An Investigation of Transformation-Based Learning in Discourse

Ken Samuel  
CIS Department  
University of Delaware  
Newark, Delaware 19716 USA  
samuel@cis.udel.edu

Sandra Carberry  
CIS Department  
University of Delaware  
Newark, Delaware 19716 USA  
carberry@cis.udel.edu

K. Vijay-Shanker  
CIS Department  
University of Delaware  
Newark, Delaware 19716 USA  
vijay@cis.udel.edu

Abstract

This paper presents results from the first attempt to apply Transformation-Based Learning to a discourse-level Natural Language Processing task. To address two limitations of the standard algorithm, we developed a Monte Carlo version of Transformation-Based Learning to make the method tractable for a wider range of problems without degradation in accuracy, and we devised a committee method for assigning confidence measures to tags produced by Transformation-Based Learning. The paper describes these advances, presents experimental evidence that Transformation-Based Learning is as effective as alternative approaches (such as Decision Trees and N-Grams) for a discourse task called Dialogue Act Tagging, and argues that Transformation-Based Learning has desirable features that make it particularly appealing for the Dialogue Act Tagging task.

1 INTRODUCTION

Transformation-Based Learning is a relatively new machine learning method, which has been as effective as any other approach on the Part-of-Speech Tagging problem (Brill, 1995a). We are utilizing Transformation-Based Learning for another important language task called Dialogue Act Tagging, in which the goal is to label each utterance in a conversational dialogue with the proper dialogue act. A dialogue act is a concise abstraction of a speaker’s intention, such as SUGGEST or ACCEPT. Recognizing dialogue acts is critical for discourse-level understanding and can also be useful for other applications, such as resolving ambiguity in speech recognition. But computing dialogue acts is a challenging task, because often a dialogue act cannot be directly inferred from a literal reading of an utterance. Figure 1 presents a hypothetical dialogue that has been labeled with dialogue acts.

Our research efforts led us to address some limitations of Transformation-Based Learning. We developed a Monte Carlo version of the algorithm that overcomes the limitation of Transformation-Based Learning’s dependence on manually-generated rule templates and enables Transformation-Based Learning to be applied effectively to a wider range of tasks. We also devised a technique that uses a committee of learned models to derive confidence measures associated with the dialogue acts assigned to utterances.

We experimentally compared our modified version of Transformation-Based Learning with C5.0, an implementation of Decision Trees, and N-Grams, which was previously the best reported method for Dialogue Act Tagging (Reithinger and Klesen, 1997). Our system performs as well as these benchmarks, and we note that Transformation-Based Learning has several characteristics that make it particularly appealing for the Dialogue Act Tagging task.

This paper begins with an overview of the Transformation-Based Learning method, describing the training phase and the application phase of the algorithm and presenting some of Transformation-Based Learning’s most attractive characteristics for Dialogue Act Tagging. The following section describes the experimental design used for the experiments presented in the paper. Then Section 4 presents two limitations of Transformation-Based Learning, a dependence on rule templates and a lack of confidence measures, and describes our solutions for these problems, a Monte Carlo strategy and a committee method. Next we present an experimental comparison between Transformation-Based Learning, N-Grams, and Decision Trees, and conclude with a discussion of this work.
2 TRANSFORMATION-BASED LEARNING

Brill (1995a) developed a symbolic machine learning method called Transformation-Based Learning. Given a tagged training corpus, Transformation-Based Learning produces a sequence of rules that serves as a model of the training data. Then, to derive the appropriate tags, each rule may be applied, in order, to each instance in an untagged corpus. For all of the results and examples in this paper, we are using Transformation-Based Learning on the Dialogue Act Tagging task, so the instances are utterances and the tags are dialogue acts. In one experiment, our system produced a learned model with 213 rules; the first five rules are presented in Figure 2.

First, the system initializes the training corpus by labeling each instance with a dummy tag. Brill (1995a) suggested using a more complex initialization step, but we found that this simple strategy is more effective in practice. Then the system generates all of the potential rules that would make at least one tag in the training corpus correct, under the restrictions described below. For each potential rule, its improvement score is defined to be the number of correct tags in the training corpus after applying the rule minus the number of correct tags in the training corpus before applying the rule. The potential rule with the highest improvement score is output as the next rule in the final model and applied to the entire training corpus. This process repeats (using the updated tags on the training corpus), producing one rule for each pass through the training corpus until no rule can be found with an improvement score that surpasses some predefined threshold. In practice, threshold values of 1 or 2 appear to be effective.

Since there are potentially an infinite number of rules that could produce the tags in the training data, it is necessary to restrict the range of patterns that the system may consider by providing a set of rule templates, such as:

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IF utterance u contains the word(s) w AND the tag on the utterance preceding u is X THEN change u's tag to Y
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This template can be instantiated to produce the last rule in Figure 2 by setting \( w = \text{"no"}, X = \text{SUGGEST}, \) and \( Y = \text{REJECT}. \)

For the first rules of the learned model, the emphasis is on getting as many tags correct as possible with no penalty imposed for changing an incorrect tag to another incorrect tag. Then for the later rules, the system must avoid changing any of the tags that are correct.

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**Figure 1: A sample dialogue**

| #  | Speaker | Utterance | Dialogue Act |
|----|---------|-----------|--------------|
| 1  | John    | Hello.    | GREET        |
| 2  | John    | I’d like to meet with you on Tuesday at 2:00. | SUGGEST |
| 3  | Mary    | That’s no good for me, | REJECT |
| 4  | Mary    | but I’m free at 3:00. | SUGGEST |
| 5  | John    | That sounds fine to me. | ACCEPT |
| 6  | John    | I’ll see you then. | BYE |

**Figure 2: Rules produced by Transformation-Based Learning for Dialogue Act Tagging**

2.1 THE TRAINING PHASE

The training phase of TBL, in which the system learns a sequence of rules based on a tagged training corpus, proceeds in the following manner:

1. Label each instance with a dummy tag.
2. Until no useful rules are found,
   a. For each incorrect tag
      i. Generate all rules that correct the tag.
   b. Score each generated rule.
   c. Output the highest scoring rule.
   d. Apply this rule to the corpus.

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\[3\] This is because Transformation-Based Learning uses an error-driven approach, only generating rules for the instances that are incorrectly labeled. If every instance is initialized with a dummy tag, then all of the labels are incorrect, and so they all contribute to learning. Alternatively, using a more involved initialization step results in a greater number of correct tags and, effectively, less training data.

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\[2\] This condition is true only for the first utterance of a dialogue.
already correct. Thus, this method tends to produce a sequence of rules that progresses from general rules to specific rules.

2.2 THE APPLICATION PHASE

To see how a rule sequence can be used to label data, consider applying the rules in Figure 2 to the dialogue in Figure 1. The first rule labels every utterance with the dialogue act SUGGEST. Next, the second rule changes an utterance’s tag to BYE if it contains the words “see” and “you”, which only holds for utterance #6. Similarly, the third rule changes utterance #5’s tag to ACCEPT. Then the fourth rule tags utterance #1 as GREET, since its length is 1 and there is no preceding utterance in the dialogue. And finally, the last rule relabels utterance #3 as REJECT, since utterance #2 is currently tagged SUGGEST, and the word “no” is found in utterance #3. Although the first five rules label these six utterances correctly, the remaining 208 rules in the sequence may continue to adjust the tags on the utterances.

2.3 ATTRACTIVE CHARACTERISTICS

For the Dialogue Act Tagging task, we selected Transformation-Based Learning for several reasons. Brill reported that Transformation-Based Learning is as good as or better than any other algorithm for the Part-of-Speech Tagging problem, labeling 97.2% of the words correctly. The part-of-speech tag of a word is dependent on the word’s internal features and on the surrounding words; similarly, the dialogue act of an utterance is dependent on the utterance’s internal features and on the surrounding utterances. This parallel suggests that Transformation-Based Learning has potential for success on the Dialogue Act Tagging problem.

Since we currently lack a systematic theory of dialogue acts, another reason that Transformation-Based Learning is an attractive choice is that its learned model consists of relatively intuitive rules (Brill, 1995a), which a human can analyze to determine what the system has learned and develop a working theory. Also, Transformation-Based Learning is good at ignoring any potential rules that are irrelevant. This is because irrelevant rules tend to have a random effect on the training data, which usually results in low improvement scores, so these rules are unlikely to be selected for inclusion in the final model. This is very helpful for Dialogue Act Tagging, since we don’t know what the relevant templates are for this problem. Ramshaw and Marcus (1994) experimentally demonstrated Transformation-Based Learning’s robustness with respect to irrelevant rules.

For these reasons, along with others that are presented at the end of the paper, we believe that Transformation-Based Learning is worthy of investigation for the Dialogue Act Tagging task.

3 EXPERIMENTAL DESIGN

All of the results presented in this paper followed the same experimental design as the third experiment in Reithinger and Klesen (1997). The corpus consisted of appointment-scheduling face-to-face dialogues in English, which was divided into a training set with 143 dialogues (2701 utterances) and a disjoint testing set with 20 dialogues (328 utterances). Each utterance was manually labeled with one of 18 abstract dialogue acts, such as SUGGEST, ACCEPT, REJECT, GREET, and BYE. The full list of dialogue acts is found in Reithinger and Klesen (1997).

The Transformation-Based Learning experiments presented in this paper were run on a Sun Ultra 1 machine with 508MB of main memory. Within a set of experiments, only the specified parameters were varied, but between sets of experiments many parameters may have been varied, so it is not possible to draw conclusions across experiment sets.

Our rule templates consist of all possible combinations of a preselected set of conditions. Some of these conditions are presented in Figure 3. Each condition consists of a feature and a distance, where the feature specifies a characteristic of utterances that might be relevant for the Dialogue Act Tagging task, and the distance specifies the relative position (from the utterance under analysis) of the utterance that the feature should be applied to.

| Feature | Distance |
|---------|----------|
| length of the current utterance | tag of the preceding utterance |
| cue patterns of the current utterance | speaker of the current utterance |
| speaker of the preceding utterance | |

Figure 3: Some conditions used in our experiments

In discourse, it is widely acknowledged that some of the short phrases (and specific words) found in an utterance provide strong clues to determine the appropriate dialogue act. Several researchers proposed different cue phrases, which are phrases that appear frequently in dialogue and convey useful discourse information, such as “but”, “so”, and “by the way”. Unfortunately, there is no universal agreement on which phrases should be considered cue phrases, and in a preliminary experiment using all of the cue phrases proposed in the literature, our system’s accuracy only

4These lists of cue phrases can be found in Hirschberg
improved by 1.03%.

In order to identify the phrases that will be useful for a particular domain, we need an automatic method for collecting a set of phrases that is tuned to that domain. So we are using a statistical approach to select relevant cue patterns from a training corpus. Assuming that a phrase is relevant if it co-occurs frequently with a few specific dialogue acts, we analyze the distribution of dialogue acts for utterances that include a given phrase, selecting those phrases that correspond to dialogue act distributions with low entropy. When using these cue patterns, our system's accuracy rose by 17.63%. For more details on this work, see Samuel, Carberry, and Vijay-Shanker (1998b).

4 TRANSFORMATION-BASED LEARNING IN DISCOURSE

4.1 TWO LIMITATIONS

Transformation-Based Learning has two serious limitations, which we will address in this section. First, although Transformation-Based Learning produces a tag for each instance, it doesn't offer any measure of confidence in these tags. Alternatively, probabilistic machine learning approaches generally label an instance with a set of tags, which are assigned numbers to represent the likelihood that they are correct. So "probabilistic methods ... provide a continuous ranking of alternative analyses rather than just a single output, and such rankings can productively increase the bandwidth between components of a modular system." (Brill and Mooney, 1997)

The second limitation of Transformation-Based Learning is that it is highly dependent on the rule templates, which are manually developed in advance. Since the omission of any relevant templates would handicap the system, it is essential that these choices be made carefully. But in Dialogue Act Tagging, no one knows exactly which conditions and combinations of conditions are relevant, so it is preferable to err on the side of caution by constructing an overly-general set of templates and allowing the system to learn which templates are useful. As discussed earlier, Transformation-Based Learning is capable of discarding irrelevant rules, so this approach should be effective, in theory.

Unfortunately, this strategy is not tractable, because for each pass through the training data, for each instance that the system has tagged incorrectly, every rule template must be instantiated in all possible ways.

Suppose that we can postulate \( f \) different features that might be relevant, and we wish to consider these features for all instances that occur within a distance \( d \) of a given instance. (In other words, we are using a contextual window of size \( 2d+1 \).) Then there are \( (2d+1)f \) conditions and \( 2^{(2d+1)f} \) possible templates, since each condition may either be included or excluded. Also, suppose that when a feature is applied to an instance, it produces \( v \) distinct values, on average. This results in \( (v+1)^{(2d+1)f} \) rules per instance, which can be proven by induction on the number of conditions. Given a training corpus with \( i \) instances, if the algorithm makes \( p \) passes through the training data, then the system must generate and evaluate \( O(ip(v+1)^{(2d+1)f}) \) rules. Some realistic values for these variables are \( f=10, d=2 \) (a contextual window of size 5), \( v=3, i=3000, \) and \( p=100 \), which generates around \( 10^{35} \) rules. Based on experimental evidence, it appears that it is necessary to drastically limit the number of potential rules that the system generates, or the memory and time costs are so exorbitant that the method becomes intractable. But this limitation would preclude considering all of the features and feature interactions that might be relevant for Dialogue Act Tagging.

4.2 A MONTE CARLO VERSION

We developed a Monte Carlo version of Transformation-Based Learning, so that the system can consider a huge number of templates while still maintaining tractability. Rather than exhaustively searching through the space of possible rules, only \( R \) of the available template instantiations are randomly selected for each training instance on each pass through the training data, where \( R \) is some small integer. With this modification, the total number of rules generated is only \( O(ipR) \), which no longer explodes with the number of templates. In fact, the formula doesn't even depend on the number of features, the contextual window size, or the value of \( v \). But one would still expect good results, because Transformation-Based Learning only needs to find the best rules, and the best rules tend to be effective for a large number of different instances. So the system has many opportunities to find these rules, and since the algorithm generally makes many passes through the training data before halting, if it should select a suboptimal rule, it can use later rules to compensate. Thus, although random sampling will miss some rules, it is still highly likely to find an effective sequence of rules.

Our experiments confirm these intuitions, as shown in Figures 4 and 5. For these runs, eight condi-

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\(^{6}\)In practice, the concept of cue patterns tends to be more general than cue phrases, including many more phrases.

\(^{3}\)For the Part-of-Speech Tagging task, Brill used only about 30 simple rule templates (Brill, 1995a).
tions were preselected, and for different values of \( n \), \( 0 \leq n \leq 8 \), the first \( n \) conditions were combined in all possible ways to generate \( 2^n \) templates. Using these templates, we trained, tested, and compared the standard Transformation-Based Learning method and our Monte Carlo version of Transformation-Based Learning.

For the standard Transformation-Based Learning method, training time rises dramatically as the number of conditions increases, as shown in Figure 4. In fact, when given seven conditions, the standard Transformation-Based Learning algorithm could not complete the training phase, even after running for more than 24 hours. But our Monte Carlo version of Transformation-Based Learning keeps the efficiency relatively stable. The reason for the slight increase in training time as the number of conditions increases is that, as the system gains access to a greater number of useful conditions, it’s likely to find a greater number of useful rules, meaning that the training phase makes a greater number of passes through the training data. Thus, \( p \) increases, and so the training time, \( O(ipR) \), also increases. But this increase is linear (or less), while standard Transformation-Based Learning’s training time increases exponentially with the number of conditions. Figure 4 supports this analysis.

This improvement in time efficiency would be quite uninteresting if the performance of the algorithm deteriorated significantly. But, as Figure 4 shows, this is not the case. Although setting \( R \) too low (such as \( R=1 \) for 7 and 8 conditions) may result in a decrease in accuracy, the lowest possible setting (\( R=1 \)) is as accurate as standard Transformation-Based Learning for 6 conditions (64 templates). For 7 and 8 conditions, training of the standard Transformation-Based Learning method took too much time, so those results could not be produced. But, as the curves for \( R=6 \) and \( R=16 \) do not differ significantly, it is reasonable to predict that standard Transformation-Based Learning would produce similar results as well. Therefore, we conclude

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7The value of \( v \) (the average number of rules generated per instance) varies slightly across the eight conditions, and so the shape of the curve might vary depending on the order in which the conditions are presented. But the critical point is that the training time rises exponentially with the number of conditions.

8The Monte Carlo version of Transformation-Based Learning can be slower than the standard method, because the Monte Carlo version always generates \( R \) rules for each instance, without checking for repetitions. (It would be too inefficient to prevent the system from generating any rule more than once.)
that our Monte Carlo version of Transformation-Based Learning (with $R=6$) works effectively for more than 250 templates (8 conditions) in only about 15 minutes of training time.

4.3 A COMMITTEE METHOD

We wanted to extend Transformation-Based Learning so that it could provide some idea of the likelihood that each of its tags are correct. So we attempted to develop a strategy for assigning confidence measures to the rules in the learned model. Then, in the application phase, a given instance’s confidence measure would be a function of the confidences of the rules that applied to that instance. Unfortunately, due to the nature of the Transformation-Based Learning method, this straightforward approach has been unsuccessful, because the rule sequence does not contain enough information to derive confidence measures; often, the same pattern of rules applies to instances that should be marked with high confidence as well as instances that should be marked with low confidence.

So, for the purpose of computing confidence measures, we adapted two techniques that were developed for very different tasks. The Boosting approach has been used to improve accuracy in tagging data (Freund and Schapire, 1996), and Committee-Based Sampling utilized a very similar strategy to minimize the required size of a training corpus (Dagan and Engelson, 1995). We applied these methods to compute confidence measures, by training the system a number of times to produce a few different but reasonable learned models, which are called committee members. Then given new data, each committee member independently tags the input, and a given tag’s confidence is based on how well the committee members agree on that tag. We are currently defining the confidence of a given tag to be the number of committee members that preferred the tag. In the future, we will investigate confidence formulas that are based on the entropy of the tags selected by the different committee members.

We considered several ways to develop the committee members, and we decided to apply the strategy that Freund and Schapire (1996) used for Boosting: The first committee member is trained in the standard way, and then the second committee member pays special attention to those instances in the training data that the first committee member did not tag correctly. To do this in Transformation-Based Learning, we adjust the improvement score formula to weight success on these “hard” instances more heavily. (In effect, it is as if we were adding multiple copies of these instances to the training corpus.) This process can be repeated to generate more committee members by basing the score for correctly tagging a training instance on the number of previous committee members that tagged that instance incorrectly. We are currently using $2^c$ as the score for correctly tagging a given instance that $c$ committee members have mistagged. This strategy tends to produce committee members that are very different, as they are focusing on different parts of the

Figure 5: Number of conditions vs. tagging accuracy on unseen data
training corpus.

| Minimum Confidence | Percentage of Instances Tagged | Average Precision |
|---------------------|--------------------------------|-------------------|
| 5                   | 45.12% ± 1.28%                 | 90.09% ± 1.51%    |
| 4                   | 69.79% ± 1.60%                 | 83.53% ± 1.27%    |
| 3                   | 92.38% ± 1.32%                 | 76.57% ± 0.79%    |
| 2                   | 99.85% ± 0.20%                 | 73.56% ± 1.10%    |
| 1                   | 100.00% ± 0.00%                | 73.45% ± 1.06%    |

Figure 6: Testing the committee method on unseen data, varying the minimum confidence considered

As a preliminary experiment we ran ten trials with five committee members, testing on held-out data. Figure 11 presents average scores and standard deviations, varying the minimum confidence, \( m \). For a given instance, if at least \( m \) committee members agreed on a tag, then the most popular tag was applied, breaking ties in favor of the committee member that was developed the earliest; otherwise no tag was output. The results show that the committee approach assigns useful confidence measures to the tags: All five committee members agreed on the tags for 45.12% of the instances, and 90.09% of those tags were correct.

Also, for 69.79% of the instances, at least four of the five committee members selected the same tag, and this tag was correct 83.53% of the time. We foresee that our module for tagging dialogue acts can potentially be integrated into a larger system so that, when Transformation-Based Learning cannot produce a tag with high confidence, other modules may be invoked to provide more evidence. In addition, like Boosting, the committee method improves the overall accuracy of the system. By selecting the most popular tag among all five committee members, the average accuracy in tagging unseen data was 73.45%, while using the first committee member alone resulted in a significantly (\( t = 5.42 > 2.88, \alpha = 0.01 \)) lower average score of 70.79%.

4.4 ALTERNATIVE METHODS

Previously, the best success rate achieved on the Dialogue Act Tagging problem was reported by Reithinger and Klesen (1997), whose system used a probabilistic machine learning approach based on N-Grams to correctly label 74.7% of the utterances in a test corpus. (See Samuel, Carberry, and Vijay-Shanker (1998a) for a more extensive analysis of previous work on this task.) As a direct comparison, we applied our system to exactly the same training and testing set. Over five runs, the system achieved an average accuracy of 75.12% ± 1.34%, including a high score of 77.44%.

In addition, we ran a direct comparison between Transformation-Based Learning and C5.0 (Rulequest Research, 1998), which is an implementation of the Decision Trees method. The accuracies on held-out data for training sets of various sizes are presented in Figure 4. For Transformation-Based Learning, we averaged the scores of ten trials for each training set (to factor out the random effects of the Monte Carlo method), and the standard deviations are represented by error bars in the graph. These experiments did not utilize the committee method, and we would expect the scores to improve when this extension is used.

With C5.0, we wanted to use the same features that were effective for Transformation-Based Learning, but we encountered two problems: 1) Since C5.0 requires that each feature take exactly one value for each instance, it is very difficult to utilize the cue patterns feature. We decided to provide one boolean feature for each possible cue pattern, which was set to True for instances that included that cue pattern and False otherwise. 2) Our Transformation-Based Learning system utilized the system-generated tag of the preceding instance. C5.0 cannot use this information, as it requires that the values of all of the features are computed before training begins.

The training times of Transformation-Based Learning and C5.0 were relatively comparable for any number of conditions, although Boosting sometimes resulted in a significant increase in training time. The accuracy scores of Transformation-Based Learning and C5.0, with and without Boosting, are not significantly different, as shown in Figure 7.

5 DISCUSSION

This paper has described the first investigation of Transformation-Based Learning applied to discourse-level problems. We extended the algorithm to address two limitations of Transformation-Based Learning: 1) We developed a Monte Carlo version of Transformation-Based Learning, and our experiments suggest that this improvement dramatically increases the efficiency of the method without compromising accuracy. This revision enables Transformation-Based Learning to work effectively on a wider variety of tasks, including tasks where the relevant conditions and condition combinations are not known in advance as well as tasks where there are a large number of relevant conditions and condition combinations. This improvement also decreases the labor demands on the human developer, who no longer needs to construct a mini-

The variation in the scores is due to the random nature of the Monte Carlo method.

The rules in Figure 2 were produced in this experiment.
mal set of rule templates. It is sufficient to list all of the conditions that might be relevant and allow the system to consider all possible combinations of those conditions. 2) We devised a committee strategy for computing confidence measures to represent the reliability of tags. In our experiments, this committee method improved the overall tagging accuracy significantly. It also produced useful confidence measures; nearly half of the tags were assigned high confidence, and of these, 90% were correct.

For the Dialogue Act Tagging task, our modified version of Transformation-Based Learning has achieved an accuracy rate that is comparable to any previously reported system. In addition, Transformation-Based Learning has a number of features that make it particularly appealing for the Dialogue Act Tagging task:

1. Transformation-Based Learning’s learned model consists of a relatively short sequence of intuitive rules, stressing relevant features and highlighting important relationships between features and tags (Brill, 1995a). Thus, Transformation-Based Learning’s learned model offers insights into a theory to explain the training data. This is especially useful in Dialogue Act Tagging, which currently lacks a systematic theory.

2. With its iterative training algorithm, when developing a new rule, Transformation-Based Learning can consider tags that have been produced by previous rules (Ramshaw and Marcus, 1994). Since the dialogue act of an utterance is affected by the surrounding dialogue acts, this leveraged learning approach can directly integrate the relevant contextual information into the rules. In addition, Transformation-Based Learning can accommodate the focus shifts that frequently occur in discourse by utilizing features that consider tags of varying distances.

3. Our Transformation-Based Learning system is very flexible with respect to the types of features it can utilize. For example, it can learn set-valued features, such as cue patterns. Additionally, because of the Monte Carlo improvement, our system can handle a very large number of features.

4. For the Dialogue Act Tagging task, people still don’t know what features are relevant, so it is very difficult to construct an appropriate set of rule templates. Fortunately, Transformation-Based Learning is capable of discarding irrelevant rules, as Ramshaw and Marcus (1994) showed experimentally, so it is not necessary that all of the given rule templates be useful.

5. Ramshaw and Marcus’s (1994) experiments suggest that Transformation-Based Learning tends to be resistant to the overfitting problem. This can be explained by observing how the rule sequence produced by Transformation-Based Learning progresses from general rules to specific rules. The early rules in the sequence are based on many examples in the training corpus, and so they are likely to generalize effectively to new data. Later in the sequence, the rules don’t receive as much contextual information as the early rules.

Other machine learning algorithms may overfit to the training data and then have difficulty generalizing to new data.
support from the training data, and their applicability conditions tend to be very specific, so they have little or no effect on new data. Thus, resistance to overfitting is an emergent property of the Transformation-Based Learning algorithm.

For the future, we intend to investigate a wider variety of features and explore different methods for collecting cue patterns to increase our system’s accuracy scores further. Although we compared Transformation-Based Learning with a few very different machine learning algorithms, we still hope to examine other methods, such as Naive Bayes. In addition, we plan to run our experiments with different corpora to confirm that the encouraging results of our extensions to Transformation-Based Learning can be generalized to different data, languages, domains, and tasks. We would also like to extend our system so that it may learn from untagged data, as there is still very little tagged data available in discourse. Brill developed an unsupervised version of Transformation-Based Learning for Part-of-Speech Tagging (Brill, 1995b), but this algorithm must be initialized with instances that can be tagged unambiguously (such as “the”, which is always a determiner), and in Dialogue Act Tagging there are very few unambiguous examples. We intend to investigate the following weakly-supervised approach: First, the system will be trained on a small set of tagged data to produce a number of different committee members. Then given untagged data, it will derive tags with confidence measures. Those tags that receive very high confidence can be used as unambiguous examples to drive the unsupervised version of Transformation-Based Learning.

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References

Brill, Eric (1995a). Transformation-Based Error-Driven Learning and Natural Language Processing: A Case Study in Part-of-Speech Tagging. Computational Linguistics 21(4):543-566.

Brill, Eric (1995b). Unsupervised Learning of Disambiguation Rules for Part-of-Speech Tagging. In Proceedings of the Very Large Corpora Workshop.

Brill, Eric and Mooney, Raymond J. (1997). An Overview of Empirical Natural Language Processing. AI Magazine 18(4):13-24.

Dagan, Ido and Engelson, Sean P. (1995). Committee-Based Sampling for Training Probabilistic Classifiers. In Proceedings of the Twelfth International Conference on Machine Learning.

Freund, Yoav and Schapire, Robert E. (1996). Experiments with a New Boosting Algorithm. In Proceedings of the Thirteenth International Conference on Machine Learning.

Hirschberg, Julia and Litman, Diane (1993). Empirical Studies on the Disambiguation of Cue Phrases. Computational Linguistics 19(3):501-530.

Knott, Alistair (1996). A Data-Driven Methodology for Motivating a Set of Coherence Relations. Ph.D. Thesis. The University of Edinburgh.

Ramshaw, Lance A. and Marcus, Mitchell P. (1994). Exploring the Statistical Derivation of Transformation Rule Sequences for Part-of-Speech Tagging. In Proceedings of the 32nd Annual Meeting of the ACL.

Reithinger, Norbert and Klesen, Martin (1997). Dialogue Act Classification Using Language Models. In Proceedings of EuroSpeech-97.

Rulequest Research. (1998). Data Mining Tools See5 and C5.0. [http://www.rulequest.com/see5-info.html]

Samuel, Ken, Carberry, Sandra, and Vijay-Shanker, K. (1998a). Computing Dialogue Acts from Features with Transformation-Based Learning. In Applying Machine Learning to Discourse Processing: Papers from the 1998 AAAI Spring Symposium.

Samuel, Ken, Carberry, Sandra, and Vijay-Shanker, K. (1998b). Dialogue Act Tagging with Transformation-Based Learning. In Proceedings of COLING-ACL.