Coaxing Confidences from an Old Friend: Probabilistic Classifications from Transformation Rule Lists

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Abstract

Transformation-based learning has been successfully employed to solve many natural language processing problems. It has many positive features, but one drawback is that it does not provide estimates of class membership probabilities.

In this paper, we present a novel method for obtaining class membership probabilities from a transformation-based rule list classifier. Three experiments are presented which measure the modeling accuracy and cross-entropy of the probabilistic classifier on unseen data and the degree to which the output probabilities from the classifier can be used to estimate confidences in its classification decisions.

The results of these experiments show that, for the task of text chunking[1], the estimates produced by this technique are more informative than those generated by a state-of-the-art decision tree.

1 Introduction

In natural language processing, a great amount of work has gone into the development of machine learning algorithms which extract useful linguistic information from resources such as dictionaries, newswire feeds, manually annotated corpora and web pages. Most of the effective methods can be roughly divided into rule-based and probabilistic algorithms. In general, the rule-based methods have the advantage of capturing the necessary information in a small and concise set of rules. In part-of-speech tagging, for example, rule-based and probabilistic methods achieve comparable accuracies, but rule-based methods capture the knowledge in a hundred or so simple rules, while the probabilistic methods have a very high-dimensional parameter space (millions of parameters).

One of the main advantages of probabilistic methods, on the other hand, is that they include a measure of uncertainty in their output. This can take the form of a probability distribution over potential outputs, or it may be a ranked list of candidate outputs. These uncertainty measures are useful in situations where both the classification of a sample and the system's confidence in that classification are needed. An example of this is a situation in an ensemble system where ensemble members disagree and a decision must be made about how to resolve the disagreement. A similar situation arises in pipeline systems, such as a system which performs parsing on the output of a probabilistic part-of-speech tagging.

Transformation-based learning (TBL) (Brill, 1995) is a successful rule-based machine learning algorithm in natural language processing. It has been applied to a wide variety of tasks, including part of speech tagging (Roche and Schabes, 1995; Brill, 1995), noun phrase chunking (Ramshaw and Marcus, 1999), parsing (Brill, 1996; Vilain and Day, 1996), spelling correction (Mangu and Brill, 1997), prepositional phrase attachment (Brill and Resnik, 1994), dialog act tagging (Samuel et al., 1998), segmentation and message understanding (Day et al., 1997), often achieving state-of-the-art performance with a small and easily-understandable list of rules.

In this paper, we describe a novel method which enables a transformation-based classifier to generate a probability distribution on the class labels. Application of the method allows the transformation rule list to retain the robustness of the transformation-based algorithms, while benefitting from the advantages of a probabilistic classifier. The usefulness of the resulting probabilities is demonstrated by comparison with another state-of-the-art classifier, the C4.5 decision tree (Quinlan, 1993). The performance of our algorithm compares favorably across many dimensions: it obtains better perplexity and cross-entropy; an active learning algorithm using our system outperforms a similar algorithm using decision trees; and finally, our algorithm has better rejection curves than a similar decision tree. Section 2 presents the transformation based learning paradigm; Section 3 describes the algorithm for construction of the decision tree associated with the transformation based list; Section 4 describes the experiments in detail and Section 5 concludes the paper and outlines the future work.

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[1]All the experiments are performed on text chunking. The technique presented is general-purpose, however, and can be applied to many tasks for which transformation-based learning performs well, without changing the internals of the learner.

2 Transformation rule lists

The central idea of transformation-based learning is to learn 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 then rules are greedily learned to correct the mistakes, until no net improvement can be made.

These definitions and notation will be used throughout the paper:

- $\mathcal{X}$ denotes the *sample space*;

- $\mathcal{C}$ denotes the set of possible *classifications* of the samples;

- The *state space* is defined as $\mathcal{S} = \mathcal{X} \times \mathcal{C}$.

- π will usually denote a *predicate* defined on $\mathcal{X}$;

- A *rule* r is defined as a predicate – class label – time tuple, (π, c, t), $c \in \mathcal{C}, t \in \mathrm{N}$, where t is the learning iteration in which when the rule was learned, its position in the list.

- A rule $r = (\pi, c, t)$ *applies* to a state (x, y) if $\pi(x) = true$ and $c \neq y$.

Using a TBL framework to solve a problem assumes the existence of:

- An initial class assignment (mapping from $\mathcal{X}$ to $\mathcal{S}$). This can be as simple as the most common class label in the training set, or it can be the output from another classifier.

- A set of allowable templates for rules. These templates determine the predicates the rules will test, and they have the biggest influence over the behavior of the system.

- An objective function for learning. Unlike in many other learning algorithms, the objective function for TBL will typically optimize the evaluation function. An often-used method is the difference in performance resulting from applying the rule.

At the beginning of the learning phase, the training set is first given an initial class assignment. The system then iteratively executes the following steps:

1. Generate all productive rules.

2. For each rule:

   (a) Apply to a copy of the most recent state of the training set.

   (b) Score the result using the objective function.

3. Select the rule with the best score.

4. Apply the rule to the current state of the training set, updating it to reflect this change.

5. Stop if the score is smaller than some pre-set threshold T.

6. Repeat from Step 1.

The system thus learns a list of rules in a greedy fashion, according to the objective function. When no rule that improves the current state of the training set beyond the pre-set threshold can be found, the training phase ends. During the evaluation phase, the evaluation set is initialized with the same initial class assignment. Each rule is then applied, in the order it was learned, to the evaluation set. The final classification is the one attained when all rules have been applied.

3 Probability estimation with transformation rule lists

Rule lists are infamous for making *hard decisions*, decisions which adhere entirely to one possibility, excluding all others. These hard decisions are often accurate and outperform other types of classifiers in terms of exact-match accuracy, but because they do not have an associated probability, they give no hint as to when they might fail. In contrast, probabilistic systems make *soft decisions* by assigning a probability distribution over all possible classes.

There are many applications where soft decisions prove useful. In situations such as *active learning*, where a small number of samples are selected for annotation, the probabilities can be used to determine which examples the classifier was most unsure of, and hence should provide the most extra information. A probabilistic system can also act as a filter for a more expensive system or a human expert when it is permitted to *reject* samples. Soft decision-making is also useful when the system is one of the components in a larger decision-making process, as is the case in speech recognition systems (Bahl et al., 1989), or in an ensemble system like AdaBoost (Freund and Schapire, 1997). There are many other applications in which a probabilistic classifier is necessary, and a non-probabilistic classifier cannot be used instead.

3.1 Estimation via conversion to decision tree

The method we propose to obtain probabilistic classifications from a transformation rule list involves dividing the samples into equivalence classes and computing distributions over each equivalence class. At any given point in time i, each sample x in the training set has an associated state $s_i(x) = (x, y)$. Let $R(x)$ to be the set of rules r_i that applies to the state $s_i(x)$,

$$R(x) = \{r_i \in \mathcal{R} | r_i \text{ applies to } s_i(x)\}$$

An equivalence class consists of all the samples x that have the same $R(x)$. Class probability assignments are then estimated using statistics computed on the equivalence classes.

An illustration of the conversion from a rule list to a decision tree is shown below. Table 1 shows an example transformation rule list. It is straightforward to convert this rule list into a decision pylon (Bahl et al., 1989), which can be used to represent all the possible sequences of labels assigned to a sample during the application of the TBL algorithm. The decision pylon associated with this particular rule list is displayed on the left side of Figure 1. The decision tree shown on the right side of Figure 1 is constructed such that the samples stored in any leaf have the same class label sequence as in the displayed decision pylon. In the decision pylon, "no" answers go straight down; in the decision tree, "yes" answers take the right branch. Note that a one rule in the transformation rule list can often correspond to more than one node in the decision tree.

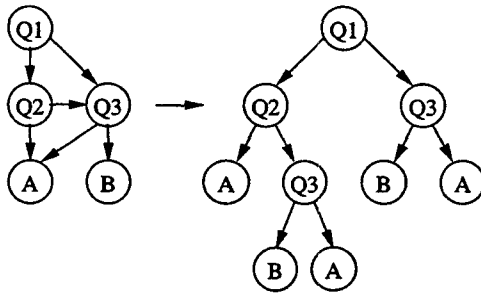| Initial label = A |
|---|
| If Q1 and label=A then label←B |
| If Q2 and label=A then label←B |
| If Q3 and label=B then label←A |

Table 1: Example of a Transformation Rule List.

Figure 1: Converting the transformation rule list from Table 1 to a decision tree.

The conversion from a transformation rule list to a decision tree is presented as a recursive procedure. The set of samples in the training set is transformed to a set of states by applying the initial class assignments. A node n is created for each of the initial class label assignments c and all states labeled c are assigned to n.

The following recursive procedure is invoked with an initial "root" node, the complete set of states (from the corpus) and the whole sequence of rules learned during training:

Algorithm: RuleListToDecisionTree (RLTDT)

Input:

- A set $\mathcal{B}$ of N states $\langle (x_1, y_1) \ldots (x_N, y_N) \rangle$ with labels $y_i \in C$;

- A set $\mathcal{R}$ of M rules $\langle r_0, r_1 \ldots r_M \rangle$ where $r_i = (\pi_i, y_i, i)$.

Do:

1. If $\mathcal{R}$ is empty, the end of the rule list has been reached. Create a leaf node, n, and estimate the probability class distribution based on the true classifications of the states in $\mathcal{B}$. Return n.

2. Let $r_j = (\pi_j, y_j, j)$ be the lowest-indexed rule in $\mathcal{R}$. Remove it from $\mathcal{R}$.

3. Split the data in $\mathcal{B}$ using the predicate π_j and the current hypothesis such that samples on which π_j returns *true* are on the right of the split:

$$\mathcal{B}_L = \{x \in \mathcal{B} | \pi_j(x) = false\}$$
$$\mathcal{B}_R = \{x \in \mathcal{B} | \pi_j(x) = true\}$$

4. If $|\mathcal{B}_L| > K$ and $|\mathcal{B}_R| > K$, the split is acceptable:

   (a) Create a new internal node, n;

   (b) Set the question: $q(n) = \pi_j$;

   (c) Create the left child of n using a recursive call to $RLTDT(\mathcal{B}_L, \mathcal{R})$;

   (d) Create the right child of n using a recursive call to $RLTDT(\mathcal{B}_R, \mathcal{R})$;

   (e) Return node n.

   Otherwise, no split is performed using r_j. Repeat from Step 1.

The parameter K is a constant that determines the minimum weight that a leaf is permitted to have, effectively pruning the tree during construction. In all the experiments, K was set to 5.

3.2 Further growth of the decision tree

When a rule list is converted into a decision tree, there are often leaves that are inordinately heavy because they contain a large number of samples. Examples of such leaves are those containing samples which were never transformed by any of the rules in the rule list. These populations exist either because they could not be split up during the rule list learning without incurring a net penalty, or because any rule that acts on them has an objective function score of less than the threshold T. This is sub-optimal for estimation because when a large portion of the corpus falls into the same equivalence class, the distribution assigned to it reflects only the mean of those samples. The undesirable consequence is that all of those samples are given the same probability distribution.

To ameliorate this problem, those samples are partitioned into smaller equivalence classes by further growing the decision tree. Since a decision tree does not place all the samples with the same current label into a single equivalence class, it does not get stuck in the same situation as a rule list — in which no change in the current state of corpus can be made without incurring a net loss in performance.

Continuing to grow the decision tree that was converted from a rule list can be viewed from another angle. A highly accurate prefix tree for the final decision tree is created by tying questions together during the first phase of the growth process (TBL). Unlike traditional decision trees which select splitting questions for a node by looking only at the samples contained in the local node, this decision tree selects questions by looking at samples contained in all nodes on the frontier whose paths have a suffix in common. An illustration of this phenomenon can be seen in Figure 1, where the choice to split on Question 3 was made from samples which tested false on the predicate of Question 1, together with samples which tested false on the predicate of Question 2. The result of this is that questions are chosen based on a much larger population than in standard decision tree growth, and therefore have a much greater chance of being useful and generalizable. This alleviates the problem of over-partitioning of data, which is a widely-recognized concern during decision tree growth.

The decision tree obtained from this conversion can be grown further. When the rule list $\mathcal{R}$ is exhausted at Step 1, instead of creating a leaf node, continue splitting the samples contained in the node with a decision tree induction algorithm. The splitting criterion used in the experiments is the information gain measure.

4 Experiments

Three experiments that demonstrate the effectiveness and appropriateness of our probability estimates are presented in this section. The experiments are performed on text chunking, a subproblem of syntactic parsing. Unlike full parsing, the sentences are divided into non-overlapping phrases, where each word belongs to the lowest parse constituent that dominates it.

The data used in all of these experiments is the CoNLL-2000 phrase chunking corpus (CoNLL, 2000). The corpus consists of sections 15-18 and section 20 of the Penn Treebank (Marcus et al., 1993), and is pre-divided into a 8936-sentence (211727 tokens) training set and a 2012-sentence (47377 tokens) test set. The chunk tags are derived from the parse tree constituents, and the part-of-speech tags were generated by the Brill tagger (Brill, 1995).

As was noted by Ramshaw & Marcus (1999), text chunking can be mapped to a tagging task, where each word is tagged with a chunk tag representing the phrase that it belongs to. An example sentence from the corpus is shown in Table 4. As a contrasting system, our results are compared with those produced by a C4.5 decision tree system (henceforth C4.5). The reason for using C4.5 is twofold: firstly, it is a widely-used algorithm which achieves state-of-the-art performance on a broad variety of tasks; and

Word	POS tag	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 of a sentence with chunk tags

secondly, it belongs to the same class of classifiers as our converted transformation-based rule list (henceforth TBLDT).

To perform a fair evaluation, extra care was taken to ensure that both C4.5 and TBLDT explore as similar a sample space as possible. The systems were allowed to consult the word, the part-of-speech, and the chunk tag of all examples within a window of 5 positions (2 words on either side) of each target example.[2] Since multiple features covering the entire vocabulary of the training set would be too large a space for C4.5 to deal with, in all of experiments where TBLDT is directly compared with C4.5, the word types that both systems can include in their predicates are restricted to the most "ambiguous" 100 words in the training set, as measured by the number of chunk tag types that are assigned to them. The initial prediction was made for both systems using a class assignment based solely on the part-of-speech tag of the word.

Considering chunk tags within a contextual window of the target word raises a problem with C4.5. A decision tree generally trains on independent samples and does not take into account changes of any features in the context. In our case, the samples are dependent; the classification of sample i is a feature for sample $i + 1$, which means that changing the classification for sample i affects the context of sample $i + 1$. To address this problem, the C4.5 systems are trained with the correct chunks in the left context. When the system is used for classification, input is processed in a left-to-right manner; and the output of the system is fed forward to be used as features in the left context of following samples. Since C4.5 generates probabilities for each classification decision, they can be redirected into the input for the next position. Providing the decision tree with this confidence information effectively allows it to perform a limited search over the entire sentence.

C4.5 does have one advantage over TBLDT, however. A decision tree can be trained using the *subsetting* feature, where questions asked are of the form: "does feature f belong to the set F?". This is not something that a TBL can do readily,

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but since the objective is in comparing TBLDT to another state-of-the-art system, this feature was enabled.

4.1 Evaluation Measures

The most commonly used measure for evaluating tagging tasks is tag accuracy. It is defined as

$$\text{Accuracy} = \frac{\#\text{ of correctly tagged examples}}{\#\text{ of examples}}$$

In syntactic parsing, though, since the task is to identify the phrasal components, it is more appropriate to measure the precision and recall:

$$\text{Precision} = \frac{\#\text{ of correct proposed phrases}}{\#\text{ of proposed phrases}}$$

$$\text{Recall} = \frac{\#\text{ of correct proposed phrases}}{\#\text{ of correct phrases}}$$

To facilitate the comparison of systems with different precision and recall, the F-measure metric is computed as a weighted harmonic mean of precision and recall:

$$F_\beta = \frac{(\beta^2 + 1) \times \text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}}$$

The β parameter is used to give more weight to precision or recall, as the task at hand requires. In all our experiments, β is set to 1, giving equal weight to precision and recall.

The reported performances are all measured with the evaluation tool provided with the CoNLL corpus (CoNLL, 2000).

4.2 Active Learning

To demonstrate the usefulness of obtaining probabilities from a transformation rule list, this section describes an application which utilizes these probabilities, and compare the resulting performance of the system with that achieved by C4.5.

Natural language processing has traditionally required large amounts of annotated data from which to extract linguistic properties. However, not all data is created equal: a normal distribution of annotated data contains much redundant information. Seung et al. (1992) and Freund et al. (1997) proposed a theoretical active learning approach, where samples are intelligently selected for annotation. By eliminating redundant information, the same performance can be achieved while using fewer resources. Empirically, active learning has been applied to various NLP tasks such as text categorization (Lewis and Gale, 1994; Lewis and Catlett, 1994; Liere and Tadepalli, 1997), part-of-speech tagging (Dagan and Engelson, 1995; Engelson and Dagan, 1996), and base noun phrase chunking (Ngai and Yarowsky, 2000), resulting in significantly large reductions in the quantity of data needed to achieve comparable performance.

This section presents two experimental results which show the effectiveness of the probabilities generated by the TBLDT. The first experiment compares the performance achieved by the active learning algorithm using TBLDT with the performance obtained by selecting samples sequentially from the training set. The second experiment compares the performances achieved by TBLDT and C4.5 training on samples selected by active learning.

The following describes the active learning algorithm used in the experiments:

1. Label an initial T_1 sentences of the corpus;

2. Use the machine learning algorithm (C4.5 or TBLDT) to obtain chunk probabilities on the rest of the training data;

3. Choose T_2 samples from the rest of the training set, specifically the samples that optimize an evaluation function f, based on the class distribution probability of each sample;

4. Add the samples, including their "true" classification[3] to the training pool and retrain the system;

5. If a desired number of samples is reached, stop, otherwise repeat from Step 2.

The evaluation function f that was used in our experiments is:

$$f(S) = \frac{1}{|S|} \sum_{i=1}^{|S|} H(C|S, i)$$

where $H(C|S, i)$ is the entropy of the chunk probability distribution associated with the word index i in sentence S.

Figure 2 displays the performance (F-measure and chunk accuracy) of a TBLDT system trained on samples selected by active learning and the same system trained on samples selected sequentially from the corpus versus the number of words in the annotated training set. At each step of the iteration, the active learning-trained TBLDT system achieves a higher accuracy/F-measure, or, conversely, is able to obtain the same performance level with less training data. Overall, our system can yield the same performance as the sequential system with 45% less data, a significant reduction in the annotation effort.

Figure 3 shows a comparison between two active learning experiments: one using TBLDT and the other using C4.5.[4] For completeness, a sequential run using C4.5 is also presented. Even though C4.5 examines a larger space than TBLDT by

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[3]The true (reference or gold standard) classification is available in this experiment. In an annotation situation, the samples are sent to human annotators for labeling.

[4]As mentioned earlier, both the TBLDT and C4.5 were limited to the same 100 most ambiguous words in the corpus to ensure comparability.
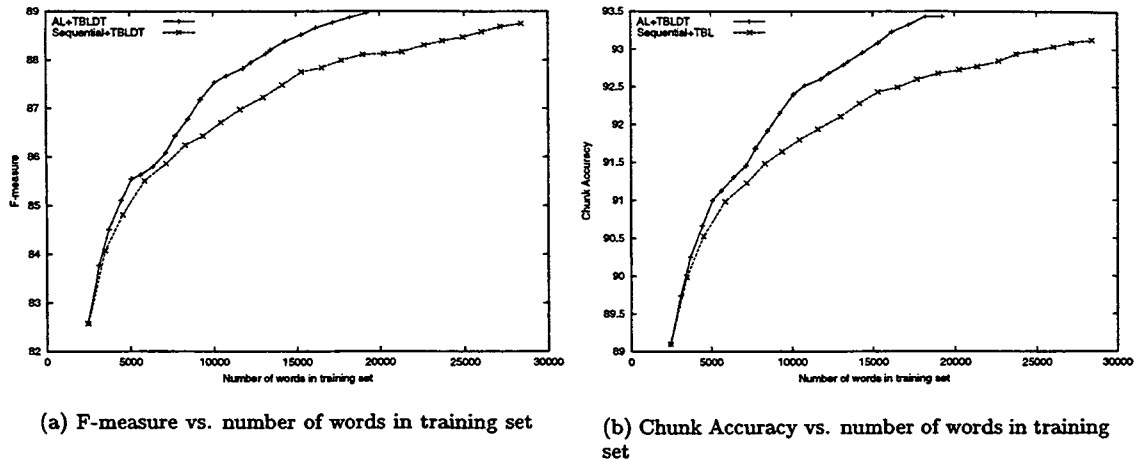
(a) F-measure vs. number of words in training set

(b) Chunk Accuracy vs. number of words in training set

Figure 2: Performance of the TBLDT system versus sequential choice.

(a) F-measure vs. number of words in training set

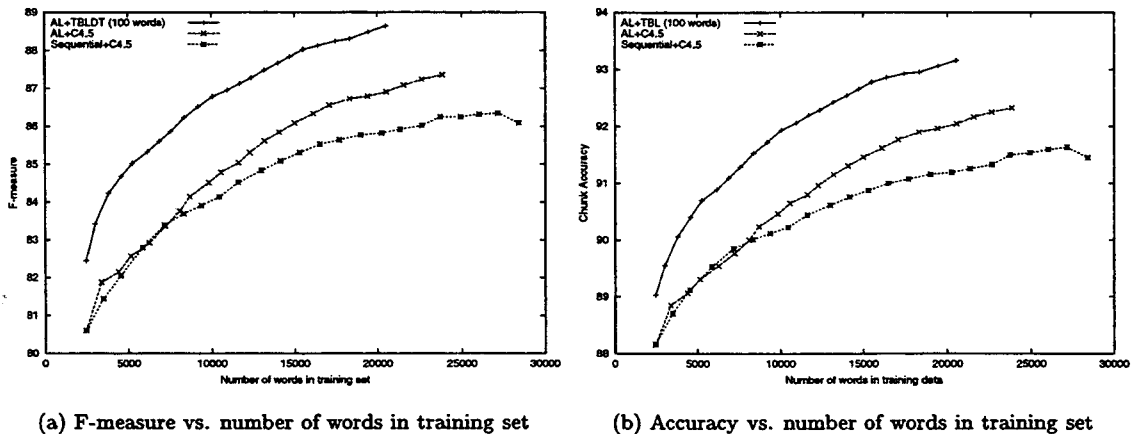(b) Accuracy vs. number of words in training set

Figure 3: Performance of the TBLDT system versus the DT system

utilizing the feature subset predicates, TBLDT still performs better. The difference in accuracy at 26200 words (at the end of the active learning run for TBLDT) is statistically significant at a 0.0003 level.

As a final remark on this experiment, note that at an annotation level of 19000 words, the fully lexicalized TBLDT outperformed the C4.5 system by making 15% fewer errors.

4.3 Rejection curves

It is often very useful for a classifier to be able to offer confidence scores associated with its decisions. Confidence scores are associated with the probability $P(C(x)$ correct$|x)$ where $C(x)$ is the classification of sample x. These scores can be used in real-life problems to *reject* samples that the the classifier is not sure about, in which case a better observation, or a human decision, might be requested. The performance of the classifier is then evaluated on the samples that were not rejected. This experiment framework is well-

established in machine learning and optimization research (Dietterich and Bakiri, 1995; Priebe et al., 1999).

Since non-probabilistic classifiers do not offer any insights into how sure they are about a particular classification, it is not easy to obtain confidence scores from them. A probabilistic classifier, in contrast, offers information about the class probability distribution of a given sample. Two measures that can be used in generating confidence scores are proposed in this section.
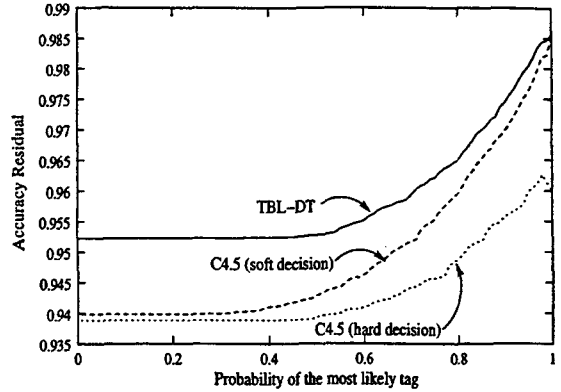
The first measure, the entropy H of the class probability distribution of a sample x, $C(x) = \{p(c_1|x), p(c_2|x) \ldots p(c_k|x)\}$, is a measure of the uncertainty in the distribution:

$$H(C(x)) = -\sum_{i=1}^{k} p(c_i|x) \log_2 p(c_i|x)$$

The higher the entropy of the distribution of class probability estimates, the more uncertain the

31
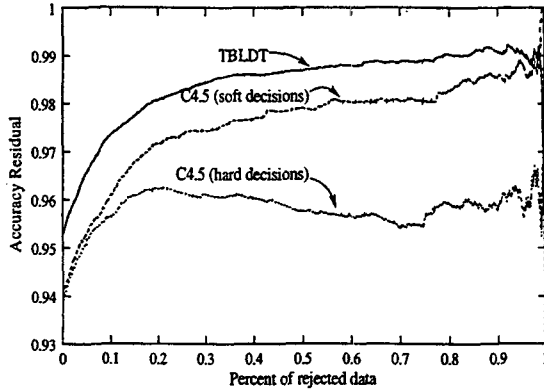
(a) Subcorpus (batch) rejection   (b) Threshold (online) rejection

Figure 4: Rejection curves.

classifier is of its classification. The samples selected for rejection are chosen by sorting the data using the entropies of the estimated probabilities, and then selecting the ones with highest entropies. The resulting curve is a measure of the correlation between the true probability distribution and the one given by the classifier.

Figure 4(a) shows the rejection curves for the TBLDT system and two C4.5 decision trees – one which receives a probability distribution as input ("soft" decisions on the left context) , and one which receives classifications ("hard" decisions on all fields). At the left of the curve, no samples are rejected; at the right side, only the samples about which the classifiers were most certain are kept (the samples with minimum entropy). Note that the y-values on the right side of the curve are based on less data, effectively introducing wider variance in the curve as it moves right.

As shown in Figure 4(a), the C4.5 classifier that has access to the left context chunk tag probability distributions behaves better than the other C4.5 system, because this information about the surrounding context allows it to effectively perform a shallow search of the classification space. The TBLDT system, which also receives a probability distribution on the chunk tags in the left context, clearly outperforms both C4.5 systems at all rejection levels.

The second proposed measure is based on the probability of the most likely tag. The assumption here is that this probability is representative of how certain the system is about the classification. The samples are put in bins based on the probability of the most likely chunk tag, and accuracies are computed for each bin (these bins are cumulative, meaning that a sample will be included in all the bins that have a lower threshold than the probability of its most likely chunk tag). At each accuracy level, a sample will be rejected if the probability of its most likely chunk

Model	Perplexity	Cross Entropy
TBLDT	1.2944	0.2580
DT+probs	1.4150	0.3471
DT	1.4568	0.3763

Table 3: Cross entropy and perplexities for two C4.5 systems and the TBLDT system

is below the accuracy level. The resulting curve is a measure of the correlation between the true distribution probability and the probability of the most likely chunk tag, i.e. how appropriate those probabilities are as confidence measures. Unlike the first measure mentioned before, a threshold obtained using this measure can be used in an online manner to identify the samples of whose classification the system is confident.

Figure 4(b) displays the rejection curve for the second measure and the same three systems. TBLDT again outperforms both C4.5 systems, at all levels of confidence.

In summary, the TBLDT system outperforms both C4.5 systems presented, resulting in fewer rejections for the same performance, or, conversely, better performance at the same rejection rate.

4.4 Perplexity and Cross Entropy

Cross entropy is a goodness measure for probability estimates that takes into account the accuracy of the estimates as well as the classification accuracy of the system. It measures the performance of a system trained on a set of samples distributed according to the probability distribution p when tested on a set following a probability distribution q. More specifically, we utilize conditional cross entropy, which is defined as

$$H\left(C|X\right) = -\sum_{x \in \mathcal{X}} q(x) \cdot \sum_{c \in \mathcal{C}} q(c|x) \cdot \log_2 p(c|x)$$

where $\mathcal{X}$ is the set of examples and C is the set of chunk tags, q is the probability distribution on the

Chunk Type	Accuracy (%)	Precision (%)	Recall (%)	F_1
Overall	95.23	92.02	92.50	92.26
ADJP	-	75.69	68.95	72.16
ADVP	-	80.88	78.64	79.74
CONJP	-	40.00	44.44	42.11
INTJ	-	50.00	50.00	50.00
LST	-	0.00	0.00	0.00
NP	-	92.18	92.72	92.45
PP	-	95.89	97.90	96.88
PRT	-	67.80	75.47	71.43
SBAR	-	88.71	82.24	85.35
VP	-	92.00	92.87	92.44

Table 4: Performance of TBLDT on the CoNLL Test Set

Chunk Type	Accuracy (%)	Precision (%)	Recall (%)	F_1
Overall	93.80	90.02	90.26	90.14
ADJP	-	65.58	64.38	64.98
ADVP	-	74.14	76.79	75.44
CONJP	-	33.33	33.33	33.33
INTJ	-	50.00	50.00	50.00
LST	-	0.00	0.00	0.00
NP	-	91.00	90.93	90.96
PP	-	92.70	96.36	94.50
PRT	-	71.13	65.09	67.98
SBAR	-	86.35	61.50	71.83
VP	-	90.71	91.22	90.97

Table 5: Performance of C4.5 on the CoNLL Test Set

test document and p is the probability distribution on the train corpus.

The cross entropy metric fails if any outcome is given zero probability by the estimator. To avoid this problem, estimators are "smoothed", ensuring that novel events receive non-zero probabilities. A very simple smoothing technique (interpolation with a constant) was used for all of these systems.

A closely related measure is *perplexity*, defined as

$$P = 2^{H(C|X)}$$

The cross entropy and perplexity results for the various estimation schemes are presented in Table 3. The TBLDT outperforms both C4.5 systems, obtaining better cross-entropy and chunk tag perplexity. This shows that the overall probability distribution obtained from the TBLDT system better matches the true probability distribution. This strongly suggests that probabilities generated this way can be used successfully in system combination techniques such as voting or boosting.

4.5 Chunking performance

It is worth noting that the transformation-based system used in the comparative graphs in Figure 3 was not running at full potential. As described earlier, the TBLDT system was only allowed to consider words that C4.5 had access to. However, a comparison between the corresponding TBLDT curves in Figures 2 (where the system is given access to all the words) and 3 show that a transformation-based system given access to all the words performs better than the one with a restricted lexicon, which in turn outperforms the best C4.5 decision tree system both in terms of accuracy and F-measure.

Table 4 shows the performance of the TBLDT system on the full CoNLL test set, broken down by chunk type. Even though the TBLDT results could not be compared with other published results on the same task and data (CoNLL will not take place until September 2000), our system significantly outperforms a similar system trained with a C4.5 decision tree, shown in Table 5, both in chunk accuracy and F-measure.

5 Conclusions

In this paper we presented a novel way to convert transformation rule lists, a common paradigm in natural language processing, into a form that is equivalent in its classification behavior, but is capable of providing probability estimates. Using this approach, favorable properties of transformation rule lists that makes them popular for language processing are retained, while the many advantages of a probabilistic system are gained.

To demonstrate the efficacy of this approach, the resulting probabilities were tested in three ways: directly measuring the modeling accuracy on the test set via cross entropy, testing the goodness of the output probabilities in a active learning algorithm, and observing the rejection curves attained from these probability estimates. The experiments clearly demonstrate that the resulting probabilities perform at least as well as the ones generated by C4.5 decision trees, resulting in better performance in all cases. This proves that the resulting probabilistic classifier is as least as good as other state-of-the-art probabilistic models.

The positive results obtained suggest that the probabilistic classifier obtained from transformation rule lists can be successfully used in machine learning algorithms that require soft-decision classifiers, such as boosting or voting. Future research will include testing the behavior of the system under AdaBoost (Freund and Schapire, 1997). We also intend to investigate the effects that other decision tree growth and smoothing techniques may have on continued refinement of the converted rule list.

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33

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