Unsupervised learning of word sense disambiguation rules by estimating an optimum iteration number in the EM algorithm

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Abstract

In this paper, we improve an unsupervised learning method using the Expectation-Maximization (EM) algorithm proposed by Nigam et al. for text classification problems in order to apply it to word sense disambiguation (WSD) problems. The improved method stops the EM algorithm at the optimum iteration number. To estimate that number, we propose two methods. In experiments, we solved 50 noun WSD problems in the Japanese Dictionary Task in SENSEVAL2. The score of our method is a match for the best public score of this task. Furthermore, our methods were confirmed to be effective also for verb WSD problems.

1 Introduction

In this paper, we improve an unsupervised learning method using the Expectation-Maximization (EM) algorithm proposed by Nigam et al. (2000) for text classification problems in order to apply it to word sense disambiguation (WSD) problems. The original method works well, but often causes worse classification for WSD. To avoid this, we propose two methods to estimate the optimum iteration number in the EM algorithm.

Many problems in natural language processing can be converted into classification problems, and be solved by an inductive learning method. This strategy has been very successful, but it has a serious problem in that an inductive learning method requires labeled data, which is expensive because it must be made manually. To overcome this problem, unsupervised learning methods using huge unlabeled data to boost the performance of rules learned by small labeled data have been proposed recently (Blum and Mitchell, 1998) (Yarowsky, 1995) (Park et al., 2000) (Li and Li, 2002). Among these methods, the method using the EM algorithm proposed by the paper (Nigam et al., 2000), which is referred to as the EM method in this paper, is the state of the art. However, the target of the EM method is text classification. It is hoped that this method can be applied to WSD, because WSD is the most important problem in natural language processing.

The EM method works well in text classification, but often causes worse classification in WSD. The EM method is expected to improve the accuracy of learned rules step by step in proportion to the iteration number in the EM algorithm. However, this rarely happens in practice, and in many cases, the accuracy falls after a certain iteration number in the EM algorithm. In the worst case, the accuracy of the rule learned through only labeled data is degraded by using unlabeled data. To overcome this problem, we estimate an optimum iteration number in the EM algorithm, and in actual learning, we stop the iteration of the EM algorithm at the estimated number. If the estimated number is 0, it means that the EM method is not used. To estimate the optimum iteration number, we propose two methods: one uses cross validation and the other uses two heuristics besides cross validation. In this paper, we refer to the former method as CV-EM and the latter method as CV-EM2.

In experiments, we solved 50 noun WSD problems in the Japanese Dictionary Task in SENSEVAL2 (Kurohashi and Shirai, 2001). The original EM method failed to boost the precision (76.78%) of the rule learned through only labeled data. On the other hand, CV-EM and CV-EM2 boosted the precision to 77.88% and 78.56%. The score of CV-EM2 is a match for the best public score of this task. Furthermore, these methods were confirmed to be effective also for verb WSD problems.

2 WSD by Naive Bayes

In a classification problem, let \( C = \{ c_1, c_2, \cdots, c_m \} \) be a set of classes. An instance \( x \) is represented as a feature
list $x = (f_1, f_2, \ldots, f_n)$.

We can solve the classification problem by estimating the probability $P(c|x)$. Actually, the class $c_x$ of $x$, is given by

$$c_x = \arg \max_{c \in C} P(c|x).$$

Bayes theorem shows that

$$P(c|x) = \frac{P(c)P(x|c)}{P(x)}.$$ 

As a result, we get

$$c_x = \arg \max_{c \in C} P(c)P(x|c).$$

In the above equation, $P(c)$ is estimated easily; the question is how to estimate $P(x|c)$. Naive Bayes models assume the following:

$$P(x|c) = \prod_{i=1}^{n} P(f_i|c). \quad (1)$$

The estimation of $P(f_i|c)$ is easy, so we can estimate $P(x|c)$ (Mitchell, 1997). In order to use Naive Bayes effectively, we must select features that satisfy the equation 1 as much as possible. In text classification tasks, the appearance of each word corresponds to each feature.

In this paper, we use following six attributes ($e_1$ to $e_6$) for WSD. Suppose that the target word is $w_i$ which is the $i$-th word in the sentence.

- $e_1$: the word $w_{i-1}$
- $e_2$: the word $w_{i+1}$
- $e_3$: two content words in front of $w_i$
- $e_4$: two content words behind $w_i$
- $e_5$: thesaurus ID number of $e_3$
- $e_6$: thesaurus ID number of $e_4$

For example, we make features from the following sentence $^1$ in which the target word is ‘kiroku’$^2$.

```plaintext
kako/saikou/wo/kiroku/suru/ha/
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Because the word to the left of the word ‘kiroku’ is ‘wo’, we get ‘e1=wo’. In the same way, we get ‘e2=suru’. Content words to the left of the word ‘kiroku’ are the word ‘kako’ and the word ‘saikou’. We select two words from them in the order of proximity to the target word. Thus, we get ‘e3=kako’ and ‘e3=saikou’. In the same way, we get ‘e4=suru’ and ‘e4=.’. Note

$^1$A sentence is segmented into words, and each word is transformed to its original form by morphological analysis.

$^2$‘kiroku’ has at least two meanings: ‘memo’ and ‘record’.

that the comma and the period are defined as a kind of content words in this paper. Next we look up the thesaurus ID of the word ‘saikou’, and find 3.1920_4 $^3$.

In our thesaurus, as shown in Figure 1, a higher number corresponds to a higher level meaning.

![Figure 1: Japanese thesaurus: Bunrui-goi-hyou](image)

In this paper, we use a four-digit number and a five-digit number of a thesaurus ID. As a result, for ‘e3=saikou’, we get ‘e5=3192’ and ‘e5=31920’. In the same way, for ‘e3=kako’, we get ‘e5=1164’ and ‘e5=11642’. Following this procedure, we should look up the thesaurus ID of the word ‘suru’. However, we do not look up the thesaurus ID for a word that consists of hiragana characters, because such words are too ambiguous, that is, they have too many thesaurus IDs. When a word has multiple thesaurus IDs, we create a feature for each ID.

As a result, we get following ten features from the above example sentence:

- $e1=wo$, $e2=suru$, $e3=saikou$, $e3=kako$, $e4=suru$, $e4=.$, $e5=3192$, $e5=31920$, $e5=1164$, $e5=11642$.

3 Unsupervised learning using EM algorithm

We can use the EM method if we use Naive Bayes for classification problems. In this paper, we show only key equations and the key algorithm of this method (Nigam et al., 2000).

Basically the method computes $P(f_i|c_j)$ where $f_i$ is a feature and $c_j$ is a class. This probability is given by$^4$

$$P(f_i|c_j) = \frac{1 + \sum_{k=1}^{D} N(f_i,d_k)P(c_j|d_k)}{|F| + \sum_{m=1}^{F} \sum_{k=1}^{D} N(f_m,d_k)P(c_j|d_k)}.$$  \quad (2)

$^3$In this paper we use the bunrui-goi-hyou as a Japanese thesaurus.

$^4$This equation is smoothed by taking into account the frequency 0.
D: all data consisting of labeled data and unlabeled data

d_k: an element in D

F: the set of all features

f_n: an element in F

N(f_i, d_k): the number of f_i in the instance d_k.

In our problem, N(f_i, d_k) is 0 or 1, and almost all of them are 0. If d_k is labeled, P(c_j|d_k) is 0 or 1. If d_k is unlabeled, P(c_j|d_k) is initially 0, and is updated to an appropriate value step by step in proportion to the iteration of the EM algorithm.

By using equation 2, the following classifier is constructed:

\[ P(c_j|d_i) = \frac{P(c_j) \prod_{f_n \in K_{d_i}} P(f_n|c_j)}{\sum_{r=1}^{|C|} P(c_r) \prod_{f_n \in K_{d_i}} P(f_n|c_r)} \]  \hspace{1cm} (3)

In this equation, K_{d_i} is the set of features in the instance d_i.

\[ P(c_j) = \frac{1 + \sum_{k=1}^{|D|} P(c_j|d_k)}{|C| + |D|} \]  \hspace{1cm} (4)

The EM algorithm computes P(c_j|d_i) by using equation 3 (E-step). Next, by using equation 2, P(f_i|c_j) is computed (M-step). By iterating E-step and M-step, P(f_i|c_j) and P(c_j|d_i) converge. In our experiment, when the difference between the current P(f_i|c_j) and the updated P(f_i|c_j) comes to less than 8 \cdot 10^{-6} or the iteration number reaches 10 times, we judge that the algorithm has converged.

4 Estimation of the optimum iteration number

In this paper, we propose two methods (CV-EM and CV-EM2) to estimate the optimum iteration number in the EM algorithm.

The CV-EM method is cross validation. First of all, we divide labeled data into three parts, one of which is used as test data and the others are used as new labeled data. By using this new labeled data and huge unlabeled data, we conduct the EM method. After each iteration in the EM algorithm, the learned rules at the time are evaluated by using test data. This experiment is conducted three times by changing the labeled data and test data. The precision of each iteration number is given by the mean of three experiments. The optimum iteration number is estimated to be the iteration number at which the highest precision is achieved.

The CV-EM2 method also uses cross validation, but estimates the optimum iteration number by ad-hoc mechanism.

First, we judge whether we can use the EM method without modification or not. To do this, we compare the precision at convergence with the precision of the iteration number 1. If the former is higher than the latter, we judge that we can use the EM method without modification. In this case, the optimum iteration number is estimated to be the converged number. On the other hand, if the former is not higher than the latter, we go to the second judgment, namely whether the EM method should be used or not. To judge this, we compare the two precisions of the iteration number 0 and 1. The iteration number 0 means that the EM method is not used. If the precision of the iteration number 0 is higher than the precision of the iteration number 1, we judge that the EM method should not be used. In this case, the optimum iteration number is estimated to be 0. Conversely, if the precision of the iteration number 1 is higher than the precision of the iteration number 0, we judge that the EM method should be used. In this case, the optimum iteration number is estimated to be the number obtained by CV-EM.

In the many cases, the CV-EM2 outputs the same number as the CV-EM. However, the basic idea is different. Roughly speaking, the CV-EM2 relies on two heuristics: (1) Basically we only have to judge whether the EM method can be used or not, because the EM algorithm improves or degrades the precision monotonically. (2) Whether the EM algorithm succeeds correlates closely with whether the precision is improved by the first iteration of the EM algorithm. Therefore, we estimate the optimum iteration number by comparing three precisions, the precision of the iteration number 0, 1 and at convergence.

The figure 2 shows a typical case that the CV-EM2 differs from the CV-EM. In the cross validation, the precision is degraded by the first iteration of the EM algorithm, and then it is improved by iteration, and the maximum precision is achieved at the k-th iteration, but the precision converges to the lower point than the precision of the iteration number 1. In this case, the CV-EM gives k as the estimation, but the CV-EM2 gives 0.

![Figure 2: Typical difference between CV-EM and CV-EM2](image-url)
5 Experiments

To confirm the effectiveness of our methods, we tested with 50 nouns of the Japanese Dictionary Task in SEN-SEVAL2(Kurohashi and Shirai, 2001).

The Japanese Dictionary Task is a standard WSD problem. As the evaluation words, 50 noun words and 50 verb words are provided. These words are selected so as to balance the difficulty of WSD. The number of labeled instances for nouns is 177.4 on average, and for verbs is 172.7 on average. The number of test instances for each evaluation word is 100, so the number of test instances of noun and verb evaluation words is 5,000 respectively. However, unlabeled data are not provided. Note that we cannot use simple raw texts including the target word, because we must use the same dictionary and part of speech set as labeled data. Therefore, we use Mainichi newspaper articles for 1995 with word segmentations provided by RWC. This data is the origin of labeled data. As a result, we gathered 7585.5 and 6571.9 unlabeled instances for per noun and per verb evaluation word on average, respectively.

Table 1 shows the results of experiments for noun evaluation words. In this table, NB means Naive Bayes, EM the EM method, and ideal the EM method stopping at the ideal iteration number. Note that the precision is computed by mixed-gained scoring(Kurohashi and Shirai, 2001) which gives partial points in some cases.

The precision of Naive Bayes which learns through only labeled data was 76.58%. The EM method failed to boost it, and degraded it to 73.56%. On the other hand, by using CV-EM the precision was boosted to 77.88%. Furthermore, CV-EM2 boosted it to 78.56%. This score is a match for the best public score of this task. As successful results in this task, two researches are reported. One used Naive Bayes with various attributes, and achieved 78.22% precision(Murata et al., 2001). Another used Adaboost of decision trees, and achieved 78.47% precision(Nakano and Hirai, 2002). Our score is higher than these scores5. Furthermore, their methods used syntactic analysis, but our methods do not need it.

In the same way, we performed experiments for verb evaluation words. Table 2 shows the results. In the experiment, Naive Bayes achieved 78.16% precision. The EM method boosted it to 78.74%. Furthermore, CV-EM and CV-EM2 boosted it to 79.22% and 79.26% respectively. CV-EM2 is marginally higher than CV-EM.

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5The best score for the total of noun words and verb words is reported to be 79.33% in (Murata et al., 2001).
Table 2: Results of experiments (Verb)

| Word | NB (%) | EM (%) | CV-EM (%) | CV-EM2 (%) | Ideal (%) |
|------|--------|--------|-----------|------------|-----------|
| aitaeru | 71.0 | 78.0 | 78.0 | 78.0 | 78.0 |
| m | 94.0 | 94.0 | 94.0 | 94.0 | 94.0 |
| ukuru | 59.0 | 64.0 | 59.0 | 64.0 | 64.0 |
| uttaeru | 84.0 | 87.0 | 87.0 | 87.0 | 88.0 |
| umareru | 69.0 | 83.0 | 82.0 | 83.0 | 83.0 |
| egaku | 58.0 | 56.0 | 56.0 | 56.0 | 58.0 |
| omou | 90.0 | 89.0 | 89.0 | 89.0 | 90.0 |
| kau | 83.0 | 83.0 | 83.0 | 83.0 | 83.0 |
| kakeru | 58.0 | 57.0 | 58.0 | 58.0 | 58.0 |
| kakaru | 72.0 | 66.0 | 72.0 | 72.0 | 72.0 |
| kawanru | 92.0 | 92.0 | 92.0 | 92.0 | 92.0 |
| kangeru | 99.0 | 99.0 | 99.0 | 99.0 | 99.0 |
| kiku | 56.0 | 55.0 | 55.0 | 55.0 | 56.0 |
| kimaru | 96.0 | 96.0 | 96.0 | 96.0 | 96.0 |
| kimeru | 93.0 | 93.0 | 93.0 | 93.0 | 93.0 |
| kuru | 84.0 | 85.0 | 86.0 | 85.0 | 86.0 |
| kwarenu | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 |
| koeru | 78.0 | 82.0 | 85.0 | 82.0 | 88.0 |
| shuru | 97.0 | 97.0 | 97.0 | 97.0 | 97.0 |
| susumuru | 50.0 | 50.0 | 50.0 | 50.0 | 50.0 |
| susumeru | 97.0 | 95.0 | 97.0 | 97.0 | 97.0 |
| datu | 35.0 | 29.0 | 35.0 | 35.0 | 36.0 |
| chigau | 100.0 | 100.0 | 100.00 | 100.00 | 100.00 |
| tsukuru | 97.0 | 97.0 | 97.0 | 97.0 | 97.0 |
| tsukuru | 69.0 | 75.0 | 78.0 | 75.0 | 78.0 |
| tsuaeru | 75.0 | 76.0 | 76.0 | 76.0 | 76.0 |
| deku | 81.0 | 81.0 | 81.0 | 81.0 | 81.0 |
| deru | 59.0 | 64.0 | 64.0 | 64.0 | 64.0 |
| tou | 69.0 | 79.0 | 79.0 | 79.0 | 79.0 |
| toru | 32.0 | 34.0 | 32.0 | 34.0 | 37.0 |
| neru | 99.0 | 99.0 | 99.0 | 99.0 | 99.0 |
| nokosu | 79.0 | 79.0 | 79.0 | 79.0 | 79.0 |
| noru | 54.0 | 54.0 | 54.0 | 54.0 | 54.0 |
| hau | 36.0 | 36.0 | 36.0 | 36.0 | 36.0 |
| hakaru | 92.0 | 92.0 | 92.0 | 92.0 | 92.0 |
| hanasu | 100.0 | 87.0 | 100.0 | 100.0 | 100.0 |
| hiraku | 86.0 | 94.0 | 94.0 | 94.0 | 94.0 |
| sukumu | 99.0 | 99.0 | 99.0 | 99.0 | 99.0 |
| matsu | 52.0 | 50.0 | 51.0 | 51.0 | 52.0 |
| matomemure | 79.0 | 80.0 | 80.0 | 80.0 | 80.0 |
| mamoru | 79.0 | 71.0 | 70.0 | 71.0 | 79.0 |
| mizeru | 98.0 | 98.0 | 98.0 | 98.0 | 98.0 |
| mitomeru | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 |
| miru | 73.0 | 71.0 | 73.0 | 73.0 | 73.0 |
| mukaru | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 |
| motsu | 57.0 | 52.0 | 57.0 | 57.0 | 62.0 |
| motomeru | 87.0 | 87.0 | 87.0 | 87.0 | 87.0 |
| yonu | 88.0 | 88.0 | 88.0 | 88.0 | 88.0 |
| yoru | 97.0 | 97.0 | 97.0 | 97.0 | 97.0 |
| wakaru | 90.0 | 90.0 | 90.0 | 90.0 | 90.0 |
| average | 78.16 | 78.74 | 80.23 | 79.26 | 79.92 |

6 Discussion

6.1 Cause of failure of the EM method

Why does the EM method often fail to boost the performance? One reason may be the difference among class distributions of labeled data $L$, unlabeled data $U$ and test data $T$. Practically $L$, $U$ and $T$ are the same because they consist of random samples from all data. However, there are differences among them.

Intuitively, learning by combining labeled data and unlabeled data is regarded as learning from the distribution of $L + U$. It is expected that the EM method is effective if $d = d(L, T) - d(L + U, T) > 0$, and is counterproductive if $d < 0$, in which $d(\cdot, \cdot)$ means the distance of two distributions.

To confirm the above expectation, we conduct an experiment by using Kullback-Leibler divergence as $d(\cdot, \cdot)$. The distribution of $L + U$ can be obtained from Equation 4 when the EM algorithm converges. The result of the experiment is shown in Table 3.

Table 3: Effects of the distribution of meanings

| improvement | deterioration |
|-------------|---------------|
| $d > 0$     | 6             |
| $d < 0$     | 7             |
| deterioration | 2       |
|             | 8             |

The columns of the table are divided into positive ($d > 0$) and negative ($d < 0$). Positive means that $L + U$ gets close to $T$ and negative means that $L + U$ goes away from $T$. The rows of the table are divided into improvement of precision and deterioration of precision. In this paper, improvement of precision is when the precision is improved by over 5%, and deterioration of precision is when the precision is degraded by over 5%.

This result indicates that there is a weak correlation between whether $L + U$ gets close to $T$ or goes away from $T$ and whether the EM method is effective or not, but we cannot conclude they are completely dependent. However, the evaluation word ‘genzai’ whose precision falls most by the EM method is precisely the above case. The $d$ for this word is the smallest, −0.30, among all evaluation words. Further investigation of the causes of failure of the EM method is our future work.

6.2 Effectiveness of estimation of CV-EM2

CV-EM2 achieved ideal estimation for 29 of 50 evaluation words, that is 58%. Furthermore, for 15 of the other 21 evaluation words, the difference between the precision through our method and that through ideal estimation did not exceed 2%. Therefore, estimation of CV-EM2 is mostly effective.

The words ‘kokunai’ and ‘kotoba’ are typical cases where estimation fails. The difference between the precision of CV-EM2 and that through ideal estimation exceeded 5%. The failure of estimation for these two words reduced the whole precision.

Figure 3 compares the precision for cross validation and that for actual evaluation for the word ‘kokunai’. In the same way, Figure 3 shows the case of the word ‘kotoba’. In these figures, the x-axis shows the iteration number of the EM algorithm. To clarify the change of precision, the initial precision is set to 0, and the y-axis shows the difference (%) between the actual and initial precision.

In the case of ‘kokunai’, the precision got worse in cross validation, but the precision got better in the actual evaluation. This means that cross validation is use-
less, so it is difficult to estimate an optimum iteration number in the EM algorithm. However, such cases are rare. In the experiment, this case arises for only this word ‘kokunai’. Consider next the case of ‘kotoba’. In cross validation, the precision improved in the first iteration of the EM algorithm, but got worse step by step thereafter. On the other hand, in the actual evaluation, the precision got worse even in the first iteration of the EM algorithm. The difference of these results in the first iteration of the EM algorithm causes our estimation to fail. In future, we must improve our method by further investigation of these words.

Figure 3: Comparison between cross validation and actual evaluation ('kokunai')

Figure 4: Comparison between cross validation and actual evaluation ('kotoba')

6.3 Comparison of CV-EM and CV-EM2

CV-EM2 is slightly superior to CV-EM. In the evaluation word ‘doujitsu’, there is a remarkable difference between the two methods.

Figure 5 shows the change of the precision for ‘doujitsu’ in cross validation, and Figure 6 shows that in actual evaluation.

The precision goes up in cross validation, but goes down largely in actual evaluation. In CV-EM, the best point is selected in cross validation, that is 3. On the other hand, CV-EM2 estimates 0 by using the relation of three precisions: the initial precision, the precision for the iteration 1 and the precision at convergence.

Let’s count the number of words for which CV-EM2 is better or worse than CV-EM. For one word ‘mae’ in nouns and three words ‘kuru’, ‘koeru’ and ‘nakuru’ in verbs, CV-EM was superior to CV-EM2. On the other hand, for four words ‘atama’, ‘kakun’, ‘te’ and ‘doujitsu’ in nouns and four words ‘ukeru’, ‘umareru’, ‘toru’ and ‘mamortu’ in verbs, CV-EM2 was better to CV-EM. These numbers show that our method is somewhat superior to CV-EM.

Figure 5: Cross validation in ‘doujitsu’

Figure 6: Actual evaluation in ‘doujitsu’

6.4 Unsupervised learning for verb WSD

In the experiments, CV-EM and CV-EM2 improved the EM method for both noun words and verb words. The effectiveness of these methods was large for noun words, but was small for verb words. We believe that the cause of this difference is the difficulty of unsupervised learning for verb WSD. In ideal estimation, the precision for noun words was boosted from 76.78% to 79.64% by the EM method, that is 1.037 times. On the other hand, the precision for verb words was boosted from 78.16% to 79.92%
by the EM method, that is 1.022 times. This shows that
the EM method does not work so well for verb words.

We consider that feature independence plays a key role
in unsupervised learning. Suppose the instance $x$ con-
ists of two features $f_1$ and $f_2$. When class $c_x$ of $x$
is judged from feature $f_1$, the probability $P(c_x|f_2)$ is
tuned to be larger. The question is whether it is actually right
or not to increase $P(c_x|f_2)$. If it is right, unsupervised
learning works well, but if it is not, unsupervised learn-
ing fails. Intuitively, feature independence warrants in-
creasing $P(c_x|f_2)$. In noun WSD, the left context of the
target word corresponds to the words modifying the tar-
get word, and the right context of the target word cor-
responds to the verb word whose case slot can have the
target word. Both the left context and right context can
judge the meaning of the target word by itself, and are in-
dependent. Left context and right context act as indepen-
dent features. On the other hand, we cannot find such an
opportune interpretation for the features of verbs (Shin-
nou, 2002). Therefore, the EM method is not so effective
for verb words.

Naive Bayes assumes the independence of features, too.
However, this assumption is not so rigid in practice.
We believe that the improvement by the EM method for
verb words depends on the robustness of Naive Bayes. In
our experiments, the EM method for noun words failed
to boost the precision. We think that the cause is the im-
balance of labeled data, unlabeled data and test data. We
should investigate this in a future study.

6.5 Related works
Co-training(Blum and Mitchell, 1998) is a powerful un-
supervised learning method. In Co-training, if we can
find two independent feature sets for the target problem,
any supervised learning method can be used. Further-
more, it is reported that Co-training is superior to the
EM method if complete independent feature sets can be
used(Nigam and Ghani, 2000). However, Co-training
requires consistency besides independence for two fea-
ture sets. This condition makes it difficult to apply Co-
training to multiclass classification problems. On the
other hand, the EM method requires Naive Bayes to be
used as the supervised learning method, but can be ap-
plied to multiclass classification problems without any
modifications. Therefore, the EM method is more prac-
tical than Co-training.

Yarowsky proposed the unsupervised learning method
for WSD(Yarowsky, 1995). His method is reported to be
a special case of Co-training(Blum and Mitchell, 1998).
As two independent feature sets, one is the context sur-
rounding the target word and the other is the heuristic of
‘one sense per discourse’. However, it is unknown how
valid this heuristic is for granularity of meanings of our
evaluation words. Furthermore, this method needs doc-
uments in which the target word appears multiple times,
as unlabeled data. Therefore, it is not so easy to gather
unlabeled data. On the other hand, the EM method does
not have such problem because it uses sentences includ-
ning the target word as unlabeled data.

6.6 Future works
We have three future works. First, we must raise the pre-
cision for verb words, which may be impossible unless
we use other features, so we need to investigate other fea-
tures. Second, we must improve the estimation method of
the optimum iteration number in the EM algorithm. The
difference between the precision through our estimation
and that through the ideal estimation is large. We can im-
prove the accuracy by improving the estimation method.
Finally, we will investigate the reason for the failure of
the EM method, which may be the key to unsupervised
learning.

7 Conclusions
In this paper, we improved the EM method proposed by
Nigam et al. for text classification problems in order to
apply it to WSD problems. To avoid some failures in the
original EM method, we proposed two methods to esti-
mate the optimum iteration number in the EM algorithm.
In experiments, we tested with 50 noun WSD problems in
the Japanese Dictionary Task in SENSEVAL2. Our two
methods greatly improved the original EM method. Es-
pecially, the score of noun evaluation words was equiva-
lent to the best public score of this task. Furthermore, our
methods were also effective for verb WSD problems. In
future, we will tackle three works: (1) To find other effec-
tive features for unsupervised learning of verb WSD, (2)
To improve the estimation method of the optimum itera-
tion number in the EM algorithm, and (3) To investigate
the reason for the failure of the EM method.

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