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Part of Speech Tagging with Min-Max Modular Neural Networks

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SUMMARY

A parts of speech (POS) tagging system using neural networks has been developed by Ma and colleagues. This system can tag unlearned data with a much higher accuracy than that of the Hidden Markov Model (HMM), which is the most popular method of POS tagging. It does so by learning a small Thai corpus on the order of 10,000 words that are ambiguous as to their POSs. However, the three-layer perceptron used in the system has slow convergence and low learning accuracy even on such a small amount of data. It is therefore difficult to improve accuracy by incrementing the epoch of learning or by increasing the amount of learning data. To solve this problem, the tagging system of this paper makes use of the min-max modular (M^3) neural network of Lu and colleagues. This new system learns faster and has a higher learning accuracy compared with the old one, by decomposing large, complicated POS tagging problems into many smaller, easier problems. Learning accuracy can be improved by using the same learning data and larger data sets can be learned, which results in a much higher tagging accuracy. © 2002 Wiley Periodicals, Inc. Syst Comp Jpn, 33(7): 30–39, 2002; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/scj.1139

Key words: POS tagging; Thai corpus; min-max neural network; parallel learning; overlearning.

1. Introduction

Identifying correct parts of speech for words that are ambiguous in context—parts of speech (POS) tagging—is fundamental to natural language processing. This technique can be applied to the preprocessing of speech synthesis, postprocessing of OCR and speech recognition, and information retrieval. Although many POS tagging systems have been proposed [1–13], these systems need a large amount of learning data, a large corpus whose data have been tagged (for example, on the order of 1 million learning data, for English) to obtain sufficient accuracy. However, for most languages, which are not so well studied as English or Japanese in regard to natural language processing, the corpora are still in the development stage. To avoid this problem, we have developed a system that can almost reach a practical level in terms of tagging accuracy [i.e., the accuracy on tagging unlearned data (the data not used in learning)] by using a small amount of data for learning [14–17]. It uses neural networks, which can be considered to be more robust against the data sparseness problem compared with statistical methods such as HMM. It has been shown to be more accurate in POS tagging than HMM, when a small Thai corpus on the order of 10,000 words that are ambiguous as to their POSs is used for learning.

However, because the three-layer perceptron used in the POS tagging system suffers from a convergence problem, it is not easy for the system to reach a learning accuracy (i.e., the accuracy on tagging the learning data) higher than

96% even with learning data on the order of 10,000 words, and the learning takes a considerable amount of time. In addition, overlearning (overfitting) may occur if the system tries to improve learning accuracy by increasing learning time, so there is no guarantee that the tagging accuracy will be improved. Moreover, the perceptron learning may not converge with more learning data. Therefore, it is difficult to improve tagging accuracy by increasing learning epochs or the amount of learning data.

To solve the problems mentioned above, we adopt the min-max modular (M^3) neural networks of Lu and colleagues [18–20]. The M^3 network is free of convergence problems and can learn POS tagging problems faster and more accurately compared with our previous system because it splits a large-scale problem into several easy and small subproblems. Because the M^3 network can guarantee learning convergence, it becomes possible to significantly decrease the number of units in the hidden layer of each module, which results in a low probability of overlearning when raising the learning accuracy. This improves tagging accuracy by either raising the learning accuracy with the same learning data or with learning a larger amount of data.

This paper is organized as follows. First, we formalize the problem of POS tagging and describe the problem decomposition and solution combination, the two intrinsic operations of the M^3 network. Next, we describe the POS tagging method of the M^3 network. Finally, we describe the experimental results and show that a POS tagging system is superior to other systems in terms of both its learning and generalization ability.

2. POS Tagging Problems

Suppose there is a lexicon:

$$V = (w^1, w^2, \cdots, w^v) \tag{1}$$

where the POSs that can be assigned to each word are listed, and suppose there is a set of POSs:

$$\Gamma = (\tau^1, \tau^2, \cdots, \tau^\gamma) \tag{2}$$

where v is the number of registered words and γ is the number of POSs. The POS tagging problem is to find a string of POSs $T = \tau_1\, \tau_2 \ldots \tau_s (\tau_i \in \Gamma, i = 1, \ldots, s)$ by the following procedure φ when a sentence $W = w_1 w_2 \ldots w_s$ $(w_i \in V, i = 1, \ldots, s)$ is given:

$$\varphi : W^t \rightarrow \tau_t,\ t = 1, \cdots, s \tag{3}$$

Here, t is the index of the target word (the word to be tagged) and W^t is the word sequence which is centered on the target word w_t and has l and r words to the left and right of the target, respectively. That is,

$$W^t = w_{t-l} \cdots w_t \cdots w_{t+r} \tag{4}$$

where $t - l \geq 1$, $t + r \leq s$. POS tagging can therefore be regarded as a classification problem by replacing the POS with a class and can be handled by using neural networks.

3. How to Solve Problems with M^3 Networks

The essential idea of solving problems with M^3 networks is how to decompose a complicated problem into simpler subproblems and how to combine the solutions of the subproblems, which are solved by independent modules, into a final solution to the original problem. In this section, we describe the fundamental aspects of the problem decomposition and solution combination. For the details, see Refs. 18–20.

3.1. Problem decomposition

In this section, we describe how a complicated and large classification problem with K classes (which we call a K-class problem) can be decomposed into small two-class problems. Let T denote the learning set of the K-class problem:

$$T = \{(X_l, Y_l)\}_{l=1}^{L} \tag{5}$$

where $X_l \in R^n$ is the input vector, $Y_l \in R^K$ is the desired output vector, and L is the number of learning data.

Generally, a K-class problem can be decomposed into K two-class problems. The learning set of each two-class problem is as follows:

$$T_i = \{(X_l, y_l^{(i)})\}_{l=1}^{L} \tag{6}$$

where $i = 1, \ldots, K$, and $y_l^{(i)} \in R^1$ is the desired output defined as

$$y_l^{(i)} = \begin{cases} 1 - \epsilon & \text{if } X_l \text{ belongs to the class } C_i \\ \epsilon & \text{if } X_l \text{ belongs to the class } \bar{C}_i \end{cases} \tag{7}$$

where ε is a small positive constant and $\overline{C}_i$ denotes all classes other than C_i. Equation (6) corresponds to the learning set of the problem where the data belonging to C_i are discriminated from the other data. Later, we will use such a learning set to define an actual classification problem.

In general, the two-class problems defined by Eq. (6) are still large and complicated, so they should be further split into the problems of discriminating the data belonging

to C_i from the data belonging to each of the other classes. First, all input vectors $X_l (l = 1, \ldots, L)$ in learning set T are split into subsets according to the class labels. As a result, K subsets of input vectors

$$\chi_i = \{X_l^{(i)}\}_{l=1}^{L_i}, \quad i = 1, \cdots, K \tag{8}$$

are obtained. Here, L_i is the number of input vectors in the i-th subset, so $\Sigma_{i=1}^{K} L_i = L$. A two-class problem defined by Eq. (6) can then be split into $K - 1$ smaller two-class problems:

$$T_{ij} = \{(X_l^{(i)}, 1-\epsilon)\}_{l=1}^{L_i} \cup \{(X_l^{(j)}, \epsilon)\}_{l=1}^{L_j} \tag{9}$$

where $j = 1, \ldots, K (j \neq i)$, $X_l^{(i)} \in \chi_i$, and $X_l^{(j)} \in \chi_j$ are input vectors belonging to C_i and C_j, respectively. Therefore, the two-class problem defined by Eq. (9) is to discriminate C_i from C_j. The larger the number of classes K, the smaller the problem defined by Eq. (9) will be, compared with the two-class problem defined by Eq. (6). In this way, the K-class problem defined by Eq. (5) can be easily split into relatively smaller $K \times (K-1)$ two-class problems as defined by Eq. (9).

Even in these $K \times (K-1)$ two-class problems, however, there will still be complicated problems. These complicated problems, as shown below, can be further split into smaller and simpler problems.

First, suppose the input set χ_i defined in Eq. (8) can be split into N_i $(1 \leq N_i \leq L_i)$ subsets:

$$\chi_{ij} = \{X_l^{(ij)}\}_{l=1}^{L_i^{(j)}}, \quad j = 1, \cdots, N_i \tag{10}$$

where $L_i^{(j)}$ is the number of input vectors in the subset χ_{ij} and $\cup_{j=1}^{N_i} \chi_{ij} = \chi_i$ holds. This partition is not unique. Here, the partition is done randomly. Using such input sets, a two-class problem defined in Eq. (9) can be split into $N_i \times N_j$ problems:

$$T_{ij}^{(u,v)} = \{(X_l^{(iu)}, 1-\epsilon)\}_{l=1}^{L_i^{(u)}} \cup \{(X_l^{(jv)}, \epsilon)\}_{l=1}^{L_j^{(v)}} \tag{11}$$

where $u = 1, \ldots, N_i$, $v = 1, \ldots, N_j$, $X_l^{(iu)} \in \chi_{iu}$ and $X_l^{(jv)} \in \chi_{jv}$ are input vectors belonging to C_i and C_j, respectively.

Therefore, if all of the two-class problems defined in Eq. (9) are split into smaller two-class problems in Eq. (11), the K-class problem is decomposed into $\Sigma_{i=1}^{K} \Sigma_{j=1(j\neq i)}^{K} N_i \times N_j$ smaller two-class problems. If the splitting is performed such that a learning set has only two different elements (i.e., $L_i^{(u)} = 1$ and $L_j^{(v)} = 1$), Eq. (11) can be expressed as

$$T_{ij}^{(u,v)} = \{(X_l^{(iu)}, 1-\epsilon) \cup (X_l^{(jv)}, \epsilon)\} \tag{12}$$

This is clearly a linearly separable problem.

3.2. Solution combination

After the modules learn the split problems, the modules must be integrated to solve the original problem. In this section, we describe how the modules are merged. For the question as to why the network formed by such a merging can solve the original problem, see Refs. 19 and 20.

We use three units, MIN, MAX, and INV, for the integration of modules. Here, let M_{ij} and $\mathrm{M}_{ij}^{(u,v)}$ denote the modules which learn the learning set T_{ij} [Eq. (9)] and $T_{ij}^{(u,v)}$ [Eq. (11)], respectively. Let M_{ij} denote the (i, j)-th element of the $K \times K$ matrix $\mathcal{M}$, and let $\mathrm{M}_{ij}^{(u,v)}$ denote the (u, v)-th element of the $N_i \times N_j$ matrix $\mathcal{M}_{ij}$, which corresponds to the element (i, j) of $\mathcal{M}$.

When solving the K-class problem T [Eq. (5)] by splitting it into $K \times (K-1)$ two-class problems T_{ij} [Eq. (9)], the modules in each row of matrix $\mathcal{M}$ are first merged using the MIN unit, which selects the minimum value from multiple inputs:

$$\mathrm{MIN}_i = \min(\mathrm{M}_{i1}, \cdots, \mathrm{M}_{ij}, \cdots, \mathrm{M}_{iK}), \quad i = 1, \cdots, K \ (i \neq j) \tag{13}$$

where, for simplicity, the symbols of the MIN unit and the modules express their outputs. Next, using the outputs of the K MIN units, the final solution can be obtained as

$$C = \arg\max_i \{\mathrm{MIN}_i\}, \quad i = 1, \cdots, K \tag{14}$$

where C is the class to which the input data belong.

If there exists a large two-class problem T_{ij}, it is further split into smaller problems $T_{ij}^{(u,v)}$. In this case, the modules $\mathrm{M}_{ij}^{(u,v)}$ that learn $T_{ij}^{(u,v)}$ are merged as follows. First, N_j modules in each row of matrix $\mathcal{M}_{ij}$ are merged by the MIN unit:

$$\mathrm{MIN}_{ij}^{(u)} = \min(\mathrm{M}_{ij}^{(u1)}, \cdots, \mathrm{M}_{ij}^{(uN_j)}), \quad u = 1, \cdots, N_i \tag{15}$$

Next, the N_i MIN units are merged into the module M_{ij} by the MAX unit, which selects the maximum value from multiple inputs:

$$\mathrm{M}_{ij} = \max(\mathrm{MIN}_{ij}^{(1)}, \mathrm{MIN}_{ij}^{(2)}, \cdots, \mathrm{MIN}_{ij}^{(N_i)}) \tag{16}$$

The merged module M_{ij} in this way is integrated into Eq. (13).

From the viewpoint of classification, the two-class problems T_{ij} and T_{ji} are identical. The only difference between them is the desired output of the modules. That is, if the desired output of the former problem is $1 - \varepsilon$ [see Eq.

(7)], then that of the latter is ε. Therefore, M_{ji} can be constructed using M_{ij} and the INV unit, which convert the input values.

4. POS Tagging with M^3 Network

4.1. POS tagging of Thai

Unlike Japanese or English, Thai words have no inflection. That is, the lexical form is fixed even when the word is in a different position or performs different roles in a sentence. Moreover, it often happens that one word serves as multiple POSs, such as verb and preposition, or verb and adverb. These facts imply that POS tagging of Thai is more difficult than in Japanese or English (for more details, see Ref. 21). On the other hand, the ambiguity rates (the rate of words ambiguous in POSs in the corpus being used) are 35% for English (Brown Corpus [22]), 56% for Japanese (Kyodai Corpus [23]), and 42% for Chinese (Tsinghua University corpus [24]), respectively, but only 19% for Thai (the corpus used in this paper*). It is not clear whether this figure (19%) reflects the actual characteristics of Thai, because the size of the corpus is small. Regardless, the tagging accuracy shown in this paper is measured only for the words that are ambiguous in POS, so the result will not be influenced by the ambiguity rate.

4.2. Decomposition of the POS tagging problem

The Thai corpus consists of 10,452 sentences. We treat a randomly selected 8322 sentences of the corpus as the learning data and the remaining 2130 sentences as the testing data. The learning data contain 124,331 words, of which 22,311 words are ambiguous in POS. The testing data contain 34,544 words, of which 6717 words are ambiguous in POS. We use only ambiguous words for the learning of the network. Although 47 kinds of POSs are defined in Thai [21, 25], only 38 of them appear in the corpus. Therefore, the POS tagging problem here can be treated as a 38-class classification problem.† The class distributions of the 22,311 learning data and the 6716 testing data are shown in Table 1.

According to Section 3.1, this 38-class classification problem is first uniquely split into $K \times (K-1) = 38 \times 37$ two-class problems $T_{ij}(i, j = 1, \ldots, K, j \neq i)$ defined in Eq. (9). However, as shown in Table 1, while the number of learning data in the smallest two-class problem ($T_{36,38}$) is only 2 + 1 = 3, that of the largest two-class classification problem ($T_{6,8}$) is 3008 + 3197 = 6205. Since such a problem is still too large, according to Section 3.1, we randomly split the data sets of the 12 classes that contain more than 481 data (C_{10}) in Table 1, so that each subset contains 300 or less data.* As a result, the two-class problems $T_{i,j}$ containing these large classes are further split into $N_i \times N_j$ two-class problems $T_{ij}^{(u,v)}$ $(u = 1, \ldots, N_i, v = 1, \ldots, N_j)$ defined in

Table 1. Distribution of data belonging to each class

Class	Number of data		Class	Number of data	
	learning	testing		learning	testing
C_1	3,041	962	C_{20}	4	0
C_2	72	13	C_{21}	76	17
C_3	1,444	385	C_{22}	4	7
C_4	2,400	701	C_{23}	9	2
C_5	1,582	399	C_{24}	57	15
C_6	3,008	1,011	C_{25}	32	11
C_7	12	0	C_{26}	90	34
C_8	3,197	1,008	C_{27}	30	5
C_9	1,537	475	C_{28}	6	1
C_{10}	481	176	C_{29}	88	23
C_{11}	705	233	C_{30}	2	1
C_{12}	787	226	C_{31}	177	58
C_{13}	601	108	C_{32}	6	0
C_{14}	124	38	C_{33}	8	0
C_{15}	906	328	C_{34}	17	1
C_{16}	90	30	C_{35}	20	3
C_{17}	213	49	C_{36}	2	0
C_{18}	875	214	C_{37}	131	37
C_{19}	476	145	C_{38}	1	0

*The Thai corpus, ORCHID (Open linguistic Resources CHanelled toward InterDisciplinary research), used in this paper is the outcome of the collaboration project [21] of the Communications Research Laboratory (CRL) and Thai National Electronics and Computer Technology Center (NECTEC) from 1996.

†Although only 38 kinds of POSs appear in the corpus, by taking into account the generalization ability, the input format of our system was designed to cope with all 47 POSs (see Section 4.3.1).

*The two values (481 and 300) may be determined by considering the trade-off in speed of convergence and number of modules (the number of parameters). If convergence speed is needed, these values should be decreased, or vice versa.

Eq. (11). Here, N_i and N_j denote the numbers of subsets derived from the learning data in class C_i and class C_j, respectively, as in Section 3.1. The numbers of subsets larger than 1 are shown in Table 2 (that the number of subsets is 1 means that the data set of the class has not been split). Therefore, for example, the two-class problem $T_{1,2}$ is split into $N_1 \times N_2 = 10 \times 1 = 10$ subproblems, and $T_{1,3}$ is split into $N_1 \times N_3 = 10 \times 5 = 50$ subproblems. On the other hand, problems like $T_{2,7}$ are not split any further. That is, $N_2 = 1$ and $N_7 = 1$ hold (note that N_2 and N_7 are not included in Table 2).

As mentioned in Section 3.2, two-class problems T_{ij} and T_{ji} are identical, so the 38-class POS tagging problem is split into

$$\sum_{i=1}^{38} \sum_{j=i+1}^{38} N_i \times N_j = 3,893 \tag{17}$$

smaller two-class problems. Among these, the largest two-class problem is $T_{10,19}$ in which the number of learning data is 481 + 476 = 957.

4.3. The M^3 network for POS tagging

4.3.1. Construction

The M^3 network is constructed by merging the above-mentioned 3893 modules that learned the 3893 two-class subproblems as shown in Fig. 1. Each module M_{ij} is constructed as in Fig. 2, if the corresponding problem T_{ij} is split (e.g., T_{13}, see Table 2). In the example in the figure, M_{13} is composed of 50 modules $M_{13}^{(u,v)}$ ($u = 1, \ldots, 10$, $v = 1, \ldots, 5$), because the problem T_{13} is split into $N_1 \times N_3 = 10 \times 5 = 50$ subproblems. $M_{ji}(j > i)$ is constructed by using M_{ij} and the INV unit.

Table 2. Number of subsets of learning data in each class

	Number of subsets		Number of subsets
N_1	10	N_9	5
N_3	5	N_{11}	2
N_4	8	N_{12}	2
N_5	5	N_{13}	2
N_6	10	N_{15}	3
N_8	10	N_{18}	3

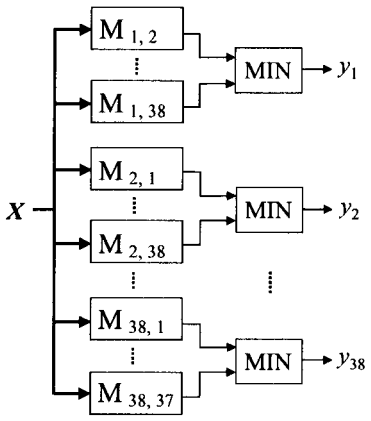

Fig. 1. Composition of the M^3 network.

4.3.2. Input and output

The input vector X (or X_l [Eq. (5)] at the learning phase) of the M^3 network is constructed from a word sequence W^t [Eq. (4)] that is centered on the target word w_t and has l and r words to the left and right of w_t, respectively:

$$X = (x_{t-l}, \cdots, x_t, \cdots, x_{t+r}) \tag{18}$$

Concretely, given the position p ($p = t - l, \ldots, t + r$) of the word w, x_p, an element of X, is a vector:

$$x_p = (e_{w1}, e_{w2}, \cdots, e_{w\gamma}) \tag{19}$$

where the dimension γ (47) of the vector is equal to the number of kinds of POSs. The dimension of the input vector X is $\gamma \times (l + 1 + r)$. If the word w appears in the learning data, each element e_{wi} is obtained as follows:

$$e_{wi} = \mathrm{Prob}(\tau^i | w) \tag{20}$$

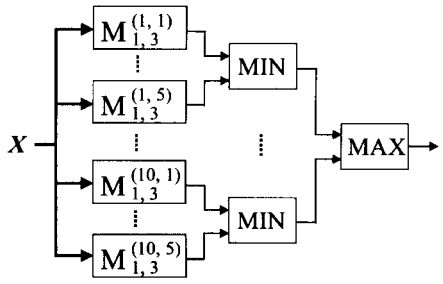

Fig. 2. Composition of module $M_{1,3}$.

where Prob($\tau^i|w$) is a prior probability of τ^i that the word w can take. It is estimated from the learning data:

$$\mathrm{Prob}(\tau^i|w) = \frac{|\tau^i, w|}{|w|} \tag{21}$$

where $|\tau^i, w|$ is the number of times both τ^i and w appear, and $|(w)|$ is the number of times w appears in the learning data. If the word w does not appear in the learning data, each element e_{wi} is given by

$$e_{wi} = \begin{cases} \frac{1}{\gamma_w} & \text{if } \tau^i \text{ is a candidate} \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

where γ_w is the number of kinds of POSs that the word w can take.*

The output vector Y is defined as

$$Y = (y_1, y_2, \cdots, y_{38}) \tag{23}$$

provided that Y is decoded as

$$\tau(w_t) = \begin{cases} \tau^i & \text{if } y_i \geqq 0.5 \ \& \ y_j < 0.5 \text{ for } j \neq i \\ Unknown & \text{otherwise} \end{cases} \tag{24}$$

where $\tau(w_t)$ is the result of tagging of the word w_t.

In the systems that have been proposed so far [16], an elasticity has been introduced to the length of inputs (l, r) to boost the accuracy of tagging. However, since these systems use gradual learning "from small networks to large networks," which fits the elasticity, the learning time of the first network used as the kernel is quite long. We do not introduce such an elasticity into the M^3 network to make the learning faster. In addition, during tagging a sentence from left to right, the words on the left side of the target word have already been tagged. In the systems proposed so far, the tagging results for these preceding words are dynamically used to construct inputs. For simplicity, we do not distinguish between left and right words, and we use the method described above for constructing inputs. Moreover, in the systems proposed so far, when constructing an input x_p [Eq. (19)], the information gain (IG) computed from the learning data is used as weights. However, in our system, we do not use IG because the exact IG for each module cannot be obtained for the split data due to the small number of learning data in this case.

5. Experimental Results

The data described in Section 4.2 were used. The length (l, r) of the word sequence given to the M^3 network was (3,3). Corresponding to this length, the number of units on the input layer is $(l + 1 + r) \times \gamma = 7 \times 47 = 329$, where γ denotes the number of kinds of POSs. Each module of the M^3 network is basically composed of a three-layer perceptron with 266 – 2 – 1 units in the input, hidden, and output layers, respectively. The learning for all modules is iterated through all the learning data of the corresponding subproblems until the error $E_{ACT}(k)$ is smaller than the objective error:

$$E_{ACT}(k) = \frac{\sum_{b=1}^{P} |D^{(b)} - O^{(b)}(k)|}{P} \tag{25}$$

where k is the number of epochs, $D^{(b)}$ is the desired output for the b-th learning data, $O^{(b)}(k)$ is the actual output for the b-th leaning data, and P is the total number of learning data. If the error is still larger than the objective error after 2000 epochs, we regard the module as nonconvergent. In this case, we perform the learning again by increasing the number of units in the hidden layer to 4 or 6.*

The previous system used for comparative experiments is composed of a three-layer perceptron with $[47 \times (l + 1 + r)]$ units in the input layer, $[47 \times (l + 1 + r)]/2$ units in the hidden layer, and 38 units in the output layer. The length (l, r) of a word sequence given is elastic. In the learning phase, (l, r) increases stepwise as (1, 1) → (2, 1) → (2, 2) → (3, 2) → (3, 3), that is, the learning proceeds gradually from small networks to large networks. In the tagging phase, (l, r) decreases as (3, 3) → (3, 2) → (2, 2) → (2, 1) → (1, 1) → (1, 0) → (0, 0) in compliance with necessity, provided that the number of units in the hidden layer is the maximum number [i.e., the one corresponding to (l, r) = (3, 3)]. A three-layer perceptron using the maximum input length (l, r) [i.e., (3, 3)] was also used for comparative experiments.

In Table 3, the POS tagging accuracies of the M^3 network are shown for six different cases. The accuracy is measured only for the words that have POS ambiguity. In case 1, the objective error is 0.005 and the number of units in the hidden layer is 2 (default). In this case, 3841 modules converged while the remaining 52 modules did not con-

*The learning and testing corpora used in the experiments of the paper are those that have been manually tagged beforehand, so they have no so-called unknown words (words that are not in the dictionary). If we set each element e_{wi} as $1/\gamma$, however, our system then can also handle the case when word w is unknown.

*When the M^3 network is used, there is no problem of convergence in the strict sense, because complicated problems can be split into simpler problems. The convergence problem arises here because we restricted the learning times and the number of units in the hidden layer.

Table 3. Tagging accuracy of M^3 networks*

Case	Objective error	Number of units in hidden layer	number of converged modules	number of unconverged modules	Accuracy (%)	
					learning	testing
1	0.005	2	3,841	52	98.4	92.6
2	0.005	2, 4	3,882	11	98.5	93.0
3	0.005	2, 4, 6	3,890	3	99.5	93.4
4	0.002	2	3,738	155	98.7	93.0
5	0.002	2, 4	3,797	96	99.3	93.1
6	0.002	2, 4, 6	3,852	41	99.8	94.2

*Accuracy was determined only for ambiguous words.

verge. In tagging, the accuracy for the learning data (i.e., the learning accuracy) was 98.4% and the accuracy for the testing data (i.e., the tagging accuracy) was 92.6%. In case 2, for the modules that did not converge after the learning of case 1, the number of units in the hidden layer was increased to 4 and the learning was performed again. In this case, only 11 modules did not converge, and the learning accuracy was 98.5% and the tagging accuracy was 93.0%. In case 3, similarly, for the modules that did not converge after the learning of case 2, the number of units in the hidden layer was increased to 6 and the learning was performed for a third time. In cases 4 to 6, the objective error was decreased to 0.002 and the learning processes of cases 1 to 3 were performed.

The results show that the M^3 network can boost learning accuracy in compliance with necessity and that tagging accuracy increases in proportion to learning accuracy. That is, the problem of overlearning did not occur in this experiment. The reason why the M^3 network is free from overlearning is thought to be that the number of units in the hidden layer is quite small. On the other hand, as for the three-layer perceptron, tagging accuracy decreased as learning accuracy increased, as shown in Table 4. That is, the three-layer perceptron suffered from overlearning.*

Table 5 lists the tagging accuracies of various methods. The baseline model uses only the POS frequencies for each word computed from the learning data and does not use contexts. The highest accuracies in Tables 3 and 4 are shown for the three-layer perceptron and the M^3 network. The methods using neural networks are generally better than the statistical methods, and the M^3 network's accuracy is more than 1% higher than that of the three-layer perceptron and is almost the same as the elastic perceptron.

The most important characteristic of the M^3 network is that a large, complicated problem can be split into smaller, simpler problems and these smaller problems can be learned with independent modules. That is, these modules can be learned in parallel. If the parallel computation is used, the computational time of the M^3 network is dominated by the learning time of the slowest module. Ignoring the speed of the computer used in the experiment, the learning time depends on three elements: data size, number of learning epochs, and number of parameters (weights between neurons) to be estimated. In Table 6, these three elements are shown for the three-layer perceptron, the elastic perceptron, and the M^3 network. For the three-layer

Table 4. Tagging accuracy of three-layer perceptron*

Case	Objective error	Accuracy (%)	
		learning	testing
1	0.005	95.8	93.0
2	0.004	97.0	92.8
3	0.003	97.4	92.6

*Accuracy was determined only for ambiguous words.

*Here, the three-layer perceptron with fixed length $[(l, r) = (3, 3)]$ of input was used. The elastic perceptron was not used in comparative experiments, because its kernel network could not converge in gradual learning when the objective error was decreased to 0.004.

Table 5. Tagging accuracy of various methods*

Method	Accuracy(%)
Baseline model	83.6
Hidden Markov Model	89.1
Three-layer perceptron	93.0
Elastic perceptron	94.4
M^3 network	94.2

*Accuracy was determined only for ambiguous words.

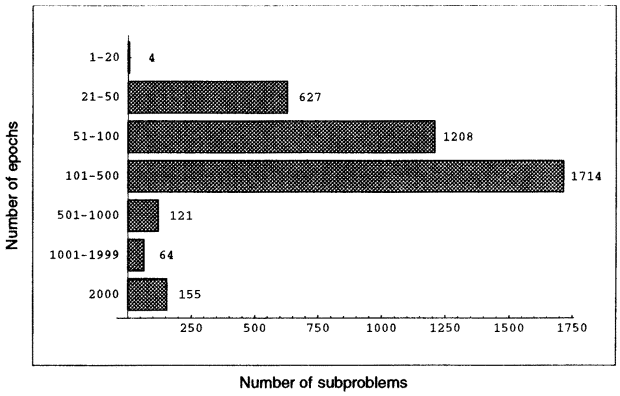

Fig. 3. Distribution of number of epochs.

perceptrons, the data size is the number of all learning data. On the other hand, for the M^3 network, the data size is the number of data in the largest subproblem, because the problem is learned by splitting. The learning of the M^3 network consists of three rounds, as shown in case 6 of Table 3; therefore, the largest data size of each round is shown in the table. The learning method of the elastic perceptron is a gradual learning method consisting of five steps (from smaller networks to larger networks). Therefore, the number of epochs and the corresponding parameters are shown. If we calculate the computational complexity by using "data size $\times$ number of epochs $\times$ number of parameters," then those of the three-layer perceptron, the elastic perceptron, and the M^3 network are 1.06×10^{11}, 3.57×10^{11}, and 5.88×10^{9}, respectively. That is, by using parallel computing the M^3 network should be more than 60 times faster than the other methods. We should note that although the number of units in the output layer of the three-layer perceptron and the elastic perceptron used in the experiment was 47, we used 38 as the number of units when computing computational complexity, the same as in the M^3 network, for a fair comparison. Furthermore, all three elements used for calculating the computational complexity of the M^3 network are the largest cases and the actual computational complexity therefore will be smaller because the three elements are not always present in one learning case.

Even if we do not use parallel computing, the computational time of the M^3 network is comparable to those of the previous methods. Figure 3 shows the distribution of learning epochs when 3893 split subproblems are learned to reach an error below 0.002 (Case 4 in Table 3). The distribution in this figure shows that most modules converge within 500 epochs and that only 4% of all the modules do not converge after learning. The computational complexities of cases 5 and 6 are therefore so small compared with case 4 that they can be ignored. Taking these facts into consideration, we can approximate the average number of learning epochs as 250, the number of parameters as 660, and the average number of learning data as the mean of the maximum and minimum values: (957 + 1)/2 = 479 (see Section 4.2). Thus, we can obtain the approximate total computational complexity: number of modules $\times$ number of parameters $\times$ average number of data $\times$ average number of epochs = $3893 \times 660 \times 479 \times 250 = 3.08 \times 10^{11}$. This value is smaller than that of the previous methods, and even if the ignored computational complexities of cases 5 and 6 are added, the total complexity is comparable to those of the previous methods.

Table 6. Computational complexity of different neural-network-based methods

Methods	Data size	Number of learning epochs	Number of parameters
Three-layer perceptron	22,311	79	60,371
Elastic perceptron	22,311	1,055/30/24/10/14	12,620/21,244/32,078/45,120/60,371
M^3 network	957/699/699	2,000	660/1,320/1,980

6. Conclusion

In this paper, we described a new POS tagging system using a modular neural network that splits a given large, complicated problem into many smaller, simple problems. This system yields almost the same tagging accuracy as the previous methods, but is 60 times faster. It does not have convergence problems and its learning accuracy can be boosted in compliance with necessity, because each module deals with only a small and simple two-class classification problem. Moreover, the number of units in the hidden layer can be set to a very small value, so that overlearning does not occur. Therefore, tagging accuracy can be boosted by increasing the learning accuracy or by increasing the learning data size. In the future, we plan to apply this method to a Chinese corpus, which includes 63 kinds of POSs and more than 100,000 words with ambiguous POSs.

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