Part of Speech Tagging in Thai Language Using Support Vector Machine

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Abstract
The elastic-input neuro tagger and hybrid tagger, combined with a neural network and Brill’s error-driven learning, have already been proposed for the purpose of constructing a practical tagger using as little training data as possible. When a small Thai corpus is used for training, these taggers have tagging accuracies of 94.4% and 95.5% (accounting only for the ambiguous words in terms of the part of speech), respectively. In this study, in order to construct more accurate taggers we developed new tagging methods using three machine learning methods: the decision-list, maximum entropy, and support vector machine methods. We then performed tagging experiments by using these methods. As supervised data for POS tagging in the Thai language we used the same corpus as in our group’s previous papers (Ma et al., 1998; Ma et al., 1999; Ma et al., 2000).

1 Introduction
The elastic-input neuro tagger and hybrid tagger, combined with a neural network and Brill’s error-driven learning, have already been proposed for the purpose of constructing a practical tagger using as little training data as possible. When a small Thai corpus is used for training, these taggers have tagging accuracies of 94.4% and 95.5% (accounting only for the ambiguous words in terms of the part of speech), respectively. In this study, in order to construct more accurate taggers we developed new tagging methods using three machine learning methods: the decision-list, maximum entropy, and support vector machine methods. We then performed tagging experiments by using these methods.

In connection with our approach, we should emphasize the following points:

• In this work, we performed POS tagging in the Thai language by using the support vector machine method. Although many studies have considered POS tagging by using machine learning methods, few studies have used the support vector machine method. This method achieves high performance, but it requires huge machine resources and does not work when we use large-scale corpora as supervised data. In addition, with large-scale corpora we can obtain good performance by using a simple method such as HMM (hidden Markov model). For the Thai language, however, large-scale corpora have not yet been constructed, so our approach is effective.

• We also carried out experiments by using the decision list and maximum entropy methods for comparison, and we confirmed that the support vector ma-
chine method produced the best precision. This paper shows data comparing the performance.

- The precision produced by the support vector machine method was slightly higher than that obtained in a previous study (Ma et al., 2000), which used the hybrid tagger combined with a neural network and Brill’s error-driven learning. Since our precision was slightly higher, we have improved the technology of POS tagging in the Thai language.

2 Problems with POS tagging

This study did not consider the segmentation of a sentence into words. We assumed that the words had been segmented before POS tagging began. In this case, a sentence is expressed as follows:

$$S = (w^1, w^2, \cdots, w^n),$$

where \( w^i \) is the \( i \)-th word in the sentence. POS tagging is the application of a POS tag to each word. Therefore, the result of POS tagging is expressed as follows:

$$T = (t^1, t^2, \cdots, t^n)$$

where \( t^i \) is the tag for the POS of word \( w^i \). Our goal is to determine the correct POS tag for each word. The categories indicated by the POS tags are defined in advance. POS-tagging problems can thus be regarded as classification problems and can be handled by machine learning methods.

3 Machine learning methods

In this paper, we used the following three machine learning methods:

- decision-list method
- maximum-entropy method
- support-vector machine method

In this section, these machine-learning methods are explained.

3.1 Decision-list Method

In this method, pairs consisting of a feature \( f_j \) and a category \( a \) are stored in a list, called a decision list. The order in the list is defined in a certain way, and all the pairs are arranged in this order. The decision list method searches for pairs from the top of the list and outputs the category of the first pair with the same feature as a given problem as the desired answer. In this study, we use the value of \( p(a|f_j) \) to arrange pairs in order.

This decision list method is equivalent to the following method using probabilistic equations. The probability of each category is calculated by using one feature \( f_j (\in F, 1 \leq j \leq k) \), and the category with the highest probability is judged to be the correct category. The probability of producing a category \( a \) in a context \( b \) is given by the following equation:

$$p(a|b) = p(a|f_{\text{max}}),$$

where \( f_{\text{max}} \) is defined as

$$f_{\text{max}} = \arg\max_{f_j \in F} \max_{a_i \in A} \tilde{p}(a_i|f_j),$$

such that \( \tilde{p}(a_i|f_j) \) is the occurrence rate of category \( a_i \) when the context includes feature \( f_j \).

Although there are also such decision-tree learning methods as C4.5, we did not use them for the following two reasons. First, decision-tree learning methods perform worse than the other methods on several tasks (Murata et al., 2000; Taira and Haruno, 2000). Second, the number of attributes used in this research was very large, and the performance of C4.5 would become worse if the number of attributes was decreased so that C4.5 could work.
3.2 Maximum-entropy Method

In this method, the distribution of probabilities \( p(a,b) \) when equation (3) is satisfied and equation (1) is maximized is calculated. The category with the maximum probability as calculated from this distribution of probabilities is judged to be the correct category [Ristad, 1997, Ristad, 1998]:

\[
\sum_{a \in A, b \in B} p(a,b)g_j(a,b) = \sum_{a \in A, b \in B} \tilde{p}(a,b)g_j(a,b) \quad (5)
\]

\[
\text{for } \forall f_j \ (1 \leq j \leq k)
\]

\[
H(p) = -\sum_{a \in A, b \in B} p(a,b) \log(p(a,b)), \quad (6)
\]

where \( A, B, \) and \( F \) are a set of categories, a set of contexts, and a set of features \( f_j (\in F, 1 \leq j \leq k) \), respectively; \( g_j(a,b) \) is a function with a value of 1 when context \( b \) includes feature \( f_j \) and the category is \( a \), and a value of 0 otherwise; and \( \tilde{p}(a,b) \) is the occurrence rate of pair \( (a,b) \) in the training data.

In general, the distribution of \( \tilde{p}(a,b) \) is very sparse. We cannot use it directly, so we must estimate the true distribution of \( p(a,b) \) from the distribution of \( \tilde{p}(a,b) \). In the maximum-entropy method, we assume that the estimated value of the frequency of each pair of category and feature calculated from \( \tilde{p}(a,b) \) is the same as that calculated from \( p(a,b) \) (This corresponds to Equation 3). These estimated values are not so sparse. We can thus use the above assumption to calculate \( p(a,b) \). Furthermore, we maximize the entropy of the distribution of \( \tilde{p}(a,b) \) to obtain one solution of \( \tilde{p}(a,b) \), because using only Equation 3 produces many solutions for \( \tilde{p}(a,b) \). Maximizing the entropy makes the distribution more uniform, which is known to provide a strong solution to data sparseness problems.

3.3 Support-vector Machine Method

In this method, data consisting of two categories is classified by dividing space with a hyperplane. When the two categories are positive and negative and the margin between positive and negative examples in the training data is larger (see Figure 1), the probability of incorrectly choosing categories in open data is thought to be smaller. The hyperplane maximizing the margin is determined, and classification is done by using this hyperplane. Although the basics of the method are as described above, for extended versions of the method, in general, the inner region of the margin in the training data can include a small number of examples, and the linearity of the hyperplane is changed to non-linearity by using kernel functions. Classification in the extended methods is equivalent to classification using the following discernment function, and the two categories can be classified on the basis of whether the output value of the function is positive or negative [Cristianini and Shawe-Taylor, 2000; Kudoh, 2000]:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b \right) \quad (7)
\]

\[
b = -\frac{\max_{i, y_i = -1} b_i + \min_{i, y_i = 1} b_i}{2}
\]

\[
b_i = \sum_{j=1}^{l} \alpha_j y_j K(x_j, x_i),
\]

where \( x \) is the context (a set of features) of an input example; \( x_i \) and \( y_i (i = 1, \ldots, l, y_i \in \{1, -1\}) \) indicate the context of the training data and its category, respectively; and the
function $\text{sgn}$ is defined as

$$\text{sgn}(x) = \begin{cases} 1 & (x \geq 0), \\ -1 & (\text{otherwise}) \end{cases},$$

(8)

Each $\alpha_i (i = 1, 2, \ldots)$ is fixed when the value of $L(\alpha)$ in Equation (9) is maximum under the conditions of Equations (10) and (11).

$$L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

(9)

$$0 \leq \alpha_i \leq C (i = 1, \ldots, l)$$

(10)

$$\sum_{i=1}^{l} \alpha_i y_i = 0$$

(11)

Although the function $K$ is called a kernel function and various types of kernel functions can be used, this paper uses a polynomial function as follows:

$$K(x, y) = (x \cdot y + 1)^d,$$

(12)

where $C$ and $d$ are constants set by experiment. In this paper, $C$ is fixed as 1 for all experiments. Two values of $d$, $d = 1$ and $d = 2$, are used. A set of $x_i$ that satisfies $\alpha_i > 0$ is called a support vector, and the portion used to perform the sum in Equation (7) is calculated by only using examples that are support vectors.

Support-vector machine methods can handle data consisting of two categories. In general, data consisting of more than two categories can be handled by using the pair-wise method (Kudoh and Matsumoto, 2000). In this method, for data consisting of $N$ categories, all pairs of two different categories ($N(N-1)/2$ pairs) are constructed. Better categories are determined by using a 2-category classifier (in this paper, a support-vector machine is used as the 2-category classifier.), and finally the correct category is determined on the basis of “voting” on the $N(N-1)/2$ pairs analyzed with the 2-category classifier.

The support-vector machine method used in this paper is in fact implemented by combining the support-vector machine method and the pair-wise method described above.

4 Features (information used in classification)

Although we have explained the three machine-learning methods, using these methods requires defining the features (information used in classification). In this section, we explain these features.

As mentioned in Section 4, when the result of word segmentation of a sentence in Thai language is input, we output the POS for each word. Therefore, the features are extracted from the input Thai sentence. Here, we define the following items as features.

- **POS information**

  The candidate POS tags of the current word, the three previous words, and the three subsequent words (e.g., “noun”, “verb”, etc. The total number of features in the Thai corpus is mentioned in Section 5).

  The candidate POSs were determined in advance for each word by using a word dictionary or the Thai corpus.

- **POS and order information**

  The pair of candidate POS tags and their occurrence order in the current word, three previous words, and three subsequent words (e.g., “noun, the first

5 In general, since the words preceding the current word have already been analyzed, we can use only the one POS used in the current context, not possible POSs. In fact, previous studies used the POSs of the results of tagging in the previous context. This paper, however, uses possible POSs in the previous context for the following two reasons. One is the easiness of processing, and the other is that we considered cases when the tagging in the previous context was performed wrongly.

6 In Ma’s previous studies the probability of a POS for each word was used. The machine learning methods (decision list method and maximum entropy method) based on features as used in this paper, however, are difficult to use with continual values such as probabilities in the features. Therefore, we used the occurrence order instead of the occurrence probability. Since the order information is at most the number of ambiguities in POS and thus not so large, the machine learning methods used in this paper can handle the order. On the other hand, the support vector machine methods can handle continual values in the features. However, we used the occurrence order rather than the occurrence probability to enable
5 Experiments

This section describes our experiments on POS tagging in the Thai language by using the machine-learning methods described in Section 3 with the feature sets described in Section 4 for the tasks described in Section 2.

The experiments in this paper were performed by using the same Thai corpus as in our previous papers (Ma et al., 1998; Ma et al., 1999; Ma et al., 2000). This corpus contains 10,452 sentences randomly divided into two sets: one with 8,322 sentences, for training; and the other with 2,130 sentences, for testing. The training and testing sets contain, respectively, 22,311 and 6,717 ambiguous words (in other words, the target words for POS tagging). The ambiguous words are those that may serve as more than one POS. The other words always serve as the same POS, and they were assigned to a POS by using a word dictionary rather than a machine learning method. 47 POSs are defined for the Thai corpus (Charoenporn et al., 1997).

The experimental results are shown in Table 1. The precisions for “Baseline method”, “HMM”, “Rule-based”, “Elastic NN”, and “Hybrid tagger” are from previous papers (Ma et al., 1999; Ma et al., 2000). In the baseline method, a word is judged to represent the POS that most frequently appears for that word in the training corpus. HMM refers to a method that performs POS tagging at the sentence level by using the hidden Markov model. “Rule-based” indicates Brill’s method, that is, the use of error-driven transformation rules. “Elastic NN” is a method our group proposed previously (Ma et al., 1999), using a three-layered perceptron in which the length of the input layer is changeable. “Hybrid tagger” is another method our group proposed previously (Ma et al., 2000), combining the elastic NN and rule-based methods. It improves elastic NN by using Brill’s error-driven learning. The precision of hybrid tagger was the best among our previous studies based on the Thai corpus used in this paper. The results in Table 1 for the other three methods (decision list method, maximum entropy method, and support vector machine method) were obtained in this study.

Among these three methods, the precision of the support vector machine method (96.1%) was the best. This result is consistent with our other previous studies (Murata et al., 2001a; Murata et al., 2001b). The precision of the support vector machine method was also higher than that of hybrid tagger (95.5%), which had produced the best precisions in the previous studies. Therefore our study has improved the technology of POS tagging in the Thai language.

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**Table 1: Experimental results**

| Method                | Precision |
|-----------------------|-----------|
| Baseline method       | 83.6%     |
| HMM                   | 89.1%     |
| Rule-based            | 93.5%     |
| Elastic NN            | 94.4%     |
| Hybrid tagger         | 95.5%     |
| Decision list         | 83.6%     |
| Maximum entropy       | 95.3%     |
| Support vector machine| 96.1%     |

(Precisions are as obtained for ambiguous words only.)

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*The precisions shown in this paper were obtained using ambiguous words only. The precision for all words, including non-ambiguous words, was 99.2%.*
Next, we compared the various methods. We first examined the three methods used in this paper. Since they used exactly the same features, the comparison was strict. The order of these methods was as follows:

Support vector > Maximum entropy > Decision list

The precision of the decision list method was very low and almost the same as that of the baseline method. This was because we did not use AND features (combination of features) as inputs for the system. We can thus say that by using only one feature the experiments were under adverse conditions for the decision list method. If we use AND features, the precision of the decision list method will increase but when we make AND features randomly, the number of features increases explosively. When we add a small number of features, we need to thoroughly examine which combinations of features must be added. In contrast, the support vector and maximum entropy methods perform estimation by using all features. Furthermore, the support vector machine method has a framework for considering AND features automatically by adjusting the constant $d$ in the kernel function. We can thus say that the support vector machine method is an effective machine learning method in that we do not have to examine AND features by hand.

Next, we compared our methods with the previous methods. We have to do this carefully, because the features used here did not match those used in the previous studies. We first compared the rule-based and hybrid tagger methods. These methods use not only POS information but also word information in the rule templates used in error-driven learning. We can thus say that these methods use almost the same features as in this study, and therefore, they can be compared to the methods used here. We can say that the order of the main machine learning methods was as follows:

Support vector > Hybrid tagger > Maximum entropy > Rule-based

Next we examined the HMM and elastic NN methods. These methods do not use word information directly: they only use the probability of the occurrence of a POS in each word. We carried out our experiments by eliminating the features of word information to create similar conditions for these methods, as shown in Table 2. All methods produced lower precision in this case than when using word information. When we compared elastic NN (94.4%) and support vector machine (93.9%) with no word information, the former had higher precision. Elastic NN, however, uses the probability of the occurrence of a POS in each word, while support vector machine uses word and order information instead. Since this provides less information than the probability of the occurrence of a POS, this is not a strict comparison. However, from these results we expect that elastic NN should have performance as high as that of support vector machine. As for HMM, we can say that it has lower performance than the support vector machine and maximum entropy methods, because its precision was much lower than for both of these methods.

| Method             | Precision |
|--------------------|-----------|
| Decision list      | 78.0%     |
| Maximum entropy    | 92.3%     |
| Support vector machine | 93.9%     |

(Precisions are as obtained for ambiguous words only.)

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9 A previous paper (Murata et al., 2000) showed that the decision list method can produce high precisions for bunsetsu identification in Japanese sentences by using AND features. In this study, the precision of the decision list method was bad because we did not use AND features.

10 Strictly speaking, hybrid tagger used the AND features, while maximum entropy method can produce better precision when AND features are used. Thus, the order of “Hybrid tagger” and “Maximum entropy” could be changed.

11 Although we have compared methods using different features, we should conduct experiments in which the features are the same.
Finally we examined the reasons why we could improve the precision. The reason that the support vector machine method produced higher precision than the HMM and Elastic NN methods is that it uses word information as well. (“HMM” and “Elastic NN” did not use word information as mentioned above.) In some cases a POS is determined by a word in the previous or subsequent context, and in many of these cases the word information is very helpful. Next, we compared the support vector machine method to rule-based and hybrid tagger methods. Since almost the same information was used among them, we can expect that the support vector machine method should have better performance than the other methods. Since hybrid tagger includes Brill’s error-driven learning, that is the rule-based method, the performance of hybrid tagger will deteriorate when the performance of the rule-based method is bad. We can thus say that we obtained better precision because we used word information and a support vector machine with good performance. As for future work, we should conduct experiments by using word information in elastic NN method.

6 Conclusions

In this paper, we examined POS tagging in the Thai language by using supervised machine learning methods. As supervised data we used the corpus described in our group’s previous papers (Ma et al., 2000). We used the decision list method, the maximum entropy method, and the support vector machine method as machine learning methods. In the experimental results, the support vector machine method produced the best precision. Its precision was slightly higher than the precision obtained in a previous study, which used a hybrid tagger combined with a neural network and Brill’s error-driven learning.

We examined and compared various machine learning methods, including those in previous studies. We discussed the good performance of the support vector machine method. We expected that elastic NN, which is one method from the previous studies, would also have good performance, but it does not use word information and its precision was lower than that of the support vector machine method. We can say that our method in this paper produced better precision because we used word information and because we used the support vector machine method whose performance is good. For the future work, we should conduct experiments by using word information in elastic NN method.

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