Word Translation Disambiguation Using Bilingual Bootstrapping

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Abstract
This paper proposes a new method for word translation disambiguation using a machine learning technique called ‘Bilingual Bootstrapping’. Bilingual Bootstrapping makes use of a small number of classified data and a large number of unclassified data in the source and the target languages in translation. It constructs classifiers in the two languages in parallel and repeatedly boosts the performances of the classifiers by further classifying data in each of the two languages and by exchanging between the two languages information regarding the classified data. Experimental results indicate that word translation disambiguation based on Bilingual Bootstrapping consistently and significantly outperforms the existing methods based on ‘Monolingual Bootstrapping’.

1 Introduction
We address here the problem of word translation disambiguation. For instance, we are concerned with an ambiguous word in English (e.g., ‘plant’), which has multiple translations in Chinese (e.g., ‘工厂’ (gongchang) and ‘植物’ (zhiwu)). Our goal is to determine the correct Chinese translation of the ambiguous English word, given an English sentence which contains the word. Word translation disambiguation is actually a special case of word sense disambiguation (in the example above, ‘gongchang’ corresponds to the sense of ‘factory’ and ‘zhiwu’ corresponds to the sense of ‘vegetation’). Yarowsky (1995) proposes a method for word sense (translation) disambiguation that is based on a bootstrapping technique, which we refer to here as ‘Monolingual Bootstrapping (MB)’.

In this paper, we propose a new method for word translation disambiguation using a bootstrapping technique we have developed. We refer to the technique as ‘Bilingual Bootstrapping (BB)’.

In order to evaluate the performance of BB, we conducted some experiments on word translation disambiguation using the BB technique and the MB technique. All of the results indicate that BB consistently and significantly outperforms MB.

2 Related Work
The problem of word translation disambiguation (in general, word sense disambiguation) can be viewed as that of classification and can be addressed by employing a supervised learning method. In such a learning method, for instance, an English sentence containing an ambiguous English word corresponds to an example, and the Chinese translation of the word under the context corresponds to a classification decision (a label).

Many methods for word sense disambiguation using a supervised learning technique have been proposed. They include those using Naïve Bayes (Gale et al. 1992a), Decision List (Yarowsky 1994), Nearest Neighbor (Ng and Lee 1996), Transformation Based Learning (Mangu and Brill 1997), Neural Network (Towell and

1 In this paper, we take English-Chinese translation as example; it is a relatively easy process, however, to extend the discussions to translations between other language pairs.
Instead of using Monolingual Bootstrapping, we propose a new method for word translation disambiguation using Bilingual Bootstrapping. In translation from English to Chinese, for instance, BB makes use of not only unclassified data in English, but also unclassified data in Chinese. It also uses a small number of classified data in English and, optionally, a small number of classified data in Chinese. The data in English and in Chinese are supposed to be not in parallel but from the same domain.

BB constructs classifiers for English to Chinese translation disambiguation by repeating the following two steps: (1) constructing classifiers for each of the languages on the basis of the classified data in both languages, (2) using the constructed classifiers in each of the languages to classify some unclassified data and adding them to the classified training data set of the language. The reason that we can use classified data in both languages at step (1) is that words in one language generally have translations in the other and we can find their translation relationship by using a dictionary.

### 3.2 Algorithm

Let $E$ denote a set of words in English, $C$ a set of words in Chinese, and $T$ a set of links in a translation dictionary as shown in Figure 1. (Any two linked words can be translation of each other.) Mathematically, $T$ is defined as a relation between $E$ and $C$, i.e., $T \subseteq E \times C$.

Let $\epsilon$ stand for a random variable on $E$, $\gamma$ a random variable on $C$. Also let $e$ stand for a random variable on $E$, $c$ a random variable on $C$, and $t$ a random variable on $T$. While $\epsilon$ and $\gamma$ represent words to be translated, $e$ and $c$ represent context words.

For an English word $\epsilon$, $T_\epsilon = \{ t \mid t = (\epsilon, \gamma), t \in T \}$ represents the links

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**Figure 1: Example of translation dictionary**
Input: \(E, C, T, L_E, U_E, L_C, U_C\), Parameter: \(b, \theta\)

Repeat in parallel the following processes for English (left) and Chinese (right), until unable to continue:

1. **for each** (\(\varepsilon \in E\))
   
   **for each** (\(t \in T_{\varepsilon}\))
   
   use \(L_{\varepsilon}\) and \(L_{\varepsilon} (\gamma \in C_{\varepsilon})\) to create classifier:
   \[
P_{\varepsilon}(t | \varepsilon, t \in T_{\varepsilon} \& P_{\varepsilon} (\tilde{\varepsilon} | \varepsilon, \tilde{\varepsilon} \in T_{\varepsilon} - \{t\})
   \]

2. **for each** (\(\varepsilon \in E\))
   
   \(NU \leftarrow \{\} ; NL \leftarrow \{\}; S_i \leftarrow \{\}; Q_i \leftarrow \{\};\)

   **for each** (\(e \in U_{\varepsilon}\))
   
   calculate \(\lambda' (e) = \max_{(\gamma \in C_{\varepsilon})} P_{\varepsilon}(t | e)\)

   let \(t' (e) = \arg \max_{(\gamma \in C_{\varepsilon})} P_{\varepsilon}(t | e)\)

   if (\(\lambda' (e) > \theta \& t' (e) = t\))
   
   put \(e\) into \(S_i\).

   **for each** (\(t \in T_{\varepsilon}\))
   
   sort \(e \in S_i\) in descending order of \(\lambda' (e)\) and put the top \(b\) elements into \(Q_i\).

   **for each** (\(e \in U_{\varepsilon}\))
   
   put \(e\) into \(NU\) and put \((e, t' (e))\) into \(NL\).

   \(L_{\varepsilon} \leftarrow L_{\varepsilon} \cup NL; U_{\varepsilon} \leftarrow U_{\varepsilon} - NU;\)

Output: classifiers in English and Chinese

\[\text{Figure 2: Bilingual Bootstrapping}\]

from it, and \(C_{\varepsilon} = \{\gamma' | (\varepsilon, \gamma') \in T\}\) represents the Chinese words which are linked to it. For a Chinese word \(\gamma\) let \(T_{\gamma} = \{ t | t = (\varepsilon', \gamma') \in T \} \) and \(E_{\gamma} = \{ e' | (e', \gamma) \in T \} \). We can define \(C_{\varepsilon}\) and \(E_{\gamma}\) similarly.

Let \(e\) denote a sequence of words (e.g., a sentence or a text) in English
\[
e = \{e_1, e_2, L, e_m\}, \ e_i \in E \ (i = 1,2,L,m).
\]

Let \(e\) denote a sequence of words in Chinese
\[
e = \{e_1, e_2, L, e_n\}, \ e_i \in C \ (i = 1,2,L,n).
\]

We view \(e\) and \(c\) as examples representing context information for translation disambiguation.

For an English word \(\varepsilon\), we define a **binary classifier** for resolving each of its translation ambiguities in \(T_{\varepsilon}\) in a general form as:
\[
P_{\varepsilon}(t | \varepsilon, t \in T_{\varepsilon} \& P_{\varepsilon} (\tilde{\varepsilon} | \varepsilon, \tilde{\varepsilon} \in T_{\varepsilon} - \{t\}),
\]

where \(e\) denotes an example in Chinese.

Let \(L_{\varepsilon}\) denote a set of classified examples in English, each representing one context of \(\varepsilon\)
\[
L_{\varepsilon} = \{ (e_i, t_i), (e_2, t_2), L, (e_m, t_m)\}, \ t_i \in T_{\varepsilon} \ (i = 1,2,L,k),
\]

and \(U_{\varepsilon}\) a set of unclassified examples in English, each representing one context of \(\varepsilon\)
\[
U_{\varepsilon} = \{ (e_i, (e_2), L, (e_m))\}.
\]

Similarly, we denote the sets of classified and unclassified examples with respect to \(\gamma\) in Chinese as \(L_{\gamma}\) and \(U_{\gamma}\) respectively. Furthermore, we have
\[
L = \bigcup_{\varepsilon \in E} L_{\varepsilon}; C = \bigcup_{\gamma \in C} L_{\gamma}; U = \bigcup_{\varepsilon \in E} U_{\varepsilon}; U_{\gamma} = \bigcup_{\gamma \in C} U_{\gamma}.
\]

We perform Bilingual Bootstrapping as described in Figure 2. Hereafter, we will only explain the process for English (left-hand side); the process for Chinese (right-hand side) can be conducted similarly.

### 3.3 Naïve Bayesian Classifier
While we can in principle employ any kind of classifier in BB, we use here a Naïve Bayesian Classifier. At step 1 in BB, we construct the classifier as described in Figure 3. At step 2, for each example $e$, we calculate with the Naïve Bayesian Classifier:

$$
\hat{P}(e | t) = \max_{\gamma \in C_e} \hat{P}(t | e) P(e | t)
$$

The second equation is based on Bayes’ rule.

In the calculation, we assume that the context words in $e$ (i.e., $e_1, e_2, \ldots, e_m$) are independently generated from $P(t | e)$ and thus we have

$$
P(t | e) = \prod_{i=1}^{m} P(t | e_i).
$$

We can calculate $P_e(e | t)$ similarly.

For $P(t | e)$, we calculate it at step 1 by linearly combining $P^{(E)}_e(e | t)$ estimated from English and $P^{(C)}_e(e | t)$ estimated from Chinese:

$$
P(t | e) = (1 - \alpha - \beta) P^{(E)}_e(e | t) + \alpha P^{(C)}_e(e | t) + \beta P^{(U)}(e),
$$

where $0 \leq \alpha, \beta \leq 1$, $0 \leq \alpha + \beta \leq 1$, and $P^{(U)}(e)$ is a uniform distribution over $E$, which is used for avoiding zero probability. In this way, we estimate $P_e(e | t)$ using information from not only English but also Chinese.

For $P^{(E)}_e(e | t)$, we estimate it with MLE (Maximum Likelihood Estimation) using $L_e$ as data. For $P^{(C)}_e(e | t)$, we estimate it as is described in Section 3.4.

### 3.4 EM Algorithm

For the sake of readability, we rewrite $P^{(C)}_e(e | t)$ as $P(e | t)$. We define a finite mixture model of

$$
P(e | t) = \sum_{\gamma \in C_e} P_{\gamma}(e | t) P(t | e)
$$

and for a specific $\gamma$ we assume that the data in $L_\gamma$ is generated on the basis of the model. We can, therefore, employ the Expectation and Maximization Algorithm (EM Algorithm) (Dempster et al. 1977) to estimate the parameters of the model including $P(e | t)$. We also use the relation $T$ in the estimation.

Initially, we set

$$
P(c | e, t) = \begin{cases} 
\frac{1}{|C_e|}, & \text{if } c \in C_e, \\
0, & \text{if } c \notin C_e 
\end{cases}
$$

We next estimate the parameters by iteratively updating them as described in Figure 4 until they converge. Here $f(c, t)$ stands for the frequency of $c$ related to $t$. The context information in Chinese is then ‘translated’ into that in English through the links in $T$.

### 4 Comparison between BB and MB

We note that Monolingual Bootstrapping is a special case of Bilingual Bootstrapping (consider the situation in which $\alpha$ equals 0 in formula (1)). Moreover, it seems safe to say that BB can always perform better than MB.

The many-to-many relationship between the words in the two languages stands out as key to the higher performance of BB.

Suppose that the classifier with respect to ‘plant’ has two decisions (denoted as A and B in Figure 5). Further suppose that the classifiers with
respect to ‘gongchang’ and ‘zhiwu’ in Chinese have two decisions respectively, (C and D) (E and F). A and D are equivalent to each other (i.e., they represent the same sense), and so are B and E.

Assume that examples are classified after several iterations in BB as depicted in Figure 5. Here, circles denote the examples that are correctly classified and crosses denote the examples that are incorrectly classified.

Since A and D are equivalent to each other, we can 'translate' the examples with D and use them to boost the performance of classification to A. This is because the misclassified examples (crosses) with D are those mistakenly classified from C and they will not have much negative effect on classification to A, even though the translation from Chinese into English can introduce some noises. Similar explanations can be stated to other classification decisions.

In contrast, MB only uses the examples in A and B to construct a classifier, and when the number of misclassified examples increases (this is inevitable in bootstrapping), its performance will stop improving.

5 Word Translation Disambiguation

5.1 Using Bilingual Bootstrapping

While it is possible to straightforwardly apply the algorithm of BB described in Section 3 to word translation disambiguation, we use here a variant of it for a better adaptation to the task and for a fairer comparison with existing technologies.

The variant of BB has four modifications.

(1) It actually employs an ensemble of the Naive Bayesian Classifiers (NBC), because an ensemble of NBCs generally performs better than a single NBC (Pedersen 2000). In an ensemble, it creates different NBCs using as data the words within different window sizes surrounding the word to be disambiguated (e.g., ‘plant’ or ‘zhiwu’) and further constructs a new classifier by linearly combining the NBCs.

(2) It employs the heuristics of ‘one sense per discourse’ (cf., Yarowsky 1995) after using an ensemble of NBCs.

(3) It uses only classified data in English at the beginning.

(4) It individually resolves ambiguities on selected English words such as ‘plant’, ‘interest’. As a result, in the case of ‘plant’; for example, the classifiers with respect to ‘gongchang’ and ‘zhiwu’ only make classification decisions to D and E but not C and F (in Figure 5). It calculates \( \hat{x}(e) = \hat{x}(e) = P(c | i) \) and sets \( \theta = 0 \) at the right-hand side of step 2.

5.2 Using Monolingual Bootstrapping

We consider here two implementations of MB for word translation disambiguation.

In the first implementation, in addition to the basic algorithm of MB, we also use (1) an ensemble of Naive Bayesian Classifiers, (2) the heuristics of ‘one sense per discourse’, and (3) a small number of classified data in English at the beginning. We will denote this implementation as MB-B hereafter.

The second implementation is different from the first one only in (1). That is, it employs as a classifier a decision list instead of an ensemble of NBCs. This implementation is exactly the one proposed in (Yarowsky 1995), and we will denote it as MB-D hereafter.

MB-B and MB-D can be viewed as the state-of-the-art methods for word translation disambiguation using bootstrapping.

6 Experimental Results
We conducted two experiments on English-Chinese translation disambiguation.

### 6.1 Experiment 1: WSD Benchmark Data

We first applied BB, MB-B, and MB-D to translation of the English words ‘line’ and ‘interest’ using a benchmark data\(^2\). The data mainly consists of articles in the Wall Street Journal and it is designed for conducting Word Sense Disambiguation (WSD) on the two words (e.g., Pedersen 2000).

#### Table 1: Data descriptions in Experiment 1

| Words | Chinese translations | Corresponding English senses | Seed words |
|-------|----------------------|-----------------------------|------------|
| interest | 兴趣 | readiness to give attention | show |
|   | 利息 | money paid for the use of money | rate |
|   | 股份, 股权 | a share in company or business | hold |
|   | 利益 | advantage, advancement or favor | conflict |
| line | 绳索, 绳绳 | a thin flexible object | cut |
|   | 行, 句 | written or spoken text | write |
|   | 线路 | telephone connection | telephone |
|   | 队伍, 队列 | formation of people or things | wait |
|   | 界线, 边界 | an artificial division | between |
|   | 产品, 品种 | product | product |

#### Table 2: Data sizes in Experiment 1

| Words | Unclassified sentences | Test sentences |
|-------|------------------------|---------------|
| interest | 1927 | 8811 |
| line | 3666 | 5398 |

#### Table 3: Accuracies in Experiment 1

| Words | Major (%), MB-D (%), MB-B (%), BB (%) |
|-------|-------------------------------------|
| interest | 54.6, 54.7, 69.3, 75.5 |
| line | 53.5, 55.6, 54.1, 62.7 |

#### Table 4: Accuracies of supervised methods

| Sense Disambiguation (WSD) on the two words (e.g., Pedersen 2000). |
|-------------------|
| Ensembles of NBC | 89 |
| Naïve Bayes | 74 |
| Decision Tree | 78 |
| Neural Network | - |
| Nearest Neighbor | 87 |

We adopted from the HIT dictionary\(^3\) the Chinese translations of the two English words, as listed in Table 1. One sense of the words corresponds to one group of translations.

We then used the benchmark data as our *test data*. (For the word ‘interest’, we only used its four major senses, because the remaining two minor senses occur in only 3.3% of the data)

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\(^2\) http://www.d.umn.edu/~tpederse/data.html.

\(^3\) The dictionary is created by Harbin Institute of Technology.
As classified data in English, we defined a ‘seed word’ for each group of translations based on our intuition (cf., Table 1). Each of the seed words was then used as a classified ‘sentence’. This way of creating classified data is similar to that in (Yarowsky, 1995). As unclassified data in English, we collected sentences in news articles from a web site (www.news.com), and as unclassified data in Chinese, we collected sentences in news articles from another web site (news.cn.tom.com). We observed that the distribution of translations in the unclassified data was balanced.

Table 2 shows the sizes of the data. Note that there are in general more unclassified sentences in Chinese than in English because an English word usually has several Chinese words as translations (cf., Figure 5).

As a translation dictionary, we used the HIT dictionary, which contains about 76000 Chinese words, 60000 English words, and 118000 links.

We then used the data to conduct translation disambiguation with BB, MB-B, and MB-D, as described in Section 5.

For both BB and MB-B, we used an ensemble of five Naïve Bayesian Classifiers with the window sizes being $\pm 1, \pm 3, \pm 5, \pm 7, \pm 9$ words. For both BB and MB-B, we set the parameters of $\beta, b,$ and $\theta$ to 0.2, 15, and 1.5 respectively. The parameters were tuned based on our preliminary experimental results on MB-B, they were not tuned, however, for BB. For the BB specific parameter $\alpha$, we set it to 0.4, which meant that we treated the information from English and that from Chinese equally.

Table 3 shows the translation disambiguation accuracies of the three methods as well as that of a baseline method in which we always choose the major translation. Figures 6 and 7 show the learning curves of MB-D, MB-B, and BB. Figure 8 shows the accuracies of BB with different $\alpha$ values.

From the results, we see that BB consistently and significantly outperforms both MB-D and MB-B. The results from the sign test are statistically significant (p-value < 0.001).

Table 4 shows the results achieved by some existing supervised learning methods with respect to the benchmark data (cf., Pedersen 2000). Although BB is a method nearly equivalent to one based on unsupervised learning, it still performs favorably well when compared with the supervised methods (note that since the experimental settings are different, the results cannot be directly compared).

### 6.2 Experiment 2: Yarowsky’s Words

We also conducted translation on seven of the twelve English words studied in (Yarowsky, 1995). Table 5 shows the list of the words.

For each of the words, we extracted about 200 sentences containing the word from the Encarta English corpus and labeled those sentences with Chinese translations ourselves. We used the labeled sentences as test data and the remaining sentences as unclassified data in English. We also used the sentences in the Great Encyclopedia Chinese corpus as unclassified data in Chinese. We defined, for each translation,
We did not, however, conduct translation disambiguation on the words 'crane', 'sake', 'poach', 'axes', and 'motion', because the first four words do not frequently occur in the Encarta corpus, and the accuracy of choosing the major translation for the last word has already exceeded 98%.

We next applied BB, MB-B, and MB-D to word translation disambiguation. The experiment settings were the same as those in Experiment 1. From Table 6, we see again that BB significantly outperforms MB-D and MB-B. (We will describe the results in detail in the full version of this paper.) Note that the results of MB-D here cannot be directly compared with those in (Yarowsky, 1995), mainly because the data used are different.

### 6.3 Discussions

We investigated the reason of BB’s outperforming MB and found that the explanation on the reason in Section 4 appears to be true according to the following observations.

(1) In a Naïve Bayesian Classifier, words having large values of probability ratio $P(e|t)$ have strong influence on the classification of $t$ when they occur, particularly, when they frequently occur. We collected the words having large values of probability ratio for each $t$ in both BB and MB-B and found that BB obviously has more ‘relevant words’ than MB-B. Here ‘relevant words’ for $t$ refer to the words which are strongly indicative to $t$ on the basis of human judgments.

Table 7 shows the top ten words in terms of probability ratio for the ‘利息’ translation (‘money paid for the use of money’) with respect to BB and MB-B, in which relevant words are underlined. Figure 9 shows the numbers of relevant words for the four translations of ‘interest’ with respect to BB and MB-B.

(2) From Figure 8, we see that the performance of BB remains high or gets higher when $\alpha$ becomes larger than 0.4 (recall that $\beta$ was fixed to 0.2). This result strongly indicates that the information from Chinese has positive effects on disambiguation.

(3) One may argue that the higher performance of BB might be attributed to the larger unclassified data size it uses, and thus if we increase the
unclassified data size for MB, it is likely that MB can perform as well as BB.

We conducted an additional experiment and found that this is not the case. Figure 10 shows the accuracies achieved by MB-B when data sizes increase. Actually, the accuracies of MB-B cannot further improve when unlabeled data sizes increase. Figure 10 plots again the results of BB as well as those of a method referred to as MB-C. In MB-C, we linearly combine two MB-B classifiers constructed with two different unlabeled data sets and we found that although the accuracies get some improvements in MB-C, they are still much lower than those of BB.

7 Conclusion

This paper has presented a new word translation disambiguation method using a bootstrapping technique called Bilingual Bootstrapping. Experimental results indicate that BB significantly outperforms the existing Monolingual Bootstrapping technique in word translation disambiguation. This is because BB can effectively make use of information from two sources rather than from one source as in MB.

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