose a hypothesis which is superior to the first-best output of the decoder. Reranking of n-best lists has recently become popular in several natural language problems, including parsing (Collins, 2003), machine translation (Och and Ney, 2002) and web search (Joachims, 2002). Each of these researchers takes a different approach to reranking. Collins (2003) uses both Markov Random Fields and boosting, Och and Ney (2002) use a maximum entropy ranking scheme, and Joachims (2002) uses a support vector approach. As SVMs tend to exhibit less problems with over-fitting than other competing approaches in noisy scenarios, we also adopt the support vector approach.

3.1 Support Vector Reranking

A support vector classifier is a binary classifier with a linear decision boundary. The selected decision boundary is a hyperplane that is chosen in such a way that the distance between it and the nearest data points is maximized. Slack variables are commonly introduced when the problem is not linearly separable, leading to soft margins.

For reranking, we assume that instead of having binary classes for the \( y_i \)'s, we have real values which specify the relative ordering (higher values come first). For this task, we get the following optimization problem (Joachims, 2002):

\[
\text{minimize } \frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \xi_{i,j} \tag{6}
\]

subject to
\[
\bar{w} \cdot \bar{x}_i \geq \bar{w} \cdot \bar{x}_j + 1 - \xi_{i,j} \tag{7}
\]

\[
\xi_{i,j} \geq 0 \tag{8}
\]

Where the \( i, j \)'s are drawn from comparable data points and \( y_i \geq y_j \) and \( C \) is a regularization parameter that specifies how great the cost of mis-ordering is. As noticed by Joachims, the condition in Equation 7 can be reduced to the standard SVM model by subtracting \( \bar{w} \cdot \bar{x}_j \) from both sides.

3.2 Reranking Feature Functions

Since our problem is closely related to that of Collins’ (2003), we use many of the same feature functions he does, though we do introduce many of
our own (those which are copied from Collins are marked with an asterisk). We view the hypothesized bracketing as a tree in a context free grammar and include features based on each rule used to generate the given tree. For concreteness, we will use the CFG rule \( \text{NP} \rightarrow \text{DT} \text{JJ} \text{NP} \) (where the NP is selected as the head) as an example.

**Rules**: the full CFG rule; in this case, the active rule would be \( \text{NP} \rightarrow \text{DT} \text{JJ} \text{NP} \).

**Markov 2 Rules**: CFG rules where 2-level Markovization has been applied. That is, we look at the rule for generating the first two tags, then the next two (given the previous one), then the next two (given the previous one), and so on. A start of branch tag ([S]) and end of branch tag ([/S]) are added to the beginning and end of the children lists.

In this case, the rules that fire are: \( \text{NP}[\text{S}] \rightarrow \text{DT}, \text{NP}[/\text{S}] \rightarrow \text{DT} \text{JJ}, \text{NP}!\text{DT} \rightarrow \text{JJ} \text{NP} \) and \( \text{NP}!\text{JJ} \rightarrow \text{NP} [/\text{S}] \). The notation is \( X \text{Y} \rightarrow \text{A B} \), where \( X \) is the true parent, \( Y \) was the previous child in the Markovization, and \( A \text{B} \) are the two children.

**Lex-Rules**: full CFG rules, where terminal POS tags are replaced with lexical items.

**Markov 2 Lex-Rules**: Markov 2-style rules, terminal POS tags are replaced with lexical items.

**Bigrams**: pairs of adjacent tags in the CFG rule; in our example, the active pairs are ([S],DT), (DT,JJ), (JJ,NP) and (NP,/[S]).

**Lex-Bigrams**: same as Bigrams, but with lexical heads instead of POS tags.

**Head Pairs**: pairs of internal node tags with the head type; in the example, (DT, NP), (JJ, NP) and (NP, NP).

**Sizes**:

- First clause: \( \text{NP} \rightarrow 3 \).
- Second clause: \( \text{NP} \rightarrow 3 \).

**Word Count**:

- First clause: \( \text{sizes} \) and total number of words under this constituent.
- Second clause: \( \text{part of the SIZES and total number of words under this constituent.} \)

**Boundary Heads**:

- First clause: \( \text{pairs of the first and last head in the constituent.} \)
- Second clause: \( \text{pairs of the first and last head in the constituent.} \)

**POS-Counts**: a scheme of features that count the number of children whose part of speech tag matches a given predicate. There are six of these: (1) children whose tag begins with \( N \), (2) children whose tag begins with \( N \) but is not \( N \), (3) children which are DTs, (4) children whose tag begins with \( V \), (5) children which are commas, (6) children whose tag is \( \text{CC} \). In this case, we get a count of \( 1 \) for rules (2) and (3), and \( 2 \) for rule (1).

**Lex-Tag/Head Pairs**: same as Head Pairs, but where lexical items are used instead of POS tags.

**Special Tag Pairs**:

- count of the lexical heads to the left and right of leaves tagged with each of \( \text{POS}, \text{CC}, \text{IN} \) and \( \text{TO} \).

**Tag-Counts**:

- another schema of features that replicates some of the features used in the maximum entropy tagger. This schema includes all the original maximum entropy tags, as well as a feature for each maximum entropy tag at position \( i \), paired with (a) the tag at position \( i \), \( i - 1 \) and \( i + 1 \), (b) the word at position \( i \), \( i - 1 \) and \( i + 1 \), (c) the part of speech + word pair at those positions, (d) the maximum entropy tag at that position.

### 3.3 SVM Training

We develop three reranking systems, differentiated by the amount of training data used. The first, RR1, is trained on the validation part of the training set (20% of sections 15-18). The second, RR2, is trained on the entire training set through cross-validation (all of sections 15-18). The final, RR3 is trained on the entire Penn Treebank corpus, except section 20.

Training the reranking system only on the validation data (RR1) results in only a marginal gain of overall f-score, due primarily to the fact that most of the features use lexical information to prefer one bracketing over another. The validation data from sections 15-18 gives rise to 2,012 training instances and 362, 415 features. In order to train the reranking system on all of the training data (RR2), we built five decoders, each with a different 20% of the training data held out. Each decoder is then used to tag the held-out 20% (this is done so that the tagger does not do “too well” on its training data). This leads to 8,935 sentences for training, with a total of 1.1 million features. Training on all the WSJ data except section 20 (RR3) gives rise to 39,953 training instances and a total of just over 2.1 million features. These examples give 1,462, 568 rank constraints.

### 4 Results

We compare our system against those reported in the literature. In all, the evaluation is over 2,012 sentences of test data. In Table 1, we display the results of state-of-the-art systems, and the system described in this paper (both with and without reranking). The upper part of the table displays results from systems which are trained only on sections 15-18 of the WSJ. The lower part displays results based on systems trained on more data.
In the table, TKS99 and TKS02 are the systems of Tjong Kim Sang (1999; 2002). KD00 is the system of (Krymolowski and Dagan, 2000). All the Col03 systems are results obtained using the restriction of the output of Collins (2003) parser. In particular, the two comparable numbers coming from Collins’ parser are \( \text{Col03}_{NP} \) and \( \text{Col03}_{Full} \). The difference between these two systems is that the NP system is trained on parse trees, with all non-NP nodes removed. The Full system is trained on full parse trees, and then the output is reduced to just include NPs. \( \text{Col03}_{Alt} \) is trained on sections 2-21 of WSJ and tested on section 23, and is thus an upper bound, since these numbers are testing on training data. Our RR3 system had the reranking component (but not the tagging component) trained on all of the WSJ except for section 20.

The Chunk row in the results table is the performance of an optimally performing NP chunker. That is, this is the performance attainable given a chunker that identifies base NPs perfectly (at 100% precision). However, since this hypothetical system only chunks base NPs, it misses all non-base NPs and thus achieves a recall of only 73.0, yielding an overall F-score below our system’s performance. Note also that no chunker will perform this well. Current systems attain approximately 94% precision and recall on the chunking task (Sha and Pereira, 2002; Kudo and Matsumoto, 2001), so the actual performance for a real system would be substantially lower.

The four criteria these systems are evaluated on are bracketing recall (BR), bracketing precision (BP), bracketing f-score (BF) and average crossing brackets (CB). Some systems do not report their crossing bracket rate. All of these metrics are calculated only on NP* and WHNP* brackets.

| System | BR  | BP  | BF  | CB  |
|--------|-----|-----|-----|-----|
| TKS99  | 76.1| 91.3| 82.8| 0.14|
| TKS02  | 78.4| 90.0| 83.8| -   |
| TAG    | 81.0| 86.0| 83.4| 0.26|
| RR1    | 82.1| 88.8| 85.3| 0.18|
| RR2    | 82.7| 89.8| 86.1| 0.14|
| Col03\(_{NP}\) | 68.6| 68.9| 68.7| 0.91|
| Col03\(_{Full}\) | 88.2| 87.7| 87.9| 0.31|
| Chunk  | 73.0| 100.0| 84.4| -   |
| Col03\(_{Alt}\) | 88.0| 89.8| 88.9| 0.18|
| KD00   | 79.3| 88.5| 83.7| -   |
| RR3    | 84.3| 90.8| 87.4| 0.12|

Table 1: Results on test data. The systems in the lower half are not directly comparable, since they were either trained or tested on different data.

3Collins independently reports a recall of 91.2 and precision of 90.3 for NPs (Collins, 2003); however, these numbers are based on training on all the data and testing on section 0. Moreover, it is possible that his evaluation of NP bracketing is not identical to our own. The results in row \( \text{Col03}_{Full} \) are therefore perhaps more relevant.
Figure 4: Proportion of sentences for which one system outperforms the other with difference at least $\epsilon$.

| Tag  | Precision | | | Recall | | |
|------|-----------|------|------|--------|------|
|      | RR2  | COL03 | RR2 | COL03 |
| NP   | 21.4 | 19.8 | 20.5 | 21.3 |
| VP   | 7.49 | 8.52 | 8.31 | 7.57 |
| NN   | 8.22 | 7.62 | 7.43 | 7.83 |
| IN   | 6.01 | 5.89 | 5.31 | 6.15 |
| PP   | 5.90 | 5.63 | 5.16 | 6.03 |
| S    | 4.96 | 5.82 | 5.44 | 5.15 |
| NNP  | 6.15 | 4.79 | 6.29 | 5.82 |

Table 2: Percentage of tags on superior system.

However, in contrast to the Precision graph, for the first 10 or so values of $\epsilon$, these proportions remain roughly the same (in fact, for a short period, Collins’ actually loses ground). This suggests that there are a relatively large proportion of sentences for which our system is performing abominably (with $>10$ recall points difference) in comparison to Collins’. However, once a critical mass of $\epsilon > 10$ is reached, the relative differences become less strong.

Since neither system is winning in all cases, in an effort to better understand the conditions in which one system will outperform the other, we inspect the sentences for which there was a difference in performance of at least 10 (for precision and recall separately). To perform this investigation, we look at the distribution of tags in the true, full parse trees for those sentences. These percentages, for the 7 most common tags, are summarized in Table 2 (for example, the relative frequency of the NP tag in sentences where the RR2 system achieved higher precision was 21.4, while for the sentences for which COL03 achieved higher precision was 19.8).

The first thing worth noticing in this table is that in general, when one system achieves higher precision, the other system achieves higher recall, which is not surprising. However, in the last row, corresponding to proper nouns, the RR2 system outperforms the COL03 (this is the “Full” implementation) in both precision and recall, suggesting that our system is better able to capture the phrasing of proper nouns. We attribute this to the fact that our model is specialized to identify noun phrases, of which proper nouns comprise a large part. Similarly, the largest gains in recall for COL03 over RR2 are in sentences with many PPs. This coincides with our intuition about the syntactic parser being better able to capture long, embedded noun phrases.

6 Conclusion

We have presented a method for performing noun phrase bracketing, which outperforms competing methods both in terms of f-score and recall. The system is based on two separate components: a maximum entropy-based tagging system and a support vector machine reranking system. The key component of the tagging system is that it produces underspecified tags that are determined only at decoding time by bracketing constraints. The tagging system operates very quickly and can tag and rerank at a rate of approximately two sentences per second. The tagger alone achieves an f-score of 83.4. This score is only 0.4% lower (absolute) than the best reported result to date of 83.8.

After tagging, we have fed 100 best lists into a support vector reranking system, which performs global optimization to choose a good bracketing. Our reranking system is able to increase the f-score of our bracketing approach from 83.4 to 86.1, im-
proving our performance beyond the best reported system to date.

As we can see from Table 1, by comparing the output of our system to that of COL00Full, there is much in the way of recall to be gained by using a full syntactic parser. However, this gain comes at two expenses. First, full syntactic parsers are computationally more expensive to run. Moreover, performance of Collins’ parser degrades significantly (from 87.9 to 68.7 in f-score) when it cannot take advantage of other constituent information. This has a strong influence when one is faced with the task of moving to a new domain. On the one hand, our system (as well as the other bracketing systems cited) requires data to only be annotated at the NP level in order to achieve high performance. Conversely, without full parses, using a parser for learning NPs is inadequate.

Despite these successes, there is still much that can be improved upon. While the reranking is very efficient in the classification phase, training a support vector reranking system is computationally very expensive. Other well grounded statistical learning systems might allow us to train this component on more data and using more features. We also hope to be able to improve our system’s performance from its current rate of 86.1 (on official data) and 87.4 (on all data) closer to the \( n \)-best optimal, depicted in Figure 3.

7 Acknowledgments

This work was partially supported by DARPA-ITO grant N66001-00-1-9814, NSF grant IIS-0097846, and a USC Dean Fellowship to Hal Daumé III.

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