Multidimensional Transformation-Based Learning

Radu Florian[†] and **Grace Ngai**[†,‡]
{rflorian,gyn}@cs.jhu.edu

[†] Johns Hopkins University, Baltimore, MD 21218, USA
[‡] Weniwen Technologies, Hong Kong

Abstract

This paper presents a novel method that allows a machine learning algorithm following the transformation-based learning paradigm (Brill, 1995) to be applied to multiple classification tasks by training jointly and simultaneously on all fields. The motivation for constructing such a system stems from the observation that many tasks in natural language processing are naturally composed of multiple subtasks which need to be resolved simultaneously; and also from the usual separation of specific natural language tasks which may possibly benefit from training off of each other.

The proposed algorithm is evaluated in two experiments: in one, the system is used to jointly predict the part-of-speech and text chunks/baseNP chunks of an English corpus; and in the second it is used to learn the joint prediction of word segment boundaries and part-of-speech tagging for Chinese. The results show that the simultaneous learning of multiple tasks does achieve an improvement upon training the same tasks sequentially,

1 Introduction

Transformation-based learning (TBL) (Brill, 1995) is one of the most successful rule-based machine learning algorithms. It is a flexible and powerful method which is easily extended to various tasks and domains, and it has been applied to a wide variety of NLP tasks, including part of speech tagging (Brill, 1995), parsing (Brill, 1996) and phrase chunking (Ramshaw and Marcus, 1994; Florian et al., 2000). It achieves state-of-the-art performance on several tasks, and has been shown to be fairly resistant to overtraining (Ramshaw and Marcus, 1994).

The processing of natural language text is usually done through a pipeline of well defined tasks, each extracting specific information. For instance, one possible sequence of actions performed could be:

1. Tokenize the text;
2. Associate part-of-speech tags with each word;
3. Parse each sentence;
4. Identify and label named entities;
5. Resolve anaphora.

In the above scenario, each task is well-defined in itself and is often performed independently and in a specific order. There are NLP tasks, however, which consist of closely-related sub-tasks, where the order and independence is hard to determine — for example, the task of part-of-speech (POS) tagging in highly inflective languages such as Czech. A POS tag in Czech consists of several sub-tags, including the main part-of-speech (e.g. noun, verb), a detailed part-of-speech (e.g. past tense verb, genitive noun, etc), gender, case, number and some other 11 sub-tags. Allowing a system to learn the sub-tasks jointly is beneficial in this case, as it eliminates the need to define a learning order, and it allows the true dependencies between the sub-tasks to be modeled, while not imposing artificial dependencies among them.

The multi-task classification we are presenting in this paper is very similar to the one proposed by Caruana et al. (1997). Instead of using neural network learning, we are modifying the transformation-based learning to able to perform multiple-task classification. The new framework is tested by performing joint POS tag and base noun-phrase (baseNP) classification on a the Penn Treebank Wall Street Journal corpus (Marcus et al., 1993), and simultaneous word segmentation and POS tagging on the Chinese Treebank's (Xia et al., 2000). In both experiments the jointly trained system outperforms the sequentially-trained system combination.

The remainder of the paper is organized as follows: Section 2 briefly presents previous approaches to multi-task classification; Section 3 describes the general TBL framework and the proposed modifications to it; Section 4 describes the experiments and the results; Section 5 does a qualitative analysis of the behavior of the system, and Section 6 concludes the paper.

2 Previous Work

Multitask Learning

(Caruana et al., 1997) describes in depth the multi-task learning (MTL) paradigm, where the individual tasks share a common representation of knowledge, and shows that such a strategy obtains better results than a single-task learning strategy. The algorithm of choice there is a backpropagation neural network, and the paradigm is tested on several machine learning tasks, including 1D-ALVINN (road-following problem), 1D-DOORS (locate doorknobs to recognize door types) and pneumonia prediction. It also contains an excellent discussion on how and why the MTL paradigm is superior to single-task learning.

Combining Classifications

A straightforward way of addressing a multiple classification problem is to create a new label for each observed *combination* of the original subtags; Hajic and Hladká (1998) describes such an approach for performing POS tagging in Czech. While it has the advantage of not modifying the structure of the original algorithm, it does have some drawbacks:

- By increasing the range of possible classifications, each individual tag label will have fewer samples associated with it, resulting in data sparseness. For example, in Czech, "glueing" together the subtags results in 1291 part-of-speech tags, a considerably larger number than in number of POS tags in English — 55. It is arguable that one would need 20 times more Czech data than English data to estimate similarly well the same model parameters.
- No new class labels will be generated, even if it should be possible to assign a label consisting of sub-parts that were observed in the training set, but whose combination wasn't actually seen.

N-Best Rescoring

Another trend in a 2-task classification is using a single-task classifier to output *n-best* lists corresponding to the first task and then using a second classifier trained to select the best candidate that maximizes the joint likelihood. Xun et al. (2000) performs a joint POS tagging / baseNP classification by using a statistical POS tagger to generate n-best lists of POS tags, and then a Viterbi algorithm to determine the best candidate that maximizes the joint probability of POS tag/ baseNP chunk. Chang and Chen (1993) uses a similar technique to perform word-segmentation and POS tagging in Chinese texts. In both approaches, the joint search obtains better results than the ones obtained when the search was performed independently.

3 Multi-Dimensional Training with Transformation-Based Learning

The multi-dimensional training method presented in this paper learns multiple *related* tasks in parallel, by using the domain specific signals present in each training stream. The tasks share a common representation, and rules are allowed to correct any of the errors present in the streams, without imposing ordering restrictions on the type of the individual errors (i.e. learn POS tagging before baseNP chunking).

Transformation-based learning (TBL) is well-suited to perform in such a framework:

- Partial classifications are easily accommodated in the TBL paradigm, as features of the samples (e.g. word, gender, number);
- The TBL paradigm allows a learner to learn rules that correct one sub-classification, then use the corrected sub-classification to correct the other classifications, in a seemingly interspersed fashion, as dictated by the data;
- The objective function used in TBL usually is the evaluation measure of the task (e.g. number of errors, F-Measure). This allows the algorithm to work directly toward optimizing its evaluation function.[1]

3.1 The Standard TBL Algorithm

The central idea behind transformation-based learning is to induce an ordered list of rules which progressively improve upon the current state of the training set. An initial assignment is made based on simple statistics, and rules are then greedily learned to correct the existing mistakes until no net improvement can be made.

The use of a transformation-based system assumes the existence of the following:

[1] This distinguishes TBL and other error-driven approaches from other feature-based methods such as maximum entropy which adjust parameters to maximize the likelihood of the data, which may not be perfectly correlated with the performance.

- An initial state generator;
- A set of allowable transform types, or templates;
- An objective function for learning — typically the evaluation function.

Before learning begins, the training corpus is passed through the initial state generator which assigns to each instance some initial classification. The learner then iteratively learns an ordered sequence of rules:

1. For each possible transformation, or rule, that can be applied to the corpus:
   (a) Apply the rule to a copy of the current state of the corpus,
   (b) Score the resulting corpus with the objective function; assign the difference in performance to the applied rule ($f(r)$)
2. If no rule with a positive objective function score exists, learning is finished. Stop.
3. Select the rule whose application results in largest gain in terms of the evaluation function; append it to the list of learned rules;
4. Apply the rule to the current state of the corpus.
5. Repeat from Step 1.

At evaluation time, the test data is first initialized by passing it through the initial state generator. The rules are then applied to the data in the order in which they were learned. The final state of the test data after all the rules have been applied constitutes the output of the system.

3.2 Multi-task Rule Evaluation Function

The algorithm for the multidimensional transformation-based learner (mTBL) can be derived easily from the standard algorithm. The only change needed is modifying the objective function to take into account the current state of all the subtags (the classifications of the various sub-tasks):

$$f(r) = \sum_{s \text{ sample}} \sum_{i=1}^{n} w_i \cdot (S_i(r(s)) - S_i(s))$$

where

- r is a rule
- $r(s)$ is the result of applying rule r to sample s
- n is the number of tasks
- $S_i(s)$ is the score on sub-classification i of sample s (1 if the sub-classification is correct and 0 otherwise).
- w_i represent weights that can be assigned to tasks to impose priorities for specific subtasks. In the experiments, all the weights were set to 1.

4 Experiments

For our experiments, we adapted the fast version of TBL presented in (Ngai and Florian, 2001) for multidimensional classification; we will call the system multidimensional transformation-based learner (mTBL). All the systems compared in the following experiments are TBL-based systems; the difference we are interested in is the performance of a sequential training of systems versus the the performance of the system that learns the tasks jointly.

4.1 English POS tagging and Base Noun Phrase/Text Chunking

The first experiment performed was to simultaneously learn to perform POS tagging and text/baseNP chunking on an English corpus. This section will give an overview of the task and detail the experiment results.

4.1.1 Part-of-Speech Tagging

Part-of-speech (POS) tagging is one of the most basic tasks in natural language processing. It involves labeling each word in a sentence with a tag indicating its part-of-speech function (such as noun, verb or adjective). It is an important precursor to many higher-level NLP tasks (e.g. parsing, word sense disambiguation, etc).

There has been much research done in POS tagging. Among the more notable efforts were Brill's transformation-based tagger (Brill, 1995), Ratnaparkhi's Maximum Entropy tagger (Ratnaparkhi, 1996), and the TnT tagger (Brants, 2000), which features a ngram approach. State-of-the-art performance on POS tagging in English for individual systems is around 96.5%-96.7% accuracy on the Penn Treebank Wall Street Journal corpus.

4.1.2 Text and Base Noun Phrase Chunking

Text chunking and base noun phrase (baseNP) chunking are both subproblems of syntactic parsing. Unlike syntactic parsing, where the goal is to reconstruct the complete phrasal structure of a sentence, chunking divides the sentence into non-overlapping phrases. For baseNP chunking, the identified phrases are the non-recursive noun phrases; in text chunking, the identified phrases are the basic phrasal structures in the sentence (e.g. verb phrase, noun phrase, adverbial phrase, etc) — words are considered to belong to a chunk given by the lowest constituent in the parse tree that dominates it.

Even though the identified structures are much less complex than that in syntactic parsing, text chunks are useful in many situations where some

System	POS Accuracy	BaseNP Chunking		Text Chunking	
		Accuracy	$F_{\beta=1}$	Accuracy	$F_{\beta=1}$
Sequential POS, Base NP	96.45 %	97.41 %	92.49	-	-
Joint POS / Base NP	96.55 %	97.65 %	92.73	-	-
Sequential POS, Text Chunking	96.45 %	96.97 %	92.92	95.45 %	92.65
Joint POS / Text Chunking	**96.63** %	97.22 %	**93.29**	95.82 %	**93.12**

Table 1: Part-of-Speech Tagging and Text Chunking

Word	POS tag	Text Chunk Tag
A.P.	NNP	B-NP
Green	NNP	I-NP
currently	RB	B-ADVP
has	VBZ	B-VP
2,664,098	CD	B-NP
shares	NNS	I-NP
outstanding	JJ	B-ADJP
.	.	O

Table 2: Example Sentence from the corpus.

knowledge of the syntactic relations are useful, as they constitute a simplified version of shallow parsing.

The established measure in evaluating performance in these tasks is the F-measure, which is based on precision and recall:

$$F_\beta = 2 \cdot \frac{\beta^2 P \cdot R}{\beta^2 P + R}$$

where

$$P = \frac{\#\text{ correctly found chunks}}{\#\text{ found chunks}}$$
$$R = \frac{\#\text{ correctly found chunks}}{\#\text{ true chunks}}$$

Ramshaw & Marcus (1999) were the first to consider baseNP chunking as a classification task; the same approach can be applied to text chunking. Because the structure is not recursive, any possible pattern can be described by assigning to each word a tag corresponding to whether the word starts, is inside or is outside of a noun phrase ("B", "I" or "O"). Table 2 shows an example sentence with POS and text chunk tags. Ramshaw & Marcus trained their system on Sections 15-18 of the Penn Treebank Wall Street Journal Corpus (Marcus et al., 1993), and achieved an F-Measure performance of 92.0%. Other notable (and comparable) efforts include Munoz et al. (1999), who used a Winnow-based system to achieve an F-Measure of 92.7, and Tjong Kim Sang (2000) who used a combination of 4 different systems to achieve an F-Measure of 93.2.

There has also been interest in text chunking in recent years. It was featured as the shared task at CoNLL 2000 (Tjong Kim Sang and Buchholz, 2000); the training set consisted of the sections 15-18 of the Penn Treebank, and as test the section 20 of the same corpus was selected. The task attracted several participants; the best individual system achieved an F-Measure performance of 92.12, and combination systems obtained up to 93.48 F-measure.

For the sake of facilitating comparisons with previously published results, this paper will report results on both text and base noun phrase chunking. Even if the base noun phrase is a subtask of text chunking, the slightly differing conventions used for pulling the structures out from the Treebank make it interesting to perform both experiments.

4.1.3 Experimental Results

The corpus used in these experiments was the Penn Treebank Wall Street Journal corpus. To facilitate evaluation comparisons, the training data consisted of sections 02-21 of the PennTreeBank's Wall Street Journal corpus and the test consisted of section 00 of the same corpus. This section will detail the results of the experiments.

As an initial state, each word are assigned the POS tag that it was most often associated with in the training set and the chunk tag that was most often associated with the initial POS tag. The rules templates are allowed to consult the word, POS tag and chunk tag of the current word and up to three words/POS tags/chunk tags to either side of it; some of the rule templates are modifying the chunk tags and other ones are modifying the POS tag.

Table 1 presents the results of the 4 experiments. Interestingly enough, extracting the base NP structures by performing text chunking obtains better F-measure, but the difference could be an artifact of the two annotation schemes not agreeing on what constitutes a noun phrase[2].

It can be seen that training the systems jointly results in better performance, especially for the

[2]We tried, as much as possible, to report numbers that are comparable with other published numbers, rather than ensuring that the results are consistent among text and baseNP chunking.

chunking tasks. An analysis of the algorithm behavior is given in the section 5. When trained jointly on the text chunking task, the POS tagger obtains an accuracy of 96.63%, which is among the state-of-the-art results for individual systems.

4.2 Chinese Word Segmentation and POS Tagging

4.2.1 Problem description

Word segmentation is a problem which is unique to some Asian languages such as Chinese and Japanese. Unlike most Indo-European languages, these languages are not written with any spaces or characters which indicate the boundaries between words. Since most existent NLP techniques are word-based techniques (rather than stream of characters techniques), word segmentation is a rather necessary task — it attempts to word-delimit a text by inserting "spaces" between characters where a pre-defined word boundary exists.

One major difficulty of performing Chinese word segmentation stems from the ambiguity of the task. The concept of a word is not clearly defined: experiments involving native speakers show an agreement rate of only around 75% (Sproat et al., 1996; Wu and Fung, 1994).

Since the character segments (words) obtained from segmentation are non-overlapping, the task can be viewed as a classification task in the same way as baseNP chunking can. Each character is tagged with a tag that marks it as either beginning a word ("B") or inside the word ("I").

Once the words in a sentence have been identified, part-of-speech tags can be assigned to words in the same fashion as in English. The Chinese treebank (Xia et al., 2000) assigns a total of 33 POS tags. Figure 1 shows an example sentence from the Chinese Treebank that has been annotated with both word segment and POS tags.

Chinese word segmentation and part-of-speech tagging has been extensively explored in the literature, and dictionary-based methods can usually achieve extremely high accuracies on the task. However, the inherent ambiguity of the problem makes system comparison very difficult. The usual method of evaluating a segmented word as correct as long as it is not unacceptably wrong also does not make it easy to objectively compare performances across systems.

Among the machine learning algorithms which have been applied to Chinese word segmentation, Palmer (Palmer, 1997) and Hockenmeier & Brew (Hockenmeier and Brew, 1998) used a transformation-based learning to tackle the problem. Their approach was to view an example as being the space between two characters. The rules learned would then insert, delete and move boundary indicators to obtain the desired words. Hockenmeier & Brew achieved an F-Measure performance of 87.8 after training on a corpus of 100,000 words, and Palmer's system achieved an F-Measure of 87.7 on a corpus of 60,000 words.[3]

4.2.2 Experimental Results

The corpus used in our experiment is the Chinese Treebank. 80% (3363 sentences, 141702 words) were randomly selected as the training set and the remaining 20% of the sentences (820 sentences, 19392 words) were held out as the test set. Since this corpus was released very recently, we believe that this is the first published results on the Chinese Treebank.

In the initial state, each Chinese character was assigned the word segment and POS tag that it was most often associated with in the training set. The rule predicates are based on conjunctions on the information (character, POS tag, segmentation tag) for the 3 characters on either side of the character to be changed.

To evaluate the performance of our system on word segmentation, the annotations in the Chinese Treebank were considered to be the gold standard — i.e. a segmented word is incorrect if it disagrees with the Treebank.

Since we are training the system to perform part-of-speech tagging together with word segmentation, and labeling part-of-speech tags on a character basis, there is a possibility that the system may assign different labels to individual characters inside the same word. In such a situation, a word is assigned the part-of-speech tag that was assigned to the majority of the characters it contains.

Table 3 presents the results of the experiments. It can be seen that mTBL achieves a respectable performance on word segmentation, and when compared to a sequential system of segmenting and then tagging words, mTBL outperforms the sequential system significantly for POS tagging and improves slightly on word segmentation.

5 Analysis

In the previous section, we presented the results of several experiments, in which training simultaneously on multiple tasks consistently performed better than the sequential training on one task at a time. In this section, we will analyze some

[3] Because of the different corpora used in training and testing, the results are not directly comparable.

[联合国][预测][明年][世界][经济][增长率]

联	合	国	预	测	明	年	世	界	经	济	增	长	率
B	I	I	B	I	B	I	B	I	B	I	B	I	I
NR	NR	NR	VV	VV	NT	NT	NN	NN	NN	NN	NN	NN	NN

Figure 1: Chinese Sentence Segmentation and POS Tagging
(Translation: "The United Nations makes a prediction on next year's world economy growth rate.")

System	Word Segmentation (F-measure)	POS Accuracy
Joint Text Segmentation/POS tagging	93.55	88.86 %
Text Segmentation, then POS tagging	93.48	88.13 %

Table 3: Chinese Text Processing: Text Segmentation and POS Tagging

of the advantages of the joint system, considering the POS tagging/text chunking experiment as case study.

Sentence chunks offer the POS tagger a way to generalize the contexts; this is due to a limitation of the template types. Our choice of predicate templates is a conjunction of feature identities (e.g. if the previous POS tag is "TO") and/or an atomic predicate that can examine one of the previous k words (e.g. if one of the previous 3 tags if "MD"). Extending the template structure to include disjunction would create a very high dimensionality search space, making the problem intractable. However, introducing the sentence chunk tags can alleviate this problem; in Figure 2, we have shown the rules learned by the 2 systems to resolve the disambiguation between the POS tags VBD (past tense) and VBN (past participle). Most verbs in English display the same form while used as past tense or past participle (all regular ones, plus some of the irregular ones), but their grammatical use of the 2 forms is completely different: past tenses usually create predicates by themselves (e.g "he drank water"), while the part participles are part of a complex predicate ("I have been present","he was cited") or are used as adjectives (e.g. "the used book"). The jointly trained system can make the distinction using just one rule, (left side of the figure), by deciding that if the current verb is inside of a verb phrase, then the form should be the past participle. The TBL system that was trained only on the POS task breaks this rule into several particular cases, which are not learned contiguously (some other rules were learned in-between). Using more general rules is desirable, as it will not "split" the data as much as a more particular rule would do. In the end, the jointly trained system made 30 less POS errors on samples labeled VBN or VBD on which the rules displayed applied (there are 2026 samples labeled VBN or VBD in the test corpus).

A second reason for the better behavior of the jointly trained system is that, for the POS case, the systems are approaching in performance the inter-annotator agreement, and therefore further improvement is difficult[4]. By training the system jointly, the system can choose to model the problematic cases (the ones that are truly ambiguous or the ones on which the annotators disagree consistently) in such a way that the second task is improved.

Another disadvantage the sequential system has compared with the jointly trained system is a discrepancy between the quality of data received during training and the one received testing. In the case of the sequential approach, the POS assignment is much more accurate during the training process (being the output of the POS system on the training data - 98.54%) than during testing (96.45%), while for the jointly trained system, the input has the same accuracy during testing and training[5] . Also, by starting from a less accurate initial point, the joint system is able to filter out some of the noise, resulting in a more robust classification.

To examine this aspect in more detail, let us consider the initial conditional probability (as assigned in the initialization phase) of a chunk tag c given a word w during testing $P_t(c|w)$ and training $P_T(c|w)$. A measure of disagreement between the probability distributions during training and testing is the Kullbach-Leibler distance

$$D\left(P_t\left(\cdot|w\right), P_T\left(\cdot|w\right)\right) = \sum_c P_t\left(c|w\right) \cdot \log\left(\frac{P_t\left(c|w\right)}{P_T\left(c|w\right)}\right)$$

[4]There are areas in which the systems can be improved; the classification for the words unseen in the training data is one of them.

[5]Assuming, of course, that the test and train data have been drawn from the same distribution.

Condition	Change To	Condition	Change To
POS_0=VBD $Chunk_0$=I-VP	VBN	POS_0=VBD $POS_{[-3...-1]}$=VBZ	VBN
		POS_0=VBD POS_{-1}=VBD	VBN
		POS_0=VBD $POS_{[-3...-1]}$=VBP	VBN
Jointly trained system		POS only	

Figure 2: Example of Learned Rules

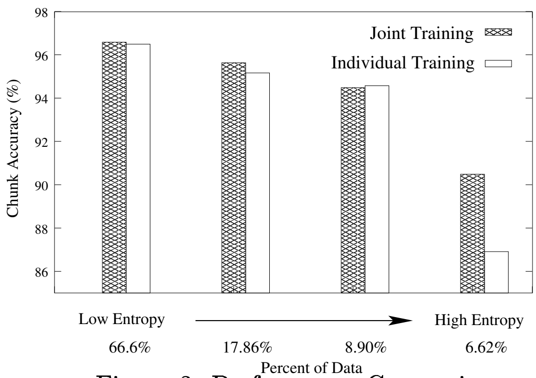

Figure 3: Performance Comparison

Figure 3 presents a decomposition of the performance of the two systems, based on partition of 4 classes of divergence between the train and test data probability distribution. The jointly trained system outperforms significantly the individually trained chunker on the class with the highest divergence — the one that matches the least the training data, proving that, indeed, the mTBL system is more robust.

6 Conclusion

In this paper, we have presented a novel method of using a transformation-based learner to train on and output multi-task classifications. The simultaneous multiple classification allows the system to learn from the signals presented in the training streams, and learned rules can choose to correct any of the streams, as dictated by the data. Our experiments show that, in both English part-of-speech tagging/text chunking and Chinese word segmentation/part-of-speech tagging, the performance of the jointly trained system outperformed each individually trained system . In the case of POS tagging for English, the resulting performance (96.63%) is very close to state-of-the-art, as reported by (Ratnaparkhi, 1996; Brants, 2000); the difference in performance against the sequential training method is statistically significant for most tasks (except for Chinese text segmentation), as verified by a t-test.

Future directions of research include applying the method to part-of-speech tag inflective languages, and extend the experiment described in Section 4.2 by incorporating text chunking. Also, an interesting research question related to TBL concerns the way the rule templates are chosen[6], the main design issue in TBL; the authors plan to investigate automated, principled ways to select the most appropriate rule templates for a given task.

7 Acknowledgments

The authors would like to thank David Yarowsky and Ellen Riloff for valuable advice and suggestions regarding this work, and also thank the anonymous reviewers for their suggestions and comments. The work presented here was funded by Grants IIS-9985033 and IRI-9618874, as well as Weniwen Technologies - Research.

References

Thorsten Brants. 2000. Tnt — a statistical part-of-speech tagger. In *Proceedings of the Sixth Applied Natural Language Processing Conference ANLP-2000*, April-May.

E. Brill. 1995. Transformation-based error-driven learning and natural language processing: A case study in part of speech tagging. *Computational Linguistics*, 21(4):543–565.

E. Brill, 1996. *Recent Advances in Parsing Technology*, chapter Learning to Parse with Transformations. Kluwer.

Rich Caruana, Lorien Pratt, and Sebastian Thrun. 1997. Multitask learning. *Machine Learning*, 28:41.

C. Chang and C. Chen. 1993. A study on integrating chinese word segmentation and part-of-speech tagging. *Communications of COLIPS*, 3(1).

R. Florian, J.C. Henderson, and G. Ngai. 2000. Coaxing confidence from an old friend: Probabilistic classifications from transformation rule lists. In *Proceedings of EMNLP-SIGDAT 2000*, Hong Kong, October. Association of Computational Linguistics.

[6] And not only for TBL — feature selection is an interesting problem for other tasks as well.

J. Hajic and Hladká. 1998. Tagging inflective languages: Prediction of morphological categories for a rich, structured tagset. In *Proceedings of the 36th Annual Meeting of the ACL and the 17th ICCL*, pages 483–490, Montréal, Canada.

J. Hockenmeier and C. Brew. 1998. Error-driven segmentation of chinese. *Communications of COLIPS*, 8(1):69–84.

M. P. Marcus, B. Santorini, and M. A. Marcinkiewicz. 1993. Building a large annotated corpus of english: The Penn Treebank. *Computational Linguistics*, 19(2):313–330.

M. Munoz, V. Punyakanok, D. Roth, and D. Zimak. 1999. A learning approach to shallow parsing. In *Proceedings of EMNLP-WVLC'99.* Association for Computational Linguistics.

Grace Ngai and Radu Florian. 2001. Transformation-based learning in the fast lane. In *Proceedings of North Americal ACL 2001.*

D. Palmer. 1997. A trainable rule-based algorithm for word segmentation. In *Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics*, Madrid.

L. Ramshaw and M. Marcus. 1994. Exploring the statistical derivation of transformational rule sequences for part-of-speech tagging. In *The Balancing Act: Proceedings of the ACL Workshop on Combining Symbolic and Statistical Approaches to Language*, New Mexico State University, July.

L. Ramshaw and M. Marcus, 1999. *Natural Language Processing Using Very Large Corpora*, chapter Text Chunking Using Transformation-based Learning. Kluwer.

A. Ratnaparkhi. 1996. A maximum entropy model for part of speech tagging. In *Proceedings of the First Conference on Empirical Methods in Natural Language Processing*, Philadelphia.

R. Sproat, C. Shih, W. Gale, and N. Chang. 1996. A stochastic finite-state word-segmentation algorithm for chinese. *Computational Linguistics*, 22(3).

E. Tjong Kim Sang and S. Buchholz. 2000. Introduction to the conll-2000 shared task: Chunking. In *Proceedings of CoNLL-2000 and LLL-2000*, pages 127–132, Lisbon, Portugal.

E. Tjong Kim Sang. 2000. Noun phrase representation by system combination. In *Proceedings of ANLP-NAACL 2000*, Seattle, Washington,USA. Morgan Kaufman Publishers.

D. Wu and P. Fung. 1994. Improving chinese word segmentation with linguistic filters on statistical lexical acquisition. In *Proceedings of Fourth ACL Conference on Applied Natural Language Processing*, Stuttgart, Germany. Association of Computational Linguistics.

Fei Xia, Martha Palmer, Nianwen Xue, Mary Ellen Okurowski, John Kovarik, Fu-Dong Chiou, Shizhe Huang, Tony Kroch, and Mitch Marcus. 2000. Developing guidelines and ensuring consistency for chinese text annotation. In *Proceedings of the second International Conference on Language Resources and Evaluation (LREC-2000)*, Athens, Greece.

E. Xun, C. Huang, and M. Zhou. 2000. A unified statistical model for the identification of english basenp. In *Proceedings of the 38th Annual Meeting of the Association for Computational Linguistics*, pages 109–116, Hong Kong, October.